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Forecasting tourism recovery amid COVID-19

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ABSTRACT

The profound impact of the coronavirus disease 2019 (COVID-19) pandemic on global tourism activity has rendered forecasts of tourism demand obsolete. Accordingly, scholars have begun to seek the best methods to predict the recovery of tourism from the devastating effects of COVID-19. In this study, econometric and judgmental methods were combined to forecast the possible paths to tourism recovery in Hong Kong. The autoregressive distributed lag-error correction model was used to generate baseline forecasts, and Delphi adjustments based on different recovery scenarios were performed to reflect different levels of severity in terms of the pandemic's influence. These forecasts were also used to evaluate the economic effects of the COVID-19 pandemic on the tourism industry in Hong Kong.

Introduction

In many places, tourism has become a strategic pillar industry, given its increasingly significant contributions to the local gross domestic product (GDP). Despite its importance, tourism is also one of the most vulnerable industries. The tourism industry has experienced significant negative effects during so-called "black swan" crisis events, such as the financial crises in 1997 and 2008, the severe acute respiratory syndrome (SARS) epidemic in 2003, and various earthquakes and episodes of social unrest. Business operations are contingent on forecasts. However, forecasts generated using traditional methods might be out-of-date and ineffective in a crisis. Therefore, a useful method that can produce accurate forecasts for both academia and business purposes is urgently needed.

Since late 2019, the coronavirus disease 2019 (COVID-19) pandemic has caused unprecedented global health and social emergencies and profound negative impacts on the global economy. By September 30, 2020, 33,561,077 confirmed cases of COVID-19 and 1,005,004 deaths had been reported worldwide (World Health Organization; WHO, 2020). The United Nations World Tourism Organization (UNWTO) reported that by April 20, 2020, all major tourist destinations had implemented travel restrictions in response to the COVID-19 pandemic (UNWTO, 2020). Tourism is among the industries most negatively affected by this pandemic. Lockdowns in many countries, widespread travel restrictions, and airport and national border closures reduced the number of international tourist arrivals by 67 million during the first quarter of 2020 (2020Q1). This decrease implies a loss of approximately US$80 billion in tourism revenue, compared with the same period in 2019 (UNWTO, 2020).

Hong Kong, which is known as the Pearl of the Orient, blends Eastern and Western cultures and is famous for its gourmet and shopping opportunities. Since the late 1980s, Hong Kong has vigorously developed its service sector. In 1989, the total tourist arrivals in Hong Kong were only 5,361,170 (Census and Statistics Department, 1990). By 2018, this number had increased to 65.15

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million, with annual tourist revenues of HK$328.2 billion (Tourism Commission, 2019). In the first half of 2019, Hong Kong welcomed 34,871,856 inbound tourists, and this number represented a 13.9% increase relative to 2018 (Gov. HK, 2020).

Nevertheless, the COVID-19 pandemic has led to severe losses in the Hong Kong tourism sector. From January 1 to September 30, 2020, 5087 confirmed cases of COVID-19 were recorded in Hong Kong. Travel restrictions were introduced on January 27, followed by a more comprehensive travel ban on all non-Hong Kong resident overseas travelers on March 25 (Gov. HK, 2020). Prior to the COVID-19 pandemic, the tourism industry in Hong Kong had already been negatively affected by the social unrest that began in July 2019; this resulted in a 39.1% reduction in tourist arrivals by the second half of the year. The COVID-19 pandemic further led to a decline of 80.9% in the number of cumulative visitor arrivals by the end of 2020Q1, compared with the same quarter in 2019 (Hong Kong Tourism Board, 2020).

Both tourism businesses and organizations rely on recovery forecasting when preparing their crisis recovery plans. Many studies on tourism demand forecasting have used statistical approaches, such as time series, econometric, and artificial intelligence (Song et al., 2019). The resulting statistical models provide objective forecasts based on large amounts of historical data without interventions (Sanders & Ritzman, 2001). However, statistical methodologies cannot capture the impacts of sudden unanticipated events, such as diseases, disasters, or other crises, on the forecasts. Therefore, statistical forecasts must be adjusted using judgmental approaches to enhance their performance under such circumstances. In this context, experts can apply their domain expertise and up-to-date information to gauge the influences of various events and make necessary adjustments to improve the forecasting accuracy of the statistical forecasts (Armstrong & Collopy, 1998; Sanders & Ritzman, 2001).

The scenario analysis and Delphi technique are widely used approaches in judgmental forecasts. Lin et al. (2014) and Lin (2013) used Delphi surveys to forecast visitor arrivals and found that their judgmental adjustments enhanced the accuracy of the forecasts relative to the single statistical forecasts. Lee et al. (2008) proved the outstanding accuracy of the integrated forecasting method. Smeral (2010) developed two scenarios to forecast the demand for foreign travel amid the economic crisis during 2009–2010. Besides, Alessi et al. (2014) used the scenario-based method to predict macroeconomic variables, including GDP growth, the unemployment rate, and inflation, in response to a global financial crisis. Chauvet and Potter (2013) predicted the U.S. output growth during the recession using projections made by Delphi panelists based on up-to-date information. These studies concluded that the crises reduced the accuracy of the forecasts generated by traditional forecasting methods, whereas the judgmental forecasts exhibited superior forecast accuracy relative to alternative models in crisis scenarios. Although tourism researchers have applied individual judgmental methods, none has used the integrated judgmental approach to predict the recovery of tourism demand in times of crisis. Besides, most tourism studies have focused on *ex post* forecasts. However, businesses and organizations require additional information associated with *ex ante* forecasts for budgeting and operation purposes, especially in the context of a crisis.

This paper describes the first attempt to combine three methods, including a quantitative model (the autoregressive distributed lag-error correction model, ARDL-ECM) and two prevalent qualitative approaches (the Delphi technique and scenario analysis), to generate *ex ante* forecasts of the recovery of tourism demand in response to the unanticipated effects of crises. The integration of these three methods was expected to overcome the shortcomings of each single method while integrating their advantages. For example, the Delphi technique might be biased by the panel members' optimism or pessimism, wishful thinking, lack of consistency, and manipulation. However, the scenario analysis can incorporate a range of possible outcomes to avoid these common types of bias. Beyond Hong Kong, the method proposed in this study could be generalized and used to forecast the recovery of travel demand at other destinations facing major crises. Furthermore, the specific recovery speed associated with each origin market could be projected, and the direct economic costs attributable to COVID-19 could be evaluated. From our perspective, this study makes important methodological and practical contributions to the literature on tourism demand forecasting.

The remainder of this paper is organized as follows. Section 2 reviews previous studies on the impacts of major crises on tourism demand forecasting. Section 3 discusses the methodologies and data used in this study and is followed by a discussion of the empirical results. Section 5 concludes our study.

Literature review

Over the past five decades, a large body of literature on tourism demand modeling and forecasting via various methodologies has emerged (for a recent review, see Song et al., 2019). In this paper, the literature review focuses only on tourism demand forecasting when a crisis affects the model accuracy/reliability. The demand for tourism in a rapidly changing environment may be affected by many unpredictable factors, such as natural disasters (e.g., earthquakes, tsunamis, hurricanes, and floods), human-made crises (e.g., terrorist attacks, wars, economic/financial crises, and political turmoil), and sudden epidemics (e.g., SARS; Wang, 2009). Most studies have mentioned these topics in terms of providing crisis management suggestions for decision-makers in the tourism industry.

The economic and financial crises in 1997–1998 and 2007–2008 severely affected the tourism industries in many countries and regions. Law (2001) used seven traditional tourism forecasting techniques to examine the accuracy of forecasts that predicted Japanese arrivals to Hong Kong in five accuracy dimensions. In that study, no single method outperformed the alternatives in any of the forecasting accuracy dimensions in the context of a crisis, although the artificial neural network outperformed the other approaches in most situations. Chu (2008) investigated how the Asian financial crisis, the September 11th terrorist attacks, and the SARS epidemic affected the volume of tourists to Singapore using the fractionally integrated autoregressive moving average model, and found that it generated more accurate forecasts than the alternatives during crises. When assessing the accuracy of forecasts of tourist flows to Indonesia, which were produced prior to the political and financial crises in 1997, Prideaux et al. (2003) concluded that the existing quantitative methods could not handle an unprecedented crisis and suggested alternative methods, such as scenario planning and chaos theory-derived models, that incorporated the effects of underlying risk factors in the forecasting process.

Song and Lin (2010) used the tourist flows to and from Asia to estimate the interval tourism demand elasticities within an autoregressive distributed lag (ARDL) framework. The estimated demand elasticities were then used to generate forecasts of these flows during 2010–2014. The authors demonstrated that interval forecasts could incorporate the effects of the financial crisis during 2007–2008 and thus generate relatively reliable forecasts. Song et al. (2010) integrated the ARDL model with a scenario analysis to investigate the effects of the financial crisis during 2007–2008 on the factors influencing the demand for Hong Kong tourism during 2009–2012. In that study, the authors showed that Hong Kong's long-haul markets would suffer more losses from the negative effects of the financial crisis than the short haul markets. Page et al. (2012) combined the time varying parameter (TVP) approach with a scenario analysis to investigate the influences of the economic and financial crisis and the roughly concurrent swine flu pandemic on the demand for inbound tourism in the United Kingdom (U.K.) from 2008Q1 to 2009Q2. The authors successfully used a counterfactual approach to separate the effects of these two crises on the tourism demand, and showed that both crises imposed significantly negative effects on the inbound demand for U.K. tourism in all 14 source markets.

The September 11th terrorist attacks in the United States (U.S.) had an extremely adverse impact on the U.S. economy and tourism sector. Lee et al. (2005) investigated the effects of these attacks on the demand for air travel using time series approaches and interventions. In fact, they found that these events had a short-lived effect on passenger travel. To evaluate the extent to which the same attacks affected the demand for tourism in Hawaii, Bonham et al. (2006) used the vector error correction model (VECM) to forecast the tourist flows to this U.S. state in the absence of the attacks and compared the results with the actual tourist flows. Saha and Yap (2014) used the panel data approach to examine the effects of political instability and terrorism on the performance of tourism in 139 countries. They argued that a reliable forecast of tourism demand requires the inclusion of political stability and terrorist attack variables.

Yeoman, Galt, and McMahon-Beattie (2005) predicted that a forthcoming war in Iraq would affect the economic environment and tourism markets, based on four scenarios. Their findings are useful for organizations that must implement plans to address contingencies in each scenario. These scholars emphasized the importance of a scenario analysis in the policy formulation process. Natural disasters and diseases also adversely affect the demand for tourism, as both types of crises increase tourists' risk perceptions of safety and wellness when they travel to the affected destinations. Huang and Min (2002) used a seasonal autoregressive integrated moving average (SARIMA) model to evaluate the recovery of Taiwan tourism after the Taiwan earthquake in 1999. By comparing the actual tourist arrivals with the forecasts, they found that the visitor volume did not recover to its original level even 11 months after the earthquake.

Chen et al. (2007) built a SARIMA model that incorporated seasonal and unprecedented incident dummies to forecast the travel demand in China. They investigated the impact of the SARS epidemic in 2003 and the bird flu outbreak in 2005 on tourism demand and revealed that the former led to a decrease in visitor arrivals to China of more than 42%. Wang (2009) used an ARDL model to examine the influences of several significant events, including the Asian financial crisis, the Taiwan earthquake in 1999, the September 11th terrorist attacks, and the SARS epidemic in 2003, on inbound tourism in Taiwan and concluded that crises that threatened human safety, such as the SARS epidemic, had the most severe effects on the tourism demand.

Page et al. (2006) used scenario planning to examine Visit Scotland, the Scottish Tourism Organization's response to the effect of the avian flu on the Scottish tourism industry. Their findings highlighted the importance of scenario planning in terms of preparing for crises. Yeoman, Lennon, and Black (2005) investigated the potential effects of foot-and-mouth disease on the tourism industry in Scotland and the U.K. using two scenarios, namely a suspected outbreak and a confirmed outbreak of foot-and-mouth disease, and concluded that the lessons learned from the events before and after contingency planning were vital because of the recurrent nature of the events.

Tourism demand forecast studies that incorporate the influences of crises can be divided into two categories: *ex post* and *ex ante* forecasts. The majority of studies have used quantitative, qualitative, or combinations of both methods to examine the effects of crises on *ex post* forecasts or to compare the forecasting accuracies of several methods. Most of those studies accounted for the effects of unexpected one-off events on tourism demand by introducing dummy variables to represent the structural changes caused by these events (Chen et al., 2007; Goh & Law, 2002; Lim & McAleer, 2002). Very few studies (Page et al., 2006; Yeoman, Lennon, & Black, 2005) have considered the effects of crises on *ex ante* tourism demand forecasts. However, tourism practitioners are more interested in *ex ante* forecasts than in *ex post* forecasts, especially during or immediately after a crisis.

Crises such as the COVID-19 pandemic are sudden, uncertain, and volatile. Traditional approaches may not be applicable or effective for forecasting a recovery of tourism demand. A more systematic and reliable forecasting method that incorporates the advantages of existing forecasting methods is needed to generate accurate forecasts in this context. Here, we propose an integrated, scenario-based Delphi adjustment approach to the production of *ex ante* forecasts of tourism demand under different impact scenarios. To the best of our knowledge, such an approach has not been used previously in tourism demand forecasting. In this study, we used this scenario-based Delphi adjustment approach to forecast tourist arrivals in Hong Kong from key source markets and predict tourism income losses due to the COVID-19 pandemic. Our findings may provide important information for governments and businesses that seek to understand the specific losses caused by the COVID-19 pandemic and take appropriate remedial measures to revive their tourism industries.

Methodology

Scenario-based Delphi adjustment approach

The scenario-based Delphi adjustment forecasting approach was designed to adjust *ex ante* forecasts to accommodate the effects of crises during the forecasting period. This method includes three stages (see Fig. 1). In the first stage of model estimation, the properties of the variables were tested for unit roots, and the co-integration relationships between the variables were verified using the bounds test (Pesaran et al., 2001). Then, the demand models were estimated using the general-to-specific modeling approach (Song & Witt, 2000). The final ARDL-ECMs for each source market were then subjected to a battery of diagnostic tests to ensure that the models were correctly specified. In the second stage, the forecasts of the explanatory variables were generated using the time series approach, after which the baseline forecasts of tourist arrivals from each source market were produced using the final ARDL-ECMs. In the final stage, the Delphi panelists adjusted the baseline forecasts to account for the influence of the COVID-19 pandemic. In this stage, three recovery scenarios based on different severities of the COVID-19 impact were developed.

Stage 1: econometric modeling by ARDL-ECM

In Stage 1, this study used ARDL-ECMs to estimate and forecast the inbound tourist arrivals to Hong Kong from 2020Q1 to 2024Q4. This approach was chosen for the following reasons. First, the ARDL-ECM is the most commonly used econometric method in tourism demand forecasting, as its forecasting performance is superior to that of alternative models (Song et al., 2000). Song et al. (2019) reviewed 211 papers on tourism demand forecasting; among the 50 papers describing the use of the ARDL and ECM, 33 indicated that these were the "best performing" models in terms of forecast accuracy. Second, unlike the time series and artificial intelligence models, the ARDL-ECM incorporates explanatory variables that affect the demand for tourism. The estimated parameters associated with these explanatory variables provide important information for policy purposes (Lin et al., 2015; Song & Li, 2008; Song et al., 2009). In contrast to other models, practitioners consider the ARDL-ECM is easy to understand and apply because it is based on economic theories. Practitioners can easily understand the economic rationale behind this model (Song et al., 2019). Third, the ARDL-ECM is dynamic and flexible because it includes lag components that incorporate both short-run and long-run effects. The bounds test proposed by Pesaran et al. (2001) is applicable to the ARDL-ECM even though the variables are not integrated in the same order.

In this study, 16 ARDL-ECMs that corresponded to tourist arrivals from 16 major source markets, including Australia, Canada, mainland China, France, Germany, Indonesia, Japan, South Korea, Macau, Malaysia, the Philippines, Singapore, Taiwan, Thailand, the U.K., and the U.S., were estimated. Tourist arrivals from these markets accounted for approximately 95% of the total tourist arrivals to Hong Kong in 2018 (Hong Kong Tourism Board, 2020). Forecasts of the tourist arrivals from these 16 source markets were then generated using the estimated ARDL-ECMs.

The inbound tourism demand is normally determined from the arrivals or expenditures of tourists or the number of nights spent by tourists at a destination (Lin et al., 2014; Song et al., 2009; Song et al., 2010; Song & Li, 2008). We measured the demand for Hong Kong tourism based on the tourist arrivals from the 16 source markets. According to Song et al. (2009), the demand for tourism is generally affected by the following factors: the tourism costs in Hong Kong relative to those in the origin markets, the substitution prices in competing destinations, and the tourists' income levels. Apart from these explanatory variables, other determinants include the marketing expenditures of the destination in the source markets and the tastes and preferences of tourists (Song et al., 2009).

Data on the quarterly visitor arrivals from 2000Q1 to 2019Q4 were collected from the official website of the Hong Kong Tourism Board (Hong Kong Tourism Board, 2020), and data on the independent variables, such as the GDP index (2010 = 100),

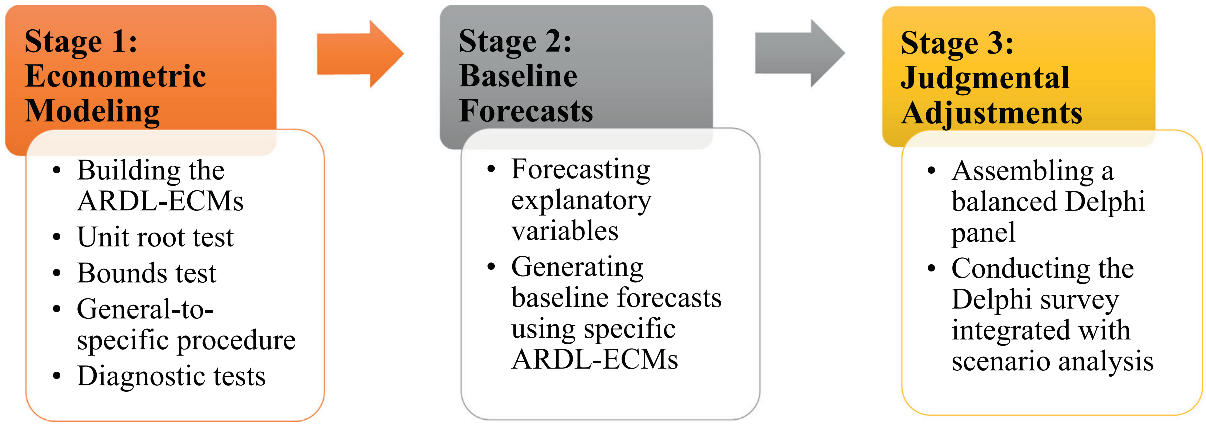


Fig. 1. Scenario-based Delphi adjustment approach.

consumer price index (CPI, 2010 = 100), and exchange rates, were obtained from the International Monetary Fund (IMF, 2020). The visitor arrivals at seven competing destinations (Macau, Taiwan, mainland China, Japan, South Korea, Thailand, and Singapore) were obtained from the Government of Macau Special Administrative Region Statistics and Census Service (2020), the Tourism Bureau Ministry of Transportation and Communications of Taiwan (2020), and the CEIC database (2020).

The ARDL-ECM is expressed as follows:

$$\Delta \ln TA_{it} = \alpha_0 + \sum_{j=1}^{p_1}\alpha_j\Delta \ln TA_{i,t-j} + \sum_{j=0}^{p_2}\beta_j\Delta \ln Y_{i,t-j} + \sum_{j=0}^{p_3}\gamma_j\Delta \ln P_{i,t-j} + \sum_{j=0}^{p_4}\delta_j\Delta \ln P_{s,t-j} + \lambda_1 \ln TA_{i,t-1} + \lambda_2 \ln Y_{i,t-1} + \lambda_3 \ln P_{i,t-1} + \lambda_4 \ln P_{s,t-1} + dummies + \varepsilon_{it} \tag{1}$$

where TA_{it} represents the tourist arrivals from source market i to Hong Kong at time t. $Y_{i,t}$ is the GDP index of source market i at time t. $P_{i,t}$ is the price of tourism in Hong Kong relative to that in the source market i ($P_{i,t} = (CPI_{HK,t}/EX_{HK,t})/(CPI_{i,t}/EX_{i,t})$). CPI and EX indicate the consumer price index (2010 = 100) and the real exchange rate in U.S. dollars, respectively. $P_{s,t}$ is the weighted price index of the substitute destinations ($P_{s,t} = \sum_{k=1}^{7}(CPI_{k,t}/EX_{k,t})w_{k,t}$). w_k is the ratio of tourist arrivals in each of the substitute destinations to the total tourist arrivals in the substitute destinations ($w_{k,t} = TA_{k,t}/\sum_{k=1}^{7}TA_{k,t}$). ε_{it} represents the error term, which follows a normal distribution with a zero mean and a constant variance of σ^2. p represents the number of lags determined using the Akaike information criterion (AIC; Song et al., 2009; Song et al., 2012). Seasonal, one-off events and specific market-related dummies, such as the SARS epidemic in 2003, the global financial crisis in 2008, and the social unrest in Hong Kong in 2019Q3 and 2019Q4, were also included in the initial model.

Before estimating Eq. (1), the augmented Dickey–Fuller unit root test (1979) was performed to check the stationarity of the variables. The cointegration test, or bounds test, was conducted to examine the existence of a level long-run relationship between a dependent variable and the independent variables, irrespective of whether the variables are integrated in the same order. The bounds test can be described as a test of the significance of the lagged levels of the variables based on *F*- and *t*-statistics. As the dependent variable and regressors are not related in levels (null hypothesis), the asymptotic distributions of the two statistics should be non-standard. Two sets of asymptotic critical values are provided and span a band of all regressors integrated on order zero, order one, or jointly cointegrated. If both the *F*- and *t*-test statistics exceed the upper bounds of the critical values, then the null hypothesis is rejected, and the existence of a long-run relationship is confirmed (Pesaran et al., 2001).

Upon confirming the cointegration relationship, Eq. (1) was re-estimated recursively to reduce the model by eliminating the insignificant variables. For a detailed process of this model reduction, see Song and Witt (2000). A series of diagnostic tests, including the Breusch–Godfrey (1978) Lagrange multiplier chi-square test for serial correlation, the Breusch–Pagan test for heteroscedasticity, the Jarque–Bera (1980) chi-square test for normality, and the Ramsey (1969) RESET test for misspecification, were performed for both the initial models and each of the reduced models to ensure that they were correctly specified.

Stage 2: baseline forecasts generated by ARDL-ECMs

To generate the forecasts of tourist arrivals from different source markets during 2020Q1–2024Q4, the values of the explanatory variables, including the income levels in the source markets, the relative own price, and the substitute price, over this period must also be forecasted. In this study, we predicted the explanatory variables using the Holt–Winter seasonal exponential smoothing method, in accordance with previous studies (Song & Witt, 2000; Song, Witt, & Li, 2003; Taylor, 2003; Song et al., 2013). Song and Witt (2000) suggested that the exponential smoothing approach is a relatively inexpensive and reliable method of forecasting the future values of independent variables in tourism demand studies. Song, Wong, and Chon (2003) mentioned that exponential smoothing methods generate more accurate forecasts of independent variables than do other time series models. After obtaining the forecasts of the explanatory variables, the baseline forecasts of tourist arrivals were generated by substituting the forecasts with the specific models derived through the model reduction process.

Stage 3: judgmental adjustments made using the Delphi-scenario technique

Among the existing qualitative approaches, the Delphi method and scenario technique are the two most commonly adopted by tourism forecasting scholars and practitioners, especially for judgmental adjustments (Lin & Song, 2015). The Delphi technique is defined as "the systematic utilization of the judgment of experts [that] aims to obtain a consensus among judges on informed predictions of future events" (Ng, 1984, p. 48). This approach is well known for its anonymity, iteration, controlled feedback, and convergence in responses (Frechtling, 2001; Lin, 2013; Lin & Song, 2015). Because the ARDL-ECMs were estimated using data from 2000Q1 to 2019Q4, the baseline forecasts could not take the COVID-19 pandemic into account. In the third stage, the baseline forecasts required adjustments in the context of COVID-19. To ensure the reliability of these adjustments, a Delphi panel of experts with rich experience in industry or academia was assembled. COVID-19 is a complex, volatile crisis; therefore, a scenario analysis was integrated into the Delphi surveys to capture other possible outcomes.

In a Delphi survey, the first step is the determination of the panel members. This step is vital to ensuring that the adjustments made by the panel are reliable and authoritative (Lin & Song, 2015). A balanced and diversified panel of experts is very important in this context. The panel should comprise experts representing a range of statures, knowledge bases, skills, and affiliations to eliminate possible extreme opinions (Kollwitz, 2011). Donohoe and Needham (2009) proffered three criteria for panel member selection. Specifically, the members should (1) have sufficient practical experience and familiarity with the issue of concern

Table 1
Composition of the Delphi panel.

Sector	Round 1	Round 2	Title	Round 1	Round 2
Academic institution	7	7	Professor	4	4
Travel agency	1	1	Assistant professor	3	3
Hotel	3	3	Senior executives	9	8
Association	1	1	Department manager	1	1
MICE	1	1			
Transportation	1	/			
Retail	1	1			
Travel agency & MICE	1	1			
Catering, hotel, & MICE	1	1			
Grand total	17	16	Grand total	17	16

(i.e., tourism demand) and be capable of identifying the cause–effect relationship between the studied factors; (2) be willing to actively participate in the survey and share the information that they possess; and (3) have first-hand domain knowledge and expertise relevant to the issue.

The panel size is also a significant factor in a qualified Delphi panel. Lin and Song (2015) summarized that since the 1970s, the panel sizes used in applications of the Delphi technique in tourism studies have ranged from 6 to more than 900. McCleary and Whitney (1994) suggested that a balanced panel should include at least 10 experts from both industry and academic institutions. Rowe and Wright (2001) asserted that the panel should comprise 5–20 experts with disparate expertise. The optimal panel size depends on the nature, scope, and topic of the study and the diversification of the panelists' domain knowledge (Sadi & Henderson, 2005). There are no definitive rules for an appropriate panel size, and this factor may affect the reliability of the results.

In light of the proffered criteria for a balanced panel, we selected 17 Delphi experts to adjust the baseline forecasts in our study. Seven of the panel members were employed at academic institutions in Hong Kong, Macau, and the U.K.. All seven academics specialized in tourism forecasting and destination management (four professors and three assistant professors). Ten of the panel members were employed in the tourism industry or by professional associations. Among them, nine were corporate-level senior executives, and one was a department manager at a major travel company in Hong Kong. The composition and profiles of the Delphi panel members are displayed in Table 1. We believe that the panel was balanced because the members originated from different sectors related to tourism. All of the participants were asked to self-rate their levels of expertise in tourism forecasting on a 5-point Likert scale, ranging from “Very little” (1) to “Excellent” (5). In Table 2, we show that 88% of the experts rated themselves as having above-average experience in and knowledge of tourism forecasting.

Two rounds of questionnaire surveys were administered via email on June 29, 2020 and July 14, 2020. At the beginning of the first questionnaire survey, we provided the panel members with a background statement that described the purpose of the survey, COVID-19-related information (confirmed cases in the origin markets and Hong Kong, travel restrictions, and vaccine development), and the statistical forecasts for each source market. Three scenarios (mild, medium, and severe) were proposed according to the severity of the impact of COVID-19-related factors on the tourism demand in Hong Kong. While making the adjustments, the experts were asked to consider the three scenarios and respond to the questions pertaining to all of them. The first round of the survey included two questions. Question 1 asked the panel members to indicate whether they agreed that the tourist arrivals from each source market would reach a minimum in 2020Q2. If the respondents disagreed with this statement, they were asked to indicate when they thought the tourist arrivals would reach a minimum. Question 2 asked the experts when they thought the number of arrivals from each origin would return to the baseline forecasts generated by the ARDL-ECM.

The experts' responses in the first-round survey were collected and aggregated. The time span between quarter A, when the tourist arrivals hit a minimum, and quarter B, when the tourist arrivals returned to the baseline forecasts, was regarded as the recovery period. The demand recovery paths were obtained using the following steps. First, based on the responses from the first-round survey, we calculated the percentage decrease in the number of tourist arrivals in quarter A. Second, we generated a recovery path by assuming the same percentage of recovery in each quarter between quarter A and quarter B. Third, we generated the adjusted forecasts by multiplying the baseline forecasts by the recovery path for each of the quarters between quarter

Table 2
Self-rating of expertise in tourism demand forecasting.

Expertise level	Number	Percentage
(1) Very little	0	0
(2) A little	2	11.8%
(3) Fair	6	35.3%
(4) Good	6	35.3%
(5) Excellent	3	17.6%

A and quarter B. Finally, we established all of the recovery paths in the three scenarios through this computation procedure. In the second round of the questionnaire survey, the initial consolidated scenario forecasts were presented to the panel members for further adjustments. The experts were asked to select the appropriate percentage increase or decrease in the forecasts of tourist arrivals obtained during the first round of the survey for all three scenarios.

The survey was not stopped until the responses from the panel members converged in terms of the statistical analysis (Lin & Song, 2015). Consensus, or convergence, refers to "the point at which the distribution of responses begins to stabilize" (Moeller & Shafer, 1983). Descriptive statistics and statistical tests are commonly used to evaluate the consensus of responses (Lee et al., 2008; Lin & Song, 2015). Descriptive statistics include the mean, median, and interquartile values, which measure the control tendency, and the standard deviation, which aims to measure the degree of convergence (Lin & Song, 2015). Statistical tests consist of the coefficient of variation (CV; Lloyd et al., 2000), the chi-square test (Spenceley, 2008), the Wilcoxon rank–sum test (Liu, 1988), and the paired *t*-test (Katsura & Sheldon, 2008).

Christie and Barela (2005) stated that convergence is achieved when at least 75% of the panel members' responses "fall between two points above and below the mean on a 10-point scale," and defined a consensus as a standard deviation less than 1.5 and an interquartile range less than 2.5. Kittell-Limerick (2005) agreed that an interquartile range less than 2.5 implies a convergence of responses. Nevertheless, other studies (Frechtling, 2001; Rayens & Hahn, 2000) illustrated that for convergence, the interquartile range should not be higher or lower than the median by more than 10%. The CV was adopted by English and Kernan (1976) and Shah and Kalaian (2009). These scholars concluded that as long as the CV is less than 0.8, there is no need to conduct an additional survey round(s). The Delphi process can be terminated as soon as convergence is realized or when the pre-defined stop criteria are met, based on time and budgetary limitations.

Results and implications

Model estimation and baseline forecasts

Regarding the model estimation results (see Table 3), all of the ARDL-ECMs passed the bounds test, indicating a long-run relationship between tourist arrivals and their influencing factors for each model. The coefficient of the error correction term was negative, implying that the models could self-correct errors that deviate from the equilibrium between the previous period and the current period. The findings enrich those of prior studies and verify that the income level determined using the GDP in the source market positively affected the tourism demand and that the relative own price growth negatively affected the tourism demand, as indicated by the estimated negative coefficients. Additionally, the results of the goodness of fit (adjusted R-square) and diagnostic tests of most of the models were acceptable. Therefore, the ARDL-ECMs were appropriately specified in this study.

Regarding the demand elasticities, the income elasticities in Canada, France, Germany, Japan, South Korea, Philippines, Thailand, and the U.K. were greater than 1. This means that international travel is an income-sensitive, luxury commodity for tourists in these markets. The price elasticities reveal that except for Australian, mainland Chinese, and Malaysian arrivals, the volatile prices in Hong Kong may not considerably affect the tourism demand. Economies worldwide have been negatively affected by the COVID-19 pandemic, and both the income levels in the source markets and the travel costs at the destination are being adjusted. Therefore, special price discounts on airline tickets, accommodations, and other tourism products might attract potential tourists and retain existing tourists.

The results of the estimations of the event dummy variables, including the SARS outbreak in 2003, the economic crisis in 2007–2008, and the social unrest in 2019, prove that these crises severely hindered the development of the tourism industry. Tourism is one of the most vulnerable sectors in times of crisis and disaster. Therefore, practitioners must implement timely and effective crisis management strategies. The statistical baseline forecasts were overestimations, especially during the first three quarters of 2020, because the model did not capture the effects of the COVID-19-related factors.

Adjusted forecasts

Fig. 2 displays the adjusted forecasts of tourist arrivals from the 16 source markets to Hong Kong during 2020Q1–2024Q4. In the first round of the Delphi survey, most of the experts agreed that the tourist arrivals from almost every source market would reach a minimum in 2020Q2, and the majority believed that in the mild scenario, the volume of tourists would return to the baseline forecasts at the end of 2020 or in 2021. In the severe case, however, the experts stated that most of the source markets could require at least 2 years to recover from the crisis.

In the second round of the survey, all panel members adjusted down the initial forecasts. The average reduction was no more than 5% in the mild scenario; in contrast, in the severe scenario, the average reductions in the majority of the origin markets ranged from 10% to 15%. Both the descriptive analysis and statistical tests were performed to evaluate whether the experts' responses reached a consensus after the second round of the survey. The descriptive analysis revealed that the mean was very close to the mode, and the difference between the interquartile and the median did not exceed 10%. The statistical tests revealed that the CVs were below 30%, consistent with many studies (Green et al., 1990; English & Kernan, 1976; Shah & Kalaian, 2009). The responses converged after the second round of the survey. The relative accuracy of the Delphi panel adjusted scenario forecasts across all 16 source markets were evaluated based on the actual data for the 3rd quarter of 2020 and it was found that the difference between the forecasts and actual arrivals is within 15–25% intervals depending on which scenario is concerned. However, given the number of data points is limited, this assessment should be treated with caution.

Table 3
Tourism demand estimation results.

Variable	Australia	Canada	Mainland China	France	Germany	Indonesia	Japan	South Korea
$\ln TA_{i,\,t-1}$	−0.408***	−0.416***	−0.231***	−0.483***	−0.511***	−0.523***	−0.415***	−0.646***
$\ln Y_{i,\,t-1}$	0.702***	1.094***	0.820***	1.386***	1.486***	0.571***	1.796*	1.878***
$\ln P_{i,\,t-1}$	−1.137***	−0.572***	−4.580***	−0.713***	−0.551***	−0.999**	−0.590***	−0.388***
$\ln P_{s,\,t-1}$	−1.076***		−2.336**		−0.314**		−0.743***	
$\Delta \ln TA_{i,\,t-1}$	−0.337***	−0.237***	−0.203**	−0.271***	−0.290***	−0.494***	−0.305***	−0.195***
$\Delta \ln TA_{i,\,t-2}$	−0.142***	−0.100***		−0.204***	−0.159***	−0.390***	−0.186***	−0.145***
$\Delta \ln TA_{i,\,t-3}$	−0.072**			−0.108***	−0.073***	−0.272***		
$\Delta \ln Y_{i,\,t}$	0.286***	0.455***	0.189**		1.615***	−4.736**	0.745**	1.213***
$\Delta \ln Y_{i,\,t-1}$				2.547*		−4.390*		
$\Delta \ln Y_{i,\,t-2}$					−1.436**	−8.102***		
$\Delta \ln P_{i,\,t}$			−1.058***	−0.294**		−0.523***	−0.508***	−0.251***
$\Delta \ln P_{i,\,t-1}$				0.392**	0.433***			
$\Delta \ln P_{s,\,t}$		0.684***	−0.540**				−0.308***	
$\Delta \ln P_{s,\,t-1}$						1.708***		
D03	−1.636***	−1.264***	−0.679***	−1.974***	−1.827***	−1.930***	−1.922***	−1.413***
D08		−0.072**	−0.124**	−0.069*	−0.080**			
D09			−0.113**			−0.138**		−0.245***
D19Q3	−0.246***	−0.266***	−0.402***	−0.188***	−0.258***	−0.439***	−0.346***	−0.649***
D19Q4	−0.344***	−0.334***	−0.434***	−0.256***	−0.196***	−0.800***	−0.643***	−1.122***
Sea_D1	−0.131***	−0.250***	0.001	−0.544***	−0.121***	−0.380***	−0.011	0.172***
Sea_D2	−0.070***	−0.306***	−0.094**	−0.131**	−0.170***	−0.451**	−0.124***	−0.073**
Sea_D3	−0.134***	−0.369***	0.114***	−0.339***	−0.360***			
Constant	4.055***	2.739***	4.276***	1.594**	2.067***	8.389***	3.376**	3.699***
$\mathrm{Adj}-\mathrm{R}^2$	0.970	0.967	0.773	0.966	0.981	0.920	0.950	0.921
Test A	1.444	6.772***	29.726***	0.510	0.536	0.279	4.208**	0.833
Test B	0.010	0.150	16.760***	0.110	0.980	0.060	0.060	0.090
Test C	0.496	2.007	49.920***	0.400	0.655	0.719	4.130	2.725
Test D	0.900	4.270***	16.760***	1.720	1.240	1.460	1.310	0.220

Variable	Macau	Malaysia	Philippines	Singapore	Thailand	Taiwan	U.K.	U.S.
$\ln TA_{i,\,t-1}$	−0.315***	−0.648***	−0.618***	−0.631***	−0.738***	−0.518***	−0.546***	−0.695***
$\ln Y_{i,\,t-1}$	0.580**	0.757***	1.042***	0.241**	1.266***	−0.036**	1.864***	0.912***
$\ln P_{i,\,t-1}$		−1.354***	−0.795**		−0.775***	−0.404**	−0.496***	−0.569***
$\ln P_{s,\,t-1}$	−0.758**				−0.691**	−0.350***		
$\Delta \ln TA_{i,\,t-1}$	−0.262***	−0.236***	−0.289***	−0.253***	−0.190***	−0.430***	−0.249***	−0.167***
$\Delta \ln TA_{i,\,t-2}$		−0.126***	−0.160***	−0.109**	−0.086**	−0.270***	−0.139***	−0.054**
$\Delta \ln TA_{i,\,t-3}$						−0.085**	−0.065**	
$\Delta \ln Y_{i,\,t}$	0.183**		0.645***	0.152**		−0.019**		0.633***
$\Delta \ln Y_{i,\,t-1}$		1.691**				0.015*		
$\Delta \ln Y_{i,\,t-2}$							−1.604**	
$\Delta \ln Y_{i,\,t-3}$							−2.076***	
$\Delta \ln P_{i,\,t}$							−0.271***	−0.395***
$\Delta \ln P_{i,\,t-1}$		0.510*			1.328***			
$\Delta \ln P_{i,\,t-2}$			−0.732**					
$\Delta \ln P_{i,\,t-3}$					0.606*			
$\Delta \ln P_{s,\,t}$	−0.239**						0.289*	0.425**
$\Delta \ln P_{s,\,t-1}$					1.224***	0.332*	0.298*	
$\Delta \ln P_{s,\,t-3}$				−0.541**		−0.362**		
D03	−0.654***	−1.898***	−1.831***	−1.964***	−2.104***	−1.294***	−1.579***	−1.759***
D08		−0.107**					−0.066**	−0.058**
D09		−0.112**			−0.111**	−0.068***	−0.073*	−0.045*
D19Q3	−0.236**	−0.496***	−0.259***	−0.553***	−0.551***	−0.407***	−0.147***	−0.273***
D19Q4	−0.324***	−0.648***	−0.200**	−0.911***	−0.987***	−0.615***	−0.323***	−0.429***
Sea_D1	−0.186***	−0.478***	−0.146***	−0.453***	−0.193***	−0.050***		−0.187***
Sea_D2	−0.125***	−0.215***	0.079***	−0.323***	−0.100***	−0.055***	−0.155**	−0.086***
Sea_D3	0.110***	−0.488***	−0.197***	−0.491***	−0.324***	0.051***	−0.251***	−0.212***
Constant	3.814***	5.149***	6.251***	5.966***	6.816***	7.762***	1.337***	5.317***
$\mathrm{Adj}-\mathrm{R}^2$	0.792	0.965	0.961	0.965	0.955	0.968	0.982	0.978
Test A	9.900***	5.833**	14.772***	12.144***	5.845**	9.075***	0.393	0.284
Test B	6.800***	0.130	0.670	0.310	0.090	0.630	0.020	0.090
Test C	38.260***	24.090***	1.300	1.170	3.413	1.279	0.306	18.190***
Test D	7.800***	2.050	3.570**	3.900**	2.660*	5.030***	2.070	1.070

Note: D03 = SARS epidemic outbreak in 2003; D08 & D09 = economic crises in 2008 and 2009, respectively; D19Q3 & D19Q4 = social unrest in Hong Kong in 2019; Sea_D1, Sea_D2, & Sea_D3 = seasonal dummies; tests A, B, C, and D are Breusch–Godfrey LM tests for autocorrelation, Breusch–Pagan test for heteroscedasticity, Jarque–Bera test for normality, and Ramsey RESET test for model misspecification, respectively. The results of the co-integration test are available on request. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively.

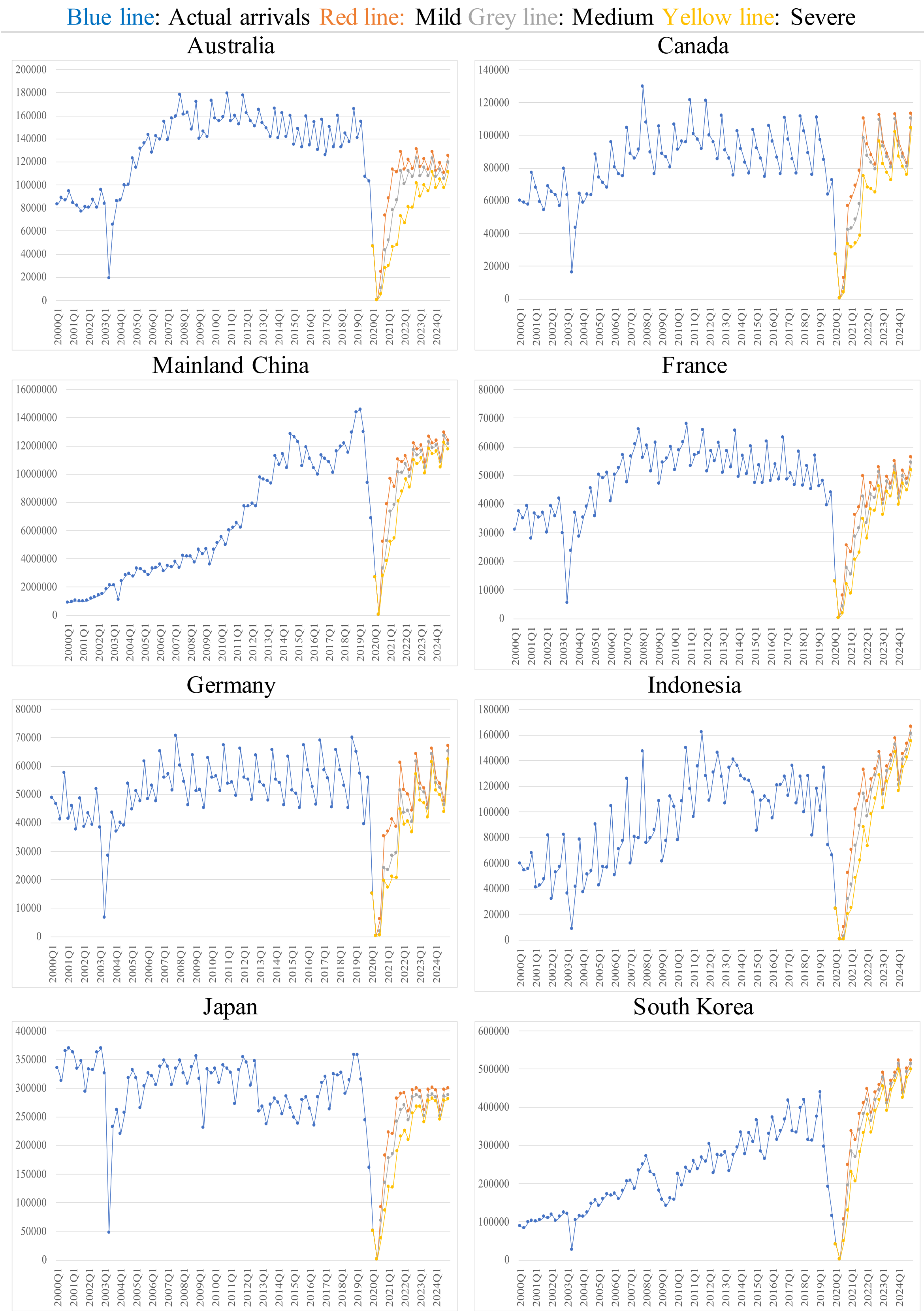
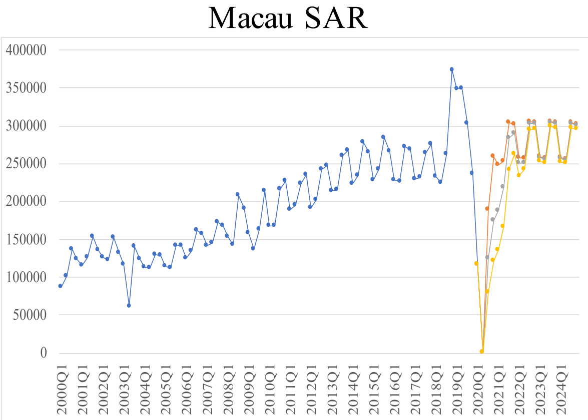


Fig. 2. Adjusted tourist arrivals in three scenarios over 2020Q1–2024Q4.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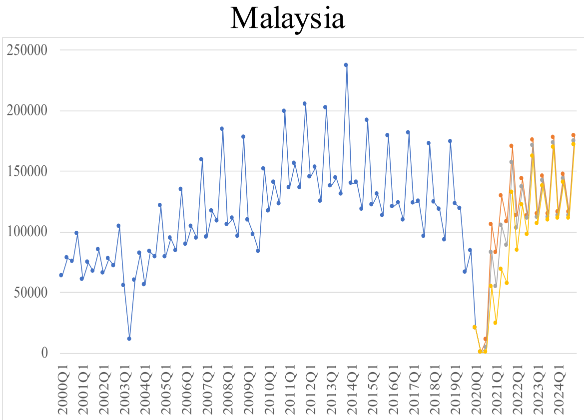
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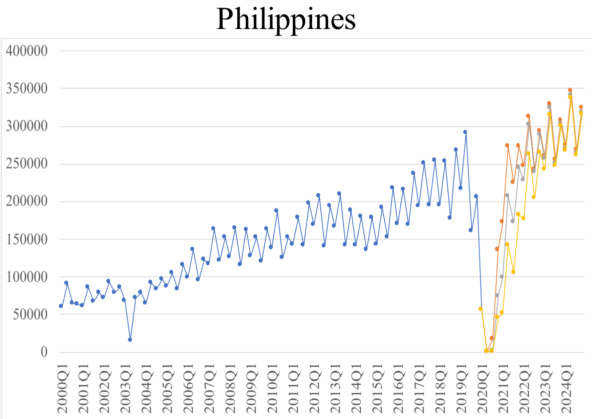
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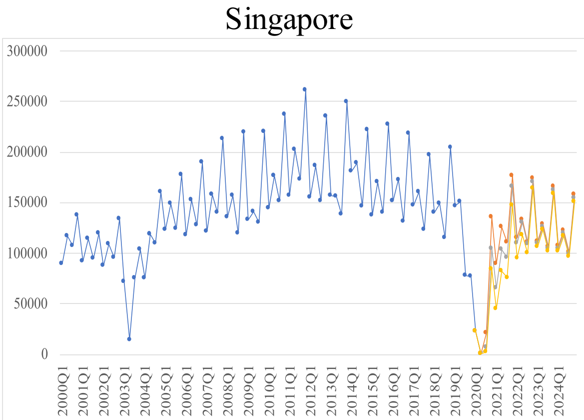
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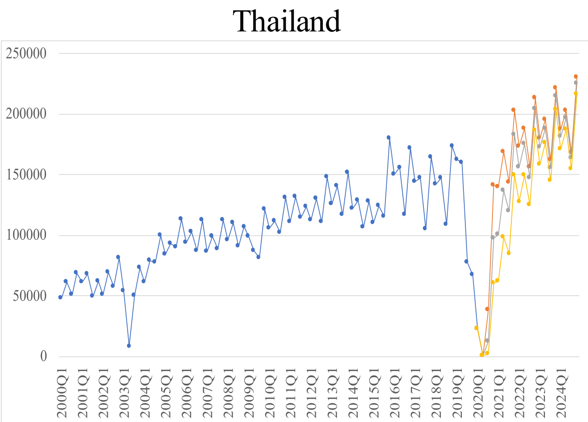
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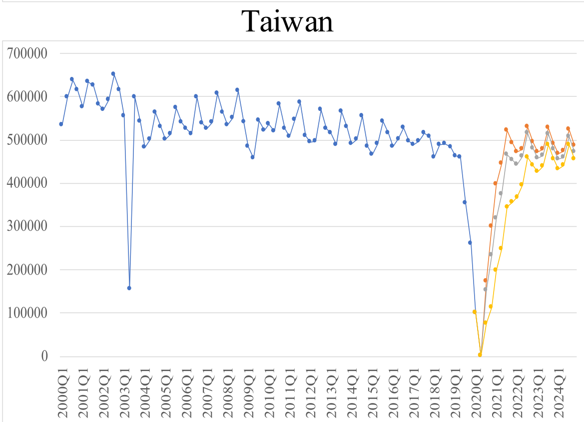
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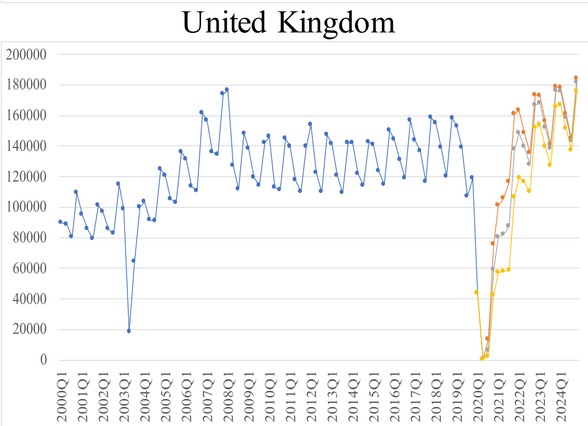
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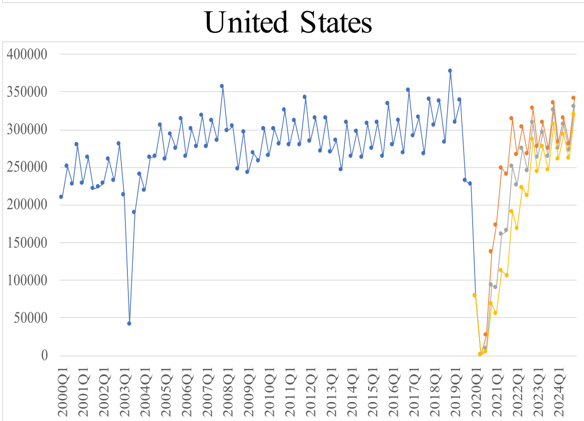
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Tourism demand recovery

As the COVID-19 pandemic has delivered a temporary shock to the tourism industry, we analyzed the potential recovery of the tourism demand from each source market according to the tourism demand forecasts. Fig. 3 shows the predicted recovery speeds, considering the COVID-19 pandemic situations, tourism-related policies such as "travel bubbles," and the reasons for recovery as provided by the Delphi experts. We divided the source markets into several groups based on their recovery predictions. The color of the box in Fig. 3 changes from light blue to dark blue to indicate the recovery speeds of varying groups in the source markets in order from fastest to slowest. Smeral (2010) stated that the demand for domestic and short-haul tourism could recover much more rapidly from the recession than the long-haul markets. As the pandemic responses move into the next phase, the progressive lifting of travel restrictions in domestic and short-haul markets may cause tourism industries to begin to recover on a limited scale. Thus, it is likely that domestic tourism (Macau, mainland China, and Taiwan) will resume first. This will be followed by demands for tourism from other Asian markets. However, long-haul markets, including the U.S., may sustain travel restrictions for relatively long periods.

The markets of Macau, mainland China, and Taiwan may recover more quickly than other source markets. They may be followed by other short-haul markets (Japan, South Korea, Malaysia, Singapore, and Thailand). If travel restrictions are lifted, tourist arrivals from Macau, mainland China, and Taiwan to Hong Kong are expected to increase significantly for several reasons. First, the COVID-19 pandemic in these markets has been controlled. Second, tourists have a strong desire to travel to relieve the depression associated with epidemic fatigue. Third, the Hong Kong government favors a tourism boom and is promulgating policies to support the tourism industry. Fourth, businesses are reconstructing the images of destinations and conducting promotional campaigns. Fifth, "travel bubble" within China (mainland, Hong Kong, and Macau) are under discussion.

Following the three origin markets mentioned above, Thailand, Malaysia, and Singapore may also rebound relatively quickly because of their small numbers of daily confirmed COVID-19 cases, short geographic distances from Hong Kong, historically stable business travel campaigns, and supportive policies, such as the "travel bubble." The recovery paths for Japan and South Korea may differ from those of other Southeast Asian markets. Safety is usually a key consideration for Japanese tourists, and the epidemic may have adversely impacted the incomes of residents. The demand for Hong Kong tourism from these countries may take longer to recover relative to other Southeast Asian markets.

Indonesia and the Philippines are short-haul markets. However, their recoveries may also take much longer than other short-haul markets. The number of confirmed cases in these countries has grown significantly and has continued to trend upward. The national public health systems in these countries may be overwhelmed and unable to treat many infected patients quickly.

Recovery	**Origin Market**
Fastest	Macau SAR
	Mainland China
	Taiwan
	Thailand
	Malaysia
	Singapore
	South Korea
	Japan
	Indonesia
	Philippines
	Germany
	United Kingdom
	Canada
	Australia
	France
Slowest	United States

Fig. 3. Tourism demand recovery forecasts.

Table 4
Tourism income losses in three scenarios (by year).
Unit: HK(US)$Million.

Year	Mild		Medium		Severe	
	HKD	USD	HKD	USD	HKD	USD
2020	176,387	22,760	209,269	27,002	225,640	29,115
2021	28,443	3670	73,172	9442	136,172	17,571
2022	15,035	1940	32,290	4166	62,071	8009
2023	12,529	1617	25,172	3248	42,305	5459
2024	12,512	1614	22,126	2855	37,360	4821
Total	244,907	31,601	362,029	46,713	503,548	64,974

Nonetheless, if COVID-19 can be brought under control in these two markets and Hong Kong's entry and exit restrictions on foreign markets are relaxed, the number of tourists from these markets will be likely to increase gradually. These markets have the advantage of being located nearer to Hong Kong than other foreign markets, and Filipino workers in Hong Kong account for a large proportion of the total number of visitor arrivals.

Regarding the long-haul markets (Australia, Canada, France, Germany, the U.K., and the U.S.), tourist arrivals from Australia may recover more quickly, as the number of confirmed cases in that country is relatively small. Of the European markets, Germany has handled the pandemic fairly well, and the European Union is encouraging movement between European countries and China. The German market may recover more quickly than the other long-haul markets. However, a longer period will be needed to rebuild tourists' confidence in ocean-liner and award-winning travel. France may be the slowest market to recover because the COVID-19 situation remains serious there. The forecasts for the U.K. differ from those of other European markets because a large group of tourists with British passports may soon return to Hong Kong to visit their relatives. Nevertheless, the pandemic is volatile. The number of daily confirmed cases in the U.K. is increasing considerably, and it remains unknown when the U.K. government will relax its travel restrictions.

In North America, Canada is facing a mild epidemic similar to that in the U.K, and large numbers of tourists travel to Hong Kong to visit friends or relatives. Hence, Canada may experience a considerably faster return than the U.S. Currently, the U.S. is the country most affected by the COVID-19 pandemic, and visa restrictions will not be lifted in the short term. Therefore, the U.S. is predicted to be the last source market to return to the baseline forecasts.

Tourism income losses

This study investigated the direct effects of the COVID-19 pandemic on tourism income in Hong Kong over the forecasting period. We calculated the tourism income loss by multiplying the per capita tourist expenditure and the number of lost arrivals from each of the 16 source markets in each scenario. The per capita tourist expenditure data for 2019, which were published by the Hong Kong Tourism Board in "Tourism Expenditure Associated to Inbound Tourism 2019," were used to calculate the total income loss per year in Hong Kong, assuming that this value would remain unchanged over the next 5 years. The results (see Table 4 and Fig. 4) show that the tourism income loss is predicted to reach approximately HK$176,387 (US$22,760) million in 2020 under the mild scenario. As tourism gradually recovers, this loss is predicted to decline significantly afterward, from HK$28,443 (US$3670) million in 2021 to HK$15,035 (US$1940) million in 2022. In 2023 and 2024, the loss is predicted to decrease further to approximately HK$12,000 (US$1548) million. Therefore, 2020 is predicted to be the most negatively affected year by the pandemic, and the tourism industry will likely begin to recover gradually from the crisis in 2022.

Table 5 and Fig. 5 indicate that the loss of tourism from short-haul markets accounts for most (approximately 90%) of the total loss because tourists to Hong Kong mainly travel from short-haul markets. According to the tourism demand recovery analysis, short-haul markets should recover more quickly than long-haul markets. Practitioners should focus on attracting tourists from domestic and short-haul markets to control the losses caused by the pandemic.

Empirical implications

Although the COVID-19 pandemic has damaged developments in the tourism industry, it has also provided practitioners with opportunities to consider tourism reform and innovation, international cooperation, and regional communication. In "Recovery and Development of World Tourism amid COVID-19" (World Tourism Cities Federation, 2020), the World Tourism Cities Federation reported that policymakers are adopting several actions to rebuild the tourism industries in their countries. Specifically, they are formulating phased recovery plans based on forecasting data, promoting smart and digital tourism, rebuilding confidence in tourist sectors, providing financial support, and stimulating consumption.

Forecasting the tourism demand is a fundamental step in the recovery process, as it informs decisions about the appropriate phases of action. Business decisions are contingent on demand forecasts, which are useful for strategic and operational planning such as budgeting, sales, marketing, and resource allocation. Due to the uncertainty and volatility of the COVID-19 pandemic, tourism recovery should involve a gradual process based on a phased-action plan aimed at corresponding markets (World Tourism Cities Federation, 2020). The rebranding of destination imagery is a critical factor in domestic and short-haul market recovery. Zenker and Kock (2020) indicated that tourists' perceptions of safety, health infrastructure, mass-tourism events, and other

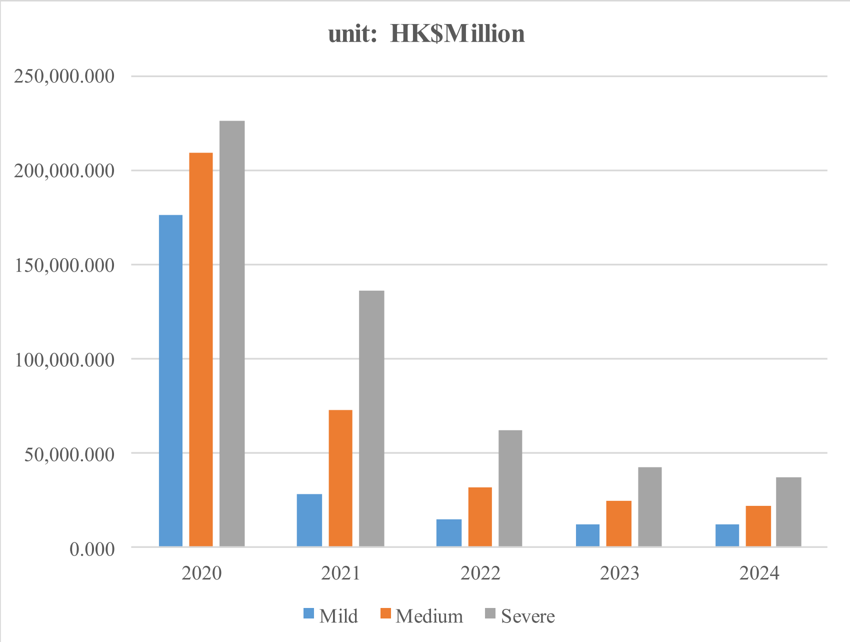

Fig. 4. Tourism income losses in three scenarios (by year).

COVID-19-affected associations could potentially affect destination imagery. Starting in 2019, social unrest and COVID-19 began to damage tourists' confidence and willingness to travel to Hong Kong. To restore and strengthen this confidence, Eugenio-Martin et al. (2005) explained that the mass media can play a vital role in promoting communication between a destination and potential tourists and in influencing public perceptions of tourist destinations. These authors emphasized the importance of marketing and promotional campaigns delivered via social media as tools to help tourists reimagine a destination.

Governments must plan discretionary policies to enhance social safety nets, allocate resources, promote communication between stakeholders, and provide financial assistance (Huang & Min, 2002; Ritchie & Jiang, 2019). To support the recovery of the tourism industry, the Hong Kong government has offered HK$700 million to the Hong Kong Tourism Board for development and established an Anti-Epidemic Fund Travel Agent Subsidy Scheme to support travel agents. Eighty percent of travel agents in Hong Kong have received a one-off HK$80,000 subsidy via this scheme (International Labor Organization, 2020).

Table 5
Tourism income losses in three scenarios (by market).
Unit: HK(US)$Million.

Market	Year	Mild		Medium		Severe	
		HKD	USD	HKD	USD	HKD	USD
Long-haul market	2020	13,920	1796	14,982	1933	15,565	2008
	2021	4212	543	8245	1064	11,677	1507
	2022	1602	207	3095	399	5925	765
	2023	1252	162	1986	256	3516	454
	2024	1041	134	1666	215	2657	343
	Subtotal	22,027	2842	29,973	3867	39,342	5076
Short-haul market	2020	153,611	19,821	183,804	23,717	198,762	25,647
	2021	22,803	2942	61,265	7905	117,686	15,185
	2022	12,684	1637	27,588	3560	53,048	6845
	2023	10,651	1374	21,933	2830	36,686	4734
	2024	10,485	1353	19,355	2497	32,844	4238
	Subtotal	210,595	27,174	313,944	40,509	439,027	56,649
	2020	8856	1143	10,483	1353	11,313	1460
	2021	1428	184	3663	473	6808	878
	2022	749	97	1608	207	3097	400
	2023	627	81	1253	162	2103	271
	2024	626	81	1106	143	1859	240
Other markets	Subtotal	12,285	1585	18,113	2337	25,180	3249

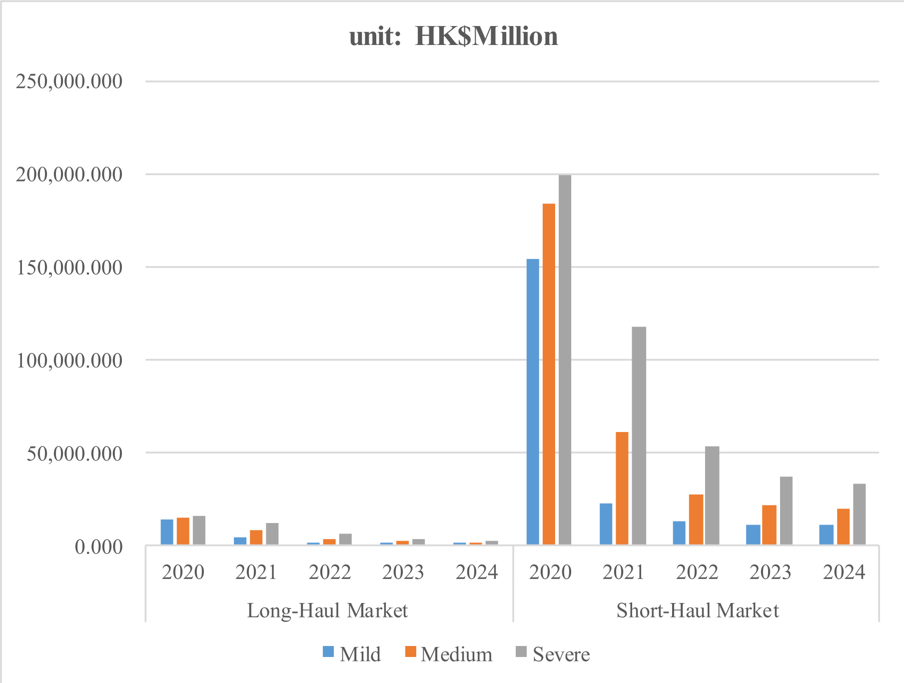

Fig. 5. Tourism income losses in three scenarios (by market).

Conclusion

In this paper, we have proposed the scenario-based Delphi adjustment forecasting approach, which integrates quantitative (ARDL-ECM) and qualitative methods (Delphi-scenario adjustments), as a method of forecasting the possible paths to the recovery of Hong Kong tourism from 16 origin markets following the COVID-19 pandemic. Because of data limitations and the unprecedented context of this pandemic, traditional statistical forecasts could not incorporate the effects of the related factors. To address this issue, we used the Delphi-scenario technique to revise the baseline forecasts in accordance with experts' insights on tourism during and after the COVID-19 pandemic. From a crisis management perspective, this study provides several suggestions for business planners and policymakers regarding the recovery of tourism demand after a crisis. We note that the forecasts for 2020Q2 and 2020Q3 may not be equal to the actual numbers because the Delphi surveys were completed before July 21, 2020. The actual tourist arrivals in June had not been released at the time of the study, and an unexpected third wave of the COVID-19 pandemic occurred in Hong Kong in late July 2020.

In future studies, we suggest using the proportionate weighting method to aggregate the experts' responses to Delphi surveys. Lin (2013) noted that although it is simple and efficient to assign equal weights to experts' responses, this may neglect more accurate responses. Thus, the responses from experts with more experience in and knowledge of tourism demand forecasting should be weighted more heavily when aggregating the responses. Forecasting also depends on the accuracy of the predicted explanatory variables. Hence, it is helpful to forecast the explanatory variables using different approaches and compare the forecast accuracies. Future studies could also design survey questions to request that the experts forecast the independent variables.

We suggest that in the first stage of forecasting tourism demand, future studies may replace the ARDL-ECM with other advanced techniques, such as the time varying parameter (TVP), almost ideal demand systems (AIDS), and hybrid models such as the TVP-ECM and time varying parameter linear almost ideal demand system (TVP-LAIDS) model. COVID-19 has hindered tourism development in many countries and regions, and this study lays a foundation for further studies of tourism demand forecasting for other destinations. The COVID-19 pandemic is complicated, and combines public health, economic, and socio-political crises. To cope with this complexity and interconnectedness, we suggest that future studies could consider chaos theory (Faulkner & Russell, 2000; Zahra & Ryan, 2007) and system theory (Zenker & Kock, 2020) as possible theoretical frameworks. In addition, Delphi surveys could consider interval forecasts with the aim of providing confidence intervals for each of the scenario forecasts.

Declaration of competing interest

In submitting this article, we declare that there is no conflict of interests among the authors.

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