

On the structural equivalence of coresidents and the measurement of village social structure[☆]

Cohen R. Simpson^{a,b,*}

^a Oxford Internet Institute, University of Oxford, United Kingdom

^b Nuffield College, University of Oxford, United Kingdom

ARTICLE INFO

Keywords:

Coresidence
Rural Villages
Multilevel networks
Social support
Nicaragua

ABSTRACT

Researchers in the social and biomedical sciences regularly measure networks spanning entire villages in low- and middle-income countries by documenting the social contacts of just one or two representatives from participating households. This “lean” approach to network measurement is cost-effective compared to a sociometric census of a village’s adult population. However, it implicitly assumes that interviewed and non-interviewed coresidents are structurally equivalent — i.e., directly connected to the same network members in the same fashion. Drawing from research on multilevel networks and intra-household heterogeneity, here I argue that this assumption is unlikely to hold for the personal social ties typically of interest to field researchers (i.e., friends and other preferred sources and targets of material, informational and emotional support). I substantiate my claim with an exploratory case study on the similarity of coresidents’ incoming and outgoing ties using data documenting unrestricted roster-based reports on the provision of tangible aid amongst all adult residents of a remote village of indigenous horticulturalists in Nicaragua (108 adults; 32 nuclear-family households). Results indicate that coresidents markedly deviate from structural equivalence and its generalisation in the form of stochastic equivalence (i.e., similar probabilities of being directly connected to the same network members in the same fashion). All in all, it is ill-advised to assume that the personal network of any one coresident, or, more generally, the manner in which a coresident tends to send and receive their personal ties, is representative of their household.

Introduction

Across the social and biomedical sciences, there is growing interest in cataloguing all relationships between all adults in spatially distinct local populations — i.e., the measurement of networks spanning whole villages.¹ Such efforts, particularly in low- and middle-income countries (LMICs), hold great promise for researchers hoping to use villagers’ social ties to address pressing issues around health and international

development like the uptake of antibiotics (Haenssger et al., 2018), mass drug administration (Chami et al., 2017), neonatal mortality (Shakya et al., 2017a), the adverse effects of food insecurity (Perkins et al., 2018), the efficacy of microfinance initiatives (Banerjee et al., 2013) and risk sharing (Caudell et al., 2015). Nevertheless, the promise of sociocentric (i.e., complete network) studies of villages in LMICs is currently undercut by cause for concern around the accuracy of analysts’ portrayals of village social structure; concern stemming from the

[☆] Code used for both the preparation of data and the execution of my analyses, as well as the saved model objects for the analyses reported herein, are available on the Open Science Framework: <https://osf.io/yrh96/>.

^{*} Corresponding author at: 1 St Giles, Oxford, OX1 3JS, United Kingdom.

E-mail address: cohen.simpson@oii.ox.ac.uk.

¹ Here I use the term “village” rather loosely to mean any self-contained, spatially distinguishable group of homes, residents and associated buildings (e.g., schools and religious temples) that are fixed in place (cf. mobile collectives (Apicella et al., 2012)). In this respect, “village” is used as a catch-all to describe “neighbourhoods”, “districts”, “communities”, “sub-villages” and other analogous local socio-geographic arrangements featured as objects of study across the broader networks literature that may or may not be administratively defined but, in principle, have clear boundaries. Also, note that children are typically excluded in published sociocentric studies of whole villages in LMICs such that they are necessarily assumed to not impact the network of adults. Whether this is a plausible assumption is an empirical question and evidence from Germany does suggest that the networks of young people and their parents are associated (Windzio, 2015). Nevertheless, in keeping with the vast majority of published sociocentric studies of LMIC villages, here I only refer to adult members of domestic units — although see recent work on youth-adult village-wide networks in Honduras (Isakov et al., 2019; Shakya et al., 2017a).

underdevelopment of best practices for deciding which residents should be used to measure a “village-wide” network.

Of course, a sociometric census — i.e., the enumeration of all ties of a given type amongst all residents — stands to yield the most precise picture of the network of interest (Larson and Lewis, 2020; Perkins et al., 2015) and, in turn, ensure the unbiased assessment of structural properties (Marsden, 1990; Smith and Moody, 2013; Smith et al., 2017). Furthermore, this strategy offers the most analytical flexibility as a field researcher could, for example, subset an inter-individual village-wide network based on the traits of resident sub-populations (e.g., married women of reproductive age) or simplify this network in line with household membership by agglomerating coresidents’ incoming and outgoing ties. Nevertheless, sociometric censuses are resource intensive in that they may demand long periods of fieldwork (months, possibly years), the coordination of ground teams and substantial financial backing.² Consequently, “lean” approaches to measuring village-wide networks that are capable of offsetting costs at the risk of introducing error have proven popular (e.g., complex sampling (Advani and Malde, 2014; Banerjee et al., 2013; Larson and Lewis, 2020; Murendo et al., 2018)).

Motivated by what Perkins et al. (2015, p. 74) call the “issue of ‘level’” in sociocentric studies of villages in LMICs, here my concern is the soundness of one common lean approach: namely, exclusively documenting the social contacts of a household head and/or some other “knowledgeable” adult representative. If there is no heterogeneity in: (i) who coresidents chose as alters; and (ii) who coresidents are chosen by as alters, then a field researcher might solely rely on household representatives to measure a village-wide network at the household level with little concern. However, should there be non-trivial distinction between coresidents’ egocentric networks (i.e., their portfolios of incoming and outgoing social ties), then field researchers relying on household representatives will overlook information about connectivity at the individual level as a result of the erroneous assumption that those who live together are structurally equivalent — that is, directly connected to exactly the same people in the same fashion (Borgatti and Everett, 1992; Burt, 1976; Wasserman and Faust, 1994). As social scientists working on topics as diverse as seed exchange (Wencélius et al., 2016), information sharing (Castilla and Walker, 2013) and physical interaction (Goeyvaerts et al., 2018) have underscored the heterogeneity inherent to the inner workings of the home, there is good reason to suspect that the latter scenario is more plausible than the first. Accordingly, in this paper, I set out to clarify whether supposing the structural equivalence of coresidents could be problematic for field researchers seeking to manage the costs of measuring an individual-level village-wide network by solely relying on the sociometric reports of household representatives.

Before advancing, an unambiguous statement on what will and will not be covered is useful. Here I only address what limiting the eligibility of respondents for sociometric interviews to household representatives might mean for comprehensively measuring a network presumed to span an entire village. For the purposes of discussion, I assume an ideal scenario wherein a field researcher could theoretically collect “complete” network data vis-à-vis a village’s boundary and thus the only conceptual comparison I make is between a village-wide network measured using all adult residents and a village-wide network measured using one or more adult representatives from all homes (i.e., complete at the individual level versus complete at the household level). I do not discuss: methods of network sampling (i.e., simple versus various types of complex sampling); the minimum proportion of a village’s adult

population one should aim to reach; the integrity of structural measures and the results of generative models of networks (Robins et al., 2005) under different sampling regimes; or challenges around building the directory of village residents and households necessary for the valid identification of egos and alters. Furthermore, the related, but distinct, issues of measurement of social relations (i.e., How should the ties constituting a village-wide network of interest be elicited?) and boundary delineation (i.e., What are the limits of a “village”?) are not addressed.³

Background and argument

Field researchers have taken a number of approaches to measuring networks within villages, where the most popular include: (i) sociometric interviews with all, or a sizeable proportion of, a village’s adult residents (Caudell et al., 2015; Ferrali et al., 2020; Haenssngen et al., 2018; Koster, 2018; Perkins et al., 2018; Power, 2017; Shakya et al., 2018, 2017a); and (ii) sociometric interviews with male and/or female representatives from all, or some sizeable proportion of, a village’s households (Banerjee et al., 2013; Beaman and Dillon, 2018; Cai et al., 2015; Chami et al., 2017; D’Exelle and Holvoet, 2011; De Weerd, 2004; Foster, 1984; Jaimovich, 2011; Johnny et al., 2017; Kasper and Borgerhoff Mulder, 2015; Lee et al., 2018; Lyle and Smith, 2014; Nolin, 2010; Ready and Power, 2018). To date, explicit guidance on how scholars in diverse disciplines might adjudicate on the relative aptness of these two approaches beyond the question of budgetary constraint has been cursory and, to the best of my knowledge, found in just two articles. Specifically, in their systematic review of the designs of twenty published sociocentric studies concerning health and development in LMICs, Perkins et al. (2015) encouraged researchers to consider, in general, what information might be lost when only recording the relations of the household head. And, in a wide-ranging essay on measuring networks in the field, Larson and Lewis (2020) framed the choice between measuring a village’s network at the household level or the individual level as one principally driven by research aims; highlighting, in particular, the need for analysts to consider whether their research question explicitly concerns households or individuals and whether answering their research question requires information that might be obfuscated through measurement at the household level (e.g., “household ethnic identity” in ethnically heterogeneous homes).

These directives are of course sensible. However, what is also needed is a discussion of how the intentionality underlying the establishment of social ties differs between the household and individual levels. *Prima facie*, the question of villagers’ agency in relation to how their social ties come into being may appear to be overly academic and thus irrelevant to practically-minded readers. Yet this basic sociological concern is inextricably linked to the level at which the relationship of interest to the field researcher ought to be measured. This is because social ties “... emerge, persist, and disappear by virtue of actions made locally at the scale of the individual actors in a network (whether they be persons or families or companies or some other social entity)” (Robins et al., 2005, p. 895) which presumably results in a degree of distinction between who

² Despite substantial advances around the use of mobile devices for the flexible mapping of face-to-face networks at scale under challenging circumstances (Hogan et al., 2016; Hogan et al., 2020; Isakov et al., 2019), sociocentric studies of villages may still be prohibitively costly — especially for early-career researchers or those lacking institutional support and access to reliable revenue streams.

³ Advani and Malde (2014), Larson and Lewis (2020), Marsden (1990), Perkins et al. (2015), Smith and Moody (2013) and Smith et al. (2017) provide useful discussions of many of these issues. See also Perkins et al. (2015) and Shakya et al. (2017b) for discussions around how to choose sociometric questions for sociocentric studies of villages, where Perkins et al. (2015) provide a list of 105 name generators for field researchers to draw from. Also relevant are discussions around informant accuracy (Brewer, 2000; Lee and Butts, 2018) and discussions of how the contacts reported by respondents may vary across interviewers (Harling et al., 2018; Herz and Petermann, 2017; Hogan et al., 2020). With respect to boundary specification — long known to be a key issue when studying village-wide networks (Entwistle et al., 2007) — discussion of how to use satellite imagery to help construct sampling frames for household surveys in LMICs will also be of interest (Haenssngen, 2015).

any two network members are directly connected to the extent that these actors create, maintain and terminate relations in line with their distinct preferences under different constraints (see Zeng and Xie, 2008). Consequently, the appropriateness of measuring a network spanning and entire village by solely relying on the sociometric reports of representatives from each home is premised on an implicit and strong assumption: namely, that the egocentric networks of these representatives, and thus their structural positions (Burt, 1976), are equivalent to the egocentric networks of those that they live with — a requirement for the calculation of the structural variables that are potentially of interest to field researchers to be impervious to who in the home is selected for a sociometric interview (e.g., centrality and eccentricity; see Borgatti and Everett, 1992, p. 6–8).

To make sense of when this assumption may be expected to hold, cognate discussions around the measurement of inter-organisational networks are an informative point of departure. Given a lack of third-party information on some inter-organisational relationship of interest (e.g., alliances reported in industry magazines (Gulati and Gargiulo, 1999) or flows of money detailed in government tax returns (Simpson, 2016)), organisational heads or “knowledgeable” organisational representatives are typically asked to report on their institution’s external relations without input from all of the organisation’s members or even all of its directorate (e.g., see Baldassarri and Diani, 2007; Brailly et al., 2016; Heaney, 2014; Heaney and Leifeld, 2018). Whilst this may seem odd to scholars who typically work with inter-individual networks, it is ultimately the supra-individual quality of an organisation — i.e., its ability to act in a unitary fashion by means of a kind of collective intentionality (List, 2016; Tollefsen, 2002) — that is of interest to the student of inter-organisational engagement and exchange. Practically speaking, this makes organisational leadership or a key organisational representative well-placed to report on their institution’s direct connections. Nevertheless, sociologists, in particular Lazega and his colleagues (Brailly et al., 2016; Lazega et al., 2008), have convincingly demonstrated that the most analytically fruitful portrayal of the social ties between a group of organisations directly references the social ties between their individual, possibly shared, members. That is to say, an inter-organisational network is, fundamentally, a multilevel network (Lomi et al., 2016) constituted by two distinct sets of actors that have the capacity to establish ties within and between sets (e.g., formal collaborative ventures between organisations and advice relations within and across organisational boundaries amongst the organisations’ employees). Although the collection of multilevel data in LMICs may be particularly burdensome (Perkins et al., 2015), anthropological work by Koster (2018) detailing the association between coresidence and alter choice has clearly shown that a multilevel perspective on the establishment of social ties within rural villages in LMICs is empirically and theoretically germane. Indeed, for my purposes, the explicit positioning of village social structure as a multilevel network (Fig. 1) is especially useful as it allows intentionality to simultaneously rest with the individual and the home. As a result, one can then posit that there are certain relations that are intrinsically between households (and not individuals) whilst other relations are the domain of individuals (and not households) with micro and meso relations linked through villagers’ residency in one or more physical dwellings “...for the purposes of eating, sleeping and taking rest and leisure, growing up, child rearing and procreating” (Hammel and Laslett, 1974, p. 76; see also Laslett (1984) on the collective life of the familial group).

That said, each level of a multilevel network is interesting in its own right as distinct logics can drive their formation (Brailly et al., 2016). Where village social structure is concerned, this obviously raises the question of how the process of establishing social ties might generally differ between the household and individual levels and what any divergence between the two implies about the appropriateness of exclusively relying on the sociometric reports of a representative from the home. On this matter, it is useful to review anthropological descriptions of how intra-village relations are organised by households —

key units of production and consumption in LMICs (Doss, 2013) and the buildings blocks of human communities (Foster, 1984; Koster, 2018).

Consider, for example, Hames’ (1987) study on garden labour exchange (e.g., weeding, planting, harvesting) in a Ye’Kwana village in Venezuela. For this particular community, Hames (1987) recounts that nuclear families, which may constitute their own household or partly comprise a “single economic entity” in the form of a joint household, ideally subsist from their unique garden such that all coresidents benefit from their gardens’ success and all coresidents stand to incur costs (e.g., loss of labour, possible plot failure) when a family member devotes his/her time to working on a garden belonging to another home. As a result, a coresident’s preferred targets of garden-related altruism are subject to a degree of intra-household negotiation wherein the relatedness of a potential recipient of aid (i.e., their genealogical proximity) becomes salient and power differentials around age, sex and child-rearing emerge (Hames, 1987).⁴ Similarly, in a study on meat sharing in two Mayangna and Miskito villages in Nicaragua, Koster (2011) observed that multiple adult members of the home — as opposed to only the individuals who acquire, butcher or cook the meat — collectively determine which other households will be the recipients of aid, a dynamic akin to the one seen by Nolin (2010) in his study on the inter-household exchange of meat, fish and vegetables in a Lamaholot village in Indonesia.

Taken together, these cases indicate that some intra-village relations are the result of coresidents coming together to act by means of joint decision-making or, to borrow a phrase from Laslett (1984, p. 354), the “conjunction of individual interests at play in the familial group”. As a result, these ties naturally sit at the level of the home in that they are functionally identical for all coresidents resulting in what we might call

⁴ For example, Hames (1987, p. 277) notes that mothers direct their daughters to labour on the garden of the mother’s preferred homes, a cooperative act that may or may not represent the altruistic desires of the child. This dynamic of course highlights the importance of explicitly considering status hierarchies within the home when deciding who is eligible for a sociometric interview — especially for scholars planning to investigate the impact of social ties on individual behaviour. Consider, for instance, a recent study in India on parents’ resistance to having their young children vaccinated against polio (Onnela et al., 2016) where the behavioural outcome of interest (i.e., parents allowing their children between zero and five to be immunised) clearly has a household-level component such that behaviour change is strongly shaped, if not fully determined, by the desires of the leader(s) of the familial unit. In scenarios such as this one, ties to/from the principle decision-makers in the home strike me as the most relevant such that a village-wide network may be defensibly measured by only eliciting ties from household heads in the style of Onnela et al. (2016). If, on the other hand, behaviour change might not purely be a function of the desires or the coercive action of the leader(s) of a familial unit — e.g., as in Chami et al.’s (2017) study in Uganda on compliance during mass drug administration by ingesting suggested medicines, where eligibility for treatment included household heads and their coresidents aged older than one (e.g., subadult children, adult children and elderly parents) — then eliciting ties solely from household heads could yield an incomplete picture of the interplay between the behaviour of interest and village social structure. In such cases, it seems prudent to allow all coresidents with a degree of autonomy relative to the behaviour of interest to be eligible for sociometric interviews and, if appropriate, agglomerate the interviewed coresidents’ connections for a household-level analysis, as was done by Chami et al. (2017) given evidence of correlated drug receipt within households in the villages they studied (Chami et al., 2016).

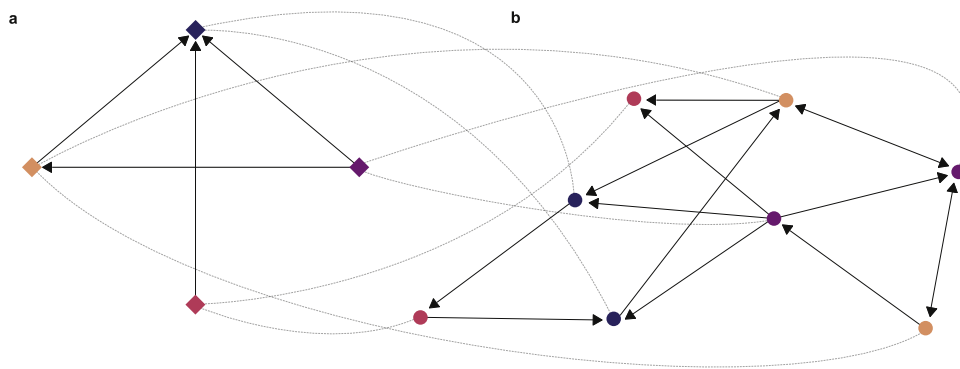


Fig. 1. Schematic of village social structure as a multilevel network. This network is comprised of: (a) a single-layer (i.e., not multiplex) one-mode network constituted by four households (diamonds) at the macro level; and (b) a single-layer one-mode network constituted by eight villagers (circles) at the micro level. The macro- and micro-level networks (i.e., the household-level and individual-level networks) are linked through a meso-level two-mode network representing coreidence (dashed curved lines). Vertices are coloured based on household membership.

de facto structural equivalence. In such a scenario, it seems uncontroversial to suggest that a field researcher can rely on a sociometric interview with a domestic representative or a group sociometric interview with one or more coresidents (Nolin, 2010) in order to measure a village-wide network at the household level (Fig. 1a) under the assumption that those interviewed can accurately speak for their home.⁵

On the other hand, consider a study on sorghum seed exchange in a Masa village in Cameroon by Wencélius et al. (2016). Here again the inner workings of households play an important role in governing how coresidents establish their social ties. Yet in Wencélius et al.'s (2016) case, and in contrast to the research site of Hames (1987), households in the Masa village are structured in a manner whereby coresidents (both men and women) autonomously command their own fields and granaries and generally engage in agricultural production independently. In light of these arrangements, Wencélius et al. (2016) stress the non-unitary nature of the Masa home, writing:

Despite the relevance of the household as the unit of investigation for some economic and social activities (e.g., common field management, cattle herding, participation in rituals, bridewealth [i.e., marriage] payment), ...Masa household composition and agricultural practices invite us to consider separately each household member's activities and decision-making patterns. In consequence, a household member's strategy should not be conflated with an *a priori* uniform household strategy, nor should the behaviour of a single member (i.e., the household head) be considered representative of all other household members' behaviours. Furthermore, it cannot be expected that a household head systematically provides reliable information as to the diversity of choices made by his coresidents. (2016, p. 3).

Wencélius et al.'s (2016) view on how members of Masa households may be expected to partake in seed exchange is a testament to the self-directed quality of some intra-village relations, i.e., relations that are the result of a coresident's independent decision-making as opposed to being the outcome of some dialectic involving multiple members of the home. For field researchers interested in self-directed ties and the individual-level village-wide networks they naturally constitute (Fig. 1b), a sociometric census of all adults seems more appropriate than exclusively relying on the sociometric reports of household representatives — especially when considering what would be necessary for

coresidents to achieve structural equivalence in a network of this kind. More specifically, the preferences of coresidents and the relational constraints coresidents face (e.g., those stemming from their primary social and economic activities (Feld, 1981) and the manner in which they traverse physical space (Small and Adler, 2019)) would all presumably need to converge in a fashion conducive to independently building identical ties with exactly the same individuals — an implausible scenario.

To further clarify why this scenario is unlikely, let us turn to research from development economics that challenges simplistic models of household behaviour, including those that are unitary in nature (Alderman et al., 1995; Alwang et al., 2017; Ambler et al., *Forthcoming*; Bardasi et al., 2011; Castilla and Walker, 2013; Doss, 2013; Doss et al., 2018; Kebede et al., 2014; Udry, 1996). Like the anthropological work of, for example, Hames (1987), Laslett (1984) and Wencélius et al. (2016), this body of economic scholarship positions households in LMICs as complex sites of disagreement, negotiation and decision-making — dialectics that may well include asymmetric access to information, divergent understandings and, as Doss (2013, p. 56–58) articulates, interlocutors with assorted social roles given household structure (e.g., husbands, wives, unmarried household heads, adult sons, adult daughters and elderly in-laws). Along this line, studies by development economists exploring the implications of intra-household heterogeneity for data collection have repeatedly shown that even information on objective matters stands to vary based on who in the home is asked.

For example, Bardasi et al. (2011) analysed the reliability of answers to household questionnaires from “proxy informants” in relation to labour statistics and discovered that the responses of surrogates (i.e., a randomly chosen coresident over 16), as opposed to self-reports, led to the underreporting of male (but not female) employment rates in an experiment in Tanzania; a result that the authors attributed to some coresidents' failure to recognise agricultural labour as “work”. Additionally, Twyman et al. (2015) probed the erasure of women in agricultural production by exploring variation in recognition of the involvement of female landowners in decision-making about their own land parcels using data from Ecuador and found that men reported lower levels of women's participation in decision-making compared to their female partners — a finding similar to those of Alwang et al. (2017). Moreover, in a study motivated by concerns over the measurement of wealth inequality, Doss et al. (2018) investigated whether men and women value the worth of their property differently given their dissimilar participation in asset markets (e.g., livestock versus consumer durables), their distinct specialisations within the home and gender-based restrictions on their ability to sell the same property for the same price. And, using data from Ghana, Ecuador and India, the authors indeed observed gender-based variation in asset valuation, with wives reporting a narrower range of monetary values compared to their husbands. Further still, Ambler et al. (*Forthcoming*) documented systematic disagreement between spouses in Bangladesh around a wife's

⁵ Depending on the research topic, analysts might also separately collect data from multiple coresidents based on their occupation of specific roles within the home and then agglomerate their connections for a household-level analysis. For example, in their study on the interplay between community-level social connectedness, household income and food security in eleven villages in Peru, Lee et al. (2018) combine sociometric reports separately collected from the male and female household head — the latter of whom is the individual with primary cooking responsibilities for the home and who solely provided information on food security, dietary diversity and food-based aid.

involvement in household decision-making and her control over household assets (both indicators of bargaining power); where women were found to be more likely than men to report that women are decision-makers and asset owners — particularly for assets that are easy to hide such as small animals and small durables (see also Alwang et al., 2017, p. 117–119 and p. 127–128 on female empowerment and the gender-based measurement of asset ownership and decision-making).

Together, development economists' enquiries around the non-unitary nature of households in LMICs plainly indicate that coresidents are likely to have different preferences, different perceptions and different access to resources such that overlooking members of the home beyond some designated household representative during data collection is ill-advised. Where network data collection is concerned, it seems wholly apt to extend this expectation of intra-household heterogeneity to include coresidents' differing access to resources by virtue of their self-directed social ties (i.e., their network capital (Wellman and Frank, 2001)).⁶ This is especially so for the types of relationships typically analysed in sociocentric studies of villages in LMICs. Specifically, past scholarship from multiple disciplines on varied topics concerning diverse locales (Banerjee et al., 2013; Cai et al., 2015; Caudell et al., 2015; Chami et al., 2017; D'Exelle and Holvoet, 2011; De Weerd, 2004; Hoddinott et al., 2009; Ferrali et al., 2020; Foster, 1984; Haenssger et al., 2018; Isakov et al., 2019; Jaimovich, 2011; Kasper and Borgerhoff Mulder, 2015; Koster, 2018; Larson and Lewis, 2017; Lyle and Smith, 2014; Perkins et al., 2015; Perkins et al., 2018; Power, 2017; Shakya et al., 2017b; Takada et al., 2019) suggests that field researchers tend to be interested in villagers' positively valenced, non-romantic *personal ties* — by which I mean friends, companions and other preferred sources and targets of material, informational and emotional aid presumably chosen in line with ego's distinct preferences as opposed to being fully determined by some group process within her home. Indeed, Kasper and Borgerhoff Mulder (2015) cite the possibility of distrust and enmity precluding the convergence of the interests of husbands and wives in justifying their decision to focus on individuals, as opposed to households, for their study on kinship and the exchange of social support amongst residents of a Pimbwe village in Tanzania (e.g., child care, loans and advice). Moreover, Caudell et al. (2015) briefly highlight the importance of obtaining reports on informal financial lenders from all adults to building an accurate picture of network embeddedness in their study on risk sharing in a Sidama village in Ethiopia. Additionally, Koster (2018) presents evidence from a Mayangna and Miskito village in Nicaragua indicating that coresidents have distinct sets of tangible support relationships (e.g., bequeathing firewood and physical assistance) with the members of other households. And, furthermore, Jaimovich (2011) precedes this paper by explicitly linking the notion of non-unitary households to the idea that the egocentric networks of household heads may not be representative of those belonging to their coresidents when discussing the design of his study on the exchange of instrumental aid in 60 Gambian villages (e.g., labour, small goods and credit).

All in all, it is my strong view that there are sufficient grounds to recommend that field researchers operate under the assumption that coresidents' will have distinct portfolios of self-directed ties such that caution is warranted when exclusively relying on the sociometric reports of household representatives to measure an individual-level village-wide network. Nevertheless, there exists no sociocentric analyses of dissimilarity between coresidents' self-directed ties. And thus, it is

unclear whether the anticipated differences between coresidents' structural positions will be non-trivial or largely ignorable — especially as some overlap of coresidents' egocentric networks should also be expected.⁷ Accordingly, in the second part of this paper, I move to substantiate my recommendation with a small, exploratory case study on the degree to which coresidents in a remote Nicaraguan community are structurally equivalent.

Data summary

Data from Nicaragua were collected in 2013 by Koster (2018) for his investigation of the impact of kinship and coresidence on the provision of social support. His fieldwork focused on the 279 residents of Arang Dak, a remote community of Mayangna and Miskito swidden (i.e., “slash-and-burn”) horticulturalists located on the Lakus River in the Bosawás Biosphere Reserve, a neotropical forest in the Department of Jinotega. At the time of data collection, Arang Dak was home to 32 households, with 108 of its 279 residents being adults (defined as age 18+). As Koster (2018) recounts, life in Arang Dak is centred around the nuclear family household which may include other adult coresidents beyond the male and female head (e.g., young couples with few or no children residing with in-laws). Extra-marital affairs are not without precedent and the spawn of these unions are neither stigmatised nor are their genealogical relations unacknowledged. Unmarried individuals (bachelors, widows, divorcees) make up roughly 30% of the adult population and, given their age, often live with their parents or adult children. Whilst residence patterns are not governed by formal rules in Arang Dak, Koster (2018) notes uxoriality (i.e., a tendency for women to live with more of their primary kin such as their parents, siblings and children (Adam, 1947)). Moreover, like many traditional communities, Arang Dak features pronounced sexual divisions in labour. That said, male-female cooperation during work does occur. For instance, men accompany women as they pan for gold, a common source of income, and women participate in multi-day hunting expeditions or *giras* in addition to assisting men in agricultural tasks during mixed-sex trips to fields (Koster, 2007; Koster et al., 2013).⁸

As for the specifics of data collection, Koster (2018) interviewed 106

⁷ For instance, Elizabeth Bott's classic study of inter-household relations in post-war London marks the beginning of sixty years of sociological research premised on the idea that the personal networks of husbands and wives can meaningfully intersect (Bott, 1955; Giudici and Widmer, 2017; Hsung et al., 2006; Ishii-Kuntz and Maryanski, 2003; Kalmijn, 2003; Kennedy et al., 2015; Milardo, 2007; Rogler and Procidano, 1986; Rözer et al., 2018; Stadtfeld and Pentland, 2015; Treas, 2011; Turner, 1967; Udry and Hall, 1965). Of particular interest here is Kalmijn (2003) who analysed data from 1,706 households in the Netherlands and found broad support for the “dyadic withdrawal hypothesis” which predicts that the personal friendship networks of those entering into a cohabitating relationship both atrophy and increasingly overlap over the course of their partnership. More recently, Stadtfeld and Pentland (2015) drew on this research in their investigation of friend choice amongst 63 married/long-term cohabitating couples in a graduate student housing community in the United States and used statistical models of network formation to further demonstrate that romantic partnership encourages the overlap of spouses' personal networks. In particular, the authors found that spouses tend to: (i) choose the same friends (i.e., the creation of partnership-friendship triads); and (ii) befriend their partner's friend's partner (i.e., the creation of partnership-friendship tetrads), amongst other dynamics. Somewhat similarly, in an anthropological study, Koster (2018) found that coresidents, as opposed to simply spouses, converge on their choice of alters across households using data from 32 homes in Nicaragua that I reanalyse here. That said, a tendency towards overlap in choice of social contacts between spouses and, more broadly, coresidents is not structural equivalence, the latter of which is the focus of this paper.

⁸ Additional information on these data and an in-depth discussion of fieldwork are provided by Koster (2018). For more information on life in Arang Dak, see also Koster and colleagues (Koster, 2007, 2011; Koster and Tankersley, 2012; Koster et al., 2013).

⁶ Network capital is a specific form of “social capital” — a sweeping concept used to refer to the benefits that individuals accrue by virtue of factors as diverse as personal networks, group norms and institutional memberships (Aldrich and Meyer, 2015; Wellman and Frank, 2001). Here, I only make a narrow reference to network capital, where readers interested in the broader treatment and measurement of social capital should see Aldrich and Meyer (2015), Lin (1999) and Portes (1998).

of the 108 adult residents of Arang Dak, gathering both sociometric data and basic demographic information (e.g., age, wealth, ethnicity). For the main sociometric task, a single question focused on the seeking of tangible support was used. Specifically, Koster (2018, p. 6) asked: “Who provides tangible support to you at least once per month?”, where respondents were prompted with relevant examples such as food, valuable items (e.g., canoes) and help with physical tasks. Respondents were also asked the inverse. That is, residents were tasked with nominating those to whom they give tangible support at least once per month. Respondents’ alters were elicited using a roster-based method whereby the names of the other 107 adult residents were randomly read aloud so that the respondent could confirm whether or not each one of these individuals provided and/or received tangible support. The two adults who were not surveyed were away from the community at the time of data collection. However, Koster (2018) did not restrict respondents’ choice of alters. Accordingly, each of the 106 respondents could name as many of the other 107 residents as they desired during the sociometric task. For my analysis, I used all 2595 of the reported support seeking ties and all 2958 of the reported support giving ties amongst the $n = 108$ adult residents so as to not bias the boundaries of the community’s network. And, in doing so, I simply assume that the two individuals away from Arang Dak reported no ties for the purposes of each sociometric task.

With regard to network construction, I drew two $n \times n$ binary directed sociomatrices x^S and x^G respectively using reports from the support seeking and support giving sociometric tasks (hereafter, the “support seeking network” and the “support giving network”). Both sociomatrices are constructed to reflect the provision of aid such that $x^S_{ij} = 1$ if resident i provides support to j according to the seeker of aid j and $x^G_{ij} = 1$ if resident i provides support to j according to the giver of aid i . Although measurement error alone may make actors appear to not be structurally equivalent (Burt, 1976; Wasserman and Faust, 1994) and despite concern around the inaccuracy of the unilateral acknowledgement of ties (Brewer, 2000; Lee and Butts, 2018), I do not create a “composite” network by combining residents’ reports (i.e., $x^C_{ij} = 1$ if resident j reports receiving support from i and resident i reports giving support to j). This is because I am interested in coresidents’ reports in and of themselves, where their veracity is an important, but secondary, concern. Furthermore, field researchers seeking to measure a social support network that spans a village may not necessarily find themselves in a situation wherein they can collect multiple reports on the same tie (e.g., due to costs or worries about respondent fatigue), instead having to choose between sociometric questions emphasising the seeking or the giving of aid. This makes any major differences in results between the two networks noteworthy.

Before advancing, it should be said that social, cultural and physical environment all stand to powerfully shape network structure and interpersonal relationships more generally (Adams and Plaut, 2003; Entwisle et al., 2007; Hruschka, 2010; Kito et al., 2017; McFarland et al., 2014; Thomson et al., 2018). Therefore, definitive conclusions demand comparative analysis — ideally using large samples of complete individual-level village-wide networks annotated with unambiguous information on household membership. Data of this kind are not available here. Nevertheless, the data from Arang Dak are unusually apt for my purposes given the following factors. First, as mentioned above, a focus on personal ties, particularly social support, is typical of sociocentric studies of villages in LMICs, with the exchange of tangible aid being of great interest to anthropologists and economists working to build an understanding of risk sharing and community resilience in rural locales (Caudell et al., 2015; De Weerd, 2004; Hoddinott et al., 2009; Power, 2017). Second, the ability of the residents of Arang Dak to nominate as many alters as they desired arguably facilitates better coverage of the village’s tangible support network compared to a sociometric task wherein respondents are constrained in the number of alters they can report. And third, the eliciting of support ties by

referencing a specific time period and using a roster-based technique — rare characteristics of data collection amongst published sociocentric studies — should provide some protection against well-known challenges around the recall of alters (Brewer, 2000).

Methods

Adopting the notation of Borgatti and Everett (1992), let the graph $G(V, E)$ represent either the support seeking network or the support giving network, where V is the set of 108 adult residents of Arang Dak and E is the set of arcs (i.e., directed ties) between them reflecting the provision of tangible aid. Additionally, let $P(i)$ denote the structural position of actor i in G , where position is categorical. Moreover, let $N^O(i)$ denote the set of actors j to whom i provides tangible aid such that $N^O(i) = \{j : (i, j) \in E\}$. Similarly, let $N^I(i)$ denote the set of actors j from whom i receives tangible aid such that $N^I(i) = \{j : (j, i) \in E\}$. Respectively, $N^O(i)$ and $N^I(i)$ are i ’s “out-neighbourhood” and “in-neighbourhood”, where i ’s “neighbourhood” — i.e., i ’s personal/egocentric network — $N(i)$ is defined as the ordered pair $(N^O(i), N^I(i))$.

In line with Borgatti and Everett’s (1992) formal restatement of Burt’s (1976) definition of structural equivalence, $P(i) = N(i)$ for all $i \in V$ and $P(i) = P(j)$ if and only if $N(i) = N(j)$ which is to say two actors occupy the same position in a network only when they have perfectly overlapping neighbourhoods or, rather, *when who they are directly connected to is exactly the same*. As I have discussed above, such perfect overlap is unlikely to occur for any given pair of coresidents when their self-directed ties are of concern⁹ whereas it is *de facto* at the household level by virtue of coresidents establishing intra-village ties through joint decision-making. That said, exact or “strong” structural equivalence is generally understood to be rare (Burt, 1976; Butts, 2008; Hanneman and Riddle, 2005; Wasserman and Faust, 1994) making it is necessary to consider equivalence in an individual-level village-wide network under less restrictive conditions.

Accordingly, I focus on how closely coresidents approach structural equivalence and how closely they approach stochastic equivalence — i.e., a generalisation of structural equivalence whereby i and j have the same probabilities of sending a tie to and receiving a tie from every other actor in a network such that i and j tend to have similar relational patterns (Hoff, 2008, 2009; Minhas et al., 2019; Wasserman and Faust, 1994). As Wasserman and Faust (1994, p. 696–697) discuss, i and j need not have identical sets of observed relationships with all other network members, only identical probabilities of these relationships forming. And thus, stochastic equivalence is a much weaker form of structural equivalence, where structurally equivalent actors will be stochastically equivalent but not vice versa.

To gauge the approximate structural equivalence of coresidents, I relied on the pairwise dissimilarity between their structural positions in the support seeking network and the support giving network. Given two coresidents, i and j , and the binary sociomatrix x , dissimilarity was measured in a straightforward fashion. Specifically, I used the Hamming distance — i.e., a kind of matching metric here indicating the number of entries that differ between: (i) a vector created by concatenating the i th row and the i th column of x , which together fully describe how i relates to, and is related to by, all network members; and (ii) a vector created by concatenating the j th row and the j th column of x . Substantively speaking, the Hamming distance may be regarded as the number of changes needed to make i ’s row-column vector — and thus i ’s structural position — identical to j ’s or vice versa; where “change” could be the addition or removal of an outgoing/incoming tie (i.e., flipping an entry

⁹ Indeed, should the two coresidents in question share a tie in an individual-level network (not guaranteed, but highly probable) and should this individual-level network not feature “reflexive loops” (i.e., ties to oneself), exact structural equivalence as it is defined by Burt (1976) cannot occur (see Borgatti and Everett, 1992, p. 6–8).

in the row-column vector from zero to one or one to zero) with the joint presence and joint absence of relationships to/from third others treated as similarity between the two actors being compared. Although approximate structural equivalence is frequently measured using the Euclidean distance following Burt (1976), I have used the Hamming distance, as implemented in the R package “sna” (Butts, 2008), due to its comparatively easy interpretation when working with binary sociomatrixes.¹⁰

To gauge the approximate stochastic equivalence of coresidents, I used the Additive and Multiplicative Effects (AME) Model of Hoff and colleagues (Hoff, 2008, 2009; Hoff, 2018; Minhas et al., 2019) — a recently proposed dyadic regression model for network and other relational data in the vein of latent class and latent distance models (e.g., the popular stochastic block and latent space models). More specifically, and given an observed $n \times n$ response matrix Y , the tie variable $y_{i,j}$ is modelled as a function of: (i) monadic covariates; (ii) dyadic covariates; (iii) node-specific random effects; and (iv) node-specific latent factors — i.e., “unobserved characteristics” used to capture dependencies in the values of Y in the form of homophily and stochastic equivalence. Accordingly, the AME model is a type of latent variable model whereby the relationship between i and j is mediated by a small number (R) of unmeasured attributes that are estimated.

For my analysis, I relied on the version of the AME model designed by Hoff and colleagues for a binary asymmetric response matrix which is a kind of probit regression whereby the observed tie variable $y_{i,j}$ is a function of an unobserved continuous latent tie variable $z_{i,j}$, with $y_{i,j}$ equalling one when $z_{i,j}$ exceeds a threshold of zero. Formally,

$$y_{i,j} = \begin{cases} 1, & \text{if } z_{i,j} > 0 \\ 0, & \text{if } z_{i,j} \leq 0, \end{cases} \quad (1)$$

with

$$\begin{aligned} z_{i,j} &= \mu + \beta_d^T x_{d,i,j} + \beta_r^T x_{r,i} + \beta_c^T x_{c,j} + a_i + b_j + \mathbf{u}_i^T \mathbf{v}_j + \varepsilon_{i,j}, \\ \{(a_1, b_1), \dots, (a_n, b_n)\} &\sim \text{i.i.d. } N(0, \Sigma_{ab}), \\ \{(\varepsilon_{i,j}, \varepsilon_{j,i}) : i \neq j\} &\sim \text{i.i.d. } N(0, \Sigma_e), \end{aligned} \quad (2)$$

where

$$\mathbf{u}_i^T \mathbf{v}_j = \sum_{r \in R} u_{i,r} v_{j,r}, \quad \Sigma_{ab} = \begin{pmatrix} \sigma_a^2 & \sigma_{ab} \\ \sigma_{ab} & \sigma_b^2 \end{pmatrix} \text{ and } \Sigma_e = \sigma_e^2 \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}.$$

In Eq. (2), μ is the intercept (i.e., the common mean of the latent sociomatrix Z), $x_{d,i,j}$, $x_{r,i}$ and $x_{c,j}$ are, respectively, d -, r - and c -length vectors of dyadic, row/sender and column/receiver covariates for i and j , where β_d^T , β_r^T and β_c^T are vectors of regression coefficients that summarise the associations between the various covariates and $z_{i,j}$. Additionally, a_i and b_j are random (i.e., varying) effects for i and j capturing row and column-specific deviations from μ . Furthermore, \mathbf{u}_i and \mathbf{v}_j are node-specific vectors of latent factors of length R (i.e., $\mathbf{u}_i = \{u_{i,1}, \dots, u_{i,R}\}$ and $\mathbf{v}_j = \{v_{j,1}, \dots, v_{j,R}\}$) that capture heterogeneity in Z that is unaccounted for by the observed covariates, the random effects, and the relationship-specific effect $\varepsilon_{i,j}$. Moreover, σ_a^2 , σ_b^2 and σ_{ab} are variance parameters that respectively summarise heterogeneity in the row-specific means (i.e., $\{\mu + a_1, \dots, \mu + a_n\}$), heterogeneity in the column-specific means (i.e., $\{\mu + b_1, \dots, \mu + b_n\}$) and the linear association between the random row effects $\{a_1, \dots, a_n\}$ and the random column effects $\{b_1, \dots, b_n\}$; where the variance of the relationship effects σ_e^2 is fixed at one and ρ is the parameter summarising the within-dyad correlation (i.e., direct reciprocity).

Regarding the interpretation of the node-specific latent factors, \mathbf{u}_i and \mathbf{v}_i respectively describe i 's behaviour as a sender and a receiver of ties such that $\mathbf{u}_i \approx \mathbf{u}_j$ indicates similarity in i and j 's behaviour as senders

and $\mathbf{v}_i \approx \mathbf{v}_j$ indicates similarity in i and j 's behaviour as receivers. However, $\mathbf{u}_i \approx \mathbf{u}_j$ and $\mathbf{v}_i \approx \mathbf{v}_j$ indicates that i and j are *approximately* stochastically equivalent conditional on the observed covariates and degree heterogeneity — where exact stochastic equivalence is then reserved for actors with identical latent values, identical covariate values and identical random sender and random receiver effects. Moreover, positive values of the multiplicative term $\mathbf{u}_i^T \mathbf{v}_j$ (i.e., the product of the transposed vector \mathbf{u}_i and the vector \mathbf{v}_j) indicates latent homophily (i.e. higher values of $z_{i,j}$), whereas latent heterophily is indicated by negative $\mathbf{u}_i^T \mathbf{v}_j$.

Similar to other latent variable models for networks, the number of latent factors R used to additionally characterise actors' behaviours as senders and receivers must be chosen by the researcher. For my analysis, I fitted three models to each tangible support network wherein R was equal to one, two or three and then adjudicated on model fit by visually assessing the degree to which a large number of networks simulated under each fitted model reflect the observed network. The best fitting model was then used to visually assess the approximate stochastic equivalence of coresidents.

All six AME models were fitted within a Bayesian framework using the R package “amen” (Hoff, 2018) and the specification of the various prior distributions detailed by Hoff and colleagues (Hoff, 2008, 2009; Hoff, 2018; Minhas et al., 2019).¹¹ With Gibbs sampling (a type of Markov chain Monte Carlo (MCMC) algorithm), each AME model was estimated using a single chain for each parameter that was run for 250,000 iterations, where the first 150,000 iterations comprised the burn-in period. Iterations were not “thinned”, resulting in a total posterior sample size of 100,000 for each parameter. The lengths of the burn-in and post-burn-in period were chosen through trial and error in an attempt to yield an effective sample size (ESS) around 10,000, a level which some applied Bayesian statisticians recommend to ensure the stability of the limits of 95% Highest Density Intervals (Kruschke, 2015).¹² Despite the long burn-in period, the ESS for some parameters failed to approach or exceed 10,000 (e.g., ρ) such that the HDIs for these parameters should be approached with caution — although note that the mean of the posterior distribution of a parameter may be confidently calculated with an ESS as small as 200 (McElreath, 2015).

Unfortunately, the version of “amen” currently available only allows one to fit models using a single Markov chain for each parameter, preventing the use of MCMC diagnostics for multiple overdispersed chains run in parallel such as the popular potential scale reduction statistic (McElreath, 2015). Accordingly, the quality of the MCMC chains was visually assessed using a combination of time-series or “trace plots” of the posterior draws, kernel density plots of the posterior draws and the ESS. The R package “coda” (Plummer et al., 2018) was used to derive each Highest Density Interval and to measure the ESS.

¹¹ Prior distributions (or simply “priors”) summarise information about each of the unknown model parameters that is independent, at least in part, of the data themselves. Practically speaking, priors influence the bounds of the probability distribution for each parameter (i.e., the “posterior distribution” or simply “the posterior”). The version of “amen” I relied on for this research (v.1.4.3; Hoff, 2018) is constructed to use a g -prior for the parameters β and the random effects a and b (i.e., a kind of multivariate prior for all coefficients in a regression model tuned via a single parameter g), a Wishart prior for Σ_{ab} , an arcsine prior for ρ and a Wishart prior for Σ_{UV} (i.e., the covariance matrix used to derive the latent factors). For additional details, see the “amen” v.1.4.3 source code and changelog on GitHub (<https://pdhoff.github.io/amen/news/index.html>; Retrieved July 2019).

¹² The 95% Highest Density Interval (HDI) indicates the values bounding 95% of a parameter's posterior distribution, where all values inside this interval have a higher probability than those outside. The effective sample size (ESS) is the posterior sample size in the absence of correlation between the values of a chain (i.e., an estimate of the amount of independent information in a chain).

¹⁰ For an accessible comparison of measures of structural equivalence, see Hanneman and Riddle (2005, Chapter 13).

Model specification

In fitting the two sets of AME models, my chief interest is approximate stochastic equivalence. Accordingly, I used a straightforward model specification intended to capture core aspects of tie formation that only differs in the number of estimated latent factors R (one, two, or three). The set of covariates is in line with Koster's (2018) original analysis of tangible support in Arang Dak. Specifically, the model specification includes sender/row and receiver/column effects for: sex; ethnicity; age; body mass index (BMI); household wealth (log); and skin tone (i.e., a score on a melanin index), the latter of which functions as a source of stigma owing to unique historical circumstances around racial categories in Nicaraguan society (Koster, 2018; Lancaster, 1991). Following Hoff (2018), I also adjusted the AME models for homophily around observed traits with dyadic covariates for: (i) the pairwise product of residents' ages, skin tones, BMIs and log household wealth (e.g., $age_i \times age_j$); and (ii) whether or not two residents have a different sex and a different ethnicity (i.e., $sex_i \neq sex_j$; dyadic inequality). In an attempt to improve the efficiency of the MCMC sampler, residents' values for age, skin tone, BMI and log household wealth were all standardised (i.e., converted to Z-Scores) before model estimation by subtracting the global mean of each variable and dividing by its global standard deviation (see Kruschke, 2015, p. 484–485). The interactions used to capture homophily are between residents' standardised values.

Using four dyadic covariates, the AME models were also adjusted for kinship — the most basic determinant of a “household” outside of coresidence itself (Hammel and Laslett, 1974). The first is for consanguineal relatedness — i.e., the degree to which two individuals are genetically related (derived using genealogical interviews). The second is for affinal relatedness — i.e., the degree to which two individuals are related through marriage (e.g., a husband and his mother-in-law). The third is for fictive or “social” kinship (i.e., family neither by blood or through marriage) in the form of a binary indicator for whether or not two individuals share a godparental relation. And the fourth is a binary indicator for whether or not two individuals are members of households linked through children spawned from extramarital affairs.¹³

Last, I included a dyadic covariate for the distance between residents' homes in metres (log transformed after adding a constant equal to one). As geographic distance necessarily takes on the value of zero for the 183 pairs of coresidents in Arang Dak, a binary dyadic indicator for whether or not two individuals live together is not included in the model specification. Unfortunately, information on which residents serve as head of their household, residents' levels of education and residents' occupations are not available. At the time of data collection, all residents

¹³ Consanguineal relatedness ranges from 0 to 1 where, for example: (i) 0 would indicate that two individuals are not related by blood; (ii) 0.25 would indicate that two individuals are half-siblings, grandparent and grandchild, uncle/aunt and nephew/niece or double first cousins; (iii) 0.5 would indicate that two individuals are parent and child or full siblings; and (iv) 1 would indicate that two individuals are identical twins (here, 0.5 is the maximum). Similarly, affinal relatedness ranges from 0 to 1 where: (i) 0 would indicate that two individuals are not related as a result of marriage; (ii) 0.5 would indicate that two individuals are, for example, genealogically one or two degrees apart through marriage (e.g., a wife and her father-in-law versus a wife and her brother-in-law); and (iii) 1 would indicate that two individuals are married (i.e., a husband's affinal relatedness to his wife is her consanguineal relatedness to herself). Moreover, members of a dyad may have both a consanguineal and an affinal relation (e.g., a mother's blood tie to her child and her affinal tie to her child via her husband). To account for this, Koster (2018) coded affinal relatedness as 0 unless affinal relatedness is greater than or equal to twice the value of consanguineal relatedness for the dyad of interest. As Koster (2018) recounts, this coding decision is ethnographically valid as it reflects perceptions of kinship in Arang Dak which give primacy to marriage-based ties in the absence of stronger blood relations. Last, in the case of multiple third-party affinal ties for i and j , affinal relatedness reflects the strongest.

of Arang Dak were Catholic and community governance had lapsed (J. Koster, personal communication, 9 May 2018) precluding inclusion of covariates around religion and local leadership. See Table 1 for descriptive statistics.

Results

Tables 2 and 3 contain results from the six AME models fit using one, two or three sender- and receiver-specific latent factors R . The posterior mean of each regression coefficient is the expected shift in the latent tie variable z_{ij} associated with a one-unit change in the corresponding covariate, where the observed tie variable $y_{i,j}$ equals one when z_{ij} exceeds zero.

Results unambiguously indicate that dyadic factors play a role in the provision of tangible support in Arang Dak irrespective of sociometric task. Specifically, and focusing on those coefficients that have 95% Highest Density Intervals (HDIs) that exclude zero (i.e., no effect) in all six models, z_{ij} is: negatively associated with increasing physical distance between the homes of the donor of aid i and the person in need j (*Geographic Distance (Log)*) and negatively associated with i and j being different sexes. In line with both Koster's (2018) original analysis of these data and new evidence on the foundations of individual-level village-wide social support networks from rural South India (Power and Ready, 2019), kinship prominently impacts the latent tie variable. More precisely, familial relations by virtue of blood (*Consanguineal Relatedness*), matrimony (*Affinal Relatedness*) and preference (*Godparental Relation*) are all positively associated with z_{ij} , where the converse is the case for residents of Arang Dak who are members of households linked through illegitimate children (*Affair Relation*). Depending on the number of estimated latent factors, there is also evidence to suggest that the ages of i and j combine to impact z_{ij} in a manner indicative of homophily (i.e., positive *Age (SenderXReceiver)*). Moreover, both sets of models indicate that the values of the relationship-specific effects are positively correlated ($\rho \approx 0.40$) which is suggestive of direct reciprocity.

Findings are less conclusive when it comes to the role of the covariates used to capture variation in who tends to be a source of tangible support (i.e., the sender effects) in that results appear to depend on the sociometric task. More specifically, and again focusing on those coefficients that have 95% HDIs that exclude zero (i.e., no effect), the latent tie variable z_{ij} is positively associated with the age of the donor of aid in the AME models of the support seeking network and the AME models of the support giving network. However, only the AME models of the support seeking network indicate that z_{ij} is associated with the darkness of an aid donor's skin tone (*Melanin Index*), where this association is negative. On the other hand, only the AME models of the support giving network indicate that z_{ij} is associated with the sex of the donor of aid, where this association is positive. As for the covariates used to capture variation in who tends to be a target of tangible support (i.e., the receiver effects), results are similarly mixed. Specifically, only the AME models of the support giving network suggest that the traits of those in need are linked to the latent tie variable, where these models indicate that z_{ij} is positively associated with the age of the recipient of aid and negatively associated with the darkness of this individual's skin tone (*Melanin Index*).

Despite differences in the results around the villagers' attributes, there is agreement between the two sets of models in terms of the quality of each specification as indicated by qualitative comparisons of features of the observed networks to distributions of these same features across 100,000 networks simulated under each fitted model (Fig. 2). These goodness-of-fit checks concern monadic, dyadic and triadic dependencies in the observed networks which are respectively operationalised as: (i) the standard deviation of the row and column means (i.e., variability in who gives and receives aid); (ii) the within-dyad correlation (i.e., direct reciprocity); and (iii) normalised measures of

Table 1
Descriptive Statistics.

Variable	Description	Mean	SD	Median	Min	Max	Levels
Sex ^a	Female = 1, Male = 0	—	—	—	0 (N = 54)	1 (N = 54)	2
Ethnicity ^a	Miskito = 1, Mayangna = 0	—	—	—	0 (N = 92)	1 (N = 16)	2
Melanin Index ^a	Measure of skin pigmentation (reflectance spectroscopy) using a resident's forehead. Higher values indicate darker skin tone.	51.55	4.65	50.65	43.4	67	—
Age ^a	Years of age estimated using various methods (e.g., self-reports, government ID, key events).	34.48	13.83	31.5	18	75	—
Body Mass Index (BMI) ^a	A resident's weight (kilograms) divided by their squared height (metres). Weight and height were measured one month before the sociometric interviews.	23.91	2.59	23.47	15.89	32.2	—
Household Wealth ^a	Approximate monetary value (Nicaraguan Córdoba) of the key possessions in a resident's home. Surveyed items include livestock and tools.	654.7	995.09	323.03	49	5259.31	—
Geographic Distance ^b	Distance (metres) between the home of <i>i</i> and the home of <i>j</i> .	518.5	977.16	209.77	0	4396.11	—
Consanguineal Relatedness ^b	Wright's coefficient of relatedness (genealogically derived) between <i>i</i> and <i>j</i> . Bounded between 0 and 1. Higher values indicate that two individuals are more closely related (see also Footnote 13).	0.05	0.11	0	0	0.50	—
Affinal Relatedness ^b	Wright's coefficient of relatedness between <i>i</i> 's spouse <i>s</i> and <i>j</i> (see also Footnote 13).	0.06	0.13	0	0	1	—
Godparental Relation ^b	Symmetric binary indicator for whether resident <i>i</i> is the godparent of resident <i>j</i> (or one or more of <i>j</i> 's children) or vice versa.	—	—	—	0 (N = 5578)	1 (N = 200)	2
Infidelity Relation ^b	Symmetric binary indicator for whether resident <i>i</i> and resident <i>j</i> are members of households with children who are half-siblings as a result of adulterous relations (e.g., $x_{i,j} = 1$ if resident <i>i</i> or one of <i>i</i> 's cohabitants has an illegitimate child in the household of <i>j</i> or vice versa).	—	—	—	0 (N = 5720)	1 (N = 58)	2

^a N = 108 adult residents of Arang Dak.^b N = 5778 dyads in Arang Dak.

transitivity and cyclicity. Both sets of AME models adequately capture monadic and dyadic dependencies in the observed networks and similarly under-perform in their capturing of triadic dependencies — where the generation of networks with an appropriate level of transitive dependence marginally distinguishes the AME models using three latent factors as best fitting. Note that time series and kernel density plots of the posterior samples for the non-varying parameters in each model qualitatively suggest stationarity and good mixing of the Markov chains as well as posterior distributions that are approximately normal in shape (see Supplementary Figures 1–12).

Turning to the question of intra-household relational heterogeneity, Fig. 3 summarises the approximate structural equivalence of coresidents as indicated by the Hamming distance between their positions in the support seeking network and the support giving network. Given two actors *i* and *j* and the sociomatrix *x*, recall that the Hamming distance indicates the number of tie changes needed to make *i*'s structural position identical to *j*'s or vice versa. As expected, exact structural equivalence — i.e., a Hamming distance of zero — is not observed in either network when considering the 183 coresident dyads in the 32 households of Arang Dak. And although some pairs of coresidents in some homes come relatively close to this ideal (e.g., those in Households 2, 15, 23 and 30), the number of “edits” that would be required to make the structural positions of any two coresidents indistinguishable varies substantially within and across the 32 households irrespective of the sociometric task (Hamming Distance: Range [Seeking] = 3–88; Median [Seeking] = 43; Range [Giving] = 4–123; Median [Giving] = 46). Qualitatively speaking, spouses, who are emphasised in Fig. 3 given the predominance of nuclear family-households in Arang Dak, do not appear to be markedly more or less structurally equivalent when visually compared to unmarried individuals.

As for approximate stochastic equivalence, Figs. 4 and 5 are collections of parallel coordinate plots of the estimated latent factors $\mathbf{u} = \{u_1, u_2, u_3\}$ and $\mathbf{v} = \{v_1, v_2, v_3\}$ associated with each resident of Arang Dak from the best-fitting AME models ($R = 3$). Recall that $\mathbf{u}_i = \{u_{i,1}, u_{i,2}, u_{i,3}\}$ and $\mathbf{v}_i = \{v_{i,1}, v_{i,2}, v_{i,3}\}$ respectively characterise *i*'s behaviour as a sender and a receiver of ties beyond that which is accounted for by the observed covariates and the random effects. With respect to the interpretation of Figs. 4 and 5, the 32 miniature plots depict \mathbf{u} and \mathbf{v} for each of the 108 residents (individual lines) grouped based on household membership, where married coresidents are again emphasised. Of interest here is the degree of overlap between coresidents' estimated latent factors across all six latent variables (i.e., how closely the lines track one another within each household), where the degree of overlap indicates the extent to which coresidents are approximately stochastically equivalent conditional on the observed covariates and degree heterogeneity.

With that in mind, it is immediately clear that simply living together is not associated with approximate stochastic equivalence in either the support seeking network or the support giving network. As is to be expected, coresidents who more closely approach structural equivalence (Fig. 3) have more comparable latent factors (e.g., Households 2, 15, 23 and 25). However, across the households of Arang Dak, the degree to which coresidents' latent factors overlap is best described as idiosyncratic such that some homes have coresidents with latent factors that track one another somewhat closely despite the Hamming distances between their observed structural positions (e.g., Households 5 and 8) whereas members of other homes have latent factors that diverge substantially both in direction and magnitude (e.g., Households 1, 3, 4, 18, 22 and 30). As with approximate structural equivalence, spouses do not appear to be markedly more or less approximately stochastically

Table 2
AME Model Parameter Estimates (Support Seeking Network).

	<i>R</i> = 1				<i>R</i> = 2				<i>R</i> = 3			
	PMEAN	HDI-L	HDI-U	ESS	PMEAN	HDI-L	HDI-U	ESS	PMEAN	HDI-L	HDI-U	ESS
Intercept	−0.658	−1.127	−0.195	18676	−0.686	−1.160	−0.186	14004	−0.670	−1.167	−0.150	12096
Sex: Female (Sender)	0.072	−0.176	0.325	49290	0.086	−0.176	0.351	45808	0.091	−0.185	0.362	38072
Ethnicity: Miskito (Sender)	0.177	−0.220	0.572	43193	0.177	−0.236	0.585	39398	0.187	−0.236	0.618	36894
Melanin Index (Sender)	−0.183	−0.316	−0.048	30898	−0.195	−0.334	−0.052	28459	−0.198	−0.343	−0.052	29352
Age (Sender)	0.283	0.166	0.404	49103	0.304	0.182	0.431	35297	0.314	0.182	0.444	26378
BMI (Sender)	0.027	−0.103	0.152	58097	0.031	−0.101	0.164	53678	0.028	−0.109	0.166	48850
Household Wealth (Log; Sender)	0.075	−0.047	0.195	43050	0.074	−0.056	0.200	37811	0.079	−0.053	0.213	29863
Sex: Female (Receiver)	0.226	−0.151	0.622	44314	0.237	−0.176	0.632	37770	0.253	−0.155	0.682	33368
Ethnicity: Miskito (Receiver)	0.075	−0.513	0.657	40860	0.060	−0.556	0.676	40427	0.057	−0.591	0.682	39729
Melanin Index (Receiver)	−0.021	−0.222	0.183	38241	−0.023	−0.234	0.190	32441	−0.021	−0.236	0.203	30268
Age (Receiver)	0.116	−0.067	0.297	49247	0.125	−0.062	0.320	42209	0.127	−0.068	0.329	39653
BMI (Receiver)	−0.156	−0.348	0.040	57201	−0.164	−0.371	0.037	51428	−0.172	−0.380	0.041	41001
Household Wealth (Log; Receiver)	0.035	−0.152	0.221	43032	0.028	−0.173	0.222	38457	0.028	−0.173	0.232	29357
Geographic Distance (Log)	−0.234	−0.284	−0.185	8229	−0.245	−0.297	−0.194	6133	−0.260	−0.315	−0.205	4803
Consanguineal Relatedness (Kinship)	5.692	5.178	6.210	9689	5.823	5.269	6.363	7789	5.975	5.392	6.560	6052
Affinal Relatedness (Kinship)	3.268	2.892	3.648	12355	3.318	2.922	3.714	10167	3.394	2.980	3.805	8542
Godparental Relation (Kinship)	0.602	0.426	0.776	29315	0.609	0.425	0.787	21050	0.652	0.461	0.842	15998
Affair Relation (Kinship)	−1.230	−1.631	−0.839	15809	−1.148	−1.580	−0.706	8801	−1.164	−1.633	−0.715	7067
Different Sex	−0.146	−0.220	−0.074	19704	−0.145	−0.223	−0.070	17367	−0.158	−0.236	−0.080	14774
Different Ethnicity	0.019	−0.140	0.183	16329	0.012	−0.152	0.179	14894	0.012	−0.162	0.180	13492
Melanin Index (SenderXReceiver)	−0.030	−0.069	0.010	16716	−0.030	−0.070	0.011	14632	−0.030	−0.073	0.011	13161
Age (SenderXReceiver)	0.054	0.018	0.091	16167	0.054	0.013	0.093	7982	0.058	0.016	0.101	7548
BMI (SenderXReceiver)	−0.009	−0.046	0.028	20675	−0.006	−0.043	0.032	18988	−0.007	−0.047	0.031	17111
Household Wealth (SenderXReceiver)	0.018	−0.019	0.057	17782	0.023	−0.017	0.063	14885	0.017	−0.026	0.060	7014
σ_a^2	0.328	0.228	0.439	15049	0.362	0.250	0.484	14208	0.390	0.270	0.524	9569
σ_b^2	0.822	0.579	1.093	5483	0.907	0.632	1.200	5015	0.964	0.675	1.279	4072
σ_{ab}	0.075	−0.037	0.191	20818	0.076	−0.047	0.206	17835	0.086	−0.051	0.222	16106
ρ	0.396	0.319	0.471	1333	0.387	0.299	0.468	1099	0.404	0.314	0.489	949

PMEAN = Posterior Mean (**BOLD** regression coefficients have an HDI that excludes zero).

HDI = 95% Highest Density Interval (Lower & Upper; **BOLD** HDIs exclude zero).

ESS = Effective Sample Size (Rounded to the nearest whole number).

Melanin Index, Age, BMI and Household Wealth (Log) are all Z-Scores.

Table 3
AME Model Parameter Estimates (Support Giving Network).

	<i>R</i> = 1				<i>R</i> = 2				<i>R</i> = 3			
	PMEAN	HDI-L	HDI-U	ESS	PMEAN	HDI-L	HDI-U	ESS	PMEAN	HDI-L	HDI-U	ESS
Intercept	−0.538	−0.969	−0.102	18556	−0.629	−1.081	−0.168	9497	−0.658	−1.118	−0.183	15470
Sex: Female (Sender)	0.393	0.060	0.725	70165	0.419	0.079	0.763	51196	0.438	0.079	0.794	46398
Ethnicity: Miskito (Sender)	−0.055	−0.571	0.451	51245	−0.054	−0.580	0.479	46355	−0.056	−0.601	0.499	41741
Melanin Index (Sender)	−0.001	−0.175	0.174	67171	−0.003	−0.187	0.174	55688	−0.008	−0.200	0.178	54353
Age (Sender)	0.210	0.049	0.362	73450	0.217	0.056	0.380	54652	0.225	0.055	0.394	53987
BMI (Sender)	−0.123	−0.292	0.041	76847	−0.124	−0.297	0.048	64218	−0.129	−0.309	0.051	57844
Household Wealth (Log; Sender)	0.049	−0.111	0.209	52369	0.050	−0.116	0.216	43630	0.056	−0.117	0.230	42014
Sex: Female (Receiver)	0.071	−0.148	0.289	54038	0.066	−0.161	0.289	43229	0.071	−0.172	0.302	33995
Ethnicity: Miskito (Receiver)	0.025	−0.333	0.367	34584	−0.001	−0.360	0.372	22813	−0.005	−0.393	0.370	20470
Melanin Index (Receiver)	−0.120	−0.238	−0.008	44744	−0.122	−0.242	−0.003	35049	−0.127	−0.252	−0.002	30930
Age (Receiver)	0.333	0.230	0.436	50547	0.353	0.247	0.465	21177	0.367	0.249	0.483	13721
BMI (Receiver)	−0.049	−0.159	0.061	55900	−0.047	−0.161	0.068	34095	−0.050	−0.166	0.074	30387
Household Wealth (Log; Receiver)	0.040	−0.064	0.148	39697	0.033	−0.078	0.143	21045	0.035	−0.083	0.148	26861
Geographic Distance (Log)	−0.226	−0.275	−0.177	8498	−0.219	−0.274	−0.165	2886	−0.229	−0.283	−0.176	6629
Consanguineal Relatedness (Kinship)	5.665	5.135	6.205	10396	5.763	5.186	6.341	5128	6.003	5.407	6.601	6263
Affinal Relatedness (Kinship)	3.232	2.853	3.606	13859	3.271	2.873	3.676	6190	3.405	2.999	3.829	8681
Godparental Relation (Kinship)	0.707	0.532	0.881	32036	0.705	0.526	0.890	17849	0.714	0.532	0.904	21505
Affair Relation (Kinship)	−1.271	−1.663	−0.890	15978	−1.362	−1.810	−0.925	6110	−1.439	−1.905	−0.970	6725
Different Sex	−0.146	−0.217	−0.075	22633	−0.154	−0.230	−0.078	6834	−0.145	−0.222	−0.066	13555
Different Ethnicity	0.118	−0.039	0.279	17144	0.124	−0.038	0.289	14927	0.128	−0.040	0.303	13109
Melanin Index (SenderXReceiver)	−0.012	−0.050	0.025	20567	−0.011	−0.048	0.028	18867	−0.011	−0.050	0.029	17455
Age (SenderXReceiver)	0.060	0.024	0.097	17807	0.057	0.013	0.102	2446	0.045	−0.005	0.096	2969
BMI (SenderXReceiver)	0.005	−0.029	0.040	25195	0.002	−0.034	0.038	13754	0.001	−0.036	0.038	19171
Household Wealth (SenderXReceiver)	−0.006	−0.043	0.031	19280	−0.003	−0.042	0.036	14644	−0.004	−0.044	0.036	13948
σ_a^2	0.602	0.418	0.804	16767	0.645	0.446	0.857	16187	0.700	0.489	0.941	14587
σ_b^2	0.245	0.169	0.328	16573	0.260	0.180	0.349	13022	0.285	0.195	0.380	11785
σ_{ab}	0.094	0.008	0.184	18461	0.096	0.005	0.193	16376	0.102	0.004	0.207	16069
ρ	0.427	0.363	0.493	1596	0.419	0.342	0.493	1263	0.434	0.355	0.508	1166

PMEAN = Posterior Mean (**BOLD** regression coefficients have an HDI that excludes zero).

HDI = 95% Highest Density Interval (Lower & Upper; **BOLD** HDIs exclude zero).

ESS = Effective Sample Size (Rounded to the nearest whole number).

Melanin Index, Age, BMI and Household Wealth (Log) are all Z-Scores.

equivalent when visually compared to those unmarried individuals in their home (e.g., Households 3, 6, 15, 18, 22 and 30).

Discussion

In this paper, I have explored the degree to which coresidents might be expected to have identical sets of social relationships — a simple matter of practical relevance to field researchers interested in exclusively relying on the sociometric reports of household representatives to measure networks spanning entire villages in LMICs. Past scholarship around intra-household dynamics and my exploratory case study on

coresidence and network position in Arang Dak both indicate that adults who live together are unlikely to substantially approach the ideal of structural equivalence or its generalisation in the form of stochastic equivalence in an individual-level village-wide network. Put simply, intra-household relational heterogeneity is not ignorable. Accordingly, field researchers planning to measure relations that do not naturally sit at the level of the household run the risk of overlooking information on the connectivity of villagers should they assume that the egocentric network of any one coresident, or, more generally, the manner in which a coresident tends to send and receive their ties, is representative of their home.

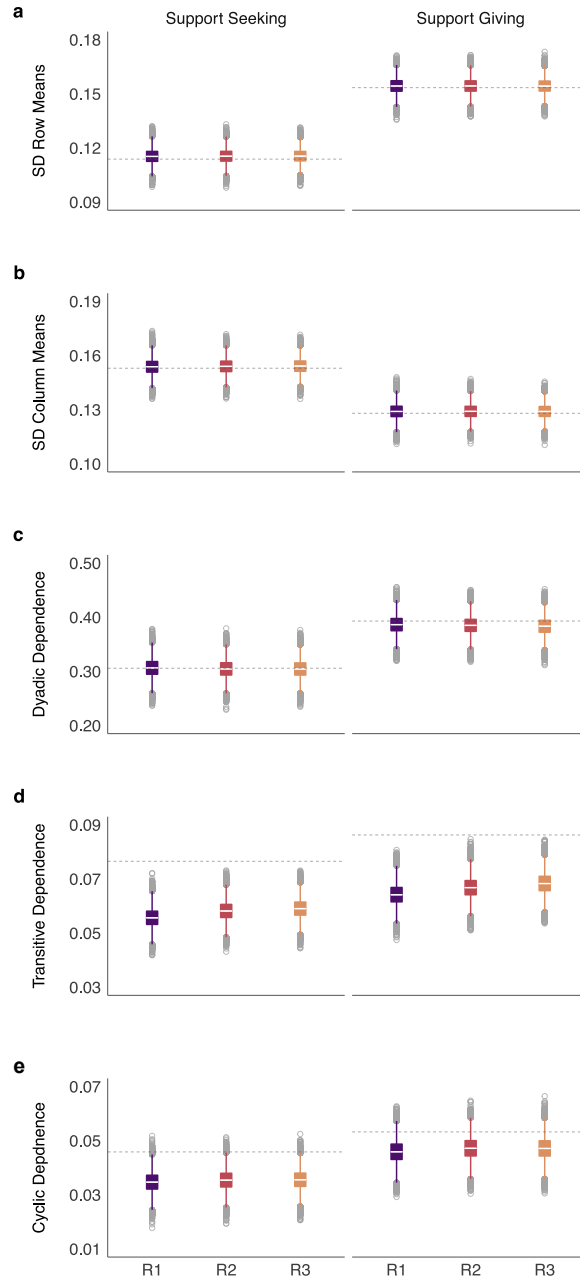


Fig. 2. Goodness-of-fit checks for the AME models of the support seeking network (left) and the support giving network (right), where each AME model was estimated using one, two or three latent factors R . Goodness-of-fit was assessed using: (a) the standard deviation of the row means of the observed connectivity matrix Y ; (b) the standard deviation of the column means of Y ; (c) the dyadic dependence of Y ; (d) the transitive dependence of Y ; and (e) the cyclic dependence of Y . The observed value of each network statistic is indicated by the horizontal dashed line whereas the boxplots represent the distribution of these statistics for the 100,000 connectivity matrices Y' generated at each iteration of the MCMC sampler. The version of the R package “amen” (Hoff, 2018) that I relied on for this research uses a normalised transitive dependence metric and a normalised cyclic dependence metric respectively calculated as $\frac{\sum_i^V \sum_{j,k \neq i}^V Y_{ij} Y_{ki} Y_{jk}}{\text{Number of Possible Triangles for } V \text{ nodes} \times \sigma_Y^3}$ and

$\frac{\sum_i^V \sum_{j,k \neq i}^V Y_{ij} Y_{ki} Y_{jk}}{\text{Number of Possible Triangles for } V \text{ nodes} \times \sigma_Y^3}$. In both instances and ignoring the diagonal elements, σ_Y^3 is the cubed standard deviation of the elements of the observed/simulated connectivity matrix, where the observed/simulated connectivity matrix is mean centred for the summation in the numerator of each equation. The dyadic dependence metric is simply the correlation between the elements of the observed/simulated connectivity matrix and its transposed version.

Of course, in casting village social structure as a multilevel network I have drawn a rather neat distinction between social ties established in line with personal preference and relations resulting from coresidents' joint decision-making. Yet, in practice, how a particular social tie comes into being, and thus the level at which it sits, may not be immediately obvious¹⁴ or it may even be subject to conflicting treatment across published research.¹⁵ Consequently, targeted data gathering to confirm whether the tie of interest sits at the household level or the individual level strikes me as a critical step in ensuring the validity of the design of sociocentric studies of villages in LMICs.

As my brief review of anthropological work on the exchange of garden labour, food and seeds makes clear, field researchers would ideally know something about the intra-household dynamics around the tie of interest before they carry out their main sociometric interviews. Usefully, a standard practice when studying villages is to begin by: (i) collating contextual data (e.g., on local history, infrastructure and environmental conditions); (ii) charting village geography (e.g., the location of households and landmarks); (iii) collecting basic information on village residents with the aid of local authorities (e.g., household membership); and, ultimately, (iv) building the sampling frame used to

select individuals for household surveys, sociometric interviews and other forms of data collection (e.g., behavioural games).¹⁶ During this preliminary fieldwork, qualitative information that can be used to ascertain whether dialectics within the home are integral to the establishment of the tie of interest should be collected from a representative sample of households in the village under study using some combination of individual and group interviews with coresidents as opposed to simply relying on household heads given the risk of non-trivial intra-household heterogeneity and, more generally, the pitfalls associated with defining and measuring headship (Budlender, 2003).¹⁷ Key relational questions to be answered during these interviews about home life include:

- I How functionally autonomous are coresidents in terms of work, leisure and other quotidian activity?
- II Under what circumstances, and in what fashions, do coresidents convene to make “family” decisions?
- III In what ways do coresidents help one another and share (or not share) resources such as food, information, money and material goods originating outside of the home?
- IV Under what circumstances, if any, do coresidents consult one another about their social contacts (e.g., “friends” and “confidantes”) and their preferred targets for the informal transfer of resources?
- V Are there general expectations — or even rigid norms — about who coresidents should (or should not) establish social relations with?

Returning to the litmus test posed in the introduction of this paper, in those cases where responses to these questions suggest that: (i) coresidents jointly decide on their alters for the tie of interest; and (ii) coresidents can reasonably be expected to be jointly selected as alters (or their incoming ties defensibly agglomerated),¹⁸ a village-wide network may be measured at the household level using sociometric interviews with one or more representatives of the home. On the other hand, should either one of these aspects of selecting alters/being selected as alters fail to characterise the establishment of the tie of interest, a sociometric census at the individual level stands to minimise loss of information on connectivity.

That said, resource constraints — whether related to time, money or manpower — and their implications for the feasibility of a sociometric census cannot be summarily dismissed. Accordingly, the primary question to be answered by the field researcher keen to manage costs by solely relying on household representatives' reports on a social tie clearly established in line with personal preference is whether the aims of their study can be met with an analysis of what is fundamentally a

¹⁴ Considering Perkins et al.'s (2015, p. 71–73) enumeration of 105 name generators used in previously published sociocentric studies of villages in LMICs, the nature of the intentionality behind some of the social relationships typically of interest to field researchers is, arguably, self-evident in that these ties are obviously personal and thus clearly sit at the level of individuals (e.g., sexual contacts and keepers of secrets). Nevertheless, the establishment of ostensibly individual-level ties may be subject to household-level dynamics. For example, in his extensive comparison of friendship across sixty cultures, Hruschka (2010, p. 66–67) details the non-voluntary nature of friendship outside of Western locales such as the United States by underscoring that in some societies friend choice can be highly restricted by third-parties — including families who may actively arrange and authorize friendships or even replicate friendships across generations along genealogical lines (see also Adams and Plaut (2003) on the differences between friendship in the US and Ghana and Kito et al. (2017) and Thomson et al. (2018) on societal-level variation in relational mobility, i.e., one's ability to establish and terminate interpersonal relationships in line with their personal preferences). Practically speaking, Hruschka's (2010) observations suggest that the same sociometric question, in this case “Who are your close friends?”, could yield data on social ties that come into being in quite different fashions across sociocultural environments. As a result, the thoughtful selection and context-specific framing of sociometric questions (e.g., with the aid of small pilot studies, secondary information sources and/or area experts) will be vital to ensuring that the social tie of interest to a researcher is measured at the level appropriate for answering their research question.

¹⁵ Indeed, researchers have collected sociometric reports on ostensibly similar ties at both the individual and household levels for their sociocentric analyses of villages — even in communities in broadly similar locales. For example, consider three studies wherein the authors measured multiple types of social support (e.g., informal financial lending, advice seeking and emergency aid) in South India using similar sociometric questions but quite different study designs. Specifically, for their well-known study on the diffusion of information about microfinance in Karnataka, Banerjee et al. (2013) effectively take a hybrid approach to the issue of level by using complex sampling based on the traits of households (gender composition, religion and location) to collect sociometric reports from household heads, the heads' spouses and women coresidents and their spouses. In contrast, Johnny et al. (2017) used some of the same name generators devised by Banerjee et al. (2013) but instead relied on the sociometric reports of “a member of the household older than 18 years of age” (p. 377) for their household-level study on income diversification in Kerala. On the other hand, Power (2017) used name generators similar in spirit to those of Banerjee et al. (2013) but conducted sociometric interviews with all adults over the age of 18 for her study on religiosity and access to various types of informal aid in Tamil Nadu.

¹⁶ For an informative long-form example of such preliminary data collection, see the field report summarising social and economic life in Nyakatoke (Mitti and Rweyemamu, 2001), a rural village in the Kagera Region of Tanzania studied by De Weerd (2004) for his work on risk sharing.

¹⁷ Of course, there may be scenarios wherein this initial data gathering is inappropriate. For example, Larson and Lewis (2017) did not perform an initial demographic census for their study on the diffusion of information in two Ugandan villages under the assumption that villagers' awareness of their presence could have biased the diffusion process.

¹⁸ For example, consider Koster's (2011) study on meat exchange wherein he notes that despite coresidents sometimes identifying specific targets of food-based altruism in another home, there is a clear understanding that meat will be shared by all members of the recipient's household.

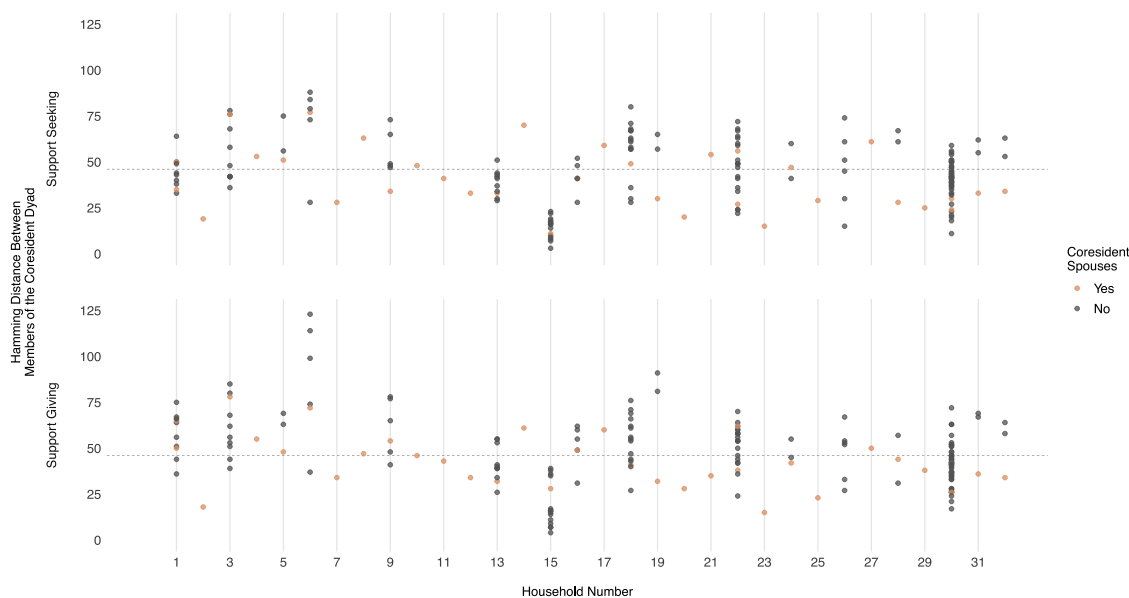


Fig. 3. Pairwise distance between the structural positions of coresidents in the support seeking network (top) and the support giving network (bottom). Each of the 183 pairs of coresidents in the 32 households in Arang Dak are represented by a bullet, where a single bullet in a single household (e.g., Household 17) indicates that a dwelling is home to just one coresident dyad (i.e. only two adults i and j). The y-axis indicates the extent to which the structural positions of i and j do not overlap using the Hamming distance — i.e., the number of tie changes needed to make i 's structural position identical to j 's or vice versa given a sociomatrix x . Bullets are coloured to reflect whether the associated coresidents are married (i.e., an affinal relatedness equal to one), where some homes may have multiple sets of spouses (e.g., Household 22). The dashed lines indicate the median value of the Hamming distance across the 183 pairs of coresidents.

subgraph of the village-wide network of interest.^{19,20} Should meeting study aims require the complete inter-individual network spanning the village and reliance on the sociometric reports of household representatives still be preferred, my empirical findings suggest that some scepticism about the representativeness of the subgraph that is ultimately measured is justified. Again, I have analysed cross-sectional data from just one community. However, the idiosyncratic variation in the degree to which coresidents depart from the ideals of structural and stochastic equivalence within and across the 32 households of Arang Dak unambiguously indicates that exclusively relying on the sociometric reports of different coresidents could easily result in the measurement of different subnetworks.

Along this line, my findings also raise concerns about the utility of any uniform application of a simple criterion for the selection of household representatives for sociometric interviews. For field researchers intending to collect cross-sectional data, it is not immediately

obvious how one might manage coresidents' idiosyncratic departures from structural and stochastic equivalence outside of heavily relying on the suggested interviews about home life to construct respondent selection strategies tailored to households with certain profiles (e.g., age composition, gender composition and types of coresident kin). However, for longitudinal studies, perhaps one path forward is the exploitation of their temporal component. Specifically, a field researcher might first conduct interviews about home life vis-à-vis the social tie of interest and then carry out a baseline sociometric census of adults in the village under study. The information from the interviews about home life could then be combined with an assessment of coresidence and structural and stochastic equivalence using the baseline network data in a manner akin to the analysis I have presented here in order to design household-specific respondent selection strategies for subsequent waves of data collection. Of course, the suggested interviews may quickly become impractical as the number of households under study grows. Furthermore, longitudinal sociocentric studies of villages are sure to bring their own unique challenges outside of path-dependent network evolution which, as [Kasper and Bergerhoff Mulder \(2015\)](#) remind us, include the instability of marriages and households over time and the shifting composition of the home stemming from the extended hosting of kin. Nevertheless, this data-driven approach seems far more preferable to the uncritical use of the sociometric reports of household representatives which may work well for some pairs of coresidents in some homes and rather poorly in others.

To close, two limitations of this work merit comment. First, "households" take on a number of basic forms including single-person, non-family, simple-family (i.e., nuclear/elementary/conjugal), extended-family and multiple-family homes (see [Hammel and Laslett, 1974](#)). As Arang Dak is centred around the nuclear family, conclusions based on my empirical findings may not directly map to scenarios wherein different types of households and residency norms dominate. That said, I submit that my theoretical argument — i.e., that village social structure is fundamentally multilevel — has wide relevance such that it is generally wise for field researchers to expect to observe some divergence in the structural positions of coresidents in an individual-level village-wide network irrespective of setting.

¹⁹ For example, in their study on Chinese rice producers' adoption of weather insurance, [Cai et al. \(2015\)](#) only measured friendship amongst the heads of rice-producing households in the villages they studied, randomly inviting some of these individuals to information sessions for the purposes of an experiment on whether farmers' occupation-relevant social ties play a role in their decision to adopt insurance.

²⁰ Although I have focused on whether field researchers ought to view one coresident's egocentric network as representative of their home, a distinct, but related, issue is whether field researchers should attempt to measure a complete individual-level village-wide network by asking one household member to report the alters of their coresidents (i.e., "proxy nominations"). Given: (i) the abovementioned anthropological work by [Wencélius et al. \(2016\)](#) and research by development economists such as [Bardasi et al. \(2011\)](#) suggesting that responses to questions on household surveys stand to differ depending on which coresidents are asked; (ii) long-recognised issues around respondents' poor recall of their own alters ([Brewer, 2000](#); [Lee and Butts, 2018](#)); and (iii) the body of work on "cognitive social structures" — i.e., scholarship premised on the idea that individuals may perceive the same network differently given the complexity, multiplexity and dynamism of social relationships (see [Brands, 2013](#)) — use of proxy nominations also strikes me as a problematic means of data collection.

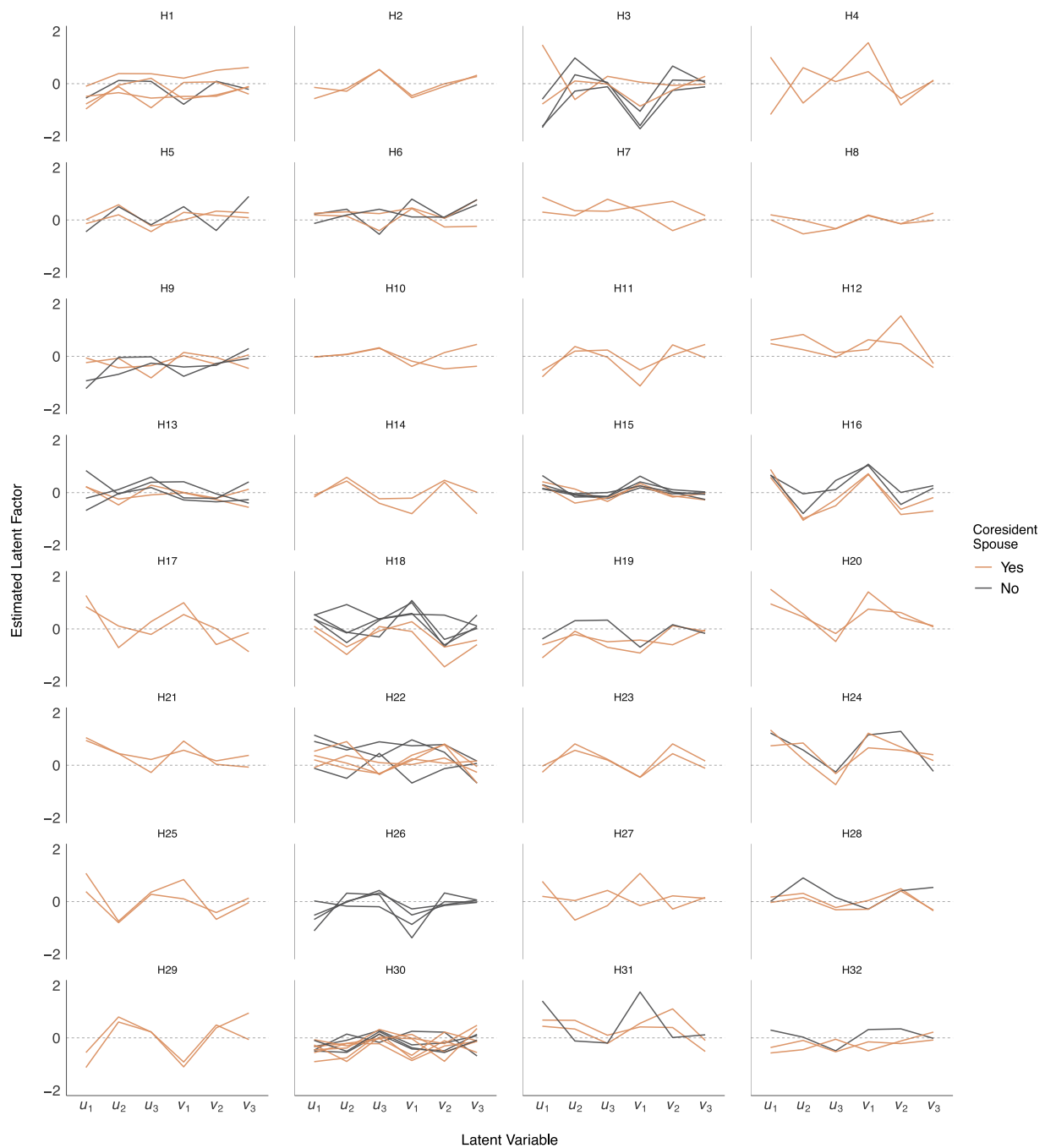


Fig. 4. A “small-multiple” of parallel coordinate plots depicting the degree to which coresidents approach approximate stochastic equivalence based on the best-fitting AME model of the support seeking network ($R = 3$). Each line represents one coresident and it links the posterior mean of each of the estimated latent factors used to summarise this coresident’s behaviour as a sender and receiver of ties over and above the observed covariates and degree heterogeneity. Given two coresidents, approximate stochastic equivalence is indicated by the overlap of lines across all estimated latent factors (e.g., Household 2 or “H2”). Each line is coloured to reflect whether or not its associated coresident is married to someone else in the home (i.e., an affinal relatedness equal to one), where some homes may have multiple sets of spouses and thus more than two coloured lines (e.g., Household 22). Note that the estimated latent factors may be arranged along the x-axis in any arbitrary fashion. Here they are simply grouped by latent variable type (i.e., Sender = u; Receiver = v) in increasing order by latent variable number (i.e., $R = 1, 2$ or 3).

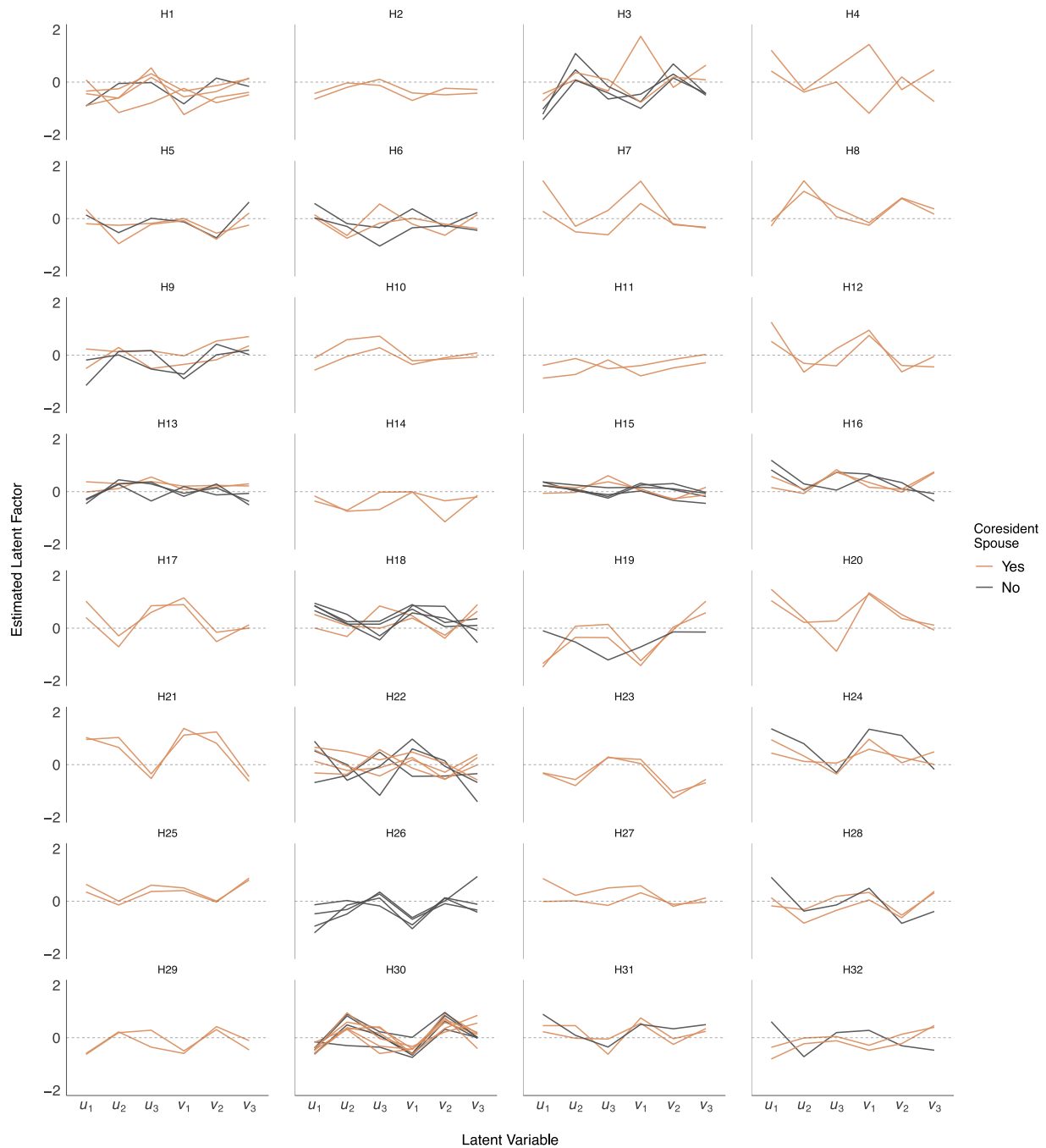


Fig. 5. A “small-multiple” of parallel coordinate plots depicting the degree to which coresidents approach approximate stochastic equivalence based on the best-fitting AME model of the support giving network ($R = 3$). Each line represents one coresident and it links the posterior mean of each of the estimated latent factors used to summarise this coresident’s behaviour as a sender and receiver of ties over and above the observed covariates and degree heterogeneity. Given two coresidents, approximate stochastic equivalence is indicated by the overlap of lines across all estimated latent factors (e.g., Household 23 or “H23”). Each line is coloured to reflect whether or not its associated coresident is married to someone else in the home (i.e., an affinal relatedness equal to one), where some homes may have multiple sets of spouses and thus more than two coloured lines (e.g., Household 22). Note that the estimated latent factors may be arranged along the x-axis in any arbitrary fashion. Here they are simply grouped by latent variable type (i.e., Sender = u ; Receiver = v) in increasing order by latent variable number (i.e., $R = 1, 2$ or 3).

And second, I have only analysed one type of tie (tangible support) in one small community in Nicaragua. Studies concerning much larger communities in India (Power, 2017; Shakya et al., 2017b) and Honduras (Isakov et al., 2019; Shakya et al., 2017a) have demonstrated that village social structure can be highly multiplex at the individual level. Where network data collection is concerned, the upshot of this work is that measuring multiple types of relationships is necessary to build the most complete understanding of how village residents relate to one another. As a result, the expected lack of structural and stochastic equivalence amongst coresidents poses a special challenge for field researchers interested in several types of self-directed ties as two people who live together may have similar portfolios of direct connections for one relation and quite different sets of alters for another. Consequently, the suggested interviews about home life and any baseline assessments of network structure should cover all ties of interest.

Acknowledgements

I thank Jeremy Koster for sharing his data from Nicaragua and graciously fielding my queries and, for their participation, I am also deeply grateful to the residents of Arang Dak. Furthermore, I thank Mark Sarazin for his invaluable feedback, Peter D. Hoff for his methodological guidance and the two anonymous reviewers for their formative critique. Finally, this research would not have been possible without the generous support of a British Academy Postdoctoral Fellowship (Grant Number: pf170158).

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:<https://doi.org/10.1016/j.socnet.2020.02.010>.

References

- Adam, L., 1947. Virilocal and uxorial. *Am. Anthropol.* 49 (4) <https://doi.org/10.1525/aa.1947.49.4.02a00220>, 678–678.
- Adams, G., Plaut, V.C., 2003. The cultural grounding of personal relationship: friendship in North American and West African Worlds. *Pers.* 10 (3), 333–347. <https://doi.org/10.1111/1475-6811.00053>.
- Advani, A., Malde, B., 2014. Empirical Methods for Networks Data: Social Effects, Network Formation and Measurement Error. Institute of Fiscal Studies. <https://doi.org/10.1920/wp.ifs.2014.1434>.
- Alderman, H., Chiappori, P.-A., Haddad, L., Hoddinott, J.F., Kanbur, R., 1995. Unitary versus collective models of the household: is it time to shift the burden of proof? *World Bank Res. Obs.* 10 (1), 1–19. <https://www.jstor.org/stable/3986564>.
- Aldrich, D.P., Meyer, M.A., 2015. Social capital and community resilience. *Am. Behav. Sci.* 59 (2), 254–269. <https://doi.org/10.1177/0002764214550299>.
- Alwang, J., Larochelle, C., Barrera, V., 2017. Farm decision making and gender: results from a randomized experiment in Ecuador. *World Dev.* 92, 117–129. <https://doi.org/10.1016/j.worlddev.2016.11.015>.
- Ambler, K., Doss, C., Kieran, C., Passarelli, S., Forthcoming. He says, she says: spousal disagreement in survey measures of bargaining power. *Econ. Dev. Cult. Change*. <https://doi.org/10.1086/703082>.
- Apicella, C.L., Marlowe, F.W., Fowler, J.H., Christakis, N.A., 2012. Social networks and cooperation in hunter-gatherers. *Nature* 481, 497–501. <https://doi.org/10.1038/nature10736>.
- Baldassarri, D., Diani, M., 2007. The integrative power of civic networks. *Am. J. Sociol.* 113 (3), 735–780. <https://doi.org/10.1086/521839>.
- Banerjee, A., Chandrasekhar, A.G., Dufo, E., Jackson, M.O., 2013. The diffusion of microfinance. *Science* 341 (6144), 1236–1240. <https://doi.org/10.1126/science.1236498>.
- Bardasi, E., Beegle, K., Dillon, A., Serneels, P., 2011. Do labor statistics depend on how and to whom the questions are asked? Results from a survey experiment in Tanzania. *World Bank Econ. Rev.* 25 (3), 418–447. <https://doi.org/10.1093/wber/lhr022>.
- Beaman, L., Dillon, A., 2018. Diffusion of agricultural information within social networks: evidence on gender inequalities from Mali. *J. Dev. Econ.* 133, 147–161. <https://doi.org/10.1016/j.jdevco.2018.01.009>.
- Borgatti, S.P., Everett, M.G., 1992. Notions of position in social network analysis. *Sociol. Methodol.* 22, 1–35. <https://www.jstor.org/stable/270991>.
- Bott, E., 1955. Urban families: conjugal roles and social networks. *Hum. Relat.* 8 (4), 345–384. <https://doi.org/10.1177/001872675500800401>.
- Brailly, J., Favre, G., Chatellet, J., Lazega, E., 2016. Embeddedness as a multilevel problem: a case study in Economic Sociology. *Soc. Networks* 44, 319–333. <https://doi.org/10.1016/j.socnet.2015.03.005>.
- Brands, R.A., 2013. Cognitive Social Structures in social network research: a review. *J. Organ. Behav.* 34 (S1), S82–S103. <https://doi.org/10.1002/job.1890>.
- Brewer, D.D., 2000. Forgetting in the recall-based elicitation of personal and social networks. *Soc. Networks* 22 (1), 29–43. [https://doi.org/10.1016/S0378-8733\(99\)00017-9](https://doi.org/10.1016/S0378-8733(99)00017-9).
- Budlender, D., 2003. The debate about household headship. *Soc. Dyn.* 29 (2), 48–72. <https://doi.org/10.1080/02533950308628675>.
- Burt, R.S., 1976. Positions in networks. *Soc. Forces* 55 (1), 93–122. <https://doi.org/10.1093/sf/55.1.93>.
- Butts, C.T., 2008. Social network analysis with “sna”. *J. Stat. Softw.* 24 (6), 1–51. <https://doi.org/10.18637/jss.v024.i06>.
- Cai, J., Janvry, A.D., Sadoulet, E., 2015. Social networks and the decision to insure. *Am. Econ. J. Appl. Econ.* 7 (2), 81–108. <https://www.aeaweb.org/articles?id=10.1257/app.20130442>.
- Castilla, C., Walker, T., 2013. Is ignorance bliss? The effect of asymmetric information between spouses on intra-household allocations. *Am. Econ. Rev.* 103 (3), 263–268. <https://www.aeaweb.org/articles?id=10.1257/aer.103.3.263>.
- Caudell, M., Rotolo, T., Grima, M., 2015. Informal lending networks in rural Ethiopia. *Soc. Networks* 40, 34–42. <https://doi.org/10.1016/j.socnet.2014.07.003>.
- Chami, G.F., et al., 2016. Profiling nonrecipients of mass drug administration for Schistosomiasis and hookworm infections: a comprehensive analysis of Praziquantel and Albendazole coverage in community-directed treatment in Uganda. *Clin. Infect. Dis.* 62 (2), 200–207. <https://doi.org/10.1093/cid/civ829>.
- Chami, G.F., et al., 2017. Community-directed mass drug administration is undermined by status seeking in friendship networks and inadequate trust in health advice networks. *Soc. Sci. Med.* 183, 37–47. <https://doi.org/10.1016/j.socscimed.2017.04.009>.
- D'Exelle, B., Holvoet, N., 2011. Gender and network formation in rural Nicaragua: a village case study. *Fem. Econ.* 17 (2), 31–61. <https://doi.org/10.1080/13545701.2011.573488>.
- De Weerd, J., 2004. Risk-sharing and endogenous network formation. In: Dercon, S. (Ed.), *Insurance Against Poverty*. Oxford University Press, pp. 197–216.
- Doss, C., 2013. Intra-household bargaining and resource allocation in developing countries. *World Bank Res. Obs.* 28 (1), 52–78. <https://doi.org/10.1093/wbro/ltk001>.
- Doss, C., et al., 2018. Do men and women estimate property values differently? *World Dev.* 107, 75–86. <https://doi.org/10.1016/j.worlddev.2018.02.012>.
- Entwistle, B., Faust, K., Rindfuss, R.R., Kaneda, R., 2007. Networks and contexts: variation in the structure of social ties. *Am. J. Sociol.* 112 (5), 1495–1533. <https://doi.org/10.1086/511803>.
- Ferrali, R., Grossman, G., Platas, M.R., Rodden, J., 2020. It takes a village: peer effects and externalities in technology adoption. *Am. J. Polit. Sci.* <https://doi.org/10.1111/ajps.12471>.
- Feld, S.L., 1981. The focused organization of social ties. *Am. J. Sociol.* 86 (5), 1015–1035. <https://www.jstor.org/stable/2778746>.
- Foster, B.L., 1984. Family structure and the generation of Thai social exchange networks. In: Netting, R.M., Wilk, R.R., Arnould, E.J. (Eds.), *Households: Comparative and Historical Studies of the Domestic Group*. University of California Press, pp. 84–105.
- Giudici, F., Widmer, E., 2017. Gendered occupational shifts in the transition to parenthood: the influence of personal networks. *Sociology* 51 (2), 429–449. <https://doi.org/10.1177/0038038515601857>.
- Goeyvaerts, N., et al., 2018. Household members do not contact each other at random: implications for infectious disease modelling. *Proc. R. Soc. B: Biol. Sci.* 285 <https://doi.org/10.1098/rspb.2018.2201>, 2018 2201.
- Gulati, R., Gargiulo, M., 1999. Where do interorganizational networks come from? *Am. J. Sociol.* 104 (5), 1439–1493. <https://doi.org/10.1086/210179>.
- Harling, G., et al., 2018. Interviewer-driven variability in social network reporting. *Field methods* 30 (2), 140–154. <https://doi.org/10.1177/1525822X18769498>.
- Haenssge, M.J., 2015. Satellite-aided survey sampling and implementation in low- and Middle-Income contexts: a low-cost/low-tech alternative. *Emerg. Themes Epidemiol.* 12, 12–20. <https://doi.org/10.1186/s12982-015-0041-8>.
- Haenssge, M.J., et al., 2018. Antibiotics and activity spaces: protocol of an exploratory study of behaviour, marginalisation and knowledge diffusion. *BMJ Glob. Health* 3 (2), e000621. <https://gh.bmj.com/content/3/2/e000621>.
- Hames, R., 1987. Garden labor exchange among the Ye'kwana. *Ethol. Sociobiol.* 8 (4), 259–284. [https://doi.org/10.1016/0162-3095\(87\)90028-8](https://doi.org/10.1016/0162-3095(87)90028-8).
- Hammel, E.A., Laslett, P., 1974. Comparing household structure over time and between cultures. *Comp. Stud. Soc. Hist.* 16 (1), 73–109. <https://doi.org/10.1017/S0010417500007362>.
- Hanneman, R., Riddle, M., 2005. Introduction to Social Network Methods. University of California Riverside. <https://faculty.ucr.edu/~hanneman/>.
- Heaney, M.T., 2014. Multiplex networks and interest group influence reputation: an exponential random graph model. *Soc. Networks* 36, 66–81. <https://doi.org/10.1016/j.socnet.2012.11.003>.
- Heaney, M.T., Leifeld, P., 2018. Contributions by interest groups to lobbying coalitions. *J. Polit.* 80 (2), 494–509. <https://doi.org/10.1086/694545>.
- Herz, A., Petermann, S., 2017. Beyond interviewer effects in the standardized measurement of ego-centric networks. *Soc. Networks* 50, 70–82. <https://doi.org/10.1016/j.socnet.2017.01.003>.
- Hoddinott, J.F., Dercon, S., Krishnan, P., 2009. Networks and informal mutual support in 15 Ethiopian villages. In: Kirsten, J.F., Dorward, A.R., Poulton, C., Vink, N. (Eds.), *Institutional Economics Perspectives on African Agricultural Development*. International Food Policy Research Institute, pp. 273–286. <http://ebrary.ifpri.org/digital/collection/p15738coll2/id/129489>.
- Hoff, P.D., 2008. Modeling homophily and stochastic equivalence in symmetric relational data. In: Platt, J.C., Koller, D., Singer, Y., Roweis, S.T. (Eds.), *Advances in Neural Information Processing Systems Workshop on Topic Models Computation, Application, and Evaluation 20*. Neuro Information Processing Systems 2007,

- pp. 657–664. In: <https://papers.nips.cc/book/advances-in-neural-information-processing-systems-20-2007>.
- Hoff, P.D., 2009. Multiplicative latent factor models for description and prediction of social networks. *Comput. Math. Organ. Theory* 15 (4), 261–272. <https://doi.org/10.1007/s10588-008-9040-4>.
- Hoff, P.D., 2018. Dyadic data analysis with "amen" (v. 1.4.3). GitHub 1–49. <https://github.com/pdhoff/amen/blob/master/inst/doc/amen.pdf>.
- Hogan, B., et al., 2020. Assessing the stability of egocentric networks over time using the digital participant-aided sociogram tool. *Network Canvas. Network Science* 8 (2), 204–222. <https://doi.org/10.1017/nws.2019.27>.
- Hogan, B., et al., 2016. Evaluating the paper-to-screen translation of participant-aided sociograms with high-risk participants. In: CHI' 16: Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems. ACM Press, pp. 5360–5371. <https://doi.org/10.1145/2858036.2858368>.
- Hruschka, D.J., 2010. *Friendship: Development, Ecology, and Evolution of a Relationship*. University of California Press.
- Hsung, R.-M., Yi, C.-C., Fu, Y.-C., 2006. Overlapping social networks: how couples manage family expenditure in Taiwan. *Curr. Sociol.* 54 (2), 187–208. <https://doi.org/10.1177/0011392106056741>.
- Isakov, A., Fowler, J., Airoidi, E., Christakis, N.A., 2019. The structure of negative social ties in rural village networks. *Sociol. Sci.* 6, 197–218. <https://www.sociologicalscience.com/articles-v6-8-197/>.
- Ishii-Kuntz, M., Maryanski, A.R., 2003. Conjugal roles and social networks in Japanese families. *J. Fam. Issues* 24 (3), 352–380. <https://doi.org/10.1177/0192513X02250890>.
- Jaimovich, D., 2011. Macrostructure and Microstructure: Evidence from Overlapping Village Networks in the Gambia. SSRN. <https://doi.org/10.2139/ssrn.2208048>.
- Johny, J., Wichmann, B., Swallow, B.M., 2017. Characterizing social networks and their effects on income diversification in rural Kerala, India. *World Dev.* 94, 375–392. <https://doi.org/10.1016/j.worlddev.2017.02.002>.
- Kalmijn, M., 2003. Shared friendship networks and the Life Course: an analysis of survey data on married and cohabiting couples. *Soc. Networks* 25 (3), 231–249. [https://doi.org/10.1016/S0378-8733\(03\)00010-8](https://doi.org/10.1016/S0378-8733(03)00010-8).
- Kasper, C., Borgerhoff Mulder, M., 2015. Who helps and why? Cooperative networks in Mpimbwe. *Curr. Anthropol.* 56 (5), 701–732. <https://doi.org/10.1086/683024>.
- Kebede, B., Tarazona, M., Munro, A., Verschoor, A., 2014. Intra-household efficiency: an experimental study from Ethiopia. *J. Afr. Econ.* 23 (1), 105–150. <https://doi.org/10.1093/jae/ejt019>.
- Kennedy, D.P., Jackson, G.L., Green, H.D., Bradbury, T.N., Karney, B.R., 2015. The analysis of duocentric social networks: a primer. *J. Marriage Fam.* 77 (1), 295–311. <https://doi.org/10.1111/jomf.12151>.
- Kito, M., Yuki, M., Thomson, R., 2017. Relational mobility and close relationships: a socioecological approach to explain cross-cultural differences. *Pers.* 24 (1), 114–130. <https://doi.org/10.1111/pere.12174>.
- Koster, J.M., 2007. Hunting and Subsistence among the Mayangna and Miskito of Nicaragua's Bosawas Biosphere Reserve. The Pennsylvania State University. <http://etda.libraries.psu.edu/catalog/7423>.
- Koster, J.M., 2011. Interhousehold meat sharing among Mayangna and Miskito horticulturalists in Nicaragua. *Hum. Nat.* 22 (4), 394–415. <https://doi.org/10.1007/s12110-011-9126-4>.
- Koster, J.M., 2018. Family ties: the multilevel effects of households and kinship on the networks of individuals. *R. Soc. Open Sci.* 5 (4), 172159. <https://doi.org/10.1098/rsos.172159>.
- Koster, J.M., Tankersley, K.B., 2012. Heterogeneity of hunting ability and nutritional status among domestic dogs in lowland Nicaragua. *Proc. Natl. Acad. Sci.* 109 (8), 2701. <https://www.pnas.org/content/109/8/E463/1>.
- Koster, J.M., Grote, M.N., Winterhalter, B., 2013. Effects on household labor of temporary out-migration by male household heads in Nicaragua and Peru: an analysis of spot-check time allocation data using mixed-effects models. *Hum. Ecol.* 41 (2), 221–237. <https://doi.org/10.1007/s10745-012-9549-5>.
- Kruschke, J.K., 2015. *Doing Bayesian Data Analysis*, 2nd ed. Elsevier Inc.
- Lancaster, R.N., 1991. Skin color, race, and racism in Nicaragua. *Ethnology* 30 (4), 339–353. <https://www.jstor.org/stable/3773689>.
- Larson, J.M., Lewis, J.I., 2017. Ethnic networks. *Am. J. Pol. Sci.* 61 (2), 350–364. <https://doi.org/10.1111/ajps.12282>.
- Larson, J.M., Lewis, J.I., 2020. Measuring networks in the field. *Political Science Research and Methods* 8 (1), 123–135. <https://doi.org/10.1017/psrm.2019.5>.
- Laslett, P., 1984. The family as a knot of individual interests. In: Netting, R.M., Wilk, R., Arnould, E.J. (Eds.), *Households: Comparative and Historical Studies of the Domestic Group*. University of California Press, pp. 353–379.
- Lazega, E., Jourda, M.T., Mounier, L., Stofer, R., 2008. Catching up with big fish in the big pond? Multi-level network analysis through linked design. *Soc. Networks* 30 (2), 159–176. <https://doi.org/10.1016/j.socnet.2008.02.001>.
- Lee, F., Butts, C.T., 2018. Mutual assent or unilateral nomination? A performance comparison of intersection and union rules for integrating self-reports of social relationships. *Soc. Networks* (55), 55–62. <https://doi.org/10.1016/j.socnet.2018.05.005>.
- Lee, G.O., et al., 2018. Social connectedness is associated with food security among peri-urban Peruvian Amazonian communities. *SSM Popul. Health* (4), 254–262. <https://doi.org/10.1016/j.ssmph.2018.02.004>.
- Lin, N., 1999. Social networks and status attainment. *Annu. Rev. Sociol.* 25 (1), 467–487. <https://doi.org/10.1146/annurev.soc.25.1.467>.
- List, C., 2016. What is it like to be a group agent? *Nos* 52 (2), 295–319. <https://doi.org/10.1111/nous.12162>.
- Lomi, A., Robins, G., Tranmer, M., 2016. Introduction to multilevel social networks. *Soc. Networks* 44, 266–268. <https://doi.org/10.1016/j.socnet.2015.10.006>.
- Lyle, H.F., Smith, E.A., 2014. The reputational and social network benefits of prosociality in an Andean community. *Proc. Natl. Acad. Sci.* 111 (13), 4820–4825. <https://doi.org/10.1073/pnas.1318372111>.
- Marsden, P.V., 1990. Network data and measurement. *Annu. Rev. Sociol.* 16, 435–463. <https://doi.org/10.1146/annurev.soc.16.080190.002251>.
- McElreath, R., 2015. *Statistical Rethinking: A Bayesian Course with Examples in R and Stan*. CRC Press.
- McFarland, D.A., Moody, J., Diehl, D., Smith, J.A., Thomas, R.J., 2014. Network ecology and adolescent social structure. *Am. Sociol. Rev.* 79 (6), 1088–1121. <https://doi.org/10.1177/0003122414554001>.
- Milardo, R.M., 2007. Conjugal roles and social networks. In: Ritzer, G. (Ed.), *The Blackwell Encyclopedia of Sociology*. Blackwell Publishing, pp. 672–674. <https://doi.org/10.1002/9781405165518.wbeosc092.pub2>.
- Minhas, S., Hoff, P.D., Ward, M.D., 2019. Inferential approaches for network analysis: AMEN for latent factor models. *Political Anal.* 27 (2), 208–222. <https://doi.org/10.1017/pan.2018.50>.
- Mitti, R.D., Rweyemamu, T.G., 2001. A Socio-Economic Profile of Nyakatoke. University of Dar es Salaam & University of Leuven. <https://www.uantwerpen.be/images/uantwerpen/personalpage32042/files/Nyakatoke%20profile.pdf>.
- Murendo, C., Wollni, M., De Brauw, A., Mugabi, N., 2018. Social network effects on mobile money adoption in Uganda. *J. Dev. Stud.* 54 (2), 327–342. <https://doi.org/10.1080/00220388.2017.1296569>.
- Nolin, D.A., 2010. Food-sharing networks in Lamalera, Indonesia. *Hum. Nat.* 21 (3), 243–268. <https://doi.org/10.1007/s12110-010-9091-3>.
- Onnela, J.-P., et al., 2016. Polio vaccine hesitancy in the networks and neighborhoods of Malegaon, India. *Soc. Sci. Med.* 153, 99–106. <https://doi.org/10.1016/j.socscimed.2016.01.024>.
- Perkins, J.M., et al., 2018. Food insecurity, social networks and symptoms of depression among men and women in rural Uganda: a cross-sectional, population-based study. *Public Health Nutr.* 21 (5), 838–848. <https://doi.org/10.1017/S1368980017002154>.
- Perkins, J.M., Subramanian, S.V., Christakis, N.A., 2015. Social networks and health: a systematic review of sociocentric network studies in low- and middle-income countries. *Soc. Sci. Med.* 125, 60–78. <https://doi.org/10.1016/j.socscimed.2014.08.019>.
- Portes, A., 1998. Social Capital: its origins and applications in modern Sociology. *Annu. Rev. Sociol.* 24 (1), 1–24. <https://doi.org/10.1146/annurev.soc.24.1.1>.
- Plummer, M., et al., 2018. Package "coda": Output Analysis and Diagnostics for MCMC (v. 0.19-2). <https://cran.r-project.org/web/packages/coda/coda.pdf>.
- Power, E.A., 2017. Social support networks and religiosity in rural South India. *Nat. Hum. Behav.* 1 (3), 0057. <https://doi.org/10.1038/s41562-017-0057>.
- Power, E.A., Ready, E., 2019. Cooperation beyond consanguinity: post-marital residence, delineations of kin, and social support among South Indian Tamils. *Philos. Trans. Biol. Sci.* 374. <https://doi.org/10.1098/rstb.2018.0070>. B37420180070.
- Ready, E., Power, E.A., 2018. Why wage earners hunt: food sharing, social structure, and influence in an Arctic mixed economy. *Curr. Anthropol.* 59 (1), 74–97. <https://doi.org/10.1086/696018>.
- Robins, G., Pattison, P., Woolcock, J., 2005. Small and other worlds: global network structures from local processes. *Am. J. Sociol.* 110 (4), 894–936. <https://www.jstor.org/stable/10.1086/427322>.
- Rogler, L.H., Procidano, M.E., 1986. The effect of social networks on marital roles: a test of the Bott Hypothesis in an intergenerational context. *J. Marriage Fam.* 48 (4), 693–701. <https://www.jstor.org/stable/352562>.
- Rözer, J., Mollenhorst, G., Volker, B., 2018. Families' division of labor and social networks in the 21st century: revisiting Elizabeth Bott's classic hypotheses. *J. Fam. Issues* 39 (13), 3436–3462. <https://doi.org/10.1177/0192513X18783230>.
- Shakya, H.B., et al., 2018. Social network correlates of IPV acceptance in rural Honduras and rural Uganda. *SSM Popul. Health* 4, 236–243. <https://doi.org/10.1016/j.ssmph.2018.02.001>.
- Shakya, H.B., et al., 2017a. Exploiting social influence to magnify population-level behaviour change in maternal and child health: study protocol for a randomised controlled trial of network targeting algorithms in rural Honduras. *BMJ Open* 7 (3), e012996. <https://bmjopen.bmj.com/content/7/3/e012996>.
- Shakya, H.B., Christakis, N.A., Fowler, J.H., 2017b. An exploratory comparison of name generator content: data from rural India. *Soc. Networks* 48, 157–168. <https://doi.org/10.1016/j.socnet.2016.08.008>.
- Simpson, C.R., 2016. Competition for foundation patronage and the differential effects of prestige on the grant market success of social movement organisations. *Soc. Networks* 46, 29–43. <https://doi.org/10.1016/j.socnet.2016.02.001>.
- Small, M.L., Adler, L., 2019. The role of space in the formation of social ties. *Annu. Rev. Sociol.* 45, 111–132. <https://doi.org/10.1146/annurev-soc-073018-022707>.
- Smith, J.A., Moody, J., 2013. Structural effects of network sampling coverage I: nodes missing at random. *Soc. Networks* 35 (4), 652–668. <https://doi.org/10.1016/j.socnet.2013.09.003>.
- Smith, J.A., Moody, J., Morgan, J.H., 2017. Network sampling coverage II: the effect of non-random missing data on network measurement. *Soc. Networks* 48, 78–99. <https://doi.org/10.1016/j.socnet.2016.04.005>.
- Stadtfeld, C., Pentland, A.S., 2015. Partnership ties shape friendship networks: a dynamic social network study. *Soc. Forces* 94 (1), 453–477. <https://doi.org/10.1093/sf/s0v709>.
- Takada, S., et al., 2019. The social network context of HIV stigma: population-based, sociocentric network study in rural Uganda. *Soc. Sci. Med.* 233, 229–236. <https://doi.org/10.1016/j.socscimed.2019.05.012>.
- Thomson, R., et al., 2018. Relational Mobility predicts social behaviors in 39 countries and is tied to historical farming and threat. *Proc. Natl. Acad. Sci.* 115 (29), 7521–7526. <https://doi.org/10.1073/pnas.1713191115>.

- Tollefsen, D.P., 2002. Collective intentionality and the social sciences. *Philos. Soc. Sci.* 32 (1), 25–50. <https://doi.org/10.1177/004839310203200102>.
- Treas, J., 2011. Revisiting the Bott Thesis on kin networks and marriage. *Soc. Sci. Res.* 40 (3), 716–726. <https://doi.org/10.1016/j.ssresearch.2010.12.005>.
- Turner, C., 1967. Conjugal roles and social networks: a re-examination of an hypothesis. *Hum. Relat.* 20 (2), 121–130 <https://doi.org/10.1177%2F001872676702000202>.
- Udry, C., 1996. Gender, agricultural production, and the Theory of the Household. *J. Polit. Econ.* 104 (5), 1010–1046. <https://www.jstor.org/stable/2138950>.
- Udry, J.R., Hall, M., 1965. Marital role segregation and social networks in middle-class middle-aged couples. *J. Marriage Fam.* 27 (3), 392–395. <https://www.jstor.org/stable/350285>.
- Wasserman, S., Faust, K., 1994. *Social Network Analysis: Methods and Applications*. Cambridge University Press.
- Wellman, B., Frank, K., 2001. Network capital in a multi-level world: getting support from personal communities. In: Lin, N., Burt, R.S., Cook, K. (Eds.), *Social Capital Theory and Research*. Aldine Transaction Publishers, pp. 233–273.
- Wencélius, J., Thomas, M., Barbillon, P., Garine, E., 2016. Interhousehold variability and its effects on seed circulation networks: a case study from Northern Cameroon. *Ecol. Soc.* 21 (1), 44–12. <https://www.jstor.org/stable/26270346>.
- Windzio, M., 2015. Immigrant children and their parents: is there an intergenerational interdependence of integration into social networks? *Soc. Networks* 40, 197–206. <https://doi.org/10.1016/j.socnet.2014.11.002>.
- Zeng, Z., Xie, Y., 2008. A preference-opportunity-choice framework with applications to intergroup friendship. *Am. J. Sociol.* 114 (3), 615–648. <https://doi.org/10.1086/592863>.