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Aviation Market Development in the New Normal Post the COVID-19 Pandemic: An Analysis of Air Connectivity and Business Travel[*]

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Abstract: *This study quantifies the effects introduced by the COVID-19 pandemic on air connectivity and passenger travel behaviour. Our analysis suggests that the pandemic has led to significant connectivity loss at all airports, especially at large hubs and tourism destinations. Low-cost carriers' operations at these airports, whose main targets are price-sensitive, non-business travellers, have been significantly reduced, too. There is preliminary evidence that network carriers at hub airports played more important roles amid the pandemic, likely due to the benefits associated with their hub-and-spoke networks. Connectivity losses at the smallest airports tended to be temporary and limited. These airports had limited aviation services to start with and, thus, it was not too costly to maintain the minimum connectivity. Empirical results obtained from a passenger*

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preference study indicate that traveller subgroups are impacted in different ways. When there is no online meeting option, nearly 80% of the respondents prefer, and are willing to pay for, pandemic control measures. These 'pro-control' passengers perceive such measures and the associated high costs/fares as valuable and necessary to lower the health-related risks during air travel. When there is an online meeting option, the share of such passengers decreases to 44.5%, with the remaining 55.5% exhibiting disutility for the increased price and time associated with pandemic control measures. The average willingness-to-pay for pandemic control measures decreases significantly, whereas the value of time saved at health checkpoints increases significantly. The aviation industry thus faces a 'double-hit' problem: operation costs will increase due to pandemic control measures, and the resultant inconvenience and extra time and costs further reduce travel demand. Unlike previous short pandemics, business travel is likely to suffer with an extended decline until the pandemic is fully controlled. These results call for financial and operational support for aviation services, especially at major airports and tourism destinations. Because these large airports are expected to be profitable post the pandemic, they may resort to low-cost finance from the capital market in the short term. Because the value of time saved at checkpoints is very high, it is more important for government agencies to make the pandemic control and health measures efficient and smooth. For operations such as vaccination records, stakeholders in different countries should cooperate to facilitate seamless control and pleasant air travel experiences.

Keywords: COVID-19, Aviation Development, Air Connectivity, Airline Contribution, Passenger Preference, Health Control Measures, Online Meeting, Willingness to Pay

JEL Classification: I18; R41; R48

1. Introduction

The aviation industry plays an important role in a nation's economy, providing services for goods and passenger transport and offering job opportunities in the aviation industry and other sectors, notably logistics, trade, tourism, and high-value-added manufacturing. The outbreak of COVID-19 has brought catastrophic impacts to the aviation industry and the overall global economy. In order to promote the sustainable development of the aviation industry and a healthy economic recovery, it is essential to obtain an updated assessment of the aviation sector's performance amid the pandemic. Substantial changes introduced to air travel, such as health declarations and controls and quarantine requirements, are expected to be retained at least in the coming few years. Meanwhile, online meeting platforms have become a crucial instrument for business communication and have been used extensively during the pandemic. The significant changes in travel arrangements and the well-accepted option of online meetings may together impose significant impacts on air travel. These are important issues to be quantified because a decline in transport demand could lead to network downsizing and connectivity loss, which reduce the attractiveness of aviation services and, thus, lead to further negative feedback effects on demand.

Most Association of Southeast Asian Nations (ASEAN) countries are not expected to develop their airports into major international hubs in the near future and, thus, have to leverage the superior aviation networks in international hubs, such as Hong Kong, by maintaining frequent services to these gateways. On the other hand, there is no domestic aviation market in city economies such as Hong Kong and Singapore. As a result, it is important for them to maintain the aviation services to regional economies in order to maintain their hub-and-spoke networks. That is, the aviation networks in major international hubs and regional airports are mutually dependent. It is important to understand how aviation networks in the region evolve in the presence of the market dynamics caused by the COVID-19 pandemic. It is also notable that different airlines operate different networks. Network airlines typically operate hub-and-spoke networks, whereas low-cost carriers usually offer point-to-point networks to avoid complex transfer/connecting passenger operations. These airlines' cost and operation structures imply that different airlines may contribute to air connectivity differently in the new normal. It is important for governments to design the right industrial policy, and airports to attract the right type of airlines, in order to maintain and improve air connectivity in a sustainable way.

This study quantifies the impacts brought by the COVID-19 pandemic on air connectivity and passenger travel behaviour so that the right policy and managerial strategy can be identified to help the aviation industry reach a sustainable 'new normal'. Two research tasks are carried out:

Task 1: To investigate the changes in air connectivity in response to major disruptions caused by the COVID-19 pandemic. We first analyse the airport connectivity of (a) Hong Kong, which is a major international hub, and (b) the three largest and smallest airports in Malaysia and Thailand, respectively. We will then investigate different types of airlines' contribution to airport connectivity. Specifically, we investigate the contributions of (a) full-service airlines, such as Cathay Pacific and Thai Airways, and (b) low-cost carriers, such as AirAsia.

Task 2**:** To investigate the effects on passenger travel behaviour of the following factors: (a) health controls and health declarations involved in air travel, and (b) the increased use of online meeting options. For this purpose, the choice to fly is examined as a function of different factors, such as the severity levels of the pandemic, travel characteristics, and pandemic control measures. Attitudes towards online meeting options, travel costs, travel times, types of business communication, and travel-associated health risks are examined through attitudinal questions and rating scales. Then, a stated preference (SP) experiment is employed to investigate how different health control strategies and disease information may affect the choice to travel internationally for business purposes.

With the cautions of the limitation and generalisability of our analysis, our investigations conducted in the aforementioned two tasks lead to the following conclusions:

- The pandemic has led to significant connectivity losses in all the countries and markets analysed, especially at large hubs or tourism cities. Major international hubs, such as airports in Hong Kong, Malaysia, and Bangkok, are important connection points consolidating regional traffic to overseas destinations. With the combined effects of demand decline and travel restrictions imposed in international markets, many overseas destinations were lost. There are also signs that airlines are consolidating traffic in one country or region.

- Although there was a significant decline in traffic volume in general, the connectivity losses at the smallest airports tend to be temporary and limited. These airports had limited aviation services to start with and, thus, it was not too costly to maintain minimum connectivity. On the other hand, large airports mostly serving tourists, such as the Phuket airport in Thailand, experienced very significant connectivity loss as discretionary travel suffered most. Low-cost carriers' operations at such airports, whose main targets are price-sensitive non-business travellers, were significantly reduced too.
- There is some preliminary evidence that network carriers at hub airports played more important roles amid the pandemic (e.g. Cathay Pacific in Hong Kong, Thai Airways in Bangkok Suvarnabhumi International Airport, and Malaysia Airlines in Kuala Lumpur), whereas low-cost carriers (LCCs) performed worse in the same markets (e.g. Hong Kong Express in Hong Kong and AirAsia in Kuala Lumpur). In theory, a hub-and-spoke network may also be better-positioned than a point-to-point network because the traffic volumes can be consolidated at the hub airport. However, such preliminary patterns were the results of many market dynamics and a general decline of traffic volume and connectivity, and more detailed analysis is needed.
- Overall, our results indicate that there are different traveller subgroups as classified by their preferences for the pandemic control and health-related measures, with their attitudes significantly affected by the availability of online meeting options. When there is no online meeting option, nearly 80% of the respondents prefer and are willing to pay for health measures. They perceive such measures, and the associated high costs/fares, as valuable and necessary to lower the health-related risks during air travel. These 'pro-control' passengers prefer face-to-face communication, have experience of frequent travel before the epidemic, and perceive a lower health risk of air travel. In contrast, a minority of the respondents has a significant disutility

towards the pandemic control requirements of providing personal information, travel history, and symptoms declarations, although they favour convenient temperature screening over no on-site checking at all.

- When there is an online meeting option, the share of 'pro-control' passengers decreases from nearly 80% to 44.5%. Compared to the rest of the population, these passengers perceive a lower health risk, have more experience in frequent travel after the epidemic, and use online meetings less extensively after the epidemic outbreak. On the contrary, the remaining 55.5% showed disutility for the increased price and time associated with the pandemic control measures. They are averse to the requirement of providing a vaccination record and mandatory mask-wearing at the airport.
- With the option of an online meeting, the average willingness to pay (WTP) for the health control services decreases. For example, amongst those 'pro-control' passengers (with an associated class membership probability), the WTP for a vaccination record decreases from HK$2,310 to HK$1,815 when an online meeting option becomes available. The weighted average WTP for compulsory mask-wearing during flights and at airports decreases from HK$2,600 to HK$979. Similarly, the weighted average WTP for tests involving sample collection and temperature screening at the airport decrease from HK$1,950 and HK$1,655 to HK$775 and HK$568, respectively. The weighted average WTP for the time saved at the checkpoint increases from HK$40/min to HK$75/min, as passengers are more averse (less supportive) to pandemic control measures.

The rest of the paper is organised as follows: Section 2 reports the air connectivity of selected markets in Hong Kong, Malaysia, and Thailand and the different roles played by network airlines and LCCs. Section 3 reports a study on passenger behaviours and business travel demand, with a focus on the effects of pandemic control-related travel requirements and the use of online meeting options. The last section concludes and summarises the study.

2. Airport connectivity and airline performance amid the pandemic

2.1. Changes in air connectivity and the implications

The aviation industry is of critical importance to regional economies and their well-being. It not only directly contributes to employment, tax revenue, and economic activities in the aviation sector but also provides essential inputs to other sectors, notably tourism, trade, logistics, and high-value-added manufacturing (Gong et al., 2018; Wang, Fu, et al., 2020; Fu, Oum, and Zhang, 2010; Fu et al., 2021; Tsui et al., 2021; Salesi et al., 2021). However, the COVID-19 pandemic has brought devastating impacts to the aviation industry, leading to unprecedented downsizing in aviation networks, traffic volumes, and economic activities, especially passenger services. Although there are promising signs that the aviation market will rebound once the pandemic is under control, it is far from clear what kind of 'new normal' the aviation market will reach and whether and how countries can fully recover their air connectivity. Answers to such questions are particularly important for developing countries, including some ASEAN Member States, as well as international hubs such as Hong Kong and Singapore.

The aviation markets in developing countries are often relatively small and not fully liberalised. Within a small aviation market, a substantial decline in traffic volume may entirely remove aviation services between small origin–destination (OD) pairs (i.e. airport–city pairs) and, thus, significantly reduce air connectivity in domestic markets. With most ASEAN countries yet to fully liberalise their aviation markets, other than Singapore and to some extent Kuala Lumpur, even the major airports in the region are not expected to grow into major hubs in the near future (Homsombat, Lei, and Fu, 2010). As a result, these developing countries will have to leverage the superior aviation networks in international hubs, such as Hong Kong, by maintaining frequent services to these major hubs. On the other hand, there is no domestic aviation market in city economies such as Hong Kong and Singapore. As a result, it is important for such major hubs to maintain their aviation services to regional economies in order to maintain their hub-and-spoke networks. That is, the aviation networks in major international hubs and regional airports are often mutually dependent. It is important to understand how aviation networks in the region evolve in the presence of market dynamics caused by the COVID-19 pandemic.

It is also notable that different airlines operate different networks. Network carriers, also referred to as full-service airlines, typically operate hub-and-spoke networks, whereas low-cost carriers usually operate point-to-point networks to avoid complex transfer/connecting passenger operations and to reduce costs. The two types of airlines service, route entry and network configurations, and the effects on airline competition and traffic volume can, thus, be significantly different (Fu et al., 2011, 2015, 2019; Wang, Tsui, et al., 2020; Su et al., 2020). Airlines' cost and operation structures imply that different airlines may contribute to air connectivity differently in the new normal. It is important for governments to design the right industrial policy and for airports to attract the right type of airlines in order to maintain and improve air connectivity in a sustainable way.

2.2. Airport connectivity and the data source

Airport connectivity is examined using weekly flight schedule data from the Official Airline Guide (OAG) database, which has been extensively used in the aviation industry. We restrict our study to direct flight operations at Hong Kong International Airport, and the largest and smallest airports in Malaysia and Thailand. This allows us to examine the connectivity changes across different types of airports in different regions. The database includes detailed information on operating airlines, departure and arrival airports, flight frequency, and available seats. The weekly data span a period of 2 years, from the first week of January 2019 to the last week of December 2020, enabling us to identify the impact of the COVID-19 pandemic.

We focus on an airport's connectivity as measured by the number of destinations (i.e. airports) served with direct flights. In addition to this measure calculated weekly, we further compare the status at the end of 2019 versus at the end of 2020. Individual airlines' contribution to airport connectivity is also analysed by examining the number of each carrier's destination airports and the corresponding share at a given airport. The numbers of cities connected with direct flights operated by different airlines are calculated to quantify the contributions of different airlines to the connectivity of an airport. In our sample, the dominant airlines at an airport include both full-service airlines (e.g. Cathay Pacific Airways and Thai Airways International) and low-cost carriers (e.g. AirAsia). Dominant airlines often significantly influence their hub airports' performance, including network connectivity, and sometimes enter into strategic vertical arrangements to secure long-term cooperative relationships (Fu et al., 2011, 2015).

The changes in airport connectivity were affected by multiple factors. On the demand side, the travel intention has been significantly reduced by the pandemic, which makes many flights commercially unsustainable. Airlines thus have to reduce flight numbers or even cancel services completely. Such a pattern is present in both international and domestic markets and is likely to be the main driving factor of airline network losses. On the supply and government regulation side, travel restrictions and alternative government regulations have been imposed that forbid aviation services between certain airports within specified periods. The aviation market around the world has been greatly impacted such that many air flights have been cut off. As international hubs and regional/local airports serve different aviation markets and customers, the pandemic is likely to have caused different impacts on these two types of airports. The influence of the pandemic on the aviation market at international airport hubs and regional airports is analysed and discussed within this subsection.

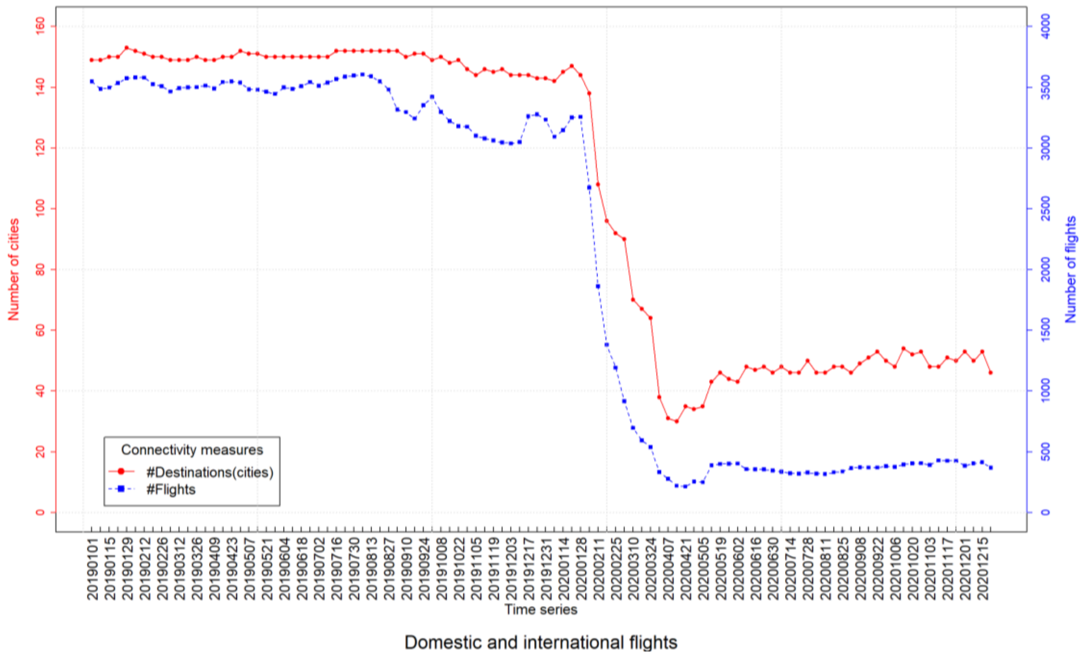
2.2.1. Connectivity at Hong Kong International Airport

The Hong Kong International Airport is a leading hub in Asia, and its connectivity during the sample period is shown in Figure 1. As of the end of January 2019, the airport was connected to 149 airports with direct flight services. On 23 January 2020, the Chinese city of Wuhan, with a population of 11 million people, entered into a complete lockdown. Hong Kong started to suspend aviation services to mainland China almost at the same time, which triggered a significant decline in connectivity. As illustrated by the figure, from the second week of February 2020, the number of cities connected by direct flights continuously dropped to the lowest level, with around only 35 cities in the fourth week of April 2020 (19 April 2020–25 April 2021), or a decline of 77% in air connectivity. The number of destinations remained stable at around 48 afterwards. The decline in the number of flights followed a very similar pattern.

In the last week of 2019, Hong Kong was connected to 45 countries/regions. Top destinations by country included 34 cities in mainland China, 17 cities in Japan, and eight cities in the United States. Overall, there were 22 countries/regions with two or more cities connected directly to Hong Kong. In comparison, at the end of 2020, the airport maintained direct flights to 28 countries/regions, including five cities in mainland China, three cities in Japan, India, Taiwan, the United States, and

Australia, respectively, two cities in Philippines, Viet Nam, Indonesia, and Canada, respectively, and only one city in other countries/regions. In terms of the number of flights, an average of 3,415 flights departed from the airport per week before the pandemic. Along with the rapid decrease in destination numbers, the number of flights also experienced a sharp decline to only 214 flights a week during the fourth week of April 2020, or a loss of about 94%. An average of 370 flights departed from the airport per week afterwards, or a loss of 89%. The decline in flight numbers is higher than the loss of connectivity in terms of cities connected. Overall, airlines tried to maintain connectivity to as many countries as possible by consolidating traffic (especially those to the same country) with a significantly reduced number of flights. As mainland China put tight restrictions on aviation services and international markets have been subject to many travel regulations, Hong Kong's aviation sector has suffered an extremely high loss.

Figure 1. Connectivity of Hong Kong International Airport



Source: Authors' compilation based on OAG data.

The full list of lost destinations linked to Hong Kong International Airport are summarised in Table A1 of Appendix I, obtained by comparing the status at the end of 2019 versus 2020 (before and after the COVID-19 pandemic).

2.2.2. Connectivity in selected airports in Malaysia

To examine the connectivity changes in Malaysia during the pandemic, we study the cases of the three largest airports by flight numbers, namely Kuala Lumpur International Airport, Kota Kinabalu Airport, and Penang Airport. We then examine the cases at the three smallest airports, namely Kudat Airport, Long Akah Airport, and Long Banga Airport.

- *Changes in major airports*

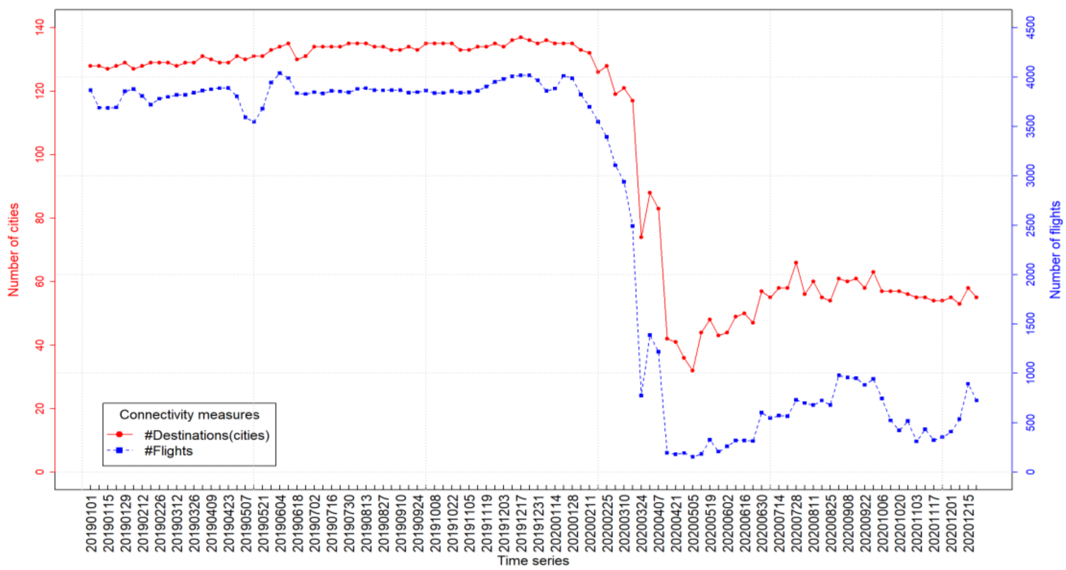
All the largest airports in Malaysia have suffered a significant loss in connectivity in both domestic and international sectors. The list of lost destinations from these airports are reported in Table A2 of Appendix I. The three airports have quite different sizes, with Kuala Lumpur being almost three times larger than the second-largest, Kota Kinabalu Airport. However, the decline in connectivity and flight numbers at these airports followed a quite similar pattern, as illustrated in Figure 2. The connectivity and flight numbers in Kuala Lumpur before the pandemic were quite stable, with 132 destinations connected by direct flights. The decline started in early February 2020 and accelerated in March and April, down to 32 destinations as of early May 2020, equivalent to a 76% decline. There was a minor recovery in the following months in 2020, reaching an average of 55 destinations in the second half of the year, about 42% of the normal level in 2019. In terms of the number of flights, weekly frequency was around 3,850 pre-pandemic, which dropped to 155 in early May 2020, or 4% of the pre-pandemic level in 2019. The moderate recovery brought this number to an average of 564 flights per week in the second half of 2020, about 15% of the normal level in 2019.

Kota Kinabalu Airport is the second-largest airport in Malaysia. The number of destinations connected by direct flights dropped from 39 in 2019 to the lowest level of 5 in April 2020, equivalent to a loss of 87%. After a moderate recovery, the destination number in the following months (May–December 2020) reached 15. The decline in flight numbers had a similar pattern, decreasing from an average of 720 flights per week in 2019 to the lowest level of 35 in late April 2020, or a 95% loss. In the second half of 2020, weekly flights fluctuated between 300 and 50, with around 170 flights on average per week, or about 24% of the normal level. Penang Airport is the third-largest airport in Malaysia. Destination numbers decreased from 23 in 2019 to 5 in early May 2020, then subsequently rebounded to 12 destinations in the rest of 2020. Weekly departing flights decreased from 715 to the lowest level of 48 in early May 2020, and recovered to about 170 departing flights in the second half of 2020.

As highlighted in Table A2, all three airports have lost connectivity to major hubs. Both Kota Kinabalu and Penang have lost connectivity to Hong Kong, whereas direct flight services between Kuala Lumpur and Hong Kong were kept. This implies that travel from Malaysia to Hong Kong will have to be connected via Kuala Lumpur. Although this introduces more inconvenience to some passengers originating outside of Kuala Lumpur, traffic volumes can be consolidated via the hub-and-spoke network so that connectivity can be maintained.

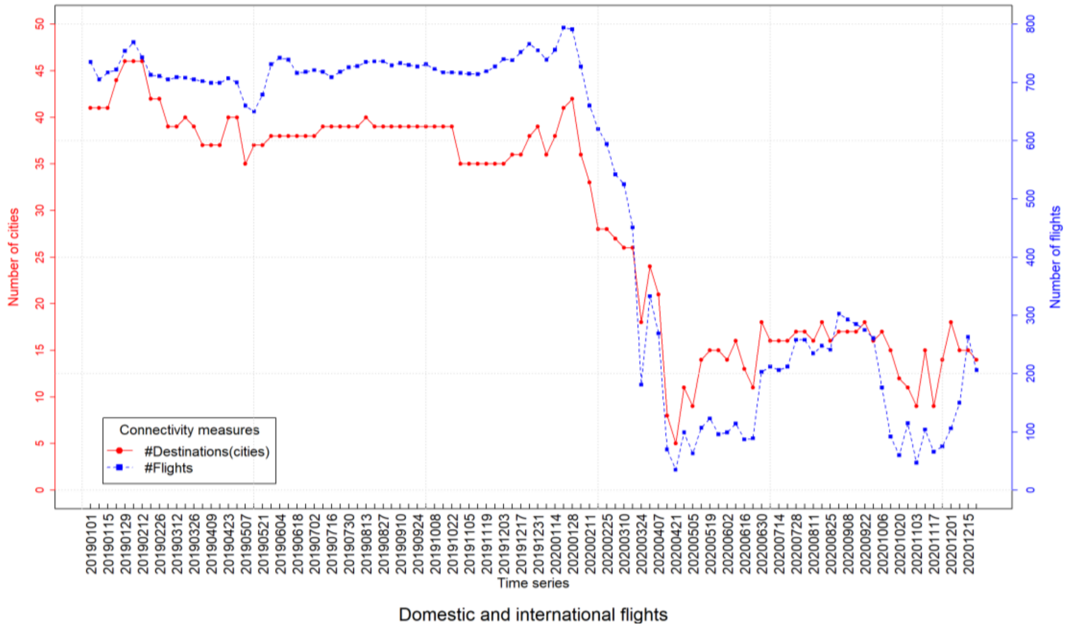
Figure 2. Connectivity at the Three Largest Airports in Malaysia

(a) Connectivity of Kuala Lumpur International Airport

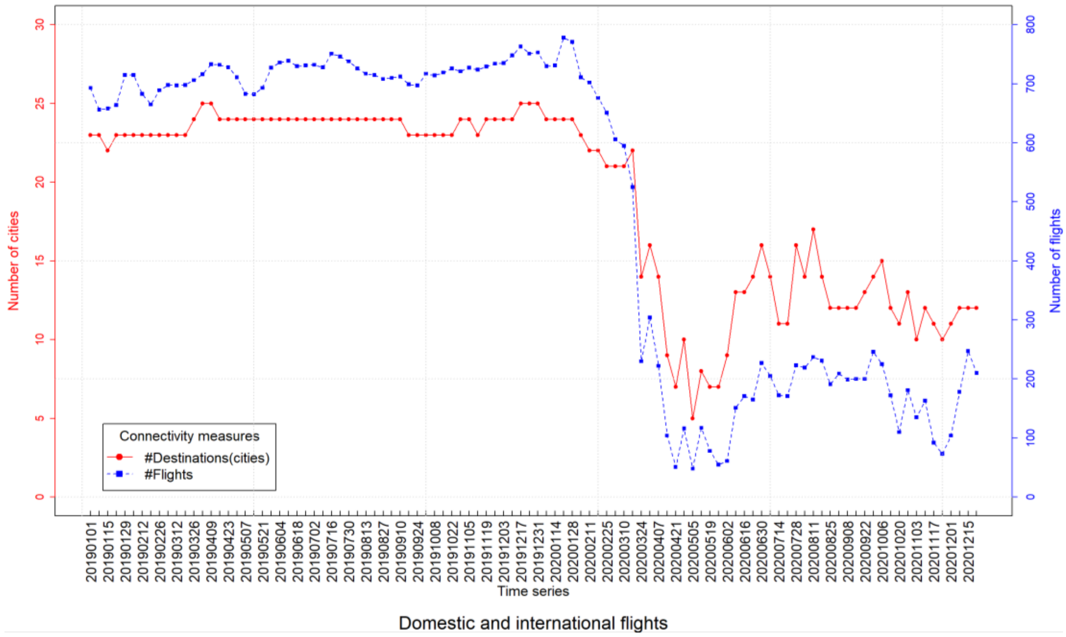


Domestic and international flights

(b) Connectivity of Kota Kinabalu Airport



(c) Connectivity of Penang Airport



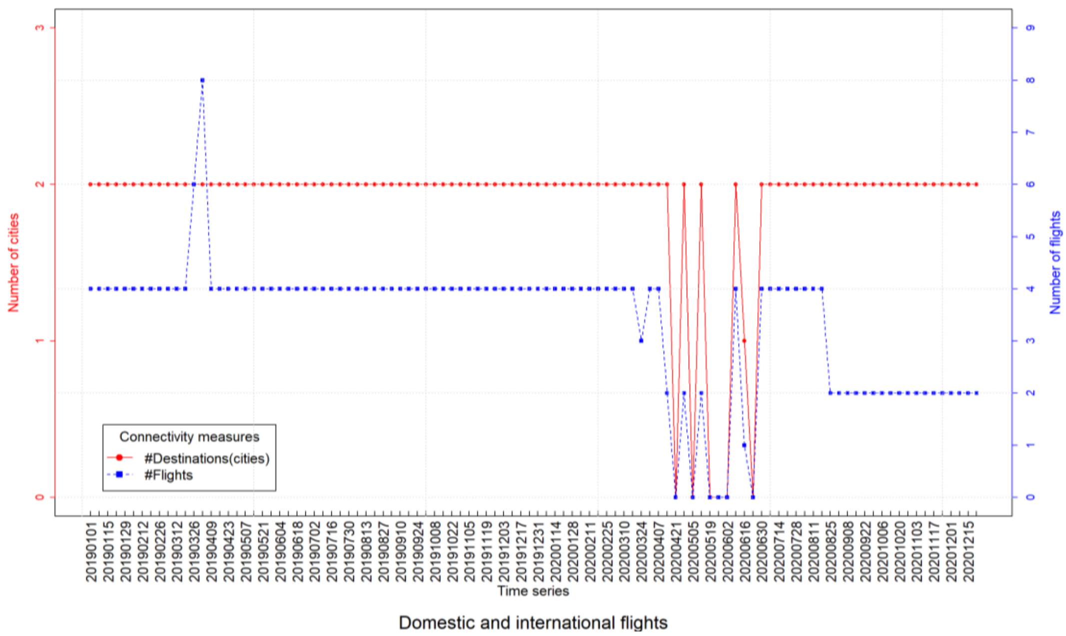
Source: Authors' compilation based on OAG data.

- *Changes in the smallest airports*

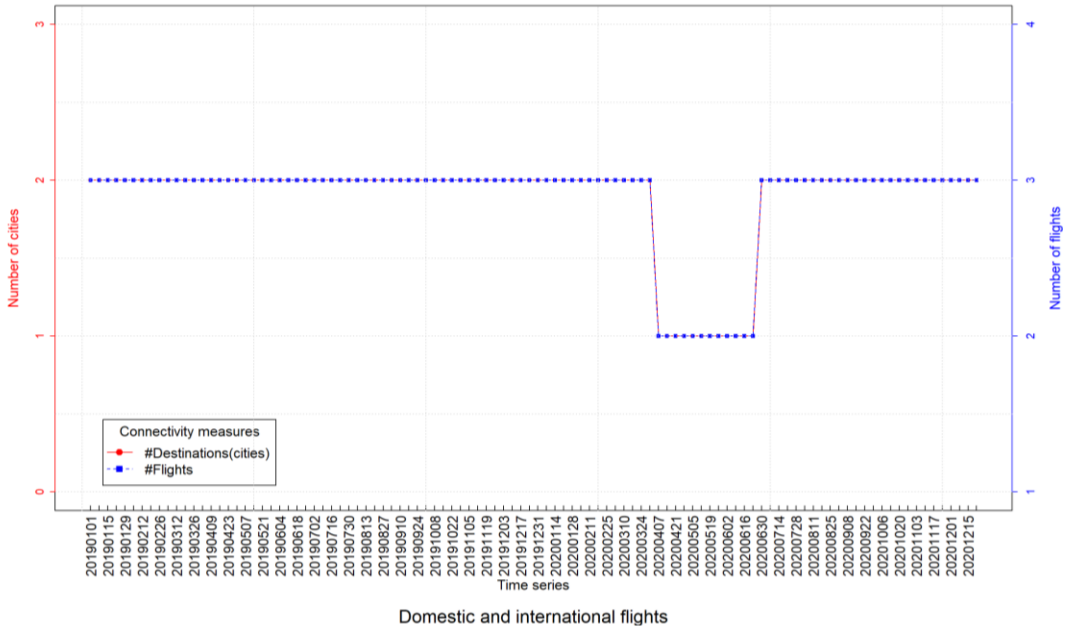
The three smallest airports in Malaysia in terms of flight numbers at the end of 2019 were Kudat Airport, Long Akah Airport, and Long Banga Airport. The development of the connectivity over the two-year period is illustrated in Figure 3. Although they have also suffered some loss over the sample period, the absolute declines were quite small. This is mainly because connectivity levels of these airports were extremely low already. In the case of Long Banga Airport, it was connected to one airport only with two flights services per week. Although the decline in travel demand was expected, the costs of maintaining such minimum connectivity should not be too much. Still, in the case of Kudat Airport, its connectivity in certain weeks during April–June 2020, when the traffic decline in Malaysia and Hong Kong was at its worst, was totally lost. However, minimum connectivity was soon resumed. In fact, in terms of both the number of destinations and weekly flights, Long Akah and Long Banga recovered to their pre-pandemic levels.

Figure 3. Connectivity at the Three Smallest Airports in Malaysia

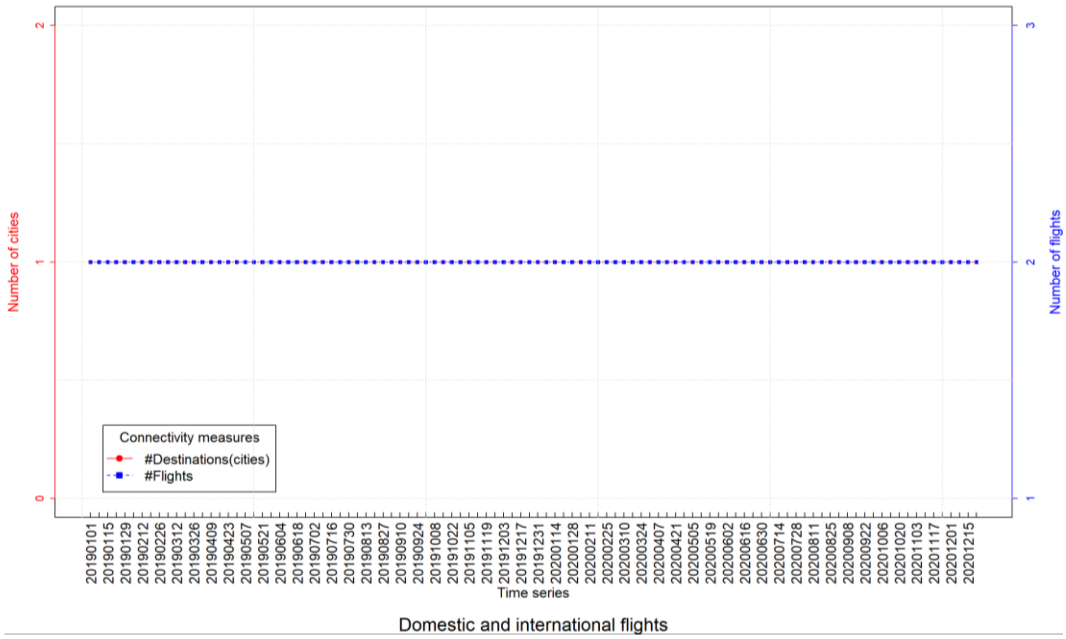
(a) Connectivity of Kudat Airport



(b) Connectivity of Long Akah Airport



(c) Connectivity of Long Banga Airport



Source: Authors' compilation based on OAG data.

2.2.3. Connectivity in selected airports in Thailand

A similar investigation is conducted for the connectivity changes in Thailand from 2019 to 2020. The three largest airports are Bangkok Suvarnabhumi International Airport, Bangkok Don Mueang International Airport, and Phuket Airport. With the new Suvarnabhumi airport built into a major hub, the old Don Mueang airport in Bangkok has been developed into a major regional airport for LCCs. Phuket Airport serves the major tourist destination of Phuket Island.

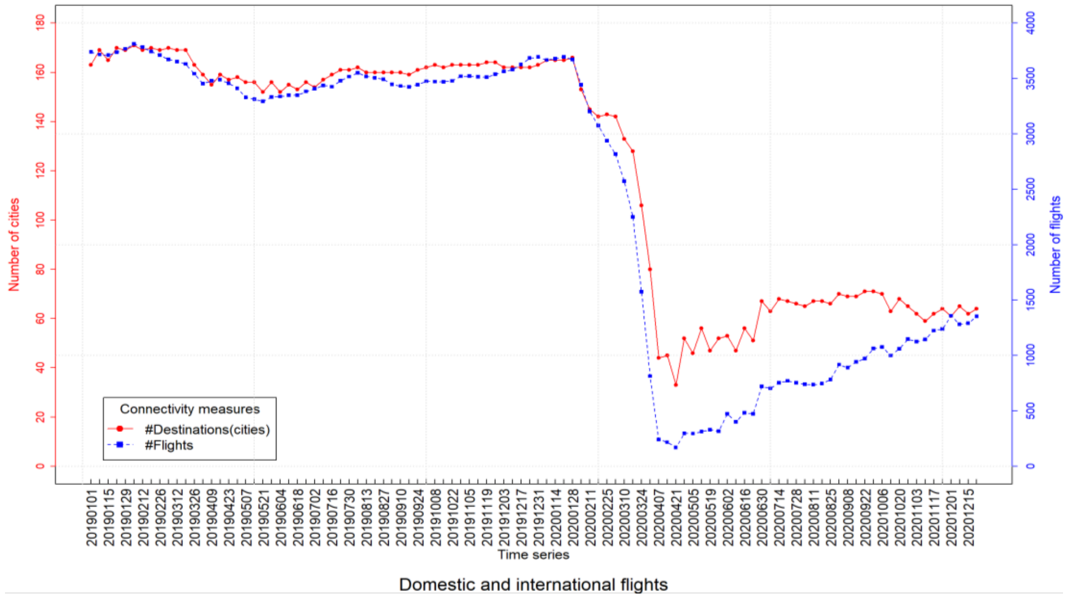
- *Changes at major airports*

  The air connectivity of the three largest airports in Thailand is summarised in Figure 4. Bangkok Suvarnabhumi International Airport is the largest airport in Thailand and an important international hub. Its connectivity had been significantly reduced, with an average of 162 destinations per week pre-pandemic compared to 33 in late April 2020, or a loss of 80%. Connectivity subsequently increased to 61 destinations by the end of 2020. Bangkok Don Mueang International Airport had direct services to 98 cities per week pre-pandemic. The number dropped to its lowest level of 14 in mid-April 2020 and only recovered to 27 by the end of the year. It is notable that Suvarnabhumi Airport hosts mostly network carriers, whereas Don Mueang hosts mostly LCCs. The analysis shows that the latter actually performed worse amid the pandemic.

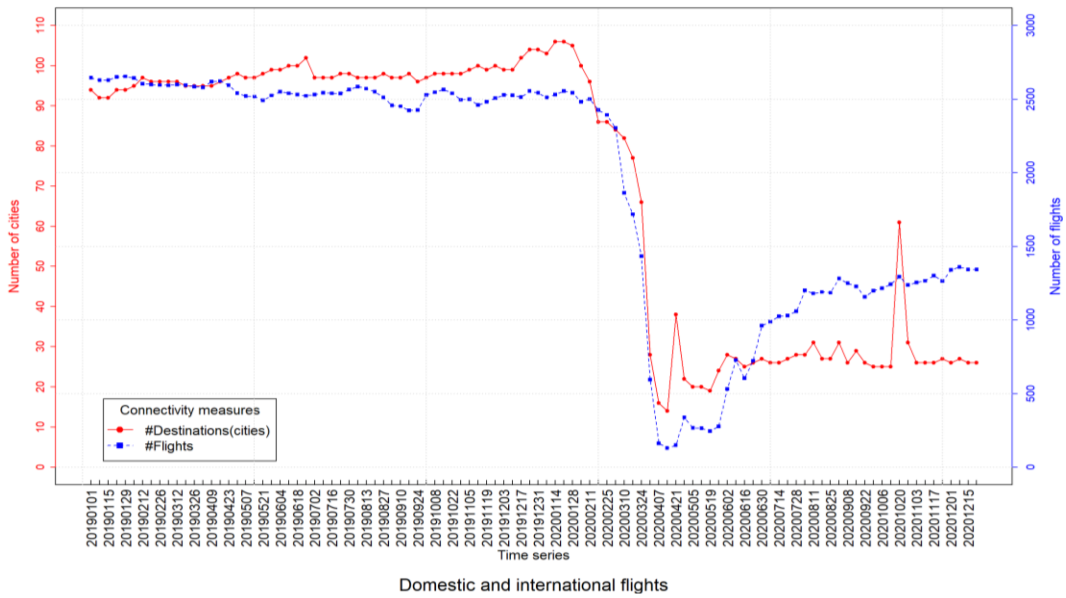
  There seemed to be significant seasonal variation in connectivity at Phuket Airport, where higher connectivity was witnessed in cold seasons (spring and winter) compared to hot seasons (summer and autumn). The average connectivity for spring and winter was 79 and 70, respectively, whilst it was 57 in summer and autumn. Phuket is an attractive tourism city in winter and spring. The airport’s connectivity was very severely damaged, with only two cities served as of April 2020. The recovery was also quite weak, back to 10 cities or 12.7% of the level before the pandemic.

Figure 4. Connectivity at the Three Largest Airports in Thailand

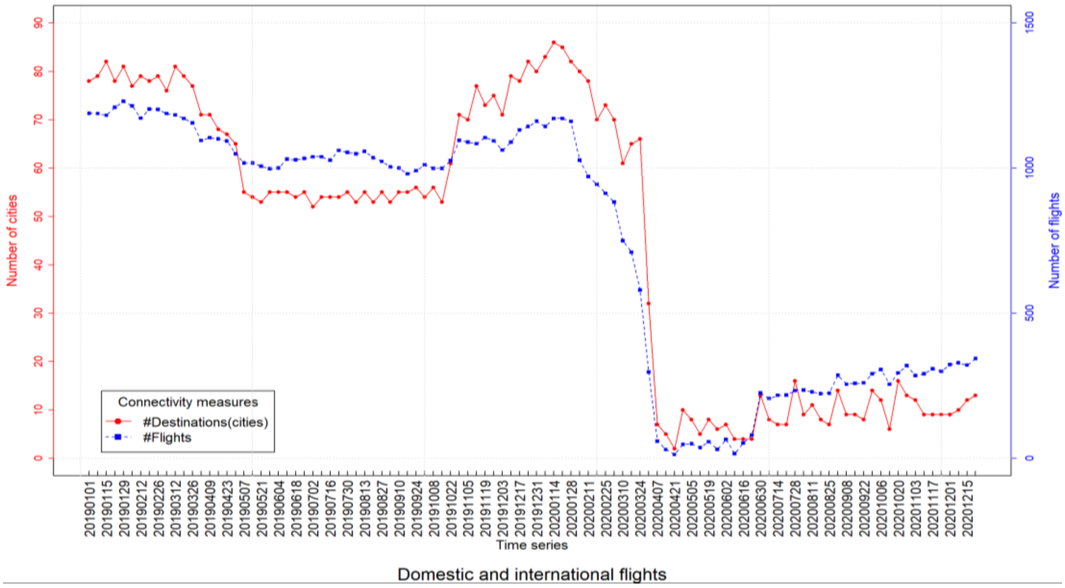
(a) Connectivity of Bangkok Suvarnabhumi International Airport



(b) Connectivity of Bangkok Don Mueang International Airport



(c) Connectivity of Phuket Airport



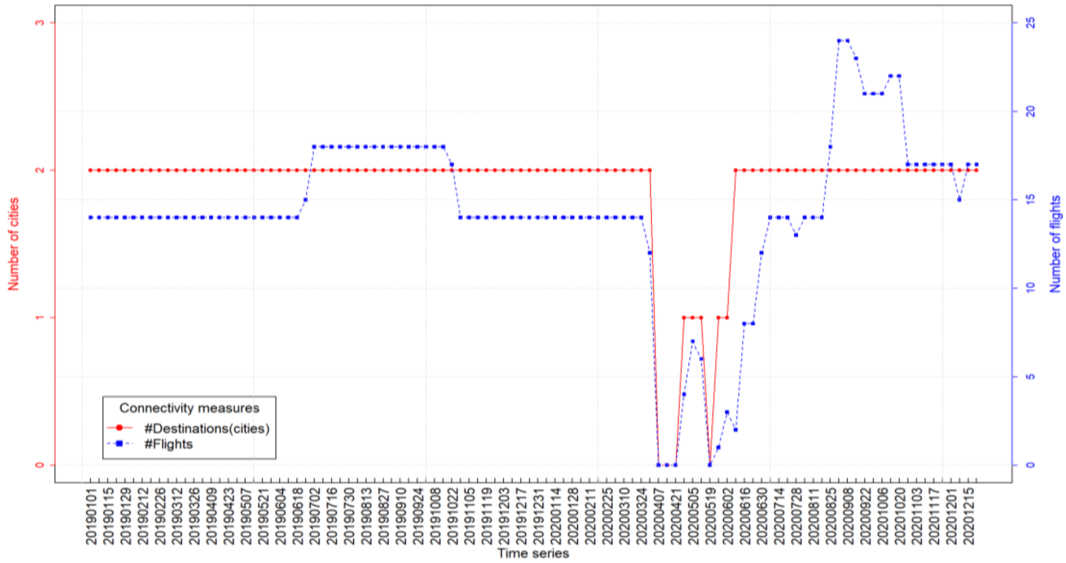
Source: Authors' compilation based on OAG data.

- *Changes in the smallest airports*

  The three smallest airports in Thailand as of the end of 2019 were Narathiwat Airport, Mae Hong Son Airport, and Hua Lin Airport. The connectivity changes at the three airports are depicted in Figure 5. Similar to the smallest airports in Malaysia, they mostly recovered at the end of the period as their connectivity levels were very low to start with. Unlike the cases in Malaysia, all of them experienced a short period when connectivity was totally lost. This was probably due to the fact that Thailand relies extensively on tourism, which was severely affected by the pandemic.

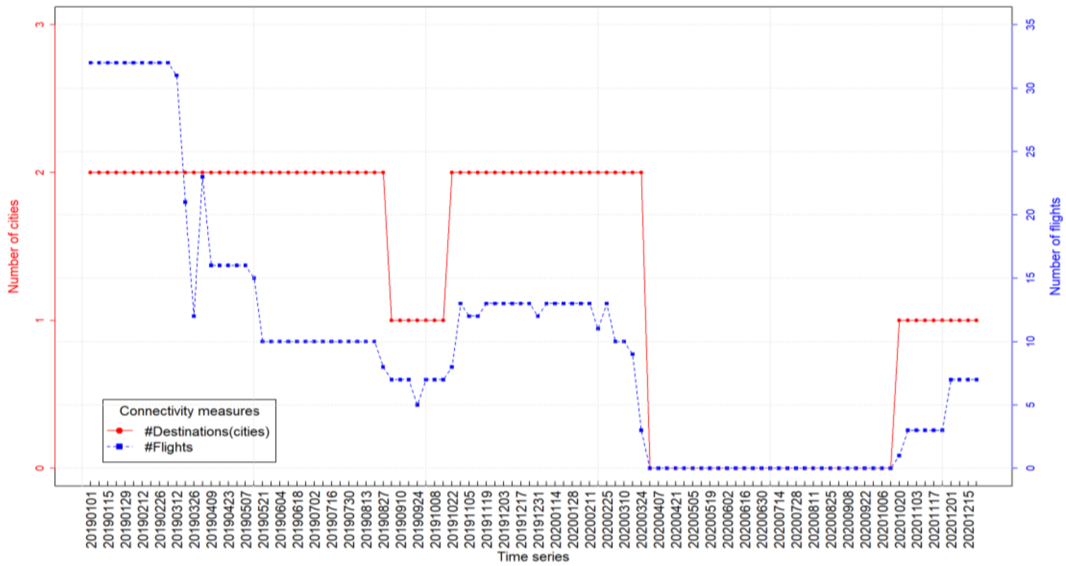
Figure 5. Connectivity at the Three Smallest Airports in Thailand

(a) Connectivity of Narathiwat Airport



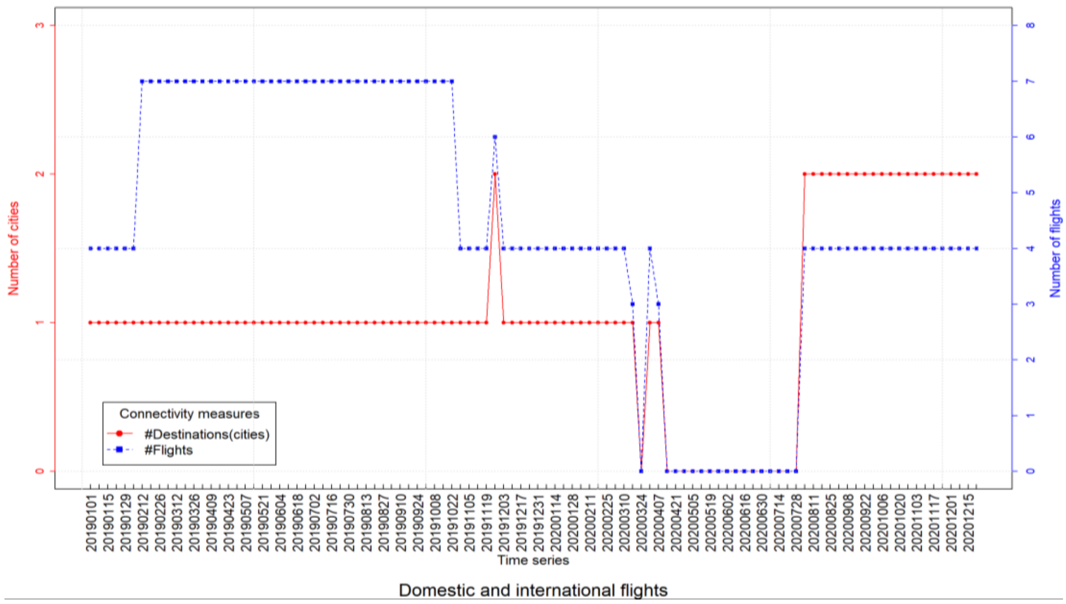
Domestic and international flights

(b) Connectivity of Mae Hong Son Airport



Domestic and international flights

(c) Connectivity of Hua Lin Airport



Source: Authors' compilation based on OAG data.

2.3. The role of airlines in shaping airport connectivity

This section investigates the roles played by leading airlines in shaping the connectivity changes. Homsombat, Lei, and Fu (2011) and Fu et al. (2015) found evidence that dominant airlines' performance significantly contribute to their hub airports' development and connectivity. Meanwhile, as network airlines and LCCs typically utilise hub-and-spoke networks and point-to-point networks, respectively, their contributions to airports' connectivity may also be different. On the one hand, LCCs typically have lower operation costs and, thus, may be more fit to serve thin routes or markets with significantly reduced traffic volume. On the other hand, hub-and-spoke networks allow airlines to consolidate traffic from spoke markets, enabling network airlines to serve a larger network. Therefore, it is unclear which type of airline will be better positioned to support airport connectivity amid the pandemic.

- *Airline performance at Hong Kong International Airport*

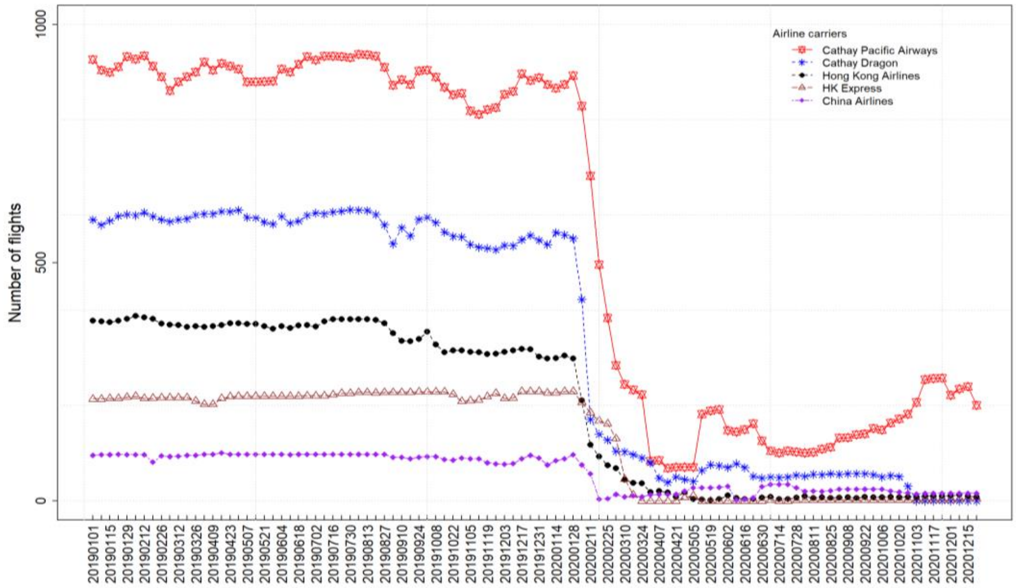
Cathay Pacific Airways is the dominant airline in Hong Kong. Cathay Dragon, previously known as Dragonair, was a subsidiary of Cathay that mainly targeted flights to mainland China and regional destinations. Hong Kong Express was an LCC owned by Hong Kong Airlines but was taken over by Cathay in July 2019. On 21 October 2020, Cathay announced that Cathay Dragon would be shut down amid the airline's decision to downsize, during which its workforce was reduced by 8,500 employees, or 24%. Hong Kong Express's operation, however, has been kept. Table 1 presents the top 10 airlines' operations and connectivity contribution to Hong Kong. Cathay and Cathay Dragon jointly contributed about 35% of the connectivity, with 53 and 46 destinations served as of 2019, respectively. It is notable that the airline group dramatically reduced the service of its subsidiary airline, Hong Kong Express, from 24 destinations at the end of 2019 to two destinations in 2020. It seems that LCCs do not offer much competitive advantage for services at hub airports. Hong Kong Airlines, which is the main competitor of Cathay, served 29 and 6 destinations at the end of 2019 and 2020, respectively. This reduced its connectivity contribution from 10.39% to 7.23%. All other airlines' connectivity contributions have also declined substantially. As a result, Cathay's share actually increased to 40.96%. For a more detailed illustration of pattern changes over the sample period, see the number of flights and destinations served by major players in Figures 6 and 7.

Table 1. Airline Operations at Hong Kong International Airport

Airline code	Airline name	Connectivity (2019)	Connectivity (2020)	Contribution share (2019)	Contribution share (2020)	Change in share (2020 vs. 2019)	Connectivity comparison
CX	Cathay Pacific Airways	53	34	19.00%	40.96%	21.97%	-35.85%
KA	Cathay Dragon	46	0	16.49%	0.00%	-16.49%	-100.00%
HX	Hong Kong Airlines	29	6	10.39%	7.23%	-3.17%	-79.31%
UO	Hong Kong Express	24	2	8.60%	2.41%	-6.19%	-91.67%
CA	Air China	6	1	2.15%	1.20%	-0.95%	-83.33%
5J	Cebu Pacific Air	5	1	1.79%	1.20%	-0.59%	-80.00%
MU	China Eastern Airlines	5	1	1.79%	1.20%	-0.59%	-80.00%
CI	China Airlines	3	2	1.08%	2.41%	1.33%	-33.33%
ET	Ethiopian Airlines	3	1	1.08%	1.20%	0.13%	-66.67%
FD	Thai AirAsia	3	0	1.08%	0.00%	-1.08%	-100.00%

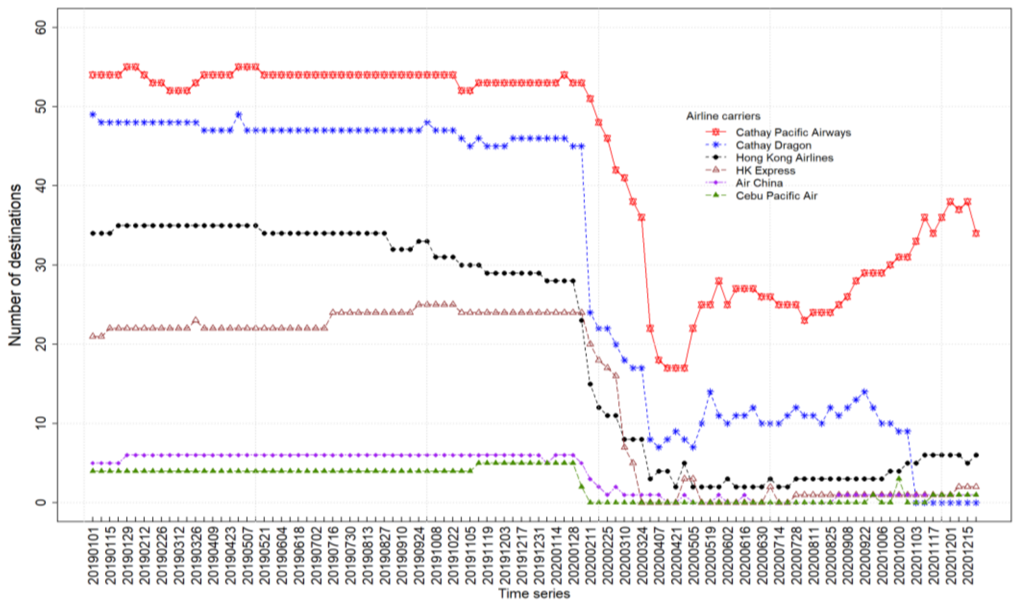
Note: Only the largest airlines are reported.
Source: Authors' compilation based on OAG data.

Figure 6. Number of Direct Flights by Different Airlines at Hong Kong International Airport



Source: Authors' compilation based on OAG data.

Figure 7. Number of Connections of Direct Flights by Different Airlines at Hong Kong International Airport



Source: Authors' compilation based on OAG data.

- *Aviation markets in Thailand*

Thai Airways is the dominant airline in Thailand, with hub operations at Bangkok Suvarnabhumi Airport and Phuket Airport. The airline also has a low-cost subsidiary, Thai Smile Airways, which plays important roles in the domestic and regional markets. The operations of the main players at the three Bangkok airports are summarised in Tables 2–4 respectively. At Suvarnabhumi Airport, Thai Airways lost more connectivity than Thai Smile, but the two brands' combined share of connectivity contribution remained almost the same. The only airline with an increased share was Thai VietJet, a low-cost subsidiary of a Vietnamese LCC, VietJet. Viet Nam achieved very good pandemic control domestically, which allowed VietJet to achieve an after-tax profit of US$3 million.

Don Mueang Airport hosts mainly LCCs, notably Thai AirAsia, Thai Lion Air, and Nok Air, which were the major contributors to the connectivity of Mueang International Airport. Other than Nok Air, the other two airlines' destinations declined almost at the same magnitudes (see Table 3) and, thus, their shares of connectivity contribution remained largely unchanged. Notably, it is obvious that Phuket Airport is a competitive airport as each airline contributed less than 10% to the airport's connectivity, and the Herfindahl-Hirschman Index (HHI) based on the connectivity contribution was only 360 at the end of 2019.

As discussed, Phuket Airport experienced a dramatic decline in traffic volume and connectivity, accompanying an almost total loss of tourism at the peak of the travel regulations in the middle of 2020. The share of Thai AirAsia increased over the period, mainly due to the significant reduction in services of other carriers during the sample period.

Table 2. Airline Operations at Bangkok Suvarnabhumi International Airport

Airline code	Airline name	Connectivity (2019)	Connectivity (2020)	Contribution share (2019)	Contribution share (2020)	Change in shares (2020 vs. 2019)	Connectivity comparison
TG	Thai Airways International	60	15	19.29%	12.71%	-6.58%	-75.00%
WE	Thai Smile Airways	30	16	9.65%	13.56%	3.91%	-46.67%
PG	Bangkok Airways	20	7	6.43%	5.93%	-0.50%	-65.00%
9C	Spring Airlines	11	1	3.54%	0.85%	-2.69%	-90.91%
CZ	China Southern Airlines	10	1	3.22%	0.85%	-2.37%	-90.00%
MU	China Eastern Airlines	9	1	2.89%	0.85%	-2.05%	-88.89%
VZ	Thai Vietjet Air	8	10	2.57%	8.47%	5.90%	25.00%
Q2	Maldivian	7	1	2.25%	0.85%	-1.40%	-85.71%
CA	Air China	6	1	1.93%	0.85%	-1.08%	-83.33%
6E	IndiGo	5	0	1.61%	0.00%	-1.61%	-100.00%
S7	Siberia Airlines	5	1	1.61%	0.85%	-0.76%	-80.00%

Note: Only the largest airlines are reported.
Source: Authors' compilation based on OAG data.

Table 3. Airline Operations at Bangkok Mueang International Airport

Airline code	Airline name	Connectivity (2019)	Connectivity (2020)	Contribution share (2019)	Contribution share (2020)	Change in shares (2020 vs. 2019)	Connectivity comparison
FD	Thai AirAsia	61	21	35.67%	38.18%	2.51%	-65.57%
SL	Thai Lion Air	43	12	25.15%	21.82%	-3.33%	-72.09%
DD	Nok Air	34	21	19.88%	38.18%	18.30%	-38.24%
XW	NokScoot Airlines	11	0	6.43%	0.00%	-6.43%	-100.00%
XJ	Thai Air Asia X	10	0	5.85%	0.00%	-5.85%	-100.00%
QZ	Indonesia AirAsia	3	0	1.75%	0.00%	-1.75%	-100.00%
AK	AirAsia	2	0	1.17%	0.00%	-1.17%	-100.00%
TR	Scoot	2	0	1.17%	0.00%	-1.17%	-100.00%
G5	China Express Airlines	1	0	0.58%	0.00%	-0.58%	-100.00%
ID	Batik Air	1	0	0.58%	0.00%	-0.58%	-100.00%

Note: Only the largest airlines are reported.
Source: Authors' compilation based on OAG data.

Table 4. Airline Operations at Phuket Airport

Airline code	Airline name	Connectivity (2019)	Connectivity (2020)	Contribution share (2019)	Contribution share (2020)	Change in shares (2020 vs. 2019)	Connectivity comparison
FD	Thai AirAsia	12	5	8.51%	27.78%	19.27%	-58.33%
ZF	AZUR air	10	0	7.09%	0.00%	-7.09%	-100.00%
N4	Nord Wind	9	1	6.38%	5.56%	-0.83%	-88.89%
RL	Royal Flight Airlines	9	0	6.38%	0.00%	-6.38%	-100.00%
SL	Thai Lion Air	9	1	6.38%	5.56%	-0.83%	-88.89%
9C	Spring Airlines	5	0	3.55%	0.00%	-3.55%	-100.00%
MU	China Eastern Airlines	5	0	3.55%	0.00%	-3.55%	-100.00%
BLX	TUIfly Nordic AB	4	3	2.84%	16.67%	13.83%	-25.00%
DD	Nok Air	4	1	2.84%	5.56%	2.72%	-75.00%
DK	Thomas Cook Scandinavia	4	0	2.84%	0.00%	-2.84%	-100.00%
TG	Thai Airways International	3	0	2.13%	0.00%	-2.13%	-100.00%

Note: Only the largest airlines are reported.
Source: Authors' compilation based on OAG data.

- *Aviation markets in Malaysia*

Unlike most other aviation markets, Malaysia's is probably the only market where an LCC overturned the incumbent flag carrier to dominate the market. AirAsia, although having recently faced major financial challenges, had been one of the most successful LCCs in Asia and controlled the lion's share in the country's three largest airports as of 2019. Tables 5–7 summarise air connectivity at the three largest airports in Malaysia. AirAsia's network was so extensive that at Kuala Lumpur International Airport, which is by far the largest hub in the country, the airline operated flights to 71 destinations. AirAsia also contributed 32.76% of the connections at Kota Kinabalu Airport with 19 connected cities. However, during the pandemic, AirAsia's services at Kuala Lumpur dropped much more significantly than those of Malaysia Airlines, the flag carrier of Malaysia. The connectivity contributed by AirAsia was downsized to 18 (a decline of 74.65%). This seems to suggest that hub-and-spoke networks are better positioned when the traffic volume drops significantly. That said, AirAsia's connectivity shares at the two other largest airports, namely Kota Kinabalu Airport and Penang Airport, actually increased, mainly because many other airlines had cut flights significantly or even left the market (eight airlines that served Kota Kinabalu in 2019 did not provide direct flight service as of the end of 2020). Again, there have been too many changes to multiple airlines' operations and, thus, it is difficult to derive solid conclusions.

Table 5. Airline Operations at Kuala Lumpur International Airport

Airline code	Airline name	Connectivity (2019)	Connectivity (2020)	Contribution share (2019)	Contribution share (2019)	Change in shares (2020 vs. 2019)	Connectivity comparison
AK	AirAsia	71	18	26.59%	16.82%	-9.77%	-74.65%
MH	Malaysia Airlines	57	39	21.35%	36.45%	15.10%	-31.58%
OD	Malindo Airways	36	10	13.48%	9.35%	-4.14%	-72.22%
D7	Airasia X	27	0	10.11%	0.00%	-10.11%	-100.00%
QZ	Indonesia AirAsia	9	4	3.37%	3.74%	0.37%	-55.56%
6E	IndiGo	3	0	1.12%	0.00%	-1.12%	-100.00%
QG	Citilink Indonesia	3	0	1.12%	0.00%	-1.12%	-100.00%
SV	Saudi Arabian Airlines	3	1	1.12%	0.93%	-0.19%	-66.67%
CZ	China Southern Airlines	2	1	0.75%	0.93%	0.19%	-50.00%
FD	Thai AirAsia	2	0	0.75%	0.00%	-0.75%	-100.00%

Note: Only the largest airlines are reported.
Source: Authors' compilation based on OAG data.

Table 6. Airline Operations at Kota Kinabalu Airport

Airline code	Airline name	Connectivity (2019)	Connectivity (2020)	Contribution share (2019)	Contribution share (2020)	Change in shares (2020 vs. 2019)	Connectivity comparison
AK	AirAsia	19	8	32.76%	44.44%	11.69%	-57.89%
MH	Malaysia Airlines	14	6	24.14%	33.33%	9.20%	-57.14%
OD	Malindo Airways	10	1	17.24%	5.56%	-11.69%	-90.00%
7C	Jeju Airlines	2	1	3.45%	5.56%	2.11%	-50.00%
MF	Xiamen Airlines Company	2	1	3.45%	5.56%	2.11%	-50.00%
ZE	Eastar Jet	2	0	3.45%	0.00%	-3.45%	-100.00%
RS	Air Seoul, Inc	1	1	1.72%	5.56%	3.83%	0.00%

Note: Only the largest airlines are reported.

Source: Authors' compilation based on OAG data.

Table 7. Airline Operations at Penang Airport

Airline code	Airline name	Connectivity (2019)	Connectivity (2020)	Contribution share (2019)	Contribution share (2020)	Change in shares (2020 vs. 2019)	Connectivity comparison
AK	AirAsia	10	6	25.64%	31.58%	5.94%	-40.00%
FY	Firefly	6	4	15.38%	21.05%	5.67%	-33.33%
QZ	Indonesia AirAsia	3	1	7.69%	5.26%	-2.43%	-66.67%
OD	Malindo Airways	2	1	5.13%	5.26%	0.13%	-50.00%
QR	Qatar Airways	2	0	5.13%	0.00%	-5.13%	-100.00%
3K	Jetstar Asia	1	1	2.56%	5.26%	2.70%	0.00%
8L	Lucky Air Co. Ltd.	1	0	2.56%	0.00%	-2.56%	-100.00%
CI	China Airlines	1	1	2.56%	5.26%	2.70%	0.00%
MH	Malaysia Airlines	1	1	2.56%	5.26%	2.70%	0.00%
SJ	Sriwijaya Air	1	1	2.56%	5.26%	2.70%	0.00%

Note: Only the largest airlines are reported.
Source: Authors' compilation based on OAG data.

2.4. Summary of key findings of the connectivity analysis

The COVID-19 pandemic has led to a significant decline in travel demand. Various travel restrictions were imposed, notably in international markets. These regulations and restrictions have further constrained air travel, causing major connectivity losses in all the markets analysed. Our analysis of air connectivity leads to the following conclusions:

- The pandemic has led to significant connectivity losses in all the countries and markets, especially at large hubs and tourism cities. Major international hubs, such as airports in Hong Kong, Malaysia, and Bangkok, are important connection points that consolidate regional traffic to overseas destinations. With the combined effects of demand decline and travel restrictions imposed in international markets, many overseas destinations were lost. There are also signs that airlines are consolidating traffic in one country or region. For example, Kota Kinabalu and Penang lost direct services to Hong Kong, whereas the service between Kuala Lumpur and Hong Kong was maintained. Similarly, Hong Kong's direct services to Amsterdam and Paris were removed, because (reduced) European traffic can be routed through the remaining hub in Heathrow.[1]
- Although there was a significant decline in traffic volume in general, the connectivity losses at the smallest airports tended to be temporary and limited. These airports had limited aviation services to start with, which means it was not too costly to maintain minimum connectivity. At the smallest airports in Malaysia and Thailand examined in our study, there were only a few flights in a week. Such low traffic volumes usually do not justify the related costs if airport investment costs and operation costs are also considered. This implies that stakeholders are likely to have strong incentives to keep such services. On the other hand, even large airports mostly serving tourists, such as Phuket Airport in Thailand, were particularly damaged as discretionary travel suffered most. LCCs' operations at such airports, whose main targets are

[1] In terms of network configuration, this implies that some direct point-to-point services/links are removed, and the resultant network is more like a so-called 'dog-bone'/'dumbbell shaped' network. For more detailed discussions on such a network configuration's implications, see Tu et al. (2020).

price-sensitive non-business travellers, were significantly reduced, as expected.

- There is preliminary evidence that network carriers at hub airports played more important roles during the pandemic (e.g. Cathay Pacific in Hong Kong, Malaysia Airlines in Kuala Lumpur, and Thai Airways at Bangkok Suvarnabhumi International Airport), whereas LCCs contributed less in the same markets (e.g. Hong Kong Express in Hong Kong and AirAsia in Kuala Lumpur). In theory, a hub-and-spoke network may also be better-positioned than a point-to-point network because the traffic volumes can be consolidated at the hub airport. However, such preliminary patterns were the result of many market dynamics and a general decline in traffic volume and connectivity. The anecdotal evidence is also based on a very small sample and, thus, more rigorous analysis is needed.

The observations also raised an important policy implication: major international hubs and airports in tourist destinations suffered most.

3. Passenger behaviour in the presence of health control measures and online meeting options

Since January 2020, the aviation industry around the world has been in the doldrums due to the outbreak of COVID-19. The number of passengers and flight movements handled by Hong Kong International Airport in April 2020 showed a year-on-year decrease of 99.5% and 73.5%, respectively. Visitor and transfer/transit traffic dropped by nearly 100%, whilst Hong Kong residents' travel fell by 99% compared to the same month before the outbreak (HKIA, 2020). It was estimated that the overall revenue passenger kilometres would be reduced by 38% in 2020 compared to 2019, leading to a revenue loss of US$252 billion (IATA, 2020a). As reported in Section 2, connectivity in Hong Kong and many ASEAN markets experienced dramatic decreases, and recovery was quite weak until the end of 2020.

It is, however, not the first time that a disease outbreak has caused a remarkably negative impact on the aviation industry. For example, the SARS epidemic in 2003 caused a serious impact on the tourism, hotel, and aviation industry in China (Dombey, 2004; Hai et al., 2004; Zeng, Carter, and De Lacy, 2005). Similarly, negative impacts of the influenza H1N1 2009 and MERS Flu 2015 pandemics on the tourism and aviation industry were also revealed (Chung, 2015). With the prevalence of viral epidemic events associated with environmental pollution and climate change (Gössling, Scott, and Hall, 2020; Hendryx and Luo, 2020), the aviation industry has had to adapt to and withstand pandemics. Indeed, there is a significant chance that COVID-19 will introduce some lasting or even permanent changes to the aviation industry. For example, it is expected that health declarations, vaccinations, and virus test requirements will be kept at least in the coming several years. This would introduce significant monetary costs related to the provision of travel services and passenger disutility related to inconvenience, extra time, and regulatory compliance. All these costs and inconveniences would discourage passenger travel desire and, thus, aviation demand, leading eventually to losses in connectivity. This could create negative feedback on travel demand and traffic volumes. Therefore, it is of paramount importance to understand travellers' attitudes and preferences for additional travel requirements and improve the design of supportive policies that can help the aviation industry rebound.

The intention for air travel decreases with the higher risk perception in the presence of the COVID-19 pandemic (Neuburger and Egger, 2020). Passengers tend to perceive a higher health risk when the disease has a higher infection rate or/and mortality rate (Ibuka et al., 2010). Implementing health control measures provides passengers with reassurance, thereby reducing their perceived travel risk (Cohen, 2016). A report released by the IATA indicated that passengers' willingness to travel is reduced due to their concerns over the risks of catching COVID-19 during air travel. However, travellers also show preferences for COVID-19 screening at airports, compulsory mask-wearing, and social distancing measures on aircraft which can provide health protection (IATA, 2020c). Health control measures commonly used include (1) flight cancellations, (2) travel advisory/restrictions, (3) temperature screening at airports to identify potential virus carriers, (4) mask-wearing requirements, (5) health declarations, (6) social distancing measures, (7) on-site virus testing, and (8) compulsory quarantine. In particular, a health declaration form requiring personal information, travel history, and possible syndromes is currently used by many regulators, and international certificates or mobile applications of vaccination are being developed to enable passengers to travel across borders.

Public attitudes towards restrictive governmental measures against COVID-19 have been examined in some recent studies. For example, pandemic control measures such as social distancing, self-quarantine, and the cancellation of mass events have won public adherence in Belgium. However, there are significant concerns about the possible economic crisis subsequent to such control measures (De Coninck et al., 2020). A study conducted in India also revealed that the public showed positive attitudes towards travel restrictions (Roy et al., 2020). On the other hand, one study conducted in Germany found that about 20% of the respondents showed an unwillingness to wear a mask during the COVID-19 pandemic, partly due to the social prejudice and peer pressure (Rieger, 2020). Moreover, Lamb et al. (2020) indicated that passengers' willingness to fly for business trips during the COVID-19 pandemic decreases due to the increase in risk perception, which is influenced by the effectiveness of control measures and the features of the disease (Lau et al., 2005) and, surely, the availability of online meeting digital platforms (IATA, 2020b).

In summary, the COVID-19 pandemic has caused a significant decline in traffic intention and volume. Whereas many passengers indicated positive support for restrictive measures, there are substantial concerns over such measures' economic implications and effectiveness. Whereas all these measures will impose extra time and inconvenience, few studies have examined their implications on passenger travel intention and demand. As such measures are likely to persist at least for the coming few years, studies on the attitudes of air travellers towards control measures are urgently needed in order to understand the related implications for travel demand and aviation operations.

Although business travellers account for a smaller proportion than leisure travellers,[2] they contribute to a high percentage of airlines' revenue and an even higher percentage of profit. This can be attributed to the difference in travel preferences between business and leisure travellers. In particular, business travellers tend to plan less prior to travel and assign more importance to convenient flight schedules whilst being less sensitive to ticket price (Milioti, Karlaftis, and Akkogiounoglou, 2015; Seetaram et al., 2018; Talluri and Van Ryzin, 2004). Despite business travellers being considered highly profitable before the pandemic, IATA holds a more pessimistic attitude towards the outlook for the recovery of business travel as online meetings appear to have made significant inroads as a substitute for face-to-face meetings (IATA, 2020b). Indeed, online meeting applications have been widely used during the pandemic. The associated long-term impacts on the aviation industry could be significant, especially for business travel. However, no study has quantified such possible effects.

Online meeting platforms enable people in different locations to have real-time communication through audio and video imaging (Gough and Rosenfeld, 2006). Compared to traditional in-person meetings, online meetings (or, interactive video conferencing) offer many advantages, such as flexibility, convenience, and time and cost savings (Lehmann, 2003; Gray et al., 2020). On the other hand, online meetings are also often exposed to various challenges, including inaccessibility to reliable internet services, hardware failures, hacking attacks, privacy invasion, and other network security issues (D'Anna et al., 2020). More importantly, online meetings may fail to contribute to personal interaction and social networking, especially where people have never met face-to-face. In past decades, researchers in sociology have emphasised the centrality of face-to-face relationships in global business life (Miller, 2003). For instance, effective face-to-face communication would be more desired when negotiating conflicts of interest in business, rather than using an online medium (Mason and Leek, 2012).

Some industry observers argue that the online meeting applications offer a

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[2] In the aviation industry travellers are often classified as business travellers, leisure travellers (mainly tourists), and visiting friends and relatives (VFR) travellers. Here, we use the term of leisure traveller to broadly refer to passengers who travel for non-business purposes.

good substitute to face-to-face meetings and, thus, will significantly reduce travel demand. However, similar predictions were made for technologies such as telephone, fax, and email. Contrary to such predictions, these IT technologies facilitated contact amongst people located far apart, building globally more dispersed networks and supply chains that could increase, rather than replace, their desire for face-to-face meetings. IT technologies may serve as complements rather than substitutes for travel. In summary, the significant changes in travel requirements and online meeting options may have significant effects on travel demand, with such effects yet to be quantified. As aforementioned, a decline in transport demand could lead to network downsizing and connectivity losses, which reduce the attractiveness of aviation services and, thus, lead to further negative feedback effects on demand. This study aims to investigate the effects of the following factors on passenger travel behaviour: (a) health controls and health declarations involved in air travel and (b) the increased use of online meeting options. This study is expected to contribute to the design of supportive policies that could facilitate the recovery of the aviation industries and help airlines to improve their service offerings to passengers, especially business travellers.

3.1. Survey method and experiment design

We aim to quantify passenger preference changes in the presence of health control and declaration measures related to air travel and the increased use of online meeting applications. The choice to fly is examined as a function of different factors, such as the severity level of the pandemic, travel characteristics, and pandemic control measures. Attitudes towards online meeting options, travel costs, travel time, type of business communication, and travel-associated health risks are examined through attitudinal questions and rating scales. Then, a stated preference (SP) experiment is employed to investigate how different health control strategies and disease information may affect the choice to travel internationally for business purpose. Consideration is also given to the effect of the online meeting option on the choice to travel.

The questionnaire has three sections: (1) travel experiences, perceptions, and attitudes, (2) SP questions regarding travel choices, and (3) demographics and employment characteristics of business travellers. The first section collects the information on business travel, online meetings, and work from home (WFH) experiences before and after the COVID-19 pandemic. In addition, some attitudinal questions are presented. The second section is the SP instrument (detailed discussion in the following sections). The third section collects information on passenger demographics (i.e. gender, age, education, marital status, and income) and employment characteristics (i.e. type of employment and industrial classification).

3.1.1. Attitudinal questions

There are a total of 19 questions where respondents are required to rate their level of agreement with each statement on an 11-point scale (0 = strongly disagree; 10 = strongly agree). The items and the corresponding statements are selected and refined based on previous travel behaviour research (Aguilera, 2008; Demir et al., 2020; Lavieri and Bhat, 2019; Neuburger and Egger, 2020). The latent constructs considered in this study include the technology acceptance of online meetings, travel cost sensitivity, preference for face-to-face communication, perceived higher risk to health when travelling in the context of the pandemic, and travel time sensitivity (as shown in Table 8). Earlier studies, such as those referenced above, suggest that these factors are important in the choice to travel, especially for business trips. Latent factor analysis is applied to identify the key descriptors summarising the attitudinal responses. The reliability analysis for the latent factors is performed to assess the degree of consistency amongst the measurement items, using Cronbach's alpha as the diagnostic indicator.

Table 8. Attitudinal Questions

Items and Statements
1. Technology acceptance of online meetings
The online meeting tool allows me to organise meetings any time (24/7).
The online meeting tool is very user friendly.
It is easy to prepare an online meeting.
I will recommend my colleagues and friends to use online meeting tools.
In general, I consider online meeting platforms/applications as very useful.
2. Travel cost sensitivity
The expenditure on the air ticket for my business travel needs to be carefully arranged.
The expenditure on the accommodation costs for my business travel needs to be carefully arranged.
Expenses for travel costs will be covered mostly by my affiliation/company. Therefore, I have no concerns about the travel costs for my business trip. (coded conversely)
My affiliation/company has stringent travel policies and trip approval procedures.
3. Preference for face-to-face communication
I prefer face-to-face communication rather than online communication.
I like meeting new people in different locations.
Instead of sitting at home or the office, I prefer to go and meet people.
I am interested in experiencing different cultures, languages, food, and customs.
4. Perceived higher risk to health
The health risk associated with air travel during the pandemic is very high.
To me, travelling during the pandemic is a very risky behaviour that leads to disease infection.
Taking actions against important health risks (e.g. disease infection) is a must.
5. Travel time sensitivity
I expect to pass the health assessment and security checks at the airport as fast as possible.
I will feel frustrated and impatient if the health assessment or security checks take a long time.
My time is very precious during business trips.

Source: Compiled by authors.

3.1.2. Stated preference design

In this study, respondents' perceptions towards the severity levels of the pandemic, travel characteristics, and preferences for different pandemic control measures are gauged through a stated choice to travel internationally by air in an SP survey. SP surveys have been widely applied to evaluate the effects of passenger screening strategies on the propensity for domestic or international travel by measuring passengers' responses under hypothetically constructed conditions (Beck, Rose, and Merkert, 2018; Patil et al., 2016; Potoglou et al., 2010). The SP questions in this study are based on the scenario with various travel restrictions in the context of the COVID-19 pandemic. The respondents are asked to imagine that they were planning to have an international business trip by air. For each question, three choices (two unlabelled alternatives and a 'no choice' alternative) are presented as three ways in which respondents might make this journey. The two alternatives are described by attributes representing disease information, travel characteristics, and pandemic control measures. There is also a 'no choice' alternative that provides a no-travel option for a choice scenario task. For each SP scenario presented, the respondent makes a choice given two preconditions, thus providing two choices. The two preconditions are defined as follows: (1) online option inapplicable, meaning that there is no option for an online meeting (without the online meeting platform/application), and (2) online meeting possible, meaning that there is an option for an online meeting (with the online meeting platform/application).

In each of the SP questions presented to respondents, the choice context is characterised by eight attributes: (1) daily confirmed cases of the current location, (2) daily confirmed cases of the destination, (3) case fatality rate (CFR), (4) average time to pass through the health and security checks, (5) increased cost of ticket (e.g. to cover the extra costs of pandemic control measures), (6) health declaration requirements, (7) mask-wearing requirement, and (8) on-site health checks at the airport. Figure 8 provides a screenshot of the content and format of a sample SP question.

The levels of the first and second attributes, the daily confirmed cases, are set based on the actual situation of COVID-19 cases in Hong Kong (Department of Health, 2021b). Hong Kong residents experienced four waves of the epidemic since the first reported case on 23 January 2020. The survey was conducted near the end of the fourth wave in late March 2021, when the number of daily confirmed cases was below 10. To achieve a more realistic perception, three levels of 10, 50, and 100 daily confirmed cases are adopted to reflect low, common, and serious pandemic situations, respectively.

The levels of the third attribute, CFR, are also set based on the reported statistics regarding the CFRs of COVID-19. The CFR is defined as the ratio between confirmed deaths and confirmed cases. In Hong Kong, the CFR of the ongoing COVID-19 epidemic was reported to be relatively low compared with other regions or countries around the world (Lui et al., 2020). Lui et al. (2020) reported a CFR of 0.4% at the time of their study as of June 2020, indicating that on average there were four deaths from COVID-19 amongst 1,000 diagnosed cases. Later, the CFR of COVID-19 in Hong Kong increased to around 1.4% in March 2021 (Department of Health, 2021a). On the other hand, the CFRs of the COVID-19 epidemic in European countries could reach over 10% (Roser et al., 2020). Therefore, three levels of CFR are considered, i.e. 0.1%, 1%, and 10%, corresponding to a low, common, and high risk of death from COVID-19.

The levels of the fourth attribute are set with reference to previous studies on the passenger screening process at airports (Beck, Rose, and Merkert, 2018; Veisten and Flügel, 2011; Blalock, Kadiyali, and Simon, 2007), with 20, 40, and 60 minutes adopted as the average times to pass through health and security checks. Three levels of the fifth attribute associated with the increased ticket cost are considered: HK$500, HK$1,000, and HK$3,000. They are set with reference to the suggested testing fee of COVID-19 for departing passengers at Hong Kong International Airport (HKIA, 2021), in the context of airfares quoted on travel websites. Finally, three levels for each of the sixth to eighth attributes associated with the pandemic control measures are set in accordance with the quarantine procedures for entry via airport and general hygienic measures adopted by the Government of Hong Kong (Department of Health, 2021b; Government of the HKSAR, 2021).

In the pilot surveys, the levels for each of the attributes were examined to ensure that they were within reasonable ranges. To summarise, the SP experiments have eight factors, each with three levels. If the full factorial design were considered, there would be a very large number (i.e. $3^8 \times 3^8$) of choice scenarios, which would be neither practical nor efficient to present to respondents. An efficient design that enables us to estimate the main effects and two-way interaction effects of attributes is adopted to reduce the number of choice scenarios (Beck, Rose, and Merkert, 2018; Hensher and Rose, 2007; Ho et al., 2018; Rose et al., 2008). Orthogonal designs focus on minimising the correlations in the data for estimation purposes. The efficient design aims to yield data that enable the estimation of parameters with as small as possible standard errors. Specifically, the efficient design aims to minimise the asymptotic standard errors of the parameter estimates. This objective can be achieved by obtaining the asymptotic variance-covariance matrix of the parameters when there is some information about the priors. The priors used in the efficient design generate the choice situations that can be derived from the results of parameter estimates in our pilot study. To assess the efficiency of an experiment design, D-error is a widely used measure of efficiency error (or it can be interpreted as a measure of inefficiency). Therefore, a D-efficient design refers to the design that is generated by minimising the D-error.

There are three types of D-errors proposed in the literature based on the availability of the information on prior parameters. First, when there is no available information, priors are set to zeros, which leads to the D_z-error. Second, priors are set to be fixed with the best guesses with the assumption that they are relatively accurate, which leads to the D_p-error. Third, rather than setting fixed priors, it is common that there is some information about the priors but with uncertainty. In this context, the priors are set to be random following a given distribution. Such a Bayesian approach then leads to the Db-error. This study applies a Bayesian efficient design to obtain the choice situations for the stated preference experiment by minimising the D_b-error. The Bayesian D-error is a function of experiment design X and the probability distribution of priors and can be computed as:

$$\mathrm{D}_b - error = \int_{\tilde{\beta}} \det\left(\Omega_1(X, \tilde{\beta})\right)^{1/M} \phi(\tilde{\beta} \mid \theta) d\tilde{\beta} \tag{1}$$

where $\tilde{\beta}$ is a vector of parameter priors, ϕ (.) is the joint probability density function of the random variables $\tilde{\beta}$ with given parameters θ for the distribution, and M denotes the number of parameters in the model.

The Bayesian approach requires the use of simulation to randomly draw different prior distributions to calculate the D_b-error for each design. In this study, 250 draws using Halton sequences are performed. Prior parameters for the attributes are obtained from the pilot study, which is constructed through an orthogonal design. The parameter estimates of the preliminary model are subsequently used as priors to generate the D_b-efficient design. Table 9 shows the considered attributes and their levels. The software package *Ngene 1.2* (ChoiceMetrics, 2018 version) is used to determine the final design based on the assumption of a multinomial logit model and normally distributed priors. The design has 24 choice situations, which are divided into four blocks. Each participant was randomly given one of the four blocks of six SP scenarios in the survey. The design is found to have a D_b-error of 0.026. A D-efficient design is achieved with a sufficiently low D-error. The entire survey instrument is presented in Appendix II.

Table 9. Attributes and Levels for Stated Preference Games

Attributes considered	Levels
Disease information	
Daily confirmed cases at current location	100 50 10
Daily confirmed cases at destination	100 50 10
Case fatality rate (CFR)	10% (one death amongst 10 confirmed cases) 1% (one death amongst 100 confirmed cases) 0.1% (one death amongst 1,000 confirmed cases)
Travel characteristics	
Average time to pass through the health and security checks	20 minutes 40 minutes 60 minutes
Increased cost of ticket to cover the pandemic control measures	HK$500 HK$1,000 HK$3,000
Pandemic control measures	
Health declaration	Provide vaccination record Provide personal information, self-reported travel history, symptoms No need to declare your health condition
Mask requirement	No mask requirements

	Compulsory at the airport, but no requirements during flight
	Compulsory mask-wearing during flight and airport
On-site health check	No
	Temperature screening
	Tests involving sample collection

Source: Authors.

Figure 8. Sample of Choice Scenario for the Stated Preference Game

Scenario 1/6:

Despite the widespread outbreak, business travel has not come to an absolute standstill. People are still undertaking essential business trips. However, online meeting platforms and applications have become popular and widely used in business collaborations, and therefore travellers are often faced with the dilemma of whether to proceed with their plans or not.

Imagine that the travel restrictions are lifted now, and you plan to make an international business trip by air. We would like you then to consider three ways in which you might make this journey. These are described with different severity levels of the pandemic, travel characteristics, and pandemic control measures.

Please select one option considering the following descriptions.

	Option A	Option B	Option C
Disease Information			I would choose not to fly under these conditions
Daily confirmed cases of current location	10	100	
Daily confirmed cases of the destination	100	10	
Case fatality rate (CFR)	10% (there is one death among 10 confirmed cases)	0.1% (there is one death among 1000 confirmed cases)	
Travel characteristics			
Average time to pass through the health and security checks	20 minutes	40 minutes	
Increased cost of ticket to cover the pandemic control measures	3,000 HKD	500 HKD	
Pandemic Control Measures			
Health declaration	Provide personal information, self-reported travel history, symptoms	No requirements	
Mask requirement	Compulsory mask-wearing during flight and airport	Compulsory at the airport, but no requirements during flight	
Onsite Health Check	No requirements	Temperature screening	
If there is no option for an online meeting (no platform/application):	☐	☐	☐
If there is an option for an online meeting:	☐	☐	☐

Source: Authors.

3.1.3. Data collection

The total sample size is set at 400, representing valid choice observations 4,800 (400 respondents × 6 scenarios × 2 preconditions). The data used in the current analysis are drawn from an online survey conducted in April 2021 from online samples of Hong Kong residents, organised by a professional data collection company (Credamo.com). The inclusion criteria of the respondents were that they (1) must have had an international business trip before the COVID-19 pandemic (in the recent 2 years), and (2) are aged 18 or above. After ethical approval, more than 400 respondents were approached. Two criteria were set to automatically exclude invalid responses (see Li, Gao, and Tu [2017]). First was the time spent for completing the questionnaire. Based on our pilot study, the attitudinal questions in Section 1 are supposed to be finished in about two to three minutes. If the respondents finished the questionnaire in less than 1.5 minutes, the responses were rejected. In addition, the SP parts in Section 2 (six choice sets) are expected to be finished in about four to five minutes. Those that were finished in less than 2 minutes were excluded as invalid responses. Second were additional screening questions. In the process of answering the questionnaire, respondents were randomly given two questions, e.g. 'Please select six as the answer for this question'. The respondents who failed to provide the right answer were considered not to be serious.

3.1.4. Model specification

In this paper, we formulate a panel latent class model (LCM) for the travel choices of respondents. Similar to the mixed multinomial logit (MMNL) model, the LCM formulation accommodates unobserved preference heterogeneity. However, there are differences in applying these two models. Random parameters with a continuous distribution assumption are used in the MMNL model to account for the unobserved heterogeneity across observations (see Chen et al. [2020]), whereas LCM addresses the unobserved heterogeneity across groups using a discrete distribution (Beck, Rose, and Merkert, 2018; Greene and Hensher 2003; Greene and Hensher, 2013; Hensher, Rose and Greene, 2015). Compared to MMNL, LCM has the advantage of linking the heterogeneity to attitudinal indicators and socio-demographic factors whilst identifying the presence and number of the segments in the sample. The panel nature of the data also requires a recognition of the correlations amongst the responses coming from the same individual. The model structure is discussed in the following paragraph. For notation, index *i* (i = 1, 2, …, I) for the decision-makers, *j* for the alternative (j = 1, 2, …, J), and *s* for the SP choice scenarios (s = 1, 2, …, S) are used. In this study, J = 3 (as indicated earlier, two unlabelled alternatives and a 'no choice' alternative) and S = 6 × 2 = 12 for all *i*. Within each of the six SP choice sets presented, the respondents are required to state their travel choice in two preconditions – an online meeting inapplicable and online meeting applicable.

In the traditional framework of utility-maximising models of choice, the utility that an individual *i* associates with the alternative *j* in choice scenario *s* is specified as follows:

$$U_{ijs} = \beta x_{ijs} + \varepsilon_{ijs} \qquad (2)$$

where x_{ijs} is a (Q×1)-column vector representing the levels associated with an attribute assessed by individual *i associated with* alternative *j* in the s^{th} choice scenario. There are eight attributes in the SP experiment. β is a corresponding (Q×1)-column vector of the average marginal (dis)utility of attribute x_{ijs} . ε_{ijs} denotes an idiosyncratic random error term specific to the choice scenario. ε_{ijs} is assumed to be identically and independently standard Gumbel distributed (extreme value type I distribution, see McFadden [1981]) and independent of x_{ijs}.

Given that the LCM accounts for *t* unobserved preference heterogeneity through the estimation of parameters that vary across groups, we assume that there exists *C* distinct classes within the sample. The determination of the number of classes (i.e. the value of *C*) is based on the goodness-of-fit of the models using the Bayesian information criterion (BIC). For a given class *c*, the probability that individual *i* will choose alternative *j* on the s^{th} choice occasion can be written as follows:

$$P_{ijs|c} = \frac{\exp(\sum_{q=1}^{Q} \beta_{q|c} x_{ijs}^{q})}{\sum_{j} \exp(\sum_{q=1}^{Q} \beta_{q|c} x_{ijs}^{q})} \tag{3}$$

where $\beta_{q|c}$ denotes the coefficient associated with the q^{th} attribute in class c.

The probability of individual i being in class c can be associated with the observable individual-specific variables, such as socio-demographic and employment characteristics, travel experience, as well as the latent constructs (i.e. the technology acceptance of online meetings, travel cost sensitivity, preference for face-to-face communication, perceived risk to health, and travel time sensitivity).

$$P_{ic} = \frac{\exp(\sum \gamma_c Z_i)}{\sum_c \exp(\sum \gamma_c Z_i)} \tag{4}$$

where γ is a vector of the mean effects of the coefficients of latent factors Z on the classification of individuals into one of the classes.

The parameters to be estimated in the model are β vectors in the class-specific choice model (Equation 3) and γ vectors for the class membership model (Equation 4). These two vectors are estimated simultaneously using the likelihood function in (5).

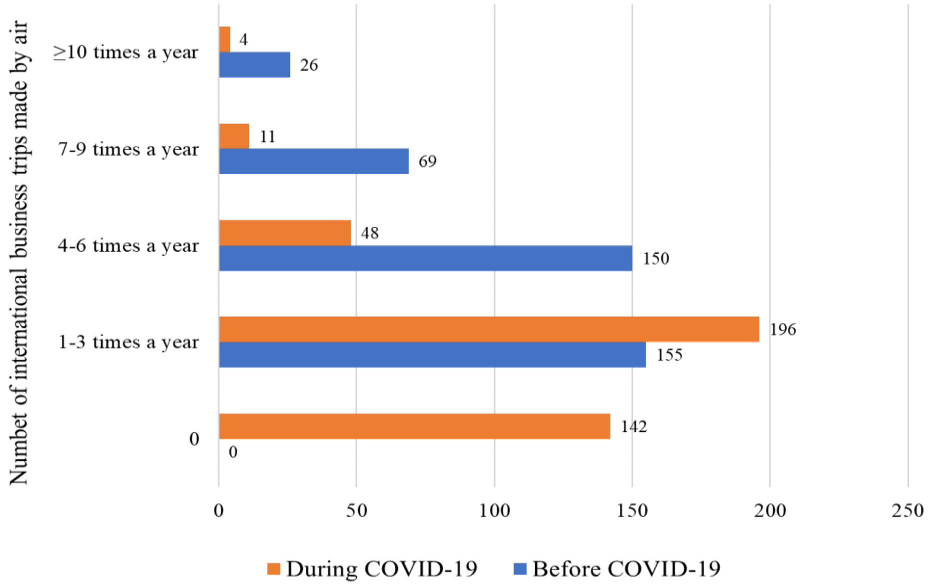
$$\ln \mathrm{L} = \sum_{\mathrm{i}} \ln \left[\sum_{c} P_{ic} \left(\prod_{s} P_{ijs|c}\right)\right] \tag{5}$$

γ are estimated for (C – 1) latent classes. The remaining class is set to be the reference group, where the coefficients are normalised to zero. The software package *NLOGIT 5.0* is used to estimate the panel LCM model.

3.2. Sample description

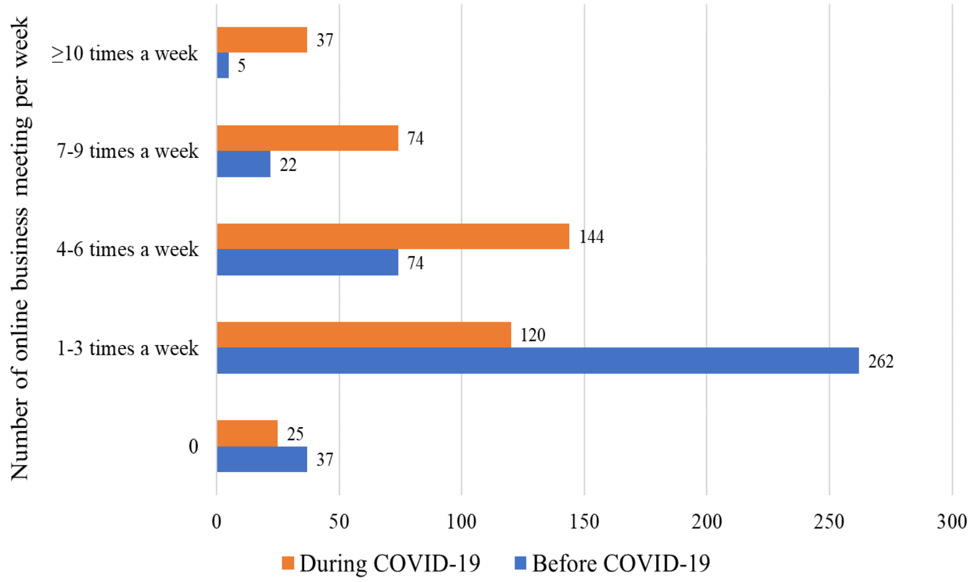
Figure 9 presents the participants' yearly business trips made by air before and during the COVID-19 epidemic. It shows that 35.5% of the participants undertook no international business trips during the COVID-19 epidemic. Moreover, the proportion of the respondents who travelled at least four times a year decreased dramatically from 61% before COVID-19 to about 16% during the pandemic. In this study, 95 respondents who travelled at least 7 times a year before the epidemic are marked as frequent travellers before COVID-19, and 63 respondents who travelled at least four times a year during the epidemic are identified as frequent travellers during COVID-19. In terms of online meeting experiences, as shown in Figure 10, 64% of the respondents in our sample had at least four online business meetings per week during COVID-19, compared with 25% before COVID-19. Of the 400 respondents, 255 who had online business meetings at least four times a week during the epidemic are considered as frequent online option users during COVID-19. Figure 11 demonstrates diversity regarding the number of days working from home (WFH), either at the extremes of no work or almost all work being done from home, or some days ranging from one to four. Before COVID-19, 32% of the respondents did not work from home at all (zero days). Respondents tend to WFH more frequently during COVID-19. For example, the proportion of those who work five or more days reached 31% during the pandemic. This could be attributed to the social distancing policy implemented by the government or the changes in companies' operating modes in order to reduce the infection risk and reduce the issue of crowded working spaces in offices.

Figure 9. Average Number of International Business Trips Made by Air per Year



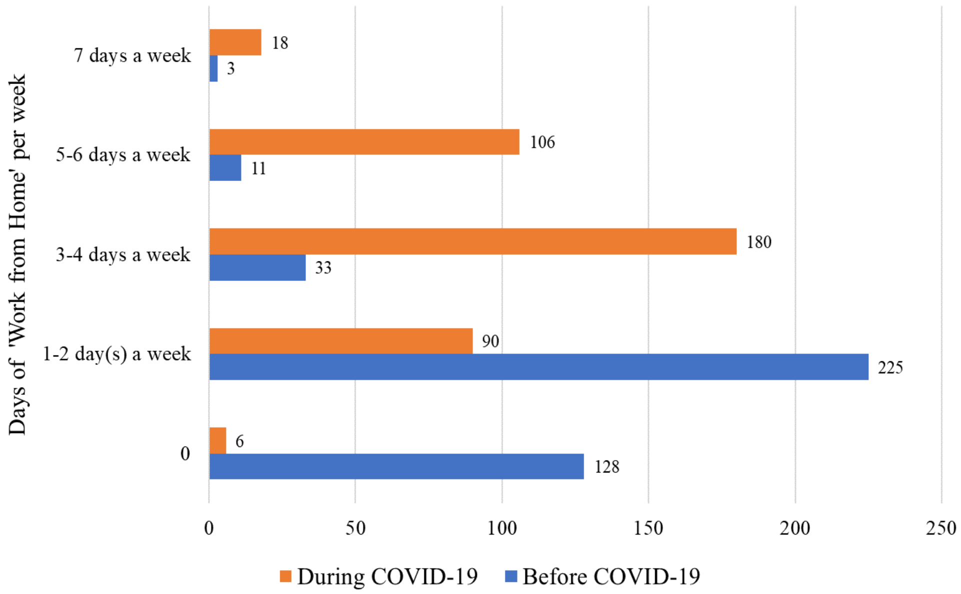
Source: Based on survey results.

Figure 10. Average Number of Online Meeting for Business Purpose per Week



Source: Based on survey results.

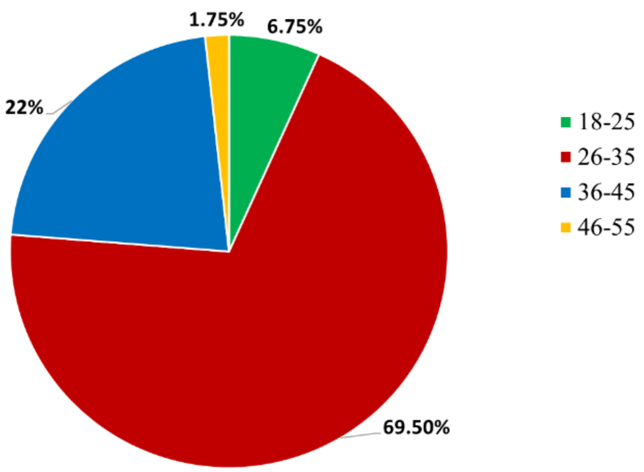
Figure 11. Number of Days Working from Home



Source: Based on survey results.

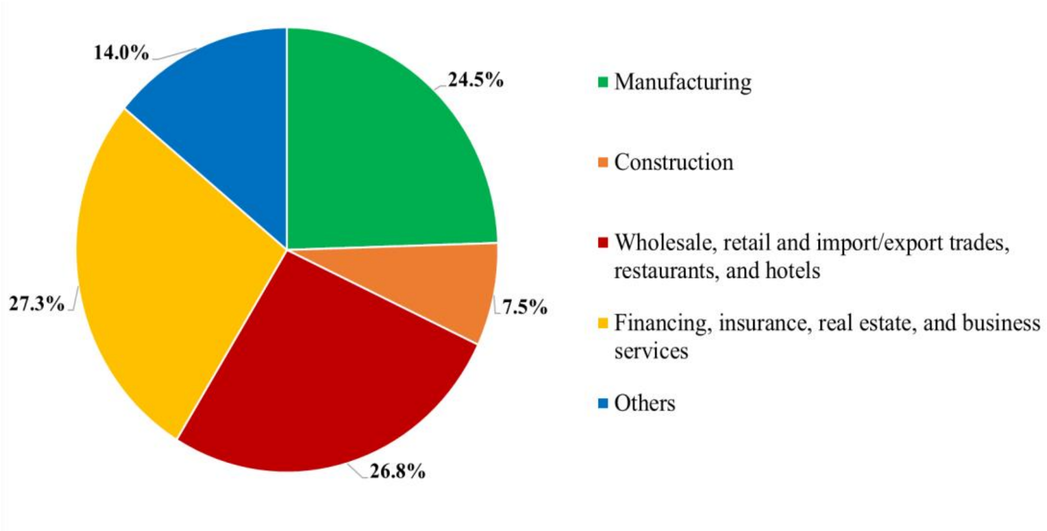
Of the participants, 54% are male (46% female). Although information on the age distribution of business travellers in Hong Kong is not available, the age groups of 26–35 and 36–45 seem to be the main business travellers based on statistics reported in previous studies of the local markets. For example, Hsu and Kang (2007) reported that 54.7% of interviewed air travellers were aged between 26 and 45; Liu and McKercher (2016) found that the share of business travellers aged between 26 and 55 was about 77% in 2012. The age distribution of our sample is shown in Figure 12. Furthermore, 99% of the respondents in our sample have attained tertiary education, and 78.5% are married or cohabiting. The latest statistics indicate that about 62% and 55% of the males and females in Hong Kong are married (Census and Statistic Department, 2018). The respondents' employment characteristics are presented in Figures 13 and 14. The employment status of the respondents is stratified into five categories: (i) full-time employee (57.5% of the sample), (ii) employer or manager (27.5%), (iii) self-employed (13.8%), (iv) part-time employee (1.0%), and (v) others (0.3%). The self-employed respondents include freelancers who travel occasionally for business purpose, whilst category (ii) refers to those who own or run a company or organisation. There are five categories for the respondents' industrial classification: (i) finance, insurance, real estate, and business services (27.3% of the sample), (ii) wholesale, retail and import/export trades, restaurants, and hotels (26.8%), (iii) manufacturing industry (24.5%), (iv) construction industry (7.5%), and (v) others (14.0%).

Figure 12. Age Distribution of the Respondents



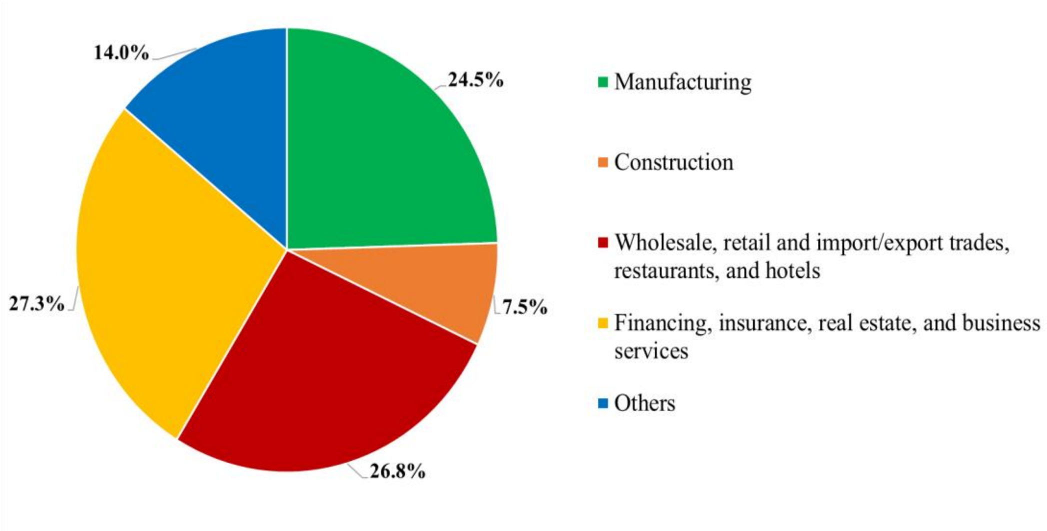
Source: Based on survey results.

Figure 13. Distribution of Employment Types



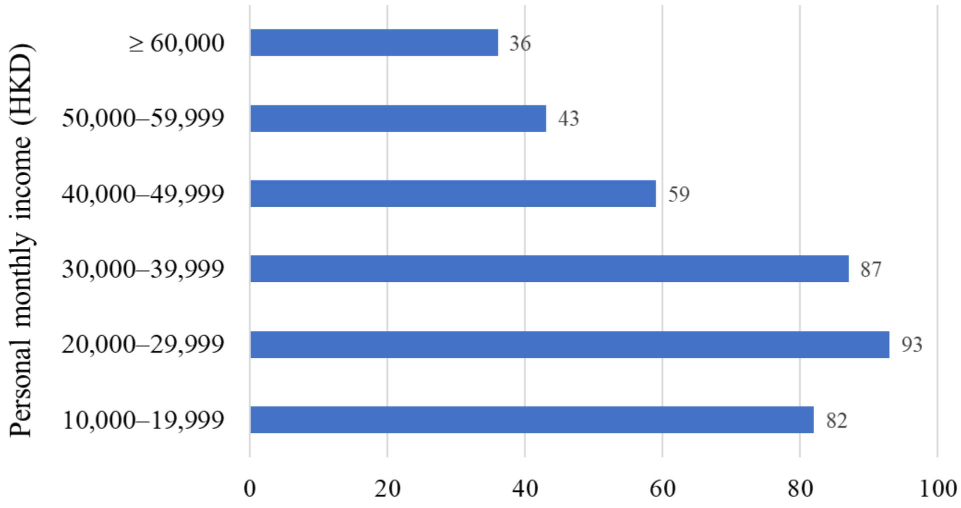
Source: Based on survey results.

Figure 14. Industrial Classification of the Respondents



Source: Based on survey results.

Figure 15. Income Distribution of the Respondents



Source: Based on survey results.

All respondents provided their monthly income values (see Figure 15). A little over 20% of the respondents had a monthly gross income of below HK$20,000 (US$2,575) and a little over 34% of the sample earned over HK$40,000 (US$5,150). Official statistics regarding the monthly income of business travellers from official reports are not available. The closest possible comparison is the latest monthly wage of all employees in Hong Kong. In 2020, the 25th, 50th, and 75th percentiles of the monthly wage of all full-time employees with tertiary education were HK$19,000, HK$29,200, and HK$44,700, respectively (Census and Statistic Department, 2020).

3.3. Estimation results and interpretation

In the following sections we present the results of the two stages – namely the factor analysis used to obtain the latent variables for use in the latent class choice models.

3.3.1. Factor analysis

Table 10 presents the results of the factor analysis. A generalised least squares (GLS) estimator using the direct-oblimin method for factor rotation is applied to extract the unobserved latent variables. Kaiser's rule (i.e. eigenvalues>1; see Kaiser [1960]) is used to determine the number of extracted factors. Three items (i.e. 'stringent travel policies and trip approval procedures', 'experiencing different cultures, languages, food, and customs', and 'taking actions against important health risks') are excluded to improve the internal consistency of the scale. Five factors are identified, which explain 68.21% of the variance. The Kaiser-Meyer-Olkin (KMO) Test is used to measure the sampling adequacy of our data (0.726, close to 1). The result ($p<0.000$) of Bartlett's test of sphericity also indicates that the data is suitable for factor analysis. For the scale reliability, the five extracted factors show a Cronbach's alpha of 0.79, 0.84, 0.75, 0.85, and 0.64 respectively, indicating a satisfactory internal consistency.

Recent studies have applied perceived usefulness and perceived ease of use to better understand students' acceptance of using online meeting applications or e-learning systems during the COVID-19 pandemic (Alfadda and Mahdi, 2021; Al-Okaily et al., 2020). As shown in Table 10, factor 1 contains five items measuring the perceived usefulness and perceived ease of use of the online meeting applications, labelled as 'technology acceptance of online meetings'. Factor 2 has three items investigating respondents' consideration of travel costs, labelled as 'travel cost sensitive'. The third (with three items) and fourth factors (with two items) are labelled as 'preference for face-to-face communication' and 'perceived higher risk to health' respectively. The last factor consists of three items measuring respondents' attitudes towards the time spent at checkpoints at the airport, labelled as 'travel time sensitive'.

Table 10. Factor Analysis of Travel-related Values (N = 400)

Latent Variables	Mean	S.D.	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
Technology acceptance of online meetings							
The online meeting tool allows me to organise meetings any time (24/7).	8.52	1.06	0.702				
The online meeting tool is very user friendly.	8.62	1.00	0.796				
It is easy to prepare an online meeting.	8.06	1.57	0.665				
I will recommend my colleagues and friends to use online meeting tools.	8.64	1.12	0.754				
In general, I consider online meeting platforms/applications as very useful.	8.76	1.04	0.818				
Travel cost sensitivity							
The expenditure on the air ticket for my business travel needs to be carefully arranged.	7.50	1.88		0.918			
The expenditure on the accommodation cost for my business travel needs to be carefully arranged.	7.70	1.95		0.934			
Expenses for the travel cost will be covered mostly by my affiliation/company. Therefore, I have no concerns about the travel cost for my business trip. (coded conversely)	5.51	2.57		0.808			
Preference for face-to-face communication							
I prefer face-to-face communication rather than online communication.	7.37	1.62			0.903		
I like meeting new people in different locations.	8.21	1.28			0.585		
Instead of sitting at home or at the office, I prefer to go and meet people.	7.69	1.59			0.926		

Perceived higher risk to health							
The health risk associated with air travel during the pandemic is very high.	8.10	1.64				0.924	
To me, travelling during the pandemic is a very risky behaviour that leads to disease infection.	8.37	1.45				0.918	
Travel time sensitivity							
I expect to pass the health assessment and security check at the airport as fast as possible.	8.61	1.18					0.543
I will feel frustrated and impatient if the health assessment or security check take a long time.	6.05	2.26					0.833
My time is very precious during business trips.	8.40	1.07					0.648
Correlations							
Factor 1			1.00				
Factor 2			-0.17	1.00			
Factor 3			0.20	-0.17	1.00		
Factor 4			0.16	-0.10	0.11	1.00	
Factor 5			0.18	-0.09	0.13	0.19	1.00
Eigenvalues			3.98	2.23	1.83	1.69	1.18
% of variance explained			24.8%	13.95%	11.46%	10.57%	7.35%
Cronbach’s alpha			0.79	0.84	0.75	0.85	0.64

Note: Zero-to-ten measurement scale. Cumulative % of variance explained by five factors = 68.21%.
Source: Estimation results of this study.

3.3.2. The choice to travel without an online meeting option

Three panel LCM specifications are estimated for the choice to travel on business when there is no option of an online meeting. The number of latent classes is determined based on the model fit through BIC values. Models with two to four classes are estimated and compared. Our results suggest that the model with two latent classes is superior to the two other counterparts, as evidenced by the lowest BIC value (Louviere, Hensher, and Swait, 2000; Beck, Rose, and Hensher, 2013). Also, the likelihood-ratio test is applied to compare the overall statistical fit of the panel LCM and MNL models. Based on the results, we can safely reject the MNL model in favour of the LCM (Greene and Hensher, 2003). Table 11 presents the parameter estimates for each of the two latent classes, the class probabilities, and the coefficients for characteristics that determine class probabilities. The characteristics considered to predict class membership include socio-demographics, employment characteristics, travel experience, and extracted latent factors. However, age, gender, marital status, employment type, industrial classification, and income level are not statistically significant. In the class membership model, only the factors significant at the 10% level are included.

The respondents who show a preference for face-to-face communication and/or have experience in frequent travel before COVID-19 are more likely to belong to class 1. On the other hand, those who perceive a higher risk to health for travelling during the pandemic are less likely to belong to class 1. Respondents in this group are less likely to have a business trip by air due to increases in the CFR or/and daily confirmed cases of the destination. They prefer providing a vaccination record for health declaration, having compulsory mask-wearing, and having on-site health checks, such as temperature screening or tests involving sample collection at the airport. Whilst 79.4% of the individuals are classified into class 1, the remaining 20.6% belong to class 2. In particular, respondents in class 2 are also likely to be deterred from a relatively severe epidemic situation (i.e. a high CFR or/and daily confirmed cases of the destination/current location). Class 2 travellers have a significant disutility towards the requirements of providing personal information, travel history, and symptoms for health declaration. Nevertheless, they favour temperature screening to no on-site checking at all. The two-way interaction effects for class 2 further indicate that they tend to accept the tests involving sample collection at the airport when the CFR increases. In addition, they are willing to provide personal information, self-reported travel history, and symptoms for health declaration if such procedures do not take much of their time at the checkpoint.

More importantly, the two classes of passengers perceive ‘time’ and ‘price’ attributes differently. Specifically, class 1 regards ‘price’ (i.e. ‘increased cost of ticket to cover the pandemic control measures’) and ‘time’ (i.e. ‘average time to pass through the health and security checks’) as indicators of health protection when travelling during the pandemic. As mentioned above, class 1 respondents are those who prefer face-to-face communication and had frequent international travel before the COVID-19 epidemic, and thus they tend to have a higher intention to travel. It is likely that they perceive the increased time and ticket costs as symbols/guarantees of safe travel. In contrast, class 2 respondents perceive a higher risk of travelling during the pandemic and are more reserved towards travel. Their utility or valuation of travel decreases with increased ticket costs and time spent at airport checkpoints. Overall, negative effects of the increased severity of the epidemic situation on the choice to fly are found for both groups. Compared to class 2, class 1 respondents have a higher tolerance for the pandemic control measures, and attach positive values to ticket costs and time spent at a checkpoint. Such a finding is supported by the results of the class membership prediction.

3.3.3. The choice to travel with an online meeting option

For the scenario where an online meeting is applicable, three panel LCM specifications are estimated for the choice of business travel. Similar to the procedure described in section 3.3.2, the model with two latent classes is selected as the final model given its lowest BIC value. Table 12 presents the coefficient estimates for the class-specific choice model, class probabilities, and the parameters for the class membership model.

Respondents who perceive a higher risk of travelling during the pandemic and/or have experience of frequent online meetings during the COVID-19 epidemic are more likely to belong to class 1. On the other hand, those who have experience for frequent travel during the COVID-19 epidemic are less likely to belong to class 1. When the online meeting option is available, respondents in class 1 are discouraged from flying for business purposes due to the increases in the CFR or/and daily confirmed cases of the destination. They also show significant disutility for providing vaccination records and the compulsory requirement of mask-wearing at the airport (but no mask requirements during flight). Yet, the two-way interaction effect for class 1 indicates that respondents are more likely to accept the requirements of providing a vaccination record when the daily confirmed cases of the destination increase. Whilst 55.5% of the individuals are classified into class 1, the other 44.5% belonged to class 2. Respondents in class 2 prefer all health control measures.

Similarly, the two classes perceive the 'time' and 'price' attributes in a different way. As shown in the class membership model, class 1 respondents have experience in frequent online meetings during the COVID-19 epidemic and perceive a higher risk to health. Thus, they tend to have a lower intention to fly when an online meeting option is provided. Class 1 respondents' utility of travel decreases significantly when the ticket cost and time spent at the airport checkpoint increase. In other words, class 1 respondents attach negative values to 'time' and 'price' attributes. In contrast, those who have experience of frequent international travel (at least four times per year) during the COVID-19 epidemic are more likely to belong to class 2. Respondents in this group attach positive values to ticket cost and time spent at a checkpoint and showed a higher intention to have a business trip by air in the context of the COVID-19 epidemic. Again, these respondents may consider that the increased time and ticket cost are necessary for ensuring safe travel and face-to-face communication.

To summarise, even when the online meeting option is available, class 2 respondents have a higher intention of flying for business and strong preferences for all pandemic control measures. One possible explanation is that they have practical experience in air travel during the COVID-19 epidemic and treat the pandemic control measures as entirely necessary. In contrast, class 1 respondents have a lower intention to fly for business. The individuals in this group are sensitive to increases in the severity level of the epidemic situation, ticket cost, and time spent at health and security checks. This could be attributed to their perceived higher risk to health and their experience in using online meeting platforms frequently.

Table 11. Results of the Panel Latent Class Choice Model (when there is no option for an online meeting)

	Latent Class 1		Latent Class 2	
Class-specific Choice Model	Coef.	Z-value	Coef.	Z-value
Daily confirmed cases of current location	0.001	0.77	-0.006**	-2.19
Daily confirmed cases of destination	-0.003***	-3.58	-0.010***	-2.98
Case fatality rate (CFR)	-0.006***	-5.93	-0.020***	-3.76
Average time to pass through the health and security checks	0.010***	4.25	-0.017**	-2.36
Increased cost of ticket to cover the pandemic control measures	0.032***	10.72	-0.023**	-2.02
Health Declaration				
No declaration requirements	*(Reference)*		*(Reference)*	
Provide vaccination record	0.729***	9.84	-0.076	-0.27
Provide personal information, self-reported travel history, symptoms	0.046	0.18	-1.698**	-2.35
Mask Requirement				
No mask requirements	*(Reference)*		*(Reference)*	
Compulsory mask-wearing during flight and at airport	1.033***	12.40	-0.040	-0.14
Compulsory at the airport, but no requirements during flight	1.089***	12.68	0.079	0.33
On-site Health Check				
No requirements	*(Reference)*		*(Reference)*	
Tests involving sample collection	0.775***	6.90	0.271	0.86
Temperature screening	0.642***	8.16	0.509*	1.66
Two-way Interaction Effect				
CFR × Sample Collection[a]	0.002	0.62	0.016**	2.30
Time × Self-reported Health[b]	0.024***	3.59	0.048***	3.05
Class Membership Model			*(Reference: Class 2)*	
Constant	1.236***	7.77		
Factor 1 (Technology acceptance of online meetings)	n.s.	n.s.		
Factor 2 (Travel cost sensitive)	n.s.	n.s.		
Factor 3 (Preference for face-to-face communication)	0.313**	2.30		
Factor 4 (Perceived higher risk to health)	-0.284*	-1.73		
Factor 5 (Travel time sensitive)	n.s.	n.s.		
Frequent international travel before COVID-19	0.802**	2.11		
Average Probability	0.794		0.206	
Model Fits				
ln L (MNL)	-2299.21			

ln L (LCM)	-1922.14
G^2 (LCM vs. MNL), χ^2(df), p value	754.14(17), 0.000
BIC (2 classes, selected model)	4077.78
BIC (3 classes)	4135.89
BIC (4 classes)	4125.48
Nr. of observations	2400

Note: ***, **, * denote significance at the 1%, 5%, and 10% levels.
n.s. = not statistically significant (removed from the model).
[a] Case fatality rate × Tests involving sample collection
[b] Average time to pass through the health and security checks × Provide personal information, self-reported travel history, symptoms
Source: Estimation results obtained in this study.

Table 12. Results of the Panel Latent Class Choice Model (when there is an option for an online meeting)

	Latent Class 1		**Latent Class 2**	
Class-specific Choice Model	Coefficient	Z-value	Coefficient	Z-value
Daily confirmed cases of current location	-0.005	-1.36	0.000	0.17
Daily confirmed cases of destination	-0.029***	-4.16	0.000	0.14
Case fatality rate (CFR)	-0.016***	-3.78	0.000	-0.23
Average time to pass through the health and security checks	-0.023***	-3.67	0.016***	8.38
Increased cost of ticket to cover the pandemic control measures	-0.030**	-2.45	0.023***	5.75
Health Declaration				
No declaration requirements	*(Reference)*		*(Reference)*	
Provide vaccination record	-1.204**	-2.52	0.416*	1.67
Provide personal information, self-reported travel history, symptoms	-0.266	-0.88	0.587***	6.47
Mask Requirement				
No mask requirements	*(Reference)*		*(Reference)*	
Compulsory mask-wearing during flight and at airport	-0.113	-0.34	0.505***	4.81
Compulsory at the airport, but no requirements during flight	-0.753**	-2.50	0.536***	5.55
On-site Health Check				
No requirements	*(Reference)*		*(Reference)*	
Tests involving sample collection	0.300	0.88	0.399***	4.47
Temperature screening	0.236	0.68	0.293***	3.18
Two-way Interaction Effect				
Daily confirmed cases of destination × Vaccination[d]	0.021**	2.09	0.002	0.45
Class Membership Model			*(Reference: Class 2)*	
Constant	-0.151	-0.82	--	--

Factor 1 (Technology acceptance of online meetings)	n.s.	n.s.	--	--
Factor 2 (Travel cost sensitive)	n.s.	n.s.	--	--
Factor 3 (Preference for face-to-face communication)	n.s.	n.s.	--	--
Factor 4 (Perceived higher risk to health)	0.436***	3.69	--	--
Factor 5 (Travel time sensitive)	n.s.	n.s.	--	--
Frequent international travel amid COVID-19	-0.661**	-2.05		
Frequent online meetings amid COVID-19	0.763***	3.29		
Average Probability	0.555		0.445	
Model Fits				
ln L (MNL)	-2383.68			
ln L (LCM)	-1497.49			
G^2 (LCM vs. MNL), χ^2(df), p value	1772.38(16), 0.000			
BIC (2 classes, selected model)	3212.91			
BIC (3 classes)	3285.04			
BIC (4 classes)	3243.67			
Nr. of observations	2,400			

Note: ***, **, * denote significance at the 1%, 5%, and 10% levels.
n.s. = not statistically significant (removed from the model).
[d] Daily confirmed cases of destination × Provide vaccination record
Source: Estimation results obtained in this study.

3.3.4. Willingness to pay

Based on the results of the latent class models, we calculated business travellers' willingness to pay (WTP) for specific service features in the context of the COVID-19 pandemic. Specifically, WTP estimates are computed as the ratio between the two coefficients of travel attribute and cost (Lavieri and Bhat, 2019; Chen, Masiero, and Hsu, 2019; Li, Hensher, and Rose, 2010). The WTP indicates the monetary value that the respondent has to sacrifice to obtain one unit of a relevant travel attribute whilst maintaining the same utility level. Table 13 reports the WTP estimates under the two preconditions (online meeting inapplicable/applicable) for each of the identified latent classes and the weighted average WTP across all classes. Note, different traveller groups perceive cost as a desirable and undesirable attribute, respectively, and the interpretation of the WTP for each group is also different.

The estimation results suggest that individuals in class 1 with an associated class membership probability of 0.794 are willing to pay an additional HK$2,310 for a business trip that requires a vaccination record when an online meeting is inapplicable. They also have perceived values of HK$ 3,274 for compulsory mask-wearing during a flight and at the airport, HK$ 3,450 for compulsory mask-wearing only at the airport, HK$ 2,456 for a test involving sample collection, and HK$ 2,035 for temperature screening at the airport. As discussed in Section 2.4.2, class 1 travellers prefer health control measures and tend to perceive cost as a positive sign necessary for safe travel. In comparison, individuals in class 2 (with an associated class membership probability of 0.206) showed a significant disutility for health control measures. They are willing to accept the requirement of providing personal information and self-reported travel history and symptoms if they are compensated HK$2,240 and are willing to accept a temperature screening at the airport for a compensation of HK$188. Moreover, the WTP for the time saved at the health and security check for class 2 individuals is HK$74/min.

Table 13. Difference in Travellers' Mean Willingness to Pay Estimates

	Online Meeting Inapplicable			Online Meeting Applicable		
	Class 1 (0.794)	Class 2 (0.206)	Weighted average WTP	Class 1 (0.555)	Class 2 (0.445)	Weighted average WTP
Class Membership Prediction						
Perceived higher risk to health	(-)	(+)	--	(+)	(-)	--
Preference for face-to-face communication	(+)	(-)	--	IS	IS	--
Frequent international travel before COVID-19	(+)	(-)	--	IS	IS	--
Frequent international travel during COVID-19	IS	IS	--	(-)	(+)	--
Frequent online meeting during COVID-19	IS	IS	--	(+)	(-)	--
Attributes						
Time taken in health and security checks	HK$31	HK$74	HK$40	HK$77	HK$72	HK$75
Provide vaccination record	HK$2,310	IS	HK$1,834	HK$3,956	HK$1,815	HK$3,003
Provide personal information, self-reported travel history, symptoms	IS	HK$2,240	HK$461	IS	HK$2,557	HK$1,138
Compulsory mask-wearing during flight and at airport	HK$3,274	IS	HK$2,600	IS	HK$2,201	HK$979
Compulsory at the airport, but no requirements during flight	HK$3,450	IS	HK$2,739	HK$2,473	HK$2,335	HK$2,412
Tests involving sample collection	HK$2,456	IS	HK$1,950	IS	HK$1,741	HK$775
Temperature screening	HK$2,035	HK$188	HK$1,655	IS	HK$1,277	HK$568

WTP = willingness to pay.
Note: Direction of the parameter: (+) positive; (-) negative; (IS) examined but not statistically significant.
Source: Estimation results obtained in this study.

When the online meeting option is available, the estimation results suggest that class 2 travellers with an associated class membership probability of 0.445 are willing to pay an additional HK$1,815 for the provision of a vaccination record and HK$2,557 for the requirements of providing personal information, travel history, and symptoms. Also, they are willing to pay an additional HK$2,201–HK$2,335 for compulsory mask-wearing requirements, HK$1,741 for a test involving sample collection, and HK$1,277 for temperature screening at the airport. In contrast, individuals in class 1 (with an associated class membership probability of 0.555) need to be compensated HK$3,956 and HK$2,473 to accept the requirements of providing a vaccination record and compulsory mask-wearing at the airport. The weighted average WTP for the time saved across classes is HK$75/min.

The WTP estimates for the time saved and for the elements of the airport health control measures seem initially to be relatively high, but in comparing the evidence with the broader literature which is all pre-COVID-19, we might anticipate a WTP value that is higher today. Because our study is amongst the first of relevant quantitative analysis, we reviewed estimates of other safety and security features and found that our empirical results are overall consistent with previous studies. The weighted average WTP for the time saved at a checkpoint in our study ranges from between HK$40/min to HK$75/min. Veisten and Flügel (2011) conducted a stated preference survey pre-COVID in Norway investigating the trade-off between a new risk-based airport screening and asserted terror risk impact. Their estimated WTP for the travel time-saving in air travel was about NOK47.9/min (approx. HK$45/min). Patil et al. (2016) conducted a pan-European study to assess the public's preference for security and surveillance measures in train stations. The estimation for the 'time to go through security checks' and 'security surcharge on top of ticket cost' indicated a WTP of €5.45/min (approx. HK$54/min) for high-income travellers. Merkert and Beck (2017) revealed that the WTP of business travellers for air travel was two times higher than that of leisure travellers. Without including the attribute of security checks at the airport in the choice scenario, the value of time saved for air travel ranged from AU$29/hr to AU$312/hr (approx. HK$174/hr to HK$ 1,871/hr) for business travellers. Later, Beck, Rose, and Merkert (2018) estimated passengers' preference towards the elements of the airport security process and found a median WTP of AU$7.83/min (approx. HK$47/min) for the time saving at the security checkpoint, with the upper estimate of the 95% confidence interval being AU$18.27/min (approx. HK$110/min).

Estimates obtained in previous studies suggest a high WTP for various security and safety measures. For example, Patil et al. (2016) found that respondents in France prefer having CCTV cameras, security personnel at the station, and stringent physical security checks. Such preferences can be attributed to the experience from terrorist attacks on rail/metro facilities in France, and therefore the respondents are likely to be more supportive of safety measures. Specifically, high-income rail travellers in France need to be compensated €166 (approx. HK$1,557) if there are no security personnel at the station. The WTP estimates for the security and safety elements for air travel should be higher due to the more severe consequences. Molin et al. (2017) revealed a mean WTP ranging from €75 to €448 (approx. HK$703 to HK$ 4,202) for safety improvements in passenger air travel. Beck et al. (2018) found a median WTP of AU$503.16 (approx. HK$3,017) for undercover security on flights, AU$528.43 for CCTV cameras with facial recognition, AU$116.94 (approx. HK$702) for passports with finger and retinal scans, and AU$176.06 (approx. HK$1,055) for X-rays with all luggage opened, etc.

Another related stream of literature is healthcare services. Pedersen, Gyrd-Hansen, and Kjær (2011) revealed a mean WTP of €100 (approx. HK$938) for a test to obtain information on cancer risk. Javan-Noughabi et al. (2017) found that when health conditions decline, the WTP for health services amongst the Iranian population increased from US$295 to US$596 (approx. HK$2,291 to HK$ 4,629). Yeung et al. (2005) estimated the WTP for health protection measures in travel (e.g. travel vaccines and masks) using survey data collected in 1998 amongst Hong Kong residents. The respondents on average had a WTP of HK$447 for the prevention of travel health problems, which is equivalent to about HK$660 in 2020 prices, adjusted by the consumer price index (Census and Statistics Department, 2021). That data was collected during a 'normal period' (without a disease outbreak). Also, the survey design did not consider certain important factors, such as the magnitude of travel health risks and the mode of travel. Recently, the mean WTP for COVID-

19 vaccination was estimated to be US$269.7 (approx. HK$2,117) in Chile and US$60.8 (approx. HK$474) for the Chinese population when measured by the purchasing power parity (García and Cerda, 2020; Wang et al., 2021). The WTP estimates for COVID-19 vaccination can be influenced by citizens' perceived severity and risk of the disease, which vary across different countries or regions (García and Cerda, 2020; Hou et al., 2014). In Chile, 99.1% of the citizens perceived the risk of catching COVID-19. In contrast, due to effective public health interventions, only 12.2% of the respondents in China perceived a high risk of infection (García and Cerda, 2020; Wang et al., 2021). This can explain why the WTP in Chile was much higher than that in China. More importantly, the distrust in technology and uncertainties in safety could be barriers to the acceptance of the COVID-19 vaccine (Wang et al., 2021; Wong et al., 2021). Particularly, Hong Kong citizens showed a strong vaccine hesitancy during the COVID-19 pandemic. Wang et al. (2021) evaluated the willingness to accept the COVID-19 vaccine between two waves of the epidemic in Hong Kong. Their results showed that compared with the first wave, the willingness to accept the vaccine in the third wave was reduced. The decreasing willingness to accept the COVID-19 vaccine amongst the Hong Kong population could be attributed to the increasing concerns over vaccine safety and growing compliance of personal protection behaviours. The civic trust in vaccine might also be jeopardised due to the perceived rush of vaccine research and development, thus leading to a low uptake rate in Hong Kong. On the other hand, the respondents in Hong Kong showed very strong compliance with mask-wearing, likely due to the painful experiences learnt during the SARS outbreak in the city in 2003. As a result, the WTP values for pandemic control measures are fairly high. Overall, the WTP estimates for health control measures in our study seem to be within reasonable ranges and are comparable to estimates obtained by previous studies.

Overall, the WTP for health control services decreases if an online meeting option is provided. A higher proportion (i.e. 79.4%) of business travellers favour health control measures and are willing to pay for such services when the online meeting option is not available. This ratio decreases to 44.5% when an online meeting is applicable. Compared to the other class, these business travellers support pandemic control measures (‘pro-control’ passengers) and are characterised by a stronger preference for face-to-face meeting, lower risk perception, richer travel experience before and during the pandemic, and less-extensive use of online meetings.

3.4. Summary and discussion of the passenger preference analysis

To study the pandemic’s implications for business travel, a stated preference survey was conducted of potential air travellers in Hong Kong. The experiment was developed with a focus to evaluate the effects of additional travel requirements on passenger preference (i.e. health declarations, mask-wearing requirements, and on-site health checks) in the presence of the increased use of online meeting options in the context of the COVID-19 pandemic. Unobserved preference heterogeneity is incorporated in passengers’ responses to travel preferences. Two latent classes have been identified for each of the two preconditions (online meeting inapplicable/applicable). Characteristics of travel experience, online meeting experience, and some latent constructs are used to model the probability of respondents being classified into each of the two classes.

When there is no online meeting option, nearly 80% of the respondents prefer and are willing to pay for health measures, such as providing a vaccination record, having compulsory mask-wearing, tests involving sample collection, and temperature screening. These control measures and the associated high costs/fares, are perceived as valuable and necessary to lower the risks of infection during air travel. These ‘pro-control’ passengers prefer face-to-face communication, have experience of frequent travel before the epidemic, and perceive a lower health risk of air travel. In contrast, a minority of the respondents have a significant disutility towards the pandemic control requirements of providing personal information, travel history, and symptoms declaration, although they favour convenient temperature screening over having no on-site checking at all.

When there is an online meeting option, the share of ‘pro-control’ passengers decreases to 44.5%. Compared to the rest of the population, these passengers perceive a lower health risk, have more experience of frequent travel during the epidemic, and use online meetings less extensively after the epidemic outbreak. The remaining 55.5% showed greater disutility for the increased price and time associated with pandemic control measures. They are averse to the requirements of providing a vaccination record and mandatory mask-wearing at the airport.

With the option of online meetings, the average willingness to pay for the health control services decreases. For example, amongst those ‘pro-control’ passengers (with an associated class membership probability), the WTP for a vaccination record decreases from HK$2,310 to HK$1,815 when an online meeting option becomes available. The weighted average WTP for compulsory mask-wearing during the flight and at the airport decreases from HK$2,600 to HK$979. Similarly, the weighted average WTP for tests involving sample collection and temperature screening at the airport decrease from HK$1,950 and HK$1,655 to HK$775 and HK$568, respectively. The weighted average WTP for the time saved at the checkpoint increases from HK$40/min to HK$75/min, as passengers are more averse (less supportive) to pandemic control measures.

4. Discussions and recommendations

The COVID-19 pandemic has brought unprecedented negative impacts on the aviation industry. To help regulators and industry practitioners develop the right policy and business strategy, this study aims to provide an updated assessment of air connectivity in selected markets in Asia and investigate passenger preferences towards new travel requirements in the presence or absence of online meeting options. The specific empirical findings have been summarised in Sections 2 and 3. Quite significant diversity is observed in the different markets analysed, and it is evident that passenger behaviour, even based on our sample from Hong Kong only, is subject to the influence of many factors and suggests different preference subgroups (i.e. classes as revealed in our model). More in-depth analysis focusing on specific markets is needed for the optimal design of policies and strategies. Nevertheless, at a risk of excessive generalisation, our empirical results may lead to a number of policy and managerial implications.

The pandemic has led to significant connectivity loss in all the countries and markets we analysed, especially at large hubs or tourism cities. It is notable that these hub airports provide essential connection services to their spoke markets and, thus, are not only important to the hosting cities but also other airports in the region. Since airlines are even more badly affected, it is important to provide improved support to them to maintain their operations until the recovery of traffic volumes. This often calls for reduced fees and tax charges from the government, together with reductions in airport charges, as observed in markets such as in mainland China and many airports in Europe. In ASEAN countries, most airports are publicly/government owned. An airport charge reduction will further increase the financial obligations and pressures of governments. Under normal circumstances, these large airports are usually the most profitable and efficient airports thanks to their high traffic volumes and the cost savings derived from economies of scale. However, these large airports tend to have high fixed costs which limit their cost-cutting efforts when travel demand is reduced dramatically. This implies that these airports face substantial financial pressure too. Indeed, Beijing Capital Airport, the world's second-largest airport, which has been quite profitable for many years, incurred significant losses in 2020 despite a relatively strong recovery in the Chinese domestic market (Czerny et al., 2021). In such a case, it is advisable for these airports to borrow money from the capital markets to finance the short-to-medium shortfall in revenue. Because these airports will be quite profitable upon market recovery, their long-term operational risks are quite low, allowing them to finance their capital needs at relatively low interest rates. In addition, governments may consider financing airport investment projects, such as new air traffic control systems, terminal renovation, and new IT systems that facilitate touchless travel and self-services.

Our analysis on passenger preference suggests that there are different traveller subgroups as classified by their preferences for pandemic control and health-related measures, with their attitudes significantly affected by the availability of online meeting options. When there is no online meeting option, nearly 80% of the respondents prefer and are willing to pay for health measures. When the online meeting option is available, the share of 'pro-control' passengers decreases to 44.5%. The remaining 55.5% show a high relative disutility for the increased price and time associated with pandemic control measures. They are averse to the requirement of providing a vaccination record and mandatory mask-wearing at the airport. These results suggest that unlike previous short pandemics (e.g. those caused by SARS in 2003, avian flu in 2005 and 2013, and the MERS flu in 2015), business travel demand is likely to sustain some extended decline until the pandemic is fully controlled. Although some passengers (i.e. 44.5% of the business travellers) perceive pandemic control positively and are happy to pay the associated extra costs, many (i.e. 55.5% of the business travellers) are averse to the pandemic control measures and need to be compensated to sustain the same travel demand. These results suggest that the aviation industry will face a 'double-hit' problem: operation costs and processing times will increase due to control measures. In addition, the resultant inconvenience and extra time and costs will further reduce travel demand. Therefore, governments should consider sharing the costs associated with pandemic control or provide direct financial support to the aviation industry to facilitate recovery. Because the value of time saved at check points is very high, it is important for government agencies to make the pandemic control and health measures efficient and smooth. For operations such as vaccination records, it is important for stakeholders in different countries to cooperate with others to facilitate seamless control and pleasant travel experiences. Considering the existence of different classes of passengers with respect to pandemic control measures, airlines may consider offering differentiated services, such as offering more travel safety features at higher costs. Our empirical results suggest that about 45% of business travellers would welcome such services even at higher costs.

Although our conclusions are obtained with updated data and rigorous analysis, it should be noted that they are based on selected markets in Hong Kong, Malaysia, and Thailand. The passenger preference analysis focused on business travel based on a survey of respondents in Hong Kong. It would be useful to conduct an in-depth investigation using a larger sample, although such an extension is beyond the scope of the current study.

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Appendix I

Table A1. The Development of Hong Kong International Airport

Airport Name	Connectivity (2019)	Connectivity (2020)	Number of Flights (2019)	Number of Flights (2020)	Lost Destinations	New Destinations
Hong Kong International Airport	143	46	3,233	369	Abu Dhabi; Addis Ababa; Mauritius; Adelaide; Brisbane; Christchurch; Nadi; Saipan; Almaty; Amsterdam; Barcelona (ES); Madrid; Brussels; Copenhagen; Munich; Manchester (GB); Milan; Rome (IT); Paris (FR); Angeles/Mabalacat; Davao; Ilo-Ilo; Puerto Princesa; Chiang Mai; Ko Samui; Phuket; Da Nang; Nha Trang; Phuquoc; Denpasar-Bali; Kota Kinabalu; Penang; Phnom Penh; Siem Reap; Yangon; Bengaluru; Hyderabad; Kolkata; Male; Changsha; Chengdu; Chongqing; Dalian; Guangzhou; Guilin; Guiyang; Haikou; Hangzhou; Hefei; Kunming; Meixian; Nanchang; Nanjing; Nanning; Ningbo; Qingdao; Quanzhou; Sanya; Tianjin; Wenzhou; Wuhan; Wuyishan; Xi'an; Xuzhou; Yantai; Yinchuan; Zhanjiang; Zhengzhou; Busan; Jeju; Hiroshima; Kagoshima; Kumamoto; Nagasaki; Nagoya; New Ishigaki; Niigata; Okayama; Okinawa; Sapporo; Shimojishima; Takamatsu; Tokushima; Yonago; Irkutsk; Novosibirsk; Vladivostok; Tainan; Ulaanbaatar; Boston; Chicago; Dallas; Seattle; Washington (US) DC; Cape Town; Johannesburg; Moscow	Nil

Table A1. The Development of Connectivity of the Three Largest Airports in Malaysia

Airport Name	Connectivity (2019)	Connectivity (2020)	Number of Flights (2019)	Number of Flights (2020)	Lost Destinations	New Destinations
Kuala Lumpur International Airport	135	55	3,965	725	Baghdad; Madinah; Muscat; Riyadh King Khalid Intl; Sharjah; Adelaide International; Brisbane; Gold Coast; Melbourne Avalon Airport; Almaty; Tashkent; Banda Aceh; Bandung; Bangkok Don Mueang International Arpt; Cantho; Cebu; Chiang Mai; Da Nang; Dalat; Denpasar-Bali; Hanoi; Hat Yai; Hua Hin; Ko Samui; Krabi; Makassar; Nha Trang Cam Ranh Airport; Padang; Palembang; Pekanbaru; Phnom Penh; Phuket; Phuquoc; Pontianak; Semarang; Siborong-Borong; Siem Reap; Sihanoukville; Surakarta (Solo); Surat Thani; Tanjung Pandan; U-Tapao; Vientiane; Amritsar; Bhubaneshwar; Hyderabad Rajiv Gandhi Intl Arpt; Jaipur; Kochi (IN); Kolkata; Male; Thiruvananthapuram; Varanasi; Vishakhapatnam; Amsterdam; Frankfurt International Apt; Beijing Capital Intl Apt; Beijing Daxing Intl.; Busan; Changsha; Chengdu; Chongqing; Fukuoka; Fuzhou; Guilin; Hangzhou; Jeju International; Kaohsiung; Kunming; Lanzhou Zhongchuan Apt; Lijiang; Macau (MO); Nanning; Osaka Kansai International Airport; Quanzhou; Sapporo New Chitose Apt; Shantou; Shenzhen (CN); Tianjin; Tokyo Intl (Haneda); Xi'an Xianyang Apt; Zhengzhou	Manado
Kota Kinabalu	39	14	755	206	Bandar Seri Begawan; Bintulu; Lawas; Manila Ninoy Aquino International Apt; Mulu; Sibu; Singapore Changi Apt; Busan; Fuzhou; Guangzhou (CN); Hangzhou; Hiroshima; Hong Kong	Quanzhou

					International Apt; Kunming; Macau (MO); Muan; Nagoya Chubu Centrair International Apt; Osaka Kansai International Airport; Shanghai Pudong International Apt; Shenzhen (CN); Taipei Taiwan Taoyuan International Apt; Tianjin; Tokyo Narita Intl; Wuhan; Xiamen; Perth	
Penang	25	12	753	210	Banda Aceh; Bangkok Don Mueang International Arpt; Bangkok Suvarnabhumi International Apt; Jakarta Soekarno-Hatta Apt; Malacca; Phuket; Surabaya; Doha (QA); Guangzhou (CN); Hong Kong International Apt; Kunming; Quanzhou; Shenzhen (CN)	Nil

Table A3. Lost and New Destinations of the Three Largest Airports in Thailand

Airport Name	**Lost Destinations**	**New Destinations**
Bangkok Suvarnabhumi International Airport	Amman Queen Alia International Apt; Kuwait; Nairobi Jomo Kenyatta International Apt; St-denis; Ahmedabad; Bandaranaike Intl; Bengaluru; Chennai; Chittagong; Gaya; Hyderabad Rajiv Gandhi Intl Airport; Islamabad; Jaipur; Karachi; Lahore; Lucknow; Almaty; Ashgabat; Tashkent; Brussels Airport; Milan Malpensa Apt; Munich International Airport; Oslo Gardermoen Airport; Rome Fiumicino Apt; Stockholm Arlanda Apt; Vienna International; Auckland International Apt; Brisbane; Melbourne Airport; Perth; Sydney Kingsford Smith Apt; Bandar Seri Begawan; Cebu; Da Nang; Dalat; Denpasar-Bali; Haiphong; Luang Prabang; Mandalay; Nay Pyi Taw; Nha Trang Cam Ranh Airport; Pakse; Penang; Phnom Penh; Phuquoc; Siem Reap; Vientiane; Yangon; Beihai; Beijing Daxing Intl.; Changsha; Cheongju; Chongqing; Daegu; Fukuoka; Fuzhou; Guiyang; Haikou; Hangzhou; Harbin; Hefei; Irkutsk; Jeju International; Jinan; Kaohsiung; Khabarovsk; Krasnoyarsk; Lanzhou Zhongchuan Apt; Lianyungang; Lijiang; Linyi; Luoyang; Macau (MO); Nagoya Chubu Centrair International Apt; Nanchang; Nanjing; Nanning; Ningbo; Okinawa Naha Apt; Ordos; Qingdao; Sapporo New Chitose Apt; Sendai; Shantou; Shenyang; Taichung; Taiyuan; Tianjin; Ulaanbaatar; Urumqi; Vladivostok; Wenzhou; Wuhan; Wuyishan; Xi'an Xianyang Apt; Xinzhou; Xuzhou; Yangzhou; Zhengzhou; Cairo International; Kiev Borispol Intl Apt; Moscow Domodedovo Apt; Moscow Sheremetyevo International Apt	Loei; Nakhon Phanom; Nakhon Si Thammarat; Nan

Bangkok Don Mueang International Airport	Ahmedabad; Bandaranaike Intl; Bengaluru; Chennai; Delhi; Dhaka; Gaya; Guwahati; Jaipur; Kathmandu; Kochi (IN); Kolkata; Male; Mumbai; Brisbane; Cantho; Da Nang; Denpasar-Bali; Hanoi; Ho Chi Minh City; Jakarta Soekarno-Hatta Apt; Johor Bahru; Kuala Lumpur International Airport; Luang Prabang; Mandalay; Manila Ninoy Aquino International Apt; Medan Kuala Namu; Nha Trang Cam Ranh Airport; Penang; Phnom Penh; Siem Reap; Sihanoukville; Singapore Changi Apt; Vientiane; Yangon; Changchun; Changsha; Changzhou; Chengdu; Chongqing; Dalian; Fukuoka; Guangzhou (CN); Haikou; Hangzhou; Hefei; Hiroshima; Hong Kong International Apt; Jinan; Kunming; Linyi; Macau (MO; Nagoya Chubu Centrair International Apt; Nanchang; Nanjing; Nanning; Nantong; Ningbo; Osaka Kansai International Airport; Qingdao; Sanya; Sapporo New Chitose Apt; Seoul Incheon International Airport; Shanghai Pudong International Apt; Shantou; Shenyang; Shenzhen (CN); Tianjin; Tokyo Narita Intl; Wuhan; Wuxi; Xi'an Xianyang Apt; Xuzhou; Yancheng; Yiwu; Zhanjiang; Zhengzhou; Tbilisi	
Phuket	Abu Dhabi International Apt; Doha (QA) 00; Dubai International; Muscat; Ho Chi Minh City; Kawthaung; Kuala Lumpur International Airport; Penang; Phnom Penh; Siem Reap; Singapore Changi Apt; Barnaul; Beijing Capital Intl Apt; Changsha; Chengdu; Chita; Chongqing; Guangzhou (CN) 00; Guiyang; Hangzhou; Hefei; Hong Kong International Apt; Huai'an; Irkutsk; Kemerovo; Khabarovsk; Krasnoyarsk; Kunming; Macau (MO); Nanjing; Nanning; Ningbo; Novokuznetsk; Novosibirsk; Omsk; Seoul Incheon International Airport; Shanghai Pudong International Apt; Shenzhen (CN); Taiyuan; Tianjin; Tomsk; Vladivostok; Wuhan; Xi'an Xianyang Apt; Yekaterinburg; Yuzhno-Sakhalinsk; Zhengzhou; Bengaluru; Delhi; Mumbai; Frankfurt International Apt; Goteborg Landvetter Apt; Istanbul Ataturk Airport; London Gatwick Apt; Manchester (GB); Oslo Gardermoen Airport; Zurich Airport; Kazan; Moscow Sheremetyevo International Apt; Moscow Vnukovo International Apt; Nizhny Novgorod; Perm; Rostov; St Petersburg Pulkovo Apt; Tyumen; Melbourne Airport; Sydney Kingsford Smith Apt; Tashkent	Ufa

Appendix II

Questionnaire Survey for Business Trip Post COVID-19 Pandemic

Section 1 Travel experience, perception, and attitudes

Screening question:

Before the COVID-19 pandemic, did you have any experience related to international business trips made by air?

☐ Yes (Turn to Question 1 Travel experience)

☐ No (End of the questionnaire)

1. Travel experience:

(1) **Before** the COVID-19 pandemic, on average, how many international business trips did you have by air per year?

☐ 1 ~ 3 times a year ☐ 4 ~ 6 times a year ☐ 7 ~ 9 times a year ☐ ≥ 10 times a year

(2) **After** the COVID-19 pandemic, on average, how many international business trips do you have by air per year?

☐ 0 time ☐ 1 ~ 3 times a year ☐ 4 ~ 6 times a year ☐ 7 ~ 9 times a year ☐ ≥ 10 times a year

(3) **Before** the COVID-19 pandemic, on average, how many domestic business trips did you have by air per year?

☐ 1 ~ 3 times a year ☐ 4 ~ 6 times a year ☐ 7 ~ 9 times a year ☐ ≥ 10 times a year

(4) **After** the COVID-19 pandemic, on average, how many domestic business trips do you have by air per year?

☐ 0 time ☐ 1 ~ 3 times a year ☐ 4 ~ 6 times a year ☐ 7 ~ 9 times a year ☐ ≥ 10 times a year

(5) **Before** the COVID-19 pandemic, on average, how many online meeting(s) for business purposes did you have per week?

☐ 0 time ☐ 1 ~ 3 times a year ☐ 4 ~ 6 times a year ☐ 7 ~ 9 times a year ☐ ≥ 10 times a year

(6) **After** the COVID-19 pandemic, on average, how many online meeting(s) for business purposes do you have per week?

☐ 0 time ☐ 1 ~ 3 times a year ☐ 4 ~ 6 times a year ☐ 7 ~ 9 times a year ☐ ≥ 10 times a year

(7) Before the COVID-19 pandemic, how many days did you work from home per week?

☐0 days ☐1-2 days ☐3-4 days ☐5-6 days ☐7 days

(8) After the COVID-19 pandemic, how many days do you work from home per week?

☐0 days ☐1-2 days ☐3-4 days ☐5-6 days ☐7 days

2. Attitudinal questions

Technology acceptance of online meetings	
(1) The online meeting tool allows me to organise meetings any time (24/7).	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ 0 1 2 3 4 5 6 7 8 9 10 (Disagree strongly Agree strongly)
(2) The online meeting tool is very user friendly.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ 0 1 2 3 4 5 6 7 8 9 10 (Disagree strongly Agree strongly)
(3) It is easy to prepare an online meeting.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ 0 1 2 3 4 5 6 7 8 9 10 (Disagree strongly Agree strongly)
(4) I will recommend my colleagues and friends to use online meeting tools.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ 0 1 2 3 4 5 6 7 8 9 10 (Disagree strongly Agree strongly)
(5) In general, I consider online meeting platforms/applications as very useful.	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ 0 1 2 3 4 5 6 7 8 9 10 (Disagree strongly Agree strongly)

Perceived higher risk to health

(1) The health risk associated with air travel during the pandemic is very high.	○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 (Disagree strongly Agree strongly)
(2) To me, travelling during the pandemic is a very risky behaviour that leads to disease infection.	○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 (Disagree strongly Agree strongly)

Preference for face-to-face communication	
(1) I prefer face-to-face communication rather than online communication.	○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 (Disagree strongly Agree strongly)
(2) I like meeting new people in different locations.	○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 (Disagree strongly Agree strongly)
(3) Instead of sitting at home or at the office, I prefer to go and meet people.	○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 (Disagree strongly Agree strongly)

Travel time	
(1) I expect to pass the health assessment and security checks at the airport as quickly as possible.	○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 (Disagree strongly Agree strongly)
(2) I will feel frustrated and impatient if the health assessment or security checks take a long time.	○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 (Disagree strongly Agree strongly)
(3) My time is very precious during business trips.	○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 (Disagree strongly Agree strongly)

Travel cost sensitivity	
(1) The expenditure on the air ticket for my business travel needs to be carefully arranged.	○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 (Disagree strongly Agree strongly)
(2) The expenditure on the accommodation cost for my business travel needs to be carefully arranged.	○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 (Disagree strongly Agree strongly)
(3) Expenses for the travel cost will be covered mostly by my affiliation/company. Therefore, I have no concerns about the travel cost for my business trip.	○ 0 ○ 1 ○ 2 ○ 3 ○ 4 ○ 5 ○ 6 ○ 7 ○ 8 ○ 9 ○ 10 (Disagree strongly Agree strongly)

Section 2 Stated preference

Despite the widespread outbreak, business travel has not come to an absolute standstill. Employees are still undertaking essential business trips. Given the increased use of online meeting options, they are often faced with the dilemma of whether to proceed with their plans or not.

Imagine that the travel restrictions are lifted now, and you plan to make an international business trip by air. We would like you then to consider three ways in which you might make this journey. These are described by different levels of diseases severity, travel characteristics, travel need, and pandemic control measures.
Please select one option considering the following descriptions.

Scenario 1

	Option A	Option B	Option C
Disease Information			
Daily confirmed cases of current location	50	50	
Daily confirmed cases of the destination	50	50	
Case fatality rate (CFR)	0.1% (there is one death among 1000 confirmed cases)	10% (there is one death among 10 confirmed cases)	
Travel characteristics			
Average time to pass through the health and security checks	60 minutes	20 minutes	I would choose not to fly under these conditions
Increased cost of ticket to cover the pandemic control measures	500 HKD	3000 HKD	
Pandemic Control Measures			
Health declaration	No Requirements	Provide personal information, self-reported travel history, symptoms	
Mask requirement	Compulsory mask-wearing during flight and airport	No requirements	
Onsite Health Check	Tests involving sample collection	Temperature screening	
If there is no option for an online meeting (no platform/application):	☐	☐	☐
If there is an option for an online meeting:	☐	☐	☐

Scenario 2

	Option A	Option B	Option C
Disease Information			
Daily confirmed cases of current location	10	100	
Daily confirmed cases of the destination	100	10	
Case fatality rate (CFR)	10% (there is one death among 10 confirmed cases)	0.1% (there is one death among 1000 confirmed cases)	
Travel characteristics			
Average time to pass through the health and security checks	20 minutes	40 minutes	I would choose not to fly under these conditions
Increased cost of ticket to cover the pandemic control measures	3000 HKD	500 HKD	
Pandemic Control Measures			
Health declaration	Provide personal information, self-reported travel history, symptoms	No Requirements	
Mask requirement	Compulsory mask-wearing during flight and airport	Compulsory at the airport, but no requirements during flight	
Onsite Health Check	No Requirements	Temperature screening	
If there is no option for an online meeting (no platform/application):	☐	☐	☐
If there is an option for an online meeting:	☐	☐	☐

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Scenario 3

	Option A	Option B	Option C
Disease Information			
Daily confirmed cases of current location	50	50	
Daily confirmed cases of the destination	100	10	
Case fatality rate (CFR)	1% (there is one death among 100 confirmed cases)	10% (there is one death among 10 confirmed cases)	
Travel characteristics			
Average time to pass through the health and security checks	40 minutes	60 minutes	I would choose not to fly under these conditions
Increased cost of ticket to cover the pandemic control measures	1000 HKD	1000 HKD	
Pandemic Control Measures			
Health declaration	Provide vaccination record	No Requirements	
Mask requirement	No requirements	Compulsory mask-wearing during flight and airport	
Onsite Health Check	Temperature screening	No Requirements	
If there is no option for an online meeting (no platform/application):	☐	☐	☐
If there is an option for an online meeting:	☐	☐	☐

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Scenario 4

	Option A	Option B	Option C
Disease Information			I would choose not to fly under these conditions
Daily confirmed cases of current location	100	10	
Daily confirmed cases of the destination	10	100	
Case fatality rate (CFR)	10% (there is one death among 10 confirmed cases)	0.1% (there is one death among 1000 confirmed cases)	
Travel characteristics			
Average time to pass through the health and security checks	20 minutes	60 minutes	
Increased cost of ticket to cover the pandemic control measures	1000 HKD	1000 HKD	
Pandemic Control Measures			
Health declaration	No Requirements	Provide personal information, self-reported travel history, symptoms	
Mask requirement	Compulsory at the airport, but no requirements during flight	No requirements	
Onsite Health Check	Temperature screening	No Requirements	
If there is no option for an online meeting (no platform/application):	☐	☐	☐
If there is an option for an online meeting:	☐	☐	☐

Scenario 5

	Option A	Option B	Option C
Disease Information			I would choose not to fly under these conditions
Daily confirmed cases of current location	50	50	
Daily confirmed cases of the destination	10	100	
Case fatality rate (CFR)	10% (there is one death among 10 confirmed cases)	0.1% (there is one death among 1000 confirmed cases)	
Travel characteristics			
Average time to pass through the health and security checks	40 minutes	20 minutes	
Increased cost of ticket to cover the pandemic control measures	1000 HKD	1000 HKD	
Pandemic Control Measures			
Health declaration	Provide personal information, self-reported travel history, symptoms	Provide vaccination record	
Mask requirement	Compulsory mask-wearing during flight and airport	Compulsory at the airport, but no requirements during flight	
Onsite Health Check	Temperature screening	Tests involving sample collection	
If there is no option for an online meeting (no platform/application):	☐	☐	☐
If there is an option for an online meeting:	☐	☐	☐

Scenario 6

	Option A	Option B	Option C
Disease Information			I would choose not to fly under these conditions
Daily confirmed cases of current location	100	10	
Daily confirmed cases of the destination	100	10	
Case fatality rate (CFR)	1% (there is one death among 100 confirmed cases)	1% (there is one death among 100 confirmed cases)	
Travel characteristics			
Average time to pass through the health and security checks	20 minutes	60 minutes	
Increased cost of ticket to cover the pandemic control measures	1000 HKD	1000 HKD	
Pandemic Control Measures			
Health declaration	Provide personal information, self-reported travel history, symptoms	Provide vaccination record	
Mask requirement	Compulsory at the airport, but no requirements during flight	Compulsory mask-wearing during flight and airport	
Onsite Health Check	Temperature screening	Tests involving sample collection	
If there is no option for an online meeting (no platform/application):	☐	☐	☐
If there is an option for an online meeting:	☐	☐	☐

Section 3 Personal information
1. Gender: ☐ Male ☐ Female
2. Age: ☐Below 18 ☐18-25 ☐26-35 ☐36-45 ☐46-55 ☐56-65 ☐Over 65
3. Education: ☐ Primary ☐ Secondary ☐ Tertiary
4. Marital status: ☐ Single ☐Married/Cohabiting ☐Divorced
5. Employment type: ☐Full-time employee ☐Part-time employee ☐Employer/manager ☐Self-employed ☐Others
6. Industrial classification： ☐ Agriculture and fishing ☐ Mining and quarrying ☐ Manufacturing ☐ Electricity, gas, and water ☐ Construction ☐ Wholesale, retail and import/export trades, restaurants, and hotels ☐ Transport, storage, and communications ☐ Financing, insurance, real estate, and business services ☐ Community, social and personal services
7. Current personal monthly income (1USD = approx. 7.85 HKD): ☐ < 10,000 HKD ☐ 10,000-19,999 HKD ☐ 20,000-29,999 HKD ☐ 30,000-39,999 HKD ☐ 40,000-49,999 HKD ☐ 50,000-59,999 HKD ☐ ≥ 60,000 HKD
8.

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