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Convergence in the Chinese airline industry: A Malmquist productivity analysis

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ABSTRACT

Our paper examines the productivity levels of Chinese airline market over the period 2006–2016 using Malmquist productivity indexes. Applying a decomposition technique on the estimated productivity index we decompose airlines' productivity levels into technological, pure technical efficiency and scale efficiency change components. The results signify that the reforms made on the Chinese airline industry have forced the airlines to enhance both their catching-up ability and their innovation capacity. This in turn is reflected on their estimated productivity levels. Then in a second stage analysis we utilize the methodological framework by Phillips and Sul (2007, 2009) and we test for the existence of convergence clubs among the estimated productivity components. The results verify the hypothesis of convergence among airlines' technological change and pure technical efficiency levels identifying distinct convergence clubs. The estimated relative transition paths reveal the insights of the enhanced competition among the Chinese airlines.

1. Introduction

With the implementation of "reform and opening up" policy as well as the industrialization and urbanization, it has witnessed the rapid development of civil airline industry in the last four decades in China (Chen et al., 2017; Tsionas et al., 2017). Moreover, as the most populated country with increasing income and largest international trade volume connected with other countries, the demands on civil air transport continues keeping the prosperity within this industry. According to the statistics of IATA (The International Air Transport Association), China has been ranked as the second largest aviation market in the world after 2005 (Chen et al., 2017; Cui and Li, 2017a, Cui and Li, 2017b, 2018). The RPK (Revenue Passenger Kilometers) has surged from 15.77 billion to 556.57 billion for the domestic flights during the period of 1990–2015. After the late 90s, and in order to decrease the monopoly power of existing airline companies, the CAAC (Civil Aviation Administration of China) further deregulated the Chinese civil aviation sector and open it to private entrants, including the low-cost carrier. Meanwhile, the three largest airlines, i.e. China Eastern, China Southern, and Air China, were partially privatized through IPOs in the stock exchange market (Chen et al., 2017). However, some legacy regulations still lies on the road and may distort the effects of reform. Therefore, the domestic aviation market exhibits some distinctive characteristics in terms of network configuration, inter-modal competition, airline cost competitiveness and profitability (Yan et al., 2018). Hence, it is necessary to evaluate the performance and its dynamics of these Chinese airline companies after decades of reform, so that to shed lights on the future deregulation in the civil aviation industry of China. Meanwhile, it also helps to understand the sources of competitiveness of these airline companies.

Moreover, the efficiency or productivity analysis is an economic and effective way to assess the performance of different DMUs (Decision-Making Units). Similar to our study, some other scholars also estimate the efficiency dynamics through the Malmqusit productivity index-MPI or Luenberger productivity index-LBI (Oum et al., 2005; Barbot et al., 2008; Greer, 2008; Chow, 2010; Wang et al., 2017). However, there is rarely any academic work, which is based on those indexes in order to investigate any productivity convergence patters among the airline industry. Given the fact that Chinese airline industry has been gone through some major restructuring which has been resulted on the enhancement competition among airlines (Chow, 2010; Wang et al., 2016). To this end, our study contributes to the relative literature by analyzing for the first time potential convergence patterns among airlines' estimated productivity levels. Specifically, in a first stage analysis

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we employ the methodological approach of Färe et al., 1994a; Färe et al., 1994b in order to estimate Chinese airlines' productivity levels over the period 2006–2016. In a second stage, we identify convergence patterns of the estimated MPI measures by applying the methodological framework by Phillips and Sul, 2007; Phillips and Sul, 2009. The applied convergence methodological framework is suitable for the adopted nonparametric productivity framework, since it does not rely on strong assumptions neither on trend nor on the stochastic stationarity of the data (productivity indicators in our case). In addition the transition paths, transition coefficients (parameters) and the convergence itself are measured in relative terms. This in turn aligns with the properties of the estimated nonparametric productivity indexes since they are also measured in relative terms (relative productivity measures) and they do not impose strong assumptions on airlines' estimated production process. As a result, the two approaches can be combined providing us with useful insights of the airlines' productivity convergence trends. The reminder of the paper is as follows: Section 2 introduces the relative literature review, while Section 3 describes the data and the methodological framework adopted, whereas, Section 4 presents the empirical findings of our analysis. Finally, the last Section concludes our paper.

2. Literature review

As an extensively regulated industry, it is essential for policy planners and decision makers to monitor and evaluate the airline's performance by employing efficiency and productivity analysis. This essentiality is well reflected on a large strand of literature focusing on this topic. Two main approaches have been employed by scholars to assess the efficiency and productivity of airlines. Firstly is the non-parametric one, i.e. Data Envelopment Analysis (DEA) and secondly the parametric one, i.e. Stochastic Frontier Analysis (SFA) (Table 1). Meanwhile, some other multi-criteria methods such as the technique for order preference by similarity to the ideal solution (TOPSIS) have been applied in order to identify benchmarks and evaluate the competitive structures of different airline industries (Barros and Wanke, 2015; Wanke et al., 2015). When comparing to the other methods, the DEA model and its derivatives seem much more popular and takes the major share of the empirical research given its advantage of flexibility on estimating airlines' production function (Table 1).

The efficiency and productivity of airlines in developed countries has been brought in sharp focus in the research. Table 1 presents the main recent studies applied to evaluate airlines efficiency and productivity levels. It is evident that with the rapid development of civil aviation industries, new research switched to pay close attention to the performance of developing countries, like China. According to Table 1, there just several empirical researchers analyzing the performance of Chinese airlines, despite its rapid growing market and demands (Chow, 2010; Tsionas et al., 2017; Chen et al., 2017). Many studies evaluate and compare the airline efficiency across different countries (Windle, 1991; Coelli et al., 1999; Lee and Worthington, 2014; Arjomandi and Seufert, 2014; Wanke and Barros, 2016; Cui and Li, 2017a; Cui and Li, 2017b; Wang et al., 2017; Cui and Li, 2018; Kottas and Madas, 2018). Some others investigate the main factors that lead to different levels of efficiency and productivity. These are mainly focused on the ownership structure, the airline status, the airline scale, age, corporate governance and alliance memberships (Chow, 2010; Lee and Worthington, 2014; Wanke et al., 2015; Tsionas et al., 2017; Kottas and Madas, 2018). Finally, it is worth mentioning the few studies, which have analyzed the development of low cost carriers (LCCs), alongside with the effects of Chinese regulations on the competitive conditions of the airline industry (Fu et al., 2015; Wang et al., 2018).

3. Variable description and methodological framework

3.1. Variable description

For the purpose of our analysis we use a sample of 11 Chinese airlines over the period of 2006-2016[1] extracted by the yearbook of "Statistics Data on Civil Aviation of China". In accordance to the previous studies measuring airlines efficiency and productivity (see Table 1) we construct airlines production process utilizing three inputs: number of employees, number of airplanes and fuels (in metric tons) and two outputs: revenue generated by freight ton kilometers (rftk), and revenue generated by passenger kilometers (rpk). The descriptive statistics are displayed in Table 2. It is evident that the airlines operating in China are from different sizes, which is evident when looking the large standard deviations of the inputs during the examined period. Finally, since we have only 11 airlines in our sample and three inputs and two outputs, our analysis will be affected by the problem of dimensionality and eventually will create a bias on our estimated productivity indexes (Dyson et al., 2001). For that reason by following Bădin et al. (2012, p.826–827) and Wilson (2018) approach we replace the three inputs by their best (non-centered) linear combination (through non-centered PCA) resulting in a univariate input factor. The same is also performed for the two outputs resulting in single output factor. Given that the studies performing efficiency and productivity analysis on airlines utilize small samples (see Table 1), as suggested by Wilson (2018) by applying data reduction techniques we are able to minimize the problem of dimensionality in relation to the size of the sample adopted.

3.2. Estimation of productivity indexes

The production process of Chinese airlines can be characterized by a set of input $\boldsymbol{x} \in \mathbb{R}_+^p$ and output $\boldsymbol{y} \in \mathbb{R}_+^q$ vectors. Then the production possibility can be defined at time t as:

$$\Psi^t = \{(\boldsymbol{x}, \boldsymbol{y}) | \boldsymbol{x} \text{ can produce } \boldsymbol{y} \text{ at time } t\}. \tag{1}$$

According to Färe et al. (1994a) the Malmquist Productivity Index-MPI (Caves et al., 1982) for two periods t_1 and t_2 can be estimated as:

$$M\left(\boldsymbol{x}_i^{t_1}, \boldsymbol{y}_i^{t_1}, \boldsymbol{x}_i^{t_2}, \boldsymbol{y}_i^{t_2}\right) = \underbrace{\left[\frac{\hat{D}_{CRS,n}^{t_2}(\boldsymbol{x}_i^{t_2}, \boldsymbol{y}_i^{t_2})}{\hat{D}_{CRS,n}^{t_1}(\boldsymbol{x}_i^{t_1}, \boldsymbol{y}_i^{t_1})}\right]}_{TE_\Delta} \times \underbrace{\left\{\left[\frac{\hat{D}_{CRS,n}^{t_1}(\boldsymbol{x}_i^{t_2}, \boldsymbol{y}_i^{t_2})}{\hat{D}_{CRS,n}^{t_2}(\boldsymbol{x}_i^{t_2}, \boldsymbol{y}_i^{t_2})} \times \frac{\hat{D}_{CRS,n}^{t_1}(\boldsymbol{x}_i^{t_1}, \boldsymbol{y}_i^{t_1})}{\hat{D}_{CRS,n}^{t_2}(\boldsymbol{x}_i^{t_1}, \boldsymbol{y}_i^{t_1})}\right]\right\}^{1/2}}_{T_\Delta} \tag{2}$$

As can be observed by equation (2) MPI consists of two parts. The first part ($TE\Delta$) represents airlines' efficiency changes (technological catch-up),[2] whereas, the second part ($T\Delta$) captures the technological changes (i.e. movements of the technological frontier) between the two periods. In addition, it must be noted that this productivity index is based on the assumption of constant returns to scale (CRS) for all the components. Moreover, Färe et al. (1994b) further decomposed the MPI index (equation (3)). The first factor ($PTE\Delta$) measures airlines' pure efficiency change over two periods. In contrast to $E\Delta$, $PTE\Delta$ measures airlines' efficiency changes under the assumption of variable returns to scale (VRS). The second factor ($SE\Delta$) measures airlines' scale efficiency levels over the two periods, whereas, $T\Delta$ captures as previously airlines' technological changes under the assumption of CRS:

Table 1
Findings of the main studies analyzing airlines' performance.

Author	Number of airports	Year	inputs/outputs	Methodology	Main findings
Kottas and Madas (2018)	30 global airlines	2012–2016	input: employees, total operational costs, number of planes output: total operational revenue, RPKs, RTKs	DEA with super efficiency	11.33% of DMUs is efficient. Alliance group membership is not associated with superior airline efficiency.
Sakthidharan and Sivaraman (2018)	7 Indian airlines	2013–2014	inputs: RPKM, FTKM outputs: ATKM, CASK, fuel per ASK, CASK ex-fuel, Maint per ASK, ownership per ASK, employees	input-oriented DEA	airlines are operating with a technical efficiency between 0.71 and 0.89.
Cui et al., 2017a; Cui et al., 2017b	19 global airlines	2009–2014	input: Number of employees, Aviation kerosene output: RTP, RPK, total revenue	Dynamic Epsilon-Based Measure DEA model	Scandinavian, Emirates and Cathay Pacific are the benchmarking airlines among the 19 airlines
Tsionas et al. (2017)	9 Chinese airlines	2006–2014	input: employees, fuel, number of planes output: cargos, passengers, delay	a stochastic distance function and SVAR	suggest a mutual dependence relationship between airline technical efficiency scores and delays
Wang et al. (2017)	49 global airlines	2008–2013	input: Liabilities, Stockholder equity, Operating expenses, Intangible assets output: Revenue, Market value	the dynamic slacks-based measure model (DSBM)	asset-light strategy significantly enables global airlines to have better corporate performance
Yu et al. (2017)	30 global airlines	2009–2012	input: Size of leased fleet, Labor expenses, Fuel expenses, Other operational expenses intermediate: ASK, FATK output: RPK, FRPK	two-stage dynamic network DEA, bootstrapped truncated regression	the overall operational efficiency shows a yearly declining trend
Omrani and Soltanzadeh (2016)	8 Iranian airlines	2010–2012	input: employees intermediate: ASK, ATK, flights output: operating revenue	dynamic network DEA	the airlines have poor performance in stage 1, rather than the stage 2
Saranga and Nagpal (2016)	13 Indian airlines	2005–2012	inputs: staff, ASK, Operating expense less employee expenditure/ASK, Employee expenditure/Staff outputs: RPK, Operating revenue/ASK	input-oriented VRS DEA and two-stage regression	the low cost carriers in India have managed to achieve significant operational efficiencies
Wanke and Barros (2016)	19 Latin American airlines	2010–2014	input: Number of Employees and planes output: Number of Domestic Flights, Latin and Caribbean Flights, World Flights	Virtual Frontier Dynamic DEA and Simplex Regression in a Two-stage Approach	the low cost carriers have higher efficiency
Barros and Wanke (2015)	29 African airlines	2010–2013	input: the number of employees, the total number of aircraft, and operating costs output: RPK and RTK	TOPSIS	the average efficiency of African airlines is low in relative terms
Li et al. (2015)	22 international airlines	2008–2012	input: employees, AK intermediate: ASK, ATK, Fleet size, RPK, RTK, Sales costs output: Total business income	Virtual Frontier Network SBM	most airlines' overall efficiency increased in the period
Mallikarjun (2015).	27 U.S. airlines	2012	input: operating expenses intermediate: ASM, RPM output: operating revenue	un-oriented Network DEA	major US airlines are more efficient than national US airlines in spending operating expenses and gaining operating revenue, but there is no significant difference in their service supply and demand efficiencies
Wanke et al. (2015)	35 Asian airlines	2006–2012	input: Operational cost, Depreciation, Salary, Employees, Planes, Total assets, Fixed assets, output: Revenues, EBIT, RPK, Passenger	two-stage TOPSIS and MCMC generalized linear mixed models	The results reveal significant impacts of cost structure, ownership type, market positioning, and mileage program offered on efficiency levels.
Arjomandi and Seufert (2014).	48 global airlines	2007–2010	input: labor, capital output: TKA, CO2	Bootstrapped DEA	many of the most technically efficient airlines are from China and North Asia, whilst many of the best environmental performers are from Europe
Lee and Worthington (2014)	42 global airlines	1994–2011	input: employees, total assets, kilometres flown output: ATK	DEA-BCC, CCR two-stage bootstrap regression	private ownership, status as a low-cost carrier, and improvements in weight load contributed to better organizational efficiency
Barros et al. (2013)	11 U.S. airlines	1998–2010	input: Total Cost, Number of Employees, Number of Gallons output: Total revenue, RPM, Passenger Load Factor	B-convex DEA model	some airlines maintaining a remarkable level of efficiency in all years.
Barros and Couto (2013)	23 European airlines	2000–2011	input: Employees, Operational cost, number of seats output: Revenue per passengers km, Revenue cargo Tonnes carried	Luenberger productivity indicator	most European airlines did not experience productivity growth
Merkert and Williams (2013)	18 European airlines	2007–2009	input: labor, ASK output: RPK, realised departures	bootstrapped DEA first stage and two-stage truncated regression	the technical efficiency scores of the worst performing carriers are better than expected.
Wu et al. (2013)	4 Chinese airlines, 8 foreign airlines	2006–2010	input: number of full time employees, operational costs and number of aircraft output: RTK and operating revenue	DEA-BCC, CCR second stage regression	an international focus has a negative impact, while the level of salaries has a positive impact. there is an inverted U-shaped relationship between efficiency and the proportion of cargo traffic.

(*continued on next page*)

Table 1 (*continued*)

Author	Number of airports	Year	inputs/outputs	Methodology	Main findings
Assaf and Josiassen (2012)	17 European airlines, 13 U.S. airlines	2001–2008	input: labor, capital, fuel, and other operating inputs output: RPK, RTK, incidental revenues	a Bayesian distance frontier model	most years European airlines were operating at a slightly higher average efficiency rate than U.S. airlines
Merkert and Hensher (2011)	58 global airlines	2007–2009	input: labor, ATK, FTE_price, ATK_price output: RPK and RTK	bootstrapped DEA first stage and two-stage Tobit regression	the effects of route optimisation are limited to airline technical efficiency, the aircraft size and number of different aircraft families in the fleet, are more relevant to successful cost management of airlines
Sjögren and Söderberg (2011)	18 major UK airlines	1990–2003	input: labor, fuel, Aircraft capacity output: passengers, freight	Input distance function	deregulation increases productivity, membership in alliances has an ambiguous effect and state ownership has no significant effect
Chow (2010)	16 Chinese airlines	2003–2007	input: employees, airline fuel and seat capacity output: RTK	DEA and Malmquist index	non-state-owned airlines are performing better than state-owned airlines
Hong and Zhang (2010)	29 international airlines	1998–2002	input: number of employees, ASK output: total revenue, RPK, freight RTK	DEA-CCR	airlines with a high share of cargo business in their overall operations are significantly more efficient than airlines with a low share of cargo business
Barros and Peypoch (2009)	27 European airlines	2000–2005	input: number of employees, operational cost, number of planes output: RPK, EBIT	DEA-CCR and Bootstrapped truncated regression	The demographic dimension of the airline's home country is of paramount importance, representing economies of scale and membership of a network is also important
Barbot et al. (2008)	49 international airlines	2005	input: number of core business workers, number of operated aircraft and fuel output: ASK, RPK, RTK	DEA-BCC, TFP analysis	low-cost carriers are in general more efficient than full-service carriers
Greer (2008)	8 U.S. airlines	2000–2004	input: labor, fuel, seats output: ASM	Standard DEA and Malmquist Productivity Index	there was a significant improvement in the productivity of the carriers at transforming labor, fuel and passenger seating capacity into available seat-miles during this period
Inglada et al. (2006)	39 International airlines	1996–2000	input: workers, fuel, the capacity of the planes output: the number of km-tons available	SFA-cost function and production function	the benefits of increasing competition in terms of efficiency, is being large for the Asian companies
Oum et al. (2005)	10 U.S. and Canadian airlines	1990–2001	input: labor, fuel, materials, flight equipment, ground property and equipment output: scheduled passenger service (RTK), scheduled freight service (RTK), mail service (RTK), non-scheduled passenger and freight services (RTK), and incidental services output	Log-linear TFP regressions	the airlines in North American improved productive efficiency by about 12% between 1990 and 2001
Capobianco and Fernandes (2004)	53 global airlines	1993–1997	input: financial leverage output: return on assets, firm size and tangibility of assets	DEA-BCC	the biggest airline companies which use capital efficiently to generate return with a low level of fixed assets
Coelli et al. (1999)	32 international airlines	1977–1990	input: labor, capital (the sum of the maximum take-off weights of all aircraft multiplied by the number of days the planes have been able to a operate during a year) output: passenger and cargo TKP	SFA	Asian/Oceanic airlines are technically more efficient than European and North American airlines but that the differences are essentially due to more favorable environmental conditions.
Windle (1991)	48 international airlines	1970–1983	input: labor, fuel, materials, flight equipment, ground property and equipment output: scheduled revenue passenger-miles, non-scheduled revenue ton-miles, scheduled revenue ton-miles of mail, scheduled revenue ton-miles of freight	SFA-cost function	U.S. airline has higher productivity.
Sickles et al. (1986)	13 U.S. airlines	1970–1981	input: labor, capital, fuel output: passenger and cargo ton-miles	Generalized-Leontief Profit Function	deregulation reduce the allocative distortion

Table 2
Descriptive statistics of the variables.

Year	Statistics	Number of Employees	Number of Airplanes	Fuels(tons)	rftk (revenue freight ton kilometers)	rpk (revenue passenger kilometers)
2006	Mean	14114	79	783447.636	44603.509	1659449.382
	Std	20761	111	1153579.695	67857.085	2339030.569
2007	Mean	15447	85	869927.091	47498.373	1948605.909
	Std	22799	121	1255251.877	72423.193	2664104.229
2008	Mean	15480	90	861495.273	45738.582	1967201.582
	Std	22452	124	1220510.287	69493.265	2646031.827
2009	Mean	18553	100	965976.182	48026.855	2307831.573
	Std	26507	135	1316108.029	69703.308	2934412.827
2010	Mean	17690	110	1116225.364	66645.427	2736893.493
	Std	24543	147	1517057.418	101281.817	3446850.461
2011	Mean	19774	121	1207877.091	71216.918	3072594.533
	Std	26483	157	1590082.762	109690.318	3702804.499
2012	Mean	23218	134	1336116.364	78997.336	3379607.509
	Std	31595	170	1731623.611	125908.637	3933548.884
2013	Mean	25447	140	1475543.455	84500.691	3768316.527
	Std	34664	168	1871991.568	132983.571	4223900.100
2014	Mean	28445	149	1655007.509	95804.263	4143415.841
	Std	38031	173	2099532.593	154153.595	4566644.325
2015	Mean	29264	164	1898097.567	105878.618	4722307.209
	Std	39376	183	2395733.650	169977.826	5086174.618
2016	Mean	30428	179	2149834.631	118264.973	5319614.445
	Std	40752	194	2630380.999	185867.497	5510488.961

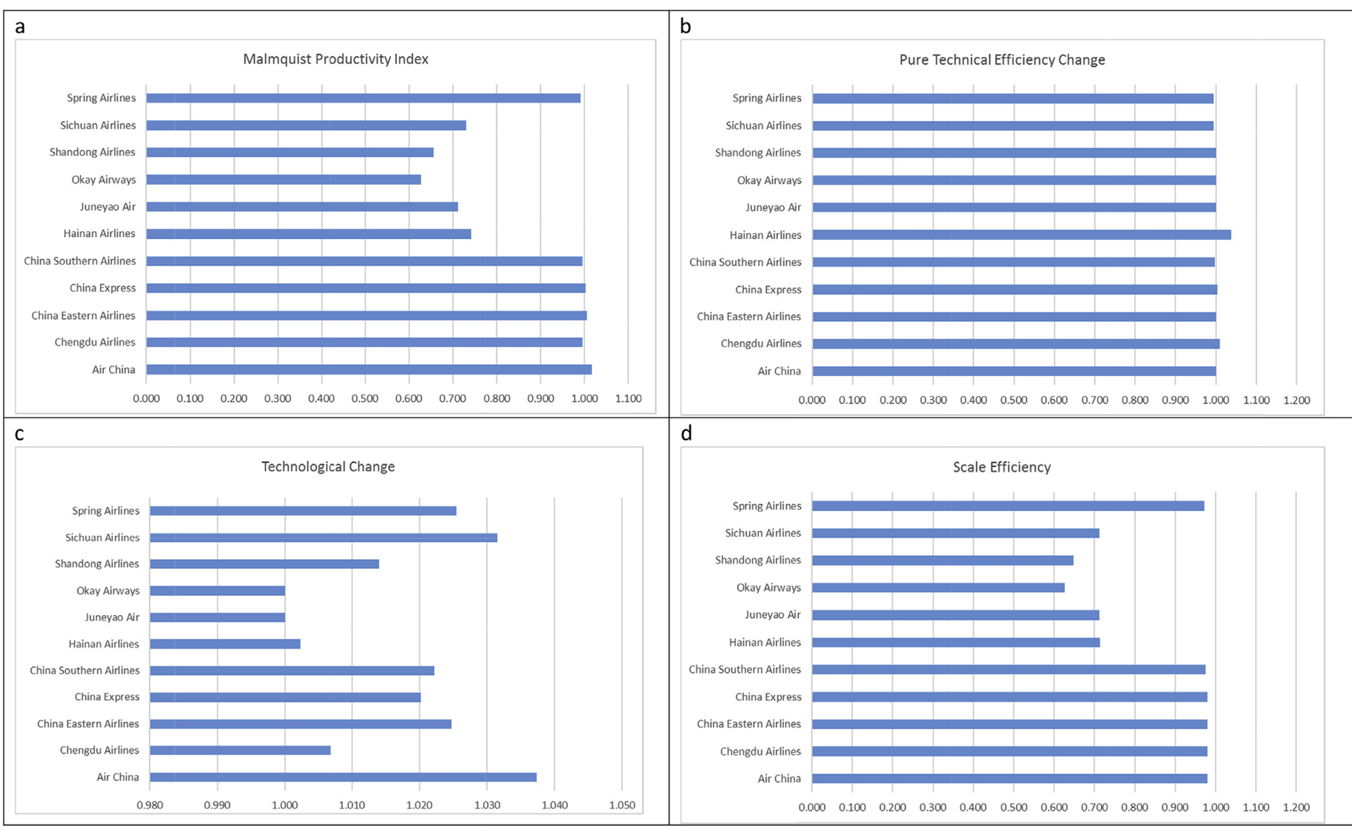

Fig. 1. Per airline productivity indexes and components for 2006–2016.

$$M(\boldsymbol{x}_i^{t_1}, \boldsymbol{y}_i^{t_1}, \boldsymbol{x}_i^{t_2}, \boldsymbol{y}_i^{t_2}) = \underbrace{\left[\frac{\hat{D}_{VRS,n}^{t2}(\boldsymbol{x}_i^{t2}, \boldsymbol{y}_i^{t2})}{\hat{D}_{VRS,n}^{t1}(\boldsymbol{x}_i^{t1}, \boldsymbol{y}_i^{t1})}\right]}_{PTE_\vartriangle} \times \underbrace{\left\{\frac{\left[\hat{D}_{CRS,n}^{t2}(\boldsymbol{x}_i^{t2}, \boldsymbol{y}_i^{t2}) / \hat{D}_{VRS,n}^{t2}(\boldsymbol{x}_i^{t2}, \boldsymbol{y}_i^{t2})\right]}{\left[\hat{D}_{CRS,n}^{t1}(\boldsymbol{x}_i^{t1}, \boldsymbol{y}_i^{t1}) / \hat{D}_{VRS,n}^{t1}(\boldsymbol{x}_i^{t1}, \boldsymbol{y}_i^{t1})\right]}\right\}}_{SE_\vartriangle}$$

$$\times \underbrace{\left\{\left[\frac{\hat{D}_{CRS,n}^{t1}(\boldsymbol{x}_i^{t2}, \boldsymbol{y}_i^{t2})}{\hat{D}_{CRS,n}^{t2}(\boldsymbol{x}_i^{t2}, \boldsymbol{y}_i^{t2})} \times \frac{\hat{D}_{CRS,n}^{t1}(\boldsymbol{x}_i^{t1}, \boldsymbol{y}_i^{t1})}{\hat{D}_{CRS,n}^{t2}(\boldsymbol{x}_i^{t1}, \boldsymbol{y}_i^{t1})}\right]\right\}^{1/2}}_{T_\vartriangle} \tag{3}$$

[1] Our sample contains also the low-cost carriers alongside with the traditional Chinese airlines. Given the extensive regulations imposed by the government, the low-cost carriers (LCCs) of China are not the same as the one in the foreign countries, especially for the ticket price. For instance, Fu et al. (2015) points out that Spring Airlines has not brought significant changes (e.g., significant price reduction or traffic volume surge) as the major LCCs in North America and Europe.

[2] Catching-up is referred to airlines' movements away/towards to the estimated technological frontier over the examined period.

Table 3
Analytical estimates of Malmquist productivity Indexes and components.

	MPI-0607	MPI-0708	MPI-0809	MPI-0910	MPI-1011	MPI-1112	MPI-1213	MPI-1314	MPI-1415	MPI-1516
Air China	0.601	1.645	1.003	1.002	1.003	1.000	1.002	1.001	1.003	1.001
Chengdu Airlines	0.368	2.583	0.979	0.994	0.988	1.006	0.983	0.934	0.964	0.984
China Eastern Airlines	0.608	1.626	1.003	1.001	1.003	1.000	1.000	1.000	0.999	0.999
China Express	0.327	3.036	1.004	0.896	0.932	0.913	0.933	0.996	0.995	0.988
China Southern Airlines	0.625	1.605	1.001	1.000	1.000	0.998	0.998	0.995	0.997	0.998
Hainan Airlines	0.568	1.831	0.998	1.002	1.000	1.001	1.001	1.000	0.999	1.000
Juneyao Air	0.370	2.187	1.000	1.000	0.997	0.992	0.997	0.999	0.995	0.998
Okay Airways	0.324	2.201	1.019	0.994	0.987	0.996	1.004	0.952	0.985	1.054
Shandong Airlines	0.517	1.896	1.004	1.003	1.001	0.996	0.998	0.998	0.998	0.998
Sichuan Sirlines	0.525	1.847	1.002	1.000	1.001	0.997	0.999	0.999	1.000	0.999
Spring Airlines	0.363	2.220	0.994	0.998	0.996	0.998	0.998	0.998	0.998	0.998
Mean	*0.472*	*2.062*	*1.001*	*0.990*	*0.992*	*0.991*	*0.992*	*0.988*	*0.994*	*1.001*
Std	*0.116*	*0.424*	*0.009*	*0.030*	*0.020*	*0.025*	*0.019*	*0.022*	*0.010*	*0.017*
	PTEΔ-0607	**PTEΔ-0708**	**PTEΔ-0809**	**PTEΔ-0910**	**PTEΔ-1011**	**PTEΔ-1112**	**PTEΔ-1213**	**PTEΔ-1314**	**PTEΔ-1415**	**PTEΔ-1516**
Air China	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Chengdu Airlines	1.037	1.001	0.995	1.005	1.000	1.000	1.000	1.000	1.000	1.000
China Eastern Airlines	0.999	0.999	1.000	1.000	1.000	1.001	0.999	0.998	1.002	1.003
China Express	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
China Southern Airlines	1.006	1.003	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Hainan Airlines	1.000	0.999	0.999	1.000	1.000	0.997	1.005	1.003	0.995	1.005
Juneyao Air	0.999	0.993	0.997	1.001	1.003	0.996	0.997	1.007	0.993	1.008
Okay Airways	0.999	0.990	1.011	1.000	1.000	1.000	1.000	0.965	0.987	1.050
Shandong Airlines	0.996	1.000	1.000	1.001	1.003	0.995	0.999	1.000	1.000	1.002
Sichuan Sirlines	0.998	0.998	1.001	0.999	1.002	0.997	1.002	1.000	0.999	1.000
Spring Airlines	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean	*1.003*	*0.999*	*1.000*	*1.001*	*1.001*	*0.999*	*1.000*	*0.997*	*0.998*	*1.006*
Std	*0.011*	*0.003*	*0.004*	*0.002*	*0.001*	*0.002*	*0.002*	*0.011*	*0.004*	*0.014*
	TΔ-0607	**TΔ-0708**	**TΔ-0809**	**TΔ-0910**	**TΔ-1011**	**TΔ-1112**	**TΔ-1213**	**TΔ-1314**	**TΔ-1415**	**TΔ-1516**
Air China	0.596	1.640	0.999	0.998	0.998	0.999	1.003	0.994	0.998	0.999
Chengdu Airlines	0.366	2.504	0.986	0.988	0.988	1.006	0.983	0.934	0.964	0.984
China Eastern Airlines	0.603	1.621	0.999	0.998	0.998	0.999	1.003	0.994	0.998	0.999
China Express	0.332	2.816	1.004	0.896	0.932	0.913	0.982	0.991	0.997	0.989
China Southern Airlines	0.618	1.596	0.999	0.998	0.998	0.999	1.003	0.994	0.998	0.999
Hainan Airlines	0.562	1.828	0.999	0.998	0.998	0.999	1.003	0.994	0.998	0.999
Juneyao Air	0.363	2.181	0.996	0.998	0.994	0.998	1.003	0.991	0.998	0.997
Okay Airways	0.332	2.209	0.991	0.994	0.987	0.997	1.003	0.989	0.997	1.003
Shandong Airlines	0.512	1.890	0.999	0.998	0.998	0.999	1.003	0.994	0.998	0.999
Sichuan Sirlines	0.519	1.845	0.999	0.998	0.998	0.999	1.003	0.994	0.998	0.999
Spring Airlines	0.363	2.220	0.994	0.998	0.996	0.998	1.003	0.993	0.998	0.998
Mean	*0.469*	*2.032*	*0.997*	*0.988*	*0.989*	*0.991*	*0.999*	*0.988*	*0.995*	*0.997*
Std	*0.113*	*0.374*	*0.005*	*0.029*	*0.018*	*0.025*	*0.008*	*0.017*	*0.010*	*0.005*
	SEΔ-0607	**SEΔ-0708**	**SEΔ-0809**	**SEΔ-0910**	**SEΔ-1011**	**SEΔ-1112**	**SEΔ-1213**	**SEΔ-1314**	**SEΔ-1415**	**SEΔ-1516**
Air China	1.009	1.003	1.005	1.003	1.005	1.001	0.999	1.007	1.004	1.002
Chengdu Airlines	0.972	1.031	0.999	1.001	1.000	1.000	1.000	1.000	1.000	1.000
China Eastern Airlines	1.008	1.004	1.004	1.003	1.005	1.000	0.997	1.007	0.999	0.997
China Express	0.988	1.078	1.000	1.000	1.000	1.000	0.950	1.006	0.998	0.998
China Southern Airlines	1.007	1.003	1.002	1.001	1.003	0.999	0.995	1.001	0.999	0.999
Hainan Airlines	1.011	1.002	1.000	1.003	1.002	1.005	0.993	1.003	1.006	0.995
Juneyao Air	1.019	1.010	1.007	1.001	1.001	0.998	0.996	1.001	1.004	0.993
Okay Airways	0.978	1.006	1.017	1.000	1.000	0.999	1.001	0.999	1.001	1.000
Shandong Airlines	1.014	1.003	1.005	1.003	1.001	1.002	0.996	1.005	1.000	0.996
Sichuan Sirlines	1.012	1.003	1.002	1.002	1.001	1.001	0.994	1.005	1.002	0.999
Spring Airlines	1.000	1.000	1.000	1.000	1.000	1.000	0.995	1.005	1.000	1.000
Mean	*1.002*	*1.013*	*1.004*	*1.002*	*1.002*	*1.001*	*0.992*	*1.004*	*1.001*	*0.998*
Std	*0.015*	*0.022*	*0.005*	*0.001*	*0.002*	*0.002*	*0.014*	*0.003*	*0.002*	*0.002*

According to Grosskopf (2003) and Lovell (2003) the overall indexes presented both in equations (2) and (3) measure airlines' productivity levels over the two periods in the notion of average product.[3]

The estimators for the distance functions described previously for the periods t_1 and t_2 can be obtained via data envelopment analysis –DEA as:

[3] As explained by Zelenyuk and Zheka (2006), under the CRS assumption we obtain a better discriminative power compared to alternative specifications imposed on returns to scale.

Table 4
Results of the relative convergence club classification.

Phillips and Sul (2007) log *t*-test	MPI	PTEΔ	TΔ	SEΔ
log t	−3313	0.51	0.422	−4749
$t_{\hat{b}}$	−3107	0.406	0.323	−2970
Convergence	No	Yes	Yes	No

Convergence Club classification PTEΔ

	Phillips and Sul (2007)			Phillips and Sul (2009)		
Category	log t	$t_{\hat{b}}$	New club	Final classification	log t	$t_{\hat{b}}$
Full sample [11]	0.51	0.406				
Club 1 [4]	2354	1620	1 + 2	Club 1	0.835	1103
Club 2 [6]	1396	−1243				
Club 3 [1]	−0.843	−0.64	3	Club 2	−0.843	−0.64

Club 1: Chengdu Airlines; China Express; Okay Airways; Sichuan Airlines
Club 2: Air China; China Eastern Airlines; China Southern Airlines; Juneyao Air; Shandong Airlines; Spring Airlines
Club 3: Hainan Airlines

Convergence Club classification TΔ

	Phillips and Sul (2007)			Phillips and Sul (2009)		
Category	log t	$t_{\hat{b}}$	New club	Final classification	log t	$t_{\hat{b}}$
Full sample [11]	0.422	0.323				
Club 1 [9]	1724	0.762	1 + 2	Club 1	0.422	0.323
Club 2 [2]	−0.134	−0.099				

Club 1: Air China; Chengdu Airlines; China Eastern Airlines; China Express; China Southern Airlines; Juneyao Air; Okay Airways; Sichuan Airlines; Spring Airlines
Club 2: Hainan Airlines; Shandong Airlines

$$\hat{D}^{t_1}_{VRS,n}\left(x^{t_1}_i, y^{t_1}_i\right) = max\left\{\vartheta|\vartheta y^{t_1}_i \le \omega Y^{t_1}_i,\ x^{t_1}_i \ge \omega X^{t_1}_i,\ i\omega = 1,\ \omega \in \mathbb{R}^n_+\right\}, \tag{4}$$

$$\hat{D}^{t_2}_{VRS,n}\left(x^{t_2}_i, y^{t_2}_i\right) = max\left\{\vartheta|\vartheta y^{t_2}_i \le \omega Y^{t_2}_i,\ x^{t_2}_i \ge \omega X^{t_2}_i,\ i\omega = 1,\ \omega \in \mathbb{R}^n_+\right\}, \tag{5}$$

$$\hat{D}^{t_2}_{VRS,\,n}\left(x^{t_1}_i, y^{t_1}_i\right) = max\left\{\vartheta|\vartheta y^{t_1}_i \le \omega Y^{t_2}_i,\ x^{t_1}_i \ge \omega X^{t_2}_i,\ i\omega = 1,\ \omega \in \mathbb{R}^n_+\right\}, \tag{6}$$

$$\hat{D}^{t_1}_{VRS,n}\left(x^{t_2}_i, y^{t_2}_i\right) = max\left\{\vartheta|\vartheta y^{t_2}_i \le \omega Y^{t_1}_i,\ x^{t_2}_i \ge \omega X^{t_1}_i,\ i\omega = 1,\ \omega \in \mathbb{R}^n_+\right\}, \tag{7}$$

$$\hat{D}^{t_1}_{CRS,n}\left(x^{t_1}_i, y^{t_1}_i\right) = max\left\{\vartheta|\vartheta y^{t_1}_i \le \omega Y^{t_1}_i,\ x^{t_1}_i \ge \omega X^{t_1}_i,\ \omega \in \mathbb{R}^n_+\right\}, \tag{8}$$

$$\hat{D}^{t_2}_{CRS,n}\left(x^{t_2}_i, y^{t_2}_i\right) = max\left\{\vartheta|\vartheta y^{t_2}_i \le \omega Y^{t_2}_i,\ x^{t_2}_i \ge \omega X^{t_2}_i,\ \omega \in \mathbb{R}^n_+\right\}, \tag{9}$$

$$\hat{D}^{t_2}_{CRS,n}\left(x^{t_1}_i, y^{t_1}_i\right) = max\left\{\vartheta|\vartheta y^{t_1}_i \le \omega Y^{t_2}_i,\ x^{t_1}_i \ge \omega X^{t_2}_i,\ \omega \in \mathbb{R}^n_+\right\}, \tag{10}$$

$$\hat{D}^{t_1}_{CRS,n}\left(x^{t_2}_i, y^{t_2}_i\right) = max\left\{\vartheta|\vartheta y^{t_2}_i \le \omega Y^{t_1}_i,\ x^{t_2}_i \ge \omega X^{t_1}_i,\ \omega \in \mathbb{R}^n_+\right\}. \tag{11}$$

In equations (4)–(11), $Y^t = [y^t_i,...,y^t_n]$, $Y^{t_k} = [y^{t_k}_i,...,y^{t_k}_n]$, $X^t = [x^t_i,...,x^t_n]$, $X^{t_k} = [x^{t_k}_i,...,x^{t_k}_n]$, denote the vectors for the two periods of the observed outputs and inputs, whereas, i is a vector of ones and ω is a vector of intensity variables.

3.3. Productivity convergence

Phillips and Sul, 2007; Phillips and Sul, 2009 developed a log t test in order to capture the heterogeneity, in panel data framework. A panel data set which consists of the estimated productivity indexes and components[4] $Z_{i,t}$, can be expressed in the following form:

$$Z_{i,t} = \varphi_i \mu_t + \varepsilon_{it}. \tag{12}$$

The first component $\varphi\mu_t$ represents the distance between $Z_{i,t}$ having a common factor μ_t , the idiosyncratic element $\varphi_{i,t}$ (systematic term) and the ε_{it} representing the error term. The principal contribution in the Phillips and Sul, 2007; Phillips and Sul, 2009 convergence test is the reformulation of equation (12) to:

$$Z_{i,t} = \varphi_{i,t}\mu_t. \tag{13}$$

In addition they define the *relative transition parameter* $\lambda_{i,t}$ expressed in the following form:

$$\lambda_{i,t} = \frac{Z_{i,t}}{N^{-1}\sum_{i=1}^{N} Z_{i,t}} = \frac{\varphi_{i,t}}{N^{-1}\sum_{i=1}^{N}\varphi_{i,t}}. \tag{14}$$

The $\lambda_{i,t}$ comprehend the next properties: firstly the cross-sectional mean of $\lambda_{i,t} = 1$, secondly, $\lambda_{i,t}$ converges to 1 and the cross-sectional variance $(\varLambda_t)$ converges to 0 if $\varphi_{i,t}$ converges to φ. This in turn mean that $t \to \infty$, thus:

$$\varLambda_t = N^{-1}\sum_{i=1}^{N}(\lambda_{i,t} - 1)^2 \to 0. \tag{15}$$

Another vital characteristic of Phillips and Sul, 2007; Phillips and Sul, 2009 framework is the creation of cross-sectional ratio $\varLambda_1/\varLambda_t$ in order to construct the log t regression used to test the convergence:

$$log\left(\frac{\varLambda_1}{\varLambda_t}\right) - 2Log\ L(t) = \hat{c} + \hat{\gamma}logt + u_t$$
$$\text{for } t = [rT],\ [rT]+1,\ ...,T \quad \text{for some } r > 0. \tag{16}$$

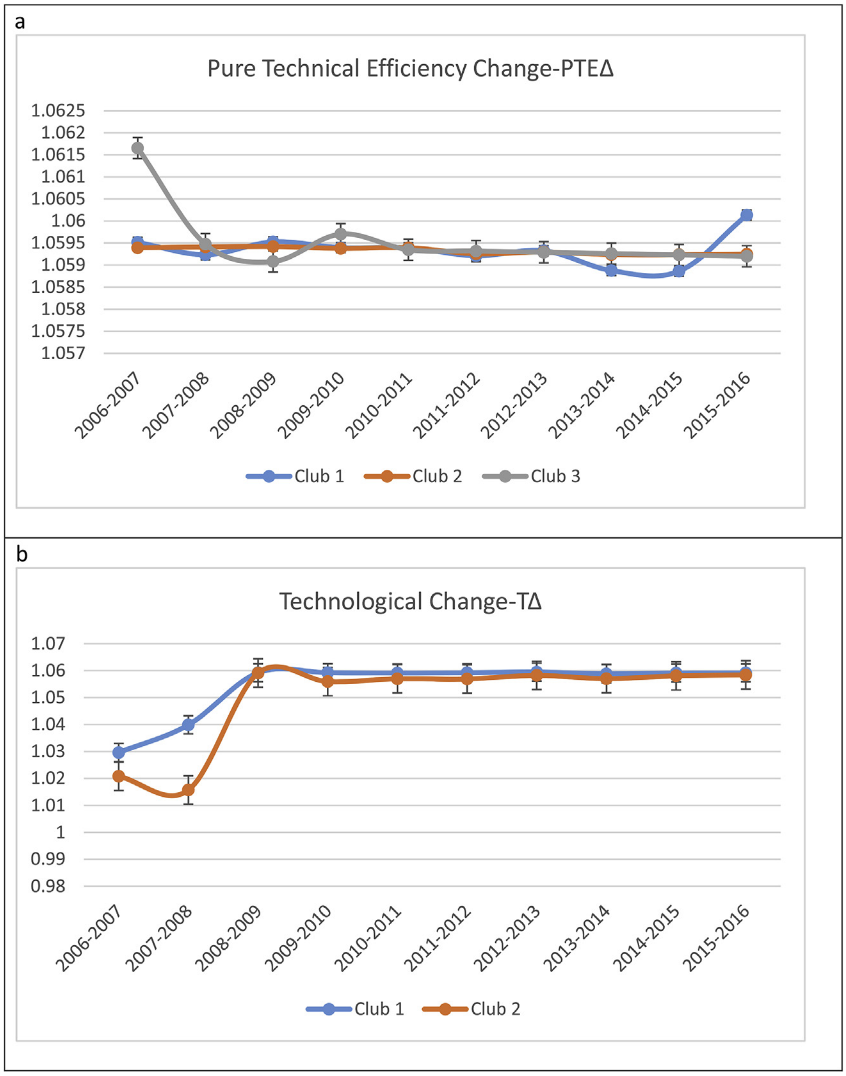

Fig. 2. Relative transition paths for the evaluated Clubs for PTEΔ And TΔ

In the expression (16) $L(t) = log(t + 1)$, with $logt = \hat{\gamma}$ and $\hat{\gamma} = 2\hat{a}$. Finally, $\hat{\alpha}$ is the estimate of a in H_0 hypothesis of convergence whereas, $r = 0.3$ which is adapted from Monte Carlo simulations. Considering the presumptions summarized by Phillips and Sul, 2007; Phillips and Sul, 2009, the null hypothesis of convergence is rejected at the 5% level if $t_{\hat{b}} < -1.65$.

Finally, apart for the Phillips and Sul, 2007 approach, we apply the Phillips and Sul, 2009 four-step procedure and in order to further cluster the estimated converge clubs obtained previously.[5]

4. Empirical results

The results from the analysis between 2006 and 2016 are presented on Fig. 1. More analytically, subFig. 1a presents our findings of the estimated Malmquist productivity index.[6] The results suggest that the higher productivity levels are reported among the Air China, China Eastern Airlines and China Express. In addition the airlines with the lowest productivity (values less than 0.9) are Hainan Airlines, Sichuan Airlines, Juneyao Air, Shandong Airlines, and Okay Airways. If we look the results of the estimated components of the obtained productivity indexes following the decomposition by Färe et al. (1994b), it is evident that airlines' productivity levels were mainly driven by their technological change levels (subFig. 1c) alongside with their ability to catch-up (subFig. 1b). In addition the result signify that the Chinese airline industry has been influenced from the restructuring changes which in turn are reflected on their scale efficiency adjustments (subFig. 1d). Our findings are also support the findings presented by Chow (2010) suggesting that those fluctuations are attributed to the restructuring of the Chinese airline market.

In contrast to Fig. 1, Table 3 presents the analytical results of the airlines' year-on-year Malmquist productivity indexes alongside with the estimated components. The results suggest that during the period 2006–2007 the industry's productivity levels was on average terms low

[4] The first studies using the Phillips and Sul (2007, 2009) approach on the estimated data envelopment analysis (DEA) eco-efficiency estimates are those conducted by Camarero et al. (2013, 2014).

[5] For estimation issues and programming codes see the study by Schnurbus et al. (2017).

[6] Note that an increase on productivity or in any other component is indicated by values > 1. However, values < 1 suggest a decrease, whereas, values = 1 signify neutrality.

(0.472), whereas, during the period 2015–2016 (last column) was reported just above unity. This finding signifies the productivity improvement of Chines airline industry over the examined period. However, it is evident that when we examine the rest of the periods we can observe some fluctuations on the estimated MPIs attributed to the reforms made on the Chines air market. In a similar manner, we observe the ability of the airlines to catch-up with the estimate technological frontier (i.e. when looking the PTEΔ index), remaining on average terms stable over the years with a PTEΔ value near unity. Moreover, if we compare the technological change levels of 2006–2007 in comparison with those of 2015–2016, we observe an increase on airlines' innovation capacity levels. The observed increase can be attributed to the undergoing peripheral competition (Wang et al., 2016) which in turn forces the airlines to engage on innovative processes in order to obtain or create their competitive advantage. Finally, the results from SEΔ signify that due to restructuring, the airlines have faced some operational scale adjustments. This is evident when comparing the periods: 2007–2008, 2008–2009 and 2010–2011 with the rest of the periods. In the first case the evidence suggest that all the airlines were having scale efficiency levels just above unity (or for some exceptions equal to unity) suggesting that were operating at optimal scale sizes. However, for the rest of the periods this is not the case. For instance for the periods: 2011–2012, 2012–2013, 2013–2014 and 2015–2016 at least half of the airlines do not operate at the optimal scale size (i.e. SEΔ < 1). This finding also verifies those studies providing evidence of an overall effect on Chinese airline market due to rapid restructuring (Chow, 2010).

Furthermore, we proceed our analysis by utilizing Phillips and Sul, 2007; Phillips and Sul, 2009 approach for identifying convergence patterns among airlines' estimated indexes over the examine periods. Table 4 presents the results from the analysis. It is evident that for the cases of Malmquist productivity index and scale efficiency change, we reject the null hypothesis of convergence since the estimated $t_{\hat{b}} < -1.65$. The values obtained for these measures are much smaller than the critical value of -1.65 and therefore we accept the alternative hypothesis of non-convergence. However, for the cases of pure efficiency change and technology change we obtain $t_{\hat{b}}$ values greater than -1.65 and therefore we accept the hypothesis of convergence for these two measures. The evidence suggest that the airlines do not convergence in terms of their MPI levels due to the non-convergence of their scale efficiency levels. These in turn signifies our previous findings suggesting that the restructuring of the Chinese airline market affected airlines' ability to operate on their optimal scale sizes. However, it is also evident that the ability of airlines to catch-up and innovative convergences over the examined period. Moreover, as indicated in Table 4 for the case of pure technical efficiency change we are able to identify three convergence Clubs. The first Club contains: Chengdu Airlines, China Express, Okay Airways and Sichuan Airlines. The second Club contains: Air China, China Eastern Airlines, China Southern Airlines, Juneyao Air, Shandong Airlines and Spring Airlines, whereas, the third Club consists only from Hainan Airlines. In addition when we employ Phillips and Sul, 2009 approach the three previously estimated Clubs, further merge into two different convergence Clubs signifying a further convergence of the airlines' PTEΔ levels over the year.

Similarly when we examine our findings for the case of TΔ we observe the existence of two convergence Clubs. The first Club consists of: Air China, Chengdu Airlines, China Eastern Airlines, China Express, China Southern Airlines, Juneyao Air, Okay Airways, Sichuan Airlines and Spring Airlines, whereas, the second Club contains Hainan Airlines and Shandong Airlines. Finally, when we further employ Phillips and Sul, 2009 approach both previously estimated clubs, merge to a unified one. Our findings confirm those by Wang et al. (2016) signifying that the restructuring made on Chinese airline market increased peripheral competition which in turn has forced the airlines to enhance their catching-up ability and their innovation capacity. As a result this is reflected upon the convergence patterns of the estimated PTEΔ and TΔ levels.

Furthermore, Fig. 2 illustrates the relative transition paths for the two productivity components and in relation to the previously identified convergence Clubs. Specifically, sub-Fig. 2a presents on average terms the relative transition paths of the three Clubs over the examined periods (in terms of their PTEΔ values). The results suggest that during the periods 2009–2010, 2010–2011, 2011–2012, 2012–2013 the three clubs indicate a behavior of transitional convergence, whereas, after these periods (i.e. for 2013–2014, 2014–2015 and 2015–2016) tent to show some transitional divergence (especially for the behavior of airlines forming Club 1). This transitional divergence appears also during 2006–2007, 2007–2008, 2008–2009, and 2009–2010. Similarly, sub-Fig. 2b presents relative transition paths for the case of airlines' technological change levels. Again it is evident some transitional divergence for the periods 2006–2007, 2007–2008 and 2008–2009. However, for the rest of the periods our findings suggest a behavior of transitional convergence among the two Clubs. The described phenomena are attributed to the deregulations implemented on China's airline industry and their reflection on the enhancement of local competition.

5. Concluding remarks

Our paper explores the productivity dynamics of the Chinese airline industry over the period 2006–2016. By applying the productivity measurement introduced by Färe et al., 1994a; Färe et al., 1994b we estimate airlines' productivity levels alongside with their main components (technological change, pure technical efficiency change and scale efficiency). The results suggest that airlines' productivity improvements are attributed on their ability to catch-up and enhance their innovation capacity levels. The high competitive conditions appeared after the restructuring of the Chinese airline market (Chow, 2010; Wang et al., 2016) are reflected on the estimated productivity fluctuations over the examined period. However, a limitation of our study is the fact that productivity measurement is one aspect of airlines' performance measurement. As has been asserted by Merkert and Pearson (2015) financial performance (i.e. profitability) can be a more important factor determining airlines' ability to operate within competitive environments. As a second stage analysis we utilize the methodological framework by Phillips and Sul, 2007; Phillips and Sul, 2009 in order to identify potential convergence patterns on the estimated productivity indexes. As explained previously the adopted framework is suited for our nonparametric analysis since it considers in relatives terms airlines' convergence paths, without imposing any strict assumptions on the data. To our knowledge this is the first study which utilizes Phillips and Sul, 2007; Phillips and Sul, 2009 framework on airlines' productivity indexes in order to identify potential convergence Clubs and reveal their relative transition convergence paths in relation to the estimated productivity components. The results signify that the convergence hypothesis is verified only for airlines' pure technical change and technological change levels. However, for their MPI and scale efficiency levels, our findings couldn't provide supportive evidence of convergence. Moreover, we identify two distinct convergence Clubs for airlines' technological change levels and three convergence Clubs for pure technical change levels. Our findings signify that the Chinese airline market is highly competitive, whereas, in few examined periods the relative transition path analysis provide evidence of some transitional divergence both for airlines' catching-up and technological change levels. This later evidence is a potential consequence of the large deregulation period imposed on the Chinese airline market.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jairtraman.2018.08.010.

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