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Airport subsidies and domestic inbound tourism in China

Clement Kong Wing Chow [a,*], Wai Hong Kan Tsui [b], Hanjun Wu [b]

[a] Lingnan University, Department of Marketing and International Business, Faculty of Business, Tuen Mun, New Territories, Hong Kong
[b] School of Aviation, Massey University, Palmerston North, New Zealand

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ABSTRACT

Since 2013, the Civil Aviation Administration of China (CAAC) has subsidized small and medium-sized airports. The key objective of this study is to empirically validate the benefits and impacts of airport subsidies in facilitating domestic tourism development. This study contributes to the aviation and tourism literature and offers important insights to policymakers regarding airport subsidies and tourism promotion. The empirical results show that increases in airport subsidies increased airport passenger throughput and indirectly brought more tourists to the cities where airports are located. In addition, the airport subsidy scheme has had a stronger effect in boosting domestic tourist arrivals in inland regions compared with coastal regions. This study empirically finds that the government's airport subsidy scheme for small and medium-sized airports has been effective in supporting aviation and tourism development in ethnic minority areas, poor or remote regions with inconvenient land transportation.

Introduction

In China, the CAAC is the primary government body that subsidizes the financially poorly performing airports. Although airports may also receive other subsidies from provincial or municipal governments, airport subsidies from provincial or city governments are not publicized. In March 2013, the Civil Aviation Administration of China (CAAC) announced that it would subsidize small and medium civil aviation airports by handing out 524.23 million yuan to 134 small- or medium-sized airports (Civil Aviation Administration of China, 2013). Since then, airport subsidy scheme has been carried out every year. The total amount of airport subsidies increased steadily (see Table 1). According to the CAAC report (2011), there are at least two major reasons for offering subsidies to small- or medium-sized airports. First, for the past 20 years, the Chinese government has been investing heavily in building new airports, especially in the more sparsely populated central and western regions or provinces (e.g. Inner Mongolia, Qinghai, and Xinjiang). These regions do not have enough population density to financially support and sustain airport operations. These airports, therefore, need subsidies to keep them afloat; importantly, such subsidies protect jobs at these airports. Second, airport activity can generate value-added in local economy (e.g. tourism, logistics, imports, and exports).

A well-developed and maintained airport may aid tourism growth, increase tourist arrivals and stimulate regional economic growth by creating jobs to the regions; in contrast, the closure of an airport can mean a serious blow to the local tourism sector's development and growth (Jian et al., 2017; Yao & Yang, 2008). Small- and medium-sized airports in China are important to facilitate people's travel and flows to remote areas. Improved airport infrastructure via airport subsidies may support and attract more airline services,[1] thus promoting the economic development of smaller Chinese cities and making them as more popular tourist

* Corresponding author.
E-mail addresses: ckwchow@ln.edu.hk, (C.K.W. Chow), w.h.k.tsui@massey.ac.nz, (W.H.K. Tsui), h.wu3@massey.ac.nz. (H. Wu).

[1] Similar to European small airports, China's small- and medium-sized airports often used airport subsidies as incentives to attract airline operations (Allroggen et al., 2013), such as discounts on airport fees (e.g. take-off and landing fees, parking and terminal fees), joint marketing activities, etc.

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Table 1
Tourism development and airport subsidies in China (2008–2017).

Year	Domestic tourist arrivals (million)	International inbound tourist arrivals (million)	Domestic tourist revenue (billion yuan)	International inbound tourist revenue (billion yuan)	Airport subsidies granted (million yuan)
2008	1712	130.03	874.93	279.15	–
2009	1902	126.48	1018.37	270.91	–
2010	2103	133.76	1257.98	303.42	–
2011	2641	135.42	1930.54	305.37	–
2012	2957	132.41	2270.62	314.66	–
2013	3262	129.08	2627.61	315.27	524.23
2014	3611	128.50	3031.19	348.25	1078.54
2015	4000	133.82	3419.51	737.76	1211.13
2016	4440	138.44	3939.00	833.98	1314.33
2017	5001	139.48	4566.08	803.44	1500.83

Remarks: Airport subsidy information was obtained from the CAAC website. Information on tourist arrivals and revenues is from the China Statistical Yearbooks.

destinations. Two remote county-level Chinese cities, Tengchong and Mohe, are examples of how functioning airports and air services are critical to the success of local tourism development (Civil Aviation Administration of China, 2011). Moreover, tourism development presumably brings benefits to regions (e.g. facilitating regional economies, adding jobs and businesses) (Li et al., 2016; Wen & Sinha, 2009), which has been expressly incorporated into the national-level development strategy in China (Jackson, 2006).

In tandem with the rapid economic growth of the Chinese economy over the past four decades, domestic tourism in China has increased rapidly (China National Tourism Administration, 2018). Compared with international inbound tourism, the contributions of domestic tourism are much more important to China's regional economies. Table 1 shows domestic and international tourist arrivals and tourist revenues for China. Domestic tourist arrivals were almost 36 times that of international tourist arrivals, and domestic tourist revenues were almost 5.6 times international tourist revenues in 2017. Domestic tourist arrivals and revenues grew at 12.65% and 20.16% from 2008 to 2017, respectively, whereas international tourist arrivals and revenues only increased by 0.78% and 12.46% during the same period. These figures show that domestic tourism makes a much more important contribution to regional economies than international inbound tourism in China.

This study contributes to the aviation and tourism literature by offering important insights regarding airport subsidies and tourism promotions. Conceptually, the importance of air transport to regional tourism development and local airports' critical roles has been studied extensively (e.g. Alderighi & Gaggero, 2019; Bieger & Wittmer, 2006; Papatheodorou, 2021). Also, governments in many countries invested substantial resources and developed various support programmes for rural and remote airports, aiming to facilitate regional economic growth (including tourism) (Donehue & Baker, 2012; Fageda et al., 2018). Besides, aviation subsidies play an important role in peripheral areas, particularly where substantial air transport development is required to improve tourism accessibility. Nevertheless, the links among airport subsidy programmes, air transport and tourism are still unclear. That is, little attention has been paid to airport subsidies' and air transport activity's overall effects on regional tourism (Wu, Liao, et al., 2020a). Thus, this study aims to advance our understanding of this less researched area regarding the effect of airport subsidies on domestic tourism development. We also believe that exploring the relationship between airport subsidies and domestic tourism is important for Chinese central and provincial governments to inform future government policies, such as the Five-Year Plans, the Western Development Strategy, and the Northeast Area Revitalisation Plan.

This paper is structured as follows. Literature review Section reviews prior literature on the relationship between airport subsidies and tourism and the factors that affect tourist flows. Data and methodology Section presents variables of interest, the methodology of two-stage least squares (2SLS) model and descriptive statistics of the variables. Empirical results Section presents the empirical results. Conclusion and discussion Section summarizes the key findings and highlights the key contributions of this study and directions for future research.

Literature review

Research on regional aviation subsidies has received considerable attention in recent decades, with the literature mostly focused on the US Essential Air Service and Europe's Public Service Obligation (Fageda et al., 2018). The route-based policy has been implemented to guarantee air services in remote regions or along thin routes where scheduled air transport services need subsidies to operate or cover losses (Wittman et al., 2016). China's small- and medium-sized airport subsidy policy is somewhat different from route-based subsidy policies in the US and Europe. Its general aim is to support capacity and safety improvements (i.e. construction of airport infrastructures) as well as future operations and maintenance of small and medium-sized airport subsidies (Wu & Qi, 2021). In China, local governments often show strong willingness to construct and upgrade their airports' capacity and facilities in attracting airline services or accommodating current and future flight operations (Zhang et al., 2017). Local governments also negotiated a variety of potentials such as strategic alliances between their airports and airlines. For example, China Express Airlines formed strategic partnerships with several local governments and airports (e.g. Quzhou city and Mangshi Airport).

With respect to tourism development, two important aspects of domestic tourism are reviewed in this section. First, we review the literature on the relationship between airport subsidies and tourism development; then, we review the literature on the determinants of domestic tourist arrivals.

Air transport, airport subsidies, and tourism development

The causal relationship between air transport and tourism development has been demonstrated in the tourism and air transport literature (Spasojevic et al., 2018). On the one hand, access to air travel facilitates tourism; on the other hand, increased tourism causes airlines to increase capacity (Bieger & Wittmer, 2006; Tsui et al., 2019). This is particularly true in countries with large land mass, strong domestic markets, isolated destinations, and distant and remote regions (Zhu et al., 2018). Extensive research has shown that air transportation infrastructure (i.e. airports) is an important component in regional air transport, tourism and economic development (e.g. Bieger & Wittmer, 2006; Castillo et al., 2017; Doerr et al., 2020). Doerr et al. (2020) analyzed data from Germany over the 2008–2016 period and concluded that new commercial airports promote tourism development in peripheral regions (e.g. increased tourist arrivals and tourism revenues). Moreover, Castillo et al. (2017) found that an encompassing infrastructure program (including a new airport) boosted job creation in the tourism sector in Argentina.

In the case of China, many inland destinations, particularly those in the western provinces, have experienced difficulty in maintaining connection with the rest of China and attracting visitors (Jackson, 2006). Hence, regional air services play a major role in increasing the accessibility of tourism destinations and promoting the development of tourist industries. Many studies have examined domestic tourism and air transport development in China (e.g. Su et al., 2019; Wu, Tsui, et al., 2020b; Zhang & Lu, 2013), but few have paid attention to the relationship between small and medium-sized airports and regional tourism development. Among the exceptions, Yang (2012) interviewed tourists who had been to Lugu Lake in Yunnan Province, China; most interviewees recommended the construction of a small airport because the lack of transportation and accessibility were major constraints on local tourism development. Jian et al. (2017) also pointed out the cost advantages of the construction of a regional airport in Yunnan, and confirmed the importance of a regional airport in improving the regional accessibility of towns for tourism. Chow et al. (2016) also noted that airport construction and development has had positive effects on the economic development of remote and inland regions in China, where tourism is an important driver of regional development.

As mentioned, small and medium-sized Chinese airports in sparsely populated areas often operate at a loss and, consequently, many are in need of government subsidies. Studies relating to China's regional air transport and tourism development have not provided a thorough analysis of the relationship between airport subsidies and domestic tourist arrivals. Therefore, the key objective of this study is to empirically validate the benefits and impacts of airport subsidies in facilitating domestic tourism development in China.

Determinants of domestic tourist arrivals

Given that tourism flows is a key indicator of regional tourism development, thus understanding the factors in determining domestic tourism growth is important. To date, many studies highlighted the factors affect tourist flows, such as income, relative tourism prices, transportation costs, and other economic or non-economic factors (e.g. Eugenio-Martin & Inchausti-Sintes, 2016; Lim, 1997; Seetaram et al., 2016). The decrease in transportation costs to/from destinations encourage domestic tourist flows (Alderighi & Gaggero, 2019; Gálvez et al., 2014). For air travel, the provision of low-cost carriers (LCCs) with reduced fares and point-to-point services generally created positive impacts on domestic tourism and air travel demand (e.g. Gálvez et al., 2014; Zhang & Lu, 2013). On the other hand, non-economic factors such as the attractiveness of the destinations, destination quality (e.g. public safety and population density), weather conditions, transportation networks, and urban development have been widely studied as other important factors affecting tourist flows (e.g. Koetse & Rietveld, 2009; Massidda & Etzo, 2012; Wen & Sinha, 2009).

Note that many previous studies are based on the chosen regions where predominantly in developed countries, few studies have investigated regions with small- or medium-sized airports as their samples of interest. As aforementioned, airport subsidies are often provided to support small- or medium-sized airports' operations, this study complements the literature with an empirical estimation of the relationship between China's airport subsidy and domestic inbound tourism. A detailed examination of the explanatory variables in this study is provided in Data and methodology Section.

Data and methodology

Data

To investigate the impact of China's airport subsidy scheme on its domestic tourism development, this study uses a sample of Chinese prefectural cities that have an airport in service. Large airports in China have an annual throughput of at least 10 million passengers, such as Beijing Capital Airport, Guangzhou Baiyun Airport, or others. In contrast, small- or medium-sized airports refer to airports with an annual throughput below 10 million passengers. Typically, Chinese cities with small- or medium-sized airports lack population and economic activity that would not be able to generate sufficient air travel demand, thus affecting airport revenues to fund operations (Wu & Qi, 2021). In general, small- or medium-sized airports less likely achieve economic feasibility, not only because of their low traffic throughput, which result in higher fixed costs but also their limited income resources (e.g. nonaeronautical revenue) (Fageda et al., 2018). Consequently, Chinese small- or medium-sized airports are inherently unable to operate commercially without subsidization. Note that CAAC's airport subsidies are mainly provided to small- and medium-sized airports with an annual throughput of fewer than 2 million passengers; thus, for the sake of meaningful comparison, this study excludes large airports and retain all small- or medium-sized airports/cities that have received subsidies during our sampled period.[2] This study uses an unbalanced panel dataset of tourist arrivals and airport passengers of 165 Chinese prefectural cities or subsidized airports in 27 autonomous cities or provinces from 2013 to 2017, as China's airport subsidy scheme was implemented in 2013.[3]

A total of 753 observations of 165 prefectural cities/airports which received subsidies from 2013 to 2017. Among these, 41 (24.8%) are located in eastern coastal provinces and the rest (124 prefectural cities/airports) are located in central and western regions. To obtain robust estimation results, the dataset is expanded to include 22 small- and medium-sized airports which have not received subsidies during the sampled period. The dataset is expanded to 812 observation with 187 prefectural cities/airports. In addition, we also further expanded the original dataset of 753 observations to include the 2008–2012 pre-subsidy period (the five years preceding the implementation of airport subsidy scheme). This enlarged dataset includes 166 prefectural cities/airports and has 1372 observations.[4] The details of data sources are reported in Table 2.

Methodology and definition of variables

This study aims to analyze the impact of airport subsidies on China's domestic tourism development (tourist arrivals) at city i in year t, $TOUR_{it}$, and the factors that explain its variations. Note that $TOUR_{it}$ includes tourist arrivals via air, rail, high-speed rail (HSR), or coach. Airport passenger throughput, APM_{it}, of an airport at city i in year t is a key variable of interest to explain its tourist arrivals because tourist visiting city i may choose air transport.[5] Additionally, air transport is always an important transport mode to and from remote and landlocked Chinese cities and/or provinces, such as Inner Mongolia, Qinghai, Tibet, and Xinjiang (Chow et al., 2016). In other words, inbound tourism of the sampled cities is likely to be more dependent on air transport. Considering the endogeneity problem between $TOUR_{it}$ and APM_{it} (i.e. APM_{it} is considered to be an endogenous variable), this study follows prior studies (Percoco, 2010; Tsui et al., 2017) in using a 2SLS model for estimating airport subsidies on China's domestic tourism, $TOUR_{it}$, and its key detriments. Table 2 presents the definitions of the variables used in the 2SLS model.

Given our target of studying domestic tourist arrivals to the sampled cities, we have a simultaneous equation model composing of two equations: Eq. (1) of domestic tourist arrivals, $TOUR_{it}$, and Eq. (2) of airport passenger throughput, APM_{it}, as below:

$$\ln(TOUR_{it}) = \gamma_1 \ln(APM_{it}) + \alpha x_{it} + u_{1it} \tag{1}$$

$$\ln(APM_{it}) = \gamma_2 \ln(TOUR_{it}) + \beta z_{it} + u_{2it} \tag{2}$$

where α is a vector of parameters, and $x_{it} = (GDPPC_{it}, POP_{it}, NGDPPC_{t-1}, RCPI_{it}, PEDU_{it}, HSR_{it}, UNESCO_{it}, COAST_i, HUM_{it}, RAIN_{it}$, and $TEMP_{it})$ is a vector of exogenous or pre-determined explanatory variables for Eq. (1).[6] β is a vector of parameters, and $z_{it} = (ASUB_{it}, GDPPC_{it-1}, POP_{it-1}, NGDPPC_{t-1}, RCPI_{it}, PEDU_{it}, HSR_{it}, DCITYC_{it}, COAST_i, HUM_{it}, RAIN_{it}, TEMP_{it}, UNESCO_{it}$, and $JFUELP_t)$[7] is a vector of exogenous or pre-determined explanatory variables for Eq. (2). u_{1it} and u_{2it} denotes the error terms.

First-stage estimation

To conduct the 2SLS estimation. We can put Eq. (1) into Eq. (2) and develop the reduced form equation of APM_{it}, and it is also the first-stage estimation in 2SLS estimation in Eq. (3):

$$\ln(APM_{it}) = \pi_1 x_{it} + \pi_2 z_{it} + \varepsilon_{it} \tag{3}$$

[2] Appendix shows the details of the sampled airports. Two types of unsubsidized airports: (i) small-sized and new airports and (ii) larger and profitable medium-sized airports. The small or new airports must have 2–3 year operation before being qualified for the CAAC's subsidies and, therefore, they do not receive subsidy during initial 2 or 3-year operations. Financially sustainable larger and profitable medium-sized airports are also not subsidized. This study includes those new airports which received subsidies, therefore their presence makes the dataset becomes unbalanced. Note that some airports received subsidies in 2013 or 2014 only. However, this study still includes these airports for the full study period (2013–2017) as they continued operation although they did not receive airport subsidies.

[3] Given the number of airports in the study period and data availability, the financial performance data of the sampled airports are not publicly available.

[4] This expanded dataset includes new airports that started operations after 2008, and a small-sized airport in Shaanxi Province, Ankang Wulipu Airport operated from 2008 to 2010. Therefore, 166 airports are included in the dataset.

[5] Airline seat capacity affects tourist arrivals. However, tourist arrivals are more associated with air passengers flying to an airport/city compared with airline seat capacity. When the airport passenger data are not available, we may use airline scheduled seat capacity to proxy for it as these two variables are closely correlated.

[6] Airfare is one of the major travel costs travelling between destinations. The airfare data are always available on route-based between two airports. However, this study only includes the airport-level information but not the route-based information and, therefore, airfare could not be included for analysis. To capture travel costs travelling between two destinations, jet fuel price is considered as a proxy for airfare. Furthermore, jet fuel price in China is set by a formula which reacts to international jet fuel price with a time lag. Also, the Chinese government controls jet fuel because it is mainly distributed by the state-owned China Aviation Oil Holding Co.

[7] Jet fuel price is considered as an exogenous variable (Sibdari et al., 2018; Wadud, 2015).

Table 2
Definitions and descriptive statistics of variables.

Variable	Definition	(2013–2017)				(2008–2017)		Data sources
		Subsidized airports		All airports		Subsidized airports		
		Mean	SD	Mean	SD	Mean	SD	
$TOUR_{it}$	Logarithm of domestic tourist arrivals at city *i* in year *t*	16.6151	1.0511	16.6042	1.0759	16.2407	1.1243	China Regional Economy Statistical Yearbooks; Provincial Statistical Yearbooks
APM_{it}	Logarithm of airport passenger throughput of an airport at city *i* in year *t*	12.5609	1.4119	12.6268	1.5345	12.1800	1.5972	CAAC
$ASUB_{it}$	Logarithm of airport subsidy deflated by provincial CPI received by airport at city *i* in year *t*	14.2057	4.7447	13.1735	5.8727	7.7966	7.8964	CAAC
POP_{it}	Logarithm of population of city *i* in year *t*	14.7239	0.9578	14.7002	0.9602	14.7481	0.9239	China City Statistical Yearbooks; Provincial Statistical Yearbooks
POP_{it-1}	Logarithm of population of city *i* in year *t*-1	14.7341	1.0110	14.7092	1.0100	14.7473	0.9556	China City Statistical Yearbooks; Provincial Statistical Yearbooks
$GDPPC_{it}$	Logarithm of GDP per capita deflated by provincial CPI at city *i* in year *t*	10.2304	0.5927	10.2494	0.6068	10.0520	0.6673	China City Statistical Yearbooks; Provincial Statistical Yearbooks
$GDPPC_{it-1}$	Logarithm of GDP per capita deflated by provincial CPI at city *i* in year *t*-1	10.1699	0.6090	10.1868	0.6210	9.9484	0.6974	China City Statistical Yearbooks; Provincial Statistical Yearbooks
$NGDPPC_{t-1}$	Logarithm of national GDP per capita deflated by national CPI in year t-1	10.6389	0.0757	10.6399	0.0763	10.4567	0.2334	China Statistical Yearbooks
$RCPI_{it}$	Ratio of provincial CPI to national CPI at city i in year t	1.2842	0.0590	1.2847	0.0615	1.2816	0.0590	China Statistical Yearbooks
$PEDU_{it}$	Proportion of provincial population with a high school education or above	0.2771	0.0509	0.2757	0.0534	0.2528	0.0583	China Statistical Yearbooks
HSR_{it}	High-speed rail station at city *i* in year *t* = 1; otherwise = 0.	0.1448	0.3521	0.1429	0.3501	0.1137	0.3176	Authors' calculation
$UNESCO_{it}$	Number of UNESCO world heritage sites at city *i* in year *t*	0.3373	0.5723	0.3448	0.5785	0.2748	0.5205	UNESCO
$COAST_i$	City *i* is in a coastal eastern province = 1; otherwise = 0	0.2510	0.4339	0.2574	0.4375	0.2558	0.4365	Authors' calculation
$DCITYC_i$	Logarithm of the distance between airport and city center at city *i*	2.5913	0.8546	2.6277	0.8535	2.5191	0.8643	CAAC; google map
HUM_{it}	Average humidity at city *i* in year *t* (%)	0.6600	0.1155	0.6553	0.1194	0.6530	0.1112	China Statistical Yearbooks
$RAIN_{it}$	Logarithm of average rainfall at city *i* in year *t* (mm)	6.6170	0.6502	6.6182	0.6561	6.5830	0.6403	China Statistical Yearbooks
$TEMP_{it}$	Logarithm of average temperature at city *i* in year *t* (°C)	2.4961	0.4418	2.4953	0.4416	2.4933	0.4393	China Statistical Yearbooks
$JFUELP_t$	Logarithm of Singapore jet fuel price in year *t*	4.2726	0.3345	4.2779	0.3326	4.4081	0.3478	Datastream
Airport number		165		187		166		
Observations		753		812		1372		

Remarks: The dataset of 2008–2017 includes new airports that started operation after 2008, and also includes a small-sized airport in Shaanxi Province, Ankang Wulipu Airport, which only operated from 2008 to 2010. Therefore, 166 airports are included in the dataset.

where $\pi_1 = \alpha\gamma_2/(1\text{-}\gamma_1\gamma_2)$, $\pi_2 = \beta/(1\text{-}\gamma_1\gamma_2)$, and $\varepsilon_{it} = (\gamma_2 u_{1it} + u_{2it})/(1\text{-}\gamma_1\gamma_2)$. ε_{it} denotes the error term. We further expand the specification of Eq. (3) of airport passenger throughput of an airport/city into Eq. (4) as follows:[8]

$$\begin{aligned} \ln(APM_{it}) = {} & \lambda_i + \pi_1 \ln(ASUB_{it}) + \pi_2 \ln(GDPPC_{it-1}) + \pi_3 \ln(POP_{it-1}) \\ & + \pi_4 \ln(NGDPPC_{t-1}) + \pi_5 RCPI_{it} + \pi_6 PEDU_{it} \\ & + \pi_7 HSR_{it} + \pi_8 \ln(DCITYC_{it}) + \pi_9 COAST_i \\ & + \pi_{10} HUM_{it} + \pi_{11} \ln(RAIN_{it}) + \pi_{12} \ln(TEMP_{it}) \\ & + \pi_{13} \ln(JFUELP_t) + \pi_{14} UNESCO_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

where λ_i denotes the fixed effects of airport/city *i*. *t* denotes the year. π_s is the coefficients to be estimated. ln denotes the natural logarithmic form. ε_{it} denotes the error term. $ASUB_{it}$ denotes airport subsidy (deflated by provincial CPI) received by an airport located at prefectural city *i*.[9] We expect airport subsidy scheme to have a positive effect on an airport's passenger throughput and tourism activity. Therefore, Hypothesis (H_1) is as follows:

[8] In principle, China's airport subsidy scheme is not used to reduce airfares. However, if small- or medium-sized airports receive subsidies, they may possibly provide financial incentives to domestic airlines, such as reducing or waiving landing/take-off fees, parking fees, gate fees, etc. These may attract them to offer flight services and increase passenger/tourist flows. Often, airports stop offering financial incentives to airlines if passenger numbers increase.

[9] This study does not test variables of interest for panel unit roots because the length of time series, T, is only five years, whereas the panel number, N, is 165 prefectural cities/airports. According to Baltagi (2005), panel unit roots are expected to be presented in panel data with large T, such as macroeconomic panel data of GDP, GDP growth rate, and exchange rates. In addition, the power of panel unit root tests is also positively related to the size of T, and they require T to be larger so that their test power will be relatively high (Baltagi, 2005; Breitung & Pesaran, 2008).

Hypothesis H_1. Airport subsidy scheme has a positive effect on passenger throughput of a city's airport, holding other factors constant.

The real GDP per capita of prefectural city *i* in year *t*, $GDPPC_{it}$, is considered to be a major factor that drives airport passenger throughput. However, airport traffic throughput (including airport passenger throughput, APM_{it}) contributes to GDP of a prefectural city where it is located and, therefore, $GDPPC_{it}$ is endogenous. Given the contemporaneous endogeneity between airport passenger throughput, APM_{it}, and $GDPPC_{it}$ (Brueckner, 2003; Percoco, 2010), so the real GDP per capita of prefectural city *i* in the previous year, $GDPPC_{it-1}$, is included in Eq. (1) to solve the endogeneity problem. The prefecture-level city population, POP_{it}, is another important variable that may affect an airport's passenger throughput. A sizable proportion of airport passenger throughput may include air travel from local residents, and their residence (or mobility) may also affect the size of the city's population. Similarly, given the contemporaneous endogeneity between APM_{it} and POP_{it} (Brueckner, 2003; Percoco, 2010), the city population of the previous year, POP_{it-1}, is included in Eq. (4) to solve the endogeneity problem. $NGDPPC_{t-1}$ is national real GDP per capita obtained by national nominal GDP per capita deflated by national CPI. As there is no information of the origins of domestic tourists arrived at the sampled cities/airports, we simply use national real GDP per capita to proxy the overall income of domestic inbound tourists. Furthermore, the cost of living of destination city affect tourists' decision to visit. In order to capture the cost of living of destination city relative to the overall national average cost of living, we use the provincial CPI to national CPI ratio, $RCPI_{it}$, to capture this effect. In addition, the infrastructural and weather-related factors are incorporated in Eq. (4).

Infrastructural factors

Three infrastructural factors are included as explanatory variables in Eq. (4). The distance of an airport from its city center (in kilometers), $DCITYC_{it}$, is an explanatory variable of APM_{it}. If an airport is located farther away from the city center, it is likely to attract fewer passengers (Wang et al., 2016). As a result, a negative relationship between APM_{it} and $DCITYC_{it}$ is expected. HSR_{it} is a dummy variable that takes a value of one if there is a high-speed rail (HSR) station at city *i*, and otherwise 0. Despite the literature emphasizing the competition between air transport and HSR services, the HSR's impact on air transport services may vary in the sparsely populated and developing regions (e.g. China's central and western cities) (Wang et al., 2017; Zhang et al., 2019). Indeed, the introduction of HSR services in general leads to a reduction in air travel demand. Considering the sampled subsidized airports are generally in the sparsely populated areas in China, HSR services may not have a stronger competitive position than they have on inter-city transportation among highly populated and developed regions. Besides, the HSR networks require significant investment, and they are less suitable for long-distance travel and less viable for low-density areas than airline networks (Wang et al., 2017; Yang et al., 2018). However, with underutilized airport capacities in China's sparsely populated areas, there is still room for cooperation between airlines and HSR through feeding passengers from HSR spokes to regional hub airports. $COAST_i$ is a dummy variable that takes a value of one if city *i* is located in the eastern coastal province, and otherwise 0. Chinese cities in the eastern coastal regions are in general well-connected and more advanced in terms of economic, social, technological and infrastructural development; thus these cities often attract more holidaymakers and tourists than inland cities or provinces (Jackson, 2006; Wen & Sinha, 2009).

Weather-related variables

Weather condition is a factor affecting airport services and output (Green, 2007). Bad weather (e.g. heavy snow or heavy rain) often causes flight delays or cancellations and disrupt airport operations. Airline service failure is also more likely to occur in bad weather (Koetse & Rietveld, 2009). Therefore, three common weather-related variables are included in Eq. (4): relative humidity (in %), HUM_{it}, rainfall (in mm), $RAIN_{it}$, and temperature (in ^{0}C), $TEMP_{it}$.[10]

Humidity increases the possibility of foggy weather, and they are thus correlated (Chow, 2015). Similarly, an increase in rainfall means a higher possibility of thunderstorms or flooding (Chow, 2015). In addition, low temperature may bring more snowstorms or blizzards. These weather-related variables are associated with interruptions to airport activity and flight operations. Therefore, it is expected that airport activity and flight operations will be negatively affected by increases in HUM_{it} and $RAIN_{it}$, but positively related to increases in $TEMP_{it}$. The China Statistical Yearbooks report the monthly meteorological data for each provincial capital, and the average monthly weather variables are converted to annual figures for analysis in this study.[11] Not that the inclusion of weather-related variables in both Eqs. (1) and (2) because China is such an enormous country that its climate varies substantially from north to south and from east to west. As a result, the three weather-related variables are to capture the effects of climatic differences on domestic tourist arrivals across the sampled cities.

Additional tourism-related variables

Apart from the above explanatory variables, two further variables, $PEDU_{it}$ and $UNESCO_{it}$, are included in the analysis. $PEDU_{it}$ is the proportion of the provincial population with a high school education or above. As the prefectural city-level information of this variable is not available, provincial information is used to proxy it. Previous research acknowledged the critical role of local residents play in tourism development, as the host community participation is an integral part of a tourism destination and image (Xu et al., 2015). There is some evidence that insufficient levels of formalized education in a host community may produce a lack of knowledge about tourism,

[10] Weather-related data are only available for some Chinese cities or provinces. Therefore, three available weather-related variables (HUM_{it}, $RAIN_{it}$, and $TEMP_{it}$) are used for all of the sampled cities in this study.

[11] China has a large land mass and its climate patterns varies substantially, and that affect airport activity, flight operations and tourist flows.

which may result in limited access to tourism benefits and less interaction between tourists and local residents involved (Saufi et al., 2014; Teye et al., 2002). Hence, we considered this variable in dealing with its impacts on tourism development. $UNESCO_{it}$ shows the number of UNESCO world heritage sites located at city i in year t. When a city has a UNESCO world heritage site, it attracts more tourists (Yang et al., 2010). The $UNESCO_{it}$ also serves as a proxy for a tourist town as well as a city that are likely to attract a lot more tourists visiting it. Finally, we also included the Singapore jet fuel price, $JFUELP_t$, because jet fuel is a major operating cost of airline operations. Changes in jet fuel price will result in different airfares for passengers.

Second-stage estimation

The predicted dependent variable, $\ln(FAPM_{it})$, estimated from the reduced-form first-stage FE Eq. (4) above is put into Eq. (1) for conducting the second-stage FE estimation for $TOUR_{it}$ in Eq. (1):[12]

$$\begin{aligned}\ln(TOUR_{it}) = {} & \eta_i + \gamma_1 \ln(FAPM_{it}) + \alpha_1 \ln(GDPPC_{it}) + \alpha_2 \ln(POP_{it}) + \alpha_3 PEDU_{it} \\ & + \alpha_4 HSR_{it} + \alpha_5 COAST_i + \alpha_6 UNESCO_{it} + \alpha_7 HUM_{it} + \alpha_8 \ln(RAIN_{it}) \\ & + \alpha_9 \ln(TEMP_{it}) + \alpha_{10} \ln(NGDPPC_{it-1}) + \alpha_{11} RCPI_{it} + u_{it}\end{aligned} \tag{1a}$$

where η_i is the fixed effect of city i. t denotes the year. α_s is the coefficients to be estimated. ln denotes the natural logarithmic form. u_{1it} denotes the error term. $FAPM_{it}$ is the fitted (predicted value) airport passenger throughput of an airport located at city i in year t, as obtained from the first-stage FE estimation. $FAPM_{it}$ is expected to have a positive effect on domestic tourist arrivals because of its close relationship with tourist arrivals by air (Bieger & Wittmer, 2006; Seetanah et al., 2019). Therefore, Hypothesis (H_2) is stated as follows:

Hypothesis H_2. Passenger throughput of an airport has a positive effect on domestic tourist arrivals to the city, holding other factors constant.

If both Hypotheses H_1 and H_2 are accepted, meaning that airport subsidies have a significant positive effect on an airport's passenger throughput, and also a significant positive effect on domestic tourist arrivals to the city where the airport is located. In other words, China's airport subsidy scheme indirectly has a positive effect on domestic tourist arrivals. The econometric package of NLOGIT 3.0 is used to estimate Eqs. (1) and (4).

Descriptive statistics of variables

The descriptive statistics of the variables of interest are shown in Table 2. Three datasets are used for analysis in this study: (i) the data of subsidized airports; (ii) the data of small- and medium-sized airports for the 5-year 2013–2017 period; and (iii) the data of subsidized airport for the 10-year 2008–2017 period. The 5-year 2013–2017 period matches the introduction of the CAAC's airport subsidy scheme for small- and medium-sized airports. Furthermore, this study examines the pre- and post-airport subsidy scheme effects on airport passenger throughput and domestic tourist arrivals. Therefore, a pre-subsidy period (the 5-year 2008–2012 period) is embedded in the 10-year 2008–2017 period.

The average values of variables of interest in the subsidized airport sample are in general similar to their counterparts in the small- and medium-sized airport sample. The average values of variables of interest in the subsidized airport sample are larger than their counterparts in the sample of the 2008–2017 period, including $TOUR_{it}$, APM_{it}, $ASUB_{it}$, $GDPPC_{it}$, $GDPPC_{it-1}$, $PEDU_{it}$, HSR_{it}, $UNESCO_{it}$, $DCITYC_{it}$, HUM_{it}, and $RAIN_{it}$. Among the 753 observations of $ASUB_{it}$, 10.08% are zero, as some medium-sized airports did not receive CAAC's subsidies during the 2013–2017 period. The average value of $ASUB_{it}$ was smaller in the all airport sample because 22 airports did not receive airport subsidies. Given a steady economic growth in China's regional economies, it is not surprising to observe that the average values of the regional socioeconomic variables (i.e. $TOUR_{it}$, APM_{it}, $GDPPC_{it}$, and $PEDU_{it}$) are similar for the two samples. Specifically, the average values of POP_{it}, POP_{it-1}, and $JFUELP_t$ for the 2013–2017 period are smaller than those for the 2008–2017 period. This indicates that the population of the sampled Chinese prefectural cities declined during the 2013–2017 period, and jet fuel price also declined during the same period.

Empirical results

Table 3 (left hand box) reports the 2SLS estimation results of Eqs. (1a) and (4) for subsidized airports during the 2013–2017 period.

For both first- and second-stage estimations, the Hausman test results indicate the acceptance of the FE model and rejection of the RE model. A significant positive coefficient of $NGDPPC_{it-1}$ is reported, and this finding indicates that higher income will have a significant impact on the sampled Chinese prefectural cities' inbound domestic tourists. However, the real GDP per capita, $GDPPC_{it-1}$, and population of destination cities, POP_{it-1}, have no significant effect on inbound airport passengers. Importantly, the key variable of interest of this study, $ASUB_{it}$, is found to be positive and statistically significant and, therefore, Hypothesis H1 is accepted. A 1% increase in airport subsidy increased passenger throughput of the sampled cities' airports by 0.0312%. This finding suggests that airport subsidy scheme in China supported the operation of unprofitable small- and medium-sized airports, which is in line with research on airport subsidies conducted in Australia and the US (Donehue & Baker, 2012; Wittman et al., 2016). Among the weather-related variables, only $TEMP_{it}$ has a positive and

[12] The Hausman test was estimated to determine the acceptance of the FE model for Eqs. (4) and (1a).

Table 3
2SLS estimation results of airport passenger movement (APM) and domestic tourist arrivals (TOUR) of subsidized/all airports (2013–2017).

Original dataset (subsidized airports)

Dependent variable	1st stage: APM_{it}		Dependent variable	2nd stage: $TOUR_{it}$			
Explanatory variables	FE model		Explanatory variable	FE model		RE model	
	Coeff.	*t*-value		Coeff.	*t*-value	Coeff.	*t*-value
Constant	–	–	*Constant*	–	–	-18.8805^{***}	−11.076
$GDPPC_{it-1}$	0.2973	1.543	$FAPM_{it}$	0.1870^{***}	3.271	0.0670^{**}	2.244
POP_{it-1}	−0.0213	−0.322	$GDPPC_{it}$	0.2973^{***}	4.117	0.2569^{***}	4.584
$DCITYC_{it}$	−0.2028	−0.778	POP_{it}	0.0538	1.552	0.1871^{***}	6.219
HSR_{it}	0.0642	0.339	$PEDU_{it}$	0.5478	1.337	0.9143^{**}	2.418
$ASUB_{it}$	0.0312^{***}	5.238	HSR_{it}	0.0813	1.174	0.1503^{**}	2.406
$COAST_{i}$	–	–	$UNESCO_{it}$	0.0275	0.509	0.1095^{**}	2.430
HUM_{it}	0.9049	0.949	$COAST_{i}$	–	–	0.1904	1.536
$RAIN_{it}$	0.0144	0.139	HUM_{it}	−0.2363	−0.700	1.1412^{***}	4.197
$TEMP_{it}$	1.0579^{**}	2.092	$RAIN_{it}$	−0.0160	−0.423	−0.0100	−0.273
$JFUELP_{t}$	0.1864^{***}	2.836	$TEMP_{it}$	-0.3314^{*}	−1.773	0.6776^{***}	6.591
$PEDU_{it}$	0.5661	0.505	$NGDPPC_{t-1}$	2.3999^{***}	9.554	2.5386^{***}	15.663
$NGDPPC_{t-1}$	3.4768^{***}	8.535	$RCPI_{it}$	−0.3145	−0.749	−0.3593	−0.959
$RCPI_{it}$	2.0778^{*}	1.942					
$UNESCO_{it}$	−0.1200	−0.807					
***Adj-R*²**	0.8735		***Adj-R*²**	0.9693		0.5633	
***F*-statistic**	30.16^{***}		***F*-statistics**	136.02^{***}		81.82^{***}	
Hausman test	31.52^{***}		**Hausman test**	122.83^{***}			
Obs.	753		**Obs.**	753		753	

Robustness check: expanded dataset (all airports)

Dependent variable	1st stage: APM_{it}		Dependent variable	2nd stage: $TOUR_{it}$			
Explanatory variables	FE model		Explanatory variable	FE model		RE model	
	Coeff.	*t*-value		Coeff.	*t*-value	Coeff.	*t*-value
Constant	–	–	*Constant*	–	–	-17.8690^{***}	−11.211
$GDPPC_{it-1}$	0.2819	1.446	$FAPM_{it}$	0.1900^{***}	3.382	0.0922^{***}	3.463
POP_{it-1}	−0.0221	−0.327	$GDPPC_{it}$	0.2621^{***}	4.030	0.2539^{***}	4.852
$DCITYC_{it}$	−0.1982	−0.742	POP_{it}	0.0559	1.617	0.2138^{***}	7.272
HSR_{it}	0.0699	0.361	$PEDU_{it}$	0.4676	1.237	1.0063^{***}	2.882
$ASUB_{it}$	0.0309^{***}	5.064	HSR_{it}	0.0916	1.327	0.1405^{**}	2.274
$COAST_{i}$	–	–	$UNESCO_{it}$	0.0192	0.367	0.1078^{**}	2.480
HUM_{it}	0.8085	0.839	$COAST_{i}$	–	–	0.1924	1.588
$RAIN_{it}$	−0.0232	−0.223	HUM_{it}	−0.2529	−0.760	1.2602^{***}	4.805
$TEMP_{it}$	1.0610^{**}	2.077	$RAIN_{it}$	−0.0179	−0.483	−0.0302	−0.846
$JFUELP_{t}$	0.1987^{***}	3.048	$TEMP_{it}$	-0.3835^{**}	−2.114	0.6766^{***}	6.825
$PEDU_{it}$	0.4291	0.403	$NGDPPC_{t-1}$	2.3765^{***}	9.591	2.3693^{***}	15.813
$NGDPPC_{t-1}$	3.5467^{***}	8.738	$RCPI_{it}$	−0.2582	−0.713	−0.2681	−0.832
$RCPI_{it}$	2.1337^{**}	2.285					
$UNESCO_{it}$	−0.1142	−0.773					
***Adj-R*²**	0.8871		***Adj-R*²**	0.9708		0.5754	
***F*-statistic**	32.86^{***}		***F*-statistics**	137.28^{***}		110.92^{***}	
Hausman test	45.65^{***}		**Hausman test**	142.69^{***}			
Obs.	812		**Obs.**	812		812	

Remarks: FAPMit is the fitted value of APM_{it} obtained from the 1st stage FE model. A Hausman test is used to choose the FE vs. RE models for estimation. Hausman test statistics are calculated by excluding $COAST_i$, which has no within group variation, in the 1st and 2nd stage estimations. A high Hausman test value indicates rejection of the RE model and acceptance of the FE model. *F*-statistics are used to test the zero restrictions of all of the explanatory variables (including FE estimates). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

statistically significant coefficient, which suggests that warmer cities in China attracted more passengers. In addition, both $JFUELP_t$ and $RCPI_{it}$ are found to have significant positive impacts on airport passenger throughput.

In the second-stage estimation, the RE model's results are also reported in Table 3, which helps checking the consistency of estimation results of the FE model and tests the effect of regional differences between the eastern coastal and central and western (inland) regions in China, $COAST_i$, although the RE model is rejected by the Hausman test. A significant positive coefficient of $FAPM_{it}$ is found in both models (FE and RE models) and, therefore, Hypothesis H2 is accepted. A 1% increase in an airport's passenger throughput increased inbound domestic tourists by 0.187% to the city where the airport is located. Inserting Eq. (4) into Eq. (1), the effect of $ASUB_{it}$ on $TOUR_{it}$ is the product of $ASUB_{it}$ in Eq. (4) and $FAPM_{it}$ in Eq. (1). The result implies that a 1% increase in airport subsidy increased domestic tourist arrivals by 0.0058%, on average.[13] The significant positive coefficient of $GDPPC_{it}$ is also reported in both models, which suggests that an increase in income level increased tourist arrivals, as expected (Naudé & Saayman, 2004). A significant positive coefficient of $NGDPPC_{it-1}$ is reported in both models, implying that domestic tourists respond to the national real GDP per capita strongly. $TEMP_{it}$ is also reported as a significant factor for domestic tourist arrivals in both models.

Note that the overall patterns of the RE estimation results[14] are similar to those reported in the FE estimation. The major differences are: (i) the coefficients of POP_{it}, $PEDU_{it}$, HSR_{it}, and $UNESCO_{it}$ are reported to be positive and statistically significant. These results are all expected: increase in population size increased domestic tourist arrivals, higher provincial education level implies higher human capital for workers who are able to deliver higher quality of hospitality services to tourists; and high-speed rail stations in the sampled cities and the presence of UNESCO world heritage sites could transport and attract more tourists; and (ii) the significant positive coefficient of HUM_{it} indicates that the warmer and more humid Chinese cities attracted more domestic tourists. Surprisingly, the effect of regional difference, $COAST_i$, cannot be found in the RE model.

Compared with the eastern coastal regions, the central and western regions in China are largely landlocked (e.g. Chow et al., 2016; Jackson, 2006). Carmignani (2015) argued that being landlocked creates a geographical barrier that hinders mobility, and thus reduces the diffusion of new ideas and technological advances. Such barriers had an adverse effect on the long-term economic growth of the central and western regions in China. As discussed, the central and western regions in China are economically backward and do not have a well-established transport infrastructure (i.e. a lower density of railway and highway networks, longer distances to major seaports and fewer direct flights to international destinations) (e.g. Tong & Yu, 2018; Yu et al., 2013). One expects that the improvement of transport networks (including air transport) can improve connectivity and generate higher value-added services in the central and western regions in China, helping these under-served and landlocked regions to transport goods and products to other destinations (Tong & Yu, 2018). Importantly, the central and western regions in China may still rely more on air transport to fly passengers and tourists for holidays and vacations. Therefore, airport subsidies to small- and medium-sized unprofitable airports in the central and western regions may promote their aviation activity and encourage more tourists to visit. To further understand the impact of airport subsidy scheme on different regions' airport passenger throughput and tourism in China, we further divided the collected dataset into two subsamples for analysis: (i) the eastern coastal regions (see Table 4) and (ii) the central and western regions (see Table 5).

Airport subsidy schemes in the eastern coastal regions (2013–2017)

Table 4 (left hand box) shows the results for the eastern coastal regions for the 2013–2017 period. For the first-stage FE estimation, the Hausman test result indicates the acceptance of the RE model and rejection of the FE model. However, we used the FE model because its adj-R^2 values (0.9123) is much larger than the RE model (0.2686). This improves the quality of $FAPM_{it}$ variable used in the second-stage estimation. Its overall estimation results are similar to those reported in Table 3, even with the smaller sample size (189 observations). Again, a significant positive coefficient of $ASUB_{it}$ is reported, which accepts Hypothesis H1. A 1% increase in airport subsidy led to a 0.0281% increase in airport passenger throughput. Likewise, the significant positive coefficients of $TEMP_{it}$ and $NGDPPC_{it-1}$ are reported in the first-stage estimation. Regarding the second-stage estimation, the Hausman test result indicates the acceptance of the FE model and rejection of the RE model. Unfortunately, the coefficient of $FAPM_{it}$ is insignificant in both FE and RE models. This rejects Hypothesis H2. Similarly, the coefficients of POP_{it}, $PEDU_{it}$, and $NGDPPC_{it-1}$ are reported to be positive and statistically significant while the coefficients of $RAIN_{it}$, $TEMP_{it}$ and $RCPI_{it}$ are negative and statistically significant, respectively.

Airport subsidy schemes in the central and western regions (2013–2017)

Table 5 (left hand box) reports the results for the central and western regions for the 2013–2017 period. For both first- and second-stage estimations, the Hausman test results indicate the acceptance of the FE model and rejection of the RE model. The overall estimation results of Table 5 are also similar to those reported in Table 3. The key variable of interest, $ASUB_{it}$, is reported to have a significant positive coefficient, which accepts Hypothesis H1. A 1% increase in airport subsidy increased passenger throughput of the sampled cities' airports by 0.0332%. This figure is similar to its counterpart (0.0312%) reported in Table 3. The significant positive coefficients of $JFUELP_t$, $NGDPPC_{it-1}$, and $RCPI_{it}$ are also reported. The results of the second-stage FE model are largely consistent with those reported in Table 3. $FAPM_{it}$ has a significant positive coefficient of 0.1770, leading to the acceptance of Hypothesis H2. The product of $ASUB_{it}$ in Eq. (4) and $FAPM_{it}$ in Eq. (1a) suggests that a 1% increase in airport subsidy indirectly increased domestic tourist arrivals by

[13] Based on the figures reported in Tables 1 and 3, one yuan of airport subsidy offered by the CAAC generates 57.02 yuan of tourist revenue; 0.0663 tourist arrivals*860 yuan = 57.02 yuan, on average, by evaluating at the means of airport subsidy, $ASUB_{it}$ and tourist arrivals, $TOUR_{it}$.

[14] As there is no variation within each prefectural city for $COAST_i$, this study cannot estimate the variable of $COAST_i$ in the FE model instead of the RE model (see Table 3).

Table 4
2SLS estimation results of airport passenger movement (APM) and domestic tourist arrivals (TOUR) for cities in the eastern coastal provinces of subsidized/all airports (2013–2017).

Subsidized airports							
Dependent variable	1st stage: APM_{it}		Dependent variable	2nd stage: $TOUR_{it}$			
Explanatory variables	FE model		Explanatory variables	FE model		RE model	
	Coeff.	*t*-value		Coeff.	*t*-value	Coeff.	*t*-value
Constant	–	–	*Constant*	–	–	-13.5645^{***}	−4.405
$GDPPC_{it-1}$	0.0706	0.175	$FAPM_{it}$	0.0480	0.576	0.0339	0.875
POP_{it-1}	0.1949	0.566	$GDPPC_{it}$	0.1468	1.367	0.3227^{***}	4.032
$DCITYC_{it}$	−0.2707	−1.088	POP_{it}	4.2162^{***}	3.414	0.3189^{***}	2.891
HSR_{it}	−0.1819	−0.527	$PEDU_{it}$	1.4297^{*}	1.667	1.0594	1.527
$ASUB_{it}$	0.0281^{**}	2.353	HSR_{it}	0.0354	0.360	0.0353	0.471
HUM_{it}	1.4168	0.620	$UNESCO_{it}$	−0.0866	−0.973	−0.0227	−0.319
$RAIN_{it}$	0.2660	1.300	HUM_{it}	−0.4593	−0.787	−0.2061	−0.463
$TEMP_{it}$	5.9225^{**}	2.465	$RAIN_{it}$	-0.1197^{**}	−2.141	−0.0514	−1.049
$JFUELP_{t}$	0.2336	1.818	$TEMP_{it}$	-1.6034^{**}	−2.508	-0.4236^{**}	−1.995
$PEDU_{it}$	3.2259	1.140	$NGDPPC_{t-1}$	2.3206^{***}	6.816	2.3697^{***}	11.970
$NGDPPC_{t-1}$	2.2107^{**}	2.410	$RCPI_{it}$	-2.2961^{*}	−1.842	−1.4128	−1.297
$RCPI_{it}$	1.3011	0.286	$FAPM_{it}$	0.0480	0.576	-13.5645^{***}	−4.405
$UNESCO_{it}$	−0.0233	−0.072					
***Adj-R*²**	0.9123		***Adj-R*²**	0.9365		0.2686	
***F*-statistic**	37.88^{***}		***F*-statistics**	55.37^{***}		6.75^{***}	
Hausman test	17.03		**Hausman test**	44.01^{***}			
Obs.	189		**Obs.**	189		189	

Robustness check: all airports							
Dependent variable	1st stage: APM_{it}		Dependent variable	2nd stage: $TOUR_{it}$			
Explanatory variables	FE model		Explanatory variables	FE model		RE model	
	Coeff.	*t*-value		Coeff.	*t*-value	Coeff.	*t*-value
Constant	–	–	*Constant*	–	–	-13.6815^{***}	−4.622
$GDPPC_{it-1}$	0.0804	0.211	$FAPM_{it}$	0.0052	0.062	0.0504	1.388
POP_{it-1}	0.1973	0.602	$GDPPC_{it}$	0.1762	1.615	0.3109^{***}	3.923
$DCITYC_{it}$	−0.2602	−1.098	POP_{it}	3.1494^{***}	2.752	0.3204^{***}	3.072
HSR_{it}	−0.1797	−0.547	$PEDU_{it}$	1.3338	1.532	0.6754	0.994
$ASUB_{it}$	0.0280^{**}	2.471	HSR_{it}	0.0318	0.316	0.0595	0.785
HUM_{it}	1.4913	0.711	$UNESCO_{it}$	−0.1080	−1.335	−0.0595	−0.902
$RAIN_{it}$	0.2362	1.260	HUM_{it}	−0.7085	−1.205	−0.3836	−0.868
$TEMP_{it}$	5.8072^{***}	2.603	$RAIN_{it}$	-0.0939^{*}	−1.697	−0.0409	−0.838
$JFUELP_{t}$	0.2350^{**}	2.090	$TEMP_{it}$	-1.4908^{**}	−2.299	-0.5120^{**}	−2.438
$PEDU_{it}$	3.4522	1.339	$NGDPPC_{t-1}$	2.4404^{***}	7.213	2.3197^{***}	12.101
$NGDPPC_{t-1}$	2.1989^{**}	2.557	$RCPI_{it}$	−1.8770	−1.505	−0.6291	−0.584
$RCPI_{it}$	1.3376	0.317					
$UNESCO_{it}$	−0.0554	−0.203					
***Adj-R*²**	0.9268		***Adj-R*²**	0.9405		0.3372	
***F*-statistic**	46.4^{***}		***F*-statistics**	59.7^{***}		12.76^{***}	
Hausman test	23.63^{**}		**Hausman test**	39.09^{***}			
Obs.	209		**Obs.**	209		209	

Remarks: $FAPM_{it}$ is the fitted value of APM_{it} obtained from the 1st stage FE model. A Hausman test is used to choose the FE vs. RE models for estimation. A high Hausman test value indicates rejection of the RE model and acceptance of the FE model. *F*-statistics are used to test the zero restrictions of all of the explanatory variables (including FE estimates). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Table 5

2SLS estimation results of airport passenger movement (APM) and domestic tourist arrivals (TOUR) for cities in the central and western provinces of subsidized/all airports (2013–2017).

Subsidized airports

Dependent variable	1st stage: APM_{it}		Dependent variable	2nd stage: $TOUR_{it}$			
Explanatory variables	FE model		Explanatory variables	FE model		RE model	
	Coeff.	*t*-value		Coeff.	*t*-value	Coeff.	*t*-value
Constant	–	–	*Constant*	–	–	-20.8270^{***}	−10.195
$GDPPC_{it-1}$	0.3718	1.645	$FAPM_{it}$	0.1770^{***}	2.637	0.0827^{**}	2.389
POP_{it-1}	−0.0281	−0.407	$GDPPC_{it}$	0.2874^{***}	3.213	0.2593^{***}	3.937
$DCITYC_{it}$	–	–	POP_{it}	0.0416	1.128	0.1748^{***}	5.453
HSR_{it}	0.1393	0.610	$PEDU_{it}$	0.3693	0.772	0.8288^{*}	1.901
$ASUB_{it}$	0.0332^{***}	4.702	HSR_{it}	0.0889	1.022	0.1572^{**}	1.969
HUM_{it}	1.1808	1.069	$UNESCO_{it}$	0.0857	1.304	0.1845^{***}	3.482
$RAIN_{it}$	0.0059	0.044	HUM_{it}	−0.5008	−1.222	1.3687^{***}	4.248
$TEMP_{it}$	0.8480	1.571	$RAIN_{it}$	0.0238	0.478	0.0391	0.812
$JFUELP_t$	0.1833^{**}	2.352	$TEMP_{it}$	−0.2615	−1.265	0.8283^{***}	7.435
$PEDU_{it}$	0.1166	0.091	$NGDPPC_{t-1}$	2.6712^{***}	8.720	2.6188^{***}	13.166
$NGDPPC_{t-1}$	3.4963^{***}	7.196	$RCPI_{it}$	0.0104	0.022	−0.1882	−0.459
$RCPI_{it}$	1.9822^{*}	1.718					
$UNESCO_{it}$	−0.1536	−0.872					
***Adj-R*^{2}**	0.8528		***Adj-R*^{2}**	0.9681		0.2763	
***F*-statistic**	25.16^{***}		***F*-statistics**	128.37^{***}		7.01^{***}	
Hausman test	34.37^{***}		**Hausman test**	111.51^{***}			
Obs.	564		**Obs**.	564		564	

Robustness check: All airports

Dependent variable	1st stage: APM_{it}		Dependent variable	2nd stage: $TOUR_{it}$			
Explanatory variables	FE model		Explanatory variables	FE model		RE model	
	Coeff.	*t*-value		Coeff.	*t*-value	Coeff.	*t*-value
Constant	–	–	*Constant*	–	–	-19.5249^{***}	−10.335
$GDPPC_{it-1}$	0.3444	1.482	$FAPM_{it}$	0.1912^{***}	2.890	0.1088^{***}	3.645
POP_{it-1}	−0.0299	−0.414	$GDPPC_{it}$	0.2419^{***}	3.107	0.2751^{***}	4.543
$DCITYC_{it}$	–	–	POP_{it}	0.0431	1.173	0.2024^{***}	6.496
HSR_{it}	0.1469	0.616	$PEDU_{it}$	0.2814	0.644	1.0028^{**}	2.518
$ASUB_{it}$	0.0328^{***}	4.453	HSR_{it}	0.0959	1.106	0.1236	1.577
HUM_{it}	1.0457	0.913	$UNESCO_{it}$	0.0941	1.440	0.2019^{***}	3.908
$RAIN_{it}$	−0.0533	−0.393	HUM_{it}	−0.4981	−1.233	1.6092^{***}	5.227
$TEMP_{it}$	0.8591	1.544	$RAIN_{it}$	0.0227	0.462	0.0134	0.286
$JFUELP_t$	0.1974^{**}	2.467	$TEMP_{it}$	−0.3169	−1.592	0.8401^{***}	7.916
$PEDU_{it}$	−0.0670	−0.055	$NGDPPC_{t-1}$	2.6135^{***}	8.616	2.4033^{***}	13.282
$NGDPPC_{t-1}$	3.5962^{***}	7.288	$RCPI_{it}$	−0.0496	−0.123	−0.1788	−0.512
$RCPI_{it}$	2.0988^{**}	2.073					
$UNESCO_{it}$	−0.1418	−0.771					
***Adj-R*^{2}**	0.8661		***Adj-R*^{2}**	0.9694		0.6149	
***F*-statistic**	26.61^{***}		***F*-statistics**	127.18^{***}		88.40^{***}	
Hausman test	40.21^{***}		**Hausman test**	132.34^{***}			
Obs.	603		**Obs**.	603		603	

Remarks: $FAPM_{it}$ is the fitted value of APM_{it} obtained from the 1st stage FE model. A Hausman test is used to choose the FE vs. RE models for estimation. A high Hausman test value indicates rejection of the RE model and acceptance of the FE model. *F*-statistics are used to test the zero restrictions of all explanatory variables (including FE estimates). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively.

0.0059%, on average.[15] Compared with the eastern coastal regions, airport subsidy scheme exerted a significant effect in bringing domestic tourist arrivals to the landlocked central and western regions during the study period. $GDPPC_{it}$, and $NGDPPC_{it-1}$ are also reported as the significant positive variables in the FE model. Similarly, $FAPM_{it}$ also has a significant positive effect on domestic tourist arrivals in the RE model, which is consistent with the FE model.

Robustness checks for the 2013–2017 period

To verify the results reported in Tables 3, 4 and 5 (left hand boxes) for the 2013–2017 period, this section presents their corresponding results in right hand boxes of three tables. As robustness checks, we expanded the original dataset to include 22 unsubsidized small- and medium-sized airports.

Table 3 (right hand box) shows the robustness checks of airport subsidy scheme's impact on domestic tourist arrivals for the 2013–2017 period. For both first- and second-stage estimations, the Hausman test results indicate the acceptance of the FE model and rejection of the RE model. The overall results are very similar to those reported in the original dataset (subsidized airports) (left hand box). Importantly, the key variable of interest, $ASUB_i$, is reported to be positive and statistically significant, which accepts Hypothesis H1. A 1% increase in airport subsidy increased airport passenger throughput by 0.0309%, which is similar to its counterpart (0.0312%) reported above for the subsidized airport sample. In the second-stage estimation, the significant positive coefficient of $FAPM_{it}$ indicates the acceptance of Hypothesis H2. A 1% increase in airport passenger throughput increased domestic tourist arrivals by 0.19%. The product of $ASUB_{it}$ and $FAPM_{it}$ shows that a 1% increase in airport subsidy indirectly increased domestic tourist arrivals by 0.0059%, on average. This figure is also similar to its counterpart (0.0058%) obtained from the subsidized airport sample.[16] Again, the overall results of the second-stage RE estimation of the expanded dataset (all airports) are largely consistent to those reported in original dataset (subsidized airports), suggesting that the estimation results of the subsidized airport sample are robust.

Airport subsidy schemes in the eastern coastal regions (2013–2017)

Table 4 (right hand box) shows the robustness checks of the eastern coastal regions for the 2013–2017 period. For both first- and second-stage estimations, the Hausman test results indicate the acceptance of the FE model and rejection of the RE model. The overall estimation results are similar to those obtained in the subsidized airport sample (left hand box). The significant positive coefficient of $ASUB_{it}$ suggests the acceptance of Hypothesis H1. A 1% increase in airport subsidy increased airport passenger throughput by 0.028%. The coefficients of $TEMP_{it}$, $JFUELP_t$ and $NGDPPC_{t-1}$ are positive and statistically significant at the 1% or 5% level. In the second-stage estimation, the coefficient of $FAPM_{it}$ is insignificant, which rejects Hypothesis H2. Similar to the results in the subsidized airport sample, the variables of POP_{it}, $NGDPPC_{t-1}$, and $TEMP_{it}$ are positive and statistically significant at the 1% level.

Airport subsidy schemes in the central and western regions (2013–2017)

Table 5 (right hand box) shows the results of the central and western provinces in the 2013–2017 period. For both first- and second-stage estimations, the Hausman test results indicate the acceptance of the FE model and rejection of the RE model. The overall estimation results are similar to those obtained in the subsidized airport sample (left hand box). The key variable of interest, $ASUB_{it}$, is reported to have a significant positive coefficient, which accepts Hypothesis H1. A 1% increase in airport subsidy increased airport passenger throughput by 0.0328%. For the second-stage FE estimation, $FAPM_{it}$ is reported to be positive and statistically significant at the 1% level, which accepts Hypothesis H2. The product of $ASUB_{it}$ and $FAPM_{it}$ suggests that a 1% increase in airport subsidy indirectly increased domestic tourist arrivals by 0.0063%, on average. This result is also similar its counterpart (0.0059%) generated from the subsidized airport sample.[17] It also clearly indicates that airport subsidy scheme has a greater effect on domestic tourist arrivals to landlocked inland (central and western) regions than the eastern coastal regions. $GDPPC_{it}$, and $NGDPPC_{t-1}$ are reported to be positive and statistically significant at the 1% level in both FE and RE models.

After disaggregating the original dataset into two regional subsamples (the eastern coastal regions vs. the central and western regions), their respective estimation results show that airport subsidy scheme positively impacted passenger throughput of airports in both regions. However, their indirect effect on boosting domestic tourist arrivals is more evident in the central and western regions than in the eastern coastal regions, as shown in Tables 5. In a nutshell, this study shows that airport subsidy scheme positively impacts domestic tourist arrivals. The consistent estimation results are reported for both samples for the 2013–2017 period via robustness checks, and this signals the robustness of the empirical results of this study.

[15] Based on the figures reported in Tables 1 and 5, one yuan of airport subsidy offered by the CAAC generates 38.84 yuan of tourist revenue; 0.0044 tourist arrivals*860 yuan = 37.95 yuan, on average, by evaluating at the means of $ASUB_{it}$ and $TOUR_{it}$.

[16] Based on the figures reported in Tables 1 and 3, one yuan of airport subsidy offered by the CAAC generates 155.83 yuan of tourist revenue; 0.1812 tourist arrivals*860 yuan = 155.83 yuan). Note that these two figures are higher than their counterparts reported in Table 3. It is because the dataset includes relatively larger medium-sized airports and more developed cities, and these larger airports handled more domestic tourists. Therefore, the response to airport subsidies turn out to be apparent while comparing the dataset with only subsidized airports.

[17] Based on the figures reported in Tables 1 and 5, one dollar of yuan of airport subsidy offered by the CAAC generates 99.69 yuan of tourist revenue; 0.1159 tourist arrivals*860 yuan = 99.69 yuan.

Table 6
2SLS estimation results of airport passenger movement (APM) and domestic tourist arrivals (TOUR) of subsidized airports (2008–2017).

Dependent variable	1st stage: APM_{it}		Dependent variable	2nd stage: $TOUR_{it}$			
Explanatory variables	FE model		Explanatory variables	FE model		RE model	
	Coeff.	*t*-statistic		Coeff.	*t*-statistic	Coeff.	*t*-statistic
Constant	–	–	*Constant*	–	–	-9.6419^{***}	−9.1167
$GDPPC_{it-1}$	0.1392	1.0725	$FAPM_{it}$	−0.0355	−0.4889	0.0075	0.2669
POP_{it-1}	−0.0614	−0.8488	$GDPPC_{it}$	0.2512^{***}	4.4613	0.2339^{***}	5.0638
$DCITYC_{it}$	0.4878^{***}	2.6097	POP_{it}	0.1592^{***}	3.7980	0.3195^{***}	9.5749
HSR_{it}	0.0207	0.1664	$PEDU_{it}$	1.1576^{***}	2.8922	1.0475^{***}	2.8139
$ASUB_{it}$	0.0182^{***}	4.0130	HSR_{it}	0.0114	0.2560	0.0403	0.9397
$COAST_{i}$	–	–	$UNESCO_{it}$	0.1772^{***}	5.0003	0.1860^{***}	5.6873
HUM_{it}	0.0382	0.0492	$COAST_{i}$	–	–	0.1989^{*}	1.7369
$RAIN_{it}$	0.0748	1.0833	HUM_{it}	1.3946^{***}	5.0968	1.8767^{***}	8.3818
$TEMP_{it}$	0.6902^{**}	1.9716	$RAIN_{it}$	−0.0222	−0.8773	−0.0261	−1.0722
$JFUELP_{t}$	0.0900	1.3915	$TEMP_{it}$	0.2976^{**}	2.2434	0.5380	6.4099
$PEDU_{it}$	1.2107	1.0949	$NGDPPC_{t-1}$	1.7643^{***}	9.1100	1.6386^{***}	16.7314
$NGDPPC_{t-1}$	1.7445^{***}	6.3311	$RCPI_{it}$	−0.5569	−1.2051	-0.9113^{**}	−2.5201
$RCPI_{it}$	3.5986^{***}	3.4572					
$UNESCO_{it}$	0.0143	0.1439					
Adj-R^2	0.8181		**Adj-R^2**	0.9526		0.6716	
F-statistic	35.45^{**}		**F-statistics**	15679^{***}		231.65^{***}	
Hausman test	52.87^{***}		**Hausman test**	65.47^{***}			
Observations	1372		**Observations**	1372		1372	

Remarks: $FAPM_{it}$ is the fitted value of APM_{it} obtained from the 1st stage FE model. A Hausman test is used to choose the FE and RE models for estimation. Hausman test statistics are calculated by excluding $COAST_i$, which has no within group variation, in the 1st and 2nd stage estimations. A high Hausman test value indicates rejection of the RE model and acceptance of the FE model. *F*-statistics are used to test the zero restrictions of all of the explanatory variables (including FE estimates). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.

Robustness checks for the 2008–2017 period

We further conducted robustness checks in estimating the subsidized airport sample (the 2013–2017 subsidized period) with the 2008–2012 pre-subsidy period (see Tables 6 and 7). Note that the 2008–2017 period represents the pre-subsidy period, which helps verify the results reported in the previous sections (i.e. the 2013–2017 period). This dataset includes 166 airports and 1372 observations.[18]

Table 6 shows the results of airport subsidy scheme's impact on domestic tourist arrivals for the 2008–2017 period. For both first- and second-stage estimations, the Hausman test results indicate the acceptance of the FE model and rejection of the RE model. Its overall estimation results of first- and second-stage estimations are similar to those reported in Table 3, except for the significant positive variable of $DCITYC_{it}$[19] is reported and the variable of $JFUELP_t$ is no longer significant. Importantly, the key variable of interest, $ASUB_i$, is reported to be positive and statistically significant, which accepts Hypothesis H1. A 1% increase in airport subsidy increased airport passenger throughput by 0.0182%. For the second-stage estimation, the coefficient of $FAPM_{it}$ is no longer significant and indicates the rejection of Hypothesis H2. The same significant positive variables of $GDPPC_{it}$ and $NGDPPC_{t-1}$, are reported, but also POP_{it}, $PEDU_{it}$, $UNESCO_{it}$, HUM_{it}, and $TEMP_{it}$. Importantly, the significant positive coefficient of $COAST_i$ is reported, indicating the regional differences existed between the eastern coastal regions and the central and western regions in attracting domestic tourists.

Airport subsidy schemes in the eastern coastal regions (2008–2017)

Table 7 (left hand box) shows the results of the eastern coastal provinces for the 2008–2017 period. In the first-stage estimation, the Hausman test result indicates the acceptance of the RE model.[20] Its overall estimation results are quite different to those obtained in Table 4. However, the significant positive coefficient of $ASUB_{it}$ is still reported and suggests the acceptance of Hypothesis H1. A 1% increase in airport subsidy increased airport passenger throughput by 0.0157%. Similar to Table 4, the variables of $TEMP_{it}$ and $NGDPPC_{t-1}$ are reported to be positive and statistically significant at the 1% level. Regarding the second-stage estimation, the Hausman test result indicates the acceptance of the FE model and rejection of the RE model. The overall pattern of estimation results of the second-stage estimation in Table 7 is quite similar to its counterpart reported in Table 4. The coefficient of $FAPM_{it}$ remains insignificant. This rejects Hypothesis H2. In addition, the coefficients of POP_{it}, $NGDPPC_{t-1}$, and HUM_{it} are positive and statistically significant at the 1% or 5% level in both FE and RE models.

[18] The all airport dataset of the 2008–2017 period includes all Chinese airports started operation after 2008. It also includes a small-sized airport in Shaanxi Province, Ankang Wulipu Airport, which operated from 2008 to 2010. Therefore, 166 airports are included in the dataset.

[19] The variable of $DCITYC_{it}$ has some within group variations because some sampled airports have been relocated when new airports opened to replace old ones. Therefore, their distances to city center changed during the study period.

[20] Adj-R^2 of the FE model (0.8767) is higher than the RE model (0.4607).

Table 7

2SLS estimation results of airport passenger movement (APM) and domestic tourist arrivals (TOUR) for cities in the eastern coastal/central and western provinces of all airports (2008–2017).

Eastern coastal regions

Dependent variable	1st stage: APM_{it}		Dependent variable	2nd stage: $TOUR_{it}$			
Explanatory variables	FE model		Explanatory variables	FE model		RE model	
	Coeff.	*t*-value		Coeff.	*t*-value	Coeff.	*t*-value
Constant	–	–	*Constant*	–	–	−7.3915***	−3.111
$GDPPC_{it-1}$	−0.6313**	−2.376	$FAPM_{it}$	−0.0424	−0.564	0.0343	0.875
POP_{it-1}	0.0126	0.041	$GDPPC_{it}$	−0.0368	−0.434	0.2037***	2.981
$DCITYC_{it}$	−0.2130	−0.930	POP_{it}	3.8170***	6.166	0.3968***	3.546
HSR_{it}	0.1453	0.881	$PEDU_{it}$	0.2170	0.359	−0.2000	−0.359
$ASUB_{it}$	0.0157**	2.145	HSR_{it}	−0.0250	−0.563	0.0296	0.715
HUM_{it}	−1.1753	−0.967	$UNESCO_{it}$	0.0377	0.666	0.0103	0.200
$RAIN_{it}$	0.3786**	2.387	HUM_{it}	0.7774**	2.138	0.6736**	2.255
$TEMP_{it}$	2.7215***	3.633	$RAIN_{it}$	0.0174	0.371	−0.0132	−0.310
$JFUELP_{t}$	0.2404**	2.244	$TEMP_{it}$	0.3626	1.398	−0.1639	−0.996
$PEDU_{it}$	0.3037	0.136	$NGDPPC_{t-1}$	1.6826***	8.375	1.6263***	12.925
$NGDPPC_{t-1}$	2.2645***	4.794	$RCPI_{it}$	−1.1233	−1.241	−0.9459	−1.332
$RCPI_{it}$	8.1647***	3.251					
$UNESCO_{it}$	0.0549	0.260					
Adj-R²	0.8767		***Adj-R²***	0.9454		0.4607	
***F*-statistic**	47.07***		***F*-statistics**	119.72***		25.92***	
Hausman test	16.21		**Hausman test**	68.38***			
Obs.	351		**Obs.**	351		351	

Central and western regions

Dependent variable	1st stage: APM_{it}		Dependent variable	2nd stage: $TOUR_{it}$			
Explanatory variables	FE model		Explanatory variables	FE model		RE model	
	Coeff.	*t*-value		Coeff.	*t*-value	Coeff.	*t*-value
Constant	–	–	*Constant*	–	–	−9.7158***	−8.127
$GDPPC_{it-1}$	0.2866*	1.889	$FAPM_{it}$	0.0262	0.273	0.0326	1.025
POP_{it-1}	−0.0843	−1.096	$GDPPC_{it}$	0.2371***	3.367	0.2262***	4.153
$DCITYC_{it}$	–	–	POP_{it}	0.1508***	3.336	0.3124***	8.759
HSR_{it}	−0.0409	−0.225	$PEDU_{it}$	1.4026***	2.934	1.3473***	3.058
$ASUB_{it}$	0.0179***	3.200	HSR_{it}	0.1033	1.528	0.1194*	1.842
HUM_{it}	0.4032	0.404	$UNESCO_{it}$	0.2201***	5.200	0.2347***	6.111
$RAIN_{it}$	0.0328	0.421	HUM_{it}	1.2236***	3.332	2.2137***	7.905
$TEMP_{it}$	0.3813	0.953	$RAIN_{it}$	−0.0213	−0.732	−0.0213	−0.754
$JFUELP_{t}$	0.0546	0.691	$TEMP_{it}$	0.2281	1.522	0.6683***	7.304
$PEDU_{it}$	1.0430	0.809	$NGDPPC_{t-1}$	1.6474***	6.152	1.5753***	13.115
$NGDPPC_{t-1}$	1.7952***	5.294	$RCPI_{it}$	−0.6157	−1.226	−0.9367*	−2.307
$RCPI_{it}$	2.4965**	2.126					
$UNESCO_{it}$	−0.0784	−0.683					
Adj-R²	0.7956		***Adj-R²***	0.9474		0.6939	
***F*-statistic**	30.19***		***F*-statistics**	136.97***		193.73***	
Hausman test	42.87***		**Hausman test**	62.32***			
Obs.	1021		**Obs.**	1021		1021	

Remarks: $FAPM_{it}$ is the fitted value of APM_{it} obtained from the 1st stage FE model. A Hausman test is used to choose the FE vs. RE models for estimation. A high Hausman test value indicates rejection of the RE model and acceptance of the FE model. *F*-statistics are used to test the zero restrictions of all explanatory variables (including FE estimates). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 level, respectively.

Airport subsidy schemes in the central and western regions (2008–2017)

Table 7 (right hand box) shows the results of the central and western regions for the 2008–2017 period. For both first- and second-stage estimations, the Hausman test results indicate the acceptance of the FE model and rejection of the RE model. The key variable of interest, $ASUB_{it}$, is reported to have a significant positive coefficient, which accepts Hypothesis H1. A 1% increase in airport subsidy increased airport passenger throughput by 0.0179%. The significant positive variables of $GDPPC_{it-1}$, $NGDPPC_{t-1}$, and $RCPI_{it}$, are reported in the first-stage estimation, respectively. The overall pattern of estimation results is also similar to those obtained in Table 5. The coefficient of $FAPM_{it}$ is insignificant, which rejects Hypothesis H2. $GDPPC_{it}$, POP_{it}, $PEDU_{it}$, $UNESCO_{it}$, HUM_{it}, and $NGDPPC_{t-1}$ are positive and significant at the 1% level in the second-stage estimation.

Overall, Tables 6 and 7 show the acceptance of Hypothesis H1 but rejection of Hypothesis H2, with the extended dataset (2008–2017): the pre-subsidy (2008–2012) and post-subsidy period (2013–2017). Therefore, the pattern of estimation results obtained in Tables 3, 4, and 5 cannot fully be extended to the dataset including both the pre-subsidy and post-subsidy periods (2008–2017).[21]

Conclusion and discussion

Using the 2SLS model, this study examines the relationship between airport subsidy scheme and domestic tourism development in China during the 2013–2017 period. The empirical findings reveal that airport subsidy scheme helped promote and support the operation of unprofitable small- and medium-sized airports and significantly increased airport passenger throughput. This study also shows that airport subsidy scheme can indirectly bring more domestic tourist arrivals to the city in which an airport is located. Given the differences in infrastructure development between different regions and provinces in China, this study further analyzes the eastern coastal regions and the central and western regions. The findings confirm the importance of airport subsidies for airport passenger throughput and domestic tourist arrivals in both the eastern coastal and central and western (inland) regions. In addition, the effect of airport subsidy scheme in boosting domestic tourism is more profound in inland regions compared with the eastern coastal regions that have better transport infrastructure. The importance of both economic (e.g. GDP per capita, the overall income of domestic inbound tourists, and population size) and noneconomic factors (e.g. education level, UNESCO world heritage sites, and weather conditions) in determining airport passenger throughput and domestic tourist arrivals are also confirmed.

The Chinese government has invested heavily in transport infrastructure, such as building new airports or expanding existing airport facilities across small- and medium-sized airports/cities. The goal has been to improve regional economic development, connectivity and standards of living. Providing subsidies to small- and medium-sized Chinese airports has been an effective way of supporting very poor regions, border regions, ethnic minority areas, and other remote regions with inconvenient land transportation. One of the key findings of this study implies that provincial and municipal governments and tourism authorities in inland regions in China should recognize the significant role of airport subsidies in regional development, economic and social welfare, and tourism. It is important for governments to facilitate airport development to accommodate the increasing number of domestic tourists. This study has some data limitations because it only investigates CAAC airport subsidies. As aforementioned, Chinese airports may also receive other forms of subsidy or support from provincial or municipal governments, but the data are not publicly available.[22]

In terms of future research, our analysis could be extended using further measures or factors, such as different types of passengers and tourists, tourist expenditures or airline capacity to better understand the relationship between airport subsidies and domestic tourism. In specific, it may be meaningful to analyze inbound and outbound passengers, as well as business and leisure tourists visiting remote regions via the sampled airports (when available), which may further improve this study's ability for showing the impact of airport subsidies on small- and medium-sized airports' passenger throughput and domestic tourist flows to inland regions. It is possible that more inbound and outbound passengers and business or leisure tourists may travel on routes that benefit from airport subsidies (e.g. due to airfare discounts). Likewise, further investigations of the impact of airport subsidies on tourism (for example, tourist expenditures, number of overnight stays) are strongly recommended. Such regional airline routes may be sustained in this way and even achieve commercial viability. On this point, airport subsidies should also be periodically evaluated. Also, this study can further examine the extent of competition between domestic airlines offering flight services, and between land transport (e.g. high-speed rail) and air transport in serving the central and western regions with inconvenient land transportation networks. These analyses point to future challenges for the Chinese domestic aviation market as the Chinese government plans to develop inland regions while facing difficult infrastructural challenges.

Declaration of competing interest

None.

[21] Appendix 2 reports the 2SLS estimation results of APM_{it} and $TOUR_{it}$ for the pre-subsidy 2008–2012 period. This dataset includes 144 airports and 665 observations. The estimation results are largely consistent with those reported in Tables 3 and 5, in which Hypothesis H2 is accepted. Hypothesis H1 cannot be tested as airports did not receive any subsidy during the 2008–2012 period.

[22] Besides airport subsidies, airline subsidies aid airlines flying passengers or tourists between destinations. To investigate the airline subsidy's impact on tourist arrivals, one needs the route-level data of airline services between cities/airports A and B. For example, Spring Airlines offers flight services between Shanghai and Baotou, Inner Mongolia. Even though the Shanghai–Baotou route data are collected, the route's subsidy amount being allocated may not be known without accessing the airline's internal information. Furthermore, the CAAC only discloses the total subsidy received by subsidized airlines but not the airline-route subsidy. Therefore, our study cannot examine the airline subsidy effect on tourist arrivals to the sampled cities/airports.

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Appendix 1. Chinese airports receiving CAAC subsidies (2013–2017)

Provinces	Subsidized airports	Unsubsidized airports
Hebei	Qinhuangdao Beidaihe Airport, Handan Airport, Tangshan Sannvhe Airport, Zhangjiakou Ningyuan Airport	Chengde Puning Airport
Shanxi	Changzhi Wangcun Airport, Datong Airport, Yuncheng Guangong Airport, Luliang Airport, Xinzhou Wutaishan Airport, Linfen Qiaoli Airport,	
Inner Mongolia	Baotou Airport, Chifeng Yulong Airport, Hailar Dongshan Airport, Tongliao Airport, Wuhai Airport, Ulanhot Airport, Manzhouli Xijiao Airport, Xilinhot Airport, Ordos Airport, Erenhot Saiwusu Airport, Bayan Nur Tianjitai Airport, Alxa Right Banner Badanjilin Airport, Alxa Left Banner Bayanhot Airport, Ejin Banner Taolai Airport, Arxan Yiershi Airport, Ulanqab Tsining Airport	Zhalantun Chengjisihan Airport
Liaoning	Dandong Langtou Airport, Chaoyang Airport, Jinzhou Jinzhouwan Airport, Anshan Teng'ao Airport, Changhai Airport, Yingkou Lanqi Airport	
Jilin	Yanji Chaoyangchuan International Airport, Baishan Changbaishan Airport, Tonghua Sanyuanpu Airport	Baicheng Changan Airport, Songyuan Chaganhu Airport
Heilongjiang	Mudanjiang Hailang International Airport, Jiamusi Dongjiao Airport, Heihe Airport, Qiqihar Sanjiazi Airport, Daqing Sartu Airport, Yichun Lindu Airport, Mohe Gulian Airport, Jixi Xingkaihu Airport, Jagdaqi Airport, Fuyuan Dongji Airport	Wudalianchi Dedu Airport, Jiansanjiang Shidi Airport;
Jiangsu	Changzhou Benniu Airport, Xuzhou Guanyin International Airport, Nantong Xingdong Airport, Yancheng Nanyang International Airport, Lianyungang Baitabu Airport, Huaian Lianshui Airport, Yangzhou Taizhou International Airport,	Sunan Shuofang International Airport
Zhejiang	Yiwu Airport, Quzhou Airport, Taizhou Luqiao Airport, Zhoushan Putuoshan Airport,	
Anhui	Anqing Airport, HuangshanTunxi International Airport, Fuyang Airport, Chizhou Jiuhuashan Airport,	
Fujian	Quanzhou Jinjiang International Airport, Wuyishan Airport, Liancheng Guanzhaishan Airport, Sanming Shaxian Airport	
Jiangxi	Jiujiang Lushan Airport, Jingdezhen Luojia Airport, Ganzhou Gold Airport, Jinggangshan Airport, Yichun Mingyueshan Airport	Shangrao Sanqingshan Airport
Shandong	Weifang Nanyuan Airport, Jining Qufu Airport, Linyi Qiyang Airport, Dongying Shengli Airport, Weihai Dashuibo International Airport, Rizhao Shanzihe Airport	Yantai Penglai International Airport
Henan	Luoyang Beijiao Airport, Nanyang Jiangying Airport	
Hubei	Yichang Sanxia Airport, Enshi Xujiaping Airport, Xiangyang Liuji Airport, Shennongjia Hongping Airport, Shiyan Wudangshan Airport,	
Hunan	Changde Taohuayuan Airport, Zhangjiajie Hehua International Airport, Yongzhou Lingling Airport, Huaihua Zhijiang Airport, Hengyang Nanyue Airport	Shaoyang Wugang Airport
Guangdong	Zhanjiang Airport, Jieyang Chaoshan Airport, Meizhou Meixian Airport, Huizhou Pingtan Airport	Foshan Shadi Airport, Zhuhai International Airport
Guangxi	Guilin Liangjiang International Airport, Liuzhou Bailian Airport, Wuzhou Changzhoudao Airport, Beihai Fucheng Airport, Baise Bama Airport, Hechi Jinchengjiang Airport	
Chongqing	Wanzhou Airport, Qianjiang Wulingshan Airport	
Sichuan	Xichang Qingshan Airport, Yibin Caiba Airport, Nanchong Gaoping Airport, Panzhihua Baoanying Airport, Guangyuan Airport, Luzhou Lantian Airport, Mianyang Nanjiao Airport, Dazhou Heshi Airport, Jiuzhai Huanglong Airport, Ganzi Kangding Airport, Aba Hongyuan Airport, Daocheng Yading Airport	
Guizhou	Zunyi Airport, Xingyi Wanfenglin Airport, Tongren Fenghuang Airport, Kali Huangping Airport, Bijie Feixiong Airport, Liupanshui Yuezhao Airport, Anshun Huangguoshu Airport, Qiannan Prefecture Libo Airport, Liping Airport	
Yunnan	Dali Airport, Xishuangbanna Gasa Airport, Dehong Mangshi Airport, Baoshan Airport, Puer Simao Airport, Zhaotong Airport, Deqing Shangri-La Airport, Lincang Airport, Wenshan Puzhehei Airport, Tengchong Tuofeng Airport, Ninglang Luguhu Airport,	Lijiang Sanyi International Airport, Cangyuan Washan Airport, Lancang Jingmai Airport
Tibet	Nyingchi Mainling Airport	Lhasa Gonggar Airport, Changdu Bangda Airport, Shigatse Airport, Nagri Gunsa Airport
Shannxi	Yanan Airport. Yulin Yuyang Airport, Hanzhong Xiguan Airport	
Gansu	Jiayuguan Airport, Qingyang Airport, Dunhuang Airport, Tianshui Maijishan Airport, Zhangye Ganzhou Airport, Gannan Xiahe Airport, Jinchang Jinchuan Airport	
Qinghai	Yushu Batang Airport, Golmud Airport, Haixi Huatugou Airport, Haixi Delingha Airport	Xining Caojiabao Airport, Guoluo Maqin Airport
Ningxia	Zhongwei Shapotou Airport, Guyuan Liupanshan Airport	Yinchuan Hedong International Airport
Xinjiang	Karamay Airport, Yining Airport, Hotan Airport, Aksu Airport, Kashgar Airport, Tacheng Airport, Kuqa Qiuci Airport, Qiemo Airport, Burqin Kanas Airport, Turpan Jiaohe Airport, Nalati Airport, Altay Airport, Hami Airport, Bole Alataw Pass Airport, Korla Airport, Fuyun Koktokay Airport, Shihezi Huayuan Airport	

Remarks: (i) All airports receiving subsidies are small- or medium-sized airports. Most of unsubsidized airports are small and new airports, which must have 2–3 years operations before being qualified to receive subsidies from the CAAC. The relatively larger and profitable medium-sized airports are not subsidized because they are financially sustainable with operational revenue.

Appendix 2. 2SLS estimation results of airport passenger movement (APM) and tourist arrivals (TOUR) of subsidized airports in the pre-subsidy 2008–2012 period

Dependent variable	1st stage: APM_{it}		Dependent variable	2nd stage: $TOUR_{it}$			
Explanatory variable	Fixed effect model		Explanatory variable	Fixed effect model		Random effect model	
	Coefficient	*t*-statistic		Coefficient	*t*-statistic	Coefficient	*t*-statistic
Constant	–	–	*Constant*	–	–	-10.1359^{***}	−6.3169
$GDPPC_{it-1}$	−0.0898	−0.4751	$FAPM_{it}$	0.1940^{**}	2.1369	0.0657^{**}	2.3495
POP_{it-1}	0.7196^{**}	2.2074	$GDPPC_{it}$	0.1856^{*}	1.7285	0.3577^{***}	5.2009
$DCITYC_{it}$	0.5148	1.1278	POP_{it}	1.2751^{***}	5.5471	0.7515^{***}	12.7672
HSR_{it}	−0.0362	−0.1876	$PEDU_{it}$	1.7077^{***}	2.7127	1.2273^{**}	2.2728
$COAST_i$	–	–	HSR_{it}	−0.0036	−0.0586	0.0344	0.5774
HUM_{it}	−0.1711	−0.1590	$UNESCO_{it}$	0.5456^{***}	4.9605	0.4911^{***}	7.5486
$RAIN_{it}$	0.1225	1.3522	$COAST_i$	–	–	0.0950	0.6982
$TEMP_{it}$	−0.0129	−0.0321	HUM_{it}	1.7392^{***}	4.8732	2.4058^{***}	8.5322
$JFUELP_t$	0.6905^{***}	2.8069	$RAIN_{it}$	-0.1106^{***}	−3.9733	-0.1156^{***}	−4.2427
$PEDU_{it}$	−1.9605	−1.0295	$TEMP_{it}$	0.0487	0.3651	0.2015^{**}	2.2232
$NGDPPC_{t-1}$	1.4278^{**}	2.5757	$NGDPPC_{t-1}$	0.6889^{***}	2.6271	0.8853^{***}	6.8636
$RCPI_{it}$	5.0676^{**}	2.4632	$RCPI_{it}$	−1.1907	−1.4305	−0.1852	−0.3218
$UNESCO_{it}$	0.6678^{**}	2.3339					
Adj-R^2	0.8483		**Adj-R^2**	0.9606		0.6968	
F-statistic	24.81^{***}		**F-statistics**	105.53^{***}		128.16^{***}	
Hausman test	44.3^{***}		**Hausman test**	29.22^{***}			
Observations	665		**Observations**	665		665	

Remarks: $FAPM_{it}$ is the fitted value of APM_{it} obtained from the 1st stage FE model. A Hausman test is used to choose the FE vs. RE models for estimation. Hausman test statistics are calculated by excluding $COAST_i$, which has no within group variation, in the 1st and 2nd stage estimations. A high Hausman test value indicates rejection of the RE model and acceptance of the FE model. *F*-statistics are used to test the zero restrictions of all of the explanatory variables (including FE estimates). *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively.
Note: This dataset has 144 small- or medium-sized airports, and the number of airports involved is smaller than Table 3, because a few new airports starting operation from 2013. The overall estimation results are similar to those reported in Tables 3 and 5, except for the significant positive variable of $UNESCO_{it}$ in the first-stage estimation. For the second-stage FE estimation, the overall estimation results are different from those reported in Tables 3 and 5. However, the significant positive coefficient of $FAPM_{it}$ is still reported, indicating the acceptance of Hypothesis H2 and aligning with the results reported in Tables 3 and 5. The significant positive variables of $GPPPC_{it}$, POP_{it}, $PEDU_{it}$, $UNESCO_{it}$, HUM_{it}, $TEMP_{it}$, and $NGDPPC_{t-1}$ are also reported in both models. The significant negative variable of $RAIN_{it}$ is reported in both models. In addition, the variable of $COAST_i$ is insignificant in the RE model, which indicates the absence of the regional differences between the eastern coastal regions and the central and western regions.

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Clement Kong Wing Chow. CHOW is an associate professor in the Marketing and International Business Department, Lingnan University. He conducts research in the areas of China aviation industry, airline service quality and tourism.
Wai Hong Kan Tsui. TSUI is an associate professor in School of Aviation, Massey University. He conducts research in the areas of aviation industry and tourism.
Hanjun Wu is a Ph.D. student under the supervision of Prof. Tsui in School of Aviation, Massey University.