International Journal of Hospitality Management 95 (2021) 102936

Contents lists available at ScienceDirect

International Journal of Hospitality Management

journal homepage: www.elsevier.com/locate/ijhm

Modeling venture capital networks in hospitality and tourism entrepreneurial equity financing: An exponential random graph models approach

Bing Liu [a,*], Chaoliang Luo [b], Fang Meng [c], Hui Jiang [c]

[a] School of Tourism Management, Sun Yat-sen University, Guangzhou 510275, China
[b] School of Business, Guizhou University of Finance and Economics, Guiyang 550025, China
[c] School of Hotel, Restaurant and Tourism Management, College of Hospitality, Retail and Sport Management, University of South Carolina, Columbia, SC, 29208, USA

ARTICLE INFO

Keywords:
Venture capital (VC)
Entrepreneurial equity financing
Network
Hospitality and tourism
Exponential random graph model (ERGM)

ABSTRACT

This study examines how venture capital (VC) networks form when financing hospitality and tourism start-ups. We propose that networks form as a result of exogenous attributes along with endogenous dependencies, which have been largely under-studied in the hospitality and tourism finance literature. Using a purposefully developed dataset of 644 VC investment deals, this study employed exponential random graph models (ERGMs) to examine how homophily in VC investor-specific attributes influences the tie formation, and to model the likelihood of future tie formation in VC networks in terms of endogenous dependencies. Results reveal that homophily among VC investors increases the likelihood of tie formation, while the establishment of future ties shows a significant tendency of multiple triangulation and connectivity in VC networks. The study provides insights into entrepreneurial equity financing from the VC perspective. It advances the network research and methodology by revealing the underlying structural processes of network formation through ERGMs.

1. Introduction

Hospitality and tourism firms are traditionally labeled as having high operational risk with intensive capital needs (Li and Singal, 2019). Thus, the issue of how to raise financial capital remains critical to the growth of these firms (Motta and Sharma, 2019). Previous studies have approached this topic using pecking order theory (Park and Jang, 2018), trade-off theory (Pacheco and Tavares, 2017), and agency theory (Tsai et al., 2011), concentrating on topics such as cost of capital, capital structure and financial leverage in the hospitality and tourism context (Kizildag, 2015; Pacheco and Tavares, 2017; Li and Singal, 2019). Essentially, these studies tend to emphasize how the mix and match of debt financing and equity financing contribute to firms' operating efficiency and sustainable growth. However, almost all previous studies in this area are built upon established firms (Olsen, 2004), yet scant attention has been paid to the entrepreneurial financing for hospitality and tourism start-ups facing survival challenges.

Most hospitality and tourism start-ups are small- and medium-sized ventures with limited sources of internal funds. Thus, they must seek external financing to address this financial dilemma (Serrasqueiro and Nunes, 2014). However, these new ventures frequently encounter difficulties in obtaining external financial capital due to their weak asset basis, high operational risks, and high probability of bankruptcy, which largely hinder lenders (e.g., banks, other financial intermediaries) from providing debt or credit to these ventures (Zhao et al., 2011). Statistics demonstrate that over 70% of China's hospitality and tourism ventures had difficulties obtaining financial capital in 2020 (China Tourism Association, 2020). In this circumstance, venture capital (VC), with the significant power of pursuing high returns accompanied by high risks, has become a vital external resource for start-ups, nurturing entrepreneurship by providing financial capital and professional value-added services (Oak and Dalbor, 2008; Drover et al., 2017). Recent years have witnessed a rapid expansion of VC investment in entrepreneurship and the overall VC market in China (Huang and Tian, 2020). According to Crunchbase, a leading platform connecting start-ups and investors in the global entrepreneurial market, China has been the second largest VC market worldwide in terms of investment deal value since 2011. Statistics from Zero2IPO, the leading database of China's entrepreneurship and investment industry, show that the VC investment deal value reached US $37.6 billion in China's hospitality and tourism industry by

* Corresponding author.
E-mail addresses: liub33@mail.sysu.edu.cn (B. Liu), luochl3@mail2.sysu.edu.cn (C. Luo), fmeng@hrsm.sc.edu (F. Meng), hj17@email.sc.edu (H. Jiang).

https://doi.org/10.1016/j.ijhm.2021.102936
Received 9 June 2020; Received in revised form 30 January 2021; Accepted 29 March 2021
Available online 13 April 2021
0278-4319/

2019.

Unlike individual investors and other institutional investors, a typical VC investment normally goes through multiple stages, from seed investment to follow-up investments and to an exit via an initial public offering (IPO), acquisition, or write-off (Zheng and Xia, 2018). In addition, VC also commonly co-invests in a target investment deal, partnering with one or more other VCs in the hospitality and tourism industry (Liu and Jiang, 2019). These practices may lead to the creation of VC syndication networks in which multiple VC investors are linked to one another through direct or indirect relationships because of co-investment in the same hospitality and tourism start-up (Vanhaverbeke et al., 2009). Consequently, such heterogeneity of VCs' co-investment calls for investigations into the entrepreneurial financing of hospitality and tourism start-ups by decoding the formation of ties among VC investors in their portfolios.

Despite the unprecedented increase in the number of hospitality and tourism start-ups in emerging markets in the last decade, extant literature has lagged behind the current managerial practices. First, previous studies primarily take the demand-side perspective, with a particular focus on hospitality and tourism firms' initiatives in seeking financial resources (Serrasqueiro and Nunes, 2014; Park and Jang, 2018; Li and Singal, 2019). Very little attention has been paid to the investment practices, patterns, and preferences of funding suppliers in the hospitality and tourism entrepreneurial market (Oak and Dalbor, 2008). Research on VC investors, key funding suppliers who are extensively involved in financing hospitality and tourism start-ups through co-investments, is even scarcer (Liu and Jiang, 2019). Second, VC networks form as the result of VC investor-specific attributes as well as through the influence of existing ties (Wang, 2020). The emergence of VC co-investment relationships leads to constant changes in the network structure; however, there is still very little research capturing the dynamic processes of how VC networks form and evolve (Cui, 2013). Third, in terms of statistical analysis, traditional hospitality and tourism network research runs the risk of inappropriate understanding of network mechanisms without revealing the underlying endogenous structural processes (Contractor et al., 2006). Specifically, network data are inherently interdependent, but the commonly used regression analysis is based on the assumption of data independence (Kim et al., 2016) and thus is unable to capture the endogenous process underlying the network formation (Provan et al., 2007). An innovative social network approach – exponential random graph models (ERGMs) – has been recently employed to examine tie formation by incorporating endogenous dependencies along with exogenous attributes (Lusher and Robins, 2013).

Therefore, this study aims to adopt a network perspective and model VC networks in hospitality and tourism entrepreneurial equity financing through the ERGMs approach. Specifically, this study examines the following research questions: (RQ1) how do exogenous attributes (i.e., node- or dyad-specific attributes) influence the formation of VC networks? (RQ2) How do existing ties influence the formation of future ties by modeling endogenous dependencies?

Recent years have witnessed a rapid growth of entrepreneurial equity financing from VC investors in China's hospitality and tourism start-ups. According to statistics from Zero2IPO, from 2010 to 2017, the total amount of VC investment in China's hospitality and tourism industry increased by 8.5 times from US $436 million to US $4119 million. Meanwhile, the annual number of VC investment transactions continuously increased, from 36 in 2010 to 572 in 2017, an increase of 213%. Among them, more than 50% of investment deals involved multiple VC investors. China is the research context in this study due to the fast growth of the Chinese entrepreneurial development and VC investment in hospitality and tourism in the past decade.

This study is of significance to the finance literature as well as network research in hospitality and tourism. First, this study provides insights into the neglected but fast-growing entrepreneurial equity financing arena. Second, this study reveals the network formation by examining exogenous attributes (i.e., VC investor attributes) and endogenous dependencies (i.e., the underlying structural processes of how existing ties between two VC investors influence the formation of future ties), which have been largely ignored in existing studies. Third, this study contributes to the development of network methodology by revealing network mechanisms through ERGMs, which is innovative in the hospitality and tourism research.

2. Literature review and hypotheses development

2.1. Financing in the hospitality and tourism industry

The hospitality and tourism industry has unique characteristics of high operational risks and intensive capital needs due to the high fixed costs (Serrasqueiro and Nunes, 2014). Moreover, as a cyclical and seasonal business, hospitality and tourism firms must be financially prepared to deal with adverse economic cycles, constantly changing environments, and other events beyond their control (del Mar Alonso-Almeida, 2013). Therefore, capital supply and demand has long been recognized as a key research theme in hospitality and tourism financial management (Tsai et al., 2011). Following the mainstream financial research, previous studies primarily focus on how debt financing, equity financing, or their blend affect taxes and performance from two major theoretical perspectives: the trade-off theory and pecking order theory (Li and Singal, 2019).

Based on the trade-off theory, firms make financing decisions in order to obtain their targeted debt-equity ratios (Graham and Harvey, 2001). In comparison, pecking order theory states that debt financing lowers the cost of capital compared to equity financing due to the information asymmetry between stockholders and managers (Serrasqueiro and Nunes, 2014), indicating that trade-off theory may not always be suitable for financial decisions. In addition, scholars propose that in reality, firms may have their own preferences on selections of debt financing or equity financing, which could be influenced by numerous exogenous factors, such as firm attributes (Park and Jang, 2018), industry classification (Abor, 2007), or cost of capital (Kizildag, 2015). Even in the same sector, firms may not take homogeneous financing decisions (Pacheco and Tavares, 2017). Thus, existing studies tend to concentrate on capital structure and its determinations by examining how the blend of debt and equity contributes to a firm's sustainable growth, as this perspective relates to both the cost of capital and the required rate of return. More recently, scholarly attention has focused on industry-specific factors in the hospitality and tourism context and their effects on capital structure (Li and Singal, 2019).

Nonetheless, the extant literature on financing practice and financial management in hospitality and tourism primarily focus on large corporations or listed firms (Serrasqueiro and Nunes, 2014), whereas most hospitality and tourism firms are small- and medium-sized and have more challenges in obtaining capital and raising external equity compared with large firms (Motta and Sharma, 2019). More importantly, the increasingly vigorous entrepreneurial activities over the past decades witnessed the critical role of VC, which has been an important driver in fostering entrepreneurship and innovation across countries rather than traditional financial intermediaries (Chemmanur and Fulghieri, 2014). However, relevant research addressing entrepreneurial financing in hospitality and tourism start-ups has been largely overlooked.

As hospitality and tourism is a relational phenomenon (Merinero-Rodríguez and Pulido-Fernández, 2016), in the specific financing context, either debt financing or equity financing activities demonstrate interactions between hospitality and tourism firms and their funders, i.e., banks, lenders, and investors. For example, Pacheco and Tavares (2017) emphasized the importance of the relationship between banks and firms in the process of financing. Falk (2016) found that the similarity between investors and investees has positive effects on hotels' foreign direct investment (FDI) projects. Nonetheless, existing studies have only taken a one-sided investigation, either from the perspective of hospitality and tourism firms (Li and Singal, 2019) or from the perspective of funders (Kot et al., 2019). The void of understanding the relational phenomenon by the "relational" approach is still to be filled.

2.2. Network research in hospitality and tourism

The hospitality and tourism industry comprises multiple related sectors with innate relationship attributes (Scott et al., 2008). Network analysis has often been perceived as a useful lens and tool in various contexts in hospitality and tourism research (Khalilzadeh, 2018). This approach identifies a variety of collaborative and cooperative relationships through linkages with counterparts in the hospitality and tourism industry or with other industries (Merinero-Rodríguez and Pulido-Fernández, 2016).

In social network research, homophily theory predicts that a tie between similar actors occurs at a higher rate than among dissimilar actors (Rogers and Bhowmik, 1970). Homophily has been used to analyze interpersonal relationships, as it addresses the dynamics of actors' exogenous characteristics at the dyad level, which captures the similarities in ascribed attributes such as race, sex, and age, as well as acquired attributes such as education and occupation (McPherson et al., 2001). Furthermore, network ties may arise through emergent structures (Zaheer and Soda, 2009), which highlights the importance of endogenous structural dependencies in network formation simultaneously (Kim et al., 2016). Given the complexity in network relationships, a comprehensive understanding of network formation mechanisms is essential to address the multiple interdependent processes that shape networks, including exogenous attributes and endogenous dependencies.

In terms of the techniques employed in network analysis, most prior studies concentrate on descriptive statistics of network indicators (e.g., Bendle and Patterson, 2013; Asero et al., 2016; Williams et al., 2017). Meanwhile, very few researchers have tried to clarify the mechanism of network formation using inferential techniques. For example, through the quadratic assignment procedure (QAP), Bertelli (2011) discussed how relation-based factors influence cooperation behavior in tourism destination communities. Liu et al. (2017) empirically examined how region, grade, and tenure proximity influence the formation of attraction networks. These studies contributed to network research in hospitality and tourism by demonstrating how dyadic relationships, which are based on actor attributes, affect network formation. However, it remains largely unknown whether and how existing ties may further influence the establishment of future ties.

ERGMs, as a methodological innovation of advanced inferential statistics models, started to emerge in the hospitality and tourism research (Lusher and Robins, 2013). Extant studies (e.g., Wäsche, 2015; Khalilzadeh, 2018; William and Hristov, 2018) adopted network analysis in the hospitality and tourism research by introducing or demonstrating ERGMs as a novel technique, but they showed limitations of small sample sizes or restricted structural terms in models. Therefore, advanced research is expected to reveal the mechanism of network formation by integrating both exogenous attributes and endogenous dependencies through ERGMs.

2.3. Hypotheses development

2.3.1. Homophily in exogenous attributes and tie formation in VC networks

A tendency toward homophily means one is more likely to create ties with self-similar others (Rivera et al., 2010). The homophily captures the similarities in actors' exogenous attributes, including ascribed attributes and acquired attributes (McPherson et al., 2001). Based on the literature and given the emerging tourism and hospitality entrepreneurial market in China, we take the geographic location and origin of capital as VC investors' ascribed attributes, and the VC investors' investment experience and reputation as their acquired attributes (Gu and Lu, 2014).

VC investors are socially embedded in innovative regions with an active entrepreneurial environment (for example, Beijing, Shanghai, and Guangdong in China) and develop local ties by forming partnerships (Soreson and Stuart, 2001). For VC investors located in such innovative regions, the homophily by location may encourage active interactions and reciprocate deal flows due to the familiarity with institutional regulations and market environments, leading to the formation of partnerships through co-investments (Dai et al., 2012). Therefore, we propose the following hypothesis:

H1. VC investors with homophily by location are more likely to form ties.

International VC investors' interest in the hospitality and tourism industry has increased in recent years (OECD, 2018). For example, Tuniu Corporation, a leading Chinese online leisure travel company that provides a large variety of packaged tours and travel-related services for leisure travelers through its website and mobile platform, raised US $72 million in its IPO on Nasdaq in 2014 (China Daily, 2014). This transaction was backed by syndicated international VC investors, such as DCM (a US VC firm), Sequoia Capital (a US VC firm), Temasek (a Singapore VC firm), and Gobi Partners (a Chinese VC firm). Due to the different origins of capital, domestic and foreign investors demonstrate distinctive practices when making hospitality and tourism investments, especially in China (Mao and Yang, 2016). Specifically, compared to domestic investors, foreign investors are more competitive in general due to the capability of information assimilation with superior managerial experiences (Kantarci, 2007). Foreign VC investors that make global investments normally have larger sizes, more extensive experiences, and relationships with predominant financial intermediaries worldwide than do domestic VC investors (Humphery-Jenner and Suchard, 2013). Benefiting from these competitive advantages, VC investors are more likely to seek partnerships of their own type (Yeniyurt et al., 2009). Therefore, we propose the following hypothesis:

H2. VC investors with homophily by the origin of capital are more likely to form ties.

VC investors can acquire knowledge by learning from previous investment experiences. Through knowledge accumulation, VC investors tend to be more competent to select investment projects and mitigate potential risks (De Clercq and Dimov, 2008). Co-investors are able to share similar investment experience and establish strong trust among partners, which helps prevent free-riders and reduce the risk of adverse selection (Cui, 2013). Moreover, this proximity may facilitate and accelerate the exchange and transmission of knowledge with mutual understanding among co-investors in the network (Zhang et al., 2017). Therefore, we propose the following hypothesis:

H3. VC investors with homophily by investment experience are more likely to form ties.

Similar to hospitality and tourism firms, the reputation of a venture capitalist is one of the non-negligible attributes, representing its competitiveness in the VC industry (Morgan et al., 2011). The reputation also signals the VC investor's capability in providing professional, high-quality services, which positively affects clients' satisfaction and reduces perceived risks (Mussalam and Tajeddini, 2016). In addition, VC investors with better reputations denote higher status in the network, i.e., centrality, leading VC investors with similar network status to team up by establishing co-investment ties (Petkova et al., 2014). Thus, we propose the following hypothesis:

H4. VC investors with homophily by reputation are more likely to form ties.

2.3.2. Endogenous dependencies and tie formation in VC networks

The social network theory identifies three general types of endogenous dependencies: activity spread, multiple triangulation, and multiple connectivity, which elucidate how existing ties influence the establishment of future ties in networks (Kim et al., 2016). Fig. 1 illustrates the underlying structural process implied in each type of dependency. *Activity spread* captures a structural process in which already-popular actors (node C in Fig. 1(a)) become even more popular, often described as "the rich get richer" (Barabási and Albert, 1999). *Multiple triangulation* indicates that two actors (nodes A and B in Fig. 1 (b)) tend to create a direct tie if they are both connected to a third actor, which illustrates a structural process from an open triangle to a closed one. *Multiple connectivity* describes actors' (nodes A and B in Fig. 1(c)) inclinations to tie to others (node D in Fig. 1(c)) in multiple paths to reduce the dependency on a single channel (Broekel and Hartog, 2013).

Popular VC investors with the highest centrality are able to help potential partners cross industrial and geographical barriers when establishing a new co-investment tie (Sorenson and Stuart, 2001). Moreover, with this network advantage, they have access to adequate information about potential investment opportunities in the future (Zheng and Xia, 2018). Therefore, co-investing with popular VC investors brings benefits of obtaining higher-quality resources and reducing potential risks at the same time (Alvarez-Garrido and Guler, 2018). Consequently, as illustrated in Fig. 1(a), VC investor C is more likely to form future ties with VC investors F and G. Thus, we propose the following hypothesis:

H5. The establishment of future ties is more likely to exhibit the tendency of activity spread in VC networks.

According to the social network theory, VC investor C's referral advantage exists when the indirect relationship between VC investors A and B remains in the open triangle in the current network, as illustrated in Fig. 1(b) (van der Pol, 2019). However, the network's overall efficiency is significantly improved in information transformation when VC investors A and B form a new tie (Shane and Cable, 2002). As a result, there is a tendency for future ties to form toward closed triangles in the network, as illustrated in Fig. 1(b). Moreover, the stability of these triadic co-investment ties among VC investors A, B, and C would strengthen the profitability of investment portfolios, since these VC investors share behavior norms and social constraints in business practices (Ter Wal et al., 2016). Therefore, we propose the following hypothesis:

H6. The establishment of future ties is more likely to exhibit the tendency of multiple triangulation in VC networks.

As hospitality and tourism start-ups generally face a high need for financial capital to invest in fixed assets (Li and Singal, 2019), a single VC investor may not be sufficient to provide the required funding. In order to obtain sufficient resources from co-investors (del Mar Alonso-Almeida, 2013), VC investors with limited self-funding are inclined to develop multiple channels for non-redundant information from mutually unconnected parties, which would increase the likelihood of potential collaboration (Ter Wal et al., 2016). As illustrated in Fig. 1(c), there is a tendency that VC investors A and B will form more two-path connections with investors other than VC investor C through co-investment relationships in the future. Thus, we propose the following hypothesis:

H7. The establishment of future ties is more likely to exhibit the tendency of multiple connectivity in VC networks.

3. Methodology

3.1. Sample and data

We drew the VC investment data from Zero2IPO, the leading database of China's entrepreneurship and investment industry, which records all VC financing investment deals on a round-by-round-basis (Gu and Lu, 2014). In line with most studies using a broader concept of the hospitality and tourism industry (García-Villaverde et al., 2017), the hospitality and tourism context in this study includes the following industry segments: restaurant, hospitality, tourism, and e-tourism. We used 2015 as a reference year for VC-specific attributes due to the mass implementation of entrepreneurship and innovation policy in China since September 2014. By tracing the full history of VC investments in each start-up in selected industries, we obtained the initial dataset of 1646 VC investment transactions from January 1, 2015 to December 31, 2017. After excluding non-Chinese investees and records with missing or inconsistent data, we created a matched sample by paring each VC investor with its target investees; this included 644 VC investment transactions involving 402 VC investors and 365 distinct investees. These transactions included initial and follow-up investment rounds, as

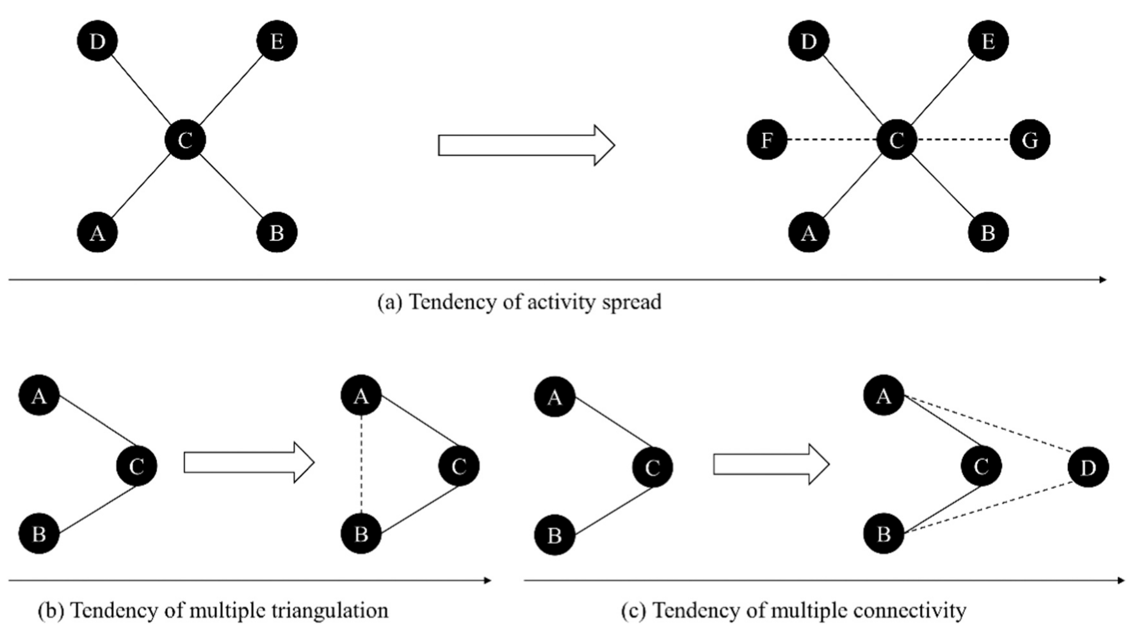


Fig. 1. Endogenous dependencies and associated structural processes. Notes: Circles represent nodes in the observed network; solid lines represent existing ties in the observed network; dotted lines represent potential ties to be connected following the current tendency of (a), (b), and (c).

well as single- and syndicated-investor investment rounds. Following our research focus on co-investment relationships, we identified a final sample size of 402 VC investors in this study.

Next, we captured a tie for each instance in which a VC investor co-invested with another VC investor in the sample. The resulting binary ties among all potential dyads were then presented in a 402 × 402 matrix, where the value in each cell represents whether the co-investment relationship exists between two VC investors for further ERGMs analysis. The corresponding cell in the matrix was labeled 1 if there was a co-investment tie and 0 otherwise. This method represents an undirected network, capturing the presence or lack of co-investment ties for each possible dyadic combination of the sampled VC investors. We observed a total of 446 co-investment ties formed in the sample.

For the independent variables in this study, including *location*, *origin*, *experience*, and *reputation*, we collected the data from a public database, National Enterprise Credit Information Publicity System in China.

Table 1
Summary of node-level and dyad-level variables.

Variables	Definitions and Measures	References
Age	A VC investor's age; continuous variable; the difference between 2015 and the founding year of the VC investor	Lee et al., 2011
Size	A VC investor's size; continuous variable; the scale of funding managed by the VC investor before 2015	Rider, 2009
Gov	A stated-owned VC investor; a dummy variable set as 1 if the VC investor is state-owned, and 0 otherwise	Abrardi et al., 2019
Location	A VC investor's geographical location; a dummy variable set as 1 if the VC investor's headquarters (or a foreign VC investor's China office) locates in Beijing, Shanghai, and Guangdong province, and 0 otherwise	Sorenson and Stuart, 2008
Origin	A VC investor's origin of capital; a dummy variable set as 1 if the VC investor is a foreign (non-Chinese) venture capitalist, and 0 otherwise	Humphery-Jenner and Suchard, 2013
Experience	A VC investor's investment experience; continuous variable; the cumulative number of VC investment deals before 2015	De Clercq and Dimov, 2008
Reputation	A VC investor's reputation; continuous variable; the cumulative number of VC investment deals through IPO exit before 2015	Gu and Lu, 2014

3.2. Variables and measures

ERGMs allow researchers to model endogenous dependencies that may shape networks along with exogenous attributes through the following testing procedures. Specifically, the node-level effect captures the tendency of nodes with actor-specific attributes to make ties with other nodes. The dyad-level effect captures the tendency of a dyad of nodes with the same actor-specific attributes to form new ties. The structure-level effect captures the tendency for the tie formation toward variations in dependencies in terms of network configurations (van der Pol, 2019). In this study, the dependent variable is the tie formation through co-investment relationships in the VC network. We constructed dyadic co-variates (i.e., *location*, *origin*, *experience*, *reputation*) as the dyad-level independent variables and a set of structural terms as the structure-level independent variables (i.e., *activity spread*, *multiple triangulation*, *multiple connectivity*). In addition, we included VC investor-specific attributes as node-level control variables (i.e., *age, size, gov*) in the models and dyad-level control variables (i.e., *co-variates [age, size, gov]*) in Model 2 and Model 3.

3.2.1. Node-level and dyad-level exogenous variables

In the ERGMs estimation for VC networks, we set VC investor-specific attributes as the node-level variables and further generated corresponding dyad-level co-variates to capture the homophily in VC investor-specific attributes. For continuous variables, we generated their corresponding dyadic co-variates by calculating absolute differences, using the term *absdiff* in the ERGM package in R. For dummy variables, we generated their corresponding dyadic co-variates by matching their types using the term *nodematch* in the ERGM package in R. Table 1 provides a summary of these variables included in this study.

3.2.2. Structure-level independent variables

Following Robins and Lusher's study (2013), we included the parameters for the degree distribution and triad closure in our model in order to properly capture the features of the network in general. *Activity spread* captures how often a VC investor initiates a co-investment tie in a hospitality and tourism start-up with other VC investors. *Multiple triangulation* refers to the likelihood of forming a co-investment tie between two VC investors that both have existing ties with a third VC investor. *Multiple connectivity* captures a tendency to form non-closure structures where two nodes are connected by multiple paths (Robins and Lusher, 2013). In this study's context, two VC investors are indirectly connected through other VC investors that share co-investment ties with these two VC investors. Table 2 provides a summary of graphical presentations of structural terms included in our ERGM estimation for VC networks.

3.3. Analysis

We applied ERGMs to examine the hypotheses. First, we examined the dyad-level effects, i.e., how dyadic exogenous attributes influence tie formation in VC networks. Second, we examined the structure-level effects to model endogenous dependencies, i.e., how existing ties influence the formation of future ties in VC networks. Unlike the conventional regression analysis based on the assumption of independence such as logit or probit regression, ERGMs provide an advanced approach for network research, as network data are inherently interdependent (Contractor et al., 2006). ERGMs incorporate a variety of network configurations and estimate the likelihood of the formation of ties and networks (Broekel and Hartog, 2013). Furthermore, ERGMs can accommodate any type of variables, including binary variables and continuous variables at different levels. Recently, ERGMs have been applied in a wide range of social science research, demonstrating the potential advantages of modeling a network's formation by incorporating exogenous factors and endogenous processes (Kim et al., 2016).

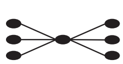
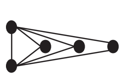
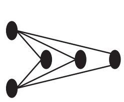
The general mathematical expression of ERGMs is defined as follows:

$$Pr(X = x) = \left(\frac{1}{k}\right) exp\left[\sum_A \beta_A z_A(x)\right]$$

Where Pr $(X = x)$ is the probability that the network (X) simulated by our models is identical to the observed network (x). The k stands for a normalized parameter, which constrains the probabilities summing up to 1. The A denotes a set of network configurations in the observed network (x). β_A coefficients refer to unknown parameters of network configurations, representing the frequency of network configuration A appearing in network (x). $z_A(x)$ is the network statistics in network configuration A; when A occurs in network (x), $z_A(x)$ is equal to 1, otherwise as 0.

Further, we estimated our models with Markov chain Monte Carlo maximum likelihood estimation (MCMC-MLE), using the NETWORK package and the ERGM package, a part of Statnet project packages in R. All parameters and terms included in our ERGMs are presented with corresponding graph configurations in Table 2. Then, we conducted goodness-of-fit tests to verify the resemblance between the simulated network (X) and the observed network (x).

Table 2
Summary of parameters in the ERGMs estimation.

Parameter	Configuration	Description	Statnet term
Node level			
Age		Tendency of VC investors of a certain length of operation to co-invest with other VC investors	nodecov (age)
Size		Tendency of VC investors of a certain size to co-invest with other VC investors	nodecov (size)
Gov		Tendency of state-owned VC investors to co-invest with other VC investors	nodefactor (gov)
Location		Tendency of VC investors located in certain areas to co-invest with other VC investors	nodefactor (location)
Origin		Tendency of foreign VC investors to co-invest with other VC investors	nodefactor (origin)
Experience		Tendency of VC investors with a certain level of experience to co-invest with other VC investors	nodecov (experience)
Reputation		Tendency of VC investors with a certain level of reputation to co-invest with other VC investors	nodecov (reputation)
Dyad level			
Co-variate (age)		Tendency for the formation of co-investment ties with VC investors in similar/different length of operation	absdiff (age)
Co-variate (size)		Tendency for the formation of co-investment ties with VC investors in similar/different size	absdiff (size)
Co-variate (gov)		Tendency for the formation of co-investment ties within state-owned VC investors	nodematch (gov)
Co-variate (location)		Tendency of the formation of co-investment ties within VC investors located in the same/ different regions	nodematch (location)
Co-variate (origin)		Tendency for the formation of co-investment ties within foreign VC investors	nodematch (origin)
Co-variate (experience)		Tendency for the formation of co-investment ties with VC investors having similar/different experience	absdiff (experience)
Co-variate (reputation)		Tendency for the formation of co-investment ties with VC investors having similar/different reputation	absdiff (reputation)
Structure level			
Edge		Baseline tendency for co-investment tie formation	edges
Activity spread		Tendency for the formation of co-investment ties from VC investor A to multiple VC investors	gwdegree
Multiple triangulation		Tendency for the closure of transitive triads (when VC investor A has a co-investment tie with investor B, and when VC investor B has a co-investment tie with VC investor C, VC investor A is more likely to have a co-investment tie with VC investor C)	gwesp
Multiple connectivity		Tendency for the formation of multiple 2-paths connecting VC investors in the co-investment network	gwdsp

4. Results

4.1. ERGMs findings

Table 3 provides the results of the ERGMs estimations. Model 1 shows the baseline model, including the node-level variables as the

Table 3
Results of ERGMs estimations.

Parameters	Model 1	Model 2	Model 3
Node level			
Age	0.028*** (0.006)	0.043*** (0.008)	0.028***(0.006)
Size	0.002 (0.002)	0.008* (0.004)	0.010*(0.005)
Gov	-0.343* (0.169)	-0.414 (0.509)	-0.159(0.425)
Location	-0.012 (0.080)	-0.224* (0.087)	-0.177*(0.077)
Origin	0.063 (0.106)	0.244* (0.123)	0.174(0.093)
Experience	0.077*** (0.020)	0.184*** (0.033)	0.120***(0.023)
Reputation	-0.002 (0.004)	-0.008 (0.010)	-0.013(0.009)
Dyad level			
Co-variate (age)		-0.031** (0.010)	-0.019*(0.010)
Co-variate (size)		-0.008 (0.004)	-0.010*(0.005)
Co-variate (gov)		-0.014 (0.530)	0.111(0.477)
Co-variate (location)		0.445*** (0.122)	0.361**(0.113)
Co-variate (origin)		0.451** (0.144)	0.310**(0.101)
Co-variate (experience)		-0.141*** (0.038)	-0.077**(0.028)
Co-variate (reputation)		0.011 (0.010)	0.016(0.010)
Structure level			
Edge	-5.600*** (0.144)	-5.937*** (0.560)	-8.174***(0.622)
Activity spread			0.306(0.248)
Multiple triangulation			4.011***(0.211)
Multiple connectivity			-0.158***(0.033)
Akaike information criterion (AIC) goodness of fit	5450	5404	3859

Notes: standard errors in parentheses,
* $p < 0.05$;
** $p < 0.01$;
*** $p < 0.001$.

control variables. Model 2 shows the intermediate model, including the node-level variables and all dyad-level co-variates without any structural terms. Model 3 shows the full model by adding the structural terms explained in Table 2, along with the node-level and dyad-level variables. Among all the hypotheses, H1, H2, H3, and H4 examined the dyad-level effects, and H5, H6, and H7 examined the structure-level effects. In addition, we controlled the dyadic co-variates (*age, size, gov*), which may potentially influence the tie formation in VC networks (Rider, 2009; Lee et al., 2011).

In ERGMs examination of the dyad-level effects, a positive and significant coefficient for dummy co-variates (using the Statnet term *nodematch*) indicated the homophily effects, whereas a negative and significant coefficient for continuous co-variates (using the Statnet term *absdiff*) indicated the homophily effects, which suggests that VC investors with similar dyad-level attributes are more likely to be tied. Thus, based on the results in Model 2, H1, H2, and H3 were supported, evidencing that VC networks exhibited significant homophily by location, origin, and experience. However, H4 was not supported in Model 2, which is consistent with the results in Model 3 after incorporating the structural terms.

Furthermore, Model 3 provides the results of the ERGMs estimation of the structure-level effects, i.e., the underlying structural processes of how VC networks could have been formed and how existing ties influence the establishment of future ties. Specifically, the *edge* term in ERGMs is equivalent to an intercept in regression (Kim et al., 2016). The result of the term *activity spread* suggested that the tendency toward concentration on the focal VC investor in the co-investment network was not significant, indicating that H5 was not supported. In terms of higher-order configurations by triads, the *multiple triangulation* term demonstrated a positive and significant coefficient as proposed in H6, whereas the *multiple connectivity* term demonstrated a negative and significant coefficient, indicating that the establishment of future ties is less likely to exhibit multiple connectivity in VC networks, which did not support H7. These findings suggested the greater likelihood of a co-investment tie formation between two VC investors when both had existing ties with a third VC investor; meanwhile, transitive structures tended to overlap the two-path co-investment ties (Lusher and Robins, 2013).

The results also revealed that H1, H2, and H3 were supported in Model 3, and more importantly, Model 3 demonstrated differences either in the significance level or the magnitude of coefficients compared to Model 2. Specifically, the significance levels of *location* and *experience* at the dyad level largely dropped, while the magnitude of the coefficient of *origin* at the dyad level decreased from 0.451 to 0.310 when comparing models with and without structural terms. These differences suggested that failure to account for endogenous structural processes may lead to an inconsistent understanding of network formation mechanisms.

We further conducted model selections between Model 2 and Model 3. The main purpose of this comparison was to examine whether adding structural terms to our examination would provide a better fit. Based on Akaike's Information Criterion (AIC), the smaller the value of AIC, the better the model fits the data (Akaike, 1998). The AIC of Model 3 (AIC=3859) was substantially smaller than Model 2 (AIC=5404), indicating that the role of endogenous factors in shaping the observed VC network in our sample was very important.

In order to visualize model fits, we further conducted graphical evaluations of goodness of fit in Fig. 2(a) and (b). The plots illustrate that the distribution of geodesic distances as a higher-order network statistic graphically demonstrates model fit, which represents the pairwise shortest distances between nodes (Goodreau et al., 2009). In this study's context, for example, if VC investors A and B have a co-investment tie, and VC investors B and C have a co-investment tie, but VC investors A and C do not have a direct tie in the network, then the geodesic distance of a pair of co-investors A and B is 1, and the geodesic distance of A and C is 2. As shown in Fig. 2(a) and (b), the tendency of the dark solid line passing through the median points of the boxplots for the range was more apparent in Model 3, suggesting a better fit than Model 2. The same finding was also evidenced by the gap between the dark solid line and the trend of the boxplots (Kim et al., 2016). Overall, Model 3 with structural terms provided distinct advantages and a better fit examined by goodness-of-fit diagnostics.

4.2. Additional analyses

In this section, further analyses were conducted to compare the results in sub-industries. First, we divided the full sample into two sub-samples: (1) the sub-sample of hospitality industry (including restaurants and hospitality new ventures) and (2) the sub-sample of tourism industry (including tourism and e-tourism new ventures). Specifically, in the hospitality industry sub-sample, we created a matched sample by paring each VC investor with its target investees; this included 241 VC investment transactions involving 152 VC investors and 139 distinct investees. Then the VC's co-investment relationship in a 152×152 matrix was developed for further ERGMs analysis. Similarly, in the tourism industry sub-sample, we created a matched sample by paring each VC investor with its target investees; this included 403 VC investment transactions involving 293 VC investors and 198 distinct investees. Then the VC's co-investment relationship in a 293×293 matrix was developed for further ERGMs analysis.

Second, for comparison purposes, we conducted ERGMs analyses in each sub-sample of hospitality industry and tourism industry, respectively (see Table 4).

Table 4 provides the results of ERGM estimations in sub-samples. In particular, we included *nature* as the control variable in the ERGMs, which is defined as the type of VC investors, including venture capitalists, private equity, corporate venture capitalists (CVC), strategic investors, and others (e.g., bank affiliates) (Block and Sander, 2009; Wang, 2016; Conti et al., 2019). Based on Chesbrough (2002), venture capitalists and private equity are financial-oriented, while CVC and strategic investors are strategic-oriented. Therefore, at the node level, *nature* was a dummy variable (1 if a VC investor is a financial investor such as

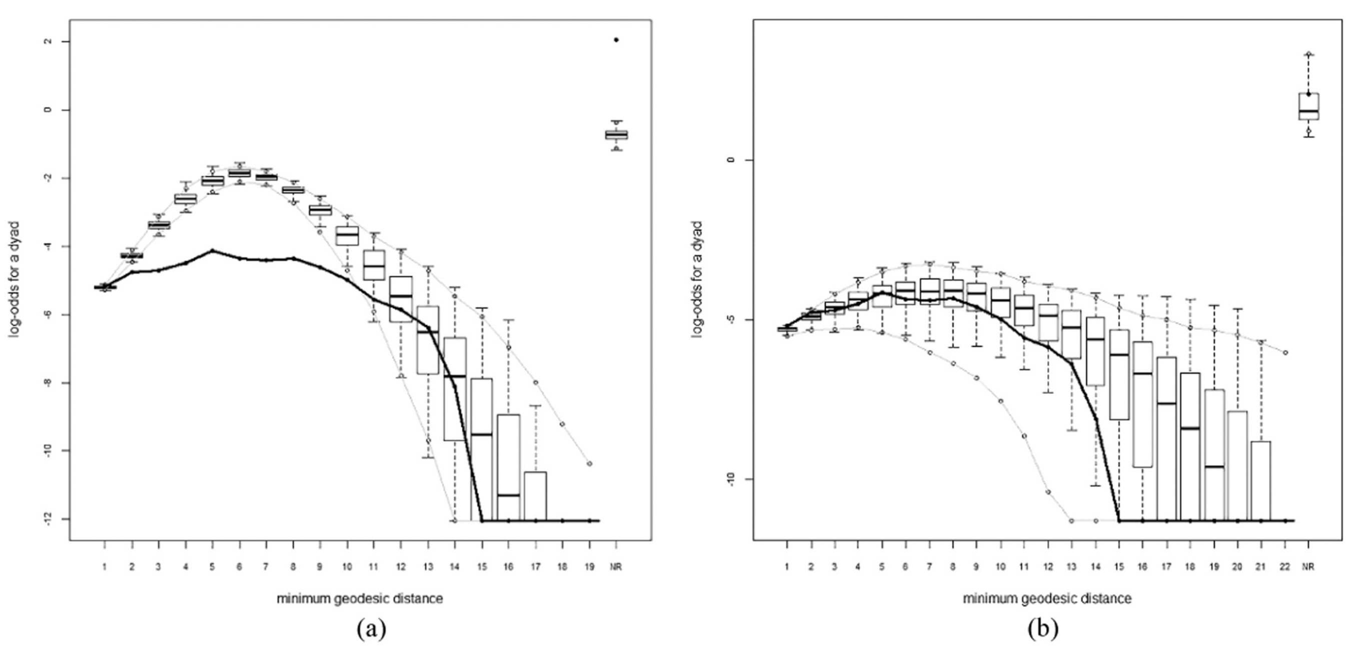


Fig. 2. Goodness-of-fit diagnostics by the distribution of geodesic distance for Model 2(a) and Model 3(b). Notes: The dark solid line stands for a given statistic from the actual observed network, while the light-gray lines stand for the range in which 95% of simulated networks fall. The boxplots stand for the same statistic from the 100 randomly generated simulated networks. The dark solid lines in boxplots represent the median of the distribution. The Y-axis is represented as a log-likelihood.

Table 4
Results of ERGMs estimations in sub-industries.

	Hospitality industry (N = 152)			Tourism industry (N = 293)		
Parameters	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Node level						
Age	0.052**(0.017)	0.071***(0.019)	0.047**(0.018)	0.025***(0.007)	0.035***(0.009)	0.028*(0.014)
Size	-0.004(0.004)	0.010(0.011)	0.007(0.012)	0.002(0.002)	0.005(0.005)	0.003(0.008)
Gov	-0.502(0.385)	-5.706(185.680)	-2.502***(0.441)	-0.231(0.186)	-0.249(0.509)	0.253(0.696)
Nature	0.239(0.137)	0.062(0.143)	0.001(0.128)	-0.003(0.090)	-0.145(0.109)	-0.207(0.116)
Location	0.020(0.178)	-0.025(0.189)	-0.011(0.183)	-0.108(0.091)	-0.268**(0.097)	-0.281**(0.130)
Origin	-0.098(0.224)	-0.355(0.402)	-0.249(0.483)	0.101(0.121)	0.327**(0.131)	0.319(0.217)
Experience	0.030(0.035)	0.102(0.063)	0.080(0.058)	0.055(0.023)	0.142***(0.038)	0.057(0.050)
Reputation	-0.007(0.008)	-0.055(0.035)	-0.043(0.038)	-0.002(0.005)	-0.002(0.010)	0.006(0.022)
Dyad level						
Co-variate (age)		-0.042(0.026)	-0.036(0.028)		-0.022(0.012)	0.007(0.021)
Co-variate (size)		-0.016(0.012)	-0.011(0.013)		-0.005(0.009)	-0.002(0.008)
Co-variate (gov)		-5.204(185.680)	-2.223***(0.401)		0.015(0.535)	0.437(0.736)
Co-variate(nature)		0.463*(0.199)	0.454*(0.203)		0.265(0.147)	0.357(0.215)
Co-variate (location)		0.106(0.208)	0.092(0.207)		0.526***(0.136)	0.461**(0.152)
Co-variate (origin)		-0.322(0.415)	-0.264(0.511)		0.615***(0.161)	0.431*(0.191)
Co-variate (experience)		-0.096(0.071)	-0.075(0.069)		-0.126**(0.045)	0.014(0.054)
Co-variate (reputation)		0.055(0.036)	0.044(0.039)		0.003(0.011)	-0.008(0.023)
Structure level						
Edge	-5.109***(0.366)	0.455(185.681)	-1.271*(0.610)	-5.151***(0.195)	-5.530***(0.583)	-4.424***(0.867)
Activity spread			-1.777***(0.412)			-1.716***(0.295)
Multiple triangulation			2.202***(0.210)			2.700***(0.188)
Multiple connectivity			-0.473***(0.097)			-0.688***(0.062)
Akaike information criterion (AIC) goodness of fit	1451	1454	1142	3703	3663	2621

Notes: standard errors in parentheses,
* $p<0.05$;
** $p<0.01$;
*** $p<0.001$.

venture capitalist and private equity, 0 otherwise). At the dyad level, the *co-variate (nature)* was measured by matching the nature of VC investors in each dyad using the term *nodematch* in ERGM package in R. Consistent with the ERGMs examination procedures, Model 1 included node-level control variables. Model 2 and Model 3 added dyad-level co-variates and structure-level terms, respectively.

Through comparisons, dyad-level results showed that in the hospitality industry, VC investors with homophily by *nature* were more likely to form ties, but no significant influence was found in the tourism industry sub-sample. Further, VC investors with homophily by *location*, *origin,* and *experience* were more likely to form ties in the tourism industry, while they did not exhibit significant effects in the hospitality industry sub-sample. Results also revealed that structure-level effects exhibited similar tendencies in both the hospitality industry and the tourism industry. In addition, compared to the full sample, in which the structural term *activity spread* did not show a significant effect in Table 3 ($\beta = 0.306$), *activity spread* showed significant effects in both sub-samples, with a negative coefficient ($\beta = -1.777$) in Model 3 (hospitality sub-sample) and a negative coefficient ($\beta = -1.716$) in Model 6 (tourism sub-sample) in Table 4. These results indicated the *activity spread* tendency declined in each sub-industry, which implies that VC investors tended to form co-investing ties across the boundary of sub-industries, and the star-like VC investors with high network centrality tended to form in the whole industry.

4.3. Robustness tests

Robustness tests were conducted to determine whether the results hold for different model specifications. Robustness checks were only taken at the node level and dyad level, as traditional statistics cannot capture endogenous dependencies in networks, which reflect the underlying structural-level effect (Contractor et al., 2006).

First, logit regression was used to capture how node-specific attributes influence tie formation with the focus of the individual VC at the node level. The results on the key variables *location*, *origin*, *experience*, and *reputation* in Table 1 were similar to the robustness check results (Model 1 in Table 5). Next, we used logit regression to capture how dyad-specific attributes influence tie formation with the focus of each VC dyad at the dyad level. Following Hallen (2008) and Sorenson and Stuart (2008), we adopted the random sampling approach and generated matched hypothetical dyads for each existing dyad, using a matching ratio of 1:5. The results of the key variables *co-variate (location)*, *co-variate (origin)*, *co-variate (experience)*, and *co-variate (reputation)* in Table 1 were similar to the results in the robustness check (Model 2 in Table 5).

5. Conclusion

5.1. Theoretical contributions

While prior studies on hospitality and tourism financing focus primarily on established firms (Olsen, 2004), very little academic attention has been paid to entrepreneurial financing, particularly the fast-growing Chinese hospitality and tourism market in recent decades (Fu et al., 2019). This study advances the understanding of hospitality and tourism entrepreneurial financing by highlighting the vital role of VC financing. Specifically, drawing on the network perspective, this study revealed the co-investment relationships and the underlying mechanism of tie formation by modeling endogenous dependencies along with exogenous attributes through ERGMs.

First, this study examined entrepreneurial financing from the VC perspective, which has been largely neglected in the hospitality and tourism finance literature. Capital supply and demand is regarded as a key theme due to the unique nature of the hospitality and tourism industry (Tsai et al., 2011). Previous hospitality and tourism finance studies focus primarily on large corporations and listed firms (Park and Jang, 2018), but most start-ups are small- or medium-sized, and their financing in the entrepreneurial market may differ (Motta and Sharma, 2019). Rather than focusing on the demand side, this study specifically examined entrepreneurial financing from the perspective of the funding

Table 5
Robustness tests for node-level and dyad-level effects.

Node-level		Dyad-level	
Model 1		Model 2	
Variables	Dependent variable: indicator= 1 if a VC's investment is syndicated	Variables	Dependent variable: indicator= 1 if the co-investment tie between the dyad is true
Age	0.060*(0.029)	*co-variate (age)*	-0.055***(0.010)
Size	0.001(0.008)	*co-variate (size)*	-0.039***(0.005)
Gov	-0.811(0.500)	*co-variate (gov)*	-2.119*(1.021)
Location	0.496(0.262)	*co-variate (location)*	0.469***(0.122)
Origin	-0.109(0.410)	*co-variate (origin)*	1.410***(0.502)
Experience	0.461*(0.182)	*co-variate (experience)*	-0.077**(0.025)
Reputation	-0.001(0.026)	*co-variate (reputation)*	0.009(0.005)
Constant	0.500*(0.255)	*constant*	-0.725***(0.108)
N	402	*N*	2676
Log likelihood	-229.288	*Log likelihood*	-1075.859
Pseudo R^2	0.044	*Pseudo R^2*	0.1077

Notes: standard errors in parentheses,
* $p < 0.05$;
** $p < 0.01$;
*** $p < 0.001$.

suppliers, i.e., the VC investors. Distinct from traditional financial intermediaries, venture capitalists act as an important driver in fostering entrepreneurship and innovation by providing financial capital and professional experience for start-ups across national borders (Chemmanur and Fulghieri, 2014). Therefore, this study contributes to the literature on hospitality and tourism finance by focusing on an important missing piece of entrepreneurial equity financing.

Second, drawing on the network perspective, this study focused on relationships formed by VC co-investing in hospitality and tourism start-ups. We proposed that the effects of exogenous attributes on network formation may be exaggerated in existing hospitality and tourism research, while endogenous structural processes underlying the network formation have been largely ignored (Khalilzadeh, 2018; Williams and Hristov, 2018). Therefore, this study modeled the tie formation of VC networks by incorporating exogenous attributes as well as endogenous dependencies through ERGMs.

Specifically, the findings showed that H1, H2, and H3 were supported, which confirmed that homophily by location, origin, and experience is positively related to tie formation in VC networks. H4 – that VC networks exhibit homophily by reputation – was not supported. This outcome is possibly due to the way a venture capitalist's reputation is accumulated and evaluated in the VC industry. Following the mainstream VC literature (Gu and Lu, 2014), we measured a venture capitalist's reputation by the cumulative number of VC investment deals through IPO exits; however, the statistics indicated that IPO exit deals in the hospitality and tourism industry were quite limited to date. We therefore inferred that a relatively large proportion of venture capitalists' successful cases through IPO exits took place in industries other than the hospitality and tourism sector. The industry heterogeneity calls for a more comprehensive measurement of a venture capitalist's reputation by including indicators on an industrial basis, such as the expertise in the focal industry and the familiarity of the focal industry.

In addition, the findings showed that VC networks exhibit significant endogenous dependencies in terms of multiple triangulation and multiple connectivity, showing the greater likelihood that a co-investment tie would form between two VC investors when both have existing ties with a third VC investor. Furthermore, transitive structures tended to overlap the two-path co-investment ties in this study context. Meanwhile, H5 was not supported, indicating that VC networks did not show a significant tendency of activity spread. This may be because star-like investors with the highest popularity are still absent in current VC networks.

In sum, this study's findings confirmed that VC networks formed as the result of VC investor-specific attributes and through endogenous dependencies. Furthermore, we modeled endogenous dependencies regarding how existing ties may influence the establishment of future ties in VC networks, which contributes to current hospitality and tourism network research by revealing the underlying mechanism of network formation.

Finally, this study contributes to the methodological development in hospitality and tourism network research from two aspects. We recapped the question of whether structure-level effects may enhance or persist node-level and dyad-level effects by comparing Model 1, Model 2, and Model 3. This approach demonstrates the unique explanatory power of ERGM techniques in comprehensively understanding the mechanism of network formation. In addition, we extended the application of ERGMs with a large sample size and multiple structural terms (*gwdegree, gwesp, gwdsp*). More importantly, we proposed and examined a critical research question on entrepreneurial financing in hospitality and tourism, which advanced the understanding of networks by contextualization with further interpretations of structural terms (Kim et al., 2016; Khalilzadeh, 2018).

5.2. Practical implications

This study's results suggest the following practical implications. First, this study offers a meaningful perspective to understand venture capitalists' practices in financing hospitality and tourism entrepreneurship, which sheds light on how new start-ups interact with key potential funding suppliers in emerging markets. Considering that seeking capital from VC investors is a mixed blessing for entrepreneurs (Zheng, 2011), acknowledging the underlying endogenous structural processes of tie formation would help understand venture capitalists' co-investment partnerships and forecast investment foci in the domain of syndicated VC investors. Therefore, this study provides valuable insights to predict the likelihood of perfectly matching VC investors to occur.

Second, this study delivers guidance to VC investors who target hospitality and tourism start-ups. Existing VC investors are encouraged to carefully identify their network status embedded in co-investment partnerships in order to benefit from existing ties and manage their investment portfolio effectively. Furthermore, new entrants may obtain signals for why, when, with whom, and how to make advantageous ties.

5.3. Limitations and future research

This study has the following limitations, which offer promising opportunities for future research. First, the study used the dataset derived from China due to its rapidly growing entrepreneurial activities in the hospitality and tourism industry in recent years. Although China's entrepreneurial practices can be a representative example for other emerging economies, a single-country setting may have limited the generalizability of the findings (Zheng and Xia, 2018). Future studies should examine the data from different countries for comparison purposes and to provide a more extensive understanding of VC networks.

Second, distinctions exist between VC investors and angel investors in terms of strategic objectives (Drover et al., 2017). However, due to the lack of data to capture this heterogeneity, this study did not strictly differentiate these two types of investors, which is consistent with most literature in entrepreneurial finance (Dutta and Folta, 2016). Instead, we reviewed the official name of each VC investor in the sample by verifying it in the National Enterprise Credit Information Publicity System in China to make sure that the official name of each VC investor contains the exact words of venture capital. Future studies with sufficient data may compare angel investors and VC investors on multiple dimensions and revisit relevant research questions and hypotheses.

Third, ERGMs can be used to analyze directed data; however, we did not consider the directions in VC networks in this study, as no sufficient and sound data disclosed which VC investor first initiated a co-investment tie to another VC investor. In addition, we primarily focused on the co-investment partnerships formed by venture capitalists, where the sequences are beyond the scope of this study. Future studies could further demonstrate the application of ERGMs with directed data in other hospitality and tourism financing contexts.

Acknowledgements

This research was supported by the National Social Science Fund of China, grant number 18BGL151.

References

Abor, J., 2007. Industry classification and the capital structure of Ghanaian SMEs. Stud. Econ. Financ. 24 (3), 207–219. https://doi.org/10.1108/10867370710817392.

Abrardi, L., Croce, A., Ughetto, E., 2019. The dynamics of switching between governmental and independent venture capitalists: theory and evidence. Small Bus. Econ. 53 (1), 165–188. https://doi.org/10.1007/s11187-018-0047-z.

Akaike, H., 1998. Information theory and an extension of the maximum likelihood principle. Selected Papers of Hirotugu Akaike. Springer, New York, NY, pp. 199–213. https://doi.org/10.1007/978-1-4612-1694-0_15.

Alvarez-Garrido, E., Guler, I., 2018. Status in a strange land? Context-dependent value of status in cross-border venture capital. Strateg. Manag. J. 39 (7), 1887–1911. https://doi.org/10.1002/smj.2777.

Asero, V., Gozzo, S., Tomaselli, V., 2016. Building tourism networks through tourist mobility. J. Travel Res. 55 (6), 751–763. https://doi.org/10.1177/0047287515569777.

Barabási, A.L., Albert, R., 1999. Emergence of scaling in random networks. Science 286 (5439), 509–512. http://www.jstor.org/stable/2899318.

Bendle, L.J., Patterson, I., 2013. The centrality of service organizations and their leisure networks. Advances in Service Network Analysis. Routledge, London, UK, pp. 33–46. https://doi.org/10.1080/02642060903580656.

Bertelli, P., 2011. Cooperation among prominent actors in a tourist destination. Ann. Tour. Res. 38 (2), 607–629. https://doi.org/10.1016/j.annals.2010.11.015.

Block, J., Sander, P., 2009. What is the effect of the financial crisis on venture capital financing? Empirical evidence from US Internet start-ups. Ventur. Cap. 11 (4), 295–309. https://doi.org/10.1080/13691060903184803.

Broekel, T., Hartog, M., 2013. Explaining the structure of inter-organizational networks using exponential random graph models. Ind. Innov. 20 (3), 277–295. https://doi.org/10.1080/13662716.2013.791126.

Chemmanur, T.J., Fulghieri, P., 2014. Entrepreneurial finance and innovation: an introduction and agenda for future research. Rev. Financ. Stud. 27 (1), 1–19. https://doi.org/10.1093/rfs/hht063.

China Daily, 2014. Tuniu's IPO on Nasdaq raises $72m. http://usa.chinadaily.com.cn/2014-05/10/content_17497703.htm. (Accessed 11 January 2019).

China Tourism Association, 2020. "Ten dilemmas" faced by venture investment and financing in culture and tourism industry. http://www.tsingyanresearch.com/?p=4375. Accessed on 7 January 2021.

Chesbrough, H.W., 2002. Making sense of corporate venture capital. Harv. Bus. Rev. 80 (3), 90–99.

Conti, A., Dass, N., Di Lorenzo, F., Graham, S.J.H., 2019. Venture capital investment strategies under financing constraints: evidence from the 2008 financial crisis. Res. Policy. 48 (3), 799–812. https://doi.org/10.1016/j.respol.2018.11.009.

Contractor, N.S., Wasserman, S., Faust, K., 2006. Testing multitheoretical, multilevel hypotheses about organizational networks: an analytic framework and empirical example. Acad. Manag. Rev. 31 (3), 681–703.

Cui, A.S., 2013. Portfolio dynamics and alliance termination: the contingent role of resource dissimilarity. J. Mark. 77 (3), 15–32. https://doi.org/10.1509/jm.11.0164.

Dai, N., Jo, H., Kassicieh, S., 2012. Cross-border venture capital investments in Asia: selection and exit performance. J. Bus. Ventur. 27 (6), 666–684. https://doi.org/10.1016/j.jbusvent.2011.04.004.

De Clercq, D., Dimov, D., 2008. Internal knowledge development and external knowledge access in venture capital investment performance. J. Manag. Stud. 45 (3), 585–612. https://doi.org/10.1111/j.1467-6486.2007.00747.x.

del Mar Alonso-Almeida, M., 2013. Influence of gender and financing on tourist company growth. J. Bus. Res. 66 (5), 621–631. https://doi.org/10.1016/j.jbusres.2012.09.025.

Drover, W., Busenitz, L., Matusik, S., Townsend, D., Anglin, A., Dushnitsky, G., 2017. A review and road map of entrepreneurial equity financing research: venture capital, corporate venture capital, angel investment, crowdfunding, and accelerators. J. Manag. 43 (6), 1820–1853. https://doi.org/10.1177/0149206317690584.

Dutta, S., Folta, T.B., 2016. A comparison of the effect of angels and venture capitalists on innovation and value creation. J. Bus. Ventur. 31 (1), 39–54. https://doi.org/10.1016/j.jbusvent.2015.08.003.

Falk, M., 2016. A gravity model of foreign direct investment in the hospitality industry. Tour. Manag. 55, 225–237. https://doi.org/10.1016/j.tourman.2016.02.012.

Fu, H., Okumus, F., Wu, K., Köseoglu, M.A., 2019. The entrepreneurship research in hospitality and tourism. Int. J. Hosp. Manag. 78, 1–12. https://doi.org/10.1016/j.ijhm.2018.10.005.

García-Villaverde, P.M., Elche, D., Martínez-Pérez, Á., Ruiz-Ortega, M.J., 2017. Determinants of radical innovation in clustered firms of the hospitality and tourism industry. Int. J. Hosp. Manag. 61, 45–58. https://doi.org/10.1016/j.ijhm.2016.11.002.

Goodreau, S.M., Kitts, J.A., Morris, M., 2009. Birds of a feather, or friend of a friend? Using exponential random graph models to investigate adolescent social networks. Demography 46 (1), 103–125. https://doi.org/10.1353/dem.0.0045.

Graham, J.R., Harvey, C.R., 2001. The theory and practice of corporate finance: evidence from the field. J. Financ. Econ. 60 (2–3), 187–243. https://doi.org/10.1016/S0304-405X(01)00044-7.

Gu, Q., Lu, X., 2014. Unraveling the mechanisms of reputation and alliance formation: a study of venture capital syndication in China. Strateg. Manag. J. 35 (5), 739–750. https://doi.org/10.1002/smj.2117.

Hallen, B.L., 2008. The causes and consequences of the initial network positions of new organizations: from whom do entrepreneurs receive investments? Adm. Sci. Q. 53 (4), 685–718. https://doi.org/10.2189/asqu.53.4.685.

Huang, Z., Tian, X., 2020. China's venture capital market. In: Amstad, M., Sun, G., Xiong, W. (Eds.), The Handbook of China's Financial System. Princeton University Press, NJ, USA, pp. 383–418. https://doi.org/10.1515/9780691205847.

Humphery-Jenner, M., Suchard, J.A., 2013. Foreign VCs and venture success: evidence from China. J. Corp. Financ. 21, 16–35. https://doi.org/10.1016/j.jcorpfin.2013.01.003.

Kantarci, K., 2007. Perceptions of foreign investors on the tourism market in central Asia including Kyrgyzstan, Kazakhstan, Uzbekistan, Turkmenistan. Tour. Manag. 28 (3), 820–829. https://doi.org/10.1016/j.tourman.2006.05.012.

Khalilzadeh, J., 2018. Demonstration of exponential random graph models in tourism studies: is tourism a means of global peace or the bottom line? Ann. Tour. Res. 69, 31–41. https://doi.org/10.1016/j.annals.2017.12.007.

Kim, J.Y., Howard, M., Cox Pahnke, E., Boeker, W., 2016. Understanding network formation in strategy research: exponential random graph models. Strateg. Manag. J. 37 (1), 22–44. https://doi.org/10.1002/smj.2454.

Kizildag, M., 2015. Financial leverage phenomenon in hospitality industry sub-sector portfolios. Int. J. Contemp. Hosp. Manag. 27 (8), 1949–1978. https://doi.org/10.1108/ijchm-07-2014-0347.

Kot, H.W., Chen, M.H., Huang, H., 2019. Understanding short selling activity in the hospitality industry. Int. J. Hosp. Manag. 82, 136–148. https://doi.org/10.1016/j.ijhm.2019.03.029.

Lee, P.M., Pollock, T.G., Jin, K., 2011. The contingent value of venture capitalist reputation. Strateg. Organ. 9 (1), 33–69. https://doi.org/10.1177/1476127011400505.

Li, Y., Singal, M., 2019. Capital structure in the hospitality industry: the role of the asset-light and fee-oriented strategy. Tour. Manag. 70, 124–133. https://doi.org/10.1016/j.tourman.2018.08.004.

Liu, B., Huang, S.S., Fu, H., 2017. An application of network analysis on tourist attractions: the case of Xinjiang, China. Tour. Manag. 58, 132–141. https://doi.org/10.1016/j.tourman.2016.10.009.

Liu, B., Jiang, H., 2019. Are distances barriers to sustainability for venture capital syndication? Sustainability 11 (15), 4126. https://doi.org/10.3390/su11154126.

Lusher, D., Robins, G., 2013. Formation of social network structure. In: Lusher, D., Koskinen, J., Robins, G. (Eds.), Exponential Random Graph Models for Social Networks: Theory, Methods and Applications. Cambridge University Press, Cambridge, UK, pp. 16–28. https://doi.org/10.1017/CBO9780511894701.004.

Mao, Z.E., Yang, Y., 2016. FDI spillovers in the Chinese hotel industry: the role of geographic regions, star-rating classifications, ownership types, and foreign capital origins. Tour. Manag. 54, 1–12. https://doi.org/10.1016/j.tourman.2015.10.011.

McPherson, M., Smith-Lovin, L., Cook, J.M., 2001. Birds of a feather: homophily in social networks. Annu. Rev. Sociol. 27, 415–444. https://doi.org/10.1146/annurev.soc.27.1.415.
Merinero-Rodríguez, R., Pulido-Fernández, J.I., 2016. Analysing relationships in tourism: a review. Tour. Manag. 54, 122–135. https://doi.org/10.1016/j.tourman.2015.10.010.
Morgan, N., Pritchard, A., Pride, R., 2011. Tourism places, brands, and reputation management. Destin. Brand.: Manag. Place Reput. 3, 3–19. https://doi.org/10.1016/b978-0-08-096930-5.10001-1.
Motta, V., Sharma, A., 2019. Lending technologies and access to finance for SMEs in the hospitality industry. Int. J. Hosp. Manag., 102371 https://doi.org/10.1016/j.ijhm.2019.102371.
Mussalam, G.Q., Tajeddini, K., 2016. Tourism in Switzerland: how perceptions of place attributes for short and long holiday can influence destination choice. J. Hosp. Tour. Manag. 26, 18–26. https://doi.org/10.1016/j.jhtm.2015.09.003.
Oak, S., Dalbor, M.C., 2008. Institutional investor preferences for lodging stocks. Int. J. Hosp. Manag. 27 (1), 3–11. https://doi.org/10.1016/j.ijhm.2007.06.003.
OECD, 2018. Towards investment and financing for sustainable tourism. OECD Tourism Trends and Policies 2018. OECD Publishing, Paris. https://doi.org/10.1787/tour-2018-7-en.
Olsen, M.D., 2004. Literature in strategic management in the hospitality industry. Int. J. Hosp. Manag. 23 (5), 411–424. https://doi.org/10.1016/j.ijhm.2004.10.003.
Pacheco, L., Tavares, F., 2017. Capital structure determinants of hospitality sector SMEs. Tour. Econ. 23 (1), 113–132. https://doi.org/10.5367/te.2015.0501.
Park, K., Jang, S.S., 2018. Pecking order puzzle: restaurant firms' unique financing behaviors. Int. J. Hosp. Manag. 70, 99–109. https://doi.org/10.1016/j.ijhm.2017.10.014.
Petkova, A.P., Wadhwa, A., Yao, X., Jain, S., 2014. Reputation and decision making under ambiguity: a study of US venture capital firms' investments in the emerging clean energy sector. Acad. Manag. J. 57 (2), 422–448. https://doi.org/10.5465/amj.2011.0651.
Provan, K.G., Fish, A., Sydow, J., 2007. Interorganizational networks at the network level: a review of the empirical literature on whole networks. J. Manag. 33 (3), 479–516. https://doi.org/10.1177/0149206307302554.
Rider, C.I., 2009. Constraints on the control benefits of brokerage: a study of placement agents in US venture capital fundraising. Adm. Sci. Q. 54 (4), 575–601. http://www.jstor.org/stable/27749358.
Rivera, M.T., Soderstrom, S.B., Uzzi, B., 2010. Dynamics of dyads in social networks: assortative, relational, and proximity mechanisms. Annu. Rev. Sociol. 36 (1), 91–115. https://doi.org/10.1146/annurev.soc.34.040507.134743.
Robins G., Lusher D., 2013. Illustrations: simulation, estimation and goodness of fit. In Exponential Random Graph Models for Social Networks: Theory, Methods and Applications, Lusher D, Koskinen J, Robins G (eds). Cambridge, UK, pp. 167–185. https://doi.org/10.1017/CBO9780511894701.015.
Rogers, E.M., Bhowmik, D.K., 1970. Homophily-heterophily: relational concepts for communication research. Public Opin. Q. 34 (4), 523–538. https://doi.org/10.1086/267838.
Scott, N., Baggio, R., Cooper, C., 2008. Network analysis and tourism: from theory to practice. Tour. Anal. 14 (3), 417–419. https://doi.org/10.3727/108354209789705057.
Serrasqueiro, Z., Nunes, P.M., 2014. Financing behaviour of Portuguese SMEs in hotel industry. Int. J. Hosp. Manag. 43, 98–107. https://doi.org/10.1016/j.ijhm.2014.09.001.
Shane, S., Cable, D., 2002. Network ties, reputation, and the financing of new ventures. Manag. Sci. 48 (3), 364–381. http://www.jstor.org/stable/822571.
Sorenson, O., Stuart, T.E., 2001. Syndication networks and the spatial distribution of venture capital investments. Am. J. Sociol. 106 (6), 1546–1588. https://doi.org/10.2139/ssrn.220451.
Sorenson, O., Stuart, T.E., 2008. Bringing the context back in: settings and the search for syndicate partners in venture capital investment networks. Adm. Sci. Q. 53 (2), 266–294. https://doi.org/10.2189/asqu.53.2.266.
Ter Wal, A.L., Alexy, O., Block, J., Sandner, P.G., 2016. The best of both worlds: the benefits of open-specialized and closed-diverse syndication networks for new ventures' success. Adm. Sci. Q. 61 (3), 393–432. https://doi.org/10.1177/0001839216637849.
Tsai, H., Pan, S., Lee, J., 2011. Recent research in hospitality financial management. Int. J. Contemp. Hosp. Manag. 23 (7), 941–971. https://doi.org/10.1108/09596111111167542.
van der Pol, J., 2019. Introduction to network modeling using Exponential Random Graph Models (ERGM): theory and an application using R-project. Comput. Econ. 54 (3), 845–875. https://doi.org/10.1007/s10614-018-9853-2.
Vanhaverbeke, W., Gilsing, V., Beerkens, B., Duysters, G., 2009. The role of alliance network redundancy in the creation of core and non-core technologies. J. Manag. Stud. 46 (2), 215–244. https://doi.org/10.1111/j.1467-6486.2008.00801.x.
Wang, P., 2020. Broadening versus reinforcing investor portfolios: social structure and the search for venture capital investors. J. Bus. Ventur. 35 (1), 105915 https://doi.org/10.1016/j.jbusvent.2018.12.001.
Wang, Y., 2016. Bringing the stages back in: social network ties and start-up firms' access to venture capital in China. Strateg. Entrepreneurship J. 10 (3), 300–317. https://doi.org/10.1002/sej.1229.
Wäsche, H., 2015. Interorganizational cooperation in sport tourism: a social network analysis. Sport Manag. Rev. 18 (4), 542–554. https://doi.org/10.1016/j.smr.2015.01.003.
Williams, N.L., Hristov, D., 2018. An examination of DMO network identity using Exponential Random Graph Models. Tour. Manag. 68, 177–186. https://doi.org/10.1016/j.tourman.2018.03.014.
Williams, N.L., Inversini, A., Ferdinand, N., Buhalis, D., 2017. Destination eWOM: a macro and meso network approach? Ann. Tour. Res. 64, 87–101. https://doi.org/10.1016/j.annals.2017.02.007.
Yeniyurt, S., Townsend, J.D., Cavusgil, S.T., Ghauri, P.N., 2009. Mimetic and experiential effects in international marketing alliance formations of US pharmaceuticals firms: an event history analysis. J. Int. Bus. Stud. 40 (2), 301–320. https://doi.org/10.1057/jibs.2008.62.
Zaheer, A., Soda, G., 2009. Network evolution: the origins of structural holes. Adm. Sci. Q. 54 (1), 1–31. https://doi.org/10.2189/asqu.2009.54.1.1.
Zhang, L., Gupta, A.K., Hallen, B.L., 2017. The conditional importance of prior ties: a group-level analysis of venture capital syndication. Acad. Manag. J. 60 (4), 1360–1386. https://doi.org/10.5465/amj.2013.1088.
Zhao, W., Ritchie, J.B., Echtner, C.M., 2011. Social capital and tourism entrepreneurship. Ann. Tour. Res. 38 (4), 1570–1593. https://doi.org/10.1016/j.annals.2011.02.006.
Zheng, Y., 2011. In their eyes: how entrepreneurs evaluate venture capital firms. J. Priv. Equity 14 (2), 72–85. https://doi.org/10.3905/jpe.2011.14.2.072.
Zheng, Y., Xia, J., 2018. Resource dependence and network relations: a test of venture capital investment termination in China. J. Manag. Stud. 55 (2), 295–319. https://doi.org/10.1111/joms.12255.