Social Networks and Migration: Theory and Evidence from Rwanda

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Abstract

How does the structure of an individual's social network affect his decision to migrate? We study the migration decisions of over one million individuals in Rwanda over a period of several years, using novel data from the monopoly mobile phone operator to reconstruct the complete social network of each individual in the months prior to migration. We use these data to directly validate several classic theories of migration that have historically been difficult to test, for instance that individuals with closely-knit networks in destination communities are more likely to migrate. Our analysis also uncovers several empirical results that have not been documented in the prior literature, and which are not consistent with common theories of how individuals derive value from their social networks. We propose a simple model of strategic cooperation to reconcile these results.

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1 Introduction

Migrants play a central role in bringing an economy towards a more efficient use of its resources. In many contexts, however, a range of market failures limit the extent to which people can capitalize on opportunities for arbitrage through migration. Recent literature documents, for instance, cases where information does not reach the migrant (Jensen, 2012), households lack insurance against the risk of migration (Bryan, Chowdhury and Mobarak, 2014), and source communities discourage exit (Beegle, De Weerdt and Dercon, 2010, Munshi and Rosenzweig, 2016). The resulting underinvestment in migration leads to the misallocation of capital, and can have severe consequences for the overall economy.[1]

The decision to migrate depends on the extent to which the migrant is connected to communities and home and in the destination. Much of the existing literature has focused on how strong ties to the destination community can facilitate migration by providing access to information about jobs (Munshi, 2003, Borjas, 1992) and material support for reecent arrivals (Munshi, 2014). The role of the home network is more ambiguous. On the one hand, robust risk sharing networks can partially insure against the risk of temporary migration (Morten, 2015), making it easier for people to leave. On the other hand, strong source networks can also discourage permanent migration if migrant households are subsequently excluded from risk sharing networks.

While there is thus general consensus that social networks play an important role in migration decisions, the exact nature of this role is unclear. This ambiguity stems, at least in part, from a lack of reliable data on both migration and the structure of social networks. Migration is difficult to measure, particularly in developing countries where short-term migration is common and reliable household survey data is limited (McKenzie and Sasin, 2007, Carletto, de Brauw and Banerjee, 2012, Lucas, 2015). Social network structure is even harder to observe. Recent empirical work on networks relies on survey modules that

[1] Bryan, Chowdhury and Mobarak (2014), for instance, link underinvestment in migration to seasonal famine. Munshi and Rosenzweig (2006) and McKenzie and Rapoport (2007) show how migration can affect inequality and the distribution of income.

ask respondents to list their social connections, but this approach is necessarily limited in scope and scale. Thus, much of the literature on networks and migration relies on indirect information on social networks, such as the (plausible) assumption that individuals from the same hometown, or with similar observable characteristics, are more likely to be connected that two dissimilar individuals.

We leverage a novel source of data to provide detailed insight into the role of social networks in the decision to migrate. Using several years of data capturing the entire universe of mobile phone activity in Rwanda, we track the internal migration decisions of roughly one million unique individuals, as inferred from the locations of the cellular towers they use to make and receive phone calls. We link these migration decisions to the structure of each migrant's social network, as inferred from the set of people with whom he or she interacts over the phone network. Merging the geospatial and network data, we observe the migrant's connections to his home community, his connections to all possible destination communities, as well as the complete higher-order structure of the network (i.e., the connections of the migrant's connections).

To structure our analysis, we develop a strategic cooperation model to characterize how an individual can obtain value from her social network. This "social value" is broadly construed to capture access to information and opportunities for risk sharing and favor exchange. Within our repeated cooperation setting, agents randomly meet their connected neighbors over time, and when two agents meet, they each contribute effort to a joint project. Effort is determined endogenously by the network structure, so the model allows us to describe in equilibrium how network structure affects the social value that agents get from the network, which in turn affects the decision to migrate.[2]

The model generates several intuitive predictions that are documented in prior work, and which are also reflected in our data. Namely, agents receive higher utility when their network

[2]See Ali and Miller (2016) for a related approach, which builds on past observations that social sanctions can improve commitment in risk sharing (Chandrasekhar, Kinnan and Larreguy, 2014, Karlan et al., 2009) and may strengthen job referral networks (Heath, 2016).

has a larger number of contacts, and when the frequency of interaction with neighbors is increased. This is consistent with several studies linking exogenously larger social networks in the destination to higher rates of migration (cf. Munshi, 2003). And in our data, we indeed see that rates of migration are increasing in the number of contacts an individual has in a destination community, and in the frequency of interaction with those contacts. Similarly, our model predicts that stronger networks in the home community will make a migrant less likely to leave, which is consistent with a story where individuals fear being ostracized from inter-family insurance networks (Munshi and Rosenzweig, 2016). Our data indicate a decreasing, monotonic, and approximately linear relationship between migration rates and the extent of the home network.

More interesting, our model and data make it possible to generate and test several hypotheses about the role of social networks in migration that the existing literature has been unable to explore. Notably, we show that social connections generate positive externalities. That is, if two agents form a link or increase their interaction over the existing link, their common neighbors (in addition to themselves) receive strictly higher utilities from the network. This generates the testable predictions that an agent should be more likely to migrate if her connections in the destination form more links among themselves; and if the frequency of interaction between common neighbors increases. As we show, each of these predictions is supported by the data, although the shape of the migration response function is not always linear or monotonic.

We also document - to our knowledge for the first time - the role that more distant network connections play in migration. Superficially, we find that an individual is more likely to migrate to a destination where his friends have more friends. However, this effect does not persist after controlling for the number of friends in the destination; instead, the marginal effect of second-order friends conditional on first-order friends is somewhat negative. For example, if both Joe and Jane have the same number of contacts living in a destination community, but Joe's contacts have more contacts in the destination than Jane's contacts do, it is (counterintuitively) Jane who is more likely to migrate.

Taken together, these results allow us to differentiate between two common approaches to modeling the economic value of social networks. In particular, we contrast the predictions of the strategic cooperation model described above with a simple model of information diffusion (e.g., Banerjee et al., 2013). The strategic cooperation model is consistent with both externalities observed in the data. This is because in the cooperation game, the agent is not aware of the action of her neighbors' neighbors, therefore her endogenous effort depends only on the actions and structure of her immediate network. The key assumption – that the individual does not have knowledge about the network outside of her immediate neighbors – is a consistent finding in the empirical literature (see, for example Krackhardt, 1990, Casciaro, 1998, Chandrasekhar, Breza and Tahbaz-Salehi, 2016). By contrast, most models of information diffusion predict that positive externalities would be global. As information is shared more often somewhere in the network, an agent is more likely to hear about it faster, and the marginal effect of second order friends should be strictly positive. This prediction is not supported by the data, which implies that the information diffusion model cannot be the sole determinant of network value in the context of migration.

Our final set of results explores heterogeneity in the migration response to social network structure. We separately study the role of the network in migration between and across rural and urban areas, in short- and long-distance moves, and in temporary vs. permanent migrations. While the main effects described above are generally consistent in each of these sub-populations, the shape and magnitude of the migration response differs significantly by migration type.

Since our approach to studying migration with mobile phone data is new, we perform a large number of specification tests to calibrate for likely sources of measurement error and to test the robustness of our results. In particular, one limitation of our approach is that we lack exogenous variation in the structure of an individual's network, so that network structure may be endogenous to decisions regarding migration. We address this concern in two principal ways. First, we derive structural properties of the migrant's social network in the period prior to migration. Our results change little even when we reconstruct each migrant's social network using communications data from several months prior to the date of migration. Second, we leverage the vast quantity of data at our disposal to control for a robust set of network characteristics and better isolate the structural parameter of interest. For instance, we condition on the number of common neighbors when analyzing the effect of the frequency of communication between common neighbors. Thus, while having a large number of contacts in a destination may be endogenous to migration, and likely migrants may even select contacts who are connected to each other, we assume migrants will be less able to control the extent to which those contacts communicate.

This paper makes two primary contributions. First, we contribute to a growing literature on the economic value of social networks (cf. Jackson, Rodriguez-Barraquer and Tan, 2012, Banerjee et al., 2013, 2014). Our model connects this literature to research on migration in developing countries, and indicates that a model of social support is more consistent with the data than a model of information diffusion. Second, we contribute to empirical research on the determinants of internal migration in developing countries (cf. Bryan, Chowdhury and Mobarak, 2014, Morten, 2015, Lucas, 2015). In this literature, it has historically been difficult to measure the effect of social networks in migration; our data make it possible to directly test several conjectures in the prior literature, and to develop new insight into the relationship between social network structure and the decision to migrate.

2 A strategic model of migration

People need their friends' help and support when moving and settling down in a new place. We model the decision to migrate as a function of the utility an agent receives from neighbors in the network. In particular, agents play cooperation games with their neighbors repeatedly over time, and the utility they get can represent the level of support they obtain from the network. The model provides micro foundations for several stylized empirical predictions, which we can bring to the data. Moreover, it deviates in important ways from alternative models of migration in social networks, for instance the information diffusion model which we will discuss in Section 2.2.

2.1 A repeated cooperation game with neighbors

Consider a population of N players, $N = \{1, \ldots, n\}$, who are connected in an undirected network G, with $ij \in G$ if agent i and j are connected. Denote agent i's neighbors as $N_i = \{j : ij \in G\}$, and her degree as $d_i = |N_i|$.

Each pair of connected agents, $ij \in G$, is engaged in a partnership ij that meets at random times generated by a Poisson process of rate $\lambda_{ij} > 0$. When they meet, agent i and j choose their effort levels a_{ij}, a_{ji} in $[0, \infty)$ as their contributions to a joint project.[3] Player i's stage game payoff function when partnership ij meets is $b(a_{ji}) - c(a_{ij})$, where $b(a_{ji})$ is the benefit from her partner j's effort and $c(a_{ij})$ is the cost she incurs from her own effort. The benefit function b and the cost function c are smooth functions satisfying $b(0) = c(0) = 0$. All players share a common discount rate $r > 0$, and the game proceeds over continuous time $t \in [0, \infty)$.

We write the net value of effort a as $v(a) \equiv b(a) - c(a)$, and we assume that it grows in the following manner.

Assumption **1.** *The net value of effort $v(a)$ is strictly increasing and weakly concave, with $v(0) = 0$. Moreover, $v'(a)$ is uniformly bounded away from zero.*

Assumption 1 implies that higher effort is always socially beneficial; concavity means it is better for partners to exert similar effort, holding their average effort constant. The following assumption articulates that higher effort levels increase the temptation to shirk.

Assumption **2.** *The cost of effort c is strictly increasing and strictly convex, with $c(0) = c'(0) = 0$ and $\lim_{a\to\infty} c'(a) = \infty$. The "relative cost" $c(a)/v(a)$ is strictly increasing.*

[3] The variable-stakes formulation is adopted from Ghosh and Ray (1996) and Ali and Miller (2016).

Strict convexity with the limit condition guarantees that in equilibrium effort is bounded (as long as continuation payoffs are bounded, which we assume below). Increasing relative cost means a player requires proportionally stronger incentives to exert higher effort.

As has been documented in several different real-world contexts, we assume agents have only local knowledge of the network.[4] Each agent only observes her local network, including her neighbors and the links among them (in additional to her own links). To be precise, agent i observes her neighbors in N_i and all links in $G_i = \{jk : j, k \in \{i\} \cup N_i\}$. Similarly, each agent learns about her neighbors' deviation and we assume this information travels instantly.

Homogenous meeting frequency

As a benchmark, we start with the case that λ is i.i.d. across agents. Following the definition from Jackson, Rodriguez-Barraquer and Tan (2012), a link ij is *supported* if they have at least one common neighbor $k \in N_i \cap N_j$, and ij is m-supported if they have m common neighbors. There are critical effort levels, for supported and unsupported links.

Unsupported cooperation. Consider a strategy profile in which each of i and j exerts effort level a_0, if each has done so in the past; otherwise, each exerts zero effort.

$$b(a_0) \leq v(a_0) + \int_0^\infty e^{-rt} \lambda v(a_0) dt. \tag{1}$$

The incentive constraint is binding at effort level a_0^*.

Supported cooperation. Consider a triangle i, j, k and a strategy profile in which each of them exerts effort level a_1, if each has done so in the past; otherwise, each exerts zero effort.

$$b(a_1) \leq v(a_1) + 2 \int_0^\infty e^{-rt} \lambda v(a_1) dt. \tag{2}$$

[4] Examples in the literature include Krackhardt (1990), Casciaro (1998) and Chandrasekhar, Breza and Tahbaz-Salehi (2016).

The incentive constraint is binding at effort level a_1^*. Notice that the future value of cooperation is higher in a triangle, $2\int_0^\infty e^{-rt}\lambda v(a_1)dt$, so it can sustain higher level of efforts $a_1^* > a_0^*$ and everyone gets a strictly higher utility.

Higher-order supported cooperation. Let $m(ij) = |N_i \cap N_j|$ be the number of agents who are common neighbors of i and j. Consider i and j sharing m common neighbors and a strategy profile in which each of them exerts effort level a_m if each has done so in the past; otherwise, each exerts zero effort.

$$b(a_m) \leq v(a_m) + \int_0^\infty e^{-rt}\lambda \left[v(a_m) + mv(a_1^*)\right] dt, \tag{3}$$

in which i and j assume other pairs cooperate on at least a_1^* when they are supported. The incentive constraint is binding at effort level a_m^*. Following the same argument, more common neighbors can sustain a higher level of cooperation between i and j, that is a_m^* strictly increases in m.

We can now characterize a simple strategy profile, which satisfies two nice properties.[5] First, it is *measurable to local networks*, such that the effort level between any pair of agents only depends on the local networks they share. Second, it is *strongly robust to social contagion*, such that any pair of agents should continue playing their strategy on the equilibrium path if neither has deviated before. The strong robustness is particularly important because agents do not need to worry about contagion of any deviation and can continue cooperating with each other. However, it is not easy to satisfy. Notice that the ostracism type of punishment agents use in equation (2) does not satisfy the strong robustness requirement, because if i deviates, j and k no longer cooperate with each other at a_1^* level. To achieve strong robustness, we need a social norm on how to punish a deviator. If agent i shirked on agent j, the game between i and any of her neighbors, say $k \in N_i$, becomes sequential: Agent i chooses an effort a_{ik}^G first as the guilty agent, and then agent k observes i's effort and chooses

[5]We use a simplified version of the strategy profile studied in Ali and Miller (2016), and later introduce heterogeneous meeting frequency to match with our data.

his effort a^I_{ki} as the innocent partner. These effort levels are set to let the guilty agent get a payoff of zero while the innocent agent get the same payoff as that on the equilibrium path.

$$b(a^I_{ki}) - c(a^G_{ik}) = 0, \text{ and } b(a^G_{ik}) - c(a^I_{ki}) = v(a_{ik}).$$

There must exist a solution satisfying $0 < a^I_{ki} < a^G_{ik} < a_{ik}$.

Strategy profile: Everyone starts off "innocent." While innocent, agent i and j choose simultaneously and they work at effort level $a_{ij} = a_{ji} = a^*_{m(ij)}$. If i shirked on j, i becomes "guilty." While guilty, the cooperation game between i and each of her neighbors becomes the sequential one above. i moves first and chooses a^G_{ik}, and then $k \in N_i$ moves second and chooses a^I_{ki} only if i chose at least a^G_{ik}, and k chooses 0 otherwise. Lastly, if someone in N_i deviates while i is guilty, then i becomes innocent and her strategy with her neighbors goes back to the simultaneous one, except she now starts to punish the new deviator.

PROPOSITION **1.** *Consider the game with homogenous meeting frequency. There exists an equilibrium, measurable to local networks and strongly robust to social contagion, in which any pair of connected agents, say i and j, cooperate on $a^*_{m(ij)}$, where $m(ij) = |N_i \cap N_j|$.*

All proofs are in Appendix A1. Intuitively, the more common neighbors a pair of agents have, the higher utility they can get from their cooperation. That is, a^*_m increases in the number of common neighbors m. Thus, in the equilibrium above each agent gets a strictly higher utility if she forms more links, or if her neighbors form more links among themselves. To generalize this intuition, we now show that if an agent's degree, support or clustering increases,[6] then she can get a higher utility from the network. In particular, while there are many possible equilibria, we restrict our attention on those in which each agent gets a positive expected payoff from each link.

PROPOSITION **2.** *Consider two networks, G and $G' = G \cup \{ij\}$ such that $ij \notin G$. For any*

[6] "Support" is defined as the fraction of one's links that are supported; "clustering" is defined as the fraction of pairs of one's neighbors that are connected.

equilibrium Σ_G in network G, there is an equilibrium $\Sigma_{G'}$ in network G' weakly dominating Σ_G and for any agent $k \in \{i,j\} \cup (N_i \cap N_j)$ in network G, k must get a higher utility in $\Sigma_{G'}$.

The proposition shows that each link not only benefits its two agents, but also exhibits positive externalities. First of all, the link ij gives agent i and j each a higher utility due to this new cooperation opportunity. As a result, they get a higher utility from cooperation and thus they face a higher punishment if they deviate. This additional punishment then sustains i and j's incentives to cooperate at a higher level with their common neighbors $k \in N_i \cap N_j$, who can observe the link. So k can get a higher utility once i and j are connected.

Heterogeneous meeting frequency

In the data, we can measure the communication frequency between any pair of agents. To examine its effect on the utility one gets from the network, we now allow heterogeneous meeting frequency, and λ_{ij} is locally observed by i, j and their common neighbors in $N_i \cap N_j$.

First, in a bilateral partnership, agents get a higher utility when they meet more often. Let $a_0^*(\lambda_{ij})$ be the unsupported effort level when only i and j are connected and they meet with the frequency λ_{ij}. The counterpart to equation (1) becomes $b(a_0) \leq v(a_0) + \int_0^\infty e^{-rt}\lambda_{ij} v(a_0)dt$. The incentive constraint is binding at effort level $a_0^*(\lambda_{ij})$. It is easy to verify that $a_0^*(\lambda_{ij})$ increases in λ_{ij}, which implies as the meeting frequency increases, the utility agent i and j can obtain from their cooperation increases.

This is also true in an arbitrary network, such that an agent can get a higher utility if her interaction frequency with her neighbors increases and/or the interaction frequency between two of her neighbors increases.

Proposition **3.** *Consider the game with heterogeneous meeting frequencies, and increase the frequency on one and only one link $\lambda'_{ij} > \lambda_{ij}$, and equal for all other links. For any equilibrium Σ_λ, there is an equilibrium $\Sigma_{\lambda'}$ weakly dominating Σ_λ and for any agent $k \in \{i,j\} \cup (N_i \cap N_j)$, k must get a higher utility in $\Sigma_{\lambda'}$.*

The proposition shows that the interaction frequency also exhibits positive externalities. As i and j meet more often, they each gets a higher utility from cooperation, which provides the incentive to not only contribute greater effort to their partnership ij, but also to partnerships with their common friends $k \in N_i \cap N_j$. Thus, k receives a higher utility from i and j as they meet more frequently.

However, the positive externalities found in Proposition 2 and Proposition 3 are local effects to agents in $\{i, j\} \cup (N_i \cap N_j)$. Other agents who only know either i or j do not know whether ij are connected or their frequency of interaction. Thus, they cannot choose their efforts based on the link ij, nor benefit from its existence or its increased frequency. This type of local knowledge seems particularly relevant when a person is considering migrating to a potential destination. Because an agent has not yet moved to the destination, it is unlikely that she knows much beyond her immediate neighbors. This local positive externality differs from the prediction of an information diffusion model outlined below.

2.2 An alternative model of information diffusion

People may also share information through the network about potential job opportunities in the destination, which can affect the migration decision. There are several diffusion models in the literature, including both mechanical communication and strategic communication (see summaries in Jackson and Yariv (2010) and Banerjee et al. (2013)).

We begin with a mechanical diffusion model and allow for possible loss of information. As before, agents meet with their neighbors randomly. The difference from the earlier model is that in this setting, when they meet, they share information with each other. Let I be the information initially learned by a subset of agents $N^I \subset N$ that people share, which could be about job openings in a new factory. If agent i knows I, when she meets each of her neighbors j who does not know I, j learns I from i with probability $p \in (0, 1)$. We assume agents never forget about I once they learn it, although it will be clear that this is not crucial to the predictions.

Proposition 4. *Consider either adding a link ij if it is not present or increasing λ_{ij} otherwise; then every agent except the initial recipients of the information, $k \in N \setminus N^I$, must learn the information with a strictly higher probability at any given time t.*

Intuitively, any additional link or increased meeting frequency speeds up the information diffusion. First of all, agent i and j can learn from each other faster. Once they are more likely to learn the information, they also share it to their neighbors, neighbors of neighbors, and to agents further away. So the positive externality of one link is global, and can affect the entire network. This is a key testable difference between the model of strategic cooperation and the model of information diffusion.

2.3 Summary

To summarize, the cooperation model of Section 2.1 has the following testable implications:

Remark 1. *In general, an agent is more likely to migrate if her network in the destination has (or she is less likely to migrate if her network in the hometown has):*

- *Higher degree;*
- *Higher support/clustering, when fixing degree;*
- *Higher own interaction frequency, when fixing the network;*
- *Higher interaction frequency between neighbors, when fixing the network.*

The number of indirect neighbors in the destination network has no effect on one's migration. However, if agents know their indirect neighbors within a certain distance at home, then the number of these indirect neighbors has a negative effect on one's migration.

3 Data

We exploit a novel source of data to test the predictions of our model. These data make it possible to observe rich information about the social network structure and migration histories of over a million individuals in Rwanda. The data were obtained from Rwanda's primary mobile phone operator, which held a near monopoly on mobile telephony until late 2009. We focus on an analysis of the operator's mobile phone Call Detail Records (CDR) covering a 4.5-year period from January 2005 until June 2009. The CDR contain detailed metadata on every event mediated by the mobile phone network. In total, we observe over 50 billion mobile phone calls and text messages. For each of these events, we observe a unique identifier for the caller (or sender, in the case of a text message), a unique identifier for the recipient, the date and time of the event, as well as the location of the cellular phone towers through which the call was routed. All personally identifying information is removed from the CDR prior to analysis.

We use these data to infer migration events, and to observe the social network structure, of each of the roughly 1.5 million unique subscribers who appear in the dataset. Summary statistics are presented in Table 1. Our methods for inferring migration and measuring social networks are described below. In Section 4.3, we address the fact that the mobile subscribers we observe are a non-random sample of the overall Rwandan population, and discuss the extent to which these issues might bias our empirical results.

3.1 Measuring migration with mobile phone metadata

We construct individual migration trajectories for each individual in three steps.

First, we extract from the CDR the approximate location of each individual at each time in which he or she is involved in a mobile phone event, such as a phone call or text message. This creates a set of tuples $\{ID, Timestamp, Location\}$ for each subscriber. We cannot directly observe the location of any individual in the time between events appearing in the CDR. The location is approximate because we can only resolve the location to the geocoordinates of the closest mobile phone tower (in standard GSM networks, the operator does not record the GPS location of the subscribers). The locations of all towers in Rwanda, circa 2008, are shown in Figure 1.

Second, we assign each subscriber to a "home" district in each month of the data in which she makes one or more transactions. Our intent is to identify the location at which the individual spends the majority of her time, and specifically, the majority of her evening hours.[7] We treat the three districts that comprise the capital of Kigali as a single urban district; the 27 other districts in Rwanda are treated as separate rural districts. Algorithm 1 describes the algorithm exactly. To summarize, we first assign all towers to a geographic district, of which there are 30 in Rwanda (see Figure 1). Then, for a given month and a given individual, we separately compute the most frequently visited district in every hour of that month (e.g., a separate modal district-hour is calculated for each of the 24×30 different hours in a 30-day month). Focusing only on the hours between 6pm and 7am, we then determine the for each day in the month, that individual's monthly modal district-day – defined as the district that is observed with the largest number of modal district-hours for the following night. Finally, we determine the modal monthly district for that individual as the district in which the individual is observed for the largest number of modal district-days.[8] After this step, we have an unbalanced panel indicating the home loaction of each individual in each month.

Finally, we use the sequence of monthly home locations to determine whether or not each

[7]A simpler approach simply uses the model tower observed for each individual in a given month as the "home" location for that person. While our later results do not change if home locations are chosen in this manner, we prefer the algorithm described in the text, as it is less susceptible to biases induced from bursty and irregular communication activities.

[8]At each level of aggregation (first across transactions within an hour, then across hours within a night, then across nights within a month), there may not be a single most frequent district. To resolve such ties, we use the most frequent district at the next highest level of aggregation. For instance, if individual i is observed four times in a particular hour h, twice in district p and twice in q, we assign to i_h whichever of p or q was observed more frequently across all hours in the same night as h. If the tie persists across all hours on that night, we look at all nights in that month. If a tie persists across all nights, we treat this individual as missing in that particular month.

individual i migrated in each month t. As in Blumenstock (2012), we say that a migration occurs in month t if three conditions are met: (i) the individual's home location is observed in district d for at least k months prior to (and including) t; (ii) the home location d' in t is different from the home location in $t+1$; and (iii) the individual's new home location is observed in district d' for at least k months after (and including) $t+1$. Individuals whose home location is observed to be in d for at least k months both before and after t are considered residents, or stayers. Individuals who do not meet these conditions are treated as "other" (and are excluded from later analysis).[9] Complete details are given in Algorithm 2. Our preferred specifications use $k = 2$, i.e., we say a migration occurs if an individual stays in one location for at least 2 months, moves to a new location, and remains in that new location for at least 2 months. While the number of observed migrations is dependent on the value of k chosen, we show in Section 4.2 that our results are not sensitive to reasonable values of k.

Figure 3 shows the distribution of individuals by migration status, for a single month (January 2008). To construct this figure, and in the analysis that follows, we classify migrations into three types: rural-to-urban if the individual moved from outside the capital city of Kigali to inside Kigali; urban-to-rural if the move was from inside to outside kigali; and rural-to-rural if the migration was between districts outside of Kigali. As can be seen in the figure, of the 15,849 migrations observed in that month, the majority (10,059) the majority occured between rural areas; 2,795 people moved from rural to urban areas and 2,995 moved from urban to rural areas.

[9]Individuals are treated as missing in month t if they are not assigned a home location in month any of the months $\{t-k, ..., t, t+k\}$, for instance if they do not use their phone in that month or if there is no single modal district for that month. Similarly, individuals are treated as missing in t if the home location changes between $t-k$ and t, or if the home location changes between $t+1$ and $t+k$.

3.2 Inferring social network structure from mobile phone metadata

The mobile phone data allow us to observe all mobile phone calls placed, and all text messages sent, over a 4.5-year period in Rwanda. From these pairwise interactions, we can construct a very detailed picture of the social network of each individual in the dataset. To provide some intution, the network of a single migrant is shown in Figure 2. Nodes in this diagram represent individuals and edges between nodes indicate that those individuals were observed to communicate in the month prior to migration. The individual i of interest is shown as a green circle; red and blue circles denote i's direct contacts (blue for people who live the migrant's home district and red for people in the migrant's destination district); grey circles indicate i's "friends of friends", i.e., people who are not direct contacts of i, but who are direct contacts of i's contacts.[10]

To test the empirical predictions of the model described in Section 2, we collapse this network structure into a handful of descriptive characteristics, separately for each of the roughly 1 million individuals in our dataset, for each of the 24 months that we study. The characteristics of primary interest are:

- **Degree Centrality:** The number of unique individuals with whom i is observed to communicate.
- **"Information":** The number of friends of friends of i. Specifically, we count the unique 2nd-order connections of i, excluding i's direct connections.
- **"Support":** The number of i's neighbors who share a common neighbor with i.
- **"Weighted" degree, information, and support:** Accounts for the frequency of interaction between neighbors, following the discussion in Section 2.1. Specifically, *weighted degree* is the number of interactions between i and her immediate neighbors.

[10] Nodes are spaced using the force-directed algorithm described in Hu (2005).

weighted information is the count of all interactions between i's neighbors and their neighbors. *Weighted support* is the count of all interactions between i's neighbors and their common neighbors of i.

To reduce endogeneity when relating network structure to observed patterns of migration, we compare network characteristics derived from data in month $t-1$ to migration behavior observed in month t. Concerns of serial correlation are discussed in Section 4.2

4 Estimation and Results

To study the relationship between social network structure and the decision to migrate, we compare characteristics of individual i's network in month $t-1$ with the migration decision made by i in month t. Our canonical specification requires that the individual remain in one district for $k=2$ months, then move to another place for $k=2$ months, to be considered a migrant. As a concrete example, when t is set to January 2008, the individual is considered a migrant if her home location is determined to be one district d in December 2007 and January 2008, and a different district $d' \neq d$ in both February 2008 and March 2008. The first column of Table 1 shows how the sample of XXX unique individuals is distributed across residents and migrants, for just the month of January 2008. To increase the power of our analysis, we then aggregate migration behavior over the 24 months between July 2006 and June 2008. Summary statistics for this aggregated person-month dataset are given in Table 1, column 2.[11]

We calculate properties of i's network in $t-1$ following the procedures described in Section 3.2 for both the individual's home and destination networks. This is a straightforward process for the home network: we determine i's home location d in $t-1$, consider all contacts of i whose home location in $t-1$ was also d, and then calculate the properties of that

[11] Note that this process of aggregation means that a single individual will appear multiple times in our analysis. While this was our intent, since repeat migration is quite common in Rwanda, in later robustness tests we show that very little changes if we restrict our analysis to a single month.

subnetwork. Calculating properties of the destination network is more subtle, since non-migrants do not have a destination. To address this, for every individual we consider all 27 districts other than the home district as a "potential" destination, and separately study each of i's 27 potential migrations. [12][13]

The first set of results we present simply compares the network characteristics of people who migrate to those who do not. We focus on the key predictions of the model in Section 2: that individuals are more likely to migrate if their destination network has (i) higher degree; (ii) higher interaction frequency, which we calculate as weighted degree; (iii) higher support, fixing degree; and (iv) greater interaction between neighbors, fixing the network, which we calculate as weighted support. To contrast with the model of information diffusion presented in Section 4, we analyze the role of (v) the number of neighbor's neighbors. We discuss each of these results in turn in the sections that follow, and summarize them in Tables 2-6.

Degree centrality and weighted degree

Figure 4a shows the relationship between the migration rates and degree centrality in the destination. We observe in the top panel that the relationship is positive, monotic, and approximately linear. We can also infer, for instance, that roughly 11% of individuals who have 30 contacts in a potential district d' in month $t-1$ are observed to migrate to d' in month t. The bottom panel of the figure shows the distribution of destination degree centrality, aggregated over individuals, months (24 total), and potential districts (27 per individual). We observe that in the vast majority of these (individual $\times$ month $\times$ potential destinations) observations, the destination degree centrality is less than 3; in roughly 500,000 cases the individual has 10 contacts in the potential destination. Figure 4b shows the corresponding relationship between migration rates and the degree centrality of the individual's home

[12] In robustness tests described in Section refsec:robustness, we remove this potential source of bias by allowing each individual to have only one potential destination. This destination is chosen as the district other than d to which i made the most phone calls in $t-1$.

[13] In ongoing work, we are developing a method to cluster standard errors by individual-month, but this approach is not implemented in the current set of results.

network.[14]

Figure 4a thus validates a central thesis of prior research on networks and migration. Individuals with more contacts in a destination community are more likely to migrate to that community. Figure 4b conversely indicates that individuals with more contacts in their home community are less likely to leave that community.

We observe similar effects for *weighted* degree, such that individuals with a higher weighted degree in the destination are more likely to migrate (Figure 5a), whereas individuals with a higher weighted degree at home are less likely to migrate (Figure 5b). Recall that the weighting accounts for the frequency of interaction between an individual and her immediate contacts; weighted degree is thus equivalent to the total number of calls from the individual to his immediate contacts.

The relationship between weighted degree at the destination and migration is attentuated after controlling for degree at destination. In other words, if Joe and Jane both have the same number of contacts in the destination, but Joe interacts more with those contacts than Jane, Joe is more likely to migrate to the destination. This effect can be seen in Figure 6a, which we construct by plotting the β values from running regressions of the form $migration_i = \alpha + \beta WeightedDegree_i + \epsilon_i$, with a separate regression for each value of degree between 0 and 50. Positive values in Figure 6a indicate that holding degree fixed, individuals who interact more frequently with their contacts in the destination are more likely to migrate. Note that this conditional effect only appears for individuals with 7 or fewer destination contacts; among people who have a large number of contacts in the destination, those who interact frequently with their contacts are no more likely to migrate. A simliar pattern is observed in Figure 6b with respect to weighted degree at home: individuals with a small number of contacts are less likely to migrate if they interact with those contacts frequently; but individuals with more than 15 contacts at home are no more likely to migrate if they

[14]Note that the degree centrality distribution in the bottom panel of Figure 4b does not match that in the bottom panel of Figure 4a, since each individual has only one home district, but 27 potential destination districts.

interact with those contacts frequently.

Support and weighted support

Figure 7 and shows the relationship between migration and support, where support indicates the fraction of i's contacts who are also contacts with another of i's contacts, as originally proposed in Jackson, Rodriguez-Barraquer and Tan (2012). The effect of destination support is ambiguous (Figure 7a), with some evidence of a negative relationship between home support and migration (Figure 7b), i.e., individuals with more supported networks at home are somewhat less likely to migrate. Holding degree fixed, the role of support is more evident. Figure 8a indicates that for individuals with a fixed number of contacts in the destination, those whose contacts are mutualy supported are significantly more likely to migrate. The converse effect is found for support at home (Figure 8b): holding degree fixed, people are less likely to leave home if their home contacts are more supported.

The strategic cooperation model presented in Section 2 also predicts that the frequency of interaction between supported contacts will affect the decision to migrate. The unconditional effect of weighted support is shown in 9; the effect holding degree fixed is shown in 10. In general, the results correspond closely to the theory.

Information and weighted information

The final result we highlight concerns the role of "information" in the decision to migrate. As motivated by the alternative model of Section and empirically defined in Section 3.2, we quantify information as the size of i's second-order network, i.e., the number of friends of i's friends. Figure 13a shows the general positive relationship between migration rate and information in the destination, while Figure 13b shows the opposite relationship for information at home.

More interesting is the relationship observed in 14. Here, we observe that holding destination degree fixed, rates of migration are lower for individuals with higher information. In other words, if both Joe and Jane have the same number of contacts living in a destination community, but Joe's contacts have more contacts in the destination than Jane's contacts do, it is Jane who is more likely to migrate.

4.1 Heterogeneity

[This section under revision, contact authors for details]

Urban and rural migrants

Temporary and permanent migration

Strong and weak ties

4.2 Robustness

The empirical results described above are robust to a large number of alternative specifications. In results available upon request, we have verified that our results are not affected by any of the following:

- **How we define "migration" (choice of k):** Our main specifications set $k = 2$, i.e., we say an individual has migrated if she spends 2 or more months in d and then 2 or more months in $d' \neq d$. We observe qualitatively similar results for $k = 1$ and $k = 3$.

- **How we define "migration" (home location sensitivity):** Our assignment of individuals to home locations is based on the set of mobile phone towers through wihch their communication is routed. Since there is a degree of noise in this process, we take a more restrictive definition of migration that only considers migrants that move between non-adjacent districts.

- **Definition of social network (reciprocated edges):** In constructing the social network from the mobile phone data, we normally consider an edge to exist between i and j if we observe one or more phone call or text message between these individuals.

As a robustness check, we take a more restrictive definition of social network and only include edges if i initiates a call or sends a text message to j and j initiaties a call or sends a text message to i.

- **Definition of social network (strong ties):** We separately consider a definition of the social network that only includes edges where more than 3 interactions are observed between i and j. This is intended to address the concern that our estimates might be influenced by infrequent events such as misdialed numbers, text message spam and the like.

- **Definition of social network (ignore business hours):** To address the concern that our estimates may be picking up primarily on business-related contacts, and not the kinship networks commonly discussed in the literature, we only consider edges that are observed between the hours of 5pm and 9am.

- **Treatment of outliers (removing low- and high-degree individuals):** We remove from our sample all individuals (and calls made by individuals) with fewer than 3 contacts, or more than 500 contacts. The former is intended to address concerns that the large number of individuals with just one or two friends could bias linear regression estimates; the latter is intended to remove potential calling centers and businesses.

- **Sample Definition (single month):** We perform the analysis separately for each of the 24 months in the dataset, and do not aggregate over months. This ensures that an individual is not double-counted across time.

- **Sample Definition (single potential destination):** Instead of allowing each individual to consider 27 potential migration destinations, we choose that individual's most likely destination, and consider that to be the only potential destination for the migrant. This ensures that an individual is not double-counted within a given month.

4.3 Population representativeness and external validity

Our data allow us to observe the movement patterns and social network structures of a large population of mobile phone owners in Rwanda. These mobile subscribers represent a non-random subset of the overall Rwandan population. Likewise, the social network connections we observe for any given subscriber are assumed to be a partial and non-random subset of that subscriber's true social network.[15]

5 Discussion

The key empirical results are summarized in Tables 2-6. In short, we observe that (i) migration rates increase when individuals have a greater number of contacts in the destination, and when they interact with those contacts more frequently; (ii) that positive externalities exist, such that migration rates are higher when destination networks provide higher support and clustering, and when the strength of supported links is greater; (iii) that these externalities are local, in the sense that individuals are not more likely to migrate to a place where they have more friends of friends, if the number of direct friends is held constant. Roughly opposite effects are found with respect to the structure of the home network: people are less likely to leave when their home network is larger and denser - with the prominent exception that the externalities are global at home.

Taken together, this evidence is largely consistent with a model of strategic cooperation in which agents observe limited information about their network, beyond their immediate neighbors. It is harder to reconcile these results with a model of mechanical information diffusion model. However, the strategic information diffusion model can be built upon our main model. Specifically, if agents can strategically choose with whom they communicate and the level of effort to invest in communication – i.e., they can increase the probability p – then agents are more likely to share the information with their neighbors, who are currently

[15] This section is under revision, contact authors for details.

in a different location and with whom they share a tighter local network and expect a higher utility from future cooperation.[16]

6 Conclusion

This paper presents new theory and evidence on the role that social network play in the decision to migrate. Our approach highlights how new sources of large-scale digital data can be used to simultaneously observe migration histories and the dynamic structure of social networks at a level of detail and scale that has not been achieved in prior work. These data make it possible to directly validate several long-standing assumptions in the literature on migration, which have been hard to test with traditional sources of data. For instance, we show that individuals are more likely to migrate to destinations where they have a large number of contacts, and that the elasticity of this response is approximately one (e.g., someone with 20 contacts in the destination is roughly twice as likely to migrate as someone with 10 contacts).

We also document several novel properties of the relationship between social networks and migration, not all which can be explained by canonical models of information diffusion. For instance, we find that migration rates are not positively correlated with the number of friends of friends that one has in the destination, but that the migration rate is negatively correlated with the number of friends of friends at home. To reconcile these results, we propose a model of strategic cooperation that characterizes how individuals obtain value from their social network, and which fits the data quite well.

There are several directions to extend our analysis. First, while we focus on how social network affects migration decision, migration could also change the network structure. For example, condition on one agent will migration or has just migrated, we can examine how he forms new links and deletes existing ones. Also, the ability to observe migration over several

[16] For example, Banerjee et al. (2013) find that agents who themselves participate in microfinance inform a given neighbor about this program with probability 45%, while others inform a given neighbor with probability 9.5%.

years could allow us to study migration cascade, and its relationship with the home network. For example, if the home network is sparse, migration cascade may not happen because the contagion is too weak; if the home network is very dense, migration cascade also may not happen because the risk-sharing at home could hold people from moving.

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Figures

Figure 1: Location of all mobile phone towers in Rwanda, circa 2008

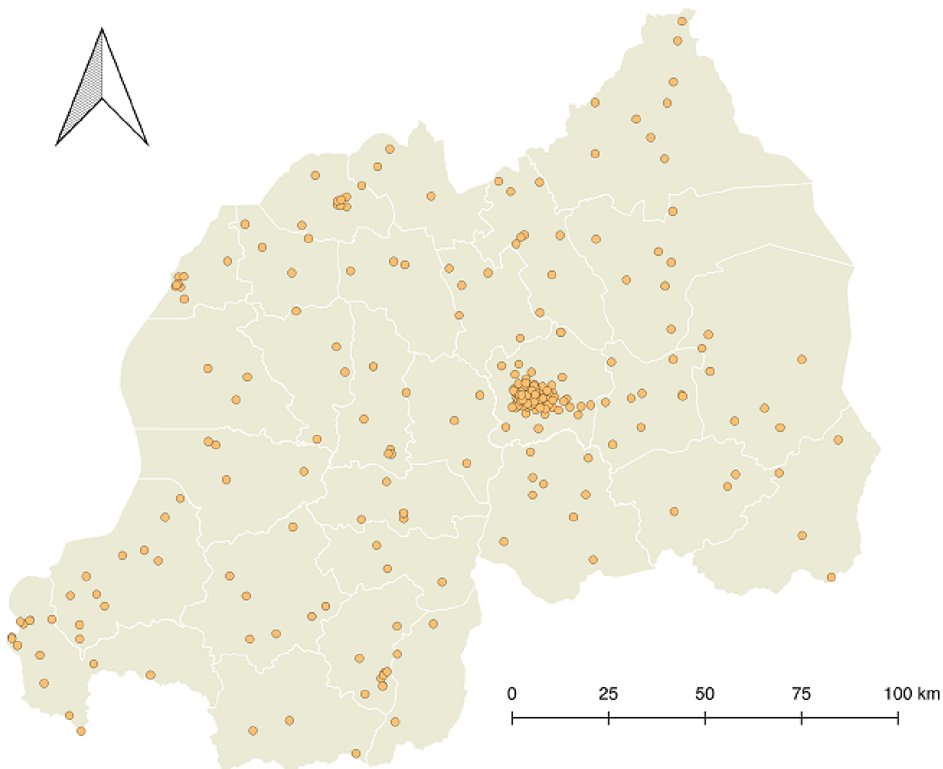


Figure 2: The social network of a single migrant

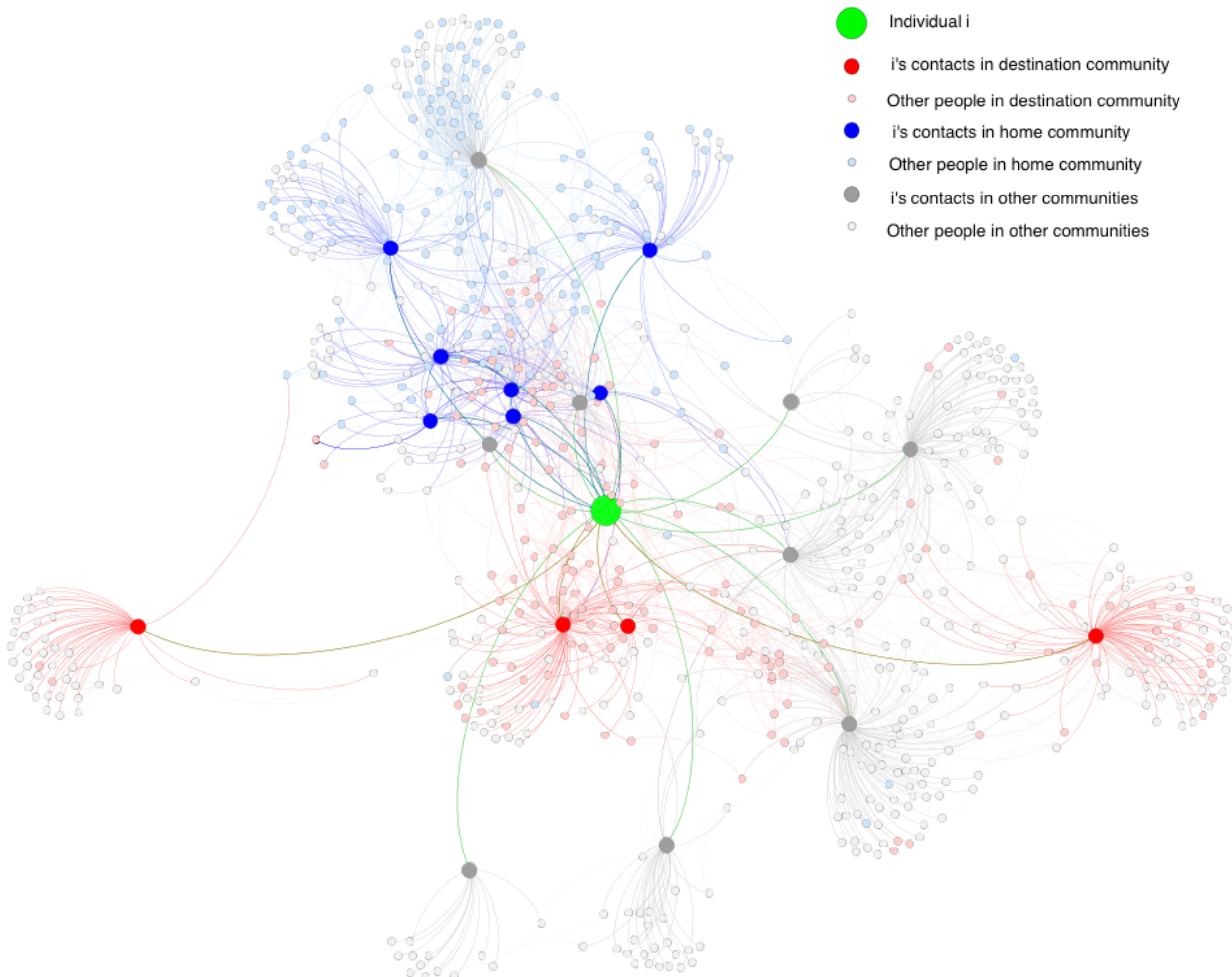
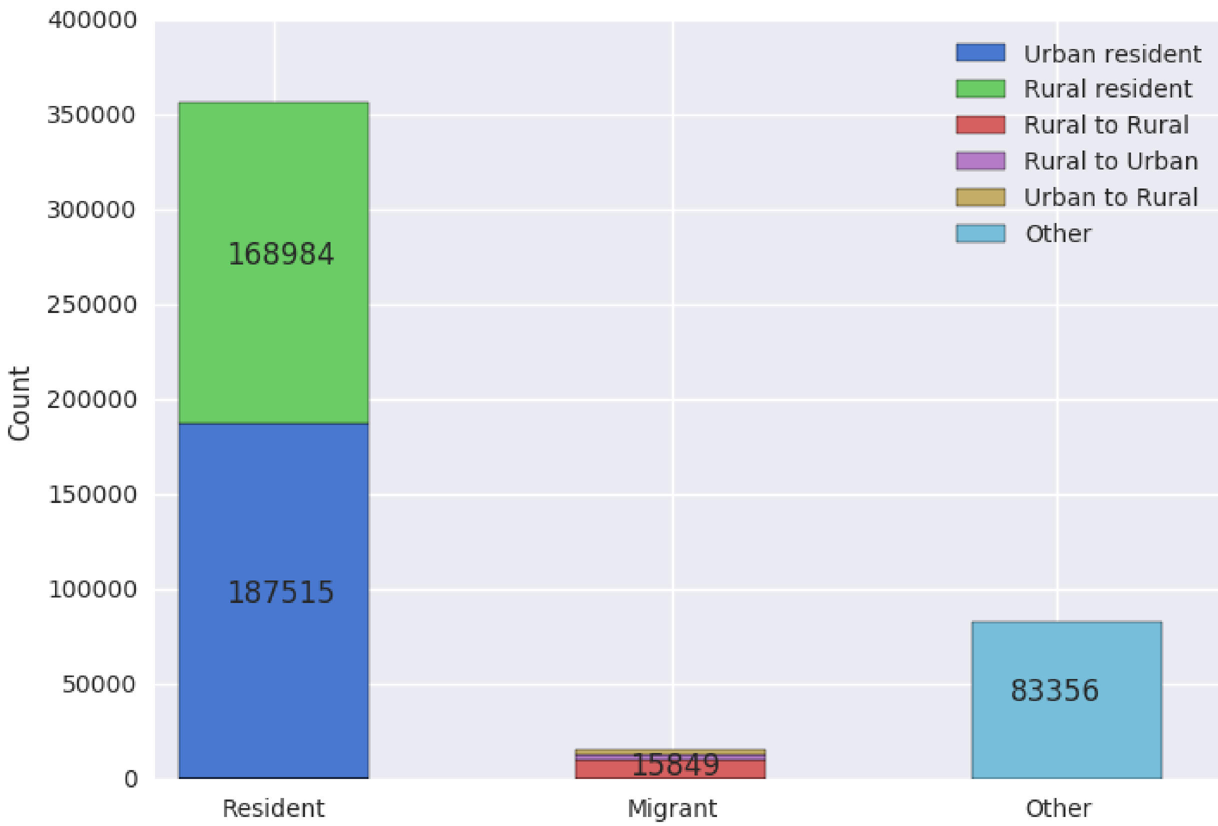
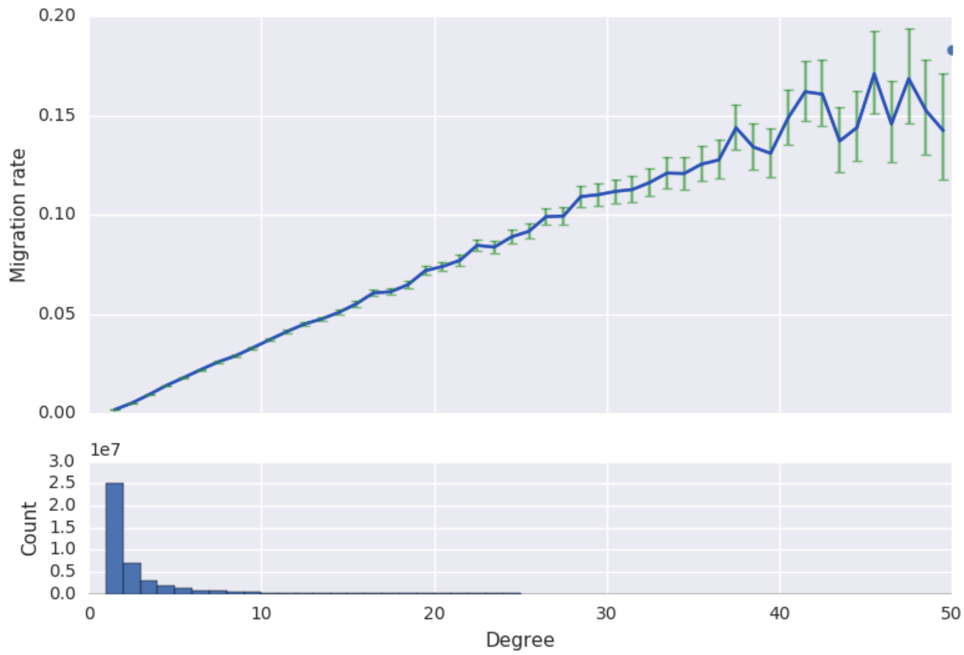
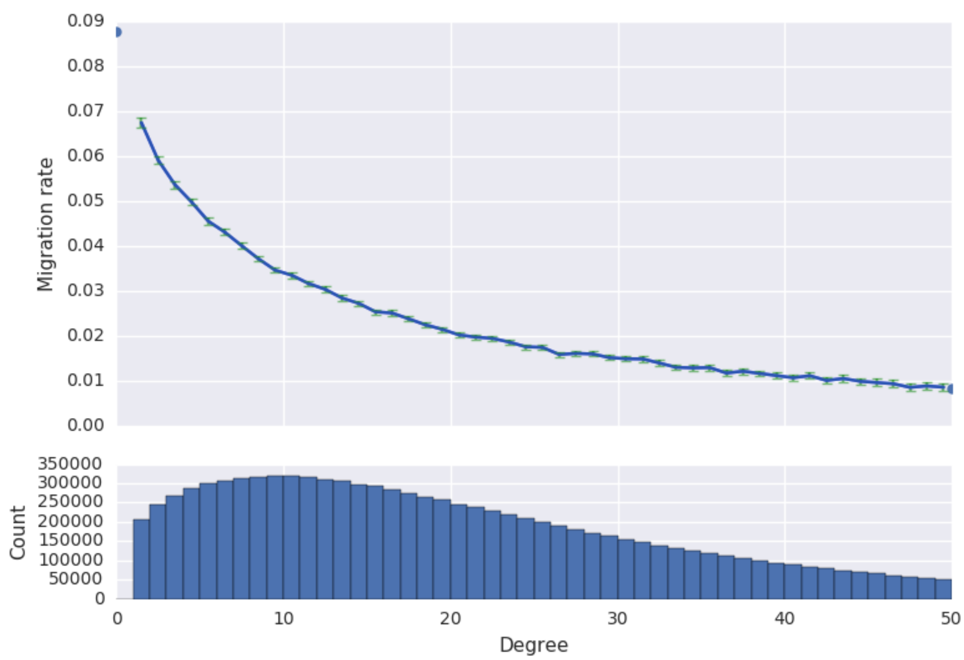


Figure 3: Population studied, by migration type



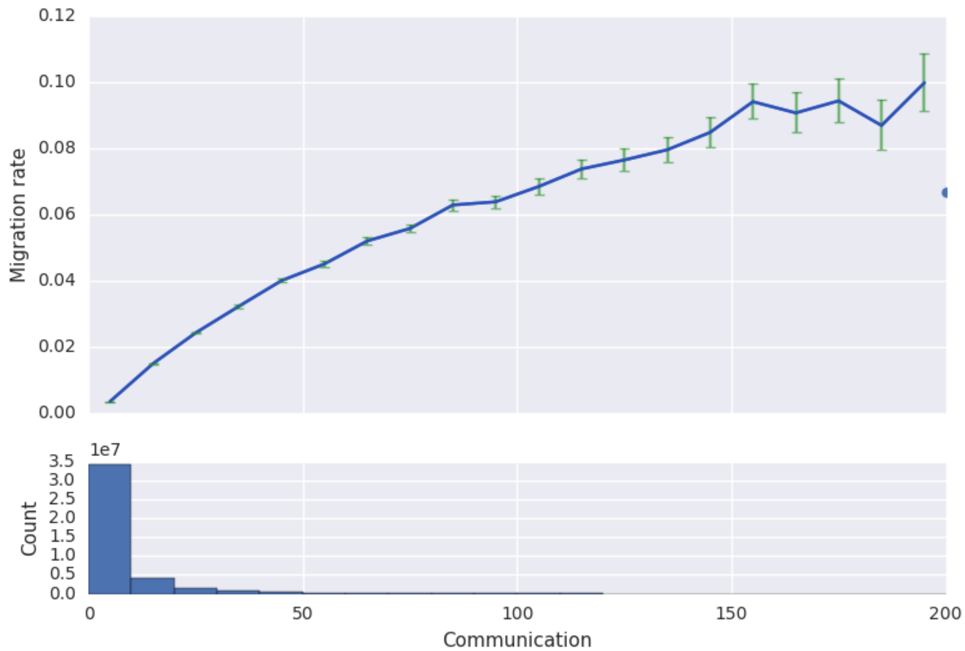


(a) Degree Centrality at Destination

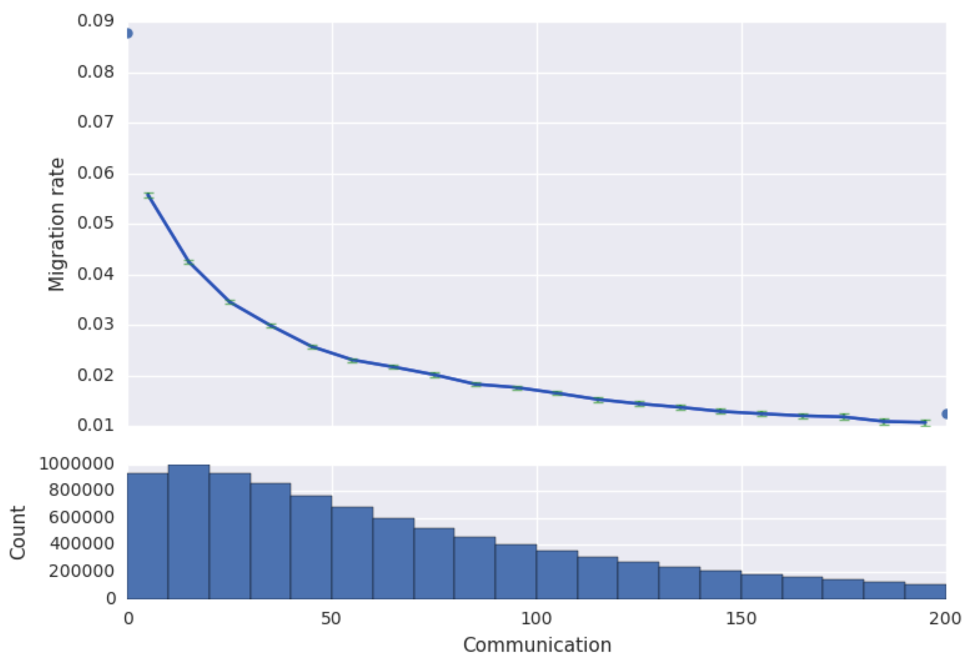


(b) Degree Centrality at Home

Figure 4: Relationship between migration rate and degree centrality (number of unique contacts in network)

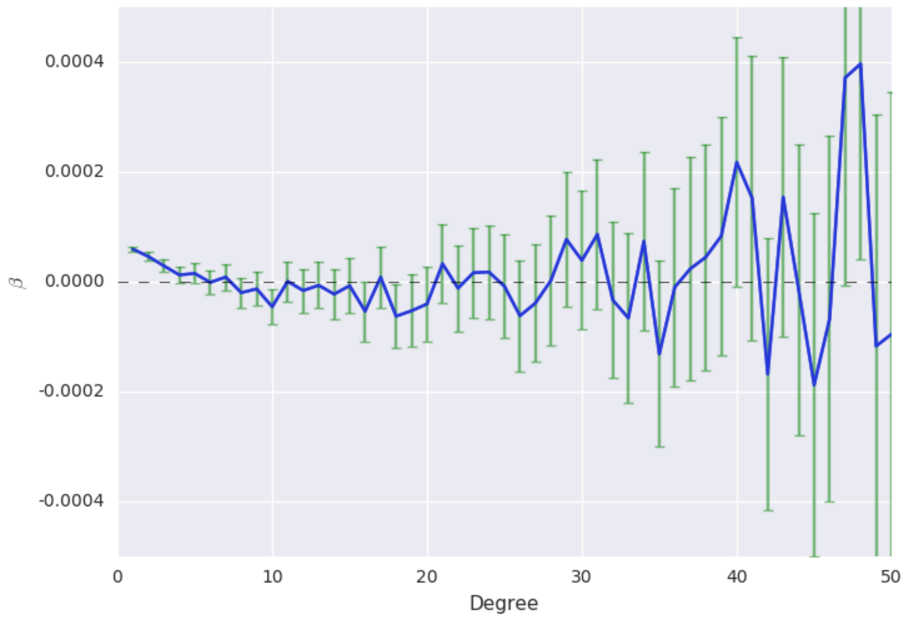


(a) Weighted Degree at Destination

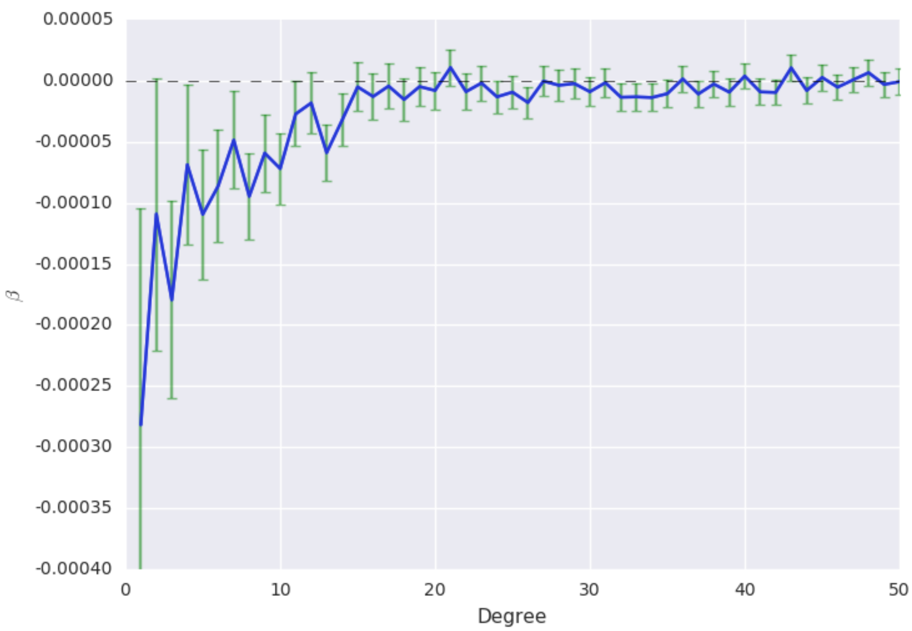


(b) Weighted Degree at Home

Figure 5: Relationship between migration rate and weighted degree (number of calls involving first-degree network)

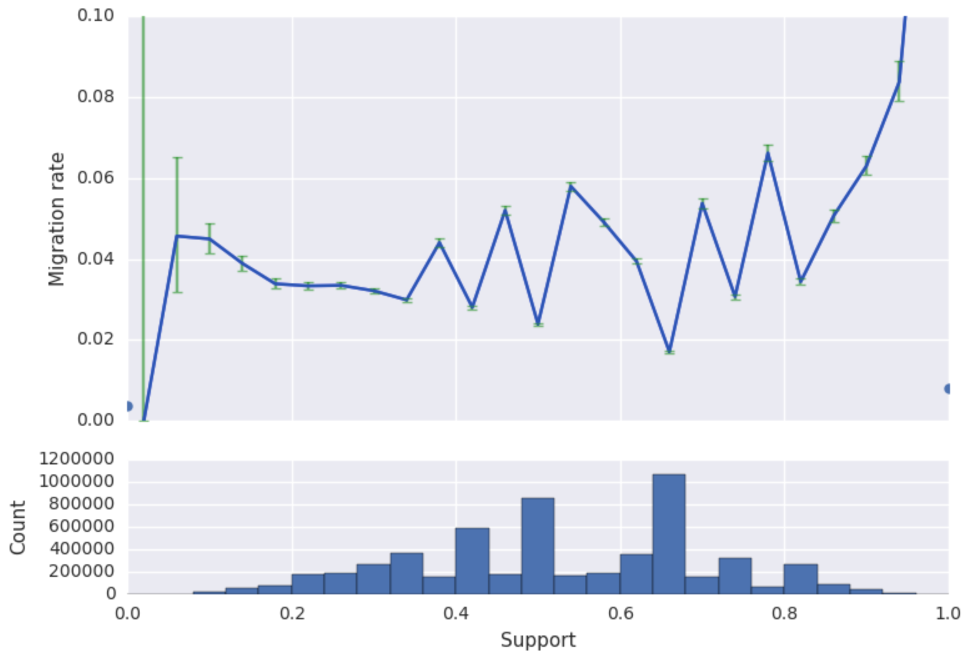


(a) Weighted Degree at Destination, Conditional on Degree

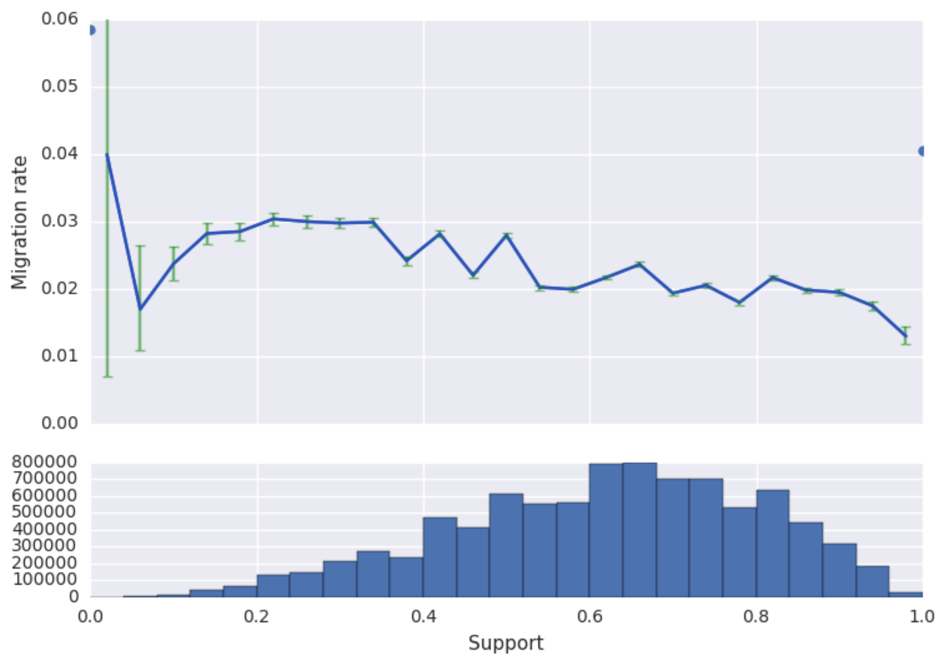


(b) Weighted Degree at Home, Conditional on Degree

Figure 6: Relationship between migration rate and weighted degree, holding degree fixed

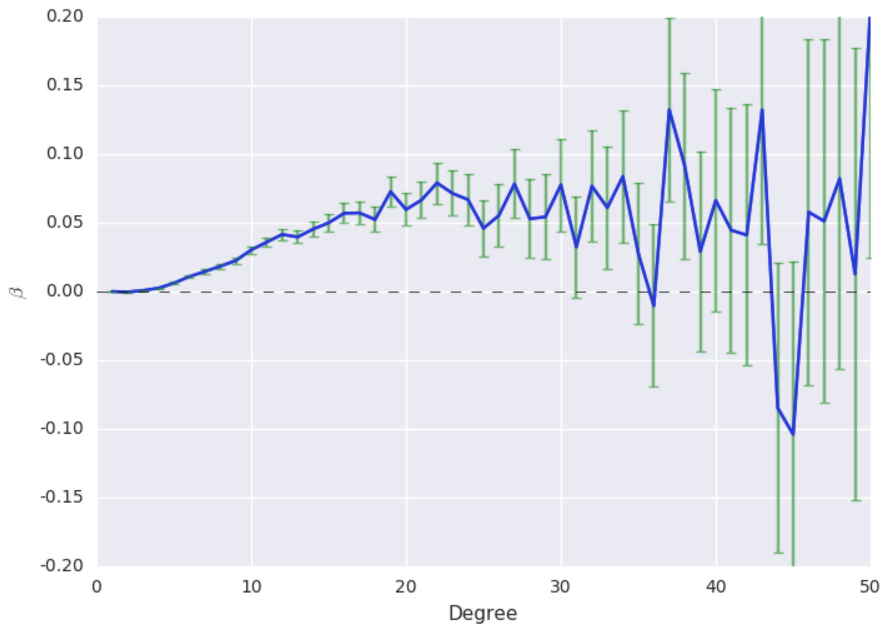


(a) Support at Destination

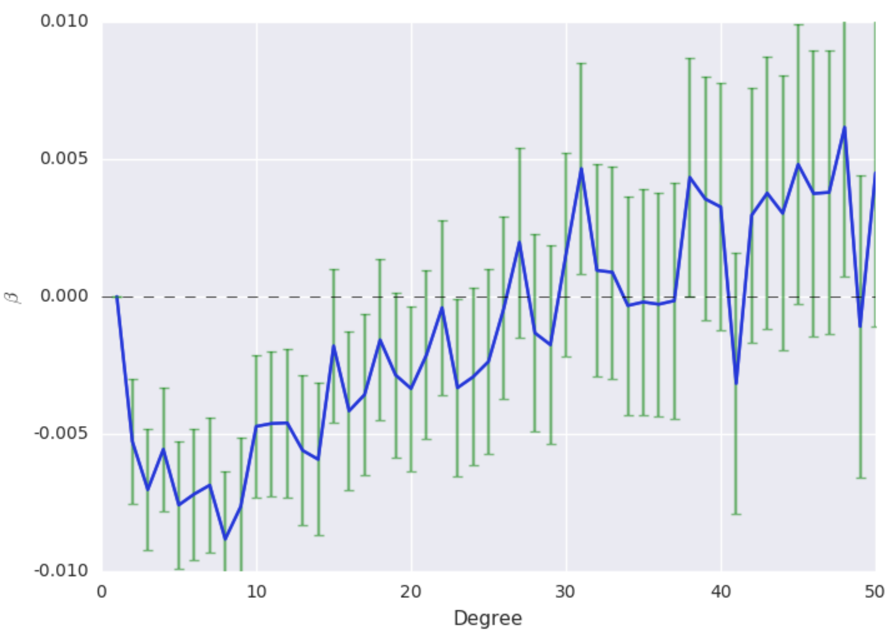


(b) Support at Home

Figure 7: Relationship between migration rate and support (fraction of contacts supported by a common contact)

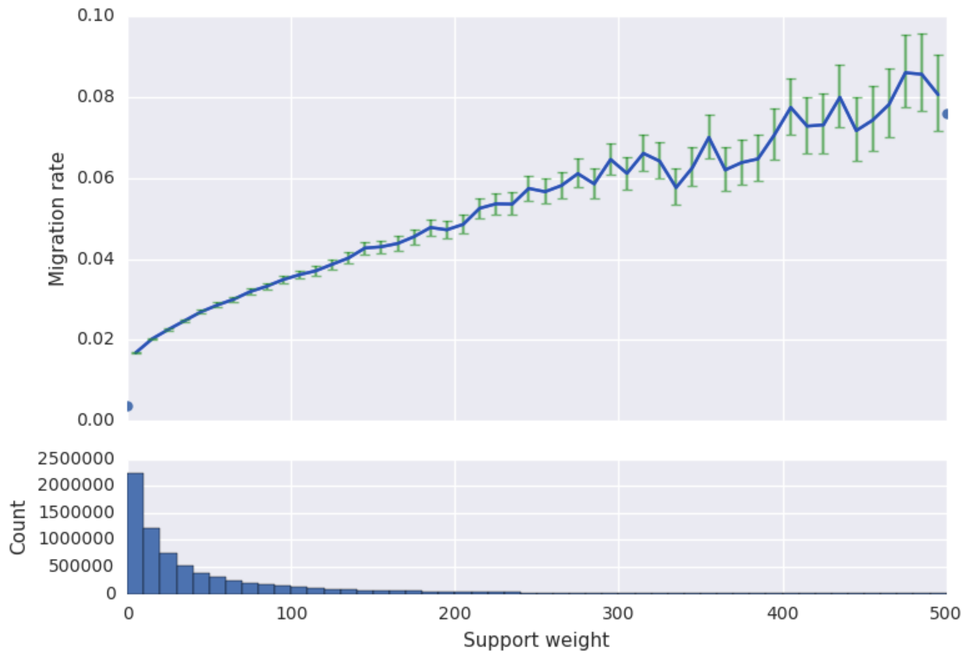


(a) Support at Destination, Conditional on Degree

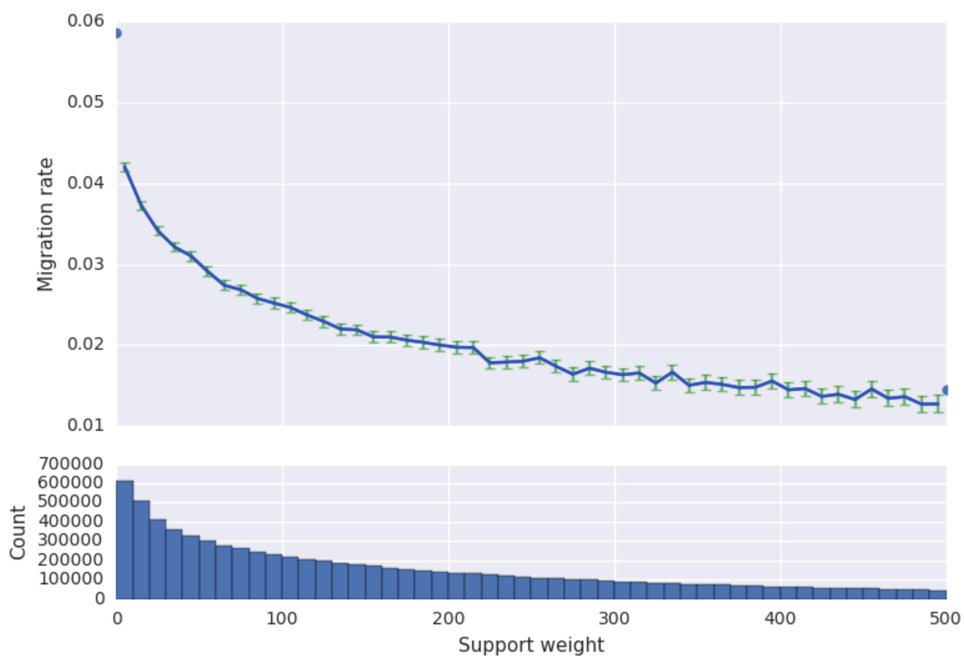


(b) Support at Home, Conditional on Degree

Figure 8: Relationship between migration rate and support, holding degree fixed

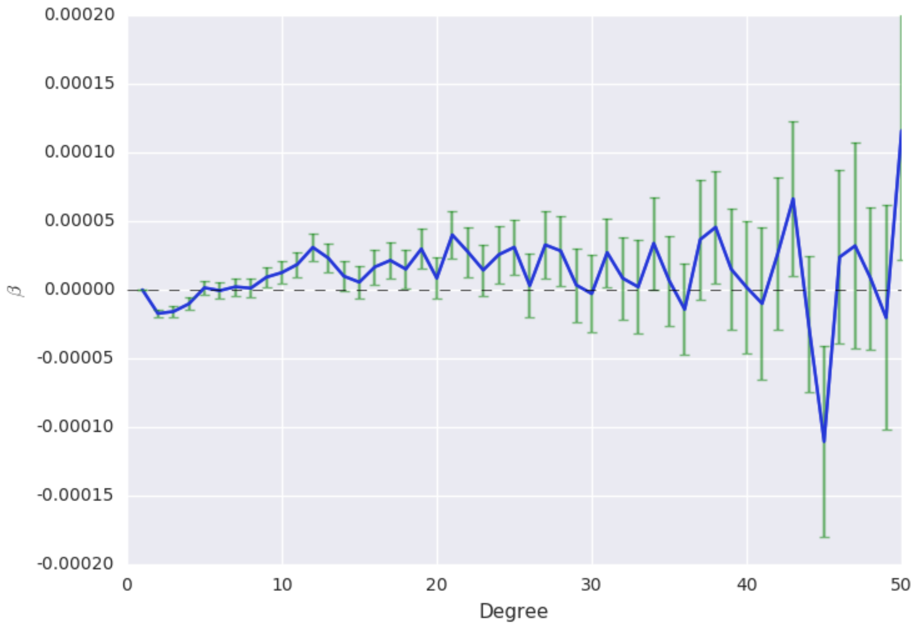


(a) Weighted Support at Destination

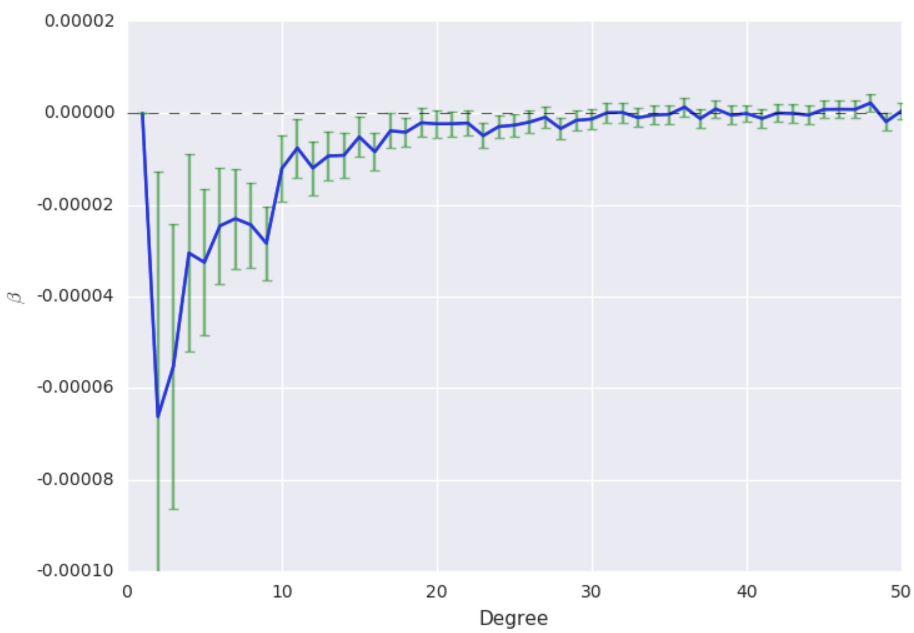


(b) Weighted Support at Home

Figure 9: Relationship between migration rate and weighted support (frequency of interaction between supported contacts)

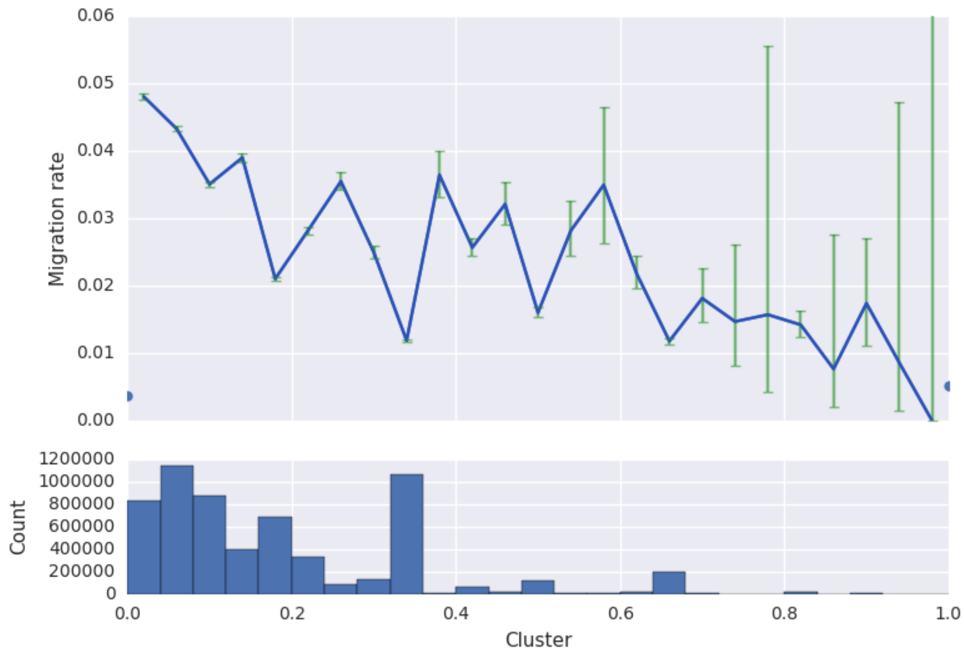


(a) Weighted Support at Destination, Conditional on Degree

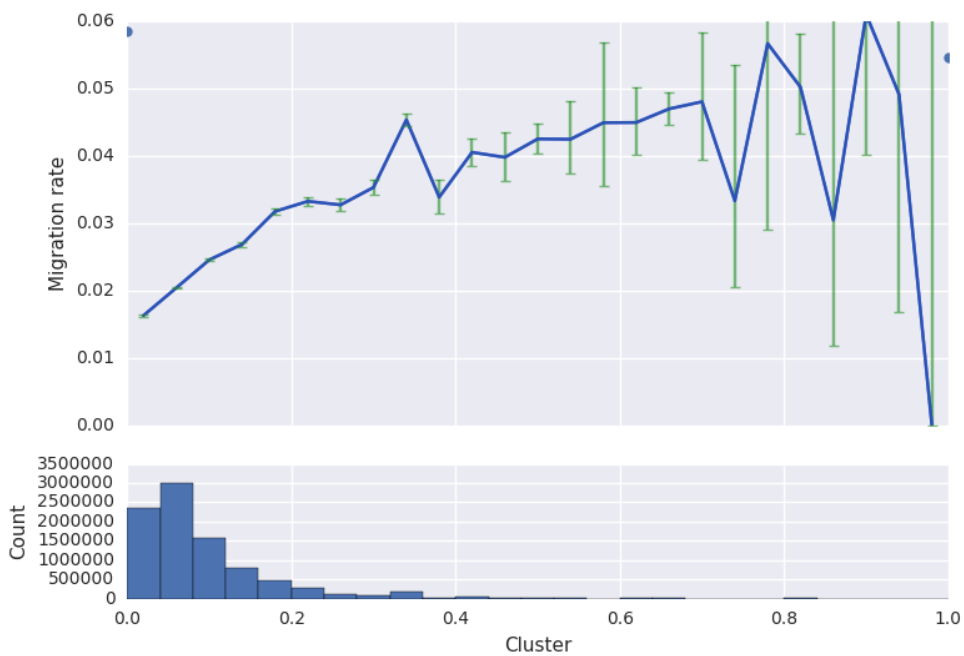


(b) Weighted Support at Home, Conditional on Degree

Figure 10: Relationship between migration rate and weighted support, holding degree fixed

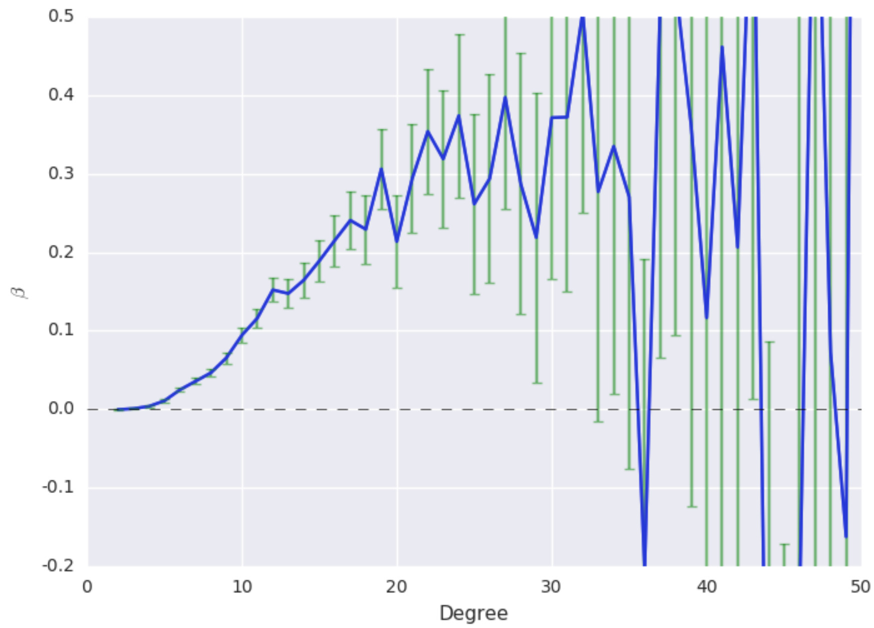


(a) Clustering at Destination

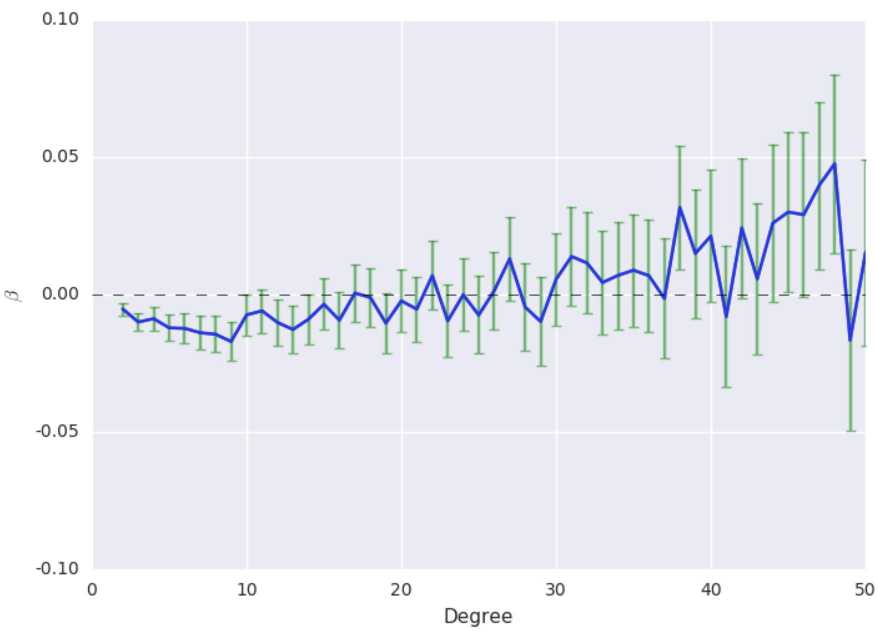


(b) Clustering at Home

Figure 11: Relationship between migration rate and clustering (the fraction of pairs of neighbors that are connected)

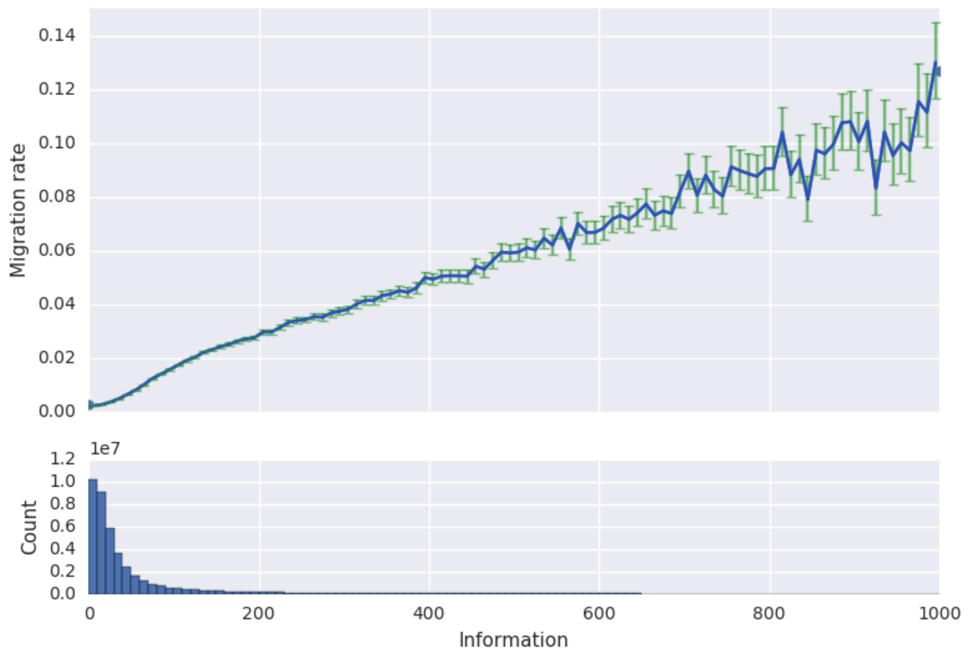


(a) Clustering at Destination, Conditional on Degree

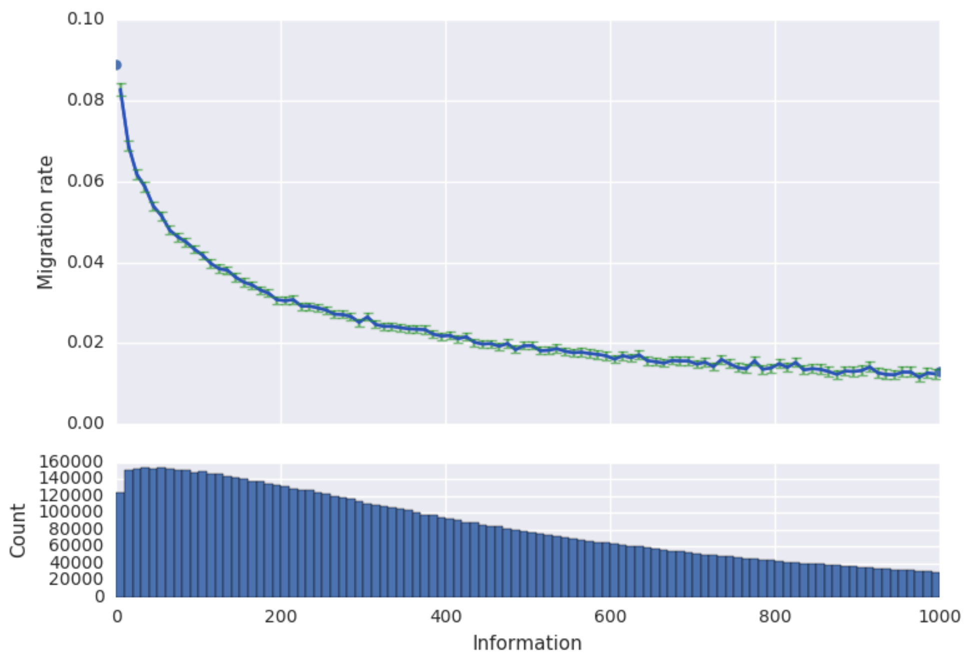


(b) Clustering at Home, Conditional on Degree

Figure 12: Relationship between migration rate and clustering, holding degree fixed

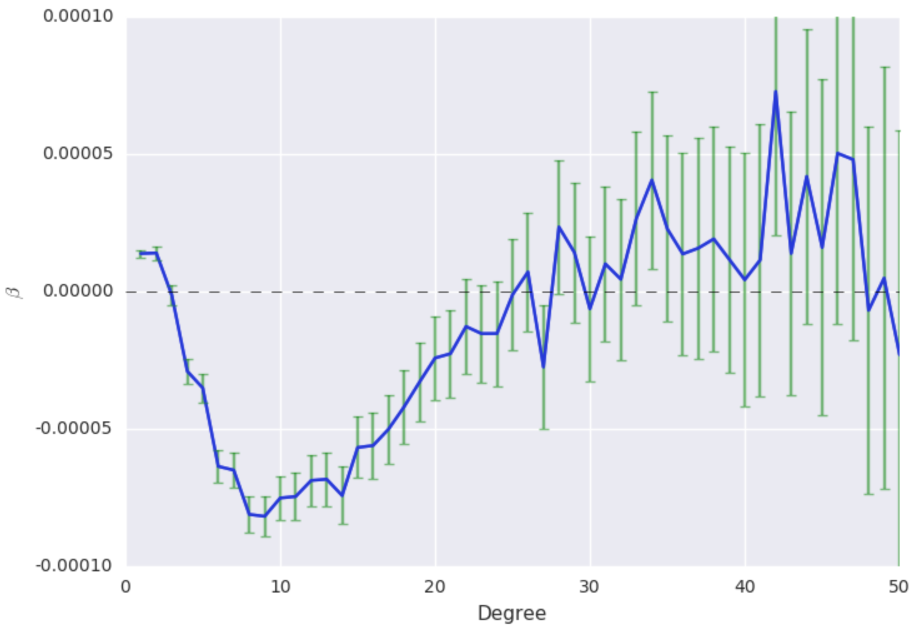


(a) Information at Destination

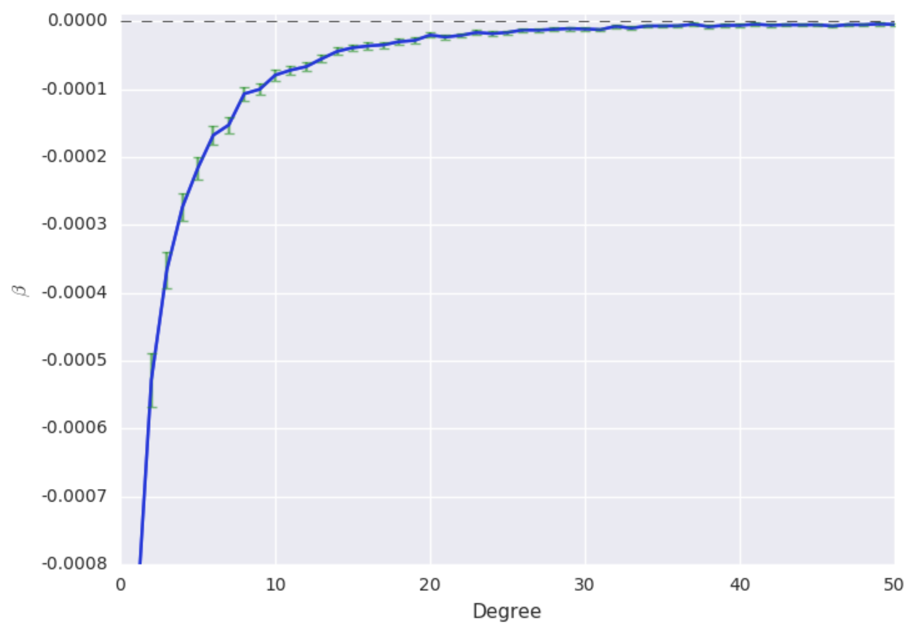


(b) Information at Home

Figure 13: Relationship between migration rate and information (number of contacts' contacts)



(a) Information at Destination, Conditional on Degree



(b) Information at Home, Conditional on Degree

Figure 14: Relationship between migration rate and weighted support, holding degree fixed

Tables

Table 1: Summary statistics of mobile phone metadata

	In a single month (Jan 2008)	Over two years (Jul 2006 - Jun 2008)
Number of unique individuals	455,704	833,542
Number of person-months	455,704	8,285,200
Number of CDR transactions	50,738,365	868,709,410
Number of migrations	15,849	272,914
Number of rural-to-rural migrations	10,059	144,513
Number of rural-to-urban migrations	2,795	65,459
Number of urban-to-rural migrations	2,995	62,942

Table 2: Single-variable OLS of migration rates on properties of destination network

	(1)	(2)	(3)	(4)	(5)	(6)
Destination degree	0.0038***					
	(0.0000)					
Destination weighted degree		0.0006***				
		(0.0000)				
Destination Support			0.0214***			
			(0.0002)			
Destination weighted support				0.0001***		
				(0.0000)		
Destination clustering					-0.0101***	
					(0.0004)	
Destination information						0.0001***
						(0.0000)
Intercept	-0.0003***	0.0122***	0.0168***	0.0190***	0.0252***	0.0096***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	6505916	6505916	6505916	6505916	6505916	6505916

Notes: Each column corresponds to a separate regression, where the dependent variable is a binary indicator of whether the individual migrated in month t. Independent variables are calculated using mobile phone from month $t-1$. Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Single-variable OLS of migration rate on properties of home network

	(1)	(2)	(3)	(4)	(5)	(6)
Home degree	-0.0007***					
	(0.0000)					
Home communication		-0.0001***				
		(0.0000)				
Home support			-0.0232***			
			(0.0002)			
Home weighted support				-0.0000***		
				(0.0000)		
Home clustering					0.0467***	
					(0.0005)	
Home information						-0.0000***
						(0.0000)
Intercept	0.0406***	0.0342***	0.0381***	0.0298***	0.0203***	0.0364***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	9593061	9593061	9593061	9593061	9593061	9593061

Notes: Each column corresponds to a separate regression, where the dependent variable is a binary indicator of whether the individual migrated in month t. Independent variables are calculated using mobile phone from month $t-1$. Standard errors in parentheses. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: OLS of migration rates on properties of destination network, controlling for degree

	(1)	(2)	(3)	(4)	(5)
Destination weighed degree	0.0000***				
	(0.0000)				
Destination support		0.0086***			
		(0.0002)			
Destination weighted support			0.0000***		
			(0.0000)		
Destination clustering				0.0074***	
				(0.0004)	
Destination information					-0.0000***
					(0.0000)
Destination degree	0.0037***	0.0037***	0.0037***	0.0038***	0.0048***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intercept	-0.0002**	-0.0024***	-0.0000	-0.0014***	-0.0015***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	6505916	6505916	6505916	6505916	6505916

Notes: Each column corresponds to a separate regression, where the dependent variable is a binary indicator of whether the individual migrated in month t. All regressions control for destination degree. Independent variables are calculated using mobile phone from month $t-1$. Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 5: OLS of migration rates on properties of home network, controlling for degree

	(1)	(2)	(3)	(4)	(5)
Home communication	0.0000				
	(0.0000)				
Home support		-0.0100***			
		(0.0002)			
Home weighted support			0.0000***		
			(0.0000)		
Home clustering				0.0053***	
				(0.0006)	
Home information					-0.0000***
					(0.0000)
Home degree	-0.0007***	-0.0007***	-0.0008***	-0.0007***	-0.0005***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intercept	0.0406***	0.0454***	0.0407***	0.0399***	0.0397***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	9593061	9593061	9593061	9593061	9593061

Notes: Each column corresponds to a separate regression, where the dependent variable is a binary indicator of whether the individual migrated in month t. All regressions control for home degree. Independent variables are calculated using mobile phone from month $t-1$. Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table 6: Relationship between migration rate and structure of home and destination network

	(1) Home Network	(2) Destination Network
Degree	-0.0286***	0.0201***
	(0.0003)	(0.0004)
Weighted Degree	0.0000	-0.0000***
	(0.0000)	(0.0000)
Support	0.0541***	-0.0250***
	(0.0008)	(0.0007)
Weighted support	-0.0000***	-0.0000***
	(0.0000)	(0.0000)
Clustering	-0.0001***	0.0043***
	(0.0000)	(0.0000)
Information	0.0000***	-0.0000***
	(0.0000)	(0.0000)
Intercept	0.0458***	-0.0027***
	(0.0001)	(0.0001)
N	9,593,061	6,505,916

Notes: Each column corresponds to a separate regression, where the dependent variable is a binary indicator of whether the individual migrated in month t. Left column shows the relationship between home network structure and migration; right column indicates relationship between destination network structure and migration. Independent variables are calculated using mobile phone from month $t-1$. Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Data: Call detail records with mobile base towers
Result: Monthly modal district

Step 1 Find each subscriber's most frequently visited tower calculate *overall daily modal districts*;
calculate *overall monthly modal districts*;

Step 2 calculate the *hourly modal districts*;

```
if tie districts exit then
    if overall daily modal districts can resolve then
        return the district with larger occurance number;
        else
            if overall monthly modal districts can resolve then
                return the district with larger occurance number
            end
        end
    end
end
```

Step 3 calculate the *daily modal districts*;

```
if tie districts exit then
    if overall daily modal districts can resolve then
        return the district with larger occurance number;
        else
            if overall monthly modal districts can resolve then
                return the district with larger occurance number
            end
        end
    end
end
```

Step 4 calculate the *monthly modal districts*;

```
if tie districts exit then
    if overall monthly modal districts can resolve then
        return the district with larger occurance number;
    end
end
```

Algorithm 1: Home location assignment

Data: Monthly modal district for four consecutive months: D_1, D_2, D_3, D_4
Result: Migration type

```
if D1 == D2 AND D3 == D4 then
    if D2 == D3 then
        if D4 == Kigali then
            migration type is urban resident
        end
        else
            migration type is rural resident
        end
    end
    else
        if D4 == Kigali then
            migration type is rural to urban
        end
        else
            if D1 == Kigali then
                migration type is urban to rural
            end
            else
                migration type is rural to rural
            end
        end
    end
end
else
    migration type is other
end
```

Algorithm 2: Classifying individuals by migrant type for k=2

A1 Proofs

Proof of Proposition 1: We will show that an agent, say i, has no profitable deviations under each of the following two cases when facing $j \in N_i$.

(Case 1) k is innocent for all $k \in N_i$

Consider the most profitable deviation for i: choose $a_{ij} = 0$ and $a_{ik} \in \{0, a_{ik}^G\}$ in any penalty stage game facing with any $k \in N_i$. However, from (3) we have

$$\begin{aligned} b(a^*_{m(ij)}) + 0 &= v(a^*_{m(ij)}) + \int_0^\infty e^{-rt}\lambda[v(a^*_{m(ij)}) + m(ij)v(a^*_1)]dt \\ &= v(a^*_{m(ij)}) + \frac{\lambda}{r}[v(a^*_{m(ij)}) + m(ij)v(a^*_1)] \\ &\leq v(a^*_{m(ij)}) + \frac{\lambda}{r}\sum_{k \in N_i} v(a^*_{m(ik)}), \end{aligned}$$

where the last inequality holds since $m(ik) \geq 1$ for all $k \in N_i \cap N_j$, and $|N_i| \geq m(ij) + 1$.

(Case 2) k is guilty for some $k \in N_i$

If i has profitable deviations in this case, then i will perform any of them after all of her neighbors become back to innocent, contradicting to what we have proved in previous case.

▮

Proof of Proposition 2: Let $a_{hl} \in \Sigma_G$ be the effort level chosen by h when meeting l. We construct $\Sigma_{G'}$ as follows. Let $a'_{ij} = a'_{ji} = a^* < a^*_0$ where $a^* > 0$ satisfies $c(a^*) < \int_0^\infty e^{-rt}\lambda v(a^*)dt$ (such a^* exists from assumption 1. and 2.), so the effort level is sustainable with positive net utility by the link itself. Also let $a'_{hl} = a_{hl}$ for all h and l such that $G(hl) = 1$ and $(h, l) \notin \{(i, k), (j, k) : k \in N_i \cap N_j\}$. For a'_{ik} and a'_{jk}, first note that

$$c(a_{ik}) \leq \sum_{h \in N_i(G)} \int_0^\infty e^{-rt}\lambda(b(a_{hi}) - c(a_{ih}))dt,$$

$$c(a_{jk}) \leq \sum_{h \in N_j(G)} \int_0^\infty e^{-rt}\lambda(b(a_{hj}) - c(a_{jh}))dt,$$

$$c(a_{kl}) \leq \sum_{h \in N_k(G)} \int_0^\infty e^{-rt} \lambda(b(a_{hk}) - c(a_{kh}))dt \;\; \text{for } l \in \{i, j\}.$$

Consider $\varepsilon > 0$ such that $C_l < \int_0^\infty e^{-rt}\lambda\Big(v(a^*) + \sum_{h \in N_i \cap N_j} \big(c(a_{lh}) - c(a_{lh} + \varepsilon)\big)\Big)dt$ where $C_l \in \{c(a^*), c(a_{lk} + \varepsilon) - c(a_{lk})\}$ and $l \in \{i, j\}$. Choosing $a'_{ik} = a_{ik} + \varepsilon$, $a'_{jk} = a_{jk} + \varepsilon$, $a'_{ki} = a_{ki}$, and $a'_{kj} = a_{ki}$ satisfies the incentive constraints among i, j, and those k's with $cl_k(G') > cl_k(G)$:

$$\begin{aligned}
c(a'_{ik}) &< c(a_{ik}) + \int_0^\infty e^{-rt}\lambda\Big(v(a^*) + \sum_{h \in N_i \cap N_j} \big(c(a_{ih}) - c(a'_{ih})\big)\Big)dt \\
&\leq \int_0^\infty e^{-rt}\lambda\Big(\sum_{h \in N_i(G)} \big(b(a_{hi}) - c(a_{ih})\big) + v(a^*) + \sum_{h \in N_i \cap N_j} \big(c(a_{ih}) - c(a'_{ih})\big)\Big)dt \\
&= \sum_{h \in N_i(G')} \int_0^\infty e^{-rt}\lambda(b(a'_{hi}) - c(a'_{ih}))dt, \\
c(a'_{jk}) &\leq \sum_{h \in N_j(G')} \int_0^\infty e^{-rt}\lambda(b(a'_{hj}) - c(a'_{jh}))dt, \\
c(a'_{ij}) = c(a'_{ji}) = c(a^*) &< \int_0^\infty e^{-rt}\lambda\Big(v(a^*) + \sum_{k \in N_i \cap N_j} \big(c(a_{ik}) - c(a'_{ik})\big)\Big)dt \\
&\leq \int_0^\infty e^{-rt}\lambda\Big(v(a^*) + \sum_{k \in N_i \cap N_j} \big(c(a_{ik}) - c(a'_{ik})\big) + \sum_{h \in N_i(G)} (b(a_{hi}) - c(a_{ih}))\Big)dt \\
&= \int_0^\infty e^{-rt}\lambda v(a^*)dt + \sum_{h \in N_i(G)} \int_0^\infty e^{-rt}\lambda(b(a'_{hi}) - c(a'_{ih}))dt,
\end{aligned}$$

$$\begin{aligned}
c(a'_{kl}) = c(a_{kl}) &\leq \sum_{h \in N_k(G)} \int_0^\infty e^{-rt}\lambda(b(a_{hk}) - c(a_{kh}))dt \\
&< \sum_{h \in N_k(G')} \int_0^\infty e^{-rt}\lambda(b(a'_{hk}) - c(a'_{kh}))dt,
\end{aligned}$$

where $l \in \{i, j\}$ and $a'_{ik} > a_{ik}$ and $a'_{jk} > a_{jk}$ yields the last (strict) inequality. For all other remaining incentive constraints, they are satisfied since their counterparts in Σ_G hold by definition. To complete the construction of $\Sigma_{G'}$, if someone deviated, then all her neighbors use the social norm with sequential move described before Proposition 1 to punish the deviator.

By the construction of this new equilibrium $\Sigma_{G'}$, we have

$$\begin{aligned} u_k(\Sigma_{G'}) &= \sum_{h \in N_k(G')} \int_0^\infty e^{-rt} \lambda (b(a'_{hk}) - c(a'_{kh})))dt \\ &> \sum_{h \in N_k(G)} \int_0^\infty e^{-rt} \lambda (b(a_{hk}) - c(a_{kh})))dt = u_k(\Sigma_G). \end{aligned}$$

for all $k \in N_i \cap N_j$. ▮

Proof of Proposition 3: For notational convenience, we define $\Delta = \lambda'_{ij} - \lambda_{ij}$, $N_{ij} = N_i \cap N_j$, $v_i = b(a_{ji}) - c(a_{ij})$, and $v_j = b(a_{ij}) - c(a_{ji})$. Let $k \in N_{ij}$ and $a_{hl} \in \Sigma_\lambda$ be the effort level chosen by h when meeting l. We construct $\Sigma_{\lambda'}$ as follows. Without loss of generality, assume $v_i > 0$. (If $v_i = 0$, we can sustain an equilibrium by increasing both a_{ij} and a_{ji} to make the assumption hold without decreasing any agent's utility). Also let $a'_{hl} = a_{hl}$ for all h and l such that $G(hl) = 1$ and $(h, l) \notin \{(i, k), (j, k) : k \in N_i \cap N_j\}$. For a'_{ik} and a'_{jk}, first note that

$$c(a_{ik}) \leq \sum_{h \in N_i(G)} \int_0^\infty e^{-rt} \lambda_{ih} (b(a_{hi}) - c(a_{ih}))dt,$$

$$c(a_{jk}) \leq \sum_{h \in N_j(G)} \int_0^\infty e^{-rt} \lambda_{jh} (b(a_{hj}) - c(a_{jh}))dt,$$

$$c(a_{kl}) \leq \sum_{h \in N_k(G)} \int_0^\infty e^{-rt} \lambda_{kh} (b(a_{hk}) - c(a_{kh}))dt \quad \text{for } l \in \{i, j\}.$$

If $v_j \leq 0$, then choose $\eta \geq 0$ such that $a'_{ij} \triangleq a_{ij} + \eta = a_{ji}$ with $v'_i = b(a_{ji}) - c(a'_{ij}) > 0$ (Such η exists since $v_i + v_j > 0$); if not, then let $\eta = 0$. Given η, there exists $\varepsilon > 0$ such that

$$\int_0^\infty e^{-rt} \Big(\Delta v'_i + \sum_{h \in N_{ij}} \lambda_{ih} \big(c(a_{ih}) - c(a_{ih} + \varepsilon) \big) + \lambda_{ij} (c(a_{ij}) - c(a'_{ij})) \Big) dt \geq c(a_{ij} + \eta) - c(a_{ij}),$$

$$\int_0^\infty e^{-rt} \Big(\Delta v'_i + \sum_{h \in N_{ij}} \lambda_{ih} \big(c(a_{ih}) - c(a_{ih} + \varepsilon) \big) + \lambda_{ij} (c(a_{ij}) - c(a'_{ij})) \Big) dt \geq c(a_{ik} + \varepsilon) - c(a_{ik}),$$

for all $k \in N_{ij}$. Define $a'_{ik} = a_{ik} + \varepsilon$, $a'_{jk} = a_{jk}$, $a'_{ki} = a_{ki}$, $a'_{kj} = a_{kj}$, and $a'_{ji} = a_{ji}$, then the incentive constraints among i, j, and those k's in N_{ij} are satisfied:

$$
\begin{aligned}
c(a'_{ik}) &\leq c(a_{ik}) + \int_0^\infty e^{-rt}\Bigg(\Delta v'_i + \sum_{h \in N_{ij}} \lambda_{ih}\big(c(a_{ih}) - c(a'_{ih})\big) + \lambda_{ij}(c(a_{ij}) - c(a'_{ij}))\Bigg)dt \\
&\leq \int_0^\infty e^{-rt}\Big(\sum_{h \in N_i} \lambda_{ih}\big(b(a_{hi}) - c(a_{ih})\big) + \Delta v'_i + \sum_{h \in N_{ij} \cup \{j\}} \lambda_{ih}\big(c(a_{ih}) - c(a'_{ih})\big)\Big)dt \\
&= \sum_{h \in N_i} \int_0^\infty e^{-rt} \lambda'_{ih}(b(a'_{hi}) - c(a'_{ih}))dt, \\
c(a'_{ij}) &\leq \sum_{h \in N_i} \int_0^\infty e^{-rt} \lambda'_{ih}(b(a'_{hi}) - c(a'_{ih}))dt, \\
c(a'_{jk}) &= c(a_{jk}) \leq \sum_{h \in N_j} \int_0^\infty e^{-rt} \lambda_{jh}(b(a_{hj}) - c(a_{jh}))dt \leq \sum_{h \in N_j} \int_0^\infty e^{-rt} \lambda'_{jh}(b(a'_{hj}) - c(a'_{jh}))dt, \\
c(a'_{ji}) &= c(a_{ji}) \leq \sum_{h \in N_j} \int_0^\infty e^{-rt} \lambda'_{jh}(b(a'_{hj}) - c(a'_{jh}))dt, \\
c(a'_{kl}) &= c(a_{kl}) \leq \sum_{h \in N_k} \int_0^\infty e^{-rt} \lambda_{kh}(b(a_{hk}) - c(a_{kh}))dt \\
&\leq \sum_{h \in N_k} \int_0^\infty e^{-rt} \lambda_{kh}(b(a'_{hk}) - c(a'_{kh}))dt \\
&= \sum_{h \in N_k} \int_0^\infty e^{-rt} \lambda'_{kh}(b(a'_{hk}) - c(a'_{kh}))dt,
\end{aligned}
$$

where $l \in \{i, j\}$. For all other remaining incentive constraints, they are satisfied since their counterparts in Σ_λ hold by definition. From this new equilibrium $\Sigma_{\lambda'}$, we have

$$
\begin{aligned}
u_k(\Sigma_{\lambda'}) &= \sum_{h \in N_k} \int_0^\infty e^{-rt} \lambda'_{kh}(b(a'_{hk}) - c(a'_{kh}))dt \\
&> \sum_{h \in N_k} \int_0^\infty e^{-rt} \lambda_{kh}(b(a_{hk}) - c(a_{kh}))dt = u_k(\Sigma_\lambda).
\end{aligned}
$$

for all $k \in N_{ij} \cup \{j\}$; particularly for i, we have

$$\begin{aligned}
u_i(\Sigma_{\lambda'}) &= \sum_{h \in N_i} \int_0^\infty e^{-rt} \lambda'_{ih}(b(a'_{hi}) - c(a'_{ih}))dt \\
&= \int_0^\infty e^{-rt} \Delta v'_i dt + \sum_{h \in N_i} \int_0^\infty e^{-rt} \lambda_{ih}(b(a'_{hi}) - c(a'_{ih}))dt \\
&= \int_0^\infty e^{-rt} \Delta v'_i dt + \sum_{h \in N_{ij} \cup \{j\}} \int_0^\infty e^{-rt} \lambda_{ih}(c(a_{ih}) - c(a'_{ih}))dt + u_i(\Sigma_\lambda) \\
&> u_i(\Sigma_\lambda).
\end{aligned}$$

∎