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Imitation strategies and interfirm networks in the tourism industry: A structure–agency approach[☆]

Jarle Aarstad[a,*], Håvard Ness[b], Sven A. Haugland[b,c], Olav Andreas Kvitastein[a]

[a] Western Norway University of Applied Sciences, Norway
[b] University College of Southeast Norway, Norway
[c] NHH Norwegian School of Economics, Norway

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ABSTRACT

The paper investigates the association between tourism firms' imitation strategies and the interfirm network structure in which they are embedded. In particular, it analyzes how imitation contributes to (1) tie formation and (2) clustered structures. It also tests reverse relationships; i.e. how tie formation and clustered structures cause imitation. The paper combines network and survey data within and across nine Norwegian destinations. Estimations with instrumental variables show that imitation is an effect, and probably also a cause, of the network structure. More specifically, clustered structures increase imitation, which increases firms' involvement and tie formation activities with other firms in the interfirm network. The study illustrates how the structure-agency duality can be addressed in a tourism destination context.

1. Introduction

Scholars emphasize the importance of understanding tourism destinations as complex coproducing systems. Specialized firms, such as activity providers and hotels, are interdependent and need to coordinate their activities to provide destination products to visitors effectively (Haugland, Ness, Grønseth, & Aarstad, 2011; Ramirez, 1999). As firms partake in coproduction, their competitiveness partly depends on the contribution of other firms to the joint destination offering. In this context, it is important to limit rivalry and develop a unified vision with shared norms between firms to enhance resource integration and coproduction (Gomes-Casseres, 2003).

Imitation is a deliberate strategy where firms aim to become similar to other successful firms (Haunschild & Miner, 1997). It attempts to achieve shared norms that enhance resource integration and coproduction, and the focus of this paper is to study associations between tourism firms' imitation strategies and the interfirm network structure in which they are embedded. Resource integration and coproduction require individual firms to establish ties to other firms, which alter the destination interfirm network structure. Simultaneously, the network structure is likely to influence strategies pursued by tourism firms, and the dynamic is often referred to as the structure-agency duality (Giddens, 1984; Sztompka, 1991). Scholars consider the structure-agency duality as crucial to understanding the interplay between actors and the context in which they are embedded. Examples include studies of network formation (Bhaskar, 2014; Dhanaraj & Parkhe, 2006; Kim, Howard, Cox Pahnke, & Boeker, 2016; Uzzi, Amaral, & Reed-Tsochas, 2007), innovation performance (Dhanaraj & Parkhe, 2006), and value co-creation (Chandler & Vargo, 2011; Taillard, Peters, Pels, & Mele, 2016). In tourism studies, examples include the duality between agency and path dependence (Ma & Hassink, 2013; Sanz-Ibáñez & Anton Clavé, 2014), tourism development in developing countries (Meyer, 2013), adaptation to climate change (Wyss, 2013), and tourism-related policy making (Bramwell & Meyer, 2007).

Although there is an emerging body of literature on the structure-agency duality in tourism studies, there is limited research addressing this duality from a social network approach. In this study, structure refers to characteristics of the interfirm network in which tourism firms are embedded, and agency refers to firms' autonomous strategic actions. The paper examines: (1) how the agency role played by firms through imitation strategies alter the interfirm network structure, and (2) how the network structure (reversely) affects firms' imitation strategies.

If some closely connected firms have adopted similar working practices (Haunschild & Miner, 1997), it may facilitate imitation as a catalyst for resource integration. Imitation can furthermore induce learning and increase performance (Aarstad, Haugland, & Greve, 2010; DiMaggio & Powell, 1983; March & Olsen, 1976; Tsui-Auch, 2003).

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* Correspondence to: Western Norway University of Applied Sciences, PO Box 7030, NO-5020 Bergen, Norway.
E-mail addresses: jarle.aarstad@hvl.no (J. Aarstad), havard.ness@usn.no (H. Ness), sven.haugland@nhh.no (S.A. Haugland), olav.andreas.kvitastein@hvl.no (O.A. Kvitastein).

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Knowledge about the structure-agency duality concerning tourism firms' imitation strategies and interfirm network structures may accordingly be important to understand destinations as coproducing systems of autonomous, yet interdependent, actors.

Tourism research has emphasized interfirm networking as a crucial vehicle for destination development (e.g. Maggioni, Marcoz, & Mauri, 2014; Ness, Aarstad, Haugland, & Grønseth, 2014). In tourism research, scholars have also examined the time span to imitate successful innovators (Brooker, Joppe, Davidson, & Marles, 2012; Piccoli, 2008), and the building of barriers to imitation (Huang, 2013). However, studies have not examined how firms' imitation strategies alter the interfirm network structure, or how the network structure influences firms' imitation strategies. In other words, in a tourism context, one lacks substantial knowledge about the structure-agency duality concerning the interfirm network typology and firms' autonomous strategic actions, both of which are important constructs for understanding coproduction and destination development.

From a practitioner's perspective, the study contributes to understanding the implications of firms' strategic behavior and whether network structures promote the spread of work practices. Policy makers and destination management organizations (DMOs) may also find this knowledge useful as they develop planning frameworks and strategies to promote local and regional development.

2. Theory and hypotheses

Imitation, as noted, is a deliberate strategy where firms aim to become similar to other successful firms (Haunschild & Miner, 1997). Imitation occurs when 'one or more organizations' use of a practice increases the likelihood of that practice being used by other organizations' (Haunschild & Miller, 1997, p. 472). In the current context, it implies that imitating firms need candidate firms to imitate from, and they do so by forming interfirm ties, which in turn will alter the network structure. The paper accordingly treats imitation as a deliberate firm strategy and distinct from the concept of mimicking (DiMaggio & Powell, 1983), which can be viewed as an unconscious adoption of other firms' strategies or behavioral patterns (Alchian, 1950).

Specifically, the paper relates imitation to two key network characteristics. First, it focuses on the number of interfirm ties a firm has to other firms. This is termed "degree centrality" and is an indicator of activity or involvement in the network (Freeman, 1979; Nieminen, 1974). Central firms play the role of transmitters of business practices within and beyond tourism destinations (Aarstad, Ness, & Haugland, 2015c). Second, it addresses the concept of clustering. If a firm has ties with two other firms and these two firms have a tie between them, they form a clustered triad (Holland & Leinhardt, 1970). Clustering can foster fine-grained information sharing and provide referral knowledge that increases trust (Ahuja, 2000; Coleman, 1988; Uzzi, 1997). Therefore, clustering may benefit tourism firms seeking to coproduce coherent and integrated products. Overall, the paper examines whether imitation is a cause or an effect of degree centrality and clustering.

An interfirm network can be defined as a set of firms and a set of ties or a lack of ties between them (partly derived from Brass, Galaskiewicz, Greve, & Tsai, 2004). In a tourism destination context, a network is often described as 'the stakeholders composing it and the linkages that connect them' (Baggio, Scott, & Cooper, 2010, p. 803; see also a recent review by Mwesiumo & Halpern, 2017). The paper examines structural, and not relational, network properties (cf. Gulati, 1998), and develops two partly competing, partly complementary arguments. One argument states that firms pursuing an imitation strategy will affect the network regarding degree centrality and clustering. This argument emphasizes firms' agency role in the network structure in which they are embedded. The other argument states that clustering and degree centrality will affect firms' imitation strategies, which emphasizes how the network structure can influence firms' strategic actions.

2.1. Imitation and degree centrality

Imitating firms need information about the external environment and other firms' practices. Scanning can be one approach to obtaining this information. Scanning 'refers to the relatively wide-ranging sensing of the organization's external environment… [and] varies in intensity from high vigilance, active scanning, to … routine scanning' (Huber, 1991, p. 97). One way to scan the environment is to play an active role in the interfirm network by forming ties with other firms. Having many interfirm ties will enable a firm to access rich and varied information about market trends, business practices, or competitors' behavior. Thus, firms scanning the environment through networking will increase the likelihood of becoming aware of preferred strategies and business practices to imitate since many direct ties increase the amount of information available and facilitate information comparison. More simply, one can claim that to imitate, a firm needs candidate firms to imitate from, and the need for involvement and active networking is a function of its proclivity to imitate other firms. However, a firm not pursuing imitation strategies will have a lower proclivity to scan the environment for business practices to adopt. The following hypothesis, therefore, is postulated:

H1a. A firm's imitation strategy will have a positive effect on its degree centrality in the interfirm network.

It can also be argued that a firm's activities and involvement in the network will have a positive effect on its imitation strategy. Receiving a large input from numerous interfirm partners may tend to make the firm aware of potential strategies to imitate. Thus, scanning its environment through interfirm ties can induce a firm to adopt an imitation strategy. Conversely, firms having fewer interfirm ties may be less aware of opportunities to imitate (because they receive less input from their environment). In contrast to H1a, the following hypothesis is therefore postulated:

H1b. A firm's degree centrality in the interfirm network will have a positive effect on its imitation strategy.

2.2. Imitation and clustering

If there is a tie between firms *i*, *j*, and *k*, they form a clustered triad (Holland & Leinhardt, 1970). Fig. 1 illustrates an interfirm network with five firms (*i*, *j*, *k*, *l*, and *m*). The straight bold lines indicate established ties, whereas the bold dotted lines indicate that *i* considers forming a tie with either *l* or *m*. The weak dotted line between *l* and *m* indicates that they are not directly connected, but indirectly through one or more intermediate firms. In general, networks can be more or less clustered (Watts & Strogatz, 1998). The network in Fig. 1 has two clustered triads at the outset (*i*-*j*-*k* and *j*-*k*-*l*). If *i* decides to form a tie with *l*, the number of clustered triads increases by two (*i*-*j*-*l* and *i*-*k*-*l*), which will not be the case if *i* instead collaborates with *m*. In other words, a single tie can have a strong impact on a network's clustering structure.

Firm *i*'s marginal contribution to clustering increases if it forms a tie with *l* (due to the increase of two more clustered triads in the network), but not if it instead forms a tie with *m*. Moreover, if *i* ceases to have a tie with *j*, *k*, or both, *i*'s marginal contribution to clustering decreases. In

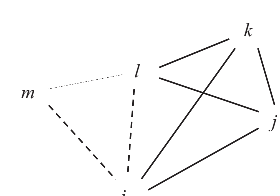

Fig. 1. The fraction of a theoretical network.

the following, the paper will argue that *i*'s marginal contribution to network clustering is associated with the firm's imitation strategy.

Imitating firms primarily search for easily available information because it limits search costs. Concerning Fig. 1, this implies that if *i* is an imitating firm, it will choose to collaborate with *l* instead of *m* because *i* has referral knowledge about *l* through information from both *j* and *k*. In other words, one can argue that imitating firms will tend to increase clustering in the interfirm network.

Staber (2010) found that imitative behavior increases identification with business clusters. Garcia-Pont and Nohria (2002) stated that firms in the automobile industry seek to imitate other firms through alliance formations that are locally proximate in the network. Hanaki, Peterhansl, Dodds, and Watts (2007, p. 1036) claim that '[p]layers not only learn which strategy to adopt by imitating the strategy of the best-performing player they observe but also choose with whom they should interact by selectively creating and/or severing ties with other players based on a myopic cost-benefit comparison.' In simulations, Baum, Cowan, and Jonard (2010) found that selecting partners based on knowledge fit creates a clustered network. Strictly speaking, seeking alliance partners as a function of imitation or complementarities in knowledge can be regarded as distinct and separate motives. However, one can contend that the conceptual connotations overlap in such a way that imitating firms seek to transfer other firms' knowledge into their own knowledge base by forming a clustered structure. Based on this reasoning and empirical illustrations, the paper proposes that a firm's imitation strategy will have a positive effect on its marginal contribution to clustering (e.g. if *i* is an imitating firm, it will prefer to collaborate with *l*—compared to collaborating with *m*—which will increase the number of clustered triads). Formally, the following hypothesis, therefore, is postulated:

H2a. A firm's imitation strategy will have a positive effect on its marginal contribution to clustering in the interfirm network.

It can conversely be argued that interfirm network clustering will tend to increase firms' imitation strategies. Studies have shown that network members conform to norms and behavior in clustered structures, and clustered structures are also associated with high levels of cognitive agreement (Krackhardt & Kilduff, 2002; Krackhardt, 1998, 1999). This can be explained as a function of the similarity of knowledge and information flowing through clustered structures (Coleman, 1988) or to avoid cognitive dissonance (Festinger, 1957). If one again assumes that firm *i* collaborates with *j* and *k* at the outset, then being embedded in a clustered triad will tend to influence the firms' cognitive agreement and conformity to norms and behavior. Furthermore, as *j*, *k*, and *l* are also embedded in a clustered triad, this may have an additional effect. If one now assumes that *i* starts to collaborate with *l*, this will increase the size of the clustered structure (from two to four clustered triads). This is likely to increase the firms' cognitive agreement and conformity to norms and behavior further. On the other hand, firms that are part of a less-clustered structure will have fewer shared agreements with other firms, and may accordingly have a lower proclivity to pursue a strategy of becoming similar to their colleagues. Therefore, it can be proposed that a firm's marginal contribution to clustering will have a positive effect on the firm's imitation strategy. In contrast to H2a, the following hypothesis is postulated:

H2b. A firm's marginal contribution to clustering in the interfirm network will have a positive effect on its imitation strategy.

3. Research context and methodology

Nine mountain destinations in southern and eastern Norway were chosen as the empirical context for the study. In total, 568 tourism firms were identified at these destinations. The data collection took place in two phases. First, interfirm network data, both within and across destinations, were collected. Tourism firms were asked to identify the stakeholders they had a relation to, and when the relation started. The data were used to model intra- and interdestination networks, and to calculate different structural network properties. Second, a survey was performed to collect data on firms' strategic actions such as imitation and innovation behavior, as well as firm characteristics such as perceived uncertainty and firm size. The same data have been used in other research (Aarstad, Ness, & Haugland, 2013, 2015b, 2015c).

3.1. Interfirm network data and variables

The general managers of the 568 identified firms were first sent information about the study, which included a list of other firms at the destination. Data were then collected by telephone interviews. The managers were asked to identify who they were currently or previously had been cooperating with. In addition to intradestination network ties, information was requested about collaboration with other firms beyond the focal firm's local destination. Interdestination ties can be classified into two separate groups: (1) direct ties between firms located at different destinations, and (2) ties between a destination firm and regional, national, or international organizations that are not localized at a specific destination (e.g. academic and research institutions, regional and national governmental bodies, airlines, ferry lines). Thus, destinations are directly connected through Type 1 ties and indirectly connected through Type 2 ties. Network data on both types of interdestination ties were gathered. Two hundred and two responses were received representing a response rate of 35.6%. Since responding firms reported network ties to nonresponding firms, it was possible to include 434 of the 568 firms identified in the network analysis.

A structural tie between two firms was modelled if one or both report collaboration. This enables the modeling of network data on firms that were not sampled, i.e. Type 2 interdestination ties and nonrespondent firms in the network sample. Network analyses were performed using the social network program, Ucinet 6.135 (Borgatti, Everett, & Freeman, 2002). The network consists of 550 firms (nodes) connected by 2686 interfirm ties.

The clustering of an aggregated network is the average of local clustering around each firm or network member (Watts & Strogatz, 1998). The level of clustering relative to a random network with the same number of network members (firms) and interfirm ties, defines the clustering coefficient, C (Watts, 1999):

$$c = \frac{Clustering \quad (real network)}{Average degree centrality / Number of actors in the network}$$

To model a firm's marginal contribution to clustering, the focal firm and its interfirm ties were excluded from the network before re-estimating C′. The procedure was repeated for all sampled firms. The operational definition of each firm's marginal contribution to clustering is ΔC = (C-C′)/C′.

Degree centrality was modelled by counting each firm's number of interfirm ties (Freeman, 1979). Fig. 2 illustrates the intra- and interdestination networks. White dots indicate the firms' degree centrality in the network.

3.2. Survey data and variables

About one year after collecting network data, survey data was collected using an electronic questionnaire targeting the same 568 firms. Three hundred twenty-five firms agreed to participate in the survey, and 72 usable responses were received. The survey data was merged with the network data, which resulted in complete data from 63 firms. Merging survey and network data that were collected independently via different procedures reduces potential problems related to common method variance (Malhotra, Kim, & Patil, 2006). Estimations with instrumental variables were also performed in some models to further increase internal validity and assess causality (for a general

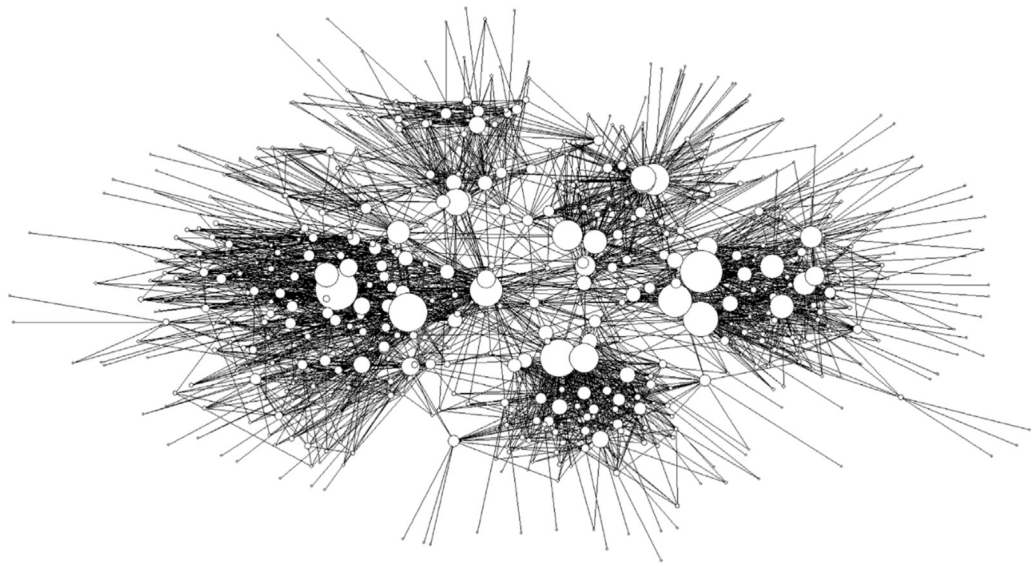

Fig. 2. Visual display of the interfirm network. The size of the white dots indicates the degree centrality of network members.

Table 1
Factor analysis.

	Innovation	Uncertainty	O-Imitation	TF-Imitation
Compared to our most important competitors, our firm is often the first to produce and supply products and services in better or more efficient ways.	**.989**	–.056	.056	–.013
Compared to our most important competitors, our firm is often the first to introduce new products and services.	**.836**	.043	–.028	.010
The demand for our products is very volatile.	.007	**1.02**	.088	–.174
In our industry, end-users' needs and preferences change rapidly.	–.004	**.653**	–.060	.228
If we observe that other firms offer high-quality products and services, we use these as role models to achieve the same in our firm (outcome-based).	–.010	.005	**.904**	–025
When we know that other firms have efficient routines or operating processes, we try to implement similar practices in our firm (outcome-based).	.121	.054	**.655**	.259
We continually seek information about successful firms in the industry (e.g. at conferences, expositions, meetings, business trips, and the like) to get information about new products and services that may be relevant for our company (trait-based).	.120	.013	–.009	**.753**
We frequently implement methods for production and sales of products and services, which we observed to be common in numerous other firms in the industry (frequency-based).	–.078	.027	.175	**.748**
Cronbach's α	.905	.808	.874	.787

N = 63. Maximum likelihood factor analysis on correlations with quartimin rotation. TF-Imitation (trait- and frequency-based imitation), O-Imitation (outcome-based imitation).

explanation, see for instance Cameron & Trivedi, 2010).

Imitation was measured by using a seven-point Likert-type scale ('strongly disagree' (1) to 'strongly agree' (7)). Haunschild and Miner (1997) suggest that imitation can be outcome-, trait-, and frequency-based. Four items were applied: two relate to outcome-based imitation, one to trait-based imitation, and one to frequency-based imitation. The four items were developed with reference to Haunschild and Miner (1997).

The study controlled for firm size, innovation, and uncertainty. Large firms are more dominant players than small firms, which reflects their networking patterns. Innovation and uncertainty may reflect different industry and market segments in which firms operate. A seven-point Likert-type scale was used to measure innovation and uncertainty. Firm size was measured as the number of employees, while innovation was measured by two items, based on Deshpande, Farley, and Webster (1993). Uncertainty was also measured by two items, based on Ganesan (1994) and Jaworski and Kohli (1993). Independent and control variables are also candidates for instrumental variables.

Table 1 shows the eight items used to model imitation, innovation, and uncertainty. The study used maximum likelihood factor analysis on correlations with quartimin rotation. Table 1 shows that the two outcome-based imitation items load on the same factor, and the items representing trait- and frequency-based imitation load on one single factor. Therefore, trait- and frequency-based imitation is treated as one variable in the analyses. Factor loadings and Cronbach (1951) alpha coefficients indicate satisfactory construct validity and reliability for all four variables.[1] The study models these four variables by applying average scores for the items representing each variable.

3.3. Results and hypothesis testing

Marginal contributions to clustering (ΔC), degree centrality, and firm size deviate from normal distributions, and the study corrects for this deviation by applying Van der Waerden (1953) method to generate normal quantile values. Correlations and descriptive statistics are presented in Table 2, which include mean, standard deviation (SD), skewness (Skew), and kurtosis (Kurt). (For ΔC, degree centrality, and firm size, the study reports transformed normal quantile values.) All variables report low absolute values of skewness and kurtosis, indicating normal distribution.

[1] Factor analysis with three factors was first carried out, but Bartlett (1954) test for sphericity rejected the assumption that three factors were sufficient to explain the variance ($p = .023$). Increasing the number of factors to four, on the other hand, did not reject the assumption that four factors were sufficient ($p = .411$). Therefore, it was concluded that the eight items load on four underlying factors.

Table 2
Correlation matrix.

Mean	SD	Skew	Kurt		ΔC	TF-I	O-I	IN	U	FS
0	.951	.00	–.39	Marginal contribution to clustering (ΔC)						
4.31	1.40	–.31	–.30	TF-Imitation (TF-I)	.075					
4.30	1.52	–.34	–.56	O-Imitation (O-I)	.070	.598***				
3.99	1.52	.11	–.47	Innovation (IN)	–.006	.341**	.347**			
3.38	1.46	.33	–.43	Uncertainty (U)	.045	.327**	.309*	.056		
.003	.943	.03	–.40	Firm size (FS)	–.098	.191	.189	.181	.139	
.002	.945	.03	–.43	Degree centrality	–.451***	.345**	.241†	–.014	.143	.225†

N = 63, †p < .10, *p < .05, **p < .01, ***p < .001, two-tailed tests.

The hypotheses were tested by applying generalized methods of moments (GMM) in Stata 14 (StataCorp., 2017). GMM is well adapted to estimations with instrumental variables and robust to possible heteroscedasticity (Hansen, 1982). Regression models report standardized (beta) coefficients, which enable comparisons of effect sizes of different coefficients measured by using different scales of units. GMM regressions that do not include instrumental variables generate identical estimates as ordinary least-square regressions. Firms located at the same destination can cause autocorrelation, which may create biased standard errors (Andrews, 1999; Self & Liang, 1987). Therefore, the study tested if the destination random effect was significant. However, it was nonsignificant for all models in this study, which rejects the assumption of autocorrelation.

When testing the hypotheses, the study first ran 'ordinary' GMM regressions, respectively, followed by GMM regressions with instrumental variables (when available) to assess causality.[2] Instrumental variables must fulfill two criteria to assess whether the independent variable is a causal agent on the dependent variable: they must be: (1) 'sufficiently' correlated with the independent variable, and (2) uncorrelated with the error term (Wooldridge, 2006). These issues are explained shortly.

3.3.1. *Testing H1a*

H1a suggests that imitation has a positive effect on degree centrality. Model 1 in Table 3 tests H1a by modeling degree centrality as a dependent variable, and trait- and frequency-, and outcome-based imitation as independent variables (clustering is not included as a control variable because degree centrality causes clustering and not vice versa; Aarstad, Ness, & Haugland, 2015a). Model 1 shows that trait- and frequency-based imitation is a significant regressor, whereas outcome-based imitation is nonsignificant. H1a thus gains partial empirical support. The variance inflation factor (VIF) is 1.68 concerning trait- and frequency-based imitation and 1.67 concerning outcome-based imitation. Collinearity is thus unlikely (see O'Brien, 2007).

In Model 2, outcome-based imitation and uncertainty are applied as instrumental variables and trait- and frequency-based imitation as instrumented independent variables.[3] The lower part of Model 3 shows that the partial effect of the instrumental variables has a significant Kleibergen-Paap rk Wald F statistic value of 16.57. This F test is appropriate because the GMM estimate is robust to possible heteroscedasticity (Hansen, 1982; Stock, Wright, & Yogo, 2002). The F value is higher than the suggested critical value of 10 (Stock et al., 2002), which indicates that the instruments are 'sufficiently' correlated with the independent variable. It thus fulfills the first requirement noted above. Hansen (1982) J Chi-square, also reported in the lower part of Model 2, tests whether the instrumental variables are correlated with the error term (i.e. testing for overidentifying restrictions). The nonsignificant p-value of .922 shows that the instrumental variables are uncorrelated with the error term and fulfill the second requirement. One can conclude that the instrumental variables are valid. Model 2 moreover shows that trait- and frequency-based imitation is a significant regressor on degree centrality.

Table 3
Generalized methods of moments (GMM) regressions (Model 3 omits relations reported as terminated when modeling degree centrality as the dependent variable).

Dependent variable:	Model 1 Degree centrality	Model 2 Degree centrality	Model 3 Degree centrality
TF-Imitation (H1a)	.330* (2.04)	.407* (2.07)	.399* (2.06)
O-Imitation (H1a)	.073 (.51)		
Innovation	–.185 (−1.43)		
Uncertainty	–.002 (–.02)		
Firm size	.182† (–1.69)		
Wald Chi-square	9.82†	4.30*	4.25*
R-square	.175		
First-stage regression partial R-square		.380	.380
Kleibergen-Paap rk Wald F statistic		16.57***	16.57***
Hansen's *J* Chi-square (p-value in parenthesis)		.010 (.922)	.009 (.925)
Instruments: O-Imitation and Uncertainty		√	√

N = 63, †p < .10, *p < .05, **p < .01, ***p < .001, one-tailed tests for hypothesis variables and two-tailed tests for control variables. Standardized (beta) coefficients with robust z-values (regression estimates divided by robust standard errors). TF-Imitation is instrumented in Model 2 and 3.

Since the survey data were gathered about one year after the network data, network ties reported as terminated were omitted and degree centrality was remodeled. Next, Model 2 was replicated using the remodeled measure of degree centrality as the dependent variable. The results are reported in Model 3, and the estimates are very similar to those reported in Model 2. Altogether, one can conclude that trait- and frequency-based imitation has a significant effect on degree centrality, and outcome-based imitation has a nonsignificant effect. Therefore, H1a gains partial empirical support.

3.3.2. *Testing H2a*

H2a suggests that imitation has a positive effect on a firm's marginal contribution to clustering. Model 1 in Table 4 tests H2a by modeling clustering as the dependent variable, and trait- and frequency-, and outcome-based imitation as independent variables.[4] Model 1 shows that trait- and frequency-based imitation is a significant regressor, whereas

[2] In unreported models, GMM regressions (with instrumental variables) in addition were replicated with two-step efficient GMM regressions (EGMM) with instrumental variables (Baum, Schaffer, & Stillman, 2007; Hayashi, 2000), but the results did not alter any statistical conclusion.

[3] Table 2 shows that outcome-based imitation and uncertainty correlate with trait- and frequency-based imitation. Outcome-based imitation and uncertainty are thus eligible candidates as instrumental variables.

[4] It has been noted that the network data were gathered about one year before the survey data, but Model 3 in Table 3—aiming at correcting for time asymmetry when measuring degree centrality—indicates that the potential concern (regarding time asymmetry) is negligible.

Table 4
GMM regressions.

Dependent variable:	Model 1 Marginal contribution to clustering	Model 2 Marginal contribution to clustering	Model 3 Marginal contribution to clustering
TF-Imitation (H2a)	.253*	.119	.354*
	(1.94)	(.53)	(1.88)
O-Imitation (H2a)	.096		
	(.73)		
Degree centrality	−.563***		−.573***
	(−3.95)		(3.90)
Innovation	−.132		
	(−.94)		
Uncertainty	.023		
	(.20)		
Firm size	−.017		
	(−.15)		
Wald Chi-square	33.12***	.28 n.s.	18.36***
R-square	.283		
First-stage regression partial R-square		.380	.340
Kleibergen-Paap rk Wald F statistic		16.57***	11.86***
Hansen's *J* Chi-square (p-value in parenthesis)		.003 (.959)	.015 (.902)
Instruments: O-Imitation and Uncertainty		√	√

N = 63, †p < .10, *p < .05, **p < .01, ***p < .001, one-tailed tests for hypothesis variables and two-tailed tests for control variables. Standardized (beta) coefficients with robust z-values (regression estimates divided by robust standard errors). TF-Imitation is instrumented in Model 2 and 3.

outcome-based imitation is nonsignificant. Thus, it can be concluded that H2a gains partial empirical support. The VIF is 1.81 concerning trait- and frequency-based imitation and 1.67 concerning outcome-based imitation. Therefore, collinearity is unlikely (cf. O'Brien, 2007).

In Model 2, trait- and frequency-based imitation is instrumented, and outcome-based imitation and uncertainty are instrumental variables (as they were in Model 2 and 3 in Table 3). It can be observed that the instrumental variables are valid (cf. previous discussion of instrumental variables), but Model 2 demonstrates that trait- and frequency-based imitation has a low and nonsignificant effect on clustering.

In Model 3, Model 2 was re-estimated after including degree centrality as an exogenous regressor.[5] It can be seen that the instruments are valid and that trait- and frequency-based imitation has a significant effect on clustering. H2a therefore gains partial support because trait- and frequency-based imitation is significant regressor on clustering in some, but not all, models, while outcome-based imitation is nonsignificant.

3.3.3. *Testing H2b and 1b*

H2b suggests that clustering has a positive effect on imitation. Model 1 in Table 5 shows that clustering is a significant regressor on trait- and frequency-based imitation, but the effect is not particularly strong. Model 2 shows that outcome-based imitation is a nonsignificant regressor. Thus, one can conclude that H2b gains partial support. The VIF, concerning clustering, is 1.39 in Model 1 and 1.38 in Model 2. Therefore, collinearity is unlikely (cf. O'Brien, 2007).

None of the continuous variables were eligible as instruments for clustering as the independent variable (thus not fulfilling either requirement. However, Model 3 shows that modeling a destination dummy for firms' geographical location as an instrumental variable gives a significant Kleibergen-Paap rk Wald F statistic value of 33.36, i.e. much higher than the suggested critical value of 10 (cf. Stock et al., 2002), and a nonsignificant J Chi-square p-value of .981 (cf. Hansen,

Table 5
GMM regressions.

Dependent variable:	Model 1 TF-Imitation	Model 2 O-Imitation	Model 3 TF-Imitation	Model 4 TF-Imitation
Marginal contribution to clustering (H2b)	.185*	.080	.275***	.577***
	(2.15)	(.70)	(4.01)	(3.38)
Degree centrality (H1b)	.315**	.098		.608***
	(2.98)	(.97)		(4.37)
O-Imitation	.395***			
	(3.18)			
TF-Imitation		.446***		
		(3.97)		
Innovation	.201*	.182		
	(1.99)	(1.46)		
Uncertainty	.139	.130		
	(1.36)	(1.17)		
Firm size	.007	.039		
	(.08)	(.39)		
Wald Chi-square	78.42***	49.82***	16.08***	20.43***
R-square	.474	.406		
First-stage regression partial R-square			.314	.276
Kleibergen-Paap rk Wald F statistic			33.36***	8.05***
Hansen's *J* Chi-square (p-value in parenthesis)			1.11 (.981)	2.77 (.838)
Instruments: Destination dummy			√	√

N = 63, †p < .10, *p < .05, **p < .01, ***p < .001, one-tailed tests for hypothesis variables and two-tailed tests for control variables. Standardized (beta) coefficients with robust z-values (regression estimates divided by robust standard errors). Marginal contribution to clustering is instrumented in Model 3 and 4.

1982). Therefore, destination dummy is a valid instrumental variable. The regression estimate in Model 3 furthermore shows that trait- and frequency-based imitation is a strongly significant regressor.

In Model 4, Model 3 was re-estimated after adding degree centrality as an exogenous regressor[5]. Clustering can be seen to have a strong and significant effect on trait- and frequency-based imitation in both models. The Kleinberg-Paap rk Wald F statistic of the destination dummy as an instrumental variable (value of 8.05), is marginally below the critical value of 10 (cf. Stock et al., 2002). Hansen (1982) J Chi-square p-value of .838 is nonsignificant.

It can be concluded that clustering has a significant effect on trait- and frequency-based imitation, particularly due to the robust results reported in Model 3 (robust and significant regression and strong instrumental variable) and Model 4 (robust and significant regression and the value of the instrumental variable marginally below a robust level). Overall, one can conclude that H2b gains partial empirical support since clustering causes an increase in trait- and frequency-based imitation, but not in outcome-based imitation.

H1b suggests that degree centrality has a positive effect on imitation. The hypothesis was tested in Model 1 and 2 in Table 5. Degree centrality cen be seen to be a significant regressor on trait- and frequency-based imitation (Model 1), but nonsignificant on outcome-based imitation (Model 2). This gives partial support to H1b. The VIF value for degree centrality is 1.47 in Model 1 and 1.64 in Model 2; thus, collinearity is unlikely (cf. O'Brien, 2007). Furthermore, Model 4 shows that degree centrality has a strong and significant effect on trait- and

[5] Table 2 shows a negative correlation between degree centrality and clustering, and a positive correlation between degree centrality and trait- and frequency-based imitation. Therefore, not including degree centrality as an exogenous variable may mask a genuine relationship between trait- and frequency-based imitation and clustering.

frequency-based imitation when modelled as an exogenous control variable. However, the study was unable to identify valid instrumental variables to assess causality. Therefore, one can conclude that degree centrality has a possible effect on trait- and frequency-based imitation.

3.4. Summary of empirical findings

Trait- and frequency-based imitation has a significant, positive effect on degree centrality (H1a), while degree centrality has a possible reversal effect on trait- and frequency-based imitation (H1b). (Since the study was unable to identify valid instrumental variables, one cannot conclude that degree centrality affects trait- and frequency-based imitation.) The study did not find any association between outcome-based imitation and degree centrality.

Trait- and frequency-based imitation increases clustering (H2a) and clustering reversely increases trait- and frequency-based imitation (H2b). However, the effect of clustering on trait- and frequency-based imitation (H2b) is more robust than vice versa (H2a). Overall, the effect of clustering on trait- and frequency-based imitation (H2b) is the most robust finding in the study.[6] The study did not find any association between outcome-based imitation and clustering.

4. Discussion and implications

4.1. Discussion of the results

This study shows that network clustering increases tourism firms' trait- and frequency-based imitation strategies, which in turn has a positive effect on firms' degree centrality. Furthermore, there is a negative association between degree centrality and firms' marginal contribution to clustering because the probability of a completely clustered network structure around a firm decreases exponentially as degree centrality increases (cf. Aarstad et al., 2015a). Therefore, degree centrality decreases clustering, but this is only partially true. High-degree firms play a crucial role in leveraging the potential for clustering. For example, a firm with two interfirm ties (a degree centrality of two) has a potential for one clustered triad, a firm with three ties has a potential for three clustered triads, and a firm with four ties has a potential for six clustered triads, and so on. Thus, degree centrality has a feedback effect on the potential for clustering. The empirical findings are shown using solid arrows in Fig. 3.

The analyses further indicated that trait- and frequency-based imitation affects clustering, which was marked with a dotted arrow in Fig. 3. This effect is less robust than the clustering effect on trait- and frequency-based imitation, but it seems that the processes of clustering and imitation reinforce each other. Finally, it is possible that degree centrality causes an increase in trait- and frequency-based imitation, which is marked with a dotted arrow in Fig. 3. A strong positive association was observed, but since the study was unable to identify relevant instrumental variables, one cannot draw clear conclusions.

4.2. Theoretical implications

The study contributes to the structure-agency approach in tourism destination contexts and beyond. On the one hand, a robust finding is

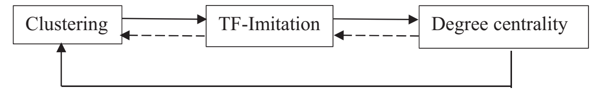

Fig. 3. An empirical model of structure-agency dualism.

that a clustered network structure increases firms' proclivity to imitate other firms. This tendency is lower in the absence of clustering, and the network structure thus delimits firms' autonomy in taking independent strategic actions. On the other hand, another finding is that firms' imitation strategies increase their degree centrality, which shows that autonomous actions by firms can play a crucial role in shaping the network structure. Firms can accordingly be 'prime movers' in developing the network (Dhanaraj & Parkhe, 2006, p. 660), while the network simultaneously limits firms' actions. Such dual processes interact in shaping both the network structure and individual firms' strategic actions. An imitation strategy reflects a firm's efforts to take strategic actions that are similar to other firms' actions. The more clustered a network is, the more likely is an imitation strategy. Furthermore, imitation increases a firm's activities and involvement in the network and thereby increases its degree centrality, which has a feedback effect on the firm's potential for network clustering.

Another implication relates to homophily in networks (McPherson, Smith-Lovin, & Cook, 2001). This is the first study to analyze how network structures form and are formed by actors' proclivity to be similar through imitation. A third implication concerns small-world networks. Small-world networks have a clustered structure (Watts & Strogatz, 1998). The study implicitly contributes to small-world knowledge by showing how clustering induces imitative behavior. High degree centrality indicates that firms are playing the role of boundary spanners (Burt, 1992), which is another crucial feature of small-world networks (Aldrich & Kim, 2007). The study further implicitly contributes to small-world knowledge by illuminating how imitating firms can play the role as boundary spanners because of their tendency to play active roles in the network. Large white dots illustrate high degree firms in Fig. 2, which are evenly spread throughout the network space. Furthermore, high degree firms are boundary spanners connecting clustered structures, but they are also observed within them. This can indicate that high degree firms play another role as catalysts of emerging clustered structures.

4.3. Managerial implications

It has been assumed in this study that firms should protect themselves from imitation. However, for firms that partake in coproduction, imitation might be beneficial because it eases resource integration. The findings from this study show that imitating firms form ties to other firms. These ties enable clustering that further increases imitation. Thus, firms should reconsider the assumption that protection and barriers to imitation are critical because coproduction might actually benefit from the spread of similar working practices.

Another managerial implication is that firm strategies have an impact on the environment. By pursuing a specific strategy, a firm can shape the network structure. The strategic management literature is mainly concerned with how firms should operate in a given environment, and pays less attention to how strategies may form the environment. However, finding that imitation affects tie formation indicates that firms can purposefully shape the environment by implementing specific strategies.

From the perspective of DMOs, an implication of the findings is that to create a shared vision among destination firms and other stakeholders; the DMOs should aim to stimulate the formation of clustered network structures. Clustered structures foster fine-grained information-sharing and provide referral knowledge that increases trust and reduces opportunism (Ahuja, 2000; Coleman, 1988; Uzzi, 1997), which are crucial factors to facilitate seamless coproduction. This study has

[6] To assess generalizability, power analysis was carried out in Stata 14. Power analysis estimates the probability of observing an effect, assuming that it is present; i.e. the probability of correctly rejecting the null hypothesis when it is false (Lachin, 1981). $N = 63$, $p < .05$, one-tailed test, and power = .80 (power = .80 is the default option in Stata; i.e. if a study was performed 1000 times, one would observe statistically significant effects 800 times). Fisher (1915) z-test returned a correlation coefficient of .310, which is analogous to a one-tailed p-value of .007 when $N = 63$. Two regression estimates have one-tailed p-values (much) lower than .007 (concerning H2b); Model 3 and 4 in Table 5. It has been noted that the models have strong and validated instrumental variables. They show that clustering increases trait- and frequency-based imitation, and the probability of observing this effect is (much) higher than 80%, according to the power estimate.

shown that clustering also fosters imitation strategies.

Public-sector policy makers also need to consider the structural properties of destination networks to realize a strategic fit with their program goals. For example, promoting clustering can foster knowledge transfer between firms and even between destinations. According to the argument, public sector policymakers should target relevant agents for clustering, such as central firms with many interfirm ties.

4.4. Limitations and future research

A limitation of the study is that it assumes, rather than explicitly studies, imitating tourism firms' de facto role in resource integration and coproduction. Therefore, future studies should investigate these issues explicitly.

Research shows that innovating firms play a "glue role" as connectors of destination networks (Aarstad et al., 2015b), and Table 1 shows that tourism firms complement imitation and innovation strategies. Tourism firms pursuing imitation and innovation strategies simultaneously are accordingly likely to pursue an ambidextrous strategy (March, 1991). Future research should nevertheless investigate empirically how such dual approaches may have implications for firm performance and destination development.

The study did not find any association between outcome-based imitation and the network concepts in this study. The items used to measure outcome-based imitation (Table 1) may indicate that the construct taps into an inherently embedded and internalized imitation strategy, while trait- and frequency-based imitation deals with an outward, action-oriented strategy. This may indicate that outcome-based imitation is a precondition for a trait- and frequency-based imitation strategy. Moreover, since outcome-based imitation is likely to be an embedded and internalized firm strategy, this may explain why the construct is less likely to associate with network constructs beyond firm boundaries. Future research is encouraged to elaborate further on these issues and study different dimensions of firm imitation in more detail.

This paper examines structural and not relational network properties (cf. Gulati, 1998). Relational aspects, e.g. trust and involvement, definitely have relevance concerning the research question, but analyzing relational and structural network properties simultaneously would make the study more complex, both theoretically and methodologically (Hinde, 1976). Consequently, network studies normally emphasize either a structural or a relational approach. Nevertheless, future research is encouraged to carry out similar work emphasizing the relational aspects of interfirm networks.

The interfirm network consisted of 550 firms, but the study only managed to analyze matched survey and network data from 63 firms. A low number of observations is not uncommon in social network studies (e.g. Gargiulo & Benassi, 2000; Giuliani & Bell, 2005; Hansen, 1999). Still, the low number requires some caution in generalizing the findings to other contexts. However, collecting and matching network and survey data is complex, and vulnerable to losing observations. This is a likely reason of why few studies use matched datasets. To add credibility to the analyses, surveyed and unsurveyed firms' degree centrality were compared showing that surveyed firms tend to have higher degree centrality than unsurveyed firms. However, when inspecting the degree centrality for surveyed firms, the minimum value is 2, and the maximum value is 76; the corresponding values for unsurveyed firms are 1 and 77. Therefore, one can argue that the sampled firms lie within a relevant range for statistical analyses. Future studies should nevertheless aim to access a complete network and survey data to increase external validity.

Although it can be argued that imitation promotes efficient coproduction, there may be limits to how much imitation is beneficial. Too much focus on imitation may undermine innovation. Destination firms cooperate and compete against each other, and there is also cooperation and competition between destinations. Therefore, the role of imitation may be limited, and these issues need to be elaborated further in future studies.

This study addresses the often very abstract structure-agency duality by using real empirical constructs. By studying the interdependence between the network context (structure) and firm strategy (agency), the study extends the current body of knowledge as few empirical studies address these issues simultaneously. The study delimits the general ideas of the structure-agency duality by focusing on specific structural network properties and firm-level actions that are particularly important to understand in coproducing networks. Reviewing the tourism literature of interfirm networks, Mwesiumo and Halpern (2017, p. 12) conclude that the duality of structural properties and firm-level actions 'present useful groundwork for further research to establish causes and effects' of interfirm relations. Such knowledge is furthermore relevant for other coproducing contexts such as ports, airports, industry clusters, supply networks, and regional development.

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