HHS Public Access
Author manuscript
Epidemiology. Author manuscript; available in PMC 2022 July 01.

Published in final edited form as:
Epidemiology. 2021 July 01; 32(4): 551–559. doi:10.1097/EDE.0000000000001352.

Social networks and HIV care outcomes in rural Kenya and Uganda

Yiqun T. Chen[1], **Lillian Brown**[2], **Gabriel Chamie**[2], **Dalsone Kwarisiima**[3], **James Ayieko**[4], **Jane Kabami**[3], **Edwin Charlebois**[2], **Tamara Clark**[2], **Moses Kamya**[3], **Diane V. Havlir**[2], **Maya L. Petersen**[5], **Laura B. Balzer**[6]

[1.]University of Washington, Seattle, WA, USA [2.]University of California San Francisco, San Francisco, CA, USA [3.]Infectious Diseases Research Collaboration, Kampala, Uganda [4.]Kenya Medical Research Institute, Nairobi, Kenya [5.]University of California Berkeley, Berkeley, CA, USA [6.]University of Massachusetts Amherst, Amherst, MA, USA

Abstract

Background—Social isolation among HIV-positive persons might be an important barrier to care. Using data from the SEARCH Study in rural Kenya and Uganda, we constructed 32 community-wide, sociocentric networks and evaluated whether less socially connected HIV-positive persons were less likely to know their status, have initiated treatment, and be virally suppressed.

Methods—Between 2013–2014, 168,720 adult residents in the SEARCH Study were census-enumerated, offered HIV testing, and asked to name social contacts. Social networks were constructed by matching named contacts to other residents. We characterized the resulting networks and estimated risk ratios (aRR) associated with poor HIV care outcomes, adjusting for sociodemographic factors and clustering by community with generalized estimating equations.

Results—The sociocentric networks contained 170,028 residents (nodes) and 362,965 social connections (edges). Among 11,239 HIV-positive persons who named ≥1 contact, 30.9% were previously undiagnosed, 43.7% had not initiated treatment, and 49.4% had viral non-suppression. Lower social connectedness, measured by the number of persons naming an HIV-positive individual as a contact (in-degree), was associated with poorer outcomes in Uganda, but not Kenya. Specifically, HIV-positive persons in the lowest connectedness tercile were less likely to be previously diagnosed (Uganda-West aRR:0.89 (95%CI:0.83, 0.96); Uganda-East aRR:0.85 (95%CI:0.76, 0.96)); on treatment (Uganda-West aRR:0.88 (95%CI:0.80, 0.98); Uganda-East aRR:0.81 (0.72, 0.92)), and suppressed (Uganda-West aRR:0.84 (95%CI:0.73, 0.96); Uganda-East aRR:0.74 (95%CI:0.58, 0.94)) than those in the highest connectedness tercile.

Corresponding author: Laura B. Balzer (LBALZER@UMASS.EDU), Mailing address: Department of biostatistics and epidemiology, school of Public health and Health Sciences, 427 Arnold House, Amherst, MA, 01003, Telephone: (413) 545-9464.

Conflicts of interest:
None declared

Availability of data and computing code: Inquiries regarding data availability should be directed to the SEARCH Scientific Committee at douglas.black@uscf.edu. Inquiries about computing code should be addressed to Yiqun Chen at yiqunc@uw.edu.

Conclusions—HIV-positive persons named as a contact by fewer people may be at higher risk for poor HIV care outcomes, suggesting opportunities for targeted interventions.

Keywords

HIV care; HIV viral suppression; Network construction; SEARCH Study; Social isolation; Social network

Introduction

With 1.7 million new infections and 770,000 HIV deaths globally in 2018, the HIV epidemic continues to pose a major challenge to global public health.[1] Antiretroviral therapy (ART) can dramatically reduce both mortality and onward transmission of HIV by suppressing viral replication, and is recommended for all HIV-positive persons.[2] However, for both HIV-positive individuals and their communities to fully realize these benefits, HIV-positive persons must be aware of their HIV status, initiate ART, and sustain viral suppression. Despite dramatic expansion in HIV testing and ART access over recent years, many regions lag behind global goals set by The Joint United Nations Programme on HIV/AIDS (UNAIDS) for 90% of all HIV-positive persons to know their status, 81% to be on ART, and 73% to be virally suppressed.[1] In 2018, only 58% of the 20.6 million HIV-positive persons in Eastern and Southern Africa had viral suppression.[3] Reducing new HIV infections and HIV-associated deaths urgently requires understanding which individuals are being left behind in order to develop HIV testing and care models that more effectively meet their needs.

An individual's social network, and in particular, social connectedness, may play an important role in affecting uptake of HIV testing and ART.[4] Social network characteristics have been associated with a range of health-related behaviors,[5–10] including HIV testing, sexual concurrency, and risk behaviors in Africa.[11–15] An individual's degree of connectedness to their larger social network, as captured by measures such as in-degree, i.e., the number of other persons in the network nominating an individual as a contact, may influence health-related behaviors and outcomes.[11,16,17] However, evaluating the role of such "sociocentric" social network characteristics requires close to comprehensive measurement of social ties across a community;[17] this is in contrast to egocentric network measures such as out-degree (i.e., the number of contacts an individual nominates). Few such networks have been constructed to date in resource-limited settings including sub-Saharan Africa.[12,19–22] Little is thus known about the role of an individual's position in their larger social network in determining or simply predicting HIV testing, treatment uptake, and viral suppression in sub-Saharan Africa.[4]

We constructed sociocentric social networks for 32 communities in rural Uganda and Kenya by applying a semi-supervised algorithm to match social contacts named during population-level testing campaigns to census-enumerated participants in the Sustainable East Africa Research in Community Health (SEARCH) Study (NCT01864603), a recently completed "Universal HIV Test-and-Treat" trial.[23] The resulting networks were used to characterize individuals who were less socially connected than other individuals in their communities, and to improve our understanding of the relationships between social connectedness and diagnosis, treatment, and viral suppression for HIV-positive persons. We hypothesized that more socially connected HIV-positive persons would be more likely to know their HIV status and be virally suppressed than their less connected counterparts.

Methods

Setting and population

The SEARCH Study was conducted in 12 communities in rural Kenya and 20 communities in rural Uganda (10 in the southwestern region — “Uganda-West” and 10 in the eastern region — “Uganda-East”). As previously described,[24] a brief door-to-door census was conducted at study baseline (June 2013–June 2014) to enumerate community residents. Following the census, two-week community health campaigns were conducted in all communities; these health fairs offered multi-disease services, including HIV testing and viral load measurement for HIV-positive persons (irrespective of ART status).[23,24] Non-attendees were contacted and offered testing and services at home or other place of their choice. As previously described, using this population-based approach, 89% of all adults (aged ≥15 years) tested for HIV at study baseline; regional HIV prevalence was 19% in Kenya, 7% in Uganda-West, and 4% in Uganda-East.[23,24]

Measures

Demographic measures, including age, sex, marital status, education, occupation, and mobility (nights spent outside the community in the prior year) were collected during the census. Income was assessed by applying a principal components analysis to a household-level survey on ownership of livestock and household items,[25] and was summarized based on quintile. Self-reported alcohol and contraceptive use were evaluated at time of HIV testing. HIV status was assessed using rapid antibody tests according to country-standard algorithms; plasma HIV RNA concentrations (i.e., viral loads) were established with commercial real-time PCR assays,[26] with suppression defined as <500 copies/ml. Both HIV status and viral loads were ascertained through the previously described, population-based approach of health fairs and follow-up testing.[23,24] Among HIV-positive persons, prior HIV diagnosis and ART use were assessed via linkage to Ministry of Health records. Persons with suppressed HIV RNA levels were considered to be on ART, and by implication, to know their HIV status. Persons with unsuppressed HIV RNA levels may have been newly diagnosed, previously diagnosed but not on ART, or previously diagnosed and on ART.

At health fairs and follow-up testing, adult residents were asked for the name, age and village of up to 6 contacts in each of 5 different social domains: food issues, health issues, monetary matters, interaction during free time, and emotional support. The name generators used were adapted from earlier work by Perkins,[19] and included questions such as: “Over the last 12 months, with whom have you usually discussed any kind of money matters?” A complete set of name generators administered is included in the Supplementary Materials.

Network construction

In each community separately, sociocentric networks were constructed by matching contacts named by each participant ("ego") to other enumerated community residents ("alters") using a semi-supervised record linkage algorithm developed for this application.[27] The algorithm's pre-processing, two-step blocked matching optimal weight determination, and post-processing are detailed in Supplementary Materials; full computing code implementing the approach is available (https://anonymous.4open.science/r/6823cec2-73b4-4ccc-a8f4-98e7bd7f2673/). While name generators were only administrated to adult residents, matching was performed for all residents, allowing children to be matched. The resulting matched contacts were used to build networks using the *igraph* package in R.[28]

Network description

The 32 resulting networks were visualized with Gephi software using the ForceAtlas2 algorithm for layout,[29] with edges corresponding to ties between named contacts and nodes corresponding to individual community residents. Descriptive statistics were calculated for each network, including average degree (number of edges for one individual), transitivity (the proportion of any three individuals who all know each other in the network, a measure of clustering), reciprocity (proportion of edges that are bidirectional, i.e., mutual ties), average path length (average number of steps it takes to travel from one individual to another), and coverage of the top connected component (proportion of interconnected individuals). We further calculated the proportion of edges that were between different households, rather than among participants from the same household.

Evaluation of HIV testing, treatment uptake, and viral suppression

We considered two measures of network connectedness: "out-degree", the number of named contacts and, "in-degree", the number of other community residents who named an individual. Importantly, out-degree only requires egocentric network data, while in-degree requires sociocentric network data. We categorized each measure of connectedness using terciles, calculated separately for each community. Terciles were selected to avoid the coarseness of a binary variable and to avoid overlapping categories when using quartiles; sensitivity analyses defined connectedness with respect to the median.

Then we evaluated whether socially isolated HIV-positive persons, defined as individuals in the lowest tercile of network connectedness for their community, were less likely to be aware of their HIV status, to have initiated ART, and to have viral suppression. To better understand drop-offs in the HIV care cascade, we further considered whether social isolation predicted not having initiated ART among persons with a prior HIV diagnosis, and whether isolation predicted non-suppression among persons who had initiated ART. To avoid misclassifying persons with missing name generator data as socially isolated based on out-degree, primary analyses were restricted to persons who named at least one contact; sensitivity analyses included individuals with no named contacts.

In each region separately, unadjusted and adjusted risk ratios for each outcome were evaluated using generalized estimating equations with the log link function and robust standard error estimates, clustered by community and using an exchangeable working covariance matrix.[30] To reduce the potential for biased variance estimation due to the small number of clusters, we employed Kauermann-Carroll corrections with t-distribution based Wald-test.[31] Multivariable analyses adjusted for individual demographic and behavioral risk factors identified *a priori* based on existing literature: sex, age, marital status, mobile resident, education level, and occupation (Details in Supplementary Digital Content).

Protection of Human Subjects

All participants provided verbal informed consent in their preferred language with fingerprint confirmation of agreement. The Makerere University School of Medicine Research and Ethics Committee (Uganda), the Ugandan National Council on Science and Technology (Uganda), the KEMRI Scientific and Ethics Review Unit (Kenya), and the UCSF Human Research Protection Program and IRB (USA) approved the consent procedures and the study.

Results

Network construction and quality metrics

A total of 334,952 individuals were enumerated during the household census;[24] of these, 168,720 (50.4%) were adults (aged ≥15 years) eligible for the name generator. While 73.3% (123,641/168,720) of adults named at least one contact, coverage varied by region: 82.6% (42,592/51,560) in Uganda-East, 75.3% (41,175/54,653) in Uganda-West, and 63.8% (39,874/62,507) in Kenya. (Additional details about the matching quality and network completeness are provided in Supplementary Table 1.) Adults in Kenyan communities named fewer contacts (median 4, IQR:0–8) than adults in Ugandan communities (Uganda-East: median 7, IQR:3–15; Uganda-West: median 11, IQR:1–16). The percentage of named contacts who were matched to enumerated residents varied across regions, both before and after accounting for variability in the proportion of named contacts living outside the community; 28.4% of all named contacts and 34.2% of within-community contacts were matched in Kenya; 55.7% of all contacts and 63.0% of within-community contacts were matched in Uganda-East; and, 48.5% of all contacts and 56.8% of within-community contacts were matched in Uganda-West.

Descriptive characteristics of the networks

Networks demonstrated substantially different topology across regions (Figure 1). Kenyan networks are comprised of a larger percentage of isolated nodes, pairs, and a lower proportion of within-household connections (74.4% in Kenya versus 84.1% in Uganda-East, 82.1% in Uganda-West; Supplementary Table 2). Kenyan networks were less dense, with an average degree of 1.60, in contrast to an average degree of 5.69 and 5.84 in Uganda-East and Uganda-West respectively. Clustering and proportion of mutual ties were more similar across regions; Kenyan communities had average transitivity 0.12 and reciprocity 0.16 compared to average transitivity 0.14 and reciprocity 0.23 for Uganda-West, and average transitivity 0.15 and reciprocity 0.24 for Uganda-East. Finally, networks in Kenya were sparser and the largest connected components (normalized by graph size) were smaller than those in Uganda-West and Uganda-East. Among those with known baseline HIV status, HIV-positive and HIV-negative persons had similar out-degree (medians 7 and 8 respectively) and in-degree (medians 1 and 1 respectively).

Social connectedness and outcomes among HIV-positive persons

Of the 13,798 HIV-positive persons, 11,239 (81.7%) named ≥1 contact and were included in primary analyses to assess social predictors of the HIV care outcomes: 2,473 in Uganda-West, 1,440 in Uganda-East and 7,326 in Kenya (Table 1). 30.9% (3,473/11,239) of HIV-positive persons were not aware of their HIV status and 43.6% (4,909/11,239) had not initiated ART. Plasma HIV RNA levels were measured in 72.6% (8,160/11,239); missing measures were primarily due to logistical barriers at the start of the study and the distribution of measured covariates was similar for those with and without a missing viral load.[26] Among those with measured HIV RNA, 49.4% (4,029/8,160) were not suppressed. Characteristics of HIV-positive persons with and without at least one named contact were similar (Supplementary Table 3; Supplementary Table 6).

Terciles of connectedness based on out-degree and in-degree differed across communities and regions (Supplementary Table 4). The median threshold below which persons were classified as less-connected (i.e., in the lowest tercile for their community) based on out-degree was 6 (IQR:5–10) in Uganda-East, 10 (IQR:8–14) in Uganda-West, and 5 (IQR:5–7) in Kenya. Corresponding thresholds for in-degree were 1 (IQR:1–2) in Uganda-East, 1 (IQR:1–2) in Uganda-West, and 0 (IQR:0–1) in Kenya.

In both Uganda-East and Uganda-West, HIV-positive persons in lower terciles of in-degree were at higher risk of poor outcomes as compared to the most socially connected individuals (Figure 2a). Specifically, in Uganda-East, persons in the lowest vs. highest tercile of in-degree were less likely to know their HIV status (57.4% vs. 69.5%; aRR:0.85; 95%CI:0.76, 0.96), to have initiated ART (46.4% vs. 59.5%; aRR:0.80; 95%CI: 0.72, 0.90), and to have viral suppression (35.3% vs 50.6%; aRR:0.74; 95%CI:0.58, 0.94) (Figure 3; Supplementary Table 5). Likewise, in Uganda-West, the least vs. most socially connected HIV-positive persons were less likely to be diagnosed (56.6% vs. 68.1%; aRR; 0.89; 95%CI: 0.82, 0.96), on treatment (45.7% vs. 57.3%; aRR:0.88; 95%CI:0.80, 0.98), and have suppressed viral replication (41.3% vs. 55.7%; aRR:0.84; 95%CI:0.73, 0.96). In multivariable analyses, additional predictors of non-suppression included male sex, mobility (≥1 month of prior year outside the community), and age <25 years.

Among HIV-positive persons with knowledge of their HIV status, lowest in-degree tercile was not predictive of prior ART initiation (aRR:0.95; 95%CI:0.88, 1.02 for Uganda-East; aRR:1.01; 95%CI: 0.97, 1.05 for Uganda-West). Among persons who had initiated ART, persons with the lowest in-degree were less likely to be suppressed than their most connected counterparts in Uganda-West (aRR:0.95; 95%CI: 0.92, 0.98), but not Uganda-East (aRR:0.96; 95%CI: 0.83, 1.10).

In Kenya, social connectedness defined using in-degree was not predictive of the prior diagnosis, ART use, or viral suppression on HIV-positive persons, either before or after adjusting for individual risk factors (Figure 3; Supplementary Table 5).

In all regions, the proportion of HIV-positive persons who knew their status was consistently lower among those in the lowest tercile of out-degree (Figure 2b). However, after adjustment for individual risk factors, social isolation defined using out-degree was not predictive of knowledge of HIV status, ART initiation, or viral suppression in any of the three study regions, (Figure 3; Supplementary Table 5), with the exception of ART use in Uganda-East. For all regions and outcomes, similar results were observed in sensitivity analyses, which i) included persons with no named contacts; ii) defined out-degree using number of matched named contacts; and iii) defined in-degree and out-degree connectedness with the median (Supplementary Figures 2–4).

Discussion

Social connectedness, as assessed through sociocentric networks, predicted HIV care outcomes in 20 rural communities in Uganda. After adjusting for known risk factors, being named as contact by fewer individuals (i.e., lower in-degree) was associated with lower knowledge of HIV status, ART initiation, and viral suppression. When we assessed drop-offs in the HIV care cascade, associations appeared to be driven primarily by lower knowledge of HIV status. These data suggest that social isolation may be an important contributor to population-level viral suppression by acting as a barrier to diagnosis of HIV infection.

To date, sociocentric network data in resource-limited settings are limited,[19,33] and very little work has been done in sub-Saharan Africa. Previously, in a single community study in Uganda, stigma among HIV-infected individuals was associated with the levels of stigma among their peers and HIV testing was associated with perceived norms.[20,34] Likewise, a study of the social networks among young men in urban Dar es Salaam found that men in network core (more connected) were 1.5 times more likely to test than those in periphery (less connected), and the perception of network HIV stigma was negatively associated with HIV testing.[12,35] Our work is the first study in sub-Saharan Africa to look at social network predictors of HIV diagnosis, treatment uptake, and viral suppression, and in the context of sociocentric networks in 32 communities. These networks included both sexes, encompassed 170,028 persons with 362,965 contacts, and harnessed population-based ascertainment on HIV care outcomes. Unlike prior studies replying on self-report, HIV status and viral suppression were directly assessed on the majority of participants, irrespective of care status, through community-wide testing; prior diagnosis and ART initiation were determined through linkage to ministry of health records.[23,24]

We found socially isolated HIV-positive persons, as measured by in-degree, were less likely to know their status, have initiated ART, and be virally suppressed in Uganda. This is consistent with research in other settings in which less connected individuals are less likely to test for HIV. For example, in China, male sex workers who had a small network or had a network where few members tested for HIV were themselves less likely to have tested for HIV;[8] in a study among Indian truck drivers and their apprentices, having many friends was positively associated with the acceptance of rapid HIV testing.[7] In our study, the lower viral suppression seen among less-connected HIV-positive persons in Uganda appeared to be largely due to lower knowledge of HIV status. This finding is consistent with evidence for peer support on engagement in care.[36]

Social networks influence health outcomes through access to resources, transmission of information, as well as social norms and social support.[37,38] The Network-Individual-Resource-Model (NIRM) predicts the success of prevention efforts or behavior change depends on reciprocal ties of individuals, their networks, and the material and psychosocial resources.[39] The socially isolated individuals in our study population may have less access to health care services and instrumental support from peers in accessing these resources.[38] They may also have been less likely to receive information about HIV testing and treatment, as more central individuals in a network are more likely to learn about new ideas and information earlier than those with fewer social ties.[38]

Interestingly, in-degree was associated with prior diagnosis, treatment uptake, and viral suppression in our Ugandan population, while out-degree was not. This suggests that sociocentric and egocentric networks capture different information. Naming many social contacts (i.e., having a higher out-degree) may not translate into equivalent social support as being named by many social contacts (i.e., having a higher in-degree). Similar observations were made in studies on the association between in-degree and out-degree in an online social network[40] and adolescence health networks.[41] In our setting, contacts who name HIV-positive persons may also be those who facilitate health care access and information sharing.

While similar relationships were observed in two regions in rural Uganda, open questions remain regarding the generalizability of these results. In particular, the same relationships were not observed in the Kenyan communities. This finding is likely due to less complete networks with a greater number of missing links. In Kenyan communities, coverage of the name generator was lower (65.5% vs. 80.9% in Uganda-East and 75% in Uganda-West), and fewer contacts were named (189,167 vs. 363,260 in Uganda-East and 459,821 in Uganda-West). Because quality of data on contacts to inform matching was lower, fewer named contacts were matched in these communities (34.2% in Kenya vs. 63% in Uganda-East and 56.8% in Uganda-West; Supplementary Table 1). The low matching rate highlights some of the real-world challenges in collecting data on and generating community-wide, sociocentric networks in resource-limited settings. While we have no reason to believe matching was differential by HIV care outcomes, limited variability in the resulting in-degree distribution likely reduced statistical power for assessing social network predictors in Kenyan communities. However, it is also possible that social isolation reflected by in-degree is less predictive of HIV testing, treatment uptake, and viral suppression in rural Kenyan communities. Further work is needed to understand how sociocentric predictors of HIV care outcomes may generalize to other settings and communities.

Generating sociocentric networks and evaluating how they predict HIV care outcomes are unique strengths of this study. Our results show that beyond known risk factors, sociocentric measures of social connectedness may be important predictors of adverse HIV care outcomes. Thus, these results suggest the possibility of leveraging social networks to facilitate effective engagement in HIV care among adults. Specifically, sociocentric network data could help identify subgroups of HIV-positive persons who would benefit from targeted care interventions; for instance, in other rural African settings, social networks have been found to amplify the effect of HIV prevention programs.[39] However, future work remains, including i) examining how HIV care outcomes vary by domains of social connectedness (measured using in-degree and out-degree) and by strength of connectedness (e.g., based on how many domains each contact was named in); ii) investigating alternative connectedness measures, such as eigen-centrality[42] and betweenness centrality[43]; and iii) exploring alternative modeling of the relationships between connectedness measures and HIV care outcomes, such as linear and cubic splines[44, 45].

Our findings are also subject to limitations. First, to avoid stigmatization, our name generator relied on self-report and was limited to five domains: food, health, money, free time interactions, and emotional support. If HIV-positive persons with poor outcomes were less likely to name their social contacts, we would have overestimated the reported associations. However, our study aimed to capture connections for all participants (i.e., sociocentric approach) instead of only eliciting perceived ties among participants' contacts (i.e., egocentric approach), thereby allowing for more accurate characterization[19,20]. Second, network connections were not measured completely. While the covariate distributions of all HIV-positive persons and those with at least 1 named contact were similar (Supplementary Table 6), only a portion of 1,012,248 named contacts were matched and among those that did match, it was not possible to verify if all matches were correct. It is possible that differential measurement of in-degree may have contributed to these findings. For example, if HIV-positive persons with poor outcomes were more likely to be missed in the matching process, the reported associations would be inflated. However, given our study's population-based assessment of the sociocentric networks, HIV diagnosis, ART use, and viral suppression, we have little reason to suspect such differential measurement occurred. Third, given the cross-sectional and observational nature of the data, we aimed to primarily improve our understanding of potential social predictors of HIV care outcomes — as opposed to assess causal effects. It is possible that prior diagnosis, ART use, or viral suppression may have improved social connectedness, rather than social isolation impeding diagnosis, ART initiation, or suppression. Finally, interpretations of the analyses between connectedness and HIV care cascade outcomes (i.e., ART use among those diagnosed, and viral suppression among those on ART) are complicated by treatment eligibility, which at the time of the study was limited to HIV-positive persons with CD4<350. It could be that more socially isolated people were less likely to start ART given eligibility but also more likely to be eligible. Longitudinal analyses in the context of universal ART eligibility will improve understanding between social connectedness and HIV care outcomes, including changes to sub-population of interest (e.g., persons who are aware of their status when examining ART initiation, and persons on ART when examining viral suppression)[46,47,48].

In the rural Ugandan communities in this study, social isolation as captured by in-degree was associated with lower viral suppression. Current evidence supports reducing population viremia to reduce new HIV infections.[49,50] In the context of universal eligibility for ART, the challenge is to design effective strategies to reach those who remain undiagnosed and out of care. This work supports the development and implementation of approaches capable of reaching those individuals with fewer connections and supporting their engagement in care as well as long-term viral suppression.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments:

We thank the Ministry of Health of Uganda and of Kenya; our research teams and administrative teams in San Francisco, Uganda, and Kenya; collaborators and advisory boards; and especially all the communities and participants involved in the study.

Sources of financial support:

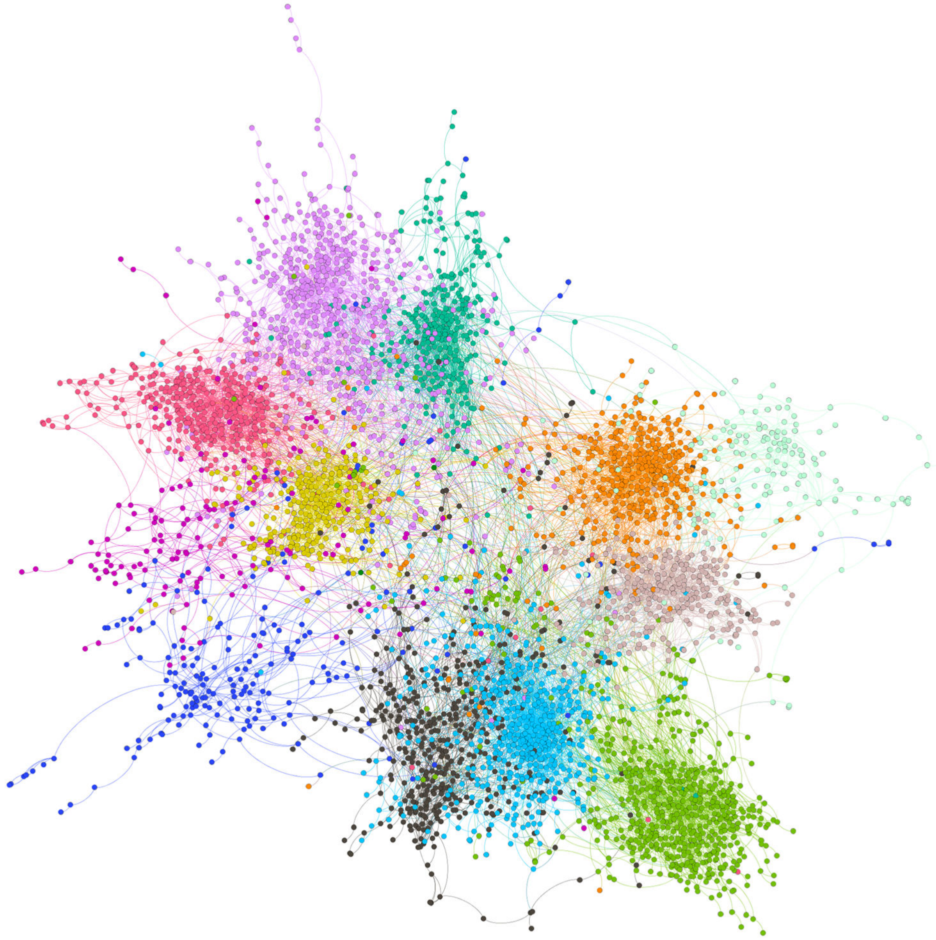
This work was supported by grant numbers U01AI099959, UM1AI068636, and R01AI074345–06A1 from National Institute of Allergy and Infectious Diseases at the National Institutes of Health; by the President's Emergency Plan for AIDS Relief; and by Gilead Sciences, which provided Truvada®.

References

1. UNAIDS. Global AIDS update 2019 — Communities at the centre https://www.unaids.org/sites/default/files/media_asset/2019-global-AIDS-update_en.pdf. Published 2019.
2. World Health Organization. Update of recommendations on first- and second-line antiretroviral regimens. https://apps.who.int/iris/bitstream/handle/10665/325892/WHO-CDS-HIV-19.15-eng.pdf?ua=1. Published 2019. Accessed 2019.
3. AIDSinfo | UNAIDS. http://aidsinfo.unaids.org/. Accessed December 2, 2019.
4. Ghosh D, Krishnan A, Gibson B, Brown S-E, Latkin CA, Altice FL. Social Network Strategies to Address HIV Prevention and Treatment Continuum of Care Among At-risk and HIV-infected Substance Users: A Systematic Scoping Review. AIDS Behav. 2017;21(4):1183–1207. doi:10.1007/s10461-016-1413-y [PubMed: 27125244]
5. Latkin CA, Forman V, Knowlton A, Sherman S. Norms, social networks, and HIV-related risk behaviors among urban disadvantaged drug users. Soc Sci Med. 2003;56(3):465–476. doi:10.1016/s0277-9536(02)00047-3 [PubMed: 12570967]
6. Barrington C, Latkin C, Sweat MD, Moreno L, Ellen J, Kerrigan D. Talking the talk, walking the walk: social network norms, communication patterns, and condom use among the male partners of female sex workers in La Romana, Dominican Republic. Soc Sci Med. 2009;68(11):2037–2044. doi:10.1016/j.socscimed.2009.03.009 [PubMed: 19356834]
7. Schneider J, Kumar R, Dandona R, et al. Social network and risk-taking behavior most associated with rapid HIV testing, circumcision, and preexposure prophylaxis acceptability among high-risk Indian men. AIDS Patient Care STDS. 2012;26(10):631–640. doi:10.1089/apc.2012.0188 [PubMed: 22973951]
8. Huang ZJ, He N, Nehl EJ, et al. Social network and other correlates of HIV testing: findings from male sex workers and other MSM in Shanghai, China. AIDS Behav. 2012;16(4):858–871. doi:10.1007/s10461-011-0119-4 [PubMed: 22223298]
9. Amirkhanian YA. Social networks, sexual networks and HIV risk in men who have sex with men. Curr HIV/AIDS Rep. 2014;11(1):81–92. [PubMed: 24384832]
10. Latkin C, Yang C, Tobin K, Roebuck G, Spikes P, Patterson J. Social network predictors of disclosure of MSM behavior and HIV-positive serostatus among African American MSM in Baltimore, Maryland. AIDS Behav. 2012;16(3):535–542. doi:10.1007/s10461-011-0014-z [PubMed: 21811844]
11. Yamanis TJ, Fisher JC, Moody JW, Kajula LJ. Young Men's Social Network Characteristics and Associations with Sexual Partnership Concurrency in Tanzania. AIDS Behav. 2016;20(6):1244–1255. doi:10.1007/s10461-015-1152-5 [PubMed: 26271813]
12. Yamanis TJ, Dervisevic E, Mulawa M, et al. Social Network Influence on HIV Testing Among Urban Men in Tanzania. AIDS Behav. 2017;21(4):1171–1182. doi:10.1007/s10461-016-1513-8 [PubMed: 27506817]

13. Mulawa M, Yamanis TJ, Hill LM, Balvanz P, Kajula LJ, Maman S. Evidence of social network influence on multiple HIV risk behaviors and normative beliefs among young Tanzanian men. Soc Sci Med. 2016;153:35–43. doi:10.1016/j.socscimed.2016.02.002 [PubMed: 26874081]
14. Hunter RF, de la Haye K, Murray JM, et al. Social network interventions for health behaviours and outcomes: A systematic review and meta-analysis. PLoS Med. 2019;16(9):e1002890. doi:10.1371/journal.pmed.1002890 [PubMed: 31479454]
15. Brown LB, Balzer LB, Kabami J, et al. The Influence of Social Networks on Antiretroviral Therapy Initiation Among HIV-Infected Antiretroviral Therapy-Naive Youth in Rural Kenya and Uganda. J Acquir Immune Defic Syndr. 2020;83(1):9–15. doi:10.1097/QAI.0000000000002199 [PubMed: 31809357]
16. Chami GF, Ahnert SE, Voors MJ, Kontoleon AA. Social network analysis predicts health behaviours and self-reported health in African villages. PLoS One. 2014;9(7):e103500. doi:10.1371/journal.pone.0103500 [PubMed: 25072820]
17. Ma X, Sayama H. Mental disorder recovery correlated with centralities and interactions on an online social network. PeerJ. 2015;3:e1163. doi:10.7717/peerj.1163 [PubMed: 26312174]
18. Marsden PV. Egocentric and sociocentric measures of network centrality. Soc Networks. 2002;24(4):407–422. doi:10.1016/S0378-8733(02)00016-3
19. Perkins JM, Subramanian SV, Christakis NA. Social networks and health: a systematic review of sociocentric network studies in low- and middle-income countries. Soc Sci Med. 2015;125:60–78. [PubMed: 25442969]
20. Takada S, Nyakato V, Nishi A, et al. The social network context of HIV stigma: Population-based, sociocentric network study in rural Uganda. Soc Sci Med. 2019;233:229–236. doi:10.1016/j.socscimed.2019.05.012 [PubMed: 31229909]
21. Shakya HB, Perkins JM, Traeger M, et al. Social network correlates of IPV acceptance in rural Honduras and rural Uganda. SSM Popul Health. 2018;4:236–243. doi:10.1016/j.ssmph.2018.02.001 [PubMed: 29854907]
22. Helleringer S, Kohler H-P, Chimbiri A, Chatonda P, Mkandawire J. The Likoma Network Study: Context, data collection, and initial results. Demogr Res. 2009;21:427–468. [PubMed: 20179777]
23. Havlir DV, Balzer LB, Charlebois ED, et al. HIV Testing and Treatment with the Use of a Community Health Approach in Rural Africa. N Engl J Med. 2019;381(3):219–229. doi:10.1056/NEJMoa1809866 [PubMed: 31314966]
24. Chamie G, Clark TD, Kabami J, et al. A hybrid mobile approach for population-wide HIV testing in rural east Africa: an observational study. Lancet HIV. 2016;3(3):e111–e119. [PubMed: 26939734]
25. Filmer D, Pritchett LH. Estimating wealth effects without expenditure data--or tears: an application to educational enrollments in states of India. Demography. 2001;38(1):115–132. doi:10.1353/dem.2001.0003 [PubMed: 11227840]
26. Jain V, Petersen ML, Liegler T, et al. Population levels and geographical distribution of HIV RNA in rural Ugandan and Kenyan communities, including serodiscordant couples: a cross-sectional analysis. Lancet HIV. 2017;4(3):e122–e133. [PubMed: 27989576]
27. Chen Y, Zheng W, Brown LB, et al. Semi-Supervised Record Linkage for Construction of Large-Scale Sociocentric Networks in Resource-limited Settings: An application to the SEARCH Study in Rural Uganda and Kenya. arXiv [statAP]. 8 2019. http://arxiv.org/abs/1908.09059.
28. Csardi G, Nepusz T. The igraph software package for complex network research. InterJournal Complex Systems. 2006. https://scholar.google.com/scholar?oi=bibs&cluster=1556604076393698320&btnI=1&hl=en.
29. Jacomy M, Venturini T, Heymann S, Bastian M. ForceAtlas2, a Continuous Graph Layout Algorithm for Handy Network Visualization Designed for the Gephi Software. PLoS One. 2014;9(6):e98679. [PubMed: 24914678]
30. Zeger SL, Liang KY, Albert PS. Models for longitudinal data: a generalized estimating equation approach. Biometrics. 1988;44(4):1049–1060. doi:10.2307/2531734 [PubMed: 3233245]
31. Li P, Redden DT. Small sample performance of bias-corrected sandwich estimators for cluster-randomized trials with binary outcomes. Stat Med. 2015;34(2):281–296. doi:10.1002/sim.6344 [PubMed: 25345738]

32. Chamie G, Kwarisiima D, Clark TD, et al. Uptake of community-based HIV testing during a multi-disease health campaign in rural Uganda. PLoS One. 2014;9(1):e84317. doi:10.1371/journal.pone.0084317 [PubMed: 24392124]
33. Christakis NA, Fowler JH. Social contagion theory: examining dynamic social networks and human behavior. Stat Med. 2013;32(4):556–577. [PubMed: 22711416]
34. Perkins JM, Nyakato VN, Kakuhikire B, et al. Food insecurity, social networks and symptoms of depression among men and women in rural Uganda: a cross-sectional, population-based study. Public Health Nutr. 2018;21(5):838–848. [PubMed: 28988551]
35. Mulawa MI, Yamanis TJ, Kajula LJ, Balvanz P, Maman S. Structural Network Position and Performance of Health Leaders Within an HIV Prevention Trial. AIDS Behav. 2018;22(9):3033–3043. doi:10.1007/s10461-018-2126-1 [PubMed: 29705931]
36. Johnson BT, Redding CA, DiClemente RJ, et al. A network-individual-resource model for HIV prevention. AIDS Behav. 2010;14(Suppl 2):204–221. doi:10.1007/s10461-010-9803-z [PubMed: 20862606]
37. Barrera D, van de Bunt GG. Learning to Trust: Networks Effects Through Time. Eur Sociol Rev. 2009;25(6):709–721. doi:10.1093/esr/jcn078
38. Valente TW. Network interventions. Science. 2012;337(6090):49–53. doi:10.1126/science.1217330 [PubMed: 22767921]
39. Kohler H-P, Behrman JR, Watkins SC. Social networks and HIV/AIDs risk perceptions. Demography. 2007;44(1):1–33. doi:10.1353/dem.2007.0006 [PubMed: 17461334]
40. Ma X, Sayama H. Mental disorder recovery correlated with centralities and interactions on an online social network. PeerJ. 2015;3:e1163. doi:10.7717/peerj.1163 [PubMed: 26312174]
41. Haas SA, Schaefer DR, Kornienko O. Health and the structure of adolescent social networks. J Health Soc Behav. 2010;51(4):424–439. doi:10.1177/0022146510386791 [PubMed: 21131619]
42. Freeman LC. A Set of Measures of Centrality Based on Betweenness. Sociometry. 1977;40(1):35–41. doi:10.2307/3033543
43. Bonacich P. Power and Centrality: A Family of Measures. Am J Sociol. 1987;92(5):1170–1182. doi:10.1086/228631
44. Frøslie KF, Røislien J, Laake P, Henriksen T, Qvigstad E, & Veierød MB (2010). Categorisation of continuous exposure variables revisited. A response to the Hyperglycaemia and Adverse Pregnancy Outcome (HAPO) Study. BMC Medical Research Methodology, 10, 103. 10.1186/1471-2288-10-103 [PubMed: 21062456]
45. Turner EL, Dobson JE, & Pocock SJ (2010). Categorisation of continuous risk factors in epidemiological publications: a survey of current practice. Epidemiologic Perspectives & Innovations: EP+I, 7, 9. 10.1186/1742-5573-7-9 [PubMed: 20950423]
46. Haber NA, Lesko CR, Fox MP, Powers KA, Harling G, Edwards JK, Salomon JA, Lippman SA, Bor J, Chang AY, Anglemyer A, & Pettifor A (2020). Limitations of the UNAIDS 90–90-90 metrics: a simulation-based comparison of cross-sectional and longitudinal metrics for the HIV care continuum. AIDS , 34(7), 1047–1055. 10.1097/QAD.0000000000002502 [PubMed: 32044844]
47. Jose S, Delpech V, Howarth A, Burns F, Hill T, Porter K, Sabin CA, & UK CHIC Study Steering Committee. (2018). A continuum of HIV care describing mortality and loss to follow-up: a longitudinal cohort study. The Lancet. HIV, 5(6), e301–e308. 10.1016/S2352-3018(18)30048-1 [PubMed: 29893243]
48. Nsanzimana S, Kanters S, Remera E, Forrest JI, Binagwaho A, Condo J, & Mills EJ (2015). HIV care continuum in Rwanda: a cross-sectional analysis of the national programme. The Lancet. HIV, 2(5), e208–e215. 10.1016/S2352-3018(15)00024-7 [PubMed: 26423003]
49. Grabowski MK, Serwadda DM, Gray RH, et al. HIV Prevention Efforts and Incidence of HIV in Uganda. N Engl J Med. 2017;377(22):2154–2166. doi:10.1056/NEJMoa1702150 [PubMed: 29171817]
50. Perriat D, Balzer L, Hayes R, et al. Comparative assessment of five trials of universal HIV testing and treatment in sub-Saharan Africa. J Int AIDS Soc. 2018;21(1). doi:10.1002/jia2.25048



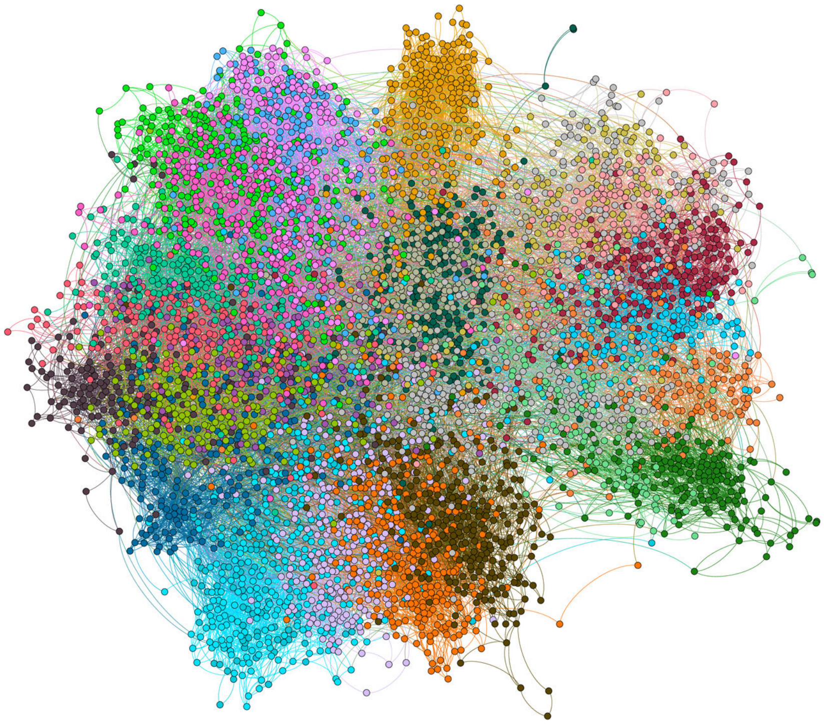


Figure 1.

Network visualization for a sample network from each region: (A): Nankoma in Uganda-East; (B): Mitooma in Uganda-West; (C): Kitare in Kenya. In each graph, nodes represent community residents, edges represent social connections, and colors correspond to residents' village within the community. Isolated individuals are not plotted.

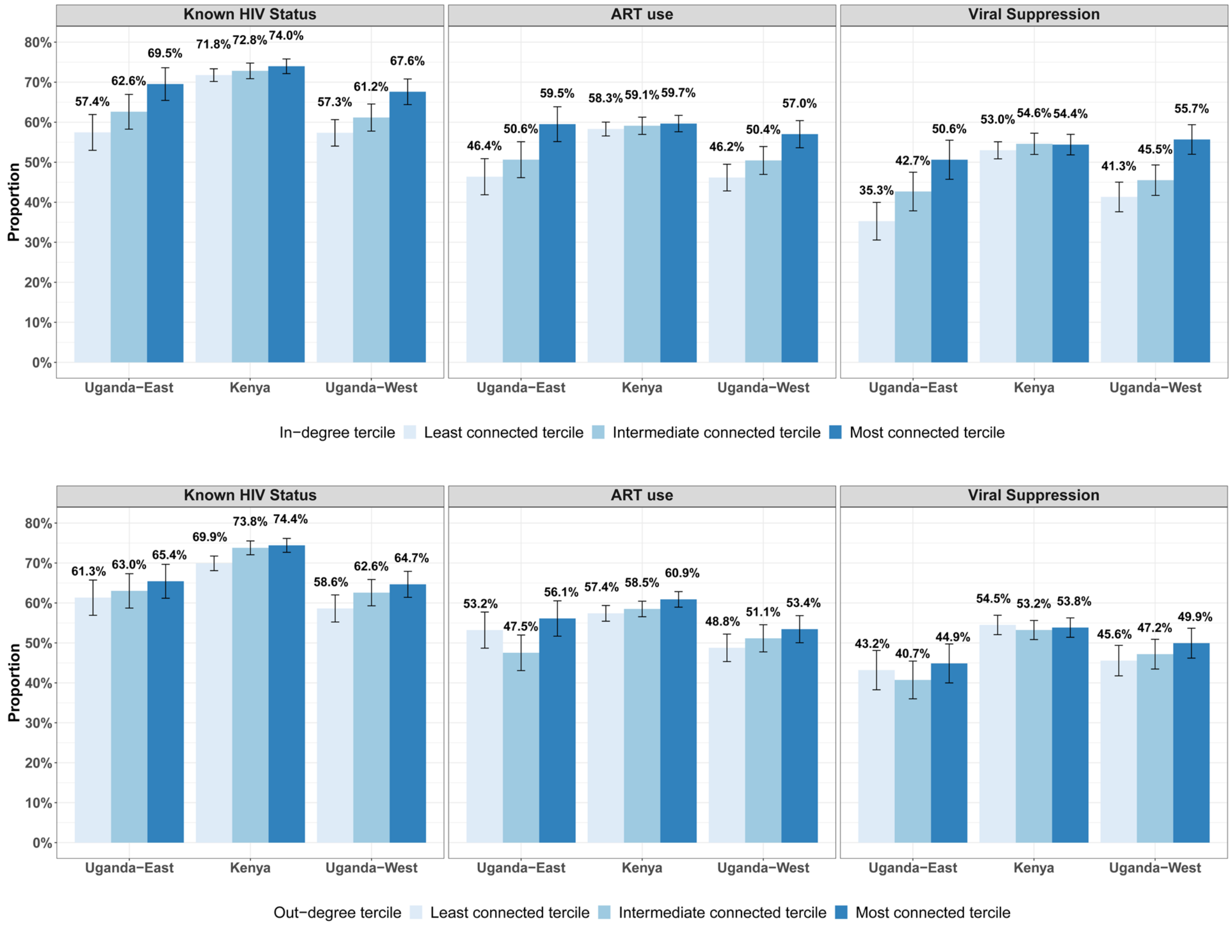


Figure 2:

Proportions of HIV-positive persons who are diagnosed, on ART, and suppressing viral replication in rural Kenya, Uganda-West, and Uganda-East as a function of in-degree tercile (A) and out-degree tercile (B). Analyses were restricted to HIV-positive persons who named at least one contact. In both panels, error bars show 95% confidence intervals for the proportion.

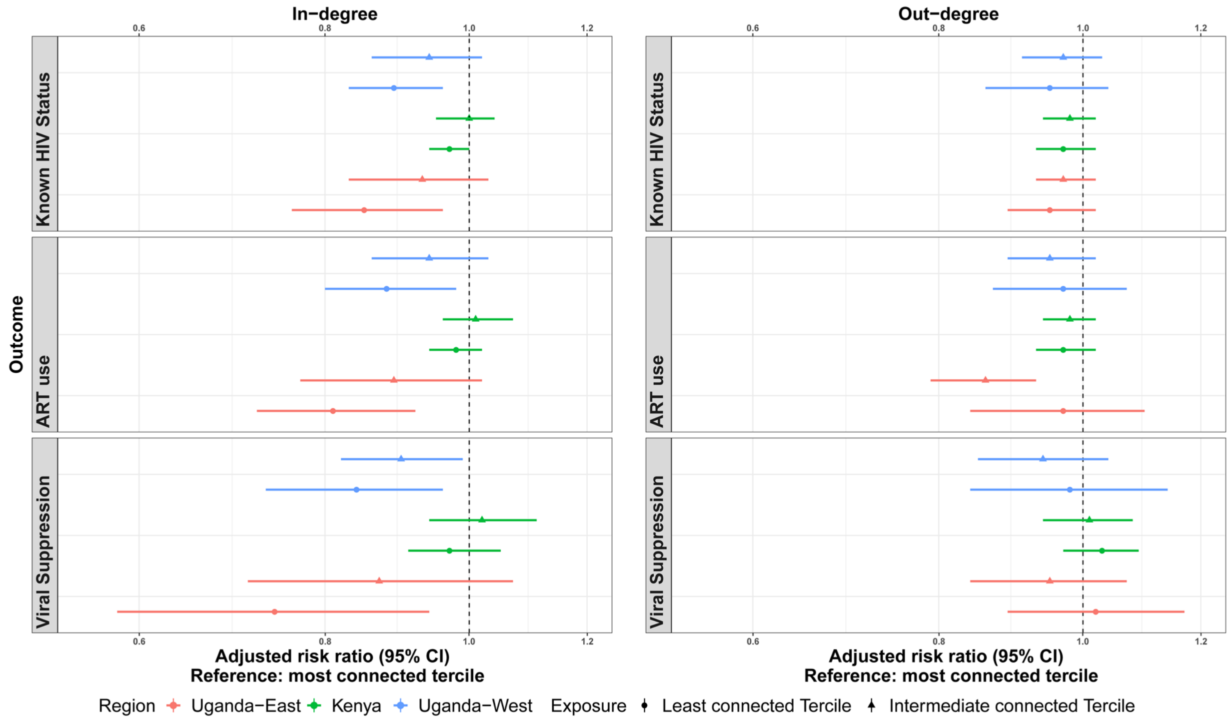


Figure 3:
Adjusted risk ratios for HIV care outcomes (known status, ART use, and viral suppression) on the logarithmic scale based on membership in the first or second tercile of connectedness, as compared to the third tercile (most-connected) among HIV-positive persons who named at least one contact. Estimates obtained using generalized estimating equations with the Kauermann and Carrol correction with t-distribution approximation for small number of clusters. Adjustment set consists of sex, age, mobile resident, marital status, education level, and occupation.

Table 1.

Characteristics of HIV-positive adult residents of 32 communities in rural Kenya and Uganda who named at least one social contact.

	Uganda-East (N=1,440)	Uganda-West (N=2,473)	Kenya (N=7,326)	Overall (N =11,239)
Sex, n(%)				
Male	502 (34.9%)	865 (35.0%)	2,240 (30.6%)	3,607 (32.1%)
Female	938 (65.1%)	1,608 (65.0%)	5,086 (69.4%)	7,632 (67.9%)
Median (Q1, Q3) Age, y	39 (29, 46)	35 (28, 44)	35 (28, 44)	36 (28, 45)
Occupation, n(%)[a]				
Formal high	102 (7.1%)	130 (5.3%)	287 (3.8%)	519 (4.6%)
Informal high	1,185 (82.4%)	1,936 (78.3%)	4,892 (66.9%)	8,013 (71.4%)
Informal low	43 (3.0%)	92 (3.7%)	1,348 (18.4%)	1,483 (13.2%)
Other	107 (7.4%)	315 (12.7%)	798 (10.9%)	1,220 (10.8%)
Marital Status, n(%)[b]				
Single	108 (7.5%)	258 (10.4%)	295 (4.0%)	661 (5.9%)
Married	932 (64.8%)	1,489 (60.2%)	5,337 (73.0%)	7,758 (69.1%)
Other	397 (27.7%)	726 (29.4%)	1,692 (23.1%)	2,815 (25.0%)
Mobile residents, n(%)				
Yes	229 (15.9%)	292 (11.8%)	584 (8.0%)	1,105 (9.8%)
No	1,211 (84.1%)	2,181 (88.2%)	6,742 (92.0%)	10,134 (90.2%)
Wealth index, n(%)[c]				
1	333 (23.1%)	774 (31.3%)	901 (12.3%)	2,008 (17.9%)
2	296 (20.6%)	590 (23.8%)	978 (13.3%)	1,864 (16.6%)
3	256 (17.8%)	504 (20.4%)	1,356 (18.5%)	2,116 (18.8%)
4	299 (20.8%)	352 (14.2%)	1,765 (24.1%)	2,416 (21.5%)
5	256 (17.8%)	252 (10.2%)	2,320 (31.8%)	2,828 (25.2%)
Suppression status, n(%)				
Suppressed	517 (35.9%)	967 (39.1%)	2,467 (36.1%)	4,131 (36.8%)
Not suppressed	691 (48.0%)	1,065 (43.1%)	2,273 (31.0%)	4,029 (35.8%)
Missing	232 (16.1%)	441 (17.8%)	2,406 (32.8%)	3,079 (27.4%)
Prior diagnosis, n(%)				
Yes	909 (63.1%)	1,533 (62.0%)	5,324 (72.7%)	7,766 (69.1%)
No	531 (36.9%)	940 (38.0%)	2,002 (27.3%)	3,473 (30.9%)
Prior ART therapy, n(%)				
Yes	751 (52.2%)	1,265 (51.2%)	4,314 (58.9%)	6,330 (56.3%)
No	689 (47.8%)	1,208 (48.8%)	3,012 (41.1%)	4,909 (43.6%)
Median (Q1, Q3) out-degree[d]	10 (5, 17)	15 (10, 22)	7 (4, 13)	9 (5, 16)
Median (Q1, Q3) in-degree[e]	2 (0, 3)	2 (1, 5)	1 (0, 2)	1 (0, 3)

ART=antiretroviral therapy, Q1=first quartile, Q3=third quartile.

[a.] Occupation classification:

- Formal high: teacher, student, government worker, military worker, health worker, factory worker
- Informal high: fishmonger, fisherman, bar owner, bar worker, worker in transportation and tourism industry
- Informal low: farmer, shopkeeper, market vendor, hotel worker, household worker, construction worker, mining worker
- Other: No job, disabled, clerical worker, manual labor
- Missing: 3 (0.2%) for Uganda-East, 0 (0.0%) for Uganda-West, 1 (0.05%) for Kenya, and 4 (0.1%) total

[b.] Marital status:

- Other includes widowed, divorced, and separated
- Missing: 3 (0.2%) for Uganda-East, 0 (0.0%) for Uganda-West, 2 (0.1%) for Kenya, and 5 (0.1%) total.

[c.] Wealth index:

- Missing: 0 (0.0%) for Uganda-East, 1 (0.1%) for Uganda-West, 6 (0.1%) for Kenya, and 7 (0.1%) total.

[d.] Out-degree of participants refers to the number of contacts the participant named

[e.] In-degree of participants refers to the number of times the participant was matched as a contact named by others.