

# Migration and the Value of Social Networks\*

Joshua Blumenstock<sup>†</sup>

U.C. Berkeley

Guanghua Chi<sup>‡</sup>

U.C. Berkeley

Xu Tan<sup>§</sup>

University of Washington

September 6, 2018

## Abstract

How do social networks provide utility to migrants? Prior work suggests two prominent mechanisms — as a conduit of information about jobs, and as a safety net of social support — that have historically been difficult to differentiate. We adjudicate these mechanisms using a rich ‘digital trace’ dataset that allows us to observe the migration decisions made by millions of individuals over several years, as well as the complete social network of each person in the months before and after migration. These data help us establish a new set of stylized facts about the relationship between social networks and migration, for instance that the average migrant is more drawn to ‘interconnected’ networks that provide social support than to ‘expansive’ networks that efficiently transmit information. These patterns motivate a structural model of network utility which, when calibrated, provides more general insight into how people derive value from their social networks.

*JEL classification:* 015, R23, D85, Z13, O12, C55

*Keywords:* Migration, Networks, Social Networks, Digital Traces, Big Data, Rwanda

---

\*We thank Lori Beaman, Francis Bloch, Margherita Comola, Marcel Fafchamps, Matthew Jackson, David Miller, Matthew Olckers, Mark Rosenzweig, Ott Toomet, Yves Zenou, as well as seminar participants at the Paris School of Economics, Stanford, U.C. Berkeley, the BREAD/CEPR/STICERD/TCD Conference on Development Economics, the NSF Conference on Network Science in Economics, the Economic Demography Workshop, and the Barcelona GSE Summer Forum for helpful feedback. We are grateful for financial support from GLM-LIC Grant C2-RA4-205 and UW RRF #65-7397. All errors are our own.

<sup>†</sup>University of California, Berkeley, jblumenstock@berkeley.edu

<sup>‡</sup>University of California, Berkeley, guanghua@berkeley.edu

<sup>§</sup>University of Washington, tanxu@uw.edu

# 1 Introduction

The decision to migrate is one of the most consequential economic decisions an individual can make. Many factors influence this decision, from employment prospects and amenity differentials to life-cycle considerations and migration costs. In each of these factors, social networks play a prominent role. It is through social networks that migrants learn about opportunities and conditions in potential destinations; at home, the structure of migrants' social networks shapes their ability and desire to leave.

The central goal of this paper is to better understand exactly *how* social networks influence an individual's decision to migrate. Here, prior work emphasizes two distinct mechanisms: first, that networks can provide migrants with access to information, for instance about jobs and conditions in the destination (Borjas, 1992, Topa, 2001, Munshi, 2003); and second, that networks can provide a safety net for recent arrivals, through material or social support (Munshi, 2014, Comola and Mendola, 2015). But which channel matters more — and even the nature of each channel in isolation — is deeply ambiguous. For instance, the prevailing view is that migrants tend to go to places where they have larger networks,<sup>1</sup> but several studies argue that larger networks may actually deter migration, for instance if migrants compete with one another over opportunities and resources (Calvó-Armengol, 2004, Calvó-Armengol and Jackson, 2004, Beaman, 2012). Similarly, robust risk sharing networks can both facilitate migration by providing informal insurance against negative outcomes (Morten, 2015), and discourage migration if migrants fear those left behind will be sanctioned for their departure (Munshi and Rosenzweig, 2016).

This ambiguity stems, at least in part, from a lack of granular data linking social networks and migration. As Chuang and Schechter (2015) note in a recent review article, “there is little evidence making use of explicit network data on the impact of networks on the initial

---

<sup>1</sup>Classic papers documenting this effect include Rees (1966), Greenwood (1969), Granovetter (1973), Montgomery (1991), and Borjas, Bronars and Trejo (1992). More recent examples include Munshi (2003), Dolfin and Genicot (2010), Patel and Vella (2012), Giulietti, Wahba and Zenou (2018) and Bertoli and Ruyssen (2018).

migration decision... Collecting migration data is quite difficult, and collecting network data is quite difficult; combining the two is even more so” (p.464).<sup>2</sup> Instead, most existing work relies on indirect proxies for a migrant’s social network, such as the assumption that individuals from the same hometown, or with similar observable characteristics, are more likely to be connected than two dissimilar individuals.<sup>3</sup> Such proxies provide a reasonable approximation of the size of a migrant’s social network but obscure most other network characteristics, such as the extent to which a migrant’s friend at the destination is well-connected, or whether the migrant’s friends are friends with each other. This higher-order network structure plays a critical role in decisions about employment, education, health, finance, and product adoption.<sup>4</sup> Yet, the role of such network structure in migration decisions has not been systematically studied.

We leverage a rich new source of ‘digital trace’ data to provide a detailed empirical perspective on how social networks influence the decision to migrate. These data capture the entire universe of mobile phone activity in Rwanda over a four-year period. Each of roughly one million individuals is uniquely identified throughout the dataset, and every time they make or receive a phone call, we observe their approximate location, as well as the identity of the person they are talking to. From these data, we can observe each subscriber’s 4-year migration trajectory, as well as the detailed structure of their social network before

---

<sup>2</sup>The difficulty of measuring migration is exacerbated in developing countries, where short-term migration is common and reliable household survey data is limited (Deshingkar and Grimm, 2005, McKenzie and Sasin, 2007, Carletto, de Brauw and Banerjee, 2012, Lucas, 2015). The challenges of measuring social network structure are discussed in detail in Breza et al. (2017) and Chuang and Schechter (2015).

<sup>3</sup>For instance, Munshi (2003) uses rainfall shocks at origin to instrument for network size at destination. Beaman (2012) exploits exogenous variation in the size of the migrant’s social network induced by the quasi-random assignment of political refugees to new communities. Kinnan, Wang and Wang (2018) take advantage of a resettlement program in China that temporarily sent 18 million urban youth to rural areas. Related approaches are taken by Card (2001), Hanson and Woodruff (2003) and Dinkelman and Mariotti (2016).

<sup>4</sup>To cherry-pick a few examples: Granovetter (1973), Burt (1992), and Karlan et al. (2009) provide examples of how higher-order network structure affects employment prospects. Banerjee et al. (2013), Beaman et al. (2015), and Ugander et al. (2012) illustrate the importance of higher-order structure in the adoption of microfinance, new plant seeds, and Facebook, respectively. Ambrus, Mobius and Szeidl (2015) find that the extent of informal insurance depends on expansiveness of a social network, and Chandrasekhar, Kinnan and Larreguy (2014) link network structure to informal contract enforcement. Keeling and Eames (2005) review how network structure influences the spread of infectious diseases. See Jackson (2010) and Easley and Kleinberg (2010) for more general overviews.

and after migration.<sup>5</sup>

We first use these data to describe and characterize internal migration in Rwanda, providing what we believe is the most spatially and temporally granular picture of internal migration offered in the literature to date. Compared to data on migration from contemporaneous Rwandan censuses and household surveys, the mobile phone-based approach yields remarkably similar estimates of long-term migration rates. In addition, the phone data reveal substantially higher rates of travel for stays lasting one or two months — a phenomenon not captured in traditional surveys. We also document significant rates of repeat, circular, and seasonal migration, and disaggregate spatial flows with much greater precision than is possible with traditional instruments.

Our main analysis then directly links each individual’s migration decision to the structure of his or her social network in the months prior to migration. The purpose of this analysis is to understand whether, *ceteris paribus*, individuals are more likely to migrate to places where their social networks have particular structural properties.<sup>6</sup> A stylized version of our approach is shown in Figure 1: we are interested in understanding whether, for instance, individual A is more likely to migrate than individual B, where both A and B know exactly two people in the destination and three people at home, and the only observable difference between A and B is that B’s contacts are connected to each other whereas A’s contacts are from two disjoint communities.

This analysis establishes a new set of stylized facts about the relationship between migration and social networks. First, we confirm the longstanding hypothesis that people move to places where they know more people; conversely, individuals are less likely to leave places where they have larger networks. While these results are expected, an advantage of our setting is that we can observe the nonparametric relationship between migration and network size. We find this relationship to be monotonic and approximately linear with elasticity one, such that the probability of migration roughly doubles as the number of contacts

---

<sup>5</sup>Limitations of these data, including selection bias and construct validity, are discussed in Section 2.

<sup>6</sup>We discuss identification and endogeneity below.



in the destination doubles. Superficially, this result diverges from a series of studies that predict eventual negative externalities from network size, as when members compete for information and opportunities (Calvó-Armengol, 2004, Calvó-Armengol and Jackson, 2004, Beaman, 2012). We also find that the probability of leaving home approximately decreases proportionally as the size of the home network increases.

Second, we document, to our knowledge for the first time, the role that higher-order network structure plays in migration decisions. Since networks can be arbitrarily complex, we focus on two primary axes of variation in network structure: the extent to which the network is *interconnected* (i.e.,  $G_2$  vs.  $G_1$  in Figure 1), and the extent to which is it *expansive* (i.e.,  $G_3$  vs.  $G_1$ ). We find that migrants are drawn to locations where their networks are interconnected (i.e., having high levels of clustering and network ‘support’), but that, on average, they are actually *less* likely to go to places where their networks are expansive (i.e., with a large  $2^{nd}$ -degree neighborhood). In other words, of the three potential migrants in Figure 1, B is most likely to migrate and C is least likely, with A somewhere in between.

Third, we show that the average effects mask considerable heterogeneity in how different types of migrants respond to network structure. Noteworthy differences exist for repeat migrants (who have previously migrated from their home to the destination), long-term migrants, and short-distance migrants. We also find that migrants are particularly drawn to places where they know recent migrants, and where they have “strong ties” (i.e., people with whom they communicate frequently). This heterogeneity also suggests one explanation for the rather surprising result that the average migrant does not value expansive networks. In particular, we find suggestive evidence that migrants value connections to people for whom there is less competition for attention, as proposed by Dunbar (1998). Specifically, the migration response is most diminished when a migrant’s contacts have a large number of “strong” ties; migration is relatively undeterred when the migrant’s contacts have many “weak” ties.<sup>7</sup>

---

<sup>7</sup>For a focused discussion of the role of strong ties in migration, see Giulietti, Wahba and Zenou (2018).

These empirical regularities raise deeper questions about how social networks provide utility to migrants, and *why* such patterns exist. Since our data are anonymized, we have limited contextual information about the individuals and real-world relationships observed in the data (for instance, one might assume that tightly clustered networks represent family groups or ethnic clans, but nothing in our data allows us to directly validate such assumptions). Instead, we use the rich network interaction data (see Figure 3) to differentiate between two archetypal mechanisms that have been argued to determine the value of social networks.

Namely, we develop a micro-founded structural model that characterizes the migration decision as, *ceteris paribus*, a tradeoff between the utility an agent receives from the home network and the utility received from a potential destination network, net the average cost of moving from that home to that destination in that month (which includes wage and amenity differentials, transportation costs, and the like), and net an idiosyncratic cost of migrating. Agents derive utility from their networks in two archetypal ways. First, as a source of information (for instance about jobs and opportunities), where information transmission is modeled as a diffusion process with possible loss of information, as in [Banerjee et al. \(2013\)](#) and [Kermack and McKendrick \(1927\)](#). And second, as a source of social support (such as with risk sharing and favor exchange), where agents engage in repeated cooperation games with their neighbors, as in the models proposed in [Jackson, Rodriguez-Barraquer and Tan \(2012\)](#) and [Ali and Miller \(2016\)](#).

We calibrate this model by maximizing the likelihood of millions of observed migration decisions, and note a final set of results. First, consistent with the reduced-form results, the average migrant is more drawn to interconnected networks that provide social support than to expansive networks that efficiently diffuse information. However, the effect is heterogeneous; individuals with fewer connections to the destination place greater value on expansive networks. We also find strong support for some form of competition or rivalry in information transmission: a model where information passes from  $i$  to  $j$  (inversely) proportional to

the number of contacts each individual has fits the data better than the original model of [Banerjee et al. \(2013\)](#), where information passes with constant probability.

Since our approach to studying migration with mobile phone data is new, we perform a large number of tests to check the robustness of our results.<sup>8</sup> Perhaps the most important limitation of our approach is that we lack exogenous variation in the structure of an individual’s network, so that the social networks we observe are almost certainly endogenous to migration decisions. We address this concern in two principal ways. First, we relate migration decisions in month  $t$  to the structure of the social network several months prior (e.g., in month  $t - 3$ ) to minimize the likelihood that the decision to migrate shaped the social network, rather than vice versa.<sup>9</sup> Second, and more important, identification is achieved through an extremely restrictive set of fixed effects that limit the potential for many of the most common sources of endogeneity. Our preferred specification includes fixed effects for each individual migrant (to control for individual heterogeneity, for instance that certain people are both more likely to migrate and to have certain types of networks), fixed effects for each possible origin-destination-month combination (to control for wage and amenity differentials that are shared by all people facing the same migration decision), and fixed effects for each possible destination network size (such that comparisons are always between places where the migrant has the exact same number of direct contacts). In this specification, our identifying variation comes from within-individual differences in network structure between destinations and over different months in the 4-year window, net the population-average differences that vary by home-destination-month, and net any effects that are common to all people with exactly the same number of friends in the destination. In further robustness tests, we use even more restrictive fixed-effect specifications, and find qualitatively unchanged

---

<sup>8</sup>Our baseline results assume each individual faces an independent migration decision in each month. She can either stay put, or migrate to one of the 26 other districts in the country of Rwanda. We regress the binary migration decision on (lagged) properties of the migrant’s social network, using either a discrete choice (conditional logit) model or a panel fixed effects specification. Our measurement strategy, these specifications, and the robustness tests are described in detail in Sections 2 and 3.

<sup>9</sup>One concern is that migrants might begin to strategically reshape their networks long in advance of migrating. We perform several tests to check for such an effect, but find no evidence of anticipatory changes in network structure.

results.

To summarize, this paper makes two main contributions. First, it provides a new empirical perspective on the determinants of migration in developing countries (cf. [Lucas, 2015](#)). In this literature, many scholars have noted the important role that social networks play in facilitating migration.<sup>10</sup> Our data make it possible to establish a more nuanced set of stylized facts — highlighting, in particular, the value migrants place on interconnected networks, and substantial heterogeneity in how different types of migrants value networks differently — that have not been documented in prior work. Second, through the study of migration, we shed light on the more fundamental question of how individuals can derive utility from social networks (cf. [Jackson, 2010](#), [Banerjee et al., 2013, 2014](#)). Specifically, we use the high-stakes, revealed preference migration decisions of roughly one million individuals to calibrate a structural model of network utility. This allows us to distinguish between the utility provided by network geometries that facilitate the free flow of information from geometries that facilitate repeated cooperation. While the models we test are highly stylized, we believe there is exciting future work to be done by calibrating structural models of network utility with population-scale social network data.

The remainder of the paper is organized as follows. The next section describes our unique dataset, paying particular attention to how we use it to measure migration and social network structure, and to the limitations inherent in using mobile phone data for such a study. Section 3 then discusses our identification strategy, and the assumptions required to make causal inferences about the effect of networks on migration. The main results and robustness checks are presented in Section 4. These results motivate a structural model of network utility, which we present and calibrate in Section 5. Section 6 concludes.

---

<sup>10</sup>Prominent examples include [Munshi \(2003\)](#), [McKenzie and Rapoport \(2010\)](#), [Dolfin and Genicot \(2010\)](#), [Beaman \(2012\)](#), [Patel and Vella \(2012\)](#), [Bertoli, Fernandez-Huertas Moraga and Ortega \(2013\)](#), [Ambrus, Mobius and Szeidl \(2015\)](#), [Morten \(2015\)](#), [Munshi and Rosenzweig \(2016\)](#), [Bertoli and Ruysen \(2018\)](#).

## 2 Data

To study the empirical relationship between networks and migration, we exploit a novel source of data that contains extremely detailed information on the migration histories and evolving social networks of over one million individuals in Rwanda. These data contain the universe of all mobile phone activity that occurred in Rwanda from January 2005 until June 2009. These Call Detail Records (CDR) were obtained from Rwanda’s near-monopoly telecommunications company, and contain detailed metadata on every event mediated by the mobile phone network. In total, we observe roughly one billion mobile phone calls between roughly one million unique subscribers. 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 call, 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.

In this section, we describe the methods used to extract from these data the migration histories of each individual (Section 2.1) and to observe the evolution of each individual’s social network in each distinct geographic region (Section 2.2). Section 2.3 discusses external validity and other measurement concerns.

### 2.1 Measuring migration with mobile phone data

Every time a person uses a mobile phone in Rwanda, the phone company records the time of the event, and the approximate location of the subscriber at the time of the event. We use these logs to reconstruct the migration history of each individual in three steps.

First, we extract the timestamp and cell phone tower identifier corresponding to every phone call and text message made by each individual in the 4.5-year period. This creates a set of tuples  $\{\text{subscriber\_ID}, \text{timestamp}, \text{tower\_ID}\}$  for each subscriber. The tower identifier allows us to approximately resolve the location of the subscriber, to an area of

roughly 100 square meters in urban areas and several square kilometers in rural areas — see Figure 2. We do not observe the location of subscribers in the time between phone calls and text messages.

Next, we assign each subscriber to a “home” district in each month that she makes one or more transactions. Our goal is to identify the location at which the individual spends the majority of her time, and specifically, the majority of her evening hours.<sup>11</sup> The full details of this assignment procedure are given in Algorithm 1. To summarize, we first assign all towers to a geographic district, of which there are 30 (we treat the three small districts that comprise the capital of Kigali as a single district). Then, for each individual, we compute the most frequently visited district in every hour of the entire dataset (i.e., there will be a maximum of 4 years \* 365 days \* 24 observations for each individual, though in practice most individuals appear in only a fraction of possible hours). We then aggregate these hourly observations, identifying the district where each individual spends the majority of hours of each night (between 6pm and 7am). Finally, we aggregate these daily observations by identifying the district in which the individual spent the majority of nights. The end result is a panel of individual-month districts.<sup>12</sup> After this step, we have an unbalanced panel indicating the home location of each individual in each month.

Finally, we use the sequence of monthly home locations to determine whether or not each 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  $t + 1$

---

<sup>11</sup>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.

<sup>12</sup>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.

is different from  $d$ ; 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).<sup>13</sup> Complete details are given in Algorithm 2.

Using these methods, we are able to characterize very granular patterns of internal migration in Rwanda. Summary statistics are presented in Tables 1 and 2. The first column of Table 1 shows total rates of migration in a single month of the data, using  $k = 2$ , which defines a migration as an instance where an individual stays in one district for at least 2 months, moves to a new district, and remains in that new district for at least 2 months. The aggregate migration rate in January 2008 is 4.9%, with the majority (76.8%) of all migrants traveling to rural destinations. Throughout, we define urban regions according to the sector boundaries provided by the National Institute of Statistics of Rwanda (see Figure A2).

Table 2 further disaggregates migration events into several sub-types that are prominent in the literature on internal migration in developing countries (cf. [Todaro, 1980](#), [Lucas, 1997](#), [2015](#)). We observe a striking number of repeat and circular migrants, with a majority of migrants traveling long distances. The rows of Table 2 show the sensitivity of our inferred migration rates to the definition of a migration that we impose on the data. This highlights an advantage of the phone data — it allows for the study of various types and durations of migration — as well as the inherent ambiguity involved in any empirical definition. Unless noted otherwise, our results use  $k = 2$ , as this most closely matches official statistics on internal migration provided by the Rwandan government (see [Blumenstock \(2012\)](#)).<sup>14</sup> However, we show in Section 4.4 that our results are not sensitive to reasonable values of  $k$ .

<sup>13</sup>Individuals are treated as missing in month  $t$  if they are not assigned a home location in month any of the months  $\{t - k, \dots, t, t + k\}$ , 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  $t + k$ .

<sup>14</sup>According to the 2012 census: 9% of Rwandans are live in a place other than the place they lived in 5 years prior. According to the 2009 Comprehensive Food Security and Vulnerability Analysis, 12% of Rwanda households have a member who migrated in 3 months prior to survey (Feb-Mar 2009).

To provide external validation for these methods, Figure A1 compares the distribution of migration destinations computed from the phone data (red bars) to the distribution of destinations calculated from the 2012 Rwandan census (blue bars) and reported in (National Institute of Statistics of Rwanda, 2014, p.29). The distributions are not identical — which is to be expected since the population of phone owners is a non-random sample of the full population captured in the census — but the broad patterns are remarkably consistent across the two measurement modalities.

## 2.2 Inferring social network structure from mobile phone data

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 intuition, the network of a single migrant, in the month before migration, is shown in Figure 3. This particular migrant (green dot) had 20 unique contacts in the months prior to migration, 7 of whom were in his home district (blue dots), four of whom were in the destination district (red dots), and the remainder were in other districts (grey dots). The large number of friends of friends are also depicted, to provide a sense for the rich structure observed in the data.<sup>15</sup>

In the analysis that follows, we will relate the network structure of each individual to that individual’s subsequent migration decisions. To facilitate this analysis, we collapse the full network structure shown in Figure 3 into a handful of summary statistics that characterize key properties of the social network. While a large number of such statistics are of potential interest, we focus our attention on a few key metrics that help motivate the model developed in Section 5. These are the (i) *degree centrality* of the individual (i.e., the number of unique individuals with whom  $i$  is observed to communicate); the *friends of friends* count (i.e.,

---

<sup>15</sup>Throughout, we use the term “friend” loosely, to refer to the contacts we observe in the mobile phone network. These contacts may be friends, family, business relations, or something else entirely. However, we find that the term “friend” makes it easier to follow the exposition.



the number of unique friends of  $i$ 's friends, not counting  $i$ 's friends), and (iii) the *common support* of the individual (i.e., the number of  $i$ 's neighbors who share a common neighbor with  $i$ ). We will also disaggregate each of these measures by the *strength* of a social tie. We measure tie strength as the number of (undirected) calls between two individuals, and denote “strong” ties as those ties in the 90<sup>th</sup> percentile of the tie strength distribution (equivalent to 5 or more calls per month).<sup>16</sup>

## 2.3 Data limitations

The mobile phone data provide granular insight into the movement patterns and social network structures of a large population of mobile phone owners in Rwanda. However, the data have several important limitations.

First, mobile subscribers are not representative of the larger population; in particular, they are wealthier, older, better educated, and are more likely to be male (Blumenstock and Eagle, 2012). While this certainly limits the external validity of our analysis, as we have noted above (and show with Figure A1 and Table 2), the patterns of migration inferred from phone data are broadly consistent with existing data on internal migration in Rwanda. And while we do not have survey data that make it possible to directly assess whether phone owners are representative of migrants more generally, we do find that the two populations have similar demographic characteristics.<sup>17</sup>

Second, the social network we observe is the network of mobile phone contacts, not the true social network of Rwandans. These contacts are systematically different from non-phone based contacts: they are biased toward the same socio-demographic categories described above; they understate certain types of relationships (such as those that are primarily face-to-face); and they may overstate other more transient or functional relationships (such as

---

<sup>16</sup>As a point of comparison, Granovetter (1973) defined a weak tie as a tie that was active just once per year.

<sup>17</sup>In particular, separate survey data indicates that the demographic distribution of migrants and non-migrants (i.e., Figures 11 and 12 in National Institute of Statistics of Rwanda (2014)) are quite similar to the demographic distribution of phone owners and non-owners (i.e., Table 2 in Blumenstock and Eagle (2012)).

with a shopkeeper). We partially address this concern through robustness tests that vary the definition of “social tie,” for instance by requiring multiple or reciprocated communication between subscribers (see Section 4.4).

Finally, the unique identifiers we observe are for phone numbers, not individuals. When multiple people share the same phone number (which Blumenstock and Eagle (2010) show was reasonably common during this period), we may overestimate the extent of an individual’s network. Related, it’s possible that a single individual might use multiple phone numbers, which would have the opposite effect (in practice, we believe this was less common, since a monopoly operator existed). In principle, our data make it possible to uniquely identify devices and SIM cards, in addition to phone numbers. However, compared to these alternatives, the phone number (which is portable across devices and SIM cards) is generally thought to bear a closer correspondence to the individual subscriber.

Taken together, these issues limit the external validity of our empirical results, which most directly speak to the role of social networks in the migration decisions of mobile phone users in Rwanda. However, through robustness checks and analysis of heterogeneity, we will argue that there is reason to believe the relationships we observe may be more broadly relevant. More importantly, for reasons that we discuss in the following section, we believe that these data limitations should not dramatically affect the internal validity of our results. In particular, we use rigid econometric specifications (such as individual fixed effects) that limit the scope for many of these measurement issues to systematically bias our main results.

### 3 Identification and estimation

The focus of this paper is on understanding how social networks influence the decision to migrate. We assume that a host of other factors influence that decision — from wage and amenity differentials to physical distance and associated migration costs — and try to understand how, holding all such factors fixed, minor variations in social network structure

systematically correlate with migration decisions. In the stylized example of Figure 1, we ask whether a person with network  $G_1$  is more likely to migrate than someone with network  $G_2$ , how they compare to someone with network  $G_3$ , and so forth. In practice, the actual network structures are much more complex (see Figure 3); we therefore use statistical models to estimate the effect of marginal changes in network structure on subsequent migration decisions.

The central difficulty in identifying the causal effect of social networks on migration is that the social networks we observe are not exogenous. Put simply, people go to places where their networks have certain characteristics, but this does not imply that the network caused them to go there. To recover a causal estimate requires additional assumptions and a more restrictive estimation strategy. Here, we discuss these identifying assumption, as well as our approach to dealing with the two primary sources of endogeneity.

## Simultaneity

The first issue is simultaneity, i.e., that migration decisions may shape social networks, rather than the other way around. This would be expected if, for instance, migrants strategically form links to destination communities in anticipation of migration, or simply make a large number of phone calls to their destination before migrating.

We superficially address this concern by analyzing lagged, rather than contemporaneous, migration decisions. Specifically, we relate the migration decision  $M_{it}$  made by individual  $i$  in month  $t$  to the structure of  $i$ 's social network  $k$  months prior. As a concrete example, when  $t$  is set to May 2008 and  $k = 2$ , we relate the May 2008 migration decision to the structure of the individual's social network in March 2008. In our preferred specification, we set  $k = 2$ , but in robustness tests we find qualitatively identical results for  $k = 3$  and  $k = 1$ .

Of course, it is possible that migrants could plan their migration, and begin influencing their network structure, several months in advance of moving. However, we find little evidence of such anticipatory behavior. For instance, Figure 4 shows, for the population of

migrants, the fraction of the migrant’s social network in the origin and destination locations. Prior to migration, roughly 40% of the migrant’s contacts are in the origin and 25% are in the destination; three months after migration, these proportions have switched, reflecting how the migrant has adapted to her new community. What is important to our identification strategy is that there is little indication that the migrant is strategically forming contacts in the destination immediately prior to migrating — if anything, migrants appear to shift the balance of calls towards the people in the community they are leaving. These compositional changes do not mask a systematic increase in the number of contacts in the destination: Figure A3 indicates that the total number of contacts increases stochastically over time, but there is no evidence of deviations from these trends in the months before migration. Figure A4 shows the corresponding figure for non-migrants, where no changes are observed in the “migration” month, as expected (since no migration takes place for this sample). Also important is the fact that the migrant appears to exert no influence on the higher order structure of the social network in the months immediately prior to migration (Figures A5 and A6).

## Omitted Variables

The second, and perhaps more serious, threat to identification is the large number of potential omitted variables. Network structure is correlated with other characteristics of the individual (such as his wealth, or friendliness) and location (such as population density, or relative wages) that also influence migration. We limit the scope for omitted variable bias by including an extremely restrictive set of fixed effects that address many of the most salient sources of endogeneity.

Our preferred specification includes fixed effects for each individual (roughly 800,000 fixed effects) and for each origin-destination-month tuple (roughly 18,000 fixed effects). The former absorbs all time-invariant individual heterogeneity (such as gender, ethnicity, personality type, family structure, and so forth), and addresses the fact that some people are

inherently more likely to migrate than others (and have inherently different social networks). The latter is perhaps the most important, as it controls for all factors that similarly affect all individuals considering the same origin-destination migration in the same month. This includes factors such as physical distance, the cost of a bus ticket, location-specific amenities that all migrants value equally, average wage differentials, and many of the other key determinants of migration documented in the literature.<sup>18</sup> Finally, when estimating the effect of a higher order network characteristic (such as the number of friends of friends) on migration, we also nonparametrically control for the number of first-degree contacts  $i$  has in the destination.<sup>19</sup>

To summarize, the identifying variation we exploit is within-individual over time and destinations, net any factors that are shared by all people considering the same origin-destination trip in the same month, and net any effects that are common to all people with exactly the same number of friends in the destination. We would observe such variation if, for instance, an individual had been considering a move to a particular destination for several months, but only decided to migrate after his friends in the destination became friends with each other (the  $G_2$  vs.  $G_1$  comparison of Figure 1) — and if that tightening of his social network exceeded the average tightening of networks in that destination (as might occur around the holidays, for instance). To interpret our estimates causally, we must assume that this conditional variation is random.

## Estimation

Formally, for a migrant  $i$  considering moving from home district  $h$  to destination district  $d$  in month  $t$ , we wish to estimate the effect of (lagged) network structure  $Z_{ihdt}$  on the migration

---

<sup>18</sup>For instance, we know that rates of migration are higher to urban centers, and that social networks in urban centers look different from rural networks. Including a destination fixed effect removes all such variation from the identifying variation used to estimate the effect of networks on migration. By going one step further, and including an origin-destination-month fixed effect, we control for those confounds, as well as more complex scenarios, such as the possibility that seasonal wage differentials correlate with (lagged) fluctuations in social network structure.

<sup>19</sup>We also show robustness to even more restrictive specifications, for instance by including fixed effects at the level of the origin-destination-*individual*, which involves over 600 million fixed effects.

decision  $M_{ihdt}$ , where  $M$  is a binary variable equal to 1 if the migrant chooses to move to  $d$  at  $t$  and 0 otherwise. We estimate this in two ways.

Our preferred specification is a linear model:

$$M_{ihdDt} = \beta Z_{ihdt} + \pi_{hdt} + \mu_i + \nu_D + \epsilon_{ihdDt} \quad (1)$$

where  $\pi_{hdt}$  are the (home district \* destination district \* month) fixed effects; and  $\mu_i$  are the individual fixed effects. We also generally condition on the degree centrality of  $i$  using a set of fixed effects  $\nu_D$  that non-parameterically control for effects that are invariant across all people with the same number of contacts in the destination. The coefficient of interest is  $\beta$ , which indicates the average effect of network property  $Z_{ihdt}$  on the probability of migration. Standard errors are two-way clustered by individual and by home-destination-month.

Specification 1 has several attractive properties: it makes it possible to condition on a rich set of fixed effects, and can be estimated relatively quickly even on a very large dataset. The difficulty with estimating equation 1 arises in how an observation is defined in the regression. In particular, for non-migrants, it is not clear what should be considered the destination network. We address this by defining an observation at the level of the individual-month-*potential destination*. Thus, in each month, each individual comprises 26 observations, one for each of the 26 potential districts to which that individual could migrate in that month.<sup>20</sup>

Our second approach uses a discrete choice (conditional logit) model of the migration decision, to address the fact that the 26 observations for each individual in each month are not i.i.d. The conditional logit is becoming increasingly common in the migration literature (Davies, Greenwood and Li, 2001, Dahl and Sorenson, 2010), and has the advantage of providing a sound microeconomic foundation of utility maximization with a random utility model (Mcfadden, 1974, Revelt and Train, 1998). It treats each monthly decision as a

---

<sup>20</sup>More precisely, an individual is included in a specific month only if she can be classified as a migrant or a non-migrant in that month. When an individual is classified as “other,” she is excluded for that month. See Section 2.

single decision with 27 alternatives (one corresponding to staying at home, and 26 migration options).<sup>21</sup> While more natural in this regard, the conditional logit has several limitations: it does not permit the inclusion of the same restrictive set of fixed effects as we include in the linear regression, thus increasing the scope for omitted variable bias; it is not obvious how to estimate the impact of individual-specific characteristics (in our case, the attributes of the individual’s home network); and the IIA assumption is problematic. Finally, the computational requirements of the conditional logit are several orders of magnitude greater than that of the corresponding regressions.<sup>22</sup> In practice, the results from the conditional logit are always qualitatively the same as those from linear regression, so our main analysis is based on specification 1, with conditional logit results provided as robustness tests in the appendices.

## Non-parametric results

Equation 1 and the corresponding conditional logit indicate the average effect of network characteristic  $Z$  on the decision to migrate. We are also interested in disaggregating these effects non-parametrically, to understand how such effects differ for migrants with networks of different sizes. We thus present a series of figures that show the coefficients from estimating the model:

$$M_{ihdDt} = \sum_{k=1}^{D^{max}} \beta_k Z_{ihdt} \cdot \mathbb{1}(D = k) + \pi_{hdt} + \mu_i + \nu_D + \epsilon_{ihdDt} \quad (2)$$

The vector of  $\beta_k$  coefficients from the above model indicates, for migrants with a fixed number of contacts  $k$ , the relationship between the migration decision and the higher order network characteristic  $Z_{ihdt}$ .

---

<sup>21</sup>Another possibility is to model the decision to migrate with a nested logit model, where the individual makes two independent decision: the first is whether or not to migrate and the second is, given the decision to move, the choice of destination (McFadden, 1984, Knapp, White and Clark, 2001). We believe this approach is less appropriate to our context, as the decision to migrate is closely related to the possible destination choices — Davies, Greenwood and Li (2001) provides a more complete discussion of this point.

<sup>22</sup>Whereas equation 1 can be estimated, even with millions of fixed effects and two-way clustered standard errors, in several minutes on our high-performance computing cluster, the panel logit takes several hours, even with minimal fixed effects. This computational constraint is particularly problematic when estimating our effects non-parametrically, as discussed below.

## 4 Results

Table 3 summarizes the main results from estimating equation 1. We find that the average effect of each additional contact in the destination is associated with a 0.37% increase in the likelihood of migration (Panel A, column 1), and each contact at home is associated with a 0.04% decrease in that likelihood (Panel B, column 1). Columns 2-4 indicate the average effect of changes in high-order structure, after controlling non-parametrically for the immediate contacts of the individual (i.e., the “degree centrality” fixed effects). In column 4, for instance, the second row in Panels A and B indicates that migrants are more likely to go to places where their destination networks are more interconnected, and less likely to leave interconnected home networks. The third row indicates that, perhaps surprisingly, people are not more likely to migrate to destinations where their contacts have a large number of contacts, but they are less likely to leave such places.

In the subsections below, we discuss these “reduced form” results in greater detail, re-estimate each average effect non-parametrically, and allow for heterogeneity in the migration response by migrant and location type. The analysis reveals considerable nuance in the relationship between networks and migration, provides some intuition behind the “surprising” result in Table 3, and establishes a set of stylized facts that we later seek to capture in a structural model of network utility.

### 4.1 The effect of network size, in the destination and at home

Our first result validates a central thesis of prior research on networks and migration, which is that individuals are more likely to migrate to places where they have more connections. The unconditional relationship between degree centrality at destination (i.e., the number of unique contacts of the individual) is shown in Figure 5a. A point on this figure can be interpreted as the average migration rate (y-axis) across individuals with a fixed number of contacts in the destination (x-axis). For instance, roughly 4% of individuals who have 10



contacts in a potential district  $d'$  in month  $t - 2$  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 destinations (26 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.

This example also provides intuition for our identification strategy and preferred empirical specification. The average migration rates depicted Figure 5a are likely confounded by a variety of omitted variables. For instance, people in rural districts typically know more people in the urban capital of Kigali than in other districts, and rates of migration to Kigali are higher than to other districts. Thus, Figure A7 re-estimates the migration rates of Figure 5a, conditioning on a series of increasingly restrictive fixed effects. In the first panel, Figure A7a reports the  $\beta_k$  coefficients and standard errors from estimating:

$$M_{ihdt} = \sum_{k=1}^{D^{max}} \beta_k \mathbb{1}(D = k) + \epsilon_{ihdt} \quad (3)$$

Mechanically, these coefficients are identical to unconditional correlations shown in Figure 5a, albeit shifted down because of the omitted global intercept. In subsequent panels, Figure A7b includes destination district fixed effects (which most immediately addresses the Kigali concern described above). Figure A7c replaces destination fixed effects with more stringed destination-origin-month fixed effects. Finally, Figure A7d adds individual fixed effects, resulting in an estimating equation similar to equation 2:

$$M_{ihdt} = \sum_{k=1}^{D^{max}} \beta_k \mathbb{1}(D = k) + \pi_{hdt} + \mu_i + \epsilon_{ihdt} \quad (4)$$

In all figures, the qualitative relationship is remarkably unchanged. Individuals with more contacts in a destination community are more likely to migrate to that community. We also

see that this relationship is positive, monotonic, and approximately linear with elasticity one. In other words, individuals with  $k$  times as many contacts in a destination district are  $k$  times more likely to migrate to that district.

Just as migrants appear drawn to destinations where they have a large number of contacts, migrants are less likely to leave origins where they have a large number of contacts. Figure 5b shows the monotonically decreasing relationship between migration rates and the individual’s degree centrality at home.<sup>23</sup>

Where the first column of Table 3 separately estimates the “pull” and “push” forces of networks on migration (cf. Hare, 1999), the first two columns of Table 4 jointly estimate both effects, to allow for a more direct comparison. Comparing the first two coefficients in the first and second rows, we note that in determining migration outcomes, the marginal effect of an additional contact in the destination is roughly 6.5 to 7.5 times as important as an additional contact at home.

## 4.2 Higher-order network structure

We next examine how the high-order structure of the individual’s network — i.e., the connections of the individual’s connections — relate to subsequent migration decisions. While a large number of network geometries are of potential interest, we focus on the archetypal comparisons depicted in Figure 1, which we later use to motivate a structural model of network utility.

### Network interconnectedness

Figure 6c documents the relationship between migration decisions and the interconnectedness of the individual’s social networks, making the generalized comparison of  $G_1$  to  $G_2$  (for the destination network) and  $G_4$  to  $G_5$  (for the origin network). As described in Section 2.2

---

<sup>23</sup>Note that the degree centrality distribution in the bottom panel of Figure 5b does not match that in the bottom panel of Figure 5a, since each individual has only one home district, but 26 potential destination districts.

and originally proposed in Jackson, Rodriguez-Barraquer and Tan (2012), we measure this interconnectedness as network “support,” or the fraction of  $i$ ’s contacts who have one or more friend in common with  $i$ . In later robustness tests, we show that related measures of network interconnectedness, tightness, and clustering, produce qualitatively similar results.<sup>24</sup>

Both at home and in the destination, the unconditional relationship between migration and interconnectedness is ambiguous (Figures 6a and Figure 6c). Both of these figures simply show the average migration rate at varying levels of network support, without controlling for any potential confounds. This unconditional relationship is misleading, however, because it obscures the fact that network support is generally decreasing in degree; in other words, the larger an individual’s network, the harder it is to maintain a constant level of support.

Holding degree fixed, a clear pattern emerges: the people whose contacts are more interconnected are significantly more likely to migrate — particularly when there are three or more direct contacts. This pattern is evident in Figure 6b, which plots the  $\beta_k$  coefficients estimated from model (2) on the destination social network. The converse effect is found in Figure 6d for support at home: holding degree fixed, people are significantly less likely to leave home if their home contacts are more interconnected — with a stronger effect found in larger social networks. Appendix Figure A8 replicates this analysis using the network clustering, instead of network support, as a measure of interconnectedness. Results are qualitatively unchanged.

This may seem obvious in retrospect, the opposite result has been found in different settings. For instance, Ugander et al. (2012) show that people are more likely to sign up for Facebook when their pre-existing Facebook friend network is closer to  $G_1$  than  $G_3$ .

---

<sup>24</sup>The distinction between support and clustering is that where the former counts the proportion of  $i$ ’s friends with one or more friends in common, the latter counts the proportion of all possible common friendships that exist – see Jackson (2010).

## Network ‘expansiveness’

The relationship between migration and network expansiveness is more subtle. Here, we focus on the number of unique friends of friends a person has in a given region, i.e., the generalized comparison between  $G_1$  and  $G_3$  in Figure 1. Without controlling for the size of an individual’s network, there is a strong positive relationship between migration and expansiveness in the destination (Figure 7a), and a strong negative relationship with expansiveness in the origin (Figure 7c). The shape of these curves resemble the relationship between migration rate and degree shown earlier in Figure 5: the average migration rate increases roughly linearly with information in the destination, and decreases monotonically but with diminishing returns relative to information at home.

Of course, the number of friends of friends a person has is largely determined by the number of friends that person has. Thus, Figures 7b and 7d show how the number of friends of friends relates to migration, holding fixed the number of friends of friends (as well as the other fixed effects in model (2)). For the home network, Figure 7d indicates the expected pattern: the fact that all of the coefficients are negative suggests that given a fixed number of friends at home, people are less likely to leave when those friends have more friends.

The surprising result is Figure 7b, which indicates that the likelihood of migrating does not generally increase with the number of friends of friends in the destination, after holding destination degree fixed. This result is difficult to reconcile with most standard models of information diffusion, such as those proposed in [Banerjee et al. \(2013\)](#) and [Kempe, Kleinberg and Tardos \(2003\)](#). Indeed, much of the literature on migration and social networks seems to imply that, all else equal, individuals would be more likely to migrate if they have friends with many friends, as such networks would provide more natural conduits for information about job opportunities and the like. Our data provide little empirical support for this prediction, particularly for the vast majority of individuals who have only a small number of contacts in destination communities.

We run a large number of empirical tests to convince ourselves that this pattern is not

an artifact of our estimation strategy, or some other peculiarity of the data. But the data consistently indicate that the average migrant is no more likely to go to places where she has a large number of friends of friends. This is perhaps most transparent in Figure A9, which simply shows the distribution of the count of friends of friends for all migrants and non-migrants with exactly 10 friends in the potential destination. Among this sample of the population, it is apparent that, on average, non-migrants have more “expansive” destination networks than migrants. Appendix Table A2 shows that the main effect estimated in column 4 of Table 3 persists under specifications that are even more restrictive than equation 2. For instance, column 2 is identified by variation within individual-destination over time; column 4 is identified by within individual-time variation across districts; and column 5, which includes over 600 million fixed effects, isolates variation within individual-home-destination observations over time. In all instances, the average effect of having more friends of friends is either insignificant or negative.

### 4.3 Heterogeneity and the ‘friend of friend’ effect

This average effects described above mask considerable heterogeneity in how different types of migrants are influenced by their social networks. In particular, Tables A3-A6 disaggregate the results from Table 4 along several dimensions that are salient in the migration literature: whether the migrant has previously migrated to the destination (Table A3); whether the migration is between adjacent districts or over longer distances (Table A4); whether the migrant stays in the destination for a long period of time (Table A5); and whether the migration is to an urban or rural destination (Table A6), as defined in the map of Figure A2.

Several patterns can be discerned from these tables, but we focus our attention on how the network “expansiveness” effect changes with these different subgroups, as that was the most unintuitive of the above results. Here, we find that for certain types of migration — repeat migrations, short-distance migrations, and long-term migrations — the number of friends of friends is positively correlated with migration rates. Each of these types of

migration are significantly less common than the typical migration event, which is a first-time, long-distance migration that lasts just a few months, hence the insignificant or negative average effect shown in Tables 3 and 4.

While inconclusive, one suggestive pattern to this heterogeneity is that many of the migrants who are positively influenced by expansive networks are the migrants who seem likely to be more familiar with the structure of their destination networks. Such an interpretation is consistent with the possibility that the average migrant may simply be unaware of the extent to which their friends are connected to other unknown individuals (which would predict a null average effect),<sup>25</sup> but that these “in the know” migrants do value having more friends of friends.

Another dimension of heterogeneity we explore is with respect to the strength of the social ties in the network (Giulietti, Wahba and Zenou, 2018, Granovetter, 1973). Empirically, we separately classify each social tie as either strong or weak, where strong ties are defined as relationships that have five or more communication events per month (the 90th percentile of communication frequency) — see Section 2.2 for details and justification. The results shown in Table A7 indicate that both strong and weak ties matter in migration. The effect of strong destination ties is roughly 1.5X that of weak destination ties; at home, the effect of a strong tie is roughly three times as large as the effect of a weak tie.<sup>26</sup>

More interesting is what we find when analyzing heterogeneity by tie strength of the higher-order network geometries. Here, the results shown in Tables A8 and A9 suggest that migrants prefer strong ties to individuals whose attention is not spread across other strong ties. Specifically, Table A8 indicates that migrants prefer destinations where their

---

<sup>25</sup>For other instances where people appear to have incomplete information about the friends of their friends, see Friedkin (1983), Casciaro (1998), and Chandrasekhar, Breza and Tahbaz-Salehi (2016).

<sup>26</sup>A similar result applies for recent migrants: people are more likely to go to places where they know recent migrants (defined as a contact who made the origin-destination migration that the individual is considering). However, controlling for recent migrants does not qualitatively change any of the main effects reported in Table 3. Coefficient estimates in Table A10 indicate that knowing a recent migrant in the destination increases the likelihood of migration by roughly 3.5X the amount as knowing anyone else in the destination. The effect is slightly larger for recent migrants who arrived in the destination very recently (last month) than for recent migrants who arrived at any point prior.

ties have a large number of weak ties (the ‘strong-weak’ and ‘weak-weak’ coefficients), but are deterred when their ties have a large number of strong ties (in particular, the ‘weak-strong’ coefficient). Similar results are found in Table A9: supported links are positively correlated with migration in all cases, except when the migrant  $i$  has a weak connection to a destination contact  $j$ , and  $j$  has a strong tie to a third party  $k$  (who is known to  $i$ ) — these are the negative coefficients in columns 6 and 8.

To summarize: we observe considerable heterogeneity in the role that different network geometries play in different types of migration decisions. This heterogeneity provides some support for the notion that migrants may not have perfect information about the full extent of their destination network, particularly when the destination network is far away and unfamiliar. We also find suggestive evidence that migrants value connections to people who have fewer high-intensity relationships, which is consistent with the notion, proposed by Dunbar (1998) and others, that there may be rivalry for the attention of the migrants’ contacts.<sup>27</sup> However, these results — and particularly the results concerning the “friend of friend” effect — are more speculative than conclusive. We take these ambiguities as motivation to develop a more coherent model of how migrants derive utility from networks, which is presented in Section 5.

## 4.4 Robustness

In the main text, and in particular in Section 4.2, we describe a variety of robustness tests that we use to confirm that the main results in Table 4 are not sensitive to the particulars of our econometric specification, for instance by using a conditional logit rather than a fixed effect regression (Table 5, and by varying the set of fixed effects included in the main specification (Appendix Table A2). In addition, in results available upon request, we verify that the main results are not sensitive to different measurement strategies used to process

---

<sup>27</sup>Dunbar originally proposed that humans could maintain roughly 150 stable relationships, since “the limit imposed by neocortical processing capacity is simply on the number of individuals with whom a stable inter-personal relationship can be maintained.”

the mobile phone data, including:

- **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 the ‘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  $j$  initiates a call or sends a text message to  $i$ .
- **How we define ‘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 and friendship 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 spammers, calling centers, and large.
- **Sample Definition (single potential destination):** Instead of allowing each individual to consider 27 potential migration destinations, we choose each individual’s most likely destination in each month (based on the non-home district to which he or she places the largest number of calls), 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.

## 5 A model of social capital and migration

The stylized results presented in Section 4 highlight *how* social networks influence migration decisions, but offer limited insight into *why* some network structures matter more than others. Since the phone data contain no identifying or socio-demographic information about the individual subscribers, we have limited ability to infer whether, for instance, interconnected networks are influential because they tend to consist of family members, co-ethnics, or some other tightly knit community. Instead, we impose structural assumptions about why different sorts of network configurations might provide utility to migrants, and use the revealed preference decisions in our data — to migrate or not to migrate — to calibrate a model of social capital and migration.

We say that an individual  $i$  receives utility  $u_i(G)$  from a social network  $G$ . In deciding whether or not to migrate, the individual weighs the utility of  $i$ 's home network  $G^H$  against the utility of the potential destination network  $G^D$ , and migrates if the difference is greater than some threshold  $\tau$  (which we will later assume to be common across all decisions that involve the same home-destination pair in the same month), plus an idiosyncratic error  $\varepsilon_i$  that can reflect, among other things, the extent to which  $i$  is averse to migrating.

$$u_i(G^D) - u_i(G^H) > \tau + \varepsilon_i. \quad (5)$$

How people derive utility from their social networks — and equivalently, how we parameterize  $u_i(G)$  — is not known *ex ante*, as people can derive social capital from their social networks in myriad ways (Jackson, 2010, 2017). We focus our model on two stylized features of social networks that the literature has consistently shown to play an important role in the decision to migrate. The first is information capital: the potential for the social network

to provide access to information about jobs, new opportunities, and the like (Topa, 2001, Calvó-Armengol and Jackson, 2004, Banerjee et al., 2013), which we denote as  $u^I$ . The second is cooperation capital: the potential for the social network to provide community enforcement which helps to sustain repeated cooperations, such as risk sharing and social insurance (Karlan et al., 2009, Jackson, Rodriguez-Barraquer and Tan, 2012, Munshi and Rosenzweig, 2016), which we denote as  $u^C$ . We provide micro-foundations for these two forms of capital below, and then combine them into a model of migration that allows for both factors to influence the migration decision.

## 5.1 Information and ‘expansiveness’

A robust theoretical and empirical literature studies the process of information diffusion on networks Jackson and Yariv (2010). We build on recent efforts by Banerjee et al. (2013) to model the value of information as a diffusion process with possible loss of information. In this model, agents meet with their neighbors repeatedly, and when they meet, they share information with each other with probability  $q \in (0, 1)$ . We enrich this model by allowing for the possibility that neighbors might compete for the attention of a common friend. This is motivated by our earlier observation that more expansive destination networks were not positively correlated with migrations, and with the evidence that suggested some rivalry for attention (see Section 4.3).

Formally, let  $cQ^\omega$  be the cost of spending  $Q$  amount of time on communicating and socializing with neighbors. In a benchmark setting, each agent evenly distributes the time to her  $d$  neighbors, that is, she spends  $q = Q/d$  amount of time with each neighbor. Her utility is given by  $u = d \cdot v(Q/d)^\beta - cQ^\omega$ , in which she receives a value of  $v(Q/d)^\beta$  from each neighbor, and the total cost of spending time  $Q$  is  $cQ^\omega$ . We assume the cost is convex in time  $\omega \geq 1$ , the value is concave in time  $\beta \leq 1$ , and they cannot be linear at the same time

$\omega > \beta$ . The agent's maximization problem becomes

$$\max_Q dv(Q/d)^\beta - cQ^\omega. \quad (6)$$

To maximize her utility, the agent's optimal time per neighbor is

$$Q/d = \frac{1}{d^{\frac{\omega-1}{\omega-\beta}}} \left( \frac{\beta v}{\omega c} \right)^{\frac{1}{\omega-\beta}}. \quad (7)$$

Notice that if the cost is linear,  $\omega = 1$ , then the optimal time per neighbor is independent of her degree:  $q = \left( \frac{\beta v}{\omega c} \right)^{\frac{1}{\omega-\beta}}$ . On the other hand, if the value is linear  $\beta = 1$ , time with neighbors are perfect substitutes. Then, the total amount of time  $Q$  is independent of her degree, and the optimal time per neighbor is  $q = \frac{1}{d} \left( \frac{\beta v}{\omega c} \right)^{\frac{1}{\omega-\beta}}$ . Otherwise, let  $\lambda = \frac{\omega-1}{\omega-\beta}$ , then according to (7),  $q$  depends on the degree in the form of  $\frac{1}{d^\lambda}$  in which  $\lambda \in (0, 1)$ .

Motivated by this observation, we let the interaction between each pair  $ij$  depend on their degrees. In particular, let  $G$  be the adjacency matrix of the network; then the strength of their interaction  $\tilde{G}_{ij} = \frac{1}{d_i^\lambda d_j^\lambda} G_{ij}$ . The modified diffusion centrality is

$$DC(G; q, \lambda, T) \equiv \sum_{t=1}^T (q\tilde{G})^t \cdot \mathbf{1}, \quad \text{and} \quad \tilde{G}_{ij} = \frac{1}{d_i^\lambda d_j^\lambda} G_{ij}. \quad (8)$$

When  $\lambda = 0$ , this is equivalent to the model in [Banerjee et al. \(2013\)](#).

Several intuitive predictions can be derived from such a model: an agent receives additional utility from each friend in the network, additional discounted utility from each friend of those friends, and so forth. When  $\lambda > 0$ , there is a tradeoff between the positive discounted utility from indirect friends and a negative effect due to competition with them for direct neighbors' attention.

## 5.2 Cooperation, support and ‘interconnectedness’

Social networks also provide community enforcement for repeated interactions, such as risk sharing, social insurance, and cooperation. We follow the setup in [Ali and Miller \(2016\)](#), and highlight the importance of *support* for cooperation. Each link is supported if the two nodes of the link share at least one common friend.

Consider a population of  $N$  players,  $N = \{1, \dots, n\}$ , who are connected in an undirected network  $G$ , with  $ij \in G$  and  $ji \in G$  if agent  $i$  and  $j$  are connected (we abuse the notation of  $G$  slightly, which differs from the matrix format in the information model). Denote agent  $i$ ’s neighbors as  $N_i = \{j : ij \in G\}$ . We say a path between agent  $i$  and  $j$  is a sequence of distinct agents  $(i_0, i_1, \dots, i_k)$  such that  $i_0 = i$ ,  $i_k = j$  and  $i_l i_{l+1} \in G$  for any  $l \in \{0, \dots, k-1\}$ . Let  $D(i, j)$  be the distance between agent  $i$  and  $j$  in the network, defined as the length of the shortest path between them.

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  $\delta > 0$ . 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.<sup>28</sup> 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. We normalize the net value of effort  $a$  as  $b(a) - c(a) = a$ , and assume the cost function  $c$  is a smooth function satisfying  $c(0) = 0$  and the following the assumption.

**ASSUMPTION 1.** *The cost of effort  $c$  is strictly increasing and strictly convex, with  $c(0) = c'(0) = 0$  and  $\lim_{a \rightarrow \infty} c'(a) = \infty$ . The “relative cost”  $c(a)/a$  is strictly increasing.*

Strict convexity with the limit condition guarantees that in equilibrium effort is bounded. Increasing relative cost means a player requires proportionally stronger incentives to exert higher effort. All players share a common discount rate  $r > 0$ , and the game proceeds over continuous time  $t \in [0, \infty)$ .

---

<sup>28</sup>The variable-stakes formulation is adopted from [Ghosh and Ray \(1996\)](#) and [Kranton \(1996\)](#).

As has been documented in several different real-world contexts, we assume agents have only local knowledge of the network.<sup>29</sup> Specifically, we assume each agent only observes her local neighborhood, including her neighbors, and the links among these neighbors (in addition to her own links). To be precise, agent  $i$  observes each  $j \in g_i \equiv \{i\} \cup N_i$ , and all links in  $G_i = \{jk : j, k \in g_i\}$ . In addition, we consider locally public monitoring, such that each agent learns about her neighbors' deviation, and this information travels instantly.<sup>30</sup>

To begin with, we introduce two benchmark cooperation levels. The first one is *bilateral cooperation*, the maximal cooperation attainable between two partners without the aid of community enforcement.

**Bilateral cooperation** Consider a strategy profile in which on the path of play each agent of the partners exerts effort level  $a$ , if each has done so in the past; otherwise, each exerts zero effort. The equilibrium path incentive constraints are:

$$b(a) \leq a + \int_0^\infty e^{-rt} \delta a dt. \quad (9)$$

The bilateral cooperation level  $a^B$  is the effort level that binds the incentive constraint. Since the grim trigger punishment is a minmax punishment and each partner's effort relaxes the other partner's incentive constraint, these are the maximum efforts that can be supported by any stationary equilibrium that does not involve community enforcement.

---

<sup>29</sup>Examples in the literature include [Krackhardt \(1990\)](#), [Casciaro \(1998\)](#) and [Chandrasekhar, Breza and Tahbaz-Salehi \(2016\)](#).

<sup>30</sup>The local public monitoring differs from the private monitoring in [Ali and Miller \(2016\)](#). It allows us to characterize the optimal equilibrium under local knowledge of the network for any network, the counterpart of which to the best of our knowledge is unknown with private monitoring, with the exception that [Ali and Miller \(2016\)](#) find the optimal equilibrium when the network is a triangle.

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

$$b(a) \leq a + 2 \int_0^\infty e^{-rt} \delta a dt. \quad (10)$$

The incentive constraint is binding at effort level  $a^T$ . Notice that the future value of cooperation is higher in a triangle because there are two on going partnership for each agent, so it can sustain higher level of efforts  $a^T > a^B$  and everyone gets a strictly higher utility.

Next, we introduce two desirable properties of the strategy profile. First, we desire that community enforcement can sustain high cooperation without requiring a player to know anything about the network or behaviors outside of her local neighborhood. If  $D(i, j) = D$ , we say  $i$  is  $j$ 's  $D$ -distance neighbor. Define agent  $i$ 's  $D$ -neighborhood as  $g_i^D = \{k : D(i, k) \leq D\}$  and  $G_i^D = \{jk \in G : j, k \in g_i^D\}$ .

**DEFINITION 1.** *A strategy profile is 2-local if each agent  $i$ 's strategy is invariant to her beliefs about interactions and network topology outside her 2-neighborhood.*

In addition, we seek to minimize contagion of deviation to the rest of the society off the equilibrium path, which follows from [Jackson, Rodriguez-Barraquer and Tan \(2012\)](#).

**DEFINITION 2.** *A strategy profile is robust if an agent's deviation only affects partnerships involving herself and between her neighbors.*

Our first result shows that high levels of cooperation can be sustained in a robust manner, with players needing only local information about the network and other players' behavior.

**PROPOSITION 1.** *For any network  $G$ , there exists a 2-local and robust equilibrium for the repeated cooperation game that maximizes each agent's utility subject to their local knowledge of the network.*

All proofs are in Appendix A1. Intuitively, each partnership  $ij$  uses the maximal level of effort subject to their shared common knowledge of the network. This maximal level of effort

depends on the level of efforts  $i$  and  $j$  can sustain with each of their common neighbors  $k$ , which in turn depends on the level of efforts  $\{i, j, k\}$  can sustain with their common neighbors  $l$ , and so on. Thus, this problem can be solved inductively, starting from the largest clique(s) of  $g_{ij} = g_i \cap g_j$ , which always exists because the population is finite.

However, the optimal equilibrium in Proposition 1 could demand a high cognitive ability and a lot of computational capacity to solve, as one needs to solve (interdependent) effort levels for all subsets of agents in her local network. To address this concern, we focus on a simple equilibrium strategy profile that maintains the two desired properties and sustains high levels of cooperation due to network enforcement. A link  $ij$  is *supported* if there exists  $k$  such that  $ik \in G$  and  $jk \in G$ ; i.e., if  $i$  and  $j$  have at least one common friend. We characterize a particularly simple equilibrium strategy profile that further highlights the value of supported links.

**COROLLARY 1.** *There exists a 2-local and robust equilibrium, in which any pair of connected agents, cooperate on  $a^T$  if the link is supported, and on  $a^B$  otherwise.*

As the triangular level of effort can be sustained by three fully-connected agents, the strategy profile is robust. For example, consider a triangle  $ijk$  plus a link  $jk'$ . Even if  $k'$  has shirked on  $j$ , which reduce the value  $j$  gets from the partnership  $jk'$ , it does not damage the incentive for the triangle  $ijk$  because it can sustain  $a^T$  by itself.

### 5.3 A benchmark model of migration

We now return to the migration decision. For an arbitrary network  $G$ , we assume that the total utility an agent  $i$  receives from  $G$  can be expressed as (we omit  $G$  when referring to an arbitrary network),

$$u_i = u_i^I + u_i^C. \quad (11)$$

In other words, we consider a linear combination of value from information and value from cooperation.<sup>31</sup>

The amount of information capital agent  $i$  gets is assumed to be her diffusion centrality,  $DC_i(q, \lambda, T)$ , which is the  $i$ -th element of (8) in section 5.1. An agent gets  $\tilde{u}$  for each unit of information. The amount of cooperation capital is derived based on the implication of Corollary 1 that supported links are more valuable. In particular, agent  $i$  gets a utility of

$$u_i^C = u_0 d_i^{NS} + u_1 d_i^S \quad (12)$$

from cooperating with her neighbors, in which  $u_0$  is the utility of cooperating on an unsupported link, and  $u_1$  is the utility of cooperation on a supported link.  $d_i^{NS}$  is the number of  $i$ 's unsupported links, and  $d_i^S$  is the number of  $i$ 's supported links.

The overall utility is thus

$$u_i = \tilde{u} DC_i(q, \lambda, T) + u_0 d_i^{NS} + u_1 d_i^S. \quad (13)$$

We want to contrast the value of information versus the value of cooperation, and contrast the value of unsupported links versus supported links. So we replace the parameters  $(u_0, u_1, \tilde{u})$  by  $(\pi^I, \pi^C, \alpha)$  and rewrite the overall utility:

$$u_i = \pi^I DC_i(q, \lambda, T) + \pi^C (d_i + \alpha d_i^S). \quad (14)$$

Substituting (14) into the original migration decision (5), we have

$$\begin{aligned} & \pi^{I,D} DC_i(G^D; q, \lambda, T) + \pi^{C,D} (d_i(G^D) + \alpha^D d_i^S(G^D)) \\ & - (\pi^{I,H} DC_i(G^H; q, \lambda, T) + \pi^{C,H} (d_i(G^H) + \alpha^H d_i^S(G^H))) > \tau + \varepsilon_i. \end{aligned} \quad (15)$$

---

<sup>31</sup>We do not imply that  $u^I$  and  $u^C$  are orthogonal or that other aspects of network do not weigh in the decision to migrate. However, this formulation allows us to contrast two archetypical properties of network structure that can be estimated with our data.



Notice that we allow agents to have different weights  $\pi$  for the home and destination networks, because it is possible that the relative value of information and cooperation is different in a home network than in a destination network. Similarly, we also allow  $\alpha$  to differ between home and destination networks. However, we assume  $(q, \lambda, T)$  is the same for home and destination networks, because they both capture information passing among agents in a single location (all locations are ‘home’ locations amongst the agents in that location). The basic formulation thus leaves three sets of structural parameters of interest:  $(\pi^{I,D}, \pi^{C,D}, \pi^{I,H}, \pi^{C,H})$ , the scaling coefficients that jointly indicate the value of home and destination utility from information diffusion relative to strategic cooperation;  $\alpha^H$  and  $\alpha^D$ , which represent the additional value from a supported link relative to an unsupported link; and  $\lambda$ , which we interpret as a measure of competition or rivalry in the information passing process.

Finally, we note that the linear combination of information capital and cooperation capital (Equation 11) provides a simple benchmark model that can be calibrated with our data in a matter of hours. However, there is a need for more general models of how agents derive social capital from their networks. We develop one possible model as a network game in Appendix A2, which allows for more complex interactions between agents. However, calibration of this model is not trivial with very large networks because the model uses global network structure. We leave further investigation of these possibilities to future work.

## 5.4 Model calibration

We use the migration decisions made by several hundred thousand migrants over a 4-year period to estimate the parameters of Model (15). The estimation proceeds in two steps. First, we draw a balanced sample of migrants and non-migrants by selecting, for every migrant who moves from  $h$  to  $d$  in month  $t$ , a non-migrant who lived in  $h$  in month  $t$ , had  $\geq 1$  contacts in  $d$ , but remained in  $h$  after  $t$ . This provides a total sample of roughly 140,000 migrants and non-migrants.

Second, we use simulation to identify the set of parameters that maximize the likelihood of generating the migration decisions observed in the data. The structural parameters of primary interest are the  $\pi$ 's, which together indicate the relative importance of 'expansiveness' and 'interconnectedness' at home and in the destination;  $\lambda$ , which indicates the level of rivalry in information transmission, and  $\alpha$ , the added value of a supported link, above and beyond the value of an unsupported link. We follow [Banerjee et al. \(2013\)](#) by setting  $q$  equal to the inverse of the first eigenvalue of the adjacency matrix,  $\lambda_1(G)$ , with  $T = 3$ .<sup>32</sup> Since a very large number of combinations of possible parameters exist, we use an iterative grid-search maximization strategy where we initially specify a large set of values for each parameters, then focus and expand the search around local maxima.<sup>33</sup>

Calibration appears to be well-behaved. To provide some intuition, calibration plots for  $\lambda$  and  $\pi^{C,D}$  are shown in Figure A10 (others available on request). To produce these figures, we run roughly 50,000 simulations, one for each possible combination of parameters, choose the top percentile of those simulations, and show the marginal distribution for a single parameter (in this case,  $\lambda$  and  $\pi^{C,D}$ ). In both cases, the likelihood function is concave around the global maximum. The optimal set of parameters correctly classify roughly 70% of the migration events. Figure A11 shows the predicted home-destination utility values for all 140,000 individuals, using the optimal parameter set — the misclassifications are the red dots above the 45-degree line and the blue dots below the 45-degree line.

## 5.5 Calibration results

Calibration of the model yields several results. First, we find that in a benchmark where no rivalry exists in information transmission — in other words, when  $\lambda$  is set to zero and the

---

<sup>32</sup>When we treat  $q$  as a free parameter and estimate it via MLE, the likelihood-maximizing value of  $q$  is very close to  $1/\lambda_1(G)$ . [Banerjee et al. \(2013\)](#) show that this approach to measuring diffusion centrality closely approximates a structural property of "communication centrality." This latter property could not be practically estimated on a network as large as the one we study.

<sup>33</sup>Specifically, for each possible set of parameters  $\langle \pi, \alpha, \lambda, \tau, \rho \rangle$ , we calculate the utility of the home and destination network for each migrant, and the total utility of migration. If the total utility of migration is positive, we predict that individual would migrate. We choose the set of parameters that minimizes the number of incorrect predictions.

utility from information is exactly as specified in [Banerjee et al. \(2013\)](#), the total utility from  $u_i^I$  (loosely, the ‘information utility’) generally dominates the total utility from  $u_i^C$  (loosely, the ‘cooperation utility’) in equation 11. This can be seen most clearly in Figure 8a, which shows the distribution of predicted utility from  $u_i^I$  and  $u_i^C$  for each of the individuals used to calibrate the simulation. The bulk of this distribution lies under the 45-degree line, where  $u_i^I < u_i^C$ . While striking, this result is expected, since the structural assumption that  $\lambda = 0$  closely reflects the reduced form results presented in Section 4, and particularly Table 4.

Second, when we allow for heterogeneity in the relative value of  $u_i^I$  and  $u_i^C$ , we find the similar differential response that was observed in Figure 7d. Namely, when we split the sample at the crossing threshold of people who have greater than or less than four unique contacts in the destination, and separately calibrate different versions of Model (15) on those two populations, the balance of  $u_i^I$  and  $u_i^C$  is qualitatively different for these two groups. In particular, individuals who are not well connected to their destination generally derive more utility from the information diffusion component of the utility function than from the cooperation component.

Finally, when the rivalry coefficient  $\lambda$  is allowed to vary from 0 to 1 and calibrated empirically, we find an optimal value of 0.5, as shown in Figure A10a. This suggests a relatively high-degree of rivalry in how information diffuses through networks to migrants. For instance, comparing individuals A and C in Figure 1, we would expect A to receive the same information utility as C when  $\lambda = 0$ , but 1.10 times the utility as C when  $\lambda = 0.5$ .

Taken together, the structural estimates provide a micro-founded validation of the reduced-form results described earlier. This is an important step, since the reduced-form results rely on the higher-order statistical properties of networks are correlated in complex ways that are not easily accounted for in a regression specification. They also provide independent support for the presence of some degree of rivalry in information diffusion — a possibility that was suggested by the heterogeneity discussed in Section 4.3, but only directly tested

through structural calibration.

## 6 Conclusion

Migrants play a central role in bringing an economy towards a more efficient use of its resources. This paper provides a new perspective on the determinants of migration, exploiting extremely detailed ‘digital trace’ to understand how structural characteristics of social networks influence the decision to migrate. Social networks have long been known to facilitate migration, but prior work has not attempted the sort of granular, quantitative analysis that is the focus of this paper.

The results shed light on *how* social networks factor into migration decisions. Perhaps the most novel finding is that while migrants uniformly value tight, clustered social networks, most migrants are not drawn to places where their social networks are expansive. Our structural results suggest that this aversion may stem from the fact that migrants may feel competition for the attention of their well-connected friends. However, this and other results are quite heterogeneous. Indeed, a strength of our data is that they clearly demonstrate that the “average migrant” can be a misleading generalization. Different types of migrants — including repeat, long-term, and short-distance migrants — value different properties of social networks differently.

Stepping back, the results encourage some speculation as to *why* social networks are important in migration decisions. Here, the limitations of the data are evident, as the transaction logs provide no direct information on the nature of the social relations we observe, nor the characteristics of the migrants themselves. However, it seems clear that migrants do not view their social networks as passive conduits of information. Since at least [Rees \(1966\)](#) and [Granovetter \(1974\)](#), a central focus of the social science literature has been on the potential for networks to transmit information about job opportunities; in such contexts, job information is often assumed to spread through social ties (cf. [Ioannides and Datcher Loury, 2004](#)).

In contexts ranging from product adoption (Banerjee et al., 2013) and disease transmission (Keeling and Eames, 2005) to the spread of new ideas and innovations (Rogers, 1962, Kitsak et al., 2010), simple models of information diffusion have seen remarkable success. But in the context of internal migration in Rwanda, we find that the network structures which these models suggests should matter do not in fact appear to weigh heavily in the decision to migrate.

Rather, migrants are consistently drawn to places with interconnected, embedded networks. This suggests that migrants are sensitive to the interlinkages of their friend and kinship networks, and value the potential for sustained, repeated interaction. This interpretation is consistent with recent evidence that migrants are sensitive to economic interactions that rely on such structure, such as risk sharing and favor exchange (Munshi and Rosenzweig, 2016, Morten, 2015).

More broadly, we are hopeful that this study can illustrate the potential for novel sources of network data to provide deeper insight into how individuals derive utility from their social networks. Such data capture incredibly rich structure, which reveal hitherto unobserved correlations between networks and consequential economic decisions. Through a combination of rich descriptives and structural estimation, we see much potential for future work aimed at understanding the value of social networks.

## References

- Ali, S. Nageeb, and David A. Miller.** 2016. “Ostracism and Forgiveness.” *American Economic Review*, 106(8): 2329–2348.
- Ambrus, A., M. Mobius, and A. Szeidl.** 2015. “Consumption risk-sharing in social networks.” *American Economic Review*, 104(1): 149–82.
- Ballester, Coralio, Antoni Calvó-Armengol, and Yves Zenou.** 2006. “Who’s who in networks. Wanted: The key player.” *Econometrica*, 74(5): 1403–1417.
- Banerjee, Abhijit, Arun G. Chandrasekhar, Esther Duflo, and Matthew O. Jackson.** 2013. “The Diffusion of Microfinance.” *Science*, 341(6144): 1236498.
- Banerjee, Abhijit, Arun G. Chandrasekhar, Esther Duflo, and Matthew O. Jackson.** 2014. “Gossip: Identifying Central Individuals in a Social Network.” National Bureau of Economic Research Working Paper 20422.
- Beaman, Lori A.** 2012. “Social networks and the dynamics of labour market outcomes: Evidence from refugees resettled in the US.” *The Review of Economic Studies*, 79(1): 128–161.
- Beaman, Lori, Ariel BenYishay, Jeremy Magruder, and Ahmed Mushfiq Mo-barak.** 2015. “Can network theory based targeting increase technology adoption.” *Unpublished Manuscript*.
- Bertoli, Simone, and Ilse Ruyssen.** 2018. “Networks and migrants intended destination.” *Journal of Economic Geography*.
- Bertoli, S., J. Fernndez-Huertas Moraga, and F. Ortega.** 2013. “Crossing the border: Self-selection, earnings and individual migration decisions.” *Journal of Development Economics*, 101: 75–91.

- Blumenstock, Joshua E, and Nathan Eagle.** 2012. “Divided We Call: Disparities in Access and Use of Mobile Phones in Rwanda.” *Information Technology and International Development*, 8(2): 1–16.
- Blumenstock, Joshua Evan.** 2012. “Inferring Patterns of Internal Migration from Mobile Phone Call Records: Evidence from Rwanda.” *Information Technology for Development*, 18(2): 107–125.
- Blumenstock, Joshua Evan, and Nathan Eagle.** 2010. “Mobile divides: gender, socioeconomic status, and mobile phone use in Rwanda.” 6. ACM.
- Borjas, George J.** 1992. “Ethnic Capital and Intergenerational Mobility.” *The Quarterly Journal of Economics*, 107(1): 123–150.
- Borjas, George J., Stephen G. Bronars, and Stephen J. Trejo.** 1992. “Self-selection and internal migration in the United States.” *Journal of Urban Economics*, 32(2): 159–185.
- Bramoullé, Yann, Rachel Kranton, and Martin D’amours.** 2014. “Strategic interaction and networks.” *American Economic Review*, 104(3): 898–930.
- Breza, Emily, Arun G Chandrasekhar, Tyler H McCormick, and Mengjie Pan.** 2017. “Using Aggregated Relational Data to Feasibly Identify Network Structure without Network Data.” National Bureau of Economic Research Working Paper 23491.
- Burt, Ronald S.** 1992. *Structural holes: The social structure of competition*. Harvard university press.
- Calvó-Armengol, Antoni.** 2004. “Job contact networks.” *Journal of Economic Theory*, 115(1): 191–206.
- Calvó-Armengol, Antoni, and Matthew O. Jackson.** 2004. “The Effects of Social Networks on Employment and Inequality.” *The American Economic Review*, 94(3): 426–454.

- Card, David.** 2001. "Immigrant Inflows, Native Outflows, and the Local Labor Market Impacts of Higher Immigration." *Journal of Labor Economics*, 19(1): 22–64.
- Carletto, Calogero, Alan de Brauw, and Raka Banerjee.** 2012. "Measuring migration in multi-topic household surveys." *Handbook of Research Methods in Migration*, 207.
- Casciaro, Tiziana.** 1998. "Seeing things clearly: social structure, personality, and accuracy in social network perception." *Social Networks*, 20(4): 331–351.
- Chandrasekhar, Arun, Emily Breza, and Alireza Tahbaz-Salehi.** 2016. "Seeing the forest for the trees? an investigation of network knowledge." *Working Paper*.
- Chandrasekhar, Arun G., Cynthia Kinnan, and Horacio Larreguy.** 2014. "Social networks as contract enforcement: Evidence from a lab experiment in the field." National Bureau of Economic Research.
- Chuang, Yating, and Laura Schechter.** 2015. "Social Networks in Developing Countries." *Annual Review of Resource Economics*, 7: 451–472.
- Comola, Margherita, and Mariapia Mendola.** 2015. "The Formation of Migrant Networks." *Scandinavian Journal of Economics*, 117(2): 592–618.
- Dahl, Michael S., and Olav Sorenson.** 2010. "The migration of technical workers." *Journal of Urban Economics*, 67(1): 33–45.
- Davies, Paul S., Michael J. Greenwood, and Haizheng Li.** 2001. "A conditional logit approach to US state-to-state migration." *Journal of Regional Science*, 41(2): 337–360.
- Deshingkar, Priya, and Sven Grimm.** 2005. *Internal Migration and Development: A Global Perspective*. United Nations Publications. Google-Books-ID: r1jHX1nyKzYC.
- Dinkelman, Taryn, and Martine Mariotti.** 2016. "The Long Run Effects of Labor Migration on Human Capital Formation in Communities of Origin." National Bureau of Economic Research Working Paper 22049.



- Dolfin, Sarah, and Garance Genicot.** 2010. "What Do Networks Do? The Role of Networks on Migration and Coyote Use." *Review of Development Economics*, 14(2): 343–359.
- Dunbar, Robin I. M.** 1998. "The social brain hypothesis." *Evolutionary Anthropology: Issues, News, and Reviews*, 6(5): 178–190.
- Easley, David, and Jon Kleinberg.** 2010. *Networks, Crowds, and Markets: Reasoning About a Highly Connected World*. . 1 edition ed., New York:Cambridge University Press.
- Friedkin, Noah E.** 1983. "Horizons of Observability and Limits of Informal Control in Organizations." *Social Forces*, 62(1): 54–77.
- Ghosh, Parikshit, and Debraj Ray.** 1996. "Cooperation in Community Interaction Without Information Flows." *The Review of Economic Studies*, 63(3): 491–519.
- Giulietti, Corrado, Jackline Wahba, and Yves Zenou.** 2018. "Strong versus weak ties in migration." *European Economic Review*, 104: 111–137.
- Granovetter, Mark.** 1974. *Getting a Job: A Study of Contacts and Careers*. Chicago:The University Of Chicago Press.
- Granovetter, M. S.** 1973. "The strength of weak ties." *American journal of sociology*, 78(6): 1360.
- Greenwood, Michael J.** 1969. "An Analysis of the Determinants of Geographic Labor Mobility in the United States." *The Review of Economics and Statistics*, 51(2): 189–194.
- Hanson, Gordon H., and Christopher Woodruff.** 2003. "Emigration and educational attainment in Mexico." Mimeo., University of California at San Diego.
- Hare, Denise.** 1999. "Push versus pull factors in migration outflows and returns: Determinants of migration status and spell duration among China's rural population." *The Journal of Development Studies*, 35(3): 45–72.

- Hu, Yifan.** 2005. “Efficient, high-quality force-directed graph drawing.” *Mathematica Journal*, 10(1): 37–71.
- Ioannides, Yannis M., and Linda Datcher Loury.** 2004. “Job Information Networks, Neighborhood Effects, and Inequality.” *Journal of Economic Literature*, 42(4): 1056–1093.
- Jackson, Matthew.** 2017. “A Typology of Social Capital and Associated Network Measures.”
- Jackson, Matthew O.** 2010. *Social and Economic Networks*. Princeton University Press.
- Jackson, Matthew O., and Leeat Yariv.** 2010. “Diffusion, strategic interaction, and social structure.” *Handbook of Social Economics*, edited by J. Benhabib, A. Bisin and M. Jackson.
- Jackson, Matthew O, and Yves Zenou.** 2015. “Games on networks.” In *Handbook of game theory with economic applications*. Vol. 4, 95–163. Elsevier.
- Jackson, Matthew O., Tomas Rodriguez-Barraquer, and Xu Tan.** 2012. “Social capital and social quilts: Network patterns of favor exchange.” *The American Economic Review*, 102(5): 1857–1897.
- Karlan, Dean, Markus Mobius, Tanya Rosenblat, and Adam Szeidl.** 2009. “Trust and Social Collateral.” *The Quarterly Journal of Economics*, 124(3): 1307–1361.
- Keeling, Matt J., and Ken T. D. Eames.** 2005. “Networks and epidemic models.” *Journal of The Royal Society Interface*, 2(4): 295–307.
- Kempe, David, Jon Kleinberg, and va Tardos.** 2003. “Maximizing the Spread of Influence Through a Social Network.” *KDD '03*, 137–146. New York, NY, USA:ACM.
- Kermack, William Ogilvy, and A. G. McKendrick.** 1927. “A contribution to the mathematical theory of epidemics.” *Proc. R. Soc. Lond. A*, 115(772): 700–721.

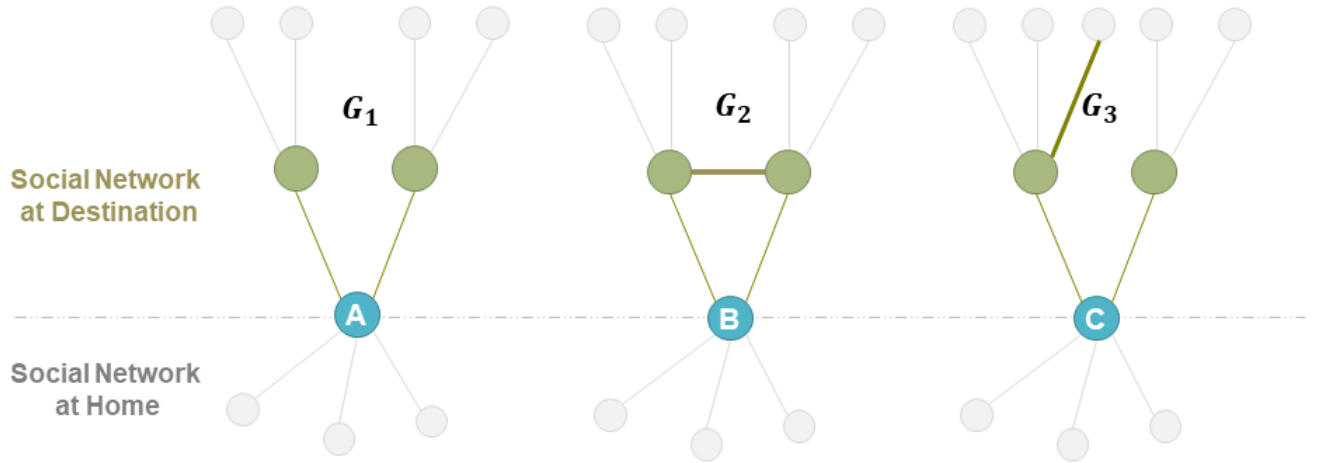
- Kinnan, Cynthia, Shing-Yi Wang, and Yongxiang Wang.** 2018. "Access to Migration for Rural Households." *American Economic Journal: Applied Economics*.
- Kitsak, Maksim, Lazaros K. Gallos, Shlomo Havlin, Fredrik Liljeros, Lev Muchnik, H. Eugene Stanley, and Hernn A. Makse.** 2010. "Identification of influential spreaders in complex networks." *Nature Physics*, 6(11): 888–893.
- Knapp, Thomas A., Nancy E. White, and David E. Clark.** 2001. "A Nested Logit Approach to Household Mobility." *Journal of Regional Science*, 41(1): 1–22.
- Krackhardt, David.** 1990. "Assessing the political landscape: Structure, cognition, and power in organizations." *Administrative science quarterly*, 342–369.
- Kranton, Rachel E.** 1996. "The formation of cooperative relationships." *The Journal of Law, Economics, and Organization*, 12(1): 214–233.
- Lucas, Robert E. B.** 1997. "Internal migration in developing countries." In *Handbook of Population and Family Economics*. Vol. 1, 721–798. Elsevier.
- Lucas, Robert E. B.** 2015. "Chapter 26 - African Migration." In *Handbook of the Economics of International Migration*. Vol. 1 of *Handbook of the Economics of International Migration*, , ed. Barry R. Chiswick and Paul W. Miller, 1445–1596. North-Holland.
- Mcfadden, Daniel.** 1974. "Conditional Logit Analysis of Qualitative Choice Behavior." In *Frontiers in econometrics*. , ed. P Zarembka, 105–142. Academic Press.
- McFadden, Daniel L.** 1984. "Econometric analysis of qualitative response models." *Handbook of Econometrics*, 2: 1395–1457.
- McKenzie, David, and Hillel Rapoport.** 2010. "Self-Selection Patterns in Mexico-U.S. Migration: The Role of Migration Networks." *Review of Economics and Statistics*, 92(4): 811–821.

- McKenzie, David J., and Marcin J. Sasin.** 2007. "Migration, Remittances, Poverty, and Human Capital: Conceptual and Empirical Challenges." Social Science Research Network SSRN Scholarly Paper ID 999482, Rochester, NY.
- Monderer, Dov, and Lloyd S Shapley.** 1996. "Potential games." *Games and economic behavior*, 14(1): 124–143.
- Montgomery, James D.** 1991. "Social Networks and Labor-Market Outcomes: Toward an Economic Analysis." *The American Economic Review*, 81(5): 1408–1418.
- Morten, Melanie.** 2015. "Temporary migration and endogenous risk sharing in village india."
- Munshi, Kaivan.** 2003. "Networks in the Modern Economy: Mexican Migrants in the U. S. Labor Market." *The Quarterly Journal of Economics*, 118(2): 549–599.
- Munshi, Kaivan.** 2014. "Community Networks and the Process of Development." *The Journal of Economic Perspectives*, 28(4): 49–76.
- Munshi, Kaivan, and Mark Rosenzweig.** 2016. "Networks and Misallocation: Insurance, Migration, and the Rural-Urban Wage Gap." *American Economic Review*, 106(1): 46–98.
- National Institute of Statistics of Rwanda.** 2014. "Migration and Spatial Mobility." Kigali, Rwanda.
- Patel, Krishna, and Francis Vella.** 2012. "Immigrant Networks and Their Implications for Occupational Choice and Wages." *The Review of Economics and Statistics*, 95(4): 1249–1277.
- Rees, Albert.** 1966. "Information Networks in Labor Markets." *The American Economic Review*, 56(1/2): 559–566.

- Revelt, David, and Kenneth Train.** 1998. “Mixed Logit with Repeated Choices: Households’ Choices of Appliance Efficiency Level.” *The Review of Economics and Statistics*, 80(4): 647–657.
- Rogers, Everett M.** 1962. *Diffusion of Innovations*. Simon and Schuster. Google-Books-ID: v1ii4QsB7jIC.
- Todaro, Michael P.** 1980. “Internal Migration in Developing Countries: A Survey.” In *Population and Economic Change in Developing Countries*. University of Chicago Press. Google-Books-ID: bX4Wq4sHGSEC.
- Topa, Giorgio.** 2001. “Social Interactions, Local Spillovers and Unemployment.” *The Review of Economic Studies*, 68(2): 261–295.
- Ugander, Johan, Lars Backstrom, Cameron Marlow, and Jon Kleinberg.** 2012. “Structural diversity in social contagion.” *Proceedings of the National Academy of Sciences*, 201116502.

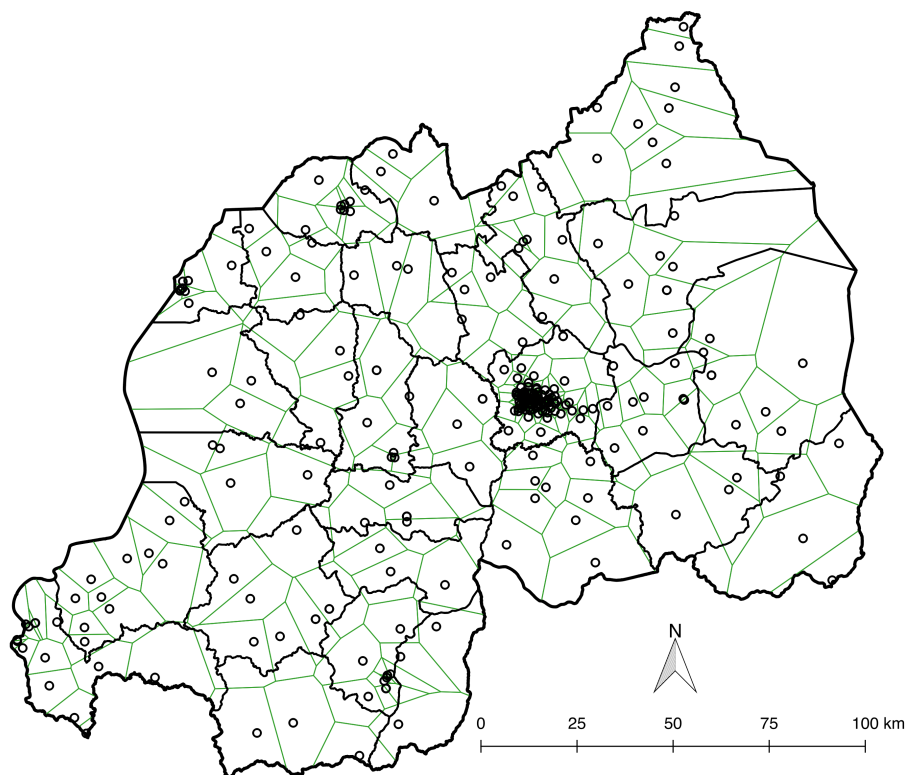
# Figures

Figure 1: Schematic diagrams of a three canonical social network configurations.



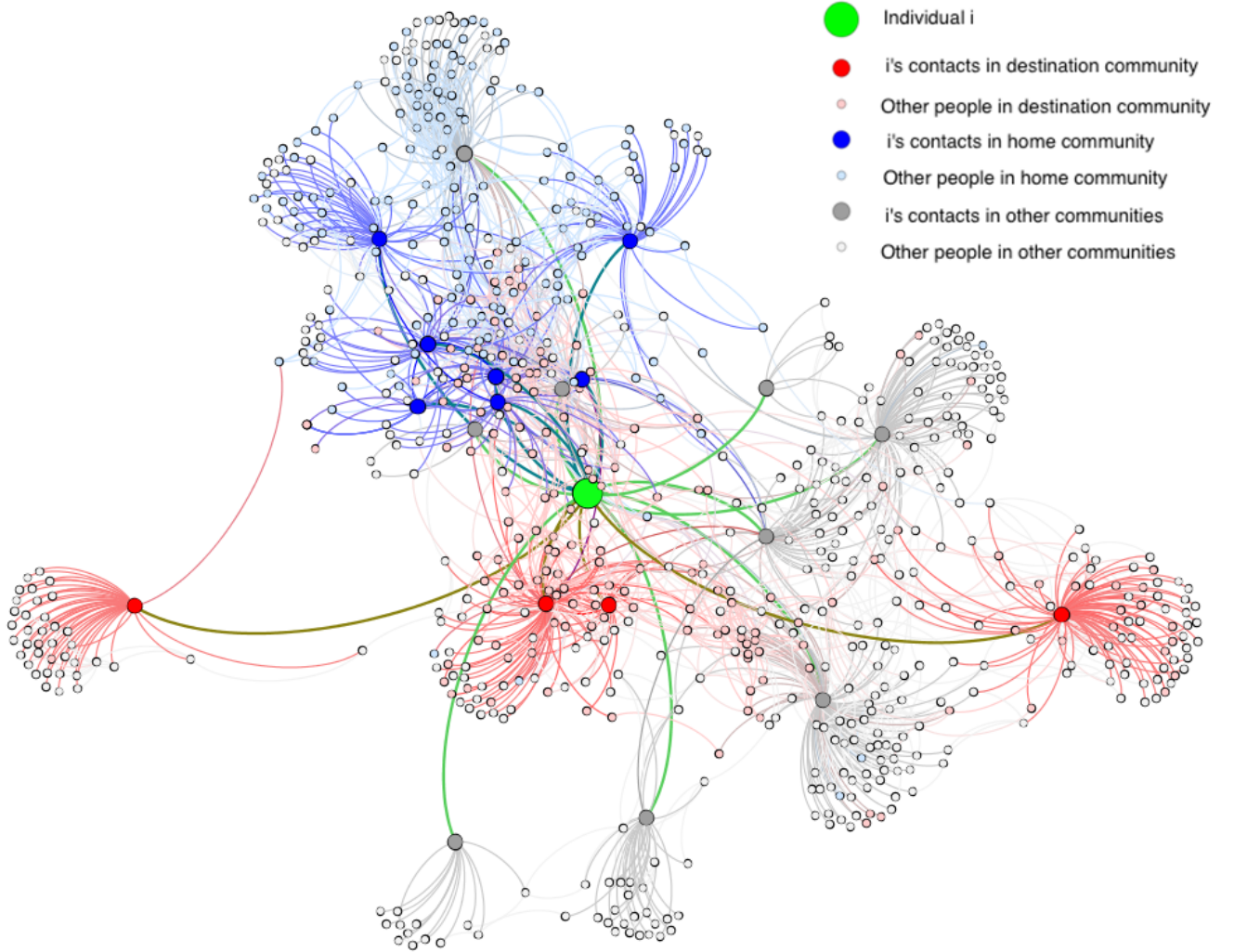
*Notes:* Each of the blue circles (A, B, C) represent a different individual considering migrating from their home to a new destination. Each individual has exactly three contacts in the home district (grey circles below the dashed line) and two contacts in the destination district (green circles above the dashed line). The social network of these three individuals is denoted by  $G_1$ ,  $G_2$ , and  $G_3$ , respectively. Our focus is on understanding the impact of minor variations in this social network structure, such as the extent to which connections in the destination are connected to each other ( $G_2$  vs.  $G_1$ ) and to others in the destination ( $G_3$  vs.  $G_1$ ).

Figure 2: Location of all mobile phone towers in Rwanda, circa 2008



*Notes:* Mobile phone tower locations are shown as black circles. Black lines show district borders. Green lines indicate the voronoi tessellation of the country — practically, the voronoi polygons divide the space into the approximate coverage region of each tower. The cluster of towers in the center of the figure are located around the urban capital of Kigali.

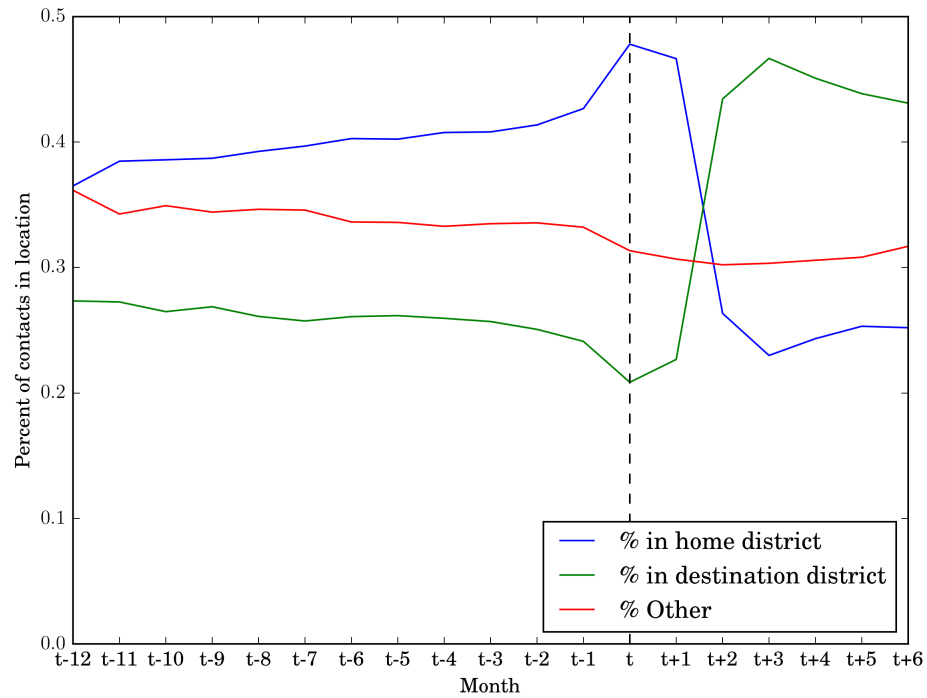
Figure 3: The social network of a single migrant



*Notes:* 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. Nodes are spaced using the force-directed algorithm described in [Hu \(2005\)](#).

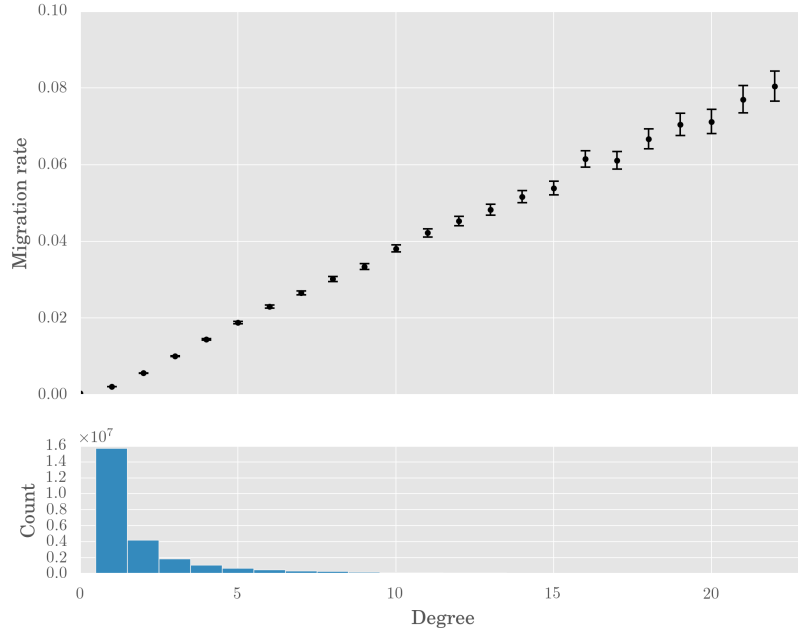


Figure 4: Network structure before and after migration – migrants

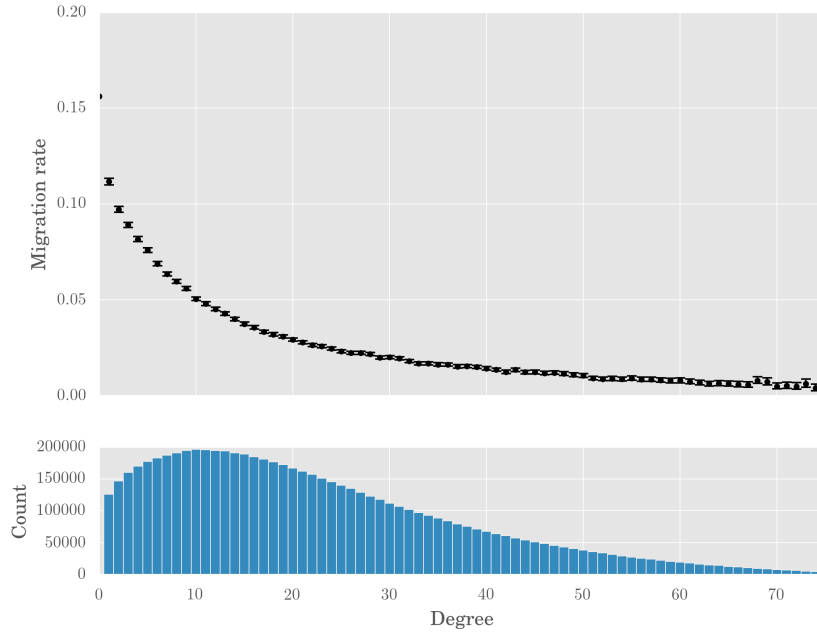


*Notes:* Figure shows, for migrants, the percentage of their contacts in their home district and their destination district, in each of the 12 months before and 6 months after migration. Prior to migration, migrants communicate more with the people in the place they leave and slightly less in the place to which they are going. After migration, the migrant reduces contact with the former home and communicates more with people in the new home.

Figure 5: Migration rate and degree centrality (number of unique contacts in network)



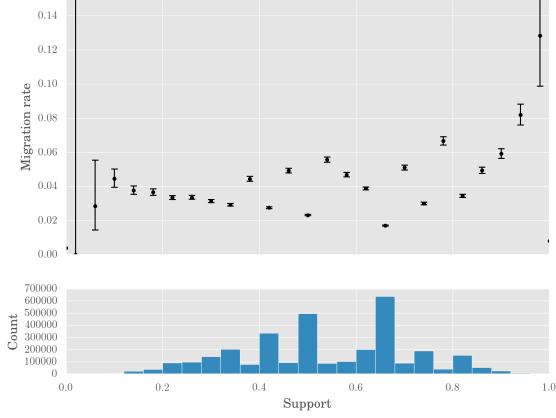
(a) Degree Centrality at Destination



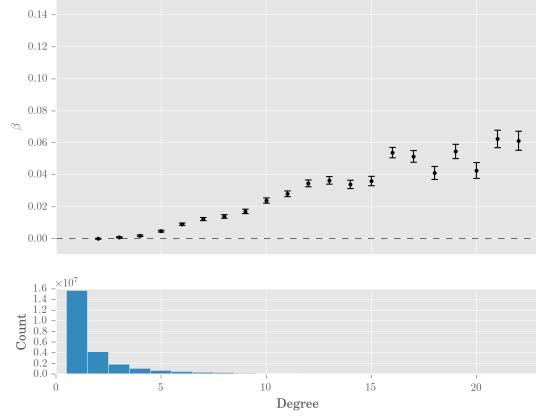
(b) Degree Centrality at Home

*Notes:* In both (a) and (b), the lower histogram shows the unconditional degree distribution, i.e., for each individual in each month, the total number of contacts in the (a) destination network and (b) home network. The upper figure shows, at each level of degree centrality, the average migration rate. Error bars indicate 95% confidence intervals, clustered by individual.

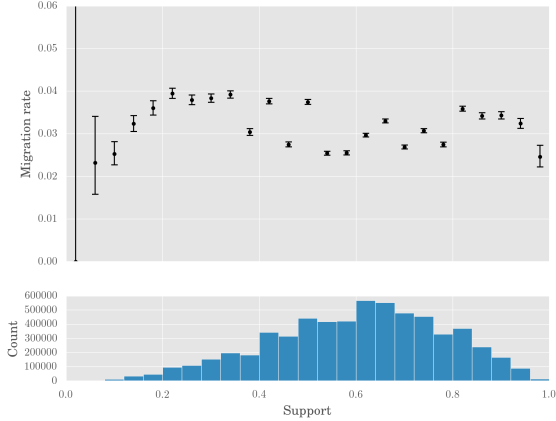
Figure 6: Relationship between migration rate and “tightness” (friends with common friends)



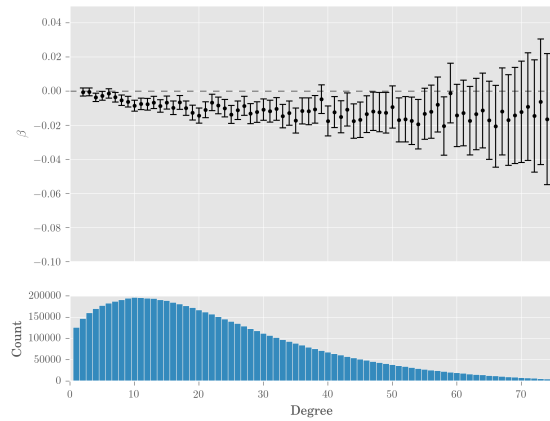
(a) Support at Destination



(b) Support at Destination, by Degree



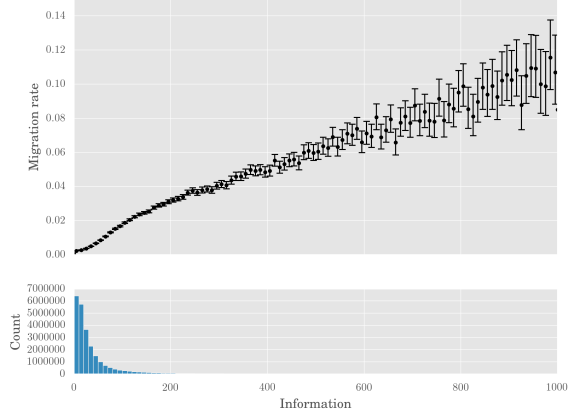
(c) Support at Home



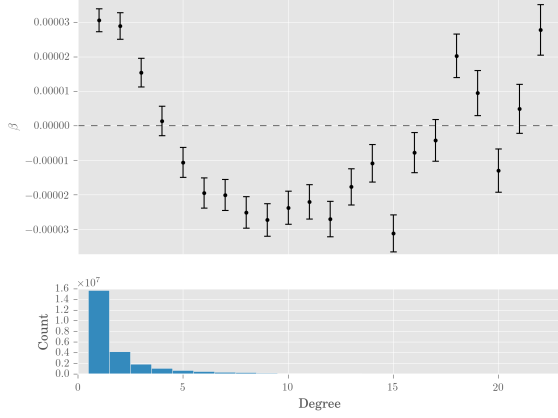
(d) Support at Home, by Degree

*Notes:* “Support” denotes the fraction of contacts supported by a common contact. In all figures, the lower histogram shows the unconditional distribution of the x-variable. Top row (a and b) characterizes the destination network; bottom row (c and d) characterizes the home network. In the left column (a and c), figures indicate, at each level of network size (“degree”), the average migration rate. In the right column (b and d), figures indicate the correlation between the migration rate and information, holding degree fixed (see equation 2). Error bars indicate 95% confidence intervals, clustered by individual.

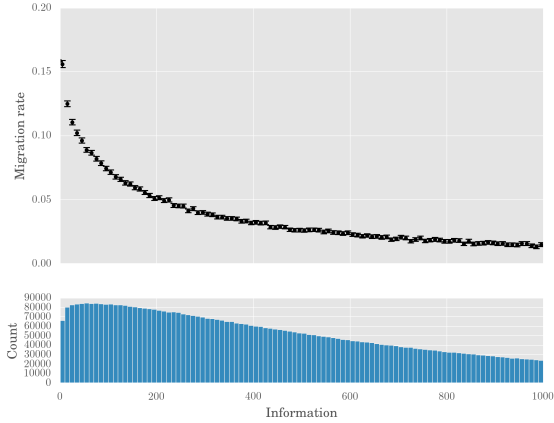
Figure 7: Relationship between migration and “expansiveness” (unique friends of friends)



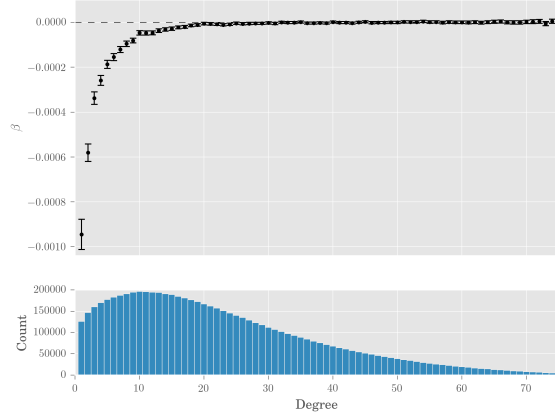
(a) Information at Destination



(b) Information at Destination, by Degree



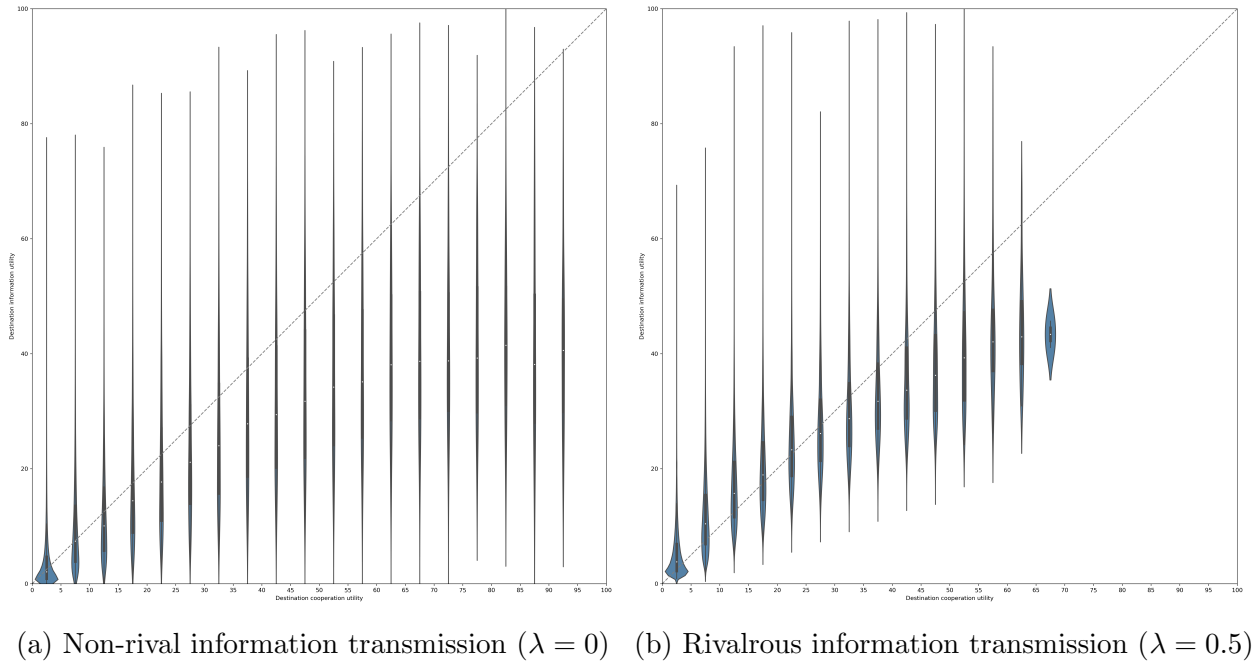
(c) Information at Home



(d) Information at Home, by Degree

*Notes:* “Information” denotes the number of unique contacts of  $i$ ’s contacts. In all figures, the lower histogram shows the unconditional distribution of the x-variable. Top row (a and b) characterizes the destination network; bottom row (c and d) characterizes the home network. In the left column (a and c), figures indicate, at each level of network size (“degree”), the average migration rate. In the right column (b and d), figures indicate the correlation between the migration rate and information, holding degree fixed (see equation 2). Error bars indicate 95% confidence intervals, clustered by individual.

Figure 8: Calibration results: ‘information’ and ‘cooperation’ utility



*Notes:* Figures show the distribution of predicted utility from ‘information’ and ‘cooperation’ (i.e., equation 11) for 140,000 migrants and non-migrants. The left figure is calculated using the parameters selected by calibrating Model 15 with  $\lambda$  fixed at zero (i.e., no information rivalry). For the right figure,  $\lambda$  ranges freely from zero to one, and the optimal value of  $\lambda$  is selected through calibration.

# Tables

Table 1: Summary statistics of mobile phone metadata

	(1)	(2)
	In a single month	Over two years
	(Jan 2008)	(Jul 2006 - Jun 2008)
Number of unique individuals	432,642	793,791
Number of person-months	432,642	8,121,369
Number of CDR transactions	50,738,365	868,709,410
Number of migrations	21,182	263,208
Number of rural-to-rural migrations	11,316	130,009
Number of rural-to-urban migrations	4,908	66,935
Number of urban-to-rural migrations	4,958	66,264

*Notes:* Migration statistics calculated from Rwandan call detail records. Left column uses data from a single month; right column includes two years of data, such that each individual can be counted more than once. “Migrations” are counted when an individual remains in one district for 2 consecutive months and then remains in a different districts for the next 2 consecutive months. “Urban” and “Rural” are defined using sector definitions provided by the National Institute of Statistics of Rwanda.

Table 2: Migration events observed in four years of phone data

Definition of Migrant ( $k$ )	Total Individuals ( $N$ )	% Ever Migrate	% Repeat migrants (to same district)	% Repeat migrants (to any district)	% Long-distance migrants (non-adjacent districts)	% Circular Migrants
1	935,806	34.565	11.171	21.923	23.181	18.457
2	680,267	21.634	1.933	8.244	13.828	5.934
3	518,156	13.960	0.405	2.893	9.216	2.007
6	263,182	5.294	0.000	0.192	3.547	0.128

*Notes:* Table counts number of unique individuals meeting different definitions of a “migration event.” Each row of the table defines a migration by a different  $k$ , such that an individual is considered a migrant if she spends  $k$  consecutive months in a district  $d$  and then  $k$  consecutive months in a different district  $d' \neq d$  – see text for details. Repeat migrants are individuals who have migrated one or more times prior to a migration observed in month  $t$ . Long-distance migrants are migrants who travel between non-adjacent districts. Circular migrants are migrants who have migrated from  $d$  to  $h$  prior to being observed to migrated from  $h$  to  $d$ . The number of individual ( $N$ ) varies by row, since an individual is only considered eligible as a migrant if she is observed continuously over  $2N$  consecutive months.

Table 3: Migration and social network structure - base specification

	(1)	(2)	(3)	(4)
<i>Panel A: Destination network characteristics</i>				
Degree (network size)	0.0036547*** (0.0000102)			
% Friends with common support		0.0014813*** (0.0001146)		0.0014808*** (0.0001146)
Unique friends of friends			−0.0000005 (0.0000009)	−0.0000002 (0.0000009)
Observations	9,889,981	9,889,981	9,889,981	9,889,981
$R^2$	0.1851423	0.1853017	0.1852869	0.1853017
<i>Panel B: Home network characteristics</i>				
Degree (network size)	−0.0003985*** (0.0000049)			
% Friends with common support		−0.0003467 (0.0002422)		−0.0005710** (0.0002424)
Unique friends of friends			−0.0000089*** (0.0000004)	−0.0000089*** (0.0000004)
Observations	9,889,981	9,889,981	9,889,981	9,889,981
$R^2$	0.1743203	0.1750909	0.1751320	0.1751325
Degree fixed effects	No	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
Home*Destination*Month F.E.	Yes	Yes	Yes	Yes

*Notes:* Each column indicates a separate regression of a binary variable indicating 1 if an individual  $i$  migrated from home district  $h$  to destination district  $d$  in month  $t$ . Standard errors are two-way clustered by individual and by home-destination-month. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.



Table 4: Jointly estimated effects of home and destination network structure

	(1)	(2)	(3)
Destination Degree (network size)	0.0048033*** (0.0000201)	0.0037637*** (0.0000238)	
Home Degree (network size)	-0.0007377*** (0.0000060)	-0.0005089*** (0.0000107)	
Destination friends of friends	-0.0000324*** (0.0000007)	-0.0000059*** (0.0000009)	-0.0000001 (0.0000009)
Home friends of friends	0.0000113*** (0.0000002)	0.0000059*** (0.0000004)	-0.0000035*** (0.0000004)
Destination % friends with support	0.0037855*** (0.0001088)	0.0017164*** (0.0001130)	0.0010618*** (0.0001146)
Home % friends with support	0.0081299*** (0.0001336)	-0.0061902*** (0.0002305)	0.0002216 (0.0002407)
Observations	9,889,981	9,889,981	9,889,981
R <sup>2</sup>	0.0213936	0.1858886	0.1868505
Degree fixed effects	No	No	Yes
Home*Destination*Month fixed effects	No	Yes	Yes
Individual fixed effects	No	Yes	Yes

*Notes:* Standard errors are two-way clustered by individual and by home-destination-month. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Table 5: Conditional logit results

	(1)	(2)	(3)	(4)
Destination Degree (network size)	0.16427*** (0.00106)	0.308192*** (0.002854)	0.11818*** (0.00114)	0.211611*** (0.003034)
Home Degree (network size)	-0.11931*** (0.00114)	-0.261790*** (0.002980)	-0.07906 (0.00128)	-0.188931*** (0.003160)
Destination friends of friends		-0.005564*** (0.000108)		-0.003503*** (0.000108)
Home friends of friends		-0.005442*** (0.000112)		0.004055*** (0.000110)
Destination % friends with support			2.49114*** (0.02788)	2.241620*** (0.030131)
Home % friends with support			-1.90396*** (0.01924)	-1.57135*** (0.042690)
Home choice	6.10215*** (0.01493)	6.114159*** (0.01514)	6.10313*** (0.01824)	6.082535*** (0.01813)
McFadden $R^2$	0.88563	0.88709	0.88864	0.88936
N individuals	433,782	433,782	433,782	433,782

*Notes:* Response variable in conditional logit is a dummy variable indicating whether individual  $i$  migrates from district  $h$  to district  $d$  in January 2008. Each choice represents one of the 27 districts in Rwanda (the three smaller urban districts in Kigali province are treated as a single district). Standard errors in parentheses. \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$ .

# A1 Proofs

**Proof of Proposition 1:** We construct the equilibrium as follows. Consider the partnership between  $i$  and  $j$ . The common knowledge they share about the network is  $g_{ij} = g_i \cap g_j$  and  $G_{ij} = G_i \cap G_j$ .

First, we generalize from the two benchmark effort levels,  $a^B$  and  $a^T$ , to effort in any clique with  $m$  agents.

$$b(a) \leq a + (m - 1) \int_0^\infty e^{-rt} \delta a dt.$$

The effort  $a^{c=m}$  binds this inequality.

Then, we claim there exists a maximal effort for the link  $ij$  subject to their shared common knowledge. If  $g_{ij} = \{i, j\}$ , then this maximal effort is  $a^B$ , otherwise it can be found by induction as explained below. From now on, we focus on  $(g_{ij}, G_{ij})$ , and say a clique  $g_{ijk_1 \dots k_h}$  is *maximal* if and only if  $g_{ijk_1 \dots k_h} = \{i, j, k_1, \dots, k_h\}$ . Suppose the largest fully-connected subset has  $h + 2$  agents.

- In step 1, find the largest subset(s) of fully-connected agents, for example,  $g_{ijk_1 \dots k_h}$ . By definition, it must be maximal. Then assign the effort  $a(k_m k_l | i j k_1 \dots k_h) = a^{c=h+2}$  to each link  $k_m k_l$  within the clique. That is, it is common knowledge among agents in the clique that each link can sustain effort at least  $a^{c=h+2}$ .
- In step 2, find all subsets of fully connected agents containing  $h + 1$  agents, including  $i$  and  $j$  (this must always hold, so omitted below). For any of them, say  $g_{ijk'_1 \dots k'_{h-1}}$ , assign  $a(k'_m k'_l | i j k'_1 \dots k'_{h-1})$  to each link  $k'_m k'_l$  to bind the inequality:

$$b(a) \leq a + \int_0^\infty e^{-rt} \delta \left( ha + \sum_{l \in g_{ijk'_1 \dots k'_{h-1}} \setminus \{i, j, k'_1, \dots, k'_{h-1}\}} a(il | i j k'_1 \dots k'_{h-1} l) \right) dt.$$

• ...

- In step  $h+1$ , the only subset containing 2 agents and including  $i$  and  $j$  is the set  $\{i, j\}$ .

The effort between them ( $a_{ij}^*$ ) must bind the inequality:

$$b(a) \leq a + \int_0^\infty e^{-rt} \delta \left( a + \sum_{l \in g_{ij} \setminus \{i, j\}} a(il|ijl) \right) dt.$$

By construction, each effort level is the highest effort that is sustainable given the (higher-order) common knowledge of the network. Thus,  $a_{ij}^*$  is the maximal effort sustainable between  $ij$  subject to their shared knowledge of the network. In addition, as long as no one in  $g_{ij}$  has deviated,  $i$  and  $j$  can sustain  $a_{ij}^*$ . Thus, the strategy is robust and 2-local. ■

## A2 A network game approach

In the benchmark model, we assume the total utility one gets from the network is a linear sum of utility from information and that from cooperation as in equation (11). To allow more complex interactions of network structures to influence the value of social network, we can consider a network game approach.

Each agent  $i$  chooses an action  $a_i$ , which could be socializing with friends, cooperating with them or both. Let  $\mathbf{a} = (a_1, \dots, a_n)$ . We use the matrix format of a network  $G$ , such that  $G_{ij} = G_{ji} = 1$  when  $i$  and  $j$  are connected. Let the matrix  $G^s$  be the matrix with  $G_{ij}^s = G_{ji}^s = 1$  if and only if  $ij$  is supported in  $G$ . Agent  $i$  derives the following quadratic utility, which has been commonly-used in network games (Jackson and Zenou 2015):

$$u_i(\mathbf{a}, G) = \pi a_i - \frac{a_i^2}{2} + \phi \sum_{j=1}^n G_{ij} a_i a_j + \alpha \sum_{j=1}^n G_{ij}^s a_i a_j. \quad (16)$$

The first two terms  $\pi a_i - \frac{a_i^2}{2}$  represent a linear benefit and a quadratic cost to agent  $i$  from choosing  $a_i$ . When  $\phi > 0$ , the third term  $\phi \sum_{j=1}^n G_{ij} a_i a_j$  reflects the strategic complementarity between neighbors' actions and own action.<sup>34</sup> And  $\alpha > 0$  reflects the additional complementarity from supported neighbors.

We add two remarks about the utility setup. First, the utility differs from a standard network setup due to the last term,  $\alpha \sum_{j=1}^n G_{ij}^s a_i a_j$ . It is inspired by results in section 5.2 that an agent may derive additional utility from a supported neighbor. Second, if  $\alpha = 0$ , then the equilibrium action will be in proportion to the diffusion centrality in section 5.1,  $DC(G; \phi, T)$  when  $T \rightarrow \infty$ . In particular,  $\phi$  could be viewed as the information passing probability  $q$ . The equilibrium action of agent  $i$  depends on the entire network structure, including her indirect neighbors and her supported links, and thus, this network approach allows for these network structures to jointly determine the equilibrium utility an agent gets

---

<sup>34</sup>While it is unlikely in our setup,  $\phi$  could be negative in some network games, which then reflects the substitution between neighbors' actions and one's action.

from the network.

Let  $\mu_1(G)$  be the spectral radius of matrix  $G$ ,  $\mathbf{I}$  be the identity matrix, and  $\mathbf{1}$  be the column vector of 1.

**PROPOSITION 2.** *If  $\mu_1(\phi G + \alpha G^s) < 1$ , the game with payoffs (16) has a unique (and interior) Nash equilibrium in pure strategies given by:*

$$\mathbf{a}^* = \pi(\mathbf{I} - \phi G - \alpha G^s)^{-1} \mathbf{1}. \quad (17)$$

Consider the first-order necessary condition for each agent  $i$ 's action:

$$\frac{\partial u_i(\mathbf{a}, G)}{\partial a_i} = \pi - a_i + \phi \sum_{j=1}^n G_{ij} a_j + \alpha \sum_{j=1}^n G_{ij}^s a_j = 0.$$

It leads to

$$a_i^* = \pi + \phi \sum_{j=1}^n G_{ij} a_j^* + \alpha \sum_{j=1}^n G_{ij}^s a_j^*. \quad (18)$$

In the matrix form:  $\mathbf{a}^* = \pi \mathbf{1} + \phi G \mathbf{a}^* + \alpha G^s \mathbf{a}^*$ , which leads to the solution in (17).

A simple way to prove Proposition 2, as noted for example by [Bramoullé, Kranton and D'amours \(2014\)](#), is to observe that this game is a potential game (as defined by [Monderer and Shapley 1996](#)) with potential function:

$$P(\mathbf{a}, G, \phi) = \sum_{i=1}^n u_i(\mathbf{a}, G) - \frac{\phi}{2} \sum_{i=1}^n \sum_{j=1}^n G_{ij} a_i a_j - \frac{\alpha}{2} \sum_{i=1}^n \sum_{j=1}^n G_{ij}^s a_i a_j.$$

The details of the analogous proof (for the game with  $\alpha = 0$ ) can be found in [Bramoullé, Kranton and D'amours \(2014\)](#) and [Jackson and Zenou \(2015\)](#).

In the equilibrium, the utility of agent  $i$  is given by

$$\begin{aligned} u_i(\mathbf{a}^*, G) &= \pi a_i^* - \frac{a_i^{*2}}{2} + \phi \sum_{j=1}^n G_{ij} a_i^* a_j^* + \alpha \sum_{j=1}^n G_{ij}^s a_i^* a_j^* \\ &= a_i^* \left( \pi + \phi \sum_{j=1}^n G_{ij} a_j^* + \alpha \sum_{j=1}^n G_{ij}^s a_j^* \right) - \frac{a_i^{*2}}{2}. \end{aligned}$$

By equation (18),  $u_i(\mathbf{a}^*, G) = a_i^{*2}/2$ , which by equation (17) depends on  $(\pi, \phi, \alpha, G)$ .

Finally, we remark that the network games can be enriched to capture the possibilities of competition with indirect neighbors, as we modeled in section 5.1. For example, [Ballester, Calvó-Armengol and Zenou \(2006\)](#) consider a global congestion effect by adding  $-\lambda a_i \sum_{j=1}^n a_j$  term to each agent  $i$ 's utility.

## A3 Algorithms

**Data:**  $\langle ID, datetime, location \rangle$  tuples for each mobile phone interaction

**Result:**  $\langle ID, month, district \rangle$  tuples indicating 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 occurrence number;

**else**

**if** *overall monthly modal districts can resolve* **then**

            return the district with larger occurrence 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 occurrence number;

**else**

**if** *overall monthly modal districts can resolve* **then**

            return the district with larger occurrence 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 occurrence number;

**end**

**end**

**Algorithm 1:** Home location assignment



**Data:** Monthly modal district for four consecutive months:  $D_1, D_2, D_3, D_4$

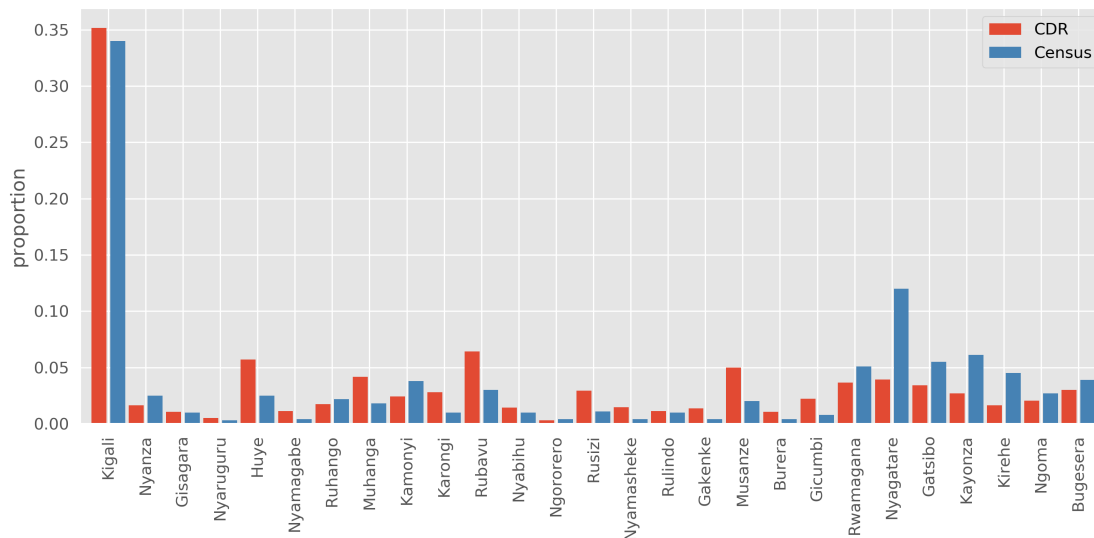
**Result:** Migration type

```
if  $D_1 == D_2$  AND  $D_3 == D_4$  then
  if  $D_2 == D_3$  then
    if  $D_4 == Kigali$  then
      | migration type is urban resident
    end
    else
      | migration type is rural resident
    end
  end
  else
    if  $D_4 == Kigali$  then
      | migration type is rural to urban
    end
    else
      if  $D_1 == Kigali$  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  $k=2$

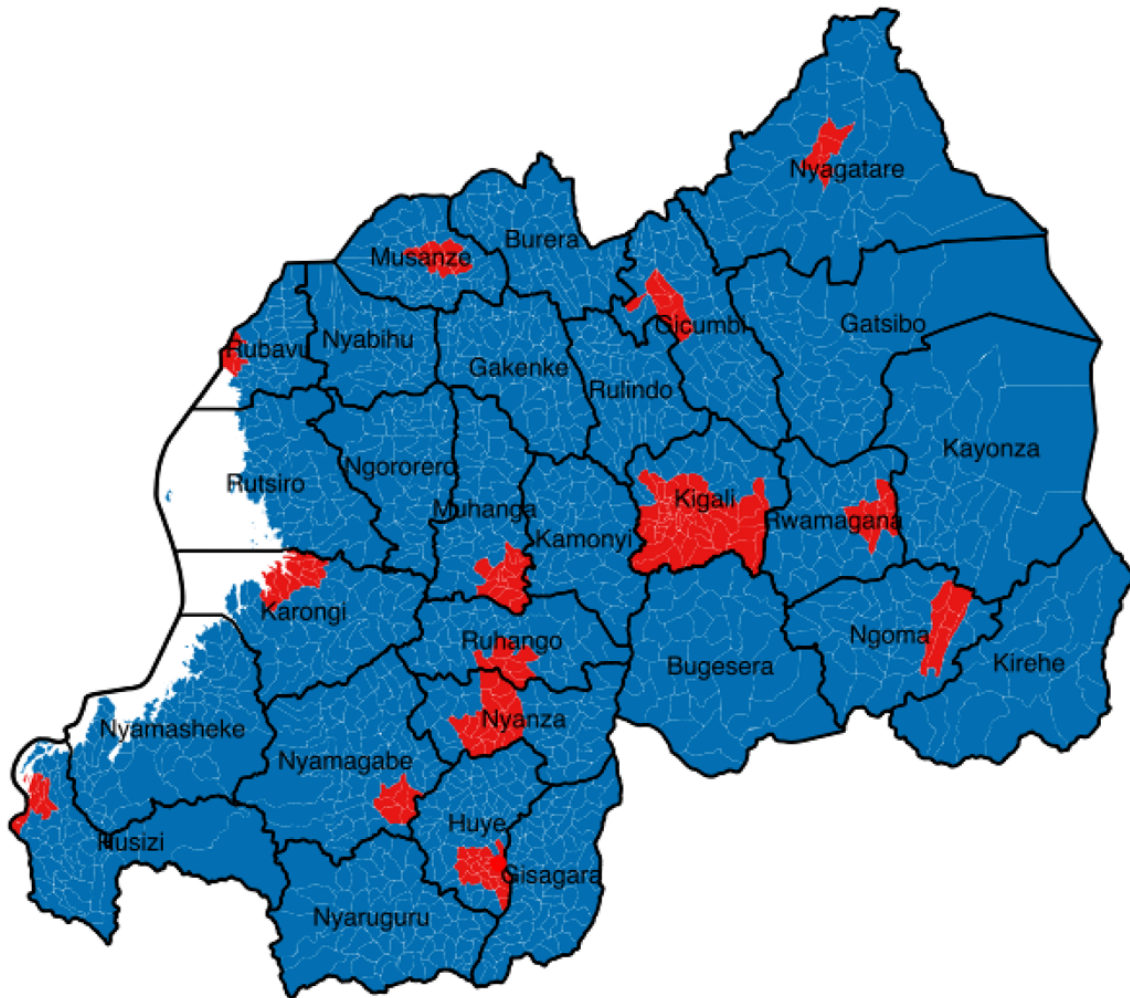
## A4 Appendix Figures and Tables

Figure A1: Validation of Migration Data



*Notes:* Figure shows the proportion of migrants to each district in Rwanda. Red bars indicate the proportion inferred from the mobile phone data; Blue bars indicate the proportion calculated from 2012 Rwandan census data, as reported by [National Institute of Statistics of Rwanda \(2014\)](#).

Figure A2: Urban and rural sectors in Rwanda



*Notes:* Urban zones shown in red; rural zones shown in blue. Urban and rural designations determined using the sector boundary dataset from the website of National Institute of Statistics Rwanda, available from <http://statistics.gov.rw/geodata>.

Figure A3: Total contacts before and after migration – migrants

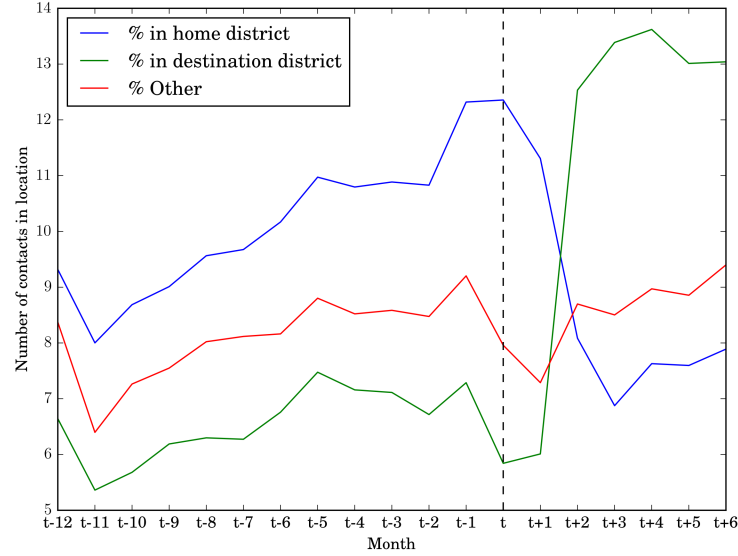
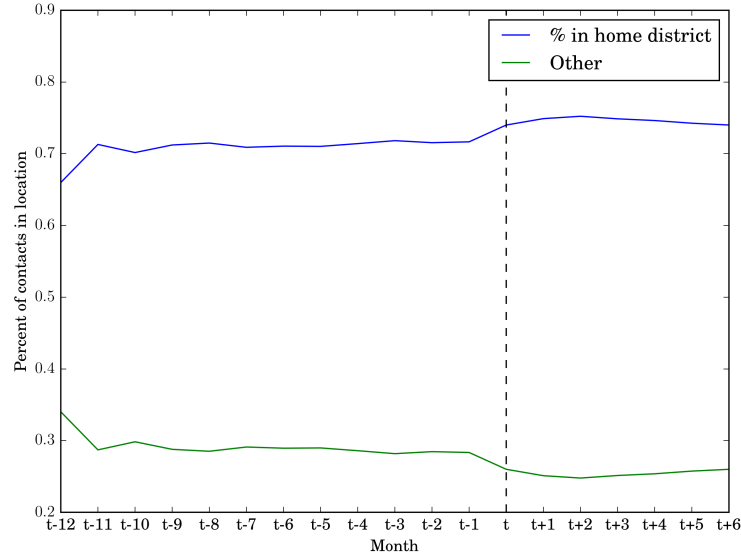


Figure A4: Network structure before and after migration – non-migrants



*Notes:* Top figure shows total number of contacts (instead of percent of contacts, as in Figure 4) migrants have in their home district and their destination district, in each of the 12 months before and 6 months after migration. Bottom figure shows percent of contacts in home and non-home locations for *non*-migrants (in this sample, the index month  $t$  is chosen randomly).

Figure A5: Number of friends of friends, before and after migration (migrants)

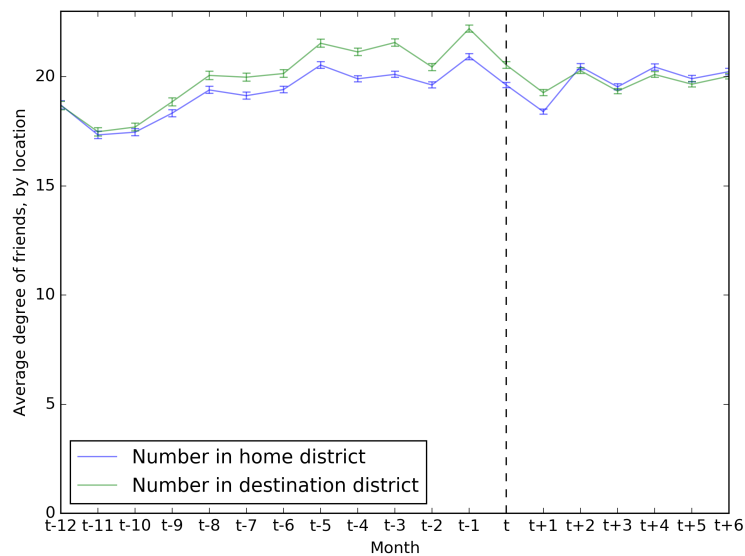
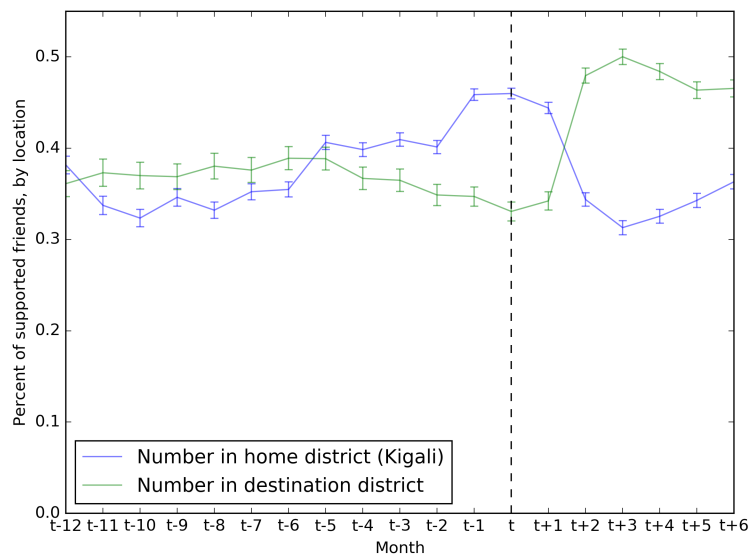
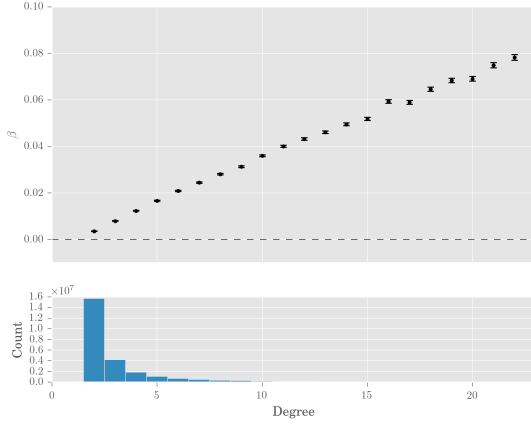


Figure A6: Percent of friends with common support, before and after migration (migrants)

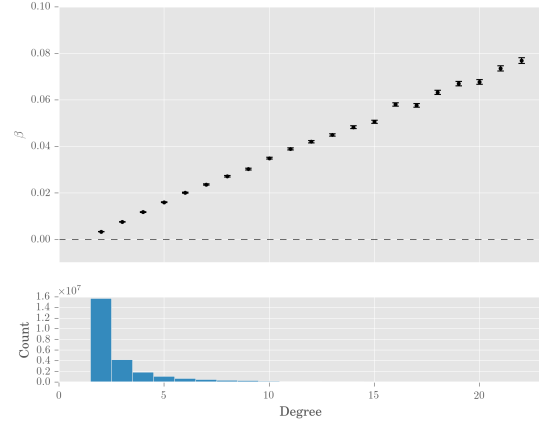


*Notes:* Top figure shows total number of friends of friends migrants have in their home district and their destination district, in each of the 12 months before and 6 months after migration. Bottom figure shows the percent of the migrants friends who have a common friend.

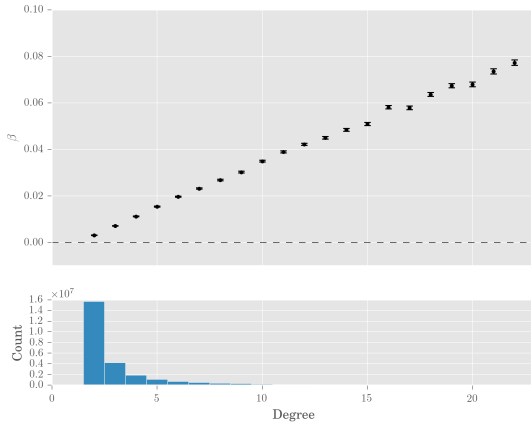
Figure A7: Migration rate and degree centrality, controlling for different fixed effects



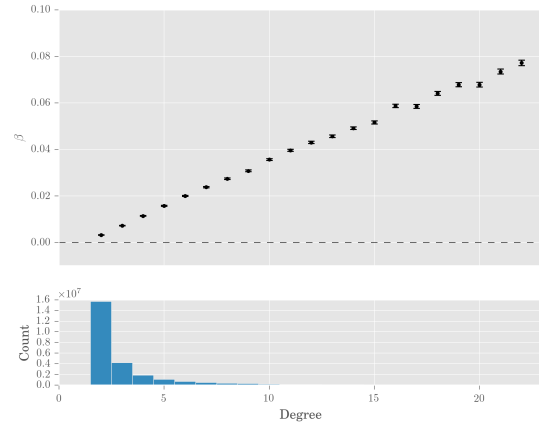
(a) No fixed effects



(b) Destination district fixed effects



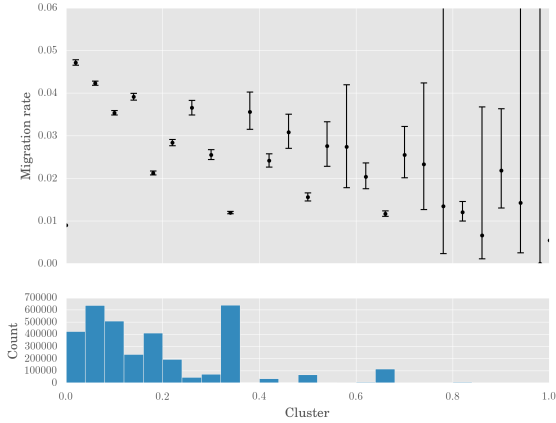
(c) Home-destination-month F.E.'s



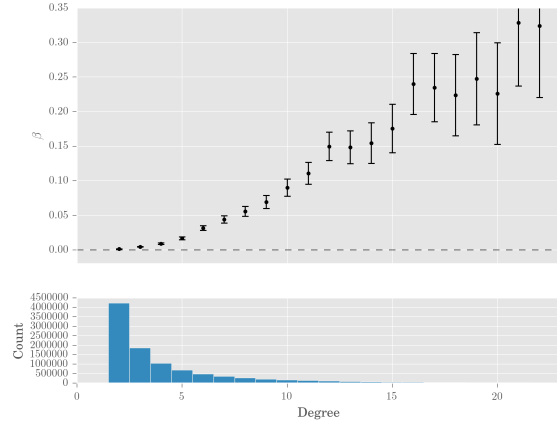
(d) Home-dest-month & individual F.E.'s

*Notes:* Each figure shows the fixed effect coefficients estimated from a regression of migration on separate fixed effects for each possible destination network size (see Section 4.1). Figure subtitle indicates any other fixed effects included in the specification. Error bars indicate 95% confidence intervals, clustered by individual.

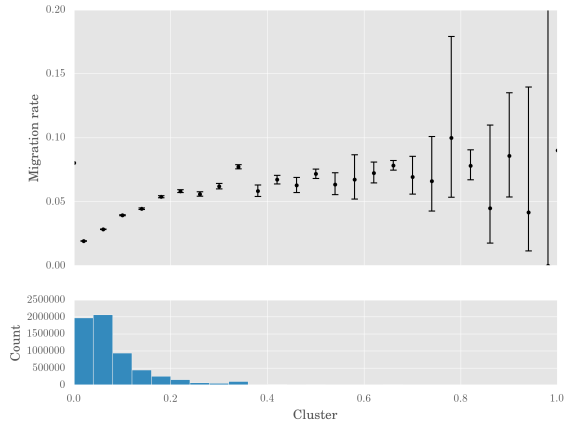
Figure A8: Relationship between migration rate and clustering



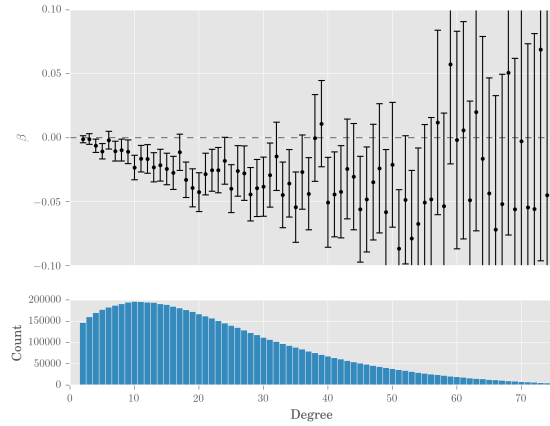
(a) Clustering at Destination



(b) Clustering at Destination, by Degree



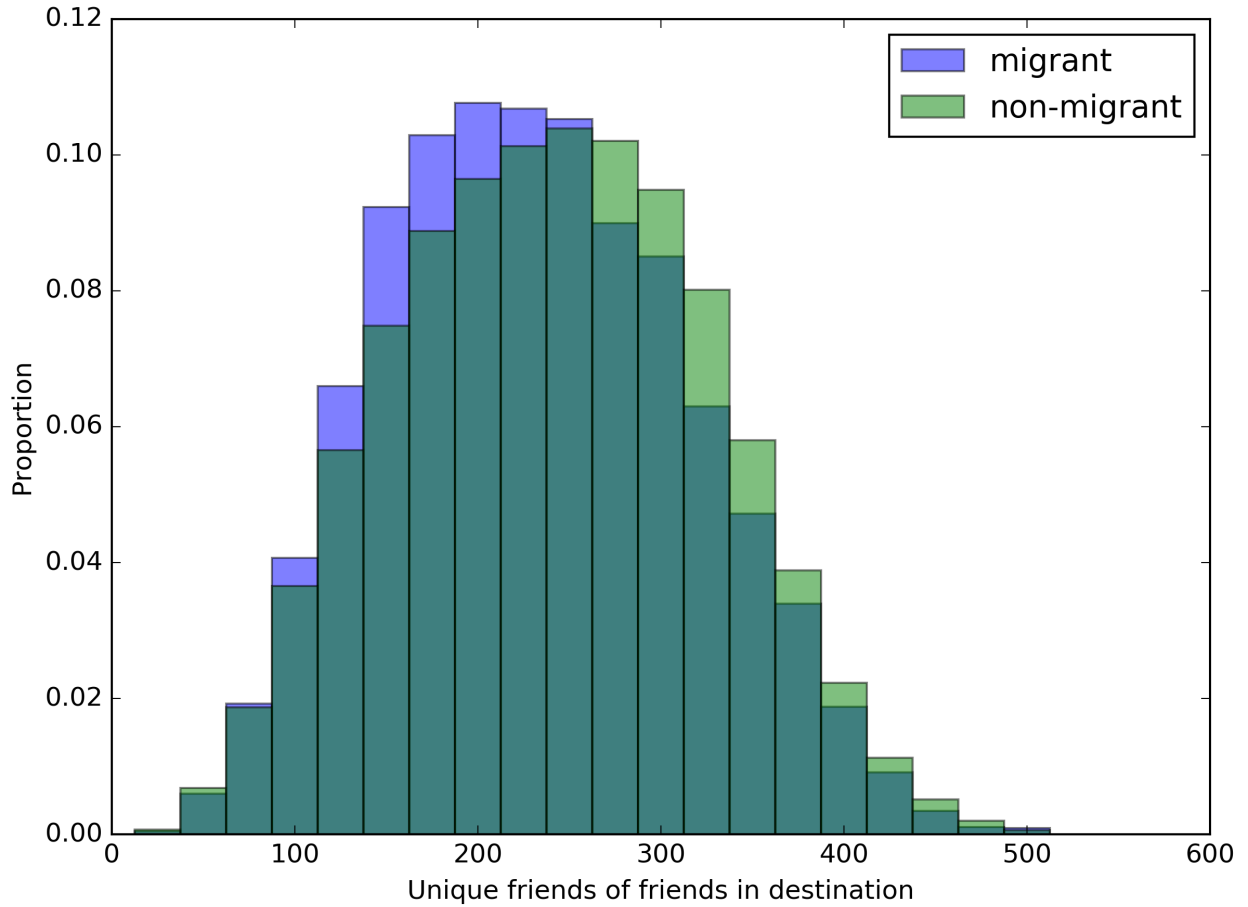
(c) Clustering at Home



(d) Clustering at Home, by Degree

*Notes:* “Clustering” denotes the proportion of potential links between  $i$ ’s friends that exist. In all figures, the lower histogram shows the unconditional distribution of the x-variable. Top row (a and b) characterizes the destination network; bottom row (c and d) characterizes the home network. For the left column (a and c), the main figure indicates, at each level of weighted degree, the average migration rate. For the left column (b and d), the main figure indicates the correlation between the migration rate and clustering, holding degree fixed. In other words, each point represents the  $\beta_k$  coefficient estimated from a regression of  $Migration_i = \alpha_k + \beta_k Clustering_i$ , estimated on the population of  $i$  who have degree equal to  $k$ . Error bars indicate 95% confidence intervals, clustered by individual.

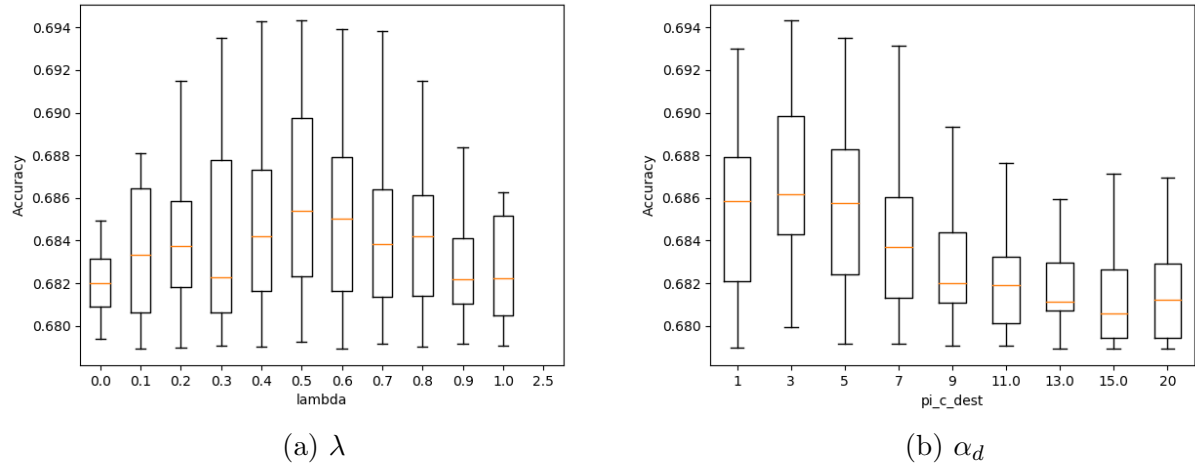
Figure A9: Migrants have fewer friends of friends than non-migrants



*Notes:* The figure focuses on all individuals who have exactly 10 unique contacts in a potential destination, and shows the distribution of the number of unique “friends of friends” in that destination. Counterintuitively, migrants have fewer unique friends of friends than non-migrants.

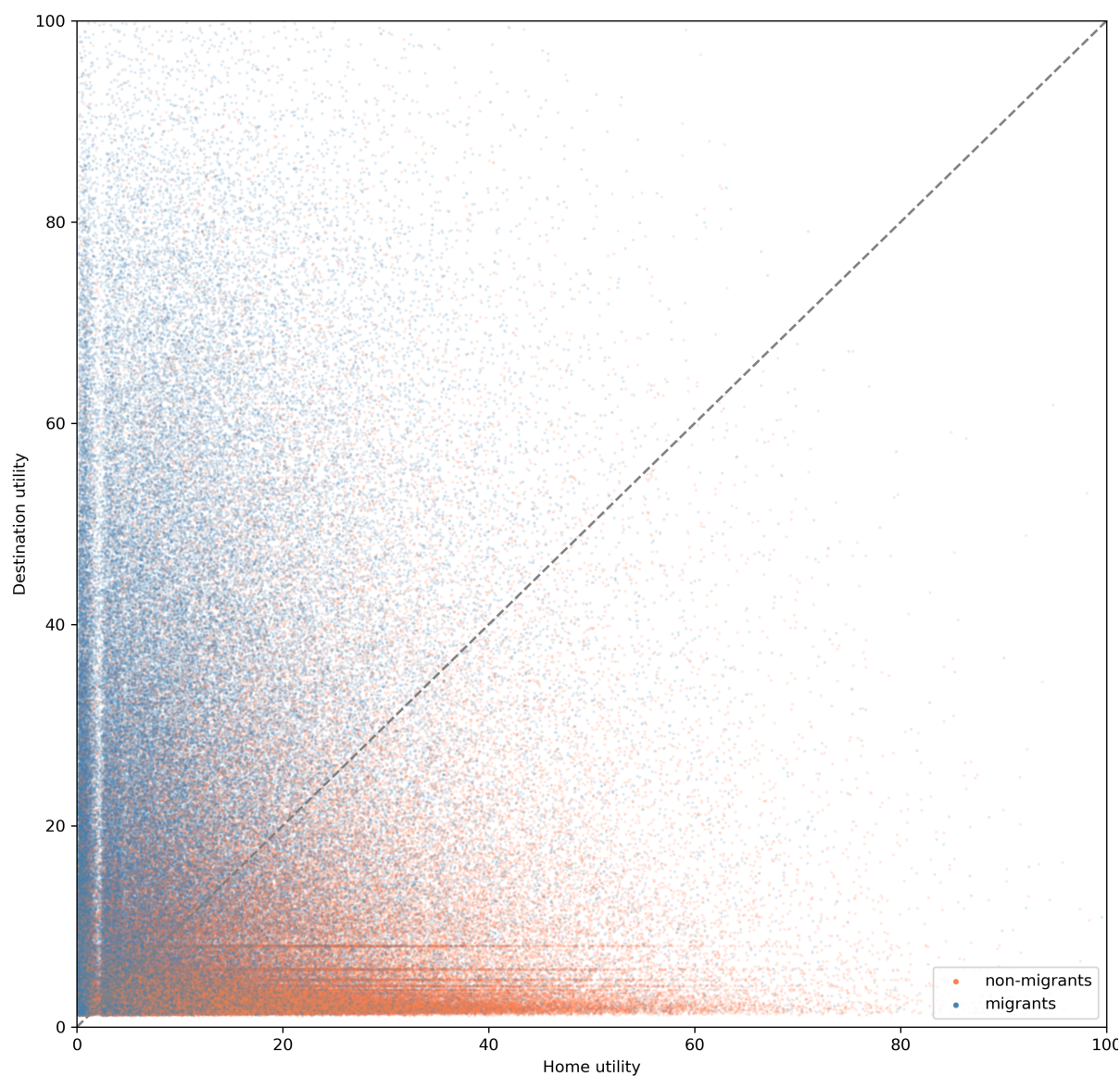


Figure A10: Calibration results: marginal plots



*Notes:* Figures show the marginal effect of varying  $\lambda$  and  $\alpha_d$  when calibrating Model 15. Each of roughly 50,000 different parameter combinations is tested; the top percentile of simulations are used to generate this marginal plot.

Figure A11: Simulated balance of home vs. destination utility for roughly 70,000 migrants (blue) and non-migrants (red).



*Notes:* After the model is calibrated, the optimal parameters are used to calculate the total utility provided to each individual by the home network and destination network. Each dot represents one individual's combination of predicted home-destination utility. Blue (red) dots above (below) the 45-degree line are correctly classified; blue (red) dots below (above) the 45-degree line are incorrectly classified.

Table A1: Robustness to alternative fixed effect specifications

	(1)	(2)	(3)	(4)
<i>Panel A: Destination network characteristics</i>				
Degree (network size)	0.0036548*** (0.0000183)			
Friends of friends	-0.00000103*** (0.0000007)	-0.0000160*** (0.0000007)	-0.00000004 (0.0000008)	-0.0000002 (0.0000009)
% Friends with common support	0.0010869*** (0.0001045)	0.0022076*** (0.0001107)	0.0028977*** (0.0001112)	0.0014808*** (0.0001146)
Observations	9,889,981	9,889,981	9,889,981	9,889,981
<i>Panel B: Home network characteristics</i>				
Degree (network size)	-0.0003957*** (0.0000060)			
Friends of friends	0.00000021*** (0.0000002)	-0.0000109*** (0.0000001)	-0.0000165*** (0.0000001)	-0.0000110*** (0.0000002)
% Friends with common support	0.0325365*** (0.0001233)	-0.0186718*** (0.0001673)	-0.0139236*** (0.0001731)	-0.0087495*** (0.0002245)
Observations	9,889,981	9,889,981	9,889,981	9,889,981
Degree fixed effects	No	Yes	Yes	Yes
Home*Destination*Month fixed effects	No	No	Yes	Yes
Individual fixed effects	No	No	No	Yes

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A2: Robustness to alternative fixed effect specifications, part 2

	(1)	(2)	(3)	(4)	(5)
Destination friends of friends	-0.0000002 (0.0000009)	-0.0000064*** (0.0000010)	-0.0000077*** (0.0000012)	0.0000011 (0.0000011)	-0.0000028*** (0.0000010)
% Destination friends with support	0.0014808*** (0.0001146)	0.0003458*** (0.0001220)	0.0006663*** (0.0000966)	0.0013719*** (0.0001491)	0.0001123 (0.0001204)
Observations	9,889,981	9,889,981	9,889,981	9,889,981	9,889,981
$R^2$	0.1853017	0.5952072	0.6680641	0.5080845	0.6332967
Fixed effects	$D, h * d * t, i$	$D, h * d * t, i * d$	$D, h * d * t, i * D$	$D, h * d * t, i * t$	$D, h * d * i, t$

*Notes:* Each column indicates a separate regression of a binary variable indicating 1 if an individual  $i$  migrated from home district  $h$  to destination district  $d$  in month  $t$ . All specifications control non-parametrically for the number of unique contacts  $D$  that  $i$  has in district  $d$ . Standard errors are two-way clustered by individual and by home-destination-month. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Table A3: Heterogeneity by Migration Frequency (Repeat and First-time)

<i>Migration Frequency</i>	(1) Any	(2) Repeat	(3) First-Time
Destination friends of friends	−0.0000001 (0.0000009)	0.0000171*** (0.0000062)	−0.0000030*** (0.0000008)
Home friends of friends	−0.0000035*** (0.0000004)	−0.0000511*** (0.0000043)	0.0000022*** (0.0000003)
% Destination support	0.0010618*** (0.0001146)	−0.0027428* (0.0014071)	0.0010934*** (0.0000920)
% Home support	0.0002216 (0.0002407)	0.0037889** (0.0018547)	−0.0007294*** (0.0001994)
Observations	9,889,981	665,780	9,224,201
R <sup>2</sup>	0.1868505	0.4382679	0.1986143
Degree fixed effects	Yes	Yes	Yes
Home*Destination*Month fixed effects	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes

*Notes:* All specifications include degree fixed effects, (home \* destination \* month) fixed effects, and individual fixed effects. Repeat migrants are individuals who have migrated one or more times from  $h$  to  $d$  prior to a  $h - d$  migration observed in month  $t$ . Standard errors are two-way clustered by individual and by home-destination-month. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Table A4: Heterogeneity by Distance (Adjacent districts vs. Non-adjacent districts)

<i>Migration Distance</i>	(1) Any	(2) Short Distance (adjacent districts)	(3) Long-Distance (non-adjacent districts)
Destination friends of friends	−0.0000001 (0.0000009)	0.0000042** (0.0000017)	−0.0000159*** (0.0000012)
Home friends of friends	−0.0000035*** (0.0000004)	−0.0000052*** (0.0000008)	−0.0000028*** (0.0000005)
% Destination support	0.0010618*** (0.0001146)	0.0010032*** (0.0002282)	0.0010780*** (0.0001362)
% Home support	0.0002216 (0.0002407)	−0.0004295 (0.0004260)	0.0002990 (0.0002933)
Observations	9,889,981	3,337,184	6,552,797
R <sup>2</sup>	0.1868505	0.3237450	0.1972246
Degree fixed effects	Yes	Yes	Yes
Home*Destination*Month F.E.	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes

*Notes:* All specifications include degree fixed effects, (home \* destination \* month) fixed effects, and individual fixed effects. Standard errors are two-way clustered by individual and by home-destination-month. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Table A5: Heterogeneity by Migration Duration (Long-term vs. Short-term)

	(1)	(2)	(3)
<i>Migration Distance</i>	Any	Long Stay (> 12 months)	Short Stay (< 6 months)
Destination friends of friends	−0.0000001 (0.0000009)	0.0000156*** (0.0000005)	−0.0000125*** (0.0000007)
Home friends of friends	−0.0000035*** (0.0000004)	−0.0000068*** (0.0000002)	0.0000007** (0.0000003)
% Destination “support”	0.0010618*** (0.0001146)	0.0002180*** (0.0000626)	0.0008051*** (0.0000846)
% Home “support”	0.0002216 (0.0002407)	0.0000928 (0.0001323)	0.0001442 (0.0001786)
Observations	9,889,981	9,782,384	9,820,778
R <sup>2</sup>	0.1868505	0.1445434	0.1857658
Degree fixed effects	Yes	Yes	Yes
Home*Destination*Month fixed effects	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes

*Notes:* All specifications include degree fixed effects, (home \* destination \* month) fixed effects, and individual fixed effects. Standard errors are two-way clustered by individual and by home-destination-month. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Table A6: Heterogeneity by destination type (Rural and Urban)

<i>Destination Type</i>	(1) All	(2) Rural	(3) Urban
Destination friends of friends	−0.0000001 (0.0000009)	0.0000022 (0.0000020)	−0.0000019 (0.0000012)
Home friends of friends	−0.0000035*** (0.0000004)	−0.0000037*** (0.0000006)	−0.0000018*** (0.0000006)
% Destination “Support”	0.0010618*** (0.0001146)	0.0009579*** (0.0001470)	0.0008771*** (0.0001612)
% Home “Support”	0.0002216 (0.0002407)	−0.0002734 (0.0003254)	0.0002481 (0.0003042)
Observations	9,889,981	4,236,638	5,918,664
R <sup>2</sup>	0.1868505	0.3103749	0.2471896
Degree fixed effects	Yes	Yes	Yes
Home*Destination*Month fixed effects	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes

*Notes:* All specifications include degree fixed effects, (home \* destination \* month) fixed effects, and individual fixed effects. Urban and rural designation determined using the sector boundary dataset from the website of National Institute of Statistics Rwanda, available from <http://statistics.gov.rw/geodata>. Standard errors are two-way clustered by individual and by home-destination-month. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.



Table A7: The role of strong ties and weak ties

	(1)	(2)	(3)	(4)
Destination “Weak tie”	0.0036077*** (0.0000123)	0.0037190*** (0.0000250)	0.0036771*** (0.0000107)	0.0037849*** (0.0000240)
Destination “Strong tie”	0.0044319*** (0.0000495)	0.0045117*** (0.0000536)	0.0044074*** (0.0001536)	0.0045034*** (0.0001549)
Home “Weak tie”	−0.0003855*** (0.0000050)	−0.0004813*** (0.0000108)	−0.0004042*** (0.0000049)	−0.0005021*** (0.0000107)
Home “Strong tie”	−0.0007742*** (0.0000152)	−0.0008799*** (0.0000179)	−0.0014034*** (0.0000755)	−0.0015449*** (0.0000761)
Destination friends of friends		−0.0000062*** (0.0000009)		−0.0000061*** (0.0000009)
Home friends of friends		0.0000058*** (0.0000004)		0.0000059*** (0.0000004)
% Destination “Support”		0.0018786*** (0.0001138)		0.0018158*** (0.0001133)
% Home “Support”		−0.0061352*** (0.0002306)		−0.0061689*** (0.0002305)
Observations	9,889,981	9,889,981	9,889,981	9,889,981
R <sup>2</sup>	0.1858262	0.1859473	0.1857898	0.1859106
Degree fixed effects	No	No	No	No
Home*Destination*Month FE’s	Yes	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes	Yes
Definition of “Strong”	90th Percentile	90th Percentile	95th Percentile	95th Percentile

*Notes:* Each column indicates a separate regression of a binary variable indicating 1 if an individual  $i$  migrated from home district  $h$  to destination district  $d$  in month  $t$ . This table disaggregates contacts at home and destination by the strength of the relationship, where strength is defined in terms of the number of phone calls observed between the two parties. Columns 1 and 2 consider strong ties to be relationships with 5 or more phone calls (the 90th percentile of tie strength); columns 3 and 4 use a threshold of 12 calls (the 95th percentile of tie strength). Standard errors are two-way clustered by individual and by home-destination-month. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Table A8: Disaggregating the friend of friend effect by the strength of the 2nd-degree tie

	(1)	(2)	(3)	(4)	(5)	(6)
Destination friends of friends (all)	0.0000004 (0.0000009)					
Friends of friends (strong-strong)		0.0000175* (0.0000104)				-0.0002288*** (0.0000202)
Friends of friends (strong-weak)			0.0000226*** (0.0000024)			0.0000696*** (0.0000047)
Friends of friends (weak-strong)				-0.0000460*** (0.0000048)		-0.0001103*** (0.0000072)
Friends of friends (weak-weak)					0.0000016 (0.0000011)	0.0000224*** (0.0000017)
Observations	10,089,959	10,089,959	10,089,959	10,089,959	10,089,959	10,089,959
R <sup>2</sup>	0.1908962	0.1908965	0.1909039	0.1909041	0.1908964	0.1909380

*Notes:* Each column indicates a separate regression of a binary variable indicating 1 if an individual  $i$  migrated from home district  $h$  to destination district  $d$  in month  $t$ . We show the destination “friend of friend” coefficient separately for geometries of different tie strength. “Strong-strong” (column 2) indicates the effect of friends when the potential migrant  $i$  is connected to  $j$  via a strong tie, and  $j$  is connected to  $k$  via a strong tie. “Strong-weak” (column 3) indicates the effect when  $i$  and  $j$  have a strong tie and  $j$  and  $k$  have a weak tie. Columns 4 and 5 follow this nomenclature. Strong ties are defined as relationships with 5 or more phone calls (the 90th percentile of tie strength) in a given month. \*p<0.1; \*\*p<0.05; \*\*\*p<0.01

Table A9: Disaggregating the network support effect by the strength of supported ties

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Destination support (all)	0.0013211*** (0.0001172)							
Destination support (sss)		0.0016200** (0.0006504)						
Destination support (sws)			0.0069022*** (0.0006493)					
Destination support (ssw)				0.0006118*** (0.0001283)				
Destination support (sww)					0.0027148*** (0.0001003)			
Destination support (wss)						-0.0005028 (0.0003166)		
Destination support (wws)							0.0009461*** (0.0003165)	
Destination support (wsw)								-0.0019032*** (0.0003918)
Destination support (www)								
Destination strong tie	0.0013544*** (0.0000477)	0.0013941*** (0.0000482)	0.0013132*** (0.0000483)	0.0013981*** (0.0000475)	0.0013135*** (0.0000475)	0.0014268*** (0.0000478)	0.0013923*** (0.0000480)	0.0014085*** (0.0000474)
Observations	10,089,959	10,089,959	10,089,959	10,089,959	10,089,959	10,089,959	10,089,959	10,089,959
R <sup>2</sup>	0.1909840	0.1909736	0.1909828	0.1909751	0.1910361	0.1909733	0.1909739	0.1909751

*Notes:* Each column indicates a separate regression of a binary variable indicating 1 if an individual  $i$  migrated from home district  $h$  to destination district  $d$  in "support" coefficient separately for geometries of different tie strength. "SSS" (column 2) indicates the effect of network support for triangles where the potential strong tie,  $j$  is connected to  $k$  via a strong tie, and  $k$  and  $i$  are connected by a strong tie. "SWS" (column 3) indicates the effect when  $i$  and  $j$  have a strong tie,  $j$  and  $k$  have a strong tie. Columns 4-8 follow a similar nomenclature. Strong ties are defined as relationships with 5 or more phone calls (the 90th percentile of tie strength). \*\*p<0.05; \*\*\*p<0.01

Table A10: The role of recent migrants

	(1)	(2)	(3)
Destination Degree (network size)	0.0037637*** (0.0000238)	0.0036358*** (0.0000244)	0.0036513*** (0.0000238)
Home Degree (network size)	-0.0005089*** (0.0000107)	-0.0005171*** (0.0000107)	-0.0005859*** (0.0000107)
Destination friends of friends	-0.0000059*** (0.0000009)	-0.0000041*** (0.0000009)	-0.0000060*** (0.0000009)
Home friends of friends	0.0000059*** (0.0000004)	0.0000060*** (0.0000004)	0.0000075*** (0.0000004)
% Destination "Support"	0.0017164*** (0.0001130)	0.0017326*** (0.0001130)	0.0017847*** (0.0001129)
% Home "Support"	-0.0061902*** (0.0002305)	-0.0061607*** (0.0002305)	-0.0063159*** (0.0002304)
Recent migrant friends		0.0011090*** (0.0000489)	0.0126456*** (0.0001135)
Observations	9,889,981	9,889,981	9,889,981
R <sup>2</sup>	0.1858886	0.1859340	0.1869832
Degree fixed effects	No	No	No
Home*Destination*Month fixed effects	Yes	Yes	Yes
Individual fixed effects	Yes	Yes	Yes
Definition of "Recent"	NA	Ever	Last month

*Notes:* Each column indicates a separate regression of a binary variable indicating 1 if an individual  $i$  migrated from home district  $h$  to destination district  $d$  in month  $t$ . Column (1) replicates the original result from Table 4; column (2) controls for the number of migrants that  $i$  knows, who ever migrated from  $h$  to  $d$  prior to  $t$ ; column (3) controls for the number of recent migrants that  $i$  knows, who migrated from  $h$  to  $d$  in the month prior to  $t$ . Standard errors are two-way clustered by individual and by home-destination-month.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01.