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Exit and transition: Exploring the survival status of Airbnb listings in a time of professionalization

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ABSTRACT

This study analyzes the survival status of shared and non-shared listings in the peer-to-peer accommodation market. Using a large data set from Airbnb in Beijing, we identify 8640 shared listings and 50,741 non-shared listings. We then investigate the exit event and the identity transition event for both types of listings by applying a discrete-time hazard model. Our results suggest that, for the exit event, the two types of listings show significant differences in terms of survival determinants, including response time, tourism specialization, market volume, professionalization, and Covid-19. For the identity transition event, we find that internal flow exists in the market, mainly from shared listings to non-shared listings, and this flow is influenced by certain factors (i.e., capacity, facility, rating, reviews, minimum stay, service quality, tourism specialization, market volume, platform professionalization, and Covid-19).

1. Introduction

Inarguably, Airbnb is one of the most successful companies in the peer-to-peer accommodation industry. At its inception, Airbnb was the prototypical exemplar of the accommodation sharing platform, where the products are extra (or underused) properties provided by amateur hosts. However, in recent years, the rapid development of Airbnb has attracted more and more private and commercial investors who usually offer more than one listing. The multi-listings provided by these commercial hosts are often clustered in the same buildings or same areas and are accompanied by quasi-standardized amenities and services. As stated by Dogru, Mody, Suess, Line, and Bonn (2020), these listings are contributing to the *professionalization* of Airbnb. Commercial hosts are increasingly employing professional listing managers to run their businesses and maximize revenue (Dolnicar, 2019), shrinking the gaps between their products and those provided by nearby hotels. In fact, such Airbnb properties can be regarded as hotels that are selling their main inventory on the Airbnb platform, rather than sharing their spare capacity. Airbnb is moving away from its sharing narrative at a noticeable speed, gradually forming a more complicated bipolar system where commercial agents and sharing agents dwell together. A professionalized sharing marketplace has thus emerged.

Previous literature claims that the proliferation of multi-listings does contribute to the professionalization of Airbnb, meanwhile, it has also hit the genuine sharing space offered by sharing hosts. Dolnicar (2019) expressed concern that whether the genuine shared accommodation (i.e., that provided by sharing hosts) is on the decline. In 2014–15, it was estimated that 16% of the hosts across 12 U.S. cities were multi-listing (O'Neill & Ouyang, 2016), while only three years later, in 2017–2018, an estimated 63.5% of hosts offered two or more listings (across all 50 states in the U.S.; Dogru, Hanks, Mody, Suess, & Sirakaya-Turk, 2020). Additionally, Gil and Sequera (2022) analyzed the evolution of Airbnb in Madrid from 2009 to 2019 and concluded that commercial hosts dominated that local Airbnb market, as 75.7% of the Airbnb supply was multi-listings. A widely held view is that the boom in multi-listings is suppressing the space available for real sharing accommodations, sounding the death knell for the people who started the sharing economy (Gyódi, 2019). Despite the growing concern about these casualties in the peer-to-peer accommodation ecosystem, little effort has been made to study how they might survive. Given the situation, it is critical to explore the survival status of the different agents in this market.

Although the survival of an economic agent in the market is an important topic, it has been little studied in the hospitality domain, especially in the context of peer-to-peer accommodations. Most

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researchers focused on the motivations for participating in the peer-to-peer accommodation market (Hamari, Sjöklint, & Ukkonen, 2016; Karlsson & Dolnicar, 2016; Lampinen & Cheshire, 2016) and the impact of new entrants on the incumbents' performance (Dogru, Hanks, et al., 2020; Dogru, Mody, & Suess, 2019; Xie & Kwok, 2017). However, as suggested by Mata, Portugal, and Guimarães (1995), what happens to the agents after their participation is at least as important as the entry process itself. Inspired by this idea, this exploratory study painstakingly investigated two types of listings (shared and non-shared) to provide a fuller view of their survival status in the market. Specifically, in response to the hot debate over the decline of shared accommodations, we first looked at the condition of sharing participants in the Beijing Airbnb market, inquiring into (1) whether shared listings really account for only a small proportion of the local market and are trending downward. Although the Airbnb market in Beijing is not representative of the global picture, it can still provide useful empirical clues for later researchers approaching this big question. After that, we dived deeper into the survival of both shared and non-shared listings in the local market. We explored (2) what factors affect the survival of both types of listings on the platform and whether these factors have similar effects on both. This part of the analysis builds on the previous part to reveal the reasons behind hosts leaving Airbnb. In addition to the exit event, this study also looked at another outcome event, identity transition, which has been largely overlooked before now. Identity transition occurs when listings switch from one type (e.g., shared) to the other (e.g., non-shared); these events can also be understood as a change in the form of survival. We closely scrutinized (3) what factors may motivate identity transition events, hoping thereby to provide some insight into the difficult-to-observe intra-market flows.

Using a large data set comprised of 59,381 listings (8640 shared listings and 50,741 non-shared listings) listed on Airbnb in the Beijing market between July 2018 and June 2020 along with the corresponding public profiles, we devised a compute-intensive workflow for this study to seek the answers to the proposed questions. The workflow diagram of this research is presented in Fig. 1. First, we designed an algorithm to identify whether a listing fits the sharing economy narrative and segmented the totality of listings into shared listings (i.e., occupied properties being shared) and non-shared listings (i.e., properties being used for short-term rental purposes, like traditional accommodation lets) to better understand the differences in their survival patterns (Crommelin, Troy, Martin, & Pettit, 2018). We also identified two outcome events that occur after listings enter the market: exit and identity transition. In this context, transition means a change in a listing's type (e.g., shared listing to non-shared listing), and exit means leaving the platform. Then, we presented listing-, host-, and market-level factors that may influence survival status of listings based on existing literature. In particular, we proposed two innovative variable operationalization methods. Finally, we performed a model-free analysis to display the dynamic of listings and employed a discrete-time hazard model to examine whether and by how much the studied factors affect the survival status of Airbnb listings.

The main contributions are summarized as follows. First, this study deliberately categorizes listings into shared listings and non-shared listings according to the nature of their hosts. Although Leoni (2020) analyzed listing survival in the Spanish peer-to-peer accommodation market, in that study the shared and non-shared listings were mixed. However, the accommodations and operation modes of shared listings are quite different from those of non-shared listings (Crommelin et al., 2018), and the survival determinants may be different across listings' categories. Accordingly, it is necessary to conduct a more fine-grained analysis to better understand business survival and mortality in the peer-to-peer accommodation sector. Second, this study provides a

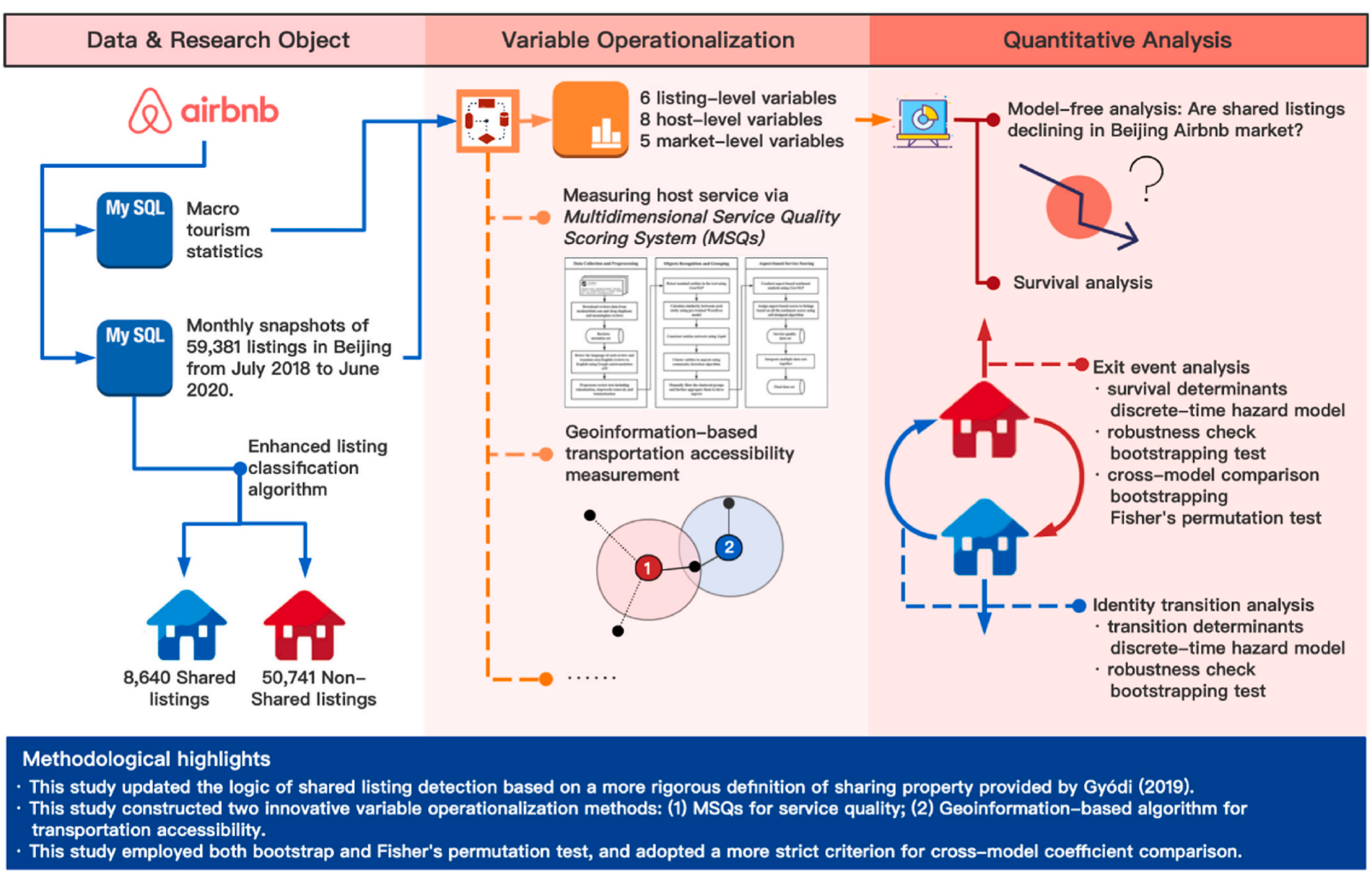

Fig. 1. Research framework of this study.

comprehensive picture of the survival status of Airbnb listings. Specifically, this study identifies two outcome events: not only exit events but identity transition events. Some listings might switch from shared to non-shared, while others might shift reversely. That means this study presents a fuller view of the dynamics of Airbnb listings' status in Beijing. Third, this study proposes two innovative variable construction methods. We develop a geoinformation-based method to measure transportation accessibility and a multidimensional service quality scoring system (MSQs) to quantify the service quality from online reviews.

2. Literature review

2.1. Peer-to-peer accommodation

The pertinent literature has focused primarily on factors in entry-related behaviors, including hosts' motivations for sharing their properties (Bremser & Wüst, 2021; Karlsson & Dolnicar, 2016), tourists' motivations for using peer-to-peer accommodation platforms (Guttentag, Smith, Potwarka, & Havitz, 2018; So, Oh, & Min, 2018), and repurchase (or rather rebooking) intentions (Sthapit, Del Chiappa, Coudounaris, & Bjork, 2020; Wang & Jeong, 2018). Many critical factors affecting entry-related behaviors were identified. In terms of hosts, financial gains and valued social interactions with guests were the most common reasons for hosting (Lampinen & Cheshire, 2016). For tourists, the motivating factors mainly included practical advantages (e.g., cost savings, household amenities, and location) and experiential benefits (e.g., social interaction, local authenticity, and novelty) (Guttentag et al., 2018; Paulauskaite, Powell, Coca-Stefaniak, & Morrison, 2017). Furthermore, Guttentag et al. (2018) stated that Airbnb guests were not homogenous and could be classified based on their reasons for choosing Airbnb. Several studies have also explored the repurchase/rebooking intentions for peer-to-peer accommodations. For example, Tussyadiah (2016) surveyed 644 tourists in the USA and found that enjoyment, economic benefits, and home amenities had a positive effect on satisfaction, which further influenced repurchase intentions. The above-mentioned studies provide valuable insights into why hosts and tourists enter this emerging market. However, a comprehensive understanding of the peer-to-peer accommodation business requires going beyond entry-related behaviors.

Recently, post-entry issues have attracted increasing research interest. For example, Huang, Coghlan, and Jin (2020) analyzed comments on Facebook and Twitter to explore the factors leading to consumer discontinuance of Airbnb usage and identified nine online and six offline service issues as the determinants of discontinuance. Chen and Tussyadiah (2021) investigated the types of service failure in peer-to-peer accommodation systems based on negative reviews and found that service failure in peer-to-peer accommodation was multi-dimensional, including tangible, informational, and relational aspects. Following this trend, the present study focuses on the post-entry performance of listings on Airbnb. Despite the importance of the survival of Airbnb listings as a topic, only a few studies have begun to explore this subject, making this study a valuable contribution to this stream of literature.

2.2. Survival analysis in the hospitality sector

Table A1 in the Appendix summarizes the main previous studies of survival analysis in the hospitality sector, which made great efforts to identify factors affecting survival. Earlier studies tended to focus on the internal (firm-level) factors, while recent studies have incorporated external (environment-level) factors into the analysis framework. Internal factors are the factors within the firm, including age (Türkcan & Erkuş-Öztürk, 2020), size (Kaniovski, Peneder, & Smeral, 2008), management practice (Gémar, Moniche, & Morales, 2016; Leoni, 2020), and financial performance (Gemar, Soler Ismael, & Guzman-Parra Vanesa, 2019; Lado-Sestayo, Vivel-Búa, & Otero-González, 2016). External factors are the elements that exist outside a firm that can impact a firm's operations, such as location (Vivel-Búa, Lado-Sestayo, & Otero-González, 2019), market concentration (Lado-Sestayo et al., 2016), market competition (Leoni, 2020), market size (Türkcan & Erkuş-Öztürk, 2020), and regional specialization (Türkcan & Erkuş-Öztürk, 2020).

This study differs from the existing literature in two ways. First, this study opens up a new discussion about business identity transition. The existing studies focused primarily on the exit event, with scant attention paid to outcomes of transition. To the best of our knowledge, this study is one of the first to investigate the identity transition event in the peer-to-peer accommodation ecosystem, deepening the understanding of the dynamics of Airbnb listings' status. Second, this study proposes several factors that have not been discussed before, including service quality, transportation accessibility, platform professionalization, and pandemic. In particular, this study develops a multidimensional service quality scoring system (MSQs) to quantify the different aspects of service quality. From this viewpoint, our work has not only contributed a new approach to the measurement of service quality but also added to the existing knowledge of survival determinants.

3. The determinants of survival status

As the present study aims to investigate the factors influencing the survival status of listings, this section discusses the determinants of survival status. Following the theoretical framework proposed by Vivel-Búa et al. (2019), this study considered two classes of factors that might affect the survival status of listings: internal factors and external factors. In our research context, internal factors refer to the intrinsic characteristics possessed by listing and host. Among the internal factors, we took into account listing-level factors (such as room type, capacity, facility, rating, and reviews) and host-level factors (such as host management practices and host service). External factors refer to the environmental characteristics of the listings' settings. The external factors in this study included transportation accessibility, tourism specialization, market volume, platform professionalization, and Covid-19. Given the continuous expansion of multi-listings and growing competition in the peer-to-peer industry, it is impossible for hosts to operate their listings without considering the impact of the external environment. Thus, external factors are indispensable to the analysis. The literature and peer-to-peer accommodations' characteristics were the grounds on which the factors were selected. Apart from the factors that were chosen in the light of Leoni (2020) and Türkcan and Erkuş-Öztürk (2020), this study also proposed several new factors based on our research context, including service, transportation accessibility, platform professionalization, and Covid-19.

3.1. Exit event

In this subsection, we discuss the impact of proposed factors on the exit event. Regarding the listing-level factors, previous research revealed that listing characteristics, such as room type, facility, etc., had important effects on survival (Leoni, 2020). This is understandable because listing features have been demonstrated to significantly influence booking rates and consequently profitability (Liang, Schuckert, Law, & Chen, 2020; Sainaghi, Abrate, & Mauri, 2021). As the basic attributes, room type and capacity will have an impact on survival. Facilities are positively related to survival, as listings with complete facilities will attract more bookings (Liang et al., 2020). Moreover, previous literature has shown that ratings and reviews positively influence revenue (Xie & Kwok, 2017). Therefore, a positive relationship between these two variables and survival is expected.

Among host-level factors, the previous literature showed that longevity, which Leoni (2020) measured from the creation of an online account, is a crucial factor in survival. However, there is no uniform conclusion as to its effect. On the one hand, the "liability of newness" held that new organizations experience a higher death risk than old ones (Stinchcombe, 2000), explained perhaps by the accumulated experience of managers (Brouder & Eriksson, 2013). Hosts' accumulated experience seems to be particularly important in the context of peer-to-peer accommodation platforms, since many hosts are not professionals and lack prior knowledge about how to manage the property. As a result, they have to start from the very beginning when joining the peer-to-peer accommodation platform and accumulate the relevant experience bit by bit. In this regard, experienced hosts are quite likely to outperform newcomers. On the other hand, the "liability of adolescence" hypothesis stated that the death risks of organizations in the early phase are low because agents often live on their initial resources and tend to monitor their performance (Bruderl & Schussler, 1990), which is also reasonable in the peer-to-peer market. Hosts just entering this emerging market often have enthusiasm for operating their properties. As time goes on, however, some of them may find this market is less ideal than they thought, and thus lose their passion and exit. Hence, we expect the host's longevity to affect survival, but the exact relationship is unclear.

Several studies have confirmed the positive relationship between management practices and hotel survival rates (Gémar et al., 2016; Gemar et al., 2019). In the context of hotel operations, management practices have a much broader sense. However, when hosts manage their business on the Airbnb platform, the measures at their disposal are the renting tools (Leoni, 2020), such as the instant booking option, response strategy, minimum stay requirement, and dynamic pricing. These renting tools make property management more efficient and thus improve profitability. For example, adopting the instant booking option and responding quickly to potential consumers can result in greater demand for accommodations (Benítez-Aurioles, 2018; Gunter, 2018). Minimum stay requirements can help allocate accommodations to consumers who will stay longer (Leoni, 2020). In addition, dynamic pricing is a good way to maximize profits, especially for tourism products (Gibbs, Guttentag, Gretzel, Yao, & Morton, 2018). Taken together, good managerial practices are ultimately reflected in the operational efficiency and profitability, and consequently influence the hosts' survival. Therefore, we postulate a positive relationship between good management practices and survival rate.

Service quality is regarded as a key factor in firm success, especially in the service-based sector. In terms of the hospitality industry, the previous literature suggested that improving service quality can help to enhance profitability and sustain competitiveness (Chen & Chen, 2014). In the peer-to-peer accommodation business, one distinguishing feature is the close social interaction between the hosts and consumers, which is embedded in the service process (Moon, Miao, Hanks, & Line, 2019). In this regard, the host's personal characteristics (e.g., openness and hospitableness) and the way they provide service will have a significant impact on consumer satisfaction, which in turn influences their performance. Accordingly, we expect service will positively affect the survival rate. Despite the importance of service quality in the hotel sector, it has rarely been discussed in the survival literature. One obstacle is that service quality is hard to quantify, due to its inherently intangible nature. But more recently, online reviews can serve as valid sources for service quality studies (Bi, Liu, Fan, & Zhang, 2020; Ding, Choo, Ng, & Ng, 2020), thanks to increasing use and the advancement of text-mining technology that allows a deeper understanding of the review contents. In light of these studies, we evaluate the quality of hosts' service by mining consumers' reviews.

In addition to internal factors, we also take into account external factors to evaluate the effects of the environment on listing survival. Among these factors, location is a basic variable whose importance has often been highlighted in hotel success (Gémar et al., 2016; Vivel-Búa et al., 2019). Lado-Sestayo et al. (2016) suggested location is key to hotel survival as it impacts tourists' demand, profitability, and occupancy. Although the influence of location may incorporate the specialization effect and competition effect, the geographic location itself matters as well (Türkcan & Erkuş-Öztürk, 2020). We thus examine both absolute location (transportation and district) and relative environment (tourism specialization and regional market volume) in turn. For geographic location variables, we control for transportation accessibility and district location. In line with prior literature, we expect a positive relationship between tourism location and survival rate.

The survival of peer-to-peer accommodation is bound to be affected by the overall development level of tourism at a destination. An aspect of the development level of tourism destinations that has attracted increasing attention is the impact of regional tourism specialization (Zhang, Tu, Zhou, & Yu, 2020). Higher tourism specialization brings in a larger number of visitors and facilitates the expansion of the hospitality market, which in turn ensures a higher demand for accommodation, thus yielding more profits (Zhang et al., 2020). Hence, accommodations located in a destination with high tourism specialization are likelier to survive. However, the increase in tourism specialization is followed by an increasingly competitive environment, and fierce market competition may result in a loss of market share for peer-to-peer accommodation, which ultimately impairs the hosts' survival. Thus, we assume tourism specialization has an impact on listing survival, but the relationship is unclear. Following Croes, Ridderstaat, and van Niekerk (2018) and Zhang et al. (2020), we measure the tourism specialization within a district by the ratio of tourism revenues to GDP.

The existing literature held that market volume influences firm survival through the effect of agglomeration economies. Agglomeration economies describe the fact that spatially clustered firms belonging to the same sector will benefit from network externality because clustering brings more suppliers and consumers. Tourism-related firms have also been affected by agglomeration economies. For example, Türkcan and Erkuş-Öztürk (2020) provided evidence that the survival rates of tourism-related businesses are higher in more concentrated areas. Similarly, listings located in clustered areas are expected to be less likely to leave the market. The most commonly used measurement of agglomeration economies is the number of firms in the industry in a certain area. Following Türkcan and Erkuş-Öztürk (2020), this study uses the number of listings available in a region as an indicator of agglomeration economies.

Platform professionalization should also influence the survival rate, as it intensifies market competition on the platform. Platform professionalization refers to the process of a platform moving away from sharing services and embracing the lodging business, which is driven by the proliferation of professional actors who are specialized in the renting business (Dogru, Mody, et al., 2020; Gil & Sequera, 2022). According to the "creative destruction" theory (Schumpeter, 1942), low concentration and a high level of competition make the market structure unstable. Accordingly, most research suggested a negative influence of market competition on survival, such as Brouder and Eriksson (2013); Leoni (2020). Therefore, we assume platform professionalization is negatively associated with survival rate.

Note that our research period overlaps with the Covid-19 pandemic. This global outbreak has triggered an unprecedented shock to the tourism and hospitality sectors in general, and the peer-to-peer accommodation market specifically (Dolnicar & Zare, 2020). Several studies have discussed the impact of Covid-19 on the peer-to-peer accommodation sector, including Gyódi (2022) and Bresciani et al. (2021). This study also takes the pandemic into account to assess its impact on the survival of listings.

3.2. Transition event

This subsection hypothesizes the identity transition mechanism. The transition event refers to the shift in the type of listing. In the peer-to-peer accommodation ecosystem, the dynamics of listings might be compared to biological evolution (Mäkinen & Dedehayir, 2014): some listings fail to adjust to the changing conditions and have to leave the market, while some listings have evolved to become more suitable for the market environment. In fact, identity transition can be regarded as an evolutionary process. The identity transition occurs because some hosts want to better survive in the marketplace by changing their model. As in the case of genetic mutations, hosts changing their model is an individual process, which is influenced by many factors at the individual level (Xie & Chen, 2019). However, from a macroscopic viewpoint, evolution has a direction. In nature, the major trend of macroevolution is the increase of function complexity (Sharov & Gordon, 2018). Similarly, actors in the peer-to-peer accommodation ecosystem are expected to evolve in more specialized directions. Evidently, non-shared listings are accompanied by more specialized amenities and services than shared listings. Therefore, we first assume that the identity transition is an asymmetric process that mainly occurs when shared listings become non-shared listings. We thus focus on the transition from shared listings to non-shared listings.

From the individual perspective, identity transition seems likely a spontaneous behavior. As a platform professionalizes, some hosts tend to actively change the type of listings to adjust to the market circumstances. Hence, understanding the motivation of hosts is crucial to comprehending the identity transition. The hosts' motivations for participating in this market can be classified into monetary motivations (e.g., earning money) and non-monetary motivations (e.g., supporting a sharing ethos, increasing social interaction, etc.) (Jung et al., 2016; Karlsson & Dolnicar, 2016). Hosts who are driven by more non-monetary motivations are more likely to adhere to a sharing ethos, whereas those who are monetarily motivated might prefer to embrace market change and chase profits. In other words, hosts who are profit-driven are more likely to change their listings' identity.

Focusing on the listing-level factors, room type may influence the occurrence of identity transition. The entire home is an independent space and is more readily utilized as a non-shared listing. Therefore, identity transition events are expected to occur more easily for entire homes. Previous literature showed that features intrinsic to a listing (e.g., capacity, facility, rating, and reviews) are positively related to booking rates and consequently revenue (Deboosere, Kerrigan, Wachsmuth, & El-Geneidy, 2019; Sainaghi et al., 2021). Listings with better intrinsic characteristics not only result in greater profits but also have the makings of a non-shared listing. Thus, a positive relationship between listing-intrinsic features and identity transition is expected.

Regarding the host-level factors, longevity is expected to positively influence identity transition, because accumulated experience can help hosts to become more professional (Xie & Mao, 2017). Previous studies suggested that responding quickly, employing dynamic pricing, and adopting the instant booking option are positively related to revenue (Deboosere et al., 2019; Kwok & Xie, 2019; Tong & Gunter, 2022), while setting a minimum stay requirement is negatively related to revenue (Sainaghi et al., 2021). Therefore, listings with a longer minimum stay requirement are less likely to transform. On the contrary, response time, being instantly bookable, and dynamic pricing are assumed to positively influence transition. Moreover, a positive relationship between service quality and transition is proposed, as non-shared listings require a higher quality of service.

Moving to the external factors, location is an important factor affecting the transition intention. A good location with convenient transportation and high tourism specialization will attract more tourists, resulting in a higher demand for accommodations and thereby more profits. Located in these areas, hosts who want to chase profits are likelier to change their listings' identity. But at the same time, hosts are exposed to a highly competitive environment, which may eliminate the intention of hosts to transform. Analogously, market volume brings agglomeration effects and also competition. Therefore, we postulate location, including transportation accessibility, tourism specialization, and market volume, will have an effect on identity transition, but the relationship is unclear. In addition, platform policy will also affect the development direction of listings. Platform professionalization is expected to have a positive effect on identity transition. Some hosts may change the identity of their listings in order to follow the trend of professionalization. Finally, we expect a positive relationship between Covid-19 and identity transition, because many consumers became concerned about the increased infection risk in shared spaces, perhaps creating more demand for non-shared spaces.

4. Methodology

4.1. Listing classification

The primary research interest of this study is to explore the survival status of shared and non-shared listings. In this study, following Gyódi (2019), we define the shared listings as listings provided by non-professional hosts (i.e., hosts should not have multiple listings listed on Airbnb) who rent their underutilized space. Except for the shared listings, the other listings are counted as non-shared listings. The first challenge in the research design is to identify two survival events and two types of listings, since none of this information is presented directly on the web. The pseudocode of Listing Classification and Event Identification is provided in Table A2 in the Appendix. Intuitively, the logic of departure events identification is as follows: Renting out an accommodation on the platform before time t but not after time t means that the listing was withdrawn from the market at time t. To identify transition events, listing classification must be performed beforehand.

In line with the definition, we designed an algorithm to distinguish the shared listings and non-shared listings based on the following criteria: ownership structure (i.e., the number of listings the host has) and listing capacity. The specific logic is: If a listing at time t is provided by hosts that only have one property on the platform *and* its rental space is smaller than its total capacity, then the listing is regarded as a shared listing at time t. Otherwise, the listing is labeled as non-shared. In the cases where a host listed two properties on the platform and stayed in one of them (i.e., share it with guests) and rented the other whole property out, the listings should be classified as non-shared listings because they do not meet the first criterion. After ascertaining the identity of each listing at each timestamp, transition events (i.e., listings switching identity) can also be detected.

4.2. Variable operationalization

In our study, we applied the explanatory variables discussed in Section 3. Brief descriptions of all variables are presented in Table 1 and descriptive statistics are presented in Table A3 in the Appendix. In particular, to measure transportation accessibility and service quality, we constructed two variables and proposed two innovative operationalization strategies. The first one is transportation accessibility. Referring to the work of Lai and Fan (2021), we operationalized this variable through the number of accessible public transportation options around the focal listing. For each listing, we first calculated the Manhattan distance from the property to each bus stop or subway station in Beijing based on their longitude and latitude data, and then counted the number of bus and subway stations whose distance to the property was less than 1 km to represent the transportation accessibility of the listing.

Another variable we constructed was the host service. Notice that it is challenging to quantify host service, which is effectively invisible and multidimensional. This study not only takes service quality into account but also explores the effects of different dimensions of the service, which is less discussed in the prior research. There are no standard rules to regulate the service of agents in peer-to-peer businesses like Airbnb, as compared to standardized hotels (Tanford, Raab, & Kim, 2012). Instead, the listing owners' personalities and their interactions with guests allow users to have a unique accommodation experience (Cheng, Fu, Sun, Bilgihan, & Okumus, 2019). Thus, the service provided by hosts has also become an integrated part of the experience in the context of Airbnb (Ert, Fleischer, & Magen, 2016). In this case, whether the hosts' service can influence their listings' survival status is also worth evaluating.

The user-generated ratings would seem appropriate to reflect the

Table 1
Description of explanatory variables.

Variables	Description	Literature source	Expected relationship	
			Exit	Transition
Internal				
Listing-level				
Shared room	Whether the listing type is shared room	Leoni (2020)	+/−	−
Entire home	Whether the listing type is entire home	Leoni (2020)	+/−	+
Capacity	Maximum number of guests the listing can house	Liang, Schuckert, Law, and Chen (2017)	+	+
Facility	Number of facilities provided in a listing	Chattopadhyay and Mitra (2019)	+	+
Rating	Overall consumer rating of a listing	Sengupta, Biswas, Kumar, Shankar, and Gupta (2021)	+	+
Reviews	Number of reviews received by a listing	Liang et al. (2020)	+	+
Host-level				
Longevity	Number of months since host's entry	Leoni (2020); Türkcan and Erkuş-Öztürk (2020)	+/−	+
Instant	Whether the host adopts the instant booking option	Wang and Nicolau (2017)	+	+
Response	Response time of the host (the value is smaller when the host responds to consumers more quickly)	Liang et al. (2020)	+	+
Minimum	Minimum number of nights consumers can book	Leoni (2020)	+	−
Pricing	Variance of the rental price	Developed from Leoni (2020)	+	+
Service_a	Score of services that can be changed by the host with no additional costs	Self-developed for this study	+	+
Service_b	Score of services that can be manipulated by the host but require additional costs	Self-developed for this study	+	+
Service_c	Score of services that cannot really be controlled by the host	Self-developed for this study	+	+
External				
Transportation	Number of subways and buses that stop within a 1-km radius of the focal listing	Developed from Lai and Fan (2021)	+	+/−
Tourism specialization	Ratio between total tourism revenue and GDP at the district level	Developed from Zhang et al. (2020)	+/−	+/−
Market volume	Number of listings at district level	Türkcan and Erkuş-Öztürk (2020)	+	+/−
Professionalization	Ratio between non-shared listings and total listings in Beijing on the Airbnb platform	Self-developed for this study	−	+
Covid-19	Taking the value of 1 for all listings in 2020 (period of the Covid outbreak) and 0 otherwise	Self-developed for this study	−	+

online reputation of the host, but there are two drawbacks related to this strategy. First, the accuracy of the user-generated rating has been debated due to its positivity bias (Bridges & Vásquez, 2018). In our description analysis, we figured out that the average rating of listings that have received ratings from guests is 4.718 on a scale of 5, which is highly skewed towards the positive end of the rating spectrum. However, previous research has demonstrated it is feasible to capture the perceived service quality by mining the guest's service experiences from online reviews and that this is less subject to positivity bias (Korfiatis, Stamolampros, Kourouthanassis, & Sagiadinos, 2019; Lawani, Reed, Mark, & Zheng, 2019). The second drawback is that the rating system achieves general feedback for listings by sacrificing description of the diversity of user evaluation aspects. Guests' perception of the cleanliness, communication, check-in, accuracy, location, and value of listings can be obtained from the rating, while some other aspects, like roommates, sleeping quality, shopping, and property attributes cannot easily be assessed from it. However, reviews are substantially more informative, so using them enables us to mine the latent aspects of guests' evaluation of the host service quality (Luo & Tang, 2019).

It is worth noting that the strategy we use to operationalize the service quality of the host via aspect-based sentiment analysis differs from existing methodologies. We designed a multidimensional service quality scoring system (MSQs) based on word embedding and network community detection. Using this system, we can calculate three dimensions of service quality, namely *Service_a* (the score of services that can be changed by the host with no additional costs), *Service_b* (the score of services that can be manipulated by the host but require additional costs), and *Service_c* (the score of services that cannot really be controlled by the host). The workflow of this system is shown in Fig. 2, and a detailed introduction is presented as supplementary material.

4.3. Data

In this study, we selected Beijing as a sample case for two reasons. First, China was the largest market for Airbnb by 2020 (Airdna, 2021), and Beijing, the capital of China, is a famous tourism destination, drawing millions of visitors and supporting a considerable number of peer-to-peer accommodations every year. As a great treasure trove of ancient Chinese culture and historical sites, Beijing has enjoyed the prosperous development of peer-to-peer accommodation (Bao, Ma, La, Xu, & Huang, 2021). According to the Annual Report of Shared Accommodation Development in China released by State Information Center (2020), Beijing ranked first in terms of the number of listings, booking volume, and the number of room nights. Second, Beijing is one of the most internationalized tourist metropolises and owns the most mature peer-to-peer accommodation market in mainland China, so it should provide a more diversified sample set and thus be able to

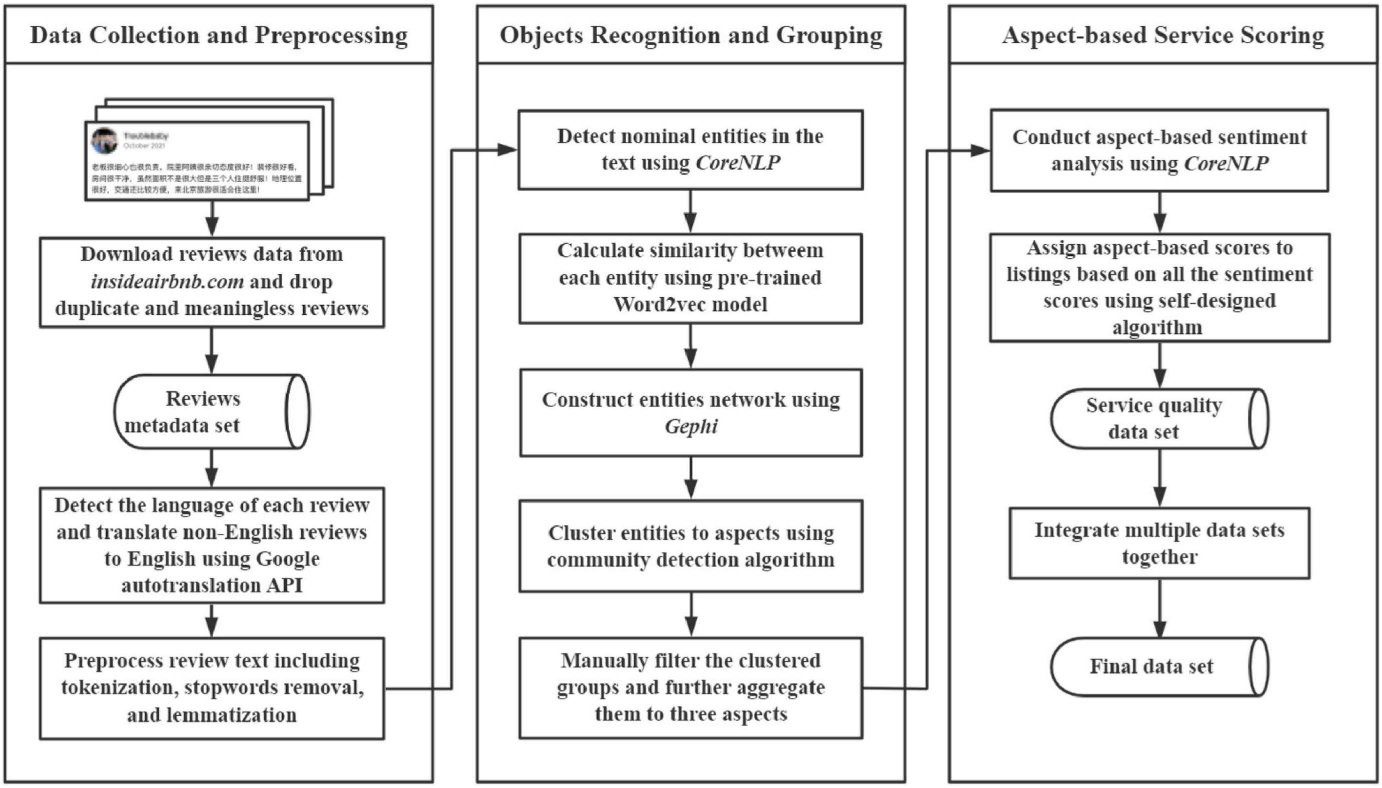

Fig. 2. The working framework of MSQs in the case of Airbnb.

generate universal insight into the survival status of Airbnb listings. Thus, selecting Beijing as the research subject ensures both adequacy and representativeness of data for our research.

The listing data were collected from Inside Airbnb, a website that provides publicly available Airbnb listing information. This data set was composed of the monthly Airbnb data during the period from July 2018 to June 2020, including property type, capacity, facility, reviews, ratings, and so on. We also acquired the Beijing public transport data from https://www.udparty.com and the tourism statistics from the Beijing Municipal Bureau of Culture and Tourism as well as Beijing Municipal Bureau Statistics.

The data set was constructed in a listing-period format. There were 8640 shared listings and 50,741 non-shared listings for 18,136 and 106,828 observations, respectively, in 4 semiannual periods. We defined *survival time* as the time elapsed between the start date of this study and the last record of each listing – either because the event of interest occurs or because the observation period ended on June 30, 2020 (Kleinbaum & Klein, 2012). A dummy variable *event* was used to indicate the occurrence of the event of interest (e.g., leaving the Airbnb platform). If the ith host experienced the event in the jth interval, then the dummy variable took the value of one for the corresponding time interval (t_j) and zero for other time points (1, 2, …, t_j-1).

Some points about the data need to be stated here. First, as the event of interest might not have occurred during the study period in some observations, the data was right censoring. Second, left censoring did not occur, as all the hosts in the data set were active at least until July 1, 2018, when the study period began. Third, interval truncation does not exist either. (Interval truncation refers to the situation in which a host leaves the platform briefly and appears again at a later point in time, which might be perceived as "resurrection.") One might assume that a host's dropping out and re-entering could be regarded as interval truncation, but in fact, once a host drops out from the platform all information in the account (such as ratings and reviews) is erased. If the host wants to re-enter the platform, she/he must start from zero, using a new identifier. As Leoni (2020) asserted, a "resurrected" host is, for the purposes of study, completely different from the original one.

4.4. Discrete-time hazard model

As the current study aims to assess whether and by how much the studied factors affect the survival status of Airbnb listings, a discrete-time hazard model was adopted following Türkcan and Erkuş-Öztürk (2020) and Basile, Pittiglio, and Reganati (2017). The discrete-time models possess several desirable features as compared with the Cox proportional hazard model (Allison, 1982). First, discrete-time models are powerful in handling data with a large number of ties. A tie means that "more than two individuals experience an event at the same time" (Allison, 1982). Second, it is convenient for incorporating time-varying covariates into the discrete-time analysis. Finally, discrete-time models can account for the heterogeneity between individuals by incorporating random effects.

The discrete-time model starts by dividing continuous time into an infinite sequence of contiguous time intervals $(0,t_1],(t_1,t_2],\dots,(t_{j-1},t_j],\dots$, where j represents the index of time intervals. Then, the discrete-time hazard function is defined as:

$$h(j,X)=1-\exp\left[-\exp\left(\beta' X+\gamma_j\right)\right], \tag{1}$$

where $\gamma_j$is the baseline hazard rate in jth time period; X is a vector of covariates that may influence the hazard rate; and β refers to the vector of corresponding coefficients that will be estimated from real data.

To estimate the discrete time hazard function, the following likelihood function is adopted:

$$L=\prod_{i=1}^{n}\prod_{j=1}^{j_i}h_{ij}^{y_{ij}}\left(1-h_{ij}\right)^{(1-y_{ij})}, \tag{2}$$

where y_{ij}denotes the event history of host i, taking the value of one if the ith host experienced the event in the time interval j and zero otherwise.

As Allison (1982) stated, the dummy variable y_{ij} can be regarded as the outcome in a logistic model and thus a discrete-time model can be specified as a type of logistic model, which provides a convenient way to obtain the maximum likelihood estimation. Hence, it is necessary to transform the discrete-time hazard function into a logistic-like form. Then, the cloglog transformation (or complementary log–log) of equation (1) is given by:

$$\mathrm{cloglog}(1-h(j,X)) \equiv \log(-\log(1-h(j,X))) = \beta' X + \gamma_j. \tag{3}$$

Next, to control for unobserved heterogeneity, the common practice is to introduce random effects into the hazard function:

$$h(j,X,v) = 1-\exp\left[-\exp\left(\beta' X + \gamma_j\right)v\right], \tag{4}$$

where v is the individual random effect, following a normal distribution $(v \sim N(m, \sigma^2))$.

The cloglog transformation of equation (4) is

$$\mathrm{cloglog}(1-h(j,X,v)) \equiv \log(-\log(1-h(j,X,v))) = \beta' X + \gamma_j + \mu, \tag{5}$$

where $\mu = \log(v)$.

5. Results

5.1. Model-free analysis

In this section, we reexamine the purported decline of shared listings, based on the full sample drawn from the Beijing Airbnb market. Fig. 3 presents the proportions of the two types of listings in the market pool and the increase rate of their relative proportions from July 2018 to June 2020. The results, contrary to the contemporary belief that shared listings are dying in the market, tell us that though the number of shared listings in the pool is relatively low (around 15% of the total), their population is not merely stable but slightly growing in Beijing over our study period (the net increase rate becomes positive after 2019).

Then we dived deeper to investigate the dynamics of listings on the platform. We systematically categorized the outcome events on the platform into three types: A) Leaving the platform; B) Changing to a non-shared listing; and C) Changing to a shared listing. We used Kaplan-Meier estimators to reflect the survival status of these three types of events. The subfigure at the top left of Fig. 4 graphically explains these transition processes we investigated, and the other three plots show the survival curves for these three events. In terms of listings' departures, we found that the survival probability of shared listings dropped faster than non-shared listings in the early life stage. But later, their survival probability gradually became stable and, after the median survival time, surpassed that of non-shared listings. This result shows that the dynamics of the outflow of the two types of listings on the platform are different. In terms of bidirectional transition, our curves illustrate the transition between shared and non-shared listings is rare and slow. The transition from non-shared listings to shared listings is a very unlikely event and can almost be ignored. However, aiming to provide a comprehensive analysis, we investigated all three of the mentioned events.

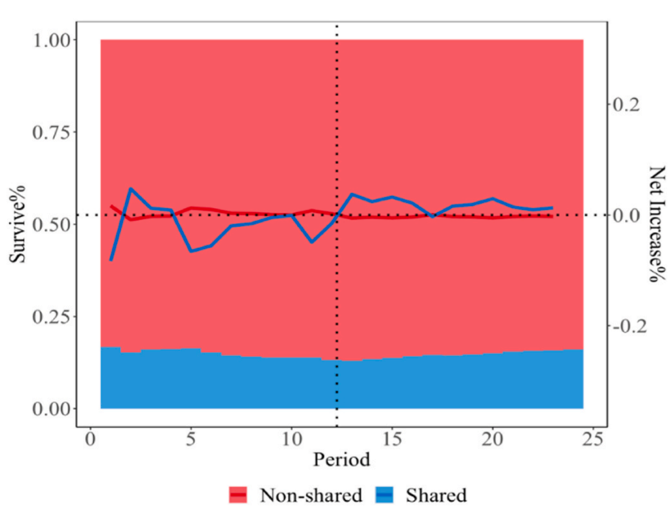

Fig. 3. Airbnb listings' survival status in Beijing (2018.07–2020.06).

In summary, we provide two lines of empirical evidence for the critical question proposed by Dolnicar (2019), namely "whether genuine peer-to-peer accommodation is on the decline." Our results intimate that the very existence of sharing accommodations is not currently endangered, at least in the Beijing Airbnb market. Though the proportion of shared listings in the market pool is somewhat low, it is stable, even growing slightly. Furthermore, the life expectancy of shared listings is longer than non-shared ones.

5.2. Exit event analysis

5.2.1. Estimation results

To assess the impact of individual heterogeneity on our findings, a non-frailty discrete-time hazard model and frailty model (i.e., a discrete-time hazard model with random effects) were estimated for comparison purposes. Apart from a series of covariates, both models included district and time dummy variables. Columns 1 and 3 of Table 1 report the estimated coefficients of the survival determinants of shared and non-shared listings based on the non-frailty model. The corresponding results for the frailty model are shown in columns 2 and 4. Meanwhile, we also provided model metrics (i.e., log-likelihood, AIC, ρ) and results of the likelihood ratio test at the bottom of the table. The parameter ρ indicates the relative importance of unobserved individual heterogeneity. As shown in Table 2, ρ of the frailty model equals 0, indicating that unobserved heterogeneity caused by individual effects was almost nonexistent and thus ignorable. In addition, likelihood ratio tests between the non-frailty model and the frailty model failed to reject the null hypothesis of $\rho = 0$; hence, we turned to the simpler model structure. In this section, a positive coefficient means that the corresponding factor increased the probability of exit. On the other hand, a negative coefficient indicates that the factor had a negative impact on the hazard and thus positively affected survival. In the following analysis, the significance level will be set at $p \leq 0.05$.

We reported the results of factors from three categories: 1) *common determinants* (i.e., variables that can influence all listings' survival); 2) *unique determinants* (i.e., variables that can only influence one type of listings' survival); and 3) *irrelevant determinants* (i.e., variables that can neither influence shared listings nor non-shared listings). A summary of estimation results is presented as follows. Starting from the listing-level internal variables, the *common determinants* included *facility*, *rating*, and *room types*. For *room types*, there were two binary variables: *entire home* and *shared room*. The results show that, in the shared listing group, entire homes were more likely to exit, while in the non-shared listing group the shared rooms were less likely to survive. *Reviews* was the unique determinant in this section since it only presented a positive effect on non-shared listings. *Capacity* was the *irrelevant determinant*. As for host-level internal variables, the *common determinants* included *longevity* and *response*. The *unique determinants* for the non-shared group were *instant*, *pricing*, and all three dimensions of service, and the *unique determinant* for the shared group was *minimum*. Turning to the external factors, the two types of listings shared many *common determinants*, including *transportation*, *market volume*, *professionalization*, and *Covid-19*. The *unique determinant* for the shared sector was *tourism specialization*.

Intriguingly, some of the results were inconsistent with our expectations. First, service exerts different effects in different groups of listings. Three dimensions of service had no significant impact on the

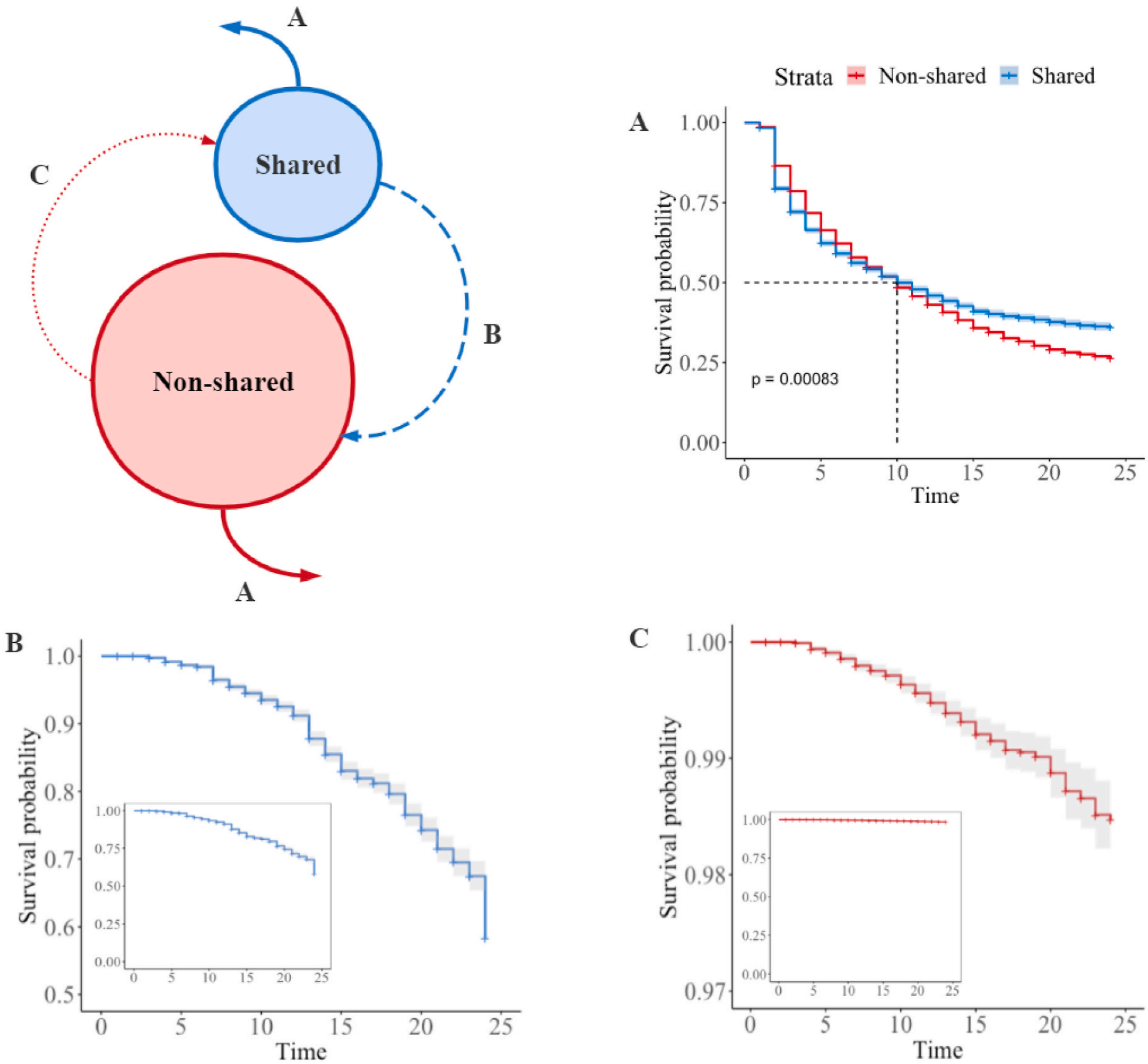

Fig. 4. Schematic illustration of the status transitions for listings in Beijing from July 2018 to June 2020 and the corresponding Kaplan-Meier estimators. A) Leaving the platform, B) Changing to a non-shared listing, and C) Changing to a shared listing. Note that the y-axis scales of plots A, B, and C are different, and the full-scale situations of B and C are presented in the subplots of B and C.

survival of shared listings. This is somewhat counterintuitive but can possibly be explained by the nature of shared listings. Shared listings are generally offered by amateur hosts who are not trained to deliver professional accommodation service (Gyódi, 2019). The intention of shared listings is not to offer considerate service like hotels, but to provide a place to sleep (Lutz & Newlands, 2018). In this case, service may not be the major concern for the target consumer. Therefore, it is not surprising that service is not an important factor affecting the survival of shared groups. For non-shared listings, although all three dimensions of service had a positive effect on survival, there was no clear difference in their effects, which means the effects of the three dimensions of service on listings' departures are likely equivalent. These results imply the quasi-hotel nature of non-shared listings. The heterogeneous effects of services on the two groups suggest that the two kinds of listings are intrinsically different.

Second, we realized that, for shared listings, the renting strategies (including the instant booking option and dynamic pricing) and host service didn't have significant effects on survival, implying that internal factors are less important for the shared listings.

Third, high transportation accessibility had a negative effect on survival. This may be because most of the places with convenient transportation are in bustling areas and thus face fierce competition. Therefore, location necessitates a trade-off between transportation accessibility and competition level.

Fourth, tourism specialization only had a positive impact on survival in the shared sector. For shared listings, being located in an area with high tourism specialization significantly improved their survival rates. For non-shared listings, the effect of tourism specialization was statistically insignificant. One possible reason is that the benefit of higher tourism specialization is offset by the increasing competition, implying non-shared listings are more affected by competition.

5.2.2. *Robustness check and coefficient comparison*

To assess the sensitivity of our estimation to the data, bootstrapping was employed next. Bootstrapping is an appropriate alternative to the traditional approach of hypothesis testing and can provide approximating distributions of statistics, estimates of standard errors and confidence intervals, and rejection probabilities of hypothesis tests (Efron & Tibshirani, 1994). Without relying on any distributional assumption, bootstrapping enables us to quantify the uncertainty associated with given estimators more accurately by repeatedly sampling with random replacement. In this case, compared with the traditional approach of hypothesis testing, it provides a better approximation of the variance of the estimators (Efron, 1987). Moreover, the estimators' distributions

Table 2
Estimation results for exit event.

	Shared		Non-shared	
	Non-frailty model	Frailty model	Non-frailty model	Frailty model
Shared room	0.107	0.107	0.092***	0.092***
	(0.083)	(0.084)	(0.029)	(0.030)
Entire home	0.180***	0.180***	−0.022	−0.022
	(0.035)	(0.035)	(0.015)	(0.016)
Capacity	−0.005	−0.005	0.005	0.005
	(0.018)	(0.019)	(0.007)	(0.007)
Facility	−0.160***	−0.160***	−0.092***	−0.092***
	(0.018)	(0.019)	(0.007)	(0.008)
Rating	−0.062***	−0.062***	−0.086***	−0.086***
	(0.021)	(0.021)	(0.009)	(0.009)
Reviews	−0.038*	−0.038*	−0.043***	−0.043***
	(0.020)	(0.021)	(0.008)	(0.009)
Longevity	0.087***	0.087***	0.143***	0.143***
	(0.018)	(0.018)	(0.008)	(0.008)
Instant	0.010	0.010	−0.056***	−0.056***
	(0.035)	(0.036)	(0.014)	(0.015)
Response	0.178***	0.178***	0.120***	0.120***
	(0.013)	(0.013)	(0.006)	(0.007)
Minimum	−0.121***	−0.121***	−0.002	−0.002
	(0.033)	(0.034)	(0.007)	(0.007)
Pricing	−0.056	−0.056	−0.043***	−0.043***
	(0.049)	(0.051)	(0.013)	(0.014)
Service_a	−0.012	−0.012	−0.015**	−0.015**
	(0.017)	(0.017)	(0.007)	(0.007)
Service_b	−0.016	−0.016	−0.014**	−0.014*
	(0.018)	(0.018)	(0.007)	(0.008)
Service_c	−0.004	−0.004	−0.014**	−0.014*
	(0.017)	(0.017)	(0.007)	(0.008)
Transportation	0.062***	0.062***	0.039***	0.039***
	(0.018)	(0.018)	(0.008)	(0.008)
Tourism specialization	−0.215***	−0.215***	−0.020	−0.020
	(0.049)	(0.050)	(0.022)	(0.023)
Market volume	−4.143***	−4.143***	−5.161***	−5.161***
	(0.093)	(0.103)	(0.045)	(0.052)
Professionalization	0.460***	0.460***	1.284***	1.284***
	(0.020)	(0.024)	(0.009)	(0.010)
Covid-19	1.238***	1.238***	2.393***	2.393***
	(0.094)	(0.098)	(0.047)	(0.051)
District dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Log-likelihood	−8568.171	−8568.171	−43683.650	−43683.650
AIC	17,210.342	17,212.342	87,441.298	87,443.298
ρ	–	0.000	–	0.000
Likelihood ratio test	Chi2-statistic	p-value	Chi2-statistic	p-value
	0	0.9957	1e-04	0.9943

Note: Standard errors are shown in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

obtained from bootstrapping can be further exploited for cross-model coefficient comparison. The bootstrap method produces assumption-free pointwise confidence intervals that are always wider but more reliable than theoretical confidence intervals (Thomas & Bradley, 1996).

In our study, the distributions of coefficients obtained according to the bootstrap method are shown in Fig. 5. It is evident that all coefficients are convergent and consistent with prior results, indicating our results are robust. Also, the differences in coefficient estimates can be visually observed based on the bootstrapped distribution (Two coefficients are considered to be significantly different if their bootstrapped distributions do not overlap). Furthermore, we adopted Fisher's permutation test following Cleary (1999) as a validation. It can be found that some pairs of coefficients show a significant difference in Fisher's test but in cases in which there are overlaps between the corresponding distributions. To make our results more reliable, we adopted a conservative and strict criterion to determine the difference in coefficients. It was considered significant only when both tests confirmed the difference. Combining the results of the distribution test and Fisher's test, we found that certain variables, including longevity, response, tourism specialization, market volume, professionalization, and Covid-19, differed significantly across the two groups, suggesting these variables exert different levels of influence on the two types of listings.

Apart from that, we also found that, compared with the shared listings, the survival of non-shared listings was affected by more internal factors. Results show that the internal unique determinants of non-shared listings included *Reviews*, *Instant*, *Pricing*, *Service_a*, *Service_b*, and *Service_c*. This signals non-shared listings are more vulnerable to the impact of inherent features along with the hosts' service quality.

Moreover, as can be seen from the coefficient distributions of market volume, professionalization, and Covid-19, non-shared listings were more strongly influenced by certain external factors than shared listings regardless of effect direction. Interestingly, professionalization exerted a larger influence on the survival of non-shared listings, suggesting the increased professionalization of the platform leads to the increase of the outflow of both non-shared and shared listings. Plus, the speed of the outflow of non-shared listings was faster than their shared counterparts. Additionally, the heterogeneous effect of Covid-19 on both types of listings confirmed the hypothesis proposed by Dolnicar and Zare (2020).

5.2.3. Remarks

Here, we present several intriguing findings based on the above results.

First, in general, many factors had heterogeneous effects on the survival of different types of listings, indicating the survival models may be fundamentally different across the two types of listings and the driving forces behind the exit decisions of listing owners are different.

Second, shared listings were greatly affected by external factors, suggesting internal factors have less to do with the decision to leave by the shared listings' owners. Moreover, the responses of shared listings to external factors were asymmetrical (i.e., reacting at different levels when impacted positively and negatively by the market). One explanation might be that hosts of shared listings are inherently semi-profit-oriented in some ways. They appear to be relatively insensitive to the negative feedback from the market because most shared listing owners treat renting as an additional income source rather than the primary one, so even if few people rent their rooms, they are less likely to respond to the market accordingly. On the other hand, when exposed to a positive market environment, hosts of shared listings, though less profit-driven than professional hosts, may still react to the market because extra income still has positive effects on them.

Third, non-shared listings were collectively influenced by internal and external factors, so it is reasonable to infer that the owners of non-shared listings are affected by both types of factors when making decisions. In addition, non-shared listings seem more vulnerable to the external environment than shared ones—a fact in line with the general belief that owners of non-shared listings are more market-oriented.

5.3. Identity transition event analysis

5.3.1. Estimation results

Our main analysis focused on the exit event, but we also explored the identity transition event, enabling us to provide a more comprehensive understanding of the survival status of Airbnb listings. Table 3 presents the estimation results of identity transition events. A positive coefficient means that larger values of the corresponding variable increased the probability of identity transition (and vice versa).

Regarding the transition from shared to non-shared listings, the random effect model was adopted because the result of the likelihood ratio test indicated that unobserved heterogeneity was present in our model, which showed substantial variability across individuals during the transition process. The results suggest that entire homes are more likely to change than shared rooms. Meanwhile, capacity, facility, rating, and reviews had a positive effect on identity transition, suggesting

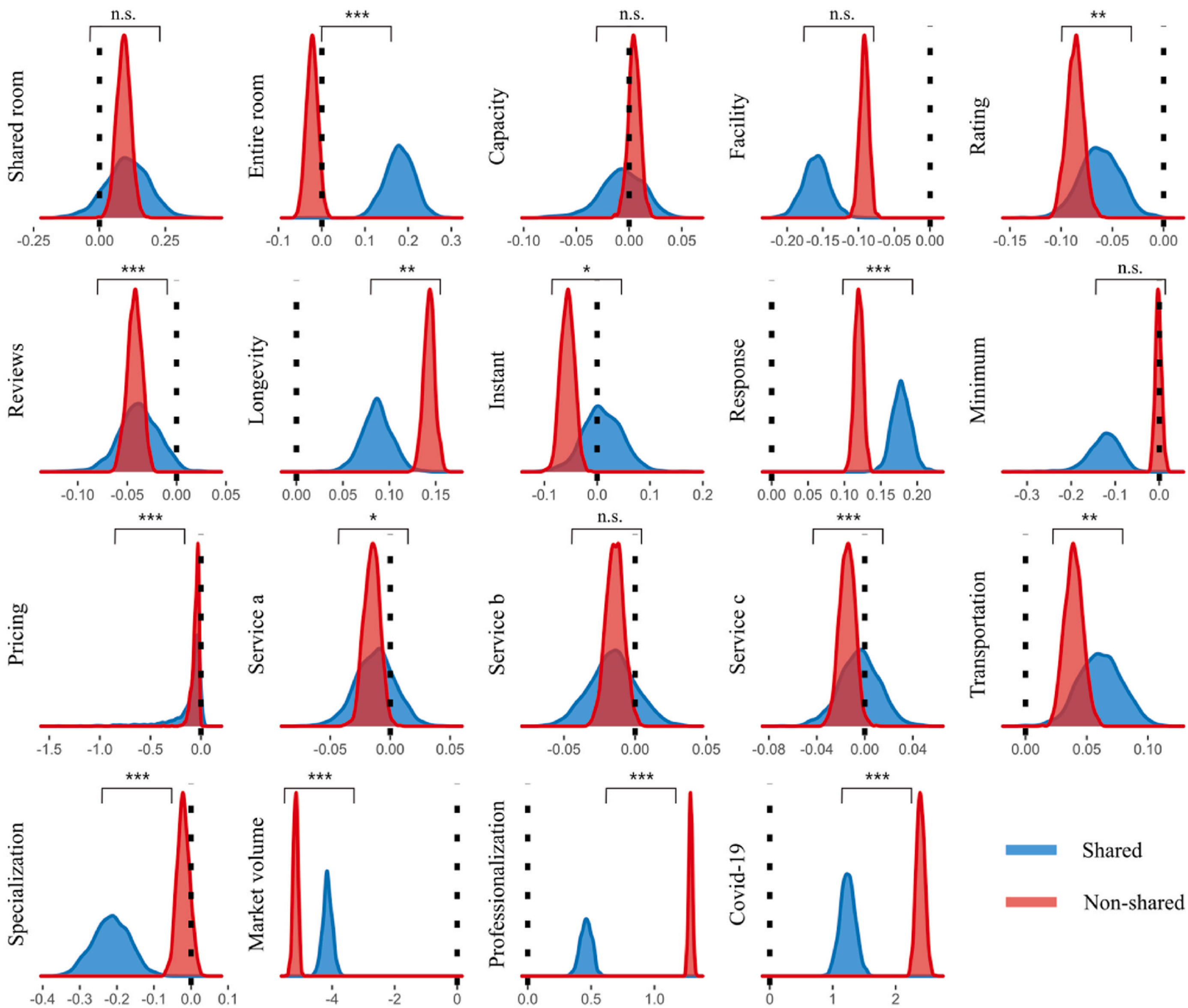

Fig. 5. Bootstrap results for all variables with respect to the exit event. *Note:* The signs present the results of Fisher's permutation test, indicating whether two coefficients were significantly different from each other. n.s. means not significant. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

that listing-level characteristics are important to explain transitions. Hosts setting a longer minimum stay requirement negatively affected the probability of transition. The existing literature has confirmed that setting a minimum stay has a negative impact on price and revenue (Sainaghi et al., 2021). It can be inferred that owners of shared listings who tend to set a longer minimum stay requirement are less profit-driven, and therefore have less incentive to change the identity of their listings.

Also, services that can be manipulated by the host but require additional costs were negatively associated with transition, implying that amateur hosts who provide high-cost services tend to keep their status. Hosts who are willing to devote money to improve the service may not be short of money, and therefore are less profit-driven. They are more likely to be self-driven. For example, they are sharing supporters or they want to improve social interactions (Sainaghi, 2020). In this case, hosts are not motivated to change their status. Apart from that, the other two dimensions of service had no significant impact on the transition.

In terms of external factors, tourism specialization and market volume had negative effects on transition, while platform professionalization and Covid-19 showed positive correlations with transition. This effect of Covid-19 could result from the need for social distancing during the pandemic. In this vein, consumers tend to choose accommodation types that guarantee physical distance (Bresciani et al., 2021). Accordingly, some amateur hosts may have switched their listings to non-shared ones under the requirements of social distancing.

We did not attempt to interpret the coefficients for the transition event from non-shared listing to shared listing based on two considerations. First, the transition from the non-shared to shared listing was a low-probability event, so the limitations in sample size could result in unreliable statistical projections and inferences. Second, after performing a bootstrap analysis, we found some variables did not converge well, implying that the results were not robust enough to draw convincing conclusions.

5.3.2. *Robustness check*

As shown in Fig. 6, the coefficient estimates with regard to the transition from shared to non-shared listing are consistent with prior results, indicating our results are robust. However, for the other identity transition event (from non-shared to shared listing), several coefficient estimates obtained from the bootstrap procedure did not converge

Table 3
Estimation results for identity transition event.

	Shared		Non-shared	
	Non-frailty model	Frailty model	Non-frailty model	Frailty model
Shared room	0.007	−0.065	−6.179	−6.181
	(0.195)	(0.693)	(6.533)	(6.539)
Entire home	0.189***	0.775***	0.907**	0.907**
	(0.064)	(0.264)	(0.359)	(0.359)
Capacity	0.243***	0.591***	−1.079***	−1.079***
	(0.015)	(0.065)	(0.360)	(0.360)
Facility	0.181***	0.202**	0.062	0.062
	(0.026)	(0.094)	(0.132)	(0.132)
Rating	0.457***	0.612***	0.406**	0.406**
	(0.038)	(0.120)	(0.194)	(0.194)
Reviews	0.103***	0.505***	0.232***	0.232***
	(0.019)	(0.078)	(0.062)	(0.062)
Longevity	0.118***	0.060	0.191	0.191
	(0.028)	(0.130)	(0.147)	(0.147)
Instant	−0.019	−0.054	0.104	0.104
	(0.061)	(0.193)	(0.308)	(0.308)
Response	0.051*	0.074	0.088	0.088
	(0.027)	(0.062)	(0.133)	(0.133)
Minimum	−0.069	−1.025***	−0.876	−0.876
	(0.047)	(0.287)	(0.661)	(0.662)
Pricing	0.029	−0.097	−0.190	−0.190
	(0.018)	(0.079)	(0.363)	(0.363)
Service_a	0.028	0.097	0.197*	0.197*
	(0.028)	(0.114)	(0.101)	(0.101)
Service_b	−0.042	−0.360***	0.062	0.062
	(0.028)	(0.109)	(0.119)	(0.119)
Service_c	0.013	−0.083	−0.106	−0.106
	(0.025)	(0.095)	(0.143)	(0.143)
Transportation	0.044	−0.059	−0.178	−0.178
	(0.033)	(0.152)	(0.179)	(0.179)
Tourism specialization	−0.012	−0.669***	0.848*	0.848*
	(0.078)	(0.180)	(0.502)	(0.502)
Market volume	−2.130***	−2.218***	−34.663***	−34.667***
	(0.277)	(0.394)	(2.620)	(2.620)
Professionalization	0.959***	1.501***	2.605***	2.605***
	(0.052)	(0.131)	(0.157)	(0.157)
Covid-19	3.653***	4.403***	41.390	44.410
	(0.031)	(0.367)	(465.890)	(3469.253)
District dummies	Yes	Yes	Yes	Yes
Time dummies	Yes	Yes	Yes	Yes
Log-likelihood	−3986.127	−2885.479	−369.290	−369.290
AIC	8046.254	6032.871	812.580	814.580
P	–	0.669	–	0.000
Likelihood ratio test	Chi2-statistic	p-value	Chi2-statistic	p-value
	2201	<2.2e-16	0	0.9992

Note: Standard errors are shown in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

successfully, meaning that the results are not robust.

5.3.3. Remarks

Some interesting findings arise from analysis of these two events. First, services provided by the hosts have different effects on the exit event and the transition event. We showed that services with different levels of adjustment flexibility had an almost identical effect on listings' exits, whereas the impact was heterogeneous for identity transition. Second, amateur hosts tend to keep their states (neither exiting nor transitioning) when their listings are located in tourism-specialized regions or listing-clustered areas.

6. Discussion and conclusions

6.1. Discussion

In light of the ongoing debate over the *professionalization* of Airbnb, this study analyzes the survival status of Airbnb listings in Beijing over the period from July 2018 to June 2020, considering each type (shared listing and non-shared listing) separately to identify differences between them. Notably, we studied not only exit events but also identity transition events, thus providing a panoramic view of the survival status of listings in the peer-to-peer ecosystem. In general, this study draws three main conclusions. First, property sharing is not dying in the peer-to-peer accommodation sector. The proportion of shared listings in the market pool is somewhat low, but it is at least stable, even growing slightly. The shared listings also have a higher expected survival rate than non-shared ones in the long term. Second, there is a significant difference between the two types of listings in terms of survival determinants, indicating survival patterns are substantially different across the two groups. Third, there exists internal flow in the system, mainly from shared listings to non-shared listings, and it is collectively influenced by internal and external factors.

One possible explanation underlying survival discrepancies is differences in the nature of shared and non-shared listings' owners. In our findings, we found that internal factors confirmed to be associated with revenue, like the pricing strategy, instant bookings, and the number of reviews can significantly influence the departure of non-shared listings but not shared ones. Interestingly, non-shared listings also appear to be more sensitive to external factors such as regional market volume, platform professionalization, and social turbulence (that is, Covid-19). Gathering all the pieces of evidence together, it can be inferred that the owners of non-shared listings are more profit-driven than the owners of shared listings. Conversely, the owners of shared listings appear relatively less motivated by profit considerations when deciding whether to withdraw from the market. What kind of motivations, then, do sharing hosts have? While our empirical results do not provide direct evidence, we sought clues in prior literature, as numerous studies have explored hosts' motivations for participating in the peer-to-peer accommodation sector. For example, Karlsson and Dolnicar (2016) identified income, social interaction, and sharing unused space as the major reasons for offering a listing on Airbnb. Kim, Lee, Koo, and Yang (2018) explored the reasons why hosts share their accommodations without any expected economic benefit (through the non-commercial CouchSurfing network) and identified four antecedents: pleasure of offering help, shared narratives, desire to make friends, and reciprocity. Sainaghi (2020), looking at for-profit sharing of accommodations, stated that earning additional income and increasing social interactions were principal motivations. It is known from the literature that apart from extrinsic (monetary) motivation, intrinsic (non-monetary) motivation also plays an important role in decisions to participate in the peer-to-peer market (Querbes, 2018). Building on the discussion above, we can reasonably infer that sharing hosts are also driven by certain intrinsic factors when making exit decisions. In other words, sharing hosts may be assumed to be more self-driven.

In our analysis, the transition from non-shared to shared listings seems rare, but this does not mean that such transitions should be ignored. Instead, this transition suggests some professional hosts may also embrace the concept of a sharing economy. Induced by certain factors, professional hosts could become motivated to share space, perhaps further transforming into a special kind of host who sells their inventory while also sharing personal living space. However, this type of host is beyond the definitions of "sharing" or "commercial" hosts considered in this study. Even so, there is no doubt that this novel "sharing-commercial" host has made greater use of idle personal resources and adjusted the balance of supply and demand in the market. The springing up of this type of host could bring about needed changes in the peer-to-peer accommodation sector and even the housing market.

6.2. Theoretical contributions

This study enriches the research about business agents' survival and mortality in the peer-to-peer accommodation sector in two respects. First, this study helps confirm that survival patterns vary between

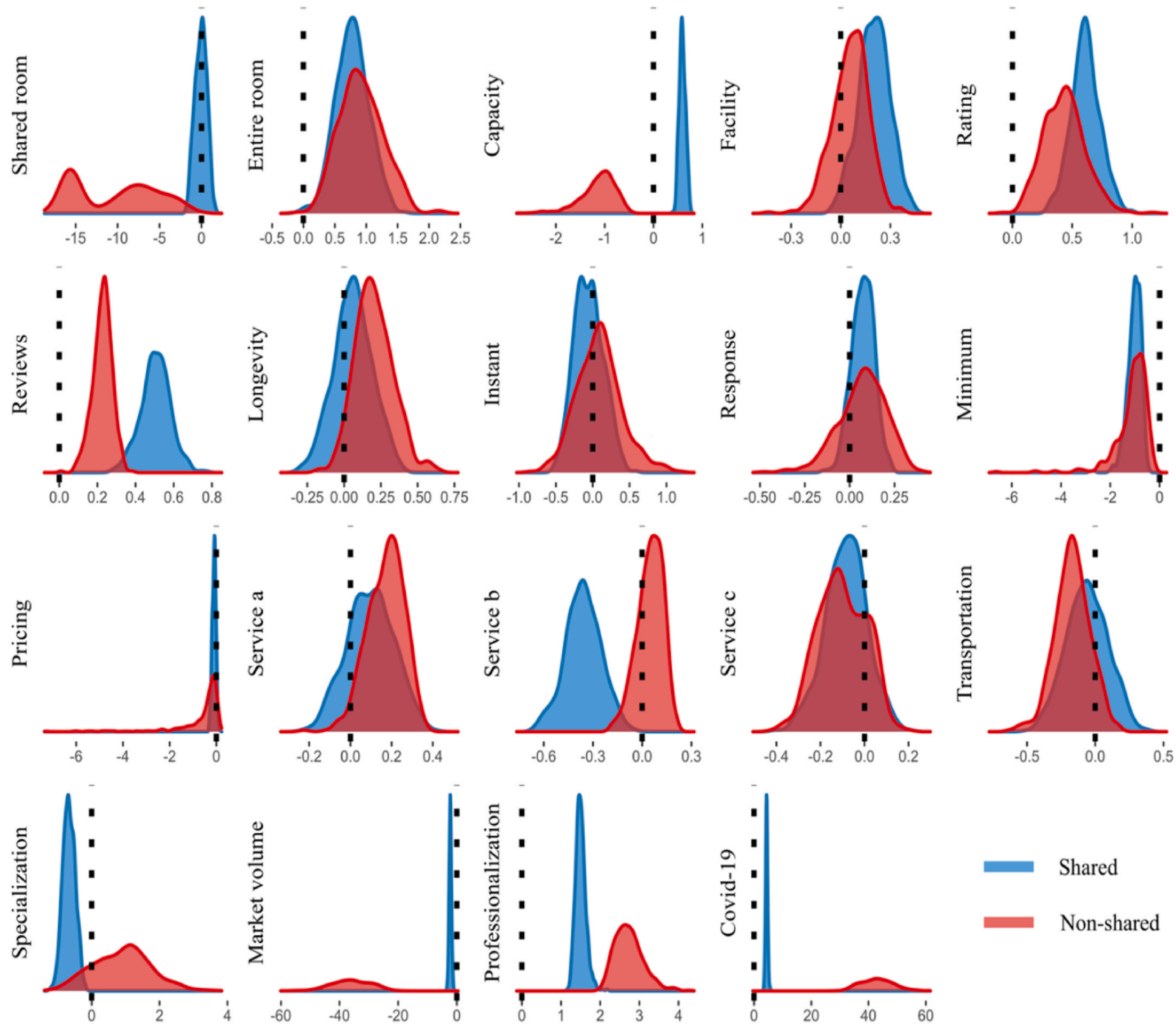

Fig. 6. Bootstrap results for all variables with respect to the identity transition event.

shared and non-shared listings. Given that the professionalization of Airbnb is currently an emerging trend (Oskam, 2019), a few studies began to consciously discuss different types of providers on the platform, and provided some valuable insights (Gunter, 2018; Xie, Heo, & Mao, 2021; Zekan & Gunter, 2021). In line with these studies, we argued that the shared listings and non-shared listings should be recognized as two distinct groups, and we explored the survival status of each type. The insights provided in this study add to our understanding of why listing segmentation is important in discussing the survival of Airbnb listings. Our findings highlight the differences in survival determinants between shared listings and non-shared listings and identify specific aspects that amateur hosts and commercial hosts must manage to improve their survival. Second, this study provides a deeper understanding of the dynamics of the professionalized peer-to-peer sharing system. While a prior study focused exclusively on exit events (Leoni, 2020), our work went further to analyze another outcome, namely identity transition events. By doing so, this study provides a fuller view of the dynamics of listings in the peer-to-peer market.

Methodologically, this study makes three contributions. The first lies in shared listing identification. Although there has been a substantial amount of research on sharing participants on Airbnb, there is still no standard method of identifying sharing agents in the marketplace. Instead, previous researchers regarded listings whose hosts only rent one accommodation as shared ones—an oversimplification. Based on a more rigorous definition of shared property provided by Gyódi (2019), this study updates the logic of shared-listing identification by narrowing the range to those sharing permanent homes. This approach can benefit future research on the sharing sector of the peer-to-peer rental market. Second, the innovative variable construction methods in our work may also have reference value for later studies. The service quality quantifying method introduced and employed in this research, MSQs, is especially worth noting because it has the potential to outperform mainstream LDA-based methods. We also provided an in-depth explanation of MSQs in the supplementary document to facilitate future reproduction and usage. Lastly, our empirical work can provide ideas for the practice of cross-model estimation comparison in the survival analysis context. This study gives an example of how to conduct rigorous quantitative analysis to identify the differences of coefficients between survival models that are trained on different data sets. Hewing to a conservative principle, we employed both the bootstrap method and Fisher's permutation test to double-check the significance of the differences. This study is thus a good model for implementing convincing comparison analysis in survival analysis research.

6.3. Practical implications

This study provides valuable practical implications for host, platform, and policymaker. Our findings provide a guide for hosts who wish to improve the survival probability of their listings. Note that some hosts are forced to leave because they can't survive on the platform, while some hosts leave the platform voluntarily. Although our empirical analysis cannot distinguish these two possibilities, the findings are still valuable for hosts who desire to stay on the platform. For professional hosts, a good managerial practice is to make use of renting strategies such as the instant book option and dynamic pricing to improve management efficiency, positively influencing survival. Professional hosts should also know the important role of service in the peer-to-peer accommodation business and exert effort to offer outstanding hospitality. For sharing hosts, offering adequate facilities, providing quick responses, and setting a minimum stay requirement are practical strategies to improve survival rates. Regarding the external environment, hosts should be aware of the negative effects of high transportation accessibility on survival. Thus, a location with high transportation accessibility may not be a good choice for peer-to-peer accommodation. Moreover, the evidence suggests that the effect of market volume is positively associated with survival rate. Thus, locations in clustered areas can benefit listings through network externality, leading to a high survival rate. The results also indicate that the increasing professionalization of the platform will jeopardize the survival of all types of listings, so limiting the expansion of multi-listings could be a strategy to improve the incumbents' survival.

The increasing professionalization of Airbnb re-opens the debate on whether Airbnb is moving away from its sharing economy narrative, which compels Airbnb as well as other sharing platforms to rethink the impact of professionalization on its brand identity and business strategy (Dogru, Hanks, et al., 2020). If the sharing economy ethos is still important to them, Airbnb-like platforms should take measures to maintain the sharing economy ecosystem. This study takes Airbnb as a representative to study the behaviors of sharing agents and sheds light on how to maintain the sharing economy model on profit-based sharing platforms. Each shared listing supplied by a sharing host helps to make, in its small way, the foundation of the sharing economy. Their survival status directly influences the vitality of the sharing ecosystem. If most of the shared listings are leaving, the sharing ecosystem will eventually crumble away. In this vein, ensuring the survival of shared listings could provide a practical way to maintain the vigor of the sharing economy at the micro-level. Based on our findings, platform managers could provide useful guidance or even vocational training for amateur hosts to help them run their businesses better. For example, Airbnb launched Airbnb Host Academy in China in 2018, aiming to offer relevant educational content to hosts online and offline (Airbnb, 2018)—a good reference perhaps for similar platforms. Finally, the difference in survival patterns between the two groups of listings should be considered by policymakers when developing policies for this market.

6.4. Limitations and future work

This work is not without limitations. First, our research is limited to a single market as well as a single platform. Future studies could use data covering more regions and more platforms to generalize the findings. Second, although we attempted to include as many factors as possible in the survival analysis, there could be other potential confounding factors that need further study, such as personal motivation, social and legal issues, and so on. Future studies can utilize interview or survey methods to better understand why hosts leave the peer-to-peer accommodation industry, fleshing out their motivations. Third, our classification method has certain deficiencies due to data limitations. Specifically, our classification method cannot deal well with some special cases. For example, the unusable capacity is used for storage rather than the hosts' own living. Future research can further improve the classification accuracy by supplementing data and updating algorithms. Last but not least, our analysis overlooks the complexity of the pandemic's effect on listings' survival. Rigorously speaking, the impacts of the pandemic on the survival status of Airbnb listings may show up in various forms. One is the direct effect – the impact that Covid-19, as a social-economic event, independently has on listings' survival. The other is the interaction effect – the pandemic's ability to change the effects of other factors on listings' survival status. In this study, only the direct effect of Covid-19 was studied, since our original intention was to provide a full view of the survival status of Airbnb listings rather than to explore the specific effects of Covid-19 on the peer-to-peer accommodation market. Besides, the insufficient post-pandemic sample did not support construction of sophisticated models on the effect of Covid-19. However, understanding how the pandemic influenced market participants and the market as a whole is an extremely meaningful topic that is worth further investigation.

This study also opens the ways for advanced research. Given the ongoing professionalization of Airbnb, its future has been a topic of much discussion (Dolnicar, 2019). This research reveals that there is a weak, asymmetric internal flow between the real sharing economy and the professional agents on the Airbnb platform, which might indicate the professional and sharing sectors of the market are bridgeable. What motivates the shift between shared and non-shared listings? How can we weaken the boundary between them (i.e., accelerate the internal circulation of the market), and will the weakening of the boundary have any impact on society and the business world? When agents can change their identities (sharing or professional) more and more flexibly in the market, does it mean that a new economic model, a hybrid economy, will rise between sharing and professionalization? Answering these questions can create a "high-level view" of the development of the industry, one that looks to structure economic or social activity in ways that create value.

Impact statement

This study investigates the dynamics of the survival status of listings in the peer-to-peer accommodation market. The analysis distinguishes between shared and non-shared listings to reveal their differing survival dynamics and their differing reactions to various survival determinants. The discussion is not limited to how listings exit the market. Transitions in listings' identities, a hard-to-observe event that is closely associated with changes in listings' survival status, are also identified in this work. Our findings provide a guide for hosts who wish to improve the survival probability of their listings. The obtained results further provide practical implications for platforms to maintain a healthy and vigorous peer-to-peer accommodation ecosystem. The difference in survival patterns between the two groups of listings should also be considered by policymakers when developing policies for this market.

Credit author statement

Ningyuan Fan: Conceptualization, Methodology, Investigation, Writing - Original Draft. **Shiyang Lai**: Software, Data curation, Formal analysis, Writing - Original Draft. **Zhi-Ping Fan**: Supervision, Funding acquisition, Writing – review & editing. **Yuan Chen**: Supervision, Writing – review & editing.

Declaration of competing interest

None.

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Appendix A

Table A1
Studies of survival analysis in the hospitality sector

Literature	Subject	Methodology	Data		Factors (sign)		Event	
			Sample size	Geographic scope	Internal	External	Exit	Transition
Kaniovski et al. (2008)	Hotel	Parametric survival models	14,000 hotels (1975–2004)	Austria	Entry size (+)	Market growth (+), net entry (?), market concentration (+), sector vintage (−), sector size (+), turnover rate (−), labor productivity (+), capital productivity (+)	✓	×
Gémar et al. (2016)	Hotel	Kaplan-Meier estimator, Cox model	1033 hotels (1997–2009)	Spain	Size (+), typology of hotel (?), management (−), profit margin (+), financial structure (?), business cycle (+)	Distance to airport >100 km (−)	✓	×
Lado-Sestayo et al. (2016)	Hotel	Kaplan-Meier estimator, Cox model	6494 hotels (2005–2011)	Spain	Hotel profitability (+), debt (?), balance (+), economic structure (−), liquidity (+), overall activity (?), size (−), efficiency of labor (?), hotel group (+), stars (−)	Demand level (+), destination profitability (+), seasonality (?), market concentration (−)	✓	×
Vivel-Búa et al. (2019)	Hotel	Kaplan-Meier estimator, Cox, Weibull, Exponential, and Gompertz models	11,558 hotels (2007–2015)	Spain	Performance (+), debt (−), cash flow (+), current ratio (?), working capital (?), size (−), asset turnover (+)	Seasonality (+ for micro hotels), market share (+ for micro and small hotels), market concentration (- for small hotels), Airport (+ for micro hotels and – for medium hotels)	✓	×
Gemar et al. (2019)	Hotel	Kaplan-Meier estimator, Cox model	354 hotels (1997–2009)	Spain	Working capital (−), legal form (+), cost structure (?), management (?), financial structure (?), business cycle (+)	Location (partially +)	✓	×
Lin and Kim (2020)	Hotel	Kaplan-Meier estimator, Cox model	45,606 hotels (2000–2018)	Texas, USA	Geographic diversification (−), brand diversification (+), segment diversification (−), franchised (+), age (−), room (−), revenue (+)	High-end hotels (+), low-end hotels (−), independent hotels (−)	✓	×
Türkcan and Erkuş-Öztürk (2020)	Hotel, restaurant, travel agency, and spa	Discrete-time hazard model	62,000 firms (2000–2016)	Antalya, Turkey	Age (+), size (+), legal form (+), foreign (?)	Tourism location (−), entry rate (−), regional specialization (−), market size (+), Herfindahl index (?), economic downturn (−), political downturn (−)	✓	×
Leoni (2020)	Peer-to-peer accommodation	Kaplan-Meier estimator, Cox model	9744 listings (2015–2016)	Ibiza, Spain	Entire property (+), private room (+), longevity (+), number of listings managed by hosts (+), minimum stay requirements (+), instant booking (−), deposit requirements (+), dynamic pricing (+), reviews (+), photos (+), rating (+)	Distance to the beach (+), local competition (−)	✓	×

Note: "+" means the corresponding factors positively affect agent survival; "-" means the factors negatively affect the survival; "?" means an unclear or unproved relationship between the factors and agent survival.

Table A2
Pseudocode of Listing Classification and Event Identification.

Algorithm A.1 Listing Classification and Event Identification	
function:	ListingClassificationAndEventIdentification(S_0): S_1
input:	S_0: **set** – the structured listing data set. Listing id is the key and the value is a list of records of that listing at different time points
global:	IDs: **list** – all listings' unique ids
output:	S_1: **set** – the processed S_0

(continued on next page)

Table A2 (*continued*)

Algorithm A.1 Listing Classification and Event Identification

```
S_1 ← φ
for all i ∈ IDs do
  u ← S_0(i)
  for t ← 1 to u.length do
    if t < 24 and t = u.length then
      u_t.exit ← 1
    else
      u_t.exit ← 0
    end if
    if u_t.capacity > u.guests_num and u_t.host_listing_count = 1 then
      u_t.shared_or_not ← 1
    else
      u_t.shared_or_not ← 0
    end if
    if u_{t-1}.shared_or_not = 1 and u_t.shared_or_not = 0 then
      u_{t-1}.transition ← 1
    else if u_{t-1}.shared_or_not = 0 and u_t.shared_or_not = 1 then
      u_{t-1}.transition ← 2
    else
      u_{t-1}.transition ← 0
    end if
S_1.append(u)
  end for
return S_1
```

Table A3
Descriptive statistics

	Mean	S.d.	Min	Max
Shared room	0.05	0.22	0	1
Entire home	0.64	0.48	0	1
Capacity	1.33	1.19	1	16
Facility	21.34	10.59	1	98
Rating	47.52	47.89	0	100
Reviews	4.27	10.47	0	236
Longevity	24.01	9.68	1	43
Instant	0.69	0.46	0	1
Response	0.29	0.76	0	3
Minimum	3.05	18.76	1	60
Pricing	20.90	324.38	0	33,810
Service_a	0.04	0.13	−1	2
Service_b	0.07	0.19	−3	4
Service_c	0.03	0.01	−2	2
Transportation	39.45	27.77	0	268
Tourism specialization	0.18	0.11	0.02	0.47
Market volume	3538.24	2969.80	53	9494
Professionalization	0.85	0.02	0.82	0.91
Covid-19	0.22	0.41	0	1

Appendix B. Supplementary material

Supplementary material to this article can be found online at https://doi.org/10.1016/j.tourman.2022.104665.

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