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# Impacts of COVID-19 on tourists' destination preferences: Evidence from China

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ABSTRACT

Using data of online ticket sales for attractions in the seven provinces of South Central China, this study focuses on the impact of COVID-19 on tourists' destination preferences after the end of lockdown. Empirical results reveal that tourists' destination preferences have changed significantly, which holds under a number of robustness checks. Specifically, we find that tourists avoid traveling to destinations with more confirmed cases of COVID-19 relative to their places of origin, especially Hubei Province, and prefer destinations close to home, especially local attractions. The empirical findings have significant implications for managers and policymakers in tourism and we provide potential mechanisms for these findings based on signaling, risk perception, and prospect theory.



## Introduction

Tourism is particularly susceptible to a range of external shocks, such as political events, natural disasters, and epidemics (Cavlek, 2002; Richter, 2003). These shocks generally cause an unexpected downturn in tourism demand of disaster areas (Blake et al., 2003; Huang & Min, 2002). At the beginning of 2020, the unprecedented COVID-19 pandemic swept the globe, affecting almost all aspects of global economics and social life, but none has been so severely affected as the tourism industry given its reliance on human mobility (Chen et al., 2020; Yang et al., 2020b). In the United States, the COVID-19 pandemic has led to a severe economic downturn in the travel sector since early March 2020, with total losses of more than $396 billion (U.S. Travel Association, 2020). In China, a series of actions were implemented such as a lockdown in Wuhan on January 23, 2020 and travel bans afterwards, which substantially restricted cross-province and cross-city population mobility and resulted in a sharp drop in the number of dominant travelers (Hao et al., 2020; Kraemer et al., 2020).

All the aforementioned losses are mainly caused by the anti-COVID-19 actions in the early stage of pandemic. China has resumed many economic activities since late March 2020, and the lockdown in Wuhan ended on 8 April 2020. Afterwards, tourist attractions in different cities have reopened successively. As a result, consumers have opportunities to embark on traveling, while unprecedented changes in tourists' destination preferences may emerge due to the pandemic. Although the negative impact of COVID-19 on tourism has received extensive attention in recent studies (Fotiadis et al., 2021; Karabulut et al., 2020), little is known about how tourists' behaviors and preferences change after the end of lockdown, and factors behind the changes deserve further investigation.

On the one hand, given the findings in prior literature that individuals who have experienced a natural disaster tend to be more risk averse than others (Cameron & Shah, 2015; Cassar et al., 2017), people are likely to become more risk averse after experiencing this pandemic. Therefore, even though the pandemic has been under control and economic activities have reopened successively in China, people

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may be less willing to travel, especially travel long distances, due to their larger risk aversion tendency than before. On the other hand, people's risk perception and attitude toward a destination may be significantly influenced by external events, such as epidemics and terrorist attacks (Seabra et al., 2013). Considering that personal safety is a primary concern for tourists, the destinations perceived to be unsafe generally fail to lure travelers (Liu & Pratt, 2017; Rittichainuwat & Chakraborty, 2009). Thus, in the context of COVID-19 pandemic, people's preferences for destinations are likely to change if more confirmed cases are reported there and they may avoid visiting those high-risk destinations. Along this line, we put forward two research questions naturally. *After the end of lockdown, do tourists less prefer the destinations with more confirmed cases, especially Hubei Province? Do tourists more prefer destinations close to home, especially local attractions?* Investigating these research questions is meaningful and helpful for managers and policy makers to formulate policies to counteract the negative effects of the pandemic.

In line with the research questions, this study aims to investigate the impact of COVID-19 pandemic on tourists' destination preferences after the end of lockdown in China. Given that the lockdown in Wuhan and other cities in Hubei Province did not end until April 2020, we focus on tousim demand as of April when the restrictions on traveling have been removed and people's travel decisions are largely determined by their preferences. Based on the aggregate provincial-level sales data of attractions tickets from Ctrip, a leading travel agency in China, we find tourists' behaviors are significantly reshaped by the pandemic. Specifically, using the difference-in-differences method and interaction effect model, we find that tourists avoid traveling to destinations with more reported confirmed cases relative to their places of origin. As the epicenter, Hubei Province experienced a sharper decline in tourism demand than other provinces. Besides, tourists prefer destinations close to home, especially local attractions.

Unlike prior research that has mainly studied the negative impact of COVID-19 on tourism demand in the early stage of pandemic (Gössling et al., 2020; Hao et al., 2020), this study sheds light on the changes in tourists' destination preferences after the end of lockdown in China. Moreover, this study contributes to existing literature by combining signaling, risk perception, and prospect theory with tourists' behavior and providing empirical foundation for the application of these theories in explaining people's behavioral responses to disasters or crises. Our findings also provide references for policy-making and enlighten managers about the directions of future recovery in the tourism sectors after the pandemic.

## Hypothesis development

### *Signaling, risk perception, and regional bias*

Signaling theory was initially developed by Spence (1978), and it shows that potential employees have to send reliable signals such as education credentials to employers to prove their ability levels due to information asymmetry. In marketing area, signaling is regarded as a way to offer consumers potential product information, reduce consumer uncertainty, and foster purchase decisions. Positive marketing signals including quality certifications, corporate social responsibility, and consumer reviews, enhance buyers' trust and contribute to higher sales and consumer satisfaction (Siu et al., 2014). In tourism literature, signals have been proven to influence traveler behavior and purchase intentions. For example, Aluri et al. (2016) find that signals conveyed through embedded social media channels on hotel websites can increase travelers' perceived informativeness, perceived enjoyment, and perceived social interaction, thus influencing their purchase intentions. Abrate et al. (2011) reveal that reputation-based quality signals help explain tariff levels, which means that price proposals also include a premium for quality assured hotels.

In the context of natural hazards, informative signals including media reports have an effect on risk perceptions, thus motivating individuals to take action to avoid, adapt to, or even ignore risks (Wachinger et al., 2013). For tourists, owing to information asymmetry across geographic locations, they generally have no access to first-hand information about safety in other regions but through media coverage such as the reported number of confirmed cases in times of the COVID-19 pandemic. In this light, tourists' risk perceptions are expected to be influenced by the reported number of confirmed cases in destinations. Besides, according to the anchoring effect, people may set certain information as a reference point and make subsequent decisions based on comparison (Sherif et al., 1958). The reported number of confirmed cases in the place of tourist origin can be recognized as an anchor or a reference point, and tourists tend to perceive risks depending on the differences of confirmed cases between destinations and places of origin. Specifically, if the reported number of confirmed cases in a destination is higher relative to that in the place of origin, tourists may have lower travel intentions toward the destination, thus showing a tendency of regional bias.

**H1.** Tourists less prefer the destinations with more confirmed cases of COVID-19 relative to their places of origin, especially Hubei Province, after the end of lockdown.

### *Prospect theory and preference for short-distance trips*

Prospect theory, as a theory of behavioral economics and behavioral finance, was developed by Kahneman and Tversky (2013) to predict consumer decisions under conditions of risk and uncertainty. It is originally applied to the contexts of lottery and gamble, but recently, other kinds of behaviors such as travel behavior have been better explained by this theory (Avineri & Bovy, 2008; Ramos et al., 2014). The theory points out an asymmetric cognition that people weight more on potential losses than potential gains (Kahneman & Tversky, 2013). In this light, literature has investigated the asymmetric shifts in people's risk preferences for losses and gains in the context of disasters (Li et al., 2011; Reynaud & Aubert, 2020). For example, Reynaud and Aubert (2020) find that households affected by a flood are more risk averse compared with unaffected households in the loss domain but not in the gain domain. Cameron and Shah (2015) find that individuals who suffered a flood or an earthquake in the past years have higher levels of risk aversion for losses than others who did not experience a natural disaster.

Prospect theory also applies to customers who have been exposed to the shock of COVID-19. For instance, Pan et al. (2021) tested the relationships among travel constraints, negativity bias, and post-crisis behavioral intentions amid the COVID-19 pandemic by referring to leisure constraints theory and prospect theory. Generally speaking, a tour is uncertain and consists of gain and loss. The gain refers to pleasure a consumer has while traveling, which is relatively stable for a specific tour. The loss of a tour generally includes the dissatisfaction with an attraction itself, hotel service, and other potential risks. In times of the COVID-19 pandemic, the expected loss of a tour increases as it involves the physical risk of getting infected given the person-to-person and airborne transmission of coronavirus.

Distance is an important factor affecting tourists' destination choosing behavior (Yang et al., 2018). In the case of COVID-19, a long-distance travel generally involves greater physical risk compared with a short-distance one since tourists are more likely to take public transportation such as airplane and train in the former, whereas they go on a road trip in the latter. Therefore, the expected loss is much higher than gain in the long-distance travel compared with the short-distance travel in the context of COVID-19 pandemic. Based on prior findings, people weight more on the loss domain, so they tend to discard the choices of long-distance trips and prefer choices with less risks, such as short-distance trips or local trips.

**H2.** Tourists more prefer destinations close to home, especially local attractions, after the end of lockdown.

## Data and methodology

### *Data*

In this study, the tourism demand is proxied with the online sales of attraction tickets in the seven provinces of South Central China.[1] The data set is offered by Ctrip, a leading travel agency in China that provides one-stop service for travelers from hotel reservations to attraction tickets and has the largest market share of approximately 60% (Barron's, 2019). Nowadays, Ctrip has become a data source widely used in the studies on the tourism industry (Sun et al., 2020).

Our study is based on regional data, which has been widely used in tourism literature (Cafiso et al., 2018; Yang & Fik, 2014). Specifically, the tourism demand is a province-month level panel data set, which differentiates the place of tourist origin and destination at the provincial level. Each observation of the data represents the monthly demand of tourists from a province of origin to a destination. The origin-destination pair data allows us to identify tourism flows and investigate the heterogenous preferences and behaviors of tourists from different places.

Considering the data availability, the destinations only include the seven provinces of South Central China, which are Henan, Hubei, Hunan, Jiangxi, Guangdong, Guangxi, and Hainan. However, for each province of destination, this data set differentiates tourists from each province of mainland China as origin. As such, for each month, there are 217 observations, which equals to the seven provinces of destination multiplied by the 31 places of origin (22 provinces, 5 autonomous regions, 4 municipalities directly under the central government) in mainland China.

The sample period of this data set is April to December in 2019 and 2020, which offers a good comparison before and after the outbreak of COVID-19 pandemic. Note that in early August 2020, the Hubei Provincial Government launched a recovery policy, named “Traveling with Love and Traveling to Hubei” with Ctrip, and provided free tickets of Hubei attractions for all Chinese people from August to December 2020, which makes the sales of Hubei attractions in these months are not a good comparison to that in 2019. Therefore, we exclude them when conducting corresponding analyses. Our data set has 3596 observations in total.

Although there are only seven provinces of destination, the tourism demand data are still a good representative. Specifically, Hainan is the number one tourist hotspot among numerous resorts in China. In terms of the economic development level, Guangdong is a relatively developed province. Henan, Hunan, Hubei, and Jiangxi are second-tier provinces, whereas Guangxi is a relatively undeveloped province. With regard to the severity of epidemic situation, these regions also display significant variations. Hubei lies in the center of this pandemic. Hunan, Henan, and Guangdong suffer less than Hubei but more than other provinces.

Additionally, we merge the tourism demand with other two data sets. One is the distances between destinations and places of origin. Typically, literature has regarded geographic distance as an important factor that influences tourism demand and widely incorporated it into the gravity model to predict tourism flows from the origin region to the destination region (Morley et al., 2014; Yang & Wong, 2012). We collect the data manually through Baidu Map, which measures the geographic distance between the capital cities of two provinces. Table 1 illustrates that the average distance is 1372 km, with the longest distance of 3652 km.

Another one is the reported number of cumulative confirmed cases in each province by the end of March, when the pandemic has been under control in China. Given that our sample period (either in 2019 or in 2020) begins in April, the number of cumulative confirmed cases by the end of March can be regarded as exogenous, which eliminates our concern about the endogenous problem. We employ the reported number of confirmed cases as a continuous treatment variable which measures the extent of treatment of a destination during the COVID-19 pandemic in a generalized difference-in-differences (DD) framework, as well as a proxy for the risk of a destination perceived by tourists to test whether tourists less prefer to visit destinations which were heavily hit by the pandemic due to perceived risk. We obtain it from Johns Hopkins CSSE Dashboard (Dong et al., 2020). Table 1 shows

[1] As defined by Ctrip, South Central China consists of Henan, Hubei, Hunan, Jiangxi, Guangdong, Guangxi, and Hainan provinces.

**Table 1**
Summary statistics for main variables.

| Variables | Obs. | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|---|
| Sales of attraction tickets | 3596 | 5131 | 24,677 | 1 | 566,608 |
| Confirmed cases | 3596 | 2631 | 11,907 | 1 | 67,802 |
| Distance (km) | 3596 | 1372 | 778 | 0 | 3652 |

Notes: Variable *Confirmed Cases* is defined as the cumulative number of confirmed cases in each province by the end of March 2020. Variable *Distance* is defined as the distance between the provincial capitals of destination and place of origin.

that the average of confirmed cases is roughly 2631 with minimum 1 and maximum 67,802.

*Empirical model and variables*

To identify tourists' preferences across regions (H1), we follow prior empirical studies (Albalate et al., 2017; Gao et al., 2021) and use fixed effects province-level panel data model with specifications (1) and (2):

$$log\left(TD_{ijt}\right) = \beta_1\ \Delta(Confirmed\ cases) \times Y2020 + \lambda_{ij} + m_i + h_j + z_t + m_i \times t + h_j \times t + \varepsilon_{ijt,} \quad (1)$$

$$log\left(TD_{ijt}\right) = \beta_1\ HB \times Y2020 + \lambda_{ij} + m_i + h_j + z_t + m_i \times t + h_j \times t + \varepsilon_{ijt,} \quad (2)$$

where $log(TD_{ijt})$ is the logarithm of monthly tourism demand of tourists from province $i$ for destination $j$ at time $t$. The continuous variable *Δ(Confirmed cases)* is defined as the gap of cumulative confirmed cases between destination and place of origin by the end of March 2020, and the variable *HB* is a dummy variable representing whether the destination is Hubei Province. In these two models, the variable *Y2020* is an indicator which takes a value of 1 for the period from April 2020 to December 2020, and 0 for the period from April 2019 to December 2019. $m_i$ and $h_j$ are fixed effects regarding destination $i$ and place of origin $j$ in each pair, respectively. We include them in our model mainly to control those unobserved characteristics of provinces that are invariant over sample time period but may influence tourism demand potentially, such as the number of tourism attractions and amenities, traffic accessibility, the quality of infrastructure, and local culture. Note that $m_i$ and $h_j$ are a set of dummy variables. Also, motivated by the literature related to tourism flows (Morley et al., 2014; Yang & Wong, 2012), we control bilateral fixed effects (destination-origin pairs) in our model, which is denoted by $\lambda_{ij}$.

Additionally, considering the monthly variations in tourism demand, we add month fixed effects $z_t$ to exclude the interference of time factor, such as macroeconomic policy shocks during our study period. Since these time-varying shocks can vary across years as well as months, for example, the shock of national holidays in each year and tourism policies implemented in a specific year, the month fixed effects in our model are actually set based on year-month pairs, which means that we control the effects regarding a specific month in a specific year (e.g. April 2019). In particular, we have 18 months in the sample, the "year-month" fixed effects set 17 dummies.

It is noticeable that there is no time-varying province-specific control variables at the right sides of Eqs. (1) and (2), such as GDP per capita and population for destinations and places of origin. In the classical tourism gravity model, these factors are important determinants of tourists' destination choice and the tourism flows (Morley et al., 2014; Patuelli et al., 2013). For destinations, GDP per capita and population can have both a positive effect on tourism demand because a destination with higher GDP per capita and population is generally more attractive in terms of economic development (Yao & Morikawa, 2005), and a negative effect when tourists prefer visiting less industrialized and more tranquil areas (Patuelli et al., 2013). Besides, GDP per capita and population in places of origin reflect the level of average income and consumption capacity, thus probably influencing the tourism demand. Although we may argue that these factors are less likely to change sharply in a short period, for example, two years, we tend to consider a more conservative model with destination-specific trends and origin-specific trends denoted by $m_i \times t$ and $h_j \times t$ in Eqs. (1) and (2). Therefore, time-varying province-specific variables can be largely controlled by adding the fixed effects of destination-specific trends and origin-specific trends in our model.

$\beta_1$ is the main parameter of interest, measuring the causal impact of COVID-19 on tourists' demand for destinations which were heavily hit by the pandemic, namely, regional bias. Since *Δ(Confirmed cases)* can be taken as a continuous treatment variable which measures the extent of treatment of a destination during the COVID-19 pandemic, Eq. (1) is a generalized DD model. Similarly, Eq. (2) is a DD model, where Hubei Province, as the hardest-hit area in this pandemic, is the treatment group, and other provinces are included in the control group. According to H1, we expect $\beta_1$ is negative and significant, which means that tourists less prefer to visit destinations with more confirmed cases, specifically, Hubei Province, even after the end of lockdown. Finally, to attain robust results, we cluster the standard errors at the provincial level (destination-origin pairs), following Cameron and Miller (2015). Since there are 7 provinces as destinations and 31 provinces as places of origin in our sample, we have 217 (7 × 31) pairs in total. Besides, as robustness checks, we also cluster the standard errors at the provincial level based on 31 provinces of origin.

To empirically test H2, we implement two interaction effects models. In this analysis, we compare the demand changes for local and non-local attractions before and after the pandemic with model (3). Additionally, we estimate the impact of COVID-19 pandemic on tourists' preferences across spatial distances with model (4).

$$log\left(TD_{ijt}\right) = \beta_1 Local \times Y2020 + \lambda_{ij} + m_i + h_j + z_t + m_i \times t + h_j \times t + \varepsilon_{ijt,} \tag{3}$$

$$log\left(TD_{ijt}\right) = \beta_1 Distance \times Y2020 + \lambda_{ij} + m_i + h_j + z_t + m_i \times t + h_j \times t + \varepsilon_{ijt,} \tag{4}$$

Similarly, $log\ (TD_{ijt})$ is the outcome variable from province $i$ for destination $j$ at time $t$, and *Y2020* is an indicator for 2020. In model (3), *Local* is a dummy variable representing whether the demand is generated by local tourists or not, and we define this according to the provincial-level matching between destinations and places of origin. Specifically, if the provinces of destination and origin are the same, *Local* is equal to 1; otherwise, it is equal to 0. In model (4), *Distance* is defined as the geographical distance between the provincial capitals of destination and place of origin. The coefficient $\beta_1$ measures the effect of COVID-19 pandemic on tourists' preferences across spatial distances, which is our main interest. Similar to models (1) and (2), $m_i$, $h_j$, and $z_t$ respectively account for the fixed effects of provinces of origin and destinations as well as month fixed effects. $m_i \times t$ and $h_j \times t$ are destination-specific trends and origin-specific trends while $\lambda_{ij}$ represents bilateral fixed effects regarding destination-origin pairs. $\varepsilon_{ijt}$ is an error term.

## Empirical results

### *Regional Bias*

We estimate the model using STATA 15. The VIF (variance inflation factor) values of all regressions indicate that our models do not suffer from the problem of multicollinearity. Table 2 presents the results for the effect of COVID-19 on tourism demand for destinations which were heavily hit by the pandemic, namely, regional bias. Columns (1) and (2) adopt different set of controls. In column (1), we control for year-month fixed effects considering the unobserved shocks varying with time, such as seasonal shocks and policy changes, and the fixed effects of destinations and places of origin to capture the unobserved specific characteristics of provinces invariant with time, as well as bilateral fixed effects regarding destination-origin pairs. In column (2), we additionally control for destination specific trends and origin specific trends to capture possible different trends of tourism demand regarding destinations and places of origin due to the interference of time-varying province-specific variables. We observe that either in column (1) or (2), the coefficient of *Y2020×Δ(Confirmed-case)* is negative and significant at 1% significance level. This indicates a significantly negative relationship between tourism demand and the reported number of confirmed cases in destination relative to that in the place of origin, which means that tourists are less willing to choose destinations with more confirmed cases after the end of lockdown.

Besides, in columns (3) and (4), we substitute the continuous variable named *Δ*(*Confirmed cases*) with the dummy variable named *HB* to conduct the DD model in Eq. (2), where Hubei Province is the treatment group, and other provinces are included in the control group. However, due to the particularity of Hubei tourism demand from August to December as stated in Section 3.1, the DD analysis is conducted with the subsample during the period between April and July in 2019 and 2020. As shown in Table 3, the interaction terms between *Y2020* and *HB* are both negative and significant at 1% level, indicating tourists are less willing to visit attractions in Hubei Province than in other provinces after experiencing this pandemic.

Therefore, H1 is supported. These findings provide insights into the literature of risk perceptions (Neuburger & Egger, 2020), and indirectly validate that as an important signal, the media coverage of confirmed cases influences tourists' risk perceptions of destinations, thus leading to a tendency to avoid traveling to high-risk destinations with more reported confirmed cases, especially Hubei Province.

### *Spatial distance preference*

Table 3 presents the results for H2. In columns (1) and (2), the dummy variable *Local* equals 1 if the demand is generated by local tourists, and equals 0 otherwise. By observing the coefficients of our interest, we find that the interaction terms between *Local* and *Y2020* are both positive and significant at 5% and 1% significance level respectively, indicating that after the end of lockdown, tourists more prefer local attractions compared with non-local ones. In columns (3) and (4), we present the results of how the tourism demand varies with travel distance. The interaction terms between *Distance* and *Y*2020 are both negative, and the coefficient of the most robust model specification in column (8) is significant at 1% significance level, indicating that the COVID-19 pandemic leads to a negative relationship between travel distance and tourism demand, and tourists prefer those destinations close to home after experiencing the pandemic. The empirical results support H2 and suggest that people tend to be more risk averse and more sensitive to potential losses during the travel after experiencing a disaster (Cameron & Shah, 2015; Cassar et al., 2017; Reynaud & Aubert, 2020). Thus, the increased expected losses prompt people to change initial plans and turn to choices with less risks, for example, local or short-distance trips (Kozak et al., 2007).

**Table 2**
Effect of COVID-19 on regional bias.

| | Dependent variable: log(demand) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Y2020 × Δ(confirmed-case) | $-0.0142^{***}$ | $-0.0151^{***}$ | | |
| | (0.00279) | (0.00544) | | |
| Y2020 × HB | | | $-1.509^{***}$ | $-2.865^{***}$ |
| | | | (0.132) | (0.260) |
| Year-month FE | Yes | Yes | Yes | Yes |
| Destination FE | Yes | Yes | Yes | Yes |
| Origin FE | Yes | Yes | Yes | Yes |
| Destination-origin FE | Yes | Yes | Yes | Yes |
| Destination specific trends | No | Yes | No | Yes |
| Origin specific trends | No | Yes | No | Yes |
| *N* | 3596 | 3596 | 1736 | 1736 |
| Adj. R-square | 0.909 | 0.920 | 0.914 | 0.927 |
| Number of clusters | 217 | 217 | 217 | 217 |

Notes: Robust standard errors clustered at the provincial level (destination-origin pairs) are in parentheses; *, ** and *** denote significance level of 10%, 5% and 1%, respectively. Since the data of Hubei Province as the destination from August to December are excluded due to the recovery policy as stated in Section 3.1, we use the subsample from April to July in 2019 and 2020 to conduct regression analysis in columns (3) and (4).

*Robustness checks*

To further strengthen our previous findings, we adopt a set of robustness checks including (1) using the full sample without dropping the data of Hubei as the destination from August to December, (2) controlling for neighbourhood effects, and (3) using standard errors clustered by places of origin. Results for these robustness checks are shown in Tables 4 and 5.

In Table 4, we conduct robustness checks with the full sample. In the previous analysis, we drop part of the sample with the sales of attraction tickets occurring in Hubei Province from August to December so as to exclude the interference of a recovery policy which was launched by Hubei Provincial Government in early August 2020. As robustness checks, we use the full sample to estimate the heterogeneous effects prior to and after August by introducing a triple interaction term. The model specification is shown in Eq. (5):

$$log\left(TD_{ijt}\right) = \beta_1\, X \times Y2020 + \beta_2\, X \times Y2020 \times AfterAugust + \lambda_{ij} + m_i + h_j + z_t + m_i \times t + h_j \times t + \varepsilon_{ijt}, \tag{5}$$

where ***X*** denote four independent variables, namely, *Δ(Confirmed cases), HB, Local,* and *Distance* in Eqs. (1)–(4). *AfterAugust* is a dummy variable representing whether the month is August or after. To capture the specific effects as of August when the policy has been implemented, we add a triple interaction term among ***X***, *Y2020* and *AfterAugust*. $\beta_1$ is the main parameter of interest, measuring the causal effects of COVID-19 on tourists' preferences for destinations before August. $\beta_2$ measures the additional effects as of August, which are mainly caused by the recovery policy.

**Table 3**
Effect of COVID-19 on spatial distance preference.

| | Dependent variable: log(demand) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Y2020 × local | $0.472^{**}$ | $0.464^{***}$ | | |
| | (0.190) | (0.173) | | |
| Y2020 × distance | | | $-0.0561^{**}$ | $-0.0950^{***}$ |
| | | | (0.0234) | (0.0287) |
| Year-month FE | Yes | Yes | Yes | Yes |
| Destination FE | Yes | Yes | Yes | Yes |
| Origin FE | Yes | Yes | Yes | Yes |
| Destination-origin FE | Yes | Yes | Yes | Yes |
| Destination specific trends | No | Yes | No | Yes |
| Origin specific trends | No | Yes | No | Yes |
| *N* | 812 | 812 | 3596 | 3596 |
| Adj. R-square | 0.933 | 0.945 | 0.902 | 0.920 |
| Number of clusters | 49 | 49 | 217 | 217 |

Notes: Robust standard errors clustered at the provincial level (destination-origin pairs) are in parentheses; *, ** and *** denote significance level of 10%, 5% and 1%, respectively. Variable *Distance* is defined as the geographical distance between the provincial capitals of destination and place of origin, and we take its natural logarithm into regression. Since our data only include seven provinces as destination in South Central China, we use the subsample with only seven origin provinces matching the seven destinations to conduct regression analysis in columns (1) and (2).

**Table 4**
Robustness checks with different sample.

| | Dependent Variable: log(demand) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Regional bias | | | | Spatial distance preference | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Y2020 × Δ(confirmed-case) | −0.0190*** | −0.0250*** | | | | | | |
| | (0.00229) | (0.00257) | | | | | | |
| Y2020 × Δ(confirmed-case) × AfterAugust | 0.0500*** | 0.0459*** | | | | | | |
| | (0.00456) | (0.00455) | | | | | | |
| Y2020 × HB | | | −1.593*** | −2.015*** | | | | |
| | | | (0.120) | (0.135) | | | | |
| Y2020 × HB × AfterAugust | | | 4.221*** | 3.929*** | | | | |
| | | | (0.150) | (0.152) | | | | |
| Y2020 × local | | | | | 0.946*** | 0.946** | | |
| | | | | | (0.267) | (0.393) | | |
| Y2020 × local×AfterAugust | | | | | −0.738 | −0.738 | | |
| | | | | | (0.742) | (0.625) | | |
| Y2020×distance | | | | | | | −0.122*** | −0.119*** |
| | | | | | | | (0.0324) | (0.0433) |
| Y2020×distance×AfterAugust | | | | | | | 0.0626 | 0.0646 |
| | | | | | | | (0.0869) | (0.0775) |
| Year-month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Destination FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Origin FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Destination-origin FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Destination specific trends | No | Yes | No | Yes | No | Yes | No | Yes |
| Origin specific trends | No | Yes | No | Yes | No | Yes | No | Yes |
| *N* | 3906 | 3906 | 3906 | 3906 | 882 | 882 | 3906 | 3906 |
| Adj. R-square | 0.903 | 0.915 | 0.922 | 0.929 | 0.850 | 0.887 | 0.833 | 0.864 |
| Number of clusters | 217 | 217 | 217 | 217 | 49 | 49 | 217 | 217 |

Notes: Robust standard errors clustered at the provincial level (destination-origin pairs) are in parentheses; *, ** and *** denote significance level of 10%, 5% and 1%, respectively.

In columns (1)–(4) of Table 4, we examine the patterns of regional bias and find that all the coefficients of interest are negative and significant at 1% significance level, which are consistent with the results in Table 2. This ensures the robustness of our findings that tourists less prefer to visit destinations with more confirmed cases, especially Hubei Province, after experiencing the pandemic. Note that the coefficients of triple interaction terms are positive and significant, which indicate that as of August, the patterns of regional bias are counteracted and even reverse due to the influence of policy or other potential factors, for

**Table 5**
Robustness checks with neighbourhood effects and different clusters.

| | Dependent variable: log(demand) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Controlling for neighbourhood effects | | | | Using standard errors clustered by origin | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Y2020 × Δ(confirmed-case) | −0.0148*** | | | | −0.0151* | | | |
| | (0.00518) | | | | (0.00878) | | | |
| Y2020 × HB | | −2.338*** | | | | −2.865*** | | |
| | | (0.246) | | | | (0.211) | | |
| Y2020 × local | | | 0.456** | | | | 0.464* | |
| | | | (0.176) | | | | (0.192) | |
| Y2020 × distance | | | | −0.0928*** | | | | −0.0950*** |
| | | | | (0.0292) | | | | (0.0338) |
| Neighbourhood | −0.109*** | −0.315*** | −0.0796*** | −0.109*** | | | | |
| | (0.0127) | (0.0538) | (0.0281) | (0.0118) | | | | |
| Year-month FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Destination FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Origin FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Destination-origin FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Destination specific trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Origin specific trends | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 3596 | 1736 | 812 | 3596 | 3596 | 1736 | 812 | 3596 |
| Adj. R-square | 0.922 | 0.931 | 0.946 | 0.922 | 0.920 | 0.926 | 0.945 | 0.920 |
| Number of clusters | 217 | 217 | 49 | 217 | 31 | 31 | 7 | 31 |

Notes: Robust standard errors in parentheses are clustered at the provincial level (destination-origin pairs) in columns (1)–(4) and at the provincial level by origin in columns (5)–(8); *, ** and *** denote significance level of 10%, 5% and 1%, respectively. Variable *Neighbourhood* is defined as the average tourism demand from the same place of origin to adjacent destinations, and we take its natural logarithm into regression.

example the natural recovery of sentiment with time. Similarly, in columns (5)–(8) of Table 4, the coefficients of interest are consistent with the results in Table 3, thus ensuring the robustness of our findings about tourists' spatial distance preferences. However, the coefficients of triple interaction terms are insignificant, indicating that there is no significant heterogeneity in the patterns of spatial distance preferences before and after August.

In columns (1)–(4) of Table 5, we control for neighbourhood effects to conduct robustness checks. Considering that the tourism demand in neighbourhood provinces may have spillover effects on a certain province (Marrocu & Paci, 2013), we construct a variable *Neighbourhood* to represent the neighbourhood effects on a specific destination by calculating the average tourism demand from the same place of origin to its adjacent destinations, and add it as a control variable. Note that *Neighbourhood* is a time-varying and destination-specific variable. We find that all the results are consistent with our previous analyses, indicating the robustness of our findings. Furthermore, in columns (5)–(8), we use standard errors clustered by places of origin to conduct robustness checks and the results are consistent as well.

### *Parallel trend assumption and placebo test*

To confirm the validity of our DD design, we check the parallel trend assumption, which requires that in the absence of a shock, there is no significant difference between the treatment and control group over time. The results are displayed in Fig. 1, where we plot the coefficients of interaction terms between monthly dummy variables and treatment variable. We find that prior to the pandemic, the coefficients of interaction terms are all insignificant, confirming that the parallel pre-trend exists in our model. After the shock, the interaction terms between the dummy variables of each month and *HB* become negative and significant, indicating that from April to July in 2020, tourists consistently show less preferences for traveling to Hubei Province. Besides, the interaction terms between the dummy variables of each month and *Δ(Confirmed cases)* become negative and significant in April, May, and July in 2020, indicating that the regional bias only exists in the first several months after the end of lockdown, and with the recovery of tourism and consumer confidence, the bias gradually disappears.

Furthermore, we conduct a placebo test to rule out the possibility of a coincidence. Although we get significant estimation from the previous analyses, the causal effect can be a coincidence. If this is true, we cannot conclude that the effect comes from the COVID-19 pandemic. Therefore, we falsely assume that the onset of treatment occurs months before it actually does, for example, in July 2019, and employ the subsample of 2019 to repeat previous analyses. Table 6 displays the results of placebo test in which columns (1)–(4) respectively test the effects of COVID-19 on tourists' preferences across regions and spatial distances, corresponding to the model in Eqs. (1)–(4). We observe that the coefficients of interest are all insignificant, indicating that our previous findings are not a coincidence.

## Conclusions and implications

In this research, we highlight that tourists' destination preferences are significantly reshaped by the COVID-19 pandemic. Specifically, we reveal that tourists less prefer the destinations with more confirmed cases of COVID-19 relative to their places of origin, especially Hubei Province, after experiencing the pandemic. This may be attributed to their perceptions of infection risk, and destinations with more confirmed cases are generally perceived to be unsafe. Besides, tourists more prefer destinations close to home, especially local attractions, considering that the expected losses outweigh the gains in long-distance travel compared with short-distance travel in the context of COVID-19 pandemic. With our findings as basis, we provide the following theoretical and managerial implications.

### *Theoretical implications*

This study provides several theoretical implications. Foremost, this study contributes to the tourism literature by revealing noticeable changes in tourists' destination preferences in light of COVID-19. Although a range of research has paid particular attention to the devastating effects of COVID-19 pandemic on tourism as well as the forecasts of tourism recovery (Fotiadis et al., 2021; Yang et al., 2020a), little is known about how tourists' destination preferences are reshaped by the pandemic. A few studies explore the impact of COVID-19 on travelers' consumption patterns but lack an empirical analysis. For example, Wen, Kozak, Yang, & Liu, 2020 predicts that COVID-19 may lead to growing popularity of free and independent travel, luxury trips and wellness tourism based on an overview of literature and news. Our study fills this gap by shedding light on the patterns of regional bias and spatial distance preferences. We find that tourists avoid traveling to high-risk destinations with more confirmed cases relative to their places of origin, especially Hubei Province. Besides, tourists more prefer short-distance trips and local trips rather than long-distance trips after experiencing the pandemic. These findings contribute to the literature by enhancing our understanding on the changes in tourists' destination preferences after the end of lockdown.

Moreover, this study contributes to the tourism literature by combining signaling, risk perception, and prospect theory with tourists' behavior and providing empirical foundation for the application of these theories in explaining people's behavioral responses in view of crises. Shin and Kang (2020) indicate that perceived health risk, as a mediator, can significantly influence hotel booking intention in the COVID-19 pandemic era. While the pandemic will wreck the tourism as we know it, a crucial shift is likely to occur in tourists' psyche (Kock et al., 2020). Building upon the risk aversion theory, prospect theory and signaling theory, we provide the underlying mechanisms behind the findings. To reduce potential infectious risks, tourists tend to change

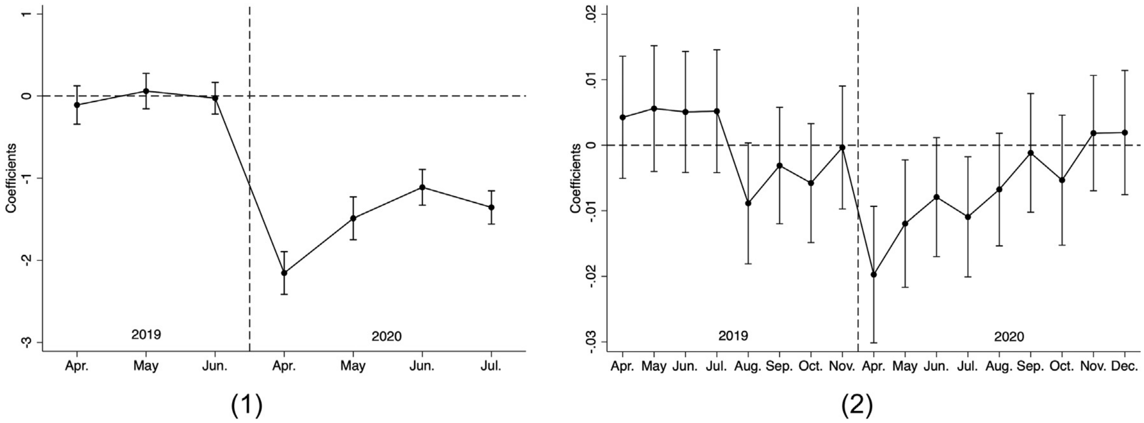


**Fig. 1.** Parallel trend test notes: panel (1) plots the coefficients of interaction terms between variable *HB* and a set of dummy variables representing each month. Similarly, panel (2) plots the coefficients of interaction terms between variable *Δ(Confirmed-case)* and a set of dummy variables representing each month. The bar at each coefficient point represents a 95% confidence interval of this coefficient.

their destination preferences, for example, shifting toward short-distance trips and local trips. In this light, our study extends the knowledge on risk perception and tourists' decision making.

## *Managerial implications*

This study also provides practical implications for tourism practitioners and managers worldwide. First, our findings support tailoring travel arrangements in view of COVID-19 pandemic. Given that in the recovery phase, short-distance and local trips appear to be the dominance and gain more popularity, managers should take full account of the new trends and focus on the development of short-distance tourist routes to capture early demand. They can reallocate the resources to hot attractions and modify existing products and services to satisfy new demands of consumers. The suggestions may help to alleviate pandemic-related stress, stimulate new tourism demand, and partially mitigate the negative effects of COVID-19 on the tourism industry.

Second, the increased safety concerns and risk-averse behaviors urge managers to take efficient measures to reduce consumers' perceived risk of COVID-19 infection, such as setting new cleaning standards and carrying out strict health screenings. In the pandemic era, how to ensure the safety of customers and employees is the top priority, so intelligent services including contactless consulting platforms, face recognition systems, and robot cleaners, have potential to be widely used in the tourism sectors to promote the post-pandemic recovery (Shin & Kang, 2020).

Third, considering the information asymmetry across regions, providing potential consumers with positive signals about regional safety is of great importance. Positive signals, serving as a commitment to consumer safety, can reduce consumers'

**Table 6**
Placebo test.

| | Dependent variable: log(demand) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Post×Δ(confirmed-case) | −0.00270<br>(0.00247) | | | |
| Post×HB | | −0.0577<br>(0.0513) | | |
| Post×local | | | 0.00214<br>(0.0890) | |
| Post×distance | | | | −0.0181<br>(0.0177) |
| Year-month FE | Yes | Yes | Yes | Yes |
| Destination FE | Yes | Yes | Yes | Yes |
| Origin FE | Yes | Yes | Yes | Yes |
| Destination-origin FE | Yes | Yes | Yes | Yes |
| Destination specific trends | Yes | Yes | Yes | Yes |
| Origin specific trends | Yes | Yes | Yes | Yes |
| *N* | 1798 | 868 | 406 | 1798 |
| Adj. R-square | 0.945 | 0.976 | 0.964 | 0.945 |
| Number of clusters | 217 | 217 | 49 | 217 |

Notes: Robust standard errors clustered at the provincial level (destination-origin pairs) are in parentheses; *, ** and *** denote significance level of 10%, 5% and 1%, respectively. We use the subsample in 2019 to conduct a placebo test. Variable *Post* is a dummy variable of counterfactual points in time which are randomly selected to represent whether the event had happened. In each column, the test shows no sign of statistical significance.

uncertainties and perceived risk about safe hazards during the decision-making processes (Bove & Benoit, 2020). Our study finds that the reported number of confirmed cases, as a perceptible signal, is negatively correlated with tourism demand. To counteract the adverse effect, managers, especially those in the hardest-hit areas, should wisely convey positive signals about regional safety and risk-reduction strategies, which are expected to allay consumers' perceived health risk and spur the recovery of tourism demand.

Fourth, policymakers should implement various recovery policies to stimulate tourism demand. For example, Hubei Province launched a recovery policy, named "Traveling with Love and Traveling to Hubei" in early August, which allows domestic tourists to visit almost 400 scenic spots inside the province for free from August 8 to the end of 2020. The free admission is intended to attract visitors, boost consumption, and accelerate the recovery of tourism. By considering the heterogeneous effects as of August, we find that the policy largely promotes tourism demand for Hubei attractions and the patterns of regional bias are counteracted and even reverse after August. Besides, according to real-time monitoring data from Ctrip, the number of hotel reservations in Wuhan has increased by 36% in August compared with that in July,[2] indicating that this policy is effective and plays an important role in tourism recovery after the pandemic.

*Limitations and future study*

Our study has limitations that give room for further research. First, this study is confined to Chinese tourism, which was the first to be involved in this crisis and reopen. However, due to the different severity of this crisis and regulations across countries, there may be distinctions among consumer responses to the pandemic. Therefore, exploring the different consumers' behavioral responses to this pandemic in different countries will be interesting, especially as it remains unaddressed. Second, this study only focuses on how spatial distance and regional number of confirmed COVID-19 cases affect tourism demand. Other changes in tourists' preferences and behaviors such as whether they prefer natural attractions or tourism hotspots after experiencing this pandemic deserve to be explored in future research. Doing so can give managers more detailed suggestions about the future recovery in tourism. Finally, due to the data access limitation, we are only provided with the aggregated data at province-month level, while attraction-level data or city-level data might reflect more patterns and can be a future direction of research.

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[2] Please see https://m.sohu.com/a/417059222_362042

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