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Impact of aviation on spatial distribution of tourism: An experiment

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A R T I C L E   I N F O

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A B S T R A C T

The paper aims to empirically examine the persistence in the spatial distribution of tourism over time and investigate whether or not, and why, such empirical regularity arises. The paper attempts to quantify how fast the spatial distribution recovers following a shock in the tourism distribution system. Using the collapse of a major Australian legacy airline as a shock in this quasi-experiment, results are indicative of a mix of effects where there was near full recovery within a decade following the shock, as well as a degree of permanent change. The paper discusses how the latter effect may be related to the fact that the collapsed legacy carrier was subsequently replaced by a low-cost carrier.

Introduction

Tourism activities are unevenly distributed across space. Although spatial distribution of tourism is positively correlated to the existing (and uneven) economic and demographic distribution (e.g., Zhang, Xu, & Zhuang, 2011, Cornelissen, 2005, etc.), tourism growth has the potential to reduce some of the developmental inequalities between the core and the periphery (Yang & Wong, 2013). This potential of tourism has been known to be part of the economic development strategy of countries concerned with the internal regional disparity in growths such as China (Wen & Sinha, 2009), as well as the regional infrastructure and investment attraction strategy of Australia (Austrade, 2016).

Common approaches to gathering evidence about the spatiality of tourism involve metrics such as concentration ratios and Gini index (Koo, Wu, & Dwyer, 2012; Lau, Koo and Dwyer 2017). In Australia, for example, the ratio of international tourism in the four largest cities against total inbound has been relatively stable over 1999–2012 (although varies across inbound markets) (Lau et al., 2017), whereas in China similar measures, including the Gini index, show greater dispersion of international visitors between 1999 and 2007 (Wen & Sinha, 2009). Another approach involves examining the rank-size distribution where the log-linear relationship between rank and size of destinations is estimated (Guo, Zhang, & Zhang, 2016; Koo, Lau, & Dwyer, 2017). The size is measured by the number of tourism trips to a destination, while the rank is the positioning of the destination against all other destinations; for example, the most popular destination will be ranked one. These studies invoke the well-known Zipf coefficient and the general power law where a rank-size log-linear relationship with a specific power law exponent can summarise the distribution of tourism trips across destinations with high degree of accuracy – determined through values such as R^2 in the linear regression. If the log-linear relationship between rank and size is statistically indifferent from "1" then this is a sign of Zipf coefficient, which is a special case of

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the general power law. Although the context in which these methods are applied are not always spatial,[1] if the exponent and the rank-order of the constituents of the distribution (e.g., the destinations) are stable across time, it can be deduced that the spatial pattern of tourism activities is also stable.

In social systems, Zipf coefficient can be found in the distribution of city sizes (Soo, 2005), which, as mentioned above, is correlated to the distribution of tourism activity and the visitor economy. But the evidence from rank-size studies of tourism distribution to-date has been inconclusive. For instance, the Zipf coefficient appears in the distribution of international and domestic tourism in China, and it has persisted between the study period, 1999–2011 (Guo et al., 2016). However, although the study revealed stability in aggregate distribution, it also found the micro-dynamics to be continuously changing with significant changes in the rank-order of destinations. Overall, Guo et al. (2016) find domestic tourism to change less than international tourism. In the case of Australia, Koo, Lau, and Dwyer (2017) found spatially stable rank-size relations for mature international markets and spatially changing relations for developing international markets. Provenzano (2012 & 2014) find that in Portugal (2002–2009), as well as in Italy and Germany (2004–2009), the rank-size distribution of tourism supply, proxied by accommodation establishments, follows a specific power law exponent which persisted over the time period examined.

In summary, to-date the evidence on the persistence of spatiality of tourism activities appears to suggest a difference between (1) domestic and international tourism and (2) tourism in matured and emerging tourism markets, and that domestic and mature markets are spatially more stable. In the context of a relatively mature domestic tourism market, what causes and processes underlie this empirical regularity in the spatiality of tourism? Specifically, can tourism develop without strong factor endowments as long as there are strong economic agents like airlines, or are factor endowments destiny for tourism development? The paper first aims to examine the persistence of the spatiality in tourism over time in this context. Given the measures on the level of spatial persistence, the second and more substantive aim is to examine competing theories that may explain such empirical regularity.

We investigate the potential theories by analysing how the spatial distribution of tourism behaves following an exogenous shock. As randomised experiment is not possible in these settings, the shock acts as an accidental 'treatment' that creates a situation where different theoretical predictions can be more clearly observed and discerned; therefore, tested with greater confidence. In this quasi-experiment (as often called in the economics literature), the shock/treatment we use is the collapse of a major legacy airline in Australia at the turn of the century. This is a particularly relevant case to consider when examining the aviation-tourism dynamics because not only that aviation capacity has been compromised, the capacity gap was then replaced by a new entrant who adopted a low-cost airline business model. Thus, this history provides for a unique setting where aviation conveniently serves a dual role as (1) a shock in the tourist distribution system through the collapse of a legacy carrier, and (2) an agent of spatial change in tourism through the emergence of a low-cost carrier in lieu of the collapsed legacy carrier. Ultimately, the paper is a preliminary attempt to shed some light on the degree to which the spatial distribution of tourism is shaped by intrinsic characteristics of the destination such as physical attributes or shaped by the interactions between economic agents such as airlines. Regardless of the nature of the results, the findings will have implications for tourism policy.

Theoretical background

Although many mechanisms can be responsible for the spatial distribution of tourism activities, the field of economic geography can help narrow the number of potential candidates. Consider, for example, the rank-size distribution (Zipf coefficient and power law) observed in tourism. One of the earliest applications of the power law in tourism was by Ulubasoglu and Hazari (2004). They rank the inbound tourist arrivals in 89 countries between 1986 and 1990 and find a near perfect (98% of the variation) fit of the splined least-squares regression line. Ulubasoglu and Hazari (2004) invoked the random growth theory and locational fundamental theories to explain the distributional pattern.

The former is originally due to Simon (1955) and later developed by Gabaix (1999) to show that simple stochastic processes can result in the Zipf coefficient of the city sizes (Davis & Weinstein, 2002). Building on Gibrat's law, Gabaix (1999) introduces a random walk process with a barrier that naturally eliminates cities below a minimum size, thereby producing an analytically tractable model that explains the emergence of the Zipf coefficient from the stochastic processes of Gibrat's law. Ulubasoglu and Hazari (2004) test the inbound tourism growth rates of different countries and find evidence consistent with Gibrat's law.

The latter – the locational fundamentals theory – suggests that the factor endowments determine the location of economic activities. For example, the proximity to natural harbour creates conditions conducive for growth in trade, and places of unique natural beauty tend to attract tourism. As noted by Davis and Weinstein (2002), however, "in contrast to random growth theory, the locational fundamentals story predicts that the size of specific locations should be robust even to large temporary shocks" (p.1270). This is because many natural advantages remain constant over time and even if there is a 'large shock', such as a substantial downturn in tourism demand due to an economic crisis or a major disruption in the mass transport systems, the effect will be temporary and the spatial distribution of tourism demand will return to the 'long-run' pattern.

In addition to random growth and locational fundamentals, another important process responsible for spatial concentration and dispersion is a family of theories concerning increasing returns (Davis & Weinstein, 2002). Increasing returns can be defined as the combined effects of two strands of literature; the system of cities literature, which emphasises knowledge spillover, labour market pooling and transport cost as forces of concentration/dispersion, and models of geographical economics (alternatively referred to as

[1] For instance, power law holds outside the spatial context such as in the way actors in the tourism sector are networked (Baggio, Scott, & Cooper, 2010) and in the distribution of words to describe a destination image on the internet (Pan & Li, 2011).

new economic geography) (Gabaix & Ioannides, 2004). The latter shows how increasing returns, imperfect competition, non-zero transport costs, endogenous firm location choice and endogenous demand come together to produce a model that traces how two seemingly similar regions may evolve into a core-periphery structure (Head & Mayer, 2004). Some of these economic properties suggest that temporary shocks and interventions in the economy can have permanent and (spatially) irreversible effects. The initial advantages accumulate and can persist over time even if the underlying economic factors were to change. Although rare, some of these ideas have been invoked in the study of aviation-tourism relation. An example is Papatheodorou and Arvanitis (2009) where deregulation of the aviation sector in Greece (representing reduced transport cost/barrier), along with the advent of low-cost carriers (increasingly mobile factor of production), was viewed as a potential environment where peripheral tourism destinations in Greece could overcome 'agglomeration shadows' cast by larger counterparts.

As noted by Davis and Weinstein (2002), the theories offer some predictions on how the temporary shock affects the spatial distribution of economic activities. They show that by looking at how the system behaves in response to exogenous shocks, it is possible to gauge how important the competing theories are in explaining the observed pattern of spatiality in a given economic activity. They state that "pure random growth theory predicts that growth follows a random walk – all shocks have permanent effects. By contrast, the locational fundamentals story holds that so long as the shock is purely temporary, even the strong shocks should shortly be reversed, as the advantages of the particular locations reassert themselves in relatively rapid growth rates on the path to recovery" (p.1271). If the geographical economics processes (i.e., increasing return theories) are at work, one must rely heavily on path dependence to explain spatial persistence even after a shock (Davis and Weinstein 200). They undertake an experiment to discern the theory most consistent with observed data: they examine the population distribution in Japan over a 8000-year period and then examine whether, or how quickly, the population distribution pattern return to its historical pattern following the shock of World War II bombing of Japanese cities. They find evidence of increasing regional specialisation during the industrialisation period (where increasing returns is expected to operate) and full recovery to pre-war regional population densities within 13 years of bombing. They conclude that the intrinsic characteristics of the locations (e.g., locational fundamentals) establish the spatial pattern of population whereas increasing returns help regions specialise.

As explained in the next section, this study follows this line of methodological approach where the persistence in the spatial pattern of tourism distribution in Australia over a 19-year period is measured and analysed. Using a major airline's collapse, which resulted in the shrinking of Australian domestic aviation capacity by 10% in one year (2000/01–2001/02), we investigate the applicability of the theories in explaining the spatial distribution of tourism. The time series does not contain a major shift in industrial processes therefore it is not possible to directly examine the geographical economic theories. However, as will be seen, the change in the airline business model offers a potential explanation for some of the reshuffling occurring at the individual destination level.

Methodology

Measuring spatial distribution of tourism

Three measures are used in this paper. The concentration ratio is the combined share of the four largest tourism destinations for a given year. Gini index is well known and its calculation method is not reproduced here. A value close to one means high level of concentration and zero means all destinations have equal market share. The power law exponent (of which Zipf coefficient is a special case) can be estimated by$P(x) = \frac{C}{x^{\alpha+1}}$ where the power law distribution ($P(x)$), which is a probability density distribution, is a function of constant (c), rank (x), and the power law exponent ($\alpha + 1$). α can be obtained by ordinary least squares regression of $ln\,(size\ of\ tourism) = \ln\,(constant) - \alpha\, ln\,(Rank)$, or sometimes $ln(Rank)$ is placed on the left-hand-side of the equation in which case the estimated coefficient would be $1/\alpha$. Size of tourism is measured by the number of tourist trips to the destination. Zipf coefficient is found when α is "one".

Analysing the persistence of a shock

We characterise the research problem in the following equation as done by Davis and Weinstein (2002) who analysed the population shares of Japanese cities. Consider the log-transformed share of tourism destination i at time t of the total tourism market at t, s_{it}, which has an observed time-invariant component (its initial share, M_i) and a stochastic component ($\varepsilon_{i\,t}$). A system characterised as such changes from time t to t + 1 by

$$s_{i\,t+1} - s_{i\,t} = (M_i + \varepsilon_{i\,t+1}) - (M_i + \varepsilon_{i\,t}) = \varepsilon_{i\,t+1} - \varepsilon_{i\,t} \tag{1}$$

The changes in the stochastic component are thus the key variation of interest. We will call them 'deviation' from initial share where the deviations contain unobserved influences on the size of the destination market share. When there is a one-off shock, the shock may have a lasting effect on the system. This persistence of a shock on $s_{i\,t}$ can be modelled as

$$\varepsilon_{i\,t+1} = \theta\varepsilon_{i\,t} + z_{i\,t+1} \tag{2}$$

where θ is the portion of deviation in the last period that carry over to the current period, which is an indication of the persistence of temporary shocks in the tourism distribution. $z_{i\,t+1}$ is the shock at $t + 1$. In other words, Eq. (2) states the deviation in the destination i's market share measured in $t + 1$ from M_i, $\varepsilon_{i\,t+1}$, at time $t + 1$ is the sum of (1) the residual remaining from the deviation at time t, $\theta\varepsilon_{it}$ and (2) the new shock $z_{i\,t+1}$ taking place at time $t + 1$. The model assumes that the shock is independently and identically distributed. It also assumes θ to be constant over time. That is, the deviation 'decays' at the same rate for all periods.

Combining the model of how a system evolves (Eq. (1)) and a model of how the shock is absorbed in the system (Eq. (2)), the following results.

$$s_{i\,t+1} - s_{i\,t} = (\theta - 1)z_{i\,t} + z_{i\,t+1} + \theta(\theta - 1)\varepsilon_{i\,t-1} \tag{3}$$

The two theories introduced in the previous section (the random growth theory and locational fundamentals theory) can be distinguished by estimating the θ in the above equations. In Eqs. (2) & (3), if $\theta = 1$, the deviations do not decay, and the model becomes a random walk (nonstationary) process where the temporary shocks have a permanent effect in the system. A θ that is statistically 1 will be suggestive of a random growth theory. If $0 \le \theta < 1$, then this is an indication that the effect of shock dies out. The magnitude of θ will show the speed of the decay (where value closer to zero means faster decay). This will mean that there is a mean reversion tendency in the destination market share, signalling that the system is recovering to its initial state, although new shocks may appear consecutively and create further disruptions. Therefore, when these shares are affected by an innovation/shock, there may exist a structural reason why these disruptions will only be temporary. In our case, the hypothesised structural reason is the locational fundamentals.

The temporary shock

The temporary shock, $z_{i\,t}$, needs to be accounted for in estimating the value of θ in Eq. (3). Given data on the spatial distribution of tourism (measured by the number of visitors per destination region), the key challenge is the identification of an event that represents a temporary shock in the tourism distribution system. This leads us to one of the determinants of the spatiality of tourism in Australia, which involves various attributes of aviation such as availability, price and service quality (Koo, Lim, & Dobruszkes, 2017).

As shown in Fig. 1, Australian domestic aviation has experienced at least two nation-wide events over the past 30 years. Most notably, the introduction of the domestic aviation deregulation in the 1990 has resulted in pilot strikes and subsequent (temporary) drop in aviation services. More recently, a major shock in aviation was the collapse of the Ansett Australia airline, which had > 40% of the market, in 2001 (Forsyth 2003). The volatility continued to at least March 2002 as there was a short-lived revival. The collapse of the carrier resulted in a 10% reduction in total domestic aviation seat capacity year-on-year. Ansett was one of the two main legacy carriers of Australia at the time along with Qantas Airways. A third domestic carrier was Virgin Australia (formerly Virgin Blue), which was established in FY2000. Due to the unavailability of a longer tourism data series, which dates back to FY1999, we have chosen the collapse of Ansett as the temporary shock.

The grounding of Ansett air services affected most regions negatively although to a different extent (see Fig. 2); between FY2001-FY2002 reduction in seat capacity occurred across 42 of the 45 airports with scheduled domestic air services ranging between 5% growth to 40% reduction with the median percentage change of −16%. Also, their recovery rate has been different. Notably, Uluru (formerly Ayers Rock), which is a major tourism destination in the centre of the Australian continent, has experienced 17% decline in domestic aviation seat capacity year-on-year following Ansett's exit from the market and has yet to reach the pre-Ansett collapse level in FY2017. On the other hand, Cairns, which is a major gateway to the Northern part of the Great Barrier Reef, experienced 11%

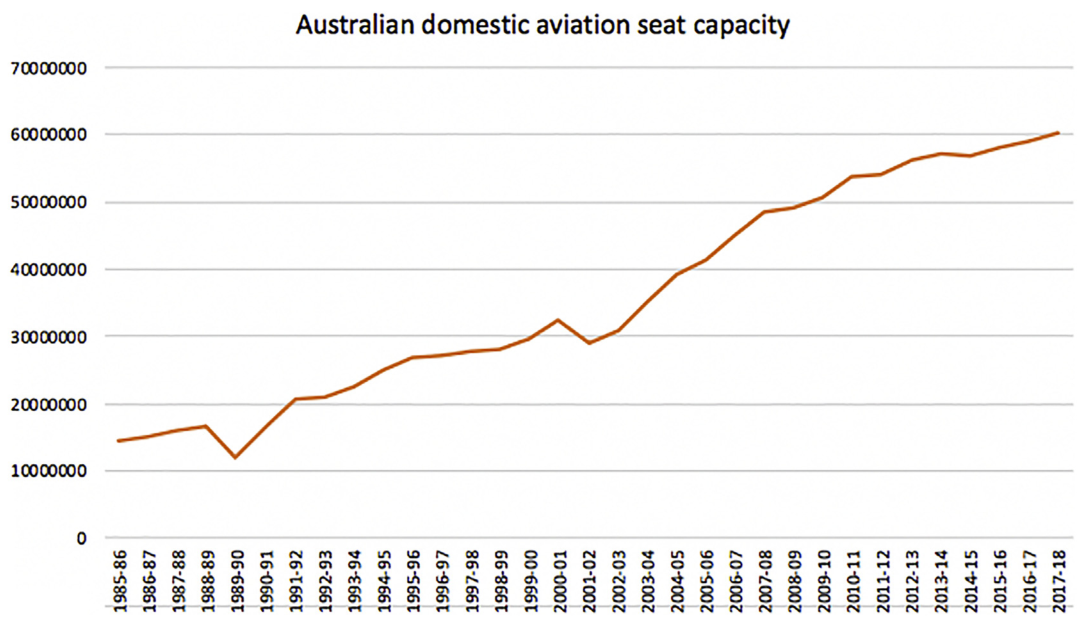

Fig. 1. Domestic aviation capacity in Australia FY1986-FY2018.
Source: Based on data from Bureau of Transport and Regional Economics, Australian government.

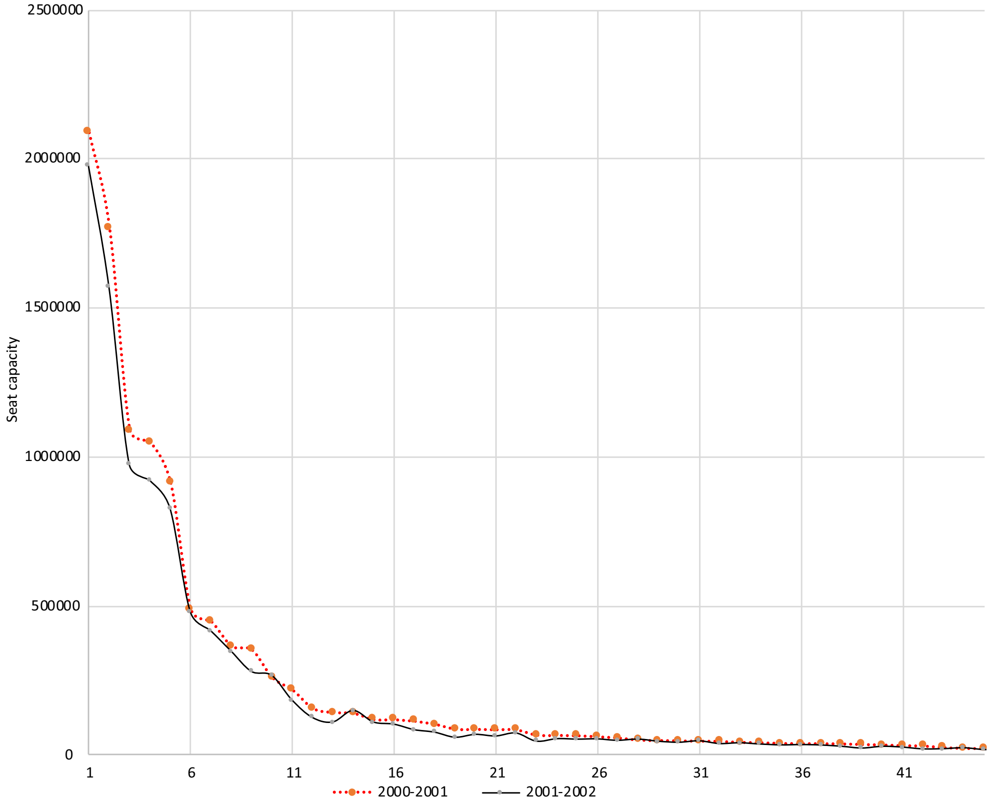

Fig. 2. The effect of Ansett collapse on airport capacity (ranked largest airport to 45th airport).
Source: Based on data from Bureau of Transport and Regional Economics, Australian government.

decline in seat capacity year-on-year but recovered to the pre-Ansett collapse level within a year. By FY2017, 39 of the 45 airports have experienced an increase in capacity compared to the pre-collapse level with the growth rate ranging between −61% to 737%. Based on knowledge about the geographic characteristics of the regions the airports are situated within, it is possible to infer that the strongest growths were evident among state capital cities, land-locked regional centres and cities along the Eastern coastline of Australia – many of which have strong tourism developments.

Using the fully enumerated aviation capacity data it was discerned that the 'shock' period was FY2001-FY2002 where the decline in capacity mostly occurred. However, the symptoms of the shock were developing earlier when Air New Zealand acquired Ansett in early 2000. Therefore, for a more comprehensive coverage of the shock, the study examined FY2000-FY2002 as well (results shown in Appendix). As can be seen in Fig. 1, there had been no other period since 1990 where the nation-wide aviation capacity fluctuated so much as it did during Ansett's exit. Thus, if the shock is to be used as the direct estimate of z_{it}, it would be measured by the tourism destination growth rate, $s_{i\ 2002} - s_{i\ 2001}$. All years noted in the subcripts are financial years. The dependent variable would be the post-Ansett collapse growth rate of tourism destinations; for example, $s_{i\ t+1} - s_{i\ 2002}$ if the post-collapse period of concern is t and $t + 1$. Thus, the regression equation estimated is

$$s_{i\ 2003} - s_{i\ 2002} = (\theta - 1)\tilde{z}_{i\ t} + e \tag{4}$$

where the proxy $\tilde{z}_{i\ t}$ is $s_{i\ 2002} - s_{i\ 2001}$ and error is iid. This means we want to examine how much of the variation in the growth rate between FY2003 and FY2002 across destination i can be attributable to the growth rate during the shock. The estimated coefficient of interest would be $(\theta - 1)$. A coefficient of -1 indicates that θ would be zero and therefore the spatial tourism system has fully recovered to its pre-shock state by FY2003 (i.e., within one-year after the shock). Coefficient between -1 and 0 will mean partial recovery by FY2003.

Data

The spatial dispersal of domestic tourists is measured by the annual visitor numbers in each tourism region. Tourism region is an artificial boundary used by regional and State/Territory tourism organisations for administration and marketing. The geographic information about each of the 76 tourism regions is available from Australian Bureau of Statistics (2018). National Visitor Survey (NVS) data managed by Tourism Research Australia (Australian Trade and Investment Commission (Austrade) of the Australian government) is used. The best time series available is a 19-year period between FY1999-FY2017. The survey is based on a random

Table 1
Concentration ratio, Gini index, and Power law exponent.

	Gini	Share of top four regions	Log rank (trips)	se
FY1999	0.426	0.276	−0.711	0.022
FY2000	0.430	0.272	−0.722	0.025
FY2001	0.435	0.287	−0.724	0.021
FY2002	0.437	0.280	−0.735	0.026
FY2003	0.440	0.281	−0.737	0.024
FY2004	0.434	0.271	−0.731	0.026
FY2005	0.435	0.275	−0.730	0.025
FY2006	0.440	0.289	−0.732	0.023
FY2007	0.438	0.285	−0.731	0.024
FY2008	0.442	0.291	−0.737	0.023
FY2009	0.452	0.299	−0.753	0.024
FY2010	0.442	0.285	−0.739	0.025
FY2011	0.461	0.304	−0.768	0.023
FY2012	0.438	0.293	−0.728	0.022
FY2013	0.444	0.295	−0.741	0.024
FY2014	0.452	0.303	−0.756	0.025
FY2015	0.440	0.299	−0.735	0.025
FY2016	0.442	0.296	−0.742	0.026
FY2017	0.439	0.297	−0.733	0.024

sample of approx. 100,000 domestic Australians each year (Austrade, 2013). As tourism regions size differ, we also use the tourism density information (calculated by the number of visitors divided by the size of the tourism region in square-kilometres) in addition to the number of visitors.

Results

Persistence in the aggregate pattern of spatial distribution of tourism

As shown in Table 1, the concentration ratios (the share of top four regions) and the Gini indices remain relatively stable over time. There is strong evidence of power law with a coefficient of 0.73 with a strong fit ($R^2 = 0.95$). This exponent is stable across the 19 years examined. The high R^2 value also indicates that the rank of a destination can be used to predict with substantial accuracy the actual number of domestic visitors to that destination region. This is shown graphically in Fig. 3. When tourism density is used as the main method of measurement, the coefficient of "1.4" was obtained. The stability of the coefficient across time is evident regardless of the method used to measure tourism size.

Effect of the shock on the aggregate distribution

To gain a more precise understanding of how the aviation shock has affected the spatiality of tourism, we estimate the model specified in Eq. (3). Our focus is to study the correlation between the post-Ansett growth rate and the during-shock growth rate, which contains information on how much and how fast the system had recovered from the shock.

As explained previously, the coefficient on the airline shock variable is an estimate of the term, $\theta - 1$ in Eq. (3). θ represents the

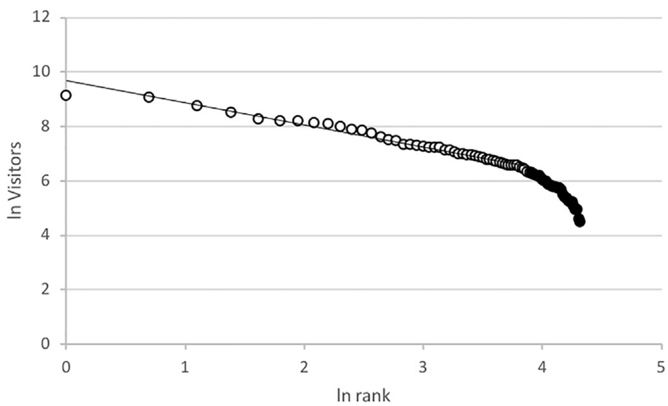

Fig. 3. Log-rank log-size plot: domestic tourism in Australia 2017 – log (visitors) against log rank of destinations (white dots represent the largest50 destinations and black dots represent the remaining regions).

Table 2
Regression results: estimated $(\theta - 1)$ from FY2002-FY2003 to FY2002-FY2017.

	Constant	se	Coefficient on θ-1	se	R^2
FY2003–2004	0.002	0.015	−0.606	0.086	0.404
FY2003–2005	0.010	0.015	−0.589	0.086	0.386
FY2003–2006	−0.007	0.015	−0.636	0.089	0.409
FY2003–2007	−0.026	0.020	−0.535	0.119	0.215
FY2003–2008	−0.016	0.019	−0.656	0.109	0.331
FY2003–2009	−0.024	0.019	−0.813	0.112	0.417
FY2003–2010	−0.033	0.022	−0.880	0.131	0.379
FY2003–2011	−0.052	0.022	−0.559	0.126	0.210
FY2003–2012	−0.026	0.021	−0.503	0.120	0.192
FY2003–2013	−0.043	0.020	−0.713	0.119	0.325
FY2003–2014	−0.042	0.024	−0.641	0.139	0.223
FY2003–2015	−0.009	0.022	−0.354	0.130	0.091
FY2003–2016	−0.010	0.024	−0.574	0.142	0.180
FY2003–2017	0.004	0.023	−0.476	0.135	0.145

remaining fraction of the shock, which tells us the degree to which the system has recovered from the shock. An estimated coefficient of zero (therefore, $\theta = 1$) means the temporary shock has a permanent effect – there is no relationship between airline shock and future growth rates of tourism. That is, the system does not return to its pre-shock shape at all, rather Eq. (3) becomes $s_{i\ t+1} - s_{i\ t} = z_{i\ t+1}$, which means the evolution of the system is the shock. Thus, this extreme case supports the random growth theory.

On the other extreme, the coefficient of negative one (therefore, $\theta = 0$) means that the post-shock growth rate is exactly the same amount as the during-shock growth rate, but in the opposite direction, i.e., $s_{i\ t+1} - s_{i\ t} = -z_{i\ t} + z_{i\ t+1}$. That is, the share of each region has reverted to the pre-shock value. Put differently, the $\theta = 0$ suggests that the effect of the shock has fully dissipated in the tourism distribution system by the specified time period. In such a case, the evidence is consistent with locational fundamentals theory because $\theta = 0$ suggests there is a tendency to revert to a deeply rooted spatial pattern, which can be influenced by fundamental factor endowments such as physical and human geography, i.e., tourism is positively correlated with population distribution, tourism attractions such as Sydney's harbour and Melbourne's Great Ocean road, or Queensland's various gateways to the Great Barrier Reef will remain popular over time. These endowments cannot be replicated easily elsewhere; therefore, there will be a structural push towards recovery following a shock in the tourism distribution system.

A coefficient between these extremes (i.e., $0 < \theta < 1$) indicates a partial dissipation (recovery) within the period examined. In such a case, the destination market share is stationary, and therefore has a tendency to revert to the mean although not to its full extent. There are two possibilities as to why this happens: 1) the system was recovering but requires a longer period to return completely to the pre-shock state, or 2) the nature of the shock partially involves a permanent effect as well as mean-reversion effect, suggesting that the spatiality of tourism flow to some extent has permanently shifted.

For the results in Table 2, the specified post-shock period is FY2002-FY2003. Direct interpretation of the coefficient is as follows. A $(\theta - 1)$ coefficient of -0.61 translates to a θ of 0.39. The results show that one year following the airline shock, the destinations on average have recovered 61% of the effect of the shock while 39% of the shock persisted. Specifically, destinations who gained share during the shock on-average lost 61% of the gain in the post-shock period and destinations who lost shares on-average recovered 61% of the loss in the post-shock period. As discussed above, we need to distinguish between the two possible causes of the coefficient between 0 and 1 - whether the period (FY2002 – FY2003) was too short for the system to achieve full recovery, or the shock had a partially permanent effect. Naturally, we attempted to extend the post-Ansett period defined in the regression to see if a longer time period will capture any further recovery. This is done in the remaining rows of Table 2 where regression Eq. (4) is repeatedly estimated with $\tilde{z}_{i\ t}$ remaining unchanged but each successive dependent variable $s_{i\ t+k} - s_{i\ t}$ incrementally changed every regression such that k increases by one every regression i.e., the interval of the post-shock period increases by one year.

The coefficient progressively drops and approaches -1 reaching -0.88 during FY2002-FY2010. The results suggest that the effect of the shock almost fully dissipated but for 12% ($\theta = 0.12$). Based on the coefficient, one can model the recovery by calculating the average per annum dissipation rate: $0.12\hat{}((t + k)/9)$ for time t + k with nine indicating the number of years since the shock, i.e., FY2010. From this we get the rate to be 0.79, indicating 21% of the shock remaining from the previous year dies out each consecutive year until 2010. After 2010, the coefficient begins to fluctuate again, potentially suggesting another shock took place and reshuffled the system in 2010 and beyond. Fig. 4 shows -50% recovery within two years of the shock (0.12ˆ(3/9)) and 76% within five years (0.12ˆ(6/9)). As can be seen in Appendix, increasing the shock period interval from FY2001–2002 to FY2000–2002 does not change the nature of the findings with near full recovery still occurring within nine years.

Discussion

This paper's first finding is that the aggregate tourism distribution over a 19-year period remainedrelatively constant. This persistence implies that the Ansett shock was insufficient to bring the spatial system out of its natural state. The modelling results have shown the tendency for destinations to revert to its past spatial pattern after a shock, which is evidence consistent with locational fundamentals theory. Despite strong total seat capacity increases in the years immediately following the shock as shown in

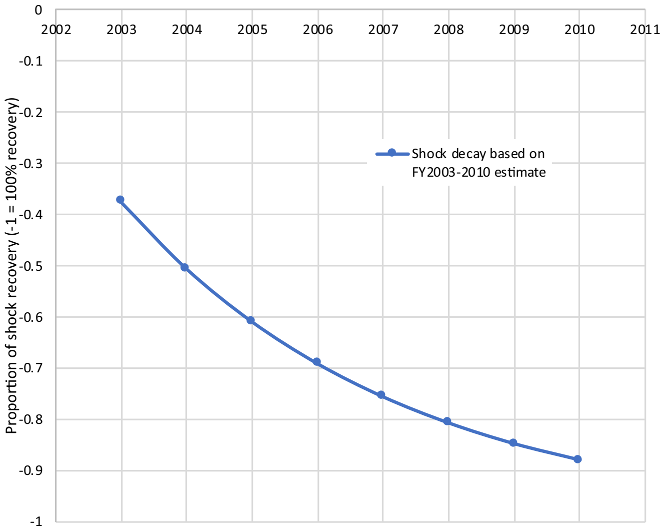

Fig. 4. Estimated $(\theta - 1)$ from FY2002-FY2003 to FY2002-FY2017.

Fig. 1, the system took 8–9 years for full recovery. Below provides an account of the changes that took place in the post-shock period.

The role of aviation in the spatial distribution of tourism activities

The exiting of Ansett airlines – a legacy carrier – has resulted in an abrupt reduction in domestic aviation capacity. This has presented a start-up Virgin Blue (now Virgin Australia), which entered the market just before the collapse of Ansett, with opportunities to fill a significant capacity gap in the market. Since Virgin Blue adopted what one may regard as the ‘typical’ low-cost carrier business model at the time (e.g., uniform B737 fleet, one class, point-point shuttles, no-frills, etc.), the shock offered opportunities for partial reset in the air transport network.

Specifically, according to domestic seat capacity data, airport seat capacity growth during the nine years following the shock (FY2002–2010) had been double- the growth that occurred during the nine years prior to the shock (FY1992–2000). This growth has affected airports differentially with the largest gains in market share occurring among many regions; for instance, in FY2002–2010 three (Brisbane, Hobart and Perth) of the eight state/territory capital cities were among the 44 airports that gained market share with the remaining five cities losing market share. Whereas, during FY1992–2000, 30 airports gained market share, and five of the capitals gained while the remaining three capitals lost market shares. Notably, among the main tourism destinations, Uluru and Cairns gained shares in FY1992–2000 but experienced share loss in the decade after the shock. Conversely, Gold Coast, which experienced the second-largest share loss in the decade pre-shock, experienced the largest gain in the decade post-shock. Thus, consistent with observations made in earlier studies (e.g., Koo, Wu, & Dwyer, 2010), there was a period of growth post-Ansett that brought about greater capacity and competitive dynamics on existing dense routes (mean reversion tendencies), as well as the expansion of turbojet air services into tourism destinations, regional centres, and towns affiliated with mining boom that were not in the interest of the legacy airlines previously or were served with smaller turboprop aircraft (a force for permanent shift).

The examples provided in the preceding paragraph are based on fully enumerated airport capacity data. These changes in the air transport environment are reflected in the tourism data as well; for example, air travel modal share by domestic visitors increased from 13.9% in FY1999 to a peak of 23% in FY2009 before stablising around that level beyond FY2011. During the post-shock decade (FY2001–2010), domestic trips *decreased* by 4.6 million trips, while domestic trips using air transport as the main mode of travel *increased* by 6 million trips suggesting a combination of generative (new air travel induced tourism) and substitution effects (modal shift from ground to air).

Although spatially differential ripple effects of the shock ensued, on average, the estimated model shows a full reversion to the pre-shock level within nine years after the initial event. Furthermore, as revealed by Table 1, the spatial concentration levels in aggregate remained relatively stable over the 19 years. This means the probability density function of tourist distribution among destinations are stable yet the micro-dynamics hidden within the distribution can be very active. For instance, between FY1999-FY2017, 48/50 tourism regions examined in the analysis experienced changes in the ranking at some point, ranging from a destination ranking change of one placing and as large a leap as up to 27 placings. Understandably, the changes in the ranking were more prevalent among smaller destinations; however, larger tourism destinations such as Brisbane, North Coast (New South Wales), Adelaide, Perth, Sunshine Coast and Gold Coast experienced these changes as well.

The airline shock is interesting in that it not only gives us a unique opportunity to examine the reaction following an aviation event on tourism, it also provides the opportunity to potentially attribute the spatial change in tourism to the significant changes in the way airlines organise their network, i.e., changes in the airline business model. As alluded to above, following the shock the airlines have helped the spatial distribution of tourism to revert to its ‘mean’ by recovering the capacity in the main/traditional markets; but the shock has also created the opportunities to reshuffle the spatiality of tourism.

Implications for research and destination management

For tourism research, the findings are suggestive of a need to take a network-wide approach when assessing the impact of aviation on tourism demand. Understandably, empirical tourism research focused on quantifying the ceteris paribus effect of aviation and related factors on tourism demand. Studies of tourism demand use various quantitative and econometric techniques to estimate the independent effects using single origin-destination pair or panel data. However, as reviewed in Koo, Lim, and Dobruszkes (2017), the network characteristics of aviation is often not explicitly considered in tourism demand research. Airline's capacity allocation behaviour is subject to its network-level decisions, which means the scheduling and flight allocation decisions aim for optimisation of performance at the network level. Thus, for a more comprehensive assessment of aviation's spatial tourism impact, we need to cast a wider net than a limited set of origin-destination pairs. The stability of spatial distribution means that an increase in one part of the distribution is accompanied by distribution-wide changes – such that it is proportionate to a specific power exponent. To this extent, the study's finding suggests when designing a study of aviation's tourism impact, it is useful to consider whether the analytical tool employed is measuring the absolute increases in tourism demand to that destination or its increases relative to other destinations. The focus on the latter will provide information about whether or not the increases are sufficient to influence the destination's rank.

As for theoretical development in the spatiality of tourism, similar to Ulubasoglu and Hazari (2004), this result highlights the importance of locational fundamentals. It was not possible to test the theories concerning increasing returns explicitly. However, there is evidence consistent with increasing returns where the regions with tourism specialisation experienced strong air transport growth in the decade following the shock. For example, Gold Coast increased its domestic air capacity share from 2.87% to 4.46%; Whitsundays (Proserpine airport) 0.09% to 0.22%; Fraser Coast 0.05% to 0.14%; and Sunshine coast 0.38% to 0.81%. This evidence is consistent with the idea that the entry of low-cost carrier business model has partly helped the regions tap into tourism as an industry of specialisation. Also, as argued in Davis and Weinstein (2002), resilient spatial persistence means path dependence may be of relevant theoretical possibility concerning increasing returns. Path dependence also occurs in the spatial configurations of airports (Burghouwt 2007), and the domestic aviation shock may have partially reset some of these dependencies through the replacement of the legacy carrier with a completely new low cost airline model. However, this is only an assertion and further studies are required to directly test for empirical evidence; ideally, this will involve a dynamic measure of air transport network (and air travel costs) and measure(s) of tourism specialisation of regions over longer period of time.

The implication for destinations wanting to materially improve their performance (assuming market share is the main concern) is for them to focus on increasing their ranking. For destinations to grow with longevity, they need to outcompete substitute destinations by taking their rank. This does not change the power exponent, rather results in the re-ordering of which destination is ranked where. This is a useful thinking tool for destination managers. For example, Guo et al. (2016) noted that one of the practical implications of the persistence in the rank-size distribution in the inbound tourist flows to top 100 Chinese cities is it can be used to observe and identify irregular patterns of growth. They argued that such observations can be used to inform appropriate policy response. If one accepts that aggregate distribution remains relatively constant over time (as measured by the power exponent), destination managers should consider how facilitating greater quantity and quality of air services links will help the destination improve its *ranking* in addition to the absolute measures of arrivals and spend.

Some of these ideas have been formally tested in Lau, Koo, and Wu (2019). They used finite Polya-urn process (a type of preferential attachment process) as a modelling device of the spatial distribution of tourism in Australia. This spatial distribution generated three distinct destination groups. The study concluded that the destination can aim to improve its ranking by acquiring a characteristic(s) that competing destinations within the same group does not possess. One such characteristic within the policy sphere is transport infrastructure and accessibility.

Conclusion

This paper attempted to learn how aviation influences the distribution of tourist flow by characterising the distribution of tourism demand as a spatial system. In doing so, the research first examined the stability of the geographic dispersal of domestic visitors in Australia by using the Gini index and power law exponent. We find evidence of power law with the estimated rank-size coefficient of 0.73 and 1.4 for domestic visitor counts and tourism density, respectively. The measured spatiality suggests high degree of spatial persistence between FY1999 and FY2017. To understand why such empirical regularity arises in the spatial distribution of tourism, we have applied an analytical strategy to help discern the applicability of two competing theories: locational fundamentals theory and random growth theory. The method involves quantifying how the spatial distribution of tourism is affected (and how fast it recovers) by an exogenous shock in the tourism distribution system. By research design, aviation (the collapse of a major legacy airline) provided for this ‘shock’ in the tourism system.

The evidence has shown partial recovery to the pre-shock state in the years immediately following the shock (approx. 50% recovery within two years), and near-full recovery within nine years of the shock, providing evidence consistent with locational fundamentals theory. We found that, because the vanished legacy carrier was replaced by a low cost carrier, the recovery occurred while a simultaneous reshuffling of the aviation network also occurred. Although not directly tested due to data constraint, the new post-shock aviation growth in regions known to specialise in tourism enables us to tentatively assert that it is the combination of an efficient airline business model and increasing returns that partly caused the spatial reshuffle. To develop a joint understanding of aviation and the tourism distribution system, it is insightful to consider a mix of theories, including locational fundamentals, random growth hypotheses as well as geographical economics models.

Where possible, research along this line should examine substantially longer time series to maximise the chances the dynamic consequences of shocks can be fully revealed. The shock in the system is modelled against a benchmark - the choice of which was constrained by data availability in this study. To some extent the benchmark is arbitrary because without the longer time series it is difficult to know M_i in Eq. (1) with certainty. In addition to increasing the power of the empirical tests, the longer time series should also allow for a greater sample of shocks from different sources such as the currency crisis, natural disasters, global health scare and so on, to be assessed.

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Appendix A

Table 2
Is the result when the shock period is defined as FY2001–2002. The appendix shows the result when the shock period is FY2000–2002.

	Constant	se	Coefficient on θ-1	se	R^2
FY2003–2005	0.021	0.017	−0.441	0.131	0.133
FY2003–2006	0.004	0.017	−0.663	0.126	0.273
FY2003–2007	−0.017	0.020	−0.678	0.152	0.212
FY2003–2008	−0.005	0.020	−0.705	0.148	0.234
FY2003–2009	−0.009	0.022	−0.702	0.168	0.191
FY2003–2010	−0.019	0.024	−0.972	0.180	0.284
FY2003–2011	−0.043	0.022	−0.672	0.163	0.186
FY2003–2012	−0.018	0.020	−0.658	0.152	0.201
FY2003–2013	−0.031	0.021	−0.850	0.157	0.283
FY2003–2014	−0.031	0.025	−0.692	0.185	0.159
FY2003–2015	−0.003	0.022	−0.423	0.167	0.079
FY2003–2016	0.000	0.025	−0.587	0.189	0.116
FY2003–2017	0.004	0.023	−0.493	0.143	0.140

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