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The evolution of 'Airbnb-tourism': Demand-side dynamics around international use of peer-to-peer accommodation in Australia

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ABSTRACT

This paper investigates the evolution of Airbnb and other peer-to-peer accommodation use by international visitors in Australia over 12 quarters, from 2015 to 2017. It applies a dynamic logistic regression to investigate how user characteristics associated with peer-to-peer accommodations evolve over time. This study contributes to understanding the development of consumption patterns around the Airbnb phenomenon. It is also the first paper to investigate the consumer dynamism in the peer-to-peer accommodation sector beyond Airbnb. Findings indicate that Airbnb consumption has evolved, showing patterns of convergence and 'normalisation', supported by a growing Asian participation and increasing regional stays. This dynamism is not shared by other platforms, which suggests peer-to-peer accommodation is becoming a single-platform story rather than a thriving broader accommodation-category.

This article also launches the Annals of Tourism Research Curated Collection on Peer-to-peer accommodation networks, a special selection of research in this field.

Introduction

'Airbnb tourism' refers to the strongly increasing importance of private short term rentals through the proliferation of internet platforms such as Airbnb. Airbnb has seen demand growths in the EU and US markets of 30% and more in the most recent years to reach market shares of 4% to 5% and a market penetration of approximately 25% (Haywood, Maycock, Freitag, Owoo, & Fiorilla, 2017; Nowak et al., 2017). To provocatively call the phenomenon 'Airbnb tourism' despite the involvement of other peer-to-peer accommodation platforms emphasises the hypothesis of a strong market leader underpinning this study.

There is limited research on behaviour and profiles of Airbnb and other peer-to-peer accommodation users. Existing literature indicates that Airbnb users differ from tourists in general in terms of travel behaviour and visitor characteristics (Volgger, Pforr, Stawinoga, Taplin, & Matthews, 2018) and that they can be further subdivided into motivational clusters (Guttentag, Smith, Potwarka, & Havitz, 2018). However, the existing literature does not provide even a rudimentarily *dynamic* investigation of these consumption patterns in the light of boom to bust patterns of trends or vis-à-vis the competitive adaption of competitors. Furthermore, existing literature does not provide an analysis of whether and how the group of other peer-to-peer accommodation providers is affected by the evolution of Airbnb usage patterns. Dredge and Gyimóthy (2015), Guttentag et al. (2018) and Volgger et al. (2018) reject claims that Airbnb-tourism might be the expression of an experiential transformation of tourism (Mody, Suess, & Lehto, 2017;

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Tussyadiah, 2015) and argue that Airbnb usage is becoming increasingly normalised and is moving towards the mainstream segments of the market. However, their static analyses remain limited and bound by being one-point-in-time snapshots.

In general, there is an ongoing debate about concentration of demand through digitisation. Many offers in the internet-based economy and particularly two-sided platforms (Reinhold & Dolnicar, 2017a) such as those characterising the peer-to-peer accommodation sector have been presented as 'winner-takes-all markets' (Straub, 2015). 'Winner-takes-all' theorising suggests that best-sellers increase their consumption share over time (McGee & Sammut-Bonnici, 2002). We might expect to see such a 'superstar effect' (Rosen, 1981) with Airbnb – and anecdotal evidence does indicate that Airbnb appears to be winning, but what does this mean for consumption profiles and is it really 'taking it all'? In addition to tracing the evolution of Airbnb usage patterns it is also important to understand who the customers are who dedicatedly stick with other peer-to-peer accommodation providers ('the long tail') despite a strong market leader and the sometimes-observed self-reinforcing power of popularity (Neuts & Nijkamp, 2012).

The purpose of this paper is to track the evolution of international Airbnb user profiles as well as those of international peer-to-peer accommodation users attracted by other platforms over 12 quarters, from 2015 to 2017, in Australia. It departs from the model presented in Volgger et al. (2018) and further develops it based on a dynamic logistic regression. The paper contributes to one of the most consistent gaps in business and social science theorising, namely the inter-temporal analysis of consumption patterns in a setting of interpersonal consumption effects (Sheth & Sisodia, 1999). With its strong empirical focus, the paper contributes to explore demand patterns at the interface between market leaders and niche offers in the particular setting of peer-to-peer accommodation. The paper does not only explore the evolution of overall demand patterns over time (e.g. winner-takes-all, long tail), but also investigates which types of user profiles underpin the overall phenomena. The analysis thereby links macro-level consumption phenomena to more micro-level consumption dynamics, which is an element often neglected in existing research on demand concentration (Brynjolfsson, Hu, & Simester, 2011). It therefore contributes to better understanding the dynamics of 'Airbnb tourism', which is one of the most impacting phenomena on today's tourism and hospitality. While the paper explicitly acknowledges the usefulness of considering both supply and demand variables, its focus is limited to dynamics on the consumption side.

Dynamic consumption in networks

In this study we adopt a theoretical position long established in sociology but only more recently gaining a stronger foothold also in psychology-influenced consumer behaviour and economics, which is the study of collective behaviour (Granovetter, 1978), contagious behaviour (Dijksterhuis & Bargh, 2001) and social interactions (Durlauf & Ioannides, 2010). The underlying phenomenon is called and framed in slightly different terms in different disciplines but generally revolves around adjusting one's consumption behaviour to what others do. The phenomenon is an 'interdependence in choice' through "social process of persuasion" (Reinstaller & Sanditov, 2005, p. 506). Assuming that the consumption of an individual is often not independent of the consumption behaviour of others (Leibenstein, 1950), two types of adaption need to be distinguished: conformity and imitation contrasts with non-conformity, differentiation and deviance ('social originality') (Lemaine, 1974). On the one hand, for instance, it is palpable that internet-mediated consumption dynamics are characterised by 'network effects' with consumers increasingly concentrating their demand with a market leader (Katz & Shapiro, 1985). This 'winner-takes-all' (Frank, 1994) or 'superstar effect' (Rosen, 1981), on the other hand, contrasts with the idea of increasingly fragmented consumption as epitomised in the emergence of micro-consumption networks such as 'neotribes' (Hardy & Robards, 2015) and 'long-tails' (Anderson, 2006). To capture this fundamental contrast, we may argue that networked consumption dynamics unfold in a tension between following crowds (consuming like others) and differentiating from crowds (consuming distinctively).

Tourism research has observed these contrasting effects of collectives on individual behaviour in the context of crowds. Crowds can generate vicious cycles of progressively accumulating people, a fact often overlooked due to the prevailing negative connotation of this concept in tourism research (Neuts & Nijkamp, 2012). Crowds can be attractive because the co-presence of others is interpreted as an indicator of quality or because co-presence is perceived as pleasant due to its socializing features (Ganzaroli, De Noni, & van Baalen, 2017). However, as is much more acknowledged in tourism research, crowds can also deter people (Goodwin, 2017; van der Borg, Costa, & Gotti, 1996), and some make consumption choices specifically to distinguish themselves from the mass. To shed some light on these phenomena, we shall first exhibit four behavioural phenomena of interpersonal consumption (network externality, consumption lock in, bandwagon effect, snob effect) and then proceed to describe two consumption structures these effects may produce ('winner-takes-all', 'neotribes').

Among the main drivers of functional benefits in interpersonal consumption situations are strong externalities such as 'network externalities', sometimes also called 'conformity effects' (Durlauf & Ioannides, 2010). A network externality exists if consumption of a good provides higher and higher value as more and more consumers join in (Katz & Shapiro, 1985). Simply put, it results in a situation where "things are more worthwhile when others are doing related things" (Banerjee, 1992, p. 800). The idea becomes immediately clear if communication systems are considered, but is also very evident in business models denoted as multi-sided platforms. Airbnb and other peer-to-peer accommodation platforms can be subsumed under this type of business model as their main purpose is to connect two sides of the market. A platform's value to a user (on either side) increases the more participants it is able to enrol on the respectively opposite side (Reinhold & Dolnicar, 2017b). This is why Reinhold and Dolnicar (2017b, p. 16) argue that "the inability of many peer-to-peer accommodation networks to build a sufficiently large pool of buyers and sellers leads to them failing in the market". In addition, functional benefits in networked consumption may be influenced by lock-in effects and path dependencies, where initial set-up investments in information search, information sharing and behavioural adaptation may be capitalised on in further transactions and may result in loyalty (Schulte, 2015). Existing literature proposes switching costs, switching outcome uncertainty, relationship-specific assets, learning effects and consumer inertia (habits) as underlying mechanisms (Maréchal, 2010; Shapiro & Varian, 1999).

It is largely known that goods are not only consumed for immediate 'functional' benefits but also because of 'nonfunctional' reasons that refer to the value other individuals place on the consumption of the good, including bandwagon and snob effects (Leibenstein, 1950). While both effects may be intimately linked to an underlying social motivation of impressing peers ('demonstration effect', Frank & Cook, 2010) or simply to facilitate conversations about purchases, they represent different approaches. The bandwagon effect is driven by an underlying intention of consumers to imitate the crowd (Leibenstein, 1950). Imitating behaviour can be related to bonding reasons (Reinstaller & Sanditov, 2005), i.e. "to conform with those they wish to be associated with or in order to be fashionable or stylish" (Granovetter & Soong, 1986, p. 84); but they can also be a decision-making heuristic in situations with high degrees of uncertainty and difficult to evaluate information (Schulte, 2015). This is particularly relevant as the time and motivation of consumers to gain knowledge about competing products is often limited (Goode, 1978). Information asymmetries and the role of reputation and trust have been shown to be relevant in the peer-to-peer accommodation sector (Abrate & Viglia, 2017; Yang, Lee, Lee, & Koo, 2018; Yang, Song, Chen, & Xia, 2017), although existing research focusses on the individual seller rather than the platform. A strategy of taking consumption behaviour of others as a signal of quality (Granovetter & Soong, 1986) tends to result in 'herding behaviour' (Banerjee, 1992). This positive feedback mechanism of popularity attracting even more popularity is coined as 'superstar phenomenon' (Benhamou, 2002; Rosen, 1981). In contrast, snob effects ('reverse bandwagons', Granovetter & Soong, 1986) result from a willingness to impress by consuming things not easy to reach for the crowd (Veblen, 1899). This can result in a situation where some individuals increase consumption of a good when others decrease it, or when its price rises. Brand prominence and awareness play a role for these mechanisms to work (Han, Nunes, & Drèze, 2010), and they are not absent from the P2P field (Anwar, 2018; Scholz, 2014).

Two particular patterns which may results from the above-outlined dynamics of interpersonal consumption are 'winner-takes-all' vs 'long tails' and 'neotribes'. Although literature on winner-takes-all situations in tourism and hospitality is almost non-existent (for an exception see Pan & Li, 2011), it may be considered one of the most characteristic contemporary concentration phenomena (Frank, 1994). Winner-takes-all systems are generally characterised by very few top performers gaining a disproportionate market share, which is not simply justified by quality differences (Rosen, 1981). Such situations of winner-takes-all have become more widespread in multiple fields in recent times: It is palpable on several ends including an increasing appetite for books of famous authors, the focus on a few stars in music and sports, on elite universities or in general the overwhelming presence of celebrities in contemporary life-worlds (Frank & Cook, 2010). For example, just two brands, Google and Facebook, cover about two thirds of the digital advertisement market, with positive tendency in capturing additional market share (Rosser, 2017).

A somewhat less homogenising interpretation of today's mass market is suggested through the concepts of 'long tails' and 'consumer tribes'. Anderson (2006) argues that the mass market is best described as a 'mass of niches', which, in aggregation, results in long tail market structures. Cova, Kozinets, and Shankar (2007) make a compelling point by arguing that today's consumers consist of manifold subsets of people, 'consumer tribes', whose behaviour and consumption choices are informed by their group-specific webs of meaning and codes of communication. Such 'neotribes' can also be considered as "temporary 'micro-groups'" (Maffesoli, 1996, p. 6). Besides situations when *overall* consumption of a good is the relevant reference value, there are other situations where consumption by *selected others* (i.e. a specific peer group) is deemed more relevant, in particular when communication is compartmentalised (Corneo & Jeanne, 1999). Today, the impact of non-functional reasons for consumption is enhanced by social media communication, which allows demonstrating one's consumption behaviour more easily and widely, but may also result in increased fragmentation.

'Alternative consumption' may be driven by a willingness of belonging, but not less relevant are motivations of marking distinctiveness (Bourdieu, 1984). It is argued that the persistence of niche consumer groups is supported by socialisation processes. For instance, some platforms, including Airbnb, proactively promote the creation of consumption communities by encouraging processes of socialisation, behavioural conventions and social evaluation systems (Dolnicar, 2017a). Hence, users have an incentive to invest into a specific platform community in order to benefit most. Reciprocity within a platform community, and lock-in, might become even more accentuated in non-monetary accommodation provisioning such as CouchSurfing (Luo & Zhang, 2016; Molz, 2013), as there is no possibility for immediate settlement of debts. Not least, niche consumption may also be aided by disloyal super-star consumers in seek of diversity (Elberse & Oberholzer-Gee, 2006).

Rarely, empirical analyses have ventured to sharply link demand macro-structures such as winner-takes-all or long tails to underlying consumption behaviour, motivation or demographics. However, it appears conceivable that network externalities and bandwagon effects are more closely associated with winner-takes-all. Consumption lock-in and snob effects may instead support the emergence of long tail and neotribal phenomena. Existing research has shown that consumption waves and fashions evolve from a co-presence of these phenomena, namely some consumers trying to distinguish themselves and others aspiring to conform (Janssen & Jager, 2001). When consumer tribes are intersected with situations of winner-takes-all 'multiple equilibria' become a likely outcome and they may allow for widened peaks beyond just a handful of winners (Suarez, 2005). This study does not aspire to clearly separate the causal links between the levels either, but it investigates the overall consumption dynamics in peer-to-peer accommodation to identify macro-phenomena and to explore underlying, dynamic consumption patterns. The paper is particularly interested in who follows the market leader and who persists with long tail consumption in peer-to-peer accommodation.

The dynamic evolution of Airbnb tourism

Although in recent years the use of terms such as 'peer-to-peer accommodation', 'sharing economy' or 'collaborative economy' has grown rapidly in academic literature, no uniform definitions have ascendancy. One reason for this might be that the phenomena covered by these concepts are relatively diverse (Cheng, 2016; Heo, 2016). However, peer-to-peer accommodation shall be understood as allowing "*regular people*, who are distinct from typical business entities, to offer hospitality (by renting out their spare bedrooms or unoccupied properties) to their peers (i.e., tourists)" (Tussyadiah, 2016, p. 70f.). Web-based technologies and business models play a central role within this socioeconomic phenomenon (Dolnicar, 2017b; Pforr, Volgger, & Coulson, 2017). While Airbnb has attracted substantial research interest, much less has been done to study consumer behaviour on other platforms (for exceptions see e.g. Decrop, Del Chiappa, Mallargé, & Zidda, 2018) and, in particular, comparative efforts to scrutinise platform demand lack from existing literature. To address this gap, this paper adds a comparative perspective to peer-to-peer accommodation research by analysing demand patterns across different platforms over a number of periods.

In general, peer-to-peer accommodation platforms can be differentiated based on their business model (Habibi, Kim, & Laroche, 2016). Offering free of charge hospitality, CouchSurfing, for instance, represents one end of the continuum as it epitomises the sharing element of the continuum (Decrop et al., 2018), whereas platforms such as Stayz.com represent more of a commercial exchange between host and guest. According to Reinhold and Dolnicar (2017b), Airbnb can be positioned in the middle of that scale. Based on user-to-user interaction, Palgan, Zvolska, and Mont (2017) also provide a model of peer-to-peer accommodation platforms. In their taxonomy, they differentiate between free (i.e. CouchSurfing), reciprocal (e.g. HomeExchange) and rental (e.g. Airbnb, 9flats) peer-to-peer accommodation arrangements.

Several peer-to-peer accommodation platforms have emerged within the last decade, but few were able to firmly establish themselves in an increasingly competitive market. Today, two (or three) market leaders of peer-to-peer accommodation platforms can be identified, Airbnb and HomeAway – and perhaps Booking.com given the amount of private accommodation options it lists (Hajibaba & Dolnicar, 2017). Booking.com and HomeAway were both established prior to Airbnb (2008), clearly starting as more traditional online booking sites before converting at least partially into peer-to-peer accommodation platforms. HomeAway, which is now part of the Expedia Group, was founded in 2005 and has since concentrated its business on holiday homes. Since HomeAway has been established, its growth strategy (different to Airbnb) has been characterised by expansion through acquisitions and mergers, which led it to swallow up > 20 competitors, including Stayz Australia and VRBO (www.forbes.com/). Booking.com, established in 1996, cannot be classified as a typical peer-to-peer accommodation network (as it is dominated by professional suppliers) and will not be further considered as such within the scope of this paper. While many of the competing peer-to-peer accommodation platforms have lacked a critical mass to survive in the market place (Hajibaba & Dolnicar, 2017), a formula for success for Airbnb has been a global organic expansion. Furthermore, Airbnb has started to expand its product range and now offers new property types and also other, travel related services (e.g. experiences, restaurants). Currently the platform hosts almost 5 million listings in > 190 countries, which according to Airbnb are "more listings than the top five hotel chains combined have rooms" (airbnbcitizen, 2017, 2018).

For Australia, Tourism Research Australia (2017) points out that in 2016 "the most common website used to book private accommodation was Airbnb, with 426,000 visitors booking through the site. Other common websites used to make bookings were Stayz (12,000) Vacation rentals by Owner (VRBO, 12,000) [both operated by HomeAway] and CouchSurfing (10,000)". Next to differences in user numbers and business model (see above), peer-to-peer accommodation platforms may also be differentiated by geographical reach, the number of listings and the degree of host interaction (Hajibaba & Dolnicar, 2017). In many of these tangible dimensions, Airbnb appears to be similar to other peer-to-peer accommodation platforms. Pricing is similar as Airbnb and most other platforms have adopted (comparable) commission-based business models with hosts requesting financial payment from guests. The most prominent exception is CouchSurfing, which excludes financial transactions between hosts and guests. As Airbnb, most of its main competitors allow for direct interaction with hosts and have a broad geographical coverage. While Airbnb does offer the largest number of listings, the effective supply-side gap to its main competitor(s) is perhaps less than the stark difference in demand figures might suggest (HomeAway has about half the number of listed properties of Airbnb worldwide, and roughly a quarter in Australia) (Farnsworth, 2018; Hajibaba & Dolnicar, 2017; Haywood et al., 2017). As is often observed in literature on winner-takes-all, the extent of demand incongruities does not appear to be purely reducible to apparent quality differences (Rosen, 1981). This dominant position makes it in any case difficult for market debutants to compete with the market leaders and, in order to survive, new peer-to-peer accommodation providers have therefore adopted specialization strategies, serving special interests markets (e.g. Camplify, Misterb&b) that are often not or not adequately captured by the leader(s) (Sigala & Dolnicar, 2017). As the market impact of such adaptive strategies remains unclear, this paper contributes to strengthening the evidence base regarding market-related competition outcomes in the peer-to-peer accommodation sector.

Consumer profiles of 'Airbnb tourists'

There is limited research on behaviour and profiles of 'Airbnb tourists' (let alone other peer-to-peer accommodation users) which leads to a situation where some company marketing supported claims may establish themselves in a relatively unquestioned manner. One such assumption is that Airbnb users are a substantially different, if not an "alternative" group of tourists. While this blanket statement may never have been true, the situation is also in continued evolution and therefore any purely static analysis risks to be outdated until it gets published. This paper thus seeks to deliver a more robust assessment of consumer profiles of Airbnb users and other peer-to-peer accommodation users by looking at their evolution over several periods.

Next to some ad hoc surveys on intentions to book with Airbnb (Poon & Huang, 2017; Varma, Jukic, Pestek, Shultz, & Nestorov, 2016), Volgger et al. (2018) present a systematic comparative profiling of international Airbnb users in a specific destination context. They find that Airbnb users constitute a specific subset of visitors in particular with respect to trip purpose, age, type of travel party and the visitors' source countries. Interestingly, specificities are also found with respect to the actual activities undertaken as well as the spatial distribution of the booked accommodation(s). Other research goes much further in emphasising the 'distinctiveness argument' and promotes a notion of experiential differences between Airbnb users and other tourists, by referring to social benefits, authenticity and sustainability related aspects (Mody et al., 2017; Tussyadiah, 2015).

In contrast, Volgger et al. (2018) in line with Guttentag et al. (2018) urge for caution in overemphasising an experiential interpretation of the identified distinctive profiles as their findings portray Airbnb users as having a keen interest in exploring well-known, iconic tourism highlights of the destination. Thus, it might be wrong to describe Airbnb adopters as 'alternative tourists', as they rather seem to represent a group of visitors that extends into the progressive mainstream market, displaying tourism behaviour that Cohen (1972) refer to as 'exploring' and 'individual mass tourism'. Another common perception challenged is that Airbnb users spend less overall than non-users (Volgger et al., 2018). This parallels an early argument by Dredge and Gyimóthy (2015, p. 296) who reject claims of the collaborative economy being a "survival phenomenon" but rather assert an above-average participation of better-off people.

Guttentag et al. (2018) similarly object that Airbnb users might constitute a profoundly 'alternative' travel group driven by a primary motivation to seek novel experiences. Guttentag et al.'s (2018) clustering of Airbnb users indicates that 'novelty seekers' were indeed attracted by the unique and exciting experience and 'collaborative consumers' appreciate the interactive and authentic nature of Airbnb. However, other clusters of Airbnb users such as 'money savers' and 'home seekers' choose Airbnb for more practical reasons (including space, household amenities and price). This research further informs the emerging distinctiveness/divergence vs convergence debate in peer-to-peer accommodation consumer behaviour. While the few studies that inform our current knowledge in this area have adopted a static perspective, this is the first study to engage in a genuinely dynamic empirical analysis of peer-to-peer accommodation use. It is also the first study to differentiate and compare between use of Airbnb and other peer-to-peer accommodation platforms.

Methods

Data

This research focusses on the segment of international visitors to Australia. Available data indicates that international visitation to Australia has substantially higher shares of peer-to-peer accommodation use than domestic tourism (Pforr et al., 2017), which leads to a situation where about 50% of Airbnb bookings in Australia can be considered to stem from international markets (Deloitte, 2017). Data was taken from the Australian 'International Visitor Survey' (IVS), which is carried out on a quarterly basis by the public Australian data collection and analysis agency Tourism Research Australia (TRA). It is an extensive survey of international tourists in Australia who are sampled and interviewed face-to-face (CAPI) when they leave Australia. Interviews are carried out in the departure lounges at Australia's eight major international airports (Sydney, Melbourne, Brisbane, Cairns, Perth, Adelaide, Darwin and the Gold Coast) in four languages (English, Japanese, Mandarin and Korean) and target around 40,000 visitors ($\geq$15 years old) each year. The sample design includes proportionate stratification by airports and country of residence on a monthly basis. Since 2015, the questionnaire also contains a question regarding the use of peer-to-peer accommodation in Australia, which includes platforms such as Airbnb, 9flats, Alterkeys, BeWelcome, Couchsurfing, Flat-Club, HomeAway, Hospitality Club, Hospitality service, Pasporta Servo, Roomorama, SabbaticalHomes.com, Servas Open Doors, Sleepout.com, Stayz, Travelmob, Tripping, Vacation Rentals by Owner and Wimdu. It may be important to note that the brands Stayz, HomeAway, Vacation Rentals by Owner and Travelmob are all operated by the HomeAway company, which can be considered the main competitor of Airbnb. Following a similar model to Airbnb, 9flats and Wimdu have a particularly strong presence in Europe. Sleepout is prominent in African countries. Singapore-based platform Roomorama has stopped trading mid of 2017. BeWelcome, Hospitality Club, Servas and Pasporta Servo are similar to the Couchsurfing model and SabbaticalHomes focusses on the specific target group of academics.

For the present analysis, all collected IVS data for the three years (or twelve quarters) between 2015 and 2017 was taken into consideration. Thus, the sample is 120,679 international visitors to Australia and satisfies requirements for logistic regression analysis (Bentler & Chou, 1987). Australia attracts about 8.1 million international visitors per year for 265 million overnight stays, which accounts for about 43% of all overnight stays in Australia (Tourism Research Australia, 2018a, 2018b).

Analysis

Statistical analysis involved logistic regression to predict the binary dependent variable indicating whether a visitor used Airbnb during their trip to Australia ($Y = 1$):

$$P(Y = 1) = \frac{e^{\beta_0+\beta_1 x_1+\ldots+\beta_k x_k}}{1 + e^{\beta_0+\beta_1 x_1+\ldots+\beta_k x_k}}$$

where the x_i are independent variables covering travel behaviour and visitor characteristics taken from Volgger et al. (2018) (plus time and quarter) and the β_i are coefficients to be estimated using maximum likelihood. This logistic regression can be represented as a standard multiple regression predicting the logodds of Airbnb use:

$$Logit\,(P\,(Y_i)) = ln\left(\frac{P\,(Y_i = 1)}{1 - P\,(Y_i = 1)}\right) = \beta_0 + \beta_1 x_1 + \ldots + \beta_k x_k. \tag{1}$$

Results of the logistic regression are interpreted as multiplicative effect on the probabilities of a visitor using Airbnb (Taplin, 2016): Exp(B) $= e^{\beta_i}$ is the multiplicative effect on the odds of Airbnb use if the variable x_i is increased by 1. Taplin (2016) suggested this interpretation can safely be applied to probabilities as well as odds for rare events where the probability is $<$ 20%, as is the case here.

To examine whether the effect of variables changed over time, dynamic logistic regressions were performed by including interaction effects between each variable and time. That is, in Eq. (1) terms such as $\gamma_i x_i t$ (where t is the time variable) were included on the right-hand side along with $\beta_i x_i$. The effect of variable x_i on the likelihood of Airbnb use is therefore captured by $\beta_i x_i + \gamma_i x_i t = (\beta_i + \gamma_i t)x_i$. A significant interaction effect (γ_i significantly different to 0) indicates the relationship between the variable and Airbnb use has changed significantly over time. Note that when γ_i is not zero, the coefficient β_i, being the effect of the variable x_i when t equals 0, is of less interest (see Taplin, 2016, for further details). Since many independent variables are categorical and quantified with more than one dummy variable, likelihood ratio tests of whether all coefficients for all dummy variables relating to an independent variable equal zero are also provided. Furthermore, an overall comparison between the static and dynamic models was performed with a likelihood ratio test using the null hypothesis that all interaction effects with time equal zero. Importantly, all analysis was repeated with the dependent variable indicating whether non-Airbnb peer-to-peer accommodation was used. All analyses were performed in SPSS version 24.

Mirroring the profiling analysis of Airbnb users in Volgger et al. (2018), all independent variables taking values on a continuum, such as number of previous visits and spending, were categorised into a few groups to avoid the impact of outliers (see Table 2). Possible seasonal effects were modelled with a variable quarter, taking the value 1, 2, 3 or 4 depending on whether data is collected between January and March, between April and June, between July and September or between October and December. Dummy variables were used for all variables to allow for non-linear relationships except for the variable 'time' (with values 1 for the first quarter in 2015 to 12 for the last quarter in 2017) because relationships between logodds and time were investigated and found to be linear. Thus the linearity assumption of logistic regression is satisfied, and the assumptions of independent observations and random sampling are satisfied by the data collection.

Results

Descriptive statistics

The number of visitors with each characteristic described by the variables that potentially predict Airbnb are provided in Table 1, along with the percentage of each subset that used Airbnb or another peer-to-peer accommodation. For example, 43,552 of the 120,679 visitors provided a holiday as their main trip purpose, and 8.3% of these 43,552 visitors used Airbnb accommodation during their trip and 0.9% of them used a non-Airbnb peer-to-peer accommodation.

The percentage of international visitors to Australia using Airbnb has increased dramatically from about 2% to 9% from 2015 to 2017 while the percentage of visitors using non-Airbnb peer-to-peer accommodation has declined from 0.92% to 0.42% (Fig. 1).

Over these three years, 6997 visitors stayed in Airbnb-delivered accommodation while only 701 stayed in non-Airbnb peer-to-peer accommodation. Both these numbers include the 101 visitors who stayed in both categories of peer-to-peer accommodation (Airbnb and non-Airbnb). Thus about 14% of the visitors that stayed in non-Airbnb peer-to-peer accommodation during their trip in Australia also stayed in Airbnb accommodation, while only 1.4% of the visitors staying in Airbnb also stayed in non-Airbnb peer-to-peer accommodation.

Determinants of Airbnb and non-Airbnb peer-to-peer accommodation use

Logistic regressions predicting Airbnb and non-Airbnb peer-to-peer accommodation use are summarised in Table 2. We focus discussion on the coefficients for individual dummy variables but p-values for each independent variable overall (testing the null hypothesis that all dummy variables for each variable equal zero) are also included in the tables. After adjusting for all other variables predicting peer-to-peer accommodation use, the proportion of visitors using Airbnb is significant and increases by 15% each quarter (see Exp(B) coefficient of 1.15 in Table 2 indicating the likelihood of using Airbnb is multiplied by 1.15 when time is increased by 1), or about 75% each year, while there is a significant decrease by 3.7% per quarter (14% per year) in the proportion of visitors using non-Airbnb peer-to-peer accommodation. Unlike Fig. 1, this relationship with time holds the other independent variables fixed over time, and hence this increase in Airbnb use cannot be explained by changes in the demographics of visitors. Note the effect of time is assumed to be the same for all visitor types in Table 2, but this assumption is relaxed in the dynamic regressions in the Section "Changes in determinants of Airbnb and non-Airbnb peer-to-peer accommodation use over time" below. Residual seasonal effects are relatively small for Airbnb use but non-Airbnb peer-to-peer accommodation use is significantly lower in quarters 3 and 4 compared to quarters 1 and 2. For example, usage in quarter 3 is only 79.6% of the usage in quarter 1.

Almost all variables are significantly related to Airbnb use, even after adjusting for the other variables. Variables are less discriminating in terms of non-Airbnb peer-to-peer accommodation users, but this may be influenced by relatively rare use of non-Airbnb peer-to-peer accommodation. Due to the large sample size, some of the significant effects are not large so we only mention some of the more substantial effects. In addition, we focus on the differences between Airbnb-users and non-Airbnb peer-to-peer accommodation users.

First, visitors from Singapore or Malaysia are 1.750 times more likely to use Airbnb, and visitors from USA or Canada are 1.486 times more likely to use Airbnb, than visitors from the UK (see the Exp(B) column in Table 2). In contrast, non-Airbnb peer-to-peer accommodation users do not have statistically significant differences between these countries. Similar to Airbnb-users, non-Airbnb peer-to-peer accommodation users are significantly less likely to come from Asian countries other than Singapore and Malaysia.

Second, differences in age groups are clearly less pronounced for non-Airbnb peer-to-peer accommodation users rather than for

Table 1
Distribution of potential predictor variables related to Airbnb and non-Airbnb peer-to-peer accommodation use in Australia (2015–2017)[a].

Variable	Categories	*n*	Airbnb (%)[b]	Non-Airbnb P2PA (%)[b]
Country of residence	UK	10,967	6.7	0.9
	Other Europe	14,958	9.2	1.3
	USA, Canada	11,311	8.9	0.6
	Singapore, Malaysia	11,092	10.0	0.5
	China, HK	18,196	5.1	0.4
	Other Asia (incl. NZ)	39,234	2.7	0.3
	Others	7924	3.4	0.6
Age group	Young (15 to 34)	51,851	7.5	0.7
	Middle (35 to 54)	39,828	5.1	0.4
	Old (55 upwards)	22,003	3.0	0.5
Number of previous visits	0	43,182	7.7	0.7
	1	18,962	6.2	0.5
	2–4	23,684	4.9	0.5
	5+	27,854	3.2	0.5
Nights (length of stay)	1–7	38,184	3.7	0.2
	8–14	21,216	7.1	0.5
	15–28	16,589	7.1	0.5
	29+	37,693	6.5	1.0
Trip purpose (main)[c]	Holiday	43,552	8.3	0.9
	VFR	32,249	3.6	0.3
	Business, education, other	37,881	4.7	0.4
Travel party type	Unaccompanied	67,257	4.9	0.5
	Couple, family	30,940	6.9	0.7
	Group of friends/relatives	11,262	8.9	0.8
	Business/school group	4223	2.5	0.0
Travel party size	1	67,257	4.9	0.5
	2	30,803	6.9	0.7
	3–5	11,071	8.1	0.7
	6+	4551	5.2	0.5
Trip activities: Outdoor, nature	NO	25,246	1.8	0.2
	YES	88,436	6.9	0.7
Trip activities: attraction points	NO	34,430	2.4	0.2
	YES	79,252	7.2	0.7
Trip activities: arts, heritage	NO	53,539	3.5	0.4
	YES	60,143	7.7	0.8
Trip activities: social, other	NO	3581	1.0	0.1
	YES	110,101	5.9	0.6
Trip activities: sports	NO	74,909	4.6	0.3
	YES	38,773	8.0	1.1
Trip Activities: indigenous culture	NO	100,359	5.2	0.5
	YES	13,323	10.2	1.4
Location of stay: Urban[d]	NO	11,602	1.4	0.9
	YES	109,077	6.3	0.5
Location of stay: regions[d]	NO	90,718	4.3	0.3
	YES	29,961	10.3	1.3
Location of stay: Outback[d]	NO	102,649	5.4	0.4
	YES	18,030	8.4	1.9
Spending p.p. (A$, excl. major transport)	< $500	24,235	1.4	0.1
	$500 - $1500	34,738	4.7	0.3
	$1500 - $4000	28,910	8.3	0.7
	> $4000	32,796	8.0	1.1
Total		120,679	5.8	0.6

[a] Note: n = 120,679.
[b] Note: Provided figures under Airbnb (non-Airbnb) are the percentage of visitors using Airbnb (non-Airbnb peer-to-peer accommodation). From likelihood ratio tests, all variables are significantly ($p < .001$) related to Airbnb and non-Airbnb, except non-Airbnb and Travel Party Size ($p = .011$).
[c] Note: "VFR" stands for "visiting friends and relatives". "Business, education, other" includes the categories "convention/conference", "business", "employment", "education", "exhibition" and the remainder category "other purposes".
[d] Note: 'Urban' refers to areas in capital cities. 'Regional' refers to semi peripheral areas including regional cities and their surroundings. 'Outback' refers to peripheral places that are relatively far away from more densely populated areas.

Airbnb users. The latter are characterised by significantly decreasing likelihood of usage in higher age groups. Third, the impact of previous visits to Australia differs for Airbnb users and non-Airbnb peer-to-peer accommodation users. While Airbnb use is slightly more likely among visitors who have not been to Australia before (compared to those who have been to Australia at least twice before), non-Airbnb peer-to-peer accommodation use is 1.302 time more likely among visitors who have previously been to Australia 2 to 4 times and 1.745 times more likely among visitors who have previously been to Australia 5+ times. Fourth, different to Airbnb

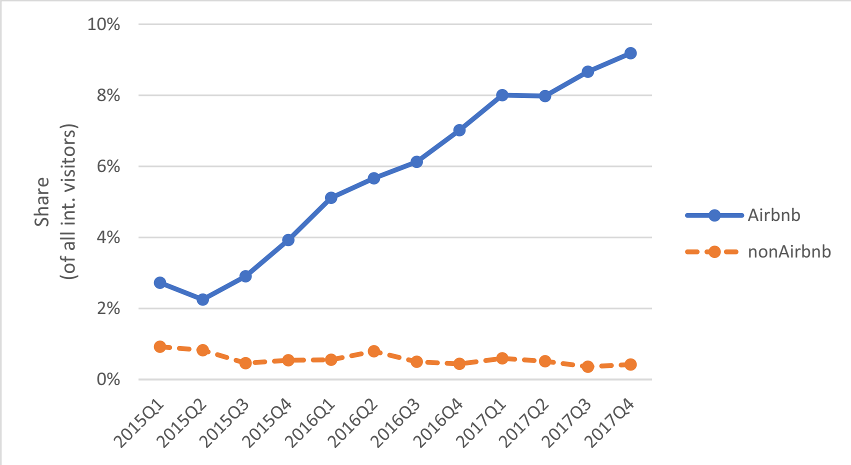

Fig. 1. Evolution of Airbnb usage and non-Airbnb peer-to-peer accommodation usage in Australia, international visitors (2015–2017), n = 120,679 (for all periods combined).

users, non-Airbnb peer-to-peer accommodation use is more likely to be found among those staying in Australia for relatively long periods of > 29 days (1.677 times more likely than among those who just stay 1 to 7 days). Fifth, while families and groups of friends exhibit a higher likelihood of being Airbnb-users than visitors travelling alone, this pattern is even more pronounced with non-Airbnb peer-to-peer accommodation: those travelling alone have 0.44 (=1/2.285 in the Exp(B) column of Table 2) times lower probabilities to use non-Airbnb peer-to-peer accommodation than couples or family groups.

Sixth, non-Airbnb peer-to-peer accommodation is significantly related to carrying out sports-related activities. Those who engage in sportive activities have 1.277 times higher probability to use non-Airbnb peer-to-peer accommodation than those who do not do sports while on vacation in Australia. In contrast, the relationship between sport-related activities and Airbnb use is not statistically significant. On the other hand, Airbnb use is more clearly associated with outdoor & nature-activities and indigenous activities, compared to non-Airbnb peer-to-peer accommodation bookings.

Seventh, Airbnb is strongly associated with stays in urban areas and semiperipheral regions. International visitors staying in Australian urban areas have 3.122 times the likelihood of staying in Airbnb than those not staying in capital cities. In contrast, those staying in Australian urban areas have only half the probability of using non-Airbnb peer-to-peer accommodation than those not staying in urban areas. Non-Airbnb peer-to-peer accommodation is strongly associated with stays in peripheral or outback areas in Australia as international visitors visiting these places have 2.593 times the probability to book a non-Airbnb peer-to-peer accommodation than those not staying in outback areas.

Eighth, spending is very strongly related to Airbnb use with visitors spending over $4000 having a probability of using Airbnb being 4.984 times the probability of visitors spending less than $500. This is only slightly higher than the 4.220 times effect for the $1500–$4000 group. A similarly strong and significant effect of spending is also observable in the group of non-Airbnb peer-to-peer accommodation users, with visitors spending over $4000 having a probability of booking non-Airbnb peer-to-peer accommodation being even 5.537 times the probability of visitors spending less than $500.

Changes in determinants of Airbnb and non-Airbnb peer-to-peer accommodation use over time

Dynamic logistic regression results for Airbnb use show some significant changes in the relationship between variables and Airbnb use over time (Table 3). The strongest change over time is with country ($p < .001$). In particular, the Exp(B) coefficient for time of 1.032 implies Airbnb usage in the UK increased by 3.2% each quarter (13% per year), after adjusting for other variables. Increases for most other countries are similar and not significantly different to the UK except for ‘China/HK’ and ‘Other Asia’. The increase in Airbnb use from these countries between the beginning of 2015 to the end of 2017 was significantly ($p < .001$) higher than the increase in the UK. Airbnb use increased by 8.5% more in China/HK and by 7.0% more in other Asia compared to the increase in the UK. Per year, this means Airbnb use increased by 13% in the UK, 39% in China, HK and by 31% in other Asia.

Furthermore, the effect of visiting a regional location on Airbnb use significantly increases over time ($p = .002$). At the beginning of 2015, the probability of a visitor using Airbnb if they visited a regional location was 1.535 times the probability of a visitor using Airbnb if they did not visit a regional location. This multiplier is itself multiplied by a factor of 1.029 with each subsequent quarter, so by the end of 2017 (12 quarters later), the probability of a visitor using Airbnb, if they visited a regional location, was $1.535*1.029^{12} = 2.163$ times the probability of a visitor using Airbnb if they did not visit a regional location. That is, the effect of visiting a regional location on Airbnb use has increased by 41% over these three years.

Changes in the effects of other variables on Airbnb use are generally insignificant or, when significant, relatively small in magnitude. For example, the large effect of spending on Airbnb use discussed in Section “Determinants of Airbnb and non-Airbnb peer-to-peer accommodation use” does not change significantly over time ($p = .388$).

Table 2
Logistic regression models explaining Airbnb and non-Airbnb peer-to-peer accommodation use in Australia (2015–2017)[a,b,c,d].

Variable	Airbnb				Non-Airbnb P2PA			
	B	SE	p	Exp(B)	B	SE	p	Exp(B)
Constant	−6.921	0.202	**0.000**	0.001	−6.928	0.519	**0.000**	0.001
Quarter			0.051				**0.001**	
Apr-Jun	−0.077	0.038	**0.042**	0.926	0.064	0.099	0.516	1.067
Jul-Sept	−0.082	0.038	**0.031**	0.922	−0.358	0.116	**0.002**	0.699
Oct-Dec	−0.095	0.037	**0.010**	0.910	−0.229	0.113	**0.044**	0.796
Time[e]	0.140	0.004	**0.000**	1.150	−0.038	0.012	**0.002**	0.963
Country (overall)			**0.000**				**0.000**	
Country (*other europe*)	0.036	0.048	0.461	1.036	0.104	0.125	0.404	1.110
Country (*usa, can*)	0.396	0.052	**0.000**	1.486	−0.168	0.161	0.299	0.846
Country (*singapore, malaysia*)	0.559	0.055	**0.000**	1.750	0.057	0.182	0.753	1.059
Country (*china, hk*)	−0.380	0.055	**0.000**	0.684	−0.575	0.170	**0.001**	0.563
Country (*Other Asia, incl. NZ*)	−0.588	0.052	**0.000**	0.556	−0.389	0.146	**0.008**	0.678
Country (others)	−0.433	0.074	**0.000**	0.649	0.140	0.181	0.439	1.150
Age group (*overall*)			**0.000**				0.763	
Age group (*35 to 54*)	−0.309	0.031	**0.000**	0.734	−0.073	0.101	0.470	0.929
Age group (*55 upwards*)	−0.814	0.049	**0.000**	0.443	−0.055	0.132	0.675	0.946
Number of prev. visits (*overall*)			**0.000**				**0.000**	
Number of prev. visits (1)	−0.030	0.036	0.400	0.970	−0.072	0.116	0.533	0.930
Number of prev. visits (*2–4*)	−0.103	0.038	**0.007**	0.902	0.264	0.115	**0.022**	1.302
Number of prev. visits (*5+*)	−0.209	0.044	**0.000**	0.812	0.557	0.125	**0.000**	1.745
Nights (overall)			**0.000**				**0.000**	
Nights (8–14)	0.072	0.041	0.080	1.075	0.281	0.155	0.070	1.325
Nights (15–28)	−0.146	0.049	**0.003**	0.864	−0.163	0.175	0.353	0.850
Nights (29+)	−0.432	0.052	**0.000**	0.649	0.517	0.166	**0.002**	1.677
Trip purpose (*overall*)			**0.000**				**0.000**	
Trip purpose (*VFR*)	−0.263	0.038	**0.000**	0.769	−0.468	0.124	**0.000**	0.626
Trip purpose (*Business, educ., other*)	−0.231	0.039	**0.000**	0.794	−0.541	0.115	**0.000**	0.582
Party type (*overall*)			**0.000**				**0.001**	
Party type (*couple, family group*)	0.297	0.081	**0.000**	1.346	0.826	0.249	**0.001**	2.285
Party type (*gr. Of friends*)	0.288	0.077	**0.000**	1.334	0.572	0.233	**0.014**	1.772
Party type (*business, school gr.*)	−0.387	0.113	**0.001**	0.679	−0.896	0.592	0.130	0.408
Party size (*overall*)[f]			0.107				**0.005**	
Party size (*2*)	0.028	0.077	0.719	1.028	−0.618	0.238	**0.010**	0.539
Party size (*3–5*)	0.111	0.080	0.162	1.118	−0.279	0.248	0.261	0.757
Activity outdoor, nature	0.464	0.054	**0.000**	1.590	0.147	0.168	0.379	1.159
Activity attraction points	0.331	0.043	**0.000**	1.393	0.271	0.134	**0.044**	1.311
Activity arts, heritage	0.244	0.031	**0.000**	1.276	0.150	0.095	0.114	1.162
Activity sports	0.041	0.030	0.173	1.042	0.245	0.096	**0.010**	1.277
Activity indigenous	0.132	0.036	**0.000**	1.141	0.019	0.096	0.846	1.019
Activity social	0.399	0.171	**0.020**	1.491	0.424	0.459	0.356	1.527
Location urban	1.138	0.081	**0.000**	3.122	−0.781	0.118	**0.000**	0.458
Location regions	0.644	0.030	**0.000**	1.904	0.516	0.091	**0.000**	1.676
Location outback	−0.204	0.039	**0.000**	0.816	0.953	0.097	**0.000**	2.593
Spending			**0.000**				**0.000**	
\$500–\$1500	0.961	0.062	**0.000**	2.614	0.899	0.228	**0.000**	2.458
\$1500–\$4000	1.440	0.063	**0.000**	4.220	1.345	0.227	**0.000**	3.838
> \$4000	1.606	0.069	**0.000**	4.984	1.712	0.236	**0.000**	5.537

Airbnb: Chi-square = 7500.449 ($p < .001$), Nagelkerke R Square = 0.168.
nonAirbnb: Chi-square = 1036.384 ($p < .001$), Nagelkerke R Square = 0.124.

[a] Dependent variables are Airbnb (whether the visitor stays in Airbnb accommodation) and non-Airbnb P2PA (whether the visitor stays in non-Airbnb peer to peer accommodation during their Australian visit).

[b] Note: Bold *p*-values are significant at $p \leq .05$.

[c] Note: The baseline is "UK" for Country, "15–34" for Age group, "0" for Number of previous visits, "1–7" for Nights, "Holiday" for Trip purpose, "unaccompanied" for Party type, "1" for Party size and < \$500 for spending.

[d] Note: n = 120,679.

[e] The variable "time" takes values between 1 (first quarter in 2015) and 12 (last quarter in 2017).

[f] Note: Party size (6+) dummy variable removed due to redundancy (Party size of "1" is equivalent to Party type of unaccompanied).

In contrast, the effect of variables on non-Airbnb peer-to-peer accommodation use has remained relatively stable over time (Table 4). There are only two statistically significant interaction effects with time. One is the 'other country' category having a significantly (p = .026) different change in usage than the UK. This effect, however, is relatively small, especially compared to the changes over time for Airbnb use. The second statistically significant interaction effect refers to an increase of the impact of visiting an outback location on non-Airbnb peer-to-peer accommodation use. The multiplier in probability increased from 1.714 (at the

Table 3
Dynamic logistic regression model explaining Airbnb use (2015–2017)[a,b,c,d].

Variable	Term				Interaction with time			
	B	SE	p	Exp(B)	B	SE	p	Exp(B)
Constant	−6.155	0.445	**0.042**	0.002				
Quarter			**0.042**					
Apr-Jun	−0.077	0.038	**0.043**	0.926				
Jul - Sept	−0.082	0.038	**0.031**	0.921				
Oct - Dec	−0.099	0.037	**0.007**	0.905				
Time	0.031	0.057	0.581	1.032				
Country (overall)			**0.000**				**0.000**	
Country (*Other Europe*)	0.215	0.114	0.059	1.239	−0.024	0.014	0.090	0.976
Country (*USA, CAN*)	0.330	0.125	**0.008**	1.391	0.009	0.016	0.550	1.009
Country (*Singapore, Malaysia*)	0.429	0.135	**0.001**	1.536	0.018	0.017	0.267	1.019
Country (*China, HK*)	−1.028	0.143	**0.000**	0.358	0.082	0.017	**0.000**	1.085
Country (*Other Asia, incl. NZ*)	−1.121	0.134	**0.000**	0.326	0.068	0.016	**0.000**	1.070
Country (Others)	−0.526	0.186	0.005	0.591	0.014	0.022	0.543	1.014
Age group (*overall*)			**0.000**				0.127	
Age group (*35 to 54*)	−0.156	0.080	**0.050**	0.856	−0.019	0.010	**0.043**	0.981
Age group (*55 upwards*)	−0.715	0.121	**0.000**	0.489	−0.013	0.015	0.389	0.987
Number of prev. visits (*overall*)			0.060				0.711	
Number of prev. visits (1)	−0.114	0.089	0.204	0.893	0.011	0.011	0.317	1.011
Number of prev. visits (*2–4*)	−0.178	0.099	0.071	0.837	0.009	0.012	0.426	1.009
Number of prev. visits (*5+*)	−0.289	0.116	**0.013**	0.749	0.010	0.014	0.474	1.010
Nights (overall)			**0.000**				0.541	
Nights (8–14)	0.052	0.106	0.621	1.054	0.002	0.013	0.871	1.002
Nights (15–28)	−0.285	0.123	**0.021**	0.752	0.018	0.015	0.227	1.018
Nights (29+)	−0.459	0.132	**0.000**	0.632	0.003	0.016	0.860	1.003
Trip purpose (*overall*)			**0.000**				0.067	
Trip purpose (*VFR*)	−0.441	0.098	**0.000**	0.644	0.023	0.012	**0.045**	1.024
Trip purpose (*Business, educ., other*)	−0.386	0.097	**0.000**	0.680	0.020	0.012	0.093	1.020
Party type (*overall*)			0.052				0.185	
Party type (*couple, family group*)	0.019	0.219	0.930	1.019	0.036	0.025	0.156	1.037
Party type (*gr. of friends*)	−0.092	0.211	0.661	0.912	0.049	0.024	**0.043**	1.050
Party type (*business, school gr.*)	−0.710	0.306	**0.020**	0.492	0.041	0.035	0.246	1.042
Party size (*overall*)[e]			0.068				0.113	
Party size (*2*)	0.406	0.209	0.052	1.500	−0.049	0.024	**0.043**	0.952
Party size (*3–5*)	0.501	0.216	**0.021**	1.650	−0.050	0.025	**0.046**	0.951
Activity outdoor, nature	0.378	0.142	**0.008**	1.459	0.011	0.016	0.519	1.011
Activity attraction points	0.202	0.110	0.067	1.223	0.017	0.013	0.191	1.017
Activity arts, heritage	0.255	0.079	**0.001**	1.290	−0.002	0.009	0.859	0.998
Activity sports	0.002	0.078	0.981	1.002	0.006	0.009	0.518	1.006
Activity indigenous	0.183	0.089	**0.040**	1.201	−0.006	0.011	0.547	0.994
Activity social	−0.045	0.352	0.899	0.956	0.064	0.047	0.169	1.067
Location urban	1.109	0.214	**0.000**	3.030	0.004	0.025	0.862	1.004
Location regions	0.429	0.076	**0.000**	1.535	0.028	0.009	**0.002**	1.029
Location outback	−0.350	0.096	**0.000**	0.705	0.020	0.012	0.087	1.020
Spending			**0.000**				0.388	
\$500–\$1500	1.196	0.169	**0.000**	3.308	−0.029	0.019	0.131	0.971
\$1500–\$400	1.707	0.170	**0.000**	5.510	−0.034	0.020	0.087	0.967
> \$4000	1.878	0.184	**0.000**	6.538	−0.035	0.022	0.108	0.966

Dynamic model is significantly superior to the static model ($p < .001$).
Chi-square = 7612.963 ($p < .001$), Nagelkerke R Square = 0.171.

[a] Dependent variable is Airbnb (whether the visitor stays in Airbnb accommodation during their Australian visit).

[b] Note: Bold *p*-values are significant at $p \leq .05$.

[c] Note: The baseline is "UK" for Country, "15–34" for Age group, "0" for Number of previous visits, "Holiday" for Trip purpose, "unaccompanied" for Party type, "1" for Party size and < \$500 for spending.

[d] Note: n = 120,679.

[e] Note: Party size (6+) dummy variable removed due to redundancy (Party size of "1" is equivalent to Party type of unaccompanied).

beginning of 2015) to 4.037 ($1.714*1.074^{12}$) at the end of 2017, which means it more than doubled. The impact of other variables such as the significant effect of the number of previous visits on non-Airbnb peer-to-peer accommodation use has remained unchanged over time.

Discussion

Findings indicate larger overall growth and stronger dynamism in the evolution of international 'Airbnb-tourism' in Australia

Table 4
Dynamic logistic regression model explaining non-Airbnb peer-to-peer accommodation use (2015–2017)[a,b,c,d].

Variable	Term				Interaction with time			
	B	SE	p	Exp(B)	B	SE	p	Exp(B)
Constant	−6.357	0.865	**0.000**	0.002				
Quarter			**0.001**					
Apr-Jun	0.062	0.099	0.532	1.064				
Jul - Sept	−0.364	0.116	**0.002**	0.695				
Oct - Dec	−0.224	0.113	**0.048**	0.799				
Time	−0.181	0.172	0.291	0.834				
Country (overall)			**0.000**				0.169	
Country (*Other Europe*)	0.478	0.248	0.054	1.612	−0.065	0.036	0.071	0.937
Country (*USA, CAN*)	0.212	0.317	0.505	1.236	−0.067	0.048	0.161	0.935
Country (*Singapore, Malaysia*)	0.277	0.356	0.436	1.319	−0.037	0.053	0.486	0.964
Country (*China, HK*)	−0.514	0.340	0.131	0.598	−0.010	0.049	0.838	0.990
Country (*Other Asia, incl. NZ*)	−0.330	0.290	0.254	0.719	−0.009	0.042	0.823	0.991
Country (Others)	0.797	0.339	**0.019**	2.220	−0.120	0.054	**0.026**	0.887
Age group (*overall*)			0.860				0.630	
Age group (*35 to 54*)	0.035	0.199	0.860	1.036	−0.019	0.030	0.522	0.981
Age group (*55 upwards*)	0.140	0.255	0.584	1.150	−0.035	0.039	0.361	0.965
Number of prev. visits (*overall*)			**0.043**				0.634	
Number of prev. visits (1)	0.040	0.224	0.857	1.041	−0.019	0.034	0.574	0.981
Number of prev. visits (*2–4*)	0.497	0.224	**0.027**	1.644	−0.041	0.034	0.231	0.960
Number of prev. visits (*5+*)	0.593	0.246	**0.016**	1.809	−0.005	0.036	0.888	0.995
Nights (overall)			0.123				0.384	
Nights (8–14)	−0.128	0.302	0.673	0.880	0.070	0.046	0.125	1.072
Nights (15–28)	−0.522	0.336	0.121	0.593	0.063	0.051	0.222	1.065
Nights (29+)	0.073	0.317	0.819	1.075	0.079	0.049	0.103	1.083
Trip purpose (*overall*)			0.053				0.413	
Trip purpose (*VFR*)	−0.542	0.243	**0.026**	0.582	0.013	0.036	0.726	1.013
Trip purpose (*Business, educ., other*)	−0.327	0.219	0.135	0.721	−0.038	0.033	0.250	0.962
Party type (*overall*)			0.459				0.840	
Party type (*couple, family group*)	0.456	0.502	0.364	1.578	0.062	0.072	0.384	1.064
Party type (*gr. of friends*)	0.312	0.472	0.508	1.367	0.044	0.067	0.509	1.045
Party type (*business, school gr.*)	−1.306	1.184	0.270	0.271	0.067	0.170	0.694	1.069
Party size (*overall*)[e]			0.845				0.322	
Party size (*2*)	−0.059	0.480	0.903	0.943	−0.096	0.069	0.162	0.908
Party size (*3–5*)	0.096	0.501	0.848	1.101	−0.062	0.072	0.383	0.939
Activity outdoor, nature	−0.017	0.315	0.957	0.983	0.030	0.049	0.537	1.031
Activity attraction points	0.612	0.266	**0.021**	1.844	−0.059	0.038	0.123	0.942
Activity arts, heritage	0.096	0.184	0.602	1.101	0.010	0.028	0.718	1.010
Activity sports	0.126	0.186	0.499	1.134	0.020	0.028	0.461	1.021
Activity indigenous	−0.006	0.192	0.977	0.994	0.004	0.028	0.882	1.004
Activity social	−0.283	0.739	0.702	0.754	0.161	0.157	0.306	1.174
Location urban	−0.601	0.235	**0.010**	0.548	−0.031	0.034	0.366	0.970
Location regions	0.496	0.177	**0.005**	1.642	0.003	0.026	0.896	1.003
Location outback	0.539	0.190	**0.005**	1.714	0.072	0.028	**0.012**	1.074
Spending			**0.000**				0.504	
$500–$1500	0.751	0.439	0.087	2.119	0.026	0.067	0.700	1.026
$1500–$400	1.295	0.436	**0.003**	3.649	0.009	0.067	0.892	1.009
> $4000	1.895	0.452	**0.000**	6.650	−0.030	0.070	0.668	0.971

Chi-square = 1075.322 ($p < .001$), Nagelkerke R Square = 0.129. Dynamic model is not significantly superior to the static model ($p = .220$).

[a] Dependent variable is non-Airbnb P2PA use (whether the visitor stays in non-Airbnb peer to peer accommodation during their Australian visit).

[b] Note: Bold *p*-values are significant at $p \leq .05$.

[c] Note: The baseline is "UK" for Country, "15–34" for Age group, "0" for Number of previous visits, "Holiday" for Trip purpose, "unaccompanied" for Party type, "1" for Party size and < $500 for spending.

[d] Note: n = 120,679.

[e] Note: Party size (6+) dummy variable removed due to redundancy (Party size of "1" is equivalent to Party type of unaccompanied).

compared to the evolution of non-Airbnb peer-to-peer accommodation use. While Airbnb use is characterised by a growth pattern in terms of market share, non-Airbnb peer-to-peer accommodation use has been decreasing in the observed period. However, at the same time as Airbnb seems gaining in breadth, other peer-to-peer accommodation platforms apparently are able to maintain their specific market segments. Although R-squared values for logistic regression require cautious interpretation, readers may also note that the presented model's Nagelkerke R-squared values are consistently higher for Airbnb than non-Airbnb, suggesting the independent variables more successfully predict Airbnb use than non-Airbnb peer-to-peer accommodation use; however the Nagelkerke R-squared values below 20% suggest future research might be worthwhile to try to identify additional variables that explain visitor use of peer-to-peer accommodation.

Regarding tourism phenomena with international exposure there is an ongoing theoretical debate of whether and to what extent consumer behaviour will differ across markets. Pizam (1999) distinguishes two main positions in this debate: one being the convergence position which argues for an increasing homogenisation of economies and cultures due to the imperatives of industrialisation and the other being the divergence position which supports the idea that divergence across markets persists because of the strong cultural boundedness. In terms of consumer behaviour in the peer-to-peer accommodation segment, findings suggest that convergence is happening with respect to the market leader Airbnb who appears to capturing bigger shares, across different source markets. However, convergence is not absolute and appears to leave space for 'long tail' phenomena (Anderson, 2006) where differences persist. These differences are partially linked to different source countries, but also influenced by non-location-based variables.

Airbnb use and developments

From 2015 to 2017, the share of international visitors using Airbnb while they stay in Australia increased from 2% to reach a market share of 9%. This translates into a quarterly increase of the proportion of visitors using Airbnb of 15% (75% each year). Although the growth in percentage points can be considered relatively constant overall, it is also interesting to note that the gains seem to have peaked in Quarter 1 of 2016 (quarter-to-quarter gains) or Quarter 2 of 2016 (year-to-year gains) and that marginal gains show a decreasing trend since then.

Beyond the mere increase in overall market share of Airbnb use in the international Australian accommodation market, qualitative usage dynamics emerge. The profiling developed in Volgger et al. (2018) is mostly confirmed in the multi-year regression: Airbnb use in Australia is more likely for international visitors who come from Singapore and Malaysia or Northern America, who tend to be younger and less experienced travellers to Australia, who stay shorter and who tend to travel in family groups or groups of friends, and who tend to spend more during their stay. Airbnb use is also more likely for those who engage in outdoor and nature-related as well as culture-related activities and who stay in urban or semi-peripheral (regional) areas.

However, this profile has evolved over the observed timeframe. In particular, typical international Airbnb users in Australia increasingly also came from Asia: The growth in Airbnb usage over the observed 12 quarters was significantly higher for China and Hong Kong as well as for 'other Asian countries' than for other source countries. This observation can perhaps be interpreted as a catching up behaviour of markets where Airbnb usage was lagging behind previously and ultimately still remains below average despite the above-average expansion. Finally, Airbnb use in Australia developed a stronger regional anchorage, with stays in semi-peripheral regions becoming a more pronounced indicator of Airbnb use over the observed three years. Again, this may be interpreted as customer segments with previously lower participation rates getting in line with more progressive segments. Overall, the catch-up patterns indicate a 'convergence' (Pizam, 1999) of Airbnb use towards mainstream areas of the market. Hence, the overall development of Airbnb usage of international visitors in Australia may be described as 'normalisation' and thus appears coherent with the winner-takes-all hypothesis.

Non-Airbnb peer-to-peer accommodation use and developments

The evolution of consumption regarding non-Airbnb peer-to-peer accommodation in Australia exhibits quite different patterns. In contrast to what can be observed for Airbnb use, the market share of non-Airbnb peer-to-peer accommodation among international visitors to Australia has been decreasing over the observed twelve quarters (from 0.92% to 0.42%).

A comparison of typical usage profiles elucidates marked difference between Airbnb user profiles and profiles of non-Airbnb peer-to-peer accommodation users. For instance, data indicates that users of non-Airbnb peer-to-peer accommodation are less likely to originate from Asian countries. Age is a less discriminating factor for this group and visitors who have already been to Australia for several times are more likely to use non-Airbnb peer-to-peer accommodation. Furthermore, different to Airbnb users, non-Airbnb peer-to-peer accommodation users are more likely to stay in Australia for relatively long periods and they exhibit higher likelihoods of engaging in sports-related activities. Finally, non-Airbnb peer-to-peer accommodation is not primarily an urban phenomenon but strongly associated with stays in peripheral or outback areas.

Different to consumer profiles of Airbnb users, temporal stability in usage patterns seems to prevail among the group of non-Airbnb peer-to-peer accommodation users. No Asian catch-up is detectable among non-Airbnb peer-to-peer accommodation users. The only apparent dynamic change in profiles is an increasing predominance of non-Airbnb peer-to-peer accommodation users staying in peripheral (outback) areas, which potentially might have been triggered by Airbnb users increasingly conquering the regions and thus potentially limiting competitive advantages of some non-Airbnb peer-to-peer accommodation platforms to outback areas. Hence, in contrast to the catch-up, convergence and normalisation patterns of Airbnb users in Australia, non-Airbnb peer-to-peer accommodation users occupy specific niches (such as long stays, sports-related activities, multiple repeat visitors to Australia), which is further reinforced in their evolution. For instance, they seem to be developing into specialists for outback locations. In other words, non-Airbnb peer-to-peer accommodation usage forms appear to maintain their divergent nature along the long tail not covered by the 'superstar' platform Airbnb.

Conclusion

This study investigated the evolution of international tourists' consumption patterns of Airbnb and other peer-to-peer accommodation platforms in Australia. The study makes several empirical and theoretical contributions. Empirically, it is the first attempt to systematically trace the evolution of consumption patterns around the Airbnb and peer-to-peer accommodation phenomena by analysing rare data collected over multiple points in time. It does so by empirically tracking overall consumption evolution and the evolution of consumer profiles. The research findings suggest that Airbnb usage patterns in Australia have evolved over the last three years, showing strong growth in market share and a normalisation of user profiles, gradually bringing Airbnb user profiles in line with overall demand patterns. This normalisation includes an increasing Asian (and particularly Chinese) participation and decreasingly urbanised visitation patterns. Therefore, these findings support the notion that Airbnb usage is moving from a niche phenomenon towards becoming part of the mainstream segments of the tourism market. Such a convergence (Pizam, 1999) has previously been hypothesised by Dredge and Gyimóthy (2015), Guttentag et al. (2018) and Volgger et al. (2018), but this study is the first to provide evidence using data collected over several points in time to support this claim.

It is also the first paper to comparatively examine the consumer profiles and their evolution in the peer-to-peer accommodation sector beyond Airbnb and thus to better understand to what extent the undisputed market leader Airbnb energises the demand for the broader segment. In comparison to Airbnb use, the evolution of non-Airbnb peer-to-peer accommodation use shows less dynamism, negative growth and a trend of retained distinctiveness of its user profiles. It is relevant to investigate the profile of those peer-to-peer accommodation users who opt against a clearly and increasingly dominating market leader. Findings show that non-Airbnb peer-to-peer accommodation relatively steadily occupies specific niches (such as non-urban long stays, sports-related activities, multiple repeat visitors to Australia). This niche-positioning is reinforced by the evolutionary trend, which for example seems turning these providers increasingly into specialists for outback locations in Australia.

From a theoretical point of view, the research contributes to the often-neglected inter-temporal analysis of interpersonal consumption dynamics (Sheth & Sisodia, 1999). In particular, it is the first attempt to link the evolution of peer-to-peer accommodation with interpersonal consumption effects and patterns. This includes network externalities (Katz & Shapiro, 1985), consumption lock in (Schulte, 2015), bandwagon and snob effects (Leibenstein, 1950). Such effects may result in macro-level consumption dynamics described as 'winner-takes-all' (Frank, 1994) and 'superstar effects' (Rosen, 1981) vs ideas of 'neotribes' (Hardy & Robards, 2015) and 'long-tails' (Anderson, 2006). On the macro-level, the paper supports the idea of mounting 'winner-takes-all' consumption in the area of the peer-to-peer economy. The evolutionary patterns of peer-to-peer accommodation use for international visitors in Australia indicate that the peer-to-peer-boom is more linked to a single platform than to the sector at large. It may thus indeed be more accurately described as 'Airbnb tourism' than as a peer-to-peer accommodation phenomenon and a reconsideration of its appealing features, with an even stronger focus on the specific features of the 'winning' platform rather than the sector, may be warranted. The study however also finds signals of persistence of smaller, but relatively stable consumption groups. Besides Airbnb, there is a long tail of other platforms in Australia which do not exhibit a similar dynamism but seem to be able to retain their differentiated communities in the shade of an increasingly mainstream market leader.

On the micro-level, given a relative similarity of supply across many platforms, herding behaviour driven by bandwagon effects (Leibenstein, 1950) seem to play a strong role in the increased concentration of peer-to-peer accommodation consumption. This is supported by a growing and increasingly 'normalised' Airbnb consumption which is progressively occupying the mainstream segments also aided by converging consumer behaviour across markets. While the study does not lend support to the long tail idea of a growing overall share of niche consumption in peer-to-peer accommodation (Anderson, 2006), it nevertheless finds supporting evidence for lock-in effects with some rigidly persisting niche consumer patterns of non-Airbnb peer-to-peer accommodation use. These compartments of peer-to-peer accommodation consumers avoiding the crowd include those engaging in sport-related activities and in longer stays in regional and remote locations. The multiple visits to Australia by several non-Airbnb peer-to-peer accommodation users may be read as an indication of persistence. It could signal loyalty of early customers as some of these platforms (such as Stayz, Couchsurfing) have been operating in Australia longer than Airbnb (since 2012). Some weaker signals may also indicate a snob effect as the highest spending visitors are over-represented in some non-Airbnb peer-to-peer accommodation – an effect steady over time. Therefore, the findings also contribute to theory by indicating that 'winner-takes-all' consumer crowding and the persistence of specific niche consumer tribes seem capable of co-existence, perhaps are mutually dependent. This is an indication that it would be wrong to consider consumption in a globalised world to result in either one uniform crowd or completely distinct individuals but homogenisation and tribalisation seem rather to be happening in conjunction.

In terms of practical implications, this study's findings imply that peer-to-peer accommodation (in the context of international visitation to Australia) is dominated by a market leader that tends to capture a bigger and bigger market share. Hence, the overwhelming focus of policy on the market leader appears justified, although it needs to be emphasised that Airbnb visitor profiles are not necessarily congruent with the visitor profiles of other peer-to-peer accommodation platforms. For Airbnb, findings imply that the company has developed from a disruptor into an incumbent and thus may now themselves be endangered by the same disruptive mechanisms. The ongoing move into the market mainstream may be a chance for the company, but may also pose risks in terms of dissent in the established community and may cause dilution of the established value proposition. Hence, this is an area which might warrant future research. For traditional accommodation providers, the development patterns indicate that the Airbnb phenomenon does not seem to be (yet) confined neither in scale nor in scope. For destination managers and policy makers, the specific activity patterns of Airbnb users, the prevalence of destination newcomers and the high spending levels may warrant cautious treatment of the phenomenon. Finally, for non-Airbnb peer-to-peer accommodation providers, findings suggest either adoption of a clear niche-strategy, including a particular focus on nurturing their specific 'consumer tribe', divestment or an exploration of disruptive approaches.

The study has some limitations which can inspire future research. Limitations of the study are linked to the fact that data was not specifically collected for the purpose of the study and that other reasons than the inferred ones may exist to explain (part) of the data patterns. Limitations also exist in regards to the availability of data, which is restricted to 12 quarters in time and due to the rare use of non-Airbnb peer-to-peer accommodation makes differentiating between different platforms difficult. This is a heterogeneous group, and hence a specific analysis of individual platforms may be valuable. However, the fact that all these platforms are united by the situation of having to compete with an overwhelming market leader justifies a joint analysis in the present paper. Another limitation is the focus on the demand side. While the non-exclusivity of listings across different peer-to-peer accommodation platforms, relatively low occupancy rates (Pforr et al., 2017) and a structural similarity of many platforms support the notion of a 'buyer's market', future research performing a combined analysis of demand and supply would be of great benefit. A further limitation, also linked to data availability, is the exclusion of domestic peer-to-peer accommodation use in Australia. The use of peer-to-peer accommodation by Australians is a relevant part of overall use and difference in results for international visitors and domestic travellers, if any, would be worthy of investigation. While this paper tried to discuss macro-level and micro-level consumption effects, it was not able to posit clear causal links between what drives the individual consumer and the resulting consumption pattern. Therefore, it is urgent that future research explicitly captures interpersonal motivations on the side of the consumer. While research exists that scrutinises functional motivations of Airbnb use (Guttentag et al., 2018; Tussyadiah, 2015, 2016), future research should more clearly include non-functional motivations to detect bandwagon or reverse-bandwagon effects; it should also model choice situations between Airbnb and non-Airbnb platforms. Two further avenues of future research appear promising: One includes research on brand awareness and brand prominence in peer-to-peer accommodation, building on recent work of Lee and Kim (2018). A second avenue is to focus on consumer loyalty in peer-to-peer accommodation (extending the initial work of Mao & Lyu, 2017) as this will be crucial in further understanding phenomena related to niche consumption of non-Airbnb peer-to-peer accommodation platforms. We also suggest to conduct future research on how the increasing presence of commercial offers on some peer-to-peer accommodation platforms may change consumer perceptions and behaviour. At the interface with supply, future research should also explore relationships between country-specific peer-to-peer accommodation demand patterns and origin of hosts or sources of property investment.

Conflict of interest

None.

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