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Bi-national Social Networks and Assimilation: A Test of the Importance of Transnationalism

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Abstract

While the concept of transnationalism has gained widespread popularity among scholars as a way to describe immigrants' long-term maintenance of cross-border ties to their origin communities, critics have argued that the overall proportion of immigrants who engage in transnational behavior is low and that, as a result, transnationalism has little sustained effect on the process of immigrant adaptation and assimilation. In this paper, we argue that a key shortcoming in the current empirical debate on transnationalism is the lack of data on the social networks that connect migrants to each other and to non-migrants in communities of origin. To address this shortcoming, our analysis uses unique bi-national data on the social network connecting an immigrant sending community in Guanajuato, Mexico, to two destination areas in the United States. We test for the effect of respondents' positions in cross-border networks on their migration intentions and attitudes towards the United States using data on the opinions of their peers, their participation in cross border and local communication networks, and their structural position in the network. The results indicate qualified empirical support for a network-based model of transnationalism; in the U.S. sample we find evidence of network clustering consistent with peer effects, while in the Mexican sample we find evidence of the importance of cross-border communication with friends.

Keywords

Transnationalism; Immigration; the adaptation and incorporation of Immigrants; Social Networks; Collecting data on immigration

Introduction

Recently, the concept of transnationalism has attracted considerable attention as a way to describe immigrants who maintain long-term social and psychological ties to their communities of origin. A search using the Social Science Citation index, for example, indicates a 489% increase in the number of published papers on transnationalism over the decade from 1999–2001 to 2009–2011 (Thomson Reuters 2012; also see Cano 2005). According to its proponents, the rising academic interest in transnationalism reflects fundamental changes in the process of immigrant adaptation and incorporation driven, at

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least partly, by dramatic changes in global telecommunication technology (Vertovec 2004a). According to a prominent review of the literature, the impact of transnationalism means that, for immigrants, "social life increasingly takes place across borders" (Levitt and Jaworsky 2007:129).

Despite—or perhaps because of—its recent popularity in the academic literature, there has been considerable debate regarding the significance of transnationalism for understanding current migration processes (Lucassen 2003; Guanizo, Portes and Haller 2003; Portes, Guarnizo, and Landolt 1999; Waldinger and Fitzgerald 2004; Waldinger 2008, 2010). On a theoretical level, a number of authors have argued that the definition of transnationalism is too ambiguous to describe the practices of migrants and needs to be clarified conceptually (Vertovec 2001; Guarnizo and Smith 1998; Boccagni 2011; Pries 2007; Guarnizo, Portes, and Haller 2003; Portes, Guanizo, and Landolt 1999; Lee 2008; Waldinger 2010; Waldinger and Fitzgerald 2004; Kyle 2001). Alejandro Portes, Luis E. Guarnizo and Patricia Landolt (1999:219), for example, argue that the definition of transnationalism in terms of the maintenance of social ties per se is too broad and that attention should focus on forms of social activity that "require regular and sustained [cross-border] contact over time". In addition, researchers have argued that the so-called transnational practices themselves are not new but simply a new way to describe things that happened just as frequently in past migration streams (Lucasssen 2003; Waldinger 2004; Alba and Nee 1997:145–6).

In addition to calls for greater conceptual clarity, a number of researchers have argued— based on the analysis of survey data—that immigrants' actual level of engagement in transnational activities is low, suggesting that transnationalism will have little impact on the way that immigrants adapt to life in receiving countries. For example, in a study of Albanian immigrants in Switzerland, Janine Dahinden (2005) argues that the immigrants in her sample are not "transmigrants" because only a small percentage maintained social contacts outside of Switzerland (also see Waldinger 2011:7). Similarly, using data from the 2002 Pew Hispanic Survey, Roger Waldinger (2008) looks at a number of different measures of transnational activity, and finds that although most Latino immigrants in the sample still identify with their home country, the majority have a stronger attachment to the U.S.: 65% plan on staying in the U.S. permanently, including almost 80% of Mexican immigrant respondents. Overall, a striking consensus from much of the recent empirical literature on the prevalence of cross-border transnational practices is that the overall prevalence of transnational activities is low (e.g., Boccagni 2012:2). Waldinger (2008:26) argues that that "few of the Latin American newcomers to the United States end up as 'transmigrants' ", and wonders "why the professional students of immigration refuse to see it this way."

In this paper, we contend that it is premature to conclude that transnationalism has only a limited impact on the process of immigrant incorporation. We argue that a central problem with the existing empirical research is that without data on the cross-border social networks that span both origin and destination communities--and the communication flows through those networks--it is difficult to truly measure the impact of transnationalism. We base our reconsideration of the empirical literature on the concept of a "transnational social field" (Levitt and Schiller 2004) which consists of the overlapping social networks of migrants that

span origin and destination communities, where possible influences on behavior, practices, and identity move in both directions and affect people who are connected to the network.

A key component to our reconsideration of the literature on transnationalism is the idea that social influence can affect change for members of a cross-border network even if they move infrequently across the border themselves. In other words, the cross-border flow of information and ideas through a transnational network may affect the identity and social practices of individuals in both sending and receiving communities—even if they have never migrated (for those in the origin community) or if they return home infrequently (for those in the destination community). Scholars talk about "social remittances" to describe how migrants export cultural influences back to their origin communities (Levitt 1998; Levitt and Lamba 2011). The idea of a social remittance—i.e., the diffusion of new cultural practices, opinions, and information—in a transnational network is analogous to the topic of peer influence and contagion effects in social networks more generally (e.g., Bramoulle 2008; Friedkin 1998, 2001).

In this paper, we use social network data from a bi-national survey (the 2010 Network Survey of Immigrant Transnationalism) linking an origin community in the state of Guanajuato, Mexico to migrants in two destination areas in the United States. We use this data to test for the effect of respondents' locations in the transnational network on their attitudes towards permanent migration, the relative effect of location on subjective well-being, and their opinion of U.S. culture. The survey consisted of 410 respondents in the origin city in Guanajuato and 197 migrants from the same origin city currently living in either the Research Triangle area of North Carolina or Houston, Texas. Respondents were asked a set of network questions concerning their friend and family ties within and between the origin and destination communities. For each network member, respondents were asked to list partial name information and basic demographic variables, which allowed us to reconstruct the underlying social network by identifying individuals who were nominated by other respondents (a similar approach was employed in Dombrowski et al. 2011). The resulting network consisted of 8,538 nominations and 5,086 uniquely identified network members. We use the data to estimate individual-level models of peer effects and cross-border communication on our outcome variables, and, in addition, to test network-level models of the clustering of respondents in the network, controlling for structural features of network formation. To the best of our knowledge, our study represents the first attempt to test a network-based model of immigrant transnationalism with data from both origin and destination communities.

Literature Review

A key focus in recent research on immigration in the United States has been whether post-1965 immigrant groups would experience the same process of assimilation that earlier waves of European immigrants are thought to have experienced in the past. While assimilation theory argues that immigrant groups gradually converge towards complete incorporation into U.S. society (Gordon 1964, Alba and Nee 1997), critics argue that the loss of middle-class blue collar jobs combined with a context of persistent racial discrimination results in multiple, nonlinear trajectories of assimilation, including downward

assimilation towards poverty for some non-white immigrant groups (Portes and Rumbaut 2001). An important twist in this debate on immigration is the idea that adapting to mainstream U.S. society while retaining aspects of one's cultural values, language, and homeland ties can promote upward mobility (Gibson 1988; Zhou and Bankston 1998; Portes and Rumbaut 2001; Portes and Zhou 1993). Proponents of this process of "accommodation without assimilation" suggest that successful migrants may selectively assimilate (Brown and Bean 2005) and that retaining a "bicultural" outlook—i.e., living between two worlds— may promote overall well-being for recent immigrants (e.g., Zhou and Bankston 1994; Feliciano 2001; Bacallao and Smokowski 2005). For instance, a considerable amount of research has focused on the so-called "Latino health paradox" where the acculturation of Latino immigrants in the United States appears to be negatively associated with certain health outcomes and behaviors such as diet, birth outcomes, and substance abuse (see Lara et al 2005 for a review).

An alternative perspective on the process of immigrant incorporation is offered by the recent literature on "transnationalism"—which may be loosely defined as the tendency of immigrants to maintain long-term ties and contacts with friends and family members in their origin community whether through visits, phone conversations, homeland politics, economic activities, or remittances. Although the intellectual history of the ideas behind transnationalism extends back to the early 20th century (Waldinger 2011), the term gained popularity through the work of ethnographic accounts of migrant communities in the 1990s (Glick-Schiller, Basch and Blanc 1995; Glick-Shiller et. al. 1992; Basch et. al. 1994). The concept of immigrant transnationalism is related to the literature on selective or bicultural assimilation described above (i.e., Zhou and Bankston 1998), where the long-term maintenance of certain origin-specific cultural traits is seen as increasingly frequent and desirable for certain groups, except that the unit of analysis now extends beyond the migrant's receiving country to include both the sending and receiving countries.

The basic idea of transnationalism is that migration streams, set in motion by global economic forces (Glick Schiller, Basch, and Blanc 1992), generate cross-border social ties between migrants and the societies they left behind—and that the ease of maintaining those ties is facilitated by modern telecommunication technologies (Vertovec 2004a) that make it easier to maintain communication by calling, texting, and emailing friends and family on the other side of an international border. According to proponents of transnationalism, the compression of space with modern technology combined with the resulting increase in the density and durability of cross-border ties makes it is possible for contemporary migrants to "live simultaneously" in both their origin and destination communities (Levitt and Schiller 2004). If the prevalence and durability of transnational ties is increasing among immigrant groups then it is conceivable that it might not only challenge conventional theories of assimilation (Faist 2000:218) but also result in fundamental transformations in national identity and the structure of the state (Vertovec 2004b; Landolt 2001) and the relationship between the migrant and the sending-state's government (Fitzgerald 2009).

On the other hand, despite the increasing popularity of transnationalism in the academic literature, a number of critical voices have emerged arguing that: (1) it is ambiguous and poorly defined, and (2) the overall prevalence of transnational practices is low, suggesting

that the real impact on host societies is limited. While there are now several useful reviews of the literature on transnationalism that discuss these issues in detail (e.g., Levitt and Jaworsky 2007; Waldinger 2010, 2011; Boccagni 2012), we briefly recap the outlines of this debate to provide motivation for our current study.

We begin by focusing on the criticism that transnationalism has not been clearly defined and is too abstract or ambiguous (Vertovec 2001; Guanizo and Smith 1998; Boccagni 2012; Pries 2007; Guarnizo, Portes, and Haller 2003; Portes, Guanizo, and Landolt1999; Lee 2008; Waldinger 2010, 2004). Luis E. Guarnizo and Michael P. Smith (1998) argue that the increasing ambiguity of the term means that it "risks becoming an empty vessel" and Portes, Guanizo, and Landolt (1999:219) argue that "if everything is called transnationalism, it means nothing" and call for a clearer, more precise definition. Richard Alba and Victor Nee (1997:6) call the term "somewhat faddish", while Ludger Pries (2007) claims that transnationalism risks becoming a "trendy catch-all like globalization", and Helen Lee (2008:14) argues that there is considerable conceptual confusion regarding what transnationalism means. Leo Lucassen (2003) and Roger Waldinger (2010:26) contend that what is called transnationalism is, in most cases, really just the maintenance of ties between two local communities, and they both argue that it should be referred to as "bi-localism" to emphasize the fact that it is not really referring to behavior at the national level.

Two definitions: Individual and Group Based

For the purposes of this paper, it is useful to differentiate between individual and group based definitions of transnationalism in order to help mitigate the concern about conceptual ambiguity and to highlight how our operationalization of transnationalism differs from the approach used in the majority of the existing literature. Waldinger (2011:3) draws a useful distinction between definitions of transnationalism that try to measure it at the individual level--by looking at which migrants are engaged in specific transnational practices (what Waldinger calls the "hard" definition of transnationalism)--and group-based definitions that attempt to describe the existence of a "transnational social space" at a level of aggregation larger than the individual.

Portes, Guarnizo, and Landolt (1999:219) provide a good example of the individual level definition, arguing that transnationalism should be defined as "occupations and activities that require regular and sustained social contacts over time across national borders." As an example of this approach, Portes (2003) measures transnationalism by enumerating participation in specific transnational activities such as transnational entrepreneurship, membership in an origin country political party, and membership in an origin town civic, charitable, or sports association. In contrast, the "group-based" definition of transnationalism looks at a higher level of aggregation than the individual to try to describe a transnational social space based on the cross-border connections and ties of multiple individuals and institutions. For example, Carmen Voigt-Graf (2004, 2005) utilizes a group-based analysis of transnationalism in a study of the cross-border connections among Punjabi, South Indian, and Indo-Fijian migrants that stretch across multiple countries. Thomas Faist (2000) provides a broad typology of several different types of transnational social spaces

based on kinship groups, circuits of trade and information, and communities or institutional organizations such as the Catholic Church.

Transnational Social Fields

In this paper we focus on a specific type of the group-based, transnational social spaces described by Faist (2000) by analyzing a transnational community that can be defined on the basis of a set of explicit interpersonal network connections. As mentioned above in the introduction, a useful network-based definition of a transnational community is provided by the idea of a transnational "social field" (e.g., Glick-Schiller, Basch, and Blanc 1992; Levitt and Schiler 2004; Dahinden 2009; Bourdieu 1985), which Peggy Levitt and Glick Schiller (2004) define as "a set of multiple interlocking networks through which ideas and practices are…exchanged." In the recent literature on transnationalism, the social field approach emphasizes the importance of incorporating the broader social world surrounding individual migrants in both origin and destination communities; Levitt and Schiller (2004:1009) describe the social field stretching from origin to destination as the "network of networks" that reveals the need for a level of analysis beyond the individual[1]. In the context of our study of immigrant transnationalism, a social field perspective highlights the importance of collecting bi-national data on the social networks of both migrants from the origin community living in the U.S. and their non-migrant friends and relatives back in Mexico. Moreover, as we argue below, an evaluation of the importance of the social field perspective involves not just collecting data on cross-border networks, but testing "how much" the network matters for understanding individual level outcomes.

Despite the increasing use of the social field terminology in the literature, a number of authors have expressed their dissatisfaction with the use of the term. Pries (2007), for example, claims that the definition of a transnational social field it is too imprecise to be useful. Guanizo and Smith (1998:28) argue that the term is misleading because it conflates social structure with its effect on outcomes, and Thomas Soehl and Roger Waldinger (2010:1491) claim that the term "leaves those [transnational] activities and the migrants who sustain them undifferentiated." This criticism is constructive, and we argue that in order to clarify what is meant by a transnational social field it is useful to think of it as consisting of two components: the structure of the field itself, composed of the intertwined social networks of the members of the transnational community, and what flows through or is expressed in the field—the ideas, cultural practices, social norms, and economic remittances. This is similar to the way that Levitt and Schiler (2004) differentiate between "ways of being" (the structure) and "ways of belonging" (signals of individual identity).[2] In our analysis, below, we distinguish between an individual's location in the transnational social field (based on our sample of social network data), and the impact that this has on their migration intentions and attitudes towards assimilation. This approach also provides insight

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[1]As noted by a reviewer, some in the literature use the terms "transnational social field" and "transnational social space" interchangeably. While we do use both in this paper, we make a weak distinction between transnational social space – encompassing all the activities associated with transnationalism – and transnational social field, consisting of explicit social network linking migrants to their origin communities.
[2]Heemskerk (2011) provides an empirical example of an attempt to measure a transnational social field using network data. Using network information on interlocking directorates from the European Union, he tests for the existence of a multi-national social field among the European corporate elite by analyzing the transnational connectedness of board membership overlaps.

on how social structure shapes practices at both the individual and group level within a transnational social field.

Empirical evidence on transnationalism

(a) The individual level definition of transnationalism—The distinction between individual and group-based definitions of transnationalism is useful because it helps us interpret the empirical evidence on the existence and prevalence of transnationalism. Because most empirical studies rely on survey data with no—or highly abstracted—network information, they end up testing a version of the individual-level definition of transnationalism. Soehl and Waldinger (2010) use data from the 2006 National Survey of Latinos to calculate three measures of cross-border activities: travel to the home country in the past year, sending remittances in the past year, and telephone communication in the past week. They define transmigrants as respondents who engaged in all three of these activities. Overall, only 10% of their sample of Latino immigrants was classified as transmigrants based on this definition, and, based on this estimate, they conclude that calling contemporary migrants "transnational" does not do a good job reflecting the reality of their cross-border ties (2010:1507). Waldinger (2008) takes a similar approach—looking at home country visits, remittances, political participation, long-term residence plans, and self-described identity—using data from the 2002 Pew Hispanic Survey and concludes that few Latino immigrants can be described as "transmigrants".

José Itziqsohn and Silvia G. Saucedo (2002) use an even stricter definition of transnational activities than Waldinger (2008), using data from the Comparative Immigrant Enterprise Project (CIEP) to measure the rate of giving money to hometown projects and participation in the following institutions: hometown associations, hometown festivities, local sports clubs, and charities linked to the hometown. They find that only 21.6% of their overall sample participates in even one of these activities on a regular basis (p.776). Guarnizo, Portes, and Haller (2003) use the CIEP to study cross-border political engagement and find that regular involvement in transnational political activities is small. Looking at samples of Columbian, Dominican, and Salvadoran immigrants, they find involvement levels ranging from 7–14% using six different indicators of political involvement such as membership in a home country political party and involvement in a home country charitable organization. They conclude that the "transnational political field is not as extensive or evenly distributed among contemporary immigrants as proposed by previous accounts" (2003:1238).

Overall, the accumulated evidence of studies that use individual-level survey information suggests rather low levels of participation in transnational practices. In a recent critical review of the literature, Paolo Boccagni (2012) argues that the question of its actual empirical prevalence and impact is in stark contrast to its increasing popularity in the academic literature: "…migrant transnationalism has gained increasing currency and salience. However what is left of its theoretical import, once established that transnational activities…aside from remittances, are relatively infrequent…?" (Boccagni 2012:2).

While Boccagni's evaluation of this empirical literature indicates an appropriate concern about the gap between theoretical popularity and empirical measurement, a potential problem with any application of the individual-based definition of transnationalism is

knowing how high to set the bar for determining who is, and who is not, a transmigrant. In some cases, the definition of transnationalism that is used may not match up with the realities of current migration patterns. For example, many recent Latino immigrants in the United States are undocumented and, as a result, they may find it difficult to travel back to their origin communities on a regular basis due to increased border enforcement. Thus, they would not be coded as transmigrants based on the definition used by Soehl and Waldinger (2011) which, as discussed above, only includes migrants who make yearly return visits to the country of origin, regardless of their level of communication with friends and family in the origin and their long-term migration intentions

(b) Social network data and influence models—In contrast to the individual-level analyses discussed above, using the "social fields" or "social spaces" definition of transnationalism leads to an attempt to measure transnationalism using network data. Dahinden (2009) uses egocentric network data on 250 individuals (including 152 immigrants) living in Switzerland to measure the proportion of cross-border social ties in respondent's networks, and shows how this measure varies across demographic groups clustered by nativity, time since immigration, and socio-economic status. Similarly, Dahinden (2005) uses egocentric data on Albanian immigrants in Switzerland and finds that only 9% of their social contacts lived outside of Switzerland, which suggests low levels of transnational engagement. In the Guarnizo, Portes, and Haller (2003) study discussed above, data on network size is used as an additional variable, but the network variable consists of a count of the number of personal ties that respondents could rely on for various needs (see Table B1, p.1241) and doesn't provide any information on cross-border ties. As a result, their analysis does not directly measure or estimate the effect of respondents' structural location within a transnational network.

Miranda J. Lubbers, José L. Molina and Christopher McCarty (2007) use extensive egocentric data – which they term the "personal network approach" because they ask egos to enumerate their perceptions of the relationships amongst their alters – on up to 45 network members for migrants in Spain to test the effect of network composition on respondents' ethnic identity (also see Lubbers et al. 2010, Brandes et al. 2010, and Maya-Jariego and Armitage (2007) for related work). Lubbers et. al. (2007) find that egocentric networks with high proportions of family members and/or individuals living in respondents' countries of origin were correlated with more ethnic-origin based self-classifications. In contrast, migrants with the largest proportions of Spanish citizens and migrants living in Spain were associated with increased prevalence of ethnically plural identifications.

Overall, an important distinction should be made between existing research that uses egocentric network data and the underlying transnational social network that connects migrants to friends and family members on both sides of the border. As noted by Linton Freeman (2004) and Prasad Balkundi and Martin Kilduff (2005) a key point of emphasis of the social networks literature is the essential difference between individuals' attributes and their structural positions in social networks. While studies such as Lubbers et al. (2007) provide important insights about the composition of migrants' networks, egocentric network data ultimately cannot map out the larger transnational networks that connect individuals together, and, as a result, cannot locate the position of respondents within those networks.

This is true for limited ego-centric designs where individuals only report their alters as well as for the more advanced collection techniques of Lubbers and colleagues (i.e., having egos report on perceived links amongst their alters) because those ties more than two steps from ego are not visible. Further, because they rely solely on individual data on immigrants in the destination country, these existing studies by Dahinden (2005, 2009) and Guarnizo, Portes, and Haller (2003) are limited to exploring only half of the transnational social field and cannot incorporate the potential influence that those in origin communities may have on transnational values and behavior.

One of the reasons that having information on respondents' structural position in the transnational network is important is provided by the idea of "social remittances" (Levitt 1998). As previously mentioned, social remittances can be used to describe how migrants transmit ideas and cultural practices back and forth in a transnational network (Levitt 1998; Levitt and Lamba 2011): The basic idea is that members of a transnational social network might be influenced by the information, ideas, and norms of other members of the network, even if they do not cross the border or directly engage in transnational activities themselves (i.e., cross-border entrepreneurship, political action etc.). While ethnographic studies have examined the impact transnationalism in both origin and destination (Bryceson and Vuorela 2003, Parreñas 2005, Dreby 2009, 2010), quantitative studies have typically been limited to half of the transnational social field, namely the destination communities where immigrants currently reside.

According to the social fields perspective, transnational networks "matter"—i.e., one's structural position and involvement in a transnational network affects outcomes through the transmission of ideas, norms, information, and influence through that network. In order to test how much transnational networks matter, we have to consider methodological questions about the causality of network effects that leads us to a broader empirical and methodological literature on peer influence models and contagion effects in social networks more generally (e.g., Bramoulle et al 2007; Friedkin 1998, 2001; Centola and Macy 2007). The key methodological issue here involves the difficulty of differentiating between the causal effect of peer influence and social contagion from the effect of social homophily, which is the tendency for similar people to become friends (McPherson, Smith-Lovin, and Cook 2001). Social homophily could result in positive correlations among friends' attitudes and behavior that mimicked what we would expect to find from peer effects even in the absence of a direct causal effect of peer influence. Charles Manski (1993), Lawrence E. Blume and Steven N. Durlauf (2005), Yann Bramoullé, Habiba Djebbari, and Bernard Fortin (2008), Cosma Shalizi and Andrew C. Thomas (2010) and Weihua An (2012) discuss the challenges involved in distinguishing between peer effects and social homophily.

Even with longitudinal data, the accurate estimation of peer effects has been a contentious issue in the academic literature (see, for example, Ethan Cohen-Cole and Jason M. Fletcher [2008] and Russell Lyons [2011]). In some cases, such as randomly assigned roommates in college dorm rooms (Sacerdote 2001), a natural experiment might exist that would allow us to disentangle peer effects from homophily, but in general caution must be exercised in interpreting the results of network models of peer effects or influence. Newer statistical

techniques are also under investigation but remain imprecise and underdeveloped (Shalizi and Thomas 2010).

Although we are not aware of any previous attempts to estimate peer influence models in transnational immigrant networks, a related empirical literature exists in demography, where peer influence models been widely used to study the impact of networks on respondents' fertility intentions and contraceptive use (Lindstrom and Munoz-Franco 2005; Avogo, Agadjanian and Casterline 2008; Behrman, Kohler, and Watkins 2002; Bernardi, Keim, and Lippe 2007; Sandberg 2005). Although the specific topics (fertility and contraception) may differ from the key issues surrounding recent research on immigrant transnationalism, the underlying methodological issues regarding attempts to test mechanisms of diffusion and social influence are very similar. David P. Lindstrom and Elisa Muñoz-Franco (2005) estimate diffusion effects on contraceptive use among women in Guatemala, using data on family- and community-level migration as proxies for the flow of (alternative) ideas about contraceptive use through migration networks. Similarly, Jere R. Behrman, Hans-Peter Kohler and Susan C. Watkins (2002) use longitudinal data from Kenya to estimate a peer effects model of contraceptive use. By using data on the 156 women who changed their contraceptive use between waves 1 and 3 of their data, they estimate a fixed-effects logit model of the effect of having at least one family planning user in the respondent's social network. Building on this literature, Laura Bernardi (2011) proposes a research design for a study of transnational families which would collect data on not only respondents themselves but a sample of the network members for each respondent to allow the estimation of a social influences model, using an empirical example of peer effects on fertility intentions in Germany.

In the analysis presented below, we use network data on three dependent variables measuring the level of incorporation and attachment to migrants' destination and origin communities to test models of network peer influence and homophily. We use several different measures of respondents' engagement in this transnational network as our key independent variables: (1) the values of the dependent variables of respondent's peers—as a measure of peer effects or clustering, (2) respondents' degree of local and cross-border communication in the network, and (3) the respondent's "betweenness centrality" as a measure of how centrally located they are in the network. We argue that if the flow of ideas, norms, and practices through transnational networks actually matters, then we should find positive effects of peers, communication flows, and betweenness centrality, even after controlling for standard measures of incorporation such as time in the U.S. and English language ability.

Although we will test for whether our results are consistent with the predictions of a model of transnational social fields, we emphasize that we see these results as a preliminary specification of a broader research agenda that would involve collecting longitudinal data on multiple cross-border networks. At the moment, with cross-sectional data from a single network, we do not claim to be able to distinguish between the causal effects of peers or social remittances and the non-random ways in which the network was formed—for example, due to the tendency for people to choose friends who are similar to them. As a result, we will attempt to identify a significant "clustering" of individuals with similar

outcome variables in the topography of the social network—keeping in mind that results that are consistent with peer effects could also be due to selection effects based on social homophily.

Data and Methods

Sample Design

The data for this paper come from the 2010 Network Survey of Immigration and Transnationalism (NSIT), which was a bi-national survey of the migration network connecting a medium size town in the state of Guanajuato, Mexico, with migrants (from that town) living in the Research Triangle area of North Carolina and Houston, Texas. North Carolina represents a relatively new destination for migrants from Mexico, with the first large cohort of migrants arriving in the early 1990s (Durand et al. 2005; Griffith 2005: 56; Kasarda and Johnson 2006). In contrast to North Carolina, Houston is an older, more traditional destination for migrants from this origin community. Overall, the survey had a sample size of 607 interviews, with 146 interviews in North Carolina, 51 in Houston, and 410 in the origin community in Guanajuato.[3]

In collecting the data, we used a link-tracing design, because, as depicted in Figure 1, we were attempting to collect data on a hard to find population in both the origin and destination communities. In general, rare populations are difficult to sample because lots of potential respondents must be contacted in order to obtain a sufficient sample size (cf. Kalton 2001).[4] Migrants in particular are challenging to locate but network approaches are an effective means of finding them (Rindfuss et al. 2007). In Figure 1, the origin community in Mexico (represented by circle "A") is in the upper left hand corner of the figure and the destination community in the U.S. (circle "B") is in the bottom right hand corner.

In order to conduct a survey of this transnational community, we wanted to sample migrants from "A" who live in "B" (the circle labeled "AB1"), and their friends and family back in A (the circle labeled "AB2"). The combined population of AB1 and AB2 consists of those individuals who are members of the transnational network connecting A to B. While a random household sample design would be preferable because of its attractive sampling properties, it is not a viable strategy to sample from our target population as defined in Figure 1. For a random household sample, the problem is that the target population represents a very small percentage of the overall population in both A and B. As a result, even with a set of preliminary questions to screen for members of the target population, many households would have to be contacted in order to obtain a sufficient sample size of members of AB1 (migrants from A) and AB2 (their friends and family back in B).

For example, based upon the results of our network survey discussed below, we estimate that members of our target population make up about 0.22% of the overall two-county

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[3]In general, when discussing the results below, we will combine the North Carolina and Houston results together as the "U.S. based sample" because the Houston sample size was too small to analyze separately. A goal of future research is to collect large enough samples from multiple destinations so that we can distinguish different effects across the different destination communities.
[4]In addition, Valentina Mazzucato (2009) provides a useful discussion the difficulties involved in collecting simultaneous network data in origin and destination communities.

population of our North Carolina study area, which would mean that we would have had to conduct approximately 64,444 screening interviews to obtain the 150 interviews that we conducted in North Carolina. In Houston, a large metropolitan area, the number of screening interviews necessary to obtain each respondent would have been even greater. Furthermore, such an approach would make it difficult to collect the structural network data of substantive interest given our theoretical framework.

Because random household sampling was not a viable method to obtain a sufficient sample size or the type of data needed to test our hypotheses, we elected to collect link-tracing samples in both the destination communities. As discussed at length in Martín Félix-Medina and Steven K. Thompson (2004), a link-tracing sample is a sample where referrals from current respondents are used to obtain the next wave of interviews. For the U.S. based data (in North Carolina and Houston) the survey began with a number of initial "seed" respondents that we had identified through previous field research (12 in North Carolina and 5 in Houston), and subsequent interviews were obtained by following the links (in the network data) from earlier respondents. Link-tracing and snowball sampling have been criticized as leading to biased samples (Erickson 1979; Rothenberg 1995; Heimer 2005), primarily because more popular members of a population will be more likely to be sampled precisely because more people will nominate them. However, recent developments in the mathematics of random walks on networks make it possible to conceptualize how to use a link-tracing sample to obtain a representative sample from a population (Lovasz 1993). If the population is connected through a social network, then a random walk on the network (by randomly selecting one link to follow from the current person to one of his or her friends), will eventually settle into a steady state distribution where the probability of being "interviewed" by the random walk is proportional to the number of friends that person has in the network (Handcock and Gile 2011; Lawler and Coyle 1999). For example, someone with 10 friends in the target population will be twice as likely to be sampled as someone with 5 friends.[5] The logic behind Google's original PageRank algorithm, for example, was based on approximating this result of the "steady state" probability of sampling a particular web page (Brin and Page 1998).

Recent innovations in link-tracing sampling from a network, such as Respondent Driven Sampling (RDS) make use of the relationship between the number of ties someone has and their (steady state) sampling probability in a random walk (Goel and Salganik 2009). In RDS, respondents are asked how many friends they have in the target population, and the inverse of this number is used as a sampling weight (cf. William W. Neely 2009 for a complete description of RDS estimation methods). Using these weights results in an unbiased sample from the population, provided respondents accurately estimate the number of friends they have and the sampling chain reaches the long-run "steady state" distribution. With our data, because we collect a detailed network roster for each respondent that allows us to reconstruct the underlying network of the population, we use the number of nominations that each respondent received from other respondents in the survey as a control variable for the popularity of each respondent in the network.[6]

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[5]This calculation assumes that the sampling is conducted with replacement.

While the U.S. based sample was conducted using a link-tracing sample design, the Mexican sample was obtained using a modified approach. First, we started with 20 randomly selected "seeds" chosen from the list of individuals in the origin community who were nominated by respondents in the U.S. sample. Then, starting with each seed respondent, we used an inverted "pyramid" approach as illustrated by the diagram in Figure 2 to sample from their network to a depth of 4 levels. The goal here was to find respondents who were not as closely linked to the original cross-border seeds, but to be inclusive of friend and family ties. As depicted in Figure 2, Level 1 is the seed. Level 2 consists of two interviews from the seed's friend contacts and two interviews from the seed's family contacts. Level 3 consists of 2 interviews with friends and family members of each of the Level 2 respondents (1 friend and 1 family member each), and Level 4 consisted of 1 (randomly chosen) friend or family member from each of the Level 3 respondents. For all the interviews, the decision of which friend or family member to interview was based on a random selection from the current respondent's friend or family network roster. The reason we opted to use this "pyramid" approach was to interview individuals with different levels of connection to the destination communities in the U.S. and to branch out to members across the Mexican based sample.

Collecting Network Data

As part of our questionnaire, we asked for detailed network rosters of the friends and family members of each respondent. In order to protect the privacy of respondents, we collected data on only the first four letters of both the first name and last name of the respondent's network members, along with key social and demographic information that we could use for identification: nickname, gender, age, occupation, and the number of children living in the household. In order to identify unique individuals in the resulting network data, we wrote a matching program in Stata that allows for a range of error in the demographic and name variables in determining whether two network nominations from different interviews represent the same person. We used the Levenshtein edit distance (the number of edits needed to match two strings, cf. Julian Reif [2010]) to allow for reporting and coding errors in the first name, last name, and nickname.

The U.S. survey asked for up to 10 friends and 6 family members currently living in the same destination community in the U.S. (North Carolina or Houston), 6 total family and friends currently living in the origin city in Mexico, and up to 5 returned migrants currently living in the origin. In the Mexican sample, we asked for data on 6 friends and 6 relatives currently living in Guanajuato, and up to 6 friends or family members living in each of the two destination locations (North Carolina and Houston). The reason the maximum number of same-location friends was higher in the U.S. than in Mexico was due to the design of the sample: in the U.S. we were using a link-tracing sample and wanted as many alters (contacts) as possible. Overall, given concerns about interviewer and respondent fatigue due to the extensive information that we collected about each alter, we did not feel that it was practical to press the respondents for an unlimited number of contacts.

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[6] see Winship and Radbill (1994) for a discussion on the benefits of un-weighted data in regressions where the weights are a function of independent variables in the analysis.

The resulting data demonstrates that the survey was successful at eliciting responses to the network questions. The 607 respondents who were interviewed listed an average of 14.06 friends and relatives on their network rosters. The final network consists of 8,538 nominations, which were matched to 5,086 unique individuals in the following locations: 964 in North Carolina, 3,516 in Guanajuato, and 606 in Houston. Figure 3 shows the resulting network of this bi-national immigrant community. Blue nodes are individuals located in North Carolina, red nodes are located in Guanajuato, Mexico, and green nodes are located in Houston, Texas. A key descriptive finding in Figure 3 is the interconnectedness of the network: there are substantial ties and overlap between the communities on different sides of the border, which would not be the case if the communities were disconnected with only a few cross-border connections.

Methods

In addition to providing an example of the collection of cross-border network data, the goal of this paper is to show how that data can be used to provide a test of the social fields perspective on transnationalism. In order to test how much these networks "matter" we use three different types of models in our analysis below that exploit the network data from our bi-national survey: (1) individual-level probit models that use the average response among the respondent's contacts as the key explanatory variable, (2) network autoregressive probit models (NAP) that incorporate additional dependencies in the network based on the degree of separation between respondents, and (3) exponential random graph (ERGM) models that jointly model the structural features of the networks and individual clustering based on covariates. James O'Malley and Peter V. Marsden (2008) provide an integrative discussion of the use of all three of these models to study contagion effects and clustering with network data. These three models are progressively more sophisticated in the way that they incorporate the network data into the analysis; while the individual level model will be the most transparent and familiar to readers, we believe, as discussed below, that the NAP and ERGM models more fully exploit the advantages of having network data vis-à-vis conventional survey data with no network ties.

The individual level models are used to estimate peer-effects models controlling for basic demographic characteristics and standard measures of immigrant incorporation (time since immigration and English language ability). These models use a "linear-in-means" approach to estimate peer effects (An 2011), keeping in mind the cautionary note above (on p.17) that in these models we do not distinguish between the causal effect of peer influence and homophily based clustering. The probit model with a linear-in-means specification for peer effects is depicted in Equation 1:

$$p(y_i=1)=\Phi\left(\alpha\overline{y}_{-i}+\beta x_i+\varepsilon_i\right) \quad (1)$$

where Φ is the cumulative density function of the normal distribution, y_i is a dichotomous dependent variable for individual i, and α and β are coefficient vectors. In addition, $\overline{y}_{-i}$ indicates average value of y for i's contacts in the network, x_i indicates a set of individual-level explanatory variables, and ε_i is an error term.

While the linear in means specification is widespread in the peer effects literature, it is possible that the $\bar{y}_{-i}$ term in Equation 1 does not capture all of the network-related dependencies in the data. Roger Leenders (2002), Keith Ord (1975) and Patrick Dorien (1989) discuss modeling the interdependencies among outcomes in a network using an autocorrelation approach similar to spatial regression models (e.g., LeSage and Pace 2009), where the correlation in outcomes between cases is considered to be a function of the distance between them. In this analysis, we construct a weights matrix W based on the inverse of the geodesic distance (the shortest path) between respondents using the full cross-border network depicted in Figure 3.[7] We estimate a "network autoregressive" model (Leenders 2002; O'Malley and Marsden 2008; Fujimoto, Chou, and Valente 2011) that extends the individual level model in Equation 1 by including the possibility of additional network-related dependencies in the data:

$$p(y_i=1)=\Phi\left(\alpha\bar{y}_{-i}+\rho Wy+\beta x_i+\varepsilon_i\right) \quad (2)$$

where W is the network weights matrix, and the parameter ρ tests for the existence of clustering or peer effects based on the inverse distance between respondents in the network, above and beyond the effect of the respondent's immediate circle of contacts which is already included in the $\bar{y}_{-i}$ term. In general, the estimation of a network or spatial autocorrelation model is more complicated with dichotomous or categorical dependent variables because we are modeling dependencies in the underlying latent variable not the observed variable (e.g., Bille and Arbia 2013), as depicted by the terms inside the parentheses on the right hand side of Equation 2. We estimate this model using the Spatial Probit package in R (Wilhelm and Godinho de Matos 2013).[8]

While both the individual-level and network autoregressive models described in Equations 1 and 2 provide intuitive tests of peer-effects, they are simplifications of the true social processes at work because they assume that the network structure is fixed. In other words, the network autocorrelation models described by Leenders (2002) have a direct analogy with spatial autocorrelation models because they treat the relational nature of the data as static—i.e., the existence (or not) of ties between individuals in a network is treated as if it were fixed in the same way that the spatial distance between geographic units is. In reality, of course, individuals can choose who they want to be friends with, and the observed network is the result of a dynamic process of friendship formation—which could lead to misleading results with either a linear-in-means or a network autoregressive model (Hsieh and Lee 2011). In order to account for this type of dependency in the data, we also estimate ERGM models, which are a recent development in the statistics literature that allow for endogenous structural dependencies in the network data (Hunter, Handcock, Butts, Goodreau, and Morris 2008; Snijders, Pattison, and Robins 2006).

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[7]W is row normalized to that the sum of each row is equal to 1. If d_{ij} If is the geodesic distance between respondent i and j, then the value of the i,j cell of the weights matrix W is $W[i,j]=\dfrac{1}{d_{ij}}\cdot\left(\sum_i\dfrac{1}{d_{ij}}\right)^{-1}$

[8]An example of an autoregressive probit model, albeit in the context of a spatial analysis, is given in Lesage (2011).

In contrast to the individual level and network autoregressive models which use individuals as cases, the ERGM models treat the entire observed network as the unit of analysis and the observed ties between individuals as the result of a process of network formation. In an ERGM model, the dependent variable is whether or not there is a tie between each possible pair of respondents. If there are strong peer or diffusion effects on any of our dependent variables, then we would to find that individuals with similar levels of those variables are more likely to be friends. What is compelling about the ERGM approach is that it allows for network effects beyond simple peer-alter interactions. For example, the notion of "triad closure" is based on the idea that two individuals are more likely to be friends if they have mutual friends in common (Hunter 2007, Goodreau, Morris, and Kitts 2008). These higher-order network processes may have substantial effects on the shape and structure of observed networks, and hence they would be important in trying to understand variation in transnational networks either over time or across different origin-destination communities.

While a full description of the estimation of random graph models is beyond the scope of this paper, we note that the basic idea is that the model uses a "Markov Chain Monte Carlo" approach that iterates back and forth between parameter estimation and simulations of networks based on those parameters, stopping only when the simulated networks resulting from the parameters of the model are a good fit for the observed network data. We estimate a basic model of network structure that allows for triad closure. We find that a simple measure of triad closure where the effect of mutual friends exhibits diminishing returns to scale provides a very good fit for the observed U.S. and Mexican based networks. This measure, the geometrically weighted edgewise partner distribution (GWESP), has been found to be effective at preventing the simulated networks from degenerating into networks with far too many friendship ties compared to the observed data across many networks (e.g., Goodreau, Morris, and Kitts 2008). We estimate these models using the ERGM package available in R (Handcock, Hunter, Butts, Goodreau, Morris, and Krivitsky 2010).

The ERGM models that we use in this paper estimate the "assortative mixing" among respondents based on observed characteristics, controlling for the structural features of the networks. As such, they treat the covariates (such as the desire for permanent residence in the United States) as fixed. A better approach for future research would be to combine the strengths of the individual level and network level approaches together to estimate models of individual level outcomes accounting for the dependent nature of the network data as well as the role of individual level variables.[9]

Results

Descriptive Analysis

Table 1 shows the distribution of network ties in the data by ego and alter location.[10] The respondent's ("ego") location is in the columns, and the contact's ("alter") location is in the

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[9]A recent working paper by Fellows and Handcock (2012) does this, jointly modeling individual and network variables, but the software needed to replicate their findings is still in development and not yet publically available. As a result, we view this as a subject of future research.

[10]In the context of our discussion of the network data, "ego" refers to the respondent and "alter" is a person who the respondent nominated on his or her network roster. All egos were interviewed, but only a subset of alters were.

rows. Of the 2,760 nominations from respondents in North Carolina, for example, 1,559 (56%) were to alters in North Carolina, and 1,201 (44%) were to alters in Guanajuato. Table 2 shows the relationship between egos and alters in the data. Overall, 53.5% of the network ties that we recorded were between friends, and the remaining ties were between non co-resident family members. The largest category of family ties, brothers and sisters, represented 12.3% of the network ties.

For each friend or family member in the respondent's network, the survey asked how frequently they talked to that person. Table 3 shows the distribution of communication frequency by friend or family ties and the respondent's location. For example, the first row of Table 3 shows the communication among U.S. respondents and their friends living in the U.S. Looking across the row, we see that 20.5% communicate with their friend daily, and 35.6% communicated weekly. Similarly, Row 3 shows that with respect to cross-border U.S. to Mexico ties, communication among friends is much less frequent, with only 3.4% communicating daily, and 48.3% communicating less than yearly. In general, comparing local to cross-border communication between the U.S. and Mexico, we see that cross-border communication with both friends and family occurs more infrequently. Nonetheless, about 35% of cross-border family ties had daily or weekly communication (compared to about 6–7% of cross-border friendship ties).

In the analysis below, we use the network data on communication frequency as a measure of the respondent's location in the transnational social field. As a measure of the volume of communication that the respondent is involved in across each of the dimensions (cross-border/local and friend/family) from Table 3, we calculate the "communication flow" as the log sum of the communication frequency with each network member by type:

$$\text{communication flow}_c = \ln \sum_c f_c \quad \text{(Equation 3)}$$

Where c indicates the type of connection (i.e., cross-border family communication) and f_c indicates the frequency of communication (1 to 5, see Table 3) with the network alter. We note that this is not a perfect measure of communication flows since it only indicates communication in one direction, but it is one that tries to strike a balance between the number of alters of each type and the intensity of communication with each.

Tables 4–6 show the key dependent variables in this paper. The variables were chosen as measures of an underlying process of assimilation or incorporation that could meaningfully be asked of respondents on both sides of the border. Table 4 shows the respondent's desire for permanent residence; respondents were asked whether they would live permanently in the U.S. if they had all the necessary documents. Fifty-seven percent of respondents in the U.S. and 14.3% of the Mexican sample said that they would reside in the U.S. if they could. Table 5 shows the results for a similar question, which is where the respondent thinks he or she would be the happiest given the choice of the U.S., Mexico, or both equally. In the U.S. sample, 29.9% believed they would be happiest in the U.S. and 44.85 % answered "Mexico", while in the Mexican sample only 4.68% thought they would be happiest in the U.S. and 88.92% answered "Mexico". What is interesting about Tables 4 and 5 is the

evidence that only a minority of respondents in the origin community—which is a high migration sending city in the state of Guanajuato, Mexico—said that they would like to live in the U.S. or thought that they would be happier living in the U.S. In the statistical analysis below we seek to understand variation in respondents' answers to these questions as a function of their position in the social network connecting respondents in the sample together.

Table 6 asks a general question about the respondent's opinion of U.S. culture, with answers ranging from 1 "I don't like it" to 5 "I like it a lot". For U.S. respondents, the modal response was "3" (48.19%), while for Mexican respondents, 46.4% said that they did not like U.S. culture (category 1). Only 12% of respondents in the U.S., and 7.9% of those in Mexico, said that, in general, they liked U.S. culture. In the analysis below, we will use this variable as an additional dependent variable in analyses of the effect of transnationalism.

Tables 7 and 8 show the results of assimilation related questions that were only asked of the U.S. based sample. Table 7 shows the response to a question that asked "how much do you want to adapt to the society, culture, and lifestyle of the U.S.?", ranging from 1 "only what is necessary" (30.6% of the sample) to 5 "I want to adapt completely" (22.8% of the sample). The results indicate a broad distribution of opinion on this question, with only a minority of respondents expressing a desire to completely adapt to life in the United States. Finally, Table 8 shows the respondents' degree of self-identification as "Mexican" (for U.S. based respondents only). As a measure of the strong identification with their country of origin among this sample of first-generation immigrant, 77.6% said that they identified as "100%" Mexican.

Multivariate Analysis

In the analysis presented below we present the results separately for the U.S. and Mexican samples, in order to allow the effects to vary by location. First, Table 9 shows the explanatory variables used in the analysis. Measures of peers' response variables are calculated as the average level of our three dependent variables across the respondent's contacts in the network (Rows 1–3 of Table 9). For the purposes of calculating these variables, we use anyone who nominated—or was nominated by—the respondent. Because only 607 of the 5,086 unique individuals identified in the data were actually interviewed, these variables are based on a sample of the respondent's network. The network roster count variables (Rows 16–18 of Table 9) show the average size of these sampled network members. For example, in Row 16, the average number of other respondents who nominated the respondent was 3.06 in the U.S. sample and 2.24 in Mexico. The sum of Row 16 and Row 17 gives the average number of other respondents who either nominated or were nominated by the focal respondent and were used, as a result, to construct the contact average variables (Rows 1–3).

As measures of the respondent's participation in communication networks, we use the cross-border and local communication flow variables (Rows 4–7 of Table 9) calculated as the log of the sum of the communication frequency variables for each type of social tie (cross border/local and family/friend), as defined by Equation 3 above. In addition to these communication variables, we also measure the respondent's position in the transnational

network as their "betweenness centrality" (Freeman 1977), calculated here based on the proportion of shortest paths between nodes in the network that pass through the respondent (see Row 20 of Table 9.). In calculating the betweenness centrality we used a subsample of the cross-border network depicted in Figure 3 consisting of all 607 sampled nodes.[11] In the U.S. sample, we also include a variable indicating whether or not the respondent sent monetary remittances back to Mexico in the past 30 days (Row 14), and whether he or she has visited Mexico in the past 4 years.[12]

For respondents in the U.S., we include the number of years the respondent has lived in the U.S (Row 5). In our statistical models presented below, we use the log number of years in the U.S. (Row 6) to allow for diminishing effects over time. In the analysis for the Mexican sample, we use a dummy variable indicating whether or not the respondent has lived in the U.S. (i.e., the 70 returned migrants in the data).[13] Education level is measured as a dichotomous variable indicating whether the respondent had a high school education or higher (Row 9), and we control for age (Row 13) and age squared. While Table 9 shows the counts and means of the raw non-imputed data, we use multiple imputations to impute any variable in Table 9 that is missing, using 10 imputations with the ICE procedure in Stata 12 (Royston 2005)[14].

In Tables 10 and 11 we estimate separate models for the U.S. and Mexican samples, which allows us to separate the effects of the key independent variables by location. In addition, we note that the sample size for each location is small—197 in the U.S. and 410 in Mexico— and the data is based on a sample of a single transnational network, so we should proceed with caution in interpreting the results. In both Tables 10 and 11, we show the regression results for our three dependent variables for the individual level probit (panel A of each table) and network autoregressive probit ("NAP") models (panel B). Model 1 estimates a probit model of the desire for permanent residence in the U.S. (see Table 4 above), Model 2 is a probit model of the respondent's opinion of U.S. culture (see Table 6), and Model 3 presents a model for a dichotomous variable indicating whether the respondent thought he/she would be happier living in Mexico compared to the United States (see Table 5 above),.[15] In all the models, we use the average value of the dependent variable among the respondent's social contacts as a key explanatory variable. These "contacts' average" variables are intended to provide a measure of the flow of information or influence which could induce a correlation between respondents who are connected in the transnational network. As discussed above, we note that a positive correlation between peer and respondent dependent variables could be the result of social homophily—the tendency of

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[11]See Handcock and Gile 2010 for a discussion of analysis using sampled networks.

[12]Respondents who migrated in the past four years are coded as zero for this variable (their recent migration will be reflected in their lower number of years in the U.S.), unless they reported a recent visit since their migration.

[13]Using a dichotomous variable for returned migrants was easier to interpret than a continuous variable for the length of time Mexican based respondents had lived in the U.S. (however, these results are available from the author by request).

[14]In the results presented in Tables 10 and 11 with the multiply imputed data, the standard errors are corrected for the use of the multiply imputed data using Rubin's rules (Rubin 1987). The coefficient estimates are the mean of the coefficients across the 10 imputations.

[15]We use a dichotomous version the variable about opinion of U.S. culture by collapsing the 5-point answer into two categories (combining 1 and 2 into "1" and 3–5 into "0"). An ordinal probit would be the preferred model, but the spatial autoregressive probit package that we use does not have an option for ordinal variables. Results for a standard ordinal probit using the specification in Equation 1 are available upon request and do not change the interpretations of the results.

similar people to choose to become friends with each other—rather than the causal effect of peer influence or information sharing. In the future, we would like to collect longitudinal data on these transnational network ties, which would permit a richer model of friend selection versus peer influence (e.g., Kandel 1978; Snijders et al. 2010).

In the U.S. sample in Table 10, all three models show a significant correlation between the contacts' average of the dependent variable and the respondent's response in both the individual-level and network approaches, which is consistent with a social influence model of the role of cross-border networks. In contrast, in the Mexican sample in Table 11, these same peer effects variables are not statistically significant in any of the three models at the p=0.05 level of significance.

In comparing the results for Panels A and B of both Tables 10 and 11, we find no substantive difference between the individual level models (Panel A) and the network autoregressive models (Panel B) in any of the key variables in Tables 10 and 11, and the estimate of ρ ("Rho") does not suggest any significant dependencies in the network based on the inverse geodesic distance matrix W discussed above.

In addition to testing for peer influence, we also include the measure of communication flows and betweenness centrality. Of the four variables for communication flows in the transnational network, only cross-border communication with friends turns out to be statistically significant (at the p=.05 level)—in Model 1 in the U.S. sample, and Models 1 and 3 in the Mexican sample. In these three cases, the direction of the coefficient indicates that cross-border friend communication is consistent with a "transnational" effect: For example, in the Mexican sample in Table 11, the level of cross-border friend communication increases the probability that the respondent desires to live permanently in the U.S. in Model 1, and decreases the probability that the respondent is happier living in Mexico in Model 3. Similarly, in the U.S. sample in Table 10, cross-border communication with friends decreases the probability that a respondent would report a desire to remain in the U.S.

The variable measuring respondent's position in the network, betweenness centrality, is not statistically significant (at the p=.05 level) in any of the models. Because the centrality measure was calculated with the combined cross-border network of sampled nodes, it identifies individuals who are located in the center of the sampled network.[16] The general lack of significance for this variable suggests that it is not centrality per se that matters, but something related to the valence of those around you on key variables—i.e. the clustering of peers in certain parts of the network—and/or participation in the network (the communication with friends variable).

Next, in the U.S. sample in Table 10, we do not find an effect of sending remittances or recent visits back to the origin community on any of the three dependent variables. While both of these variables are, arguably, important indicators of transnationalism in their own right, they do not seem to be correlated with migration intentions and opinions of U.S. culture.

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[16]The inclusion or exclusion of the number of nominations in the survey does not affect the significance of the betweenness centrality measure (results available upon request).

As a counterargument to the "transnationalism" variables measured by network peer effects and cross-border communication rates, we also include variables consistent with the assimilation perspective—migration experience in the U.S. and English ability. In Table 10, cumulative years in the U.S. has no effect in any of the models, while English ability has an effect in Model 3—respondents who speak English poorly are more likely to report that they would be happier living in Mexico—which is consistent with an assimilation-based interpretation.[17] In contrast, in the Mexican sample in Table 11, we find a strong and consistent effect on the variable for return migrants: compared to non-migrants, return migrants are more likely to desire permanent residence in the U.S., less likely to say they are happier living in Mexico, and they have a more positive opinion of U.S. culture. This suggests a twist on the conventional story about assimilation: return migrants living in Mexico have higher rates of "incorporation" in U.S. society—at least as measured by these dependent variables. As a result, it might be reasonable to consider these returned migrants as "transmigrants" themselves—in the sense that they may be keeping up with things in the destination community and, at least to some degree, imagining a potential return to the other side of the border.

So far, Tables 10 and 11 have tested models that treat the ties in the network as fixed or exogenous, which is a simplification since individuals choose who they want to become friends with. In order to test a model of similarity between respondents that controls for the underlying processes of network formation, Table 12 presents Exponential Random Graph Models (ERGM) of the correlation of the dependent variables among respondents who nominated each other in the network. As discussed above in the methods section, the benefit of the ERGM models is that they model the formation of ties in the network as an endogenous process, which allows us to incorporate the dependent nature of the ties between respondents directly into the model. As mentioned above, Goodreau, Morris, and Kitts (2008) provide a valuable discussion of use of ERGM models to analyze friendship homophily in social networks. We estimate ERGM models of the network of sampled respondents, analyzing the data separately by location similar to the analysis in Tables 10 and 11. Both samples include cross border nominations, but the respondents themselves are located in either the U.S. or Mexico. In general, the parameters can be interpreted in terms of a standard logit model predicting the probability of a connection between any pair of respondents. First, the variable measuring triad closure, GWESP, is a significant predictor of a connection between nodes in both samples. Although we estimated additional models that included other measures of network structure, we found that the GWESP variable along with the intercept fits the structure of the network very well, consistent with the results in Goodreau, J Kitts and Morris (2008) for different data.

In addition to the triad closure variable, the intercept is a measure of the overall density of the network, and the other "sociality" coefficients indicate the effect of covariates on number of ties; for example, the sociality coefficient on female is −0.039 in the U.S. sample, which indicates that women have (slightly) fewer connections in the data than men.

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[17]The collective effect of the English language variable in Model 3 of Table 10 is not significant, despite the fact that one of the indicator variables ("Good") is.

For our purposes, the key variables are the "selective mixing" variables, which measure the correlation in these variables among connected members of the network. There is a high level of gender homophily, for instance, in the data, as the coefficient is significant at the p=.001 level for both the U.S. and Mexican samples. In the U.S. sample (but not in the Mexican sample), we find a significant degree of selective mixing between respondents on the basis of the three dependent variables from Table 10 (desire for permanent residence, happier living in Mexico, and opinion of U.S. culture). The negative coefficient on opinion of U.S. culture reflects the fact that this variable is measured as the absolute value of the difference in this variable (which goes from 1–5) between pairs of respondents—hence agreement in this variable is a positive predictor of a connection between them. Again, similar to the discussion above in Table 10, the significant effects of these three variables are consistent with both peer effects and social homophily. Even though we are modeling the dependent nature of the network data using the ERGM models, any attempt to truly disentangle peer effects from homophily will require some combination of longitudinal network data and/or a "natural experiment" that could plausibly identify exogenously formed friendship ties. Nonetheless, the results presented here indicate the benefit of applying network-level statistical models to analyze the interrelations and connections between members of transnational communities.

Finally, because the results are presented in three different tables, we present one additional table that summarizes the key findings. A "+" sign indicates a result consistent with the transnational or assimilation perspectives for at least two of the three dependent variables, and a "~" indicates a significant result for one of the three.

As discussed above, we believe one set of findings are the significant results for peer effects/ homophily in the U.S. sample, indicated by the "+" sign in Rows 1–2 of Table 12. We argue that these results are consistent with a social influence model of how the respondent's location in the network affects their answer to these questions. Similar to the literature in demography discussed above on peer effects and cultural diffusion with respect to fertility desires and contraceptive use, the underlying logic is that the flow of information and ideas through these networks will affect individual behavior and opinions. At the same time, we do not find similar evidence of peer effects in the Mexican sample. Based on the analysis of a single transnational network, we cannot say whether this is a finding that would hold in origin communities in general, or whether it is a feature of this particular network.[18] Similarly, we believe it is possible that the results here could vary across different origin-destination communities and that this could be the subject of future research.

In contrast to the results for peer effects, we do find evidence of significant effects of communication with cross-border friends in the Mexican sample (row 3 in Table 12), as well as large effects for returned migrants. Overall, taking the complexity of the findings in Tables 10–12 into account, we interpret the combined results as indicating qualified support for a transnational perspective on these measures; while not all of the key independent variables have significant effects across all the models and samples, there is partial evidence

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[18]As an example of empirical evidence of variation in transnational migration, David Kyle (2001) finds important differences in migration patterns to New York City in an ethnographic study of four sending communities in Ecuador.

of peer and/or homophily effects in the U.S. and the role of cross-border friend communication in Mexico.

Discussion and Conclusion

In this paper, we argue that the current debate on transnationalism and assimilation is incomplete because of the absence of data on the actual social networks that connect individuals in transnational social fields. We use data from the 2010 Network Survey of Immigrant Transnationalism (NSIT) which is a network survey of immigrants from Mexico in North Carolina and Houston, and their friends and family members back home in the origin community in the state of Guanajuato, Mexico. In our analysis in Tables 10–12, we use three dependent variables to measure migration related behavior and attitudes: the desire for permanent residence in the U.S., opinion of U.S. culture, and a question on where (the U.S. or Mexico) the respondent thought he or she would be happiest. As summarized above in Table 13, we find qualified support for our measures of transnationalism: we find evidence consistent with of the existence of peer effects in all three dependent variables in the U.S., and we find evidence of communication flow effects in Mexico.

In contrast to the results we have presented here, most survey evidence in the transnational/ assimilation debate consists of randomly collected respondents without information on their embeddedness in cross-border networks. This is surely not due to a theoretical omission in the literature, as a discussion of the role of social networks and cross-border connections figures centrally in the literature on transnationalism (e.g., Levitt and Schiller 2004), but rather the methodological difficulty of collecting bi-national network data with a hidden population such as a migrant social network. While the advantages of using large-scale surveys are obvious in terms of sample size, they provide only indirect information on the network of ties that connect respondents across borders and allow them to live simultaneously—at least at some level—in two places.

In sum, this paper demonstrates the advantages of collecting network data on individuals in both origin and destination communities. While collecting binational network data increases the cost and effort involved in conducting a survey, we argue that it provides a better test of the prevalence and impact of transnationalism, which, on a theoretical level, results in effects that flow in both directions across international borders. We believe that this same type of survey could be conducted on other immigrant groups, and it would be interesting to map out the cross border networks in situations that are different than the U.S.–Mexico migration streams, where the levels of migration are particularly high and the context of incorporation may be significantly different than that experienced by other groups. In the future, we plan to extend this research by incorporating a broader range of destination communities and by collecting longitudinal data, which would allow us to analyze how these networks change over time and would enable us to estimate more sophisticated models of the effect of changes in network structure on the peer relationships and communication flows. While collecting and analyzing transnational network data presents methodological challenges, we believe it is a promising avenue for future research because it increases the sociological realism of empirical models by incorporating the connections and ties between individuals and communities both within and across international borders.

Acknowledgments

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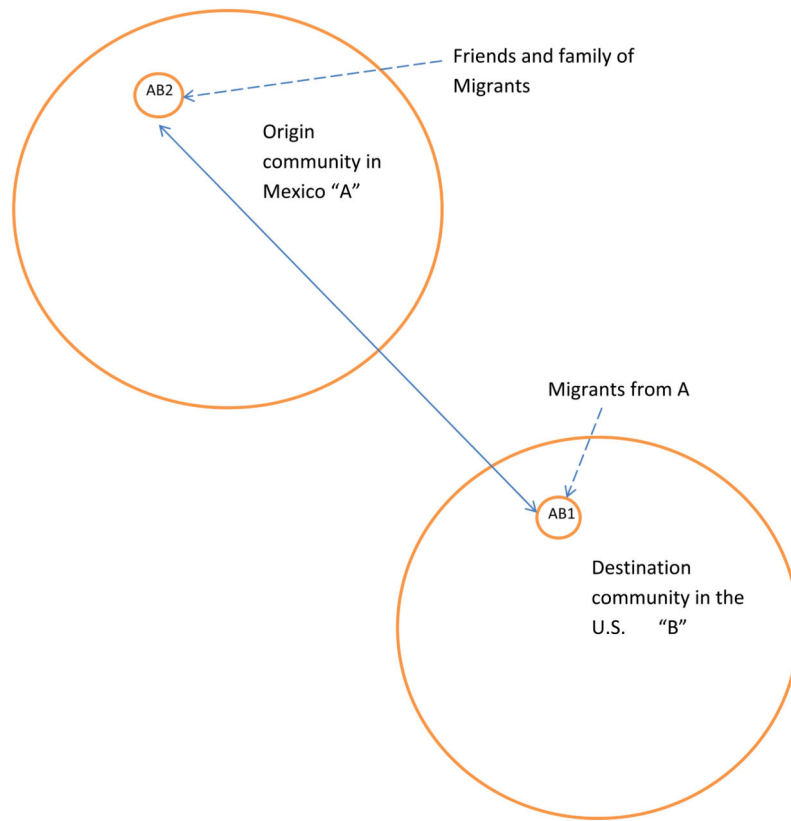
Figure 1.
Sampling migrant networks—the "needle in a haystack" problem

Friendship Branch   Level1 | Mexico Seed | *Family Branch*

Level 2   FR   FR   FA   FA

Level 3   FR   FA   FR   FA   FR   FA   FR   FA

Level 4   R   R   R   R   R   R   R   R
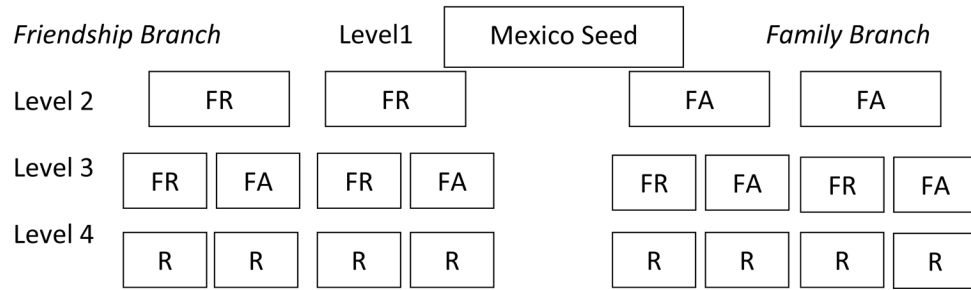
FR=friend tie

FA=family tie

R= random (50% friend, 50% family)

Figure 2.
Selection of Friend and Family Network Members in Mexico
FR=friend tie
FA=family tie
R= random (50% friend, 50% family)
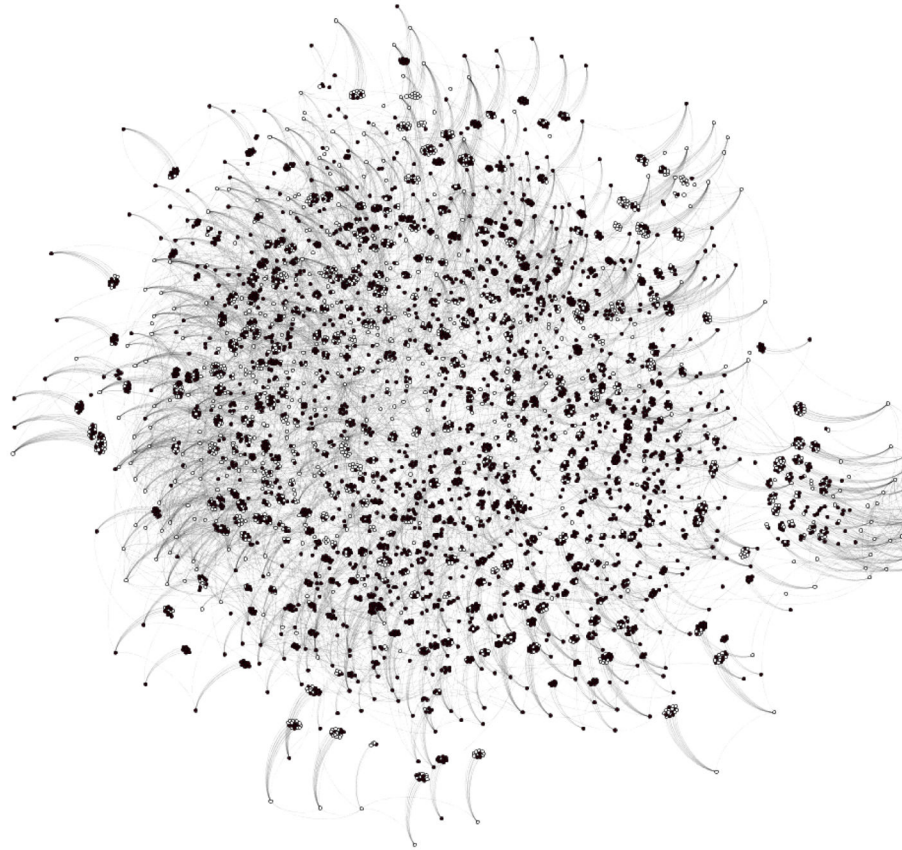
Figure 3.
The binational network of sampled and nominated individuals in the 2010 Network Survey
of Immigrant Transnationalism.
Notes: White nodes are located in the United States (North Carolina or Houston), black
nodes are located in Mexico.

Table 1

Location of Networks Ties

	Ego (Respondent) location			
	North Carolina	**Houston**	**Guanajuato**	**Total**
Alter location				
North Carolina	1,559		698	2,257
Houston		528	383	5,370
Guanajuato	1,201	291	3,878	911
Total	2,760	819	4,959	8,538

Table 2

Relationship between Ego and Alter in the network data

	Freq.	Percent
Friend	4,569	53.51
Spouse	34	0.4
Child	193	2.26
Brother/sister	1,050	12.3
Parent	213	2.49
grandson/daugher	23	0.27
Mother/father in law	32	0.37
Cousin	817	9.57
Uncle/aunt	631	7.39
Other relative	976	11.43
Total	8,538	100

Table 3

Communication Frequency in a Transnational Community.

Row #		1. Less than yearly	2. yearly	3. monthly	4. weekly	5. daily	Totals	(N)
	A. Friend ties							
	Local							
1	U.S→U.S.	0.085	0.062	0.293	0.356	0.205	1	(1418)
2	Mex→Mex	0.010	0.017	0.148	0.373	0.451	1	(2061)
	Cross-border							
3	U.S.→ Mex	0.483	0.297	0.134	0.052	0.034	1	(650)
4	Mex→U.S.	0.252	0.502	0.186	0.048	0.011	1	(440)
	B. Family ties							
	Local							
5	U.S→U.S.	0.039	0.066	0.175	0.392	0.329	1	(669)
6	Mex→Mex	0.013	0.015	0.140	0.402	0.429	1	(1817)
	Cross-border							
7	U.S.→ Mex	0.171	0.178	0.321	0.277	0.053	1	(842)
8	Mex→U.S.	0.162	0.335	0.242	0.226	0.034	1	(641)

Table 4

Respondent's Desire for Permanent Residence

	Respondent's location		
	R in the U.S.	R in Mexico	
Would you live permanently in the U.S. if you could?			**Total**
No	42.8	85.7	72.1
Yes	57.2	14.3	27.9
Total (N)	100.0 (187)	100.0 (405)	100.0

Table 5

Where R thinks he/she would be happiest

	Respondent's location		
	R in the U.S.	R in Mexico	
Where do you think you would be happiest?			**Total**
in the U.S.	29.90	4.68	12.83
in Mexico	44.85	88.92	74.67
Equal	25.26	6.40	12.50
Total (N)	100.0 (194)	100.0 (406)	100.0 (600)

Table 6

What is your opinion of U.S. culture? (Column percentage)

	Respondent's location		
	R in the U.S.	R in Mexico	Total
1. I don't like it	9.33	46.40	34.40
2	9.84	14.39	12.92
3	48.19	24.81	32.38
4	19.69	6.45	10.74
5. I like it (me encanta)	12.95	7.94	9.56
Total	100	100	100
Number of respondents	(193)	(403)	(596)

Table 7

Desire to Adapt to the U.S. (U.S. respondents only, column percentage)

"How much do you want to adapt to the society, culture, and lifestyle of the U.S.?"	Percent
1. Only what is necessary	30.6
2	8.3
3	26.9
4	11.4
5. I want to adapt completely	22.8
Total	100
Number of respondents	(193)

Table 8

R's self-identification as Mexican (U.S. respondents only)

Degree of identification as Mexican	Percent
0%	0.5
25%	0.5
50%	7.3
75%	14.1
100%	77.6
Total	100.0
Number of cases	(192)

Table 9

Summary statistics of variables used in the analysis

Variable	U.S. Sample			Mexico Sample		
	(N)	Mean	Std. Dev.	(N)	Mean	Std. Dev.
Contacts' average of:						
1. Desire for permanent residence ("zperm_us")	184	0.469	0.329	373	0.167	0.238
2. Happier living in Mexico ("zhapmex")	188	0.528	0.309	373	0.845	0.230
3. Opinion of U.S. culture ("zopinion_us")	188	3.05	0.648	373	2.25	0.826
Communication Flow measures[2]:						
4. Family communication, cross-border	196	2.42	0.645	407	1.00	1.11
5. Family communication, local	196	2.31	1.04	407	2.77	0.802
6. Friend communication, cross-border	196	1.63	0.868	407	0.623	0.943
7. Friend communication, local	196	2.97	1.00	407	2.96	0.672
8. Number of years in the U.S.: current migrants	197	11.52	9.48			
9. Ln(years in the U.S.): current migrants	197	2.11	1.05			
10. Number of years in the U.S.: returned migrants[1]				70	4.28	4.65
11. Ln(years in the U.S.): returned migrants[1]				70	1.26	0.93
12. Education: High school or higher	197	0.534		410	0.64	
13. Age	189	36.4	12.30	391	39.1	16.28
14. Sent remittances (in the last 30 days)	191	0.408				
15. Recent visit to Mexico (in the last 4 years)	173	0.370				
Network roster count variables:						
16. Number of other respondents who nominated R.	197	3.06	4.67	410	2.24	2.72
17. Number of other respondents R nominated.	197	3.96	3.20	410	2.96	2.98
18. # of nominations R made in the network roster.	197	18.41	5.96	410	12.07	6.06
19. Female	194	0.440		407	0.558	
20. Betweenness centrality x 100	174	0.25	.0069	366	0.16	.0027
English ability (excluded category: very good)						
21. Good	194	0.155		407	0.061	
22. Not good	194	0.485		407	0.204	
23. Not at all	194	0.253		407	0.722	

Notes:

[1] There are 70 returned migrants in the data. The number of years in the U.S. is 0 for the non-migrants in the Mexico sample

[2] The network communication variables are the log sum of the communication frequencies. See the text for an explanation.

Table 10

Probit and Network Autoregressive Probit (NAP) models of three measures of destination country incorporation, U.S. respondents

Model	A: Probit Models.			B: Network Probit Models.		
	1A	2A	3A	1B	2B	3B
Variables	Desire for permanent residence	Opinion of U.S. culture	Happier living in Mexico	Desire for permanent residence	Opinion of U.S. culture	Happier living in Mexico
Contacts' average of:						
Desire for permanent residence ("zperm_us")	1.037** (0.351)			1.082** (0.355)		
Opinion of U.S. culture ("zopinion_us")		0.557* (0.234)			0.548* (0.239)	
Happier living in Mexico ("zhapmex")			0.796* (0.348)			0.838* (0.352)
Family communication, cross-border	−0.045 (0.223)	−0.130 (0.256)	0.284 (0.197)	−0.053 (0.220)	−0.161 (0.252)	0.301 (0.188)
Family communication, local	−0.000 (0.106)	−0.074 (0.114)	0.051 (0.098)	0.006 (0.108)	−0.080 (0.112)	0.050 (0.097)
Friend communication, cross-border	−0.387** (0.137)	−0.023 (0.150)	0.169 (0.128)	−0.412** (0.140)	−0.027 (0.143)	0.175 (0.127)
Friend communication, local	−0.130 (0.121)	−0.043 (0.123)	−0.172 (0.107)	−0.134 (0.121)	−0.042 (0.125)	−0.173 (0.107)
Betweenness centrality	−0.638 (0.389)	0.024 (0.212)	0.219 (0.202)	−0.704 (0.397)	0.040 (0.223)	0.278 (0.226)
Sent remittances	0.017 (0.227)	0.093 (0.243)	0.119 (0.210)	0.015 (0.230)	0.094 (0.235)	0.118 (0.210)
Recent visit to Mexico	−0.109 (0.249)	0.297 (0.266)	0.071 (0.232)	−0.109 (0.255)	0.271 (0.263)	0.069 (0.236)
Ln(years in the U.S.)	0.231 (0.162)	0.194 (0.145)	0.103 (0.136)	0.243 (0.165)	0.200 (0.145)	0.104 (0.137)
Female	0.143 (0.241)	−0.017 (0.237)	−0.175 (0.210)	0.148 (0.251)	−0.015 (0.237)	−0.186 (0.211)
English ability (excluded category: very good)						
Good	0.168 (0.481)	0.490 (0.512)	0.202 (0.493)	0.178 (0.492)	0.502 (0.523)	0.240 (0.491)
Not good	0.217 (0.430)	0.335 (0.440)	0.932* (0.437)	0.228 (0.428)	0.337 (0.439)	0.983* (0.436)
Not at all	0.063 (0.448)	0.324 (0.465)	0.962* (0.459)	0.062 (0.454)	0.318 (0.469)	1.016* (0.458)
Education: High school or higher	−0.437 (0.248)	0.119 (0.269)	0.345 (0.233)	−0.460 (0.251)	0.118 (0.265)	0.352 (0.235)
Age	−0.020 (0.043)	−0.036 (0.048)	−0.002 (0.039)	−0.016 (0.047)	−0.046 (0.048)	−0.006 (0.041)
Age²	−0.000 (0.000)	0.000 (0.001)	0.000 (0.000)	−0.000 (0.001)	0.000 (0.001)	0.000 (0.000)
Number of nominations in the survey	−0.012 (0.030)	−0.011 (0.030)	−0.006 (0.028)	−0.013 (0.032)	−0.011 (0.030)	−0.007 (0.029)
Constant	1.347 (1.143)	−0.185 (1.361)	−2.524* (1.024)	1.325 (1.204)	0.300 (1.456)	−2.588* (1.058)
ρ ("Rho")				−0.046 (0.508)	−0.351 (0.459)	−0.180 (0.496)
(N)	(197)	(197)	(197)	(197)	(197)	(197)

Standard errors in parentheses.

**
p<0.01,

*
p<0.05,

+
p<.1

Table 11

Probit and Network Autoregressive Probit (NAP) models of three measures of destination country incorporation, Mexican respondents

	Probit Models			Network Probit Models		
Model	**1A**	**2A**	**3A**	**1B**	**2B**	**3B**
Variables	Desire for permanent residence	Opinion of U.S. culture	Happier living in Mexico	Desire for permanent residence	Opinion of U.S. culture	Happier living in Mexico
Contacts' average of:						
Desire for permanent residence ("zperm_us")	0.226 (0.361)			0.215 (0.359)		
Opinion of U.S. culture ("zopinion_us")		0.137 (0.085)			0.144 (0.085)	
Happier living in Mexico ("zhapmex")			-0.156 (0.410)			-0.135 (0.407)
Family communication, cross-border	0.023 (0.079)	0.118 (0.065)	-0.032 (0.084)	0.029 (0.079)	0.123 (0.066)	-0.027 (0.085)
Family communication, local	0.023 (0.125)	-0.077 (0.093)	0.119 (0.118)	0.026 (0.117)	-0.075 (0.094)	0.099 (0.113)
Friend communication, cross-border	0.230 * (0.092)	0.092 (0.081)	-0.315 ** (0.096)	0.221 * (0.098)	0.094 (0.081)	-0.304 ** (0.109)
Friend communication, local	0.102 (0.160)	0.072 (0.118)	-0.054 (0.160)	0.115 (0.153)	0.073 (0.117)	-0.080 (0.152)
Betweenness centrality	-0.313 (0.399)	-0.529 (0.324)	0.208 (0.393)	-0.280 (0.386)	-0.556 (0.332)	0.188 (0.389)
Return migrant	0.808 *** (0.222)	0.965 *** (0.208)	-0.596 ** (0.230)	0.824 ** (0.250)	1.001 *** (0.212)	-0.582 * (0.246)
Female	0.102 (0.193)	0.216 (0.151)	-0.074 (0.196)	0.106 (0.191)	0.221 (0.155)	-0.076 (0.193)
English ability (excluded category: very good)						
Good	-1.527 * (0.734)	0.089 (0.671)	-0.478 (0.730)	-1.837 * (0.779)	0.078 (0.712)	-0.524 (0.741)
Not good	-1.699 * (0.704)	0.175 (0.643)	-0.082 (0.709)	-2.002 ** (0.750)	0.164 (0.684)	-0.135 (0.716)
Not at all	-1.732 * (0.701)	-0.065 (0.641)	0.006 (0.711)	-2.020 ** (0.746)	-0.080 (0.680)	-0.042 (0.716)
Education: High school or higher	-0.092 (0.208)	0.312 (0.174)	0.215 (0.216)	-0.064 (0.203)	0.322 (0.178)	0.196 (0.206)
Age	-0.014 (0.027)	-0.042 (0.022)	0.024 (0.030)	-0.013 (0.026)	-0.043 (0.022)	0.020 (0.029)
Age^2	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)
Number of nominations in the survey	0.001 (0.037)	0.044 (0.031)	0.002 (0.038)	0.005 (0.036)	0.048 (0.031)	-0.001 (0.038)
Constant	0.162 (0.930)	-0.448 (0.807)	0.938 (1.048)	0.212 (1.007)	-0.542 (0.841)	1.400 (1.108)
ρ ("Rho")				-0.276 (0.489)	-0.424 (0.434)	-0.322 (0.474)
(N)	(410)	(410)	(410)	(410)	(410)	(410)

Standard errors in parentheses.

**
p<0.01,

*
p<0.05,

+
p<.1

Table 12

Exponential Random Graph Models of Selective Mixing in the U.S. and Mexico based networks.

	U.S. based network.		Mexico based network.	
	Estimate	**Std. Error**	**Estimate**	**Std. Error**
Sociality				
Intercept	−4.873	0.817***	−6.042	0.956***
Female	−0.039	0.067	−0.053	0.074
Desire for permanent residence	−0.065	0.069	−0.006	0.114
Happier living in Mexico	−0.113	0.077	0.107	0.296
Opinion of U.S. culture	−0.021	0.039	0.069	0.038
Selective Mixing				
Female	0.465	0.118***	0.489	0.094***
Desire for permanent residence	0.271	0.085**	0.140	0.189
Happier living in Mexico	0.180	0.076*	0.027	0.294
Opinion of U.S. culture (Absolute value of difference between respondents)	−0.147	0.059*	−0.050	0.038
Triad Closure				
GWESP	1.403	0.145***	1.445	0.078***

Notes:

***
p<0.001,

**
p<0.01,

*+
p<0.05

GWESP = "Geometrically weighted shared partner distribution"

Table 13

Summary of Overall Results

Variable	U.S. sample	Mexican sample
Transnationalism variables:		
1. ERGM peer effects/homophily (Table 12)	+	0
2. Peer effects/homophily	+	0
3. Cross-border friend communication	~	+
4. All other communication variables	0	0
5. Network betweenness centrality	0	0
Assimilation variables:		
6. Migration experience/returned migrants	0	+
7. English language ability	~	~

"+" indicates significance in at least 2 of the 3 dependent variables.

"~" indicates significance in 1 of the 3 dependent variables.

Notes: All variables are from Table 10 (U.S. sample) and Table 11 (Mexican sample) except for the ERGM results in the first row. "Significance" means statistically significant at least at the p=.05 level.