Introduction

DMOs currently face remarkable challenges in local, regional, national and international contexts (Pearce & Schänzel, 2013). DMOs were originally defined as organisations closely associated with the *promotion of destination* amenities (Pike, 2007). However, in light of recent developments, it may be more appropriate to define DMOs as management-focused organisations (Harrill, 2009) assuming greater resource management and leadership roles in destinations (Volgger & Pechlaner, 2014). English destinations and DMOs were once heavily dependent on the public purse, mainly through regional government support (Fyall, Fletcher, & Spyriadis, 2009). The *2011 UK Government Tourism Policy* proposed replacing existing tourism management and support structures on a regional level, namely Regional Tourist Boards (RTBs) and Regional Development Agencies (RDAs), in favour of more locally-positioned DMOs and Local Enterprise Partnerships (LEPs) (Kennell & Chaperon, 2013). These reshaped DMOs are expected to have sole responsibility for ensuring long-term financial sustainability of their organisations whilst also exercising strategic destination decision-making (Coles, Dinan, & Hutchison, 2012).

Increasingly, DMOs are attempting to accomplish these tasks as part of a network involving businesses, government and civil society (Beritelli, Bieger, & Laesser, 2007). By linking these differing organizations, DMOs seek to establish a network identity (Huemer, Becerra, & Lunnan, 2004), in which members adopt roles that include responsibility for sharing information and encouraging collective action. The resulting inter-organizational knowledge interactions (Hristov & Ramkissoon, 2016) can support development and implementation of collective activities that help achieve an intended outcome of financial sustainability (Beritelli, Buffa, & Martini, 2015).

Tourism network literature has grown rapidly over the past decade (Williams, Inversini, Ferdinand, & Buhalis, 2017) and is increasingly applied to examine DMOs and destinations (Reinhold, Laesser, & Beritelli, 2015). Existing work, however, tends to use networks as a metaphor for understanding organisations and organisational behaviour (Merinero-Rodríguez & Pulido-Fernández, 2016), including relational dynamics (Tran, Jeeva, & Pourabedin, 2016). These studies were able to identify individuals and organizations that may be influential, but were not able to determine the extent of this influence. Whilst an emerging stream of tourism research has begun to employ inferential techniques, such as the Quadratic Assignment Procedure (Liu, Huang, & Fu, 2017), most Social Network Analysis (SNA) research relies on descriptions of networks to explain relationships among entities (Shumate & Palazzolo, 2010). However, these approaches do not enable researchers to determine if patterns identified in networks could have occurred by chance (Hunter & Handcock, 2006). Researchers have raised concerns when attempting to infer network characteristics from descriptive metrics; for example, clustering coefficient values, which indicate that entities or actors are important in networks, can be observed in randomly created networks (Newman, Strogatz, & Watts, 2001) . This suggests these metrics will require additional qualitative or quantitative data about network actors or characteristics in order to support robust research.

The aim of this paper is to examine the emergent network identity in a DMO network by identifying relational and node property influences on the structure of a communications network in a DMO. Using data collected from the Destination Milton Keynes initiative, the communication network of a DMO was modelled using an Exponential Random Graph approach. These models identified the extent to which node (organizational characteristics) and structure influence the distribution of communication ties in the network.

Literature Review

Network theory (Granovetter, 1973) and the analytical approach of SNA can be used to examine the arrangement of relationships between interacting entities, such as individuals, groups and organisations (Wang & Xiang, 2007). In the tourism and management domain, this perspective advocates that organisations no longer act solely as individual entities but through relational networks where value is created by initiating and nurturing collaboration (Fyall et al. 2009). SNA examines structural and relational properties of networks, such as density (Table 1), to identify patterns that can be used to explain social behaviour (Prell, 2012). SNA literature in business and management (Borgatti & Foster, 2003) seeks to demonstrate how the concept is able to visualise otherwise invisible social networks. Once depicted, invisible social networks, such as communication structures, may be leveraged for visible results in organisations (Conway, 2014).

However, to date, little research has been undertaken to examine communication among destination organizations, particularly through the lens of SNA (Asero, Gozzo, & Tomaselli, 2016). SNA has often been perceived as a network tool that produces largely descriptive data without providing deeper insights (Prell 2012). Within this context, scholars have argued that social network studies often over-emphasise the quantity of network relationships and interactions rather than their quality (Conway 2014).

Table 1: SNA Terms

Term	**Description**
Node	Entity in a network which can be human or non-human actors
Edge	A tie from one node to another which can be an interaction, relationship or shared property
Attribute	Node characteristic which is independent of ties to other nodes
Communication network	Network where ties are communications between entities
Degree centrality	Number of ties nodes have with other nodes in the network.
Density	The ratio of actual ties in the network to potential ties
Authority	This metric is an indicator of the extent to which information from the node is valued by other nodes in the actor
Closeness centrality	This metric is an indicator of the relative distance information from a given node will have to travel to reach others in the network
Betweeness centrality	This metric identifies the extent to which a given node is a member of the path information has to travel from one part in the network to another.
Transitivity	The tendency for a given node to be connected by edges if it shares a mutual partner
Exponential random graph model (ERGM)	A group of approaches to perform inferential statistical analysis of networks

Adapted from Krivitsky (2012)

Network Theory and SNA Adopted in DMO Research

DMOs often represent a number of key destination management and leadership-interested actors in their respective destinations (Ness, Aarstad, Haugland, & Grønseth, 2014). Extant SNA literature in the DMO domain has focused largely on how inter-organizational linkages can influence governance of these institutions including related domains, such as knowledge management, policy formulation and cooperation (Czernek, 2013). Network theory has been used to examine DMOs as complex systems (Pforr, 2006) . Studies have examined network collaboration and knowledge-sharing practices in public, private (Longjit & Pearce, 2013)or mixed network clusters (Del Chiappa & Presenza, 2013) within specific geographic boundaries (Baggio & Cooper 2008).

For DMOs, the shift from marketing to management implies the need to engage with a network of stakeholders for an expanded range of activities. The extent to which the DMO can influence network interactions, such as communication between members, has not yet been identified (van der Zee & Vanneste, 2015). Researchers have determined previously that organizations can establish a collaborative “network identity” in which members are viewed by their relational roles and positions (Huemer et al., 2004). This emergent, jointly-held perception can indicate the ability to contribute (Anderson, Håkansson, & Johanson, 1994), forming the basis for interaction within the network and the benefits derived from membership (Astley & Zammuto, 1992). Whilst individual organizations may adopt particular roles, the focal or initiating organization has an opportunity to shape overall interactions and, hence, the nature of the collective network identity (Ellis, Rod, Beal, & Lindsay, 2012). The network identity framed by this organization helps define the nature and volume of activities with which members are involved (Gadde, Huemer, & Håkansson, 2003).

To date, network identity has been explored by inductive examination of member discussions, most notably by the International Marketing and Purchasing group (Morlacchi, Wilkinson, & Young, 2005). Research has examined the influence of network identity on interactions in supplier, project and creative inter-organizational networks. Research has not yet examined the structure of relationships in these networks which may provide insight into the nature of and extent to which network identity can influence interactions such as communications between organizations.

Research has explored the influence of relational properties on communication processes in the DMO network of bodies involved in strategic destination decision-making (Baggio, 2017). Network structure influences the rate or efficiency of communication and knowledge-sharing in destination networks (Argote & Ingram, 2000). High density networks can provide a large number of potential contacts to members, supporting rapid knowledge diffusion (Gloor, Kidane, Grippa, Marmier, & Von Arb, 2008). They can help in adaptation to a changing environment through efficient information exchange of practices, techniques and market requirements among members. Network structure can also influence the pattern of diffusion of knowledge, enabling innovation by exposing actors to differing perspectives (Chen & Hicks, 2004). Previous research on the destination of Elba suggests that DMO communication networks are sparse with low levels of local collaboration and cooperation (Baggio & Cooper, 2010). Since communication can underpin activities, such as resource sharing and activity coordination in a DMO network, there is a need to understand the patterns of communication between members. An examination of these interactions using SNA can provide an opportunity to understand the nature and extent of identity in DMO networks.

Inferential Network Analysis with Exponential Random Graph Models (ERGM)

Statistical approaches to SNA in the form of Exponential Random Graph Models (ERGM) (Wasserman & Pattison, 1996) have been developed to enable prediction of relationship patterns (van Duijn & Huisman, 2011). ERGM linkages or ties between entities, along with entity attributes, are used to predict network characteristics (Krivitsky, 2012). ERGMs take the perspective that relationship creation among actors in a network is a temporal process. The goal of ERGM analysis is to identify a specific model of relationships among a set of actors similar to the observed network resulting from this temporal process (Broekel, Balland, Burger, & van Oort, 2014). The approach is model-based rather than sample-based and inferences based on the analysis relate to the observed network only. Calculations are performed using Markov Chain Monte Carlo Maximum Likelihood Estimation, which requires creation of a distribution of random graphs from an initial set of network parameter values. These are then evaluated by comparison with the observed or real world graph in an interactive manner until the model converges; that is, the parameters stabilize.

ERGMs have particular strengths in determining how a real world network varies from a random graph (Rivera, Soderstrom, & Uzzi, 2010). In real world networks, actors or entities will not have the same ability to form ties. These networks may exhibit homphily, which is the tendency of entities with similar attributes to form ties preferentially with each other (Cross, Laseter, Parker, & Velasquez, 2006). This property suggests that differences among actors will result in clusters or subgroups within networks. Communication in networks across different subgroups based on actor types can be slower as there are fewer connections among them.

Early studies have identified homophily in social groups by utilising demographic characteristics, such as age, background and gender (Loomis, 1946), using qualitative techniques. Later work adopted quantitative research to analyse networks in social institutions, such as schools (Shrum, Cheek & Hunter, 1988) which enabled examination of multiple dimensions of homophily at the same time. Subsequent in this area has identified the influence of homophily on organizational development and innovation (Aldrich, Reese, & Dubini, 1989). Current research in this area attempts to identify homophily by similarities in network position (Mitteness, DeJordy, Ahuja, & Sudek, 2016). This body of research proposes that actors with shared characteristics, such as beliefs or behaviours, are more likely to interact with each other and occupy similar network positions (Kwon, Stefanone, & Barnett, 2014). Researchers have found organizations exhibit homophily by geography, industry and capabilities (Cowan, 2005). At the organizational level, this property has been used to explain why firms with similar network positions are also more likely to engage in joint activities, such as alliances (Brass, Galaskiewicz, Greve, & Tsai, 2004). Entities not sharing these characteristics are “peripheral” and possess no influence (Boschma, 2005).

Real world networks may also exhibit higher levels of transitivity than random networks (Louch, 2000). This tendency of nodes to cluster in these networks has been found to be greater than expected when compared to a random network with a similar degree distribution (Newman & Park, 2003). To capture these properties, Hunter and Handcock (2006) proposed geometrically-weighted, edgewise, shared partnerships (GWESP), which capture transitivity characteristics in real world networks, such as clusters of nodes more highly connected to each other than the rest of the network. This measure assumes two actors share a partner if both have edges connecting with the same partner. These shared partners form a triangle if the original two actors are connected to each other. The shared partner count is measured by each edge in the network and the resulting distribution is used to estimate transitivity in the network.

Interpreting the statistics of ERGMs is similar to binary logistics regression. Network linkages or ties are the outcome to be predicted and network structures help to explain the probability of these linkages (Hunter, Goodreau, & Handcock, 2008). ERGMs have been used in domains, such as politics, to examine alliances or conflicts (Cranmer, Desmarais, & Kirkland, 2012). However, little effort has been made thus far to apply these approaches to examine tourism-related phenomena, such as communication in destination networks.

Research Propositions

Communication and interconnections between tourism stakeholders is a frequently examined phenomenon. Previous researches have analysed the linkages between websites of destination stakeholders, along with connections between actors (Baggio, Scott, & Cooper, 2010). However, whilst empirical research in other domains has examined how real world networks differ from random networks (Shumate & Palazzolo, 2010), tourism research has not yet confirmed that connections in observed networks could not have arisen by chance. Verification that networks are not random can support inferences made by examination of network metrics, such as centrality. The first research proposition is therefore:

Proposition 1: Communication relationships in a DMO network did not arise in a random fashion.

Network structures have been found to influence the nature of collaboration and therefore the effectiveness of DMO networks (van der Zee & Vanneste, 2015). Research in economic geography has indicated that homophily, or the tendency to form connections preferentially, can be observed in members of a policy group (Hazir & Autant-Bernard, 2014). If a network identity was established, members of the DMK initiative should communicate preferentially with each other. Proposition 2 is therefore:

Proposition 2: Members exhibit homophily by membership in the DMK initiative.

Past research has indicated that members of networks have exhibited homophily through shared attributes, such as age, race and gender (van Duijn & Huisman, 2011). However, it is not yet known if the same effect could be observed in tourism organizations operating in the same industry. Proposition 3 is therefore:

Proposition 3: Members of the DMK network exhibit homophily by industry

Research Setting: The DMK Network of DMO Member Organisations

Destination Milton Keynes (DMK) was established in 2006 by 13 founding organisations representing local authorities, businesses, sustainability trusts and community organisations acting as the official provider of tourist information services for Milton Keynes; thus, exercising marketing functions predominantly (Hristov & Zehrer, 2015). As the political and economic context changed (Coles, Dinan, & Hutchison, 2014), DMK was expected to take on board a wider array of responsibilities. Currently, DMK functions as an independent, not-for-profit company and its funding structure includes a mixture of membership fees, grants from Milton Keynes Council and commissions from its members (Hristov & Zehrer, 2015). DMK is an official DMO network of key destination businesses, the council and other public bodies, along with a diverse mix of not-for-profit and community organisations. Having clear geographic boundaries, the DMK network covers 70 member organisations located in central Milton Keynes and the surrounding market (Hristov & Zehrer, 2015). Among the core objectives of DMK are to encourage inward investment, to promote Milton Keynes as a viable visitor destination and to explore opportunities for developing further business, leisure, heritage and other types of urban and rural destination products.

Such activities are expected to be carried out under the guidance of Destination Management Plans (DMPs) and by involving key interested destination actors who serve businesses, local government and third sector organisations. DMPs are an expression of a government-mandated, current policy-driven approach to guiding the work of private-led DMOs in England.

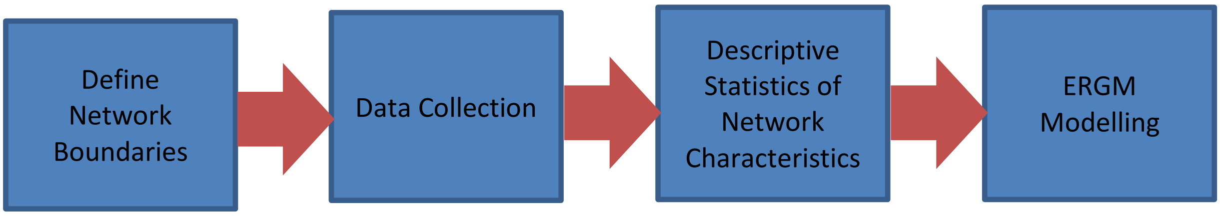
DMK and the UK is not a unique case but its relevance and applicability spreads across a number of countries with tourism sectors. DMOs face an increasingly networked environment and significant changes in their funding and governance (Coles, Dinan and Hutchison 2014). Such disruptions to the operational environment for DMOs are evident in a number of countries, such as Switzerland (Beritelli, Bieger & Laesser 2014), Australia (Pforr, Pechlaner, Volgger, & Thompson, 2014) China (Wang & Ap 2013) and the UK (Hristov & Zehrer 2017).

In the case of Switzerland, Pietro, Thomas & Christian (2013) highlighted that many Swiss DMOs have to restructure into networks that engage a wider range of stakeholders in order to demonstrate value for money and to diversify their funding streams. Similarly, in Australia, Pforr, Pechlaner, Volgger & Thompson (2014) concluded DMOs are increasingly being confronted with limited funds and organisations often need to incorporate input from the private sector in order to offer a continued justification for their existence. In the case of China, DMOs or Tourism Administrative Organizations (TAOs) restructured their operations to support similar transformations to network tourism governance (Wang & Ap, 2013) . Equally, in the case of the UK, DMOs have been under increased scrutiny within a new funding and governance landscape, resulting in a focus on the distribution of leadership and the pooling of knowledge and resources (Hristov & Zehrer, 2017).

Research Methods

The research method adopted a four-step process, as seen in Figure 1

Figure 1: Research Process



1) *Define Network Boundaries*

Network research aims to study whole populations, individuals, organisations or entities in a given cohort (Galaskiewicz & Wasserman, 1993). Researchers need to determine the extent or boundary of networks, which then shapes subsequent data collection (Laumann, Marsden, & Prensky, 1989). Collecting network data thus implies that network actors are not independent units of analysis (Scott, 1988), but rather embedded in a myriad of social relations, as in the case of this study, in which all target organisations are members of DMK.

When conducting studies investigating large networks, the collection and subsequent analysis of network data often becomes unmanageable (Conway 2014). This study overcomes such complexities by applying a rule of inclusion (Murty, 1998) that limits the data collection organizations involved with the DMK DMO post-2011 in a Government Tourism Policy context. For this research, data was collected from a network of 70 member organisations on board DMK. They included businesses representing a number of sectors of the economy related to Milton Keynes, as well as local authorities, such as Milton Keynes Council, and a range of not-for-profit organisations.

2) *Data Collection*

Network survey questionnaires facilitate the task to construct collectively and depict the investigated network subsequently (Moody, McFarland, & Bender-deMoll, 2005) by using binary network data. For the purpose of network data collection, the study used a web-based platform, Organisational Network Analysis (ONA) Surveys, which is available on https://www.s2.onasurveys.com on a subscription basis. The survey content and structure were initially developed in MS Word, which allowed the researcher the opportunity to visualise the full survey prior to embedding it in ONA

Surveys. Once agreed, the content and structure of the DMO network survey was embedded in ONA Surveys and tested with the assistance of DMK management. Then, names and contact details of those testing the survey were replaced with Destination Milton Keynes's full network of member organisations. The full member list was collected from the DMK official website on 1 July 2014 and research was undertaken in order to identify senior prospects within DMK's member organisations.

To ensure ethical data collection and to minimize potential risk, it was made clear in the survey introduction that the study was only interested in existing links within the complete network of DMK member organisations. As such, the study does not extend beyond DMK's membership network to capture any private networks of individual DMO member organisations. Respondents were required to provide data concerning the nature of their relationships with other DMK member organisations, such as the frequency of information-sharing and the impact of developmental resource-sharing between respondent organisations.

3) Descriptive Statistics of Network Characteristics

Gephi (Gephi.org) was employed to perform initial exploratory analysis and visualisation of the communication network (Cherven, 2015). Gephi has a number of network and actor-level measures that target structural and relational properties of networks. Gephi also provides a range of network layout algorithms used for transforming network data into network depictions.

4) Exponential Random Graph Modelling

Modelling was conducted using the statnet package in R. Four models were developed:

1: Edges only model. The purpose of this model is to determine if the distribution of edges in the observed network differs significantly from a random network (Research proposition 1). This model is known as the the Bernoulli or Erdos-Reyni model and is useful as it helps determine if the patterns of relationships in the communication network identified by the descriptive statistics could have arisen by chance.

2: Edges and the actor property of membership in DMK. The purpose of this model is to identify homphily by DMK membership; that is, network members communicate with each other more than they do with non-members (Research proposition 2).

3: Edges, membership and the network property of GWESP. This model incorporates a network statistic that identifies how the transitivity of the communication network varies from random distribution of edges.

4: Edges, GWESP, actor properties of membership and industry background. The purpose of this model is to identify homophily by Industry membership (Research proposition 3).

The fit of all models will be assessed by the Akaike information criterion (AIC) and Bayesian information criterion (BIC) (Akaike, 1992). Whilst they have no direct interpretation, they serve as a means for comparing differing models and lower values are preferred.

Results

The membership portfolio of DMK consists of founding (corporate) and non-corporate members. Founding (corporate) members initially established the DMO in 2006 and member organisations joined later; i.e. post-2006 until January 2014 when this study was conducted. Corporate members represented 18.5% of the overall DMO membership network, whilst non-corporate members accounted for 81.5% of the DMO membership base. The investigated network itself is diverse; i.e. a number of key sectors of the economy are represented on board (Table 2) and hospitality establishments and not-for-profit organisations are dominant stakeholder groups (sectors defined as per the above classification) at 24.7% and 18.5%, respectively.

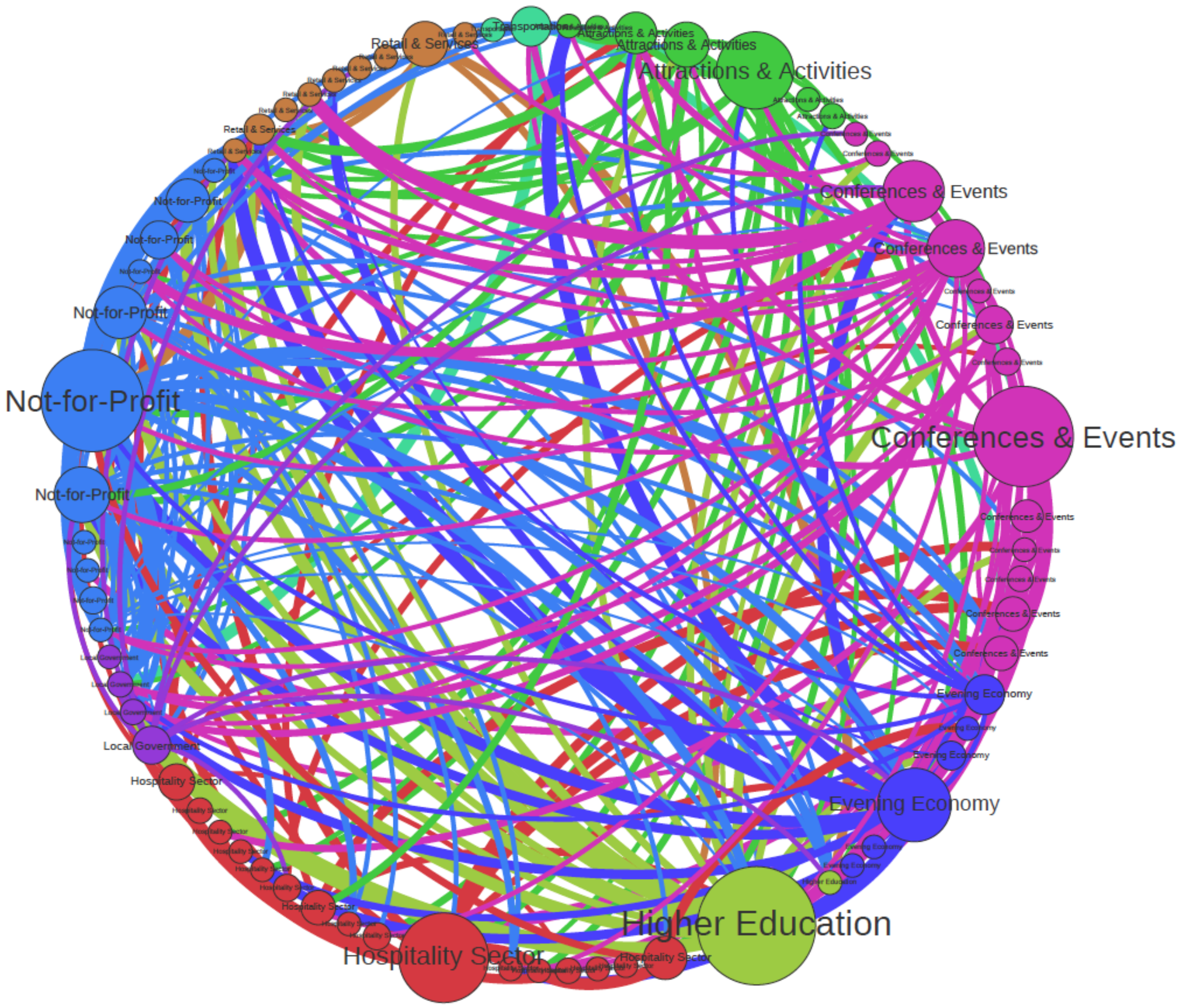
Table 2: DMK Network by Sector (from January 2014)

Type of organisation	Network share (%)
Hospitality Sector	24.7
Not-for-Profit	18.5
Conferences and Events	14.8
Retail and Services	13.6
Evening Economy	9.9
Attractions and Activities	8.6
Local Government	6.2
Higher Education	2.5
Transportation	1.2

Within the context of communication patterns and exchange of information, edge colours correspond to the colour of source nodes to depict the initiators of this communication; i.e. network actors who reported a link with other DMK member organisations. Edge (communication flows) corresponds to the colour of source; i.e. identifying key communicators. The thicker a link, the higher the frequency of communication and knowledge exchange between the source and target nodes.

Figure 2 provides a view of all interaction flows related to communication and exchange of information across the DMK network.

Figure 2: DMK Network Information Flows



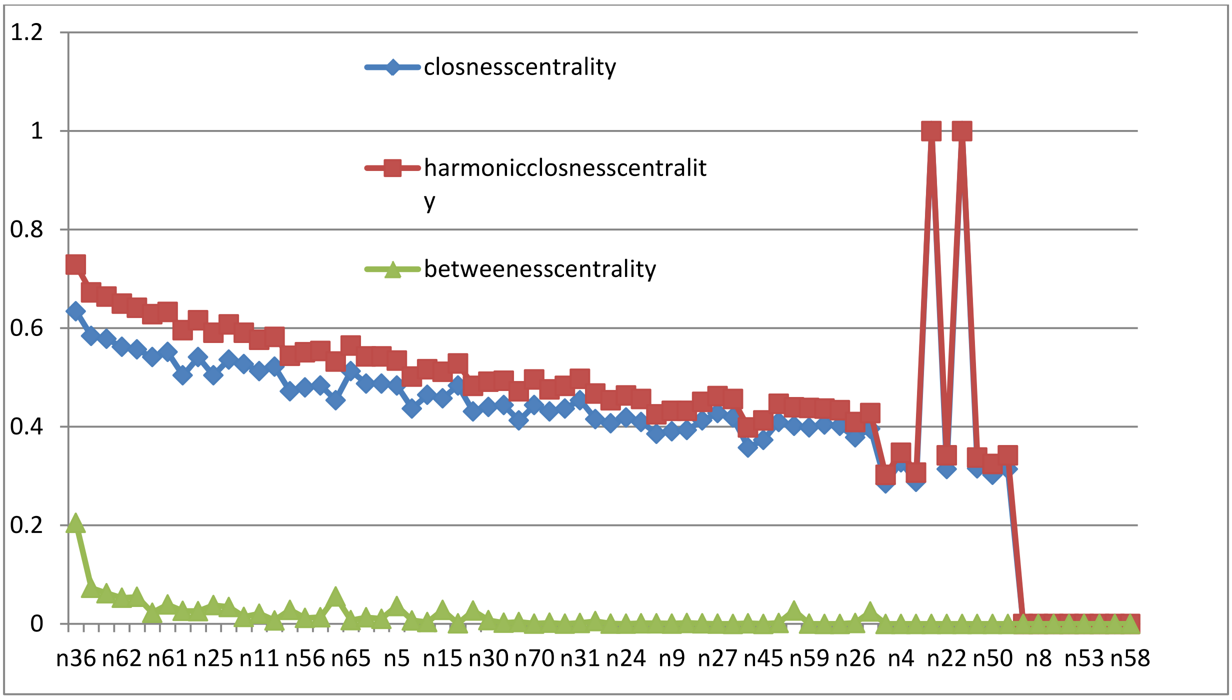
An examination of the metrics for 5 firms with the highest scores in the network indicates they are service providers. Further, the highest score for degree and centrality belongs to a higher education firm. Firms with these scores will be more likely to be involved in communications across the entire network than other firms. The reason for this may be that service providers work with a large number of network entities as part of their operations. In this way, they become network “hubs” that connect otherwise isolated firms to each other.

Table 3: Network Metrics (all numbers except degree are normalized)

Company Type	*Degree*	*Authority*	*Hub*	*Closeness centrality*	*Harmonic closeness centrality*	*Betweenness centrality*
Higher Education	28	0.300301	0.300301	0.634409	0.728814	0.204854
Not-for-Profit	22	0.274315	0.274315	0.584158	0.672316	0.073002
Evening Economy (Entertainment)	21	0.278143	0.278143	0.578431	0.663842	0.062341
Conferences & Events	20	0.263588	0.263588	0.561905	0.649718	0.052777
Not-for-Profit	19	0.219769	0.219769	0.556604	0.641243	0.054806

Furthermore, examination of the distribution of normalized network metrics indicates they fall within a narrow range with a few outliers for harmonic centrality. Whilst large networks may exhibit a power law or exponential distribution, smaller networks may have a less extreme distribution of metrics. This finding indicates that no single firm holds dispoportinate control over communication in the network.

Figure 3



After mapping and visualizing the network, exponential random graph modelling was carried out to determine the network and node properties that infulenced communication ties. Four models were developed:

1: A simple edges only model

2: Edges and the actor property of membership in DMK

3: Edges, membership and the network property of GWESP

4: Edges, GWESP, actor properties of membership and industry background.

Model 1

The first model examines if the network's observed structure of ties could have been produced from a random process. The section below presents the output of R analysis for Model 1 in Table 4 below:

Table 4: Model 1 (Edges only)

	Estimate	Std. Error	MCMC %	p-value
Edges	-1.99904	0.06981	0	<1e-04 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Null Deviance: 2795 on 2016 degrees of freedom				
Residual Deviance: 1515 on 2015 degrees of freedom				
AIC: 1517 BIC: 1523 (Smaller is better.)				
Formula: y ~ edges Iterations: 5 out of 20				

Findings from the analysis indicated the network was not random at a significance level of .001. The probability of ties in the observed network can be determined as exp(-1.99904)/(1+exp(-1.99904)) = 0.1193, which corresponds to the density of the observed network. The model fit shows the result is significant at the 0.001 level, indicating that the edges in the network were not randomly distributed. This finding provides some support for the validity of the hubs and metric distributions identified by the previous analysis in Table 3 and Figure 3.

Model 2

In model 2, an actor property, membership in the DMK network, was added to identify its impact on the probability of ties in the network. This identifies if a network identity was established. The R output is presented below in Table 5:

Table 5: Model 2 (Edges and Membership)

	Estimate	Std. Error	MCMC %	p-value
Edges	-1.94246	0.11736	0	<1e-04 ***
Nodematch.Members	-0.08656	0.14600	0	0.553
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Null Deviance: 2795 on 2016 degrees of freedom				
Residual Deviance: 1515 on 2014 degrees of freedom				
AIC: 1519 BIC: 1530 (Smaller is better.)				
Formula: y ~ edges + nodematch ("Members") Iterations: 5 out of 20				

The findings suggest that the Association Membership property was not a significant determinant of ties in the network. AIC and BIC are similar to Model 1, indicating this model does not provide an improved basis for explaining the distribution of ties in the network.

Model 3

The third model adds the clustering tendency in the form of the Geometrically-Weighted Edgewise Shared Partner (GWESP) parameter to determine if the transitivity patterns exhibited in the DMK communication network could have occurred randomly.

Table 6: Model 3 (Edges, Membership and Transitivity)

	Estimate	Std. Error	MCMC %	p-value
Edges	-4.1177	0.2743	0	<1e-04 ***
Nodematch.Members	-0.0498	0.1168	0	0.67
GWESP.fixed.0.25	1.4988	0.1943	0	<1e-04 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Null Deviance: 2795 on 2016 degrees of freedom				
Residual Deviance: 1403 on 2013 degrees of freedom				
AIC: 1409 BIC: 1426 (Smaller is better.)				
Formula: y ~ edges + nodematch("Members") + gwesp(0.25, fixed = TRUE) Iterations: 3 out of 20				

The findings indicate GWESP is significantly different from a random network and helps to predict the probability of ties in the DMK network. The GWESP figure suggests the network is robust with multiple redundant ties among members. Communication in this network will therefore be rapid as information can be shared quickly. This model is a stronger basis for explaining the distribution of ties in the network as AIC and BIC are lower than in Model 1 or 2.

Model 4

The final model adds the actor term of sector membership, which enables the comparison of sector identity with network identity.

Table 7: Model 4 (Edges, Membership, Sector and Transitivity)

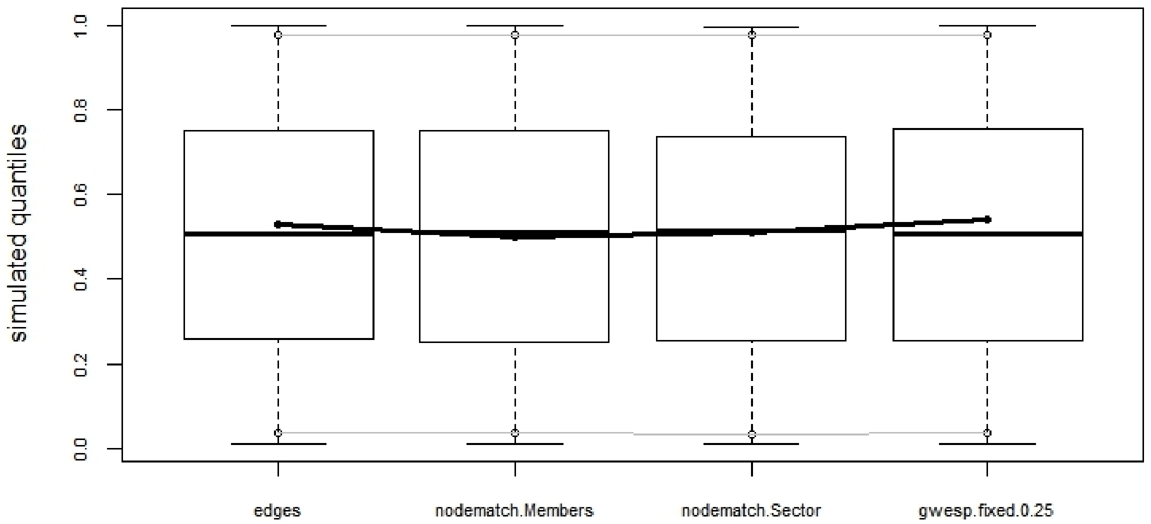
	Estimate	Std. Error	MCMC %	p-value
Edges	-4.1244	0.2781	0	<1e-04 ***
Nodematch.Members	-0.1145	0.1197	0	0.3387
Nodematch.Sector	0.4147	0.1695	0	0.0145 *
GWESP.fixed.0.25	1.4878	0.1973	0	<1e-04 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Null Deviance: 2795 on 2016 degrees of freedom				
Residual Deviance: 1398 on 2012 degrees of freedom				
AIC: 1406 BIC: 1428 (Smaller is better.)				
Formula: y ~ edges + nodematch("Members") + nodematch("Sector") + gwesp(0.25, fixed = TRUE)				

The findings indicate sector or industry membership is a significant property influencing the distribution of network ties and, hence, the structure of the communications network in a DMO. This indicates that network members display homophily by sector, meaning actors in the DMK network have a higher tendency to form ties with the same sector than those from other sectors. Communication will therefore be higher between same sector members than with members representing other sectors in the network. A goodness-of-fit (GOF) test was performed to identify the extent to which the estimates reproduce the terms in the model. A significant difference would indicate errors in the estimation process. The model below and the boxplot indicate the estimates were an accurate reproduction of the terms in the model. The mean figures of the simulated model closely match the observed statistics for the properties of edges, members, sector and GWESP, indicating the models proposed in this study were a good fit.

Table 4: Goodness-of-Fit for Model Statistics

	obs	min	mean	max MC	p-value
Edges	233.0000	178.0000	235.2300	296.0000	0.98
Nodematch. Members	150.0000	104.0000	149.8400	205.0000	1.00
Nodematch. Sector	44.0000	25.0000	44.4700	64.0000	1.00
GWESP.fixed. 0.25	254.8915	181.4986	258.4607	340.1921	0.92

Figure 5: Goodness-of-Fit for Model Statistics



Discussion

DMOs have recognised the need to adopt a more inclusive approach to destination management (Morgan, 2012) y linking government, businesses and civil society. Whilst the focus of destination marketing has been considered *outward* (e.g. establishing links with different markets with the purpose to attract visitors), destination management, requires incorporation of a more *inward* focus – it is interested in the operations and experience of the destination (Scott & Marzano, 2015). DMOs are now expected to be at the forefront of destination management and leadership activities with little or no support from the public sector (Coles et al. 2014). Cooperation between member organizations is therefore critical for destination governance (Laesser & Beritelli, 2013).

Earlier literature on destination governance in the marketing paradigm focuses on the steering and controlling destinations by norms, structures and processes (Bieger, & Laesser 2007). DMOs are increasingly expected to manage the complex system of relationships at a destination (Volgger & Pechlaner, 2014) In this new scenario, DMOs are expected to create structures that define the boundaries of the network and articulate a vision for empowering members to participate as well as facilitate the pooling of resources and sharing of expertise to continuously develop a tourism product (Beritelli et al. 2015).

However, while DMOs may have a degree of formal authority , governance of a network requires engaging with members to negotiate outcomes jointly (Pechlaner & Volgger, 2013) . Communication forms a key part of the process for engaging network members to ensure there is a mix of destination actors in terms of sectorial diversity and organisation size and scope. The development of a collaborative network identity can support this engagement process, enabling members to determine the potential benefits of collaborating with an exchange partner within a network (Anderson et al. 1994).

The focal organization, DMK, engaged in the process of establishing a collective network identity that could have influenced perceptions at the individual member, intra member and non-members. This collective network identity could then facilitate communication and alignment of activities (Öberg, 2016). The development of these identities is not a deterministic, lifecycle process (Beech & Huxham, 2003). When a focal organization attempts to create a collaborative network, potential tendencies towards homophily and existing relationships (Newman & Dale, 2007) will need to be adjusted. The reshaped relationships introduce new activities, resources and relationships that change practices of members mutually (Brown & Starkey, 2000). Existing network identity studies have used inductive or quantitative survey-based approaches to examine the benefits and challenges of a collaborative network identity. However, these studies are based on the implicit assumption that a network exists and exerts influence on member organizations. Unlike existing network identity research, a combined descriptive and inferential network analysis approach was able to verify that the distribution of ties in the network was not random and therefore a network exists (Research Proposition 1). Subsequent analyses (Research propositions 2-4) were able to examine the extent to which this identity influenced communication within members.

Transitivity has been extensively examined as a network characteristic in social networks as it can indicate the influence of a node. Nodes having a high degree of transitivity have multiple links to other nodes and can be more influential than nodes with fewer connections. GWESP findings suggest the transitivity differs from random networks and is a significant property of the DMK communication network. Communication connections within this network are “strong” where members have redundant connections with each other (Granovetter, 1973) . The outcome is typical of networks in which members meet frequently with each other and have established multiple points of contact (Beritelli & Laesser, 2011). Actors in the DMK network are in closely linked clusters (Guzman, Deckro, Robbins, Morris, & Ballester, 2014), indicating that the DMK project established a robust communication network that is difficult to disrupt and may persist over time. This communication network can underpin future activities and initiatives, contributing to the development of the region.

The findings indicate that while the DMK network is robust, distribution of ties in the DMK network are significantly influenced by industry membership. These nodes demonstrate homophily by industry type, which is a powerful network property that influences decision-making, leadership, activity and, now, communication. Prominent organizations in industry clusters can act as bridges within their immediate network communities, facilitating communication in the group. This distribution of relationships may act as an enabler of consensus because communication is rapid within industry groups in the network (Louch, 2000). However, it can constrain innovation as there are fewer inter-industry ties in the network bringing in new ideas and bridging differing social worlds and industry contexts.

Network membership was not found to be a significant influence on the formation of ties in the DMC communication network. The findings of this research are similar to Volgger and Pechlaner (2014), who suggested DMOs face difficulty in implementing the above strategies successfully. Communication was not influenced by operating under the common brand of DMK and homophily (shared properties) by membership is not present. Organizations may be members of the DMO network but that does not influence communication interactions, suggesting a network identity was not established. The creation of a joint brand in the form of DMK may be useful as an administrative construct for external stakeholders but this did not influence the creation of ties among members.

The relatively poor linkages across industries within the examined DMO may be of concern as ties between dissimilar actors help information flow across the network. New ideas may not enter since there are few weak ties (Granovetter, 1973) connecting different types of members. Homophily and clustering by industry suggests that members are focused more on activities in their own sub-groups than the network as a whole (Beimborn, Jentsch, & Lüders, 2015).

Focal organizations may invest in network level processes, such as member associations that establish to encourage adoption of network level communication mechanisms to create an identity based on group-sharing (Dyer & Nobeoka, 2000). Once established, the benefits from identity can be enhanced by creating group-level routines that identify, filter and integrate knowledge. By establishing these routines, the lead firm creates a net benefit to network membership that differentiates it from non-members and encourages a shift from current groups (Kogut & Zander, 1992). If successful, these routines are self-reinforcing and create a collective network identity in which members’ alignment of activities and sharing of knowledge continue to provide benefits to members and attract new members. This collective identity helps define membership, create joint strategies, cooperation and learning. Research on network identity in supplier networks indicate that routines for collective learning are particularly valuable for the development of network norms (Dyer & Hatch, 2004). These are routines for the development and dissemination of explicit knowledge that is either network-specific, such as coordination within the network, or resides in several member firms, such as activity improvement.

However, formal mechanisms identified for establishing a network identity in manufacturing supply chains may need to be adapted to the characteristics of DMO members. Tourism organizations can be service SMEs who may not have a high level of explicit knowledge to share within the network (Durst & Runar Edvardsson, 2012). These organisations also experience seasonal variations in demand, unlike manufacturing/supply chain organizations that experience consistent levels of demand. These conditions do not support the development of significant levels of codifed, explicit knowledge that can be transferred via formal knowledge-exchange mechanisms. Sharing tacit knowledge requires strong ties that may exist within the industry groups identified in this study but not across them.

In these conditions, the lead organization may need to leverage existing intra-group ties held by service and educational firms to facilitate tacit knowledge exchange. When joining a network, each member brings their history or accumulated experience of not just internal work practices but also collaboration. Organizations who may have contracted relationships as a main mode of operation, such as the service organizations in this study, can have a higher accumulated experience of collaboration and are used to adapting their activities to the requirements of other organizations (Hietajärvi & Aaltonen, 2018). These firms therefore establish and maintain a number of linkages with organizations in the network, resulting in their central position in the network, a finding from the descriptive statistics. Research has suggested these organizations can create temporary flexible groups by selectively activating and terminating ties (Ibarra, Kilduff, & Tsai, 2005), enabling a higher level of collaboration than other firms. The ties managed by these firms can support the development of integrating routines by the lead firm which can deliver the benefits of a collaborative network identity.

Implications

This paper makes an early contribution as it identifies homophily in destination networks by using an inferential statistical approach. An ERGM approach is valuable as it can advance analysis of tourism network research from descriptive to prescriptive. Specifically, ERGM analysis was able to identify network and node properties that influence communication ties in organizations in this research.

The findings indicate a network identity may not be established by the formation of an initiative as communication was not influenced by membership in the DMK. Instead, industry sector membership was an influence on communication, possibly because it is a historical attribute that would have built a range of inter- and intra-organizational connections over time (Moody et al., 2005). Whilst organizations may join the initiative, it may take some time before historical patterns of communication within industry group sectors change to reflect membership in the initiative.

This suggests that future research seeking to understand the impact of interventions, such as the formation of DMKs, should examine the link formation processes in networks, either by using longitudinal or multiple repeated observations of ties between organizations. Research can also identify the processes leading to the emergence nodes that link differing groups (Clauset, Newman, & Moore, 2004). In this network, these nodes were non-profit and service organizations that held multiple connections across industry boundaries. DMO managers may seek to work with the intra-industry relationships already established by these organizations to encourage members to change historical patterns of communication and to establish a network identity.

Inferential network analysis works alongside descriptive statistics to enhance DMO research. Descriptive statistics identify key actors and inferential statistics can verify the validity of these findings. These metrics can be used to measure the health of network initiatives beyond membership figures. Destination development capacity-building policy instruments can propose initiating a network or association as an explicit goal (Lynch, Holden, & O'Toole, 2009). Inferential network analysis can be a useful tool for evaluating the effectiveness of these policies. This approach enhances existing DMO research to go beyond the identification of important entities to examine the combined influence of relationships. It suggests that organizations seeking to support these networks need to incorporate network measures as an evaluation tool. Particularly in the area of policy evaluation (DeLeon & Varda, 2009), these metrics may indicate the health of the network and can support the design of interventions to ensure planned benefits are realised.

The concept of network identity can be useful for DMOs in the new funding landscape where they are required to be hubs that coordinate activities rather than disburse state funding. Future work could examine temporal or situational influences on network identity. Events and festivals have been viewed as experience-production systems (Ferdinand & Williams, 2013) where loosely connected firms align activities at particular times to deliver an annual experience. This suggests that network identities may be dynamic and situational and can shift as circumstances dictate.

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