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Influence of Covid-19 on Air Passenger Market in China Based on Dynamic Distributed Lag Model

Huan Cheng[1,a], Jinmei Ge[1,b], Dingrong Liu[1,c], Xianfeng Qi[1,d]

[1]*Statistical Analysis Center, China Academy of Civil Aviation Science and Technology, Beijing, China*

[a]*chenghuan@mail.castc.org.cn*, [b]*gejm@mail.castc.org.cn*, [c]*liudr@mail.castc.org.cn*, [d]*qixf@mail.castc.org.cn*

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Abstract: This paper studied the influence of COVID-19 on air passenger market in China. Affecting factors were selected from economic recovery, epidemic development and vaccination. Dynamic distribution lag model was established to simulate the influence mechanism. Research results showed that economic recovery and vaccination could significantly promote the recovery of air passenger market. The impact of economic recovery was obviously time lagged. The impact on air passenger market recovery between China and the United States was significantly different. Based on three scenario assumptions of the epidemic development, it was predicted that China's air passenger volume in 2021 would be between 530 and 560 million. The recovery of China's air passenger market in 2021 would be fluctuated by about 5-6 percentage points due to different epidemic situation.

1. Introduction

COVID-19 epidemic is the second global public health emergency that has occurred in China since the SARS epidemic in 2003. It has had a huge impact on the air passenger market in China. In 2020, the volume of passengers and RPKs dropped to 63% and 56%respectively, compared with 2019. Recently, the global epidemic situation is still severe. Variant strains increase the epidemic risk and also increase the uncertainty of the recovery of air passenger market. In the paper, the key factors that affected air passenger's recovery as well as the affecting mechanism were studied. The results were significant for predicting market recovery and formulating industry policies.

The current researches upon the affection of public emergencies on air passenger market mainly focused on the predication of air passenger indicators as well as policy recommendations to deal with the impact. It was lack of research on the factors and mechanisms of market recovery under abnormal conditions. Peng Zheng (2020) assumed different scenarios with flight cancellation rates and load factor levels to predict the impact on the China's civil aviation in 2020 caused by COVID-19. Zhu Nuo (2020) used the cellular automaton model to predict the volume of air passenger in China under different epidemic scenarios in 2020. Dai Teqi (2011) used time series intervention model to analyze the impact of SARS on air passenger market, which pointed out that civil aviation in the rapid development stage had stronger ability to resist external shocks from public emergencies.

Zhou Jian (2020). analyzed the impact of "SARS" on transportation industry and pointed out that the impact of COVID-19 on various fields of transportation would be significant different. .

This paper focused on the impact of COVID-19 on air passenger in China. Firstly, the main factors that affected the market recovery under the abnormal conditions were analyzed. Secondly, with the consideration that the affection would be time lagged, a dynamic distributed lag model was established to simulate the impact mechanism. The results were significant for analyzing the recovery of our country's air passenger market in the post-epidemic era.

2. Research Method

It was obvious that the impact of the epidemic and economic recovery on the air passenger market was time lagged. Even though the epidemic was effectively controlled, its impact on air passenger market would still last for a while. The recovery of the air passenger market was not only affected by the current epidemic situation and economic recovery, but also depended on that of the past period. Considering the characteristics of time lagged, a dynamic distribution lag model was established to simulate the impact of epidemic and economic recovery on air passenger market.

The distributed lag model used time series of explanatory variables to conduct model fitting. It replaced the explanatory variable of the static model with the historical time series of the explanatory variable, which had much more clearer explanatory meaning. There were two types of distributed lag models, one was the Koyck lag model, and the other was the polynomial distributed lag model (PDL). The Koyck lag model assumed that the influence of variables decreased geometrically with the extension of the lag period. Its general form was shown in (1).

$$\begin{aligned} &y_t = \alpha + \beta x_t + \lambda\beta x_{t-1} + \lambda^2\beta x_{t-2} + \ldots + \varepsilon_t \\ &= \alpha + \beta\sum_{i=0}^{\infty} x_{t-i} + \varepsilon_t \\ &|\lambda| < 1 \end{aligned} \tag{1}$$

Since the random disturbance term in the Koyck lag model always had first-order negative correlation, which caused that the parameter estimation was very complicated. As a result, the PDL model was adopt in the paper. The general form of the PDL model was shown in (2).

$$y_t = \alpha + \sum_{i=0}^{\infty} \beta_i x_{t-i} + u_t \tag{2}$$

Due to the multi-collinearity between explanatory variables, OLS could not be used for parameter estimation. As a results, the estimated parameters were decomposed as following.

$$\begin{aligned} &\beta_i = \alpha_0 + \alpha_1(1-\bar{p}) + \alpha_2(1-\bar{p})^2 + \ldots + \alpha_q(1-\bar{p})^q \\ &\bar{p} = \begin{cases} p/2, p = 2k \\ (p-1)/2, p = 2k-1 \end{cases} (k \in N) \end{aligned} \tag{3}$$

Where, i=0,1,2,...,p, p<q. Each parameter in (2) could be expressed by a polynomial. And so (2) could be rewritten as a polynomial distributed lag model, as shown in (4).

$$\begin{aligned} &y_t = \alpha + \alpha_0 z_{0t} + \alpha_1 z_{1t} + \ldots + \alpha_q z_{qt} + \mu_t \\ &\text{where,}\ z_{jt} = \sum_{i=0}^{p} (i-\bar{p})^j x_{t-i}, (j = 0,1,\ldots,q) \end{aligned} \tag{4}$$

In addition, constraints could be imposed on the model. The proximal constraint assumed that the first-period leading effect of x on y was 0.

$$\beta_{-1} = \alpha_0 + \alpha_1(-1-\bar{p}) + \ldots + \alpha_q(-1-\bar{p})^q = 0 \quad (5)$$

The far-end constraint assumed that the effect of x on y greater than the lag period p to be 0.

$$\beta_{p+1} = \alpha_0 + \alpha_1(p+1-\bar{p}) + \ldots + \alpha_q(p+1-\bar{p})^q = 0 \quad (6)$$

In summary, the determinants of the PDL model included: lag period p, polynomial degree q, and constraint conditions.

3. Model demonstration

3.1. Affecting Factors Analysis and Data Collection

What were the main factors affecting the air passenger market recovery under the abnormal situation? Normally, economy was the most important factor affecting the air passenger market. Studies conducted by the World Bank, IATA, OAG and other research institutions had shown that GDP was the key factor affecting air passenger demand. Based on the current research and the tracking of the epidemic impact, the key factors which affected the recovery of air passenger market were analyzed from three aspects: economy recovery, epidemic situation and vaccination.

Economy recovery was the most important factor affecting the recovery of air passenger demand. PMI was the leading indicator of comprehensive economy, which could effectively reflect the trend of economic development. PMI of service industry was chosen as the index of economic recovery. Data from January 2020 to May 2021 showed that the change trend of PMI in the service industry was highly consistent with the recovery trend of China's air passenger, as shown in Fig.1. The highly consistency indicated that economic recovery played an important role in the recovery of air passenger demand.

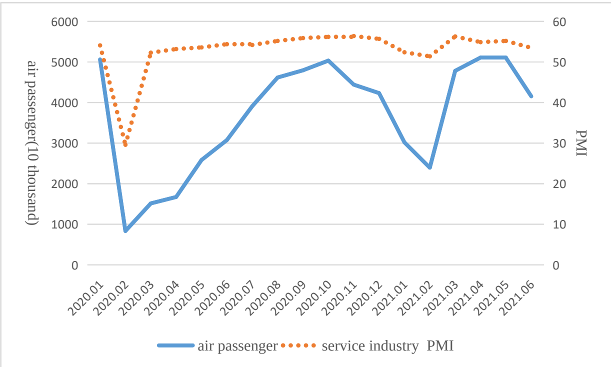

Figure 1: PMI in service industry and air passenger volume in China

COVID-19 was the most direct factor that caused the fluctuation of air passenger market. The data of new confirmed cases and air passenger volume in China showed that the reduction of air passenger was highly related to the epidemic development, as shown in Fig.2. The outbreak of the epidemic leaded to sharply decrease of air passenger volume. The epidemic situation repeated leaded to the fluctuation of the air passenger volume. After comprehensive analysis, the cumulative confirmed cases was selected as the epidemic factor index. In addition, vaccination played an important role in the prevention and control of the epidemic. And then the vaccination per 100 people was selected as the index of epidemic factor.

Figure 2: New confirmed cases and air passenger volume in China

Based on the above analysis, three influencing factor indicators were selected, including PMI in the service industry, cumulative confirmed cases and vaccination per 100 people. All the three indicators were monthly data. Data was collected from January 2020 to May 2021. The service industry PMI data was released by the China National Bureau of Statistics. The cumulative confirmed cases and vaccination per 100 people were derived from GETHUB. The air passenger data was published by the China Civil Aviation Administration.

3.2. Model Establishment

A dynamic distribution lag model was established to analyze the impact of COVID-19 on the air passenger in China. Air passenger volume was the explained variable, while PMI in the service industry, cumulative confirmed cases and vaccination per 100 people were explanatory variables, as shown in (7).

$$P_t = \alpha + \sum_{i=0}^{p_1} \beta_i PMI_{t-i} + \sum_{i=0}^{p_2} \chi_i TC_{t-i} + \sum_{i=0}^{p_3} \delta_i VPH_{t-i} + \mu_t \quad (7)$$

In which, P_t was the volume of air passengers in t period, $PMI_{t-i}(i=0,1,2,3,...,p_1)$ was the service industry PMI in t-i period, $TC_{t-i}(i=0,1,2,3,...,p_2)$ was the total cumulative confirmed cases in t-i period, $VPH_{t-i}(i=0,1,2,3,...,p_3)$ was the vaccination per 100 people in t-i period, while μ was random interference item. $\alpha, \beta_i, \chi_i, \delta_i$ were parameters to be estimated. p_1, p_2, p_3 were the lag period of PMI, TC and VPH.

1) Stationarity test

Table 1: ADF unit root test for each variable

Variable	**Unit Root Test**				
	ADF	***1% Critical value***	***5% Critical value***	***10% Critical value***	***Conclusion***
$\Delta \ln P_t$	-9,19***	-3.95	-3.08	-2.68	stable
$\Delta \ln PMI_t$	-11.59***	-3.95	-3.08	-2.68	stable
$\Delta \ln TC_t$	-57.13***	-3.92	-3.06	-2.67	stable
$\Delta \ln VPH_t$	-3.05**	-3.95	-3.08	-2.68	stable

Note: ***,** referred to reject the original unit root hypothesis at the significance level of 1% and 5% respectively, which meant that the variable was stable at the corresponding significance level. Δrepresented the first order difference.

Conduct logarithmic transformation on original data to obtain unified dimensional standard data series. In order to avoid pseudo-regression, the data were tested by stationarity test and cointegration test. The stationarity test was carried out by ADF test using Eviews10.Test results were shown in Table 1. The original sequence of the four variables was unstable. After conducting the change of first-order difference, they were all stable at the significance level of 5%. The results showed that each variable had first-order simple integration, which could be further tested for cointegration.

2) Cointegration test

The purpose of cointegration test was to determine the long-term and stable relationship between linear combination variables. The common methods for cointegration test were EG two-step method and Johansen test. EG two-step method was suitable for the case of two variables, while Johansen test was suitable for multiple variables. In this paper, the Johansen test was used to carry out the cointegration test. The cointegration equation of (7) was set as there was a definite linear trend and the cointegration equation had only intercept. The specific test results were shown in Table 2. The test results showed that both Trance statistics and Max-Eigen statistics rejected the assumption that there were 0 cointegration vectors and accepted the hypothesis that there was one cointegration vector at 5% significance level. Thus it could be seen that there was a unique cointegration relationship among the variables in (7). It could be further analyzed by the distributed lag model to analyze the impact of various factors on air passenger volume.

Table 2: Results of Johansen cointegration test

Hypothesis	**Johansen Test**			
	Trance value	***5% Critical value***	***Max-Eigen value***	***5% Critical value***
0	99.34	47.85	72.11	27.58
At least 1	27.23	29.79	18.02	21.13
At least 2	9,21	15.49	8.65	14.26
At least 3	0.55	3.84	0.55	3.84

3) Model optimization

The lag orders of PMI, TC and VPH indexes were set respectively. The model was fitted several times with different indexes settings and the test results were compared. Finally, the explanatory variables were determined as the current PMI and PMI two-order lag, TC and VPH, and the final fitting model was shown in (8). The estimation results were shown in Table 3.

$$LN\,P_t = 7.45 * LNPMI_t + 1.16LNPMI_{t-1} + 0.98 * LNPMI_{t-2}$$
$$-1.84 * LNTC_t + 0.096 * LNVPH_t \tag{8}$$

Table 3: Model estimation results

Variable	**Estimation Results**			
	Coefficient	***Std Error***	***T-Statistic***	***Pro***
LNPMI	7.451705	1.172896	6.353255	0.0001
LNPMI(-1)	1.161552	0.217853	5.331818	0.0003
LNPMI(-2)	0.980029	0.210161	4.663224	0.0009
LNTC	-1.842552	0.395951	-4.653481	0.0009
LNVPH	0.095576	0.025241	3.786505	0.0036
R-squared	0.937652			
Adjusted R-squared	0.912712			

3.3. Model Interpretation

1) Economic recovery was conducive to promoting the recovery of air passenger market in China.

The coefficient of the service industry PMI was positive and was significant at 99% confidence level. It indicated that the economic recovery had a significant positive stimulating effect on the recovery of the air passenger market. The first-and second-order lag coefficients of PMI were positive and were significant at 99% confidence level, indicating that the impact of economic recovery on the air passenger market was time-lagged. Air passenger was jointly affected by PMI of the current period and the two previous cycles.

2) The epidemic situation had an inhibitory effect on the recovery of air passenger in China.

The coefficient of cumulative confirmed cases (TC) was negative and significant at 99% confidence level. It indicated that the epidemic situation was an important factor affecting the recovery of air passenger in China. The increase of cumulative confirmed cases had a reverse inhibitory effect on the recovery of air passenger volume.

3) The promotion of vaccination was beneficial to the recovery of air passenger in China.

The coefficient of VPH was positive and significant at 99% confidence level, indicating that vaccination could promote the recovery of air passenger. The absolute value of VPH coefficient was less than that of TC coefficient, indicating that the incentive effect of vaccination was less than the inhibitory effect of the deterioration of epidemic situation. In order to promote the further recovery of air passenger, more attention should be paid to epidemic prevention and control as well as promoting vaccination.

4) The influence of COVID-19 on air passenger in China and the United States was different.

The same explanatory variables were selected to explain the influence of COVID_19 on air passenger market in the United States. Stationarity test and cointegration test were conducted and the dynamic distribution lag model was established. The model was shown in (9) and the model test results were shown in Table 4.

$$\begin{aligned} LN\,P_t &= 8.68 + 1.32 * LNPMI_t + 1.12 LNPMI_{t-1} \\ &- 0.09 * LNTC_t \end{aligned} \tag{9}$$

The coefficient of service industry PMI and its first-order lag were positive and significant at 99% confidence level. It indicated that the recovery of air passenger was affected by the current and previous PMI. The economic recovery had a positive incentive effect on the recovery of air passenger market in the United States. The impact time-lag of PMI on air passenger in China was longer than that of the United States.

Table 4: Model estimation results for the United States

Variable	**Estimation Results**			
	Coefficient	***Std Error***	***T-Statistic***	***Pro***
C	8.676248	1.327386	6.536339	0.0000
LNPMI	1.321750	0.499624	2.645491	0.0214
LNPMI(-1)	1.116759	0.504630	2.213026	0.0470
LNTC	-0.091302	0.022603	-4.039300	0.0016
R-squared	0.811866			
Adjusted R-squared	0.764832			

The coefficient of TC was negative and significant at 99% confidence level, indicating that the epidemic had a significant reverse inhibitory effect on air passenger market in the United States.

Compared with the coefficient of TC in (8), the absolute value of TC's coefficient in (9) was obviously smaller. It indicated that the influence of epidemic on air passenger volume in the United States was lower than that of China.

The impact difference of COVID_19 on air passenger market between China and the United States may be related to the different epidemic prevention and control policies adopted by the two countries. As the top two aviation markets in the world, there were significant differences in epidemic prevention and control policies between China and the United States. China had adopted a strict and proactive epidemic prevention and control policy, including policies such as "not leaving the city without necessity" and specific prevention and control measures such as wearing face masks strictly in public places. as well as civil aviation industry epidemic prevention guidelines, international flight circuit breaker mechanism and other industry measures. Compared with China, the United States adopted a relatively loose epidemic prevention policy. Epidemic prevention policy had a certain impact on the market recovery.

5) Prediction for China's air passenger in 2021.

Assuming that the economy still maintains a medium-to-high recovery rate from August to December in 2021, the PMI in service industry shows a similar trend with that of the same period in 2020. Vaccination continues to advance according to the current vaccination rate. With regard to the epidemic development, three scenarios of hypothesis were made. The recovery of China's air passenger market in 2021 was predicted based on the .three hypothesis.

Scenario 1: Optimistic hypothesis, epidemics caused by Delta mutant would be effectively controlled in mid-late August in China. The domestic epidemic situation would be stable and controllable from September to December. There would be no more outbreaks in many places.

Scenario 2: Meso hypothesis, epidemics caused by Delta mutant would be effectively controlled in mid-late August in China. Multiple mutated strains appeared again at the end of 2021.

Scenario 3: Pessimistic hypothesis, epidemics caused by Delta and other mutated viruses continue to affect.

Based on the three scenarios of optimism, moderation and pessimism, it was estimated that the air passenger volume in China in 2021 would reach 564 million, 548 million and 528 million respectively, as shown in Fig.3. Under the three scenarios, air passenger volume in 2021 would decrease by about 14.6% and 20% compared with 2019.

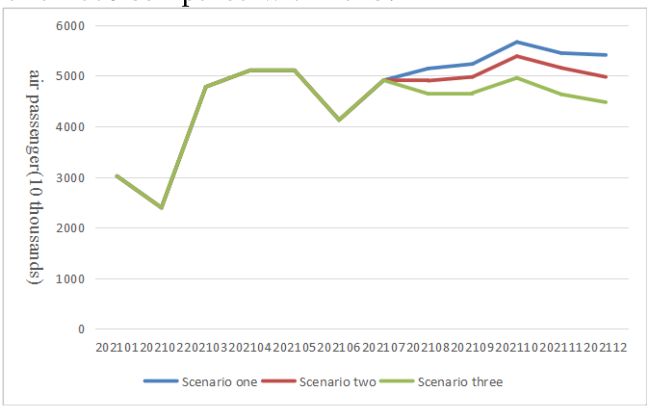

Figure 3: Estimation of China's air passenger volume in 2021

4. Conclusion

The main factors affecting the recovery of China's air passenger market was analyzed in the paper from the aspect of epidemic prevention and control and economic recovery. A dynamic distribution lag model was established which could effectively capture the characteristic of time lagged influence.

The main conclusions were as follows.

(1) Economic recovery and vaccination played a significant role in promoting the recovery of air passenger market. The development of the epidemic had an inhibitory effect on market recovery. The impact of economic recovery had obvious time lagged characteristic.

(2) The impact of COVID-19 on the recovery of air passenger was different between China and the United States. The difference might be related to the different epidemic prevention and control strategies adopted by the two countries.

(3) China’s air passenger volume in 2021 was estimated based on different hypothesis of the epidemic. It was predicted that China's air passenger volume in 2021 would be 530-560 million, which would return to 80%-85% compared with 2019. Effective control of the epidemic situation would be the important guarantee to promote the recovery of air passenger market.

Due to the duration of the epidemic, the size of sample data in this paper was limited. In the future, we will continue to track the development of the epidemic and the recovery of air passenger market, expand the sample database, and improve the model. The research results would be of great significance to enhance the industry's ability to deal with public health emergencies.

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