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Social networks and international migration in Honduran villages

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Social relationships are central to shaping international migration patterns, yet the link between widescale network structure and mobility decisions remains poorly understood. Here, we investigate two key mechanisms by which social networks influence migration behavior: transmission of information and resources, and comparison of social status. These mechanisms suggest distinct sets of alters that an ego may emulate with respect to their migration behaviors, resulting in divergent mobility trajectories within and across communities. Leveraging longitudinal data from 73 Honduran villages ($N = 15{,}480$ individuals) over six years, we use a Linear Network Autocorrelation Modeling framework to disentangle the effects of kinship, friendship, and economic ties on international migration decisions. Our findings reveal that incorporating social network factors as predictors significantly improves model fit. While indicators for resource-sharing processes substantially contribute to model performance, the inclusion of structural comparison mechanisms does not provide additional explanatory power. These results underscore the critical role of information and resource transmission within social networks in facilitating migration behaviors.

social networks | network autocorrelation models | social influence | international migration

Significance

Over the last decade, the origin of migration flows through the southern U.S. border has shifted from Mexico to Central American countries. We hypothesize that social networks are a key factor in migration and use detailed social network information from 73 sending villages in the western highlands of Honduras to identify the mechanisms of social influence. Our results show that a process of information or resources diffusing across family or friendship ties is the most plausible mechanism for network effects in migration in this setting. This research demonstrates the importance of including social networks as facilitators of migration, further develops the mechanisms through which social influence occurs, and helps shed light on the dynamics of modern Central American migration.

International migration is affected by a variety of demographic, economic, environmental, and social processes. In the past decade, migration rates to the United States from Central America have increased dramatically. In 2021, around 700,000 Honduran immigrants lived within the United States (1) with more than 50,000 monthly encounters between border enforcement and migrants each month since 2021 outside official ports of entry. While unauthorized migration (only one portion of the migration flow) has recently fallen from Honduras (from 18,993 migrant encounters in December 2023 to 4,465 encounters in August 2024), many central American migrants are still crossing the southern border of the US (2).With projected increases in migration over the coming decades from existing and emerging (e.g., climate- or violence-related) sources, (3) there is a growing need to understand the mechanisms through which international migration transpires. Here, we explore several network-based mechanisms from the perspective of sending communities.

Prior work on migration has highlighted diverse factors that contribute to an individual's migration choices. Many people move to seek economic opportunities (4) or to diversify risks to their household's economic prospects (5). Individuals also move because migration has become a rite of passage or a part of the culture within communities (6); because they are forced to do so by violence, conflict, or natural disasters (7, 8); or because they are connected to other migrants (9).

While social networks have been identified as an important facilitator of migration (9), difficulties in data collection have prevented a thorough exploration of network-based mechanisms. Many migration models simply proxy for the presence of social networks with the presence or absence of a migratory family or community member (10). While this technique certainly captures some information about the local social environments that individuals inhabit, it cannot fully capture the broader social structure in which people are embedded within their communities.

Here, we focus on international migration and consider social influence, whereby one person migrating plays a role in the migration of others to whom they are directly or indirectly connected. Specifically, we aim to understand the ways in which social networks (such as kinship, friendship, or prospective borrowing relations) influence the migration process. Given the difficulty and risks of international border-crossing, prior research (9, 11) shows that migrants often draw on the experiences of their friends and kin (who are deemed more trustworthy) in taking on the journey. Given the costs of clandestine crossing, migrants often need to borrow money to fund their trip. Such monetary networks within sending communities are understudied and represent another potential facilitator of mobility; migration might even function as a business venture within the

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sending community. Our data allow us to consider the role of these three kinds of relationships (kinship, friendship, and economic ties) in migration decisions from Honduras.

Social Influence and Migration. Theoretical work has proposed mechanisms through which networks may influence migration. One mechanism highlights resource exchange, whereby prospective migrants benefit from migrant family and friends that provide them with information or help necessary for migration (12, 13). Another mechanism underlines social status comparisons, whereby prospective migrants react to relative deprivation induced by migration of others in their social groups (14, 15). Prior empirical work has provided some direct evidence of the former mechanism (16) and indirect evidence for the latter (5).

Social influence processes related to resource sharing and relative deprivation in migration are closely aligned with similar concepts found in the broader social network literature. Prior work has highlighted the importance of considering networks with regard to flows of information and influence within communities (17–21), as well as the importance of network structure (22, 23). Combining insights from the migration and network literatures, we focus on two mechanisms: a) "resource sharing" or "communication," and b) "relative deprivation" or "structural comparison." The migration literature favors the former label while the networks literature uses the latter. We use these terms interchangeably.

The first mechanism points to migration flows that are facilitated by access to social resources such as information or help. The second mechanism, by contrast, highlights migration behaviors that are based on social status considerations that are likely to be culturally subscribed (e.g., through social roles tied to network positions). Importantly, our data measure social ties in communities, not what flows through those ties. With our methodology, we assume that different groups of alters are more likely to offer different kinds of influence. Direct and indirect connections among friends or kin are likely conduits for information, whereas ties capturing potential financial exchange can offer access to funds. Kin or friends who occupy similar network positions form reference groups for social comparison. And so, our analysis involves a particular operationalization of the two mechanisms that is possible with the data.

Relative deprivation (structural comparison) based influence is likely to rely on a process of status comparison whereby individuals measure themselves against migrants within their social circle. As we argue above, potential migrants may use those who are in similar structural positions within the network as a reference group for this social comparison. In the migration literature, there is no consensus on who would be used as a salient reference group for this comparison process. Still, "structural equivalence" can be used to codify structural positions that may form a salient reference group (24). Two people are structurally equivalent if they have the same social ties to the same alters. People in similar structural positions may influence each other at a greater rate (25). Additionally, structurally equivalent nodes are likely to be members of the same groups, as both nodes would need ties to the same set of people (e.g. siblings would be structurally equivalent if they both have two kinship ties to their parents).

These structural positions have been shown to relate to a variety of outcomes, such as group maintenance (26) and social influence (27, 28). Prior work has highlighted the importance of structural equivalence in defining relevant peers who may transmit social influence (27–29). Galaskiewicz and Burt argue that contagion across structurally similar peers acts as a form of "symbolic communication" (30), where social influence is exerted by virtue of being in the same role or structural group as others. In this context, salience is particularly important when considering social influence and is related to the mechanism through which the social comparison mechanism operates. Here, we are measuring relative deprivation via the effect of structural equivalence. This specification for the relative deprivation effect is only one of a set of reasonable operationalizations. Other reference groups (than those who are structurally equivalent) may function differently, as we discuss below. The choice of a reference group is particularly important, as it will determine who can induce relative deprivation in an individual. For a full discussion of the importance of reference group specification, alongside a set of potential other reference groups, see *Discussion*.

Resource sharing (communication) based influence likely works through information or capital exchange. Given the difficulty and risks of international border-crossing, migrants draw on the experiences of their kin (who are typically deemed more trustworthy) when deciding whether to make the journey. However, younger populations often follow their friends on migration journeys and even make spur-of-the-moment decisions (31). We capture resource sharing via the effect of social distance.

We test these two mechanisms describing the association of social networks with migration using data from 73 rural, isolated villages in the western highlands of Honduras, along the border with Guatemala. These data were collected through a series of in-person surveys across a 6-y period as a part of a multiyear cohort study (21). These Honduran communities are small, ranging in size from around 100 people to over 700. Across these 73 villages, the mean village size is 212 people (range 67 to 793). We consider kinship, friendship, and economic relations constructed from name-generator questions. Fig. 1 provides an example of a social network from one community, highlighting the different proposed mechanisms through which community members may influence each other. Notably, social networks are one factor among many related to migration in Honduran communities. Our data allow us to measure their potential impact more precisely than prior work; and our analysis controls for other demographic and economic factors.

We use a linear network autocorrelation model (LNAM) framework. Building on prior research, we test three primary hypotheses: First, migrant alters in kinship, friendship, and economic networks will increase an ego's likelihood of migration to the degree those alters are relevant to a resource-sharing process given their network position relative to the ego. The shorter the social geodesic distance between an alter and an ego, the higher the impact. Second, migrant alters in the kinship, friendship, and economic networks will increase an ego's likelihood of migration to the degree they are relevant to a relative deprivation process. The higher the degree of structural equivalence between an alter and ego, the greater the impact (Fig. 2). Finally, we test whether the copresence of resource-sharing and relative-deprivation processes boosts an ego's migration likelihood relative to presence of either process alone. The LNAM framework allows us to consider these network mechanisms while controlling for alternative facilitators of migration. In our case, each mechanism is represented by migration behaviors of alters that are relevant to that (resource-sharing or relative-deprivation) mechanism.

Our results indicate that migration behaviors of network alters are associated with ego's migration decisions above and beyond demographic and economic factors. Alters relevant for a resource-sharing based influence mechanism matter the most. This holds across friendship, kinship, and economic ties. The resource-sharing mechanism (operating through social distance) outperforms the relative-deprivation mechanism (working through

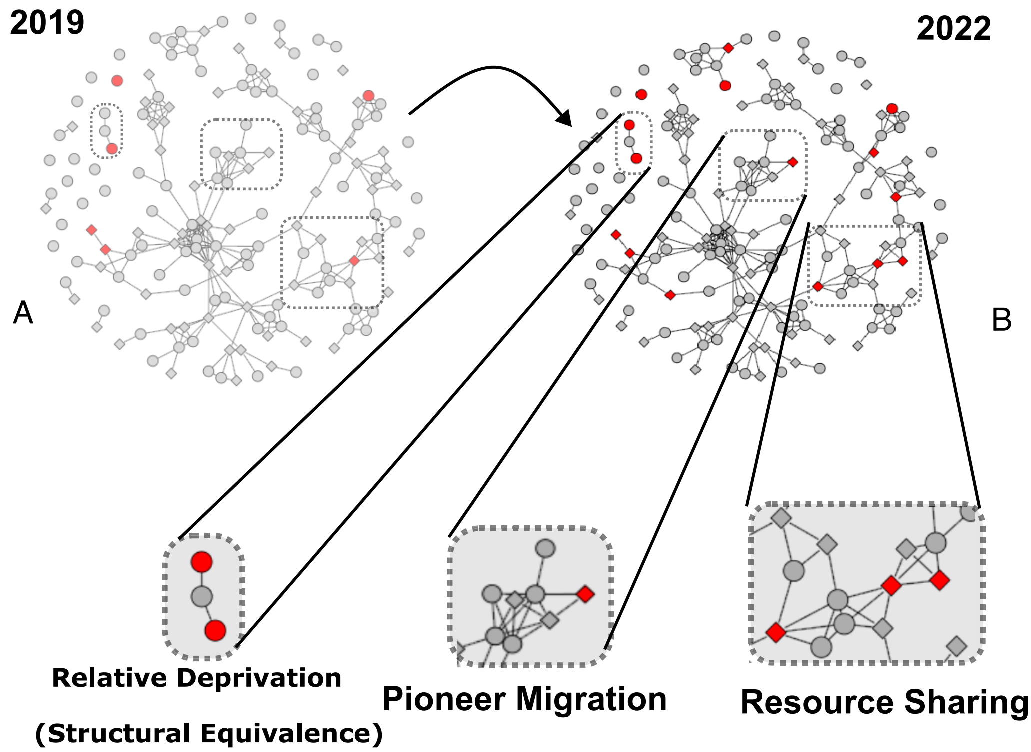

Fig. 1. (*A*) Kinship network for one illustrative village with nodes colored (red) by 2019 migration behavior. (*B*) Kinship network for the same village with nodes colored by 2022 migration behavior. Both networks have nodes and edges that are fixed with the structure of the 2022 social network. Node colors correspond to migration status, with red nodes currently migrating out of Honduras. Node shape corresponds to gender, with circles representing females and squares representing males. As time goes on, we see that patterns in migration spread across the network. Potential relative-deprivation (structural comparison) and resource-sharing (communication) structures are highlighted here. While social networks are likely to drive some migration patterns, migration is still a complex phenomenon driven by a variety of factors. Some nodes may choose to migrate independent of their position in the network, as we highlight through a case of "pioneer migration" (following the terminology from ref. 32). We try to capture this process through our demographic controls, which are related to existing theories on mobility.

structural equivalence) with respect to model fit, highlighting the importance of resources offered by migrants within a community to propagate the mobility process.

Migrant Demographics in Western Honduras Align with Other Central American Migrants

The results from the Linear Network Autocorrelation Models (LNAM) are in Tables 1–3, for kinship, friendship, and economic ties respectively.The base model, which contains no network influence effects, describes how socio-demographic factors contribute to individual migration decisions. This model is identical across all networks.

The base model identifies that migrants in western Honduras tend to be younger and male. Likelihood of migration increases with education but does not vary by perception of economic standing. Indigenous status and marriage both decrease the likelihood of mobility. Additionally, those with prior migration histories tend to continue to migrate. These results align with research that focuses on migration patterns in Mexico (33) and other Central American and Caribbean contexts (34).

Including Kinship and Friendship Networks Produces Dramatic Improvements to Model Fit

We introduce measures representing each mechanism into our baseline model. We expect the network models to perform better than the baseline. We then include both mechanisms to build a more comprehensive model. By comparing across models (baseline, single mechanism, both mechanisms) and types of relations (kinship, friendship, and economic), we explore which process and alters matter most to migration choices, using the AIC and BIC metrics (28).These metrics are computed by weighing the model fit against the model complexity and can be used to select the best-performing model in a nested structure. The BIC more strongly penalizes the addition of new terms to the model than the AIC, and thus prefers models with fewer terms. The main test that we focus on is the difference in model fit criteria between the base model (Model 1) and the models that contain one of the proposed mechanisms driving migration (single mechanism models). We fit a set of LNAM models to each community in our sample (for more details, see *Materials and Methods*).

It is difficult to discriminate between models to reach a conclusion across all communities because the AIC or BIC for a model in one community cannot be directly compared to that in other communities. To address this issue, we use the Condorcet voting schema described in *Materials and Methods*, and compute the distribution of model performances across all communities, as shown in Fig. 3. This figure can be read looking at the tables, where the value in any cell is the proportion of communities in which the row model outperformed the column model. For example, when using the AIC as a model selection tool and examining friendship, we can see that, in 75% of communities, the resource-sharing via social-distance model outperforms the base model. Likewise, the resource-sharing model outperforms the relative-deprivation via structural-equivalence model and full models (Models 3 and 4, respectively) 89 percent of the time. This approach allows us to make claims such as that

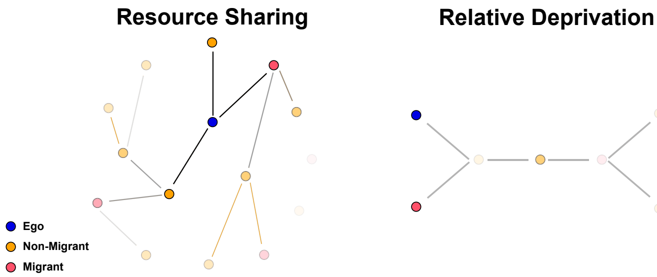

Fig. 2. Two different hypotheses for how influence propagates across social networks are schematically illustrated. The opacity of a given node describes how salient that node is when an ego is making a decision. Under the resource-sharing influence process, prospective migrants may look for resources that may be shared across their direct or indirect social ties within their local networks. Resources from migrants they are directly tied to will be more salient than resources from indirect contacts within their communities. The relative-deprivation process implies that people who occupy more structurally similar positions are more likely to influence each other. Those who are structurally equivalent to each other form the comparison reference group. A prospective migrant will examine people in similar positions, taking cues for their migration behavior from such people. Structural equivalence was used to highlight similarity here. Structural equivalence is measured (0-1), where nodes that are in more similar structural locations have values closer to 1. The two nodes on the left-hand side of the sociogram (labeled as ego and a migrant) are exactly structurally equivalent (they have the same tie to the same alter), while ego is close to structurally equivalent (needing 1 tie to be severed) with the node in the center of the sociogram.

resource-sharing processes are the most plausible mechanism driving migration in the Honduran communities under the current mechanism specifications.

Across the kinship and friendship tie types and both model statistics, the Condorcet tables show that there are identical model orderings for the AIC, and very similar results for the BIC. With the AIC, the base model performs worse than models that contain the resource sharing terms (Model 2). While the base model outperforms the relative deprivation model for kinship and friendship, it never outperforms the resource sharing or full models (Models 2 and 4) in the majority of communities. When using the BIC as the model selection tool, the results are similar, with the exception of the baseline model (no mechanisms) outperforming the full (both mechanisms) kinship model (Model 4). These results are robust to alternative specifications of both mechanisms that are possible with our data (*SI Appendix*).

The economic networks show markedly different results. For these models, the base model (Model 1) consistently outperforms all other models, both with the AIC and BIC. Thus, in our sample, we find that borrowing networks do not plausibly drive migration through either of our mechanisms. One potential reason for this finding is that we do not consider the potential effect of migrant remittances in funding migration (since we lack such data). Nevertheless, we confirm that social influence processes work across kinship and friendship relations in shaping migration behaviors.

Resource Sharing Is a Key Process for Understanding Migration

While the inclusion of the resource-sharing processes in the models reduces the model selection criteria for kinship and friendship models, indicating better fitting models, the resource-sharing and relative-deprivation processes do not improve model fit equivalently. Adding communication indicators dramatically improves model fit, while including structural comparison measures only sometimes improves model performance. This trend holds for alternative specifications of the relative-deprivation process, the results for which are included in *SI Appendix*.

The difference between models that contain resource-sharing and relative-deprivation effects is important, as these effects capture specific mechanisms through which networks can plausibly drive migration under the operationalization used here. Specifically, the structural patterns associated with a process of resources diffusing across social network ties produces models that fit much better than models that contain the structural motifs associated with the process of comparison to structurally similar peers. This is a pattern that persists when groups other than the structurally equivalent are used as the reference for the relative-deprivation hypothesis. Further discussion of this can be found in *Discussion* and *SI Appendix*. Furthermore, models containing both processes tend to perform very well (as discussed below). This could indicate a potential dependency on the resource-sharing process for relative deprivation to function, as the full model often outperforms both the base and relative-deprivation only models.

Inclusion of Both Resource Sharing and Relative Deprivation Does Not Improve Model Fit

Models 2 and 3 include the effect of a single influence process. We now consider a model where resource-sharing and structural-comparison mechanisms are parameterized jointly. Once again, the model-fit statistics help discriminate between models and choose the one that most accurately and parsimoniously describes the migration process. These statistics highlight that the full model does not outperform the single-parameter resource-sharing models for kinship and friendship. For economic ties, the full model performs worst out of all models.

The meta-analytic results shown in Tables 1–3 shed some additional light on the migration process in Honduran communities. However, as these effects are aggregated across the entire sample of communities, they lack the ability to directly speak to heterogeneity in the processes across communities. Indeed, we find that there is significant variation present in the coefficient estimates. Estimates of I^2, a measure of how much the heterogeneity in coefficient estimates across communities drives the effect, are consistently high across all the meta-analyses. Furthermore, coefficient plots (Fig. 4, with all influence plots in *SI Appendix*) indicate that the structural-comparison effect in particular is likely to be spurious here, as it is driven by the high magnitude of the relevant coefficient in several outlier communities. Despite these limitations, the meta-analysis still provides us with the general effects of our predictors across the entire sample.

Tables 1–3 contain the results of the meta-analysis, and highlight that, for kinship and economic networks, the resource-sharing via social-distance effect is positive and significant. The relative-deprivation via structural-equivalence effect is also highlighted as a predictor, although, as discussed, this effect may be spurious. This indicates that, for these network types, potential migrants may be subject to both (resource sharing and relative deprivation) influences from their kinship and economic ties in their migration decisions. For both models, the structural-comparison effect is more tenuous than the communication effect (as it is driven by a small number of communities). This highlights the significant heterogeneity in how models behave across communities. (See *SI Appendix* for influence coefficient plots across all communities.) By contrast, for friendship networks, only the resource sharing parameter is positive and statistically significant in the full model (Model 4).

Table 1. Kinship model meta-analysis results

Parameter	Model 1	Model 2	Model 3	Model 4
Intercept	0.197*** (0.018)	0.180*** (0.017)	0.179*** (0.018)	0.173*** (0.017)
Education	0.028*** (0.005)	0.021*** (0.005)	0.027*** (0.005)	0.021*** (0.005)
Gender	−0.085*** (0.007)	−0.084*** (0.007)	−0.085*** (0.008)	−0.086*** (0.008)
Indigenous	−0.012* (0.005)	−0.009* (0.004)	−0.012* (0.005)	−0.008 (0.004)
Prior migrant	0.199*** (0.018)	0.181*** (0.016)	0.186*** (0.018)	0.178*** (0.016)
Marital status	−0.018*** (0.005)	−0.020*** (0.005)	−0.016** (0.005)	−0.021*** (0.005)
Age	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)
Very low economic perception	0.002 (0.009)	0.004 (0.009)	0.002 (0.009)	0.006 (0.009)
Low economic perception	−0.004 (0.007)	−0.001 (0.006)	−0.002 (0.007)	0.000 (0.006)
Middle economic perception	0.007 (0.006)	0.006 (0.006)	0.007 (0.006)	0.007 (0.005)
Resource sharing (social distance)		0.257*** (0.030)		0.234*** (0.017)
Relative deprivation (structural Eq.)			0.061* (0.025)	0.010** (0.003)
I^2 statistic	69.4%	69.0%	74.4%	64.2%

Model parameters for the Kinship network LNAM meta-analysis. SEs are in parentheses. Reference category for economic effects is High economic perception. Significance stars represent * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

For kinship and friendship networks, the full model (including both relative-deprivation and resource-sharing parameters) represents a substantial improvement over the baseline model, but not over the models with a single influence process (Models 2 or 3). Fig. 3 highlights this result. When we use the AIC as the model-performance criterion and consider kinship networks, the full model outperforms the baseline model in 70% of the communities. But, the full model falls behind the resource-sharing-only model (Model 2) 79% of the time. This trend is emblematic of the model performance patterns in both kinship and friendship networks.

For economic networks, the full model performs worse than the resource sharing-only and relative deprivation-only models (Models 2 and 3). Based on the AIC, the resource sharing model outperforms the full model 82% of the time, and the relative deprivation model 59% of the time.

Model Fit Parameters Vary Significantly Across Communities

Fig. 3 describes the distribution of model fits across the communities. While there are clear patterns in model fit across network modes and statistics, there is also heterogeneity across communities. For example, when considering friendship with the AIC, the relative-deprivation via structural-equivalence model consistently falls behind all other models. However, for 11% of the communities (8 villages), this model still outperformed the base model. We observe similar heterogeneity in model performance across all three networks. This tells us that network effects in migration may work differently in different communities. The BIC indicates less heterogeneity, although this is likely due to the measure penalizing additional model terms more highly than the AIC. Additional tests in *SI Appendix* show that this heterogeneity cannot be attributed to structural network cohesion.

While we do not directly compare results between different network types (friendship, kinship, and economic), we observe some heterogeneity in the results. Overlap in network ties across network types (see *SI Appendix* for more details) prevents us from fully disentangling the sources of this heterogeneity. But we can see that resource sharing process ranks highest in inducing migration in friendship and kinship ties followed by the relative-deprivation (via structural comparison) process. Neither process seems to work in influencing migration across economic ties.

Discussion

Network effects are important in migration. Theory suggests that prior migrants might provide information about the journey; help with financing; or induce feelings of relative deprivation that encourage more people in their communities to migrate.

Table 2. Friendship model meta-analysis results

Parameter	Model 1	Model 2	Model 3	Model 4
Intercept	0.197*** (0.018)	0.126*** (0.013)	0.191*** (0.019)	0.125*** (0.013)
Education	0.028*** (0.005)	0.022*** (0.005)	0.028*** (0.005)	0.022*** (0.005)
Gender	−0.085*** (0.007)	−0.062*** (0.005)	−0.084*** (0.007)	−0.063*** (0.005)
Indigenous	−0.012* (0.005)	−0.011* (0.004)	−0.013** (0.005)	0.011* (0.004)
Prior migrant	0.199*** (0.018)	0.170*** (0.015)	0.198*** (0.018)	0.170*** (0.015)
Marital status	−0.018*** (0.005)	−0.003 (0.005)	−0.016** (0.005)	−0.003 (0.005)
Age	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)
Very low economic perception	0.002 (0.009)	0.007 (0.009)	0.004 (0.009)	0.011 (0.010)
Low economic perception	−0.004 (0.007)	0.004 (0.006)	−0.005 (0.007)	0.004 (0.006)
Middle economic perception	0.007 (0.006)	0.009 (0.006)	0.006 (0.006)	0.010 (0.006)
Resource sharing (social distance)		0.443*** (0.031)		0.435*** (0.028)
Relative deprivation (structural Eq.)			0.056 (0.037)	−0.030 (0.040)
I^2 statistic	69.4%	58.4%	68.2%	56.9%

Model parameters for the friendship network LNAM meta-analysis. SEs are in parentheses. Reference category for economic effects is High economic perception. Significance stars represent * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3. Borrowing model meta-analysis results

Parameter	Model 1	Model 2	Model 3	Model 4
Intercept	0.197*** (0.018)	0.181*** (0.017)	0.187*** (0.018)	0.167*** (0.017)
Education	0.028*** (0.005)	0.028*** (0.005)	0.028*** (0.005)	0.028*** (0.005)
Gender	−0.085*** (0.007)	−0.082*** (0.007)	−0.085*** (0.007)	−0.082*** (0.007)
Indigenous	−0.012* (0.005)	−0.015** (0.005)	−0.010* (0.005)	−0.013** (0.005)
Prior migrant	0.199*** (0.018)	0.193*** (0.017)	0.195*** (0.018)	0.188*** (0.017)
Marital status	−0.018*** (0.005)	−0.011* (0.005)	−0.018** (0.005)	−0.010* (0.005)
Age	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)	−0.002*** (0.000)
Very low economic perception	0.002 (0.009)	0.003 (0.008)	0.000 (0.009)	0.001 (0.009)
Low economic perception	−0.004 (0.007)	−0.004 (0.007)	−0.005 (0.007)	−0.005 (0.007)
Middle economic perception	0.007 (0.006)	0.006 (0.006)	0.006 (0.006)	0.006 (0.006)
Resource sharing (social distance)		0.173*** (0.021)		0.178*** (0.020)
Relative deprivation (structural Eq.)			0.002*** (0.001)	0.003*** (0.001)
I^2 statistic	69.4%	65.9%	65.7%	61.9%

Model parameters for the borrowing network LNAM meta-analysis. SEs are in parentheses. Reference category for economic effects is High economic perception. Significance stars represent * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

These ideas have been illustrated with qualitative case studies or tested with survey data recording family and village ties to prior migrants. Only few data sources (e.g., the Nang Rong data from Thailand) have allowed for measuring social ties to migrants directly. Prior work used these data to establish network effects in internal migration (20), but could not go deeper to distinguish the alternative mechanisms underlying these effects.

Using data from 73 communities in western Honduras, our analysis represents a step forward. We considered two mechanisms for network influence. The migration literature refers to these mechanisms as "resource sharing" and "relative deprivation," while networks scholars describe similar processes as communication and comparison. The resource-sharing mechanism assumes prior migrants provide useful information and resources to their social ties; the relative-deprivation mechanism suggests prior migrants induce feelings of inferiority among structurally similar individuals. We operationalized each mechanism by identifying the most relevant alters and recording their migration behaviors. For the resource-sharing mechanism, the alters include those with direct and indirect ties whose influence decreases with geodesic distance from the ego. For the relative-deprivation mechanism, the alters are those who occupy structurally equivalent positions whose influence is proportional to the inverse square of the structural equivalence distance between the two

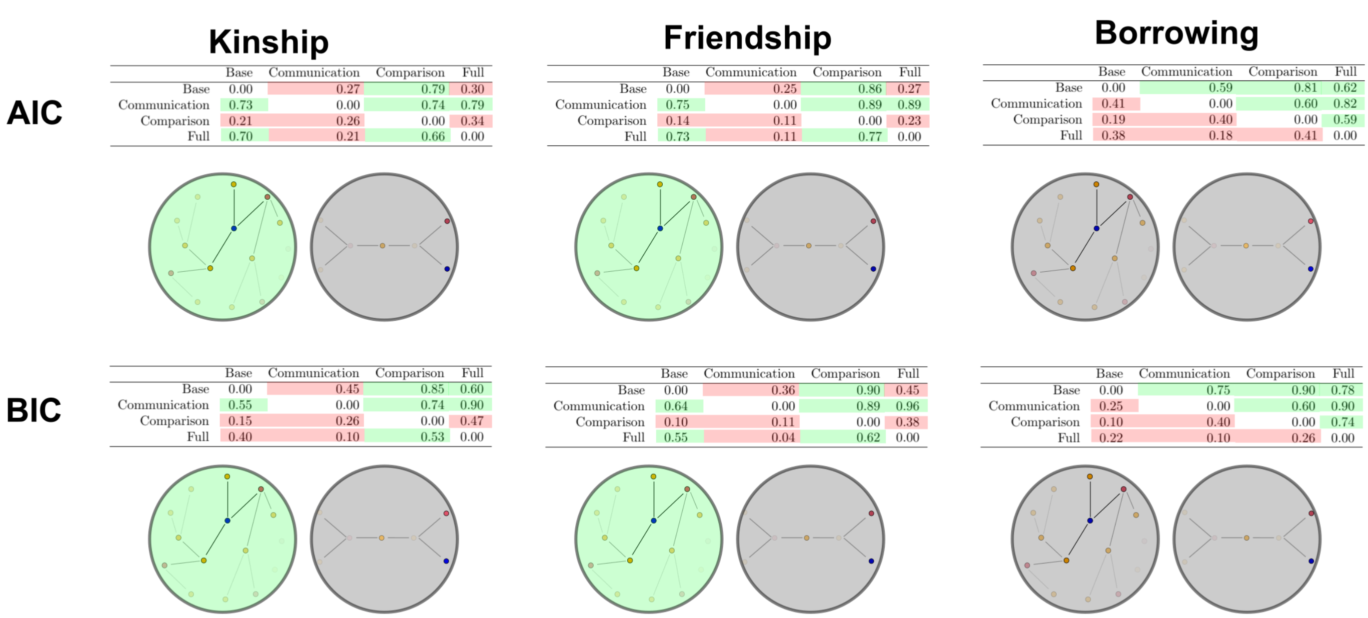

Fig. 3. A figure describing the distribution of model orderings across all communities. Each Condorcet table describes the proportion of models on each row that outperform the model on the column. A cell in the Condorcet table highlighted green indicates that the row model outperforms the column model (i.e. more than 50% of the communities have a model ordering with the row model beating the column model). For example, if we look at kinship models, selecting by the AIC, we can see that the resource-sharing (communication) model (on the second row) beats the baseline model 73% of the time, and is colored green. The full model (on the *Bottom* row) beats the resource-sharing (communication) model only 21% of the time, and is colored red. Mechanisms are colored below the tables representing which mechanisms are supported as most plausible, across all communities in the sample. Green indicates a supported mechanism and gray indicates a mechanism that is not supported (i.e. does not outperform the majority of the other models). A Condorcet winner exists for all three network modes. With the AIC, looking at kinship and friendship, the Condorcet ordering is Resource Sharing (Communication) > Full > Base > Relative Deprivation (Structural Comparison). This can be seen in the table, as the resource sharing models wins all 3 match-ups against the other models, the full model wins 2 match ups, and the base model wins 1. For borrowing, the ordering is Base > Resource Sharing (Communication) > Relative Deprivation (Comparison) > Full. When examining the BIC results we observe similar patterns. The kinship ordering is Resource Sharing (Communication) > Base > Full > Relative (Comparison). The friendship and borrowing model orders are both concordant with the AIC.

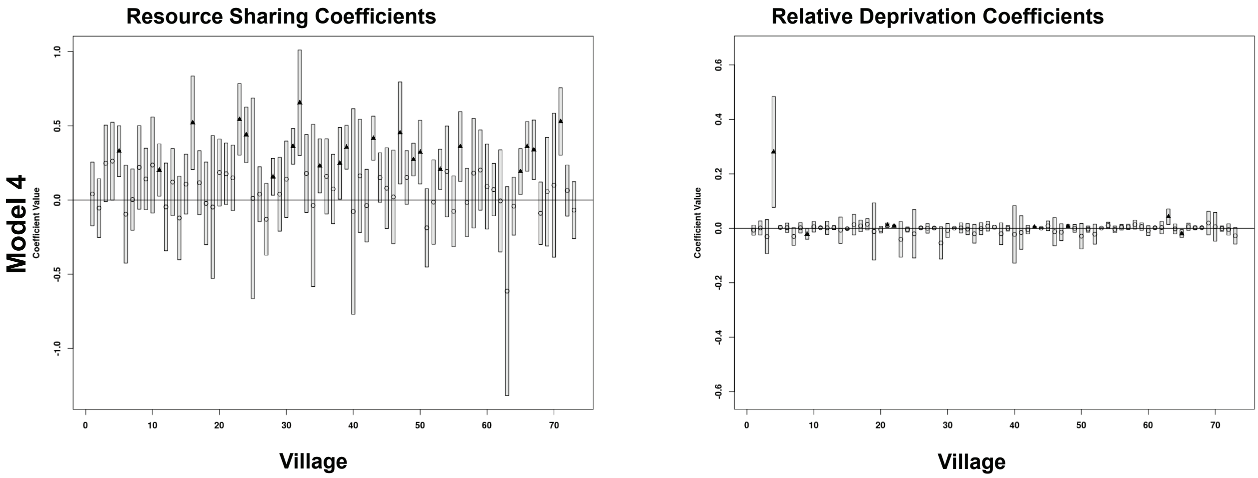

Fig. 4. A coefficient plot showing the resource sharing (communication) and relative deprivation(structural comparison) coefficients across all communities for the full borrowing network model. Coefficient estimates are solid triangles when the relevant coefficient is significant. Open circles indicate nonsignificant coefficients. 95% CIs are shown. The resource-sharing coefficients are consistently positive, while the relative-deprivation coefficients are far more heterogeneous. A single community has a very large coefficient relative to the other villages, and this likely drives the reported comparison effect in Table 3. Plots of all influence coefficients are included in *SI Appendix*. Similar outliers with the relative deprivation effects were identified for the other models.

nodes. We find that the resource-sharing-based influence process is more robust in explaining individual migration decisions than the relative-deprivation process, given the chosen specifications.

Our models were fit at the community level, allowing us to understand the heterogeneity in facilitating mechanisms across the whole population of villages. While many studies use meta-analysis to identify aggregate population dynamics (35, 36), we conduct a Condorcet analysis to better understand how between-community variation manifests. We find that the results from the meta-analysis are unable to capture this heterogeneity and may be driven by a subset of the communities (especially in the case of the relative-deprivation effects). While the Condorcet analysis does not provide population-level coefficients, it shines light on how the different mechanisms are ordered within the population and builds theory that can be applied to other settings.

While we interpreted the results from the models of kinship, friendship, and economic ties together, these three network types are likely driven by different processes. For example, most of the ties that make up the kin networks are based on relations that are not strictly chosen (parent, child, sibling). By contrast, the friendship networks are based entirely on relations involving choice (spending free time with others, closest friend, etc.). Borrowing relationships are also likely generated by choice and availability of resources within communities and may be driven by the status structure of a community. The difference in the magnitude of the influence coefficients may be in part driven by differences in the meaning of each mechanism for each network type. We do observe some qualitative differences between the meta-analytic coefficients in the two (resource-sharing via social-distance and relative-deprivation via structural-equivalence) models. In kinship and economic ties, we observe that both network mechanisms are positive and significant. In friendship, only resource sharing drives migration behaviors in our estimation.

Institutional context is likely to produce different expectations for each type of network. When considering potential migration pathways to the United States (where many Honduran migrants are moving), kinship networks may allow for migration via family reunification, whereas friendship ties would not afford this opportunity. Unfortunately, we have no data on documentation status of current or prior migrants (or of the documentation status of their relatives or friends), and cannot test this hypothesis. Likewise, kinship and friendship ties are likely to transmit different types of information, social support, and meanings attached to that support. Future qualitative work may be able to better investigate these differences.

Our study captures a period (2016 to 2022) with a rapidly changing context at the US border. It is possible that resource sharing via connections to migrants is especially relevant in this context where up-to-date information about conditions for border crossing is increasingly important. While the temporal resolution of our data prevents us from directly investigating this hypothesis, future research may consider this mechanism further. The migration literature often also assumes that migration information and capital does not decay over time (14). This assumption could also be relaxed in the future by studying communities across a longer period of time.

Family reunification is a key mechanism for obtaining legal status in the United States. In fiscal year 2022, nearly 15 thousand Hondurans obtained Legal Permanent Resident (LPR) status. Nearly half were spouses, children, or parents of U.S. citizens (37). Only naturalized citizens and LPRs can petition to bring family members. The Pew Research Center estimates that the majority (60%) of foreign-born Hondurans are undocumented migrants (38).

Our data do not allow us to identify migrants with family members already in the United States. We would expect such migrants to be more likely to rely on kinship ties, thus amplifying the importance of this network (relative to friendship or borrowing ties) and that of the relative deprivation mechanism (which gives more weight to lower degree connections). While we speculate about these patterns, due to data limitations, we cannot test them directly.

Our results suggest that the process of relative deprivation between structurally similar positions within the network does not contribute to prospective migrant decisions as plausibly as resource sharing across social ties. This is supported by the Condorcet results where the resource-sharing-only model (Model 2) consistently outperforms the other models. While this is an important finding, there are potential ways in which relative deprivation may still matter if it is specified differently (for example, using different reference groups or alternative measures of structural similarity). Future research could investigate the effect of relative deprivation between structural roles using alternative metrics such as regular or automorphic equivalence (39).

Our measure of structural equivalence is one of the stricter measures of structural position because it considers ties to the same alters. It is advantageous because it incorporates information about group structure. For example, in an undirected network, structurally equivalent nodes are second-order neighbors. For this application, structural equivalence has a plausible interpretation for the relative deprivation process as articulated and implemented in prior work (28). Future work that examines other equivalence relations would be valuable but requires advances in measuring distance between nonequivalent nodes.

While the results consistently show the importance of resource-sharing-based influence in driving migration, the meaning of the mechanisms discussed here is not constant. For example, in a kinship network, the resource-sharing hypothesis entails relying on immediate family and extended kin for support. In the borrowing networks, the meaning of resource sharing is likely different, and that of higher-order contacts is also different, involving the monetary lending structure of a community. While the networks are not disjoint, and kin may be nominated as potential lenders, it is still important to consider how these mechanisms may vary based on the social meaning of ties in question. The relative-deprivation hypothesis highlights this point more strongly, when using structural equivalence to determine the reference group. Among highly structured family relationships, structural equivalence has some alignment with family roles within a single family. (e.g., siblings necessarily have the same ties to their parents and to one another). However, for the borrowing relations, this qualitative meaning is very different. If the economic network is highly hierarchical, for instance, structural equivalence between nodes roughly corresponds to the degree to which they fall at the same place in this status hierarchy.

To ensure that our results are robust to other specifications of the social network structures and the parameterization of the effects, we fit additional models, with results reported in *SI Appendix*. One alternative specification tested is a version of kinship in which partner ties are excluded. These horizontal ties may differ qualitatively from other kin ties, as they are chosen ties, and may be driven by selection. These models highlight that while resource sharing remains the best fitting mechanism, the removal of the partnership ties slightly diminishes the fit of this mechanism over the baseline model.

Another robustness analysis tested alternative specifications of the relative-deprivation mechanism. Structurally equivalent alters are not the only plausible reference group for status comparisons. We considered three categories of reference groups. Under the first category, we included alters who have structural similarity. In one analysis (reported in *SI Appendix*, Tables S1–S3), for example, we used a version of the structural-equivalence specification, but row-normalized the W matrix, to indicate that all nodes experience the same level of relative deprivation from migrants. In another analysis, we prevented direct ties from transmitting relative deprivation (reported in *SI Appendix*, Table S9). Our results remained similar.

Under the second category of reference groups, we included alters who share economic or social attributes. In their original formulation, Stark and Taylor (40) base the relative deprivation hypothesis on the income distributions in the community. Data limitations prevent us from testing this exact specification. Instead, we consider a social reference group based on the roles that individuals take within their communities (*SI Appendix*, Fig. S3). The results are qualitatively unchanged; the relative deprivation mechanism thus specified still has weaker effects on migration relative to the resource sharing model.

The third category of reference groups is based on the community culture. Cumulative causation theory indicates that migration can become a self- sustaining process over time (14) if prior migrants create a "culture of migration" (6). In that case, any migrant within a community may be part of a reference group for relative deprivation. Because our models are fit at the community level, we cannot directly test this mechanism, but identify it as a potential object for future research.

As mentioned above, we tested an alternative reference group that falls under the first—structural—category. This alternative specification considers relative deprivation as a nonlocal process, and excludes direct family, friends, or lenders from the relevant alters. Thus, the resource-sharing model describes a highly local effect, while the relative-deprivation model is explicitly nonlocal in the network structure. These results are qualitatively similar to the current reference group. The relative-deprivation model still performs worse than the resource-sharing model, on average. Full details on these models are included in *SI Appendix*.

While we aim to disentangle the two types of network effects from each other, future qualitative work may be needed to fully disambiguate the resource-sharing and relative-deprivation mechanisms. Our models can only determine whether the pattern of migration within a community is consistent with a given process as operationalized here. Our data do not capture the context of a social tie or what flows through it. It is possible that the presence of a migrant alter is consistent with the resource-sharing hypothesis, but the same alter could also induce relative deprivation.

We also tested an alternative reference group, which falls under the second (sociodemographic) category, using the structure of roles within a community. There are several roles that community members can take on, including religious leaders, members of governing committees, and health providers. We consider the comparison reference group to be those that are in overlapping roles to a potential migrant, normalized by the size of these groups. The results from these models also do not show a significant departure in model orderings from the ones reported in the main text.

The alternative specifications highlight that there are several different reference groups that are relevant for a relative deprivation mechanism underlying international migration decisions. However, in the western Honduran communities, none of these reference groups facilitate migration more plausibly than ties involved in the tested resource-sharing mechanism. From a theoretical perspective, we may expect that the salient reference group may change over time as the migration process progresses. Early in the migration process, where migration resources are rare and the benefits of migration are not yet widespread, aspirational ties for reference groups may be most salient. Later, measures like structural equivalence may become more facilitatory of migration. Future research can test these ideas if longer-horizon panel data become available. Additionally, we cannot claim that the alternative reference groups we have tested here are exhaustive. Indeed, there are some reference measures that are discussed in the literature on international migration [e.g., based on the income distribution in the community (40)] that were not testable with our data and modeling strategy. Future research may be able to test other reference groups in other contexts.

Finally, we have also examined the effects of stratification by gender on the resource-sharing and relative-deprivation effects. The results of this test, reported in *SI Appendix*, highlight that men and women are affected by both of our mechanisms differently. For example, men are more affected by both resource-sharing and relative-deprivation processes. These results are consistent with literature that highlights how men and women may benefit differently from resources in the environment (41, 42). Both processes produce significant effects with the same sign for women, although the magnitude of these effects is markedly less than for men.

Limitations. While we cannot necessarily generalize these results to other contexts in which the meaning of kinship or friendship may be different (e.g. familial relations in Western Honduras are very broad and far reaching within communities), our findings that resource sharing facilitates migration are consistent with other studies of migration in Mexico. Prospective migrants with more ties to other migrants tend to be more mobile themselves. This related research has identified several demographic trends among migrants, as well as postulated that migrants within the community may act as valuable resources for potential migrants (13, 14). Our finding that resource sharing tends to be a more plausible social mechanism than relative deprivation (based on the set of reference groups described above) is robust within our sample of communities. However, future work should test this hypothesis in other social and geographic contexts to better understand the widespread validity of our results.

A second limitation of this work is in the interpretation of our models. Kinship, friendship, and economic relations all carry complex social meanings. These social meanings are encoded in the group structure of a community, the demographic characteristics, and the connections that community members have to those outside of their community. We consider the structure of the networks fixed within this analysis, but future work may consider the endogenous evolution of networks as migration and other social processes occur. Furthermore, as the LNAM modeling framework is cross-sectional, we cannot capture changes in the process of migration. Given that migration is an inherently dynamic process (14), future work should aim to further characterize the temporal nature of the process.

We also highlight several data limitations. The surveys did not capture retrospective migration histories. We only observe migration events between 2016 and 2022. As a result, it is difficult to characterize the broader mobility process of these communities. That said, the data allow us to model how prior migration patterns (between 2016 and 2019) can influence future migration behaviors (observed in 2022). In that way, our cross-sectional models reveal how the patterns of autocorrelation in international migration behaviors during a short time period align with the telltale patterns for each proposed network process.

Additionally, the data record migrant destinations coarsely (*SI Appendix*). There are two possible international destinations within our data: the United States and any other country. Future work on Honduran migration may be able to better disentangle effects based on where a migrant is traveling to. While the majority of the international migrants within our communities indeed moved to the United States, others might be moving to transit countries as a "first-step" migration destination. If migrants choose to continue their migration journeys beyond the reported destination, we are unable to capture this secondary mobility. As a result, we only conceptualize the results in this paper as describing the process leading to an individual leaving their country rather than the full process of international mobility. This full process would also include integration in the receiving society, which we are unable to measure.

Due to data limitations, some of our measures do not fully capture nuances of network effects in migration theory. While the resource-sharing measure aligns very closely to its description in existing literature, the relative-deprivation measure leans more on the literature around social influence (26, 27, 29, 30). This measure assumes that individuals pay more attention to migrants among their structurally similar alters. Our data also do not allow us to ascertain whether the migrants are seen as "successful," which, according to relative deprivation theory, is key to others following in their footsteps (5). Our measure relies on the assumption that migration, on average, brings success such as material wealth that others can observe. This assumption is supported by empirical evidence from many contexts, such as Mexico (43, 44) and Guatemala (45). Furthermore, recent research suggests that remittance receipt is linked to better health outcomes among children in Honduras (46) and remittances make up almost a quarter of the Honduran GDP; therefore, households with migrants are likely to enjoy higher wealth and status in Honduran communities (47).

Similarly, our data offer an imperfect measure for network effects across economic ties. Our measure captures the potential for exchange of small amounts of money across a short period of time rather than the larger amounts and longer time frames of a migration trip. Thus, it is possible that the null results that we obtain (in aggregate from the Condorcet analysis) are a function of the economic ties capturing a different social and economic process than the one relevant for international migration.

Scholars and policymakers are increasingly looking to understand and predict international migration (48). With migration rates around the world rising, investigations that leverage both rich data on social network structures and socio-demographic and economic factors can provide valuable insights into the mechanisms that drive mobility. Additional data collection that incorporates both standard demographic drivers of migration (e.g. gender, age, education, etc.) in addition to new data on social network structures within communities would support additional inquiry to build a more general understanding of how networks and mobility are linked across geography and contexts.

Conclusion

We have highlighted two different potential mechanisms through which networks could facilitate migration. We show that, of these two mechanisms, a process of resource sharing between close friends and kin is more plausible than the mechanism of relative deprivation between structurally similar network positions. Our results are significant given that different network mechanisms carry different implications for the perpetuation of migration. Where resource-sharing-driven migration would be affected by a resource constraint (e.g. drought) facing the community, a relative-deprivation-driven constraint functions via a different mechanism. Relative deprivation would not be as sensitive to resource constraints (49) as it relies on the relative (rather than absolute) standing of community members. It would then follow that, under constraint, we may expect migrants to be selected differently, based on the network process that is operating.*

That is, our results highlight the potential to understand how migration patterns are likely to change as a function of changes in local environment, social structure, or economic conditions. In the event that a shock hits a community, the two mechanisms that we test may yield very different reactions. The resource-sharing hypothesis, upheld in this work, would

*We highlight different facilitators of migration (including social networks). We do not consider immobility as the complement of migration (50). Understanding immobility and its association with social ties requires a different research design. Future work could take this question on, which is understudied in the literature.

allow community members to rely on a broad base of support from their overlapping cohesive subgroups to find resources and remain mobile. Relative-deprivation processes based on structural or role based reference groups, on the other hand, may remain more limited in diffusing international migration. While the finding that networks are important in facilitating migration has been understood for some time, our results help to better understand why.

Materials and Methods

Honduran Community Networks. We focus on the interpersonal networks from a set of Honduran communities (21).[†] Secondary use of these data was reviewed and approved by the Princeton IRB (IRB #16213). Specifically, of the 176 communities that had data collected from an ongoing longitudinal cohort, we use data from a set of 73 villages. Inclusion criteria required that a community be enrolled in the survey for 6 y, encompassing 4 waves of data collection, which was the case for only 82 of the 176 villages (these 82 were chosen exogenously between waves 3 and 4, when the cohort was halved in size, as planned given funding constraints). Of these 82 communities, 9 communities with singular migration or covariate vectors were excluded because models could not be fit to them.

The study communities are from the western part of the country, and the collected data include networks based on a census of all members in the village. We focus on three types of social networks: kinship, friendship, and economic ties (based on borrowing). Each input graph was produced from name generators gathered during data collection. The kinship network is the union of five measures (father, mother, sibling, partner, and child over 12 y old). Friendship was produced as the union of 3 measures (spending free time together, discussing personal or private matters, and closest friends). Borrowing ties are based on a single name generator, which asked who an ego would go to in order to borrow a sum of money. In total, we use 29,460 kin ties, 68,281 friend ties, and 27,703 prospective borrowing ties. These networks are cumulative, meaning that all nodes and ties present in 2016 or 2019 are carried forward into 2022. This is a necessary choice for this modeling framework, as the cross-sectional nature of the LNAM models would not easily allow for changes in the node set of a network. Additionally, if we have different network sizes over time due to migration in and out of a community, traditional methods would not be appropriate for modeling these different sized networks. For more details on the specific measures used to construct these networks, including information on overlap between the three network modes, see *SI Appendix*.

Migration is also measured within these communities. For a person to be marked as a migrant, they must first be present in the community at a time point (2016 or 2019). When a wave of subsequent data collection occurs, if a community member is not present, other residents of the community are asked where they have gone. If that community member has migrated out of the community, people are asked about where they have gone to. The reported migration destinations are very coarse (the United States, and other country). Community members who are marked as being in an international destination during data collection in 2022 are considered migrants for the purpose of the outcome measure in this study.

Migration is a relatively common occurrence in western Honduras, with many international migrations departing for destinations within the United States. Given the high-level poverty (with a quarter of the population earning less than \$3.65 per day, and almost half the population earning less than \$6.85 per day) (51), many Hondurans may migrate in search of better economic opportunities. Research also suggests violence as a driver of migration from this setting (52). Regardless of the economic pull factors or crime-related push factors, we expect migration from this setting to be socially patterned.

Network Autocorrelation Models. Our primary interest is to investigate the influence structure of the social networks, and the way that this structure might be associated with migration. To that end, we use the Linear Network Autocorrelation Model framework (LNAM) to test several hypotheses about the ways in which communication and comparison may function within these Honduran communities. These cross-sectional models have been used in prior work to examine different influence processes within social networks (28). They quantify the degree to which patterns of autocorrelation across a network for some behavior (i.e. international migration) is consistent with a given influence process. LNAM models extend the linear regression framework, and inherit many of the assumptions included there. Their main advantage is to explicitly parameterize the effect of autocorrelation on social behaviors in a social network context. For more information on the form of these models, see *SI Appendix*.

The core idea we use for testing network influence processes is the specification of a W matrix, which defines the proposed influence process that takes place within the network. This W matrix has size NxN, where N is the number of nodes in the network, and $W_{i,j}$ is the influence exerted on node i by node j.

We propose two hypotheses for the ways in which influence propagates across the social network (each encoded as a W matrix), following the proposed mechanisms from the migration and social influence literature. First, we examine the case in which people seek resources from their immediate social ties, or from people within a close geodesic distance to them (friends of friends, etc.). The neighborhoods of a given ego are thus responsible for transmitting influence on migration. The structure of the W matrix can be written as

$$W = \Sigma_{i=1}^{3} \alpha^{i} G^{i},$$

where G is the matrix representation of a community network, α is an attenuation parameter describing how quickly the influence decays across an edge, and i represents path lengths in the network of up to three. In this way, W acts as a truncated version of the Katz Measure (53). The reason for including influence beyond immediate relationships with friends and kin is derived from the literature on diffusion and contagion. Research has indicated that the influence a person can exert is often felt up to 3 social links away from the original ego (21, 28, 54). Once the W matrix has been constructed, we row-normalize it. This normalization implies that a potential migrant is influenced equally by all their ties to migrants.

The second hypothesis we examine is the case in which potential migrants compare themselves to their structural peers when making migration decisions. In this case, we consider the influence exerted by a migrant to be proportional to the inverse square of structural distance between the migrant and the prospective migrant. We represent this W matrix as

$$W = \frac{1}{\gamma^{2}},$$

where γ is the number of toggles required for two nodes to become structurally equivalent. This distance is represented as a Hamming distance, or the number of social ties that would need to be toggled on or off within the network for two nodes to become structurally equivalent. Two nodes are structurally equivalent if they have the same ties to the same alters. For example, within the friendship network, two nodes that have exactly the same set of friends would be structurally equivalent (as long as they are not friends with each other). We set the value of W to 1 when γ is equal to 0. Leenders describes this mechanism of influence as one of comparison, especially when this matrix is parameterized in a way that excludes any direct ties present in the adjacency matrix (28). The W matrices that we include in these models describe the effects of autocorrelation on migration behavior. Some alternative specifications of LNAM models may describe how autocorrelation in the error term affects behavior (or deviations from expected values), but this is beyond the scope of this work.

Importantly, when considering the substantive meaning of these two influence processes, our data do not allow us to measure the substantive content of a social tie. However, when describing resource sharing, we refer to the communication matrix specified above. Likewise, when considering relative deprivation, we refer to the structural equivalence matrix specified here. Fig. 2 schematically describes each of these influence processes.

In addition to the influence effects, we also parameterize the effects for individual attributes (education, gender, indigenous status, marital status, age,

[†]While data collection was not a part of this study, the data collection procedures for the RCT were approved by the Yale IRB (protocol number 1506016012) and the Honduran Ministry of Health. All participants provided informed consent for data collection. For more details on the data collection process and the RCT, see ref. 21.

and perception of economic standing). Specific information on each of these covariates is included in *SI Appendix*.

We also include a control for prior migration status. This variable encodes whether an individual in the network has migrated prior to the 2022 observations. Anyone who was observed in 2016, but was recorded as a migrant in 2019, would be considered a prior migrant. We only consider migration to known destinations, but do not require these destinations to be international. Potential destinations include the United States, other counties, communities within the western Honduran regions, or other destinations within Honduras. The inclusion of this term in the model allows us to understand the effect of prior migration behavior on an individual's likelihood of being observed as a migrant in 2022. It also allows us to observe the expected effect of the influence processes described above, net of the effect of prior migration.

We fit these models to the set of networks and covariates collected in the final wave of the survey, during 2022 using the sna package in R (55). For each community, we fit the same set of 10 LNAM models. Each of these models contains the set of demographic controls, and one or more influence processes. Each model is specified for a single network (kinship, friendship, or borrowing). These models describe the migration behavior in 2022, using mostly cross-sectional data. Where values are not available in 2022 (often due to migration), data are interpolated from prior time points. Models' coefficients are fit using maximum likelihood estimation, and we assume that model errors are normally distributed (i.e. default values for the LNAM function in the above package).

Importantly, each case in the data is a person in a specific village. There is some mobility within the sample, meaning that some individuals may be present in multiple village networks. In total, we have 15,480 observations of people spread across 73 village networks (9 communities are excluded from the analysis for having singular response or prediction vectors; for more details on the communities, see *SI Appendix*). After all 73 models are fit for a network type and influence process, we use a random effects meta-analysis to examine the coefficients across all models simultaneously. Random effects meta-analysis combines the effects from a series of models, and assumes that each model provides an estimate of the effects, sampled from a data generating process. This meta analysis takes the coefficients from each model and the corresponding model variance/covariance matrix as inputs. All the variables in our analysis are computed in the same way across all communities, and carry the same meaning as a result. The random effects meta-analysis is conducted using the mixmeta package in R (56), using maximum likelihood techniques.

Model selection. We fit several LNAM models for each network measure, and evaluate whether the inclusion of one or more of the network influence processes improves model behavior. Following Leenders (28),we use both the AIC and BIC to evaluate model fit, and select the best model. The BIC provides a more conservative test as it more harshly penalizes model complexity. Table 4 describes the model specifications for each of these models. We fit models at the community level, so we consider the ensemble of model orderings (selected by AIC or BIC) to select the best fitting model across all communities.

Table 4. Model specifications

Effects	Model 1	Model 2	Model 3	Model 4
Individual level effects	X	X	X	X
Resource sharing (communication)		X		X
Relative deprivation (comparison)			X	X

Model specifications for LNAMs.

In total, we fit 3 unique models for each network type. We fit one additional model that includes no network influence terms. This base model is shared across all four network types, due to its lack of consideration of any network data. Each of the three influence hypotheses is evaluated by a set of community models, rather than a single unified model across the full set of communities. As a result, we assess each hypothesis using a set of AIC and BIC values. These values are not comparable across communities, so we instead evaluate the ordering of models for a given community. We then use a Condorcet voting schema (57) to determine the most plausible hypothesis across the entire sample.

Data, Materials, and Software Availability. Some study data are available. Data are gathered as part of an ongoing public health RCT study, led by N.A.C. Data are not publicly available at this time, although all data and code used in this work are archived on internal servers. IRB protocols allowing use of these data for L.J.T. prevent sharing of data. For inquiries about data access, please contact N.A.C. (nicholas.christakis@yale.edu). Meta-analytic models used in the main paper are available in a public facing repository, with DOI: 10.5281/zenodo.17713241 (58).

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