An examination of DMO network identity using Exponential Random Graph Models

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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); 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 (Völgger & 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 supporting 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 the 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 may 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 the 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 (Borgatti, Mehra, Brass, & Labianca, 2009; Stephen P Borgatti, Mehra, Brass, & Labianca, 2009). 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 influenced the distribution of communication ties in the network.

**Literature Review**

Network theory (Granovetter, 1973) and the analytical approach of SNA (Borgatti et al., 2009) can 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. 2012). 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 that does not provide deeper insights (Prell, 2012). Within this context, scholars have argued that social network studies often over-emphasise the quantity rather than the quality of network relationships and interactions (Conway, 2014).

Table 1: SNA Terms

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

Adapted from Robins et al. (2009)

**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 et al., 2014). Extant SNA literature in the DMO domain has been largely focused on how interorganizational linkages can influence the governance of these institutions to date (Ahmed 2012), 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 et al., 2014). 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, moving 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 previously determined 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 interorganizational 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.

Little research has explored the 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 the 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 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.

Towards inferential network analysis

Recently, statistical approaches to SNA in the form of Exponential Random Graph Models (ERGM) (Wasserman & Pattison, 1996) have been developed which enable prediction of patterns of relationships (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 that is
similar to the observed network resulting from this temporal process (Broekel, Balland, Burger, & van Oort, 2014). 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. The approach is model-based rather than sample-based and inferences based on the analysis relate to the observed network only.

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 homophily, which is the tendency of entities with similar attributes to preferentially form ties 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 theses 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 sex (Loomis, 1946), with qualitative techniques. Later work adopted quantitative research to analyse networks in social institutions, such as schools (Shrum, Cheek Jr, & MacD, 1988), which enabled examination of multiple dimensions of homophilly at the same time. Subsequent work examined connections among organizations that facilitate 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,
Entities not sharing these characteristics are “peripheral” and do not possess 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 of 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 that are more highly connected to each other than the rest of the network. This measure assumes that 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 estimate transitivity in the network. Interpreting the statistics of ERGMs is similar to binary logistics regression in which network linkages or ties are the outcome 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 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 the connections that exist in observed networks could not have arisen by chance. Verification that networks are not random can support inferences made by an 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 homophilly, or the tendency to preferentially form connections, 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 homophilly by membership in the DMK initiative.

Past research has indicated that members of networks have exhibited homophilly by shared attributes such as age, race and sex (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 homophilly by industry

Research Setting: The DMK network of DMO member organisations

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 predominantly marketing functions (Hristov & Petrova, 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 & Petrova, 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 & Petrova, 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 both urban and rural destination products (DMK, 2014). Such activities are expected to be carried out under the guidance of the DMP and by involving key interested destination actors who serve businesses, local government and third sector organisations.

DMK and the UK is not a unique case but its relevance and applicability spreads across a number of countries with traditionally strong tourism sector. DMOs face an increasingly networked environment and significant changes in their funding and governance (Coles, Dinan and Hutchison, 2014; Hristov & Petrova, 2015). Such disruptions to the operational environment for DMOs are evident in a number of countries, such as 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, Beritelli, Bieger, & Laesser (2014) highlighted that many Swiss DMOs have to restructure in order to demonstrate value for money and diversify their funding streams. Equally, in the case of Australia, Pforr, Pechlaner, Volgger, & Thompson (2014) conclude that DMOs are increasingly being confronted with limited funds and organisations often need to restructure in their effort to offer a continued justification for their existence. In the case of China, DMOs or Tourism Administrative Organizations (TAOs), Wang & Ap (2013) discussed the complexities in the tourism policy landscape in the country that signal forthcoming changes to tourism governance. Equally, in the case of the UK, DMOs have been under increased scrutiny as within a new funding and governance landscape, which according to Hristov & Zehrer (2017) leads to a change in the funding model for DMOs to focus on the distribution of leadership and the pooling knowledge and resources.

**Research Methods**
The research method adopted a four step process, as seen in Figure 1
1) **Define network boundaries:**

Network research tends to study whole populations (e.g. all individuals belonging to a group, such as organisations) and this is often carried out by means of a census, rather than by a sample (Ahmed, 2012). Adopting a census approach involves all individuals, organisations or entities in any given cohort (Galaskiewicz & Wasserman, 1993). Researchers need to determine the extent or boundary of networks, which 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, where 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 collectively construct and subsequently depict the investigated network (Moody, McFarland, & Bender-deMoll, 2005) by using binary network data. For the purpose of network data collection, the
study used a web-based platform, namely 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 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 the respondent organisations.

3) Descriptive statistics of network characteristics

Gephi 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 that are 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 DML. The purpose of this model is to identify homophilly 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 homophilly 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 to compare 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 were 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) with 24.7% and 18.5%, respectively.
Table 2: DMK Network by Sector (from January 2014)

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

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. This approach is helpful as it yields key network communicators, who often exhibit strong knowledge among all members in the network (Panda et al., 2014).

Importantly, the approach aims to surface how and whether these key network communicators connect with diverse sectors on board DMK with the aim to communicate a common vision, mission and purpose (Angelle, 2010). 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 node and the target node. The bigger the node, the higher the capacity of that node to act as a key communicator; i.e. distributing important information and knowledge across the complete network.

Figure 2 provides a helicopter view of all interaction flows related to communication and exchange of information across the network and thus surfaces key network communicators in this practice across sectors and on board DMK.
An examination of the metrics of the 5 firms with the highest scores in the network indicates they are service providers, with the highest score for degree and centrality belonging to a higher education firm. These metrics indicate that these firms will likely be a part of a higher proportion of communications in the network than other firms. The reason for this may be that service providers work with a large number of these firms in the network 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)

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

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 disproportionate 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 influenced communication ties. Four models were developed:

1: A simple edges only model
2: Edges and the actor property of membership in DML
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:

**Formula:** y ~ edges

**Iterations:** 5 out of 20

**Monte Carlo MLE Results:**

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Std. Error</th>
<th>MCMC %</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edges -1.99904</td>
<td>0.06981</td>
<td>0</td>
<td>&lt;1e-04</td>
</tr>
</tbody>
</table>

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.)

Findings from the analysis indicated that the network was not random at a significance level of .001. The probability of ties in the observed network can be determined as $\text{Pr}(y) = \frac{\exp(-1.99904)}{1+\exp(-1.99904)} = 0.1193$, which corresponds to the density of the observed network. The model fit shows that 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:

Formula: $y \sim \text{edges} + \text{nodematch ("Members")}$

Iterations: 5 out of 20

Monte Carlo MLE Results:

<table>
<thead>
<tr>
<th></th>
<th>Estimate</th>
<th>Std. Error</th>
<th>MCMC %</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edges</td>
<td>-1.94246</td>
<td>0.11736</td>
<td>0</td>
<td>&lt;1e-04  ***</td>
</tr>
<tr>
<td>Nodematch.Members</td>
<td>-0.08656</td>
<td>0.14600</td>
<td>0</td>
<td>0.553</td>
</tr>
</tbody>
</table>

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.)

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 that 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.

Formula: $y \sim \text{edges} + \text{nodematch("Members")} + \text{gwesp(0.25, fixed = TRUE)}$

Iterations: 3 out of 20
Monte Carlo MLE Results:

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Std. Error</th>
<th>MCMC %</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edges</td>
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<td>0.2743</td>
<td>0</td>
</tr>
<tr>
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<td>0.1168</td>
<td>0</td>
</tr>
<tr>
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<td>1.4988</td>
<td>0.1943</td>
<td>0</td>
</tr>
</tbody>
</table>

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.)

The findings indicate that 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 to network identity.

Formula: \( y \sim \text{edges} + \text{nodematch("Members")} + \text{nodematch("Sector")} + \text{gwesp(0.25, fixed = TRUE)} \)

Iterations: 3 out of 20

Monte Carlo MLE Results:

<table>
<thead>
<tr>
<th>Estimate</th>
<th>Std. Error</th>
<th>MCMC %</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edges</td>
<td>-4.1244</td>
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<td>0</td>
</tr>
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<td>Nodematch.Members</td>
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<td>0.1197</td>
<td>0</td>
</tr>
<tr>
<td>Nodematch.Sector</td>
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<td>0.1695</td>
<td>0</td>
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<tr>
<td>GWESP.fixed.0.25</td>
<td>1.4878</td>
<td>0.1973</td>
<td>0</td>
</tr>
</tbody>
</table>

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.)
The findings indicate that 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, which means 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 that 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 that the models proposed in this study were a good fit.

### Table 4: Goodness-of-fit for model statistics

<table>
<thead>
<tr>
<th></th>
<th>obs</th>
<th>min</th>
<th>mean</th>
<th>max MC</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
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<td>178.000</td>
<td>235.230</td>
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<td>Nodematch. Members</td>
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<td>1.00</td>
</tr>
<tr>
<td>Nodematch. Sector</td>
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<td>44.470</td>
<td>64.000</td>
<td>1.00</td>
</tr>
<tr>
<td>GWESP.fixed. 0.25</td>
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<td>181.4986</td>
<td>258.4607</td>
<td>340.1921</td>
<td>0.92</td>
</tr>
</tbody>
</table>

### Figure 5: Goodness-of-fit for model statistics
Discussion

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; Hristov & Zehrer, 2017). Cooperation between member organizations is therefore critical for destination governance (Laesser & Beritelli, 2013). Little effort has been expended to examine emergent DMO communication networks, a critical factor in cooperation among organizations. Furthermore, the researchers are not aware of any research having examined these networks using techniques that can enable statistical inference to identify significant node and relational patterns that influence communication in these networks.

Existing studies have used inductive or quantitative survey based approaches to examine) focuses on the outcomes experienced by an organisation as a result of its perceived attractiveness as an exchange partner within a network(Anderson et al., 1994. However, these studies are based on the implicit assumption that a network identity exists and exerts influence on member organizations. The findings of this research challenges this assumption. In this case, 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 resource transfer and alignment of activities. (Öberg, C., 2016. What creates a collaboration-level identity?. Journal of Business Research, 69(9), pp.3220-3230). The development of these identities is not a deterministic, lifecycle process, but a co evolutionary process involving self, subgroup and intra group identities (Beech and Huxham (2003). This process can be path dependent may be influenced by the memory of previous individual and collaborative identities (Tomlinson (2008). The development process may also be
slow (Brown and Starkey, 2000) unless there is an external shock such as an acquisition by another organization or a significant reordering of the network. There is therefore a need to verify the existence and influence of a network, a factor overlooked in extant research.

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 were not random and therefore a network exists. The stated membership in an initiative does not necessarily mean that organizations have adapted their activities in order to obtain network benefits. Subsequent analyses (Research propositions 2-4) were able to examine the extent to which this identity influenced communication within members.

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, these metrics may indicate the health of the network and can support the design of interventions that can ensure that planned benefits are realised.

Inferential network analysis can be a useful policy evaluation tool. Many capacity building instruments have developing a network as an explicit goal. However, they do not use network based approaches to evaluate whether or not these networks have been established. The use of descriptive and inferential network approaches can help open up the “black box” of invisible network formation processes. It can provide a complementary perspective based on behaviour that can mitigate against the outcomes as evaluated by surveys and interviews.

The descriptive findings were able to identify prominent nodes in the network. These organizations were generally service providers holding multiple links to other industry members. When a focal organization attempts to create a collaborative network, potential tendencies to homophily (Newman and Dale 2007) and pre-existing relationships (Blair 2000), will need to be adjusted to incorporate new relationships. These new relationships introduce new activities, resources and relationships that mutually change practices and discourse of members, creating a collaborative network identity. Further, each member brings their history or accumulated experience of not just work practices but of collaboration itself. (Vivian and Sudweeks 2003:1435). Organizations who may have projects or 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 more used to adapting their activities to the requirements of other organizations. Research has suggested that these organizations hold large numbers of weak ties and create temporary flexible groups by selectively activating and terminating ties (Nohria and Eccles 1992; Ibarra et al. 2005). These firms therefore establish and maintain a number of linkages with organizations both within and outside of the network, resulting in their central position in the network.
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. 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.

DMOs have recognised the need to adopt a more inclusive approach to destination management (Morgan 2012; Volgger and Pechlaner 2014) by 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 the adoption of more inward focus – it is interested in the destination (e.g. destination competitiveness, creating a welcoming environment, management of natural and built destination resources, ensuring seamless visitor experience alike) (Beritelli and Bieger 2014).

There is a need to rethink existing governance structures (Coles et al. 2012; Fyall et al. 2009; Laesser and Beritelli 2013; Morgan 2012). Earlier literature on destination governance focuses on the steering and controlling destinations by norms, structures and processes (Beritelli and Bieger 2014). This approach is often imposed by the public sector (Ruhanen et al. 2010; Strobl and Peters 2013) in the face of local, regional and national government.

The shift to destination management encourages businesses and local communities to provide input into their destinations’ direction of development (Presenza and Cipollina 2010). DMOs are expected to facilitate such interaction by managing the complex system of relationships (Laws et al. 2011) at a destination. However, while DMOs may have formal authority (Hoppe and Reinelt 2010), governance of a network requires engaging with emergent and informal leaders to jointly negotiate outcomes (Pechlaner and Volgger 2013). Communication forms a key part of the process of engaging network leaders (Zehrer et al. 2014) to ensure
that there is a mix of destination actors in terms of both sectoral diversity and organisation size and scope. Current network research has given considerable attention to conceptualising destinations as networks (Bregoli and Del Chiappa 2013). However, to date, just a few studies have explored DMOs as networks (Del Chiappa and Presenza 2013). This research has taken a qualitative approach to examining inter-network collaboration (Ahmed 2012).

In a network of DMO stakeholder, leadership can be enacted by formal or informal means (Benson and Blackman 2011). Lead organizations in industry clusters can be viewed as a type of *Network in-community leaders* which act as bridges within their immediate network communities, facilitating communication in the group. Service organizations may be seen as a *Network cross-community leaders* that connect act as bridges across network communities, linking industry groups. They enable communication across often distant network communities.

These leaders may supplement DMO’s requirements to provide core leadership functions, rather than assuming sole responsibility for the marketing and management of destinations (Hoppe and Reinelt’s 2010). This shift implies a change in not just function, but of governance. In this new scenario, DMOs are expected to create structures that define the boundaries of the network, articulate a vision for the empowerment of members to participate in the network (Vogler and Peichler 2014), facilitating the pooling of resources and sharing of expertise to continuously develop a tourism product (Beritelli et al. 2015).

The findings indicate that the while the 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 affects decision-making, leadership, activity and, now, communication. This distribution of relationships may act as an enabler of consensus, as 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. 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 that 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 findings of this research are similar to Volgger and Pechlaner (2015) who suggested that DMOs face difficulty in successfully implementing the above strategies.

Overall, the DMO network examined in this research can enable efficiency by reducing communication time but it restricts innovation, limiting its ability to respond to change. The relatively poor linkages across industries on board the examined DMO may be of concern as ties between dissimilar actors help information flow across the network. New ideas will not enter since there are few weak ties (Granovetter, 1973) connecting different types of members. Homophily and clustering by industry suggests that members are more interested in their own sub-groups than the network as a whole (Beimborn, Jentsch, & Lüders, 2015). Lead organizations can establish a network identity by creating group level routines that identify, filter and integrates knowledge. By establishing these routines, the lead firm creates a net benefit to network membership that differentiates it to non members and encourages a shift from existing routines and workgroups (Kogut and Zander 1992: 383). 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, corporation and learning.

Focal organizations may invest in network level processes such as member associations that establish and encourage adoption of network norms and network level knowledge management mechanisms to create an identity based on group sharing. Research on network identity in supplier network indicate that routines for collective learning are particularly valuable for the development of network norms. 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 (marketing). After successful establishment of a network, the strong ties that exist will be valuable for distribution of tacit knowledge as joint social capital exists that can facilitate this transfer.

SERVICE AND EDUCATIONAL FIRMS AS INFORMAL NETWORK MEMORY AND KNOWLEDGE EXCHANGE MECHANISMS. EMERGENT STRATEGY AS OPPOSED TO TOYOTA’S DELIBERATE STRATEGY.

FORMAL NETWORK MECHANISMS NEED TO TAKE DESTINATION/TOURISM SPECIFIC CHALLENGES INTO ACCOUNT:

1) SEASONALITY. MANUFACTURING/SUPPLY CHAIN NETWORKS CAN LIMIT/MANAGE DEMAND. TOURISM FIRMS EXPERIENCE A PEAK LOAD ISSUE AND MAY BE EMPTY REST OF THE YEAR
Inferential network analysis works alongside descriptive statistics to enhance DMO research. Can identify important nodes for later verification of insights. Descriptive stats identifies key actors, inferential checks validity. Existing studies of network identity have used qual and quant means. They assume that the network exists. This approach verifies that the network exists and if the identity exists. Networks and ID with networks as a new measurement/organizational tool. It’s not enough to use network membership as a metric. You need to use interaction metrics. New measurement approaches to examine network health as part of policy?

Inferential network analysis can be a useful policy evaluation tools. Many capacity building instruments have developing a network as an explicit goal. However, they do not use network based approaches to evaluate weather or not these networks have been established. The use of descriptive and inferential network approaches can help open up the “black box” of invisible network formation processes. It can provide a complementary perspective based on behaviour that can mitigate against the outcomes as evaluated by surveys and interviews.

The concept of network identity is useful for DMOs in the new funding landscape where they are required to be hubs that coordinate activities rather than disburse state funding. With the increased challenges to destination image from social media communication, a distinct network identity can help reinforce marketing and other collaborative efforts to protect the destination’s brand.

Implications
This paper is among the first to identify homophilly 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, in this research, ERGM analysis was able to identify network and node properties that influence communication ties in organizations.

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 as 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 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 establish a network identity.

Temporary network identity. Events and Festivals have been viewed as experience production systems 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.

What do new forms and tools of communication mean for network identity. Does it encourage DMOs to increasingly pursue network type strategies to deal with networked actors?

The complementary nature of SNA/Network identity as an explanatory tool compared to other theoretical perspectives such as ANT/stakeholder theory


