Forecasting Hotel Room Demand amid COVID-19

Abstract

The COVID-19 pandemic has hindered international travel considerably, greatly affecting the hotel industry. Hong Kong, as a well-known international tourist destination, has also been hit hard by the crisis. Recovery forecasts for hotel room demand are critical to managing this ongoing crisis. This study employs the autoregressive distributed lag error correction model to generate baseline forecasts of hotel room demand for Hong Kong followed by compound scenario analysis to optimize forecasts considering the pandemic's impacts. The COVID-19 Travelable Index is designed to group source markets by their pandemic situations, vaccinations, policy responses, and health resilience. To capture pandemic-related uncertainty, this study presents three scenarios describing recovery patterns based on trough duration, the quarter for lifting travel restrictions, and the quarter for returning to baseline forecasts. Hotel demand forecasts geared towards each source market are also analyzed, revealing strategies to help hotel businesses manage this crisis.

Keywords: COVID-19, hotel demand forecasting, scenario analysis, tourism index, vaccinations, crisis management

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Introduction

The COVID-19 pandemic has been widely described as a "black swan event" which is rare and unprecedented. The pandemic continues to evolve geographically and chronologically amid great uncertainty and has brought catastrophic damage to the global economy. As a vulnerable industry, tourism has suffered greatly from this crisis. Hotel practitioners are thus keen to obtain future-oriented information regarding inbound tourism amid a volatile situation influenced by multiple driving forces. Reliable and accurate forecasts generated by the professional demand forecasting method will be essential in helping businesses navigate this challenging time.

Studies on hotel demand forecasting in times of crisis are not as abundant as those in tourism demand forecasting. To demonstrate an innovative hotel room forecasting methodology during COVID-19, this research takes Hong Kong as a sample case. Hong Kong has long been a top international destination with diversified international source markets and has been adversely affected by the pandemic.

Tourism is one of Hong Kong's pillar industries, accounting for 4.5% of the region's gross domestic product (GDP) in 2018. Surging tourism demand from major source markets, such as mainland China, boosted visitor arrivals in Hong Kong to roughly 65.1 million in 2018 with a compound average growth rate of 7.7% over 2010–2018 (HKTB, 2011–2018). Tourists from mainland China accounted for about one–third of hotel room demand followed by other developed Asian markets. Hong Kong’s major long-haul source markets include the United States and United Kingdom.

Social unrest in July 2019 tempered the hotel industry’s prosperity: the number of international conferences, exhibitions, and events held in Hong Kong was slashed. Furthermore, the COVID-19 outbreak in late 2019 has had severe impacts on the tourism industry. Government-mandated travel bans and social restrictions helped to curb the virus’s spread but hindered international travel mobility. HKTB (2021a) revealed that total visitor arrivals dropped by 14.2% in 2019 and by 93.6% in 2020. Hotel room demand also witnessed a record low occupancy rate of 46% in 2020, a significant decline from 79% in 2019. Hong Kong’s average daily room rate fell by 27% to 887 HKD (114 USD) in 2020.

The Hong Kong Hotel Classification System (HKTB, 2019) categorizes hotels into three types using a composite score (CS) based on five indicators (i.e., facilities, location, staff-to-room ratio, average achieved room rate, and business mix). Hotel options fall into high tariff A (CS>=3.00), high tariff B (3.00>CS>=2.00), and medium tariff (2.00>CS>=1.00) categories. The market supply of the first two hotel tiers accounted for more than 60% of Hong Kong’s total supply in 2019.

As Figure 1 illustrates, mainland China, Taiwan, the United States, Japan, South Korea, the United Kingdom, Australia, the Philippines, Singapore, and Malaysia collectively accounted for around 69.5%, 70.1%, and 72.1% of Hong Kong’s total market share for high tariff A hotels, high tariff B hotels, and medium tariff hotels, respectively. Mainland China is Hong Kong’s largest source market, representing the largest proportion of hotel room demand in all three hotel categories. More than 44% of the market share for medium tariff hotels can be attributed to demand from mainland China; such demand is substantially greater than that for high tariff A hotels (31%). The choices of hotel categories by the tourists from South Korea, Malaysia, and Taiwan were similar to that of the visitors from mainland China. By comparison, travelers from long-haul markets (e.g., the United States, United Kingdom, and Australia) prefer the first two hotel tiers; for example, demand for high tariff A hotels from U.S. visitors accounts for approximately 11.7% of total demand.

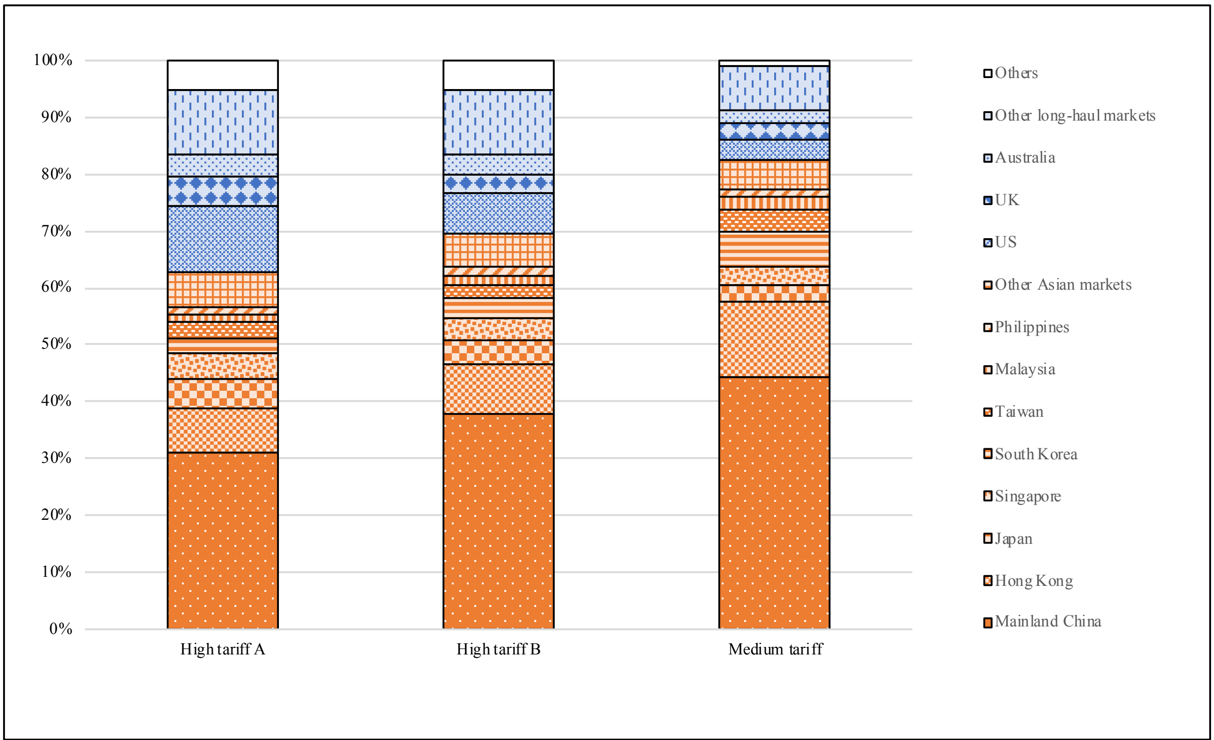


Figure 1. Hong Kong hotel market share by category in 2017.

Given the effects of COVID-19, hotel industry practitioners and policymakers are now seeking to identify market-based changes. Reliable hotel demand forecasts are crucial for making strategic decisions and responding effectively to the crisis. Industry stakeholders could particularly benefit from forecasts of demand recovery incorporating multiple scenarios. In general, scenario forecasts help business operators prepare to navigate unforeseen situations and minimize operational costs. Forecasts further aid government officials in assessing events' potential impacts with an eye towards introducing policies to boost visitor demand. Researchers have hence been prompted to develop professional and credible hotel demand forecasting methods that can capture the pandemic's volatility across source markets.

To answer this call, a compound scenario forecasting method is proposed in this study to produce ex-ante forecasts of hotel room demand. The contributions of this approach are multifold: (1) the COVID-19 Travelable Index was created to reflect international travel mobility between destination and source markets and to group major source markets according to the most up-to-date COVID-19–related information; (2) the compound scenario forecasting is dynamic and in line with reality since destinations are likely to remove travel bans intermittently instead of eliminating restrictions for all source markets simultaneously; (3) compound scenarios incorporate dynamic recovery stages to capture pandemic-related uncertainty as well as potential recovery outcomes for various source markets based on their pandemic status and mobility restrictions; and (4) different source markets' recovery patterns can be generated to help hotel businesses tailor recovery strategies to specific market segments.

The remainder of this paper is organized as follows. The next section reviews work on hotel demand forecasts in crisis periods and corresponding research approaches. Section 3 presents the data and methodology employed in this study, followed by the empirical results and discussion. The final section concludes this paper.

Literature Review

Compared to the substantial literature on tourism demand forecasting, studies on hotel demand forecasting are relatively thin (Wu et al., 2017). Relevant research mainly focuses on micro-level individual hotel demand forecasts (e.g., to support better revenue management) or macro-level forecasts in a specific country or region (e.g., to benefit destination management). Hotel demand is commonly measured by the number of rooms (Corgel et al., 2013; Pan et al., 2012; Song et al., 2011), occupancy rate (Schwartz and Hiemstra, 1997; Wu et al., 2010; Yang et al., 2013), guest arrivals (Weatherford and Kimes, 2003), and hotel revenue (Toma et al., 2009).

In a review of the literature, Wu et al. (2017) classified hotel demand modeling and forecasting methods into three groups. The first category included time series methods, such as the naïve model, exponential smoothing models, autoregressive moving average models, and the structural time series model. Recent trends in time series models incorporate external variables to improve forecasting accuracy; such variables include business sentiment indicators (Guizzardi and Stacchini, 2015), web traffic (Yang et al., 2013), and search engine query data (Pan and Yang, 2016). However, time series analysis is not especially useful for identifying causal relationships between hotel demand and its various determinants. Artificial intelligence (AI)–based methods are common in hotel and tourism demand forecasts given these approaches' predictive accuracy and ease of implementation. For example, in forecasting the number of guest nights in hotels, Teixeira and Fernandes (2012) compared feedforward, cascade forward, and recurrent architecture methods and found that an artificial neural network generated more accurate forecasts than an autoregressive integrated moving average model. Yet similar to most AI-based forecasts of tourism demand, AI models forecasting hotel demand reveal little about practical implications or the effects of economic factors that influence hotel demand. Econometric forecasting approaches have played distinctive roles in mapping cause-and-effect relationships between hotel demand and its influencing factors. They continue to be popular given their power to generate insight for businesses and destination managers. Advanced econometric methods such as the error correction model (ECM), vector autoregressive models, time-varying parameter model, and panel data approaches can overcome the limitations of traditional econometric models.

According to Song et al. (2008), the autoregressive distributed lag (ARDL) model opens with a general specification incorporating many possible explanatory variables along with lagged variables of both the dependent and explanatory variables. Then, following a general-to-specific modeling reduction process, the general ARDL model can be reduced to a specific model based on the nature of data, statistical significance, and a set of diagnostic tests. Derived from the ARDL model, the ECM addresses the problem of spurious regression; policymakers and planners often favor this model for its ability to uncover long-run equilibrium and short-run disequilibrium relationships. As a popular means of forecasting competition, econometric approaches are frequently employed to account for one-off events such as economic crises (Smeral, 2009, 2010) and continuous events such as changes in the climate (Goh, 2012; Moore, 2010), market (Durbarry and Sinclair, 2003), and consumption

(Syriopoulos, 1995). When forecasting hotel demand, Song et al. (2011) adopted an ARDL-ECM to identify demand elasticities and measure the responsiveness of hotel demand to shifts in economic determinants; the authors ultimately generated interval hotel demand predictions. Falk (2014) investigated the effects of weather conditions on hotel guests' length of stay (i.e., number of nights) using an ECM and discovered short- and long-run impacts of climate change on hotel nights.

Volatility is a unique feature of tourism (Ritchie, 2009) and renders tourist activities vulnerable to catastrophe. Hotel demand forecasts have been generated in cases of economic crises (Song et al., 2011), natural disasters (Chen, 2011), terrorist attacks (Corgel et al., 2013), and public health events (Wu et al., 2010). It is important to note that crisis threatens model stability. The data generating process (DGP), a type of mathematical modeling process that re-specifies an unstable demand model to achieve a stable one (i.e., encompassing all existing models), can capture the effects of structural changes (Song et al., 2008). Assuming constant model parameters, dummy variables have been widely adopted in hotel demand forecasts to discern the significance of crisis-related impacts that would be difficult to quantify otherwise. The time-varying parameter method, in which a demand model's parameters are thought to change over time, also incorporates uncertainties related to structural changes (see, for example, Pan et al., 2012). Using the independent component analysis approach, Wu et al. (2010) interpreted the impact of an infectious disease based on event timing after major components were identified. Most of the aforementioned crisis studies compared forecasting accuracy based on the mean absolute percentage error and root mean square percentage error.

Others have uncovered potential influential relationships between explanatory variables and demand variables in light of a crisis.

Forecasts can be classified into two major types, namely ex-post and ex-ante. Ex-post forecasts are often used to evaluate model accuracy by holding out some time series observations. Ex-ante forecasts based on all data available at the time of forecasting. While ex-ante forecasting involves quantitative techniques such as time series, econometric, and AI models, it also integrates a judgmental approach to account for possible effects of a crisis.

The Delphi approach and scenario analysis are popular when dealing with limited sample data or when quantitative forecasts require adjustment, especially if unexpected uncertainties exist. For instance, the Delphi method is often used to predict tourism trends (Lin et al., 2011; Zhang et al., 2021) when future information is asymmetric and thus affects forecasting accuracy. Scenario analysis, which generates multiple forecasts under different assumptions, is equally helpful. For example, Song et al. (2013) incorporated experts' adjustments into a web-based tourism demand forecasting system to produce scenario forecasts of such demand. Liu et al. (2021) generated scenario forecasts of tourism industry recovery amid COVID-19 according to the percentage of deepest impact, the time when the deepest impact would occur, and the recovery rate via an integrated COVID-19 risk exposure index. Assuming that forecast quality would not degrade, Kourentzes et al. (2021) formulated model-based scenarios to reduce mental load by considering the evolution of COVID-19, government restrictions, foreign affairs approaches, and border limitations. Fotiadis et al. (2021) developed scenarios based on training data from previous major crises (e.g., the 2003 outbreak of severe acute respiratory syndrome (SARS), the 2008–09 global financial crisis, and Middle East respiratory syndrome) and compared the impacts of these events.

Judgmental adjustments to quantitative forecasts can be incorporated into the influencing factors of tourism demand to account for a crisis's impact on tourism demand forecasts. Song et al. (2011) integrated the effects of the global economic crisis in the income variable using forecasts from the International Monetary Fund (IMF) and Euromonitor International, which were based on expert opinion. Apparently, there is a trend that scholars have recently endeavored to reduce human bias in scenario analysis.

The current study makes several contributions to the literature. Specifically, by considering the impacts of pandemic on hotel industry, this study presents the COVID-19 Travelable Index to capture the most up-to-date information shaping demand for Hong Kong hotels from four perspectives and generates scenario forecasts. To the best of our knowledge, such an approach has not yet been employed in hotel demand forecasts either academically or practically. These findings should help hotel industry personnel in Hong Kong better understand hotel demand recovery patterns over the next five years, thus enabling firms to formulate proper recovery strategies.

Methodology

Compound scenario forecasting method

The compound scenario forecasting method was proposed to predict hotel room demand amid a crisis. This approach consists of two stages along with two sub-steps in Stage 2 (see Figure

2). In the first stage, ARDL-ECMs were used to estimate demand elasticities and generate baseline forecasts of hotel room demand in three tariff categories per source market. In the second stage, we created the COVID-19 Travelable Index and generated compound scenario predictions. These scenario forecasts were based on source market groups as classified by the COVID-19 Travelable Index.

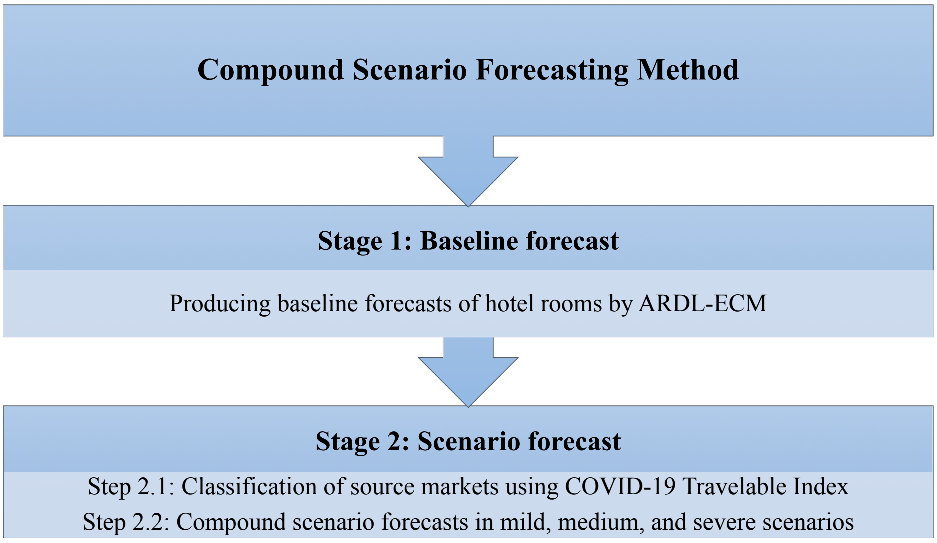


Figure 2. Compound scenario forecasting method.

Stage 1: baseline forecasts using ARDL-ECM

In Stage 1, we adopted the ARDL-ECMs to estimate and forecast hotel room demand across three hotel types—high tariff A hotels, high tariff B hotels, and medium tariff hotels—using data from the first quarter of 2000 (2000Q1) to the fourth quarter of 2019 (2019Q4). Hotel room demand for each source market as the dependent variable was calculated through two steps. First, the number of occupied rooms in a hotel category was calculated by multiplying hotel room supply by the occupancy rate. Second, the number of rooms that each source market demanded in each hotel category was equal to the total number of occupied rooms multiplied by the market share of each hotel category for the corresponding source market. Thirty ARDL-ECMs related to hotel demand from 10 major source markets (i.e., Australia, mainland China, Japan, South Korea, Malaysia, Singapore, Philippines, Taiwan, the United Kingdom, and the United States) were established. Baseline forecasts for hotel room demand from 2020Q1 to 2025Q4 were then generated with these models.

The hotel demand model can be written as

$$\begin{aligned}\Delta \ln RQ_{it}^{k} = \alpha_0 &+ \sum_{j=1}^{p_1} \alpha_j \Delta lnRQ_{i,t-j}^{k} + \sum_{j=0}^{p_2} \beta_j \Delta lnY_{i,t-j} + \sum_{j=0}^{p_3} \gamma_j \Delta lnP_{i,t-j}^{k} \\ &+ \sum_{j=0}^{p_4} \delta_j \Delta lnP_{i,t-j}^{s} + \lambda_1 lnRQ_{i,t-1}^{k} + \lambda_2 lnY_{i,t-1} + \lambda_3 lnP_{i,t-1}^{k} + \lambda_4 lnP_{i,t-1}^{s} \\ &+ dummies + \varepsilon_{it} \qquad (1)\end{aligned}$$

where RQ_{it}^{k} represents the number of rooms demanded by source market *i* to Hong Kong at time *t* for each hotel category *k*; $Y_{i,t}$ is the GDP index of source market *i* at time *t*; P_{it}^{k} is the room rate for each hotel type in Hong Kong, adjusted by the exchange rate $\left(P_{it}^{k} = RR(k)\left(\frac{EX_{i,t}}{EX_{HK,t}}\right)\right)$; EX indicates the real exchange rate in U.S. dollars and RR represents the room rate for hotels in each category; P_{it}^{s} is the weighted room rate index of substitute hotels ($P_{it}^{s} = \sum_{s=1,\ s\neq k}^{3} RR(s)\, w_{it}^{s}$); w_{it}^{s} is the ratio of room demand for substitute hotels in category *s* by tourists from source market *i* at time *t* ($w_{it}^{s} = RQ_{it}^{s} / \sum_{s=1,\ s\neq k}^{3} RQ_{it}^{s}$); ε_{it} represents the error term following a normal distribution with a zero mean and a constant variance; and *p* indicates the number of lags determined using the Akaike information criterion (Song et al., 2008). Seasonal, one-off events and specific market-related dummies (e.g., the SARS epidemic, global financial crisis, and social unrest in Hong Kong from 2019Q3 to 2019Q4), were also included in our initial models.

Quarterly data on occupancy rates, hotel room supply, hotel room rates, and overnight tourists were collected from the official HKTB website (HKTB, 2020; 2021a; 2021b). The GDP index in US dollars (2010=100) and exchange rates were obtained from IMF's database (IMF, 2021). Market share data for each source market were gathered from Hong Kong hotel industry review (HKTB, 2000–2017).

Data related to market share were not consistently recorded over the study period. From 2000 to 2014, market share was denoted according to the Hong Kong Hotel Classification System (i.e., high tariff A, high tariff B, and medium tariff); from 2014 onwards, market share was classified based on the room rate (i.e., HKD 2,351 and above; HKD 1,651–HKD 2350, HKD 951–HKD 1,650; and HKD 950 and below). However, we could collect data recorded in both ways in 2014. We therefore adjusted post-2014 data according to the correlation between the two groups of data in the same year to make them consistent.

First, according to average room rates for different hotel categories in 2014, we assumed that hotels priced at or above HKD 2,351 were high tariff A hotels. Those priced at or below 950 were deemed medium tariff. Hotels with room rates between HKD 1,651 and HKD 2,350 fell into either the high tariff A or high tariff B category, while rates between HKD 951 and HKD 1,650 were in the high tariff B or medium tariff category. Second, we calculated the difference in market share between each corresponding two groups of hotels and then divided the difference by the data in the matching group categorized by room rate. We took the average of data in the middle groups and calculated the difference ratio between the two matching groups as in the previous step. Next, we multiplied adjustment ratios and added them to the market share classified by room rate for the following years. Revised market shares were ultimately obtained through this adjustment procedure.

Before estimating equation (1), the augmented Dickey–Fuller unit root test was conducted to check the stationarity of the variables. The bounds test was performed to assess the presence of long-run correlations between a dependent variable and its regressors based on the *F*-statistic and *t*-statistic. This test incorporates two sets of asymptotic critical values, which span a band covering all explanatory variables, irrespective of whether they are integrated in the same order (Pesaran et al., 2001). This characteristic represents a unique advantage over other cointegration tests. Equation (1) was then specified via the general-to-specific procedure by deleting insignificant variables (Song and Witt, 2000). To ensure that the models were specified correctly, a battery of diagnostic tests were completed: the Durbin-Watson statistic and Breusch–Godfrey LM tests for autocorrelation, the autoregressive conditional heteroskedasticity (ARCH) LM test, the Breusch–Pagan/Cook–Weisberg test for heteroskedasticity, the Jarque–Bera test for normality, the Ramsey RESET test for model misspecification, and the variance inflation factor for multicollinearity.

Stage 2: compound scenario forecasts using COVID-19 Travelable Index

In the second stage, we carried out a compound scenario analysis to produce forecasts for each source market. Similar to most other Asian destinations, Hong Kong implemented relatively strict anti-pandemic policies. It would therefore be unlikely for this region to simultaneously lift travel restrictions for all source markets unless the pandemic wanes worldwide. Varying pandemic conditions across the ten source markets led to distinct troughs and points of recovery in hotel demand. Hence, in the first sub-step of scenario analysis, we created the COVID-19 Travelable Index associated with four indicators (i.e., pandemic situation, vaccination coverage, health resilience, and policy response) to categorize source markets into three groups. Hong Kong will likely lift travel restrictions intermittently due to source markets' distinct COVID-19 circumstances.

During the pandemic, international travel has been determined bilaterally based on mobility restrictions in destinations and source markets. Hence, in the second sub-step of the scenario analysis, this study made the forecasts considering three scenarios (i.e., mild, medium and severe) of the pandemic to capture the uncertain and volatile nature of the pandemic on both sides.

These three scenarios were determined by the trough duration, the quarter in which the travel ban was fully lifted, and the quarter in which demand returned to baseline. Trough duration refers to the period in which the number of occupied rooms per source market was less than 90% of that in 2019, which was predicted to exist in 2020Q2–2021Q1, 2020Q2–2021Q2, and 2020Q2–2021Q3 in the mild, medium, and severe scenarios, respectively. The quarter in which the travel ban was lifted refers to the point when Hong Kong completely relaxed travel restrictions for a given source market. The quarter in which demand returned to baseline reflects the point when demand was equal to the baseline forecast generated in the first step. We labeled the duration between the last trough quarter and the first quarter in which travel bans were lifted as the "adjustment period." During this period, hotel demand was expected to recover gradually from the trough because quarantine policies would be still in place. Once travel bans were fully lifted, recovery was anticipated to accelerate more quickly than in the adjustment period.

Step 2.1: COVID-19 Travelable Index

We constructed the COVID-19 Travelable Index to reflect the likelihood of international travel based on four indicators: pandemic situations, vaccination coverage, health resilience, and policy responses (e.g., travel restrictions; see Figure 3). The index is expressed as follows:

$$\begin{aligned}\text{COVID}-19\ \text{Travelable Index} = f(&\text{Recent pandemic indicator},\\ &\text{Vaccination coverage indicator},\\ &\text{Health reslience indicator},\\ &\text{Policy response indicator})\end{aligned}$$

where the recent pandemic indicator is determined by the latest number of confirmed COVID-19 cases and the corresponding average growth rate of confirmed cases; the vaccination coverage indicator denotes the number of vaccine doses administered per 100 persons and the associated average growth rate; health resilience is indicated by the recovery rate of confirmed cases; and policy responses constitute an aggregated index combined with the stringency index, the government responses index, and the COVID-19 containment and health index included in the coronavirus Government Response Tracker (OxCGRT) (Hale et al., 2020; Liu et al., 2021).

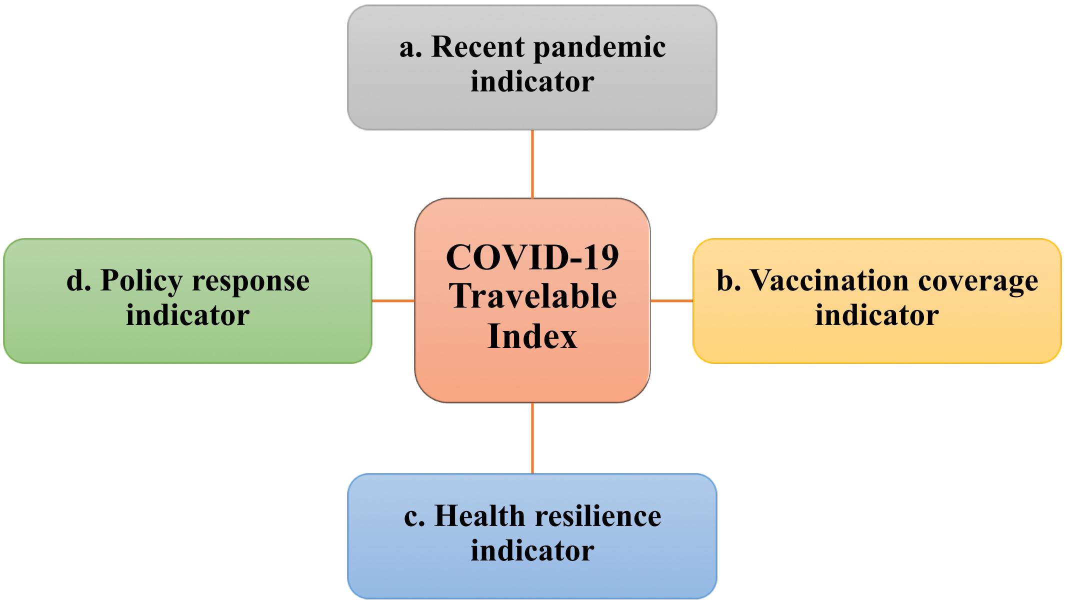


Figure 3. COVID-19 Travelable Index.

Cluster analysis was performed to categorize the 10 source markets into three groups according to the above four indicators. We first standardized all variables using the z-score to eliminate measurement-based influence. Principal component analysis was performed next to collapse multi-factor indicators into one major component. The formulated factor score was then taken as the variable to conduct hierarchical cluster analysis based on between-group linkages and the squared Euclidean distance. Meanwhile, COVID-19 Travelable Index values were re-scaled into ordinal numbers. For instance, the pandemic situation indicator was specified using a higher number if the recent number of confirmed cases for source market A exceeded that of other markets. Apart from quantitative statistical analysis, judgmental analysis was adopted to group source markets in terms of travel bubbles, travel distance, and current government policies. Travel bubbles, also known as travel corridors, are partnerships between two or more destinations where the pandemic has been under control; these "bubbles" permit the mobility necessary for international travel.

The results of cluster analysis appear in Figure 4. According to the four indicators of the COVID-19 Travelable Index, the United Kingdom and United States were classified into one group, Singapore represented another group, and the remaining source markets constituted the third group. Hong Kong reached a travel bubble agreement with Singapore on November 22, 2020, but the measure was postponed due to fluctuations in COVID-19. However, as long as the pandemic is controlled, this policy will likely be implemented. Travel distance also exerted significant impacts on international travel mobility amid COVID-19, with long-haul markets seeming less attractive than short-haul markets. These statistical analyses and judgmental adjustments resulted in three source market groups (see Figure 5).

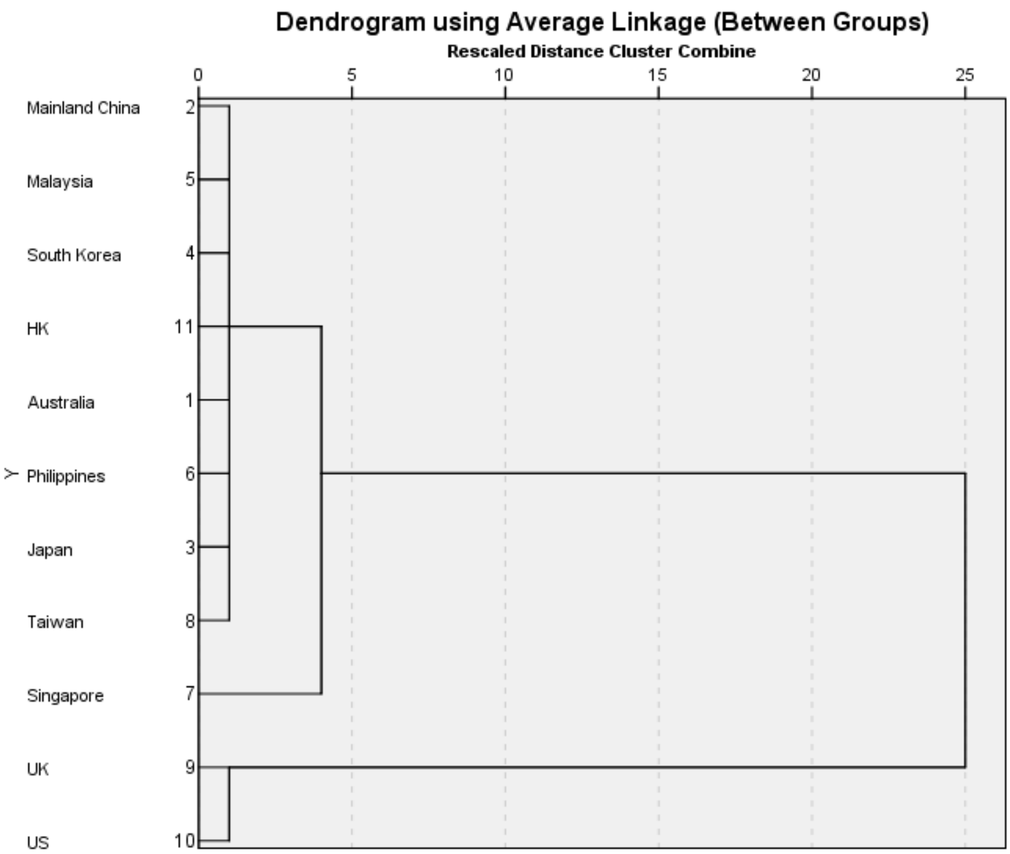


Figure 4. Cluster analysis for source markets.

Group	Rank	Source market	Travelable Index
A	1	Singapore	3.00
B	2	Taiwan	4.00
	3	Australia	5.00
	4	South Korea	5.50
	5	Malaysia	5.50
	6	Mainland China	5.75
	7	Japan	5.75
C	8	United States	5.75
	9	United Kingdom	6.50
	10	Philippines	8.25

Figure 5. Source market groups by COVID-19 Travelable Index.

Step 2.2: Compound scenario forecasts

Once source markets were grouped, we produced dynamic scenario forecasts in mild, medium, and severe scenarios. The pandemic situation in Hong Kong and in source markets remains volatile; thus, we sought to provide an array of potential outcomes to capture multiple possibilities, such as another pandemic wave or viral mutations in the destination and source markets.

The design of the compound scenarios is shown in Table 1. The COVID-19 Travelable Index indicated that Hong Kong is predicted to lift travel restrictions earlier for source markets in Group A (Singapore). As such, hotel demand will presumably return to baseline earlier in 2022Q3, 2023Q2, and 2024Q1 in the mild, medium, and severe scenarios, respectively. For source markets in Group B (Australia, mainland China, South Korea, Malaysia, Japan, Taiwan), Hong Kong is likely to completely relax travel restrictions later than for Group A;

demand is thus expected to return to baseline in 2023Q1, 2023Q4, and 2024Q3 in the three scenarios. The international travel mobility of Group C (United Kingdom, Philippines, United States) appears more discouraging given these countries' severe COVID-19 status across the four indicators. We expect Hong Kong to relax travel restrictions for these source markets no earlier than 2022Q1 in the mild scenario and that demand will recover to baseline in 2023Q3, 2024Q2, and 2025Q1 in the mild, medium, and severe cases, respectively.

Table 1. Compound scenario analysis.

Key indicator	Group A			Group B			Group C		
	Mild	Medium	Severe	Mild	Medium	Severe	Mild	Medium	Severe
Trough duration	2020Q2 | 2021Q1	2020Q2 | 2021Q2	2020Q2 | 2021Q3	2020Q2 | 2021Q1	2020Q2 | 2021Q2	2020Q2 | 2021Q3	2020Q2 | 2021Q1	2020Q2 | 2021Q2	2020Q2 | 2021Q3
Quarter to lift travel bans	2021Q3	2022Q1	2022Q3	2021Q4	2022Q2	2022Q4	2022Q1	2022Q3	2023Q1
Quarter to return to baseline	2022Q3	2023Q2	2024Q1	2023Q1	2023Q4	2024Q3	2023Q3	2024Q2	2025Q1

The adjustment procedure for scenario forecasting is introduced below. First, before Hong Kong government eliminates travel bans, hotel demand was assumed to increase to 30%, 20%, and 10% of baseline forecasts with unequal growth in the mild, medium, and severe scenarios, respectively. Second, we calculated the percentage decline in hotel occupancy in the adjustment period and generated a recovery path assuming the same recovery percentage per quarter once travel bans were completely lifted. Third, adjusted forecasts were produced by multiplying the baseline forecasts by the recovery path for each scenario.

We employed compound scenario forecasting method for several reasons. First, international travel is a bilateral activity involving destination and source markets; this approach considers pandemic circumstances on both sides. Second, we created the COVID-19 Travelable Index using four indicators to classify source markets into groups, which could then be generalized to predict hotel demand in other markets. Third, this dynamic scenario design considers the international travel mobility of each source market to Hong Kong during COVID-19 and captures various possibilities. Finally, compound scenario forecasting is dynamic and in line with reality; that is, destinations are more likely to lift travel bans gradually rather than eliminating bans for all source markets at once. Forecasts generated using this method thus carry valuable research and policy implications in times of crisis.

Results and Discussion

Model estimation and demand elasticities

Thirty ARDL-ECMs were specified to (a) estimate demand for different hotel room types among guests from 10 source markets and (b) generate corresponding baseline forecasts for the next five years. The augmented Dickey–Fuller unit root test and the bounds test (Pesaran et al., 2001) were performed to check the stationarity of data and the existence of long-run relationships between the dependent variable and its regressors. According to the unit root test, some variables were stationary at level (I[0]), but most became stationary after integration of the first order (I[1]). Bounds test results appear in Table 2. Because the *F*-statistic and *t*-statistic each surpassed the critical values for I(1) variables, the null hypothesis (no level relationship) was rejected. All 30 models passed the bounds test, confirming long-run relationships between variables.

Table 2. Bounds test results.

Category	Statistic	Australia	Japan	Mainland China	Malaysia	Philippines
High	F-statistic	14.614	29.290	11.575	26.592	11.881
Tariff A	t-statistic	-4.505	-10.417	-5.399	-7.160	-5.676
High	F-statistic	23.127	29.215	22.533	24.413	26.485
Tariff B	t-statistic	-4.877	-8.398	-4.841	-5.356	-8.932
Medium	F-statistic	22.861	16.654	12.642	25.751	18.934
Tariff	t-statistic	-5.755	-6.442	-4.941	-9.111	-7.885
Category	Statistic	Singapore	South Korea	Taiwan	United Kingdom	United States
High	F-statistic	45.608	7.886	13.000	12.514	77.786
Tariff A	t-statistic	-11.176	-4.870	-4.195	-4.634	-16.247
High	F-statistic	30.179	14.599	28.182	22.221	54.581
Tariff B	t-statistic	-9.141	-6.777	-8.791	-7.711	-12.385
Medium	F-statistic	30.549	17.908	27.902	41.630	50.285
Tariff	t-statistic	-10.489	-5.487	-8.398	-10.913	-10.578

The long-run demand elasticities were consistent with those suggested by demand theory in terms of sign and magnitude, corroborating earlier work (see Table 3). Price and income were key factors influencing tourists' demand for different hotel types. In most models, the income level represented by the GDP index had a significant, positive impact on hotel room demand. Additionally, price elasticities implied a negative relationship between hotel demand and room rate.

Overall, short- and long-haul markets were both more income elastic in terms of demand for high tariff A hotel rooms. Most short-haul markets (e.g., South Korea, Mainland China, Malaysia, Philippines) were also sensitive to income changes for high tariff B and medium tariff hotels. The prices of high tariff A hotels significantly influenced hotel room demand among guests from mainland China, Malaysia, and the Philippines.

Dummy variables for events such as SARS in 2003, the global financial crisis in 2008/2009, and Hong Kong's social unrest in 2019 had significant negative effects on hotel room demand. Besides, most diagnostic statistics suggested that the models applied to forecast hotel room demand were well specified and generally did not suffer from misspecification.

Table 3. Elasticity estimates by source market.

Category	Results	Australia	Japan	Mainland China	Malaysia	Philippines
High tariff A hotels	Income	1.99***	1.14	1.23***	1.80***	1.16***
	Own price	-3.12***	-0.40*	-1.95***	-1.26***	-2.20***
	Sub. price	0.91**	/	1.24**	0.09	1.08***
	R-squared	0.92	0.88	0.85	0.94	0.93
	Test A	1.38	1.55	1.11	1.39	1.00
	Test B	1.45	1.62	12.93***	0.01	1.60
	Test C	1.16	4.36	0.73	3.99	2.62
	Test D	4.06**	15.04***	15.66***	5.76***	8.37***
	Test E	5.48	5.88	9.99	7.06	53.76
High tariff B hotels	Income	2.82***	2.56**	1.03***	2.81***	0.26**
	Own price	-2.04***	-0.73***	-0.76**	-2.04**	0.31**
	Sub. price	/	/	/	/	/
	R-squared	0.89	0.93	0.87	0.91	0.91
	Test A	1.40	1.80	0.92	1.26	1.26
	Test B	0.45	0.22	9.79***	3.88**	0.78
	Test C	51.15***	0.12	1.30	18.43***	4.49
	Test D	3.88**	16.26***	29.64***	6.48***	8.73
	Test E	4.67	5.91	8.29	8.75	7.34
Medium tariff hotels	Income	1.10	1.64	0.89***	0.16	1.04***
	Own price	-1.42***	0.31	-0.45*	0.34	1.03***
	Sub. price	0.62*	/	/	0.28***	/
	R-squared	0.85	0.90	0.84	0.93	0.95
	Test A	1.13	1.56	0.98	1.04	1.53
	Test B	0.73	1.09	18.52***	1.78	2.12
	Test C	0.07	12.41***	0.34	3.48	10.56***
	Test D	22.14***	6.04***	11.49***	11.39***	8.53***
	Test E	4.75	4.48	5.65	9.28	7.45

Category	Results	Singapore	South Korea	Taiwan	United Kingdom	United States
High tariff A hotels	Income	0.94***	1.44***	1.92***	2.24**	1.15***
	Own price	-0.66***	0.30	1.09	-0.60	-0.05
	Sub. price	0.11	/	/	0.21	/
	R-squared	0.95	0.83	0.86	0.87	0.91
	Test A	1.14	1.26	1.08	1.39	1.09
	Test B	1.53	1.59	9.11***	0.09	8.56***
	Test C	1.51	1.36	3.40	10.05***	2.50
	Test D	11.07***	8.09***	15.47***	18.70***	20.94***
	Test E	5.27	3.59	9.77	3.88	4.23
High tariff B hotels	Income	0.80***	1.22***	0.72***	0.84**	1.56***
	Own price	0.14	-0.80**	-0.52*	-0.54***	-0.10
	Sub. price	/	0.57	0.54***	0.91***	/
	R-squared	0.86	0.88	0.95	0.91	0.91
	Test A	1.09	1.74	0.99	1.30	1.48
	Test B	1.00	1.39	1.27	0.71	2.95*
	Test C	15.42***	27.91***	0.08	10.43***	0.14
	Test D	11.25***	7.30***	6.30***	8.84***	15.32***
	Test E	2.92	30.88	11.87	7.25	2.33
Medium tariff hotels	Income	0.64***	4.42***	2.06***	2.84***	0.25
	Own price	1.33***	-0.81	0.29	-0.14	-0.24
	Sub. price	/	/	/	0.04	/
	R-squared	0.92	0.88	0.96	0.91	0.90
	Test A	1.27	1.21	1.57	1.16	1.37
	Test B	1.80	7.86***	0.24	6.91***	0.05
	Test C	2.39	3.75	0.77	1.09	6.98**
	Test D	10.26***	21.19***	10.08***	10.60***	4.47***
	Test E	7.46	5.73	13.23	5.07	5.03

Notes: Sub. price is the abbreviation of the substitute price. R-squared measures the goodness of fit for each model. Tests A, B, C, D, and E are the Durbin-Watson statistic for autocorrelation, Breusch–Pagan test for heteroscedasticity, Jarque–Bera test for normality, Ramsey RESET test for model misspecification, and vif test for multicollinearity. The results of the other tests are available on request. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively.

Hotel demand forecasts

Before generating hotel demand forecasts, we predicted explanatory variables including income, relative price, and substitute price using the Holt-Winters seasonal exponential smoothing method, as done in prior studies (Song et al., 2013; Taylor, 2003). However, to incorporate the impacts of the COVID-19 crisis on independent variables, we adjusted income-level forecasts according to the World Economic Outlook (IMF, 2021). The forecasts for explanatory variables were then used to generate demand forecasts for different types of hotel rooms among residents from the 10 source markets.

Figure 6 depicts the hotel demand forecasts in three scenarios over the period of 2021Q1–2025Q4 together with baseline forecasts. The number of occupied rooms in 2020 was adjusted based on the reduction in overnight tourists versus 2019. Overnight tourist arrivals declined by roughly 99% for nearly all Hong Kong source markets from 2020Q2 to 2020Q4. We therefore concluded that the trough spanned the entire year of 2020.

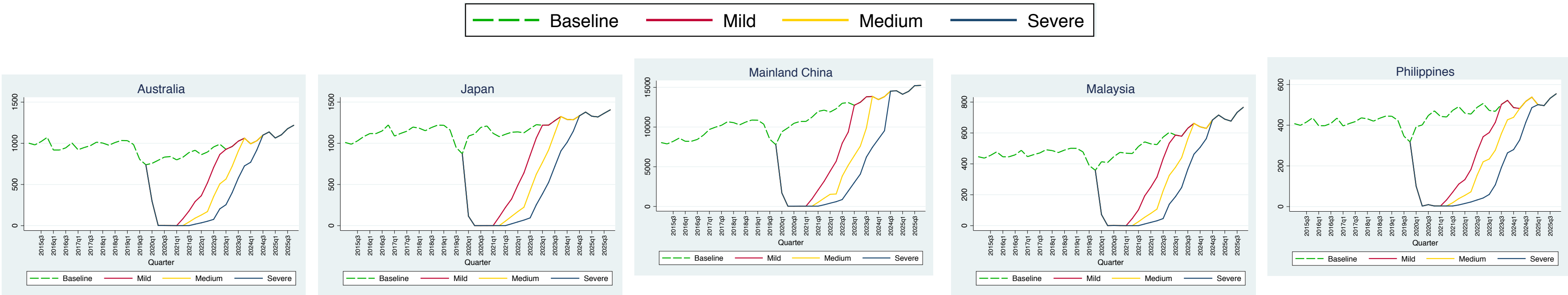
With gradually increasing vaccine administration and the possible implementation of vaccine passports, we predicted that the trough in hotel demand will not last beyond 2021. The hotel industry should recover steadily beginning in 2021Q2 in the mild scenario and from the fourth quarter of 2021 in the severe case. However, because Hong Kong government will not open its borders to all source markets at once, travel bans will likely be lifted in different quarters across the three scenarios. Before travel restrictions are eliminated completely, hotel room demand should increase slowly due to tourists' concerns about quarantining, health, and safety. Hotel room demand is hence expected to reach 30%, 20%, and 10% of baseline in the mild, medium, and severe scenarios, respectively. Once Hong Kong and its source markets remove travel bans completely, hotel demand is anticipated to rise quickly and substantially. The recovery paths resemble a slim U-shaped curve, a medium U curve, and a fat U curve in the mild, medium, and severe scenarios, respectively.

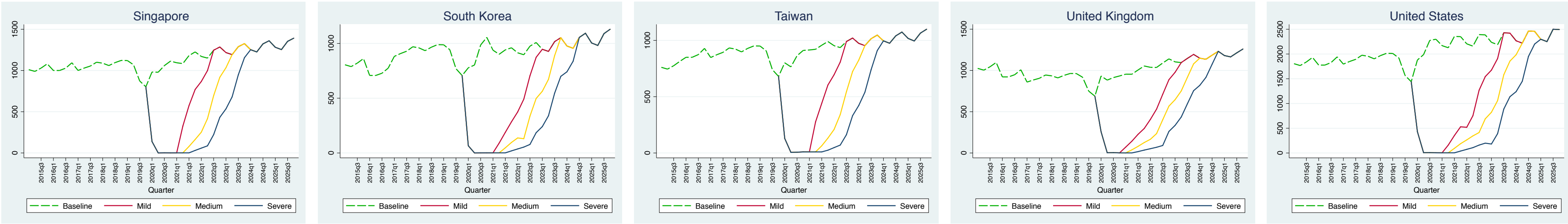
Specifically, hotel demand among tourists from Singapore should return to baseline forecasts more swiftly than the other markets. Hong Kong is more likely to relax travel bans earliest for Singapore for the following reasons. First, cumulative confirmed cases over the past 14 days were readily controllable. Second, in terms of health resilience, the recovery rates were 99.95% for Singapore, implying that its healthcare systems and medical capacity to respond to COVID-19 appeared reliable. Regarding vaccinations, 28.5 was administered in Singapore per 100 population until April 6, 2021. The inoculation rate in Singapore was much higher than in most other source markets. Hong Kong has reached a travel bubble agreement with Singapore that will launch in May 26th, 2021. Policy responses of Singapore are flexible, implying a greater possibility of lifting travel restrictions for residents visiting Hong Kong. Singaporean tourists' demand for high tariff A hotels accounted for the largest percentage compared with the other two hotel categories. Thus, demand for high tariff A hotels among tourists from Singapore should recover faster than the other two hotel classes.

Regarding other short-haul markets, mainland China, Taiwan, South Korea, Japan, and Malaysia fell into Group B. The pandemic has been relatively well controlled in mainland China for the past year; vaccine doses administered per 100 population reached 10.14. Mainland China thus represents a qualified travel bubble market. The Hong Kong government announced the "Return2hk" scheme at the end of April 2021. The scheme indicated that Hong Kong residents returning from mainland China and Macao are free of compulsory quarantine. Although this new policy could attract tourists, the recovery rate should be low due to perceived risks and strict travel bans in mainland China. Mainland China has been Hong Kong's largest source market, whose market share of medium tariff hotels was clearly greater

High Tariff A Hotel Demand Forecasts in Three Scenarios

High Tariff B Hotel Demand Forecasts in Three Scenarios





Medium Tariff Hotel Demand Forecasts in Three Scenarios

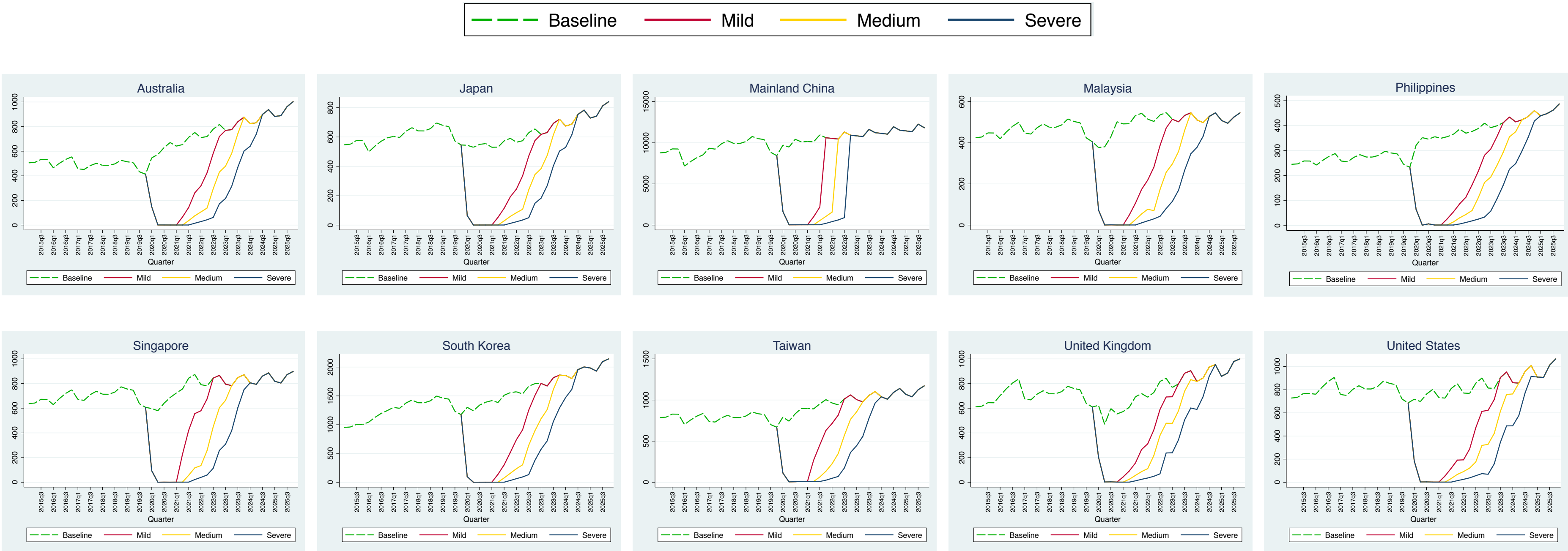


Figure 6. Hotel demand forecasts in three scenarios.

than that of high tariff A hotels. Hence, tourists' demand for high tariff A hotels may recover more slowly than the other two hotel categories.

The pandemic was controlled relatively well in Taiwan before May 2021; the number of confirmed cases was lower than 50. The number of overnight tourists from Taiwan began to increase in February 2021, jumping by around 11% over January 2021 (-99%). Hotel room demand among tourists from Taiwan seemed to be recovering from the trough in 2021Q1. Nevertheless, the pandemic situation in Taiwan has been rather volatile: the number of confirmed cases has increased considerably since mid-May, soaring to 554 on May 28, 2021. In addition, Taiwan's inoculation rate was somewhat low (0.08 per 100 population). Hong Kong is less likely to implement travel bubbles with Taiwan in the short term in this case. South Korea, Japan, and Malaysia recently witnessed a large number of confirmed cases, although case growth remained much lower than in Group C markets. Additionally, these three markets' vaccination rates were less than 2%. Japan has enacted strict containment measures related to international travel. However, these markets' recovery rates exceeded 98%, and all represent short-haul markets for Hong Kong. Travel bubbles between Hong Kong and these markets particularly warrant closer attention, as these agreements suggest a relatively optimistic travel outlook.

Australia also fell into Group B. The number of recently confirmed cases in Australia was below 200, indicating that the pandemic is not severe there. Australia has already implemented travel bubbles with New Zealand. Therefore, Hong Kong will likely relax travel restrictions for Australian tourists relatively soon. Hong Kong has begun to increase flights with Australia, and visitor arrivals are expected to climb in the near future. Nevertheless, because Australia is a long-haul market for Hong Kong, the costs and procedural complexity of travel may keep Australian tourists from visiting.

By comparison, hotel room demand forecasts among tourists from the United Kingdom, United States, and Philippines were not optimistic given these countries' total number of infections and soaring confirmed cases. Recent cases over the past two weeks were 131,606, 912,338, and 61,027 in the United Kingdom, United States, and Philippines, respectively. Many cases also involved a more highly transmissible viral mutation whose spread was difficult to control. Although sizeable proportions of the United States and United Kingdom residents have been vaccinated, Hong Kong is unlikely to remove associated travel bans until the number of confirmed cases in these markets declines to an acceptable level. The market share of high tariff A hotels far exceeds that of other hotel types in these markets. Therefore, tourists' demand for high tariff A hotels might recover slowly.

Forecasted hotel room demand among tourists from the Philippines differed from that of other short-haul source markets. The number of overnight tourists grew slightly, from 209 people in January to 366 people in February 2021. However, the sharp increase in recent confirmed cases, viral mutations, and a low vaccination rate (0.67%) kept Hong Kong from lifting travel restrictions. The jump in imported cases from the Philippines also led Hong Kong to strengthen control measures for tourists from Philippines.

Figures 7–9 depict the total quarterly scenario forecasts for room demand by hotel category between 2021Q1 and 2025Q4. Regarding forecasts for high tariff A hotels, we predicted that the number of hotel rooms might recover to the 2019 average (14,263 rooms) by 2023Q1 in the mild scenario.

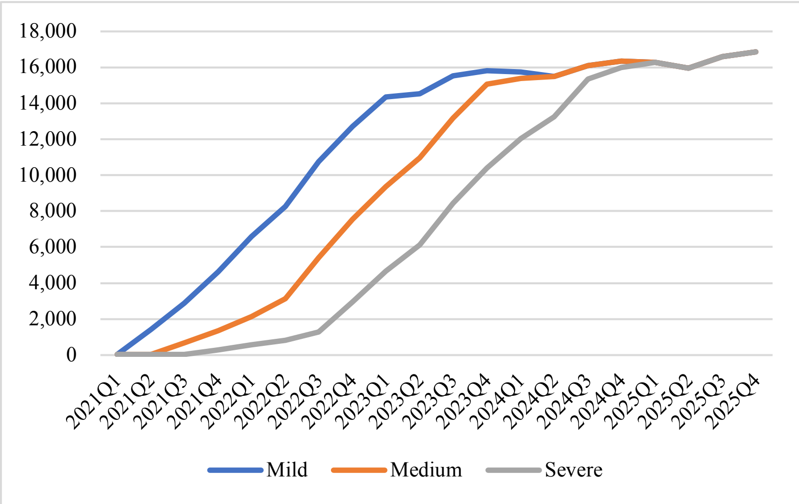


Figure 7. High tariff A hotel demand forecasts.

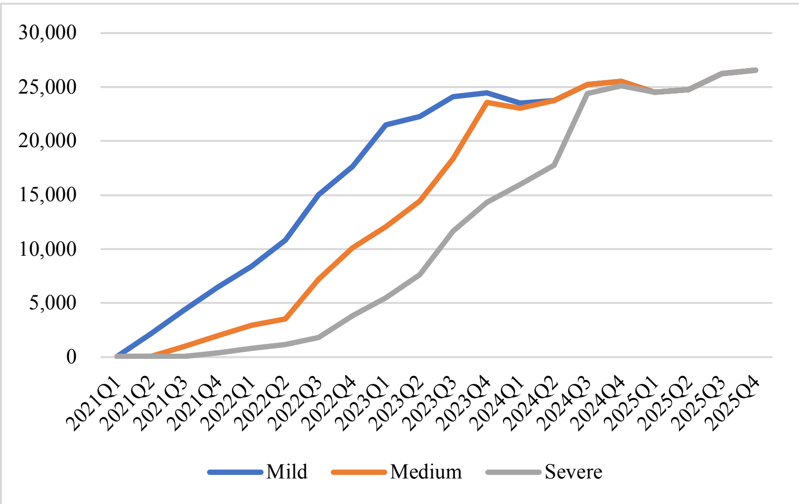


Figure 8. High tariff B hotel demand forecasts.

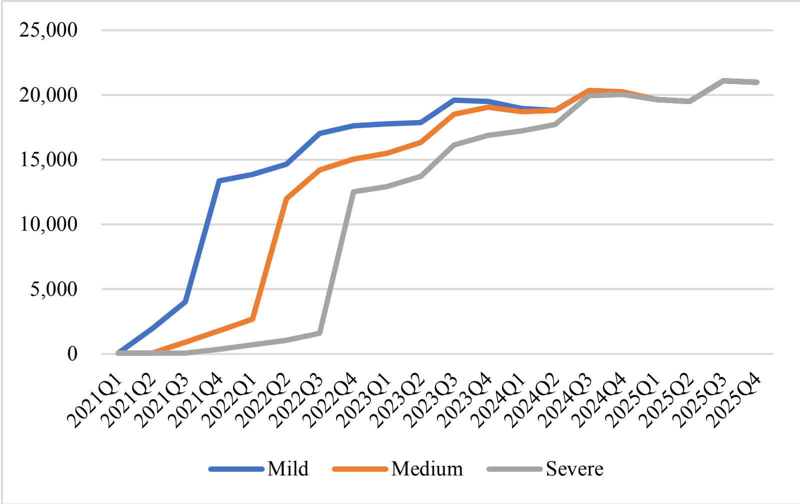


Figure 9. Medium tariff hotel demand forecasts.

Interestingly, across all scenarios, the demand forecasts for high tariff B hotels exceeded those for medium tariff hotels (Figure 10). This pattern indicates that potential tourists might pursue higher-quality stays and thus prefer accommodations offering satisfactory services and relatively advanced facilities. The lowest proportion of market share comprised high tariff A hotels, largely for two reasons: (1) price is a main factor affecting tourists' demand for hotel accommodations; and (2) source markets where guests mainly demand for hotel rooms in the high tariff A category were facing severe pandemic conditions that precluded the mobility necessary for international travel. Thus, to attract potential tourists, hotel businesses should improve their service quality and set an appropriate quality–price ratio. Figure 11 depicts the forecasts in terms of the total hotel room demand from all source markets for Hong Kong in mild, medium, and severe scenarios.

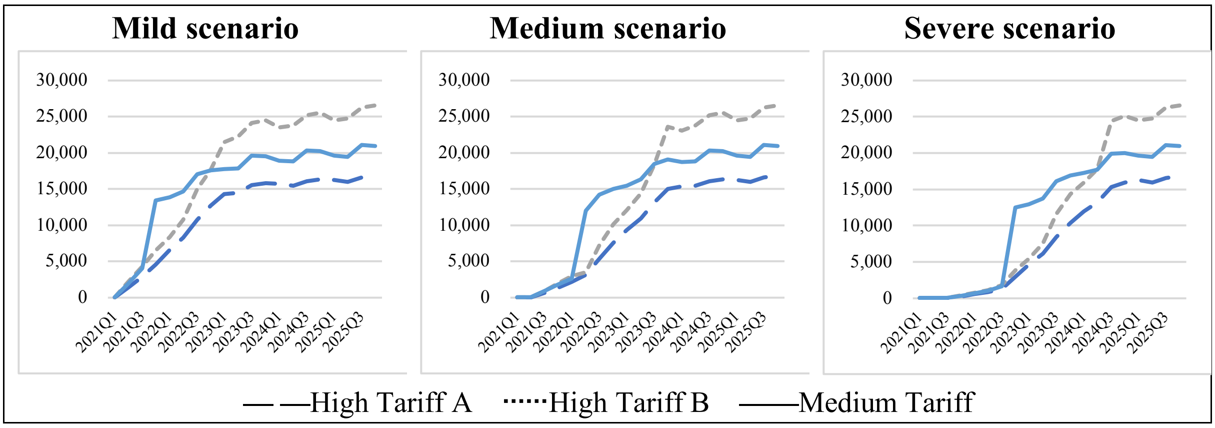


Figure 10. Hotel demand forecasts in three scenarios (by categeory).

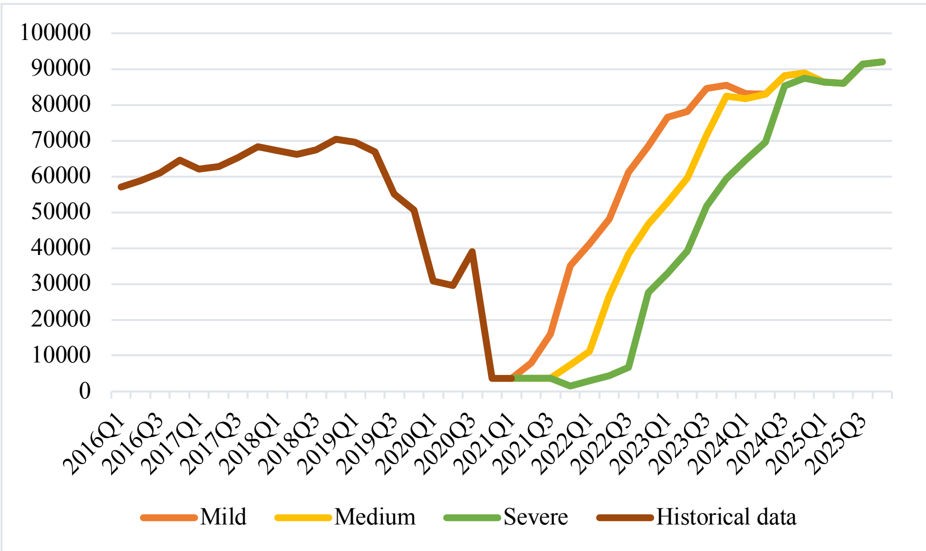


Figure 11. Total hotel demand forecasts.

Empirical implications

Price and income were found to considerably influence hotel demand, even in times of crisis. Tourists' income was adversely affected by COVID-19 in many source markets. Thus, practitioners should implement appropriate pricing strategies and marketing campaigns to draw tourists from corresponding markets with the aim of maximizing total revenue (Song et al., 2011). Apart from basic factors such as price and income, COVID-19 influenced hotel demand in several ways: real-time pandemic circumstances in Hong Kong and its source markets, vaccination protocols, travel restrictions, health resilience, travel distance, and other aspects were at play. Positive policies such as travel bubbles have sparked hope for the industry's revival. Businesses can now develop tailored services and commodities according to guests' preferences in markets where travel bubbles with Hong Kong seem imminent.

As the predicted recovery rates vary for hotel room demand from different source markets, it is important for hotel operators to foresee the differences of market segments. Considering market share by hotel type, the proportion of guests from short-haul markets in medium tariff hotels was 63.1% in 2017—higher than that for high tariff B hotels (56.1%) and high tariff A hotels (48.9%). On the contrary, long-haul tourists prefer high tariff A hotels to high tariff B hotels and medium tariff hotels, indicated by the market share of 20.6%, 14%, and 8.9% for these three types of hotel rooms, respectively. Our forecasts show that demand from short-haul markets should recover first and more swiftly than that from long-haul markets. Occupancy rates for medium tariff hotels and high tariff B hotels should therefore rise much faster than for high tariff A hotels.

Furthermore, based on historical data and hotel room demand forecasts over the next five years by category (see Figure 11), the room demand for medium tariff hotels is predicted to rise more swiftly than that for other types of hotels at the beginning of the recovery period. The room demand for high tariff B hotels is likely to catch up soon and even exceed the medium tariff hotels room demand afterwards. The market share of high tariff A hotels appears lower than that for the other two hotel types. First, price is a key driver behind tourism demand. Second, the market share of tourists preferring high tariff B hotels and medium tariff hotels accounted for higher proportions of total consumer demand for Hong Kong hotels. Nevertheless, demand forecasts for high tariff B hotel rooms are predicted to exceed demand for medium tariff rooms during the next five years. Although price is an essential feature of tourists' hotel room demand, service quality and the quality–price ratio also appear important to attracting international tourists.

Therefore, to earn long-run profit, medium tariff hotels need to implement appropriate marketing strategy and improve service quality to attract potential guests post crisis. Hotels in high tariff A and high tariff B category should focus on cost management in the short run and maintain service quality.

In addition, staycations have become quite common in Hong Kong over the past year, which supported most of the hotels to survive amid COVID-19. Staycations especially boosted demand for medium tariff and high tariff B hotel rooms. Since 2020Q2, local residents have heavily supported the hotel industry's development; hotel occupancy were largely attributable to staycations, quarantine package and long-stay package (Horwath, 2020).

Until policymakers completely relax travel restrictions for inbound tourists, staycations could remain one of the primary drivers of hotel revenue. Hence, hotel operators need to focus on effective cost management and put more effort on stimulating local demand in the short term. In the long run, the revival of the hotel industry should still mainly rely on inbound tourism. Forecasts for hotel room demand are critical for hotel industry to revive amid crisis.

Conclusion

In this paper, we combined an econometric model with compound scenario analysis to generate quarterly hotel demand forecasts in three hotel categories (i.e., high tariff A, high tariff B, and medium tariff) in Hong Kong among tourists from 10 source markets considering the impacts of the COVID-19. Econometric models using historical data cannot capture the true effects of unprecedented events such as COVID-19. Compound scenario forecasting method involving two layers of scenario analysis was thus applied to forecast hotel demand against baseline predictions generated using the ARDL-ECM model.

In the first step of compound scenario forecasting, hotel room demand among the 10 source markets was clustered into three groups according to the COVID-19 Travelable Index. Classification was based on source markets' pandemic situations, vaccinations, policy responses, and health resilience. In the second step, three scenarios (mild, medium, and severe) were designed for each source market group to describe demand recovery patterns in light of pandemic-related uncertainty in Hong Kong and its source markets. General and source market–specific forecasts of hotel demand unveiled several valuable suggestions for hotel businesses in terms of navigating post-COVID-19 recovery.

Crises often occur without warning. Evaluating the potential impacts of a crisis is paramount to businesses' survival. As COVID-19 continues to evolve, this study offers timely insight for public and private sector decision makers to mitigate the impact of the pandemic on Hong Kong's hotel industry. Compared to recent tourism demand forecasting research amid COVID-19, this study fills a gap in hotel demand forecasting and demonstrates the utility of

ADRL-ECM together with scenario analysis. Our findings illuminate recovery paths of hotel room demand in addition to identifying relationships between hotel room demand and associated influencing factors together with corresponding elasticities. The forecasting methods proposed herein are believed to produce accurate hotel demand forecasts while acknowledging the volatile nature of COVID-19. The accuracy of these forecasts can be further evaluated (e.g., based on the root mean square error and mean absolute percentage error) once actual hotel demand data become available.

Furthermore, scholars could incorporate other crisis-related factors into econometric models or include more updated information in the COVID-19 Travelable Index to enhance forecasting accuracy. Additional explanatory variables such as climate change could also be considered in ARDL-ECMs to improve forecasting performance.

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