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Economies of Scale in China's Civil Aviation Transportation Industry

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Abstract:

To distinguish between economies of scale and economies of density, operational variables are introduced into the traditional translog cost function model. Financial and operational data of listed airlines in China (2005-2019) are used to measure factor cost elasticity, economies of scale, and their influencing factors in the air transportation industry. This research's findings show that economies of scale and density values of China's air transportation industry are 1.2728 and 1.2280, respectively. The economies of scale values of state-owned airlines and private airlines are 1.2994and 1.2374, respectively, and the economies of density values are 1.2386 and 1.2139, respectively. The former is better than the latter, because state-owned airlines have natural advantages in capital and personnel, and are more competitive for high-quality routes and time resources. The regression analysis shows that asset size does not have significant effects on economies of scale. The number of bases and the average size of aircraft types have a significant positive effect on economies of scale. Findings further reflect that an appropriate reduction of fleet commonality index is conducive to enhancing market adaptability. Thus, it reduces operating costs. The growth rate of economies of scale is faster than that of economies of density. This indicates that the impetus for the rapid development of China's air transportation industry mainly comes from the rapid expansion of the size of the airline network.

Keywords: *Airline, Transport economics model, Economies of scale, Economies of density, Influencing factors*

I. INTRODUCTION

In the National Civil Aviation Work Conference in 2021, Director Feng Zhenglin mentioned that the development of civil aviation during the 14th Five-Year Plan is high-quality development. The key tasks of the transportation industry both at present and in the future are to deepen the structural reform on the supply side, reduce costs and increase efficiency. Appropriate resource allocation will allow for resource conservation which will promote usage efficiency of various resource elements, for better efficiency and economy of production and operation. Economies of scale is one of the most important features of the air transportation industry according to the development practice of the world civil aviation industry[1]. This is the fundamental driving force for the development of the entire industry and the strategic behavior of companies such as mergers, restructuring and expansion. Extensive research has been done by several

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Chinese scholars to investigate whether there are economies of scale in China's air transportation industry and the development trend of economies of scale. However, there is a need for more conclusive evidence. More scientific and rigorous methods in addition to detailed data are needed for empirical analysis.

Drawing on economic theory, the definition of economies of scale is the phenomenon of increasing returns to scale in the production process as the average cost per unit of output decreases and the scale of production continues to increase[2]. Economies of scale has continued to attract significant interest from international scholars. Oum and Waters (1996) pointed out that the first purpose of studying the transportation cost function is"cost structure of the industry, notably whether or not there are economies of scale. These are important for assessing the feasibility of competition between firms of different size, and the long run equilibrium industrial organization of an industry"[3]. Economies of scale has been studies mostly from the perspective of transportation economics. For instance, Manuel (2005) estimated the total cost function and variable cost function of the European air transportation industry using a translog cost function model. He argued that European airlines have significant density economies, and most have network scale economies and spatial scope economies[4]. A symmetric generalized McFadden function was used by Subal C. Kumbhakar (1990). He introduced the number of points serving as a network size variable. Results of his study reflected decreased economies of scale and economies of density, but increased technology in the U.S. air transportation industry[5]. Creel and Farell (2001) analyzed the cost structure of the U.S. air transportation industry after deregulation using a Fourier function form. They found that economies of scale do exist at moderate output levels but die off at high levels[6]. The degree of concentration in the U.S. airline industry was measured through the HHI index and the concentration ratio by Johnston et al. (2011). They found that deregulation increased the concentration of the airline industry while the size and number of airlines increased. This finding suggests the existence of economies of scale[7]. Caves et al. (1984) used a translog cost function model and introduced the number of points served as a network size variable. Their study findings showed that that economies of scale remained essentially constant for local and trunk airlines in the U.S.[8]. Basso and Jara-Díaz (2006a) used a log-linear equation model to study economies of scale with constant network size and variable route structure. Their findings show that the economies of scale for U.S. airlines were increasing while the economies of density were closer to exhaust[9]. Johnston et al. (2013) used updated data and chose the number of city pairs served as the network size variable. They found that there are significant economies of scale and economies of density for all major U.S. airlines. Their findings reflected increasing economies of scale and decreasing economies of density effects[10].Sang-Lyul Ryu et al. (2019) used a translog cost function model to study the change in economies of scale in the airline industry since the emergence of low-cost carriers in Korea. They found that scale economies seem to be exhausted for full-service carriers, whereas LCCs have enjoyed economies of scale[11].

China has experienced a rapid growth in its transportation market. This has attracted the interest of some scholars to study economies of scale in the air transportation industry. Concepts such as scale economies, density economies and spatial scope economies have been identified in the in the air transportation literature[12-14]. Chen Lin (2012) conducted an empirical analysis of China's air transportation industry using the Cobb-Douglas production function and concluded that there are economies of scale[15]. Yu Liangchun and Yao Li (2006) used the method of comparative analysis of indicators, they found that the economies of scale in China's airline industry is not strong; the three major state-owned airlines showed diseconomies of

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scale[16]. Using the translog cost function, Zhu Nana (2018) measured the output-cost elasticity of China's listed airlines from 2011 to 2016. Their findings showed that China's listed airlines as a whole have diseconomies of scale[17]. The same method was employed by Zhang Peiwen et al. (2017) to measure the cost elasticity of China's listed airlines from 2006 to 2015. They found that there are economies of scale for China's airlines that are gradually optimized[18]. Zhang Jinqi(2018) investigated the density economy of different route networks using a translog cost function, he found that the density economics of the world's major airlines are not significant, while the density economics of low-cost airlines are more significant than the traditional airlines[19].

Obvious contradictions and inconsistencies are noted in the above research findings. We believe they may exist for two reasons: (1) research perspectives are different with most researchers' focus being from a purely economic perspective. The meaning of economies of scale in the air transportation industry is significantly different from that of the traditional economic perspective. This is due to the existence of network economic effects; (2) different research methodologies have been employed. Several scholars use Cobb-Douglas production function, traditional translog cost function and non-parametric method DEA, etc widely. The conditions of use of these methods and the selection of metrics will directly affect the empirical results.

It is necessary to fully consider the network effects to accurately measure the economies of scale in the air transportation industry. Hence, we introduce operational characteristics variables into the traditional translog cost function to distinguish economies of scale from economies of density. In the present study, we use China's listed airlines from 2005 to 2019 as our research sample to empirically study the economies of scale in China's air transportation industry. We establish a panel econometric model, and analyze the influencing factors of economies of scale using the multiple regression method to provide a reference for decision making to understand the operation status of China's airline industry as well as to optimize the efficiency of resource allocation.

In Section 2 we describe the econometric model used to estimate cost function. Section 3 presents the assessment index system of this paper. Section 4 describes the panel data used to estimate the parameters of the cost structure. In Section 5 we present and analyze the results of the estimated cost functions and indices mentioned above. Section 6 describes the analysis of factors influencing economies of scale. In Section 7 we discuss our conclusions and recommendations.

II. ECONOMETRIC MODEL

The Cobb-Douglas cost function has some limitations. Christensen et al. (1973) proposed the Translog Cost Function (TCF) model, which was further extended by Fuss and McFadden et al. (1978)[20-21]. The latter model takes into account the interaction terms of input-output indexes, input factors, and log-squared terms of output, and is obtained by using a second order Taylor Series expansion on the total cost function. The TCF model has been widely used by academics at both domestic and international level since it can be used to directly determine the effectiveness of a firm's scale, allowing for time-varying variables of scale

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economies. Further, its model form is intuitive, economically meaningful, and easy to estimate.

We introduce operational characteristic variables into the standard TCF model to develop an improved translog cost function model. This allows for a more accurate measure of air transportation economies of scale and is modeled as follows:

$$\begin{aligned}\ln TC = \alpha_0 + \sum_T \alpha_T + \sum_F \alpha_F + \alpha_Y \ln Y + \sum_i \beta_i \ln W_i + \sum_i \phi_i \ln Z_i \\ + \frac{1}{2}\delta_{YY}\left(\ln Y\right)^2 + \frac{1}{2}\sum_i\sum_j \gamma_{ij}\ln W_i \ln W_j + \frac{1}{2}\sum_i\sum_j \psi_{ij}\ln Z_i \ln Z_j \\ + \sum_i \rho_{Yi}\ln Y \ln W_i + \sum_i \mu_{Yi}\ln Y \ln Z_i + \sum_i\sum_j \lambda_{ij}\ln W_i \ln Z_j\end{aligned} \tag{1}$$

Where TC represents the total cost; Y represents the output of the airline; W_i represents the price of the ith input factor; Z_i represents the operational characteristics variable, $i = 1, 2 \cdots m$; α_T is the time dummy variable, and α_F is the firm dummy variable.

The following standard restrictions were imposed on the parameters:

$$\begin{aligned}\sum_i \beta_i = 1; \sum_i \gamma_{ij} = 0, (\forall j); \sum_i \rho_{Yi} = 0; \sum_i \lambda_{ij} = 0, (\forall j); \\ \gamma_{ij} = \gamma_{ji}; \psi_{ij} = \psi_{ji}; \lambda_{ij} = \lambda_{ji}\end{aligned} \tag{2}$$

This was to ensure that the estimated cost function is homogenous of degree one in input prices and to ensure symmetric cross effects.

According to Shephard's lemma the elasticity coefficient of input prices, i.e., the input factor cost share equation, can be derived as follows:

$$C_i = \beta_i + \sum_j \gamma_{ij}\ln W_j + \rho_{Yi}\ln Y + \sum_j \lambda_{ij}\ln Z_j \tag{3}$$

Where the elasticity coefficient of cost with respect to output (E_Y), the elasticity coefficient of the network size variable (E_{Zi}), the density economy of airlines (RTD), and the economy of scale (RTS) expressions are:

$$E_Y = \frac{\partial \ln TC}{\partial \ln Y} = \alpha_Y + \delta_{YY}\ln Y + \sum_i \rho_{Yi}\ln W_i + \sum_i \mu_{Yi}\ln Z_i \tag{4}$$

$$E_{Zi} = \frac{\partial \ln TC}{\partial \ln Z_i} = \phi_i + \sum_j \psi_{ij}\ln Z_j + \mu_{Yi}\ln Y + \sum_j \lambda_{ij}\ln W_j \tag{5}$$

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$$RTD = 1/E_Y \tag{6}$$

$$RTS = 1/(E_Y + E_{Zi}) \tag{7}$$

To make the first order coefficients of the variables directly interpretable as elasticities of cost it is necessary to standardize the data by subtracting the mean of each variable from each individual observation when using the translog cost function model. Based on the principles of economies of scale and economies of density calculations, to improve the efficiency of the cost function estimation, the input factor cost share equation is estimated in conjunction with equation (1) to construct a joint cubic equation model, and the model parameters are estimated using the seeming unrelated regression (SUR) method.

Economies of scale and economies of density have been explained by Caves et al. (1984) in terms of transportation economics, where economies of scale (RTS) refers to the phenomenon in which the price of input factors, average load factor and average stage length are held constant, and output increases in the same proportion as network size, resulting in a lower average cost. Economies of density (RTD) refers to the phenomenon in which network size, average load factor and average stage length are held constant, and output increases resulting in a lower average cost[8]. Generally speaking, when RTS<1, the total cost change rate is greater than the output change rate, and the company is in a state of scale diseconomies; when RTS=1, the total cost change rate is just equal to the output change rate, and the company is in the best scale state; when RTS>1, the total cost change rate is less than the output change rate, and the company is in a state of scale economies. Similarly, when RTD < 1, RTD = 1, RTD > 1, the company is in the density diseconomies, optimal and economic state respectively.

III. ASSESSMENT INDEX SYSTEM

In this study, a total of 81 samples of seven listed airlines in China from 2005 to 2019 are selected for unbalanced panel analysis. The input, output and operational characteristics indicators selected for the indicator system (Table I) should reflect the operating performance of the airlines. Further, this is to also avoid strong linear correlation among the indicators.

TABLE I. Airline economy of scale and economy of density assessment index system

Type	Name	Variable Symbols	Indicator content and calculation method
Input	Capital Price	W_1	(Depreciation Expense + Finance Expense)/(Total assets at the beginning of the year + Total assets at the end of the year)/2
	Labor Price	W_2	Employee compensation payable/Number of employees in service
	Fuel Price	W_3	Fuel Expense /Available Seat Kilometers
Output	Output	Y	ASK
Operational characteristics	Load factor	Z_1	Revenue Passenger Kilometers /Available Seat Kilometers

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indicators	Stage Length	Z_2	Revenue Passenger Kilometers / Passengers
	Network size	Z_3	Number of routes
Cost	Total Cost	TC	Finance Expense + Depreciation Expense + Labor Expense + Fuel Expense

The following evaluation indicators are determined with reference to the studies of Manuel, Caves, Johnston and other scholars on economies of scale and economies of density[4,8,10]. According to the service characteristics of airlines: input factor prices include capital price (W_1), labor price (W_2), and fuel price (W_3); output variable is available seat kilometers (Y); operational characteristics variables include average load factor (Z_1), average stage length (Z_2), and network size (Z_3); and total cost variable (TC).

The price of capital is defined as the ratio of cost of ownership to average assets, where the cost of ownership is the sum of depreciation and finance costs for the year, and average assets is the average of total assets at the beginning of the year and total assets at the end of the year. The price of labor is defined as the ratio of payroll expenses to the number of employees; payroll expenses is the sum of cash paid to employees and the balance of compensation to employees payable. Fuel price is the actual cost per unit of fuel. Listed airlines in China however only disclose the cost of fuel use in their annual reports. No information regarding the amount of fuel used (tons or gallons) is made available, hence the actual fuel price data is not available. However, since fuel use is highly correlated with output (ASK), we use the ratio of fuel expense to output in this study as an approximation.

The output is the total amount of product produced. The subject of this study is mainly passenger airlines; available seat kilometers (ASK) is used to represent it including both sold and unsold components.

Average load factor is defined as the ratio of revenue passenger kilometers to available seat kilometers among the operational characteristic variables, which is directly available in the annual report; average stage length is defined as the ratio of revenue passenger kilometers to passengers. The most commonly used proxy variables for network size shown in a review of extant literature are: the number of points served, number of routes served, and number of city pairs served. However, Manuel (2005) pointed out that using the number of routes generates a more accurate network size measure than other variables[4]. Hence, we use the number of routes to represent this variable.

Total cost is defined as the sum of capital cost, labor cost, and fuel cost. It is important to note that total cost is not the total operating cost of the airline, but the sum of the costs of the inputs. This is a prerequisite for using the cost minimization theorem in Shephard's lemma and the linear homogeneity constraint of the input terms.

Due to the existence of network effects in the air transportation industry, the introduction of operational characteristics variables in the cost function is necessary to distinguish between economies of scale and economies of density. This is an important gap in the literature in studies of economies of scale for China's

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airlines. The average stage length is introduced to ensure that the route network structure remains unchanged. This is due to changes in segment distance which can be caused by changes in service destinations or by route network connections, both of which can affect airlines' economies of scale. The average load factor indicator is chosen from an operational point of view to ensure that the increase in total output, with a constant load factor, is mainly due to changes in flight frequency or aircraft type size. The latter is a concrete expression of the airline's density economics. Further, it is also necessary to include this variable in the model as the number of routes also affects the economies of scale and economies of density of airlines.

IV. DATA ANALYSIS

We empirically analyze the economies of scale and density of China's listed airlines. In the present study, our research sample consists of a selection of seven listed airlines including Air China Group Corporation (CA), China Southern Airlines Group Corporation (CZ), China Eastern Airlines Group Corporation (MU), Hainan Airlines Group Corporation (HU), Shandong Airlines Group Corporation (SC), Spring Airlines (9C) and Juneyao Airlines (HO) from 2005 to 2019. The unbalanced panel data of the airlines were used to build an econometric model.

4.1 Data

The data were obtained from the annual reports of the listed airlines. The operating route data of some airlines were obtained from Varifight.com. All data are based on 2005 as the base year, and inflation is excluded using the producer price index PPI for each year (PPI index is obtained from the National Bureau of Statistics).Table II shows the descriptive statistics.

TABLE II. Descriptive statistics of raw data of sample listed airlines

Carrier	Time	Expenses (millions)	ASK (millions)	Capital price	Labor price(0000)
CA	Mean	45769	167258	7.13	19.73
	Std.dev	17897	72414	1.3	5.66
	2005	22205	74087	7.56	11.76
	2019	68693	287788	5.86	27.05
MU	Mean	42911	145793	7.6	20.94
	Std.dev	17382	68506	1.3	7.37
	2005	15444	52428	7.67	9.43
	2019	66236	270254	5.93	29.16
CZ	Mean	47947	187983	6.87	18.17
	Std.dev	19318	82121	1.41	4.87
	2005	17075	88361	7	12.21
	2019	77314	344062	5.95	25.45
HU	Mean	15100	68970	5.93	16.98

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	Std.dev	9225	51557	0.88	6.43
	2005	5633	20968	6.83	7.97
	2019	33057	174345	5.58	17.82
SC	Mean	6365	29315	7.44	24.78
	Std.dev	1502	11821	1.13	3.57
	2011	4262	13202	8.08	20.2
	2019	8595	44812	6.23	27.66
9C	Mean	5130	31098	4.17	30.24
	Std.dev	1562	9235	0.41	3.53
	2014	3648	19630	4.25	24.18
	2019	7211	43706	3.51	32.9
HO	Mean	5177	28196	4.67	30.96
	Std.dev	1726	9362	0.52	4.48
	2014	3356	15301	5.38	22.46
	2019	7592	40797	3.83	34.24

TABLE III. Descriptive statistics of raw data of sample listed airlines (continued)

Carrier	Time	Fuel price	Average load factor	Average stage length	Number of routes
CA	Mean	0.15	0.79	1880	358
	Std.dev	0.04	0.02	83	173
	2005	0.18	0.74	1844	218
	2019	0.11	0.81	2028	770
MU	Mean	0.15	0.77	1526	631
	Std.dev	0.04	0.05	98	188
	2005	0.17	0.69	1498	380
	2019	0.11	0.82	1702	1167
CZ	Mean	0.14	0.78	1599	853
	Std.dev	0.03	0.04	179	239
	2005	0.14	0.7	1404	600
	2019	0.11	0.83	1879	1300
HU	Mean	0.12	0.83	1636	581
	Std.dev	0.03	0.03	154	98
	2005	0.14	0.79	1294	480
	2019	0.1	0.83	1779	817
SC	Mean	0.13	0.8	1251	163
	Std.dev	0.04	0.03	182	40
	2011	0.19	0.81	956	110
	2019	0.1	0.84	1457	225
9C	Mean	0.09	0.92	1726	150
	Std.dev	0.02	0.02	68	46
	2014	0.12	0.93	1596	81
	2019	0.08	0.91	1773	210

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HO	Mean	0.09	0.86	1621	184
	Std.dev	0.02	0.01	46	99
	2014	0.13	0.84	1574	90
	2019	0.09	0.85	1579	345

4.2 Model Estimation Results and Analysis

Based on equation (1), a translog cost function model was established using the airline sample data. The regression estimation results are shown in Table III, and the modified R^2 of the regression equation reached 0.999.

TABLE IV. **Parameter estimates for the regression analysis**

Variable Symbols	Parameter estimates	z-value	Variable Symbols	Parameter estimates	z-value
First order terms			Year dummies		
Constant	-0.5982*	-5.47	2006	0.0127	0.63
Output	0.8091*	18.19	2007	0.0288	1.1
Capital Price	0.1901*	8.18	2008	0.0511*	2.17
Labor Price	0.2644*	10.11	2009	0.0988*	3.54
Fuel Price	0.5455*	16.94	2010	0.1219*	2.89
Load factor	-0.5674*	-2.80	2011	0.1431*	2.88
Stage Length	-0.1171	-1.11	2012	0.1610*	3.07
Number of routes	-0.0348***	-1.20	2013	0.2040*	3.51
Second order terms			2014	0.2306*	4.03
(Output)2	0.0005	0.02	2015	0.2510*	3.26
Output*Capital	-0.0477*	-4.37	2016	0.2408*	2.75
Output*Labor	0.0497*	4.82	2017	0.2531*	2.72
Output*Fuel	-0.0020	-0.26	2018	0.2600*	2.65
Output*Load factor	-0.0972	-0.35	2019	0.3002*	2.88
Output*Stage Length	-0.1479	-0.84	Firm dummies		
Output*Number of routes	-0.0142	-0.33	CA	0.5842*	5.61
(Capital Price)2	0.2294*	10.24	CZ	0.6038*	5.42
Capital*Labor	-0.1074*	-6.56	HO	-0.0448*	-1.6
Capital*Fuel	-0.1219*	-9.18	HU	0.3928	5.63
Capital*Load factor	0.4668*	3.37	MU	0.5622*	6.01
Capital*Stage Length	0.2459*	5.71	SC	-0.0514	-1.12
Capital*Number of routes	0.0650*	5.58	Capital share equation R^2=0.68		
(Labor Price)2	0.1768*	11.00	Capital Price	0.2294*	10.24
Labor*Fuel	-0.0694*	-7.00	Output	-0.0477*	-4.37
Labor*Load factor	-0.4895*	-3.64	Labor Price	-0.1074*	-6.56
Labor*Stage Length	-0.2206*	-5.15	Fuel Price	-0.1219*	-9.18
Labor*Number of routes	-0.0397	-3.68	Load factor	0.4668*	3.37

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(Fuel Price)2	0.1913	15.97	Stage Length	0.2459*	5.71
Fuel*Load factor	0.0227	0.26	Number of routes	0.0650*	5.58
Fuel*Stage Length	-0.3962*	-3.11	Constant	0.1954*	37.32
Fuel*Number of routes	-0.0253*	-2.85	Labor share equation	R^2=0.78	
(Load factor)2	-2.1402	-1.19	Capital Price	-0.1074*	-6.56
Load factor*Stage Length	-0.9213	-0.98	Output	0.0497*	4.82
Load factor*Number of routes	-0.0052	-0.02	Labor Price	0.1768*	11.00
(Stage Length)2	0.0262	0.06	Fuel Price	-0.0694*	-7.00
Stage Length*Number of routes	0.2313	1.45	Load factor	-0.4895*	-3.64
(Number of routes)2	-0.0321	-0.80	Stage Length	-0.2206*	-5.15
			Number of routes	-0.0397*	-3.68
			Constant	0.2813*	62.12

* significant at the 0.01 level. ** significant at the 0.05 level. *** significant at the 0.1 levels.

The first order coefficient values in Table IV indicate the cost elasticity of each indicator. According to the model setting, the coefficient values of the input factor price variables sum to 1. The elasticity coefficients of capital price, labor price, and fuel price are 0.1901, 0.2644, and 0.5455, respectively, all significant at the 1% level. This suggests that that an increase in any of the input factor prices will lead to an increase in total cost when all 1% increase in the price of input factors leads to 1% increase in total cost. Findings also show that the change in total cost is mainly caused by the change in fuel price, which contributes more than 50%.

Among the operating characteristics variables, the elasticity coefficient of the average load factor is -0.5674, significant at the 1% level. This finding indicates that for every 1% increase in the average load factor, the total cost decreases by 0.57%. The elasticity coefficient of average stage length is -0.1171 and is not significant. This suggests that an increase in average stage length leads to a decrease in total cost, however, this effect is not significant.

The elasticity coefficient of output is 0.8091, significant at the 1% level. This indicates that a 1% increase in output leads to a 0.81% increase in total costs. The elasticity coefficient of the number of routes is -0.0348 and is significant at the 10% level, indicating that a 1% increase in the number of routes leads to a 0.04% decrease in total costs. Drawing on the implications of economies of scale, this result indicates that a 1% increase in output and number of routes leads to a 0.77% increase in total costs with constant average stage length, average load factor, and input factor prices. A value of 0.78% was noted in Johnston et al. (2013) study on economies of scale in the U.S. airline industry[10]. This suggests that the economies of scale in China's airline industry effect is slightly better than that of the United States, which may be attributed to China’s growing air transportation market. A large number of new routes are opening up with rapid growth in passengers. China's air transportation market hence has more prominent economies of scale. Drawing on the economies of density, the regression results show that without changing the scale and structure of the network, every 1% increase in output leads to a 0.81% increase in total costs. Johnston et al. (2013) however found that the value is 0.61% for the U.S.[10]. This suggests that the density economies effect of China's airline industry is weaker than that of the U.S., which may be due to the inherent limitations of China's

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network structure, for instance, point-to-point network structure itself does not have the function of convergence and merging of traffic flows. Hence, it is difficult to generate strong density economies.

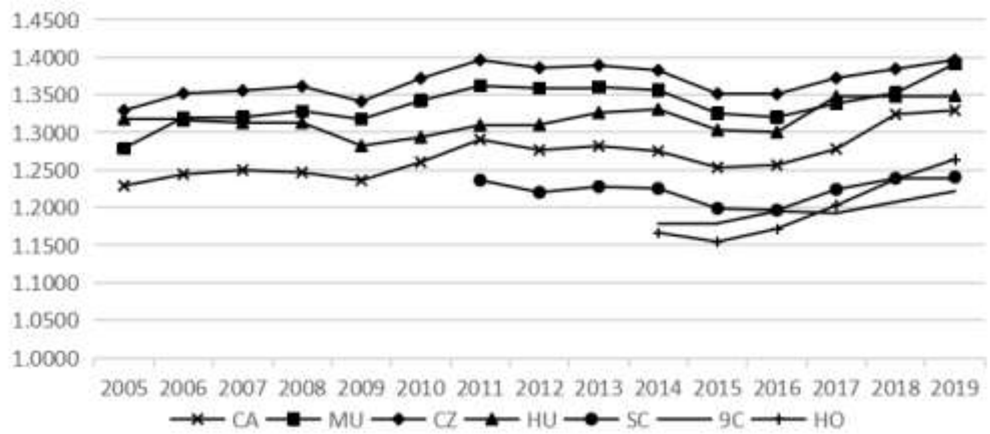

Figure 1: Economies of scale for different airlines

The scale economies effect of state-owned airlines is significantly better than that of private airlines, with the average values of 1.2994 and 1.2374 respectively (see Figure 1). It can also be found that the average growth rate of scale economies effect of state-owned airlines is higher than that of private airlines, 0.45% and 0.20% respectively. This can be attributed to state-owned airlines having a more complete network structure and a significant network effect, and the route opening cost being lower under the same conditions.

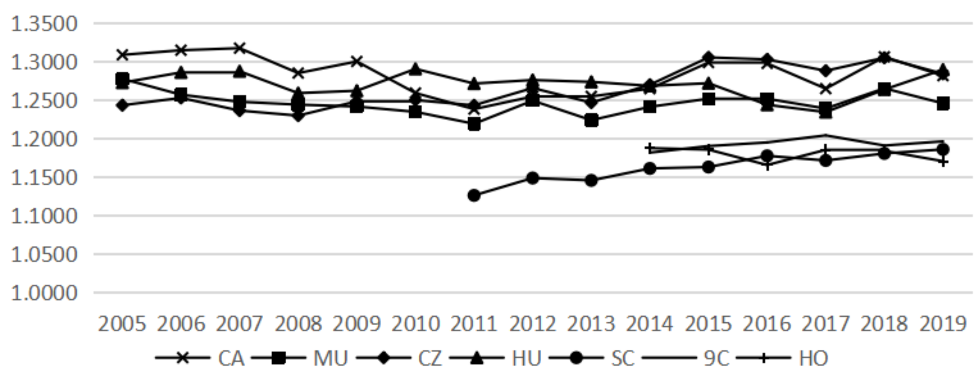

Figure 2: Economies of density for different airlines

The density economies effect of state-owned airlines is significantly better than that of private airlines, with mean values of 1.2386 and 1.2139 respectively (see Figure 2). The reason is that state-owned airlines mostly operate high-density trunk routes and also have the advantage of flight time. Further, aircraft size tends to be larger and flight frequency tends to be higher, which leads to higher density economies. The average growth rate of density economies effect of state-owned airlines is higher than that of private airlines, 0.24% and 0.10% respectively. These results further suggest that state-owned airlines have a natural

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first-mover advantage in terms of routes and flight times, and occupy a larger market potential.

V. ANALYSIS OF FACTORS INFLUENCING ECONOMIES OF SCALE

Several studies have shown that factors such as asset size, fleet commonality index, number of bases, ownership structure, average size of aircraft types, and number of routes can affect economies of scale. To further investigate the issue, we constructed the following econometric model:

$$\begin{aligned} RTS_{it} &= c(0) + c(1)asset_{it} + c(2)commonality_{it} + c(3)bases_{it} + c(4)\,property_{it} \\ &\quad + c(5)asset_{it} \times property_{it} + c(6)size_{it} + c(7)routes_{it} + \varepsilon \end{aligned} \tag{8}$$

Where RTS_{it} is the economy of scale value of the ith airline in year t; $asset_{it}$ is asset size, using total assets as a proxy variable; $commonality_{it}$ is fleet commonality index; $bases_{it}$ is the number of bases; $property_{it}$ is a 0-1 variable, indicating the property structure, and $property_{it}=1$ and 0 indicate state-owned airlines and private airlines, respectively; $asset_{it}$ *$property_{it}$ is the cross product term of the asset size variable and the ownership structure variable; $size_{it}$ is the average size of the aircraft types; and $routes_{it}$ is the number of routes. Among them, the fleet commonality index is calculated based on the formula (9) proposed by Joost Zuidberg (2014)[22]. The estimated results are shown in Table V.

$$Fleet\ commonality\ index = \left(\frac{N\ of\ common\ aircraft\ type\ in\ fleet}{N\ of\ aircraft\ in\ fleet} + \frac{1}{N\ of\ aircraft\ types\ in\ fleet} \right) / 2 \tag{9}$$

TABLE V. Regression results of influencing factors

Variable Symbols	Parameter estimates	Standard deviation	t-value	P-value
Constant	1.0995*	0.0638	17.2404	0.0000
Asset	5.33E-06	1.11E-05	0.4816	0.6323
Commonality	-0.0794*	0.0244	-3.2577	0.0021
Bases	0.0080*	0.0020	4.2766	0.0001
Property	0.0399*	0.0138	2.1795	0.0343
asset * property	-4.08E-05*	1.03E-05	-3.9503	0.0003
Size	0.0007*	0.0003	2.2809	0.0271
Routes	0.0110*	0.0019	5.7002	0.0000

* significant at the 0.01 level. ** significant at the 0.05 level. *** significant at the 0.1 levels.

Our findings show that the coefficient of the asset size variable is positive but not significant, indicating that the larger the asset size, the slightly stronger the economies of scale effect of airlines, but the difference is not significant (see Table V). This can be explained as follows: (1) airlines with larger asset size may have asset diversification, which affects the economy of scale in air transportation; (2) according to economic theory, there should be an optimal size of the company, and there is no definite linear relationship between economies of scale and size. Our findings align with Creel and Farell (2001)

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study.

The fleet commonality index is a positive indicator, the larger the index, the higher the fleet commonality. This indicates that the airline fleet is more homogeneous. The coefficient of the fleet commonality index is negative and significant at the 1% level, suggesting that higher fleet commonality results in lower economies of scale. Although lower fleet commonality brings higher operating costs, it is also more adaptable to the market. Under the condition that China operates both trunk and regional airlines, it is conducive to improving the utilization rate and load factor of the fleet. This can result in lower operating costs; when the reduced costs exceed the costs brought about by the diversity of aircraft types, it will generate economies of scale.

The coefficient of the number of bases is positive and significant at the 1% level. The more the number of bases, the better the airline's route network layout, the easier it is for aircraft parking, overnight and maintenance activities to produce the advantage of intensification, and the more centralized management of facilities, equipment and personnel. These can effectively reduce operating costs and as a result produce the economies of scale effect.

The coefficient of ownership structure is positive and significant at 1% level. This suggests that the economies of scale effect of state-owned airlines is more obvious compared with private airlines. This can be explained as follows: state-owned airlines are funded and operated by the government, established earlier, have strong capital, and have a large number of high-quality routes and prime flight time. Private airlines on the other hand are relatively deficient in capital and personnel, which makes it difficult to obtain enough high-quality routes and flight time. This limits the economies of scale effect of private airlines.

The coefficient of the cross product term of the property rights structure variable and the asset size variable is negative and significant at 1% level. This finding suggests that the growth of airline asset size reduces the marginal elasticity of the economies of scale effect on the property rights structure variable, i.e., as the size of state-owned airlines increases, their advantages over the economies of scale of private airlines become weaker. It shows that the scale growth of private airlines will narrow the gap between them and state-owned airlines, which is consistent with the reality.

The coefficient of the average size of aircraft type variable is positive and insignificant at 1% level, indicating that the larger the aircraft average size is, the more obvious the economies of scale are, because the aircraft with larger aircraft size has lower seat or ASK average cost. The data show that the average size of aircraft has increased by 1.99% annually in the past five years, and the flight frequency has reached 7.56%, indicating that the density-related output increase is caused by the increase in the size of aircraft and the flight frequency.

The coefficient of the number of routes variable is positive and significant at the 1% level, indicating that the economies of scale of airlines increase with the number of routes. The data show that the average annual growth rate of the number of airlines' routes in the last five years is 11.62%, while the output is

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11.81%. This is highly consistent with each other suggesting that the economies of scale in China's air transportation industry mainly come from the rapid expansion of the size of the route network.

VI. CONCLUSIONS AND RECOMMENDATIONS

Using improved translog cost functions based on the financial data and operational data of listed airlines in China, in this study we have estimated the economies of scale and economies of density of China's air transportation industry. We considered input factors prices, output, and network configuration. These specific estimates are calculated by evaluating the first derivative of the cost function with respect to output and the number of routes at various points in the data, and are impacted by the second order coefficients or interaction terms related to outputs and the number of routes. Finally, a regression model of the influencing factors is developed. We conclude the following:

1. There are obvious economies of scale and economies of density in China's air transportation industry, with mean values of 1.2728 and 1.2280, respectively. Compared with the United States, China's scale economies are stronger and density economies are weaker. This is mainly due to the fact that China's transportation market is in a rapid growth period and the scale effect of route expansion is more obvious; the route network structure is mainly point-to-point mode, resulting in the economies of density is limited.

2. The mean values of scale economies for state-owned airlines and private airlines are 1.2994 and 1.2374, respectively. The mean values of density economies are 1.2386 and 1.2139, respectively, both of which are better than the latter. The reason is that state-owned airlines have a more complete route network structure and lower route expansion costs. Most however operate high-density trunk routes and have advantages in terms of flight times, etc. This leads to the difference in economies of scale and economies of density between the two. The growth of scale economies is significantly faster than that of density economies; this suggests that the rapid development of China's air transportation industry is driven by the expansion of network size.

3. The regression results of the influencing factors show that asset size has no significant effect on economies of scale. The number of bases and aircraft type size have a significant positive effect on economies of scale; the lower the fleet commonality index, the stronger the economies of scale. The economies of scale of state-owned airlines is significantly higher than that of private airlines; this finding is consistent with the second conclusion. Finally, the scale economies increases with the number of routes. This further suggests that the scale economies of China's air transportation industry mainly comes from the rapid expansion of route network size.

We make the following recommendations drawing on our findings: (1) In order to achieve better economies of scale, airlines need not only expand their route scale to stimulate air transport demand, but also improve company management, tap their own potential, reduce costs and increase efficiency, and achieve high-quality development of civil aviation; (2) As China has a wide range of routes, it can moderately consider increasing the type of aircraft and reducing the fleet commonality index to improve the matching degree between the fleet and routes, enhance market adaptability, and systematically reduce operating costs. (3) The development of private airlines is relatively lagging behind and is a shortcoming of China's civil aviation development. It is therefore necessary to enhance the competition mechanism and improve efficiency. At the same time, private capital should be actively guided to expand regional airline business. This can assist to form a supplement and auxiliary to mainline, and build a hub-and-spoke route network with Chinese characteristics.

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