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The Home and Guest Effects in Aviation Market: A Case Study in China and United States

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Abstract: The average delay time of local airlines in China's hub airports is shorter than that of other airlines operating at the same airport. However, by now, no scholars in the academic community can support such research through accurate data. This paper aims to propose solutions to the problems that cannot be measured between different types of airlines and specific airports based on aviation big data drive and to explore the differences of flight delay propagation level between local airlines and other airlines in the same airport, i.e., the host guest field effect. Specifically, it reveals the delay propagation differences of different airlines in the same airport under the same conditions, finds out the description index of the host guest effect, and answers the existing form and distribution characteristics of the host guest effect. In addition, we also compared the delay data of the United States hub airport, and explained the problem of whether the main and passenger field effects only exist in the Chinese aviation market.

1. Introduction

In recent years, China's civil aviation industry has developed rapidly, and the number of flights out of the port ranks the second in the world. However, due to the particularity of air traffic, the problem of flight delay that has long plagued the development of civil aviation still exists, and the punctuality rate of flights is affected [8]. According to statistics, from 2006 to 2015, the number of flights of Air China continued to grow rapidly, with an increase of 130% in 10 years and an average annual growth of 10.8%. However, the punctuality rate of flights also showed a downward trend. Before 2009, the punctuality rate of flights was more than 80%, and began to decline continuously in 2010. In 2015, it dropped to 66.91%, with an average annual decline of 1.46%. Since 2016, flight punctuality has improved. According to [4][5], China's civil aviation airports will complete 352 million passenger throughput in 2019, an increase of 6.9% over the previous year, but the punctuality rate is only 75.57%. The average arrival delay of passenger flights is 14 minutes while the average departure delay is 28.11 minutes. This is similar to the conclusion mentioned in [12] that the overall arrival OTP of Chinese flights is better than the departure OTP. See Fig.1 for details.

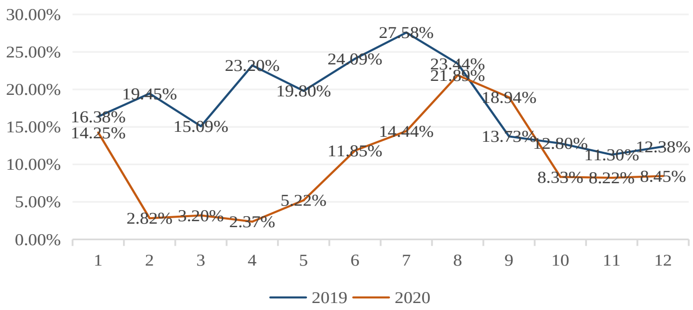

Figure 1: Comparison of flight delay rate in China from 2019 to 2020

Figure 2 shows the top 10 countries in terms of flight take-off and on-time rates in the world.

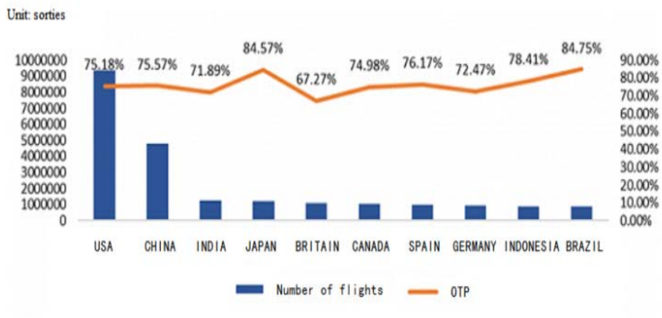

Figure 2: Top 10 countries in 2019 in terms of flight volume and punctuality

From the data of the U.S. Department of transportation, since 1998, the overall number of flight delays and cancellations has increased by 62%. In 2019, the number of departing flights reached 9 million, ranking first in the world. However, the punctuality rate of flights is only 75.18% (U.S., CAA, 2019). The problem of flight delays in the U.S. has always been serious. Among them, the most serious flight delays are the three major airports in the New York area: Kennedy Airport, Newark Airport and LaGuardia Airport (CAA, 2007).

As shown in Fig.3 drawn according to [3], about 56.88% of flights were delayed caused by extreme weather. Followed by airlines, which accounted for 16.35% of the total, including late flights, technical and coordination problems. Besides, there is airport congestion. [1] used the OTP data of major US airports to demonstrate that airport congestion can be shaped by the airline market power (i.e., airline self-internalization of the congestion). Others, [6][16][22] have also done relevant research on airport congestion. [19] found that the limited air space for civil aviation further hinders airlines to maintain OTP. Airport congestion is usually caused by limited airport resources, poor flight punctuality, unfavorable ground traffic control, traffic flow control. The FAA and the Department of transportation (DOT) of the United States adopt the method of increasing the airport capacity to maximize the number of flights taking off and landing to improve the existing airport capacity, so as to reduce the delay (FAA, DOT, 2008). China usually increases flight buffer time to alleviate delay. [2][9][10][11] show that flexible use of flight buffer time can effectively alleviate delay propagation, but it will increase the operating cost of airlines and reduce aircraft utilization. E.g., [15] found that American Airlines did not increase flight buffers between 1988 and 2000, hoping to save the high labor costs. According to the statistics of CAAC, by the end of 2019, there are 3818 transport aircraft in the whole industry with an annual flight volume of 4.611 million. The average daily flight of each aircraft in the domestic aviation sector is 3.3 times while the aircraft utilization rate of the United States is twice that of China.

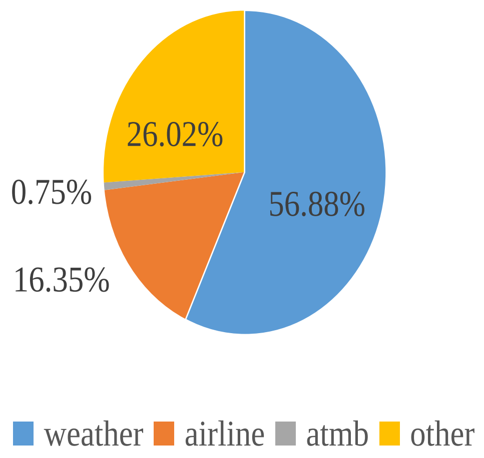

Figure 3: Causes of flight delay in 2020

There is always a connection relationship between airport flights which is embodied in the same aircraft will perform multiple continuous flights in a day. When the arrival delay of current sequence flights occurs, the downstream flights will be easily affected by the delay. Generally, the later the flight schedule, the more serious the flight delay especially the delay of the early flight in one day will cause the cumulative delay of the subsequent flights, we call this phenomenon as the spread of flight delay (delay propagation). Based on the U.S. market data, [17] suggest that delay propagation can be more serious at major hub airports while it is unclear whether this phenomenon is applicable to China. At present, [14] propose an analytical-econometric approach to calculate the delay propagation in the US market. [18] has come to the conclusion that the average departure delay of the follow-up flights is 7.4 minutes per 10 minutes of arrival delay of the previous flights by establishing the regression analysis model. From this conclusion, we found that in the case of flight arrival delay, the airline company and the airport can shorten the departure delay of subsequent flights by speeding up the ground service speed and improving the operation efficiency. The actual arrival time of the preceding flight and the actual departure time of the next flight are usually called the aircraft transit time. The length of aircraft transit is not only related to the operational efficiency of the aviation department, but also determined by the cooperation between the airport and the airlines. The effective cooperation between airlines and airports can effectively control the delay propagation.

In the aviation market, Airlines operating at an airport can be divided into local airlines and other airlines. The local airlines usually refer to the airline which take an airport as its main operation base, they usually set up headquarters in the location of the airport, most of the departure flights of the airport are operated by the base airlines, and the business volume generally accounts for more than 50% [16]. E.g., the number of flights of American Airlines accounts for 73.5% at Atlanta hub airport. American Northwest Airlines accounts for 79.8% of the number of flights at Detroit hub airport. German Lufthansa Airlines accounts for 60.8% at Frankfurt hub airport. The above data shows that local airlines have advantages in the base airport, which are reflected in the flight schedule configuration and airport ground service. In order to visualize the advantages of local aviation, referring to [7], we have quantified the flight data of major airlines in China's three major hub airports: Beijing Capital Airport (PEK), Shanghai Hongqiao Airport (SHA) and Guangzhou Baiyun Airport (CAN) in 2019. Table 1, Table 2 and Table 3 described the average arrival delay and departure delay of all airlines operating at Beijing Capital Airport, Shanghai Hongqiao Airport and Guangzhou Baiyun Airport in 2019.

Table 1: Arrival delay and departure delay of airlines at Beijing Capital Airport in 2019

NO	Airline Name	Delay time at PEK (min)	
		Arrival Delay	Departure Delay
1	Shanghai Airlines	10.54	23.15
2	**China Eastern airlines**	**15.58**	**29.00**
3	East China Sea Airlines	18.95	15.73
4	**Air China**	**17.30**	**28.10**
5	**China Southern airlines**	**17.35**	**29.72**
6	Xiamen Airlines	25.10	32.44
7	Lucky Airlines	23.47	19.07
8	Sichuan Airlines	17.31	29.65
9	Grand China Airlines	15.83	15.21
10	Shandong Airlines	9.98	18.98
11	Jiangxi Airlines	0.74	16.39
12	Hainan Airlines	23.00	26.86
13	Shenzhen Airlines	22.31	34.42
14	Lucky Air	74.00	14.91
15	Tibet Airlines	7.75	31.59
16	Changlong Airlines	17.22	13.89
17	Capital Airlines	22.04	21.85

[a]The data comes from China's three major hub airports in 2019.

Table 2: Arrival delay and departure delay of airlines at Shanghai Hongqiao Airport in 2019

NO	Airline Name	Delay time at SHA (min)	
		Arrival Delay	Departure Delay
1	Shanghai Airlines	16.48	21.40
2	**China Eastern airlines**	**12.13**	**24.66**
3	**Air China**	**11.88**	**36.55**
4	China United Airlines	13.60	31.35
5	**China Southern airlines**	**14.54**	**36.61**
6	Xiamen Airlines	15.12	29.60
7	Lucky Airlines	14.89	24.43
8	Tianjin Airlines	8.35	32.01
9	Shandong Airlines	7.98	19.20
10	Chengdu Airlines	10.86	33.59
11	Spring airlines	13.58	17.66
12	Hebei Airlines	11.25	25.31
13	Hainan Airlines	11.01	37.16
14	Shenzhen Airlines	21.92	44.98
15	Lucky Air	10.19	23.99
16	Tibet Airlines	9.99	21.49

[b]The data comes from China's three major hub airports in 2019.

Table 3: Arrival delay and departure delay of airlines at Guangzhou Baiyun Airport in 2019

NO	Airline Name	Delay time at CAN (min)	
		Arrival Delay	Departure Delay
1	Shanghai Airlines	18.77	34.98
2	**China Eastern airlines**	**15.64**	**31.86**
3	East China Sea Airlines	0.00	45.40
4	**Air China**	**21.20**	**29.08**
5	China United Airlines	36.25	49.91
6	Nine dollar Airlines	23.45	27.14
7	Beibu Gulf Airlines	9.00	19.16
8	**China Southern airlines**	**20.39**	**26.50**
9	Xiamen Airlines	21.24	46.03
10	Lucky Airlines	22.91	22.48
11	Sichuan Airlines	10.67	29.38
12	Tianjin Airlines	10.67	29.38
13	Okay Airways	42.18	66.76
14	Shandong Airlines	43.48	17.98
15	Chengdu Airlines	10.81	23.59
16	kunming airlines	3.60	19.48
17	Spring airlines	20.58	29.33
18	Hebei Airlines	18.49	39.21
19	Hainan Airlines	39.82	47.55
20	Shenzhen Airlines	20.80	29.64
21	Lucky Air	23.14	35.52
22	Western Airlines	15.07	40.80
23	Changlong Airlines	10.82	33.12
24	Capital Airlines	16.25	33.07

[c]The data comes from China's three major hub airports in 2019.

As can be seen from the above table. The delay time of the local airlines is obviously less than that of other airlines operating at the same airport which lends support to the theory that the main aviation department has certain advantages in its main base airport than others. Nevertheless, there are few related researches in academic circles, at least so far, no scholars can support such findings through accurate data. This paper aims to propose solutions to the problems that cannot be measured between different types of airlines and specific airports based on aviation big data drive and to explore the differences of flight delay propagation level between local airlines and other airlines in the same airport, i.e., the host guest field effect. Specifically, all the historical flight data of China and the United States hub airports in 2019 are collected, and conducted regression analysis based on this data set. It reveals the delay propagation differences of different airlines in the same airport under the same conditions, finds out the description index of the host guest effect, and answers the existing form and distribution characteristics of the host guest effect. In addition, we also compared the delay data of the United States hub airport, and explained the problem of whether the main and passenger field effects only exist in the Chinese aviation market. The study is useful for future research on the analysis of international aviation market trends and the causes of flight delay and it is of great significance to monitor the operation of airlines and airports, improve the operation efficiency of airports and strengthen the cooperation between airlines and airports. However, it should be noted that the data set used in this paper is limited to 2019, and does not quantify the flight data of other years. Therefore, there are still limitations in this study and only provide reference for future research.

2. Literature Review

At present, [13] have found the differences between base airlines and other airlines in the allocation of flight schedule, airport ground service and other resources, but there is no data support. [21] carried out a study on the relationship between the main base airlines and the hub airport in the construction of the aviation hub, pointed out the problems existing between the main base airlines and the airport, and gave suggestions for their cooperation, but did not discuss the relationship between the flight punctuality rate and the main airport. [18] have come to the conclusion that the average departure delay of the follow-up flights is 7.4 minutes per 10 minutes of arrival delay of the previous flights by establishing the regression analysis model. Few foreign scholars have made quantitative explanation on the host guest effect of aviation market.

3. Data and Econometric Model

3.1. Data collection

In view of the particularity of regression analysis, we collected all domestic flight data from January to December of 2019 and historical flight information of three major hub airports in the United States from the data warehouse of UMETRIP, The amount of data reaches 8 million, and the data set includes the departure place, arrival place, flight company, flight date and other basic information. The weather information of the flight was obtained from the weather station, including wind speed, temperature, weather condition, temperature difference, etc. In addition, in order to study the relationship between the host guest field effect and regional factors, the representative airport information of 34 provinces in China were also collected from major websites, including airport scale, airport operation mode and airport geographical location The accuracy of the data was further verified on the official websites of airlines and airports. Refer to Table 4.

Table 4: Classification of major airports in China

NO	Airport Code	Airport Name	Airport Level
1	PEK	Beijing Capital	4F
2	PVG	Shanghai Pudong	4F
3	CAN	Guangzhou Baiyun	4F
4	CKG	Chongqing Jiangbei	4F
5	KMG	Kunming Changshui	4F
6	CTU	Chengdu Shuangliu	4F
7	WUH	Wuhan Tianhe	4F
8	CGO	Zhengzhou	4F

NO	Airport Code	Airport Name	Airport Level
		Xinzheng	
9	TNS	Tianjin Binhai	4F
10	HGH	Hangzhou Xiaoshan	4F
11	SZX	Shenzhen Bao’an	4F
12	XIY	Xi'an Xianyang	4F
13	NKG	Nanjing Lukou	4F
14	CSX	Changsha Huanghua	4F
15	KWL	Guilin liangjiang	4F
16	HKG	Hong Kong Airport	4F
17	TPE	Taipei Taoyuan	4E
18	SHA	Shanghai Hongqiao	4E
19	XMN	Xiamen Gaoqi	4E
20	TYN	Taiyuan Wusu	4E
21	TNA	Jinan Yaoqiang	4E
22	SHE	Shenyang Taoxian	4E
23	HFE	Hefei xinqiao	4E
24	ZUH	Zhuhai Jinwan	4E
25	HAK	Haikou Meilan	4E
26	SYX	Sanya Phoenix	4E
27	CZX	Changzhou Benniu	4E
28	NNG	Nanning Wuwei	4E
29	NGB	Ningbo Lishe	4E
30	LHW	Lanzhou Zhongchuan	4E
31	TAO	Qingdao Liuting	4E
32	FOC	Fuzhou Changle	4E
33	KHN	Nanchang Changbei	4E
34	WUX	Sunan Shuofang	4E
35	INC	Yinchuan Hedong	4E
36	YNT	Yantai Lai	4E
37	CGQ	Changchun Longjia	4E
38	XUZ	Xuzhou Guanyin	4E
39	DDG	Dandong Langtou	4E
40	YTY	Yangzhou Taizhou	4E
41	LXA	Gongga in Lhasa	4E
42	DSN	Ordos ejinholo	4E
43	KHG	Kashgar Airport	4E
44	SJW	Shijiazhuang Zhengding	4E
45	KWE	Guiyang Longdongbao	4E
46	DLC	Dalian Zhoushuizi	4E
47	HRB	Harbin Taiping	4E
48	HET	Hohhot Baita	4E
49	WNZ	Wenzhou Longwan	4E
50	URC	Urumqi diwobao	4E

NO	Airport Code	Airport Name	Airport Level
		Airport	
51	TLQ	Turpan Jiaohe Airport	4E
52	MFM	Macau Airport	4E
53	NAY	Beijing Nanyuan	4D
54	SWA	Jieyang Chaoshan	4D
55	JJN	Quanzhou jinjiang	4D
56	NTG	Nantong Xingdong	4D
57	BPE	Qinhuangdao Beidaihe	4D
58	XIC	Xichang Qingshan Airport	4D
59	TXN	Huangshan Tunxi	4D
60	LJG	Lijiang Sanyi	4D
61	LYG	Lianyungang baitabu	4D
62	BPX	Changdu Bangda Airport	4D
63	NZH	Manzhouli western suburb	4D
64	WEH	Weihai dashuipo	4D
65	TEN	Tongren Fenghuang	4D
66	XNN	Xining caojiabao	4D
67	JZH	Jiuzhai Huanglong	4D
68	JHG	Xishuangbanna GASA	4D
69	KRL	Korla Airport	4D
70	LZH	Liuzhou Airport	4D
71	LYI	Linyi Airport	4D
72	WET	Weifang Nanyuan	4D
73	DOY	Dongying Shengli	4D
74	HDG	Handan Airport	4D
75	YIH	Yichang Three Gorges	4D
76	ZHA	Zhanjiang Airport	4D
77	NNY	Nanyang Jiangying	4D
78	LYA	Luoyang Beijiao	4D
79	MIG	Mianyang Nanjiao	4D
80	DYG	Zhangjiajie Hehua	4D
81	YIW	Zhejiang Yiwu	4D
82	ACX	Xingyi Wanfenglin	4D
83	BAV	Baotou Erliban	4D
84	CGD	Changde Taohuayuan	4D

[d]China's airports are divided into 4F, 4E, 4D, 4C and 3C, of which 4F is the highest level.

3.2. Data processing

3.2.1 Data processing of independent variable

The situation of flight delay in different time periods of a day may be different. e.g., people are usually accustomed to travel in the daytime and tend to choose the means of transportation in the normal work and rest time, resulting in the number of flights in the daytime far more than at night. Therefore, it is obvious that airports are more prone to congestion during the day. In order to eliminate the impact of flights at different times on delay analysis, we divided a day into one hour time windows to obtain 24 time windows (slots). In addition, we also divided the flight data in 2019 into 12 months (January to December) to eliminate seasonal interference through this way. Based on this premise, the following research is carried out.

We define the arrival delay of a flight as the time difference between the actual arrival time and the expected arrival time. According to CAAC, flight delay refers to the situation that the flight landing time (actual arrival block time) is more than 15 minutes later than the planned landing time (time on the flight schedule) or the flight is canceled. Thus, delays can be classified into ordered categories such as less than 15 minutes, 15-30 minutes, etc. [18]. Therefore, we regard the flight whose arrival delay is less than 15 minutes as arriving on time, and set the calculated arrival delay value as zero.

Transit flight refers to the aircraft that need to get on and off passengers or refuel passing through an airport. Generally speaking, after a short stay, the aircraft still has a mission. The transit time of domestic flights (the difference between the estimated departure time of subsequent flights and the estimated arrival time of previous flights) is approximately 30 minutes, while the transit time of international flights is 45 minutes to 1 hour. It is worth mentioning that when the arrival delay of the previous flights occurs, the flight transit time is also affected by the work efficiency of the airline company. So as to alleviate the pressure caused by delay propagation, The aviation department has taken a series of measures, such as improving work efficiency, so as to minimize the delay of subsequent flights when prejudging the occurrence of delay. This explains why the subsequent flights can take off on time despite the serious arrival delay of the previous flights. For fear of the influence of airline factors on flight delay, we segment the remaining transit time (The time difference between the expected departure time of the subsequent flights and the actual arrival time of the previous flights) into $\sigma\tau 1$, $\sigma\tau 2$, $\sigma\tau 3$ in advance and make regression analysis in each period.

$\sigma\tau 1$ is the remaining transit time is within 40 minutes.

$\sigma\tau 2$ is the remaining transit time is 40-70 minutes.

$\sigma\tau 3$ is the remaining transit time is more than 70 minutes.

In particular, the weather factor used in the study is not numerical, we need to deal with the weather in a special way We model and analyze the weather information according to the severity of the weather, and get the impact of different severity of weather conditions on flight departure delay [18]. It will be shown in Table 5.

[20] shows that airport's total number of departures (i.e., the aircraft movements) and capacity (e.g., number of runway) could determine airport congestion level and flight delay. Therefore, we count the number of aircraft take-off and landing at a certain time to represent the degree of Airport congestion. Also, based on the data collected in the early stage, we have classified the types of airlines operating in a particular airport. According to the data published by the airline company and the airport official website, we divided all airlines operating at an airport into main base airlines and passenger airlines. We define the main aviation company ($A\eta$) of an airport as who takes the airport as its main operation base and establishes its head office locally. The details of the summary data will be shown in Table 3. On the contrary, other airlines for this airport belong to the guest airlines,

namely the passenger airline company ($A\gamma$).

Table 5: Weather factors included in weather condition variables

Index	Weather factors included in weather condition variables		
	Weather condition	Weather rank	Coefficients
1	Sunny/Cloudy/Floating Dust /Mist	Level _1	0.001*** (0.003)
2	Drizzle/Mist/Scouther/ Weak smoke/Light rain	Level _2	0.033*** (0.008)
3	Rain /Floating dust/Weak shower/Weak sand/Fog	Level _3	0.031*** (0.003)
4	Snow/Sleet	Level _4	0.098*** (0.021)
5	Weak thunderstorm	Level _5	0.046*** (0.005)
6	Heavy rain	Level _6	0.150*** (0.035)
7	Heavy snow	Level _7	0.012*** (0.018)
8	Thunderstorm /Hail	Level _8	0.228*** (0.083)
9	Severe thunderstorm	Level _9	-0.159*** (0.018)
10	Fog/Haze/Sand/Smoke/ Frozen fog	Level _10	0.061*** (0.061)
11	Sandstorm /Severe sandstorm	Level _11	-0.017*** (0.005)

[e]The weather rank is divided into 11 grades. The higher the grade, the worse the weather. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

3.2.2 Data processing of dependent variable

Article 152 of "air traffic management rules of civil aviation of China" stipulates that the time of aircraft take-off should be the moment of aircraft take-off and taxiing. Therefore, flight departure delay is considered as the time difference between the actual departure time and the planned departure time. In addition, our model also excludes the flight departure delay caused by specific factors, because the weather, airport congestion, wind, climate, seasonality and other specific factors in the model are controlled. Notice that this paper is limited to the subsequent flight delay caused by the delay of the previous flight.

3.3. Data filter

There are some small airlines in China with few flights and serious delays. So we need to filter out outliers of abnormal flight delay (e.g., long delay time) and further deal with missing values and outliers of data to eliminate the interference of inaccurate data on model analysis. Besides, we convert the time-of-flight to Beijing standard time to avoid the data inaccuracy caused by the time difference of international flights.

With such data, we can calculate the delay propagation level of different airlines at the same airport and under the same conditions, then, these data are used to describe the host guest field effect.

3.4. Econometric Model

The objective of this research is to quantify the different delay propagation levels of the main base airlines and the passenger airlines at the same airport and under the same conditions, and to describe the main and passenger effects in the aviation market in this way. We conduct multiple linear regression analysis on the historical flight data of each month in 2019, and establish the main passenger effect model. We define this model as:

The objective of this research is to quantify the different delay propagation levels of local airlines and other airlines in the same airport and under the same conditions, so as to describe the host guest effect in the aviation market. The historical flight data in 2019 were analyzed by multiple linear regression, and the model was established as:

$$\Psi(H\Gamma) = \phi\,(\,\Sigma A\eta\gamma(\tau 1)\,,\,\Sigma A\eta\gamma(\tau 2)\,,\,\Sigma A\eta\gamma(\tau 3)\,,\,\Xi\iota\,,\,®\iota\,) \quad (1)$$

$\Sigma_{A\eta\gamma}(\tau 1)$ is the delay propagation of main base airlines and other airlines when the remaining transit time is less than 40 minutes.

$\Sigma_{A\eta\gamma}(\tau 2)$ is the delay propagation of main base airlines and other airlines when the remaining transit time is between 40 minutes and 70 minutes.

$\Sigma_{A\eta\gamma}(\tau 3)$ is the delay propagation of main base airlines and other airlines when the remaining transit time is more than 70 minutes.

Ξ_ι is the specific factors of flight delay, such as weather, airport congestion, wind, climate, season and other factors (ι = 1,2... ν)

$\mathfrak{R}_\iota$ is the coefficient corresponding to the independent variable Ξ_ι (ι = 1,2... ν)

The multiple linear regression analysis is formulated as:

$$\phi\ = ®1\Sigma A\eta(\tau 1) + ®2\Sigma A\gamma(\tau 1) + ®3\Sigma A\eta(\tau 2) + ®4\Sigma A\gamma(\tau 2) + ®5\Sigma A\eta(\tau 3) + ®6\Sigma A\gamma(\tau 3) + ®\iota\Xi\iota + \Sigma \quad (2)$$

Where Ξ_ι, and $®_\iota$ (ι = 1,2... ν) are the same variables already defined above. $\Sigma_{A\eta}(\tau 1-\tau 3)$ is the arrival delay of the previous flight of the home airline company under the three categories. $\Sigma_{A\gamma}(\tau 1-\tau 3)$ refers to the arrival delay of the previous flight of other airlines under three categories. The error term ε is assumed to follow a standard normal distribution (i.e., $\varepsilon \sim N(0,1)$).

Considering the relatively short ground buffer time of hub airports in the United States, it is almost impossible to exceed 40 minutes. We conducted modeling and analysis again. In the new model, $\Sigma_{A\eta\gamma}(\tau 2)$ and $\Sigma_{A\eta\gamma}(\tau 3)$ are deleted. We redefine this model as:

$$\Psi(H\Gamma) = \phi\,(\,\Sigma A\eta\gamma,\ \Xi\iota\,,\,®\iota\,) \quad (3)$$

The multiple linear regression analysis is reformulated as:

$$\phi\ = ®1\Sigma A\eta + ®2\Sigma A\gamma + ®\iota\Xi\iota + \Sigma \quad (4)$$

$\Sigma_{A\eta}$ is the arrival delay of the previous flight of the home airline company ($A\eta$).

$\Sigma_{A\gamma}$ refers to the arrival delay of the previous flight of other airlines ($A\gamma$).

4. Estimation Results and Discussions

Through the analysis, we calculated the different flight delay propagation levels of the main base airlines and other airlines in the same airport and under the same conditions. Detailed data are given in the Table 6.

Table 6: Host guest filed effect model of Chinese airports

Independent variable	Dependent variable: Departure delay (min)		
	Overall	Top 10 hub airports	4F Airports
$\Sigma_{A\eta}(\tau 1)$	0.6791*** (0.002)	0.6662*** (0.002)	0.6609*** (0.002)
$\Sigma_{A\gamma}(\tau 1)$	0.8952*** (0.001)	0.8894*** (0.001)	0.8909*** (0.001)
$\Sigma_{A\eta}(\tau 2)$	0.1895*** (0.005)	0.1749*** (0.004)	0.1826*** (0.005)
$\Sigma_{A\gamma}(\tau 2)$	0.3194*** (0.004)	0.3111*** (0.004)	0.3167*** (0.004)
$\Sigma_{A\eta}(\tau 3)$	0.0241*** (0.001)	0.0198*** (0.001)	0.0216*** (0.001)
$\Sigma_{A\gamma}(\tau 3)$	0.0405*** (0.001)	0.0357*** (0.001)	0.0381*** (0.001)
Wind power	0.8112*** (0.019)	0.7251*** (0.019)	0.6435*** (0.019)
Weather condition	0.5123*** (0.008)	0.6464*** (0.010)	0.6086*** (0.009)
Airport congestion	0.0157*** (0.002)	0.0370*** (0.003)	-0.0119*** (0.002)
Observations	2508589	1602071	1918386
R-squared	0.330	0.303	0.313
Independent variable	**Dependent variable: Departure delay [minute]**		
	4E Airports	4D Airports	
$\Sigma_{A\eta}(\tau 1)$	0.8276*** (0.004)	0.9002*** (0.010)	
$\Sigma_{A\gamma}(\tau 1)$	0.9535*** (0.003)	0.9231*** (0.006)	
$\Sigma_{A\eta}(\tau 2)$	0.1761*** (0.008)	0.0347 (0.035)	
$\Sigma_{A\gamma}(\tau 2)$	0.4020*** (0.012)	0.1254*** (0.029)	
$\Sigma_{A\eta}(\tau 3)$	0.0237*** (0.002)	-0.0532*** (0.007)	
$\Sigma_{A\gamma}(\tau 3)$	0.0695*** (0.004)	-0.0032 (0.008)	
Wind power	1.1024*** (0.059)	-2.8970*** (0.144)	
Weather condition	0.1357*** (0.018)	2.3585*** (0.109)	
Airport congestion	0.1041*** (0.008)	1.0698*** (0.057)	
Observations	1306816	500784	
R-squared	0.367	0.403	

[f]Robust standard errors in parentheses. The following control variables are included in all

Regressions but not reported: Cargo. Standard error in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

From the above data, the R-squared of this model is 0.330, the coefficient of the model is significant and the standard error $\Sigma \in (0,1)$. The robustness of the model is guaranteed.

The overall regression analysis results shown that the delay propagation coefficient of main base airlines is 0.6791 while other airlines is 0.8952 in the case of $\Sigma_{A\eta\gamma}(\tau 1)$. That is to say, in China's hub airports, every 10 minutes delay in the arrival of the prior flights of the main base airlines within 1 hour before departure will lead to an average delay of 6.79 minutes in the departure of the subsequent flights while other airlines' subsequent flights reached to 8.95 minutes on average under the same conditions. For every 10 minutes delay in arrival of the previous flight, the delay of the subsequent flight of local airlines with the airport as its main operation base is 2.16 minutes less than that of other airlines. Especially note that the average departure delay of subsequent flights is 7.87 minutes without distinguishing the attributes of airlines. This is close to the conclusion of [18] that every 10 minutes delay in the arrival of the preceding flights will lead to an average departure delay of 7.4 minutes for the subsequent flights. Similarly, in the case of $\Sigma_{A\eta\gamma}(\tau 2)$, Every 10 minutes delay of the arrival of the previous flights under the aviation division of the main base will lead to an average departure delay of 1.9 minutes for the subsequent flights while the average departure delay of other airlines is 3.19 minutes per10 minutes. For every 10 minutes delay in arrival of the previous flight, the delay of the subsequent flight of local airlines with the airport as its main operation base is 1.3 minutes less than that of other airlines. And in the case of $\Sigma_{A\eta\gamma}(\tau 3)$, Every 10 minutes delay of the arrival of the previous flights under the aviation division of the main base will lead to an average departure delay of 0.24 minutes for the subsequent flights while the average departure delay of other airlines is 0.41 minutes per10 minutes. For every 10 minutes delay in arrival of the previous flight, the delay of the subsequent flight of local airlines with the airport as its main operation base is 0.17 minutes less than that of other airlines. However, owing to the small amount of data in $\Sigma_{A\eta\gamma}(\tau 3)$, the regression results are only for reference. All the above studies are verified that there exist host guest field effect in most airports in China. The local aviation department has certain advantages in its main base airport than others which is entirely because of the attribute of whether the airline company takes the airport as the main operation base and whether it is registered in the local airport as the head office. And the delay propagation will change while the remaining transit time is different.

The regression results of China's top 10 hub airports show that in the case of $\Sigma_{A\eta\gamma}(\tau 1)$. At the same airport and under the same conditions, for every 10 minutes delay in the arrival of the previous flights, the main base airlines will delay 2.23 minutes less than the subsequent flights of other airlines, reaching the average value.

China's airports are divided into 4F 4E, 4D, 4C and 3C, of which 4F is the highest level. The overall delay propagation level of 4E airports is higher than that of 4F airports, and the average delay of the main base airlines is 1.26 minutes less than that of the follow-up flights of the away airlines. The main base of 4D airports has 0.23 minutes less delay than the follow-up flights. The regression results of 4F airports, 4E airports and 4D airports shown that the lower the airport level is, the worse the delay propagation control is. There is no significant difference in the delay propagation level between the main base airline and the away airline in the low-level airport, and the effect of the main and away airports is not intense.

It can be seen from the data in Table 7. Shanghai Pudong Airport, Shenzhen Bao'an Airport, Kunming Changshui Airport and Shanghai Hongqiao Airport have the more intense host guest field effect. Among them, for every 10 minutes delay in the arrival of the previous flight, the main base airlines will delay 3.31 minutes less than the subsequent flight of other airlines, far exceed average target. Surprisingly, another hub airport in Shanghai, Shanghai Hongqiao Airport, has a large difference in the delay propagation level between the local airlines and others airline. We guess that this phenomenon may be related to the geographical attributes of Shanghai. As we all know, Shanghai, as the most representative and prosperous southern city, has a strong sense of happiness among local residents, and there has been a long-term phenomenon of exclusion.

Table 7: The average delay propagation coefficient of the main airline and others in the case of airlines arrival delay within 1 hour before departure of China's top 9 hub airports

Ranking	Airport Code	Airport Name	Propagation coefficient of flight delay within 1 hour before departure (min)		
			Aη	Aγ	D-value
1	**PVG**	**Shanghai Pudong**	**0.576**	**0.907**	**0.331**
2	**SZX**	**Shenzhen Bao'An**	**0.614**	**0.827**	**0.213**
3	**KMG**	**Kunming Changshui**	**0.708**	**0.928**	**0.220**
4	SHA	Shanghai Hongqiao	0.771	0.969	0.198
5	CTU	Chengdu Shuangliu	0.747	0.871	0.162
6	CAN	Guangzhou Baiyun	0.769	0.929	0.160
7	CKG	Chongqing Jiangbei	0.726	0.873	0.147
8	PEK	Beijing Capital	0.774	0.859	0.086
9	XIY	Xi'An Xianyang	2.284	0.876	-0.408

[g]The local resident airline company of Xi'an XianYang Airport is happy airlines. Happiness Airlines takes Xi'an as its main operation base and is a subordinate unit of China Eastern Airlines which with less flights and serious delays.

What is more, it is not difficult to see from the data in the Table 6, Beijing Capital Airport and Xi'an Xianyang Airport are both northern cities with the weakest effect of main and guest filed effect among China's top10 hub airports. Actually, on account of Beijing Daxing airport has been officially opened in 2019 and some airlines that originally took Beijing Capital Airport as the main operation base moved to Beijing Daxing International Airport, so the data may be biased. There is another important point to be noted. The local resident airline company of Xi'an XianYang Airport is happy airlines. Happiness Airlines takes Xi'an as its main operation base and is a subordinate unit of China Eastern Airlines which with less flights and serious delays. Therefore, negative data does not mean that there is no host guest field effect at this airport.

Table 8: The average delay propagation coefficient of the main airline and others in the case of flight arrival delay between 1-2 hours before departure of China's top 9 hub airports

Ranking	Airport Code	Airport Name	Propagation coefficient of flight delay between 1-2 hours before departure (min)		
			Aη	Aγ	D-value
1	**SHA**	**Shanghai Hongqiao**	**0.225**	**0.766**	**0.541**
2	**PVG**	**Shanghai Pudong**	**0.160**	**0.635**	**0.456**
3	**KMG**	**Kunming Changshui**	**0.092**	**0.398**	**0.306**
4	CKG	Chongqing Jiangbei	0.048	0.321	0.272
5	CAN	Guangzhou Baiyun	0.189	0.387	0.198
6	CTU	Chengdu Shuangliu	0.183	0.380	0.197
7	SZX	Shenzhen Bao'An	0.110	0.250	0.134
8	XIY	Xi'An Xianyang	0.142	0.242	0.100
9	PEK	Beijing Capital	0.341	0.413	0.071

[h]The delay propagation coefficients of Shanghai Pudong Airport and Shanghai Hongqiao Airport are quite different, which may be related to the geographical attributes.

The different delay propagation levels of the local airlines and other airlines of the top10 hub airports under $\Sigma_{A\eta\gamma}(\tau 2)$ and $\Sigma_{A\eta\gamma}(\tau 3)$ will be given in Table 8 and Table 9. Table 10 shows the main guest field effect of each airport by airport level. The top3 airports are Shanghai Pudong Airport, Kunming Changshui Airport and Shenzhen Bao'an Airport.

Table 9: The average delay propagation coefficient of the main airline and others in the case of flight arrival delay between 2-3 hours before departure of China's top 9 hub airports

Ranking	Airport Code	Airport Name	Propagation coefficient of flight delay between 2-3 hours before departure (min)		
			Aη	Aγ	D-value
1	**CKG**	**Chongqing Jiangbei**	**0.010**	**0.020**	**0.102**
2	**CAN**	**Guangzhou Baiyun**	**0.002**	**0.049**	**0.047**
3	**SHA**	**Shanghai Hongqiao**	**-0.008**	**0.028**	**0.036**
4	PVG	Shanghai Pudong	-0.007	0.026	0.034
5	CTU	Chengdu Shuangliu	0.000	0.027	0.027
6	SZX	Shenzhen Bao'An	0.003	0.020	0.017
7	PEK	Beijing Capital	0.005	0.012	0.007
8	KMG	Kunming Changshui	0.028	0.027	-0.001
9	XIY	Xi'An Xianyang	0.084	0.025	-0.060

[i]The flights of arrival delay between 2-3 hours before departure is less, Therefore,

Reference data only, not for technical specifications. A negative number means that the delay of arrival does not affect the departure of subsequent flights. Due to a long time of ground buffer, subsequent flights may still take off ahead of time.

Table 10: Ranking of the intensity of the main and passenger field effects of airports in China

Ranking	Difference of delay propagation coefficient between home and guest airport (min)		
	Airport Name (Airport Code)	Airport Level	Arrival delay of previous flight within 1hour before departure
1	**Shanghai Pudong (Pvg)**	**4F**	**0.331**
2	**Kunming Changshui (Kmg)**	**4F**	**0.220**
3	**Shenzhen Baoan (Szx)**	**4F**	**0.213**
4	Hangzhou Xiaoshan (Hgh)	4F	0.212
5	Shanghai Hongqiao (Sha)	4E	0.198
6	Chengdu Shuangliu (Ctu)	4F	0.162
7	Guangzhou Baiyun (Can)	4F	0.160
8	Mianyang Manjiao (Mig)	4D	0.148
9	Chongqing Jiangbei (Ckg)	4F	0.147
10	Tianjin Binhai (Tsn)	4F	0.101
11	Beijing Capital (Pek)	4F	0.086
12	Jinan Yaoqiang (Tna)	4E	0.052
13	Quanzhou Jinjiang (Jjn)	4D	-0.025
14	Guilin Liangjiang (KWL)	4F	-0.088
15	Shijiazhuang Zhengding (Sjw)	4E	-0.097
16	Xi’An Xianyang (Xiy)	4F	-0.408

[j]The local airlines of Jinjiang Airport, Liangjiang Airport, Zhengding Airport and Xianyang Airport belong to small airlines with less flights and more serious delays. Therefore, negative data does not means that there is no host guest effect at this airport.

In order to study the change law and seasonality of the main guest field effect, we conducted a regression for the top5 hub airports by month. See Table11 for details.

Table 11: Monthly delay propagation difference of the top 5 airports with main and guest effects in 2019

Month	Difference of delay propagation coefficient between home and guest airport (min)					
	PVG	KMG	SZX	HGH	SHA	Average
Jan	0.191	**0.413**	0.041	0.188	0.083	**0.183**
Feb	0.464	0.236	0.259	0.010	0.086	**0.211**
Mar	0.178	0.154	0.291	0.283	0.345	**0.250**
Apr	0.262	0.177	0.189	**0.558**	0.280	**0.293**
May	0.368	0.180	0.269	0.230	0.121	**0.234**
Jun	0.372	0.111	0.066	0.248	0.176	**0.195**
Jul	**0.931**	0.314	0.105	0.264	0.298	**0.382**
Aug	0.514	0.121	0.288	0.156	0.221	**0.260**
Sep	0.231	0.351	0.334	0.111	0.099	**0.225**
Oct	0.296	0.112	0.226	-0.281	**0.386**	**0.148**
Nov	0.214	0.117	0.181	0.505	0.149	**0.233**
Dec	-0.054	0.359	**0.303**	0.275	0.133	**0.203**

[k]The flight data of 2019 comes from the non accurate platform.

Through research, we discovered that host guest field effect exists always, especially in July and August, which may be related to the heavy rainfall in July and August. The severe delay of flights affected by this kind of weather is more likely to cause airport congestion. In case of airport congestion, airport resources will become more valuable to all airlines. At this time, the advantage of the local airlines will be reflected. This explains why this effect in these two months are stronger than other months. Fig.4 shows the change of each month. Fig.5 compares the monthly changes of the top5 airports, and the data indicate that Shanghai Pudong Airport has the strongest effect in July and August.

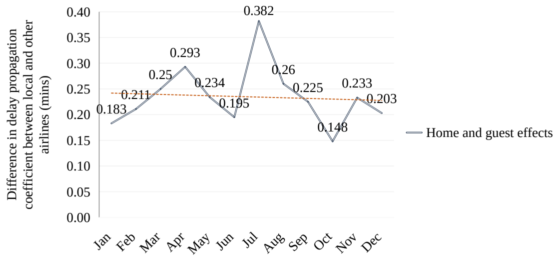

Figure 4: Monthly trends of the top 5 airports in the home and guest effects

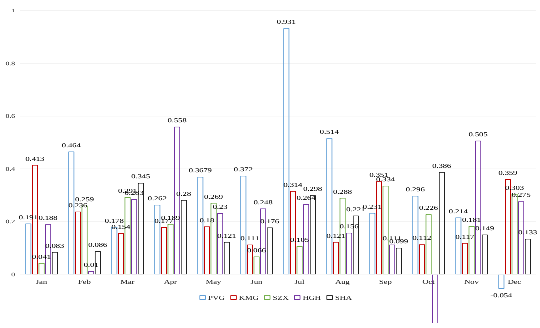

Figure 5: On the premise that the arrival of the previous flight is delayed within 1 hour before departure, the change of the host guest effect of China's top 5 airports with months

This paper summarized the aviation information of the main bases corresponding to the three major hub airports (ATL, lax and ORD) in the United States and carries out the modeling and realize the quantitative research on the delay propagation of the three major hub airports. The delay propagation data of the three major U.S. hub airports are given in Table 12.

Table 12: The main airlines Department corresponding to the three major hubs in the United States

No	Airport Code	Airport Name
1	ATL	ATLANTA AIRPORT
2	LAX	LOS ANGELES
3	ORD	CHICAGO O`HARE

[l]The data of the relationship between the airport and the airline company comes from Baidu Encyclopedia, the official website of the airport and the official website of the airline company.

Table 13: A model of the main and passenger effects of the hub airports in the United States

Independent variable	Dependent variable: departure delay (min)			
	Overall	ATL	LAX	ORD
$\Sigma_{A\eta}$	0.5730*** (0.001)	0.4897*** (0.002)	0.3508*** (0.003)	0.6771*** (0.001)
$\Sigma_{A\gamma}$	0.7897*** (0.002)	0.7201*** (0.003)	0.7858*** (0.002)	0.8636*** (0.003)
Wind power	0.8036*** (0.019)	0.2351*** (0.019)	0.5862*** (0.060)	-0.1174*** (0.037)
Weather condition	0.3784*** (0.018)	0.9535*** (0.021)	0.1357*** (0.018)	0.0280 (0.039)
Airport congestion	0.0059*** (0.001)	-0.0125*** (0.002)	0.0515*** (0.005)	0.0106*** (0.003)
Observations	502577	205448	129766	167363
R-squared	0.537	0.450	0.556	0.615

[m]Robust standard errors in parentheses. The following control variables are included in all Regressions but not reported: Cargo. There was no more than one hour's delay at the U.S. hub airport. Standard error in parenthesis. *** p<0.01, ** p<0.05, * p<0.1

According to Table 13, in the U.S. aviation market, among the various causes of flight delays, the cause of delay propagation accounts for a larger proportion than that of China. For every 10 minutes delay in arrival of the previous flight, the average departure delay of the follow-up flights of the local airlines is 5.73 minutes while the average departure delay of other airlines is 7.9 minutes under the same conditions of the same airport. The flight delay of the local airlines is 2.17 minutes less than that of other aviation division. It is certain that there is still a host guest effect in the three major hub airports in the United States.

In addition, from the regression analysis results of the three major hub airports, LAX has the strongest host guest effect. United Airlines and American Airlines, as the main bases of Los Angeles

International Airport, have obvious advantages in this airport. For every 10 minutes delay of the previous flight, the departure delay of other airlines under the same conditions will be 4.35 minutes more.

Table 14: Average of the main and passenger field effects of the three major hub airports in the United States

Month	Difference of delay propagation coefficient between home and guest Airport (min)		
	ATL	LAX	ORD
Jul	0.072	**0.062**	0.055
Aug	0.190	0.029	0.016
Sep	**0.209**	-0.050	**0.134**
Oct	**0.274**	-0.056	**0.187**
Nov	**0.227**	**0.099**	**0.219**
Dec	0.191	**0.045**	-0.178

[n]Atlanta and O'Hare Airport in September, October and November, the main and guest effect is relatively strong.

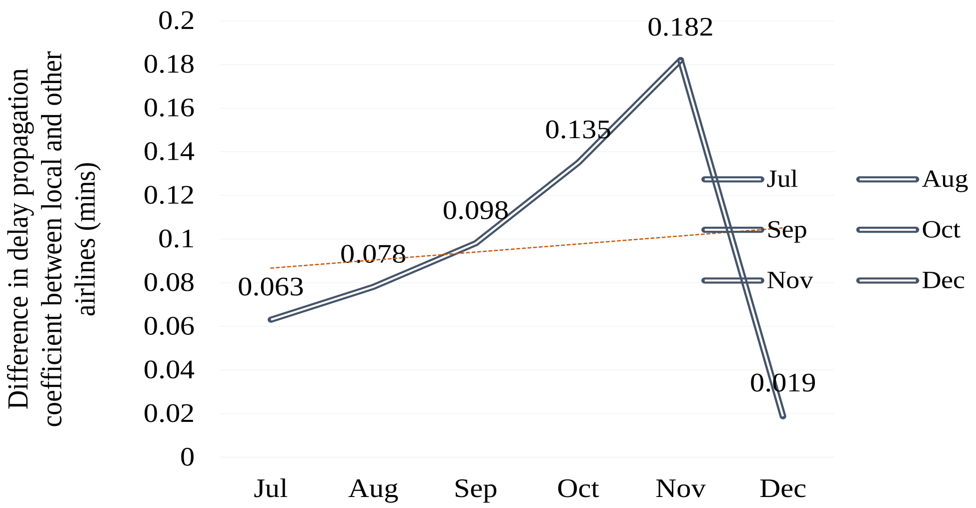

Figure 6: The trend of the main and guest effects of the three major hub airports in the United States in the second half of 2019

The data were regressed by month so as to observe the seasonality of the host guest field effect. Data will be shown in Table 14. Different from the data of China's hub airports, among the three major hub airports in the United States, ATL, LAX and ORD have the strongest host guest effect in October and November in the second half of 2019. In order to ensure the accuracy of the results, the three hub airports are regressed separately by month, we average the host guest field effect of each month. For details, see Table 15. The results show that the average effect value of the three hub airports are weaker, this may be due to the impact of certain month is not intense, thus reducing the average. Fig.6 shows the trend of the main and guest effects of the three major hub airports in the United States in the second half of 2019.

Table 15: Average of the main and passenger field effects of the three major hub airports in the United States

Ranking	Airport Code	Airport Name	Propagation coefficient of flight delay within 1 hour before departure (min)		
			Aη	Aγ	D-value
1	**ATL**	**Atlanta**	**0.728**	**0.922**	**0.194**
2	ORD	O`Hare	0.836	0.908	0.072
3	LAX	Los Angeles	0.839	0.861	0.022

°In order to observe the seasonality of the home and away effects, the data were regressed by month. The above data are the average of the delay propagation coefficient of main and passenger field in 2019 for the three major hub airports in the United States.

5. Conclusion

By considering the problem of flight delay, we quantified the propagation of flight delay of local airlines and other airlines respectively, and then describes the host guest field effect in China and the United States aviation market. This paper reveals the delay propagation differences of different airlines in the same airport under the same conditions, finds out the description index of the host guest field effect, and answers the existing form and distribution characteristics of the host guest field effect. In addition, we also compared the delay data of the United States hub airport, and explained the problem of whether the main and passenger field effects only exist in the Chinese aviation market. It should be noted that the data set used in this paper is limited to 2019, and does not quantify the flight data of other years. Nevertheless, still passed the robustness test of regression analysis. This study are useful for future research on the analysis of international aviation market trends and the causes of flight delay and it is of great significance to monitor the operation of airlines and airports, improve the operation efficiency of airports and strengthen the cooperation between airlines and airports.

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