A personal network approach to the study of immigrant structural assimilation and transnationalism

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ABSTRACT

This paper proposes a personal network approach to the study of structural assimilation and structural transnationalism among international immigrants. Structural assimilation and transnationalism are defined as embeddedness in native social networks of the host society, and in co-national social networks of the origin society, respectively. Data on the personal networks of international immigrants, each including 45 alters, are obtained from two surveys among Moroccan, Senegalese and Gambian immigrants in Spain (N = 139), and among Sri Lankan immigrants in Italy (N = 102). Measures on the size of different national and geographical classes of alters, and on the cohesion within and between these classes, are used to quantify the degree and type of structural assimilation and transnationalism. Linear regression models show that these measures are significantly associated with outcomes of cultural and economic assimilation of immigrants.

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1. Introduction

A growing number of people move across national borders in contemporary societies. Migration trajectories have changed, becoming more complex and multidirectional in comparison to historical migration flows in the 1900s (Castles et al., 2013). Driven by diverse motivations (King, 2002), following different migration channels (Meissner and Vertovec, 2015), and experiencing unprecedented technological advances in international communication and mobility (Elliott and Urry, 2010), contemporary migrants may cyclically return home, move across several countries, and maintain simultaneous relationships with distant places and societies.

Throughout the 1900s, the adaptation of international immigrants to receiving countries was explained by sociologists in terms of assimilation, conceived as the decline and ultimately the disappearance of social, cultural and economic differences between an immigrant minority and a native majority (Alba and Nee, 1997; Fitzgerald, 2014). Different dimensions of assimilation were identified, including structural, cultural, economic, and spatial assimilation. A central reference for canonical assimilation theory, Gordon (1964) emphasized the preeminence of structural assimilation, defined as the immigrant’s entrance into the “social cliques, clubs, and institutions” of the host society “at the primary group level”. Structural assimilation occurs when immigrants “have entered fully into the societal network of groups and institutions, or societal structure,” of the host country (Gordon, 1964:70). In Gordon’s account, structural assimilation is the “keystone of the arch of assimilation” (Gordon, 1964:81), in that it is a sufficient condition that leads to assimilation in other dimensions, including cultural assimilation, or acculturation, and economic assimilation.

Subsequent research has heavily criticized the idea, implied in the first assimilation theories, that assimilation occurs as a linear, one-way and inevitable process in which immigrants grow increasingly closer to a homogeneous mainstream society in the receiving country, to the same extent that they depart and disengage from the culture and society of origin. Alternative ideas have been proposed, such as the ethnic disadvantage model (Glazer and Moynihan, 1970), the “bumpy-line” theory of ethnicity (Gans, 1992), and the notion of segmented assimilation (Portes and Zhou, 1993). Especially in European migration studies, the notion of assimilation has been at times confused with acculturation, and associated with normative views that reject multiculturalism and see the abandonment of origin cultures as a necessary step in the way towards successful incorporation of immigrants in
destination countries (Kivisto, 2005). Other research, however, has more recently reformulated the idea of assimilation as a specific social scientific concept, amenable to precise operationalization and measurement but devoid of any normative assumption or prescription. Evidence has been shown that the trajectories of contemporary immigrants to America can still be explained in terms of assimilation in socioeconomic status, language, residential distribution, and marriage patterns (Alba and Nee, 1997, 2003; Waters and Jiménez, 2005). This updated notion of assimilation is today effectively used in both American and European migration studies (e.g. Guarnizo et al., 2003; Diehl and Schnell, 2006; Qian and Lichter, 2007; Greenman and Xie, 2008; Mouw et al., 2014; Koopmans, 2016).

For all their strengths in the analysis of immigrant adaptation to receiving societies, assimilation models have tended to disregard the different types of relationships that immigrants may maintain with the origin country and the co-national diaspora. This bias was criticized in the early 1990s by proponents of the notion of transnationalism, who viewed the maintenance of stable and regular relationships between immigrants and their home country as a central and distinctive feature of contemporary migration (Glick Schiller et al., 1992; Basch et al., 1994). Transnationalism refers to a situation in which immigrants live in receiving countries while continuing to participate in the political, economic and cultural life of sending societies and the co-national diasporas, in different domains and to various degrees (Levitt and Jaworsky, 2007; Bauböck and Faist, 2010). While empirical research has suggested that regular practices of political and economic transnationalism characterize only a minority of contemporary immigrants (Landolt, 2001; Portes et al., 2002; Guarnizo et al., 2003), the maintenance of transnational social networks is likely a more widespread phenomenon (Mouw et al., 2014; Vertovec, 2004). In fact, from the very onset of this line of research, studies of immigrant transnationalism have invariably used network terminology and metaphors, describing economic, political and cultural transnational involvement as fundamentally sustained by stable cross-national social networks between immigrants and their country of origin, including family, friends, and political or business associates (Basch et al., 1994; Landolt, 2001; Portes et al., 2002; Guarnizo et al., 2003; Levitt and Glick Schiller, 2004; Dahinden, 2005; Rusinovic, 2008). In parallel with the notion of structural assimilation, we can refer to the maintenance of primary-group transnational social networks as structural transnationalism.

Since social networks have always been considered as a crucial factor sustaining immigrants’ movements and adaptation trajectories (extensive reviews are provided by Boyd, 1989 and Gold, 2005), it is not surprising that personal network data and methods are increasingly appearing in studies of immigrant assimilation and transnationalism, in conjunction with recent analytical and computational advancements of social network research (e.g. Dahinden, 2009; Lubbers et al., 2007, 2005; Brandes et al., 2016a; Haikola, 2011; Richter and Nollert, 2014; Bolíbar et al., 2015; Bilecen and Sienkiewicz, 2015; Herz, 2015). Personal networks capture all direct and active relationships involving a focal individual (McCarty et al., 1997), and have been extensively used in anthropology and sociology to operationalize “personal communities” (Chua et al., 2011) or, in other words, primary groups. In line with the traditional sociological notion (Cooley, [1909] 2009), we define a primary group as any social group held together by direct, personal knowledge and interaction between people, established through regular face-to-face, telephone or online contacts.

Existing personal network studies have made important contributions to our understanding of immigrants’ personal communities and adaptation patterns, yet most of them have focused primarily, if not exclusively, on the composition of immigrant personal networks. On the other hand, the structure of personal networks has rarely, and only marginally, been taken into account in migration studies, although structural measures have been meaningfully applied to personal network data in other research (McCarty, 2002). We argue that personal network structure contributes to a better understanding of assimilation and transnationalism patterns among international immigrants. A central intuition in sociology and social network analysis is that a group is more than the sum of its members, and a network is more than the sum of its dyadic ties. A cohesive group of personal contacts exposes the individual to a fundamentally different set of constraints, resources and opportunities than a set of five separate contacts. We argue that this is also the case for international immigrants and their outcomes of assimilation and transnational involvement.

In general, we hypothesize that embeddedness in more cohesive structures within a given society results in deeper involvement, attachment, and identification with that society. Following this intuition, our study focuses on the different degrees and types of structural embeddedness in the host and home society that can be observed through immigrant personal networks. Theoretically, we aim to contribute to the development of a framework that links the sociological notion of embeddedness to the structural dimension of assimilation and transnationalism, and, in turn, to outcomes of assimilation and transnationalism in other dimensions, such as the cultural and the economic domains. Empirically, we use personal networks to operationalize the notion of embeddedness, and propose network compositional and structural measures to simultaneously describe structural assimilation and structural transnationalism. Consistently with the view, proposed by traditional assimilation theory, that structural assimilation is a sufficient condition which sustains assimilation in other dimensions, this study conceives of structural assimilation and structural transnationalism as independent variables that affect assimilation outcomes in the cultural and economic domains. These outcomes are measured at the individual level using non-network metrics, namely an acculturation rating scale for cultural assimilation, and net monthly income for economic assimilation.

This article is structured as follows. The remainder of Section 1 discusses the notions of structural assimilation and structural transnationalism in connection with the sociological concept of embeddedness in social networks. Section 2 introduces measures of structural assimilation and transnationalism based on the size and cohesion of classes of personal contacts, and formulates the main hypotheses of this study. Section 3 presents the data. Section 4 reports results from descriptive analysis and predictive models using the proposed measures of structural assimilation and transnationalism. Section 5 discusses the findings in light of the hypotheses stated in Section 2, and Section 6 concludes the article.

1.1. Embeddedness, structural assimilation, and structural transnationalism

Structural assimilation is an eminently social network concept, evoking the immigrant’s embeddedness within primary-group

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social networks in the host society. A powerful but seemingly
generic concept, the notion of embeddedness has in fact a specific
meaning in the sociological literature, and one that is fundament-
ally tied to social network structure. Granovetter (1985) originally
demonstrated that individual purposive action, particularly in the
domains of job search and professional advancement, can be facil-
itated or constrained by the "concrete, ongoing systems of social
relations" in which people are embedded. Subsequent research has
extended this idea to a wider array of individual actions and deci-
sions, including but not limited to the economic dimension (Portes
and Sensenbrenner, 1993; Mingione, 2006). In Granovetter's origi-

nal formulation, embeddedness embraces two different aspects,
a relational and a structural one. While relational embeddedness
refers to the "quality and depth" of a dyadic relation, structural
embeddedness is the extent to which "a dyad's mutual contacts are
connected to one another" (Granovetter, 1992:35). Social network
scholars have later defined the structural embeddedness of a dyadic

tie as the degree to which the two connected actors are linked to
the same third contacts (Wellman, 1982; Feld, 1997). Thus, structural
embeddedness is a function of transitive closure in social networks,
and, more in general, of an actor's or dyad's nestedness within
cohesive subgroups. Expanding on this argument, White, Moody
and Harary developed graph-theoretical definitions and measures
of structural embeddedness as an actor's depth of involvement in
cohesive social network structures (White and Harary, 2001;
Moody and White, 2003).

Structural assimilation can be defined in terms of the immi-
grant's embeddedness in primary-group social networks of native
contacts in the host country. Hence, recalling the link between
embeddedness and cohesive subgroups, structural assimilation
can be operationalized as the degree to which the immigrant
is involved in cohesive networks of native personal contacts in
the host country. In the same way that embeddedness in the
host society is a central dimension of assimilation, continuing
embeddedness in the sending society is a fundamental dimen-
sion of immigrant transnationalism. Thus, in a symmetrical notion
to structural assimilation, we can define structural transna-
tionalism as the immigrant's embeddedness in primary-group social
networks based in the home country. We operationalize this
notion as the degree to which the immigrant is involved in cohe-
sive networks of co-national personal contacts in the sending
country.

In addition to examining cohesion among contacts from the
same nationality and in the same country of residence, an analysis
of structural assimilation and transnationalism would be incom-
plete without also taking into account the cohesion between contacts
from different nationalities and geographies. Given the
same level of embeddedness in a personal network of natives or
co-nationals in the home country, an immigrant's broader personal
network might be characterized by connectedness and integra-
tion, or rather by separation and segregation, between contacts
from different nationalities and countries of residence. In the lat-
er case, the immigrant would be a broker between disconnected/native and co-national contacts. The literature on structural holes
and bridging social capital identifies different advantages result-
ing from brokering positions (Burt, 2001; Faist, 2014), which might
benefit immigrants' economic incorporation in the host society.
Furthermore, structural holes might reflect cultural differences or
"cultural holes" (Pachucki and Breiger, 2010) between separate
areas of a social network, a cultural diversity that might be associ-
ated with immigrants' cultural adaptability. Thus, different patterns
of structural cohesion between contacts from diverse nationalities
and geographies might be linked to different outcomes of economic
incorporation and cultural assimilation among immigrants.

Compared to previous studies taking into account structural
characteristics of personal networks (e.g. Wellman and Frank,
2001; Lubbers et al., 2007, 2009; Brandes et al., 2010a), we apply
notions and measures of structural cohesion to a specific prob-
lem, namely the operationalization and measurement of structural
assimilation and transnationalism, and the test of hypotheses on
their relationship with outcomes of assimilation in other dimen-
sions. We draw on Brandes and colleagues' (Brandes et al., 2010a,b)
insights on the analysis of cohesion within and between classes
of contacts in personal networks. However, we propose differ-
ent measures of structural cohesion, which we deem to be better
grounded in sociological theories of embeddedness and assimila-
tion, and more suitable for the study of patterns and outcomes of
immigrant assimilation.

2. Methods: measuring embeddedness and structural
cohesion in classes of personal contacts

In our data, a personal network is a network of primary-
group contacts (alters) for one focal immigrant (ego). We begin
by identifying different categories or classes of alters, as defined
by specific combinations of nationality (country of birth) and
geography (country of residence). Two alter classes are par-
ticularly relevant to the analysis of structural assimilation and
transnationalism: (1) Natives, i.e., alters who were born in ego's
host country; (2) Origin Co-nationals, i.e., alters from the same
nationality as ego, who currently live in ego's country of origin.
We operationalize structural assimilation and structural transna-
tionalism as the immigrant's embeddedness in the Native and
in the Origin Co-national classes, respectively. All personal con-
tacts who are not Natives or Origin Co-nationals (e.g. co-national
contacts residing in ego's country of immigration, or contacts
from a third nationality) are grouped into a residual, Other alter
class.

Given the definition of embeddedness as the degree of involve-
ment in cohesive structures, a measure of ego's embeddedness in
a social group (e.g. the group of natives in the host society) should
take two different aspects into account, namely the size and the
cohesion of the group in ego's personal network. The size of the
group in ego's personal network is a simple proxy for the num-
ber of people that ego knows in the group. An immigrant can be
reasonably considered as more embedded in the group of natives
if she has twenty personal contacts from that group, compared to
someone who only has five native personal contacts. The size of
the group, however, is a compositional measure that does not take
into account the second, structural component of embeddedness,
namely the extent to which ego's contacts in the group form a cohe-
sive structure. The size and the cohesion of a group in a personal
network are two conceptually distinct aspects of embeddedness.
We might imagine two egos, A and B, who both know five natives.
In the case of ego A, none of these five alters know each other.
In the case of ego B, all the five alters know each other, resulting in
a clique of five native contacts. Although in terms of group size A
and B exhibit the same degree of embeddedness in the native group,
in terms of involvement in a cohesive structure ego B is clearly more
embedded in the group than is ego A. In this study, we separately
measure these two aspects of embeddedness as the size and the
cohesion of an alter class.

2.1. A measure of structural cohesion within alter classes

White, Moody and Harary provide a comprehensive review and
a theoretically grounded proposal for definitions and measures
of structural cohesion and embeddedness in social networks (White
and Harary, 2001; Moody and White, 2003). In general, they define
the structural cohesion of a group as the degree to which the

group is held together by social relations among its members. A

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group is structurally cohesive to the extent that, thanks to multiple relational paths existing between the majority of its members, its existence and unity as a group are not vulnerable to unilateral action, such as departure, of one or few of its members. Translating to graph theoretical terms, a group is structurally cohesive when multiple node-independent paths exist between its members, or when it is robust to disconnection by removal of one or few of its members. In graph theory, these two ideas are in fact equivalent, and they are both captured by the notion of node connectivity.

The node connectivity $k$ of a graph is the minimum number of nodes that need to be removed to disconnect the graph. A set of nodes whose removal would disconnect a graph is called a cut set, and a graph has connectivity $k$ (is $k$-connected) if it has no cut set with less than $k$ nodes. Theorems in graph theory prove that node connectivity $k$ is also the minimum number of node-independent paths that connect every pair of nodes in the graph (Harary, 1969:47), and the minimum degree that a node in the graph can have (Harary, 1969:43). White and colleagues measure of structural cohesion, which we call the White–Harary cohesion, is obtained as the sum of connectivity (an integer number) and conditional density (a decimal number between 0 and 1). Intuitively, given a graph with connectivity $k$, conditional density is the additional number of edges that the graph has, in excess over the minimum number of edges that the graph would need to preserve its connectivity $k$.

In addition to measuring cohesion at the whole network level, connectivity also provides the foundation for a method to detect cohesive subgroups within a network, known as cohesive blocking (Moody and White, 2003). By recursive removal of the smallest cut sets, cohesive blocking finds maximal subgraphs with increasingly higher connectivity, or cohesive blocks, nested deeper and deeper into the original network. The procedure yields a hierarchical set of subgraphs, nested into each other, with increasing levels of cohesion. At the end of the nesting hierarchy lies the most cohesive block, that is, the maximal subgraph with the highest connectivity within the original graph. Cohesive blocking reveals a crucial connection between structural cohesion and embeddedness. If embeddedness, as the characteristic of individual nodes in the network, is an actor’s depth of involvement in cohesive structures, then actors sitting deeper in the nesting structure, within cohesive blocks with higher connectivity, are more embedded in the network. Therefore, Moody and White (2003) propose to measure an actor’s structural embeddedness in the network as the connectivity of the deepest and most cohesive block to which the actor belongs.

We apply this idea to the measurement of ego’s structural embeddedness in an alter class. Performed on a personal network, cohesive blocking identifies the most cohesive block, with the highest connectivity, lying at the end of the network’s nesting structure. Ego’s embeddedness in the personal network can be measured as the White–Harary cohesion of this block. The same method can be applied to the subgraph of a specific alter class, instead of the entire personal network. Thus, ego’s structural embeddedness in an alter class can be measured as the White–Harary cohesion of the most cohesive block in the subgraph of that alter class in ego’s personal network. It should be noted at this point that, by construction of a personal network, ego is tied to every actor in the network and in any of its subgroups. Therefore, ego is part of any cohesive subgroup emerging in the personal network, and higher cohesion of a subgroup of alters necessarily implies higher embeddedness of ego in that subgroup. In the following, we indicate the White–Harary cohesion of the most cohesive block in a class subgraph as $k_j^*$, where $j$ indexes the class ($j = 1$ for the Native class and $j = 2$ for the Origin Co-national class). For simplicity we refer to $k_j^*$ as class cohesion, although it is technically the cohesion of the most cohesive block in the class subgraph, rather than the cohesion of the class subgraph itself. Fig. 1 illustrates the measures of class size ($n_j$) and class cohesion ($k_j^*$) in an actual immigrant’s personal network.

### 2.2. A measure of structural cohesion between alter classes

Being calculated on the subgraph of a single alter class, $k_j^*$ leaves aside the question of structural cohesion between different classes. However, the ties within single alter classes and the ties between different alter classes are two logically distinct dimensions of structural assimilation and structural transnationalism. Given the same level of cohesion within the Native class, the broader personal network of an immigrant might be characterized by structural cohesion or by structural separation between Natives and Origin Co-nationals. The issue of cohesion or separation between different alter classes can be treated as a problem of segregation of classes in the cohesive subgroups of a personal network. In a personal network with high cohesion between alter classes, Natives and Origin Co-nationals tend to belong to the same cohesive subgroups, with low levels of class segregation in network structure (Fig. 2B). By contrast, in a personal network with low cohesion between alters from different classes, Natives and Origin Co-nationals tend to fall into separate cohesive subgroups, with high levels of class segregation in network structure (Fig. 2A).

We measure class segregation in cohesive subgroups by developing an index suggested by studies of residential segregation in cities. This is the entropy index of spatial segregation, which measures the level of segregation of population subgroups (e.g. ethnic groups) in the neighborhoods of a city by comparing subgroup diversity in the whole city to subgroup diversity in single neighborhoods (White, 1986; Reardon and O’Sullivan, 2004). Intuitively, segregation is high if a high diversity at the city level corresponds to low diversity at the neighborhood level, indicating that different subgroups exist in the city as a whole, but each subgroup tends to fall in its own homogenous neighborhood. Conversely, segregation is low if the city and its single neighborhoods display similar levels of subgroup diversity, indicating that the different subgroups existing in the city as a whole tend to mix within single neighborhoods. We apply the same logic to a personal network (the “city”) and its cohesive subgroups (the “neighborhoods”), and compare alter class diversity at the whole personal network level with alter class diversity within single cohesive subgroups. Cohesive subgroups are identified using the Girvan–Newman algorithm for community detection (Newman and Girvan, 2004), and class diversity is measured as generalized variance (Budescu and Budescu, 2012) with respect to three categories of alters (Natives, Origin Co-nationals, and Others). Generalized variance ($GV$) can be interpreted as the probability that two alters randomly drawn from the population (i.e., all actors in the personal network or in the cohesive subgroup) belong to two different classes.

The index we propose is an inverse measure of cohesion between alter classes, which we call index of subgroup segregation:

$$S = GV - GV^*$$

$$GV^*$$ is class diversity in the whole personal network, and $GV$ is average class diversity in subgroups, weighted by subgroup size:

$$GV = \sum_{i=1}^{l} \frac{n_j}{N} GV_i$$
where i indexes the Girvan–Newman subgroups of three or more nodes found in the personal network, i is the total number of such subgroups, \( GV_i \) is class diversity in subgroup i, \( n_i \) is the number of nodes in subgroup i, and \( N \) is the total number of nodes in the personal network. \( S \) measures the relative decrease in class diversity that is observed going from the whole network level to the level of single cohesive subgroups. High \( S \) indicates a high relative decrease of diversity in subgroups, i.e., high segregation of alter classes within subgroups, or low structural cohesion between classes.

The combination of network diversity (\( GV^* \)) and subgroup diversity (\( GV^c \)) can discriminate between personal networks approaching one of three different cases: (1) segregation (Fig. 2A): the personal network includes alters from different classes (high \( GV^c \)), but different classes tend to fall into different cohesive subgroups (low \( GV^* \); (2) Mix (Fig. 2B): the personal network includes alters from different classes (high \( GV^* \)) who tend to fall into the same cohesive subgroups (high \( GV^c \); (3) homogeneity (Fig. 2C): the personal network does not include alters from different classes (low \( GV^* \)), thus it necessarily displays low subgroup diversity (low \( GV^c \)) as well. \( S \) can also be seen as a direct measure, interpretable in terms of diversity, of ego’s brokering role between different alter classes. While class size and class cohesion measure ego’s embeddedness in the host society’s and the home society’s social networks separately, the combination of network diversity and subgroup diversity provides a measure for the extent to which ego is a broker or bridge between disconnected nationalities and geographies in her personal network (segregation), or rather is embedded in a pattern of mix and high connectedness between Natives, Origin Co-nationals, and Other alters (Mix).

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1. Brandes et al. (2010a,b) propose an interesting, inverse method to measure cohesion between different classes of personal contacts. While we first identify structural subgroups, and then measure average class diversity within them, Brandes and colleagues first identify alter classes, then measure structural cohesion between them. This is an insightful method, however it does not yield a single
While different methods are available to identify cohesive subgroups in order to calculate $GV$, we select the Girvan–Newman algorithm for different reasons. In the first place, this algorithm yields intuitive and meaningful results on small-scale networks such as our 45–alter personal networks. In the second place, our segregation index assumes non-overlapping cohesive subgroups, because a comparison between network diversity and average subgroup diversity is only meaningful if each node only belongs to one subgroup. Several other methods for extraction of cohesive subgroups, including cohesive blocking, produce overlapping subgroups. In the third place, the Girvan–Newman algorithm does not require to arbitrarily predetermine the number of cohesive subgroups, or to set a threshold to “cut” a hierarchical nesting of subgroup partitions, like other methods do. When cohesive subgroups must be extracted on each of hundreds of personal networks, it is not feasible to determine a specific a priori number of subgroups or ex post cutting threshold for each.\(^4\)

All analyses for this paper were conducted with R (R Core Team, 2015). The R code to calculate $n_j$, $k_j^+$, $GV$, $\bar{GV}$ and $S$ in large collections of personal networks is available upon request.

2.3. Summary and hypotheses

Summarizing the discussion so far, our arguments can be stated as follows.

i. There exist two distinct aspects of structural assimilation and structural transnationalism, namely the size and the internal cohesion of Native and Origin Co-national social networks, respectively. These two aspects can be separately measured as the size of the relevant alter class ($n_j$), and the White–Harary cohesion of the most cohesive block in the subgraph of the same class ($k_j^+$).

ii. Class size $n_j$ and class cohesion $k_j^+$ are not redundant. Specifically, there is a significant variability of $k_j^+$ given the same value of $n_j$ in large collections of personal networks. The combination of $n_j$ and $k_j^+$ effectively indexes the degree of structural assimilation or structural transnationalism. In particular, $n_j$ and $k_j^+$ measure the degree of ego’s embeddedness in the Native class, i.e., structural assimilation; $n_2$ and $k_2^+$ measure the degree of ego’s embeddedness in the Origin Co-national class, i.e., structural transnationalism.

iii. An additional aspect of structural assimilation and transnationalism is the cohesion between personal contacts from different nationalities and countries of residence. This dimension is logically distinct from the dimensions of size and internal cohesion of alter classes, and can be separately measured by personal network diversity, $GV$, and subgroup diversity, $\bar{GV}$.

iv. $GV$ and $\bar{GV}$ are not redundant. In particular, holding constant the value of $GV$, there is a considerable variability in $\bar{GV}$, determining different levels of subgroup segregation $S$, between the opposite cases of Segregation (high $GV^+$, low $\bar{GV}$) and Mix (high $GV^-$, high $\bar{GV}$). A third case, homogeneity, is observed when the personal network as a whole is homogeneous with respect to alter class (low $GV^+$, low $\bar{GV}$). Subgroup segregation is equivalent to the lack of structural cohesion between alter classes. Thus, the combination of $GV^+$ and $\bar{GV}$ indexes the type of structural assimilation and structural transnationalism, distinguishing a brokering type (structural segregation between classes) from a cohesive type (structural cohesion between classes).

We hypothesize that, taken together, the size of the alter classes, the cohesion within alter classes, and the cohesion between alter classes effectively describe structural assimilation and structural transnationalism among international immigrants. Hence, we expect that they predict outcomes of immigrant assimilation in other domains, specifically the cultural and the economic domain. This expectation can be articulated in the following hypotheses.

**H1.** Higher levels of structural assimilation are associated with better outcomes of cultural and economic assimilation.

**H1** posits that both $n_j$ and $k_j^+$ significantly and positively contribute to explaining cultural and economic assimilation. This hypothesis corresponds to the prediction, formulated in canonical assimilation theory, that structural assimilation is a sufficient condition for assimilation in all other dimensions, including the cultural and economic domains (Gordon, 1964; Alba and Nee, 1997).

**H2.** Higher levels of structural transnationalism are associated with poorer outcomes of cultural and economic assimilation.

**H2** posits that both $n_j$ and $k_j^+$ significantly and negatively contribute to predicting cultural and economic assimilation. This is the naive hypothesis that can be derived from canonical assimilation theory, which posits that immigrants’ increasing adoption of host cultural traits and economic upward mobility in the new country of settlement parallel a gradual separation from the society and culture of origin. It should be noted, however, that this hypothesis has been repeatedly questioned by more recent literature documenting the concurrence of transnational engagement and assimilation in various domains (Guarnizo et al., 2003; Itzigsohn and Saucedo, 2002; Portes et al., 2002; Snel et al., 2006).

**H3.** Lower cohesion, or higher segregation, between personal contacts from different nationalities and geographies is associated with better outcomes of cultural and economic assimilation.

We hypothesize that the brokering type of structural assimilation and transnationalism, rather than the cohesive type, results in better assimilation outcomes. With respect to cultural assimilation, we expect that diversity and cultural holes in personal networks foster cultural adaptivity in international immigrants. With respect to economic assimilation, we hypothesize that structural holes between different classes of alters function as bridging social capital and are associated with better economic outcomes for ego. **H3** implies that $GV^+$ and $\bar{GV}$, taken together, significantly contribute to explaining cultural and economic assimilation, above and beyond $n_j$ and $k_j^+$ ($j = 1, 2$). Given the definition of the index of subgroup segregation $S$, higher levels of $GV^+$, with $\bar{GV}$ being equal, correspond to higher segregation and lower cohesion between alter classes. By contrast, higher levels of $\bar{GV}$, with $GV^+$ being equal, correspond to lower segregation and higher cohesion between classes. Thus, **H3** posits a significant positive effect of $GV^+$, and a significant negative effect of $\bar{GV}$, in predictive models for cultural and economic assimilation.
Table 1
Number of values (N), mean, standard deviation (SD) and correlations (r) of the continuous variables used in the predictive models.

<table>
<thead>
<tr>
<th></th>
<th>Spanish sample: all nationalities</th>
<th>Spanish sample: Moroccans</th>
<th>Spanish sample: Senegambians</th>
<th>Italian sample: Sri Lankans</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Mean (SD)</td>
<td>r</td>
<td>N</td>
</tr>
<tr>
<td>1 Acculturation rating scale (ARS)</td>
<td>139</td>
<td>-.93 (1.04)</td>
<td></td>
<td>70</td>
</tr>
<tr>
<td>2 Monthly income*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 Age</td>
<td>139</td>
<td>29.2 (8.4)</td>
<td></td>
<td>70</td>
</tr>
<tr>
<td>4 Years since migration</td>
<td>139</td>
<td>7.0 (6.7)</td>
<td></td>
<td>70</td>
</tr>
<tr>
<td>5 Natives: size (n_1)</td>
<td>139</td>
<td>9.6 (8.8)</td>
<td></td>
<td>70</td>
</tr>
<tr>
<td>6 Natives: cohesion (k_1)</td>
<td>118</td>
<td>4.8 (4.1)</td>
<td>.78</td>
<td>64</td>
</tr>
<tr>
<td>7 (n_1, k_1)</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8 Origin Co-nationals: size (n_2)</td>
<td>139</td>
<td>16.5 (13.4)</td>
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<td>70</td>
</tr>
<tr>
<td>9 Origin Co-nationals: cohesion (k_2)</td>
<td>127</td>
<td>11.3 (9.8)</td>
<td>.63</td>
<td>63</td>
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<tr>
<td>10</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11 Network diversity (GV')</td>
<td>139</td>
<td>.47 (.15)</td>
<td>.87</td>
<td>70</td>
</tr>
<tr>
<td>12 Subgroup diversity (gV')</td>
<td>139</td>
<td>.34 (.15)</td>
<td>.64</td>
<td>70</td>
</tr>
</tbody>
</table>

* Net monthly income in €.

k_1 and k_2 do not have a definite value when the corresponding class does not appear in the personal network (i.e., n_1 = 0 or n_2 = 0), resulting in lower N for these variables.

3. Data

This study uses two datasets, which result from two different surveys and are kept separate in all analyses. The first dataset includes personal networks and individual attributes for a sample of Moroccan and Senegambian immigrants in Spain (N = 139). The second dataset covers similar characteristics for a sample of Sri Lankan immigrants in Italy (N = 102). The same independent variables of interest, i.e., the same personal network measures of structural assimilation and transnationalism, can be calculated from both datasets. However, two different outcome variables are available in the two data sources, for cultural assimilation in the Spanish case and for economic assimilation in the Italian case.

The first dataset was produced by a personal network survey conducted in the provinces of Barcelona and Girona, Spain, in 2004–2006 (Lubbers et al., 2007). Immigrants from Argentina, Dominican Republic, Morocco, Senegal and Gambia were selected via snowball sampling starting from multiple key informants in several community centers. Computer-assisted, face-to-face interviews were conducted using the software program EgoNet (McCarty and Smith, 2015) for ego-centric network surveys. Analyses in this paper are limited to the subsample of Moroccan (N = 70) and Senegambian immigrants (N = 69), for which a valid measure of cultural assimilation is available.5

One of the earliest in Spain, Moroccan immigration has been mostly driven by economic reasons and family reunions, resulting in 560,000 Moroccans living in Spain in 2006, the largest non-European immigrant nationality in the country that year.6 Approximately one-third of this population, 190,000 Moroccans, lived in Catalonia, the autonomous community where Barcelona and Girona are located, representing the largest non-European national group in that region too. Also driven by economic reasons, Senegalese and Gambian immigration to Spain started more recently, and about 50,000 Senegalese or Gambian nationals resided in Spain in 2006, of which 25,000 lived in Catalonia, constituting together the 10th largest non-European national group in Spain that year, and the 7th largest in Catalonia. In the 2000s, Moroccan and Senegambian immigration to Spain was being replenished yearly, which is reflected in the Spanish sample including, on average, 28–30 years old, first-generation immigrants, who had been in Spain for 9.4 (Moroccans) and 4.6 years (Senegambians; Table 1).

The second dataset used in this study results from a personal network survey conducted among male Sri Lankan immigrants (N = 102) in Milan, Italy, in 2012. Interviews used the software program VennMaker for the collection of ego-centric network data (Schönhuth et al., 2014). Respondents were sampled in two ways. Approximately 70% of the sample was recruited through informational materials, such as leaflets and posters, circulated in central places in Milan, particularly within Sri Lankan ethnic neighborhoods, including public transportation stations, street markets, Sri Lankan churches and temples, and Sri Lankan diplomatic buildings. The remaining 30% of the sample was recruited through snowball sampling starting from a dozen of key informants in the Sri Lankan community in Milan, including leaders of Sri Lankan religious associations; teachers in Sri Lankan schools; managers of Sri Lankan TV channels in Milan; Sri Lankan political organizers and leaders of cultural associations; employers and employees in Sri Lankan businesses.

One of the earliest among non-European migration flows to Italy, Sri Lankan economic migration to the country started in the 1970s and steadily increased over the following four decades, heavily shaped and facilitated by Sri Lankan social networks across the two countries (Pathirage and Collyer, 2011). As a result, in 2012 Sri Lankans were one of the largest immigrant nationalities in Italy and Milan, with about 80,000 Sri Lankans living in the country (the 11th largest non-European nationality in Italy that year), and approximately 16,000 Sri Lankans residing in Milan (the 7th largest non-European nationality in the city that year). In the Italian sample, the average Sri Lankan respondent is a 41-years-old, first-generation immigrant who has been in the country for 8.7 years (Table 1).

The personal network name generator was exactly the same in the two surveys: “Would you list the names of 45 persons whom you know and who know you, with whom you have had some contact in the past two years (face-to-face, by phone, or by the Internet), and whom you could still contact if you needed to?” The fixed-size list of 45 alters was intended to yield a representative sample of the respondent’s total personal network (McCarty et al., 1997). Respondents were also asked a set of fixed name interpreters about each alter, including questions on nationality and country of residence.

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In both surveys, personal network structure was collected by asking respondents to report on the relationship existing in every pair of alters. The relevant question was: “How likely is it that these two persons contact, meet or talk to each other independently of you?” For each of 990 pairs of alters (all the undirected pairs between 45 alters), respondents could answer that the two contacts certainly met and talked with each other, maybe met and talked with each other, or certainly did not meet and talk with each other. Here we consider two alters as connected in the personal network if ego has evaluated them as either certainly or maybe meeting and talking with each other.

In the Spanish data, cultural assimilation is measured on each respondent using an acculturation rating scale (ARS) readapted from the Acculturation Rating Scale for Mexican Americans II or ARS-II (Cuellar et al., 1995). Originated in cross-cultural psychology, ARS-II and its older version, ARSMA, are the most popular acculturation scales for Mexican Americans (Thomson and Hoffman-Goetz, 2009), and have been successfully adapted to other populations as well, including immigrants of Arabic and Asian origin (Jadalla and Lee, 2015; Lee et al., 2006; Farver et al., 2002). ARSMA-II measures individual traits on four distinct factors considered to be relevant to acculturation: (1) language use and preference; (2) ethnic identity; (3) cultural heritage and ethnic behavior; (4) perception of contact and interaction with host society and co-nationals. Proximity to the host culture and distance from the origin culture are indexed as two separate dimensions, in the assumption that learning and adoption of the host culture does not necessarily imply departure from the origin culture. This results in two separate subscales, namely an immigrant-origin orientation subscale (OOS) and a host-culture orientation subscale (HOS). The final acculturation score is calculated as HOS minus OOS. The result is an index that ranges from −4 (maximum origin culture orientation) to +4 (maximum host culture orientation), with negative values indicating higher closeness to the origin culture and positive values indexing higher proximity to the host culture.

Our ARS index translates ARSMA-II to the context of Moroccan and Senegambian immigrants in Spain, by asking 28 Likert-type questions that require respondents to evaluate, on a 1–5 scale, the intensity or frequency of their behaviors, practices or tastes in the four acculturation factors (e.g. speaking the host-country language, identifying with the home country, cooking host-country food, reading books in the language of origin). In our sample of 139 immigrants in Spain, the Origin Orientation Subscale and the Host Orientation Subscale have an internal validity, as measured by Cronbach’s alpha, of .80 (on 15 items), and .78 (on 13 items), respectively.7 ARS ranges between −3.15 and 2.33, with a mean of −.92 (SD = 1.04, Table 1). The negative mean and the bias of the distribution towards negative values reflect the expected higher proximity to origin culture in this sample of first-generation immigrants.

In the Italian data, economic assimilation is measured by the immigrant’s individual net monthly income. We model this variable as a linear function of relevant predictors, after the usual logarithmic transformation. The analysis is restricted to cases with positive income (i.e., definite log-income), thus removing 6 out of 102 respondents who reported no monthly income. In line with a long research tradition in sociology and economics, we use individual income as an index of economic attainment and upward social mobility among immigrants. While other measures are possible, such as regular employment or successful self-employment, each necessarily focuses on a specific aspect of overall economic assimilation. Higher income is usually considered as an overall proxy for stable employment, access to higher-quality jobs, higher return to human capital, and, in general, dwindling of economic disparity between immigrants and native population (Chiswick, 1978; Borjas, 1983; Kalmijn, 1996; Alba and Nee, 1997; Borjas, 2000; Xie and Gough, 2011). Positive monthly income in the Sri Lankan sample ranges between €150 and €2,500, with a mean of €879.5 (SD = 492.1, Table 1). The 2011 poverty threshold in Northern Italian metropolitan areas was €785 in monthly income, which corresponds to the 38th percentile of our sample.

4. Results

4.1. Cohesion within alter classes

Size and internal cohesion of the Native and the Origin Co-national classes exhibit different average patterns in the data (rows 5–6 and 8–9 in Table 1). In the average personal network from the Spanish sample, over 20% of all personal contacts are Native Spaniards (9.6 out of 45 alters, SD = 8.8), and at least 4 contacts would need to be removed to disconnect the most cohesive block of the Native subgraph (average $k^H = 4.8, SD = 4.1$). In the Italian data, average structural assimilation is lower, with a smaller and less cohesive Native class in the average personal network. Just about 10% of the personal contacts are Italian (average $n = 4.4, SD = 3.6$), and the departure of a single Italian alter would disconnect the most cohesive subgroup of Natives in the average Sri Lankan personal network (average $k^H = 1.9, SD = 1.8$). Average size and cohesion are substantially higher for the Origin Co-national class, indicating higher levels of structural transnationalism than structural assimilation among these first-generation immigrants. In both samples, over a third of the average immigrant’s personal network is based in the home country (more than 16 out of 45 alters), and as many as 11 (in the Spanish sample) or 10 (in the Italian sample) Origin Co-nationals, on average, would have to interrupt their relationship with ego in order to disconnect the most cohesive Origin Co-national subgroup in which ego is embedded. Senegambians and Sri Lankans emerge as the most structurally transnational immigrants in the data, embedded in large and cohesive co-national social networks based in the country of origin.

On the other hand, Sri Lankan personal networks are characterized by the lowest levels of structural assimilation, with very low degrees of embeddedness in the Native alter class. At the opposite end, Moroccan respondents show similar levels of structural assimilation and structural transnationalism in the average personal network.

As suggested by the average patterns, $n_i$ and $k^H_i$ are positively correlated. One source of correlation is the fact that $k^H_i$ is bounded above to $(n_i - 1)$, the maximum possible value for class cohesion, observed when the $n_i$ alters in the class form a complete subgraph. Table 1 shows correlation values between .70 and .87 for size and cohesion within the same alter class. Taking these correlation patterns into account, we propose two alternative ways of using $n_i$ and $k^H_i$ as measures of structural assimilation and transnationalism. One approach is to analyze class size and cohesion separately, and to enter them as two different covariates in regression models. Depending on the dataset at hand, this does not necessarily imply critical multicollinearity problems (see Appendix A). A second approach is to use cluster analysis to combine the two continuous variables into a single categorical index of embeddedness in an alter class. The former approach has the advantage of potentially identifying separate patterns and effects of class size and class cohesion on an outcome variable. The latter approach has the advantage of accounting for the correlation between $n_i$ and $k^H_i$, and avoiding collinearity problems. Other methods for combining

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7 These values are slightly lower, but reasonably close, to the Cronbach’s alpha values of the original ARSMA-II subscales, namely .88 (OOS) and .86 (HOS), as reported in the original study by Cuellar et al. (1995).
$n_j$ and $k^+_j$ into a single index are available too, for example based on principal component analysis.

Fig. 3 shows results from cluster analysis on size and cohesion of the Native and the Origin Co-national classes separately, using the PAM algorithm for $k$-medoid cluster analysis (Kaufman and Rousseau, 1990). The clustering partitions classify personal networks into clusters or profiles of embeddedness that simultaneously reflect class size and class cohesion. Thus, cluster analysis on $n_j$ and $k^+_j$ produces a categorical measure for the degree of structural assimilation, and cluster analysis on $n_j$ and $k^-_j$ generates a categorical measure for the degree of structural transnationalism (see Table 2 for the distribution of these measures in our data). The number $C$ of clusters to be detected, which is required as an input by the PAM procedure, was selected on the basis of silhouette (a goodness–of–fit index for clustering partitions, see Rousseau, 1987), and the interpretability of the resulting clusters as a meaningful typology of embeddedness in personal networks. $C = 3$ was found to yield the best silhouette and interpretability in all cases, except for the cluster analysis of embeddedness in the Native class in the Sri Lankan sample, for which $C = 4$ better accounted for a small outlier cluster with relatively high levels of $n_j$, generating a much higher silhouette.

Consistently with the standard deviation values in Table 1, Fig. 3 shows higher variability in class size than class cohesion. At the same time, a substantial variability of $k^+_j$ emerges, given the same value of $n_j$. This suggests that $n_j$ and $k^+_j$ are non-redundant variables, whose combination yields a better measure of class embeddedness than either variable taken separately. Results from the cluster analysis support this conclusion. In both samples, the emergent clusters are ordered types of personal networks with increasing levels of embeddedness in the Native class or in the Origin Co-national class. The higher variance of class size results in the clusters primarily reflecting variability in $n_j$. However, the clusters are also different with respect to $k^+_j$, and could not be reproduced by intervals of $n_j$ taken alone. In other words, the emergent personal network clusters reflect variability in both class size and cohesion, yielding a categorical measure of embeddedness that incorporates both variables. The clusters correspond to ordered intervals of a function $f(n_j, k^+_j)$ (i.e., degree of embeddedness) that is increasing with both $n_j$ and $k^+_j$. Given the same value of class cohesion, higher values of class size correspond to clusters with higher embeddedness; and given the same value of class size, higher values of class cohesion also correspond to clusters with higher embeddedness.

4.2. Cohesion between alter classes

Two randomly selected alters in the average Moroccan or Senegambian personal network have a .47 probability of belonging to two different classes between the Native, Origin Co-national, and Other class (average $GV^* = .47, SD = .15$; Table 1). The same probability is slightly higher in the average Sri Lankan network (average $GV^* = .52, SD = .07$), indicating higher class diversity in the average whole personal network. Moving to the level of single cohesive subgroups, the average probability that two random alters in the same cohesive subgroup belong to two different classes is remarkably lower, with average $GV^*$ equal to .34 and .31 in the Spanish and Italian data respectively. This shows that a certain degree of class segregation exists on average in our personal networks, as expected, with alters from the same class tending to fall in the same cohesive subgroups, and class diversity being typically lower in subgroups than in the whole personal network. Fig. 4 reveals a significant variability in network diversity, subgroup diversity, and subgroup segregation within the two samples. Network diversity and subgroup diversity are not redundant, and $GV^*$ has equal or higher standard deviations than $GV^*$ in the data. As predicted, all the three cases of Segregation (high $GV^*$, low $GV^*$), Mix (high $GV^*$, high $GV^*$) and Homogeneity (low $GV^*$, low $GV^*$) are represented in both the Spanish and the Italian samples.
Table 2
Distribution of the categorical variables used in the predictive models. N: absolute frequency. Prop: relative frequency.

<table>
<thead>
<tr>
<th></th>
<th>Spanish sample: all nationalities</th>
<th>Spanish sample: Moroccans</th>
<th>Spanish sample: Senegambians</th>
<th>Italian sample: Sri Lankans</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>N</td>
<td>Prop</td>
<td>N</td>
<td>Prop</td>
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<tr>
<td>Senegambian</td>
<td>69</td>
<td>.50</td>
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<tr>
<td>Sri Lankan</td>
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<tr>
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<td>70</td>
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<tr>
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<tr>
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<td>.58</td>
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<td>Female</td>
<td>59</td>
<td>.42</td>
<td>43</td>
<td>.61</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>139</td>
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<td>70</td>
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<td>.10</td>
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<td>Other</td>
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<td><strong>Total</strong></td>
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<td><strong>Cluster of embeddedness in Native class (n1, k1)</strong></td>
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<td></td>
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</tr>
<tr>
<td>A</td>
<td>56</td>
<td>.40</td>
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<td>.17</td>
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<td>B</td>
<td>42</td>
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<td>27</td>
<td>.39</td>
</tr>
<tr>
<td>C</td>
<td>41</td>
<td>.29</td>
<td>31</td>
<td>.44</td>
</tr>
<tr>
<td>D</td>
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<td><strong>Cluster of embeddedness in Origin Co-national class (n2, k2)</strong></td>
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<td>A</td>
<td>44</td>
<td>.32</td>
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<td>.41</td>
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<td>.41</td>
</tr>
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<td>C</td>
<td>45</td>
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<td>.17</td>
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<td><strong>Total</strong></td>
<td>139</td>
<td>1</td>
<td>70</td>
<td>1</td>
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</tbody>
</table>

4.3. Predictive models for cultural assimilation

We use linear regression to test the hypothesis that personal network measures of structural assimilation and transnationalism predict levels of cultural assimilation, or acculturation, in the Spanish data. Acculturation, as measured by ARS, is modeled as a linear function of structural assimilation and transnationalism, while controlling for other, potentially confounding ego-level characteristics (Table 3). Model 1 predicts ARS using control variables only, including nationality, sex, age, years since migration, and educational level. Age and years since migration are centered on the mean and scaled to intervals of five years. Age has a significant negative effect on acculturation, but a positive coefficient is associated to its quadratic term, suggesting a U-curve pattern in which the negative association flattens out for older immigrants and inverts into a positive relationship after a certain age threshold. As expected, years since migration are positively associated with acculturation, suggesting that immigrants grow closer to host cultural traits with longer periods of time spent in the receiving country – a finding that is consistent with classical assimilation theory. The significant negative coefficient for this predictor's quadratic term, however, reveals a non-linear relationship with decreasing marginal effects associated with more years since migration.

In Models 2 and 3, personal network measures for the degree of structural assimilation and transnationalism are added as predictors, in the continuous and discrete versions respectively. The

Fig. 4. Network diversity, subgroup diversity, and subgroup segregation in the two samples. Boxplot statistics for the marginal distributions are shown on the left and bottom sides of each panel: □ Median, -- Inter-quartile range, * Lower and upper whisker extremes.

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Table 3
Linear model for Acculturation Rating Scale (ARS). Age and years since migration are centered on the mean and scaled to intervals of 5 years. Class size (n1, n2) and class cohesion (k1, k2) are centered on the mean and scaled to intervals of 3 network members. Network diversity (GV) and subgroup diversity (CV) are centered on the mean and scaled to .1 intervals. In Models 2 and 4, missing values in k1 and k2, due to no alter in class (i.e. n1 = 0 and n2 = 0), are imputed as 0.

<table>
<thead>
<tr>
<th>Acculturation Rating Scale (ARS) (N=139)</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Intercept)</td>
<td>−0.618</td>
<td>0.279**</td>
<td>−0.730</td>
<td>−0.258*</td>
<td>−0.887</td>
</tr>
<tr>
<td><strong>Controls</strong></td>
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<td><strong>Nationality</strong></td>
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<tr>
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<td>0.153</td>
<td>−0.44</td>
<td>0.144</td>
<td>−0.035</td>
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<td>Senegambian (ref)</td>
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<td><strong>Sex</strong></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Male (ref)</td>
<td>−0.238</td>
<td>0.047**</td>
<td>−0.198</td>
<td>0.044**</td>
<td>−0.197</td>
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<td>−0.235</td>
<td>0.136</td>
<td>−0.251</td>
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<tr>
<td><strong>Age</strong></td>
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<tr>
<td>(Age^2)</td>
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<td>0.061</td>
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<tr>
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<td>0.336</td>
<td>0.084**</td>
<td>0.408</td>
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<tr>
<td>(Years since migration)^2</td>
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<td>0.027**</td>
<td>−0.071</td>
<td>0.026**</td>
<td>−0.090</td>
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<tr>
<td><strong>Education</strong></td>
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</tr>
<tr>
<td>No education (ref)</td>
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<td>0.254</td>
<td>−2.96</td>
<td>0.239</td>
<td>−2.73</td>
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<td>0.295</td>
<td>0.114</td>
<td>0.280</td>
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<td>University</td>
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<td>0.316</td>
<td>−0.228</td>
<td>0.291</td>
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<td><strong>Degree of embeddedness</strong></td>
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</tr>
<tr>
<td>Size of Native class (n1)</td>
<td></td>
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<tr>
<td>Cohesion of Native class (k1^*)</td>
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<td>0.037</td>
<td>0.079</td>
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<tr>
<td>Size of Origin Co-national class (n2)</td>
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</tr>
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<td>0.039</td>
<td>0.072</td>
<td>0.040</td>
<td>0.093</td>
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<td>Cluster of embeddedness in Native class (n1, k1^*)</td>
<td>0.152</td>
<td>0.059**</td>
<td>0.210</td>
<td>0.069*</td>
<td>−0.017</td>
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<tr>
<td>A (ref)</td>
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<td>0.190</td>
<td>0.054</td>
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<td>0.183</td>
<td>0.299</td>
<td>0.241</td>
<td>−0.017</td>
</tr>
</tbody>
</table>

* p < 0.05 (two-tailed tests).
** p < 0.01 (two-tailed tests).
*** p < 0.001 (two-tailed tests).

Continuous covariates, which are centered on the mean and scaled to intervals of 3 network members for better interpretability, significantly increase the predictive power of the model, with an increase of R^2_adj from .467 to .566. The increase in R^2_adj is also significant, although lower in absolute value, in Model 3 compared to Model 1 (.467 to .524). Personal network measures for embeddedness explain part of the variability in ARS that was attributed to age and time since migration in Model 1, resulting in lower absolute values of coefficient estimates for those control variables. Class sizes n1 and n2 are significantly associated with changes in acculturation, with more Native contacts corresponding to higher acculturation, and more Origin Co-national contacts associated with lower acculturation. The continuous measures of class cohesion do not show a significant effect on ARS in this version of the model. In Model 3, only categorical degree of embeddedness in the Native alter class is significantly and positively associated with ARS.

Models 4 and 5 add network diversity and subgroup diversity, centered on the mean and scaled to .1 intervals. The two covariates significantly improve model fit, in both the continuous version (Model 4 compared to Model 2) and the discrete version (Model 5 compared to Model 3) of the measures for degree of embeddedness. In particular, network diversity is significantly and positively associated with acculturation, whereas no significant association emerges for subgroup diversity. Model 4, including the diversity predictors and the continuous measures of class size and cohesion, explains the highest proportion of variability in immigrant acculturation (R^2_adj = .586). In this model, personal networks with 3 more Native contacts are associated with +.110 acculturation, while 3 additional Origin Co-national contacts are associated with −.091 ARS. The cohesion of the Origin Co-national class also emerges as a significant predictor, but with an opposite effect compared to the corresponding class size. Given the same number of Origin Co-national contacts, a higher structural cohesion between them characterizes the personal networks of more acculturated immigrants. An inverse pattern is found for embeddedness in the Native alter class, with class size positively correlated with ARS, and class cohesion negatively, although not significantly, correlated with acculturation.

The opposite and compensating effect of class cohesion (k1^*) compared to class size (n1) can be interpreted considering that lower cohesion indicates a sparser and more factional class subgroup, likely revealing a more extensive underlying network that reaches to different social circles within a given alter class. Thus, given the same number of Native personal contacts (n1), a sparser Native network (lower k1^*) with Natives from multiple social circles, might be associated with higher acculturation. On the other
hand, given the same number of Origin Co-national contacts (n2), a sparser Origin Co-national network (lower k*n) connected with different circles and environments in the home country (e.g. family and business associates), is associated with lower acculturation.

In Model 4, network diversity is a significant predictor of acculturation, but no significant effect emerges for subgroup diversity. A .1 increase in GV* corresponds to an increase of +.152 units in ARS, while controlling for GV. This result reveals a positive association between acculturation and structural segregation of alter classes (i.e., higher network diversity while holding subgroup diversity equal). In other words, more acculturated immigrants show more diverse personal networks, and networks in which ego brokers between disconnected alters from different classes. The addition of network diversity predictors reveals a significant effect of sex on acculturation, with female immigrants exhibiting −.312 ARS units on average (Model 4), other characteristics being equal.

4.4. Predictive models for economic assimilation

In the Italian data, the natural logarithm of net monthly income is modeled as a linear function of personal network characteristics and control variables, including age, years since migration, educational level, and legal status (Table 4). Using control variables only, Model 1 finds a significant positive effect of years since migration, with a significant negative quadratic term. This suggests an inverse-U relationship in which more years since migration are associated with higher income, but the marginal effects are decreasing and the association flattens out for higher values of the independent variable. The positive effect of years since migration is consistent with traditional assimilation theory, indicating that economic attainment in the receiving society improves as immigrants spend longer periods of time in the country of settlement. Among other controls, educational level significantly contributes to predicting monthly income, with university education associated to increased earnings. Model 1 also shows that average income is significantly lower for undocumented Sri Lankans, reflecting harder access to the Italian labor market among irregular immigrants. The results on control variables remain fundamentally unchanged in Models 2–5, although effect sizes decrease as part of the variability in log-income is explained by personal network characteristics.

Models 2 and 3 add personal network measures for the degree of structural assimilation and transnationalism, in the continuous and discrete versions respectively. Only Model 3 exhibits a significant improvement in overall fit over Model 1. The categorical measure for degree of embeddedness in the Native class significantly contributes to predicting monthly income. In particular, average levels of structural assimilation (Cluster B) are associated with higher income than the lowest levels (Cluster A, the reference category), with an average +.43% increase (e^0.357 = 1.43). The association disappears with even higher levels of embeddedness (Clusters C and D), suggesting that an average level of structural assimilation, rather than the lowest or the highest degrees of embeddedness in the Native class, is associated with the best economic outcomes. Interestingly, the categorical measure

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### Table 4

Log-linear model for net monthly income (in €). Age and years since migration are centered on the mean and scaled to intervals of 5 years. Class size (n1, n2) and class cohesion (kC1, kC2) are centered on the mean and scaled to intervals of 3 network members. Network diversity (GV*) and subgroup diversity (CV) are centered on the mean and scaled to 0.1 intervals. In Models 2 and 4, missing values in kC1 and kC2, due to no alter in class (i.e. n1 = 0 and n2 ≈ 0), are imputed as 0.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
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<td>Coeff.</td>
<td>S.D.</td>
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<td>.285</td>
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<tr>
<td>(Years since migration)^2</td>
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<td>.018**</td>
<td>−.056</td>
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<td>.121**</td>
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<td>.171***</td>
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<td>B</td>
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<td>.142**</td>
<td>.446</td>
<td>.166***</td>
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<td>.212</td>
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<td>Type of embeddedness</td>
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<td>Subgroup diversity (CV)</td>
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<td>.412</td>
<td>.427</td>
<td>.429</td>
<td>.452</td>
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of embeddedness is more effective than the continuous version in this case, identifying an association between structural assimilation and income that would not emerge if \( n_1 \) and \( k_1^j \) were only used in their continuous form. Structural transnationalism, as measured by embeddedness in the Origin Co-national alter class, is not significantly associated with changes in monthly income.

In Models 4 and 5, the measures for type of embeddedness significantly contribute to explaining variability in log-income. Model 5 in particular, where network and subgroup diversity are added to the categorical measures for degree of embeddedness, shows the highest fit with the data (\( R^2 = .452 \)). Only subgroup diversity, however, is significantly correlated with log-income, with a +1 variation in \( \log \) transmigrating into a 12% increase in monthly income on average (\( e^{0.105} = 1.12 \)). By contrast, no significant effect on earnings is estimated for network diversity. This result indicates that better outcomes of economic assimilation among Sri Lankans in Milan are associated with structural cohesion between alter classes (i.e., higher subgroup diversity, given the same value of network diversity). The addition of the diversity predictors also increases the estimated association between monthly income and degree of embeddedness in the Native class. In Model 5, a 56% higher income (\( e^{0.446} = 1.56 \)) is observed, on average, in the cluster with average levels of structural assimilation (Cluster B), as compared with the reference category.

5. Discussion

Our data show a substantial variability, among international immigrants, in both the size and the cohesion of the two types of social networks that sustain structural assimilation and structural transnationalism, namely native social networks in the host society and co-national social networks in the home country. Theoretically, size and cohesion of alter classes can be considered as two distinct dimensions of structural assimilation and structural transnationalism. Empirically, the personal network measures \( n_1 \) and \( k_1^j \) capture variability along these two dimensions. While positively correlated, \( n_1 \) and \( k_1^j \) are not redundant, both contributing to an effective measurement of the degree of structural assimilation and transnationalism. Our analysis also shows a considerable variability in network diversity, subgroup diversity, and subgroup segregation, as measured by \( G^v \), \( \overline{G^v} \) and \( S \). Evidence is consistent with our prediction that the personal networks of international immigrants would approach one of the three cases of Homogeneity. Segregation or Mix of alter classes in network structure, corresponding to different brokerage positions of ego. Thus, the combination of network diversity and subgroup diversity effectively indexes the type of structural assimilation and transnationalism, in a continuum between brokering and cohesive embeddedness in Native and Origin Co-National social networks.

Some, but not all, measures for the degree of structural assimilation (\( n_1^j \) and \( k_1^j \)) and structural transnationalism (\( n_2 \) and \( k_2^j \)) are significant predictors of cultural and economic assimilation. The size, but not the cohesion, of the Native alter class is positively associated with acculturation of international immigrants. Size and cohesion of the Native class, in their combined and discrete form, are significantly and positively associated with economic performance. These two findings support hypothesis H1 that higher degrees of structural assimilation are associated with better outcomes of cultural and economic assimilation. On the other hand, hypothesis H2 is not supported by our data, as size and internal cohesion of the Origin Co-national class are not significant predictors of economic assimilation.

A higher number of Native contacts is observed in connection with higher levels of acculturation. This is consistent with the hypothesis, formulated in canonical assimilation theory, that participation in native primary groups of the host society is a sufficient condition for gradual acculturation. By contrast, a higher number of Origin Co-national contacts is associated with lower acculturation. As suggested by Brandes and colleagues (2010a), higher contact with co-nationals in the sending country can be viewed as a reflection of Berry’s separation/mode of acculturation, which results in lower inclination to accept cultural models of the host society (Berry, 1997). However, the direction of causality between structural transnationalism and poorer acculturation cannot be discerned in these data. Regular contact, communication and interaction with a higher number of relatives, friends and acquaintances in the home country might reinforce attachment to origin cultural traits and discourage adoption of host culture, with causality going from structural transnationalism to poorer acculturation. Alternatively, a preexisting lower inclination to adopt host culture, and a higher attachment to origin culture might make immigrants more prone and better able to maintain social relationships with the home society, with causality going in the opposite direction. Compared to class size, internal cohesion of the two alter classes appears to have an opposite effect on cultural assimilation. The lack of cohesion between Origin Co-national alters, which likely reflects ego’s connections with a broader variety of groups and circles in this class, is linked with higher attachment to origin cultural traits.

Our models for economic assimilation suggest that average levels of embeddedness in Native social networks are associated with better economic outcomes compared to both the lowest and the highest levels of structural assimilation. While a very low number of native contacts indicates lack of structural assimilation, very high numbers of Natives in the personal network might reflect poorer social capital among co-national immigrants in the host country, particularly given the fixed size imposed to personal networks in our data. Social capital with co-nationals in the receiving country, however, is known to play an important role for successful economic incorporation among immigrants, because it facilitates access to ethnic niches in the labor market and provides knowledge and material resources for entrepreneurial activity (Portes and Sensenbrenner, 1993; Portes, 1998a; Light and Gold, 2000; Schrover et al., 2007; Solano, 2016). Thus, optimal economic outcomes might rely on a balanced personal network composition, in which significant levels of embeddedness in native social networks co-exist with a substantial degree of embeddedness in networks of co-national immigrants as well. On the other hand, no association emerges in our data between structural transnationalism, as measured by the size and cohesion of Origin Co-national networks, and economic performance. This result is consistent with existing evidence that transnational social relationships are not necessarily associated with marginal economic status among international immigrants (Portes et al., 2002).

5.1. Cultural assimilation and brokerage between differences

Network diversity \( G^v \) is associated with higher acculturation after controlling for the size and internal cohesion of alter classes, providing partial support for hypothesis H3. Given a certain degree of embeddedness in the Native and Origin Co-national classes, having a nationally and geographically more diverse personal network is associated with higher cultural assimilation. Thus, once a certain threshold of embeddedness within host-country social networks is reached, nationally and geographically diverse social networks might be the best predictors of successful cultural adaptation. This result is consistent with research in cross-cultural psychology showing that cultural integration, defined as a balanced strategy in which the immigrant incorporates some cultural traits from the receiving society while still maintaining other cultural traits from
the country of origin, is the most successful mode of acculturation in terms of immigrants’ physical and psychological well-being (Berry et al., 1987; Berry, 1997).

Consistently with hypothesis H3, higher acculturation is observed when the personal network is comprised of different, and structurally separate, national and geographical classes of contacts, with ego brokering between them. In other words, the brokering type of structural assimilation and transnationalism, rather than the cohesive type, is associated with higher acculturation. Previous research on international immigrants in Spain found that stronger ethnic self-identification, typically a correlate of lower cultural assimilation, is linked to higher proportions of Origin Co-national contacts, and to more dense and cohesive personal networks (Lubbers et al., 2007). Our results are consistent with these findings, showing that higher cultural adaptation is associated with a lower number of Origin Co-national alters and with ego’s brokerage between alter classes, a characteristic of less cohesive, more factional personal network structures (e.g. compare panel A to B and C in Fig. 2).

Pachucki and Breiger’s (2010) notion of cultural holes contributes to the interpretation of these findings. According to this notion, structural holes in social networks are likely to reflect cultural differences between separate and internally homogeneous subgroups. Bridging structurally separate areas of a network, and spanning the corresponding cultural holes, often means mediating and reconciling contrasts between different cultural models and identities, which also implies negotiating and adapting one’s models and identity. Thus, structural and cultural brokerage might be linked to plural identities and cultural adaptivity. Adding to this argument, we find that structural brokerage in personal networks, particularly when it bridges contacts from different nationalities and geographies, is linked to higher cultural adaptation among international immigrants.

5.2. Economic assimilation and diversity within closure

In contrast with hypothesis H3 and with arguments on structural holes as social capital, the cohesive type of structural assimilation and structural transnationalism, rather than the brokering type, is associated with economic incorporation among Sri Lankans in Milan. Higher average income is observed in connection with lower structural segregation and more cohesive personal networks in which Natives, Origin Co-nationals, and Other alters (e.g. immigrant co-nationals) know and interact with each other in the same network subgroups. We describe this characteristic as diversity within closure.

Migration studies have often emphasized the role of network closure as a source of social capital for international immigrants (Coleman, 1988; Portes and Sensenbrenner, 1993; Portes, 1998b). Network closure fosters ethnic solidarity and mutual support between members of the same immigrant minority; facilitates enforceable trust, a form of trust between parties of an economic transaction that is enforced by the closely-knit community to which both parties belong; and often reflects multiplex relationships, which encourage mutual trust and reciprocal obligations. On the other hand, closure is also known to have negative effects on individuals (Burt, 2001). Particularly in an immigrant population, tightly-knit social networks can entail exclusion from non-ethnic, non-redundant information and resources, as well as heightened social control, pressure to conform to the group, or resistance to innovation (Portes and Sensenbrenner, 1993; Portes, 1998b). Our findings suggest that an optimal network configuration for immigrant economic advancement is one that preserves the advantages of closure social capital, while limiting its drawbacks. Diversity within closure brings together two social resources, namely the solidarity, support and trust coming from highly cohesive networks, and the connections to different social circuits resulting from national and geographical diversity of personal contacts. In this balanced configuration, ego is connected with different social circuits, resources and models, but diversity is not associated with social fragmentation.

In particular, diversity within closure facilitates transnational enforceable trust in immigrant communities. Enforceable trust, based on reputation, close communication and monitoring in tightly-knit communities, is crucial to many aspects of immigrant economic life, from accessing informal loans to starting up domestic or transnational businesses. While enforceable trust has typically been studied among co-ethnic immigrants living in the same city or country (e.g. Light, 1972; Portes and Sensenbrenner, 1993), our ethnographic research observed the emergence of enforceable trust as a transnational mechanism produced by transnational closure of social networks between Sri Lankans in Italy and Sri Lanka. In these cohesive transnational communities, for example, families left in Sri Lanka are held fully responsible for the financial obligations of their immigrant relatives in Milan. If a Sri Lankan does not pay for his debt in Milan, the reputation of not being trustworthy will likely reach his hometown and affect his family’s ability to borrow in Sri Lanka. At the same time, having a well-off and trustworthy family in Sri Lanka, which is well-known in the co-national community in Italy, is a valuable collateral asset for Sri Lankans who need an informal loan in the immigrant community in Milan. Pathirage and Collyer’s (2011) multi-sited ethnography in Sri Lanka and Italy provides further examples of transnational enforceable trust operating in cross-border, tightly-knit social networks of Sri Lankans based in both countries.

Finally, diversity within closure may also be an index of family-based migration or family reunification, which has been linked with better economic outcomes for international immigrants (Nee and Sanders, 2001). If ego’s Sri Lankan relatives are in Italy, they are more likely to meet ego’s Italian friends, resulting in structural cohesion between the Native and the Other alter class. At the same time, a dense family network in Italy is likely to preserve connections with family and friends back in Sri Lanka, resulting in structural cohesion between the Origin Co-national and the Other alter class. Both connectivity patterns translate into higher diversity within network closure (higher GV, lower S).

6. Conclusions

Personal network measures for the degree and type of structural assimilation and transnationalism predict assimilation outcomes in our data, above and beyond the effect of individual characteristics such as nationality, age, years since migration, and educational level. Personal network structure, in particular, uniquely contributes to explaining assimilation outcomes by capturing the structural component of embeddedness, as well as the patterns of structural cohesion between personal contacts from different nationalities and countries of residence. In some cases, personal network measures are better predictors of assimilation outcomes than basic socio-demographics such as educational level. Our findings indicate a distinctive and unique association between structural assimilation and transnationalism on the one hand, as observable in immigrants’ personal networks, and cultural and economic assimilation on the other hand. This conclusion is consistent with the general hypothesis, implied in most migration research, that immigrant assimilation and transnational involvement are sustained by specific types of social networks. On the other hand, the causal direction of the relationship between personal network characteristics and assimilation outcomes cannot be discerned in the kind of cross-sectional
data analyzed in this paper (Shalizi and Thomas, 2011). Possible future directions of research to elucidate the causal mechanisms at play include the analysis of longitudinal personal network data, and the integration between quantitative analysis and in-depth ethnographic work in immigrant communities. It should be noted, in this respect, that the conceptualization of network characteristics as independent variables is in agreement with most sociological theory, which has consistently viewed immigrants’ social networks as the cause, rather than the effect, of assimilation trajectories and transnational involvement.

Personal network methods offer a unique advantage in the study of immigrant assimilation and transnationalism. Defined around a focal ego, personal networks do not assume boundaries. They originate in a particular place, but are not constrained within a particular social or geographical group, unlike typical socio-centric networks. As such, personal networks do not require the researcher to arbitrarily delimit the social space within which to investigate relationships and interactions. The relevant social spaces are inductively derived from the data, rather than deducted from a priori assumptions. Thus, personal networks allow researchers to capture unbounded primary groups, and to simultaneously examine immigrant embeddedness in different national and geographical contexts (Molina et al., 2015). In general, personal network research designs might represent an effective strategy to depart from methodological nationalism in the social sciences, an orientation which is often seen as a major flaw in traditional migration studies (Wimmer and Schiller, 2002).

While in this study nationality and country of residence where the two most adequate alter attributes for the operationalization of structural assimilation and transnationalism, this might not always be the case. The methods proposed here, however, are entirely applicable to different definitions of alter classes. When the appropriate alter attributes are collected, the Origin Co-national class can be split into different categories based, for example, on alter ethnicity or different locations within ego’s country of origin. Ego’s transnational embeddedness in different co-national ethnic groups (e.g. Mestizos versus Indigenous people in Mexico) or geographic sub-populations (e.g. rural versus metropolitan areas in China) might have different impacts on the outcomes of interests. Native alters might also be classified into different ethnic or socio-economic classes, especially in cases in which segmented assimilation of immigrants in different sub-populations of the receiving country is a focus of study.

The methods proposed in this article are also applicable to different sampling designs, including multi-site studies in the sending and receiving countries, and both ego-centric and socio-centric designs, provided that the collected data allow for a good approximation of the total personal networks of respondents. While personal network interviews can be burdensome, methods for reducing respondent burden have been proposed (McCarty et al., 2007), and less demanding name generators than the one used in this study can effectively yield representative samples of personal networks (McCarty et al., 1997). In addition, increasingly more effective software for personal network data collection, including online surveys and smartphone- or tablet-assisted interviews, has been actively developed in the last few years (Kennedy and Zhang, 2016). Although social network studies can greatly contribute to our understanding of international migration, the collection of social network data seems particularly challenging in highly mobile and hard-to-reach populations such as international immigrants and their primary groups, which are typically dispersed across several countries. Even assuming that a meaningful socio-centric network boundary could be identified for multi-sited data collection (Mazzucato, 2010; Beauchemin, 2014), fieldwork in sending and diaspora countries would likely be costly or, in the case of forced migration, unfeasible due to political instability or armed conflicts. In this respect, personal network methods might be the most viable option to collect social network data in migration studies. As a future direction for research, the development of methods to overlap ego-centric data into whole socio-centric networks (e.g. Mouv et al., 2014), or to infer socio-centric characteristics from ego-centric networks (e.g. Smith, 2012), could prove extremely valuable to advance the study of social networks in international migration.

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**Appendix A. Collinearity diagnostics.**

The positive correlation between size ($n_j$) and cohesion ($k_j$) of an alter class in our data might cause problems of multicollinearity in Models 2 and 4 for cultural assimilation (Table 3) and economic assimilation (Table 4). Multicollinearity is a problem when it is sufficiently high to cause coefficient standard deviation to increase, or equivalently, coefficient confidence intervals to expand, beyond reasonable levels. High standard errors and wide confidence intervals imply that coefficient estimates are unstable and unreliable, being susceptible to substantial change across different samples. Thus, the paramount indicator of multicollinearity being a serious problem in a regression is the width of a coefficient’s confidence interval, or the square root of the variance inflation factor (VIF), which is the factor by which coefficient standard deviation, and consequently confidence intervals, expand due multicollinearity (Fox, 2008; Pedhazur, 1997). Tables 5 and 6 report these diagnostics for the relevant models. For completeness, Generalized VIF to the power of 1/(2*df) is reported, which reduces to the square root of VIF in the classical case of single-degree-of-freedom covariates (df = 1; Fox, 2008:322). Both Generalized VIF values, standard deviations, and the 95% confidence intervals are within acceptable levels for the potentially problematic coefficients in our regressions, namely those corresponding to $n_1$, $k_1$, $n_2$ and $k_2$. We also note that multicollinearity is a data problem, not a model problem. In other words, high multicollinearity is a characteristic of the specific dataset being used to estimate a model, not of the model itself. In the presence of high multicollinearity, a
particular dataset might be inadequate to reliably estimate the coefficient associated with a certain independent variable \( x \), because the data do not include sufficient variation of \( x \) conditional on other independent variables. However this does not mean in any sense that the model itself is invalid or misspecified. The same model might be very precisely estimated using other datasets with lower multicollinearity.

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