



Faculty of Economics and Business

**Impact of Climate Change on Tourism Demand in
Selected Asia Pacific Countries**

Jong Meng Chang

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Impact of Climate Change on Tourism Demand in
Selected Asia Pacific Countries

Jong Meng Chang

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DECLARATION

I declare that the work in this thesis was carried out in accordance with the regulations of Universiti Malaysia Sarawak. Except where due acknowledgements have been made, the work is that of the author alone. The thesis has not been accepted for any degree and is not concurrently submitted in candidature of any other degree.



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Signature

Name: Jong Meng Chang

Matric No.: 19010011

Faculty of Economics and Business

Universiti Malaysia Sarawak

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ABSTRACT

This study aims to construct the relative tourism climate index (RTCI) and relative holiday climate index (RHCI) to examine their impact on tourism industry in Asia Pacific region. In general, the ten most visited countries in Asia Pacific have been chosen in this study. A detailed analysis of tourism driving forces for each country will be further explored after the selection of targeted countries in Asia Pacific region. The quarterly data spans from 2010 to 2020 will be utilized and analysed using panel Autoregressive Distributed Lag (ARDL) approach in this study. The gravity model has been chosen to formulate the tourism demand models for the ten countries in the Asia Pacific region. The modification has been made on the core gravity model by adding the tourism price and climatic variables to gather more comprehensive tourism information. In general, the climate condition is a significant factor influencing the tourism demand in the Asia Pacific region regardless whether the country is a four seasons or one season country. Besides that, the tourists' income commonly identifies as an important variable affecting their travel decision, however, it is not their main concern in certain case depends on the travel distance between the countries. Besides that, a mixture results of tourism price and transportation cost have been found mainly due to the travel distance between the countries. To conclude, this study highlighted the importance of the climatic impacts on the tourism industry. Other factors are also important depends on the tourists' preferences. Therefore, continuous studies in different perspectives are needed because the demand of the tourists will be changed over the time.

Keywords: Relative tourism climate index, relative holiday climate index, tourism, panel ARDL analysis

Kesan Perubahan Iklim terhadap Permintaan Pelancongan di Negara-negara Asia Pasifik Terpilih

ABSTRAK

Kajian ini bertujuan untuk membina indeks iklim pelancongan relatif (RTCI) dan indeks iklim percutian relatif (RHCI) untuk mengkaji kesannya terhadap industri pelancongan di Asia Pasifik. Secara umumnya, sepuluh negara yang paling banyak dikunjungi di Asia Pasifik telah dipilih dalam kajian ini. Analisis terperinci mengenai daya penggerak pelancongan bagi setiap negara akan diterokai dengan lebih lanjut selepas negara yang disasarkan telah terpilih di Asia Pasifik. Data suku tahunan dari 2010 hingga 2020 akan digunakan dan dianalisis dengan menggunakan pendekatan panel ARDL dalam kajian ini. Model graviti telah dipilih untuk merumuskan model permintaan pelancongan bagi sepuluh negara terpilih di Asia Pasifik. Pengubahsuaian telah dibuat pada model graviti teras dengan menambah harga pelancongan dan pembolehubah iklim untuk mengumpulkan maklumat pelancongan yang lebih komprehensif. Secara umumnya, keadaan iklim merupakan faktor penting yang mempengaruhi permintaan pelancongan di Asia Pasifik tanpa mengira sama ada negara itu adalah negara empat musim atau satu musim. Selain itu, pendapatan pelancong biasanya dikenal pasti sebagai pembolehubah penting yang mempengaruhi keputusan perjalanan mereka, namun, ia bukanlah factor utama mereka dalam kes tertentu bergantung kepada jarak perjalanan antara negara. Selain itu, hasil campuran harga pelancongan dan kos pengangkutan didapati terutamanya disebabkan oleh jarak perjalanan antara negara. Sebagai kesimpulan, kajian ini menekankan kepentingan kesan iklim terhadap industri pelancongan. Faktor lain juga penting bergantung pada pilihan pelancong. Oleh itu, kajian berterusan dalam perspektif berbeza diperlukan kerana permintaan pelancong akan berubah mengikut peredaran masa.

Kata kunci: *Petunjuk iklim pelancongan, indeks iklim percutian, pelancongan, pendekatan panel ARDL*

TABLE OF CONTENTS

	Page
DECLARATION	i
ACKNOWLEDGEMENT	ii
ABSTRACT	iii
ABSTRAK	iv
TABLE OF CONTENTS	vi
LIST OF TABLES	x
LIST OF FIGURES	xiv
LIST OF ABBREVIATIONS	xvi
CHAPTER 1: INTRODUCTION	1
1.1 Introduction	1
1.2 Background of the Study	15
1.3 Problem Statement	33
1.4 Research Questions	35
1.5 Objectives of the Study	36
1.5.1 General Objective	36
1.5.2 Specific Objectives	36
1.6 Significance of the Study	36
1.7 Organization of the Study	38

CHAPTER 2: LITERATURE REVIEW	39
2.1 Introduction	39
2.2 Theoretical Review	39
2.3 Empirical Review	46
2.3.1 Climate Condition	46
2.3.2 Income Level	56
2.3.3 Population	58
2.3.4 Tourism Price	59
2.3.5 Transportation Cost	63
2.3.6 Exchange Rate	64
2.3.7 Tourism Security	65
2.3.8 Trade Volume	67
2.3.9 Lagged Dependent Variables	67
2.3.10 Dummy Variables	68
2.4 Literature Gap	69
CHAPTER 3: METHODOLOGY	71
3.1 Introduction	71
3.2 Estimation Models	71
3.3 Estimation Methods	79
3.3.1 Panel Unit Root Tests	79

3.3.2	Wald Cointegration Test	82
3.3.3	Panel PMG/ARDL	83
3.4	Data Description	85
CHAPTER 4: RESULTS AND DISCUSSIONS		92
4.1	Overview	92
4.2	Empirical Results for China Tourism Industry	92
4.3	Empirical Results for Thailand Tourism Industry	98
4.4	Empirical Results for Japan Tourism Industry	102
4.5	Empirical Results for Malaysia Tourism Industry	107
4.6	Empirical Results for Hong Kong Tourism Industry	112
4.7	Empirical Results for Macau Tourism Industry	116
4.8	Empirical Results for Vietnam Tourism Industry	119
4.9	Empirical Results for India Tourism Industry	123
4.10	Empirical Results for South Korea Tourism Industry	128
4.11	Empirical Results for Singapore Tourism Industry	132
CHAPTER 5: CONCLUSION AND RECOMMENDATIONS		137
5.1	Introduction	137
5.2	Conclusion	137
5.3	Policy Recommendations	147
5.4	Limitations of the Study	149

5.5	Room for Further Studies	150
	REFERENCES	152

LIST OF TABLES

	Page
Table 1.1 Average Growth Rate of International Tourist Arrivals in the World and by Regions, 2010-2019	17
Table 1.2 Average Growth Rate of International Tourist Receipts in the World and by Regions, 2010-2019	17
Table 1.3 GDP Contribution and Tourism Employment for the Ten Most Visited Countries in the Asia Pacific Region, 2019	19
Table 1.4 Top Ten Most Visited Countries with Its Major Origin Countries in the Asia Pacific Region, 2019	31
Table 3.1 Weightages of TCI and HCI	73
Table 3.2 Classification Schemes for TCI and HCI	74
Table 3.3 Source of Variables	87
Table 4.1 Results of Panel Unit Root Tests for China Tourism Demand Models	92
Table 4.2 Result of Wald's Cointegration Test for China - RTCI	93
Table 4.3 Result of Wald's Cointegration Test for China - RHCI	93
Table 4.4 Autoregressive Distributed Lag Model Coefficients for China: Relative Tourism Climate Index (3, 4, 4, 4, 4, 4)	94
Table 4.5 Autoregressive Distributed Lag Model Coefficients for China: Relative Holiday Climate Index (5, 4, 4, 4, 4, 4)	96
Table 4.6 Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in China, 2010-2020	98
Table 4.7 Results of Panel Unit Root Tests for Thailand Tourism Demand Models	98
Table 4.8 Result of Wald's Cointegration Test for Thailand - RTCI	99
Table 4.9 Result of Wald's Cointegration Test for Thailand - RHCI	99
Table 4.10 Panel Autoregressive Distributed Lag Model Coefficients for Thailand: Relative Tourism Climate Index (3, 3, 3, 3, 3, 3)	100

Table 4.11	Panel Autoregressive Distributed Lag Model Coefficients for Thailand: Relative Holiday Climate Index (5, 3, 3, 3, 3, 3)	101
Table 4.12	Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Thailand, 2010-2020	102
Table 4.13	Results of Panel Unit Root Tests for Japan Tourism Demand Models	103
Table 4.14	Result of Wald's Cointegration Test for Japan - RTCI	103
Table 4.15	Result of Wald's Cointegration Test for Japan - RHCI	103
Table 4.16	Panel Autoregressive Distributed Lag Model Coefficients for Japan: Relative Tourism Climate Index (4, 5, 5, 5, 5, 5)	105
Table 4.17	Panel Autoregressive Distributed Lag Model Coefficients for Japan: Relative Holiday Climate Index (3, 1, 1, 1, 1, 1)	106
Table 4.18	Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Japan, 2010-2020	107
Table 4.19	Results of Panel Unit Root Tests for Malaysia Tourism Demand Models	108
Table 4.20	Result of Wald's Cointegration Test for Malaysia - RTCI	108
Table 4.21	Result of Wald's Cointegration Test for Malaysia - RHCI	108
Table 4.22	Panel Autoregressive Distributed Lag Model Coefficients for Malaysia: Relative Tourism Climate Index (5, 4, 4, 4, 4, 4)	109
Table 4.23	Panel Autoregressive Distributed Lag Model Coefficients for Malaysia: Relative Holiday Climate Index (3, 1, 1, 1, 1, 1)	110
Table 4.24	Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Malaysia, 2010-2020	111
Table 4.25	Results of Panel Unit Root Tests for Hong Kong Tourism Demand Models	112
Table 4.26	Result of Wald's Cointegration Test for Hong Kong - RTCI	113
Table 4.27	Result of Wald's Cointegration Test for Hong Kong - RHCI	113
Table 4.28	Panel Autoregressive Distributed Lag Model Coefficients for Hong Kong: Relative Tourism Climate Index (4, 3, 3, 3, 3, 3)	113
Table 4.29	Panel Autoregressive Distributed Lag Model Coefficients for Hong Kong: Relative Holiday Climate Index (4, 3, 3, 3, 3, 3)	115

Table 4.30	Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Hong Kong, 2010-2020	116
Table 4.31	Results of Panel Unit Root Tests for Macau Tourism Demand Models	116
Table 4.32	Result of Wald's Cointegration Test for Macau - RTCI	117
Table 4.33	Result of Wald's Cointegration Test for Macau - RHCI	117
Table 4.34	Panel Autoregressive Distributed Lag Model Coefficients for Macau: Relative Tourism Climate Index (1, 1, 1, 1, 1, 1)	118
Table 4.35	Panel Autoregressive Distributed Lag Model Coefficients for Macau: Relative Holiday Climate Index (3, 1, 1, 1, 1, 1)	118
Table 4.36	Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Macau, 2010-2020	119
Table 4.37	Results of Panel Unit Root Tests for Vietnam Tourism Demand Models	120
Table 4.38	Result of Wald's Cointegration Test for Vietnam - RTCI	120
Table 4.39	Result of Wald's Cointegration Test for Vietnam - RTCI	120
Table 4.40	Panel Autoregressive Distributed Lag Model Coefficients for Vietnam: Relative Tourism Climate Index (3, 2, 2, 2, 2, 2)	121
Table 4.41	Panel Autoregressive Distributed Lag Model Coefficients for Vietnam: Relative Holiday Climate Index (3, 4, 4, 4, 4, 4)	122
Table 4.42	Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Vietnam, 2010-2020	123
Table 4.43	Results of Panel Unit Root Tests for India Tourism Demand Models	124
Table 4.44	Result of Wald's Cointegration Test for India - RTCI	124
Table 4.45	Result of Wald's Cointegration Test for India - RHCI	124
Table 4.46	Panel Autoregressive Distributed Lag Model Coefficients for India: Relative Tourism Climate Index (5, 3, 3, 3, 3, 3)	125
Table 4.47	Panel Autoregressive Distributed Lag Model Coefficients for India: Relative Holiday Climate Index (4, 3, 3, 3, 3, 3)	126
Table 4.48	Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in India, 2010-2020	127

Table 4.49	Results of Panel Unit Root Tests for South Korea Tourism Demand Models	128
Table 4.50	Result of Wald's Cointegration Test for South Korea - RTCI	128
Table 4.51	Result of Wald's Cointegration Test for South Korea - RHCI	129
Table 4.52	Panel Autoregressive Distributed Lag Model Coefficients for South Korea: Relative Tourism Climate Index (4, 3, 3, 3, 3, 3)	129
Table 4.53	Panel Autoregressive Distributed Lag Model Coefficients for South Korea: Relative Holiday Climate Index (4, 3, 3, 3, 3, 3)	130
Table 4.54	Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in South Korea, 2010-2020	132
Table 4.55	Results of Panel Unit Root Tests for Singapore Tourism Demand Models	132
Table 4.56	Result of Wald's Cointegration Test for Singapore - RTCI	133
Table 4.57	Result of Wald's Cointegration Test for Singapore - RHCI	133
Table 4.58	Panel Autoregressive Distributed Lag Model Coefficients for Singapore: Relative Tourism Climate Index (5, 1, 1, 1, 1, 1)	134
Table 4.59	Panel Autoregressive Distributed Lag Model Coefficients for Singapore: Relative Holiday Climate Index (4, 2, 2, 2, 2)	135
Table 4.60	Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Singapore, 2010-2020	136

LIST OF FIGURES

	Page
Figure 1.1 International Tourist Arrivals and Tourism Receipts by Region, 2018	4
Figure 1.2 International Tourist Arrivals and Tourism Receipts by Region, 2019	5
Figure 1.3 International Tourist Arrivals and Tourism Receipts by Region, 2020	7
Figure 1.4 International Tourist Arrivals and Tourism Receipts by Region, 2021	8
Figure 1.5 International Tourist Arrivals and Tourism Receipts by Region, 2022	10
Figure 1.6 UNWTO Sustainable Development Goals	11
Figure 1.7 Top Ten Tourism Destination Countries in Asia Pacific Region, 2019	18
Figure 1.8 Monthly Tourist Arrivals and Average Temperature in China, 2010M01-2019M12	21
Figure 1.9 Monthly Tourist Arrivals and Average Temperature in Thailand, 2010M01-2020M12	22
Figure 1.10 Monthly Tourist Arrivals and Average Temperature in Japan, 2010M01-2020M12	23
Figure 1.11 Monthly Tourist Arrivals and Temperature in Hong Kong, 2010M01-2020M12	24
Figure 1.12 Monthly Tourist Arrivals and Temperature in Malaysia, 2010M01-2020M12	25
Figure 1.13 Monthly Tourist Arrivals and Temperature in Macau, 2010M01-2020M12	26
Figure 1.14 Monthly Tourist Arrivals and Temperature in India, 2010M01-2020M12	27

Figure 1.15	Monthly Tourist Arrivals and Temperature in Vietnam, 2010M01-2020M12	28
Figure 1.16	Monthly Tourist Arrivals and Temperature in South Korea, 2010M01-2020M12	29
Figure 1.17	Monthly Tourist Arrivals and Temperature in Singapore, 2010M01-2020M12	30

LIST OF ABBREVIATIONS

ARDL	Autoregressive Distributed Lag
BCI	Beach Climate Index
CEPII	Centre d'Etudes Prospectives et d'Informations Internationales
CIA	Daily Comfort Index
CID	Daytime Comfort Index
CIT	Climate Index for Tourism
COVID-19	Coronavirus Disease 2019
CPI	Consumer Price Index
DOLS	Dynamic Ordinary Least Squares
FMOLS	Fully Modified Ordinary Least Squares
GDP	Gross Domestic Product
HCI	Holiday Climate Index
IPCC	Intergovernmental Panel on Climate Change
RP	Relative Price
RHCI	Relative Holiday Climate Index
RTCI	Relative Tourism Climate Index
SDGs	Sustainable Development Goals
SARS	Severe Acute Respiratory Syndrome
SP	Substitute Price
TCI	Tourism Climate Index
UNESCAP	United Nations Economic and Social Commission for Asia Pacific
UNWTO	World Tourism Organization

CHAPTER 1

INTRODUCTION

1.1 Introduction

In recent decades, the tourism industry has emerged as a key driver of global growth and development across the world. Tourism involves individuals traveling to foreign countries or unfamiliar destinations outside their typical surroundings for leisure, business, or professional purposes, encompassing social, cultural, and economic aspects. Today, tourism has expanded to include sport tourism and medical tourism, further diversifying its scope. Irrespective of a country's economic classification, whether low, middle, or high-income, tourism contributes multi-layered and cross-sectoral benefits.

The tourism industry comprises several key players, including the airline industry, accommodation industry, foods and beverages industry, and other supporting industries. Recognizing the substantial benefits of tourism on economic and social development, its economic effects have been increasingly considered in recent years. These advantages encompass rising incomes for governments and communities, foreign exchange earnings, increased job opportunities, redistribution of international wealth, and the sharing of advanced technology and expertise.

Furthermore, open economic policies, relaxed travel restrictions between countries, improved visa facilitation, and various tourism agreements have accelerated the growth of world tourism. The rapid expansion of the airline industry, offering more affordable flight ticket prices, has also played a significant role in boosting tourism by enabling easier travel

between destinations worldwide. The prosperity of the travel and tourism industry has far-reaching effects that benefit nations and societies through its numerous positive impacts.

Governments worldwide recognise the potential of the tourism industry and has launched a series of programmes to further develop and promote it. One such initiative is the Silk Road tourism project, introduced at the World Tourism Organization (UNWTO)'s General Assembly in Indonesia in 1993. The project aims to enhance tourism development and economic impacts by reviving ancient trading routes and fostering cultural exchange among three continents, covering 12,000 km. This exemplifies the UNWTO's commitment to revitalizing and transforming the tourism industry through mutual collaboration among member states and key players fostering new opportunities for healthy and sustainable growth.

Moreover, the tourism industry has become a potential instrument for diversifying economic risks and uncertainties in both developed and developing countries. By expanding and developing the tourism sector, countries can mitigate adverse impacts from external shocks such as economic recessions, oil price slumps, and unexpected events like SARS and the COVID-19 pandemic. Therefore, the country can further diversify its economic risks through tourism expansion and development of the tourism industry.

Tourism expansion is supported by advancements in the airline industry, closer collaboration between countries, developments in the telecommunication industry, and improvements in other related industries. The wealth generated by the tourism industry leads to various benefits for society, including economic development, increased job opportunities, improved living standard, and higher foreign exchange earnings. In addition, tourism revenue received by the country can be reinvested into the tourism industry or other

potential industries to increase the size of the economy. Governments play a crucial role in promoting unique tourism destinations and special products to attract both local and foreign tourist.

The economic and employment contributions of the tourism industry have been extensively quantified for over 70 years. The UNWTO estimated that the number of international tourists was just around 25 million people in 1950. The projection of international tourist arrivals worldwide for leisure, business and other purposes will reach 1.8 billion by 2030 with an average annual growth rate of 3.3% (UNWTO, 2011). The majority of these arrivals are expected to be in emerging countries, constituting 58% of the total.

In 2018, international tourist arrivals grew by 5%, reaching 1.4 billion and exceeding previous predictions for 2020. The growth was mainly driven by the strong global economy, rapid growth of emerging countries, technological advances and visa facilitation. This target was reached two years ahead of UNWTO's long term forecast issued in 2010. At the same time, the world tourism has generated USD 1.7 trillion of international tourism exports, a 4% increase compared to 2017. In the following year, the tourism industry contributed USD 8.8 trillion, accounting for 10.4% of global income, and created 319 million job opportunities, representing one-tenth of all jobs worldwide. In summary, the tourism industry plays a crucial role in improving the lives of millions of people and transforming communities on a global scale.

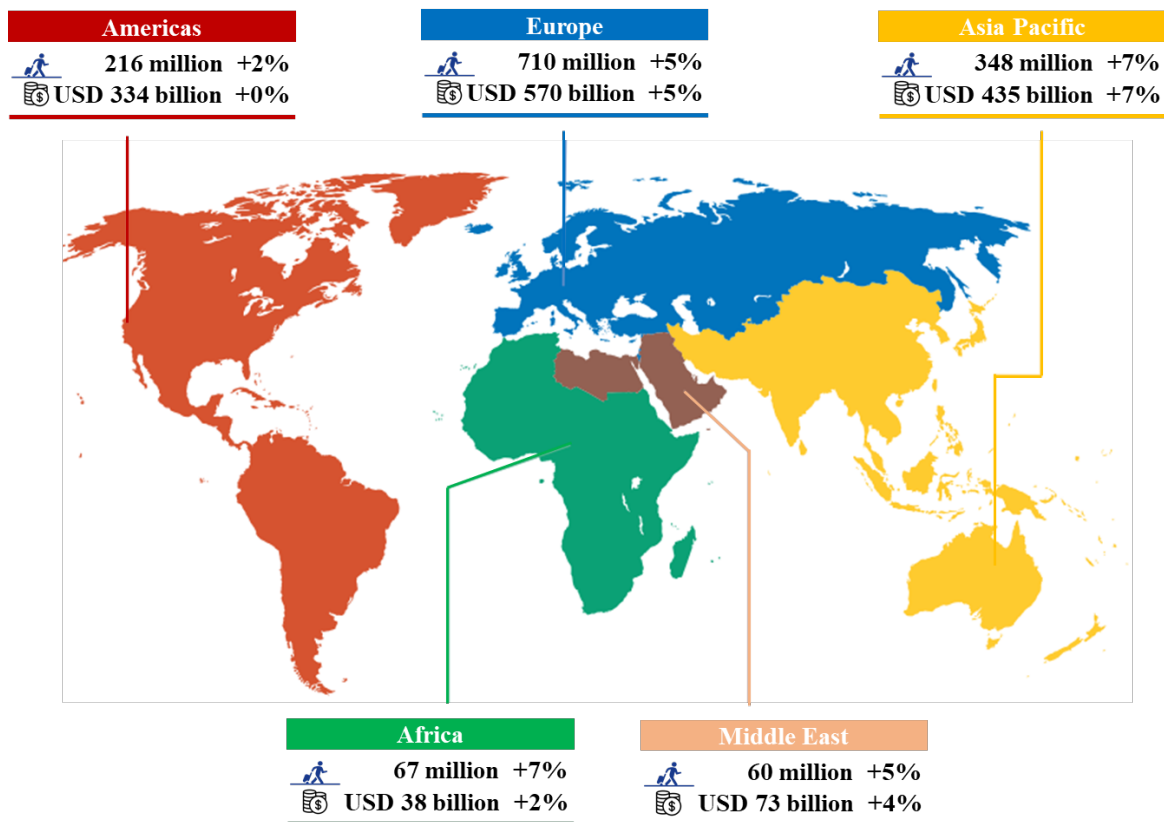


Figure 1.1: International Tourist Arrivals and Tourism Receipts by Region, 2018
(Source: UNWTO, 2019)

Figure 1.1 illustrates the number of international tourist arrivals and tourism receipts for the Americas, Europe, Asia Pacific, Africa and Middle East regions in 2018. Compared to the previous year, the number of international tourist arrivals received in both Asia Pacific and Africa regions has increased by 7%, which is higher than the world's average of 5%. This suggests that the Asia Pacific region's tourism performance outperformed other regions globally. The Asia Pacific region topped the chart in both tourist arrivals and tourism receipts growth. With a 7% increase in both categories compared to the previous year, the Asia Pacific region is demonstrating its strong potential in driving further development and contributing significantly to the world economy through tourism. The robust performance of the region indicates a promising outlook for the future of tourism, making it a crucial area to watch for stakeholders and policymakers in the travel and tourism industry.

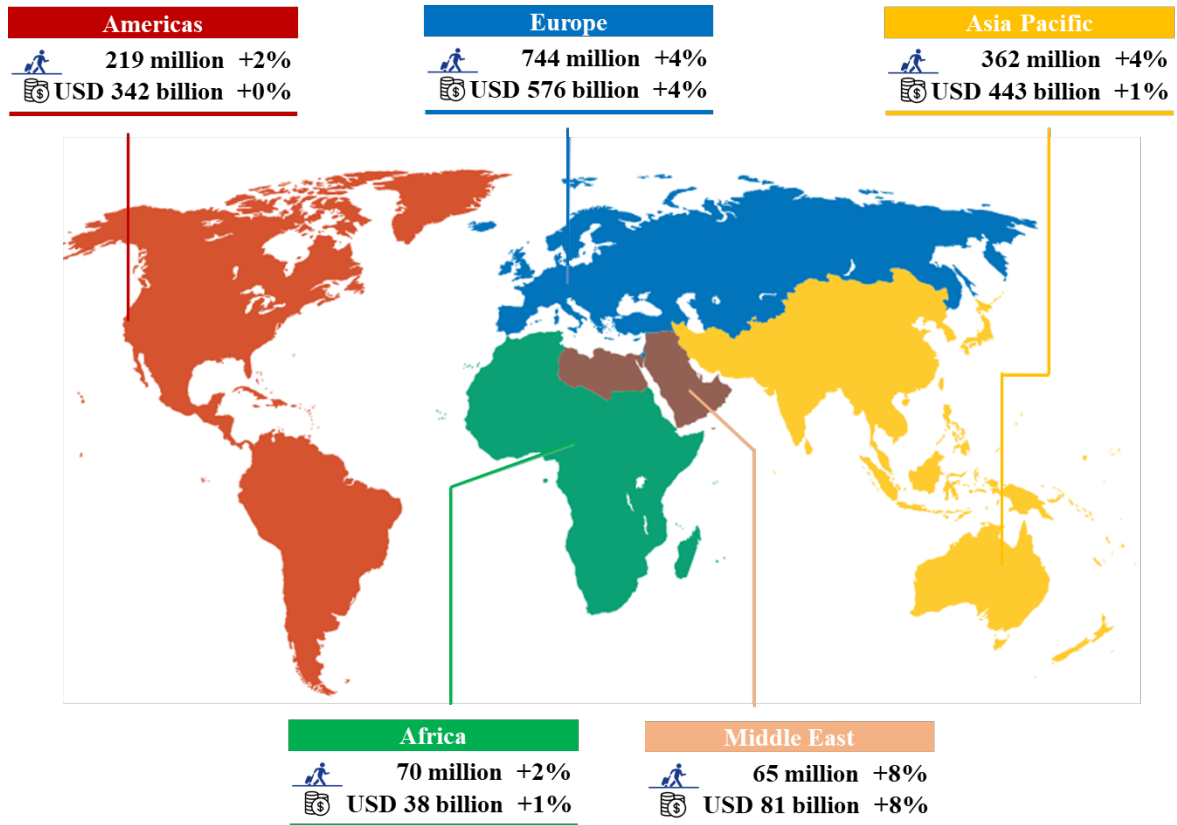


Figure 1.2: International Tourist Arrivals and Tourism Receipts by Region, 2019
(Source: UNWTO, 2020)

The world tourism industry witnessed significant growth in 2019, with 1.46 billion international tourist arrivals generating USD 1,458 billion worldwide (UNWTO, 2020). International tourist arrivals increased by 4% compared to the previous year, while international tourist receipts grew by 3%. Despite this growth, the tourism industry's overall performance in 2019 was weaker than in 2018. The uncertainty surrounding Brexit, the collapse of Thomas Cook's travel group, and the global economic slowdown contributed to this decline. Nonetheless, all regions experienced an increase in international tourist arrivals with the Middle East leading at 8%, followed by Asia Pacific and Europe at 4% each, and the Americas and Africa at 2% growth.

In 2019, the Asia Pacific region emerged as a powerhouse in global tourism, contributing a remarkable 34% (USD 3.0 trillion) to the world's GDP, standing as the foremost contributor among all regions worldwide (WTTC, 2020). Additionally, 182 million job opportunities were created by the region, represented 55% of all sectors' jobs globally in the same year. Notably, the Americas region also made substantial contribution to the world GDP, generating USD 2.5 trillion in tourism revenue and fostering 45.3 million job opportunities. For Europe region, it contributed USD 2.0 trillion to the global GDP and generated 37.1 million job employments. According to WTTC (2020), Germany (USD 347 billion), Italy (USD 260 billion), the United Kingdom (USD 254 billion), France (USD 229 billion), and Spain (USD 198 billion) stood out as the leading contributors to the significant tourism share in European countries for the year 2019 as illustrated in Figure 1.2.

The Middle East region emerged as the second fastest growing region, following closely on the heels of the Asia Pacific. The region demonstrated a robust economic performance, contributed a total of USD 245.5 billion to the global GDP and created 6.7 million job opportunities. Simultaneously, the African region, though contributing comparatively less, still wielded significant economic impact, adding hundreds of billions of dollars to the global GDP. In 2019, it contributed USD 168.5 billion in tourism revenue, fostering 24.6 million jobs. Key contributors within the region included Egypt, South Africa, and Nigeria, collectively accounting 42.8% of the tourism revenue in the region.

Unfortunately, the outbreak of the COVID-19 pandemic at the end of 2019 had a severe impact on the global tourism industry. Movement restrictions and border closures implemented by many countries to control the virus's spread led to a dramatic decline in both international tourist arrivals and revenue worldwide. In 2020, the tourism industry

suffered a staggering loss of USD 4.5 trillion, experiencing a decline of 49.1% in tourism contribution compared to the preceding year (WTTC, 2021). International tourist arrivals decreased by 74%, reaching only 381 million worldwide, due to travel restrictions imposed globally (UNWTO, 2021). The Asia Pacific region was the hardest hit, with international tourist arrivals decreasing by 84% from 362 million people to 59 million people compared to 2019. Africa and the Middle East saw a decline of 73% each, while Europe and the Americas experienced a decline of 68% each. These figures underscore the sensitivity of the tourism industry to external events as shown in Figure 1.3.

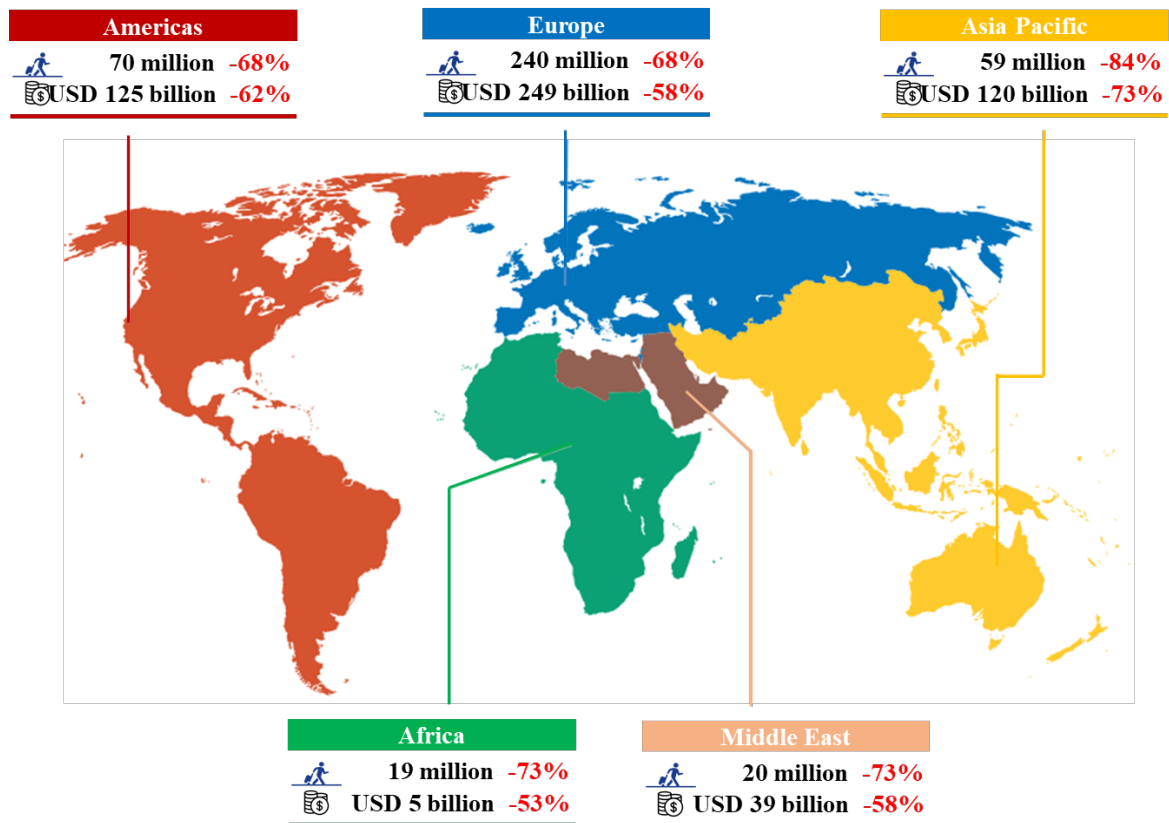


Figure 1.3: International Tourist Arrivals and Tourism Receipts by Region, 2020
(Source: UNWTO, 2021)

In 2021, the tourism industry showed signs of recovery as vaccination programmes were implemented, and some countries eased travel restrictions. The global tourism received 415 million international tourist arrivals and generated USD 1.9 trillion in revenue (UNWTO, 2022). Though there was a 4% growth in international tourist arrivals compared to 2020, the numbers remained 72% lower than the pre-pandemic year of 2019, as concerns about the Omicron variant and COVID-19 still impacted tourism confidence. In the following year, more than 900 million tourists have travelled internationally (UNWTO, 2023). This figure is double the number in 2021, but still 37% fewer than in 2019, indicating the lasting impact of the pandemic on the tourism industry. Cautionary measures and sustainable practices are necessary for long-term growth in the tourism sector.

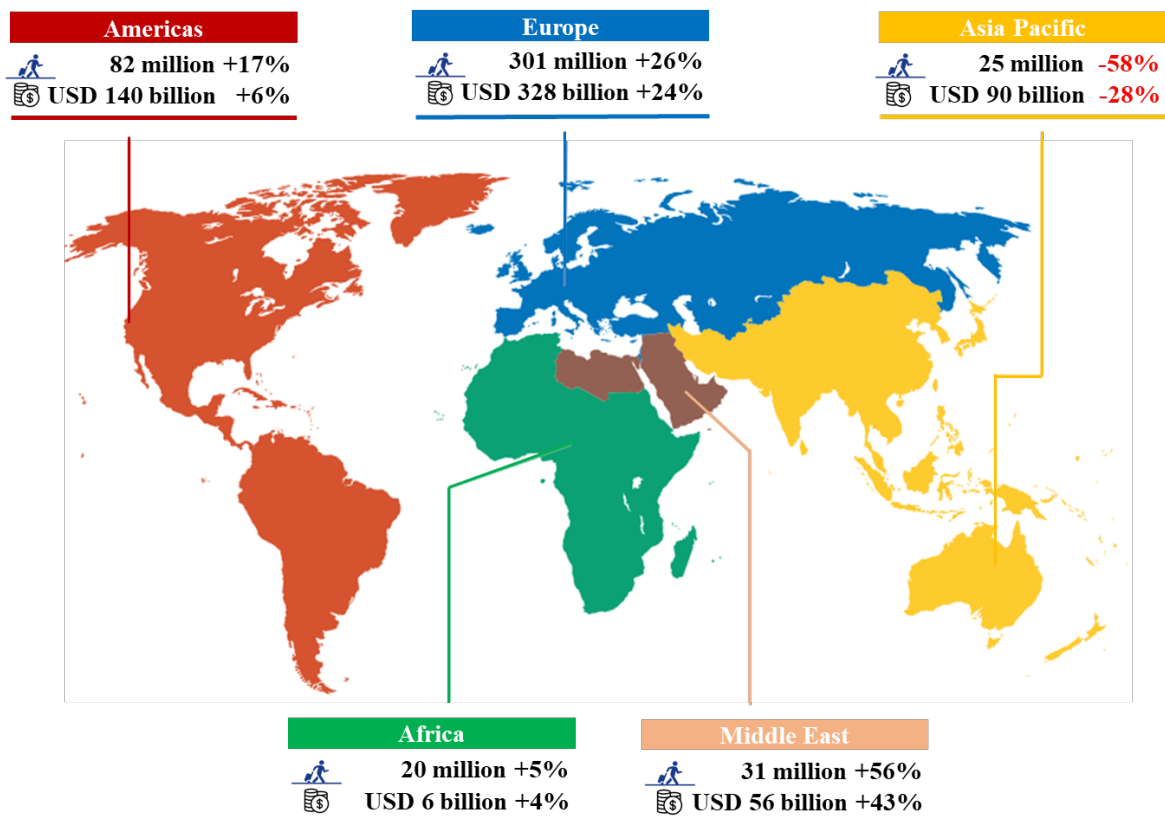


Figure 1.4: International Tourist Arrivals and Tourism Receipts by Region, 2021
(Source: UNWTO, 2022)

Figure 1.4 illustrates an overall tourism performance across all regions in 2021. The figure portrays a substantial rebound in both tourism receipts and tourist arrivals, reflecting the positive impact of most countries reopening their borders. All regions demonstrated positive growth, with the exception of the Asia Pacific region. The main reason is that China has maintained its border closure as a measure to break the chain of the pandemic. In 2021, the Middle East region emerged as a powerhouse, showcasing the most robust growth in both tourist arrivals and tourism receipts, boasting a remarkable 56% and 43% surge, respectively. Following closely, the Europe region demonstrated a commendable 25% growth in tourist arrivals and a 24% increase in tourism receipts. Meanwhile, the Americas region experienced an additional 17% surge in tourist arrivals and a 6% uptick in tourism receipts. The Africa region also contributed positively, with a 5% growth in tourist arrivals and a corresponding 4% increase in tourism receipts. Unfortunately, the Asia Pacific region faced challenges, displaying negative growth rates of -58% in tourist arrivals and -28% in tourism receipts for the period.

In the subsequent year, the global tourism industry experienced a notable upswing, with the Asia Pacific region leading the surge in international tourist arrivals, recording an impressive growth rate of +312%. This represented a threefold increase compared to the preceding year, underscoring the region's sensitivity to its surrounding environment. Furthermore, both the Africa and Middle East regions witnessed substantial growth, more than doubling their numbers with increases of 137% and 125%, respectively. Concurrently, the Europe and Americas regions also demonstrated robust performance, achieving growth rates of 98% and 91%, respectively (refer to Figure 1.5).

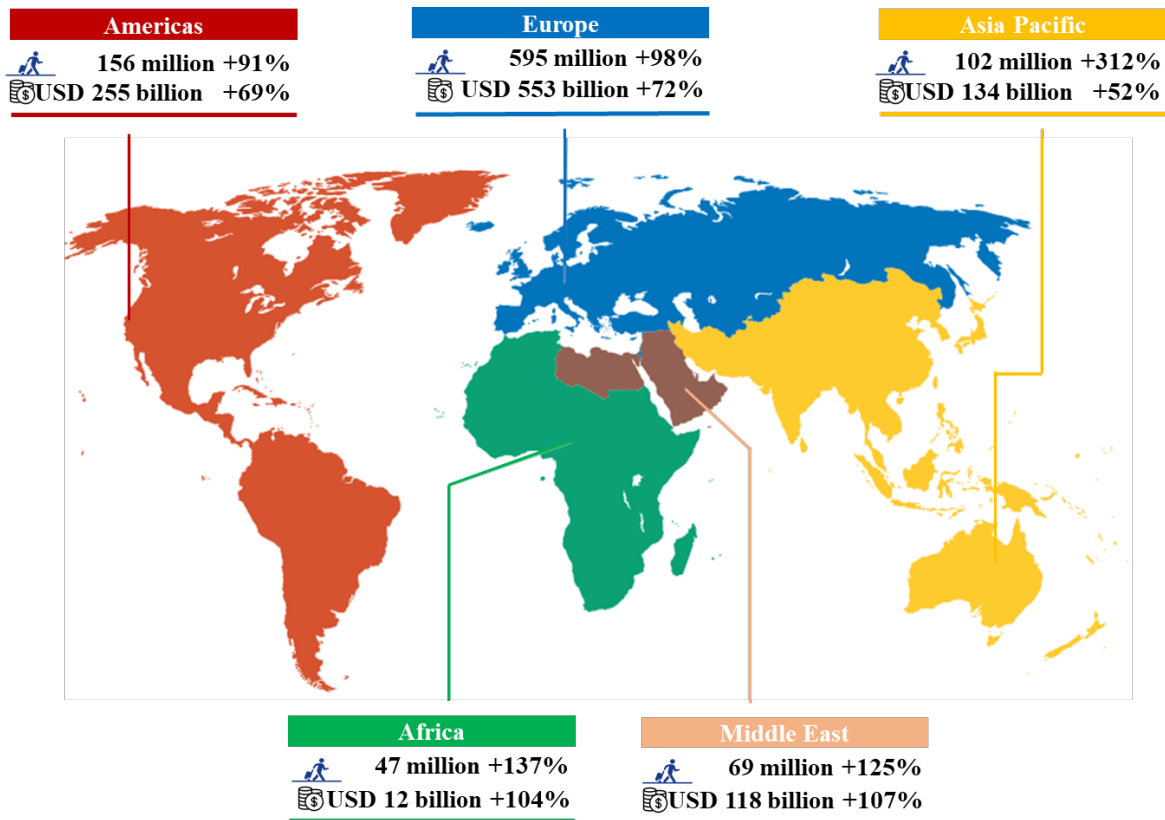


Figure 1.5: International Tourist Arrivals and Tourism Receipts by Region, 2022
(Source: UNWTO, 2023)

Amidst the recovery, it is vital for countries to manage their tourism industry sustainably, considering factors such as digitalization, innovation, and greater accessibility. While the tourism destinations and key industry players need to remain their competitiveness, environmental responsibility should be emphasised, aligning with the Sustainable Development Goals (SDGs) to protect the planet and support better living standards. In 2015, a significant milestone in global development was reached when World Tourism Organization (UNWTO) embraced the 2030 Agenda for Sustainable Development, along with the corresponding SDGs. They believed tourism industry potentially to contribute to the achievement of all the goals directly or indirectly. Under UNWTO SDGs, there are 17 goals set by the organisation (refer to Figure 1.6). The agency advocates tourism

responsibility and offer leadership and support to the tourism industry of its 156 member countries in advancing the knowledge and tourism policies around the world.



Figure 1.6: UNWTO Sustainable Development Goals
(Source: UNWTO, 2023)

Among the goals, climate, as a universal goal under the SDGs, play a significant role in tourism development led by the UNWTO. Tourism is both a contributor to and impacted by climate change. Stakeholders in the tourism industry should take a leading role in the worldwide efforts to address climate change, actively implementing both adaptation and mitigation measures.

Weather conditions, climate patterns, and seasonality affect tourism demand and destination attractiveness for both local and international visitors. As such, keeping records of weather patterns is a valuable information for the tourism industry to predict and plan suitable tourism activities and events during different season. Scott et al. (2012) stated that the climate is the key factor considered by tourists for tourism planning or as a primary motivator to travel. An unfavourable climate such as extremely cold or extremely hot in the

home country provides a strong impetus to travel abroad. A tourism destination with a favourable climate condition, friendly people, attractive scenery, and a variety of resources awaiting to discovery will attract tourist arrivals as well.

The Intergovernmental Panel on Climate Change (IPCC) (2019) reported that the tourism industry has been affected by the global warming with an increased risk of 1.5°C of warming in the specific regions and for certain seasonal tourism including sun, beach and sports destinations. They also pointed out that the risks to less climate-sensitive tourism markets will be lower, while the risks to coastal tourism will be relatively higher, particularly in subtropical and tropical regions. The year 2019 was ranked as the second warmest year on record since 1880 and 0.98°C warmer than 1951 and 1980 (NASA, 2020). 2015 was the hottest year (NASA, 2016). Such climate fluctuation poses challenges to tourism seasonality.

Tourism seasonality is generated caused by natural or institutional factors. The natural factors are climate-related factors such as temperature, precipitation, cloudiness, sunshine, visibility, and winds that are beyond the control of decision-makers and tourists. Institutional factors refer to predictable and determinable factors such as holiday, festive season, and sport seasons. Among these two categories of tourism seasonality factors, the natural factors dominate the institutional factors, particularly for seaside and mountain activities. The seasonal patterns and volatility of tourist arrivals are closely related to climate, particularly for countries with four seasons. In countries with a dominating season throughout the year, the stable climate gives rise to the variability in natural environment that enhances tourist experience. In short, understanding tourists' preferences for different climate conditions can aid in tourism decision-making.

Currently, existing climate indices in tourism studies include the Tourism Climate Index (TCI), Beach Climate Index (BCI), Climate Index for Tourism (CIT), Modified Climate Index for Tourism (MCIT), Holiday Climate Index (HCI), Relative Tourism Climate Index (RTCI), and Relative Holiday Climate Index (RHCI). The TCI was constructed by Mieczkowski (1985) by integrating several climatic variables into a single index to reflect the climatic conditions for general tourism activities. However, it has been received argument by numerous literatures that the weightages of TCI are based on Mieczkowski's own judgment.

To address this limitation, Morgan et al. (2000) developed the BCI, specifically designed to capture the impacts of climate change on beach tourists. However, a major limitation in developing the BCI is the selection of respondents, as it only included beach users, excluding other respondents such as those in the sea. This limitation leads to an ambiguous correlation between adjectival descriptions and numerical values of bathing water temperature, and an inability to consider the duration of rainfall rather than the total amount.

Furthermore, Freitas et al. (2008) introduced the Climate Index for Tourism (CIT), while Yu et al. (2009) constructed the Modified Climate Index for Tourism (MCIT) to overcome the limitations of the Tourism Climate Index (TCI). These indexes were designed for beach activities. Although they aim to address the drawbacks of TCI, they only cover the 3S tourism segments (sun, sea, and sand) instead of the general tourism industry. Therefore, TCI remains desirable for the general tourism industry, and it has been chosen as one of the indexes in this study. Additionally, Scott et al. (2016) developed the Holiday Climate Index (HCI) to overcome the limitations of all these indexes. Recent studies have employed both

TCI and HCI to compare and validate their relationship with tourist arrivals. Thus, both TCI and HCI were chosen for this study.

TCI and HCI are important indexes used to measure the climate conditions for general tourism activities. They assess the overall climatic suitability of a destination for tourism based on factors such as temperature, precipitation, wind speed, and other weather-related parameters. They provide a standalone measure of a destination's climate suitability, which is useful for understanding the inherent climatic conditions without direct comparison to other locations. However, both indexes are unable to identify climate differences between origin and destination countries. The climatic information of the destination country relative to the origin countries is also crucial for a tourism destination because it can be a pull or push factor for that destination.

For comparison studies, RTCI and RHCI are the indexes employed in existing literature. Both indexes involve comparing the tourism climate of a destination relative to others. They provide a comparative perspective, helping tourism players understand how climate conditions affect the demand for a tourism destination. The relative indices can be valuable for businesses, policymakers, and tourists looking to make informed decisions by considering the relative attractiveness of different destinations. RTCI and RHCI are valuable for understanding the overall climate attractiveness of a destination relative to its competitors or similar destinations. Limited studies on RTCI and RHCI in existing literature motivated this study to be conducted.

In 2019, the tourism as an economic powerhouse is the world's third-highest export earnings category, accounting for 10.4% of world GDP, 30% of services exports, and 1 in all 10 jobs in the world (WTTC, 2020). As such, the tourism destinations need to adopt the

Global Code of Ethics to make significant contribution in achieving the 17 SDGs and 169 targets set by the UNWTO for the planet and our future generations. In this regard, sustainable research and practices are crucial to ensure long-term growth and contribution towards achieving the SDGs. By embracing responsible practices and fostering innovation, the tourism industry can build a resilient and thriving future.

1.2 Background of the Study

The Asia Pacific region has the largest population among all regions, home to 4.61 billion inhabitants or 60% of world's population in 2019 based on the statistics reported by United Nations Economic and Social Commission for Asia Pacific (UNESCAP) (UNESCAP, 2019). Notably, China and India hold the largest populations at 1.39 billion and 1.37 billion, respectively, highlighting its diversity and potential for economic growth. Despite its vast population, the Asia Pacific region has managed to foster economic development and is renowned for hosting competitive economies like China, Japan, Korea, and India. The cultural diversity in the region continues to fuel creativity, ambition, and a unique competitive edge.

The tourism industry in the Asia Pacific region has increasingly recognized its role in sustainable development and the achievement of the 2030 Agenda. Governments across the region are actively development and promoting their tourism industries to strengthen their contributions to the regional economy and enhance their competitiveness. In 2018, the Asia Pacific region led with the highest growth of 7% in both tourist arrivals and tourism receipts among all regions, underscoring its vital role in fostering international relations, boosting economic growth, and acting as a foreign exchange earner. Additionally, it stimulates investments and employment opportunities, driving economic growth within the

region. Remarkably, the Asia Pacific region has maintained its status as the fastest-growing in terms of international tourist arrivals since 2005 (UNWTO, 2018).

As reported by UNWTO, the growth in the Asia Pacific region carries global significance. The rapid growth of regional economic, rising of air connectivity, extensive development of the travel facilitation as well as the development of infrastructure projects have boosted the international tourism in the region. The number of international tourists visiting the Asia Pacific region has tripled from 2000 to 2018, while the global figure doubled over the same period (UNWTO, 2019). This strong growth of the tourism industry in the Asia Pacific region not only benefits the region itself, but also signifies substantial contributions to sustainable development.

In 2018, the region received 347.7 million international tourist arrivals, representing a quarter of worldwide arrivals. According to UNWTO's long term forecast, this share is expected to reach 30% or equivalent to 535 million international tourists by 2030. This positive outlook from a reputable international organization confirms the tourism industry's crucial role in driving economic growth within the Asia Pacific region and on a global scale.

Table 1.1 shows the average growth of international tourist arrivals in the world and by regions from 2010 to 2019. The data indicates that the Asia Pacific region experienced the highest average growth rate in international tourist arrivals, surpassing the overall global average at 5.3%. Additionally, it outperformed other regions, including Europe (5.2%), Americas (4.6%), Africa (4.5%), and the Middle East (0.9%). The remarkable growth of international arrivals in the Asia Pacific region indicates that the tourism industry is playing the crucial role in contributing to the region's long-term economic development. This robust

performance underscores the region's attractiveness to international travelers and its ability to foster sustainable growth within its boundaries.

Table 1.1: Average Growth Rate of International Tourist Arrivals in the World and by Regions, 2010-2019

Destination	2010 (Million Person)	2019 (Million Person)	Average Annual Growth (2010-2019)
World	956.0	1,460.0	5.3%
Asia Pacific	208.2	360.7	7.3%
Europe	490.6	745.2	5.2%
Middle East	56.1	61.4	0.9%
Americas	150.3	219.4	4.6%
Africa	50.4	73.1	4.5%

Source: UNWTO (2020).

Table 1.2: Average Growth Rate of International Tourist Receipts in the World and by Regions, 2010-2019

Destination	2010 (USD Billion)	2019 (USD Billion)	Average Annual Growth (2010-2019)
World	979.0	1,478.0	5.1%
Asia Pacific	254.3	443.0	7.4%
Europe	427.1	572.9	3.4%
Middle East	52.15	82.2	5.8%
Americas	215.2	341.7	5.9%
Africa	30.5	38.4	2.6%

Source: UNWTO (2020).

Table 1.2 shows the average growth of international tourist receipts worldwide and across different regions from 2010 to 2019. In 2019, the global tourism industry received USD 1,478.0 billion international tourism receipts, with an average annual increase of 5.1% over the period. Notably, the Asia Pacific region demonstrated the highest average growth rate in international tourism receipts, standing at 7.4%. This region outperformed others, such as the Americas (5.9%), Middle East (5.8%), Europe (3.4%), and Africa (2.6%).

The strong growth in both international tourist arrivals and international tourism receipts experienced by the Asia Pacific region, as shown in Table 1.1 and Table 1.2, respectively, highlights the robust tourism demand in the region. This underscores the importance of understanding the determinants of tourism demand in the Asia Pacific region to foster sustainable long-term growth.

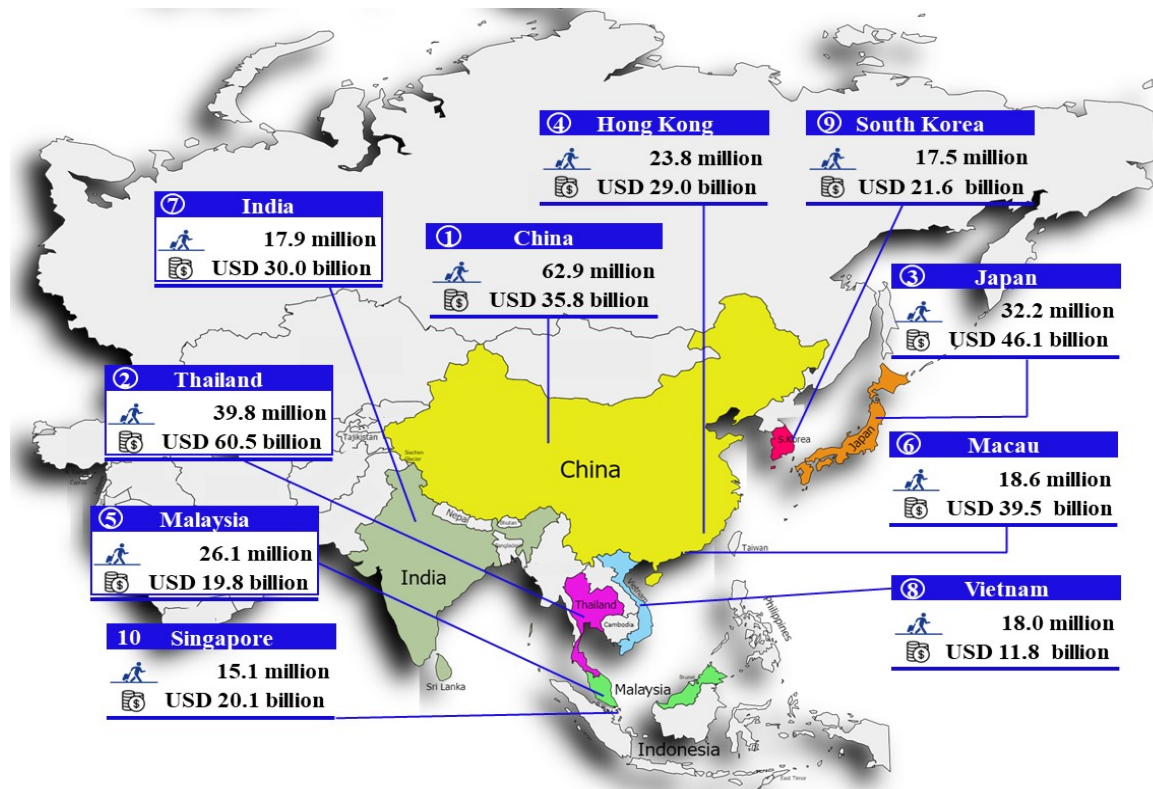


Figure 1.7: Top Ten Tourism Destination Countries in Asia Pacific Region, 2019
(Source: UNWTO, 2020)

Figure 1.7 provides insight into the main destination countries visited by the highest number of tourists in the Asia Pacific region in 2019. These top ten countries collectively received 271.9 million international tourist arrivals, accounting for 75.2% of the total international arrivals in the region during that year. With the noteworthy contributions of these ten countries, they have been chosen in this study. Notably, mainland China emerges as a significant focal point and top tourism destination in the Asia Pacific region.

Additionally, countries like Thailand, Japan, and India showcase positive growth trends in attracting international tourists.

As the number of tourists visiting the Asia Pacific region continues to rise steadily, it becomes paramount for both public and private sectors to collaborate in supporting tourism development and crafting captivating experiences that entice travellers to explore the region. Such efforts will not only drive economic growth, but also ensure the industry's sustainability over the long term. The tourism sector significantly contributes to the Asia Pacific region's economic development, job creation, and foreign exchange earnings. Recognizing its substantial impact, the present study seeks to identify the factors influencing tourism demand in the Asia Pacific region, aiming to secure its enduring and responsible growth trajectory.

Table 1.3: GDP Contribution and Tourism Employment for the Ten Most Visited Countries in the Asia Pacific Region, 2019

Country	GDP Contribution		Tourism Employment	
	USD Billion	Percentage	Million Jobs	Percentage
China	1,824.1	11.6	82.2	10.8
Thailand	95.8	19.1	7.8	20.8
Japan	306.5	7.2	5.9	8.7
Hong Kong	45.5	12.1	0.6	14.5
Malaysia	44.8	11.7	2.3	15.1
Macau	45.9	84.5	0.2	62.4
India	217.3	7.0	40.1	8.3
Vietnam	24.1	6.8	4.9	8.9
South Korea	68.8	4.4	1.4	5.0
Singapore	43.8	11.0	0.5	14.4

Source: WTTC (2023).

Table 1.3 tabulated the GDP contribution and tourism employment for the ten most visited countries in the Asia Pacific Region in 2019. Among the countries, China has the highest GDP contribution, followed by Japan (USD206.5 billion) and India (USD217.3 billion), indicating that these countries playing significant role in the region.

Meanwhile, the tourism industry in Macau has the biggest GDP share among the sectors. In addition, majority people in Macau were involved in the tourism industry which accounted for 62.4% of total job employment in Macau. These indicated that the economy of Macau is heavily dependent on the tourism and hospitality industry, particularly due to its status as a major global gambling destination.

Besides that, Thailand has a substantial tourism-driven economy, with 19.1% of its GDP coming from the tourism sector. The high percentage of tourism employment (20.8%) underscores the importance of the industry for job creation in Thailand. The notable GDP tourism contribution in Hong Kong, Malaysia, and Singapore signified the importance role of this industry to their economic growth. South Korea has relatively lower percentages of GDP and employment from tourism compared to other countries within the region, suggesting that tourism is not as dominant in their economies. However, the absolute numbers may still be significant given the size of their populations and economies.

The Asia Pacific region encompasses a diverse range of member countries, each with its own unique culture, language, lifestyle, climate conditions, and specific attractions that draw global tourists to explore their lands. Among the factors influencing tourists' travel decisions, climate has been identified as a critical determinant. The member countries in the Asia Pacific region exhibit varying climatic conditions; some experience four distinct seasons, while others maintain a stable climate throughout the year.

Among the top ten most visited countries in the Asia Pacific region, there are six countries with a four-season climate - China, Japan, Hong Kong, Macau, India and South Korea. The remaining countries fall under the category of one-season climates. As pressures on natural resources grow and climate disruptions continue to impact societies and economies, the tourism-dependent countries in the region are particularly susceptible to various economic and environmental risks. Thus, a comprehensive analysis of how climate affects international tourism flows in the Asia Pacific is imperative for ensuring sustainable growth and striving for a balanced equilibrium between different segments.

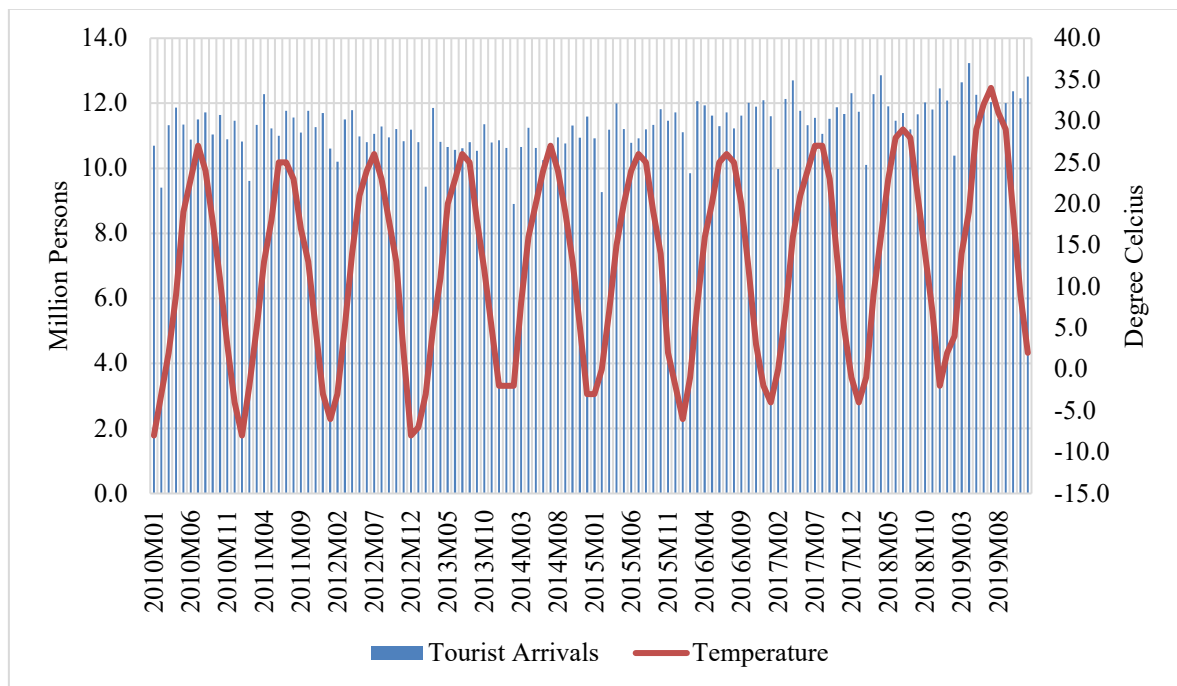


Figure 1.8: Monthly Tourist Arrivals and Average Temperature in China, 2010M01-2019M12

(Sources: Ministry of Culture and Tourism China, 2020; The Weather Online, 2020)

Figure 1.8 Illustrating the trends between monthly tourist arrivals and temperature in China from January 2010 to December 2019, the available tourism data extends only until the year 2019 due to the pandemic. Notably, during the winter and summer seasons, the influx of tourists visiting China tends to be comparatively lower than in other months. This

phenomenon could be attributed to the discomfort experienced by tourists when temperatures are either excessively high or low.

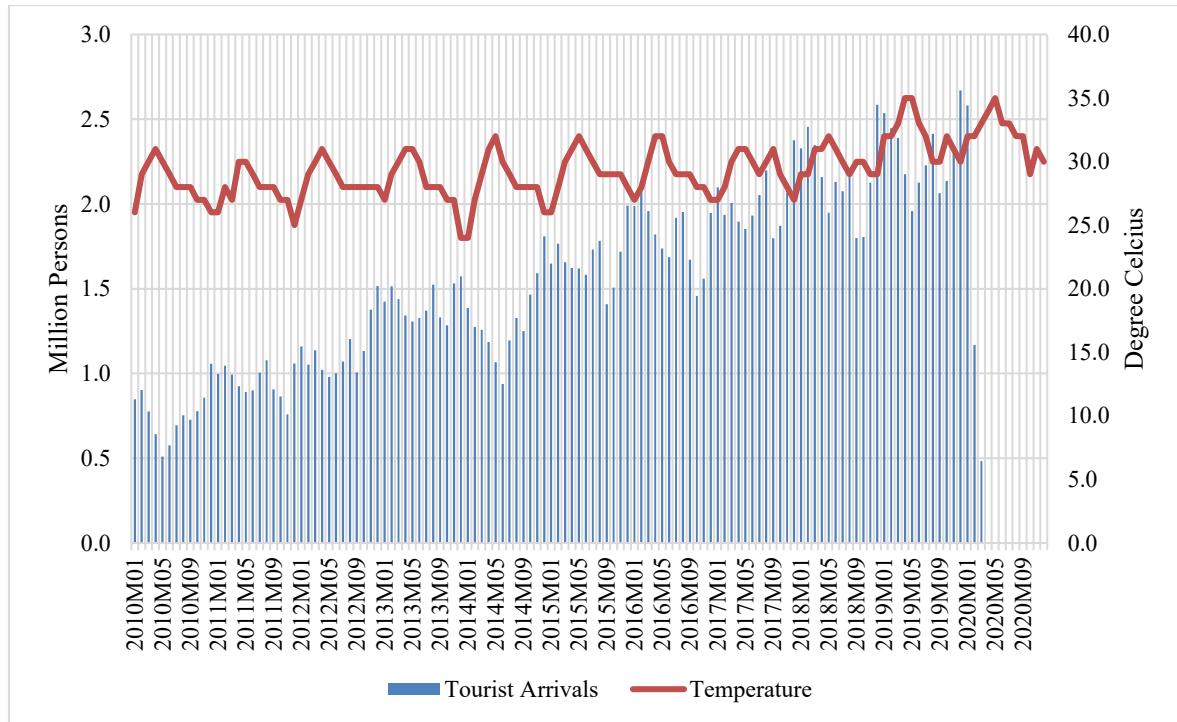


Figure 1.9: Monthly Tourist Arrivals and Average Temperature in Thailand, 2010M01-2020M12

(Sources: Ministry of Tourism and Sports Thailand, 2021; The Weather Online, 2020)

Thailand enjoys a tropical climate influenced by seasonal monsoon winds. In May, the southwest monsoon brings a flow of warm, moist air from the Indian Ocean to Thailand, resulting in substantial rainfall across the nation, particularly in mountainous areas. During the summer season, Thailand experiences higher temperatures throughout the year, leading to lower tourist arrivals. Meanwhile, the northeast monsoon starting in October brings cold and dry air over major parts of Thailand. Therefore, Thailand experiences cooler temperatures during the months of November to February. These cooler temperatures are deemed comfortable for tourists, leading to a higher volume of tourist arrivals during these months. This indicates that Thai tourism is potentially influenced by climate conditions.

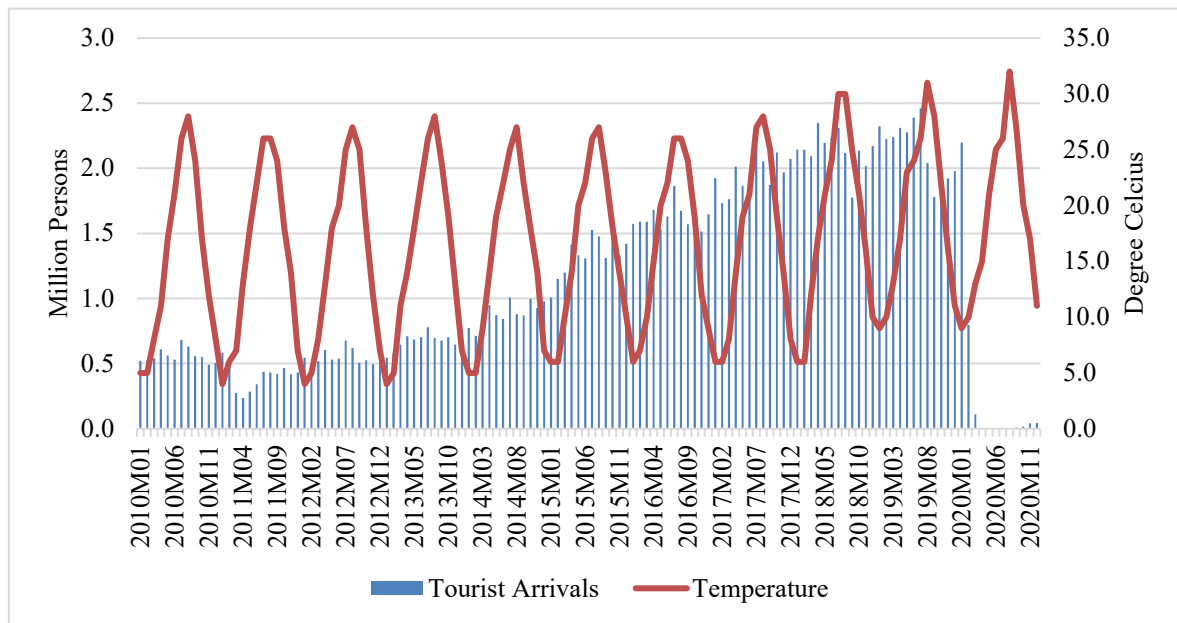


Figure 1.10: Monthly Tourist Arrivals and Average Temperature in Japan, 2010M01-2020M12

(Sources: Japan National Tourist Organization, 2021; The Weather Online, 2021)

Japan is a nation renowned for its four distinct seasons, each presenting its own unique wonders. One of the most popular travel periods in Japan are during April to May as shown in Figure 1.10. The blooming cherry blossom trees in this period attracting substantial volume of domestic and international tourists to visit Japan. Besides that, Japan also offered various tourism activities such as surfing, sunbathing, snorkelling, and river rafting during the summer season. In fall season, the beautiful autumn leaves and cool weather make August and September a popular time for visiting Japan. Winter season is another period receiving high popularity of the tourists, as the snow falling is beautiful and for winter sports enthusiasts, this is the best time to visit to Japan.

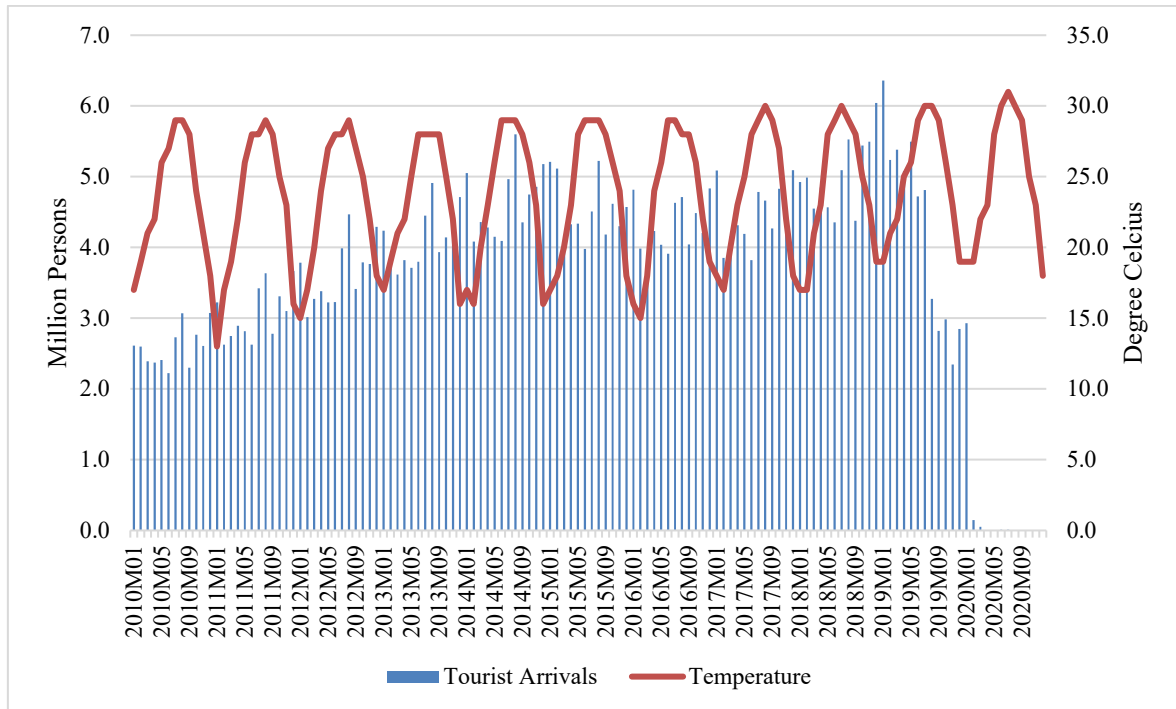


Figure 1.11: Monthly Tourist Arrivals and Temperature in Hong Kong, 2010M01-2020M12

(Sources: Hong Kong Tourism Board, 2021; The Weather Online, 2021)

Figure 1.11 illustrates the relationship between tourist arrivals and temperature in Hong Kong. It is clearly observed that Hong Kong receives a higher volume of tourist arrivals during the winter and summer seasons. Although the temperature is cooler during the months of December to February, Hong Kong experiences an increased number of tourist arrivals. One possible reason is that the weather conditions in Hong Kong are relatively more comfortable than the main source countries. During the summer season, Hong Kong also receives a high number of tourists, despite the weather being perceived as less comfortable.

The number of tourist arrivals and average temperature in Malaysia are illustrated in Figure 1.12. Malaysia enjoys an equatorial climate with relatively consistent weather throughout the year, ranging between 25°C and 31°C. It is categorized as a year-round tourist destination due to its consistent weather conditions. Tourists can enjoy the natural beauty

and diverse cultural attractions in Malaysia without being restricted by extreme temperature fluctuations.

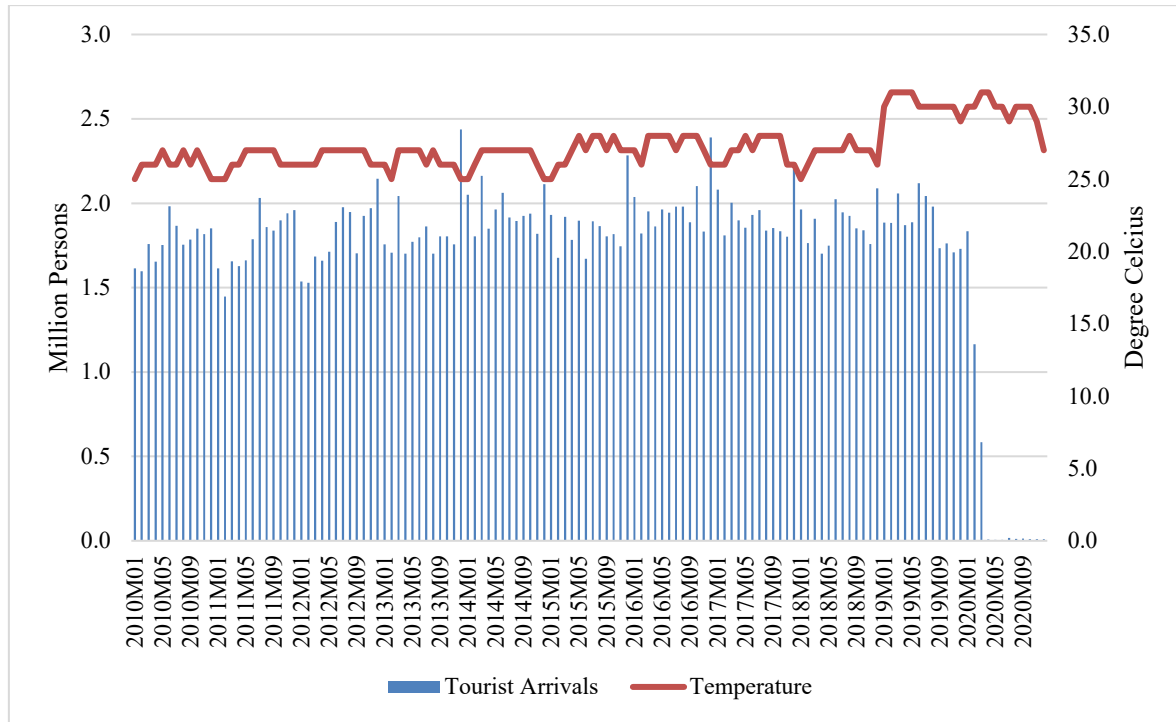


Figure 1.12: Monthly Tourist Arrivals and Temperature in Malaysia, 2010M01-2020M12

(Sources: Tourism Malaysia, 2021; The Weather Online, 2021)

Figure 1.13 shows tourist arrivals and temperatures in Macau from January 2010 to December 2020. The relationship between tourist arrivals and temperature in Macau exhibits a similar pattern to the tourism industry in Hong Kong because both are neighbouring destinations. Similar to Hong Kong, Macau experiences peak tourist seasons during winter and summer. In winter, Macau's temperature averages around 12°C, deemed comfortable compared to China, the main source country, where some provinces experience sub-zero temperatures. Meanwhile, during the summer season, the weather condition in Macau reaches around 30°C, which is also deemed comfortable compared to certain provinces in China, where temperatures may reach around 40°C.

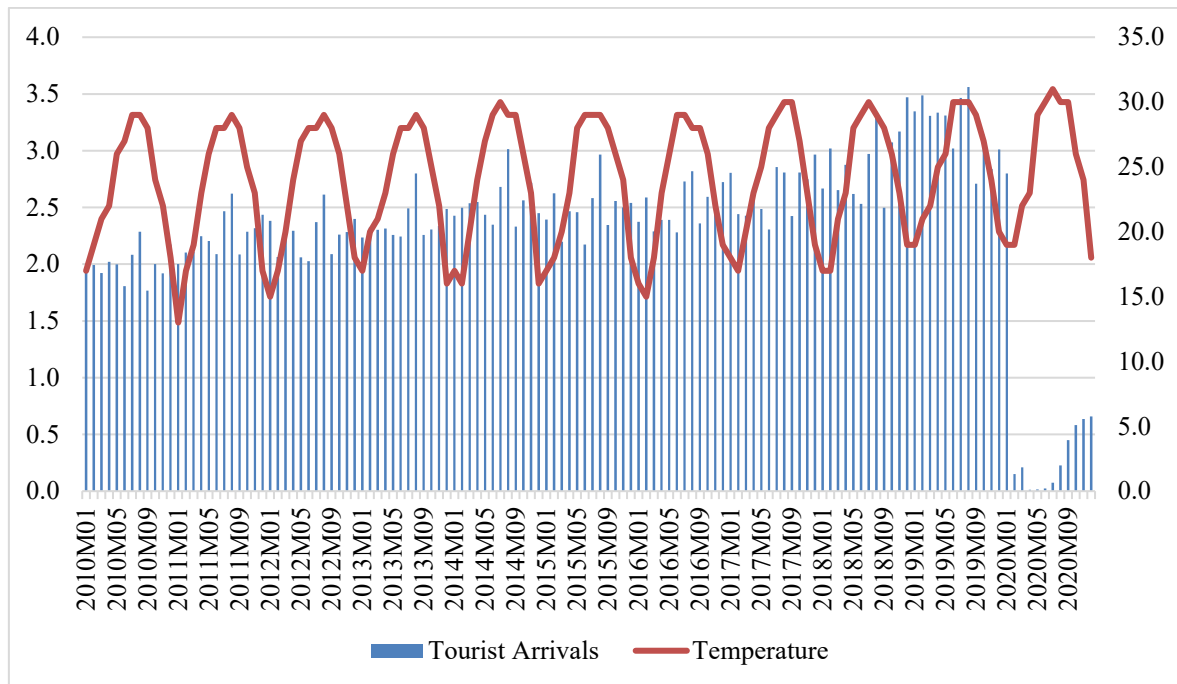


Figure 1.13: Monthly Tourist Arrivals and Temperature in Macau,
2010M01-2020M12

(Sources: Statistics and Census Service of Macau, 2021; The Weather Online, 2021)

Figure 1.14 shows the trends for temperature and monthly tourist arrivals in India from January 2010 to December 2020. It is clearly observed that the hottest month in India is June, while the coolest month is January. In terms of tourist arrivals, India receives a lower number of tourists during the hot season and experiences a higher volume of arrivals during months with cooler weather. This indicates a clear relationship between the climate and the tourism industry in India, with an adverse impact.

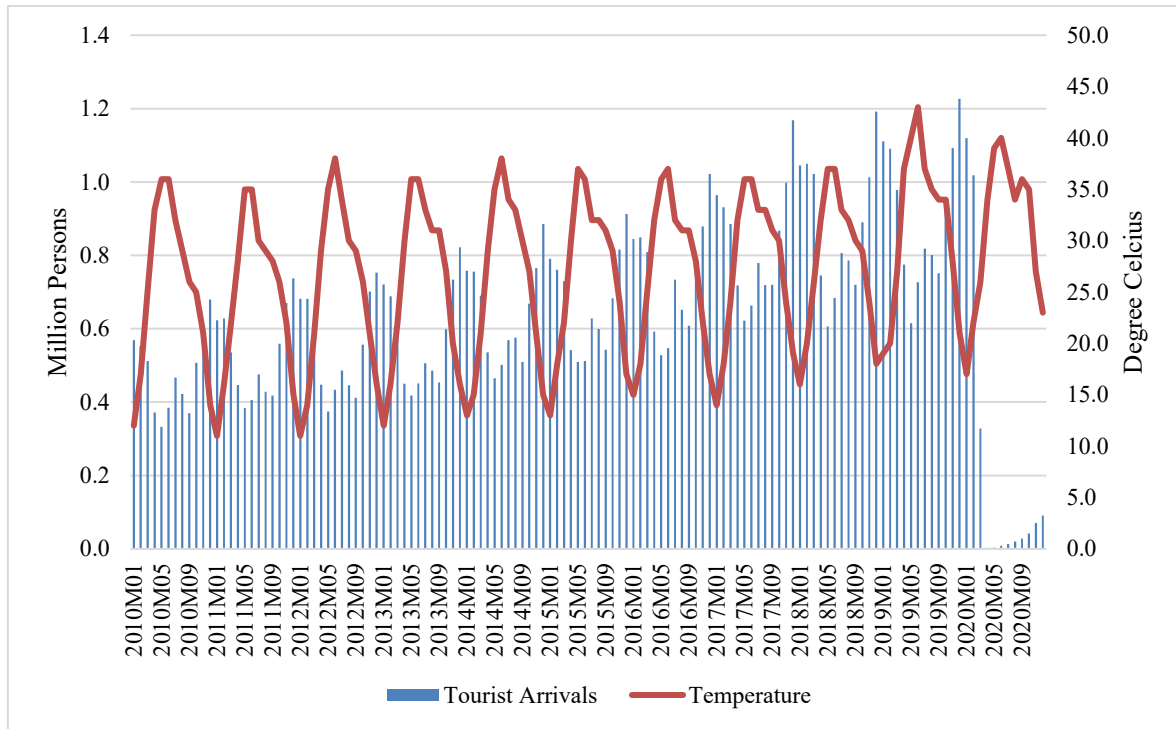


Figure 1.14: Monthly Tourist Arrivals and Average Temperature in India, 2010M01-2020M12

(Sources: Ministry of Tourism of India, 2021; The Weather Online, 2021)

Figure 1.15 exemplified the monthly tourist arrivals and average temperature in Vietnam from January 2010 to December 2020. Vietnam boasts diverse geographical features, encompassing mountains, plains, and coastlines. The distinct regions undergo varying temperatures, thereby shaping the spectrum of available tourism activities. Vietnam receives a higher number of tourists during the months of November to February when the weather conditions are relatively cooler, making it more conducive for tourists. In April and May, Vietnam experiences a lower number of tourists due to higher temperatures, which are less comfortable for outdoor activities. Therefore, the climate condition potentially impacts the tourism industry in Vietnam.

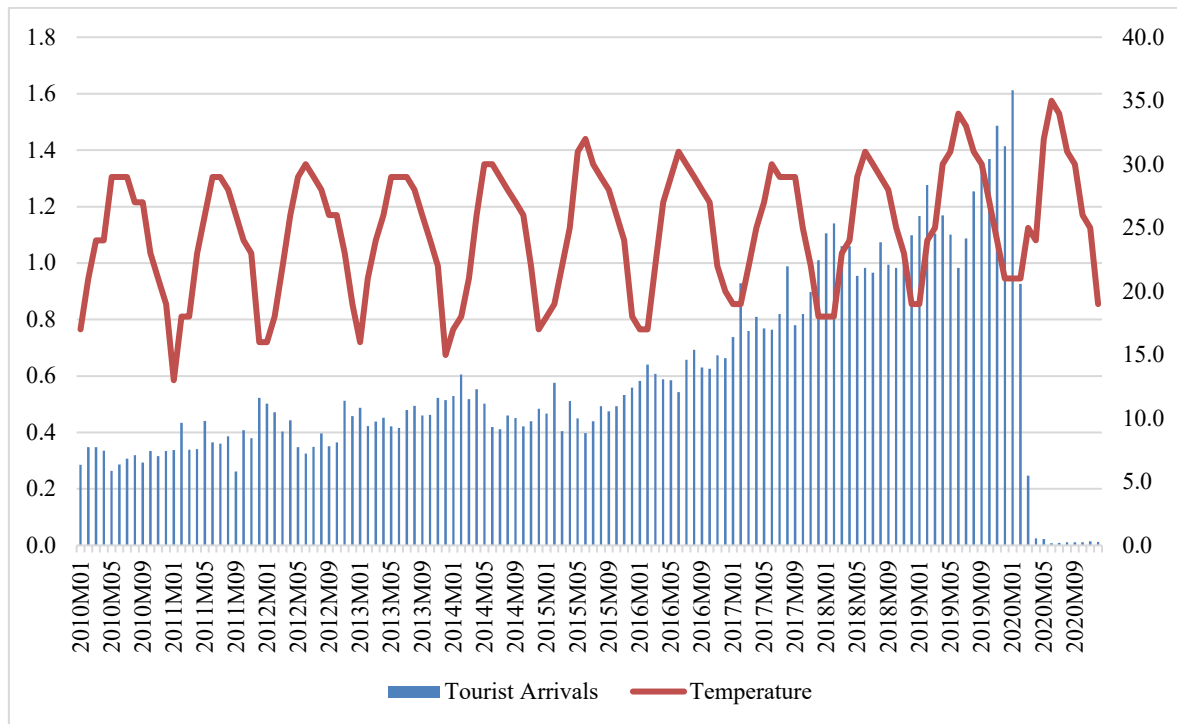


Figure 1.15: Monthly Tourist Arrivals and Average Temperature in Vietnam, 2010M01-2020M12

(Sources: General Statistics Office of Vietnam, 2021; The Weather Online, 2021)

The trends between tourist arrivals and temperature in South Korea are illustrated in Figure 1.16. Interestingly, there is a positive relationship between climate conditions and the number of tourist arrivals in South Korea. The country receives a higher number of tourists when it experiences higher temperatures, and vice versa. South Korea is a year-round tourism destination, with many tourists visiting during the winter season to enjoy the snow. Although South Korea receives fewer tourists in winter compared to summer, it still welcomes nearly millions of tourists per month in recent years. Additionally, the blooming of cherry blossoms during the months of March to May attracts numerous tourists globally to visit South Korea. Despite higher temperatures during the summer season, it also offers ideal conditions for hiking.

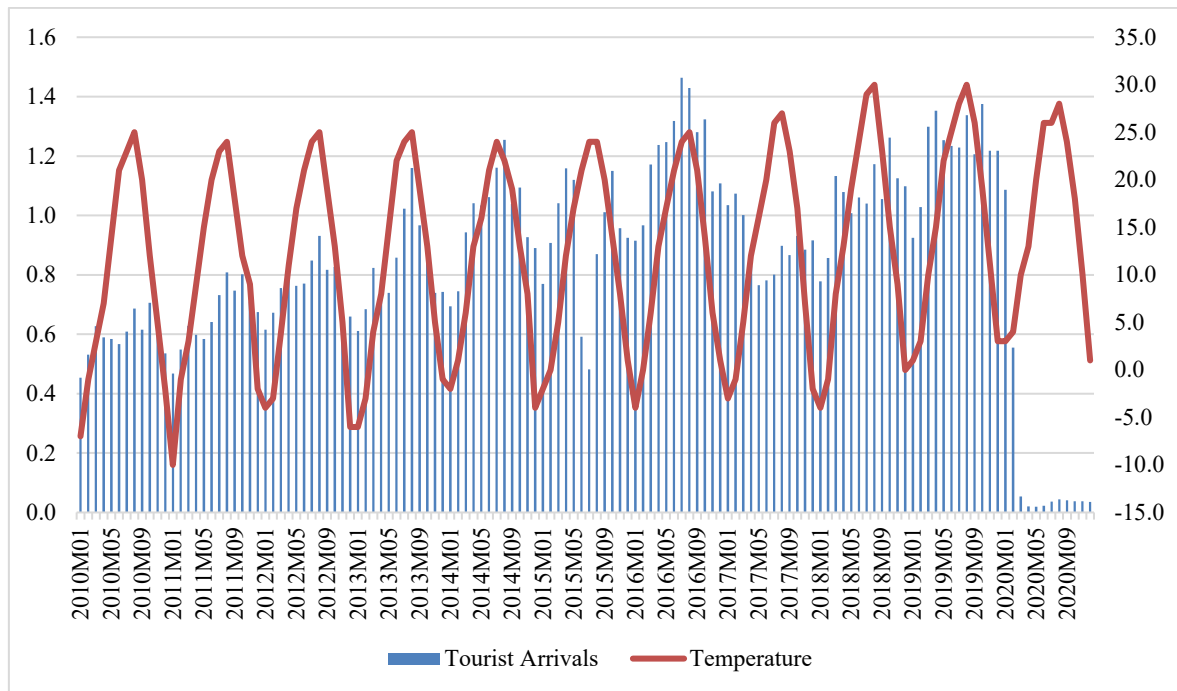


Figure 1.16: Monthly Tourist Arrivals and Average Temperature in South Korea, 2010M01-2020M12

(Sources: Korea Tourism Organization, 2021; The Weather Online, 2021)

Singapore is a year-round tourism destination due to its consistent temperature throughout the year, averaging around 26°C to 31°C. It consistently attracts tourists throughout the year, as indicated in Figure 1.17. The number of tourist arrivals to Singapore is more than three times the population of the country, highlighting the crucial role of the tourism industry in Singapore. Consistent rainfall is recorded during the months of December and January, while hot weather is generally experienced between March and May. Singapore offers a variety of indoor and outdoor tourism activities, allowing tourists to visit at any time.

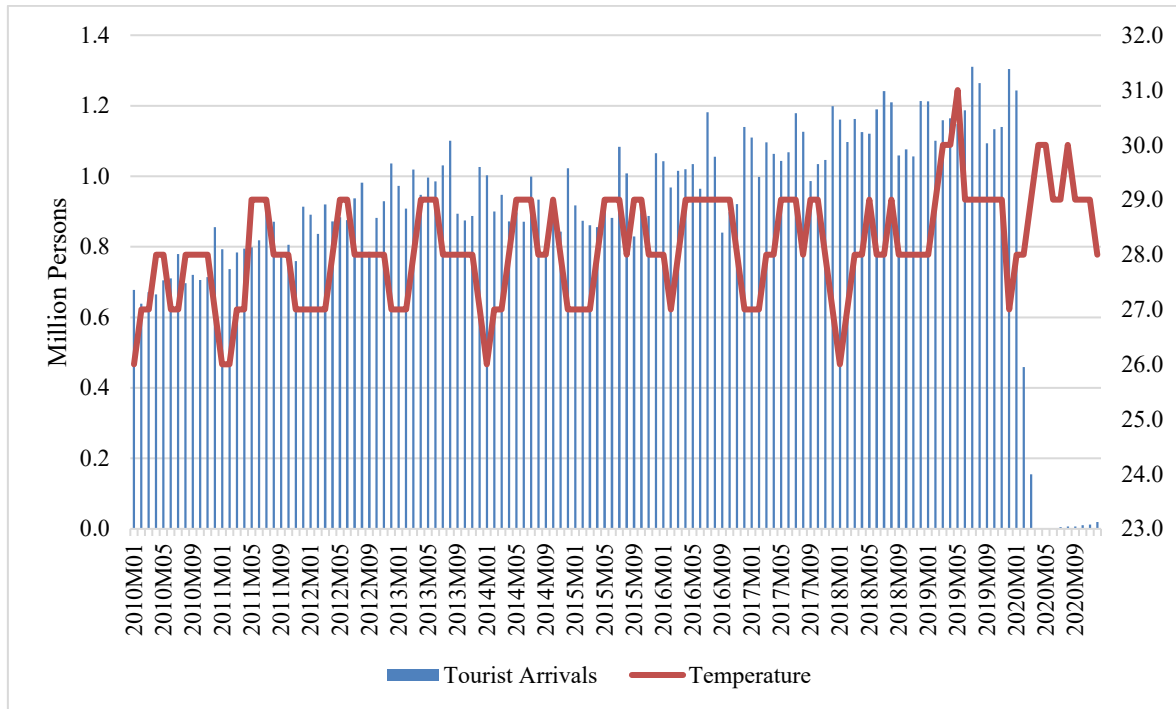


Figure 1.17: Monthly Tourist Arrivals and Average Temperature in Singapore, 2010M01-2020M12

(Sources: Singapore Tourism Board, 2021; The Weather Online, 2021)

For an in-depth understanding of tourism trends, this study delved further into the top ten inbound tourist sources for the major countries in the Asia Pacific region. As illustrated by Table 1.4, China emerged as the country receiving the highest number of tourist arrivals in the region in 2019. The top ten source countries for tourists visiting China are Hong Kong (107.29 million persons or 73.84%), South Korea (4.35 million persons or 2.99%), Russia (2.72 million persons or 1.87%), Japan (2.68 million persons or 1.84%), USA (2.41 million persons or 1.66%), Mongolia (1.86 million persons or 1.28%), Malaysia (1.38 million persons or 0.95%), Philippines (1.18 million persons or 0.81%), Singapore (1.01 million persons or 0.70%), and India (0.87 million persons or 0.60%) in 2019. These ten countries collectively contributed to 86.54% of the total tourist arrivals in China.

Table 1.4: Top Ten Most Visited Countries with Its Major Origin Countries in the Asia Pacific Region, 2019

Destination	China	Thailand	Japan	Hong Kong	Malaysia	Macau	India	Vietnam	South Korea	Singapore
Ranking	Million Person	Million Person	Million Person	Million Person	Million Person	Million Person	Million Person	Million Person	Million Person	Million Person
	Percent	Percent	Percent	Percent	Percent	Percent	Percent	Percent	Percent	Percent
1	Hong Kong	Thailand	China	China	Singapore	China	Bangladesh	China	China	China
	107.29	11.00	9.59	43.77	10.16	27.92	2.58	5.81	6.02	3.63
	73.84%	27.58%	30.09%	78.29%	38.94%	70.86%	23.58%	32.24%	34.41%	18.97%
2	Korea	Malaysia	Korea	Taiwan	Indonesia	Hong Kong	United States	Korea	Japan	Indonesia
	4.35	4.22	5.58	1.54	3.62	7.35	1.51	4.29	3.27	3.11
	2.99%	10.58%	17.52%	2.75%	13.88%	18.66%	13.83%	23.83%	18.69%	16.27%
3	Russia	India	Taiwan	United States	China	Taiwan	United Kingdom	Japan	Taiwan	India
	2.72	2.00	4.89	1.11	3.11	1.06	1.00	0.95	1.26	1.42
	1.87%	5.00%	15.34%	1.98%	11.93%	2.70%	9.15%	5.29%	7.20%	7.42%
4	Japan	Korea	United States	Japan	Thailand	Korea	Australia	Taiwan	United States	Malaysia
	2.68	1.89	1.72	1.08	1.88	0.74	0.37	0.93	1.04	1.22
	1.84%	4.74%	5.41%	1.93%	7.22%	1.89%	3.36%	5.15%	5.96%	6.39%
5	USA	Laos	Thailand	Korea	Brunei	Philippines	Canada	United States	Hong Kong	Australia
	2.41	1.85	1.32	1.04	1.22	0.42	0.35	0.75	0.69	1.14
	1.66%	4.65%	4.14%	1.86%	4.66%	1.07%	3.22%	4.14%	3.97%	5.98%
6	Mongolia	Japan	Australia	Philippines	India	Japan	China	Malaysia	Thailand	Japan
	1.86	1.81	0.62	0.88	0.74	0.30	0.34	0.61	0.57	0.88
	1.28%	4.53%	1.95%	1.57%	2.82%	0.75%	3.11%	3.37%	3.27%	4.63%

Table 1.4 continued

Destination	China	Thailand	Japan	Hong Kong	Malaysia	Macau	India	Vietnam	South Korea	Singapore
Ranking	Million Person	Million Person	Million Person	Million Person	Million Person	Million Person	Million Person	Million Person	Million Person	Million Person
	Percent	Percent	Percent	Percent	Percent	Percent	Percent	Percent	Percent	Percent
7	Malaysia	Russia	Philippines	United Kingdom	Korea	Malaysia	Malaysia	Thailand	Vietnam	Philippines
	1.38	1.48	0.61	0.52	0.67	0.21	0.33	0.51	0.55	0.83
	0.95%	3.72%	1.92%	0.93%	2.58%	0.52%	3.06%	2.83%	3.16%	4.34%
8	Philippines	United States	Malaysia	Australia	Japan	United States	Sri Lanka	Australia	Philippines	United States
	1.18	1.17	0.50	0.51	0.42	0.20	0.33	0.38	0.50	0.73
	0.81%	2.93%	1.57%	0.90%	1.63%	0.51%	3.03%	2.13%	2.88%	3.82%
9	Singapore	Singapore	Vietnam	Thailand	Philippines	Indonesia	Germany	France	Malaysia	Korea
	1.01	1.06	0.50	0.47	0.42	0.17	0.26	0.29	0.41	0.65
	0.70%	2.65%	1.55%	0.84%	1.62%	0.43%	2.42%	1.60%	2.33%	3.38%
10	India	United Kingdom	Singapore	Singapore	Vietnam	Thailand	Russia	Cambodia	Russia	United Kingdom
	0.87	0.99	0.49	0.45	0.40	0.15	0.25	0.23	0.34	0.61
	0.60%	2.49%	1.54%	0.81%	1.53%	0.38%	2.30%	1.27%	1.96%	3.18%
Subtotal	125.75	27.47	25.84	51.36	22.66	38.53	7.33	14.74	14.68	14.22
	86.54%	68.88%	81.04%	91.86%	86.81%	97.78%	67.06%	81.83%	83.84%	74.37%
Total	145.31	39.87	31.88	55.91	26.10	39.41	10.93	18.01	17.50	19.12
	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

Sources: Ministry of Culture and Tourism (2020), TAT Intelligence Center (2020), Japan National Tourist Organization (2020), Hong Kong Tourism Board (2020), Tourism Malaysia (2020), Statistics and Census Service Macau (2020), Ministry of Tourism India (2020), Vietnam General Statistics Office (2020), Korea Tourism Organization (2020), and Singapore Tourism Board (2020).

1.3 Problem Statement

Under the Sustainable Development Goals (SDGs), climate action stands as a universal priority to combat climate change and its adverse effects on nature and societies worldwide (UNWTO, 2016). Climate change significantly impacts several key economic sectors, with tourism being especially vulnerable. Changing climate conditions can lead to shifts in tourist preferences and behaviours, potentially redistributing tourism contributions across different destinations globally. This redistribution can affect the quality of tourism seasons, influencing the timing, distribution, and expenditures of domestic and international tourism flows.

The UN Economic and Social Commission for Asia Pacific (UNESCAP) predicts that the Asia Pacific region will face the worst combined environmental and economic effects of climate change, and over 100 million people within the region will potentially fall into poverty by 2030 due to these impacts. Despite significant economic growth, climate change posing challenges to the sustainability of the tourism industry. As shown in Figure 1.8 to Figure 1.17, the climate and weather conditions are potentially influencing the tourism demand of the ten selected countries in Asia Pacific region. The potential influence of the climate on tourism demand motivated this study to be conducted for long term sustainability growth.

Effective measurement of tourism demand is vital for ensuring the industry's sustainable growth. Implementing sustainable tourism measures brings long-term benefits for countries, tourists, local communities, and the environment, fostering a positive outcome for all stakeholders and investors prioritizing environmental concerns recognize the necessity of safeguarding endangered environments and reaping future benefits from the

industry. Adverse weather conditions, influenced by climate change, pose environmental risk factors affecting various industries within the tourism sector, including accommodations, food and beverages, transportation, and related services.

Climate change profoundly impacts the tourism sector, influencing traveler preferences and destination choices. The existing TCI and HCI serve as crucial tools in assessing the climatic conditions of destinations. To gather more comprehensive tourism information, this study will design the RTCI and RHCI to examine the impact of climate differences between the origin and destination countries on the tourism industry. The empirical outcomes of relative climate conditions between the countries can identify whether the climate condition in the destination country serves as a push or pull factor for tourists.

This study aims to construct the relative tourism climate index (RTCI) and relative holiday climate index (RHCI) to explore their impacts on tourism demand in the Asia Pacific region. These indices, integrated with climatic and macroeconomic variables, will provide insights into the region's tourism trends. With a comprehensive understanding of climate conditions, governments and industry players can better address key issues, enhance competitiveness, and promote sustainable development. By tailoring tourism products to different climate preferences, the region can attract diverse tourists and adapt to changing demands. The empirical finding is expected to give better understanding on the underlying information behind the fluctuating tourism industry and providing a more accurate and comprehensive evaluation of the climatic conditions influencing tourism demand in selected Asia Pacific countries.

From 2010 to 2019, the Asia Pacific region enjoyed the highest growth rate in both average tourist arrivals and generated tourism receipts. However, with an increasing demand on tourism, identification of key performance indicators has become crucial to sustain its performance. This has to be coupled with climate change indicators, and TCI has become a popular indicator in this sense albeit a common agreement on the lack of some basic features. These include the weighting of indices and timing, but most have been somewhat resolved in HCI.

Nonetheless, various indicators are necessary to better understand the tourism-climate relationship for better planning. The comparison between RTCI and RHCI is a crucial step towards determining optimal travel months within the Asia Pacific region, enriching tourism planning and decision-making. With proper comparison, the preferable months to travel within Asia Pacific region can be determined. Given the limited research on the climate conditions of origin countries affecting domestic and international tourism demand in the Asia Pacific region, this study aims to fill this gap and assess the climatic impacts on tourism demand comprehensively. The study's findings are expected to offer valuable insights into climate-related influences on tourism phenomena, aiding the industry's understanding and planning.

1.4 Research Questions

The research questions of this study are:

RQ 1: What are the determinants of affecting tourism demand in Asia Pacific region?

RQ2: How the impact of climate change on tourism demand in ten selected Asia Pacific countries?

RQ3: How do TCI and HCI scores interact with the tourist visitation patterns in the ten selected Asia Pacific countries?

1.5 Objectives of the Study

1.5.1 General Objective

This study aims to construct and compare the relative tourism climate index (RTCI) and relative holiday climate index (RHCI) to examine their impact on the tourism demand in the Asia Pacific region through an augmented gravity model.

1.5.2 Specific Objectives

The specific objectives of this study are as follows:

- i. To investigate the determinants of tourism demand in ten selected Asia Pacific countries;
- ii. To determine the impact of climate change on tourism demand in ten selected Asia Pacific countries; and
- iii. To compare the TCI and HCI indexes with the tourists' visitation patterns in the ten selected countries of the Asia Pacific region.

1.6 Significance of the Study

The tourism industry stands as a pivotal contributor to economic advancement, employment generation, foreign exchange earnings, and the elevation of living standards across the Asia Pacific region. The ongoing discourse on climate-related matters engages scholars, industry stakeholders, governmental bodies, and non-governmental organizations.

Urgent measures to combat climate change are imperative to mitigate its adverse repercussions on society, economic development, and the natural world.

Exploring the impact of climate conditions on the tourism sector is believed to provide useful information to decision-makers, travel agencies, hoteliers, insurance companies, and other key industry players to formulate low-risk plans, offers, and travel packages to attract tourists all year round. For instance, tour operators could curate indoor activities during months with high precipitation or extreme temperatures. Additionally, climate-related information proves advantageous to insurance providers by enabling them to gauge risks related to factors like rainfall, subsequently offering optimal coverage to tourists. In essence, the estimation of tourism climate indices provides travellers with the means to plan their trips during optimal periods while aiding and facilitating strategic tourism planning that optimally allocates economic resources.

The development of data-driven climate indices for specific tourism markets, particularly those highly susceptible to climate variations, remains a critical realm of ongoing research and climate service development. Initial indications of positive correlations between arrivals data and indices signify a promising step forward. Lastly, the findings obtained from this study can add to the limited body of the research related to the index comparison and validation research. The findings from this study constitutes a valuable stride in advancing the development of climate-tourism demand models, enhancing our comprehension of the intricate interplay between tourism and climate factors.

1.7 Organization of the Study

In this study, Chapter 1 provides a comprehensive overview of the global and regional tourism industry. The context of tourism within the Asia Pacific region is elaborated in Section 1.2, while Section 1.3 delves into the focal research issue. The study's aims are discussed in Section 1.4, highlighting its objectives, and Section 1.5 explicates the study's significance. The chapter concludes by detailing the organizational structure of the research.

Chapter 2 is dedicated to a meticulous examination of relevant literature in the field of tourism. Chapter 3 lays out the research methodology employed in this study. Chapter 4 encapsulates the empirical findings derived from the study. Lastly, the conclusion, policy recommendations, limitations of the study and room for further studies are discussed in Chapter 5.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter presents an exhaustive exploration of past literature pertaining to tourism demand studies. Section 2.2 discusses the theoretical underpinnings prevalent in existing literature. Section 2.3 is structured into ten distinct sub-sections, each devoted to one of the independent variables utilized in prior tourism demand research. Lastly, Section 2.4 discusses the literature gaps identified through the present study.

2.2 Theoretical Review

In existing studies on tourism demand, researchers mainly employ consumer theory, as outlined by Morley (1992). This theory posits that an individual's utility is derived from the intention to visit different destinations, as well as the consumption of goods and services. The function expressing the individual's utility can then be formulated as follows:

$$U_{ijt} = f(N_{ijt}, Q_{it}, ZO_{it}, ZD_{jt}) \quad \text{Equation 2.1}$$

U_{ijt} = utility of an individual from the origin country i visiting to destination country j during period t ;

N_{ijt} = number of visits by an individual from origin country i to destination country J during period t ;

Q_{it} = vector of consumption of other goods;

ZO_{it} = vectors of site qualities of dimension to the origin country; and

ZD_{it} = vectors of site qualities of dimension to the destination country.

Under consumer theory, it expresses how an individual makes his or her decision based on the limited resources allocated to maximize their satisfaction or utility. It is a fundamental concept in understanding the behaviour of consumers in the marketplace, and crucial in determining the demand of the market, price elasticity, and the impacts of changes in income or prices on consumer choices. In tourism market, the consumers (tourists) will make their travel decisions based on the budget and time availability. Therefore, they will choose the travel destination that can maximize their utility based on the budget and time availability. Besides that, Divisekera (2003) mentioned that the utility stems from destination attributes such as agreeable climate, beautiful scenery, and/or sociocultural features. The tourism demand study that utilized consumer demand theory can be found in the studies of Isik et al. (2020), and Lorde et al. (2016).

Işık et al. (2020) examined the determinants affecting tourism demand in United States based on consumer theory. The selected parameters consist of economic policy-related uncertainties, real GDP per capita, and real exchange rate. Their findings found that a long run relationship between the selected variables and tourism demand in United States. The positive impacts of real GDP per capita and real exchange rate on tourist arrivals have been detected in their study. Meanwhile, the economic policy-related uncertainties adversely influence the demand of tourists visited to United States.

Divisekera (2003) investigated the determinants affecting tourism demand in United States, United Kingdom, Japan, and New Zealand. The findings indicated that given the high elasticity of expenditure demands, it is probable that newly emerging destinations, like Australia and New Zealand for Japanese tourists, will capture a growing portion of the expanding tourist expenditure. Nevertheless, the positive impacts resulting from increased

tourist expenditure in home countries may be counteracted by declines in demand attributed to rising prices, a phenomenon observable in cases with relatively elastic demands.

Another theoretical framework employed in tourism demand studies is Newton theory. Furthermore, the newton theory stated that two objects attracted by each other under gravity theory. In this case, gravity model is the preferable model to study the tourism demand because the tourists visit to other travel destinations due to the attractiveness and uniqueness in the travel destination. Additionally, the gravity model owns its advantages in estimating tourism demand. The advantages of this technique are the geographical distance and source country characteristics can be explicitly taken into account (Morley et al., 2014). Tinbergen (1962) developed the gravity model as a means to explain patterns in international trade. Gravity models has found applications beyond trade, including migration, international trade flows, and foreign direct investment (Morley et al., 2014). Examples for its application in international trade (Yotov, 2022; Golovko & Sahin, 2021; Chaney, 2018; Anderson & Wincoop, 2003; Rose, 2000; McCallum, 1995), migration (Gil-Pareja et al., 2007; Karemera, et al., 2000), and foreign direct investment (Falk, 2016; Bergstrand & Egger, 2007) are well-established. However, its disadvantage is obvious in a lack of precise explanation for the factors underlying the gravitational phenomenon (Luoma & Palomaki, 1983). Generally, the researchers employed the gravity model when the travel distance variable is incorporated in the estimation model.

In various studies, including Özdemir and Tosun (2023), Tong et al. (2023), Cevik (2022), Jong et al. (2020), Kaplan and Aktas (2016), Priego et al. (2015) and Morley et al. (2014), they have employed the gravity model to examine the factors affecting tourism demand. The core gravity model consists of three variables, which are GDP in the origin country, GDP in the destination country, and the distance between the origin and destination

country. Tourism demand is expected to have a positive relationship with GDP or income level while a negative relationship with distance. The core gravity model is shown in Equation 2.1:

$$F_{ijt} = B \frac{(GDP_{it})^\alpha (GDP_{jt})^\lambda}{(Dist_{ijt})^\xi} U_{ijt} \quad \text{Equation 2.1}$$

where

F_{ijt} = tourism flows between the origin country and destination country;

GDP_{it} = gross domestic product for origin country;

GDP_{jt} = gross domestic product for destination country;

$Dist_{ijt}$ = geographical distance between the origin and the destination country;

U_{ijt} = log-normal distributed error term.

Equation 2.1 is transformed into logarithm form for estimation purposes, as shown in Equation 2.2:

$$LF_{ijt} = \beta_0 + \alpha LGDP_{it} + \lambda LGDP_{jt} + \xi LDist_{ijt} + \varepsilon_{jit} \quad \text{Equation 2.2}$$

where

LF_{ijt} = logarithm form of tourism flows between the origin country and destination country;

$LGDP_{it}$ = logarithm form of gross domestic product for origin country;

$LGDP_{jt}$ = logarithm form of logarithm form of gross domestic product for destination country;

$LDist_{ijt}$ = geographical distance between the origin and the destination country;

ε_{jit} = error term.

The tourism industry can be seen as a special type of trade within the services sector due to its focus on the movement of people between regions. The basic gravity model as shown in Equation 2.2 has been expanded upon by various researchers based on the nuances of their respective studies.

In past research, the size of an economy has been proxied by indicators such as GDP (Puah et al., 2022; Kalimeris et al., 2020; Zhang & Zhang, 2021; Gouveia et al., 2017) and population (Gouveia et al., 2017; Taplin & Qiu, 1997). For instance, Gouveia et al. (2017) found that both GDP per capita and population had a significant and positive impact on international tourism demand in Portugal. Similarly, Santeramo and Morelli (2015) observed an identical trend in Italy whereby the larger the population, the higher the tourism demand. In the United States, the income level of tourists was highlighted as a key determinant affecting tourism demand (Yazdi & Khanalizadeh, 2017). They found that income elasticity was 0.33 in the long-run, suggesting that international tourists considered tourism as a non-luxury service in the USA. In the context of Turkey, GDP positively affected inbound tourists, and Kaplan and Aktas (2016) pointed out that income growth in both Turkey and the origin countries had a positive impact on tourism demand. Puah et al. (2022) and Jong et al. (2020) also found that the tourists' income and tourism demand are positively correlated with each other in Macau and Sabah, respectively.

Within the gravity model, the distance parameter is determined by calculating the geographical distance in kilometers between the capitals of the origin and destination countries. The great circle formula is commonly employed to determine the geographic distance between two points on a sphere (Mayer & Zignago, 2011). Some studies have used the distance between capital cities to proxy for transportation costs, while others have multiplied the distance by oil prices to estimate transportation costs, as demonstrated in studies like Jong et al. (2020), and Lorde et al. (2016). This is because oil price fluctuations can impact transportation costs for suppliers and tourists. Eryigit et al. (2010) also mentioned that tourist flows tend to decrease when the distance between the origin and destination country increases because of the increased transportation cost.

Previous studies have consistently discovered an inverse correlation between transportation costs and tourism demand such as Fan et al. (2023), Puah et al. (2022), Ulucak et al. (2020), Tavares and Leitaó (2017), and Priego et al. (2015). Santeramo and Morelli (2015) also concluded that distance negatively influenced tourism demand in Italy at the 1% significance level. Moreover, distance also affected the duration of stay, as indicated by their empirical findings. An adverse relationship between tourism demand and transportation cost was also identified in the study of Lorde et al. (2016). Their findings suggested that a 1% increase in transportation costs led to a reduction of 0.5% and 1.3% in short-run and long-run arrivals, respectively.

In the context of tourism, the assessment of tourism climate comfort is derived on the theoretical consideration on biometeorological literature related to human comfort. Biometeorology is a scientific discipline that reviews the connections between weather, climate, and living organisms, including humans, animals, and plants. It focuses on understanding the effects of weather and climate on biological systems and their well-being.

Within tourism studies, biometeorology often focuses on the impacts of climate on human thermal comfort. The key meteorological variables usually include temperature, humidity level, wind speed, and duration of sunshine. Thermal comfort refers to the satisfaction level of an individual with the surrounding environment.

The concept of human thermal comfort can be associated with the ASHRAE Standard 55 developed by the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE). It provides the guidelines and calculations for environmental conditions in specific locations. ASHRAE 55 has been widely applied in tourism literature such as Jong et al. (2023), Tian et al. (2022), Lopes et al. (2021), Xi et al. (2020), and Nasrollahi et al. (2017) to examine the impact of human thermal comfort on the tourism industry.

Nasrollahi et al. (2017) examined the best time to visit historical sites in Isfahan, Iran, using thermal comfort as a metric. Surveying 291 tourists, they found that despite experiencing a heatwave, a majority (78.57%) were satisfied with the thermal conditions in the Isfahan while the remaining visitors were dissatisfied. Their findings also indicated that the visitors' thermal comfort preferences aligned with typical comfort zones found in warm climates although they are from different origin countries. Furthermore, they identified that the most comfortable time to visit the historical areas was the early morning.

Similarly, Lopes et al. (2021) and Xi et al. (2020) investigated the impact of climate on thermal comfort in tourist destinations through primary data in Portugal and China, respectively. Xi et al. (2020) found that outdoor tourist activities were not influenced by the outdoor thermal environment, likely due to tourists' pre-planned activities. In addition, Lopes et al. (2021) revealed that climatic conditions were not strongly correlated with human

thermal comfort in Porto, Portugal, suggesting that tourists have a higher tolerance for varying temperatures.

2.3 Empirical Review

2.3.1 Climate Condition

An international survey conducted by Wall and Badke (1994) concluded that climate and weather condition are the key tourism determinants of their countries or regions, as agreed by 81% of 66 national and regional tourism organizations. This perspective has been supported by subsequent studies such as Arabadzhyan et al. (2021), Rутty et al. (2020), Hejazizadeh et al. (2019), Scott et al. (2016), Scott and Lemieux (2010), and Freitas et al. (2008), all of which emphasized climate as a fundamental determinant of travel patterns and choices.

Arabadzhyan et al. (2021) and Moore (2010) also stated that climate change has the potential to impact both supply and demand of regional tourism products. On the supply side, more intense and frequent weather events, such as tropical storms, could affect the hotel industry and tourist attractions. On the demand side, climate change could lead to shifts in tourist patterns as preferences change.

According to Hartman and Spit (2014), climate can have both positive and negative influence on tourist satisfaction and influence their experiences. This presents a challenge for tourism planners in an era of changing climates. A favourable climate not only attracts tourists, but also enhances tourist loyalty, increasing the likelihood of repeat visits (Martin & Belen, 2005). Denstadli et al. (2011) found that inaccurate climate information could influence the perception of tourists and their intention to return to the tourist destination.

Bigano et al. (2006) mentioned that the success level of the tourism destination is critically affected by weather and climate conditions, not to mention that climate greatly affects travel decisions. Tour schedules are often designed around different seasons, as such changes in climate are expected to alter tourism's seasonal patterns in the long run. This has also been supported by Yu et al. (2009).

In recent years, concerns about climate change's impact on tourism demand have grown. Tourism is a highly complex and interlinked industry. Climate change can have an impact on transport systems such as aircraft, rail and ship movements, the accommodation industry, and even energy consumption during a hot day. Not only that, unexpected changes in weather greatly affect tour organizers, communities, insurers, investors, and national tourism organizations in predicting and planning activities. While climate is just one of many factors influencing travel decisions, some tourists are driven entirely by climatic considerations (Mieczkowski, 1985). Even for tourists with non-climatic motives, travel times may still be chosen based on favourable climate conditions.

Climate strongly contributes to the seasonality of the tourism industry. According to Butler (1994), there are two core factors leading to tourism demand seasonality, which are climatic conditions and leisure time. For Hadwen et al. (2011), the main driver of tourism seasonality in tropical, equatorial, desert, grassland and temperate zones is also their climate condition. Climate factors like maximum temperature, relative humidity, and sunshine hours influence the quality, timing, and length of travel stays to varying degree depending on the location (Kulendran and Bwyer, 2012) with specific tourism activities being highly seasonal, such as beach activities, water sports, and winter sports. For this reason, climate is clearly

an important input to tourism products formulation as well as affecting tourism seasonality (Martin, 2005).

Lin and Matzarakis (2011) also concluded in their study that climate conditions in different seasons have an impact on travel schedules. Favourable climatic conditions can attract more tourist arrivals and vice versa, not to mention that a cooling weather also reduces energy consumption to cool down buildings. Zhang and Kulendran (2016) investigated the impact of climate and tourism seasonality on tourism demand in Hong Kong. The study concluded that climatic variable plays a dominant role in shaping tourism seasonality. Besides that, the number of tourist arrivals also fluctuated between the seasons, not just by climate factors, but also other macroeconomic factors.

Furthermore, risk assessment related to climate change plays a critical role to provide useful information that can enhance tourist loyalty. This is done by minimizing the gap between tourists' experiences and prior perceptions regarding the exact climatic condition in destination country. It goes beyond evaluating climate advantage and provides practical strategies to mitigate potential impacts of destructive weather patterns. Olya and Alipour (2015) mentioned that risk assessment in tourism climate can identify both favourable and unfavourable tourism climates, thereby providing valuable input to tourists and ensuring their expectations are met.

Li et al. (2017) investigated how maximum temperature in China influence tourism arrivals from Hong Kong. They found that the maximum daily temperature and average daily humidity back at the home significantly and positively affected their decision to visit China. On the other hand, minimum daily temperature and average precipitation adversely affected their decision to travel. Both average daily sunshine hours and average daily temperature

back at home did not significantly affect travel decision. These findings illustrate that the residents of Hong Kong tend to travel to China when it is hot and humid back at home, but not when there is frequent rain.

Uyarra et al. (2005) and Hamilton and Lau (2006) conducted a public survey on climate issues. Both concluded that environmental features such as warm temperatures, clear waters and health risks greatly affect travel decisions. Hamilton and Lau (2006) also found that majority (73%) of the tourists have taken initiative to understand the destination's climate with 42% actively surveying the weather before travelling. Another similar study was done by Lee et al. (2018), which concluded that shifting in rainfall patterns also influence travel decision besides rising temperatures.

Yu et al. (2009) pointed out that average temperature alone is insufficient to represent climate resources. However, Priego et al. (2015) found that temperature was significant in explaining domestic tourism movements in Spain. Their finding showed that temperature was positively related to the destination province and negatively related to the home province. In other words, when a destination outside of home is warmer, the tourists become motivated to travel. The desire to travel also increases when it becomes colder back at home. Chen et al. (2016) incorporated weather uncertainty as a variable to study tourism demand in Taiwan. Their finding concluded that temperature uncertainty and rain adversely influenced tourism demand. Tourism activities were also lesser during rainy days.

Rainfall is another key element influencing tourism demand. Mieczkowski (1985) suggested that tourists' well-being is adversely influenced by the rainfall exceeding 60 mm per month. However, Roshan et al. (2009) found no significant correlation between annual rainfall and the Tehran tourism. Forland et al. (2013), on the other hand, argued that low

visibility due to persistent rainfall negatively affects tourists' experiences. Olya and Alipour (2015) also found that high level of precipitation exposes the destination to high risk, as seen in the low TCI score for North Cyprus. Kubokawa et al. (2014) investigated meteorological indices and their impact on the number of tourists in Japan. They found that while indices like CIA, CID, sunshine hours, and wind had minimal interannual variations, rainfall exhibited significant interannual changes in tourist arrivals. Rainfall's influence was particularly evident during the summer season in Morioka, Japan, resulting in a considerable reduction in tourist arrivals. Overall, these findings consistently demonstrated an adverse relationship between precipitation and tourists' well-being and comfort, indicating the importance of rainfall in influencing tourists' decision and experience.

With the significant influences of several climatic elements on tourism industry, it is vital to integrate important climatic elements into a single index to ease formulation and understanding. In relation to this, Mieczkowski (1985) constructed the tourism climate index (TCI) by integrating five tourism-related climatic elements into a single index. Each element or sub-index was assigned with their own weightage to represent its relative importance to tourists' welfare. The TCI was developed based on theoretical insights derived from biometeorological literature that specifically focused on human comfort. TCI has been applied in the studies of Jong et al. (2023), Ma et al. (2023), Ruttu et al. (2020), Hejazizadeh et al. (2019), Bakhtiari et al. (2018), Li et al. (2017), and Roshan et al. (2009) used the TCI to mainly determine the preferred month for certain tourism activities as well as the impact of climate on tourism. Bigano et al. (2006) found that tourists prefer sunny yet mild climates for their travel destinations. Roshan et al. (2009) also employed TCI to assess the impact of urban sprawl on Tehran's tourism, identifying specific months as excellent for tourists. The ideal seasons are the spring season (April, May and June), followed by early fall season

(September and October). Most tourists prefer not to travel during late fall and winter seasons.

Tourism seasonality is one of the major challenges in tourism industry. Studies such as Rutty et al. (2020), Scott et al. (2016), Fang and Yin (2015), Siedlecki (2015), and Moore (2010) have used TCI to measure tourism seasonality. Tourism seasonality is influenced by both natural and institutional factors. The natural factors are obviously related to the climate of the destination, such as temperature, sunshine hours and rainfall while institutional factors are related to social norms and practices, such as festive and holiday seasons (Fang & Yin, 2015). Michailidou et al. (2016) found that moderate temperature changes could lead to increased domestic tourism expenditure. In the study of Scott and Lemieux (2010), the domestic tourism expenditure increased by 4% during warmer than normal summer season in Canada.

Nunes et al. (2013) studied the effect of maximum summer temperatures and minimum winter temperatures on domestic tourism, and reported that rising temperature decreases the number of domestic tourists during the warmer months. In addition, when a country's temperature rises, it deters tourists from British, Germany and the Netherlands from visiting, as reported in the study of Berrittella et al. (2006), Hamilton (2004), and Lise and Tol (2002).

Kubokawa et al. (2014) employed TCI to study the climate's impact on the tourism industry in Japan. The empirical findings showed that the summer season is the most favourable and comfortable to travel. In addition, decrease in tourist arrivals can be due to reasons other than unfavourable weather, such as economic downturn. A small interannual variation was found for CIA, CID, sunshine hours, and wind, which concluded that these

meteorological indices did not affect interannual changes in the number of tourists. The only significant factor that caused obvious interannual changes was rainfall. Nevertheless, Hamilton and Tol (2007) mentioned that, when the home country's weather is comfortable, most prefer to stay rather than travel to a different country.

Li et al.'s (2018) study highlighted an interesting finding that the TCI of the destination country can adversely affect tourist arrivals. This could be attributed to tourists' motivation to seek different climate experiences. When they further investigated by considering both origin and destination climate variables, they found a positive effect of the TCI of the tourists' origin on tourist arrivals, whereas the TCI of the destination showed an adverse impact on the tourism industry. This suggests that tourists are attracted to destinations with climates that differ from their own, but destinations with overly favourable climates might not be as appealing due to the desire for diverse experiences.

In addition, Morgan et al. (2000) designed a user-based beach climate index for Malta and Turkey. By distributing surveys to beach users, they aimed to understand how people perceive thermal sensations during the summer season in these coastal destinations. The findings from Rutty and Scott (2010) emphasized the importance of considering how people experience extreme heat, particularly in Mediterranean coastal regions during the hottest months. The ideal temperatures for beach tourism in Costa Brava lie within the summer months between July and August. For Cyprus, the ideal temperatures are in April and May while June and September are the ideal climatic condition for Nice. May and September are the ideal months for Milos, whereas the ideal months for Antalya are May and October. A total of ten months has been categorized as ideal temperatures across the five destinations.

Despite its wide use, TCI has some limitations. There are four drawbacks mentioned in multiple studies. Firstly, TCI was initially constructed subjectively by Mieczkowski, and thus its weighting system and components lack empirical verification against tourist preferences (Rutty et al., 2016; Scott et al., 2016; Jacobsen et al., 2011; De Freitas, 2003). Furthermore, it failed to consider the potential impact of significant factors on physical climatic parameters, such as wind patterns and precipitation levels.

As an illustration, surveyed tourists have indicated that the presence of rainfall holds relatively greater significance compared to temperature conditions for sightseeing holidays. This observation arises from the allocation of weights to different physical factors, where the collective weight is set at 30%. Rainfall is allotted a weight of 20%, while wind contributes 10% to the overall weighting. However, this weighting structure might not accurately capture the precise influence of these physical parameters on tourists' decisions regarding travel. Additionally, TCI uses monthly data, which may not capture daily weather variations. Mieczkowski used monthly data because daily data was relatively difficult to obtain during the pre-internet era, although it is imperative in planning a trip. Furthermore, the TCI does not account for the diverse climatic needs of different tourism segments and destinations such as beach activities, winter sports and water sports.

The limitations of the TCI have served as a catalyst for Morgan et al. (2000) to develop the Beach Climate Index (BCI), while Freitas et al. (2008) introduced the Climate Index for Tourism (CIT). Yu et al. (2009) constructed the Modified Climate Index for Tourism (MCIT) for beach activity. Although the BCI, MCIT and CIT are designed to overcome the drawbacks of TCI, they can only cover the 3S tourism segments (sun, sea and sand) instead of the general tourism industry.

A more generic index is the Holiday Climate Index (HCI) developed by Scott et al. (2016) to measure climate impact on tourism or more accurately the climatic suitability of a tourism destination. A major advancement compared to the TCI is in the rating scales and component weighting system of the climatic variables, which are based on an extensive literature on climate preferences of tourists in the decade preceding its formulation. The construction of HCI is in line with the conceptual design suggested by Freitas, Scott and Mcboyle (2008) that have accounted for the overwhelming effect of physical variables like wind and rain. Also, the index employs daily data instead of monthly data. The considered areas are generalized into urban and rural areas only instead of more specific segmentation.

Hejazizadeh et al. (2019) utilized both TCI and HCI to understand the influence of climatic seasons on tourism in the desert regions and Makran coasts of Iran. Both indexes showed similar result in the winter and fall seasons. During the spring and summer seasons, HCI has relatively higher score because of higher temperature. For this reason, the HCI is not a preferable index to use for dessert area and hot seasons. The study concluded that TCI is a better index for the eastern and southeastern regions.

TCI has been criticized by a number of studies, but in some cases, it has performed better than the HCI. HCI, as pointed out by Hejazizadeh et al. (2019), tends to be higher for desert areas and hot seasons, making it unsuitable to measure climate changes in certain condition. Nevertheless, the identification of relationship between climate and tourism demand remains a continuous pursuit (Denstadli, et al., 2011; Scott & Lemieuxdd 2010; Lohmann & Kaim 1999). Thus, it remains important to understand the impact of climate on tourism industry at all levels.

Rutty et al. (2020) used both TCI and HCI to study the effect of climate variables on the pattern of Canadian tourists to the Caribbean. According to the mean of monthly arrival data, the most popular months to visit the Caribbean are from December to March while June to September had the lowest tourist arrivals. The TCI was the lowest in July and October, scoring just between 30 and 35. This can be attributed to the higher emphasis on the thermal comfort sub-index, as well as the elevated temperatures observed during these specific months. Also, when compared with the mean arrivals, the TCI showed no preferred month to travel to the Caribbean.

However, the HCI scores have been consistently high, ranging from good to excellent, for three tourism destinations. This indicates that the HCI is more effective in reflecting the data on tourist arrivals to the region. Furthermore, when compared with the TCI, the HCI score for beach areas and urban areas showed significant differences at higher temperatures, signifying a preference for warmer climate conditions. The HCI score for beach areas was 10 while that for urban areas was 7 against a TCI score of 6. In term of precipitation, a great difference between TCI and HCI has been observed when the daily precipitation is less than 3mm. As an illustration, the HCI was 9 while the TCI was between 5 and 9. A good tourism climate index would provide a measure of the integrated effects of the atmospheric environment that is useful for both tourists and the tourism industry.

Masoudi (2021) and Roshan et al. (2016) reached contradicting findings for the TCI for Iran. Nevertheless, both studies could conclude on the same ground that climate condition is particularly unfavourable during the winter season in the cities of Caspian coast, Iran because of the increased cloud cover and precipitation. Cities in the southern region generally have favourable climate conditions, even in the winter months. These cities boast

sufficiently cool climates and clear skies even in the winter, making them attractive destinations for tourists. In spring, the Caspian coast remains unfavourable due to high precipitation. The northern region, which are higher, now becomes the favoured cities as the southern region becomes too hot and humid. Apart from the normal seasonal change, both studies also cited the adverse impact of heat and cold stress on tourist arrivals as well as heavy precipitation.

In conclusion, climate condition is an important factor in tourism, although some tourists may accept less favourable climates in exchange of unique experiences (Jacobsen, 2001). General findings in relation to this, such as the studies done by Rutty et al. (2020), Hamilton et al. (2005), and Scott et al. (2004), emphasized that assessment on the climate differences between the origin and destination countries is crucial. These climate disparities can serve as both push and pull factors, influencing tourist behaviour and destination choices.

2.3.2 Income Level

The income level of tourists is another variable commonly adopted in tourism demand studies. The income for the origin country means the cash flows earned by tourists from work (salary), capital (interest on profit), or land (rent) over a certain period. In other words, income is the amount that can be spent by an individual during a period without being financially worse-off. A positive correlation is expected between the income of tourists' origin and demand for tourism, as evidenced in studies by Puah et al. (2022), Jong et al. (2020), Puah et al. (2018), Kaplan and Aktas (2016), and Kum et al. (2015). This implies that demand for goods and services increases when people are earning better income. Similarly, tourism demand increases when the income level of the tourists improves.

In certain contexts, national income can be used to indicate the market size of a country. Income can be proxied by Gross Domestic Product (GDP) and GDP per capita. Income in the origin country is one of the key factors influencing the demand for tourism, as suggested by Crouch (1994). Additionally, Jong and Soh (2021), Jong (2020) and Lim (1997) reviewed numerous of published papers and concluded that income in the origin country has been the most frequent variable employed in tourism demand studies. Furthermore, Lim (1997) also mentioned that most studies employed Gross National Product (GNP), nominal or real GDP per capita, and nominal or real GDP to proxy tourist's income. Song and Witt (2006) also supported that GDP is an important factor that influences tourism demand. Their result of impulse response suggests that GDP is an important element affecting tourism demand. To conclude, most studies usually employ real or nominal GDP, or GNP to proxy tourist's income in tourism demand studies (Peng et al., 2015).

However, some studies have different view on income's impact on tourism demand. Some researchers mentioned that nominal income has a different impact on tourists' travel decision, and argued that shifts in current income may not sway travel decisions (Lim, 1997). Additionally, income is not a significant factor influencing tourism demand, such as the study done by Dogru et al.'s (2017) for Turkey's tourism industry. The result suggested that the tourism demand has been influenced by other unobserved factors.

Puah et al. (2022), Jong et al. (2020), and Kulendran and Wilson (2000) stated that the income of the destination country is expected to have a positive impact on tourism demand. They assert that real income in the destination country effectively captures opportunities for international trade and business travel. An upsurge in domestic income corresponds to an increase in domestic tourism, as more resources are allocated to advancing

the tourism sector, enhancing facilities, technological adoption, and expertise. This, in turn, enhances the tourism industry's reputation and appeal, attracting more tourists.

In the study by Chaisumpunsakul and Pholphirul (2018), the income elasticity and demand for Thailand's tourism had a positive correlation in both short- and long-run. Result showed that a 1% increase in tourists' income would increase tourist arrivals by 0.049-0.402 in the short-run and 0.86-1.28 in the long-run. In another study, Yang et al. (2014) discovered that the domestic tourism demand in China has been influenced by income in both rural and urban regions. Chaiboonsri et al. (2009) found that Thailand has received more international tourists with a long term growth in income (GDP) in major markets. This finding aligns with the study done by Chaiboonsri et al. (2010) and Chaitip and Chaiboonsri (2009). In addition, an increase in the level of real GDP tends to increase outbound business travels from the origin country (Kulendran & Wilson, 2000).

2.3.3 Population

Some studies have used population to proxy the size of the country. Gil-Pareja et al. (2007) opined that population is the most suitable variable to represent economic size, particularly in scenarios involving the movement of people such as migration and tourism. A nation boasting a larger population implies a greater potential pool of tourists capable of traveling to other countries. Hanafiah et al. (2010) also discovered a positive correlation between population size and tourism demand in Malaysia. Surugiu et al. (2011) identified a positive relationship between population and tourist arrivals in Romania, indicating a 1.61% increase in international tourist arrivals with every percent increase in population.

2.3.4 Tourism Price

Tourism price refers to the costs of goods and services paid by tourists during their trip. A substantial body of evidence within the gravity model underscores its significant influence on tourism demand. Typically, this influence is negative, exerting an adverse impact on tourism demand. However, Gouveia et al. (2017) provided a noteworthy exception whereby tourism prices did not significantly impact international tourism demand in Portugal, which suggested that the cost of living in Portugal was not a driving factor for international demand in its river cruising sector. Conversely, the tourism price was statistically significant and had negatively influenced tourism demand in the USA (Yazdi & Khanalizadeh, 2017). The elasticity of the price variable was -0.08, which suggested that the tourism price has reduced tourist arrivals due to a slight change in the Consumer Price Index (CPI). Similarly, the study by Dogru et al.'s (2017) highlighted that relative prices and substitute prices, standardized by exchange rates, were influential determinants affecting tourism demand in Turkey. The review results of Jong et al. (2020) and Lim (1997) also demonstrated the consistent inclusion of tourism prices as a variable of interest.

Bergstrand (1985) pointed out that the inclusion of the prices in the origin and destination country was important to avoid misspecification bias. This critical aspect holds true particularly in the context of tourism demand studies, where theoretically, the cost of tourism-related goods and services negatively influences demand. Nevertheless, studies conducted on the subject matter has yielded diverse results. Crouch (1996) mentioned that a positive relationship between tourism price and demand for tourism could exist if the tourist income effect is stronger or when the tourism products in the destination country are Giffen or Veblen goods, dependent on income effects. However, Kulendran and Wilson (2000)

argued that the relationship should be negative, in line with demand theory, where an increase in price corresponds to a reduction in demand.

Song and Li (2008) emphasized the importance of several determinants in influencing tourism demand. These include the tourism price in competing destinations; the tourism price in the destination country; tourist's income; and the exchange rate. Tourism price can be divided into Relative Price (RP) and Substitute Price (SP). Martin and Witt (1988) described RP as the prices in the destination country in relation to the prices in the origin country. On the other hand, SP refers to the prices in the destination country compared to the prices in competing countries. These measures are used to gauge tourist preferences based on price discrepancies.

The RP is measured using CPI to reflect the prices of goods and services in the destination country (Lim, 1997), which is mathematically expressed as:

$$RP = \frac{CPI_{Origin}}{CPI_{Destination}} \quad \text{Equation 2.3}$$

The CPI ratio is usually adjusted by the exchange rate between the countries to measure the effective prices of goods and services in the destination country. This assumes that the goods and services bought by the tourists are homogeneous between the origin and destination countries. Therefore, by incorporating the exchange rate, the reflection of precise prices for these commodities and services is achieved. This is consistent with the study of Kulendran and Wilson (2000), which used CPI adjusted by exchange rate to capture the actual tourism price in the tourism industry.

In addition, certain studies have employed the RP to measure the tourism price without accounting for the tourists' purchasing power through the bilateral exchange rate. However, Dogru et al. (2017) underscored that such an approach can be misleading if the

RP in the destination country is not standardized by the exchange rate. An increase in the RP signifies that the tourism prices in the destination country are comparatively higher than those in the origin country. This discrepancy may be attributed to factors such as high inflation rate or an appreciation of the exchange rate in the destination country. The impact of inflation and the exchange rate can be calculated through Equation 2.4:

$$RP_{ijt} = \frac{CPI_{it}}{CPI_{ij}} \times ER_{ijt} \quad \text{Equation 2.4}$$

where RP_{ijt} = relative price in destination country at time period of t ;

CPI_{it} = consumer price index in destination country at the time period of t ;

CPI_{ij} = consumer price index in origin country at time period of t ;

ER_{ijt} = exchange rate between origin and destination countries at time period of t .

CPI is included as a separate variable in the equation to measure the price in the destination country. This approach is taken in consideration of the fact that the CPI encompasses various other elements that are intertwined with tourist expenditures. Notably, even one of the most substantial costs, such as transportation expenses, is encompassed within the same index, as highlighted by Lorde et al. (2016). In the study conducted by Dogru et al.'s (2017), the RP is utilized as a distinct variable, so the CPI in the origin country is excluded.

$$SP = \frac{CPI_{Destination}}{(CPI_{Origin} \times 0.5) + (Weighted\ CPI_{Competiting\ destinations} \times 0.5)} \quad \text{Equation 2.5}$$

Hence, the new SP model excluding CPI in the origin country becomes:

$$SP = \frac{CPI_{Destination}}{Weighted\ CPI_{Competiting\ destination}} \quad \text{Equation 2.6}$$

Incorporating both the RP and SP as distinct independent variables in the study can yield supplementary insights. Some studies have included CPI to proxy tourism price albeit with different approach. Some used CPI in both origin and destination countries to proxy the tourism price in the destination country. Some multiplied CPI with bilateral exchange rate. This approach effectively captures the relative living costs between the destination and origin countries, considering factors such as inflation rate and currency appreciation in the destination country. This technique is especially relevant since it assumes that the goods and services purchased by tourists in the destination country are comparable to those in the origin country, reflecting tourists' preferences for international travel.

The RP and SP, when standardised by the exchange rate, is an important formula to calculate the tourism price in the destination country. Such standardisation takes into account the purchasing power of tourists in relation to factors like inflation rate and currency appreciation in the destination country, as demonstrated in Dogru et al.'s (2017) study. The tourism price and tourism demand are expected to have a negative relationship because tourists need extra money to purchase similar goods in the destination country. In the UK, tourism demand is sensitive to tourism price, exerting a negative impact on the country's tourism demand (Durberry, 2008).

The finding in Dogru et al.'s (2017) study showed that the standardised RP and SP became significant determinants affecting tourism demand in their study. This confirms its validity to determine its effect on tourism demand. Song and Witt (2006) and Song et al. (2003) also utilized a standardized tourism price adjusted by the exchange rate as a representation of the tourism price. However, certain studies have included the exchange

rate as an additional variable such as the study of Lim and McAleer (2001), Vanegas and Croes (2000), and Uysal and Crompton (1984).

Nevertheless, it is worth noting that several studies have highlighted the potential issue of multicollinearity if the model included both tourism prices standardised by the exchange rate and the exchange rate as a separate variable. In the study of Dogru et al. (2017), an almost perfectly negative correlation (-0.99) was detected when the exchange rates were included along with the RP standardised by the exchange rate.

2.3.5 Transportation Cost

Transportation cost refers to the cost paid by tourists to transportation services providers during their trip to a destination country. This includes the airfare price, the cost for public and private transportation services, and other costs during the tourist's trip. The studies conducted by Soh et al. (2022), Ulucak et al. (2020), Kaplan and Aktas (2016), Priego et al. (2015), Eryigit et al. (2010), and Chaiboonsri et al. (2009) all revealed a negative correlation between transportation costs and tourism demand.

Low-cost air carriers have become one of the main drivers for tourism development as stated in Juan and Federico (2016), Dobruszkes and Mondou (2013), Zhang and Lu (2013), Chung and Whang (2011) and Graham and Dennis (2010). In addition, tourists will travel to other destinations when the price of airfares are lower and there are more flight selections (Budd et al., 2014; Chang & Hung, 2013; Dresner, 2006; Mason, 2000). In the study conducted by Tsui (2017), a positive correlation between low-cost carriers and tourism demand has been identified for New Zealand. A similar finding was also found in Dresner's (2006) study, which mentioned that the expansion of low-cost airlines has been a key

element in promoting domestic tourism in the USA. In Alghero, Pulina and Isabel (2010) note that low-cost carriers influenced both domestic and international tourism demand.

Jet fuel price is one of the transportation costs in tourism demand studies. Chaitip and Chaiboonsri (2009) mentioned that a 1% increase in jet fuel price decreases the number of British tourists visiting Thailand by 0.12%. However, similar increase in jet fuel price has caused the number of tourists from China and Taiwan visiting Thailand to increase by 0.9% each. This means that the decision to travel is not affected by jet fuel price, but other factors. Moreover, the gravity model elucidates the impact of elevated travel costs on curbing tourism demand in Malaysia (Hanafiah et al., 2010). Consequently, governments may consider measures like reducing aviation fuel taxes for airplanes to lower airfare costs.

In a gravity model, distance is a basic variable to proxy the transportation cost in a study of tourism demand. Jong et al. (2020), Ulucak et al. (2020) and Chaisumpunsakul and Pholphirul (2018) found that this distance has negatively affected tourist arrivals. All studies have also identified both short- and long-term effects of transportation costs on tourism demand, whereby a 1% decrease in transportation costs have increased the number of tourists by 0.023% in the short-run and 0.404% in the long run. The study of Surugiu et al. (2011) has also found a negative relationship between distance and international tourism demand in Romania.

2.3.6 Exchange Rate

The exchange rate is another important determinant frequently incorporated in tourism demand models such as in the studies of Chaudhry et al. (2022), Jong et al. (2022), Puah et al. (2022), Jong et al. (2020), and Dogru et al. (2019). Chaiboonsri et al. (2009) stated that the exchange rate was an important determinant for international tourist' behaviour in Thailand's tourism market. Their findings revealed a compelling connection,

wherein a 1% appreciation in Thai Baht would reduce international tourist arrivals from major markets such as Malaysia by 5.0%, England by 1.2%, Germany by 4.0%, France by 23.6%, and the USA by 5.8%. A similar outcome was also found in Chaitip and Chaiboonsri's (2009) study, which mentioned that the exchange rate between Thailand and Germany showed a positive association with the number of German tourists arriving in Thailand. Based on their findings, it was indicated that a 1% rise in the real exchange rate would result in a 0.4% increase in tourist arrivals from Germany. Obviously, depreciation of the Thai Baht will make travelling to Thailand more affordable for tourists from Germany.

Vita and Kyaw (2013) and Martin and Witt (1988) stated that a model that includes the exchange rate alone without adding the tourism price is inappropriate to study tourism demand. This is because tourists react differently to the exchange rate as compared to the tourism price. While tourists might know something about exchange rates prior to their visit, their awareness of the tourism price may only emerge upon their arrival in the destination country (Martin & Witt, 1998). Notably, Lim (1997) advocated for a separate inclusion of the exchange rate and relative tourism price within the same equation to explore the impact of nominal exchange rates on international tourism demand in select studies. However, Dogru et al. (2017) argued that a study that included both the exchange rate and the tourism price may lead to multicollinearity problems because both variables are a measurement of the tourism price.

2.3.7 Tourism Security

The relationship between tourism and security is inherently intertwined, as safety of travellers is paramount in the tourism industry to encourage sustainable performance and growth (George, 2003; Pizam et al., 1997). Researchers like Sonmez and Graefe (1998) have

begun to pay attention to safety in tourism since the 1990s. Among all determinants affecting tourism demand, tourism security is viewed as one of the top factors influencing travel decisions. Tourism security includes political stability, threats from terrorism, and war. Hall et al. (2004) opined that tourism issues not only affect individual decision making, but also travellers' economic and political confidence. On the contrary, Mawby (2000) found that tourists might not necessarily be dissuaded from revisiting a destination, even if they have been victims of an incident.

Nevertheless, a tourist's impression of feeling unsafe or threatened can be a potent deterrent, resulting in detrimental effects on a destination's tourism sector (George, 2003) such as a decline in tourist arrivals. Llorca-Vivero (2008) pointed out that local and international terrorism leaves a negative impact on international tourist flows, especially in developing countries, where tourism is crucial for promoting economic growth. This is because political violence damages the destination's reputation and causes tourists to feel unsafe. For example, Egypt lost an estimated USD1 billion in tourism revenue due to terrorism issues over a 12 months period in 1999 (Allen, 1999). George (2003) stated that younger tourists are more likely to feel unsafe than older tourists for several reasons. Firstly, younger tourists are more inclined to explore during the evening hours, potentially exposing themselves to higher risk. Moreover, older tourists' experience and wisdom tend to influence their sense of safety. Lastly, younger tourists often opt for budget accommodations, which might be located in areas perceived as less safe.

2.3.8 Trade Volume

Trade volume is also a pivotal determinant influencing the flow of international tourists. This influence stems from the premise that as trade between countries burgeons, so does the familiarity and visibility of the destination country. This heightened familiarity, often fostered by increased business travel, contributes to a surge in both inbound and outbound tourism. The seminal works of Yotov, (2022), Golovko and Sahin (2021), Santana-Gallego et al. (2016), Leita0 (2010), Hanafiah et al. (2010), and Habibi et al. (2009) collectively pointed out that trade volume positively affects tourism demand. In the study of Chaisumpunsakul and Pholphirul (2018), a 1% increase in trade openness between Thailand and its trade partners increases tourist flow by 0.05% in the short-run and 0.81% in the long-run.

2.3.9 Lagged Dependent Variables

A lagged dependent variable has been used to capture habitual persistence and word-of-mouth effects, such as in Preko et al. (2021), Dogru et al. (2017), Song and Li (2008), and Lim (1997). Peng et al. (2015) stated that this variable describes a tourist's intention to introduce a tourism destination to their friends or colleagues or to revisit the same destination again, which may influence other people's behaviour or decision making. Additionally, the study conducted by Dogru et al. (2017) revealed that the lagged dependent variable emerged as a significant factor for all countries except Russia when used to identify the influence of habitual persistence and the word-of-mouth effect.

2.3.10 Dummy Variables

In specific studies on tourism demand, a dummy variable has been incorporated to capture the impact of special tourism events such as the COVID-19 pandemic (Falk et al., 2023; Ikasari et al., 2022). Tsui et al. (2014) employed a dummy variable to capture an earthquake in Christchurch that has led to a decrease in tourist arrivals in 2011. Mazzocchi and Montini (2001) also performed the same for an earthquake in Assisi. However, certain studies have shown contradicting outcome. For example, the study conducted by Hanafiah et al. (2010) showed that an economic crisis has negatively influenced tourism demand from ASEAN countries, but boosted tourism demand in the western and other regions. In other words, the occurrence of an economic crisis has deterred tourist arrivals from ASEAN countries, but tourists coming from the western and other regions have increased.

Some studies have used a national border to examine its impact on tourism demand such as Priego et al. (2015). A country that shares a land border is represented by a dummy variable using unity (Gil-Pareja et al., 2007). The country that shares the same border tends to have more tourists visiting from the neighbouring country. Dummy variable has also been used to represent a pair of islands each in the origin and destination countries (Gil-Pareja et al., 2007). However, it is noteworthy that not all scenarios yield the same outcome. In contrast, the UK presents an interesting counterpoint. Durbarry's empirical study (2008) divulged that tourists originating from neighbouring countries to the UK appeared to spend approximately 52% less than those arriving from more distant locales.

Furthermore, linguistic commonality emerges as a compelling influencer of tourism flow. When the origin and destination nations share a common language, a tangible advantage is often observed in terms of attracting tourists from the origin country to the

destination. This has been explored by Gil-Pareja et al. (2007), where the presence of a common language fosters enhanced tourism exchanges. Durberry's (2008) finding also depicted a positive association between a common language and tourism demand in the UK. In addition, their study concluded that tourists who shared a common language with the destination country tended to spend 7% more than the tourists who did not share a common language.

2.4 Literature Gap

The field of tourism research has been illuminated by an array of prior studies, spanning diverse perspectives. Climate, in particular, has emerged as a pivotal focal point for industries, government and non-government agencies. Tourism is a vulnerably industry to climate change. In previous studies, many have attempted to study its impact on tourism, including countries in the Europe and the Americas, such as Turkey, Canada, America and Spain. Similar studies for the Asia Pacific region using both TCI and HCI are considerably scarce.

Both the TCI and HCI have been employed in previous studies as key indicators of tourism climate conditions, each with its advantages and disadvantages. The major argument surrounding TCI is in its weighting system of the sub-indices. This is because TCI has been constructed purely based on Mieczkowski's own judgement without being empirically examined. To overcome this limitation, Scott et al. (2016) constructed the HCI with the variable rating scale designed based on a growing literature on climate preferences of tourists, collected over a decade.

Despite some limitations reported in previous studies, TCI continues to captivate interest, with several more recent studies incorporating both TCI and HCI to analyse climate conditions over distinct time periods to extract valuable insights into tourism dynamics. The relationship between these indices and tourism demand has proven to be both positive and negative, contingent upon the nature of the tourism products offered by the destination country.

This study intends to construct both TCI and HCI for the Asia Pacific region. In addition, current studies on the differences in climate conditions between the origin and destination countries are limited. Therefore, this study has further formulated the relative tourism climate index (RTCI) and relative holiday climate index (RHCI) to address this gap. These indices aim to probe the climate disparities between nations, which can significantly influence travelers' decision-making processes, both as motivating factors and deterrents.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter presents the data and methodology employed in this study. Section 3.2 discusses the estimation models employed in this study. Then, the estimation methods used in this study are presented in Section 3.3. Lastly, Section 3.4 describes data description.

3.2 Estimation Models

This study aims to construct the relative tourism climate index (RTCI) and relative holiday climate index (RHCI) to explore their impacts on tourism demand in the Asia Pacific region. These indices, integrated with climatic and macroeconomic variables, will provide insights into the region's tourism trends. With a comprehensive understanding of climate conditions, governments and industry players can better address key issues, enhance competitiveness, and promote sustainable development. By tailoring tourism products to different climate preferences, the region can attract diverse tourists and adapt to changing demands. The empirical finding is expected to give better understanding on the underlying information behind the fluctuating tourism industry in Asia Pacific.

From 2010 to 2019, the Asia Pacific region enjoyed the highest growth rate in both average tourist arrivals and generated tourism receipts. However, with an increasing demand on tourism, identification of key performance indicators has become crucial to sustain its performance. This has to be coupled with climate change indicators, and TCI has become a popular indicator in this sense albeit a common agreement on the lack of some basic features.

These include the weighting of indices and timing, but most have been somewhat resolved in HCI.

This study has chosen the TCI and HCI because both indices are designed for the general tourism segment. Unlike other tourism climate indices such as Beach Climate Index (BCI) and Climate Index for Tourism (MCIT), which are tailored specifically for certain activities like beach or mountain activities, TCI and HCI are designed to encompass various tourism activities in a destination. The intention behind constructing these climatic indexes is to assess climatic preferences and the sustainability of tourism destinations from a tourist's perspective. By formulating these indices, the study aims to elucidate the diverse impacts of climatic conditions on tourism throughout the year.

A better understanding of climatic impact on tourism industry in the Asia Pacific region gives both tourists and stakeholders a valuable tool in making informed decisions about their travel plans and tourism-related activities. Given the complex nature of weather conditions, researchers have long sought to understand its impact on the tourism industry from perspectives. An index becomes the right tool in this sense because it can integrate several key climatic elements into a single form. Another advantage is that such a climatic index allows for an objective comparison and understand its impact on resource distribution for regional and global tourism.

The TCI was constructed by Mieczkowski (1985) while the HCI was an improved index by Scott et al. (2016). Both formulation involved the integration of several main climatic variables, which are temperature, humidity, precipitation, hours of sunshine, cloud cover and wind speed into a single numerical index. The TCI has seven tourism- and climate-related components, combined into five weighted sub-indices as daytime comfort index

(CID), daily comfort index (CIA), precipitation (P), sunshine (S), and wind speed (W). CID is the combination of maximum daily temperature and minimum daily relative humidity while CIA represents mean daily temperature and mean daily humidity. Both sub-indices were formulated to measure the human thermal comfort. Equation 3.1 shows the formulation of TCI:

$$TCI = 2 \times [4(CID) + CIA + 2(P) + 2(S) + W] \quad \text{Equation 3.1}$$

Table 3.1: Weightages of TCI and HCI

Facet	TCI		HCI	
	Sub-index	Weightage	Sub-index	Weightage
Thermal Comfort	Daytime Comfort Index	40%	Daytime Temperature	40%
	Daily Comfort Index	10%		
Physical	Precipitation	20%	Precipitation	30%
	Wind	10%	Wind	10%
Aesthetic	Hours of Sunshine	20%	Cloud Cover	20%

Sources: Scott et al. (2016) and Mieczkowski (1985).

Each sub-indices is weighted according to its relative importance to tourism and traveling quality of the tourists. CID has the highest weighted of 40%, as shown in Table 3.1, for the reason that most tourists are active during daytime. The second and third highest weighted sub-indexes are sunshine and precipitation, each at 20%. The remaining 20% is equally distributed between daily comfort index and wind speed. In addition, a maximum score of 5.0 is assigned to each sub-index. A maximum score of 100 indicates the ideal tourism conditions and a minimum score of 30 indicates an extremely uncondusive and impossible climatic condition for tourism (see Table 3.2).

The rating and weighting system of TCI are the concerns of many researchers because the numbers are purely based on Mieczkowski's opinion with an over-emphasis on thermal comfort. In his calculation, Mieczkowski assigned 50% of the total index to thermal comfort at 40% for CID and 10% for CIA. This has been highlighted several times by De Freitas (2003), Moreno et al. (2009) and Nicholls and Amelung (2008). Nevertheless, TCI continues to receive attention from numerous studies such as Hejazizadeh et al. (2019), Bakhtiari et al. (2018), Li et al. (2017), and Roshan et al. (2009).

Table 3.2: Classification Schemes for TCI and HCI

TCI		HCI	
Score	Descriptive Category	Score	Descriptive Category
$90 \leq \text{TCI} \leq 100$	Ideal	$90 \leq \text{HCI} \leq 100$	Ideal
$80 \leq \text{TCI} \leq 89$	Excellent	$80 \leq \text{HCI} \leq 89$	Excellent
$70 \leq \text{TCI} \leq 79$	Very good	$70 \leq \text{HCI} \leq 79$	Very good
$60 \leq \text{TCI} \leq 69$	Good	$60 \leq \text{HCI} \leq 69$	Good
$50 \leq \text{TCI} \leq 59$	Acceptable	$50 \leq \text{HCI} \leq 59$	Acceptable
$40 \leq \text{TCI} \leq 49$	Marginal	$40 \leq \text{HCI} \leq 49$	Marginal
$30 \leq \text{TCI} \leq 39$	Unfavorable	$30 \leq \text{HCI} \leq 39$	Unacceptable
$20 \leq \text{TCI} \leq 29$	Very unfavorable	$20 \leq \text{HCI} \leq 29$	Unacceptable
$10 \leq \text{TCI} \leq 19$	Extremely unfavorable	$10 \leq \text{HCI} \leq 19$	Unacceptable
$-30 \leq \text{TCI} \leq 9$	Impossible	$0 \leq \text{HCI} \leq 9$	Dangerous

Sources: Scott et al. (2016) and Mieczkowski (1985).

To overcome the limitations of TCI, Scott et al. (2016) designed the HCI according to available literature on climate tourism preferences, obtained from numerous surveys over the past ten years. This eliminates the biases in TCI. HCI includes all facets of climatic components, which are thermal comfort (TC), aesthetic (A), physical (P), and wind (W). Thermal comfort is the combination of daily maximum temperature and average relative humidity. For aesthetic, it refers to cloud cover while physical component is a combination of precipitation and wind. Equation 3.2 presents the equation for HCI:

$$\text{HCI: } 4(\text{TC}) + 2(\text{A}) + 3(\text{P}) + \text{W} \quad \text{Equation 3.2}$$

In HCI, each climatic variable is rated on a scale from 0 to 10. Unlike TCI, the HCI does not define any climatic condition as “unconducive and impossible”, but it uses 0 to represent a climatic condition that is potentially dangerous for tourists. This is in view that some tourists tend to deliberate seek for extreme weathers to gain unique experiences, such as strong wind for wind surfing and etc. The dangerous thermal conditions expressed here include extreme heat or cold, excessive wind, or high precipitation.

Typically, the lower the HCI score, the more dangerous the weather condition. A score lower than 40 signifies an undesirable climatic condition for most tourists while the score of 100 reflects an ideal condition for tourism activities. Among the four weighted sub-indices, an equal weightage of 40% has been assigned to each of the physical facet and thermal comfort. This equal weighting is designed to ensure that the high HCI score is not achievable when the physical index rating is low. It also with the purpose to reduce the over-emphasis on thermal comfort, which is less important when the physical climatic variables are dominant. Therefore, the TCI and HCI scores obtained from Equation 3.1 and Equation 3.2 will be utilized for comparison with the number of tourist arrivals to answer Objective 3 in this study.

Upon obtaining the TCI and HCI scores, a computation process will integrate both scores to formulate the Relative Tourism Climate Index (RTCI) and Relative Holiday Climate Index (RHCI). Both indexes can measure the climate differences between the origin and destination countries. The RTCI and RHCI are presented in Equation 3.3 and Equation 3.4.

$$RTCI = \frac{DTCI - OTCI}{OTCI} \quad \text{Equation 3.3}$$

$$RHCI = \frac{DHCI - OHCI}{OHCI} \quad \text{Equation 3.4}$$

where

DTCI = TCI of destination country;

OTCI = TCI of origin country;

DHCI = HCI of the destination country; and

OHCI = HCI of the origin country.

The timing of the travel can be influenced by climate condition of both origin and destinations, this is the main reason leading to tourism seasonality (Goh, 2012; Lim & McAleer 2001). The differences can be a push or pull factor in the tourism industry. Nevertheless, Jacobsen (2001) mentioned that some tourists may visit destinations with less favourable weather condition than their home country to gain unique experience. By employing both RTCI and RHCI, a better understanding of the climatic situation in the Asia Pacific region can be better captured to provide comprehensive tourism information throughout the year.

The core gravity demand model has been augmented by including the climate variable to identify the favourable and unfavourable climate condition, offering valuable insights to ensure tourists' expectations and satisfaction are met. There are several advantages to including both macroeconomic variables and climatic elements into the same tourism demand model. Firstly, it captures the seasonal variation influenced strongly by the climate. Secondly, it helps to identify the seasonal variation led by climate and

macroeconomic conditions. These are important to understand the impact of both economic variables and the non-economic variable of climate on tourism demand.

To comprehensively gather tourism information for the Asia Pacific region, both the RTCI and RHCI have been adopted in the gravity model. The gravity model, rooted in Newton's law, effectively outlines patterns of international trade or trade flows between destinations. This model's applicability extends to diverse fields such as international trade, migration, foreign direct investment, and the tourism industry. A notable advantage of the gravity model lies in its ability to account for geographical distance and source country characteristics (Morley et al., 2014).

According to the core gravity model, the number of tourists between the origin and destination country is expected to change when measured against income level and transportation cost, proxied using geographical distance between the two locations. In essence, with constant income level, the shorter the distance, the higher the number of tourists visiting the destination and vice versa. As such, the fundamental structure of the gravity model can be represented as:

$$T_{ijt} = \beta_0 \frac{(GDP_{it}) \times (GDP_{jt})}{Dist_{ijt}} U_{ijt} \quad \text{Equation 3.5}$$

Equation 3.5 indicates the basic form of the gravity model (Chaney, 2018; Kaplan & Aktas, 2016; Yazdi & Khanalizadeh, 2017; Tinbergen, 1962). The symbol i refers to the origin country, j indicates the destination country, β_0 is the constant term and U_{ijt} is the error term. In addition, T_{ijt} presents the tourism flow between countries; GDP refers to the economic size of the countries; $Dist$ is the geographical distance between the capitals of countries.

For estimation purposes, Equation 3.5 is expressed in logarithmic form as shown in Equation 3.6:

$$LT_{ijt} = \beta_0 + \alpha LGDP_{it} + \lambda LGDP_{jt} + \xi LDist_{ijt} + \varepsilon_{ijt} \quad \text{Equation 3.6}$$

In 2019, the top ten inbound countries were China, Thailand, Japan, Hong Kong, Malaysia, Macau, India, Vietnam, South Korea, and Singapore. These countries contributed 75.2% of total inbound tourists in Asia Pacific at the same year. With their significant contribution to the regional tourism market, it is crucial to examine their climatic impacts. Therefore, the RTCI and RHCI have been constructed for these ten countries in the Asia Pacific region.

After selecting the target countries, this study delved into understanding the driving forces of tourism for each country individually. This entails identifying the ten major market sources for each country based on the number of international tourist arrivals (refer to Table 1.4). Following the concept of gravity model, the tourism determinants are comprised of the income levels of origin countries; income level of destination country; and geographical distance between the origin and destination countries. In this study, the constructed RTCI and RHCI have been added into the equation separately to examine the climate impacts on the tourism industry of the ten chosen countries as Equation 3.7 and Equation 3.8. Both equations are employed to answer the Objective 1 and Objective 2.

$$LTD_{ijt} = \beta_0 + \beta_1 LGDP_{it} + \beta_2 LGDPD_{jt} + \beta_3 LTC_{ijt} + \beta_4 LTP_{jt} + \beta_5 LRTC_{ijt} + \varepsilon_{ijt} \quad \text{Equation 3.7}$$

$$\begin{aligned} LTD_{ijt} = & \beta_0 + \beta_1 LGDP_{it} + \beta_2 LGDPD_{jt} + \\ & \beta_3 LTC_{ijt} + \beta_4 LTP_{jt} + \beta_5 LRHCI_{jt} + \varepsilon_{ijt} \end{aligned} \quad \text{Equation 3.8}$$

LTD refers to tourism demand, which is proxied by the number of tourist arrivals; LGDP represents the income levels of the tourists; LGDPD indicates income levels in the destination countries; LTC represents transportation, which combines the travel distance between the capitals of the country and international crude oil prices to capture the actual transportation cost; LTP proxies tourism price; LTCI is the tourism climate index; and lastly, LHCI refers to the holiday climate index. Both indexes are used to measure the climate conditions of the tourism destination.

After the construction of the tourism demand models, the models were analysed using panel Pooled Mean Group/Autoregressive Distributed Lag (panel ARDL/PMG) approach. This approach offers distinct advantages over time series and cross-sectional data, including greater degrees of freedom, reduced omitted variable bias, and alleviated multicollinearity. By employing the panel PMG/ARDL approach, the impacts of the relative climate conditions and other selected key independent variables can be empirically tested based on the quarterly panel data of the top ten most visited countries in the Asia Pacific region.

3.3 Estimation Methods

3.3.1 Panel Unit Root Tests

Panel unit root tests are the statistical tests used to identify the stationarity levels of parameters within a panel dataset. It is a crucial step before estimating models, as it helps to avoid the problem of spurious regression by determining whether the variables are stationary in their series or not. The results of these tests indicate whether a variable is integrated at

order $I(0)$, $I(1)$ or $I(2)$. Several panel unit root tests are available for this purpose, which include the Fisher-type tests using Im, Pesaran and Shin (2003); Levin, Lin and Chu (2002); Choi (2001); Hadri (2000); Augmented Dickey-Fuller (ADF) and PP tests-Maddala and Wu (1999). According to Im, Pesaran and Shin (IPS) (2003); Levin, Lin and Chu (LLC) (2002); and Maddala and Wu (1999), panel-based root tests tend to be more powerful than traditional time series unit root tests. These panel tests are especially advantageous when dealing with cross-sectional dependence and can provide more accurate results in the presence of heterogeneity among individual units.

LLC panel unit root test is designed to address potential cross-sectional dependence and heterogeneity among individual units. The LLC test extends the Augmented Dickey-Fuller (ADF) test to panel data. It considers the individual-specific fixed effects and cross-sectional dependence. The LLC test is particularly useful when analyzing panel datasets with potential cross-sectional dependence and individual-specific fixed effects. The hypotheses under LLC panel unit root test are as follows:

$$H_0: \alpha = 0$$

$$H_1: \alpha < 0$$

Under the null hypothesis, there is a unit root, while under the alternative, there is no unit root in LLC unit root test.

Besides that, IPS begin by defining an individual Augmented Dickey-Fuller (ADF) regression for each cross-section. It is designed to assess the stationarity of variables in a panel data setting, considering both cross-sectional dependence and heterogeneity among individual units. The IPS test allows for individual-specific fixed effects, recognizing that

there may be heterogeneity among cross-sectional units. The null and alternative hypotheses of IPS are as follows:

H_0 : There is a unit root

H_1 : There is no unit root

In addition, Maddala and Wu (1999) panel unit root test is another test designed to investigate the stationarity level of variables in panel data. It is an extension of the augmented Dickey-Fuller (ADF) test to panel datasets, accounting for potential cross-sectional dependence. It also accounts for potential cross-sectional dependence in the panel data. Cross-sectional dependence can arise when observations across different entities are not independent. The Maddala and Wu test allows for heterogeneity across cross-sectional units, recognizing that different entities within the panel may have distinct characteristics. Implementation of the test involves estimating the individual ADF regressions, computing the pooled test statistic, and comparing it to critical values to determine the stationarity of the panel data. The hypotheses of this test are:

H_0 : There is a unit root

H_1 : There is no unit root

Similar with LLC and IPS tests, the null hypothesis of Maddala and Wu panel unit test indicates that the panel data series have a unit root, indicating that the variables are non-stationary across cross-sectional units. Meanwhile, the alternative hypothesis suggests that the panel data series do not have a unit root, suggesting that the variables are stationary across cross-sectional units.

3.3.2 Wald Cointegration Test

The Wald cointegration test is a statistical test used in panel data analysis to assess the presence of cointegration among variables. Cointegration is a concept related to the long-run relationship between the variables. In the context of panel data, where data is collected on multiple entities or individuals over time, the Wald cointegration test examines whether there is a stable linear combination of the variables that remains constant across individuals. Panel cointegration occurs when there is a cointegrating relationship across the panel, suggesting a long-term equilibrium or connection between the variables for all parameters in the panel model.

Prior to the long run and short run analysis of the model, the cointegration among the variables are determined using Wald cointegration test. The null and alternative hypotheses of the Wald cointegration test are as below:

$$H_0: \alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5 = \alpha_6 \quad \text{Equation 3.9}$$

$$H_0: \alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq \alpha_5 \neq \alpha_6 \quad \text{Equation 3.10}$$

The null hypothesis indicates that there is no cointegration among the variables in the model while the alternative implies that the existence of the long run relationship among the variables. If the computed F -statistic for Wald's test exceeds the critical value, the null hypothesis of there is no cointegration will be rejected. This suggests the presence of a long-run equilibrium relationship among the set of economic variables.

3.3.3 Panel PMG/ARDL

The Mean Group (MG) estimator is a method used to estimate parameters in a panel data model where coefficients may vary across cross-sectional units but are assumed to have a common mean. In other words, the model allows for individual-specific effects while assuming that the average effect is the same across all units. The MG estimator typically involves estimating individual-specific models and then averaging the results to obtain the mean.

The Pooled Mean Group (PMG) estimator is an extension of the MG estimator that combines the individual-specific estimates with the assumption that the common mean relationship is stable over time. The PMG approach pools information across cross-sectional units while allowing for unit-specific dynamics. It is often applied in dynamic heterogeneous panels, where the parameters can vary across entities but have a common dynamic structure.

Both MG and PMG approaches are utilized in econometric analyses, particularly in studies involving panel data with heterogeneous entities and time-series observations. The selection between MG and PMG techniques depends on the characteristics of the data and the assumptions about the homogeneity of the underlying relationships. If there is evidence that the common dynamics are stable over time, the PMG estimator may be more appropriate. However, if there is substantial variation in dynamics across units, the MG estimator, which allows for unit-specific variation, might be preferred.

Panel PMG/ARDL is the standard least squares regressions which include lags of both the dependent variable and independent variables as regressors. This technique is applicable to small and large dataset. In this study, the top ten inbound countries in the Asia Pacific region (N=10) were selected with a time frame from 2010Q1 to 2020Q4 (T=44) with

a total of 440 observations, excluding China with 400 observations (N=10; T=40) due to data availability. Therefore, the short panel approaches such as statis (Pooled OLS Model, Random Effect Model, and Fixed Effect Models) and dynamic panels (system and difference GMM model) are not appropriate in this study. In addition, the Fully Modified OLS (FMOLS) and Dynamic OLS (DOLS) required all variables are stationary at $I(1)$, and mixture of $I(0)$ and $I(1)$ or $I(2)$ variables are not allowed. Among the panel approaches, panel PMG/ARDL technique is the most suitable technique in this study because there is a mixture of $I(0)$ and $I(1)$ variables, and none of the variable is stationary at $I(2)$.

The main advantage of this panel PMG/ARDL technique is it allows variables integrated at $I(0)$, $I(1)$, or a mixture of both, but does not allow for $I(2)$ variables (Pesaran et al., 2001). Besides that, it also automatically takes care of issue of endogeneity among the parameters. The panel PMG/ARDL technique helps to estimate the long run and short run relationships between the dependent and independent variables.

The panel PMG/ARDL for model I (RTCI) in this study is formulated as follows:

$$\begin{aligned}
LTD_{it} = & a_0 + \beta_i \sum_{j=1}^p \Delta LTD_{it-j} + \beta_i \sum_{j=1}^p \Delta LGDP_{it-j} + \beta_i \sum_{j=1}^p \Delta LGDP_{it-j} + \beta_i \sum_{j=1}^p \Delta LTC_{it-j} \\
& + \beta_i \sum_{j=1}^p \Delta LTP_{it-j} + \beta_i \sum_{j=1}^p \Delta LRTCI_{it-j} + \pi ECT_{t-1} + \lambda_1 LTD_{it-1} \\
& + \lambda_2 LGDP_{it-1} + \lambda_3 LGDPD_{it-1} + \lambda_4 LTC_{it-1} + \lambda_5 LTP_{it-1} + \lambda_6 LRTCI_{it-1} \\
& + \varepsilon_{it}
\end{aligned}$$

Meanwhile, the panel PMG/ARDL for model II (RHCI) is as below:

$$\begin{aligned}
LTD_{it} = & a_0 + \beta_i \sum_{j=1}^p \Delta LTD_{it-j} + \beta_i \sum_{j=1}^q \Delta LGDP_{it-j} + \beta_i \sum_{j=1}^q \Delta LGDP_{it-j} + \beta_i \sum_{j=1}^q \Delta LTC_{it-j} \\
& + \beta_i \sum_{j=1}^q \Delta LTP_{it-j} + \beta_i \sum_{j=1}^q \Delta LRHCI_{it-j} + \pi \varepsilon_{t-1} + \lambda_1 LTD_{it-1} \\
& + \lambda_2 LGDP_{it-1} + \lambda_3 LGDPD_{it-1} + \lambda_4 LTC_{it-1} + \lambda_5 LTP_{it-1} + \lambda_6 LRHCI_{it-1} \\
& + \varepsilon_{it}
\end{aligned}$$

where Δ indicates the difference operator; β_i refers to the short run coefficients; λ proxies the long run coefficients; p and q represent the maximum number of lag length, and ε_{it} is the error term. The optimal lag length of the model is based on Akaike Info Criterion (AIC).

3.4 Data Description

In this study, the ten major inbound tourist countries in the Asia Pacific region have been chosen to examine the impact of climatic conditions and the macroeconomic determinants on tourism demand within the region. These include China, Thailand, Japan, Hong Kong, Malaysia, Macau, India, Vietnam, South Korea, and Singapore. To achieve this, a panel PMG/ARDL approach has been employed as the methodological framework.

The dependent variable in this study is represented by a proxy of the number of tourist arrivals for the ten countries aforementioned. Meanwhile, the selected independent variables are tourists' incomes (GDP); income levels of destination country (GDPD); transportation cost (TC); tourism price (TP); relative tourism climate index (RTCI); and relative holiday climate index (RHCI). The expected signs for GDP, GDPD, RTCI and RHCI

are positive while TC and TP are expected adversely impacting the tourism demand of the selected countries in the Asia Pacific region.

The data for the number of international tourist arrivals, income levels of the origin and destination countries and tourism price were obtained from their respective websites. Meanwhile, the geographical distances between the capitals of the countries were collected from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII)¹. Lastly, the climatic data were gathered from the World Weather Online². The studies that utilized the data obtained from World Weather Online can be found in Kurwadkar et al. (2023) and Terence et al. (2015). Detailed data sources are tabulated in Table 3.3. The sample size of this study spans from 2010Q1 to 2020Q4.

¹ The website link is http://www.cepii.fr/CEPII/en/bdd_modele/bdd_modele.asp

² The website link is <https://www.worldweatheronline.com/>

Table 3.3: Source of Variables

Country	TA	GDP	GDPD	TC	TP	RTCI	RHCI
China	Ministry of Culture and Tourism China	World Bank	World Bank	Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) and The U.S. Energy Information Administration (EIA)	National Bureau of Statistics	The Weather Online	The Weather Online
Thailand	Ministry of Tourism Sports Thailand	World Bank	World Bank	Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) and The U.S. Energy Information Administration (EIA)	Bureau of Trade and Economic Indices	The Weather Online	The Weather Online

Table 3.3 continued

Country	TA	GDP	GDPD	TC	TP	RTCI	RHCI
Japan	Japan National Tourist Organization	World Bank	World Bank	Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) and The U.S. Energy Information Administration (EIA)	Statistical Bureau	The Weather Online	The Weather Online
Hong Kong	Hong Kong Tourism Board	World Bank	World Bank	Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) and The U.S. Energy Information Administration (EIA)	Census and Statistics Department	The Weather Online	The Weather Online

Table 3.3 continued

Country	TA	GDP	GDPD	TC	TP	RTCI	RHCI
Malaysia	Tourism Malaysia	World Bank	World Bank	Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) and The U.S. Energy Information Administration (EIA)	Department of Statistics Malaysia	The Weather Online	The Weather Online
Macau	Statistics and Census Service, Macau	World Bank	World Bank	Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) and The U.S. Energy Information Administration (EIA)	Statistics and Census Service	The Weather Online	The Weather Online

Table 3.3 continued

Country	TA	GDP	GDPD	TC	TP	RTCI	RHCI
India	Ministry of Tourism, India	World Bank	World Bank	Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) and The U.S. Energy Information Administration (EIA)	Ministry of Statistics and Programme Implementation	The Weather Online	The Weather Online
Vietnam	General Statistics Office of Vietnam	World Bank	World Bank	Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) and The U.S. Energy Information Administration (EIA)	General Statistics Office	The Weather Online	The Weather Online

Table 3.3 continued

Country	TA	GDP	GDPD	TC	TP	RTCI	RHCI
South Korea	Korea Tourism Organization	World Bank	World Bank	Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) and The U.S. Energy Information Administration (EIA)	Statistics Korea	The Weather Online	The Weather Online
Singapore	Singapore Tourism Board	World Bank	World Bank	Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) and The U.S. Energy Information Administration (EIA)	Singapore Department of Statistics	The Weather Online	The Weather Online

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Overview

This chapter discusses the empirical findings and justification of this study. Section 4.2 discusses the empirical findings for the tourism industry in China and the remaining sections report on the estimated results for the remaining countries in the Asia Pacific region.

4.2 Empirical Results for China Tourism Industry

Table 4.1: Results of Panel Unit Root Tests for China Tourism Demand Models

Variables	IPS		ADF	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept
<i>Level</i>				
LTA	0.2212(3)	2.2901(2)	19.5018(3)	9.6375(2)
LGDP	-0.5257(3)	-2.4185(6)***	28.9255(3)*	34.2279(6)**
LGDPD	-0.0927(5)	-4.2514(4)***	11.6903(5)	47.3100(4)
LTC	0.7221(0)	1.4877(0)	9.9059(0)	7.4270(0)
LTP	1.2385(10)	2.0335(8)	16.9832(10)	13.7167(8)
LRTCI	-9.1880(3)***	-16.3595(5)***	145.654(1)***	282.207(1)***
LRHCI	-10.7733(1)***	-12.8740(1)***	162.427(1)***	255.623(1)***
<i>First Difference</i>				
Δ LTA	-2.4376(2)***	-2.6642(2)***	41.4529(2)***	40.8551(2)***
Δ LGDP	-5.9101(2)***	-2.9324(9)***	83.8823(2)***	58.9319(9)***
Δ LGDPD	-4.2975(4)***	-2.5690(4)***	51.1693(4)***	30.1919(4)*
Δ LTC	-16.118(0)***	-14.601(0)***	228.467(0)***	185.058(0)***
Δ LTP	-6.3578(3)***	-4.8545(5)***	96.0888(3)***	76.0338(5)***
Δ LRTCI	-34.9149(2)***	-35.5111(1)***	320.078(1)***	1335.62(2)***
Δ LRHCI	-33.9671(1)***	-34.9243(0)***	314.059(1)***	1061.44(1)***

Notes: Asterisks ***, ** and * indicate statistically significant at 1%, 5% and 10% levels, respectively. The figures in brackets () refer to the lag length.

Table 4.1 presents the results of panel unit root tests for the tourism demand models in China. The outcomes of IPS and ADF unit roots tests showed that the parameters are stationary at $I(0)$ and $I(1)$, and none of the variables are stationary at $I(2)$. Therefore, the panel ARDL approach was employed in this study.

Next, the cointegration relationship among the variables in the estimation models was examined. Table 4.2 shows the result of Wald's cointegration test for the RTCI model in China while Table 4.3 indicate the Wald's cointegration result for RHCI model.

Table 4.2: Result of Wald's Cointegration Test for China - RTCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	540.0442	(5,155)	0.0000
Chi-square	2700.221	5	0.0000

Both tables revealed that the *F*-statistic values are statistically significant at 1% level, thereby revealing the existing of long run relationship among the tourist arrivals, tourists' income, income level of destination countries, transportation cost, tourism price, and climatic variables in both RTCI and RHCI models.

Table 4.3: Result of Wald's Cointegration Test for China - RHCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	14.3190	(5,135)	0.0000
Chi-square	71.5950	5	0.0000

Table 4.4: Autoregressive Distributed Lag Model Coefficients for China:
Relative Tourism Climate Index (3, 4, 4, 4, 4, 4)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	-0.8301	0.4331	-1.9166*
LGDP	0.1980	0.0562	2.2662**
LGDPD	0.1556	0.0687	-7.3306***
LTC	-0.0759	0.0104	-4.7289***
LTP	-0.4393	0.0929	2.7592***
LRTCI	0.0771	0.0280	3.5246***
<i>Short Run Equation</i>			
ECT	-0.1727	0.0783	-2.2047**
D(LTA(-1))	0.3000	0.0552	5.4329***
D(LTA(-2))	0.2551	0.0619	4.1175***
D(LGDP)	-0.2692	0.2974	-0.9052
D(LGDP(-1))	0.1080	0.2444	0.4419
D(LGDP(-2))	-0.0153	0.1408	-0.1084
D(LGDP(-3))	-0.0664	0.0560	-1.1859
D(LGDPD)	0.0622	0.0976	0.6377
D(LGDPD(-1))	-0.0279	0.1074	-0.2593
D(LGDPD(-2))	0.0223	0.1170	0.1903
D(LGDPD(-3))	0.0525	0.0992	0.5295
D(LTC)	0.0154	0.0188	0.8206
D(LTC (-1))	-0.0140	0.0246	-0.5682
D(LTC (-2))	0.0079	0.0172	0.4573
D(LTC (-3))	0.0198	0.0133	1.4851
D(LTP)	0.5041	0.2814	1.7916*
D(LTP(-1))	0.0629	0.3061	0.2056
D(LTP(-2))	0.2489	0.1879	1.3241
D(LTP(-3))	0.1004	0.3030	0.3314
D(LRTCI)	0.0018	0.0084	0.2160
D(LRTCI (-1))	-0.0030	0.0059	-0.5113
D(LRTCI (-2))	-0.0045	0.0079	-0.5672
D(LRTCI (-3))	0.0033	0.0050	0.6615

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

Then, the long run and short run coefficients of both models were estimated. The empirical findings of panel ARDL for RTCI model in China are reported in Table 4.4 while the outcomes for RHCI model are presented in Table 4.5. The findings of the RTCI model

demonstrate the significant impact of all variables on tourism demand in China, as illustrated in Table 4.4.

The outcome suggests that the income level of tourist originating countries (GDP) is positively affecting the tourist arrivals in China. The finding indicates that a 1% increase in tourists' income leads to a 0.20% rise in tourist flow to China. In addition, the GDP of China is positively associated with the tourist arrivals in China. The tourist arrivals in China increase by 0.16% when the income level in China improves by 1%. This is expected to generate positive spill-over effects on the tourism industry in China.

As expected, the transportation cost and tourism price exert a negative influence on the tourism demand in China, which is in line with the study of Liu et al. (2018) and Yang et al. (2010). This is because both variables are the cost of travelling for the tourists. The findings revealed that 1% increase in transportation cost and tourism price decreases the tourist arrivals in China by -0.08% and -0.44% in the RTCI model, respectively. In addition, the relative climatic condition has a positive impact on the tourism industry in China.

The finding in Table 4.4 also showed that climate condition is statistically and positively affecting the tourism demand in China, which is consistent with Li et al. (2018). The result shows that 1% increase in RTCI will attract 0.08% of tourist arrivals in China. This indicates that tourists tend to travel to China when the climatic condition in China is better than their home countries. Lastly, the error correction term (ECT) is negative, less than one, and statistically at 1% level at -0.17, signifying that the disequilibrium among the variables needs nearly six quarters to adjust back to equilibrium.

Table 4.5: Autoregressive Distributed Lag Model Coefficients for China:
Relative Holiday Climate Index (5, 4, 4, 4, 4, 4)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	0.1199	0.0317	3.7807***
LGDP	-0.5565	0.2549	-2.1832**
LGDPD	0.5496	0.2091	2.6281***
LTC	-0.3514	0.1093	-3.2145***
LTP	-1.0541	0.3154	-3.3424***
LRHCI	0.7000	0.2006	3.4898***
<i>Short Run Equation</i>			
ECT	-0.0536	0.0181	-2.9599***
D(LTA(-1))	0.2486	0.0514	4.8420***
D(LTA(-2))	0.2510	0.0643	3.9002***
D(LTA(-3))	0.1630	0.0475	3.4293***
D(LTA(-4))	-0.4325	0.0695	-6.2261***
D(LGDP)	-0.3292	0.3380	-0.9741
D(LGDP(-1))	-0.0771	0.1121	-0.6876
D(LGDP(-2))	-0.0260	0.1012	-0.2570
D(LGDP(-3))	0.1220	0.1270	0.9606
D(LGDPD)	0.0833	0.0566	1.4723
D(LGDPD(-1))	0.0293	0.0415	0.7066
D(LGDPD(-2))	-0.0006	0.0412	-0.0136
D(LGDPD(-3))	0.0467	0.0382	1.2198
D(LTC)	0.0181	0.0188	0.9623
D(LTC (-1))	0.0172	0.0326	0.5283
D(LTC (-2))	0.0120	0.0196	0.6118
D(LTC (-3))	0.0278	0.0106	2.6241***
D(LTP)	0.4979	0.2536	1.9631*
D(LTP(-1))	0.0017	0.2149	0.0080
D(LTP(-2))	0.1667	0.2132	0.7820
D(LTP(-3))	-0.0255	0.2230	-0.1142
D(LRHCI)	-0.0426	0.0205	-2.0779**
D(LRHCI (-1))	-0.0446	0.0214	-2.0841**
D(LRHCI (-2))	-0.0339	0.0169	-2.0032**
D(LRHCI (-3))	-0.0236	0.0092	-2.5788**

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

Table 4.5 presents that tourists' income is negative and significantly affecting tourism demand in China. This indicates that the tourists tend to visit other competitive countries when their purchasing power increased. The results showed that all parameters are statistically significant, and the relative climatic condition positively influences the tourist

arrivals in China. A 1% increase in RHCI attracts 0.70% of tourists to visit China. Another few selected variables, which are GDP of China, transportation cost, and tourism price are also significantly affecting the tourism demand in China.

In the short run, both transportation cost and relative holiday climate index are found to be significantly affecting the tourism demand in China. This can be attributed to the fact that travellers place a higher emphasis on minimizing travel distances, particularly during short travel periods such as public holidays. The ECT values for both models in China are significant, less than one, and negative. These indicate that a long run relationship exists in the models. Moreover, it reflects that, following an economic shock within the tourism industry, both models tend to gradually revert back to its long-term equilibrium.

The adoption of panel data offers several advantages, such as increased degree of freedom and higher speed of adjustment. On top of that, Togru (2018) opined that this technique can control for heterogeneity in measuring economic issues. According to the asymptotic theory, diagnostic tests for the normal distribution of residuals are not obligatory when the sample size is substantial (Wooldridge, 2015). Thus, the diagnostic tests are not necessary in this study.

Finally, the comparison of the TCI and HCI are outlined in Table 4.6 reported that the climate condition in months of May until September is most comfortable and rated as “excellent” and “ideal”. Although the TCI and HCI score in the winter season (November until March) are relatively lower than other months, China continues to observe a substantial influx of tourist arrivals. This is likely due to the tourists tend to seek for different climate experiences compared with their home country although the climate conditions are perceived less comfortable to them (Jacobsen 2001).

Table 4.6: Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in China, 2010-2020

Month	Tourist Arrivals	TCI		HCI	
	Million Person	Score	Rating	Score	Rating
January	9.88	58	Acceptable	71	Very Good
February	9.89	62	Good	72	Very Good
March	9.90	67	Good	77	Very Good
April	9.91	73	Very Good	82	Excellent
May	9.91	88	Excellent	92	Ideal
June	9.92	89	Excellent	94	Ideal
July	9.93	86	Excellent	94	Ideal
August	9.94	87	Excellent	94	Ideal
September	9.95	81	Excellent	88	Excellent
October	9.96	67	Good	81	Excellent
November	9.97	63	Good	73	Very Good
December	9.98	59	Acceptable	71	Very Good

4.3 Empirical Results for Thailand Tourism Industry

Table 4.7: Results of Panel Unit Root Tests for Thailand Tourism Demand Models

Variables	IPS		ADF	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept
<i>Level</i>				
LTA	0.0115(6)	-1.3051(3)*	16.9862(6)	102.909(3)***
LGDP	-0.8082(0)	-1.5733(1)*	24.2542(0)	30.9187(1)*
LGDPD	0.2673(0)	-5.2303(0)***	11.9975(0)	59.3681(0)***
LTC	0.0299(0)	-1.3494(0)*	13.2278(0)	22.8744(0)
LTP	3.3969(0)	0.4983(2)	18.8025(0)	15.3126(2)
LRTCI	-13.6767(1)***	-14.0890(2)***	134.900(1)***	467.731(2)***
LRHCI	-7.5734(2)***	-7.0385(2)***	123.295(2)***	126.660(2)***
<i>First Difference</i>				
ΔLTA	-6.6223(5)***	-6.2321(4)***	115.656(4)***	96.4358(4)***
ΔLGDP	-8.9283(0)***	-7.0295(1)***	127.960(0)***	115.553(1)***
ΔLGDPD	-16.2579(1)***	-14.9835(1)***	239.942(1)***	198.949(1)***
ΔLTC	-20.7233(0)***	-19.7590(0)***	308.619(0)***	273.750(0)***
ΔLTP	-16.9230(0)***	-17.3030(0)***	247.637(0)***	250.246(0)***
ΔLRTCI	-36.4581(2)***	-36.6557(2)***	276.354(2)***	1325.04(2)***
ΔLRHCI	-32.4340(2)***	-29.0572(2)***	270.127(2)***	1381.09(2)***

Notes: Asterisks ***, ** and * indicate statistically significant at 1%, 5% and 10% levels, respectively. The figures in brackets () refer to the lag length.

Similar to the estimation approach for China, a series of panel unit root tests were conducted to identify the level of stationary of the variables for Thailand before a long-run estimation was conducted. Table 4.7 presents the panel unit root tests' results for IPS and ADF-Fisher panel unit root tests. The findings showed that all variables in the tourism demand of Thailand are statistically significant at $I(0)$ or $I(1)$, and none are stationary at $I(2)$. The mixture of $I(0)$ and $I(1)$ variables means that the panel ARDL model is best suited for the model.

Table 4.8 and Table 4.9 present the results of Wald's cointegration for RTCI and RHCI models for Thailand. These F -statistic values are statistically significant at 1% level, which depict the presence of long-run equilibrium relationship in both models.

Table 4.8: Result of Wald's Cointegration Test for Thailand - RTCI

Test Statistic	Value	df	Probability
F -statistic	471.5702	(5, 155)	0.0000
Chi-square	2357.851	5	0.0000

Table 4.9: Result of Wald's Cointegration Test for Thailand - RHCI

Test Statistic	Value	df	Probability
F -statistic	4.3093	(5, 225)	0.0009
Chi-square	21.5464	5	0.0006

Table 4.10 and Table 4.11 depict the empirical findings for the RTCI and RHCI tourism models for Thailand, respectively. Both models show that climate condition has positively and significantly affected the tourism demand in Thailand. Both models showed that a 1% increase in relative climate condition has increased tourist arrivals by 0.22% and 1.50% in Thailand, respectively. It also means that tourists tend to travel to Thailand when the climate condition in their home country is less comfortable than Thailand in the long run.

Table 4.10: Panel Autoregressive Distributed Lag Model Coefficients for Thailand:
Relative Tourism Climate Index (3, 3, 3, 3, 3, 3)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	-10.7509	5.9824	-1.7971*
LGDP	0.1149	0.2240	0.5131
LGDPD	1.2230	0.1908	6.4086***
LTC	-0.1480	0.0431	-3.4353***
LTP	1.3081	0.4489	2.9144***
LRTCI	0.2197	0.0936	2.3476**
<i>Short Run Equation</i>			
ECT	-0.7078	0.4162	-1.7008*
D(LTA(-1))	-0.6194	0.4179	-1.4822
D(LTA(-2))	-2.2846	0.5104	-4.4757***
D(LGDP)	-0.7732	2.3586	-0.3278
D(LGDP(-1))	-1.3487	2.4666	-0.5468
D(LGDP(-2))	1.7977	2.4408	0.7365
D(LGDPD)	-0.6064	0.8313	-0.7295
D(LGDPD(-1))	-2.2278	1.0119	-2.2016**
D(LGDPD(-2))	5.4082	1.6168	3.3450***
D(LTC)	0.0547	0.2826	0.1936
D(LTC(-1))	-0.4823	0.3535	-1.3645
D(LTC(-2))	-0.8181	0.3944	-2.0741**
D(LTP)	-0.2825	6.2263	-0.0454
D(LTP(-1))	-7.8893	3.4494	-2.2871**
D(LTP(-2))	9.7449	5.8302	1.6714*
D(LRTCI)	-0.0738	0.1285	-0.5742
D(LRTCI(-1))	-0.2045	0.1322	-1.5467
D(LRTCI(-2))	0.1957	0.0735	2.6641***

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

In addition, the tourists' income is found to be insignificant in both models. The possible reason is that Thailand is an affordable tourism destination for most tourists (Ushakov et al., 2018). As reported in Table 4.10, tourism price is a significant factor affecting tourists' travel decision; a 1% increase in tourism price has led to 1.31% increase in tourist arrival in Thailand. This can be attributed to Thailand's strategic positioning as a destination that offers exceptional service quality at an affordable price point, as expounded by Rittichainuwat et al. (2020).

Table 4.11: Panel Autoregressive Distributed Lag Model Coefficients for Thailand:
Relative Holiday Climate Index (5, 3, 3, 3, 3, 3)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	5.6738	2.6178	2.1674**
LGDP	-3.5759	2.1760	-1.6433
LGDPD	2.3639	0.7671	3.0816***
LTC	-0.7217	0.3439	-2.0986**
LTP	-8.1405	5.1883	-1.5690
LRHCI	1.5018	0.9051	1.6593*
<i>Short Run Equation</i>			
ECT	-0.2054	0.0811	-2.5331**
D(LTA(-1))	-1.1674	0.3185	-3.6650***
D(LTA(-2))	-2.8952	0.5931	-4.8818***
D(LTA(-3))	-0.4716	0.4448	-1.0604
D(LTA(-4))	-0.1610	0.3943	-0.4083
D(LGDP)	-2.0628	1.9737	-1.0451
D(LGDP(-1))	0.5582	2.6443	0.2111
D(LGDP(-2))	2.5805	2.4167	1.0678
D(LGDPD)	0.9514	1.1539	0.8246
D(LGDPD(-1))	-1.7622	0.9264	-1.9022*
D(LGDPD(-2))	5.4316	1.7027	3.1900***
D(LTC)	-0.4001	0.3534	-1.1321
D(LTC(-1))	-0.3313	0.3030	-1.0936
D(LTC(-2))	-0.8473	0.4120	-2.0563**
D(LTP)	2.8574	5.1786	0.5518
D(LTP(-1))	-5.4695	6.7555	-0.8096
D(LTP(-2))	13.0962	6.7479	1.9408*
D(LRHCI)	-0.2454	0.1431	-1.7150*
D(LRHCI(-1))	-0.2795	0.1347	-2.0752**
D(LRHCI(-2))	0.3312	0.1393	2.3781**

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

The ECT results tabulated in Table 4.10 and Table 4.11 are less than one, negative and significant, signifying that both models tend to return to the long run equilibrium after a shock. The results showed that the RTCI model requires 1.41 quarters while RHCI requires 4.87 quarters to return to long run equilibrium after a shock.

Table 4.12: Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Thailand, 2010-2020

Month	Tourist Arrivals	TCI		HCI	
	Million Person	Score	Rating	Score	Rating
January	1.73	94	Ideal	96	Ideal
February	1.60	96	Ideal	98	Ideal
March	1.49	95	Ideal	95	Ideal
April	1.34	93	Ideal	91	Ideal
May	1.26	88	Excellent	88	Excellent
June	1.29	87	Excellent	88	Excellent
July	1.40	84	Excellent	87	Excellent
August	1.49	81	Excellent	86	Excellent
September	1.27	75	Very Good	83	Excellent
October	1.30	71	Very Good	84	Excellent
November	1.45	83	Excellent	93	Ideal
December	1.69	90	Ideal	96	Ideal

Table 4.12 offers a comparative analysis of the average monthly scores for both TCI and HCI with average tourist arrivals in Thailand from year 2010 to 2020. The results imply that the best months to visit Thailand are in January and December, but it is conducive to visit throughout the year.

4.4 Empirical Results for Japan Tourism Industry

The empirical results of the panel unit root tests for Japan are reported in Table 4.13. The findings report that all the selected parameters in the Japanese tourism demand model are either stationary at $I(0)$ or $I(1)$ level. In addition, the $I(2)$ variable is not detected in the models. Thus, the panel ARDL approach has been employed to examine the impacts of climate condition and selected key variables in influencing tourism demand in Japan.

Table 4.13: Results of Panel Unit Root Tests for Japan Tourism Demand Models

Variables	IPS		ADF	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept
<i>Level</i>				
LTA	-2.9304(0)***	3.6703(0)	38.9690(0)***	16.8582(0)
LGDP	-0.4442(4)	-1.3762(0)*	25.0075(0)	28.1695(0)
LGDPD	-0.8381(5)	3.5636(5)	16.4804(5)	1.4852(5)
LTC	0.0299(0)	-1.3494(0)*	13.2278(0)	22.8744(0)
LTP	-2.8069(0)***	-2.9431(0)***	50.5648(0)***	39.8408(0)***
LRTCI	-1.2129(1)	-3.6841(6)***	41.3784(1)***	65.2797(6)***
LRHCI	-4.2089(0)***	-8.2896(0)***	66.1396(0)***	317.319(0)***
<i>First Difference</i>				
Δ LTA	-17.2677(0)***	-13.8482(1)***	271.401(0)***	205.353(1)***
Δ LGDP	-8.9024(0)***	-7.0556(1)***	127.822(0)***	118.655(1)***
Δ LGDPD	-6.0419(4)***	-4.9238(4)***	73.1858(4)***	55.0439(4)***
Δ LTC	-20.7233(0)***	-19.7590(0)***	308.619(0)***	273.750(0)***
Δ LTP	-13.8737(0)***	-10.5832(0)***	202.341(0)***	152.033(0)***
Δ LRTCI	-31.9289(2)***	-27.2616(2)***	295.279(2)***	926.408(2)***
Δ LRHCI	-34.5905(2)***	-35.5959(2)***	355.252(2)***	1419.58(2)***

Notes: Asterisks *** and * indicate statistically significant at 1% and 10% levels, respectively. The figures in brackets () refer to the lag length.

Table 4.14: Result of Wald's Cointegration Test for Japan - RTCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	214.8045	(5, 145)	0.0000
Chi-square	1074.023	5	0.0000

The Wald's cointegration test results for Japan are reported in Table 4.14 and Table 4.15. The *F*-statistic values for both modes are significant at 1% level, signifying the existence of a long run relationship among the variables.

Table 4.15: Result of Wald's Cointegration Test for Japan - RHCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	424.5723	(5, 185)	0.0000
Chi-square	2122.861	5	0.0052

Table 4.16 and Table 4.17 present the panel ARDL estimation results for the Japanese tourism demand models. Both models found that climate is a significant variable that positively influenced the number of tourist arrivals in Japan; this is in line with the finding of Kubokawa et al. (2014). The outcome showed a 1% increase in RTCI has increased tourist arrivals by 1.73% (see Table 4.16). Consistently, a 1% increase in RHCI has increased tourist arrivals by 1.92% in Japan.

As expected, both tourists' income and GDP of Japan are positively associated with the tourist arrivals in Japan. A 1% increase in tourists' income increase tourists arrival by 0.58% and 0.32% in the RTCI and RHCI models, respectively (refer Table 4.16 and Table 4.17). The transportation cost is also a significant factor impacting tourism demand, whereby a 1% increase in transportation cost has led to 1.04% and 0.67% reduction in tourist arrivals in the RTCI and RHCI models, respectively. This implies that long-haul tourists are less likely to travel to Japan.

Besides that, tourism price has adversely influenced the tourism demand in Japan as reported in Table 4.16 and Table 4.17. This discernible trend underscores that tourists tend to exhibit a reluctance to travel to Japan when the prevailing tourism prices are comparatively higher than those in their respective home countries. Lastly, the ECT value for RTCI model is -0.67, indicating that the tourism industry in Japan needs 1.49 quarters to return to long run equilibrium after a shock. Meanwhile, the ECT value for RHCI is -0.51, signifying that the model needs two quarters to return to long run equilibrium.

Table 4.16: Panel Autoregressive Distributed Lag Model Coefficients for Japan:
Relative Tourism Climate Index (4, 5, 5, 5, 5, 5)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
LGDP	0.5802	0.0483	12.0241***
LGDPD	0.3852	0.1110	3.4702***
LTC	-1.0379	0.0818	-12.6826***
LTP	-2.8479	1.5631	-1.8219*
LRTCI	1.7289	0.4662	3.7089***
<i>Short Run Equation</i>			
ECT	-0.6728	0.3392	-1.9836**
D(LTA(-1))	0.4661	0.2995	1.5561
D(LTA(-2))	0.3970	0.3125	1.2705
D(LTA(-3))	-0.5186	0.5325	-0.9739
D(LGDP)	-4.7538	10.5253	-0.4517
D(LGDP(-1))	-4.3819	5.0761	-0.8632
D(LGDP(-2))	-1.6236	2.8213	-0.5755
D(LGDP(-3))	-0.3591	3.8249	-0.0939
D(LGDP(-4))	3.4311	5.3273	0.6441
D(LGDPD)	6.0139	2.1464	2.8019***
D(LGDPD(-1))	-0.2497	1.4763	-0.1691
D(LGDPD(-2))	-4.9567	3.7668	-1.3159
D(LGDPD(-3))	-1.4913	3.2326	-0.4613
D(LGDPD(-4))	-2.1087	2.3872	-0.8833
D(LTC)	0.6984	0.6623	1.0545
D(LTC(-1))	4.2184	0.9459	4.4598***
D(LTC(-2))	2.0736	1.1434	1.8136*
D(LTC(-3))	2.3613	0.5336	4.4248***
D(LTC(-4))	-0.7783	0.3795	-2.0506**
D(LTP)	-18.7313	12.6308	-1.4830
D(LTP(-1))	-7.3153	8.9736	-0.8152
D(LTP(-2))	5.3827	11.7871	0.4567
D(LTP(-3))	35.1535	15.6648	2.2441**
D(LTP(-4))	39.1460	12.8507	3.0462***
D(LRTCI01)	-2.6827	0.7349	-3.6502***
D(LRTCI(-1))	-3.4483	0.9750	-3.5369***
D(LRTCI(-2))	-3.5428	1.0451	-3.3900***
D(LRTCI(-3))	-2.4364	0.9506	-2.5631**
D(LRTCI(-4))	-0.5867	0.7285	-0.8054

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

Table 4.17: Panel Autoregressive Distributed Lag Model Coefficients for Japan:
Relative Holiday Climate Index (3, 1, 1, 1, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
LGDP	0.3154	0.0718	4.3925***
LGDPD	0.2801	0.1373	2.0393**
LTC	-0.6692	0.0696	-9.6162***
LTP	-3.4163	0.6889	-4.9594***
LRHCI	1.9235	0.2465	7.8046***
<i>Short Run Equation</i>			
ECT	-0.5115	0.2944	-1.7373**
D(LTA(-1))	0.4361	0.2502	1.7429**
D(LTA(-2))	0.3967	0.2781	1.4262
D(LTA(-3))	0.7834	0.5896	1.3287
D(LTA(-4))	1.0134	0.3912	2.5905**
D(LGDP)	-1.8597	9.4826	-0.1961
D(LGDP(-1))	12.3598	3.4279	3.6056***
D(LGDP(-2))	2.3290	4.2769	0.5446
D(LGDP(-3))	7.1263	4.7809	1.4906
D(LGDPD)	3.9454	1.1768	3.3527***
D(LGDPD(-1))	-2.0063	1.0831	-1.8524*
D(LGDPD(-2))	-5.3896	1.4243	-3.7841***
D(LGDPD(-3))	2.7145	1.2404	2.1884**
D(LTC)	0.3381	0.2510	1.3471
D(LTC(-1))	2.8530	0.3573	7.9839***
D(LTC(-2))	-0.4402	0.3004	-1.4652
D(LTC(-3))	0.5512	0.3933	1.4015
D(LTP)	-10.0775	12.6253	-0.7982
D(LTP(-1))	-3.5156	7.7586	-0.4531
D(LTP(-2))	18.4505	13.6575	1.3509
D(LTP(-3))	-0.3538	8.7439	-0.0405
D(LRHCI01)	-0.8218	0.6146	-1.3370
D(LRHCI(-1))	-0.8643	0.5308	-1.6281
D(LRHCI(-2))	-0.0902	0.3557	-0.2537
D(LRHCI(-3))	0.5497	0.3276	1.6779*

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

Lastly, the mean tourist arrivals, TCI and HCI are outlined in the Table 4.18. The tourism industry received a higher number of tourist arrivals in the months of January, February, March, April, November and December although the scores of the climate indexes are relatively lower in these few months. This can be attributed to tourists' inclination to explore diverse experiences during the winter holiday period in Japan. The blooming of

cherry blossoms in March and April has been attracting millions of visitors every year in spite of a less favourable climate. This interplay of unique cultural attractions and seasonal natural phenomena could be pivotal in driving Japan's tourism demand, even in the face of less optimal climatic conditions.

Table 4.18: Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Japan, 2010-2020

Month	Tourist Arrivals Million Person	TCI		HCI	
		Score	Rating	Score	Rating
January	1.29	61	Good	71	Very Good
February	1.13	61	Good	69	Good
March	1.07	63	Good	70	Good
April	1.17	68	Good	73	Very Good
May	1.10	80	Excellent	79	Very Good
June	1.13	83	Excellent	82	Excellent
July	1.27	93	Ideal	88	Excellent
August	1.15	96	Ideal	94	Ideal
September	1.03	86	Excellent	87	Excellent
October	1.14	69	Good	75	Very Good
November	1.07	62	Good	75	Very Good
December	1.13	65	Good	73	Very Good

4.5 Empirical Results for Malaysia Tourism Industry

The results of the panel unit root tests for Malaysia are reported in Table 4.19. Only $I(0)$ and $I(1)$ variables have been identified in the tourism demand models, which supported the use of panel ARDL technique for the dataset.

Table 4.19: Results of Panel Unit Root Tests for Malaysia Tourism Demand Models

Variables	IPS		ADF	
	Intercept	Trend &	Intercept	Trend &
		Intercept		Intercept
Level				
LTA	0.3678(0)	2.4316(0)	16.1406(0)	9.1477(0)
LGDP	-1.2546(0)	-2.1139(0)**	22.0023(0)	34.4555(0)**
LGDPD	-3.3915(1)***	-1.9000(2)**	41.1738(1)***	26.0040(2)
LTC	0.02988(0)	-1.3494(0)*	13.2278(0)	22.8744(0)
LTP	1.2213(1)	1.7728(1)	15.3095(1)	12.2882(1)
LRTCI	-1.2925(0)*	-1.8314(0)**	49.6858(0)***	59.7463(0)***
LRHCI	-5.4174(1)***	-13.4019(1)***	91.1502(1)***	258.301(1)***
First Difference				
ΔLTA	-24.2529(0)***	-24.9992(0)***	353.317(0)***	398.991(0)***
ΔLGDP	-10.3891(1)***	-8.6669(1)***	150.021(1)***	118.213(1)***
ΔLGDPD	-2.2684(0)**	-0.9889(0)	29.7319(0)*	20.3404(0)
ΔLTC	-20.7233(0)***	-19.7590(0)***	308.619(0)***	273.750(0)***
ΔLTP	-16.4020(0)***	-15.7752(0)***	237.729(0)***	212.199(0)***
ΔLRTCI	-31.9354(2)***	-22.8767(2)***	320.098(2)***	505.359(2)***
ΔLRHCI	-27.0895(2)***	-23.9341(2)***	368.030(2)***	473.634(2)***

Notes: Asterisks ***, ** and * indicate statistically significant at 1%, 5% and 10% levels, respectively. The figures in brackets () refer to the lag length.

Table 4.20: Result of Wald's Cointegration Test for Malaysia - RTCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	9.3072	(5, 175)	0.0000
Chi-square	46.5358	5	0.0000

Table 4.20 and Table 4.21 depict the results of the Wald's cointegration tests for RTCI and RHCI models, respectively. The *F*-statistic values are statistically significant at 1% level, indicating that the variables have a long run relationship.

Table 4.21: Result of Wald's Cointegration Test for Malaysia - RHCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	2942.918	(5, 3355)	0.0000
Chi-square	14714.59	5	0.0000

Table 4.22 and Table 4.23 display the long-run coefficients of the tourism demand models in Malaysia. In Table 4.22, the RTCI model showed that climate condition is the significant factor influencing tourism demand in Malaysia. However, this is not depicted in the RHCI model.

Table 4.22: Panel Autoregressive Distributed Lag Model Coefficients for Malaysia:
Relative Tourism Climate Index (5, 4, 4, 4, 4, 4)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	-7.4304	2.2524	-3.2989***
LGDP	0.9623	0.2792	3.4465***
LGDPD	0.7381	0.5331	1.3846
LTC	-0.0201	0.0971	-0.2073
LTP	1.6886	0.6432	2.6255***
LRTCI	1.5831	0.3603	4.3940***
<i>Short Run Equation</i>			
ECT	-0.9141	0.3408	-2.6823***
D(LTA(-1))	0.6728	0.3009	2.2363**
D(LTA(-2))	0.8151	0.3267	2.4947**
D(LTA(-3))	-0.0811	0.4064	-0.1995
D(LTA(-4))	1.1116	0.5371	2.0695**
D(LGDP)	5.3338	8.5383	0.6247
D(LGDP(-1))	-0.6205	3.3726	-0.1840
D(LGDP(-2))	-0.0986	2.5618	-0.0385
D(LGDP(-3))	-1.9898	2.9987	-0.6635
D(LGDPD)	-4.8440	9.4176	-0.5144
D(LGDPD(-1))	1.7216	3.5499	0.4850
D(LGDPD(-2))	-7.3555	2.7658	-2.6594***
D(LGDPD(-3))	5.3531	2.0801	2.5734**
D(LDIST01)	-0.0153	0.4243	-0.0361
D(LTC(-1))	2.9278	0.7283	4.0198***
D(LTC(-2))	1.0975	0.6217	1.7654*
D(LTC(-3))	0.6309	0.3131	2.0148**
D(LTP)	18.2109	14.1216	1.2896
D(LTP(-1))	7.4400	8.9830	0.8282
D(LTP(-2))	30.7576	8.4815	3.6264***
D(LTP(-3))	-7.8973	5.1377	-1.5371
D(LRTCI01)	-1.3701	0.7168	-1.9115*
D(LRTCI(-1))	-0.7651	0.8189	-0.9342
D(LRTCI(-2))	-0.4626	0.8255	-0.5604
D(LRTCI(-3))	-0.3142	0.6489	-0.4843

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

This pattern can potentially be explained by the fact that a substantial proportion of tourists originate from neighboring countries like Singapore, Indonesia, and Brunei. Given that these countries share similar climatic conditions with Malaysia, it appears that climate might not be the primary factor influencing their travel choices when it comes to visiting Malaysia. Instead, other factors such as cultural affinity, proximity, and economic considerations might exert a more prominent influence on their decision-making process.

In addition, the income level of tourists emerges as a significant factor shaping their inclination to visit Malaysia. This is evident across both models. In the RTCI model, a 1% increase in tourists' income level has led to 0.96% increase in tourist arrivals in Malaysia. Similarly, in the RHCI model, a 1% increase in income has led to 0.28% in tourist arrivals. These findings align with the research conducted by Puah et al. (2018), Wakimina et al. (2018), and Hanafiah et al. (2010).

Table 4.23: Panel Autoregressive Distributed Lag Model Coefficients for Malaysia:
Relative Holiday Climate Index (3, 1, 1, 1, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
LGDP	0.2800	0.0757	3.6974***
LGDPD	0.1888	0.2133	0.8853
LTC	0.5700	0.1949	2.9246***
LTP	2.2755	1.3554	1.6788*
LRHCI	0.5793	0.4550	1.2733
<i>Short Run Equation</i>			
ECT	-0.4713	0.1843	-2.5570**
D(LTA(-1))	0.2458	0.1532	1.6051
D(LTA(-2))	0.4308	0.1627	2.6473***
D(LGDP)	-2.2891	5.9876	-0.3823
D(LGDPD)	9.0782	2.8591	3.1752***
D(LTC)	-1.0133	0.2131	-4.7547***
D(LTP)	40.6617	10.3819	3.9166***
D(LRHCI)	-0.1377	0.2906	-0.4738

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

The influence of transportation cost is an interesting case. In the RTCI model, transportation cost is not a significant variable, but it is significant in the RHCI model. This divergence can be explained by the nature of Malaysia's tourism landscape. In the RTCI model, it might be attributed to the fact that over 60% of tourists are from neighbouring countries. For these short-haul tourists, the distance travelled might not be their primary concern. Conversely, the RHCI model's finding of transportation cost as a significant variable aligns with the notion that the convenience of travel plays a pivotal role in the tourism demand for Malaysia. This outcome lends further support to the idea that a considerable portion of Malaysia's tourist arrivals stem from neighbouring countries or short-haul destinations, solidifying Malaysia as their preferred vacation choice.

Table 4.24: Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Malaysia, 2010-2020

Month	Tourist Arrivals	TCI		HCI	
	Million Person	Score	Rating	Score	Rating
January	1.85	84	Excellent	89	Ideal
February	1.65	87	Excellent	92	Ideal
March	1.79	84	Excellent	90	Ideal
April	1.60	82	Excellent	88	Ideal
May	1.66	82	Excellent	88	Ideal
June	1.75	84	Excellent	91	Ideal
July	1.77	86	Excellent	91	Ideal
August	1.71	85	Excellent	92	Ideal
September	1.65	84	Excellent	91	Ideal
October	1.71	83	Excellent	89	Ideal
November	1.65	81	Excellent	86	Ideal
December	1.93	84	Excellent	89	Ideal

As reported in Table 4.24, the climate conditions in Malaysia are categorized as excellent and ideal. the climate conditions in Malaysia are categorized as excellent and ideal. The number of tourist arrivals in Malaysia has been quite consistent throughout the year,

which is in line with the TCI and HCI scores. This indicates that Malaysia is conducive to visit throughout the year.

4.6 Empirical Results for Hong Kong Tourism Industry

The panel unit root tests results shown in Table 4.25 revealed that the variables for the Hong Kong tourism demand model are a mixture of $I(0)$ and $I(1)$ variables. Therefore, this study utilized the panel ARDL approach to analyze the determinants of tourism demand in Hong Kong.

Table 4.25: Results of Panel Unit Root Tests for Hong Kong Tourism Demand Models

Variables	IPS		ADF	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept
<i>Level</i>				
LTA	8.1425(0)	7.3381(6)	1.8977(0)	7.7107(6)
LGDP	-0.5572(0)	-1.2145(0)	26.1427(0)	28.3919(0)
LGDPD	-2.2036(1)**	-15.0942(1)***	0.9040(4)	0.1911(1)
LTC	0.0299(0)	-1.3494(0)*	13.2278(0)	22.8744(0)
LTP	-2.7483(3)***	1.5916(0)	49.1138(3)***	26.0200(0)
LRTCI	-17.3214(1)***	-20.1413(1)***	227.479(1)***	505.078(1)***
LRHCI	-13.6469(1)***	-13.8889(1)***	192.864(1)***	239.676(1)***
<i>First Difference</i>				
Δ LTA	-13.5176(0)***	-14.3617(0)***	199.135(0)***	193.979(0)***
Δ LGDP	-10.0560(1)***	-8.2438(1)***	146.614(1)***	135.179(1)***
Δ LGDPD	1.4406(3)	1.3190(3)	184.207(1)***	289.111(2)***
Δ LTC	-20.7233(0)***	-19.7590(0)***	308.619(0)***	273.750(0)***
Δ LTP	-18.9754(0)***	-21.8108(2)***	276.468(0)***	344.123(2)***
Δ LRTCI	-31.3300(2)***	-28.1778(2)***	396.238(2)***	718.720(2)***
Δ LRHCI	-23.6452(2)***	-22.6355(2)***	329.149(2)***	448.534(2)***

Notes: Asterisks ***, ** and * indicate statistically significant at 1%, 5% and 10% levels, respectively. The figures in brackets () refer to the lag length.

The outcomes of Wald's Cointegration Test, as presented in Table 4.26 and Table 4.27 showed that the F -value of the Wald test for both RTCI and RHCI are significant at 1% level, indicating that the parameters are cointegrated in the long run.

Table 4.26: Result of Wald's Cointegration Test for Hong Kong - RTCI

Test Statistic	Value	df	Probability
F -statistic	8.5330	(5,245)	0.0000
Chi-square	42.6650	5	0.0000

Table 4.27: Result of Wald's Cointegration Test for Hong Kong - RHCI

Test Statistic	Value	df	Probability
F -statistic	5.4506	(5,245)	0.0001
Chi-square	27.2529	5	0.0001

The outcomes of the panel ARDL analysis for the RTCI model in Hong Kong are presented in Table 4.28. The findings proved that climate condition, transportation cost, and tourism price do not have a significant impact on tourism demand in Hong Kong. This is attributed to the fact that over 80% of tourists visiting Hong Kong are from China and Taiwan. Therefore, the climate condition, transportation cost and tourism price are not their main concerns when deciding to travel to Hong Kong.

Table 4.28: Panel Autoregressive Distributed Lag Model Coefficients for Hong Kong: Relative Tourism Climate Index (4, 3, 3, 3, 3, 3)

Variable	Coefficient	Std. Error	t -Statistic
<i>Long Run Equation</i>			
LGDP	1.3904	0.7380	1.8839*
LGDPD	-1.7655	0.9050	-1.9508*
LTC	-0.1654	0.2560	-0.6459
LTP	3.8719	3.3078	1.1705
LRTCI	-1.3960	0.9500	-1.4695
<i>Short Run Equation</i>			
ECT	-0.2432	0.0930	-2.6152***
D(LTA(-1))	0.4889	0.1380	3.5426***

Table 4.28 continued

D(LTA(-2))	-0.0297	0.1954	-0.1521
D(LTA(-3))	1.9769	0.5958	3.3182***
D(LGDP)	5.5184	2.4918	2.2146**
D(LGDP(-1))	-4.1002	1.9826	-2.0681**
D(LGDP(-2))	-3.7007	0.9031	-4.0979***
D(LGDPD)	9.6779	2.3253	4.1619***
D(LGDPD(-1))	4.8174	1.2320	3.9104***
D(LGDPD(-2))	9.2982	1.8973	4.9007***
D(LTC)	-0.4459	0.1518	-2.9366***
D(LTC(-1))	1.4487	0.2923	4.9571***
D(LTC(-2))	-0.1637	0.0980	-1.6692*
D(LTP)	-6.7774	3.2538	-2.0829**
D(LTP(-1))	11.6562	2.4219	4.8128***
D(LTP(-2))	1.0059	3.7383	0.2691
D(LRTCI)	0.3210	0.1582	2.0287**
D(LRTCI(-1))	-0.0755	0.1086	-0.6958
D(LRTCI(-2))	-0.0754	0.1390	-0.5421

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

In addition, both RTCI and RHCI models consistently showed that tourists' incomes are an important element in affecting their intention to travel to Hong Kong. Both models revealed a significant and positive relationship between income levels of tourists and tourism demand in Hong Kong. Tourists are more likely to visit Hong Kong when their income levels are higher. The number of tourist arrivals in Hong Kong is projected to increase by 1.39% and 2.50% with a 1% improvement in their income, as indicated in Table 4.28 and Table 4.29. Lastly, the ECT values for RTCI and RHCI models are significant, negative, and less than one. These indicate that the RTCI model needs 4.17 quarters while RHCI model requires 7.14 quarters to return to the long run equilibrium.

Table 4.29: Panel Autoregressive Distributed Lag Model Coefficients for Hong Kong:
Relative Holiday Climate Index (4, 3, 3, 3, 3, 3)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
LGDP	2.5002	0.6189	4.0400***
LGDPD	-2.2069	0.8988	-2.4554**
LTC	-0.7673	0.3737	-2.0531**
LTP	-6.0629	5.5965	-1.0833
LRHCI	2.1717	0.9211	2.3577**
<i>Short Run Equation</i>			
ECT	-0.1402	0.0580	-2.4158**
D(LTA(-1))	0.3549	0.0894	3.9701***
D(LTA(-2))	-0.0574	0.1443	-0.3976
D(LTA(-3))	1.7546	0.5402	3.2482***
D(LGDP)	5.3647	3.2287	1.6615*
D(LGDP(-1))	-2.1721	1.4937	-1.4542
D(LGDP(-2))	-3.2239	1.0180	-3.1667***
D(LGDPD)	7.8023	1.8201	4.2867***
D(LGDPD(-1))	5.5425	1.0669	5.1951***
D(LGDPD(-2))	7.7440	1.7194	4.5039***
D(LTC)	-0.3861	0.1571	-2.4568**
D(LTC(-1))	1.7071	0.3332	5.1228***
D(LTC(-2))	-0.1194	0.1314	-0.9085
D(LTP)	-3.0593	3.0535	-1.0019
D(LTP(-1))	15.6337	2.4073	6.4942***
D(LTP(-2))	0.6461	4.2513	0.1520
D(LRHCI)	-0.0943	0.1091	-0.8648
D(LRHCI(-1))	-0.5047	0.1312	-3.8469***
D(LRHCI(-2))	-0.2727	0.0713	-3.8230***

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

Table 4.30 tabulates the mean of tourist arrivals with the average monthly scores for the TCI and HCI in Hong Kong. Generally, the climate conditions are comfortable to the tourists because the scores for the indexes are above 70.

Table 4.30: Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Hong Kong, 2010-2020

Month	Tourist Arrivals	TCI		HCI	
	Million Person	Score	Rating	Score	Rating
January	4.38	64	Good	73	Very Good
February	3.58	64	Good	71	Very Good
March	3.48	69	Good	72	Very Good
April	3.60	74	Very Good	76	Very Good
May	3.54	79	Very Good	78	Very Good
June	3.34	79	Very Good	77	Very Good
July	3.95	80	Excellent	82	Excellent
August	4.10	77	Very Good	80	Excellent
September	3.32	79	Very Good	83	Excellent
October	3.74	83	Excellent	87	Excellent
November	3.57	77	Very Good	80	Very Good
December	4.03	67	Good	76	Very Good

4.7 Empirical Results for Macau Tourism Industry

The panel unit root tests results for the tourism demand model of Macau are outlined in Table 4.31. The results showed that the parameters are stationary at $I(0)$ and $I(1)$, thus the panel ARDL model is appropriate in this study.

Table 4.31: Results of Panel Unit Root Tests for Macau Tourism Demand Models

Variables	IPS		ADF	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept
<i>Level</i>				
LTA	-0.9048(2)	0.5682(2)	49.7430(2)***	48.5819(2)***
LGDP	0.2227(5)	0.1616(0)	18.5683(5)	20.8168(0)
LGDPD	13.5721(1)	17.5886(1)	0.0013(1)	0.0000(1)
LTC	0.0299(0)	-1.3494(0)*	13.2278(0)	22.8744(0)
LTP	-2.1453(0)**	5.9502(0)	35.8539(0)**	2.3495(0)
LRTCI	-13.7329(1)***	-15.7338(1)***	205.777(1)***	274.942(1)***
LRHCI	-7.7753(1)***	-8.3693(1)***	115.160(3)***	121.062(1)***
<i>First Difference</i>				
Δ LTA	-9.5166(1)***	-8.6901(1)***	146.550(1)***	122.368(1)***
Δ LGDP	-6.5695(1)***	-5.7670(4)***	94.7739(1)***	103.492(4)***
Δ LGDPD	32.9883(0)	34.2848(0)	0.0000(0)	0.0000(0)

Table 4.31 continued

ΔLTC	-20.7233(0)***	-19.7590(0)***	308.619(0)***	273.750(0)***
ΔLTP	-9.2568(0)***	-15.6731(0)***	144.129(0)***	227.611(0)***
$\Delta LRTCI$	-27.7355(2)***	-24.7092(2)***	375.628(2)***	499.954(2)***
$\Delta LRHCI$	-22.2831(2)***	-22.3653(2)***	321.353(2)***	414.953(2)***

Notes: Asterisks ***, ** and * indicate statistically significant at 1%, 5% and 10% levels, respectively. The figures in brackets () refer to the lag length.

Table 4.32: Result of Wald's Cointegration Test for Macau - RTCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	2.1030	(5, 365)	0.0644
Chi-square	10.5149	5	0.0619

Table 4.32 and Table 4.33 depict the Wald test results for RTCI and RHCI models, respectively. The *F*-statistic values of the models are significant at 1% level, indicating that the variables have a long run relationship.

Table 4.33: Result of Wald's Cointegration Test for Macau - RHCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	3.3300	(5, 365)	0.0059
Chi-square	16.6500	5	0.0052

Both Table 4.34 and Table 4.35 implied that climate condition, transportation cost and tourism price are not significant factors impacting the tourism demand in Macau in the RTCI and RHCI models, respectively. The possible reason is that majority tourists are from China, Hong Kong and Taiwan. Thus, the travel distance is not the main concern to them.

Table 4.34: Panel Autoregressive Distributed Lag Model Coefficients for Macau:
Relative Tourism Climate Index (1, 1, 1, 1, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	-4.2268	0.6804	-6.2119***
LGDP	0.6973	0.3146	2.2166**
LGDPD	-0.6435	0.2358	-2.7294***
LTC	0.0099	0.1161	0.0857
LTP	0.6661	0.8061	0.8264
LRTCI	-0.0916	0.1138	-0.8054
<i>Short Run Equation</i>			
ECT	-0.8409	0.0598	-14.0557***
D(LGDP)	-2.3652	1.4812	-1.5968
D(LGDPD)	-0.3895	0.7316	-0.5324
D(LTC)	0.8049	0.2809	2.8653**
D(LTP)	1.5119	2.6531	0.5698
D(LRTCI)	0.0214	0.1586	0.1347

Asterisks (***) and (**) indicate statistically significant at 1% and 5% levels, respectively.

Table 4.35: Panel Autoregressive Distributed Lag Model Coefficients for Macau:
Relative Holiday Climate Index (3, 1, 1, 1, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	-6.3141	0.8735	-7.2281***
LGDP	0.7739	0.2812	2.7521***
LGDPD	-0.6577	0.2048	-3.2110***
LTC	0.1059	0.0943	1.1225
LTP	0.9136	0.6642	1.3755
LRHCI	-0.1669	0.1266	-1.3181
<i>Short Run Equation</i>			
ECT	-0.8933	0.0662	-13.4989***
D(LGDP)	-2.5254	1.4958	-1.6884*
D(LGDPD)	-0.4198	0.8038	-0.5223
D(LTC)	0.7549	0.3194	2.3636**
D(LTP)	-0.5324	1.6214	-0.3283
D(LRHCI)	-0.1914	0.1439	-1.3299

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

In addition, they share similar climatic conditions. The ECT values of both models are significant, negative and less than one. The RTCI model needs 1.19 quarters to return to long term equilibrium while the RHCI model requires 1.12 quarters to achieve long term equilibrium.

Table 4.36: Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Macau, 2010-2020

Month	Tourist Arrivals	TCI		HCI	
	Million Person	Score	Rating	Score	Rating
January	2.49	64	Good	79	Very Good
February	2.30	63	Good	79	Very Good
March	2.20	68	Good	80	Excellent
April	2.29	73	Very Good	83	Excellent
May	2.20	80	Very Good	84	Excellent
June	2.08	78	Very Good	82	Excellent
July	2.43	78	Very Good	85	Excellent
August	2.64	77	Very Good	81	Excellent
September	2.12	79	Very Good	84	Excellent
October	2.38	81	Excellent	90	Excellent
November	2.36	78	Very Good	83	Excellent
December	2.48	66	Good	81	Excellent

The mean monthly scores for the TCI and HCI indexes as well as the average monthly tourist arrivals in Macau are presented in Table 4.36. The TCI implies majority months are categorized as Good and Very Good climatic conditions while most of the months are considered as Excellent in HCI for Macau. Both indexes show the different scores is likely due to different weightages of the sub-index among them.

4.8 Empirical Results for Vietnam Tourism Industry

Table 4.37 shows the IPS and ADF panel unit root test results for the parameters of the tourism demand model for Vietnam. The empirical outcomes revealed that the variables are stationary at $I(0)$ and $I(1)$ levels. This implies that the panel ARDL model is suitable for investing the factors that influence tourism demand in Vietnam.

Table 4.37: Results of Panel Unit Root Tests for Vietnam Tourism Demand Models

Variables	IPS		ADF	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept
<i>Level</i>				
LTA	-0.0516(0)	1.6514(0)	16.1918(0)	9.3925(0)
LGDP	-0.0910(1)	-0.8978(0)	21.9567(1)	25.0040(0)
LGDPD	-0.8653(1)	1.5169(1)	18.7263(1)	7.2582(1)
LTC	0.0299(0)	-1.3494(0)*	13.2278(0)	22.8744(0)
LTP	-12.0673(0)***	-5.9503(0)***	167.148(0)***	75.0192(0)***
LRTCI	-10.7011(1)***	-11.0716(1)***	162.038(1)***	173.174(1)***
LRHCI	-6.9001(0)***	-9.7923(0)***	100.321(0)***	146.101(0)***
<i>First Difference</i>				
Δ LTA	-17.5114(0)***	-17.5535(0)***	256.858(0)***	240.314(0)***
Δ LGDP	-7.2153(1)***	-5.6776(1)***	101.932(1)***	103.020(2)***
Δ LGDPD	-7.4915(0)***	-6.2096(0)***	92.2746(0)***	70.7046(0)***
Δ LTC	-20.7233(0)***	-19.7590(0)***	308.619(0)***	273.750(0)***
Δ LTP	-7.8472(0)***	-8.7414(0)***	99.7505(0)***	106.657(0)***
Δ LRTCI	-29.7834(2)***	-29.6466(2)***	382.029(2)***	774.142(2)***
Δ LRHCI	-29.3422(2)***	-29.2605(2)***	317.007(2)***	1034.54(2)***

Notes: Asterisks ***, ** and * indicate statistically significant at 1%, 5% and 10% levels, respectively. The figures in brackets () refer to the lag length.

Table 4.38: Result of Wald's Cointegration Test for Vietnam - RTCI

Test Statistic	Value	df	Probability
F-statistic	4.4986	(5, 295)	0.0006
Chi-square	22.4932	5	0.0004

Table 4.38 and Table 4.39 tabulated the Wald's tests results for the RTCI and RHCI models in Vietnam, respectively. In both tests, the resultant F-statistic values are significant at 1% level, indicating that the variables have a long run relationship.

Table 4.39: Result of Wald's Cointegration Test for Vietnam - RHCI

Test Statistic	Value	df	Probability
F-statistic	8.9002	(5, 195)	0.0000
Chi-square	44.5012	5	0.0000

Table 4.40 demonstrates the long run estimated results for the RTCI model for Vietnam while the results for the RHCI model are reported in Table 4.41. The findings of both models concluded that climatic condition is the significant variable affecting tourism demand in Vietnam, but the relationship is negative.

Table 4.40: Panel Autoregressive Distributed Lag Model Coefficients for Vietnam:
Relative Tourism Climate Index (3, 2, 2, 2, 2, 2)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	-18.4765	3.5449	-5.2121***
LGDP	4.7025	1.9108	2.4610**
LGDPD	-2.5703	2.1307	-1.2063
LTC	0.4225	0.2416	1.7488*
LTP	-1.7133	2.4737	-0.6926
LRTCI	-1.4064	0.7186	-1.9572*
<i>Short Run Equation</i>			
ECT	-0.4335	0.0748	-5.7939***
D(LTA(-1))	0.3772	0.1159	3.2557***
D(LTA(-2))	0.3923	0.1084	3.6201***
D(LGDP)	-5.4415	4.5524	-1.1953
D(LGDP(-1))	13.0644	6.0197	2.1703**
D(LGDPD)	-8.2842	4.5669	-1.8140*
D(LGDPD(-1))	-7.8704	2.7785	-2.8326***
D(LTC)	-0.3152	0.1488	-2.1191**
D(LTC(-1))	2.4582	0.2988	8.2268***
D(LTP)	-4.1443	3.4983	-1.1846
D(LTP(-1))	-17.1188	2.0906	-8.1884***
D(LRTCI)	0.6383	0.1294	4.9323***
D(LRTCI(-1))	0.2905	0.1608	1.8066*

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

As expected, tourists' income level is also a significant factor, which is line with the results reported by Puah et al. (2019). This means that tourists tend to travel to Vietnam when their income increases. Interestingly, while individual income seems to impact tourism demand, the expansion of Vietnam's GDP does not appear to be a significant variable in these models. This might be attributed to the Vietnamese government's allocation of

resources across various industries, or it could indicate a need for a cautious approach in terms of directing investments towards the tourism sector.

Table 4.41: Panel Autoregressive Distributed Lag Model Coefficients for Vietnam:
Relative Holiday Climate Index (3, 4, 4, 4, 4, 4)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	-29.4004	5.8806	-4.9996***
LGDP	2.7832	0.7499	3.7114***
LGDPD	-0.3353	0.8216	-0.4081
LTC	0.2254	0.1509	1.4938
LTP	-6.4192	2.2520	-2.8504***
LRHCI	-1.8283	0.6463	-2.8289***
<i>Short Run Equation</i>			
ECT	-0.7625	0.1738	-4.3875***
D(LTA(-1))	0.5678	0.2552	2.2245**
D(LTA(-2))	0.4298	0.2702	1.5902
D(LGDP)	-1.3556	6.5249	-0.2078
D(LGDP(-1))	14.0905	6.4507	2.1843**
D(LGDP(-2))	6.5015	5.3902	1.2062
D(LGDP(-3))	10.3148	6.3452	1.6256
D(LGDPD)	-12.1648	10.1366	-1.2001
D(LGDPD(-1))	-6.4670	6.0810	-1.0635
D(LGDPD(-2))	-13.1279	3.3801	-3.8839***
D(LGDPD(-3))	-12.5525	2.3795	-5.2754***
D(LTC)	-0.1518	0.2198	-0.6906
D(LTC(-1))	2.8080	0.5222	5.3776***
D(LTC(-2))	0.8129	0.4605	1.7651*
D(LTC(-3))	1.5521	0.2682	5.7865***
D(LTP)	1.0360	4.1245	0.2512
D(LTP(-1))	-20.1751	3.9391	-5.1217***
D(LTP(-2))	2.2896	5.1672	0.4431
D(LTP(-3))	-6.776	4.5521	-1.4886
D(LRHCI01)	1.4983	0.3411	4.3929***
D(LRHCI(-1))	1.1704	0.3389	3.4532***
D(LRHCI(-2))	0.9786	0.3155	3.1011***
D(LRHCI(-3))	0.1521	0.2982	0.5101

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

The climate condition is a significant factor in affecting tourism demand in Vietnam as reported in Table 4.40 and Table 4.41. Lastly, the ECT values of both RTCI and RHCI models are significant, less than one and negative. These indicate that the disequilibrium of both models will return to equilibrium in the long run.

Generally, the climate conditions in Vietnam are “Excellent” when measured using both TCI and HCI, as shown in Table 4.42. Despite this comfortable climate perception among the population, the long-run coefficients as presented in the RTCI and RHCI models appear to be negatively impacting tourism demand in Vietnam. As a result, it becomes evident that further investigation is warranted to delve into the underlying factors that influence tourism demand within Vietnam.

Table 4.42: Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Vietnam, 2010-2020

Month	Tourist Arrivals	TCI		HCI	
	Million Person	Score	Rating	Score	Rating
January	0.71	61	Good	73	Very Good
February	0.71	72	Very Good	77	Very Good
March	0.57	82	Excellent	82	Excellent
April	0.57	86	Excellent	87	Excellent
May	0.53	87	Excellent	87	Excellent
June	0.50	87	Excellent	87	Excellent
July	0.54	84	Excellent	88	Excellent
August	0.60	82	Excellent	86	Excellent
September	0.55	82	Excellent	88	Excellent
October	0.57	83	Excellent	87	Excellent
November	0.62	80	Excellent	87	Excellent
December	0.64	69	Good	77	Very Good

4.9 Empirical Results for India Tourism Industry

Table 4.43 reports the panel unit root tests results for India’s tourism demand model. The findings showed that the parameters are cointegrated at $I(0)$ or $I(1)$. Thus, the panel ARDL is applicable to the tourism demand model in India.

Table 4.43: Results of Panel Unit Root Tests for India Tourism Demand Models

Variables	IPS		ADF	
	Intercept	Trend &	Intercept	Trend &
		Intercept		Intercept
Level				
LTA	1.5268(3)	7.7443(2)	14.3081(3)	3.9901(2)
LGDP	-1.5936(3)*	-0.9335(4)	29.3625(3)*	26.2460(4)
LGDPD	6.8395(9)	-5.4611(1)***	0.1035(9)	63.5482(1)***
LTC	0.0299(0)	-1.3494(1)*	13.2278(0)	22.8744(0)
LTP	-1.4485(2)*	-1.4411(4)*	25.6751(2)	24.7927(4)
LRTCI	-5.6867(1)***	-9.5205(1)***	75.8004(3)***	145.038(2)***
LRHCI	-4.3578(0)***	-3.5205(0)***	64.6274(0)***	61.4280(0)***
First Difference				
ΔLTA	11.7772(2)	13.9677(2)	2.0259(5)***	4.8742(5)*
ΔLGDP	-6.7541(2)***	-5.1957(2)***	95.2377(2)***	96.9946(2)***
ΔLGDPD	-5.4532(0)***	-1.8827(8)**	64.5187(0)***	21.4739(8)
ΔLTC	-20.7233(0)***	-19.7590(0)***	308.619(0)***	273.750(0)***
ΔLTP	-7.8877(3)***	-10.0306(2)***	120.276(3)***	152.810(2)***
ΔLRTCI	-32.4036(2)***	-32.5089(2)***	312.627(2)***	1232.72(2)***
ΔLRHCI	-34.9316(2)***	-27.6335(2)***	322.587(2)***	1057.74(2)***

Notes: Asterisks ***, ** and * indicate statistically significant at 1%, 5% and 10% levels, respectively. The figures in brackets () refer to the lag length.

Table 4.44: Result of Wald's Cointegration Test for India - RTCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	76.8504	(5,225)	0.0000
Chi-square	384.2522	5	0.0000

Table 4.44 and Table 4.45 present the results for the Wald cointegration test. The findings showed that the *F*-statistics in both models are statistically significant at 1% level, signifying that all selected variables are cointegrated in the long run.

Table 4.45: Result of Wald's Cointegration Test for India - RHCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	83.6010	(5,235)	0.0000
Chi-square	418.0049	5	0.0000

Table 4.46: Panel Autoregressive Distributed Lag Model Coefficients for India:
Relative Tourism Climate Index (5, 3, 3, 3, 3, 3)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	-9.5332	5.1405	-1.8545*
LGDP	0.8441	0.0946	8.9243***
LGDPD	-0.0151	0.0636	-0.2370
LTC	-0.0173	0.0191	-0.9064
LTP	0.2658	0.1071	2.4816**
LRTCI	0.2133	0.0353	6.0427***
<i>Short Run Equation</i>			
ECT	-0.6946	0.3749	-1.8529*
D(LTA(-1))	0.6374	0.4179	1.5251
D(LTA(-2))	2.7614	0.8980	3.0752***
D(LTA(-3))	1.4509	0.4488	3.2325***
D(LTA(-4))	1.0359	0.5182	1.9989**
D(LGDP)	0.9153	1.3677	0.6692
D(LGDP(-1))	0.4859	0.8915	0.5451
D(LGDP(-2))	0.3734	0.5561	0.6714
D(LGDPD)	-2.5844	1.2725	-2.0310**
D(LGDPD(-1))	0.2295	0.8846	0.2594
D(LGDPD(-2))	0.5916	1.2959	0.4566
D(LTC)	0.1022	0.0866	1.1798
D(LTC(-1))	0.0556	0.1038	0.5355
D(LTC(-2))	0.1212	0.0951	1.2744
D(LTP)	1.4577	1.2612	1.1558
D(LTP(-1))	-0.3866	1.1268	-0.3431
D(LTP(-2))	0.9951	1.9475	0.5109
D(LRTCI)	-0.0809	0.1318	-0.6142
D(LRTCI(-1))	-0.0307	0.0501	-0.6122
D(LRTCI(-2))	-0.0001	0.0357	-0.0033

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

Table 4.46 and Table 4.47 report the Panel ARDL results for the RTCI and RHCI models for the tourism industry in India. The findings underscore that climate conditions significantly influence the tourism sector in India. Notably, the models indicate that when the climate conditions in India are comparatively more favourable than those in the tourists' home countries, it tends to attract a greater number of travellers to visit India. The findings also showed that a 1% change in climate attract 0.21% and 0.20% of tourist arrivals to India

in the RTCI and RHCI models, respectively. In addition, tourists' income is also a significant variable in affecting the tourism demand in India. In both RTCI and RHCI models, a 1% increase in income level has increased tourists arrival by 0.84% and 0.88%, respectively.

Another significant factor detected in affecting the tourism demand in India is tourism price. Both RTCI and RHCI models consistently showed that tourism prices are positively associated with the tourism demand in India. This suggests that tourists are still willing to purchase more goods and services in India, even when prices increase, due to their perceived value. Furthermore, the analysis reveals that the growth of India's GDP and transportation costs do not exert a significant influence on tourism demand in the country. This can be attributed to the fact that a considerable portion of tourists come from neighbouring countries such as Bangladesh. For these tourists, travel distance is not a significant deterrent in their decision to travel to India.

Table 4.47: Panel Autoregressive Distributed Lag Model Coefficients for India:
Relative Holiday Climate Index (4, 3, 3, 3, 3, 3)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	-7.6736	3.8641	-1.9858**
LGDP	0.8798	0.0747	11.7779***
LGDPD	-0.0382	0.0789	-0.4846
LTC	-0.0152	0.0218	-0.6948
LTP	0.4459	0.1400	3.1843***
LRHCI	0.2005	0.0421	4.7643***
<i>Short Run Equation</i>			
ECT	-0.5510	0.2774	-1.9864**
D(LTA(-1))	0.6314	0.4247	1.4868
D(LTA(-2))	2.6445	1.0187	2.5960**
D(LTA(-3))	1.1767	0.3034	3.8780***
D(LGDP)	0.9991	1.4214	0.7029
D(LGDP(-1))	0.3702	1.2946	0.2860
D(LGDP(-2))	0.5477	0.4061	1.3487
D(LGDPD)	-1.8991	0.7241	-2.6226***
D(LGDPD(-1))	0.4535	1.0181	0.4454

Table 4.47 continued

D(LGDPD(-2))	0.1740	0.4703	0.3700
D(LTC)	0.0763	0.0743	1.0280
D(LTC(-1))	0.0630	0.1053	0.5984
D(LTC(-2))	0.0825	0.0790	1.0443
D(LTP)	0.7430	1.0149	0.7321
D(LTP(-1))	-0.4603	1.1608	-0.3966
D(LTP(-2))	-0.5415	0.7855	-0.6894
D(LRHCI)	-0.0958	0.0637	-1.5032
D(LRHCI(-1))	0.0065	0.0504	0.1285
D(LRHCI(-2))	-0.0038	0.0532	-0.0715

Asterisks (***) and (**) indicate statistically significant at 1% and 5% levels, respectively.

Lastly, the ECT values for RTCI and RHCI models in India are significant, less than one, and negative. This means that, in the long run, tourism demand will return back to equilibrium after an economic shock. The disequilibrium in the RTCI model needs 1.45 quarters to recover while that in the RHCI model requires 1.81 quarters to recover.

Table 4.48: Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in India, 2010-2020

Month	Tourist Arrivals	TCI		HCI	
	Million Person	Score	Rating	Score	Rating
January	0.32	69	Good	82	Excellent
February	0.32	82	Excellent	88	Excellent
March	0.33	92	Ideal	96	Ideal
April	0.33	93	Ideal	90	Ideal
May	0.33	85	Excellent	86	Excellent
June	0.33	82	Excellent	84	Excellent
July	0.34	83	Excellent	84	Excellent
August	0.34	87	Excellent	86	Excellent
September	0.34	88	Excellent	91	Ideal
October	0.34	91	Ideal	97	Ideal
November	0.34	87	Excellent	94	Ideal
December	0.35	78	Very Good	85	Excellent

The climate condition in India is considered to be comfortable for tourists since most months have been rated as “Ideal” and “Excellent”, as shown in Table 4.48. This is in line with the number of tourist arrivals received by India that is consistent every month.

4.10 Empirical Results for South Korea Tourism Industry

Table 4.49 tabulates the panel unit root test results for the selected variables in the tourism demand model for South Korea. The findings revealed a mixture of $I(0)$ and $I(1)$ variables, and none of the variable is cointegrated at $I(2)$ level. This means that the panel ARDL technique is a suitable estimation technique.

Table 4.49: Results of Panel Unit Root Tests for South Korea Tourism Demand Models

Variables	IPS		ADF	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept
<i>Level</i>				
LTA	1.2382(0)	4.3344(0)	11.8588(0)	5.2910(0)
LGDP	0.0662(5)	0.3329(0)	19.9736(5)	20.6728(0)
LTP	-0.1817(4)	-2.3183(6)**	12.5612(4)	26.9250(6)
LTC	0.0299(0)	-1.3494(0)*	13.2278(0)	22.8744(0)
LTP	-0.2711(0)	-0.9384(0)	27.7883(0)	29.4339(0)*
LRTCI	-10.861(0)***	-11.922(0)***	171.612(0)***	181.043(0)***
LRHCI	-13.448(0)***	-12.158(0)***	188.042(0)***	219.933(0)***
<i>First Difference</i>				
Δ LTA	-18.6042(0)***	-17.7987(0)***	273.154(0)***	243.410(0)***
Δ LGDP	-6.6548(1)***	-5.8341(1)***	95.8981(2)***	104.344(2)***
Δ LTP	-6.4198(6)***	-5.4457(6)***	79.1516(6)***	61.4954(6)***
Δ LTC	-20.7233(0)***	-19.7590(0)***	308.619(0)***	273.750(0)***
Δ LTP	-16.5884(0)***	-17.1546(0)***	243.484(0)***	241.549(0)***
Δ LRTCI	-22.6431(2)***	-21.9639(2)***	314.273(2)***	448.022(2)***
Δ LRHCI	-24.7848(2)***	-23.7186(2)***	357.786(2)***	413.291(2)***

Notes: Asterisks ***, ** and * indicate statistically significant at 1%, 5% and 10% levels, respectively. The figures in brackets () refer to the lag length.

Table 4.50 and Table 4.51 report the results of the Wald’s cointegration test for South Korea. The findings reveal that all the variables have a long run relationship.

Table 4.50: Result of Wald's Cointegration Test for South Korea - RTCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	82.7168	(5, 235)	0.0000
Chi-square	413.5840	5	0.0000

Table 4.51: Result of Wald's Cointegration Test for South Korea - RHCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	2.8714	(5, 235)	0.0155
Chi-square	14.3572	5	0.0135

Table 4.52: Panel Autoregressive Distributed Lag Model Coefficients for South Korea: Relative Tourism Climate Index (4, 3, 3, 3, 3, 3)

Variable	Coefficient	Std. Error	<i>t</i> -Statistic
<i>Long Run Equation</i>			
C	-4.2618	2.7017	-1.5774
LGDP	-0.4690	0.2630	-1.7831*
LGDPD	0.1276	0.3509	0.3637
LTC	0.7559	0.1800	4.2003***
LTP	-2.2167	0.3395	-6.5296***
LRTCI	0.2667	0.1698	1.5709
<i>Short Run Equation</i>			
ECT	-0.6406	0.3600	-1.7796*
D(LTA(-1))	0.6276	0.3161	1.9854**
D(LTA(-2))	0.4742	0.3330	1.4240
D(LTA(-3))	0.5932	0.3422	1.7333*
D(LGDP)	-2.4472	5.9878	-0.4087
D(LGDP(-1))	3.9808	1.8379	2.1659**
D(LGDP(-2))	1.0632	3.0289	0.3510
D(LGDPD)	-0.5328	1.1355	-0.4692
D(LGDPD(-1))	-2.3107	0.6781	-3.4078***
D(LGDPD(-2))	-1.2787	1.5777	-0.8105
D(LTC)	-0.2980	0.2758	-1.0805
D(LTC(-1))	1.5492	0.3754	4.1269***
D(LTC(-2))	-0.1830	0.1369	-1.3370
D(LTP)	-1.1822	9.6535	-0.1225
D(LTP(-1))	0.3144	5.1733	0.0608
D(LTP(-2))	-6.8458	5.7707	-1.1863
D(LRTCI)	-0.3077	0.0980	-3.1413***
D(LRTCI(-1))	-0.1174	0.1440	-0.8148
D(LRTCI(-2))	-0.1453	0.1009	-1.4391

Asterisks (***), (**), and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

Table 4.52 tabulates the Panel ARDL results for RTCI model for South Korea. The model showed that climate condition and GDP are not significant variables in affecting the tourism demand in South Korea. The significant variable is tourists' income, but when tourists' income increased by 1%, number of tourist arrivals has reduced by 0.47% as reported in Table 4.52. This trend could be attributed to the inclination of tourists to explore other countries when their purchasing power increases.

Table 4.53: Panel Autoregressive Distributed Lag Model Coefficients for South Korea:
Relative Holiday Climate Index (4, 3, 3, 3, 3, 3)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	7.9332	4.0417	1.9629*
LGDP	0.9366	0.7377	1.2697
LGDPD	-4.4425	2.1775	-2.0402**
LTC	-0.3851	0.2337	-1.6480
LTP	-3.1260	1.8532	-1.6868*
LRHCI	4.0374	1.7637	0.0230**
<i>Short Run Equation</i>			
ECT	-0.1564	0.0759	-2.0591**
D(LTA(-1))	0.0761	0.1149	0.6621
D(LTA(-2))	0.0706	0.0859	0.8223
D(LTA(-3))	0.2232	0.3047	0.7324
D(LGDP)	-2.9349	6.3508	-0.4621
D(LGDP(-1))	2.9600	2.2552	1.3125
D(LGDP(-2))	2.9157	2.7702	1.0525
D(LGDPD)	0.4720	0.9312	0.5069
D(LGDPD(-1))	-1.3143	0.9979	-1.3171
D(LGDPD(-2))	-0.8118	1.5413	-0.5267
D(LTC)	0.2586	0.2235	1.1572
D(LTC(-1))	1.8125	0.4055	4.4700***
D(LTC(-2))	0.2805	0.2164	1.2965
D(LTP)	-6.1507	9.3855	-0.6553
D(LTP(-1))	-1.7405	5.4763	-0.3178
D(LTP(-2))	-8.9780	5.8784	-1.5273
D(LRHCI)	-0.3132	0.1774	-1.7655*
D(LRHCI(-1))	-0.1706	0.2234	-0.7633
D(LRHCI(-2))	-0.0765	0.1329	-0.5761

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

Other than tourists' income level, transportation cost and tourism price have also affected tourism demand in South Korea significantly. Interestingly, the transportation cost is positively associated with tourism demand, which contradicts findings from many other studies. The possible reason is that a substantial portion of tourist arrivals in South Korea originates from neighbouring countries like China, Japan, and Taiwan. As such, the relatively shorter travel distance has become a pivotal factor influencing travellers' decisions to visit South Korea even when transportation cost is high. Table 4.52 tabulates the Panel ARDL results for RTCI model for South Korea. The model showed that climate condition and GDP are not significant variables in affecting the tourism demand in South Korea. The significant variable is tourists' income, but when tourists' income increased by 1%, number of tourist arrivals has reduced by 0.47% as reported in Table 4.52. This trend could be attributed to the inclination of tourists to explore other countries when their purchasing power increases.

Table 4.53 shows that the relative climate condition is a significant variable in affecting tourism demand in South Korea. The finding indicates that tourists tend to visit South Korea when its climate is better than back at home. Lastly, the ECT values for both RTCI and RHCI models are significant, negative, and less than one. This signals that the models will return to long run equilibrium after an economic shock.

The empirical findings in Table 4.54. showed that most tourists are satisfied with the weather in South Korea, with most months rated as "Good" and "Very Good". The TCI scores are comparatively lower than HCI, lying within the region of "Acceptable" when the HCI scores indicated "Good" and "Very Good" in the months of January, February, November and December. This is mainly due to the different weightages of both indexes.

Table 4.54: Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in South Korea, 2010-2020

Month	Tourist Arrivals	TCI		HCI	
	Million Person	Score	Rating	Score	Rating
January	0.76	52	Acceptable	68	Good
February	0.78	58	Acceptable	68	Good
March	0.86	64	Good	71	Very Good
April	0.86	65	Good	75	Very Good
May	0.83	74	Very Good	80	Excellent
June	0.81	83	Excellent	85	Excellent
July	0.86	72	Very Good	77	Very Good
August	0.96	79	Very Good	84	Excellent
September	0.88	74	Very Good	81	Excellent
October	0.94	63	Good	78	Very Good
November	0.81	56	Acceptable	71	Very Good
December	0.80	54	Acceptable	67	Good

4.11 Empirical Results for Singapore Tourism Industry

Table 4.55: Results of Panel Unit Root Tests for Singapore Tourism Demand Models

Variables	IPS		ADF	
	Intercept	Trend & Intercept	Intercept	Trend & Intercept
<i>Level</i>				
LTA	-1.6656(0)**	-0.3267(0)	28.4385(6)*	16.2525(0)
LGDP	-1.0758(0)	-1.6748(1)**	26.3841(0)	27.4237(1)
LGDPD	-3.9957(0)***	-4.9916(0)***	47.1263(0)***	56.7032(0)***
LTC	0.0299(0)	-1.3494(0)*	13.2278(0)	22.8744(0)
LTP	3.5216(6)	-2.2666(6)**	17.7793(6)	35.8959(0)**
LRTCI	-10.0535(0)***	-17.0513(0)***	142.275(0)***	327.234(0)***
LRHCI	-6.5641(0)***	-15.6449(0)***	138.967(0)***	265.361(0)***
<i>First Difference</i>				
Δ LTA	-21.8186(0)***	-15.2935(0)***	324.055(0)***	247.205(0)***
Δ LGDP	-7.6293(1)***	-6.3098(4)***	102.962(2)***	106.150(4)***
Δ LGDPD	-21.1617(0)***	-11.7199(1)***	315.286(0)***	148.913(1)***
Δ LTC	-20.7233(0)***	-19.7590(0)***	308.619(0)***	273.750(0)***
Δ LTP	-15.3319(0)***	-13.2159(0)***	226.938(0)***	195.517(0)***
Δ LRTCI	-29.3358(2)***	-28.9952(2)***	348.637(2)***	827.382(2)***
Δ LRHCI	-19.2978(1)***	-13.5018(3)***	293.692(1)***	202.982(3)***

Notes: Asterisks ***, ** and * indicate statistically significant at 1%, 5% and 10% levels, respectively. The figures in brackets () refer to the lag length.

Table 4.55 an overview of the outcomes from the panel unit root tests conducted on the parameters of the tourism demand model for Singapore. A mixture of $I(0)$ and $I(1)$ parameters have been detected in the tourism demand model of Singapore. Therefore, this study employed the panel ARDL approach to examine the factors affecting tourism demand in Singapore.

Table 4.56 and Table 4.57 tabulate the Wald's cointegration test results for RTCI and RHCI model in Singapore, respectively. The findings showed that the variables have a long run relationship in both models.

Table 4.56: Result of Wald's Cointegration Test for Singapore - RTCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	9.3171	(5, 325)	0.0000
Chi-square	46.5855	5	0.0000

Table 4.57: Result of Wald's Cointegration Test for Singapore - RHCI

Test Statistic	Value	df	Probability
<i>F</i> -statistic	2.9667	(5, 285)	0.0125
Chi-square	14.8332	5	0.0111

The estimation results of the RTCI and RHCI panel ARDL models are reported in Table 4.58 and Table 4.59. The results of the RTCI model found that all variables, except for transportation cost, have significantly affected the tourism demand in Singapore. As expected, the income levels of the tourists as well as the GDP of Singapore have significantly and positively affected tourism demand in Singapore. This suggests that, as tourists' income increases, the tourism industry in Singapore is likely to experience a rise in tourist arrivals.

Table 4.58: Panel Autoregressive Distributed Lag Model Coefficients for Singapore:
Relative Tourism Climate Index (5, 1, 1, 1, 1, 1)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	-41.4718	10.6458	-3.8956***
LGDP	0.7039	0.3510	2.0053**
LGDPD	2.8873	0.7729	3.7358***
LTC	-0.0041	0.0864	-0.0475
LTP	6.1822	1.7564	3.5198***
LRTCI	-0.3090	0.1568	-1.9709**
<i>Short Run Equation</i>			
ECT	-0.9416	0.2410	-3.9068***
D(LTA(-1))	0.9538	0.1993	4.7864***
D(LTA(-2))	0.9819	0.2387	4.1142***
D(LTA(-3))	-0.4350	0.6644	-0.6547
D(LTA(-4))	0.7137	0.6625	1.0773
D(LGDP)	0.9558	2.0813	0.4592
D(LGDPD)	18.1600	1.5304	11.8665***
D(LTC)	-0.6704	0.1386	-4.8373
D(LTP)	0.4875	5.2524	0.0928
D(LRTCI)	0.1271	0.1067	1.1913***

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

In fact, a 1% increase in tourists' income has increased tourist arrivals by 0.70% as shown in Table 4.58. Furthermore, the growth of Singapore's GDP is shown to have a positive impact on its tourism demand. This can be attributed to the government's increased capacity to invest in tourism development, which positively affects the industry, as evidenced in both the RTCI and RHCI models for Singapore (see Table 4.58 and Table 4.59).

However, both Table 4.58 and Table 4.59 show that the transportation cost is not a significant variable in affecting the tourism industry in Singapore. also showed that transportation cost is not a significant variable in affecting the tourism industry in Singapore. This is due to the majority of tourists originating from neighbouring countries such as Malaysia, Indonesia, and the Philippines, where travel distance is not their primary in choosing to visit Singapore.

Table 4.59: Panel Autoregressive Distributed Lag Model Coefficients for Singapore:
Relative Holiday Climate Index (4, 2, 2, 2, 2)

Variable	Coefficient	Std. Error	t-Statistic
<i>Long Run Equation</i>			
C	-31.5131	6.9362	-4.5433***
LGDP	0.6544	0.5768	1.1345
LGDPD	5.0691	1.9929	2.5435***
LTC	-0.2339	0.1876	-1.2470
LTP	14.5681	6.4393	2.2624**
LRHCI	0.3196	0.4125	0.7749
<i>Short Run Equation</i>			
ECT	-0.4870	0.1078	-4.5180***
D(LTA(-1))	0.4058	0.1138	3.5647***
D(LTA(-2))	0.5979	0.1112	5.3750***
D(LTA(-3))	-0.9330	0.6165	-1.5134
D(LGDP)	1.1675	2.9710	0.3930
D(LGDP(-1))	0.6493	2.6903	0.2413
D(LGDPD)	15.0990	1.4183	10.6459***
D(LGDPD(-1))	3.8826	1.0786	3.5997***
D(LTC)	-0.3315	0.1434	-2.3119**
D(LTC(-1))	0.1987	0.1635	1.2155
D(LTP)	-3.7512	3.8684	-0.9697
D(LTP(-1))	2.9345	4.7189	0.6219
D(LRHCI)	-0.5527	0.1477	-3.7420***
D(LRHCI(-1))	-0.7905	0.1706	-4.6343***

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively.

Climate is an important variable in the RTCI model, but not the RHCI model. This has been attributed to the different structural design of the two indexes (Rutty et al., 2020; Scott et al., 2016). In the short term, the relative climatic impacts are significantly influencing the tourism demand in Singapore as presented in Table 4.58 and Table 4.59. Lastly, the ECT values for both models are statistically significant at 1% level, less than one, and with a negative sign. This means that both models will return to long term equilibrium after an economic shock. Specifically, the RTCI model needs 1.06 quarters while the RHCI model requires nearly two quarters to return to the said equilibrium.

Table 4.60 provides a comparison between the average monthly scores of the TCI and HCI with the mean tourist arrivals in Singapore. The findings showed that the climate conditions in Singapore are very comfortable with a minimum score of 72 (Very Good) based on TCI and 81 (Excellent) based on HCI. Throughout the year, Singapore consistently received high volume of tourists, ranging from 0.80 million to 1 million. The HCI scores even showed that only August has been rated as “Ideal” while the rest of the year has been rated as “Excellent”.

Table 4.60: Comparison between the Average Monthly Scores for the TCI and HCI with Mean Tourist Arrivals in Singapore, 2010-2020

Month	Tourist Arrivals Million Person	TCI		HCI	
		Score	Rating	Score	Rating
January	1.00	77	Very Good	83	Excellent
February	0.87	83	Excellent	89	Excellent
March	0.89	80	Excellent	89	Excellent
April	0.85	74	Very Good	84	Excellent
May	0.87	79	Very Good	87	Excellent
June	0.87	83	Excellent	88	Excellent
July	0.97	85	Excellent	89	Excellent
August	0.93	84	Excellent	91	Ideal
September	0.80	83	Excellent	89	Excellent
October	0.84	79	Very Good	88	Excellent
November	0.84	72	Very Good	82	Excellent
December	0.98	73	Very Good	81	Excellent

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The current chapter serves to encapsulate and draw conclusions from the comprehensive study conducted. Aside from the general conclusions, this chapter also presents some policy recommendations, limitations of the study, and lastly the room for further studies based on the identified limitations.

5.2 Conclusion

This study has undertaken an extensive investigation into the ramifications of climate change on the tourism demand across ten prominent nations in the Asia Pacific region. These countries are China, Thailand, Japan, Hong Kong, Malaysia, Macau, India, Vietnam, South Korea, and Singapore. In this study, the gravity model has been chosen to examine the factors affecting the tourism demand in the Asia Pacific region. The core gravity model consists of the income levels of the origin countries; income level in the destination country; and geographical distance between the capitals in the origin and destination countries. In order to gather more insightful tourism information for the aforementioned ten countries, the additional variables included are relative tourism climate index (RTCI), relative holiday climate index (RHCI), and tourism price.

The climatic variables, denoted by RTCI and RHCI, are meticulously derived from the Tourism Climate Index (TCI) and Holiday Climate Index (HCI) established by Scott et al. (2016) and Mieczkowski (1985), respectively. These indices amalgamate crucial meteorological components - temperature, humidity, precipitation, wind speed, and cloud

cover - into a single quantifiable metric reflecting the climatic conditions in the respective tourist destinations. The TCI is an integration of five sub-indexes, which are daytime comfort index (CID), daily comfort index (CIA), precipitation (P), sunshine (S), and wind speed (W). Both CID and CIA were computed to reflect the human thermal comfort level.

In addition, each index is assigned with their own weightage. The highest weightage has been assigned to CID (40%), followed by duration of sunshine (20%), precipitation (20%), and CIA (10%). However, TCI has been criticized due its over emphasis on thermal comfort (CID + CIA). Scott et al. (2016) designed the HCI to overcome the limitation of TCI. The HCI includes all climatic components, which are thermal comfort (TC), aesthetic (A), physical (P), and wind (W). The thermal comfort is weighted 40% and it is computed based on existing literature collected over the past decade.

Both indexes have been assigned with a maximum score of 100 to reflect an ideal climatic condition (refer to Table 3.2). The minimum score for the TCI is -30, which indicates an impossible climatic condition. In HCI, the worst condition is a “dangerous climate”, not “impossible” because they assumed some tourists are seek for extreme weather such as high wind for wind surfing, so they ranked this type of climatic condition as dangerous.

Capturing monthly climatic data from 2010 to 2020, the augmented gravity model is employed to construct tourism demand models for these nations. The model incorporated parameters such as GDP of origin and destination countries, transportation cost, tourism price, and climatic variables. However, since monthly data is not available for all macroeconomic variables, the model had to use quarterly data. Before any estimation was done, unit root tests were administered to ascertain the stationarity levels of variables. The

findings demonstrated a mix of $I(0)$ and $I(1)$ variables, thus warranting the panel PMG/ARDL approach. Subsequently, Wald cointegration tests ascertained the existence of long-term relationships in all models.

In China, all the selected determinants are significantly influencing its tourism demand. The empirical results evidenced the tourists' income (LGDP) is one of the key factors affecting their decision to visit China. A positive relationship has been detected between the income levels of the tourists and China tourism demand in RTCI model, indicating the tourists tend to travel to China when their purchasing power is higher. Besides that, the economic condition (LGDPD) in China also plays a crucial role in the tourism industry. The expansion of China's economy will stimulate the tourism demand. This is because the country can invest more capital on tourism industry such as upgrading the tourism infrastructure, establish new tourism products and well maintained on the tourism products to enhance their better travel experience during their visit in China. Furthermore, China boasts rich historical and cultural attractions, allowing it to offer a diverse range of tourism products catering to the varied interests and preferences of tourists.

As expected, both transportation cost and tourism price adversely impacting the tourism demand in China. The tourists' utility to visit will be reduced when their total traveling cost is increased which is consistent with consumer theory. Lastly, the climate conditions in China positively affects tourism demand in China as evidenced in both RTCI and RHCI models. The tourists tend to travel to China when the climate conditions in China is better than their home country. Thus, the climate conditions are the pull factor to attract more tourists visit to China. To capitalize on the diverse climate conditions in China and attract tourists throughout the year, various tourism policies are necessary. Policy makers

can introduce different tourism packages tailored to each season, aiming to attract tourists and offer them memorable experiences year-round.

Interestingly, the income levels of tourists do not emerge as a significant factor impacting tourism demand in Thailand. This is likely due to Thailand being an affordable destination for most tourists. A contradictory finding has been identified in Thailand's RTCI model regarding tourism prices. The results indicate that tourists are more inclined to visit Thailand when the tourism price is increased. A strategic tourism plan positioning Thailand as a destination that offers exceptional service quality at an affordable value is crucial. Tourists should feel that the price paid for their trip is worthwhile. Continuous tourism planning is imperative for sustainable long-term growth. Thailand's expanding economy and favourable climate further contribute significantly to influencing tourism demand. Lastly, transportation costs are found to adversely impact the tourism industry in Thailand. Therefore, collaboration with more airline operators to offer additional international direct flights to Thailand could reduce tourists' travel costs and time.

The empirical outcomes from the tourism demand models for Japan suggest that both tourists' income and Japan's economic performance are significant variables positively influencing the tourism industry's demand in Japan. Consistent with numerous studies, both transportation costs and tourism prices are significant factors with adverse effects on tourism demand in Japan. Lastly, tourists show a preference for visiting Japan when they perceive the climate conditions to be relatively better than those in their home country. The promotion and marketing strategies devised by Japan are crucial for ensuring the sustainable growth of its tourism industry. Government bodies and stakeholders must consistently market Japan's diverse attractions, which encompass cultural heritage sites, natural landscapes, culinary

experiences, and traditional festivals. This necessitates comprehensive marketing campaigns and roadshows conducted both domestically and internationally. Given the adverse influence of transportation costs on Japan's tourism industry, there is a pressing need to enhance infrastructure development. Continuous investment in infrastructure is vital for improving the overall tourism experience. This entails upgrading transportation networks, including airports, railways, and highways, as well as developing tourist facilities, accommodation options, and tourist information centres.

In Malaysia, the income levels of tourists show a positive association with tourism demand. Surprisingly, the country's economic expansion is not identified as a significant factor influencing its tourism demand. In contrast, the transportation cost is found to have a positive influence on the number of international tourist arrivals in the RTCI model. This is attributed to the fact that a significant portion of tourists comes from neighbouring countries, such as Singapore, Brunei, and Indonesia, making Malaysia a preferred short-haul tourism destination for them. Moreover, tourism price is a significant variable positively influencing the number of tourist arrivals in Malaysia. Tourists continue to express a willingness to visit Malaysia even with an increase in tourism prices, indicating that Malaysia can offer quality tourism experiences at a reasonable cost. The climate condition in Malaysia is identified as a significant variable impacting tourism demand in the RTCI model, while it is insignificant in the RHCI model. This discrepancy is likely due to the different weightage assigned to each index, influencing the research outcomes.

To ensure the sustainable growth and competitiveness of the industry, the government should prioritize the development of cost-effective infrastructure supporting tourism. This includes enhancing transportation networks, expanding accommodation

options, and improving tourist facilities. Through strategic investments in efficient infrastructure, Malaysia can offer competitive pricing while delivering comfortable and convenient experiences for travellers. Furthermore, collaborating with key industry players such as airline companies, travel agencies, and tour operators to offer competitive pricing packages and promotions for travellers is essential. Through cooperation, stakeholders in the tourism industry can leverage economies of scale and negotiate competitive rates that benefit both industry players and tourists.

The income levels of the tourists and the economic condition in Hong Kong are identified as the significant variables affecting tourism demand in Hong Kong. Additionally, the transportation cost is detected as negatively influencing tourism demand in Hong Kong, which is in line with most of the existing studies. Furthermore, the findings reveal that the tourism price is not a considerable determinant when deciding on their trip to Hong Kong. This is due to the fact that the majority of the tourists are derived from its neighbouring countries, which are China and Taiwan. The climate condition is a significant variable affecting tourists' travel decisions to Hong Kong in the RHCI model, while it is insignificant in the RTCI model. This is mainly due to the different weightages of the sub-indexes in both indexes. Hong Kong needs to continuously promote itself as a tourist destination through marketing campaigns and promotional activities. The industry players and related agencies have to keep promote and showcase the city's attractions, events, and cultural offerings to domestic and international audiences through various channels, including digital platforms, travel fairs, and media partnerships.

The income levels in both origin and destination countries are the key factors affecting the tourism demand in Macau. Other selected determinants, which are transportation cost, tourism price, and climate conditions are not the major variables impacting the demand of tourism industry in Macau. The main reason is the main tourists visiting to Macau are from neighbouring destinations such as China, Hong Kong, and Taiwan. Macau is under the Portuguese colony until 1990s and it is the only location where gambling is legalized in China. Therefore, majority of the tourists visit to Macau for the gambling activities and to experience the unique culture with a mix of East Asia and Western Europe. Both income levels of origin and destination countries are identified as crucial factors influencing tourism demand in Hong Kong. Therefore, close collaboration between Macau and key industry stakeholders, including tourism operators, hoteliers, restaurateurs, and cultural organizations, is essential to developing and implementing tourism policies and initiatives. This collaboration aims to increase the multiplier effects of the industry and thereby enhance the overall economic performance of the country. Consequently, the country will have more capital to further develop the industry and enhance tourists' travel experiences in Macau.

In Vietnam, tourists' income levels is a significant factor influencing their travel decisions to the country. A positive relationship between tourists' income and tourism demand is detected in Vietnam. Meanwhile, the empirical outcome indicates that the economic condition in Vietnam is not a significant parameter. The transportation cost and tourism price can be significant or insignificant variables based on the RTCI and RHCI models. This is because the main tourist arrivals in Vietnam come from both developing and developed countries. Therefore, the influence of travel distance and price factors on Vietnam's tourism industry depends on the background of the tourists. Vietnam can diversify

its tourism offerings to appeal to a wide range of travellers. The country is rich in natural landscapes, beaches, UNESCO World Heritage sites, and other tourism products. With more tourism attractions, tourists' intention to visit Vietnam will be higher as their income levels improve over time.

The empirical findings evidence that tourists' income levels is one of the key significant variables influencing tourism demand in India. The outcomes suggest that tourists' income levels positively affect the Indian tourism industry. Besides that, tourism price and relative climate conditions are another two main factors impacting tourists' travel decisions to India. Both factors are positively associated with tourism demand in India. Meanwhile, the GDP of India and transportation cost are not significant factors affecting Indian tourism demand. Tourism infrastructure and facilities are crucial elements for the industry. India needs to invest more in infrastructure development to improve accessibility and connectivity for tourists. This entails the expansion and modernization of airports, railways, roads, and other transportation networks, as well as the development of tourist facilities, accommodation options, and tourist attractions.

In South Korea, the income level is a significant parameter influencing the number of international tourist arrivals under the RTCI model. The finding shows that it adversely influences tourism demand in South Korea. This indicates that tourists tend to visit other competitive countries when their income level increases. Notably, the result from the RHCI model exhibits that the economic condition of South Korea is also a significant variable but affects tourism demand adversely. In addition, the transportation cost also substantially impacts tourists' intention to visit South Korea with a negative sign. Lastly, the relative climate condition is detected as positively influencing tourism demand in South Korea,

indicating that tourists prefer to visit South Korea when its climate condition is more comfortable than their home country. This implies that the tourism players need to revise their tourism policies to increase its competitiveness and proper tourism investment.

As expected, tourists' income levels are positively associated with Singaporean tourism demand. Additionally, better economic performance in Singapore can improve its tourism industry. The findings evidence that the number of international tourist arrivals to Singapore will increase when Singapore's economic condition improves. This is likely due to the country having additional tourism investment capital to develop and maintain the industry to maximize tourists' travel experience in Singapore. Meanwhile, transportation cost is not a significant aspect for tourists in deciding their trip to Singapore because the majority of them are from neighbouring countries such as Malaysia and Indonesia. Lastly, the RTCI model presents that the climate condition is a significant component affecting tourism demand in Singapore, while it is insignificant in the RHCI model. The safety and security, efficient transportation, shopping and dining options, as well as the hospitality, make Singapore a highly valuable destination for tourists seeking memorable experiences and meaningful travel adventures. Therefore, the country needs to review and revise its tourism master plan from time to time to ensure sustainable growth in the long term.

In summary, the findings in the present study underscore the pivotal role of climate as a determining factor in tourism demand across the Asia Pacific. Generally, all ten nations significantly influenced by climate variables (RTCI or RHCI), except Macau, it is apparent that climatic conditions play a central role in shaping travel decisions. In addition, the results reveal that the impact of RHCI is generally larger than RTCI in affecting the tourism demand of the ten selected countries in Asia Pacific region. Furthermore, the income levels of tourists

emerge as a crucial driver, impacting tourism demand across the region. While increased income boosts tourism arrivals in most countries, the opposite effect is witnessed in South Korea, where higher income levels correspond to decreased tourism demand.

Transportation costs also proved influential in travel decisions for several countries, albeit not for Macau, India, and Singapore. Proximity matters more for neighbouring countries' tourism industries, rendering transportation costs a minor factor. Lastly, tourism prices have varying influences on tourism demand, depending on the tourists' preferred destinations. It can either positively or negatively affecting the tourism demand of a particular tourism destination. An adverse relationship between the tourism price and tourism demand implies that the tourism destination is sensitive to the tourism market conditions and highly competitive. The tourists tend to travel to other countries when the tourism price is increased. In contrast, a positive relationship between the tourism price and tourism demand suggests that tourists are still willing to purchase more goods and services in India, even when prices increase, due to their perceived value and worthiness.

This study's comprehensive analysis unveiled climate as significant in the Asia Pacific's tourism dynamics. Tourists gravitate towards nations with favourable climatic conditions, reinforced by other determinants such as income levels and transportation costs. As climate change reshapes global landscapes, understanding these intricate interplays is invaluable for informed policy and decision-making across the region's vibrant tourism sector.

5.3 Policy Recommendations

This section presents a series of recommendations to guide policy formation, aimed at sustaining and elevating the tourism industry across the Asia Pacific region. The empirical results highlighted that comfortable climate condition is pivotal in influencing tourism demand across most countries in this region, especially when the destination country's climate is more favourable than the origin country's weather. Therefore, the government can design specific tourism products and organize different types of tourism promotion to attract different groups of tourists throughout the year. This approach calls for meticulous planning and timing to create unique and appealing experiences that resonate with potential visitors.

Acknowledging the pivotal role of tourists' income in shaping travel patterns, governments and industry stakeholders should collaboratively devise strategies to maximize the benefits of tourism while ensuring its long-term sustainability. This can involve robust destination marketing and promotional plans that attract larger tourist inflows and encourage higher spending. Customized marketing approaches should highlight each country's distinct tourism products, whether cultural, heritage, or shopping-oriented, to cater to diverse visitor preferences.

The development and diversification of tourism products are crucial to meet varying tourist preferences and boosting tourists' expenditures within destination countries. Government and local community can work together to identify the niche tourism products in a specific place to create unique and high-quality experiences that resonate with a global audience. Collaborative efforts between local communities, governments, and private stakeholders can bring innovative products to life, fostering competitiveness and perceived value.

Infrastructure investment plays a pivotal role in enhancing the attractiveness of tourism destinations. Improving transportation networks, including airports, roads, and public transportation, can significantly impact tourists' access to various attractions. As shown in this study, travel distance is a factor that has adversely impacted the tourism demand in the Asia Pacific. As such, the airline industry should open more direct international routes to shorten travel time. Besides that, the improvement of the public transport also crucial in increasing the demand of the tourism destination. Well-developed public transportation systems also contribute to a more seamless and enjoyable tourist experience, encouraging repeat visits and positive word-of-mouth promotion.

Lastly, collaboration among stakeholders is crucial for the successful implementation of diversification strategies. The government, private stakeholders, local communities, and non-profit organizations should work together to design the comprehensive tourism plans and policies for long term sustainability growth beneficial for all countries. Public-private partnerships can facilitate the tourism investment, tourism development, sharing of expertise, and design of the short term and long-term tourism plans.

Regional partnerships among the countries in the Asia Pacific region play a vital role in promoting collaboration, fostering mutual understanding, and unlocking the full potential of tourism as a driver of economic growth, cultural exchange, and sustainable development within and across regions. By working together, countries and regions can create synergies, amplify their collective impact, and create more inclusive and resilient tourism destinations that benefit both visitors and host communities alike. In addition, visa policy also plays a significant role to the country. The country offers visa-free policies to the partner countries not only promote its tourism industry, but also attract more foreign investment, and foster

international cooperation. The recent visa relaxation between Malaysia and China, as well as between Singapore and China, is believed to boost their tourism industries in a significant way.

5.4 Limitations of the Study

This study has repetitively highlighted the positive impact of climate conditions on tourism demand across ten countries in the Asia Pacific region. However, it is essential to acknowledge certain limitations that could impact the accuracy and applicability of these results.

Firstly, the study utilized the RTCI and RHCI as proxies for climate conditions. These indices are designed for general tourism activities and may not fully capture specific nuances of various tourism market segments. For instance, while they provide insights into overall comfort, they might not accurately predict tourist arrivals for specialized segments like beach tourism, which might require more tailored climate indicators.

Besides that, this study used monthly climatic data, incorporated into a quarterly tourism demand model due to the unavailability of corresponding macroeconomic variables at monthly level. The monthly data compressed into quarterly data are the climatic data such as temperature, humidity level, wind speed and other key climatic variables. However, monthly or even daily data may make more sense to tourists. This can lead to potential information loss and may not fully capture tourists' concerns about monthly or even daily fluctuations in climate conditions, which are often more relevant for travel decisions.

Last but not least, the outbreak of COVID-19 has had tremendously impact on the tourism industry around the globe. The outbreak caused all countries to close their borders, aircrafts are grounded, millions of people lost their jobs, and many more lost their lives. These factors significantly impacted travel demand and introduced uncertainties that extend beyond the scope of the study. The limited post-pandemic data availability also restricts a comprehensive understanding of the pandemic's long-term effects on tourism demand. The study's dataset covered a period up to 2020 only. A lack of more recent data limits the study's ability to provide a real-time assessment of the pandemic's influence on tourism demand.

5.5 Room for Further Studies

This study has laid the foundation for understanding the climatic impacts on the tourism industry in the Asia Pacific region. However, there are still room for further research to deepen our understanding and provide more insights.

Firstly, future studies could expand beyond the Asia Pacific region to examine the impacts of climate on tourism in diverse geographic and climatic locations. Additionally, investigating the preferences of tourists in specific market segments like beach tourism, adventure tourism, cultural tourism, and more could reveal how different types of tourists respond to climate conditions.

Secondly, the research can be conducted at a more granular level, such as the province or city level, to provide insights into how climate conditions impact targeted locations. Considering that certain countries in the Asia Pacific region have vast land areas, climate conditions can vary significantly across different provinces or cities within a country. Gathering more detailed tourism data at these levels would enable tourism planners to devise more precise and informed strategies.

Thirdly, future study should also take into account the disaggregated tourism segments such as the purpose of visit; role of common language; word of mouth; and other relevant components. Different set of tourism segments will provide different tourism information that is useful to the policy makers in planning tourism development from different perspectives.

Fourthly, given the ongoing repercussions of the COVID-19 pandemic on the tourism industry, further research is crucial to fully comprehend its lasting effects. Understanding how the pandemic has reshaped travel behavior, preferences, and perceptions will be vital for planning the industry's recovery.

Fifthly, it is recommended that the HCI ratings can be validated against actual visitation patterns at specific destinations or attractions to provide insights into the accuracy of the ratings in predicting tourist behaviour. While the HCI framework used in this study was developed for urban destinations and general tourism activities such as sightseeing, future studies may explore and validate specifications specifically tailored for beach destinations as proposed by Scott et al. (2015), or even design specifications for other significant tourism segments such as winter sports tourism, golf tourism, or mountaineering.

Lastly, continued research and the advancement of climate services are essential for the creation of data-driven climate indices that cater to specific tourism markets, both domestic and international. This is particularly crucial for destinations that are highly susceptible to climate variability. Establishing positive correlations between arrivals data and these climate indices signifies a promising step towards the right direction in terms of providing effective climate services and supporting the tourism industry.

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