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The Impact of Climate Change on Tourism Demand in China

Meng-Chang Jong[1], Chin-Hong Puah[1,2]*, Mohammad Affendy Arip[1]

[1]Faculty of Economics and Business, Universiti Malaysia Sarawak, 94300, Kota Samarahan, Sarawak, Malaysia, [2]Institute of Sustainable and Renewable Energy (ISuRE), Universiti Malaysia Sarawak, 94300 Kota Samarahan, Sarawak, Malaysia.
*Email: chpuah@unimas.my

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ABSTRACT

This paper aims to examine the climatic impact on the demand of international tourism industry in China. Due to rising awareness and urgency to combat climate change, there is a growing need to better grasp the possible implications and the risk of climate change to the tourism industry. The tourists' travel decision can be influenced by both climatic and non-climatic factors, and thus this study has integrated both factors into the models. The climatic variables are represented by Tourism Climate Index (TCI) and Holiday Climate Index (HCI) while the selected non-climatic determinants are tourists' income, tourism price, exchange rate and transportation cost. The empirical findings showed that climate conditions significantly and adversely affect China's tourism demand. Tourists' income level, as expected, positively affects their decision to travel to China. Meanwhile, the tourism price, exchange rate, and transportation cost negatively impact China's tourism industry. Although some valuable results have been found, more works are required to understand its long-haul significance to the tourism industry, especially during extreme events such as extreme weathers, pandemics, financial crises and etc.

Keywords: Climate Change, Tourism Demand, Tourism Climate Index, Holiday Climate Index, Panel Autoregressive Distributed Lag
JEL Classifications: C33, N50, Z32

1. INTRODUCTION

The tourism industry is one of the fastest growing industries around the globe. Prior to the COVID-19 pandemic, the travel and tourism industry had generated USD 9,630 billion (10.3%) to global GDP (WTTC, 2022) and recorded 1.46 billion international tourist arrivals in 2019 (WTTC, 2020). The industry had also created 10.6% job opportunities, involving 334 million people globally in the same year. Among the regions, the Asia Pacific region recorded the highest growth in international tourist arrivals and tourism receipts, with an average growth of 6.3% for international tourist arrivals and 8.8% of international tourism receipts from 2010 to 2019 (UNWTO, 2020). According to UNWTO (2020), China alone had received 145 million international tourists (40.2% of total international tourist arrivals in Asia Pacific region) in 2019, topping all other countries of the same region. The industry had also contributed USD 1,856.6 billion (or 11.6%) to the country's GDP in 2019 (WTTC, 2022). In terms of inbound international tourists, China received 31.88 million tourists in 2019, a 5.5% increase from the previous year. Furthermore, 82.2 million people were employed in the tourism industry; this is equivalent to 10.8% of total jobs in China.

The tourism industry is a nature-based product, and this unique feature makes it sensitive to climate change. A location's climate is undoubtedly its tourism resource, but it is also the restraining element for further tourism development. In short and as stated by Yu et al. (2009), a pleasant climatic condition increases tourists' satisfaction and vice versa. A good climate elevates the enjoyment, satisfaction, and safety (such as thunderstorm, heatwave and blizzards etc.) of the tourists (Amelung et al., 2007; Martin, 2005). Different climate conditions can influence tourists' emotion and behaviour, and ultimately affect the attractiveness and demand of the tourism destination (Arabadzhyan et al., 2021; Boivin and

Tanguay, 2019). Therefore, it is crucial to examine the climatic impacts on the tourism industry in China. This is important to understand the dynamic and complex link between climate and tourism industry.

The climate condition of a tourism destination is closely linked to its sustainability in the long term. This is because a change in climate may alter the tourists' duration of stay and also the quality of their experience. Rosselló et al. (2020) and Falk (2014) stated that the demand on tourism destination can be influenced by extreme weather. According to the World Meteorological Organization (WMO) (2022), the serious and unpleasant impacts brought by climate change have already seeped through the economy and society in China. Since June 2022, WMO (2022) had documented record-breaking extreme weathers in China such as heatwaves, severer drought, and deadly rainfall. The regional severe heatwave in June 2022 was the highest recorded since 1961. Some provinces and cities had been experiencing severe drought with low precipitation and long-lasting high temperature since July 2022. In certain places, the precipitation was lower than 80% of the normal period, accompanied with rising risk of forest fires (WMO, 2022). Thus, improvement in the adaptation mechanisms and monitoring capabilities are vital at every level of the government as well as the private tourism sector. Therefore, early warning of the extreme weather is needed for sustainable tourism development. This critical issue has motivated us to consider climatic variables in our empirical models to investigate their impact on the tourism industry in China.

2. LITERATURE REVIEW

The close linkage between tourism and climate has long been discussed in the existing tourism studies. In the 1980s, Mieczkowski (1985) constructed the tourism climate index (TCI) to examine the climatic impact on the tourism industry. The TCI is the first climatic index constructed to measure the appropriateness of the climatic condition for the travel destination. TCI is one of the most widely applied indexes in the tourism literature. The TCI has been employed in the studies of Le et al. (2022), Hejazizadeh et al. (2019), Fang and Yin (2015), Olya and Alipour (2015), Amelung and Viner (2006). Mieczkowski (1985) constructed the TCI by integrating temperature, humidity, duration of daily sunshine, and other key tourism climatic variables into a numerical index. This index will reflect the climatic condition of the tourism destination. The index incorporated five sub-indexes, which are comfort index in daytime (CID), daily comfort index (CIA), precipitation (P), duration of sunshine (S), and wind speed (W). This is shown in Equation (1).

$$TCI = 2 \times (4CID + CIA + 2P + 2S + W) \quad (1)$$

Where the combination of the maximum daily temperature (°C) and minimum daily relative humidity (%) to proxy CID; CIA is the combination of mean daily temperature (°C) and mean daily relative humidity (%); P is rainfall (mm); S is the duration of sunshine (hours); and W represents wind speeds (km/h or m/s). Each sub-index has a weightage to reflect its level of importance. The CID is weighted with the highest weightage (40%). This is to reflect the fact that tourists are generally most active during the daytime. For precipitation and sunshine, the weightages of both sub-indexes are equally 20%. Lastly, both CIA and wind speed are weighted at 10%. The highest score of 5.0 will be given to each sub-index to obtain a maximum score of 100 (ideal climatic condition) and a minimum of −30 for impossible climatic condition.

Although TCI has been widely applied in many studies, it has also received substantial critiques by numerous previous researchers (e.g.: Ma et al., 2020; Rutty et al., 2020; Scott et al., 2016; de Freitas et al., 2008; Amelung et al., 2007). In general, TCI is said to have four main limitations. Firstly, the weighting and rating scheme are purely based on Mieczkowski's own judgement. There is an over-emphasis on the thermal comfort of a location whereby the combination of CID and CIA alone is already 50% of the total weightage. Secondly, the TCI neglects the overriding effects of physical parameter (rainfall and wind). For precipitation and wind speed, the combined weightage is only 30%, which hugely undermines the adverse effect of extreme rainfall and typhoon. Thirdly, the TCI uses low temporal climate data. The monthly data employed is inadequate to reflect tourists' day-to-day behaviour due to daily weather change. Fourthly, the TCI is designed for general tourism segments and neglects the different geographical location such as seaside and winter tourism activities.

Due to the shortcomings of the TCI, Morgan et al. (2000) designed the Beach Climate Index (BCI) to overcome these limitations. Furthermore, de Freitas et al. (2008) established the Climate Index for Tourism (CIT) to measure the climatic conditions of the tourism destination. In addition, Yu et al. (2009) designed the Modified Climate Index for Tourism (MCIT) to overcome the drawbacks highlighted in the TCI. However, the major drawback for the MCIT is in the development of the rating and weighting systems, which is sadly not based on existing literatures. Therefore, Scott et al. (2016) designed the Holiday Climate Index (HCI) to overcome all the drawbacks argued by the researchers on the existing climatic indexes.

Unlike other indexes, HCI was designed for major tourism segments. The rating and weighting schemes are built based on the existing literature on the tourists' preferences toward the climatic condition over the past decade is another main improvement of the HCI. This improvement addressed the key criticisms of the TCI by using empirically validated data. Similar to TCI, the HCI was constructed by integrating a few climatic variables into a numerical index to reflect the climatic condition. This is shown in Equation (2):

$$HCI = 4TC + 2A + 3P + W \quad (2)$$

Where TC refers to thermal comfort. TC is constructed by combining the daily maximum temperature (°C) and mean relative humidity (%). A is the aesthetic, which is proxied by cloud cover (%). P refer to the precipitation (mm) while W stands for wind speed (km/h). Each sub-index is rated on a scale of 0-10 to obtain a maximum score of 100 (ideal for tourism) and a score of 0 for potentially dangerous climate condition for tourists. The HCI is different from TCI, as it does not define any climate condition as “impossible.” This is because certain tourists are actively seeking for an adverse weather condition for specific activity such as storm watching and wind surfing (Scott et al., 2016).

Nevertheless, Mieczkowski (1985) mentioned that the climate condition is only one of the influencing factors for some tourists, although some tourists do decide on their tourism destination purely based on the climate. Dogru et al. (2019) mentioned that the inclusion of both climatic and non-climatic variables are necessary in the tourism demand model. The non-climatic variables employed in the existing tourism studies including tourists’ income (Puah et al., 2022; Jong et al., 2020; Kumar and Kumar, 2020; Cheng, 2012), exchange rate (Puah et al., 2022; Ulucak et al., 2020; Meo et al., 2019; Puah et al., 2014; Cheng, 2012), tourism price (Jong et al., 2020; Kumar and Kumar, 2020; Tang and Tan., 2016), and transportation cost (Soh et al., 2022; Soh et al., 2020; Tanjung et al., 2017).

Tourism sustainability is another key issue in tourism development. Notable studies in this area include Jong et al. (2022); Sharpley (2020); Asmelash and Kumar (2019); and Perry (2006). Jong et al. (2022) investigated the effect of carbon emissions and climate change on the tourism sustainability of South Africa and concluded on a negative relationship. They figured out that the carbon emissions and climate change adversely impacting the tourism sustainability, and thus the government and tourism players need to balance the tourism development for long term sustainable growth. Meanwhile, Asmelash and Kumar (2019) had constructed and validated a series of tourism sustainability indicators. They have selected 158 tourism related indicators and retained only 53 indicators after a series of filtering process. The construction of sustainability indicators is vital to ensure the long term sustainability of the tourism industry.

3. DATA AND METHODOLOGY

To examine the climatic impacts more accurately on the tourism industry in China, both the TCI and the HCI were employed in this study. According to Dogru et al. (2019), it is necessary to include both climatic and non-climatic variables in the tourism demand model because both elements can gather more comprehensive tourism information to develop more effective and adaptive tourism strategies. The present study included both climatic and non-climatic variables to model the tourism demand functions in China as shown in Equation (3) and Equation (4).

$$TA = f(TCI, GDP, TP, EXCO, TC) \quad (3)$$

$$TA = f(HCI, GDP, TP, EXCO, TC) \quad (4)$$

Where TA is the number of international tourist arrivals to proxy tourism demand. The climatic variables were divided into two models to examine and validate its impact to the tourism industry of China. The climatic variables, TCI, is included in Equation 3 whereas HCI is integrated in Equation (4) while other non-climatic variables remained. The selected non-climatic determinants are the income levels of the tourists (GDP), tourism price (TP), exchange rate in origin countries (EXCO), and transportation cost (TC). The TC is measured by multiplying the geographical distance between the capitals of the origin countries and destination country with the crude oil price to better capture the transportation cost (Jong et al., 2020). For the estimation purpose, all variables were transformed into the logarithm form as shown below:

$$LTA_{ijt} = \beta_0 + \beta_1 LTCI_{ijt} + \beta_2 LGDP_{ijt} + \beta_3 LTP_{ijt} + \beta_4 LEXCO_{ijt} + \beta_5 LTC_{ijt} + \varepsilon_{ijt} \quad (5)$$

$$LTA_{ijt} = \beta_0 + \beta_1 LHCI_{ijt} + \beta_2 LGDP_{ijt} + \beta_3 LTP_{ijt} + \beta_4 LEXCO_{ijt} + \beta_5 LTC_{ijt} + \varepsilon_{ijt} \quad (6)$$

The β_0 indicates the beta; β_{1-5} refer to the marginal coefficients of the variables; *i* and *j* are destination country and origin countries, respectively; *t* is time and ε refers to stochastic error term.

In this paper, the panel autoregressive distributed lag (ARDL) models with data from top 10 tourist originating countries in China were used. The quarterly data spanning from 2010Q1 to 2020Q4 have been employed in this study. These tourists were from Hong Kong, South Korea, Japan, United States, Russia, Mongolia, Malaysia, Philippines, Singapore, and India. The number of tourists from these destinations accounted for more than 85% of inbound tourists in China. The weather data such as temperature, humidity, duration of sunshine and others were gathered from a website called “The Weather Online.” Meanwhile, the data for TA, GDP, TP and EXCO were gathered from CEIC. The travel distance was obtained from the Centre d’Etudes Prospectives et d’Informations Internationales (CEPII), and lastly the crude oil price was obtained from the U.S. Energy Information Administration (EIA).

Prior to the panel ARDL estimation, panel unit root tests were conducted to verify the stationarity level of the variables. This paper employed IPS (Im et al., 2003) and ADF (Dickey and Fuller, 1979) unit root tests to test that the parameters are cointegrated at $I(0)$, $I(1)$ or a mixture of both and to ensure that the $I(2)$ order does not exist in our empirical models. Then, the cointegration relationships among the variables were examined through Wald test. The null hypothesis of the Wald test states that there is no cointegration vector among the explanatory variables (H_1: $\alpha_1 = \alpha_2 = \alpha_3 = \alpha_4 = \alpha_5$) while the alternative hypothesis states that the long run cointegrated vector is exists among the variables (H_1: $\alpha_1 \neq \alpha_2 \neq \alpha_3 \neq \alpha_4 \neq \alpha_5$). The experiment proceeds to the panel ARDL cointegration test after the long run cointegrated vector has been identified in the models.

4. RESULTS

Table 1 shows the empirical findings of the IPS and ADF unit root tests. Both tests revealed a combination of $I(0)$ and $I(1)$ variables. Thus, the empirical results of the unit root tests validated the use of the panel ARDL technique in this study.

Table 2 presents the Wald’s cointegration test result for TCI model while the result for Wald’s cointegration test of HCI model is

Table 1: Unit root tests results

Variables	IPS		ADF	
	Intercept	Trend and Intercept	Intercept	Trend and Intercept
Level				
LTA	0.2212	2.2901	19.5018	9.6375
LGDP	−0.5257	−2.4185***	28.9255*	34.2279**
LTP	1.2385	2.0335	16.9832	13.7167
LEXCO	−0.6109	0.7110	23.0198	16.2095
LTC	0.7221	1.4877	9.90592	7.4270
LTCI	−4.2271***	−2.8343***	43.6177***	271.686***
LHCI	−8.6310***	−7.2701***	127.549***	237.611***
First difference				
ΔLTA	−2.4376***	−2.6642***	41.4529***	40.8551***
ΔLGDP	−5.9101***	−2.9324***	83.8823***	58.9319***
ΔLTP	−6.3578***	−4.8545***	96.0888***	76.0338***
ΔLEXCO	−14.4760***	−12.3696***	202.879***	162.145***
ΔLTC	−16.1182***	−14.6014***	228.467***	185.058***
ΔLTCI	−31.2188***	−36.8468***	268.734***	1427.50***
ΔLHCI	−30.8489***	−28.2557***	309.798***	843.488***

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively. TCI: Tourism climate index

revealed in Table 3. Table 2 shows that the *F*-statistic value is significant at 1% level, which means the long run equilibrium is existed among the number of international tourist arrivals, climate condition, tourists' income, tourism price, exchange rate, and transportation cost. Similar result has also been found in the HCI model whereby the *F*-statistic value is significant at 1% level (Table 3). These results demonstrated the existence of long run cointegrated vectors in both climatic models in China. In addition, the error correction term (ECT) is negative, <1, and significant. This means that the parameters will converge to the long run equilibrium, and the converge rate is 0.11% and 0.08% quarterly in the TCI and HCI models, respectively.

The panel ARDL results for the tourism demands in China are reported in Tables 4 and 5, respectively. The findings clearly showed that both TCI and HCI are adversely influencing the tourism demand in the long run. The finding from the TCI model as presented in Table 4 indicated that 1% increase in TCI significantly reduce the number of international tourist arrivals to China by 0.45% in the long run. Consistently, the HCI developed by Scott et al. (2016) also indicated that the climate is a significant variable in influencing tourists' travel decision to China at 1% significant level in the long run as shown in Table 5. The result of the HCI model signifies that 1% increase in HCI discourage tourist inflow to China by 2.37%. The possible reason is that the tourists tend to stay at their home countries rather than travel to China when the climate condition at their home countries is better. However, in the short run, the climate condition is not a key factor in affecting tourists' travel decision. This is because tourists do not have sufficient time to response to the climate change and have other more important factors to consider deciding on a short trip.

Furthermore, the findings indicate that the income levels of the tourists positively influence tourist arrivals in China. These outcomes are in line with the studies of Jong et al. (2020), Tanjung et al. (2017), Puah et al. (2014), and Crouch (1995). The results revealed that a 1% rise in tourists' income motivate them to travel to China by 0.16% and 0.82% in the TCI and HCI models, respectively. With increased income, it motivates a person to travel

Table 2: Wald's cointegration test for TCI model

Test statistic	Value	df	Probability
F-statistic	30.4717	(4, 145)	0.0000
Chi-square	121.8868	4	0.0000

TCI: Tourism climate index

Table 3: Wald's cointegration test for HCI model

Test statistic	Value	df	Probability
F-statistic	10.0296	(4, 165)	0.0000
Chi-square	40.1182	4	0.0000

to other countries for leisure. As expected, the tourism price has a negative impact on the demand of tourism in China. In consumer theory, the price variable is a key factor in affecting the demand of the goods and services. Jong et al. (2020) and Tang and Tan (2016) also proved that the price factor is one of the key determinants in influencing tourists' travel decision. The TCI model implies that tourism price adversely impacts the tourism demand in China at 1% significant level. The tourism demand reduces by 1.58% when the tourism price rise by 1% level. The HCI model also reported a similar trend, albeit not statistically significant.

The exchange rate is a significant variable in affecting tourism demand in China under the HCI model. Exchange rate adversely impacts the tourism demand in both short term and long term. Table 5 reveals that the appreciation of the tourists' exchange rate reduces the number of international tourist arrivals to China by 0.54% at the 10% significance level in the long term. This declines to 0.09% for the short term. This is because tourists tend to travel to other countries rather than China when their currency appreciates against Renminbi. However, the result of the TCI model presented in Table 4 shows that the exchange rate is not a key determinant in affecting tourism demand in the long term. This is because most travellers to China are short haul tourists such as from Hong Kong and Macau, and thus the exchange rate is not their main consideration during their trip to China.

The results from both the TCI and HCI models consistently found that the transportation cost, used as a proxy of travel distance

Table 4: Panel ARDL results: TCI model

Variable	Coefficient	Standard error	t-statistic
Long run equation			
LTCI	−0.4534	0.1814	−2.4988**
LGDP	0.1631	0.0734	2.2231**
LTP	−1.5758	0.4467	−3.5278***
LEXCO	−0.1571	0.2162	−0.7268
LTC	−0.2051	0.0253	−8.0968***
Short run equation			
ECT	−0.1119	0.0416	−2.6893***
ΔLTA(−1)	0.4786	0.0829	5.7730***
ΔLTCI	0.0314	0.0162	1.9412*
ΔLTCI(−1)	0.0453	0.0181	2.4974**
ΔLTCI(−2)	0.0045	0.0136	0.3342
ΔLTCI(−3)	−0.0038	0.0100	−0.3862
ΔLGDP	−0.2570	0.3141	−0.8180
ΔLGDP(−1)	0.3121	0.2819	1.1073
ΔLGDP(−2)	0.0610	0.0612	0.9969
ΔLGDP(−3)	0.0255	0.0407	0.6252
ΔLTP	0.2745	0.2557	1.0733
ΔLTP(−1)	0.2142	0.4422	0.4845
ΔLTP(−2)	0.4061	0.2866	1.4171
ΔLTP(−3)	0.1309	0.2903	0.4509
ΔLEXCO	0.0182	0.0590	0.3089
ΔLEXCO(−1)	0.0903	0.0511	1.7672*
ΔLEXCO(−2)	−0.0682	0.0411	−1.6602*
ΔLEXCO(−3)	−0.0624	0.0340	−1.8342*
ΔLTC	0.0272	0.0310	0.8784
ΔLTC(−1)	−0.0040	0.0123	−0.3296
ΔLTC(−2)	0.0143	0.0134	1.0705
ΔLTC(−3)	0.0262	0.0116	2.2501**

Asterisks (***), (**) and (*) indicate statistically significant at 1%, 5% and 10% levels, respectively. TCI: Tourism climate index

Table 5: Panel ARDL results: HCI model

Variable	Coefficient	Standard error	t-statistic
Long run equation			
LHCI	−2.3710	0.4789	−4.9507***
LGDP	0.8187	0.2059	3.9766***
LTP	−0.4145	0.6019	−0.6886
LEXCO	−0.5402	0.2844	−1.8991*
LTC	−0.2302	0.0660	−3.4880***
Short run equation			
ECT	−0.0865	0.0416	−2.0820**
ΔLHCI	0.1844	0.1025	1.7996*
ΔLHCI(−1)	0.1535	0.0922	1.6640*
ΔLHCI(−2)	0.0878	0.0716	1.2261
ΔLHCI(−3)	0.0311	0.0379	0.8209
ΔLTA(−1)	0.2968	0.1063	2.7909***
ΔLTA(−2)	0.1606	0.0842	1.9067*
ΔLTA(−3)	0.0620	0.0751	0.8258
ΔLGDP	−0.2900	0.2928	−0.9893
ΔLGDP(−1)	0.2635	0.1736	1.5175
ΔLGDP(−2)	0.1048	0.1297	0.8084
ΔLGDP(−3)	−0.0596	0.0599	−0.9947
ΔLTP	0.0719	0.3511	0.2047
ΔLTP(−1)	0.2583	0.5677	0.4551
ΔLTP(−2)	0.2438	0.3061	0.7965
ΔLTP(−3)	0.1091	0.3345	0.3264
ΔLEXCO	0.0130	0.0672	0.1935
ΔLEXCO(−1)	0.1223	0.0809	1.5121
ΔLEXCO(−2)	−0.0499	0.0624	−0.8003
ΔLEXCO(−3)	−0.0859	0.0359	−2.3910**
ΔLTC	0.0274	0.0326	0.8401
ΔLTC(−1)	0.0084	0.0280	0.3014
ΔLTC(−2)	0.0253	0.0154	1.6488
ΔLTC(−3)	0.0427	0.0177	2.4163**

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

multiplied with crude oil price, significantly affect tourism demand in the short term and long term. These findings are in line with Soh et al. (2022), Jong et al. (2020), and Soh et al. (2020).

Interestingly, transportation cost influences the tourism demand positively in the short term while adversely in the long term. The main reason is that the number of short haul tourists from Hong Kong and Macau takes up 75% of the total tourists in China. They have more flexibility to travel to China than other long-haul tourists. For example, during the short holiday or weekend, China becomes their main choice for their short vacation. The long-haul tourists, on the other hand, need longer time to plan their trip and the related expenses. The TCI model implies that, when the transportation cost increases by 1%, the international tourists to China increase by 0.03% in the short run. However, it declined by 0.21% in the long run. In the HCI model, every 1% increase in transportation cost increases the number of tourists visiting China by 0.04% in the short run and reduced by 0.23% in the long run.

5. CONCLUSION

This paper aims to examine the climatic impacts on tourism demand in China. The climatic variables employed in this study are TCI and HCI. Both variables integrated several climatic variables (temperature, humidity, rainfall and etc.) to reflect the climatic condition. Dogru et al. (2019) mentioned that it is crucial to include both climatic and non-climatic variables in an estimation model. Therefore, this study included another four non-climatic variables, which are tourists' income, tourism price, exchange rate and transportation cost to design the tourism demand models. To carry out the empirical analysis, this paper adopted the panel ARDL technique covering 10 major tourist generating countries in China for the period of 2010Q1-2020Q4. The empirical results clearly showed that climatic condition is a significant determinant and adversely influence the tourism demand in China. This shows that tourists travel to China when the climate condition is more favourable. Our other major finding showed that the tourists' income level positively affects the tourism demand in China. On the other hand, tourism price, exchange rate and transportation cost adversely influence tourists' decision to visit China in the long term.

The sustainable enhancement of the tourism demand is a crucial task for all countries. Therefore, to attract more tourists, the tourism plans and strategies formulated by the government is important in ensuring the tourism destinations stay attractive and competitive. Since climate change plays a crucial role in tourism demand, special attention needs to be invested in mitigating its adverse effects. This is also in line with the United Nations' Tourism and the Sustainable Development Goals - Journey to 2030 that calls for a balance in economic, social, and environmental sustainability in both short term and long term.

Although some valuable results have been found in this study, more works are required to understand its long-haul significance to the tourism industry, especially during extreme events. The industry is a fragile one by nature, sensitive to any global event and changes in its operating environment. The recent COVID-19 pandemic has clearly disrupted the world economy with the tourism industry being the most impacted. However, this has not been discussed in this paper. In addition, this research has yet to include political stability, trade openness and other important variables that may affect tourism. Last but not least, this study only used lower frequency data, which is quarterly data. Some small, but significant trends, might have been ignored due to this. These can all be incorporated in future studies on the same topic. Not only that, it is also advisable to focus on specific regions or provinces, since China is a big country with varying weather condition throughout the year. This may provide more insightful information for more effective and efficient planning for tourism.

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