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Linking perspectives: a field experiment on the role of multi-layer networks in refugee information sharing

Aaron Thomas Clark[1], Jennifer M. Larson[1*] and Janet I. Lewis[2]

*Correspondence: jennifer.larson@vanderbilt.edu

[1] Department of Political Science, Vanderbilt University, 230 Appleton Place, Nashville 37212, TN, USA
[2] Department of Political Science, George Washington University, 2115 G St. NW, Washington, DC 20052, USA

Abstract

The social networks that interconnect groups of people are often "multi-layered"—comprised of a variety of relationships and interaction types. Although researchers increasingly acknowledge the presence of multiple layers and even measure them separately, little is known about whether and how different layers *function* differently. We conducted a field experiment in twelve villages in rural Uganda that measured real multi-layer social networks and then tracked their use in response to new, discussion-provoking information about refugees. We find that people who received our information treatment discussed refugees with more people, selected discussion partners from neighbors in the multi-layer network, and used most of the layers to do so. Treatment kicked off conversations throughout the villages that also included control respondents; treated and control both selected discussion partners from their networks who shared their attitudes towards refugees and were particularly interested in the subject. Our results point to multi-layer networks of day-to-day interactions as a source of prospective discussion partners when new information arises, especially layers based on shared meals, homestead visits, and money borrowing. When a relationship is based on multiple of these layers, it is even more likely to facilitate discussion. Furthermore, the selection of discussion partners from these networks depends less on any one particular layer and more on characteristics of the tie relative to the topic at hand.

Keywords: Multi-layer networks, Discussion networks, Link function, Uganda

Introduction

Social networks tend to be comprised of a rich variety of relationships and interaction types, and hence are "multi-layered" (Bianconi 2018; Dickison et al. 2016; Boccaletti et al. 2014; Gondal 2022; Kivelä et al. 2014). Scholars studying networks empirically often collect data on multiple layers, such as friends, kin, discussion partners, sources of assistance, and so on (Bandiera and Rasul 2006; Kremer and Miguel 2007; Banerjee et al. 2013; Larson and Lewis 2017; Ferrali et al. 2020; Larson et al. 2022; Atwell and Nathan 2022). These networks are of interest because they likely *do* something—spread information, apply peer pressure, share resources—that matters to outcomes across the social sciences (Bramoullé et al. 2016; Light and Moody 2020; Victor et al. 2017).

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Understanding how exactly links function is an important step in the process of understanding when and why networks matter (Larson and Lewis 2020), especially since certain links may function differently than others. For instance, some links may be based on deep trust, facilitating the spread of sensitive information from person to person, while others may be shallower, only allowing non-sensitive information to pass through (Granovetter 1973; Aral and Van Alstyne 2011; Larson 2017). When links are not interchangeable in their function, researchers need to account for this in their measurement strategy, and aggregating links across layers could be misleading (De Domenico et al. 2015; Kivelä et al. 2014; Cozzo et al. 2013; Larson and Rodríguez 2022; Larson and Rodriguez 2023). An important question is then: which links do what and when?

This question is expansive, and a complete answer surely depends on the context in question. A productive way forward would be to amass a collection of studies of link functions in multi-layer networks across contexts. This article contributes one. It focuses on a case which allows deep exploration of the function of different links in the context of rural Ugandan villagers learning new information about refugees.

Specifically, we conducted a field experiment in twelve villages in northwestern Uganda in which we elicited four layers of social networks for all households: who shares meals with whom, who visits whose homesteads, who consults whom in the presence of rumors, and who one turns to in order to borrow money. After measuring networks and collecting additional information in a baseline survey, a treatment was administered to a randomly selected 40% of households in each village. Our treatment presented new information about the experiences of refugees and walked the respondent through a perspective-taking conversation to more deeply engage with it.[1] Two weeks later, all participants were surveyed again and asked to name the people with whom they had conversed about refugees in the interim. By matching these names with the social network, we can determine whether people used any of the four layers to discuss refugees and the features that distinguish the ties they turned to from those they did not.

Our intervention was designed to be thought-provoking, and the study design allowed time for respondents to turn to others—including their social network ties—to discuss their reactions to it. The presence of this kind of "social processing" has been documented in a related study in the region (Larson and Lewis forthcoming) and is corroborated by qualitative evidence from the current study. After the baseline survey which includes treatment for some, people talk with one another. And, since it takes two to converse, both the treated and control respondents can be involved in these discussions.

This design allows us to examine both the character and the use of real multi-layer networks. Consistent with previous studies that also measure multi-layer networks, we find that the overlap between layers is imperfect and each contributes distinct sets of links and structural features (Szell et al. 2010; González-Bailón et al. 2011; Maoz 2012; Larson and Rodríguez 2022; Larson and Rodriguez 2023; Larson and Lewis 2024). Each layer has a component that comprises a large majority of the nodes in the village, though they vary in the size of the largest component. The densest layer—visiting homesteads—has

[1] A strong majority of refugees are received by developing countries. Uganda is one of the largest receivers, host to approximately one million refugees. These study villages are in the West Nile and Western regions of Uganda, near the borders with South Sudan and Democratic Republic of Congo.

the largest component that is most expansive, though this layer does not have the highest transitivity (sharing meals does), nor does it have the highest in-degree (the rumor layer does).

These data not only provide a view of the multi-layer networks that shape daily life in rural Uganda, but also the way they are used in the presence of new information that sparks discussions. We investigate use in two ways. First, we focus on the direct effect of treatment. Did the respondents who received treatment—who received the information about refugees directly and participated in the perspective-taking conversation with a member of the research team—use their social network links at a different rate or in a different way? Here we find that indeed, the treated report having had a discussion with .5 more people than control on average, and they spoke with more of their contacts in the meal, visit, and borrow layer than did the control. However, the difference appears to be exclusively in terms of volume: when we compare the social network links the treated and control used, we detect no differences in terms of attributes of the alter or of homophily.

Second, because the study generated discussion about refugees throughout each village in the two week interim, we probe whether discussion occurred within the multilayer network for everyone, control included, and if so, along which links. Although people were free to reach out to anyone, we find that a majority of respondents did turn to social network neighbors (as opposed to others in the village or beyond) to discuss the new information. In one village, 70% of respondents who talked to anyone did so with a network neighbor. Across villages, discussion partners were connected to the respondent most often in the visit layer (65%), followed by the meal layer (53%), then borrow (44%) and rumor (39%).

We then compare people linked to the respondent in the social network who were named as discussion partners (1212 total links) with people linked to the respondent who were not (6593 total links) to try to understand why respondents made use of the links they did. We consider whether alter characteristics such as personal experience as a refugee, social relationships with refugees, occupation, views on the topic, and interest in the topic matter. Of these, only the alter's level of interest in refugees significantly differentiates the two groups: alters who see refugees as a very pressing issue are more likely to be named as discussion partners. We also consider whether homophily with respect to religion, language, personal refugee status, views on the topic, and level of interest in the topic matter. Of these, both views on refugees and interest in the topic do: alters who agree on the level of threat refugees pose and the importance of the topic are more likely to be selected by the respondent as a discussion partner. Homophily on views is driven by matching on the most positive views towards refugees, and homophily on interest is driven by matching on the highest level of interest. Finally, we show that multiplexity is a strong predictor of link use. Links based on multiple layers are more likely to be used to discuss refugees than those based on a single layer. The more layers a relationship is based on, the more likely it is to be used.

Our results point to multi-layer networks of day-to-day interactions as a source of prospective discussion partners when new information arises. In the context of new refugee information in rural Uganda, the selection of particular discussion partners seems to depend less on the layer and more on the tie, specifically characteristics of the tie relative to the topic at hand. Shared meals, homestead visits, and money borrowing layers may function equally well to spread information of this sort.

Methods

Our data were collected with a two-part survey in 12 villages in northwestern Uganda in 2023. The first part was administered door-to-door, visiting all households within a village. The second part was also administered door-to-door to all households approximately 2 weeks later. The field experiment occurred as part of the first survey. 40% of households were selected at random from each village to receive treatment which took the form of a guided conversation about refugees (described below). We refer to the remaining 60% of households who did not receive treatment as control households.[2]

Participation in the survey, each component question, and the treatment conversation were voluntary; we carefully trained enumerators to request informed consent. We conducted the study with prior approvals from the authors' university Institutional Review Boards, from Uganda's National Council on Science and Technology, from a local Ugandan IRB (Mildmay Uganda Research Center) and from the relevant district-level officials.

Village networks

We used four name-generator questions in a baseline survey to measure social networks in each of the twelve villages. Each respondent was asked to name up to five adults in response to each of the following prompts:

- the adult villagers whose homes you visit in a typical week who don't live in your household;
- the adult villagers who you share a meal with in a typical week who don't live in your household;
- the adult villagers who you go to if you need to borrow money who don't live in your household; and
- when you hear news or rumors that seem surprising or unusual, the adult villagers outside your household that you typically first turn to to chat about it.

These four layers were chosen because they measure trusted relationships in this setting, the kind that might be used to discuss new information, share news of the day, and vet new ideas (Larson and Lewis 2017; Larson et al. 2022). Table 1 describes the resulting social network for each village, here represented as the union of the four layers. Nodes are households, links are directed, and the count of links indicates the number of times one household lists someone in another in response to at least one of the four name generator questions. The table also reports features of these networks, including the mean total degree, the maximum in-degree, the number of nodes who have in-degree or out-degree equal to zero, mean transitivity, and the proportion of households in the largest component.

[2] These data are part of a broader study which aimed to detect spillovers from treatment; more respondents are in the control condition so that more were eligible for spillovers.

Table 1 Aggregated social network by village

Village	Nodes	Links	Degree	Max In	0 Out	0 In	Trans	Lg Comp
1	132	799	12.11	33	5	12	0.30	0.99
2	114	505	8.86	34	3	16	0.21	1.00
3	148	962	13.00	27	5	13	0.29	0.99
4	125	938	15.01	34	5	18	0.29	0.99
5	163	1030	12.64	31	6	14	0.25	0.98
6	126	692	10.98	28	2	11	0.35	0.99
7	121	456	7.54	23	7	19	0.18	0.99
8	130	437	6.72	17	9	21	0.20	0.98
9	112	803	14.34	33	9	23	0.38	0.96
10	104	364	7.00	12	8	15	0.30	0.99
11	180	492	5.47	23	29	53	0.13	0.96
12	149	327	4.39	24	27	51	0.15	0.89

Notably, these multi-layer networks interconnect almost every household in almost all villages. Village 12 has the smallest largest component, but even it includes 89% of the village.

Table 2 separates the networks into the four layers and reports the same structural features. The values are reported as averages across the villages by layer. On average, a village has 134 household nodes in the network. Each layer contributes differently to the overall village network. The visit layer has the most links on average, though the links are distributed more unevenly in the rumor layer and so it has the highest in-degree—more people point to the same person to vet rumors than to visit in their home. The meal layer has the highest transitivity; households who have members who share meals with the same household are more likely to share meals with one another as well. The borrow layer has the largest number of nodes with out-degree and in-degree equal to zero; many households have no one they would borrow money from, and many households would not be asked.

For illustration, we pick one of the villages and visualize the four layers. Figure 1 shows each of the layers for village 7, holding the node placement fixed. Nodes are sized proportional to degree.

Respondents were asked about the four layers separately, and so were free to list the same people for multiple layers. Table 3 shows the pairwise overlap in layers, pooled across villages. It shows the proportion of the row layer's links that are also present in the column layer. So, for instance, 46% of the links in the borrow layer are also present in the meal layer, while 37% of the borrow layer's links are also in the rumor layer. None of these proportions is too surprising given the relative density of the layers; the meal and visit layers are denser than the rumor and borrow layers, and so tend to include more links from the other layers. No pair of layers is particularly disproportionately overlapping.

For any link, the extent to which it appears in multiple layers—its multiplexity—can range from 1 to 4. Of the 7805 total links in the 12 villages' social networks, the modal multiplexity is 1. Most links appear in just one layer. Figure 2 shows the distribution of links by a measure of multiplexity, the count of the number of layers in which it is

Table 2 Characteristics of each of the four layers averaged over the 12 villages

Layer	Nodes	Links	Degree	Max In	0 Out	0 In	Trans	Lg Comp
Meal	134	298	4.56	11	31	43	0.20	0.87
Visit	134	344	5.23	14	24	38	0.18	0.92
Rumor	134	220	3.31	15	39	57	0.13	0.81
Borrow	134	204	3.10	14	46	64	0.16	0.74

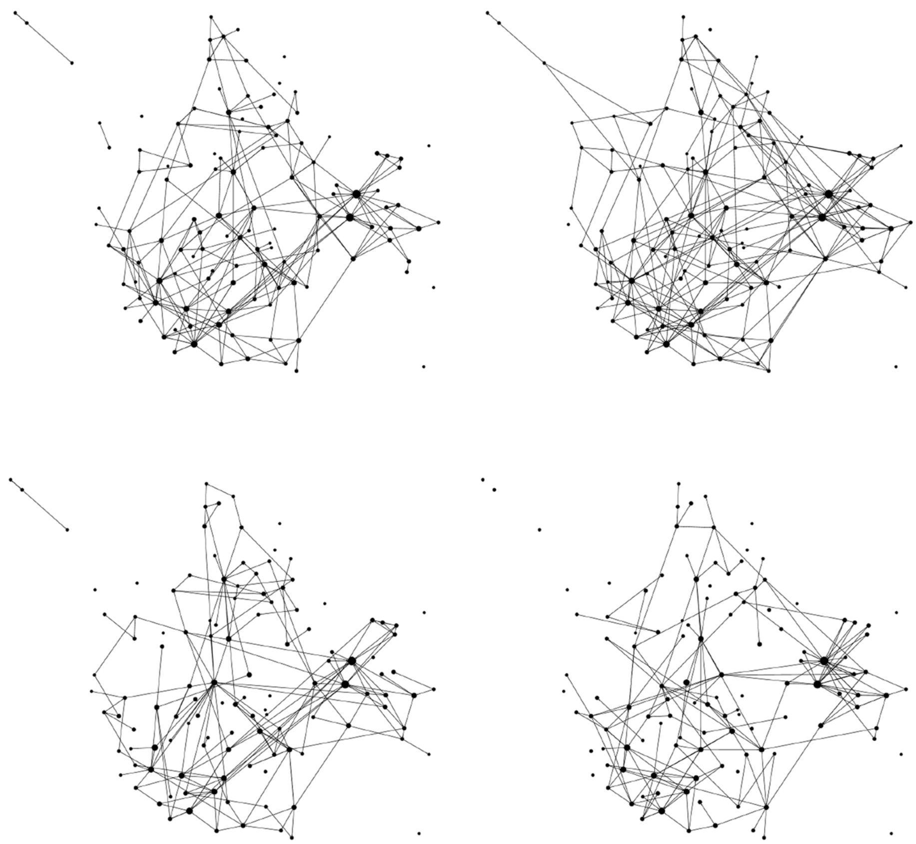

Fig. 1 The four layers of the multi-layer household network for Village 7. From top left to bottom right: shared meals, visit homestead, discuss rumors, borrow money

Table 3 Network overlap; proportion of the row layer's links that are also present in the column layer

	Meal	Visit	Rumor	Borrow
Meal	1	0.49	0.29	0.31
Visit	0.42	1	0.28	0.28
Rumor	0.39	0.44	1	0.34
Borrow	0.46	0.47	0.37	1

present. Within a count value, the figure shows the breakdown of the combination of layers that comprise it. For links that appear in just one layer, the visits layer (V) is most typical, followed by the meals (M), then rumors (R), then borrow (B), which

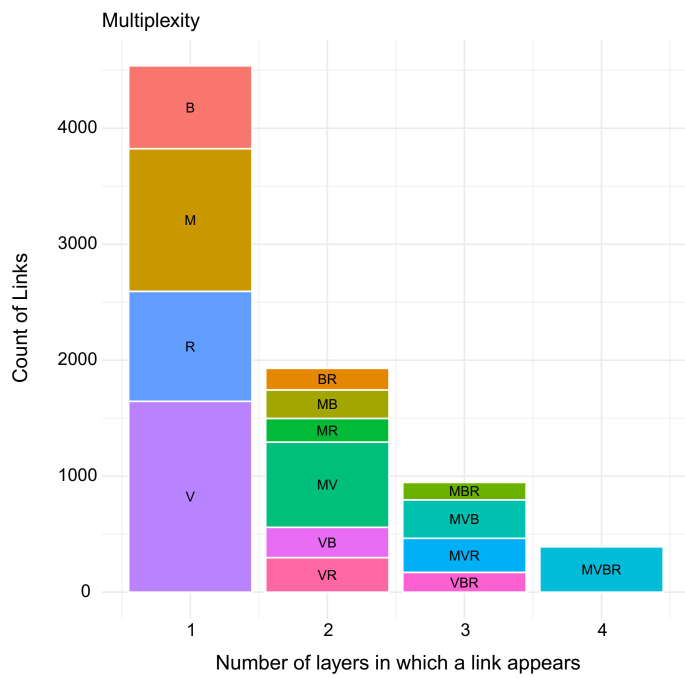

Fig. 2 Distribution of the number of layers in which links appear, broken down by combinations of layers

again mirrors the relative densities of the four layers. For links that appear in more than one layer, the most typical sets of layers are again those involving meals and visits.

Experimental intervention

The baseline survey was followed by treatment for 40% of households selected at random in each village. Our treatment took the form of a brief (approximately 10–15 min) conversation about refugees, modeled on Broockman & Kalla's "perspective-taking" intervention (Broockman and Kalla 2016; Kalla and Broockman 2020). A member of the research team guided a respondent through considering the experience of a single South Sudanese refugee's life, reminding the respondent that this refugee is part of a much larger group currently residing in Uganda. The conversation involved non-judgmentally exchanging narratives about refugees and encouraging taking their perspective.

Previous work (Larson and Lewis, forthcoming) shows that such an intervention can not only warm attitudes in developing country contexts, but it does so by kicking off an abundance of follow-up conversations among villagers—both those treated and those in the control condition—after treatment.

Our primary expectation is that treatment leads the treated to converse about refugees, which should result in the treated listing more refugee discussion partners than the control. Moreover, since it takes two to converse, the control should also engage in some conversations about refugees as a result of the treated being treated. We first show that this is indeed the case in these 12 villages, and then focus on how villagers used their multi-layer networks for these conversations in response to treatment occurring in their village.

Treatment effect on network usage for refugee discussion

In the second survey two weeks after the baseline, all respondents were asked to think back over the past two weeks and name up to five people with whom they had had a conversation about refugees. Respondents could name anyone; they were not prompted to list anyone they listed in response to the network elicitation questions in the baseline survey, nor were the restricted to doing so. Our first dependent variable labeled All Discussion Partners is a count of the names listed.[3] The names counted to construct this variable can be a mix of names offered in response to the social network questions collected two weeks prior as well as other names (see Appendix Table 9 for more details). Our second set of dependent variables counts the number of names listed who are also linked to the respondent in the multi-layer social network, separated into the four layers Meal, Visit, Rumor, and Borrow.[4]

To examine the extent to which our perspective-taking treatment exerted a direct influence on network usage to discuss refugees, we conducted simple Ordinary Least Squares (OLS) analyses. Within a village, it is possible that a count of the number of names offered by one respondent is not independent of the number of names offered by another. Consequently, in addition to reporting the standard errors from the OLS (parentheses in Table 4), we also report corrected *p*-values from a Quadratic Assignment Procedure (QAP) test (Krackhardt, 1988; Cranmer et al., 2020). The QAP holds the observed network structure fixed for each village, randomly shuffles the treatment assignment within a village, and generates the distribution of regression coefficients we would observe given this network structure under the null hypothesis that treatment is unrelated to the number of discussion partners. The QAP scores (square brackets in Table 4) report the probability of observing a coefficient as extreme as the observed value under the null conditional on these villages' networks. Given the observed heterogeneity across villages in the multi-layer networks, we also include village fixed effects to be sure that the results are not due to differences between villages (though the Appendix shows that the results are nearly identical if village fixed effects are excluded, see Table 10). Table 4 presents the results.

The analyses in Table 4 show the effect of treatment on the number of conversation partners and the use of different layers in the multi-layer social network. First, we regress the number of total links (i.e., all conversation partners named) with whom a respondent reported discussing refugees (Model 1). The coefficient suggests that, across all villages, treated individuals report, on average, 0.47 more discussion partners than those in the control. Indeed, this increase is statistically-significant at $p < 0.01$ levels (even when accounting for dependencies with the QAP), conforming to our expectations. The treated reach out to more people than the control do to discuss refugees.

Next, we separate the regressions by a count of discussion partners who appear within the multi-layer networks in each of the four layers (meal, visit, rumor, borrow),

[3] Figure 3 in the Appendix shows this variable's distribution. Among those who listed any names, we see good variation across the options of 1 to 5. Appendix Table 9 shows how the proportion of respondents listing any refugee discussion partner names is distributed across villages; it ranges from 44% in Village 1 to 71% in Village 5.

[4] Specifically, All Discussion Partners is a count of the number of names the respondent offered in response to the question asking for a list of refugee discussion partners in the past two weeks. We then count the number of these names that also appear as that respondent's out-link in the network name-generator questions from the baseline survey. Meal, Visit, Rumor, and Borrow are counts of the number of discussion partner names that also appear in that network layer.

Table 4 Treatment Effect on Network Link Usage

	All Discussion Partners (1)	Meal (2)	Visit (3)	Rumor (4)	Borrow (5)
Treatment	0.472***	0.128***	0.095**	−0.005	0.094***
	(0.096)	(0.034)	(0.039)	(0.028)	(0.030)
	[0.000]	[0.001]	[0.012]	[0.879]	[0.003]
Constant	1.352***	0.139**	0.235***	0.169***	0.168***
	(0.168)	(0.060)	(0.068)	(0.049)	(0.052)
Village FE	Yes	Yes	Yes	Yes	Yes
Observations	1,604	1,604	1,604	1,604	1,604
Adjusted R^2	0.031	0.031	0.025	0.021	018

*p<0.01; **p<0.005; ***p<0.01

Standard errors from OLS model shown in parenthesis. Corrected *p*-values from QAP shown in square brackets. Additional detail on the corresponding QAP can be found in Appendix Fig. 4

examining the treatment effect on the number of links *in that layer* with whom respondents also reported discussing refugees (Models 2–5). Our results indicate that, across all link types, with the exception of rumor links, treatment increased the number of links with whom respondents engaged in refugee discussions. On average, of treated respondents' meal, visit, and borrow links, they report engaging in refugee discussions with 0.13 ($p < 0.01$), 0.10 ($p < 0.05$), and 0.09 ($p < 0.01$) more of those links, respectively, than their control counterparts. Thus, the findings from our field experiment conform to our expectation that the treatment encourages conversations about refugees, and that the treated seek out conversation partners from their existing village social networks. The meal, visit, and borrow layers are especially prevalent sources of discussion partners for the treated.

Use of village social networks to discuss refugees

The treated speak to more people about refugees. Table 5 shows how this difference varies by village. Two patterns stand out. First, the pattern holds within every village except Village 3, in which the control list more refugee discussion partners. Second, while the treated talk to more people, the control are talking as well. This conforms to our expectation that treatment would induce conversations by the treated, but this would result in the control engaging in conversations as well (the same pattern can be seen in Larson and Lewis, forthcoming). On average, the treated have 2.1 discussion partners, while the control have 1.6.

Next we zoom out to all respondents, treated and control, who said they did have a conversation about refugees with anyone in the past two weeks. Table 6 shows the total number of the names respondents offered that also appear as their neighbors in at least one layer of the social network on average across respondents within each village. The four subsequent columns break these totals apart into the number of names that appear as a link in each of the four layers of the social network, reported as an average number of names. For village 1, on average 1.07 people listed are also network neighbors; these people are distributed across the four layers as.43 names in the meal layer,.62 in the visit layer,.38 in the rumor layer, and.47 in the borrow layer. The four layers do not sum to the total number of people because they are not mutually exclusive; a link between a respondent and an alter can appear in more than one layer, so a name can appear in more than one layer for a respondent.

Overall, respondents are discussing refugees with social ties in the visit layer most frequently, followed by the meal layer, then borrow, then rumor. Comparing with Table 2, the visit and meal layers are also the densest, but the rumor layer has more links than the borrow layer. As we saw in the treatment effect results above, respondents seem to find those with whom they would discuss a surprising rumor to be least relevant to discussing refugee information.

Other data collected in the survey allow us to examine more deeply the factors that distinguish the links in the network that were used to discuss refugees from those that were not. That is, for each respondent, we know the set of network neighbors across all layers, and we know that some, but not all, of them were selected as discussion

Table 5 Number of discussion partners by treatment condition

Village #	Treated	Control
1	2.0	1.2
2	2.7	1.9
3	1.4	1.6
4	1.6	1.5
5	2.5	1.9
6	2.2	1.4
7	2.6	2.2
8	2.2	2.0
9	2.3	1.5
10	1.5	1.2
11	1.9	1.5
12	2.4	1.6
Pooled	2.1	1.6

Table 6 Breakdown of discussion partners by layers of network

Village	Total in NW	#inMeal	#inVisit	#inRumor	#inBorrow
1	1.07	0.43	0.62	0.38	0.47
2	1.35	0.81	0.83	0.43	0.67
3	1.18	0.56	0.58	0.41	0.38
4	1.11	0.56	0.70	0.38	0.53
5	1.20	0.53	0.66	0.54	0.43
6	1.13	0.68	0.74	0.25	0.49
7	1.23	0.67	0.89	0.52	0.52
8	1.22	0.74	0.84	0.62	0.51
9	1.14	0.41	0.71	0.28	0.47
10	0.90	0.43	0.63	0.31	0.39
11	0.47	0.24	0.25	0.27	0.19
12	0.63	0.24	0.38	0.36	0.23
Pooled	1.05	0.53	0.65	0.39	0.44

partners about refugees. Was the selection random with respect to link, or do we observe differences between used and unused links?

Our next set of analyses zooms in on the links present in the social network and compares the links in this network that were used to discuss refugees to those that were not. For each link attribute that we consider, we report the mean value across all social network links that were used, the mean value across all social network links that were not used, the p-value from a two-sided difference in means test, and then a QAP score which reports a corrected p-value that accounts for dependencies between links. For comparisons where the link attributes are functions of node attributes (the first 12 rows of Table 7), the QAP score is calculated by permuting a village's nodes' attributes among that village's nodes, recalculating link attributes implied by these randomly shuffled node attributes given our observed village networks, and reporting the proportion of difference in means that would be as extreme as our observed values. For comparisons where link attributes are not functions of node attributes (rows 13 and 14 of Table 8), the QAP score is calculated by permuting the link attributes among each village's network's links. Additional details, including the resulting distributions, can be found in Appendix Figs. 6 and 7.

We first investigate two sets of attributes of the links, still compiling all respondents together (i.e., treated and non-treated). Table 7 presents our findings. One set of link attributes centers around node attributes of the alter (rows 2–6). We might think that alters who have relevant experience, for instance by having been a refugee once themselves (this is true for about a third of our respondents) or who themselves know refugees personally, would be prioritized. Or we might think that alters who have a connection to the land, one of the key resources in question when refugee issues come up, in their occupation as farmers, would be prioritized. Or maybe an alter's views on refugees[5] or the extent to which she finds refugees to be a pressing issue are important to respondents when selecting discussion partners.[6] Out of all of these alter characteristics, the only one that distinguishes the alters selected from those that are not is the alter's interest in refugees: links to alters who find the issue of refugees to be more pressing are more likely to be used to discuss refugees.

Likewise, we consider homophily as a possible distinguishing factor between links in the social network used to discuss refugees and those that were not (rows 7–11). We consider both religious and language homophily to see if common values or assured ability to communicate are relevant. We also consider shared refugee status, which would be relevant if respondents who were once refugees sought out their network neighbors who also shared this experience (or respondents who have never been a refugee might seek out like neighbors as well). Shared views about refugees, and a shared interest in the topic, could also facilitate conversations. In fact shared interest in refugees distinguishes links used from those that were not in the network, and shared views does as well, though at a lower level of statistical significance.

[5] Our survey asks respondents to react to the statement "Refugees threaten the way of life in my community" with a five point scale from strongly agree to strongly disagree. Larger values indicate stronger disagreement, and hence warmer attitudes towards refugees.

[6] Our survey asks respondents how important they find the issue of refugees to be on a five point scale. Smaller values indicate greater importance.

Table 7 Comparing the links in the multilayer social network that were used to discuss refugees to those that were not

	Network link used	Network link not used	*p*-value	QAP score
Link Count	1212	6593		
Alter was refugee	0.33	0.32	0.55	0.80
Alter knows refugee	0.73	0.72	0.37	0.56
Alter farmer	0.82	0.81	0.54	0.67
Alter's views	3.61	3.54	0.21	0.53
Alter's interest	1.36	1.48	0.00	0.00
Relig homoph	0.76	0.74	0.13	0.20
Language homoph	0.85	0.84	0.46	0.75
Refugee status homoph	0.62	0.64	0.41	0.73
Refugee views homoph	0.36	0.33	0.08	0.15
Interest homoph	0.56	0.52	0.01	0.04
Positive views homoph	0.21	0.20	0.00	0.04
High interest homoph	0.50	0.45	0.01	0.08
In multiple layers	0.62	0.38	0.00	0.00
Count of layers	2.02	1.57	0.00	0.00

Showing *p*-values from two-sided difference in means test that assumes independence between links, and two-sided QAP scores that account for the dependencies (see appendix for details)

Table 8 Examining the treatment effect on the characterization of links in the multilayer social network that were used to discuss refugees (all links)

	Control	Treatment	*p*-value
Links	1243	910	
Alter was ref	0.32	0.33	0.58
Alter knows ref	0.75	0.73	0.36
Alter farmer	0.82	0.84	0.47
Alter's views	3.57	3.58	0.82
Alter's interest	1.39	1.41	0.55
Relig homoph	0.74	0.73	0.60
Language homoph	0.83	0.84	0.42
Refugee status homoph	0.63	0.63	0.97
Refugee views homoph	0.37	0.35	0.35
Interest homoph	0.54	0.53	0.56
Positive views homoph	0.24	0.24	0.99
High interest homoph	0.47	0.46	0.65
In Multiple Layers	0.34	0.36	0.32
Count of Layers	1.13	1.14	0.84

Because views and interest are measured on multi-point scales, we further explore whether matching on certain values of the range is more discriminating between links used and not used (rows 12–13). We find this to be the case. For views, it is matching on the most positive option and for interest it is matching on the highest level of interest that drives the relationship between homophily and link use. Appendix Tables 11 and 12 show that these regions of the range dominate homophily with respect to views and interest. Table 7 compares social network links used and not used with respect to sharing the most positive views (Positive views homoph) and the highest level of interest (High interest homoph). Links used feature substantially more homophily with respect to these views and interest level relative to those that are not used, again substantiated with QAP.

Finally, we consider whether a link's multiplicity relates to whether it was used to discuss refugees (rows 14–15). When we compare links used and not used in terms of the proportion of links that appear in more than one layer, we see a large difference. 62% of the links used to discuss refugees were present in multiple layers, compared to just 38% of the links in the social network that were not used; most unused links appear in just one layer. Figure 8 in the Appendix shows that links appearing in three or four layers are especially predictive of a link being used to discuss refugees. Multiplex links in the social network are much more likely to be used to discuss refugees.

Treatment effect on characterization of network usage

Finally, we investigate the extent to which our perspective-taking treatment exerted an influence on the characteristics of network links that *were* used. In other words, we investigate the interaction between treatment and choice of alter. Table 8 compares the links used to discuss refugees, separated by whether the ego was in the control condition or the treatment condition. Significant differences between these two sets of links would suggest that the treated and control seek out alters with different characteristics. In fact, we see no such differences.[7]

Examining the same two sets of attributes as found in the previous table, we find that the perspective-taking treatment exerts no significant effect on the type of individuals that respondents seek out in their network to discuss refugees. While Table 8 compiles all four link types together, we find that this pattern widely holds even when dissecting the treatment effect across different link types (see Appendix Tables 13, 14, 15, 16). Though our treatment significantly influences the *number* of links with whom respondents engage in discussions related to refugees (Table 4), these findings suggest that the treatment does not significantly change the *characteristics* of the individuals with which respondents engage in such discussions.

Conclusion

Villagers in rural Uganda have social networks with four quite different layers when measured in terms of shared meals, regular homestead visits, gossip partners, and borrowing sources. When these villagers are presented with new information in the form of a perspective-taking intervention about the experiences of refugees, they are significantly more likely to turn to their network neighbors with whom they share meals, have visits, and from whom they would borrow. Not everyone they turn to is a network neighbor in one of these layers, and not every network neighbor is selected as a discussion partner. The visits layer is the most popular choice—alters selected as discussion partners are more frequently linked to the respondent in the visit layer across the twelve villages, though this layer is also the most dense.

[7] Here even the overly precise p-values from a difference in means test assuming independence are far from statistically significant, so there is no need to further inflate the p-values to conclude a null result.

The choice of discussion partner from among the network neighbors appears to be orthogonal to the occupation, refugee experience, and attitudes towards refugees of the alter. It also appears orthogonal to shared language, religion, or personal refugee status. Instead, when examining all villagers together, what distinguishes the network links used to discuss refugees (relative to those not used) is the level of importance that the person ascribes to the topic. Links to alters who find the issue more pressing are more likely to be used, and links to alters who agree on the issue's high level of importance are also more likely to be used. Shared views about refugees—agreement on the extent to which refugees do or do not threaten the village's way of life—also predicts link use to discus refugees, though with less precision. View similarity is also driven by a subset of the range, specifically the most positive views. It seems as though village social networks create a pool of possible discussion partners; people select among them based primarily on relevance to the topic at hand.

Furthermore, a strong predictor of link use is multiplexity. When two people are connected in their village social network via multiple layers, they are more likely to discuss refugees with one another. This could be because when two people's relationship is based on multiple kinds of interactions such as sharing meals, visiting homesteads, borrowing money, and chatting about rumors, their frequency of interaction is especially high. Opportunities to discuss new information such as the refugee information spread by the study would be more plentiful. This could also be because multiplex ties are stronger, perhaps featuring greater intimacy or trust, and so also serve as the most likely sources of discussion partners when presented with new information that warrants careful thought.

This basic pattern holds whether or not the person was presented with the new information directly. Our treatment did not change the characteristics of the links that a person selected on when choosing a discussion partner from their multi-layer social network. What our treatment *did* do was change the volume of discussion partners. The treated spoke with.47 more people than the control, and selected them from their meal, visit, and borrow social network layers. In other words, while our perspective-taking intervention increased the sheer number of individuals with whom respondents discussed refugees, the individuals with whom treated individuals discussed refugees were not significantly different from the individuals with whom non-treated respondents discussed refugees.

Overall, these findings paint a picture that in the context of new information about a topic salient to rural villagers in Uganda, social networks play an important role in discussing it. Some layers are used more than others, though all were used to some extent in all villages. That no one layer dominates the others suggests that these conversations were not particularly sensitive or rigidly tailored to a certain kind of relationship. The information that would spread as a result is unlikely to exhibit tie-specific diffusion, which indicates that aggregating the layers to understand the consequences of conversations such as these may not mask results to a great extent (Larson and Rodríguez 2022; Larson and Rodriguez 2023). One implication is that although these networks are multi-layered in theory—there are distinct layers defined by conceptually distinct interactions—they may not need to be treated as multi-layered in practice, at least not with respect to the spread of new information about refugees.

Of course these results come from a single instance of network use—discussing new information about refugees—in a single context—rural Uganda. The more cases of networks in action that can be studied in more contexts, the better our understanding of the true role of multi-layer networks will be.

Appendix 1: Supporting description and analyses

See Tables 9, 10, 11, 12, 13, 14, 15, 16 and see Figs. 3, 4, 5, 6, 7, 8.

Table 9 The number of respondents who listed any names in response to the question of whom they discussed refugees with over the past two weeks, separated by village

Village	# Names>0	Prop >0	Any In NW
1	58	0.44	0.64
2	63	0.55	0.63
3	78	0.53	0.67
4	66	0.53	0.56
5	116	0.71	0.62
6	69	0.55	0.64
7	83	0.69	0.66
8	82	0.63	0.70
9	58	0.52	0.64
10	49	0.47	0.59
11	108	0.60	0.36
12	86	0.58	0.40

Also shows that number as a proportion of respondents in that village. Final column reports the proportion of respondents in the village whose discussion partners include anyone they listed in any of the four layers of the social network, measured two weeks prior

Table 10 Treatment effect on network link usage, simplest specification (no village fixed effects)

	Total Links (1)	Meal (2)	Visit (3)	Rumor (4)	Borrow (5)
Treatment	0.471***	0.127***	0.092**	−0.006	0.093***
	(0.097)	(0.035)	(0.039)	(0.028)	(0.030)
	[0.000]	[0.001]	[0.017]	[0.833]	[0.004]
Constant	1.644***	0.247***	0.325***	0.232***	0.206***
	(0.061)	(0.022)	(0.025)	(0.018)	(0.019)
Observations	1,604	1,604	1604	1,604	1,604
Adjusted R^2	0.014	0.008	0.003	−0.001	0.005
F Statistic (df = 1; 1602)	23.437***	13.233***	5.536**	0.042	9.437***

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

Standard errors from OLS shown in parentheses. Corrected p-values from QAP shown in square brackets. Additional detail on the corresponding QAP can be found in Appendix Fig. 5

Table 11 OLS regression of the number of refugee discussion partners on a factor variable that subcategorizes view homophily in terms of the view

	All Conversation Partners
Views both 5	0.034***
	(0.011)
Views both 4	−0.010
	(0.022)
Views both 3	−0.152
	(0.138)
Views both 2	−0.007
	(0.019)
Views both 1	−0.021
	(0.028)
Constant	0.152***
	(0.005)
Observations	6,731
Adjusted R	0.001

*$p < 0.1$;**$p < 0.05$;***$p < 0.01$

Views both 5 are links whose view homophily entails matching on the most pro-refugee value of 5, and so on. Omitted category is no view homophily. The relationship between view homophily and conversation partners is being driven by homophily with respect to the most positive views

Table 12 OLS regression of the number of refugee discussion partners on a factor variable that subcategorizes interest homophily in terms of the level of interest

	All Conversation Partners
Interest both 4	−0.145
	(0.210)
Interest both 3	−0.052
	(0.056)
Interest both 2	0.028
	(0.021)
Interest both 1	0.025***
	(0.009)
Constant	0.145***
	(0.006)
Observations	6,735
Adjusted R^2	0.001

*$p < 0.1$;**$p < 0.05$;***$p < 0.01$

Interest both 1 are links whose interest homophily entails matching on the highest level of interest of 1, and so on. Omitted category is no interest homophily. There are no links that both have interest level 5 (the lowest level). The relationship between interest homophily and conversation partners is being driven by homophily with respect to the highest interest

Table 13 Examining the treatment effect on the characterization of links in the multilayer social network that were used to discuss refugees (meal links only)

	Control	Treatment	*p*-value
Link Count	361	298	
Alter was ref	0.35	0.34	0.83
Alter knows ref	0.76	0.69	0.06
Alter farmer	0.81	0.82	0.62
Alter views	3.58	3.58	0.96
Alter interest	1.33	1.37	0.49
Relig homoph	0.75	0.75	0.90
Language homoph	0.84	0.87	0.33
Refugee status homoph	0.60	0.63	0.43
Refugee views homoph	0.39	0.36	0.43
Interest homoph	0.60	0.54	0.16
Positive views homoph	0.27	0.25	0.57
High interest homoph	0.54	0.49	0.23
In Multiple Layers	0.79	0.83	0.20
Count of Layers	1.13	1.14	0.84

Table 14 Examining the treatment effect on the characterization of links in the multilayer social network that were used to discuss refugees (visit links only)

	Control	Treatment	*p*-value
Link Count	450	325	
Alter was ref	0.32	0.35	0.45
Alter knows ref	0.74	0.70	0.22
Alter farmer	0.80	0.84	0.18
Alter views	3.60	3.63	0.82
Alter interest	1.35	1.39	0.51
Relig homoph	0.75	0.75	0.90
Language homoph	0.84	0.85	0.68
Refugee status homoph	0.62	0.59	0.49
Refugee views homoph	0.37	0.39	0.69
Interest homoph	0.59	0.57	0.55
Positive views homoph	0.26	0.27	0.65
High interest homoph	0.51	0.51	0.96
In Multiple Layers	0.76	0.79	0.28
Count of Layers	2.36	2.35	0.91

Table 15 Examining the treatment effect on the characterization of links in the multilayer social network that were used to discuss refugees (rumor links only)

	Control	Treatment	*p*-value
Link Count	308.00	188.00	
Alter was ref	0.31	0.25	0.19
Alter knows ref	0.71	0.74	0.57
Alter farmer	0.80	0.80	0.83
Alter views	3.68	3.40	0.05
Alter interest	1.38	1.44	0.38

Table 15 (continued)

	Control	Treatment	*p*-value
Relig homoph	0.76	0.78	0.69
Language homoph	0.84	0.90	0.06
Refugee status homoph	0.62	0.66	0.32
Refugee views homoph	0.37	0.32	0.23
Interest homoph	0.59	0.51	0.10
Positive views homoph	0.23	0.22	0.85
High interest homoph	0.53	0.46	0.13
In Multiple Layers	0.83	0.82	0.73
Count of Layers	2.62	2.61	0.91

Table 16 Examining the treatment effect on the characterization of links in the multilayer social network that were used to discuss refugees (borrow links only)

	Control	Treatment	*p*-value
Link Count	288.00	229.00	
Alter was ref	0.31	0.37	0.18
Alter knows ref	0.70	0.71	0.94
Alter farmer	0.84	0.82	0.56
Alter views	3.77	3.66	0.41
Alter interest	1.36	1.38	0.80
Relig homoph	0.72	0.75	0.60
Language homoph	0.85	0.87	0.56
Refugee status homoph	0.66	0.62	0.35
Refugee views homoph	0.35	0.37	0.66
Interest homoph	0.55	0.57	0.72
Positive views homoph	0.25	0.27	0.68
High interest homoph	0.50	0.51	0.77
In Multiple Layers	0.86	0.86	0.82
Count of Layers	2.73	2.65	0.34

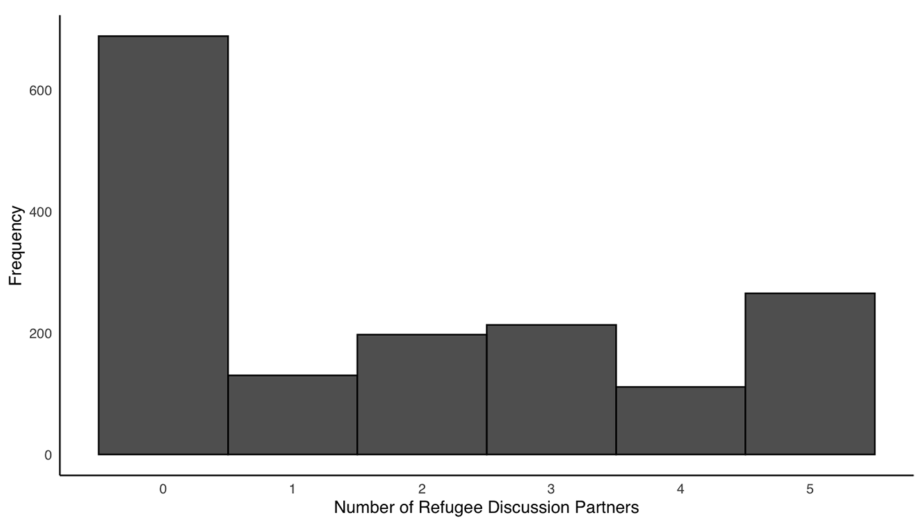

Fig. 3 Distribution of Number of Refugee Discussion Partners, All Respondents

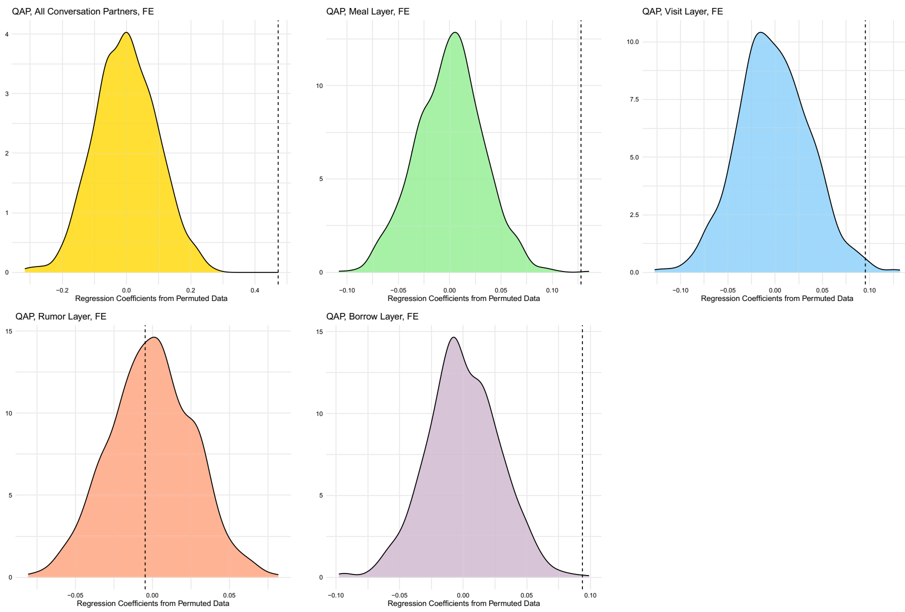

Fig. 4 Quadratic Assignment Procedure corresponding to Table 4. For each, network structure and link use was held constant, and the village's treatment vector was shuffled among the nodes within each village. These plots are the distribution of OLS regression coefficients on treatment across the shuffled attributes. Observed regression coefficient shown as a dashed vertical line. QAP scores calculated as the proportion of permuted datasets resulting in a regression coefficient at least as extreme as the observed value (two-sided)

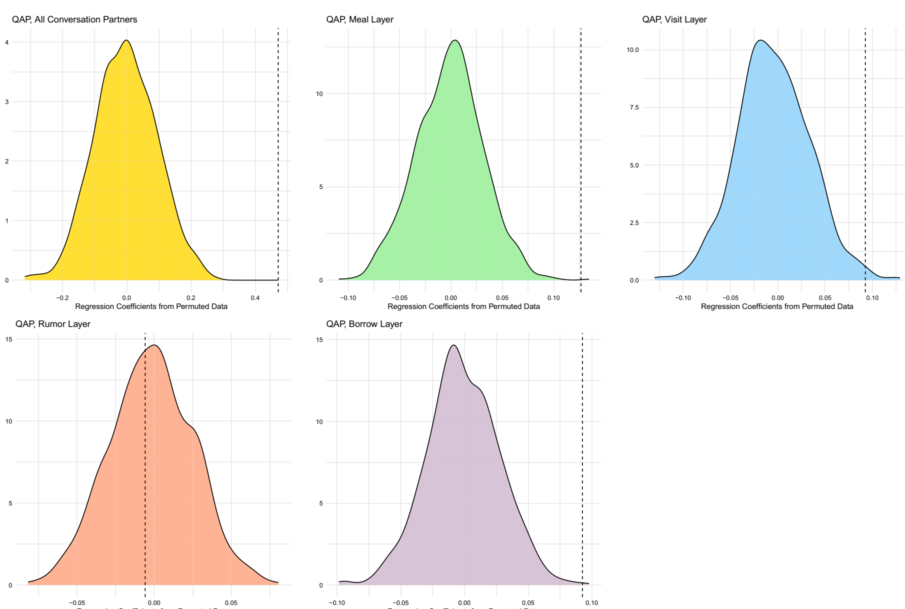

Fig. 5 Quadratic Assignment Procedure corresponding to Table 10. For each, network structure and link use was held constant, and the village's treatment vector was shuffled among the nodes within each village. These plots are the distribution of OLS regression coefficients on treatment across the shuffled attributes. Observed regression coefficient shown as a dashed vertical line. QAP scores calculated as the proportion of permuted datasets resulting in a regression coefficient at least as extreme as the observed value (two-sided)

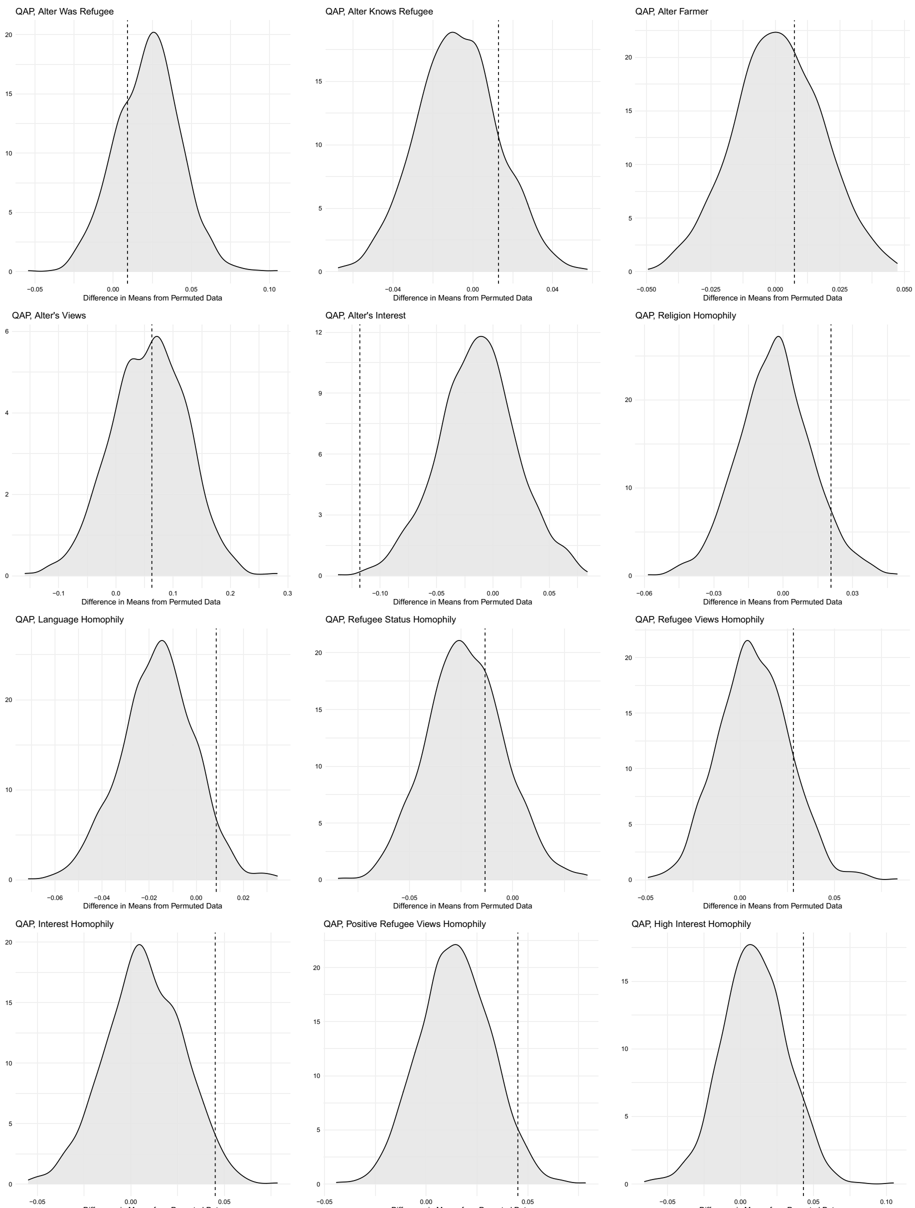

Fig. 6 Quadratic Assignment Procedure corresponding to Table 7. For each, network structure and link use was held constant, and attributes were randomly shuffled among the nodes within villages. For each permutation, a new link dataset was formed with new homophily measures calculated. These plots are the distribution of differences in means between links used and not used in terms of the shuffled attributes. Observed difference in means indicated with vertical dashed lines. QAP scores calculated as the proportion of permuted datasets resulting in a difference in means at least as extreme as the obeserved value (two-sided)

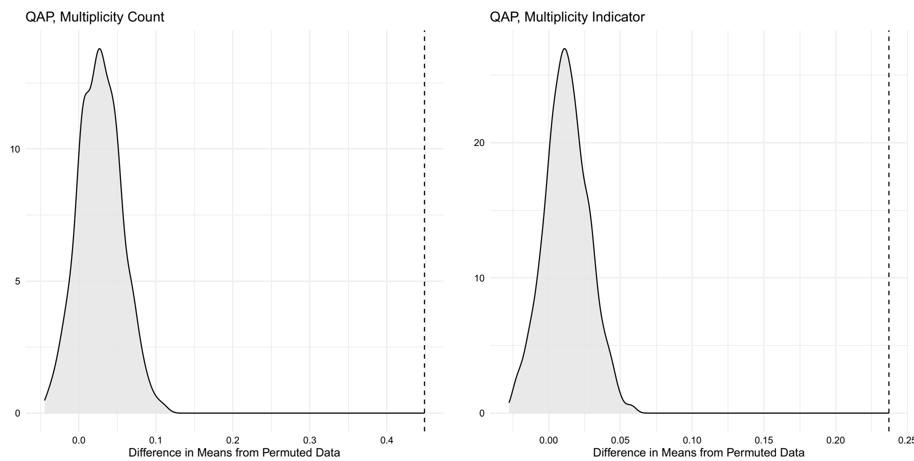

Fig. 7 QAP applied to multiplicity. For these tests the set of links—the unique pairs of nodes—was held fixed, as was whether the link was used to discuss refugees, and a village's set of multiplicity counts was randomly shuffled among that village's links. These were then used to construct a multiplicity indicator which takes the value of 1 if the count is 2 or larger. The difference in mean values of the multiplicity count and multiplicity indicator was then calculated between the set of links that were used to discuss refugees and the set that was not. These distributions show the sampling distribution of the difference of means across datasets permuted in this way, with the observed value indicated with a dashed vertical line

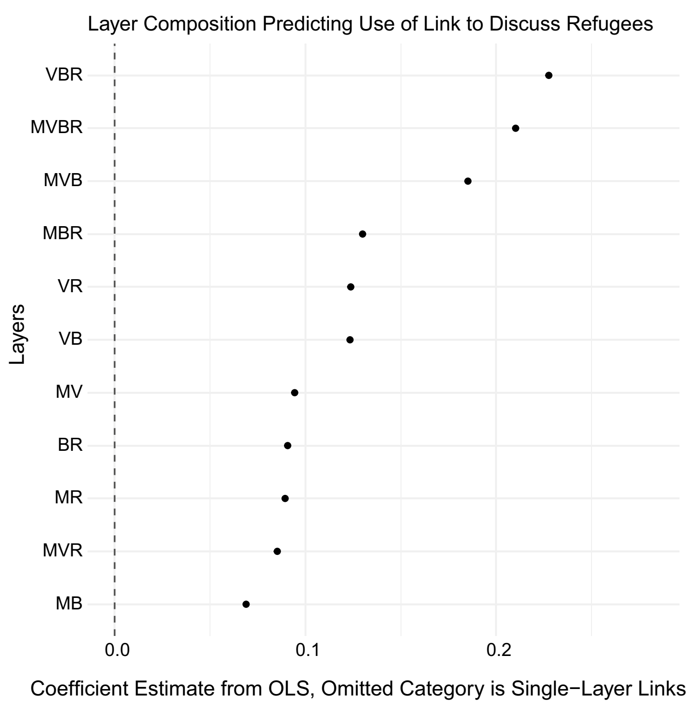

Fig. 8 Predicting link use as a function of its multiplicity. Relative to links that appear in only one layer (M, V, B, R), appearing in three or four layers is in general more predictive of a link being used to discuss refugees, though the three-layer set comprised of meals, visits, and rumors is an exception

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Author contributions
J.I.L. and J.M.L. designed the survey and experiment. J.I.L. led data collection. J.M.L. and A.T.C. performed the analyses and completed the write-up. All authors read and approved the final manuscript.

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Data availability
The datasets analysed during the current study and the code to perform the analyses are available in the Harvard Dataverse, https://doi.org/10.7910/DVN/TMB5NQ.

Declarations

Competing interests
The authors declare that they have no Conflict of interest.

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