Emergent relational structures at a ”sharing economy” festival

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Abstract. How do participants to an event engage with others ? This paper examines the emergent relational structure at a "sharing economy" festival, the 2016 OuiShare Fest. A multi-level network analysis design explores the linkages between participation patterns of the "elite" (speakers) and other participants, to unveil the social processes through which status hierarchies emerge and actors manage ensuing tensions. Newly developed specifications for exponential random graph models reveal a tension between cooperation (among actors with shared thematic interests) and competition for audience, whereby conformism and differential use of reciprocity in attendance relationships generate an informal pecking order.

Keywords: Social networks, status, ERGM

1 Introduction

Events such as trade fairs, congresses and festivals contribute to the creation of new markets in the global economy [3, 5]. They do so by bringing stakeholders physically together in one place in "temporary clusters" [4] that cut across organizational and geographical boundaries. Networks formed at events are a complement to distant (online) relationships [27], heightening participants' awareness of being involved in a common undertaking and enhancing their involvement with one another [2].

The question of how participants engage with others at an event speaks to the relational standpoint of network science, and scholars have indeed contributed answers especially in the case of trade events, where buyers negotiate commercial agreements with sellers [8]. But interactions related to the program of the event, where the goal is to exchange ideas rather than goods, have been less systematically explored. How do participants decide whom to pay attention to, and if they are speakers, how do they attract attention to themselves?

Program-related interactions are ties of *attendance* – who appears at the talks (or panels, workshops etc.) of whom. Attendance is a way to gain awareness of others, to display one's interest for specific topics, to pay respects to high-profile speakers, to meet like-minded attendees. The more options participants have (with parallel sessions for example), the more their attendance choices are disclosive of individual specificities.

Attendance choices are the hybrid product of institutional constraints (event settings and upstream choices made by the organizers, such as schedule and venue) and of patterns emerging from the autonomous interactions of individual participants. One of the resulting social processes, both formal and informal, is status formation. Attendance is an act of deference: acknowledging the relevance, prestige or importance of the speaker(s). Status is commonly defined as accumulation of acts of deference [23], and can be represented as a network of such acts within a relevant social setting [25]. The structure of this network may reveal potential tensions between individual status pursuits and the development of collective undertakings.

This paper maps and analyzes attendance choices at a festival of the "sharing economy". This nascent, still loosely-defined field of economic activity, encompasses a diverse range of participants (from technology start-ups to NGOs and government agencies) and topics (from smart city and blockchain to climate change and the future of work). Because its identity is in the making and interactions between participants may contribute to shaping its future development, the "sharing economy" is an almost ideal setting to study. The event, the OuiShare Fest, took place in Paris yearly from 2013 to 2017. Its relatively large size, global scope and unequaled breadth of outlook gave it prominence, making it a worldwide reference. It was not a marketplace (no commercial transactions going on) but rather an inspirational gathering, built around an ambitiously wide-ranging program and meant to raise awareness and share knowledge:

> OuiShare Fest is an interdisciplinary festival that gathers creative leaders, entrepreneurs, movement builders, purpose-driven organizations and communities from across sectors and countries who want to drive systemic and meaningful change[1].

Focus on a single festival involves a sociological case-study approach, which may seem to depart from the complex systems tradition that typically deals with larger networks. Yet complexity enters the research in a different way. Though small-sized, the network structure under study is very rich with a wealth of attributes derived from the specific build-up of the data, and captured through the tools and concepts of state-of-the-art "multi-level" network analysis [17]. Through network richness, I aim to contribute to a growing effort toward a more interdisciplinary network science blending the methods of social science and complex networks [9].

2 Multi-level network structures

Speakers embody the attractiveness of the program of an event such as OuiShare Fest. Theirs is a privileged position reserved to a minority [13] and entitles to, among other things, free entrance throughout the duration of the event. Speakers enjoy high visibility: they all have a profile on the Fest's web page (see below), their talks are advertised in advance to prospective participants, they are live-streamed and live-tweeted, and videos are posted online after the event. They bring prestige and epistemic authority: a well-known speaker attracts attendees and raises the standing of the event. Hence, speakers can be said to be an "elite" among participants.

[1] OuiShare Fest website, URL: http://ouisharefest.com/

OuiShare Fest Speakers are diverse in their backgrounds, areas of expertise and political views. They seek the attention of participants, who must choose between up to seven parallel sessions at any one time. These choices can be represented as a network graph whose nodes are individuals and ties indicate attendance. The left panel of Figure 1 sketches the attendee-to-speaker (*A*2*S*) attendance network, which has "two-mode" structure in that nodes can be either senders (*A*) or receivers (*S*) of ties, but not both. The graph is valued (attendee A_i may choose to attend one or more sessions of speaker S_j) and directed (mutual attendance may or may not occur).

It is especially interesting to ask *who, from among the elite of speakers, attends (sessions of) whom*. Speakers are also participants and, outside the session(s) assigned to them for their talks (or performances, workshops etc.), they can spend their extra time at the event by attending sessions of other speakers. In other words, besides spreading their own message, they may listen to the messages of others. The central panel of Figure 1 is the speaker-to-speaker (*S*2*S*) attendance graph, which is valued, directed, and one-mode (any node may be sender and/or receiver of an attendance tie).

Juxtaposed, these two graphs form a richer, "multi-level" network structure *A*2*S*2*S* driven by two different sources of agency (right panel in Figure 1) [17].

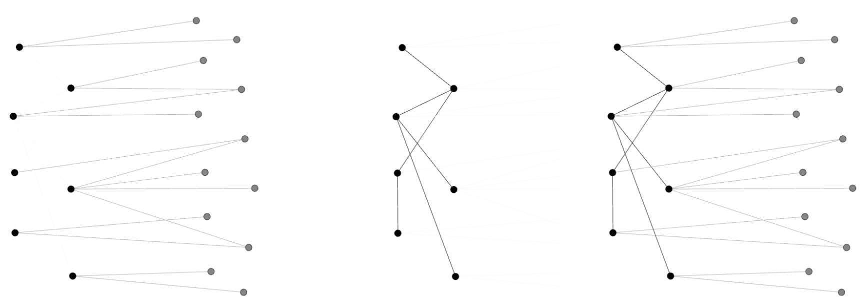


Fig. 1. Left: attendee-to-speaker two-mode network *A*2*S*, where black dots are speakers, gray dots are non-speaking attendees, and light gray lines are attendance choices. Center: speaker-to-speaker one-mode network *S*2*S*, where black dots are speakers, dark gray lines are attendance choices. Right: multi-level combination of both *A*2*S*2*S*.

3 Empirical setting and data

I use data from the fourth OuiShare Fest, which took place on 18-20 May 2016 in Paris. With 1505 participants from 50 countries, the event was structured into 139 sessions with different formats (conferences, panels, workshops etc.) involving 258 speakers (in the roles of keynotes, panelists, moderators, performers etc.).

I retrieved attendance choices from the event's software application, "Sched", and additional information from the register of participants kept by the organizers. Sched is an online and mobile tool that allows participants to create a personal profile (with name, photo, organization, job title, self-description), to import contacts (among other participants to the event) from social media such as Twitter and LinkedIn, and most importantly for the purposes of this paper, to put together a personalized schedule of what to attend. The latter function was particularly attractive as no printed version of the program was distributed. Sched attendance choices were visible to all online, and can thus be seen as quasi-endorsements, reminiscent of the “Like” function of some social media platforms[2].

Of the 1505 attendees of 2016, 733 filled their Sched profiles at least partly. This includes the 258 speakers, who all have at least some profile elements and the session(s) in which they were listed as speakers. All received at least one attendance choice from participants; 88 of them also chose themselves a program of sessions to attend beyond the one(s) in which they were scheduled to speak.

4 Variables and measures

I aim to explain the one-mode, directed network of speakers choosing to attend other speakers *S2S*, recoded as a dyadic variable with values for each pair of the 258 OuiShare Fest 2016 speakers. Disregarding self-attendance, it corresponds to $258 \times 257 = 66306$ dyads. For analytical convenience and without significant loss of information, its values are binarized[3].

I expect *S2S* to depend on a set of independent variables, also defined at dyadic level (n= 66306). They operationalize the endogenous and exogenous social mechanisms that according to extant literature, may operate in this setting.

4.1 Thematic affinity

A potential driver of speakers’ attendance choices relates to their areas of activity and expertise. In general, actors with similar interests and background will easily recognize the value of each other’s competences. Having to deal with the same problems, they will acknowledge the same arguments. Research suggests two reasons why thematic affinity may drive attendance choices. First, attending a speaker who is an expert in one’s own area can be a way to be comforted in one’s stances, to see them indirectly confirmed [11]. Second, it can be part of an effort to (indirectly) affirm the importance of one’s own area of interest and to legitimate its place, especially in uncertain situations where inclusion of specific areas or categories is ambiguous or contested [2].

I map speakers to themes using the categorization proposed by the event organizers, who had assigned each session to either a general category (for sessions such as Fest Opening and Closure) or one of six themes[4]. Formally, this is a dyadic, binary, symmet-

[2] Because physical attendance was not monitored, it cannot be assumed that Sched choices always resulted in actual meetings with the speakers or other attendees.

[3] Only choices outside speakers’ own sessions are considered, taking out cases in which attendance is imposed by the organizers (for example, speakers who present in the same panel.

[4] These were: “Building Enterprises for the Digital Age”, “Digital Institutions and The City”, “Education and Personal Development”, “Power and Capital in the 21st Century Organization”, “The (Present) Future of Work”, “Understanding Decentralization and The Blockchain”.

ric variable TA (table 1) whose value $TA_{ij} = TA_{ji}$ is 1 if speakers i and j (with $i \neq j$) have at least one theme in common (an indicator of affinity), 0 otherwise.

4.2 Status

What matters is the status of the receiver, rather than the sender, of attendance choices – the potential object of others' deference. Hence for each of the 66306 pairs of speakers $[i, j]$, focus is on the status of j. But status is complex because it is both an exogenous and an endogenous factor. Exogenously, status may derive from some given, observable quality of speakers – which prompts others to attend their sessions. To capture this dimension, I retrieve two indicators from speakers' Sched profiles (variable $St1$: whether they were founders of sharing economy organizations, a highly respected role in this milieu) and from registration information (variable $St2$: whether they had participated in the 2015 and/or 2014 OuiShare Fest, to denote experience and notoriety, see table 1).

Endogenously, status rankings may result from self-reinforcing processes: for example when individual qualities are not observable, attendance choices may be based on *popularity* – attending those speakers that others also attend. Over time, this process may amplify initially small quality differences between individuals [20]. One measure of popularity is the number of attendees that each speaker received through Sched. I compute this indicator by summing over the attendance choices of all participants with a Sched profile, without distinguishing those among them who were themselves speakers, and those who were not (variable $St3$, taken on the $A2S2S$ network structure).

Another operationalization of popularity is the number of followers that speakers had on social media, insofar as it was imported into, and made visible through, Sched. Social media matter because Fest participants are heavy users of technologies, interacting online as much as face-to-face. Variable $St4$ is the count of the number of times each speaker appears as an online contact in the Sched pages of Fest participants, summing over all those (speakers and non-speakers, $A2S2S$ network) who had linked their Sched profiles to their social media accounts.

Popularity effects can also be fully endogenous to the speaker-to-speaker ($S2S$) network: are there differences in the propensity of individual speakers to be attended by other speakers – independently of the other attendees they might get from the broader population of participants? Differential propensity to receive ties from among the elite may create status disparities regardless of other individual qualities. Formally, it can be modeled through *indegree effects*, one measure of which are counts of so-called k-instars, defined as a node N and a set of k different nodes $O_1, \ldots, O_k$ such that the ties O_j, N exist for $j = 1, \ldots, k$ (see table 2).

4.3 Positional similarity

If two speakers attract essentially the same attendees (whether themselves speakers or not), they will display similar patterns of ties in the attendance network and will therefore occupy similar – in the limit, the same – network positions. Similarity induced by structure is what the literature calls "equivalence" [18], and can be seen as endogenous to the composite $A2S2S$ network (right panel in Figure 1). But then, will speakers with similar multi-level network positions attend each other's talks, or rather avoid each other? A long tradition of research emphasizes how actors with similar ties are likely to be competitors [10] because they depend on the same resources and face the same opportunities – thereby leading to the prediction that they will likely avoid each other.

A commonly used measure of positional similarity is the Jaccard index which, for any two speakers, is defined as the number of common attendees (intersection), divided by the cardinality of the union (sum of the attendees of each of the two speakers, both separately and jointly). Scaling by the size of the union rules out the possibility that similarity scores are affected by the tendency of more prominent speakers to receive more attendees than less-known ones [7]. I compute this dyadic variable *Ja*, which varies between 0 and 1, for each pair of speakers (table 1).

4.4 Reciprocity

Reciprocity is the tendency of individuals to send ties to those from whom they receive a tie. It is a plausible social mechanism, whereby people invest in their ties and expect rewards from these investments. Observed in much empirical research, reciprocity may flatten status hierarchies [14]. Here,it can only be defined endogenously to the $S2S$ network: do speakers attend other speakers who attended their talks?

Reciprocity may also be indirect, if there are different ways in which the balance of what is given and received in a relationship can be satisfying for an individual [6]. The question is whether speakers who attend a lot of talks of others, also receive many choices themselves – not necessarily from the same others.

Direct reciprocity can be modeled as the tendency of network structure to be symmetric, while indirect reciprocity can be captured through so-called *mixed two-paths*, that is, tendency of outgoing and incoming ties to co-occur, involving tendency toward correlation of indegrees and outdegrees (table 2).

4.5 Controls

Other potentially relevant factors are participation in the previous edition of the event, 2015, which may facilitate integration of participants (variable $T1$), place of residence (distinguishing, for simplicity, France where half of the participants and about 40% of speakers came from, and other countries: variable *Fr*) and gender (variable *Ge*). They are originally monadic and taken from the organizers' register. To adapt them to the dyadic structure of the data, I compute an exact match indicator for each variable, to identify pairs of speakers in the same category (for example, both from France).

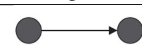
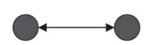
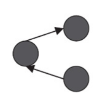
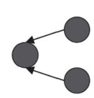
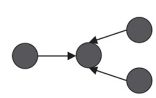
5 Exponential Random Graph Model of the attendance network

The observed network structure partly results from exogenous factors – such as epistemic affinity and the observable dimensions of status – and is partly self-sustained through an endogenous tendency to reproduce existing network structures. The number of attendees/followers of a speaker as a measure of status, and the Jaccard index of positional similarity, are feedback effects of the multi-level relational structure $A2S2S$

Table 1. Dyadic variables included in empirical model specification: definitions and descriptive statistics. Those in italics are endogenous to the multi-level *A2S2S* network.

Variable	Construct	Min	Max	Mean	St.Dev
Speaker-to-speaker attendance	Dependent variable	0	1	0.058	0.235
TA: Common themes	Thematic affinity	0	1	0.205	0.404
St1: Founder of organization	Status (receiver)	0	1	0.31	0.463
St2: Experience	Status (receiver)	0	2	0.527	0.753
St3: Number attendees	*Status (receiver)*	*1*	*500*	*117.597*	*74.414*
St4: Number online followers	*Status (receiver)*	*0*	*63*	*4.77*	*10.621*
Ja: Jaccard index	*Positional similarity*	*0*	*1*	*0.145*	*0.119*
T1: Participation previous year	Control (match)	0	1	0.314	0.465
Fr: Residence in France	Control (match)	0	1	0.376	0.485
Ge: Gender	Control (match)	0	1	0.616	0.487

Table 2. Structural dependencies to be modeled, representing endogenous feedback effects to the *S2S* network. Description and count in dataset.

Variable	Construct	Configuration	Count
Arc	Directed tie		3898[a]
DR: Reciprocity	Direct reciprocity		266[b]
IR: Mixed-two-paths	Indirect reciprocity		60228
2I: 2-instar	Indegree effects		40929
3I: 3-instar	Indegree effects		360677

[a] Network density 0.0588. [b] Reciprocity rate 7%.

onto $S2S$ – the latter being a sub-structure of the former. There are also fully endogenous effects of the $S2S$ network onto itself, notably reciprocity (direct and indirect) and indegree effects. The presence of such systematic dependencies between network ties requires explicit modeling and cannot be left to standard statistical inference approaches which assume independence of observations [21].

Newly developed Exponential Random Graph Models (ERGM) specify the dependence among relations that such micro-mechanisms entail, in addition to modeling the effects of exogenous covariates [24, 26]. These models address the dependencies that arise with network data, whereby one node may be involved in multiple relationships with other nodes. They do not only "control for" such dependencies but represent them directly, uncovering specific local (sub-graph) configurations implied by dependence mechanisms, and testing their statistical significance [1].

ERGM provide a tool for inference with network data, whereby an outcome variable is predicted by several independent variables. Parameter values help identify a probability distribution for all graphs of the same size, and estimates aim at finding the parameter values that best match the observed network structure. This is obtained via Markov Chain Monte Carlo Maximum Likelihood (MCMCML) or other simulation-based techniques [19].

5.1 Results

Table 3 reports ERGM estimates of a model in which the dependent variable is the network of attendance choices between speakers $S2S$, based on three broad categories of explanatory factors: exogenous covariates, $A2S2S$- and $S2S$-endogenous network dependencies. I do not model outdegree effects but constrain the estimation process to preserve observed outgoing ties (that is, only networks whose outdegrees are the same as those in the data have non-zero probability), to account for the fact that only a specific sub-group of speakers made online attendance choices. The model is estimated with R package 'ergm' in the Statnet suite [15].

Model diagnostics (not reported here) are good. The MCMC sample statistics vary randomly around the observed values at each step and the difference between observed and simulated values of the sample statistics have a roughly bell-shaped, zero-mean distribution indicating stationarity. Comparison of the network statistics measured in the original data and networks simulated from the fitted model [16] indicates good fit[5]. Multi-collinearity checks performed as per [12] do not point to major concerns.

6 Discussion and conclusions

Interpretation of table 3 resembles that of a logistic regression: a large positive (negative) parameter indicates that the corresponding configuration is observed in the network more (less) frequently than what would be expected by chance alone, conditional on the presence of configurations associated with other effects in the data.

[5] Goodness of fit has been calculated for indegree, geodesic distances, shared partner distributions, triad census and and the terms of the original model as recommended in [16].

Table 3. ERGM Maximum Likelihood estimates. Dependent variable: network of attendance choices $S2S$, independent variables: covariates and endogenous structural dependency statistics outlined in Table 1 (upper section) and Table 2 (lower section).

Variable	Estimate	Std. err.	p-value	Signif.[a]	Odds-ratio
Thematic affinity					
Mutual ($TA_{ij,ji}$)	0.9118	0.1963	$<$ 1e-04	***	2.4888
Upper (TA_{ij})	0.2904	0.0734	$<$ 1e-04	***	1.3369
Lower (TA_{ji})	0.4507	0.075	$<$ 1e-04	***	1.5694
Status					
Receiver founder	0.0606	0.0375	0.106		1.0624
Receiver experience	-0.057	0.0286	0.0463	*	0.9446
Receiver No. attendees	0.0098	0.0009	$<$ 1e-04	***	1.01
Receiver No. followers	-0.0033	0.0022	0.1334		0.9967
Positional similarity					
Mutual ($Ja_{ij,ji}$)	-0.2875	0.0472	$<$ 1e-04	***	0.7502
Upper (Ja_{ij})	0.038	0.2657	0.8861		1.0388
Lower (Ja_{ji})	-0.1027	0.2756	0.7094		0.9024
Controls					
Co-presence past year	-0.1128	0.0431	0.0089	**	0.8934
Both from France	0.2248	0.0413	$<$ 1e-04	***	1.2521
Same gender	0.0437	0.0417	0.2938		1.0447
Structural dependencies					
Reciprocity					
Direct reciprocity	0.127	0.174	0.4655		1.1354
Mixed-2-paths	0.0001	0.0008	0.873		1.0001
Indegree effects					
2-instar	0.0804	0.0091	$<$ 1e-04	***	1.0838
3-instar	-0.0034	0.0004	$<$ 1e-04	***	0.9966
Gwidegree[b]	-1.6607	0.3274	$<$ 1e-04	***	0.19

[a] Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
[b] Geometrically-weighted indegree distribution controls for higher-level (in)degree effects and helps avoid model degeneracy (a common problem with ERGM)
N = 66306, AIC: -2133, BIC: -1969

6.1 Thematic affinity confers self-deference

Thematic affinity is positive and significant: speakers give and receive choices from others with similar interests, and this is true whether their choice is reciprocated ("mutual" effect) or not (ij and ji combinations respectively). Their behavior is highly cooperative provided there is a shared interest: they give back if they receive, but are also happy to give without a return. It follows that, if attendance choices are deference gestures toward another speaker, they also bring benefits to the choice-makers. One reason is that they reinforce their thematic interest and contribute to legitimizing it. In this sense, attendance choices are a way for speakers to promote their ideas beyond their own talks, by publicly displaying interest in thematically similar others.

6.2 Preference for novelty over status

Regarding the observable dimensions of status, being founder of an organization does not matter, while surprisingly, experienced speakers are slightly less likely to be attended by other speakers. Negative and significant co-participation the year before magnifies this effect: all other things equal, a returning speaker is less likely than a newcomer to attend the talk of another returning speaker. While this result seems to counter extant evidence that past co-participation facilitates tie formation [8], it indicates alignment with OuiShare's explicit orientation towards creativity, innovation, and entrepreneurship, gainst the rigidity of an inherited (albeit recent) past. Preference for what is new and novel and avoidance of long-term involvement offer the advantages of flexibility and openness at the expense of durability and fixed anchors.

6.3 Popularity produces conformity

Popularity, as unobservable dimension of status, is operationalized in the $A2S2S$ network by counting number of online followers and number of attendees: the former has no effect while the latter is positive and significant. Within the $S2S$ network, popularity is measured through indegree effects, all significant: two-in-star is positive, meaning that ties are more likely to be directed at nodes that already have an incoming tie, while three-in-star and geometrically weighted indegree distribution, a higher-order effect, are negative, meaning that after accounting for all other model terms, nodes with large numbers of ties are less likely to receive more ties. Taken together, these results indicate that a speaker does not want to be the first to pay deference to another speaker, but does not follow mere popularity either. Distinction from peers is valued, but nobody would go as far as taking the risk of setting entirely new trends. That speakers value distinction while being reluctant to overly-differentiate themselves suggests a form of conformity often observed in middle-status individuals [22], which tends to curb status hierarchies and is suggestively indicative of the position where they perceive the sharing economy to be in today's social structure.

6.4 Unreciprocated ties in competition

Direct reciprocity is not significant: attending the talk of someone else does not increase one's odds of being attended. Neither is indirect reciprocity (two-paths) significant: using Sched to choose one's own agenda does not affect the chances of receiving attendance choices by others, so there is no tendency toward correlation of in- and out-degrees. Even more surprising is the finding that speakers go as far as *countering* reciprocity when they compete for attention of the same third parties: positional similarity has a strong negative effect only on reciprocal ties. Put differently, if speaker i attends speaker j and they attract largely the same attendees, then j is less likely to attend i's talks, than would be the case if i sent no tie to j.

Against an empirical literature suggesting that dislike of symmetry is uncommon[14], there is an obvious irony in that reciprocity is absent in a festival formed around the premise of sharing. However, as noted in 6.1, there is a significant tendency to reciprocate among speakers who share thematic interests, that is, in collaborative contexts; while a significant tendency *not* to reciprocate is observed only under competitive conditions. Reciprocity appears to be a flexible instrument to manage one's position in the social structure of the event, whereby speakers use it differentially depending on whether the goal is to secure support for their theme or to get many attendees. They aim to gain individual status, although the overall effect is uncertain – steepening hierarchy if competitive conditions prevail, flattening it if collaborative behaviors dominate.

These results also highlight a tension between what is institutionally structured and what is relationally driven, as the official framing of the event and actual practices do not always align: if individuals enact the drive toward novelty promoted by OuiShare organizers in their choice to attend talks of less experienced and new speakers (see 6.2), competitive conditions lead them to deviate from supposedly shared norms, notably reciprocity. As before, global impact is indeterminate as openness to novelty mitigates status hierarchies, while rejection of reciprocity fuels them.

Along similar lines, thematic affinities have a dual function: while encouraging co-operative behaviors among speakers with shared interests, they may increase competition between representatives of different areas who all aim at recognition and prominence, potentially at the expense of others. Once again, systemic effects are ambiguous.

Under such opposing forces, a status hierarchy appears but because endogenous factors (especially indegree-related effects, see 6.3) do not unequivocally exacerbate it, it remains globally mild. All in all, it seems that the OuiShare Fest elite has not developed strict social norms to regulate deference – perhaps in a way that is best suited to the "sharing economy" whose definition, scope and boundaries are still moving.

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