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Neither global nor local: Heterogeneous connectivity in spatial network structures of world migration

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ABSTRACT

For a long time, geographic regions were considered the dominant spatial arbiter of international migration of people. However, since the late 1970s, many scholars have argued that movements reach beyond contiguous regions to connect distant, dispersed, and previously disconnected countries across the globe. The precise structure of world migration, however, remains an open question. We apply network analysis that incorporates spatial information to international migration-stock data to examine what multilateral structures of world migration have emerged from the interplay of regional concentration (local cohesion) and global interconnectedness (global cohesion) for the period 1960–2000. In the world migration network (WMN), nodes represent countries located in geographic space, and edges represent migrants from an origin country who live in a destination country during each decade. We characterize the large-scale structure and evolution of the WMN by algorithmically detecting international migration communities (i.e., sets of countries that are densely connected via migration) using a generalized modularity function for spatial, temporal, and directed networks. Our findings for the whole network suggest that movements in the WMN deviate significantly from the regional boundaries of the world and that international migration communities have become globally interconnected over time. However, we observe a strong variability in the distribution of strengths, neighborhood overlaps, and lengths of migration edges in the WMN. This manifests as three types of communities: global, local, and glocal. We find that long-distance movements in global communities bridge multiple non-contiguous countries, whereas local (and, to a lesser extent, glocal) communities remain trapped in contiguous geographic regions (or neighboring regions) for almost the whole period, contributing to a spatially fragmented WMN. Our findings demonstrate that world migration is neither regionally concentrated nor globally interconnected, but instead exhibits a heterogeneous connectivity pattern that channels unequal migration opportunities across the world.

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1. Introduction

The migration of people is a self-perpetuating process (Hägerstrand, 1957; Massey, 1990; Massey et al., 1998) such that, once established, migratory movements tend to connect multiple countries across the world in structured large-scale networks (Kritz et al., 1992: 15). Mapping and analyzing the structure and evolution of networks of movements between countries can therefore advance understanding of how migration opportunities are distributed worldwide and what migration connections are likely to form and evolve in the future. Although there is a growing agreement that bilateral approaches to migration are insufficient and that movement of people between each pair of countries is better understood in the context of broader groups or networks of movements (Kritz et al., 1992; Salt, 1989), there is much less consensus about the structure of these networks and the basic mechanisms from which they arose.

One body of literature views migratory movements between countries as channeled within geographic regions (Abel et al., 2016; DeWaard et al., 2012; Salt, 1989; Salt, 2001; Zlotnik, 1992). The view of "regional concentration" of migration is an example of

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"geography of regions, not relations", to paraphrase Batty (2005: 149). In the "geography of regions", geographic boundaries come first (Knappett et al., 2008: 1009). Migration relations between regions, although acknowledged (Skeldon, 1997; Zlotnik, 1992), are secondary and are rarely expected to alter regional boundaries. World migration is thus viewed as an agglomeration of mostly local movements (within geographic regions and to neighboring regions) that arise predominantly from physical proximity. Another body of literature has argued that international migration has become "global in scope" since the mid 1970s. They pointed to the increasing number of world countries involved in migration (Castles and Miller, 2009), the diversification of origin countries (International Organization for Migration, 2003; Vertovec, 2007), and the tendency of migration to defy spatial constraints, which manifests in the many long-distance movements that span continents (King, 2002) and contribute to "global interconnectedness" (Held et al., 1999: 284). In contrast to the view of regional concentration, global interconnectedness implies that long-distance movements from multiple origins cut across regional boundaries, thereby decoupling international migration from the regional map of the world and creating an interconnected network of movements over time.

Although features of these contrasting—regional and global—tendencies are documented (see Held et al., 1999: Chap. 6), the implications for the large-scale structure of international mobility remain an open question. What are the structures of world migration that have emerged from the interplay of regional concentration and global interconnectedness in world migration? How have these structures evolved and shaped migration opportunities across the world? In this paper, we address these questions by employing theoretical insights and formal methods at the intersection of social network analysis (Borgatti et al., 2009; Granovetter, 1973; Wasserman and Faust, 1994) and spatial network analysis (Adams et al., 2012; Barthelemy, 2011; Expert et al., 2011).

2. World migration as a social and spatial network

2.1. Spatial and social network analysis

Spatial and social network analyses provide theoretical insights and tools for quantitatively describing and analyzing the contrasting tendencies of spatial concentration and global interconnectedness in world migration. The spatial network structures that emerged as an outcome of those tendencies have received little attention, as prior research either prioritized one tendency over another in world migration or focused on attributes of migration movements rather than on their interactions (e.g., Massey et al., 1998).

Spatial network analysis acknowledges that the formation (and the strength) of an edge in geographic space is typically associated with a cost (e.g., travel and information costs), such that nodes that are closer to one another are more likely to be connected to each other (Barthelemy, 2011; Expert et al., 2011). Consequently, one observes disproportionately more short-distance edges connecting nodes within the same neighborhood (spatial clustering) than long-distance edges between different neighborhoods (Watts, 1999: 129). Spatial network analysis has the potential to shed light on the spatial properties of migration (Hägerstrand, 1957; Malmberg, 1997) and how geographic regions, in combination with economic constraints (Mayda, 2010) and restrictive migration policies (Hatton and Williamson, 2002), can have a significant localizing effect on migration movements of people by channeling those movements between contiguous countries in a region. For example, it has been estimated that about 80 percent of the movements in the developing world are directed to a contiguous country (e.g., Bangladesh to India) (Population Division of the Department of Economic and Social Affairs, 2013; Ratha and Shaw, 2007).

However, there is more than physical space to international migration. Despite being less numerous, long-distance and global movements of people (but also information, goods, and investments (Castells, 1996; Dicken et al., 2001)) now connect geographically disperse countries (and broader regions) in novel patterns of relationships. Social network analysis (Borgatti et al., 2009; Wasserman and Faust, 1994) is particularly well-equipped to describe, analyze, and predict such emerging patterns of relationships among interacting entities. Network structure is a source of opportunities and constraints, and it can therefore influence the outcomes (e.g., access to resources) of particular nodes and edges, depending on their position in a network (Borgatti et al., 2009: 894; Wasserman and Faust, 1994: 3). For example, research on international trade (e.g., Smith and White, 1992) has documented that it is mostly the pattern of relationships between nation-states in the global trade network—and, to a lesser extent, nation-states' attributes (e.g., gross domestic product)—that determines the role that a country plays in the global economy. Likewise, the network structure of migration can have an impact on the distribution of migratory movements from and to a particular country or region.

2.2. The world migration network (WMN)

To begin to account for the coexistence of regional concentration and global interconnectedness, we represent world migration as a "social–spatial" network using data on international migration stocks that were reported in the Global Bilateral Migration Database (Özden et al., 2011). A *social–spatial network* is a set of nodes (e.g., countries, organizations, or individuals) located in geographic space that are connected to each other via a set of edges associated with length (and cost) (Barthelemy, 2011; Newman, 2010; Wasserman and Faust, 1994). The world migration network (WMN) is a set of world countries (and territories) that are located in geographic space (see Fig. 1A). The countries in the network are connected to each other via migration edges of various distances, and an edge represents the number of migrants from a sending country i who live in in a receiving country j at a particular point of time. The spatial aspect of the WMN comes both from the topographical positions of nodes (i.e., countries) and from the geographic constraints on edges between them. Because of technological advancements, migration is unlikely to diminish with an increase of distance in a manner predicted by the "inverse-distance rule" (Zipf, 1946), but the length of a migration edge is still associated with a cost, so longer-distance migration is likely to bear a higher cost (Barthelemy, 2011; Gastner and Newman, 2006).

In addition to spatial considerations, the WMN is directed (i.e., the edges have a direction that represents out- and in-migration) and weighted (i.e., edges have weights that represent, in our study, the volume of migrant stock between countries), and it evolves over time. To account for temporal changes, we represent the WMN as a multilayer network (Kivelä et al., 2014). Each layer represents bilateral migration stock between 226 world countries and territories recorded in 1960, 1970, 1980, 1990, and 2000.

2.3. Regional concentration versus global interconnectedness

An extensive body of literature views cross-border migration as concentrated within international migration systems (Bakewell, 2014; Fawcett, 1989; Kritz et al., 1992; Malmberg, 1997; Portes and Böröcz, 1989), defined as "a group of countries that exchange relatively large numbers of migrants with each other" (Kritz and Zlotnik, 1992: 2). International migration systems seldom form among random pairs of countries; instead, they arise among partic-

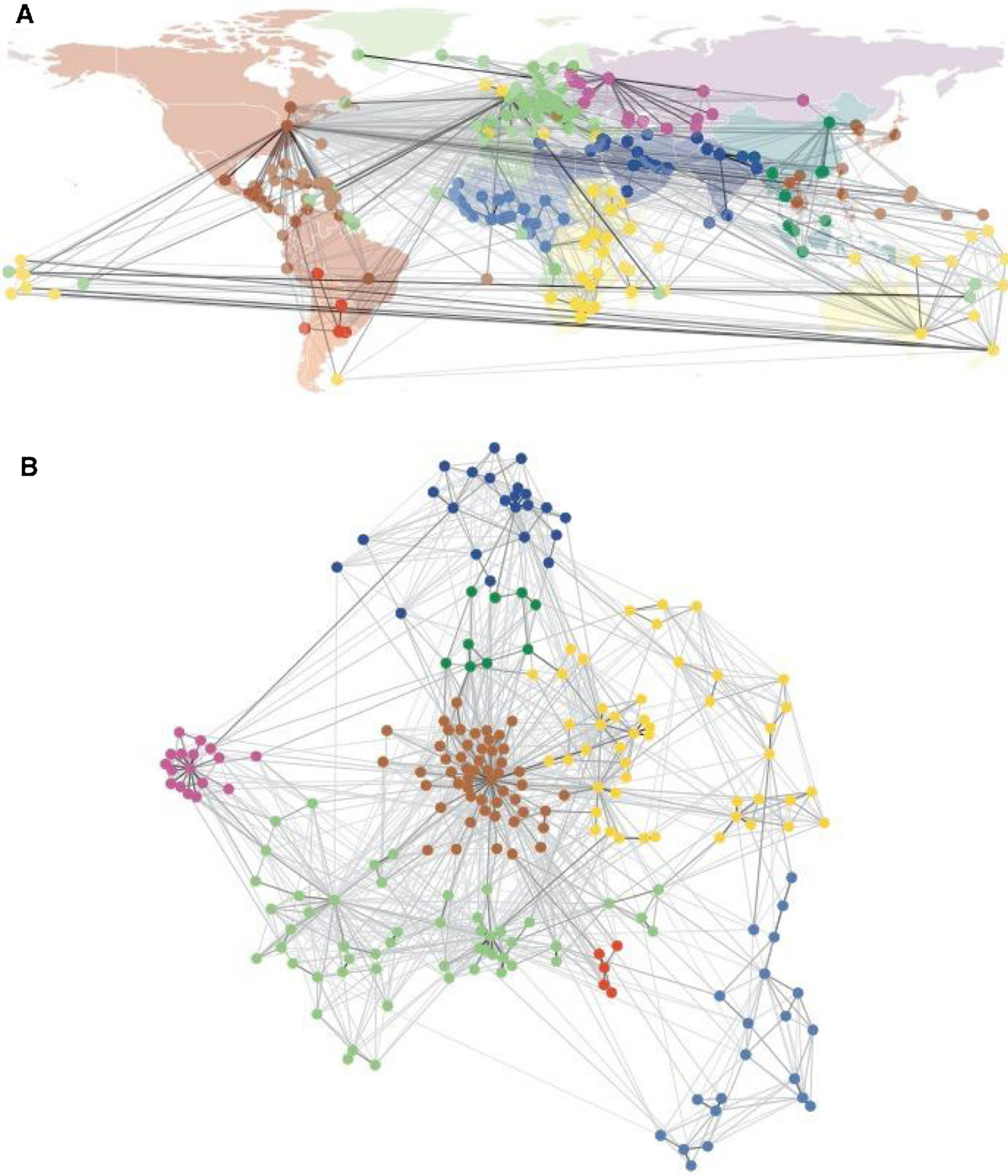

Fig. 1. World migration networks (WMNs). (A) An example of international migration community structure in space. The color of the nodes indicates community membership, and the position of the nodes indicates the geographic location of countries and territories. The edges represent migratory movements between countries. (B) An example of migration communities with different types of local and global connectivity. The 226 nodes in the WMN are assigned to one of eight different communities. For visualization, we use code from Traud et al. (2009) and Jeub et al. (2015) in MATLAB; for the world map, we use the package "rworldmap" in R (South, 2011).

ular countries that are enmeshed in a multiplex of social, economic, and cultural linkages that result from "prior contact" (Fawcett, 1989; Portes and Böröcz, 1989). Because the linkages are assumed to correlate positively with geographic proximity, systems were typically defined in regional terms (Kritz and Zlotnik, 1992: 4), such that Europe (Massey et al., 1998) or Western Europe (DeWaard et al., 2012; Salt, 1989; Salt, 2001) are construed as international migration systems. In the same vein, recent empirical research on European migration for 2003–2007 reported that systems are "more or less geographically discrete" (DeWaard et al., 2012). Likewise, Abel et al. (2016) concluded that systems in world migration for 1960–2010 are "geographically concentrated".

Others have argued that there has been a process of restructuring of world migration since the 1970s (Audebert and Doraï, 2010; Castles and Miller, 2009; King, 1993a; Vertovec, 2007). An important aspect of the restructuring is the "compression" or "shrinkage" of geographic and socio-cultural distances as a consequence of technological advancements (Harvey, 1989) and transformations in the world economy (Castells, 1996), such that many previously-detached regions have become interconnected via flows of goods, information, and people (Brunn and Leinbach, 1991: xvii–xviii; International Organization for Migration, 2003: 16; Lash and Urry, 1994: 26). Hence, many have observed that major migratory movements are now over long distances (e.g., China to the USA) rather than, as in the recent past, exclusively between contiguous countries (e.g., Ireland to England) or bound by past colonial relationships (e.g., Bangladesh to Britain) and bilateral agreements (e.g., between Germany and Turkey) (Agnew, 2009: 170; Castles and Miller, 2009: 7–12; International Organization for Migration, 2003: 4; King, 2002: 94).

In further support of world-migration restructuring, some scholars have emphasized the progressively increasing number of countries that are involved in migration (Castles and Miller, 2009: 7–12; Audebert and Doraï, 2010: 203), focusing particularly on the diversification of origins (Vertovec, 2007) and the shift to newly emerging high-income destinations since the 1970s (Sassen, 2007). In the same vein, Vertovec (2010: 3–4) argued that post-1945 migration patterns until the late 1970s involved mainly "large numbers moving from particular places to particular places" (e.g., Algeria–France, Turkey–Germany), whereas global migration since the 1980s has involved "small numbers moving from many places to many places". Some of the above propositions are supported by recent research (Davis et al., 2013; Fagiolo and Mastrorillo, 2013) that viewed the network of international migration as shifting from geographic fragmentation in 1960 to a more interconnected structure in 2000.

Held et al. (1999: 283–326) argued that regional systems and global interconnectedness coexisted in the latter half of the 20th century, and their proposition is consistent with recent data on global migration (Abel and Sander, 2014; Özden et al., 2011). In Held et al.'s (1999) account, patterns of global interconnectedness were represented in economic migrations to Europe, Australasia, North America, and the Gulf countries. Those movements were global in geographic scope (as they were both transoceanic and transcontinental), but they were less intense (i.e., there were fewer migrants) than the migration in either regional systems or the "mass migration" (Hatton and Williamson, 1998) to the New World in the period from 1850 to 1913 (Hirst and Thompson, 1999). Alongside global movements, Held et al. (1999) observed features of regional movements—contiguity, clustering, and high intensity—in Africa, Latin America, and East Asia.

2.4. Network regions beyond geography

The coexistence of regional concentration and global interconnectedness is likely to generate multilateral migration structures that are irreducible to preexistent geographic boundaries or independent migration exchanges between pairs of countries. To characterize these emerging multilateral structures of migration, we first decompose the WMN into mesoscale network structures known as "communities" (also called "modules" or "cohesive groups"), which consist of densely-connected nodes that are connected relatively sparsely to other densely connected nodes (Fortunato and Hric, 2016; Porter et al., 2009). An international migration community[1] is a tightly-knit group of countries with dense internal migration connections (relative to a null model, which describes random connections for a given distance range) but sparse connections to and from other countries in a network (see Fig. 1B). To detect international migration communities, we employ generalizations of the widely-used method of modularity maximization (Newman and Girvan, 2004) that were developed for studying spatial networks (Expert et al., 2011; Sarzynska et al., 2016), temporal networks (Mucha et al., 2010), and directed networks (Arenas et al., 2007; Leicht and Newman, 2008).

Prior research informed by the migration-systems approach (Abel et al., 2016; DeWaard et al., 2012) and network theory (Davis et al., 2013; Fagiolo and Mastrorillo, 2013) decomposed international migration into communities based only on connectivity information (that is, which countries are connected to each other) and the volume of migration exchanges. They ignored node attributes, such as location in geographic space. Consequently, in the methodologies used in prior research, each country is supposed to connect to any other country in the world with a probability that is independent of geographic proximity. When spatial forces are in places, as in international migration, failing to account for the impact of distance yields communities that are shaped predominantly by geographic proximity. Consider a situation in which countries i and k are close geographically and countries j and k are also close to each other. Nodes i and j are thus also close to each other, so they are likely to be connected to each other because of geographic proximity, irrespective of their connection to k. A methodology that insufficiently controls for underlying geographic effects is likely to overemphasize the impact of strong edges and spatial concentration and to underemphasize the role of long-distance (and perhaps weaker) migration in forming international migration communities.

We account for spatial information by employing a modularity null model for spatial networks (Expert et al., 2011). The model, in the context of the WMN, favors international migration communities that include pairs of countries that exchange more migrants than expected based on the distance between them. This approach can highlight the importance of "spatially surprising" migration connections in the formation and evolution of international migration communities. Once the effect of geographic proximity is disentangled from the network structure of world migration, one can more readily detect communities that are generated by a mixture of non-spatial[2] mechanisms of social (e.g., similar language), economic (e.g., capital flows via foreign direct investments), and historical (e.g., former colonial relationship) nature, as theorized in the literature on international migration (Fawcett, 1989) and globalization (Sassen, 2007). Using a null model that incorporates space also acknowledges the contribution of regional movements with limited geographic reach that involve more migrants than expected for that distance in the WMN. A spatial null model therefore facilitates the identification of both patterns of substantial regional concentration and patterns of global interconnectedness.

What does it mean for there to be an international migration community? First, international migration communities are "functional regions" (Ratti et al., 2010) in the WMN. Different communities may perform distinct functions in the WMN; these range from channeling regional mobility to bridging distinct regions. Second, as Simmel (Carrington and Scott, 2011; Martin, 2009; Simmel, 1950[1908]) observed, once cohesive structures crystallize, they can maintain their own existence—and they can thereby confront and enable further migration interactions—even when the reasons that they arose initially have vanished. In parallel, a large body of literature on migration perpetuation (Massey, 1990), migrant networks (Palloni et al., 2001), and chain migration (MacDonald and MacDonald, 1964) have documented how once two or more locations are enmeshed in migration, they "have a tendency to perpetuate themselves because migrations at any given time are dependent on preceding migrations" (Hägerstrand, 1957: 130). The property of self-perpetuation of migration suggests that movements between two or more countries in a migration community increase the likelihood of remaining within the community in the future. Community membership can thus be helpful for forecasting future movements. Third, communities typically differ from

[1] We use the term "community" in the standard sense of network analysis, so the term refers to a set of densely-connected nodes. In our analysis, nodes represent countries. Thus, throughout the manuscript, a "community" refers to a group of countries rather than a group of people.

[2] The expectation that one can uncover the impact of non-spatial (e.g., socio-economic) factors after controlling for the impact of geographic proximity is based on the assumption that the two sets of factors are relatively uncorrelated (Cerina et al., 2012). When this assumption is not satisfied, attempting to factor out spatial effects may also disrupt the social structure of communities.

how regional boundaries are drawn on economic and geographic maps (Maoz, 2011: 37). An arrangement of relationships into network communities typically cuts across a hierarchy of spatial scales (Knappett, 2011: 10–11). Thus, international migration communities can encode various combinations of global (i.e., between regions and continents) and regional (i.e., within regions) migration, and it can provide an opportunity to investigate the interplay of these movements in a system.

2.5. Local versus global cohesion in the WMN

To distinguish a pattern of regional concentration from a pattern of global interconnectedness across international migration communities, we draw upon Granovetter's strength-of-weak-ties theory at the group level (Borgatti and Lopez-Kidwell, 2011; Granovetter, 1973). The theory (Borgatti and Lopez-Kidwell, 2011: 42) postulates that networks with many strong edges are likely to have strong local cohesion (tightly-knit communities) but weak global cohesion (bridging edges between communities). In contrast, networks with many weak edges are more likely to have strong global cohesion but weak local cohesion. Further, the distribution of local and global cohesion in a network is hypothesized to have an impact on differences in social outcomes, such as social mobilization (Borgatti et al., 2009: 894; Granovetter, 1973: 1375).

We define migration edge strength between a pair of countries as the number of people from a sending country who live in a receiving country at a given time. The strength of a migration edge is a local property, as it captures the intensity of migration between two countries. Edge strength, which is equal to edge weight in our study, lies on a continuum between weak and strong. Weak edges typically have a higher probability of overcoming spatial constraints, whereas strong edges are likely to be induced by spatial factors in social networks (Granovetter, 1973; Martin, 2009: 34).

In the context of the WMN, the strength-of-weak-ties theory proposes that a stronger migration edge between a pair of countries entails a higher probability that their neighborhoods overlap (Granovetter, 1973; Onnela et al., 2007). That is, they are more likely to connect to a set of common third countries. Neighborhood overlap is a form of local clustering. The neighborhood overlap of a migration edge between countries i and j is the number of countries that are adjacent (i.e., connected directly) to both i and j as a proportion of all countries that are adjacent to either i or j (Easley and Kleinberg, 2010: 52; Onnela et al., 2007). The positive relationship between edge strength and edge-neighborhood overlap is likely to be stronger when network relationships are "localized" not only in physical space but also in social space (Martin, 2009: 32–36). This is because individuals, groups, and societies are more likely to interact if they are similar in relevant social characteristics (e.g., language similarities in international migration (Fawcett, 1989)), a tendency that is known as "homophily" (McPherson et al., 2001). Both physical and social spaces are likely to contribute to the formation of tightly-knit communities associated with strong local cohesion but weak global cohesion (e.g., the blue community in the lower-right corner of Fig. 1B).

In contrast, bridging edges—i.e., edges that connect nodes from distinct communities—are likely to be weak due to the tendency of strong edges to cluster within communities. By implication, long-distance movements that bridge regions in the WMN are also likely to be weak ties. This is because, as Martin (2009: 34) put it, "weak ties are more likely to defy the closure implicit in spatial logic". Different definitions of bridges were proposed in the literature. Originally (Granovetter, 1973: 1364–1365), a bridging edge was defined as one that connects two nodes (or components) that will disconnect if the bridging edge is removed. A more nuanced concept is that of a local bridge, which refers to an edge that lies on a shortest path between two nodes. To facilitate empirical investigation of larger networks, Onnela et al. (2007) proposed a definition of "almost local bridges" for edges that have very low neighborhood overlap. In the context of the WMN, we expect migration edges with low neighborhood overlap to be those that bridge separate migration communities, thereby generating global cohesion in the WMN. For an example of a community with strong global cohesion (between communities) but weak local cohesion (within communities), see the brown community in the center of Fig. 1B.

Consider the observation of increasing diversification of origin countries in world migration (Vertovec, 2007) in the context of the strength-of-weak-ties theory. Although some of the resulting novel migration edges may have been weak, thereby contributing to an increasing ethnic diversity in the host societies (Vertovec, 2007), the important question is whether they were bridges in world migration. If novel weak edges were formed between countries with overlapping neighborhoods (i.e., countries that exchange migration with common third countries), those migration edges should remain within communities. In this situation, although novel, they would contribute little to the global interconnectedness in world migration. Instead, they would contribute to regional concentration associated with network fragmentation. In contrast, if many of the novel weak edges bridge distinct communities, one should observe an increase of global interconnectedness in world migration.

2.6. Research questions

Our study of spatial network structures in world migration considers two levels of analysis: (1) mesoscale spatial network structures and dynamics in the WMN and (2) properties of international migration communities over time. At a mesoscale level, we ask whether the network regions in world migration align with (to produce "regional concentration") or deviate significantly from (to yield "global interconnectedness") the world's regional boundaries over time. This question is important, because international migration is known to exhibit self-perpetuating tendencies (Massey et al., 1998). Hence, a spatially fragmented structure of world migration is not a transient phenomenon, as it can perpetuate long-lasting movements of people in geographically bounded regions over decades. Similarly, a pattern of global interconnectedness enables multilateral migration opportunities that are extensive in geographic scope.

Our second question concerns individual communities in international migration, with a focus on the distribution of local cohesion and global cohesion across international migration communities for the period 1960–2000. We are interested in the extent to which the global migration connectivity reported in the literature (Held et al., 1999) has spread relatively evenly across the world versus the extent to which different tendencies predominate in different communities over time. It is unrealistic to expect that a pattern of global interconnectedness should be indicated in the emergence of a single global migration community. Neither a single global migration nor a single global labor market have materialized (Castells, 1996; Hirst and Thompson, 1999). A more realistic indicator of global interconnectedness is a situation in which an increase of global cohesion (through bridging migration edges) across international migration communities has contributed to an increased integration of the WMN over time (as reflected by larger edge weights across communities). In contrast, an uneven distribution of global cohesion across the WMN, with some communities appearing as isolated from the rest of the network in 2000 as they were in 1960, would provide evidence for a heterogeneous network structure.

Our contributions, which are mostly methodological and empirical, are threefold. First, using recent advancements in network analysis, we employ a method for network decomposition that accounts for key features of world migration—in particular, we incorporate temporality, edge directionality, and spatial composition—and allows an in-depth examination of mesoscale structures in world migration. Prior research (DeWaard et al., 2012; Fagiolo and Mastrorillo, 2013) on large-scale structures in world migration used methodology that pays insufficient attention to the role of spatial attributes in the formation of mesoscale structures. Second, we use tools from social and spatial network analyses to test empirically-grounded propositions from international migration studies (Castles and Miller, 2009; Held et al., 1999; Kritz et al., 1992; Salt, 1989), thereby helping adjudicate contrasting views about the current structure of world migration. Third, to attempt to understand the formation and evolution of boundaries in world migration, we examine (in greater detail than in prior research (DeWaard et al., 2012; Fagiolo and Mastrorillo, 2013)) international migration communities, with a focus on the relationship between intra-community and inter-community migration edge strength, edge-neighborhood overlap, and edge length (as specified in Section 3.2.2).

3. Data, methods, and diagnostics

3.1. Global migration-stock data

We construct the WMN from aggregate migration stocks recorded in 1960, 1970, 1980, 1990, and 2000 and compiled in the Global Bilateral Migration Database (Özden et al., 2011). In this database, migrants were defined primarily on the basis of birth country, but other criteria—e.g., country of citizenship—were also considered (Özden et al., 2011). The database includes comprehensive information about migration stocks (i.e., the number of people that were born in country i and lived in country j) from national decennial censuses and population registers for 226 countries and territories, resulting in five 226×226 matrices. National census surveys are typically carried out at the end of a decade, gathering information about the number of foreign-born people (or foreign citizens) that resided in a given country for at least one year during the preceding decade.

Aggregate migration stocks have several shortcomings. The data can overlook differences among types of migration (e.g., labor or education) or dynamic forms of migration (e.g., "stepwise" migration (Paul, 2011)). Additionally, migration-stock data favor stability at the expense of change, so they can overlook temporal fluctuations in migration, particularly for evolution on a time scale that is different from the 10-year measurement period. However, we concur with Bilsborrow and Zlotnik (1994: 66) that in comparison to flow data, migration stocks represent "the long-term effects of migration and [are] thus a more stable component" of international migration. By recording non-transient exchanges, stock data are instrumental for examining mesoscale network structures in the WMN.

To account for the dissolution of countries, such as the former Soviet Union (1922–1991), and the formation of new countries, Özden et al., 2011 used the most current list (from the year 2000) of countries and territories over the entire time period. To enable historical comparability, migration stocks were reassigned accordingly. (For example, movements from Czechoslovakia were disaggregated, so migration from Slovakia to Germany were reported for the entire time frame, even though Slovakia did not exist as a country before 1993.)

To analyze the effect of geographic proximity, we compute the great-circle (geographic) distance (Furrer et al., 2013) using the longitude and latitude of the capital cities[3] of the 226 world countries and territories.

3.2. Methods and diagnostics

3.2.1. Community detection

To characterize mesoscale structures of the WMN and examine the extent to which they align with or depart from the world's regional boundaries, we use recent generalizations of the modularity-maximization method for community detection (Fortunato and Hric, 2016; Porter et al., 2009) that can account for the directionality (Leicht and Newman, 2008), time-dependence (Mucha et al., 2010), and spatiality (Expert et al., 2011) of world migration. Modularity (denoted by Q) is an objective function that construes a good decomposition of a network as one in which there is large total edge weight within communities but small total edge weight between communities relative to what one would expect "at random" according to some null model (Newman, 2006; Newman and Girvan, 2004). The modularity function for weighted networks is

$$Q = \frac{1}{2W}\sum_{ij}[W_{ij} - \gamma P_{ij}]\delta(c_i, c_j), \tag{3.1}$$

where c_i denotes the community assignment of node i and c_j is the community assignment of node j, the Kronecker delta function $\delta\left(c_i, c_j\right)$ is 1 if nodes i and j are placed in the same community (i.e., $c_i = c_j$) and 0 otherwise, W_{ij} is the weight of the edge from node i to node j in the weighted adjacency matrix (for the WMN, $W_{ij} \geq 1$ if a weighted edge between country i and j exists, and $W_{ij} = 0$ otherwise), $\sum_{ij}$ is the summation operation over pairs of nodes (i and j) that are assigned to the same community (i.e., $\delta(c_i, c_j) = 1$), the null-model matrix $\mathbf{P}$ has elements P_{ij}, the quantity γ is a resolution parameter (we use a standard resolution of $\gamma = 1$), and $W = \frac{1}{2}\sum_{ij} W_{ij}$ is the total edge weight in the network. The total edge weight W is a normalization factor, so the modularity value Q of a partition of the WMN ranges from −1 (all edges are between communities) to 1 (all edges are within communities).

One can factor out "statistically unsurprising" connectivity by considering different null models, and which ones it is relevant to consider depends on what constraints are hypothesized to have an effect on mesoscale structures in a network (Expert et al., 2011; Newman, 2012). Because patterns of out-migration differ from patterns of in-migration in migration-stock data (Özden et al., 2011), we take account of the directionality of edges in the WMN using Leicht and Newman's (2008) modularity null model for directed networks. In the LN null model, the expected weight P_{ij} of an edge between node i and j is

$$P_{ij}^{\mathrm{LN}} = \frac{s_i^{\mathrm{out}} s_j^{\mathrm{in}}}{W}, \tag{3.2}$$

where s_i^{out} and s_j^{in} are the out-strength and in-strength of node i and node j (these strengths are defined, respectively, as the sum

[3] Admittedly, there are some limitations in using two points to represent distances between a pair of areas (e.g., countries or regions). As Gleditsch and Ward (2001) pointed out, distance measures that rely on midpoints, such as capital cities, typically overstate real distances, particularly for larger regions. This issue was examined recently using ideas such as weighted distance (Mayer and Zignago, 2006) and minimum distance (Gleditsch and Ward, 2001). However, the databases associated with these distance measures do not include estimates for a substantial fraction of the 226 countries and territories that we consider, and it is hard to obtain reliable information about multiple longitude and latitude locations to impute the numerous missing distances between countries.

of the weights of the out-edges and in-edges attached to a node), and W is the total edge weight in the network. Using the LN null model, maximizing modularity estimates whether a partition of the WMN has more edge weight within international migration communities than expected in a reference random network with the same expected out-strength and in-strength sequences as the WMN.

To account for the constraining role of geographic location on the formation and weight of migration edges, we extend Expert et al.'s (2011) spatial null model to directed networks:

$$P_{ij}^{\mathrm{Spa}} = N_i^{\mathrm{out}} N_j^{\mathrm{in}} f(d_{ij}), \tag{3.3}$$

where P_{ij}^{Spa} is the expected migration stock between countries i and j, the quantities N_i^{out} and N_j^{in} measure the migration potential of origin i and attractiveness of destination j (we measure migration potential and attractiveness, respectively, as a country's total out-migration and in-migration), and the "deterrence function" $f(d_{ij})$ measures the effect of distance. As in gravity models[4] (Anderson, 2011; Haynes and Fotheringham, 1984), the intuition behind Expert et al.'s spatial null model is that N_i^{out} and N_j^{in} are sources of opportunities (e.g., possible interactions between a pair of countries), and the distance d_{ij} is a source of constraints. Expert et al. (2011) proposed the following deterrence function:

$$f(d) = \frac{\sum_{\{i,j|d_{ij}=d\}} W_{ij}}{\sum_{\{i,j|d_{ij}=d\}} N_i^{\mathrm{out}} N_j^{\mathrm{in}}}. \tag{3.4}$$

In the context of the WMN, the deterrence function $f(d)$ is the weighted mean of the probability $\frac{W_{ij}}{N_i^{\mathrm{out}} N_j^{\mathrm{in}}}$ for a migration edge weight to exist from country i to country j at a certain distance range. The deterrence function uses bins to calculate the expected migration for a certain distance range. After examining several choices of values, we set the bin size to 500 km. A larger positive value for spatial modularity Q^{Spa} indicates a higher density of edge weights inside communities than one would expect for the given distance range. The spatial null model is designed to allocate a larger contribution to (spatially surprising) edges between distant nodes than to edges between nearby nodes.

We represent the five time periods of the WMN using a modularity function for multilayer networks (Mucha et al., 2010). In a multilayer representation of a temporal network, the layers are ordered so that contiguous layer are connected via interlayer edges (Kivelä et al., 2014: 15). We use a form of multilayer modularity that incorporates a temporal resolution parameter ω that regulates the strength of coupling between time layers. By varying the values of ω, the strength of the connection between a node in layer l (at time t_l) and itself in layer $r = l + 1$ (at time t_{l+1}) changes: nodes across layers are independent when $\omega = 0$, and they have a stronger incentive to belong to the same community as one increases ω. (We report results for $\omega = 1$.) We thus write multilayer modularity as (Bassett et al., 2013; Mucha et al., 2010)

$$Q_{\mathrm{multilayer}} = \frac{1}{2\mu} \sum_{ijlr} \{(W_{ijl} - \gamma_l P_{ijl})\delta_{lr} + \delta_{ij}\omega\} \delta\left(g_{il}, g_{jr}\right), \tag{3.5}$$

where g_{il} is the community of node i in layer l (and g_{jr} is the community of node j in layer r), the Kronecker delta $\delta(g_{il}, g_{jr}) = 1$ if node i in layer l and node j in layer r are placed in the same community and $\delta\left(g_{il}, g_{jr}\right) = 0$ otherwise, ω is the interlayer coupling strength, the quantity W_{ijl} is the element of the weighted adjacency array of layer l, the null-model array element P_{ijl} gives the expected connectivity between nodes in layer l (see our above discussion of possible choices), the quantity γ_l is the intralayer resolution parameter for layer l (we take $\gamma_l = 1$ for each layer), the quantity k_{jr} is the intralayer strength of node j in layer r, and $\mu = \frac{1}{2}\sum_{jr} k_{jr}$ is the total edge weight in the network. Multilayer modularity explicitly incorporates dependence between layers, instead of assuming independence, as is done when temporal networks are represented as a sequence of time-independent networks (Bazzi et al., 2016; Mucha et al., 2010).

Maximizing modularity is NP-hard (Brandes et al., 2007), and it also has some well-studied limitations, such a resolution limit and extreme near-degeneracies among local maxima with high modularities (Good et al., 2010). The former limitation refers to the tendency of modularity maximization to overlook communities that are smaller than some characteristic size (Fortunato and Barthelemy, 2007), although one can ameliorate the issue by incorporating a resolution parameter γ in the modularity function (Porter et al., 2009; Reichardt and Bornholdt, 2006). The latter issue refers to the numerous near degeneracies in the rugged landscape of the modularity function, and partitions with similar high-modularity scores can arise from rather dissimilar structures (Good et al., 2010). To take into account near-degeneracies in the modularity landscape, we identify consensus partitions (Bassett et al., 2013; Bazzi et al., 2016; Lancichinetti and Fortunato, 2012; Sarzynska et al., 2016) across multiple optimizations (see Appendix A in Supplementary material). Consensus partitions increase robustness to variation across optimizations, thereby lessening the severity of the near-degeneracy issue. We optimize modularity using the generalized Louvain heuristic (Blondel et al., 2008; Jutla et al., 2011–2014).

3.2.2. Diagnostics

To discriminate between overlapping and bridging migration edges, we compute their neighborhood overlap $O_{ij} = \frac{N(i) \cap N(j)}{N(i) \cup N(j)}$. The neighborhood overlap O_{ij} of an edge between nodes i and j is the number N of neighbors that nodes i and j have in common normalized by the total number of neighbors of either i or j (Easley and Kleinberg, 2010: 52; Onnela et al., 2007: 7334). The neighborhood overlap O_{ij} ranges from 0 to 1.

High edge-neighborhood overlap is typically associated with stronger edges and geographic proximity (Granovetter, 1973). Neighborhood overlap is a property that involves more than two countries and is thus multilateral, whereas edge strength and edge length are dyadic properties of a pair of countries. In the WMN, the strength of a migration edge is the number of migrants from country i that live in country j in each of the five decades. The length of a migration edge is the distance of the edge from country i to country j multiplied by the number of migrants that have traveled that distance.

A central question in our analysis is the extent to which migration has been trapped in tightly-knit communities (i.e., regional concentration) for geographic, economic, or policy reasons and the extent to which long-distance migration edges bridge international migration communities across the globe (i.e., global interconnectedness). To address this question, we compute E–I indices to measure the proportion of external (E) to internal (I) edge strength, edge-neighborhood overlap, and edge length for each international migration community. An E–I index is a widely-used measure of local (i.e., internal) and global (i.e., external) group cohesion in network analysis (Hanneman and Riddle, 2011; Krackhardt and Stern,

[4] We note that gravity models are typically used in migration research to explain bilateral migration (Mayda, 2010), while in Expert et al. (2011) the gravity model serves as a baseline/null model. For a spatial null model for modularity maximization that does not utilize the gravity model, see Sarzynska et al. (2016).

1988). (A related measure is conductance; see Jeub et al. (2015)). We generalize the E–I index to weighted networks by calculating

$$\text{E-I index} = \frac{E_w - I_w}{E_w + I_w}. \tag{3.6}$$

The index (3.6) compares the amount I_w of internal weight to the amount E_w of external weight. An E–I index takes values between −1 to +1. As the value of an E–I index approaches −1, most edge weights are inside international migration communities. As the value approaches +1, most edge weights are outside the communities. We compute E–I indices (1) for the whole WMN across time points to measure the distribution of local and global cohesion given the community structures that we identify by maximizing multilayer modularity for directed and spatial networks and (2) for individual communities to measure variations in their local and global cohesion. In addition to edge weights, we also compute the community-level E–I indices for edge-neighborhood overlap and migration-edge length.

4. Results

4.1. Mapping the landscape of the WMN

The first step of our analysis is to detect migration communities using modularity maximization and two different null models: the LN null model for directed networks and a directed spatial null model. We will refer to using the LN null model as "maximizing LN modularity" and to using the spatial null model as "maximizing spatial modularity". The two procedures yield different results, which we describe in Sections 4.1.1 and 4.1.2, respectively.

4.1.1. Communities detected by maximizing multilayer LN modularity

In Fig. 2A, we show world maps[5] of consensus community assignments for each decade from 1960 to 2000 that we obtain by maximizing multilayer modularity with the LN null model, which is designed for directed networks. We observe eight[6] international migration communities in 1960. As one can see, geographic distance and regional boundaries play important roles in demarcating the structure of more than half of the international migration communities, including those centered on India (IND)[7] the former Soviet Union (RUS), and China (CHN), as well as those confined to Sub-Saharan Africa (COD) and West Africa (CIV).

In support of the proposition that international migration often arises from "prior contact" (Fawcett, 1989; King, 1993b), two international migration communities consist of countries with former colonial relationships: France and countries in North Africa (FRA); and countries in South Europe, South America, and Angola in Africa (ARG). Although the geography of "prior contact" correlates positively with physical proximity in the former community (FRA), the cross-continental grouping between the latter set of countries (ARG) is relatively independent of distance.

We also identify cross-continental communities that overcome geographic constraints. This tendency occurs in the largest community in 1960 (USA), which includes North America, Australia, New Zealand, and the bulk of Western, Central, and Northern Europe. This community is fairly unexpected, because it groups long-distance migration between non-contiguous, geographically dispersed countries in a period that precedes advancements in transportation. In addition to the USA community, the groupings of South America and Mediterranean countries in Europe (ARG) and of North Africa and France in 1960 (FRA) suggest that cross-continental migration may play an important role in mesoscale structures in world migration. This illustrates that migration groupings need not be confined to the world's continental boundaries, an assumption that many (e.g., Massey et al., 1998; Salt, 1989) needed to make in the past due to the lack of available world-migration data.

The aggregate structure of communities remains mostly intact in the subsequent three decades (1970, 1980, and 1990), but one change is worth noting. Since 1970, the global community (USA) involving Western, Northern, and Central Europe extended to Eastern Europe and reached Turkey in the South, reflecting the increased migration exchanges between Germany and Turkey that followed the bilateral recruitment agreement between the two states that was signed in 1961 (King, 1993b).

Mesoscale structures in the WMN changed more noticeably in 2000. Aside from the United Kingdom, all European countries (which were previously separated into two communities) are now assigned to one integrated community (DEU). This result is consistent with Salt's (2001: 3) observation that a characteristic feature of European migration in the mid and late 1990s is "[t]he increasing incorporation of Central and Eastern Europe into the European migration system as a whole". However, European migration is not separated from other continental "wholes", as it includes North African countries. Although movements from North Africa to Europe are well-reported in the literature (e.g., King, 1993a; Zlotnik, 1998), this is not reflected in the demarcation of migration systems, which is often done on the basis of regional boundaries (e.g., Western Europe) (see Salt, 1989; Zlotnik, 1992; Salt, 2001) or geopolitical divisions (e.g., the European Union) (see, e.g., Massey et al., 1998: 110). However, our findings from maximizing multilayer modularity using the LN null model suggest that migration from North Africa to Europe is larger than one may expect by chance, and those intercontinental migration connections appear to be more stable over time than many intracontinental groupings. Therefore, groupings that include cross-continental areas seemingly not only better reflect prior movements but also improve our ability to forecast future movements. Finally, the United Kingdom, Australia, and New Zealand are no longer part of the largest international migration community, but instead form a Commonwealth community that also includes countries in Southeast Africa (GBR). This community exemplifies the role of "prior contact" and homophily (e.g., language similarity) in connecting geographically dispersed countries.

4.1.2. Communities detected by maximizing multilayer spatial modularity

Although the international migration communities that we identified by maximizing multilayer LN modularity reflect some instances of homophilous relationships between distant countries, particularly in year 2000, the communities generated by maximizing multilayer spatial modularity capture more refined non-spatial structures over time. For example, although Europe appears to become increasingly integrated over time when using LN modularity, maximizing modularity with the spatial null model suggests the opposite tendency (see Fig. 2B). European migration breaks into a set of small, spatially-noncontiguous communities. This is particularly noticeable in the year 2000. The community boundaries often escape the typical classification of Western, Northern, Southern, and Eastern Europe, a finding that disagrees sharply with previous research that reported that international migration sys-

[5] We use the package "rworldmap" in R (South, 2011) to plot the maps that illustrate community structure in the WMN.

[6] Compared to the original partitions, the consensus partitions tend to decompose a network into a smaller number of communities that are more similar across different runs of the Louvain-like heuristic for maximizing modularity.

[7] We label international migration communities with the ISO 3166-1 alpha-3 code of the country that has the largest intra-community migration strength, where a country's "intra-community strength" indicates its out- and in-migrations that are within the its own community.

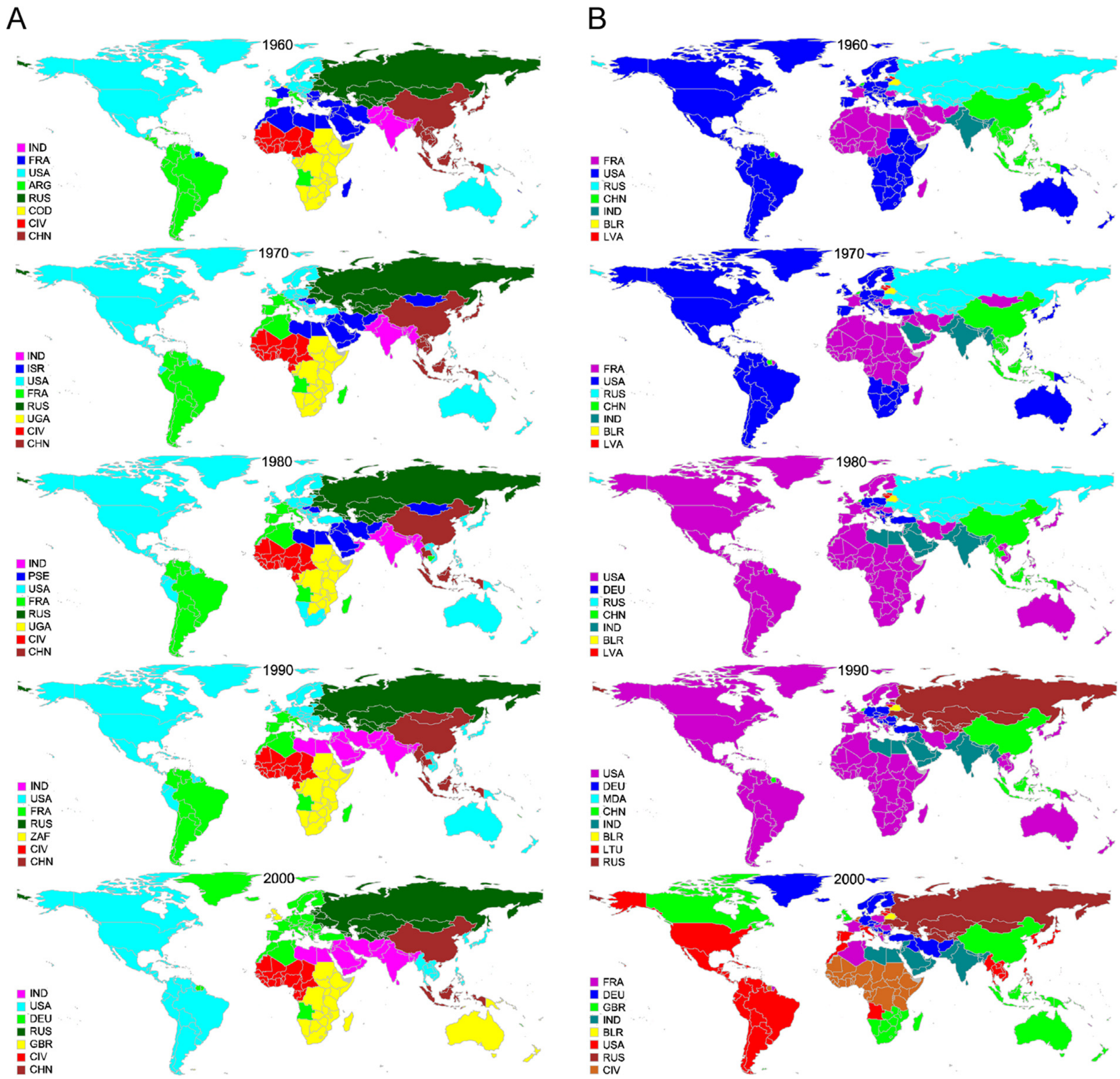

Fig. 2. International migration communities detected by maximizing multilayer (A) LN modularity and (B) spatial modularity at resolution values of $\gamma = 1$ and $\omega = 1$. The colors indicate community assignments.

tems in Europe are "more or less geographically discrete" (DeWaard et al., 2012). For example, Poland is no longer tied to Germany, but instead it is part of a spatially-noncontiguous community centered on France.

In parallel to the tendency towards fragmentation in European migration, a distinctive feature of the communities that we obtain from maximizing spatial modularity is the tendency to merge many distant regions and countries. For example, France and Romania are part of the same spatially-discontiguous community in 1960, 1970, and 1980. Moreover, almost all countries in Europe are assigned to communities that reach other continents. Finally, large parts of North and South America are part of the same community for the whole period. This suggests that processes of cross-regional and cross-continental integration appear to have accompanied the processes of spatial fragmentation.

A body of literature in migration studies provides evidence in support of the above pattern of European migration (King, 1993a). It has been observed that movements in 1950–1960 were predominantly intracontinental, directed from "south" (e.g., Italy, Spain, Portugal, and Yugoslavia) to "north" (e.g., Germany and France). Many of those movements were between relatively nearby countries and based on bilateral agreements (Skeldon, 1997: 78; White, 1993). Since 1970, the pattern has been different, as there were many migratory movements from distant ex-colonial regions (e.g., West Indies, South Asia, and sub-Saharan Africa) to Europe (King, 1993b: 20). More changes have occurred since the 1980s: origins and destinations have diversified and have evolved relatively independently from geographic proximity and former colonial relationships (Bonifazi, 2008; Golini et al., 1993: 70; King, 2002; Skeldon, 1997: 45; Vertovec, 2007).

Maximizing spatial modularity yields a community structure with regional fragmentation and cross-continental integration that is consistent with the migration patterns that have been reported in the literature, thereby advancing understanding of migration patterns beyond maximizing LN modularity and what was ascertained in prior research (Davis et al., 2013; DeWaard et al., 2012; Fagiolo and Mastrorillo, 2013). The reasons for the effectiveness of maximizing modularity with the spatial null model are twofold.

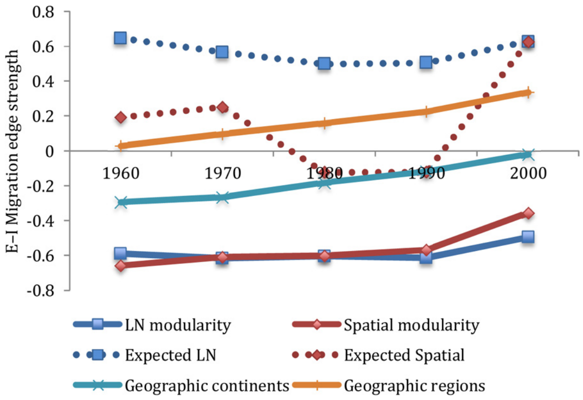

Fig. 3. Relationship between migration weights (i.e., edge strengths) that are internal and external to international migration communities and geographic regions.

First, this approach minimizes[8] the contribution to modularity of migratory movements between nearby countries. Because geographic space "glues" together nearby nodes, extracting the effect of geographic distance leads naturally to spatially-fragmented communities. Second, maximizing spatial modularity also increases the contribution of small migratory movements between distant nodes, giving non-contiguous countries a higher probability to be assigned to the same international migration community.

4.2. *Increasing interconnectedness of the WMN*

Our first question (see Section 2.6) tests the extent to which the structure of the WMN is fragmented, with migration movements trapped in regions (based either on network structure or on geography), and the extent to which global cohesion has increased due to movements that bridge relatively distinct communities or geographic regions. By computing E–I strength indices for the whole network between 1960 and 2000 (see Fig. 3), we find that the preponderance of inter-community over intra-community migration edge strengths has increased since the 1990 census, implying an increase in the global interconnectedness of the WMN over time. The changes in the E–I strength indices over time are more pronounced in the communities that we detect by maximizing spatial modularity (−0.66 in 1960, −0.36 in 2000) than by maximizing LN modularity (−0.59 in 1960, −0.50 in 2000). This makes sense, because the spatial null model factors out "statistically unsurprising" migration connectivity between nearby countries, thereby recovering patterns of global interconnectedness that are underrepresented when maximizing LN modularity. Our results are significant compared to an expected value specified in a permutation null model,[9] and they are consistent with the findings reported by Davis et al. (2013) and Fagiolo and Mastrorillo (2013).

[8] An undesirable outcome that is associated in part with the minimized contribution of migration exchanges between nearby countries in spatial modularity is the detection of singleton communities (i.e., communities that consist of only one country).

[9] Because mesoscale properties, such as internal and external community connectivity, can be conditioned on global properties, such as network density, we compare our mesoscale E–I indices to a permutation null model. In each case, we perform 1,000 permutations and compute the number of times that the observed E–I index is significantly smaller than the expected E–I index measured in an ensemble of permuted WMNs in which rows (out-migration) and columns (in-migration) are simultaneously shuffled (using a uniform shuffling). We find that the observed E–I index is significantly different ($p < 0.01$) from the expected E–I index for each time point and modularity null model (see Fig. 3). We conclude that the distribution of intra-community and inter-community movements reflects mesoscale properties of the WMN, rather than being exclusively an outcome of global connectivity.

The WMN maps (see Fig. 2) illustrate that a geographic signature is imprinted in several communities that are confined to geographical regions (e.g., South America and West Africa) and geo-political regions (e.g., Russia). The alignment of regional boundaries and migration movements supports claims that international migration systems are "more or less geographically discrete" (DeWaard et al., 2012) and "geographically concentrated" (Abel et al., 2016). To examine the relationship between geographic and migration boundaries, we compare the E–I strength indices for our international migration communities to corresponding E–I indices that we compute using the geographic continents and mesoscale regions (e.g., Northern Europe and Southern Europe) that are described in the United Nations (UN) Statistical Division.[10] The E–I indices that we report in Fig 3 indicate that, compared to established continental and regional divisions, the international migration communities that we obtain by maximizing LN and spatial modularities include substantially more migration within communities than between them. Moreover, for all decades (and particularly after 1960), we observe more migration between geographic regions rather than within them. The tendency for world migratory movements to operate across geographic regions rather than within them after 1960 suggests that a regional approach for boundary specification of migration systems (as advocated in Zlotnik (1992)) has become less useful for delimiting migration patterns. Continental boundaries appear to include more migration internally than externally until the 2000 census. In 2000, the amount migration within continents is approximately equal to that between continents.

The E–I indices for both the continental and regional divisions increase monotonically over time. This indicates that geographic divisions have become decreasingly effective at grouping world migration since 1960. This tendency is particularly noticeable for the geographic regions, which include more migration externally than internally throughout the studied period, but it is also present for the continents, which in 2000 include almost as much migration internally as externally.

4.3. *Global and local cohesion of international migration communities*

Our second question (see Section 2.6) concerns the distribution of local cohesion and global cohesion across individual communities. We quantify the distribution of global and local cohesion using three indicators: edge strength, edge-neighborhood overlap, and edge length. We focus on the communities that we detect by optimizing multilayer spatial modularity. To examine individual communities, we first generate "community adjacency matrices" for edge strength (we use the notation C^S for these matrices), edge-neighborhood overlap (C^O), and edge length (C^L) across each decade (see Fig. 4A–C). We define such a matrix as follows. Consider C^S, the community adjacency matrix of edge strengths. For each decade, we distinguish internal edge strengths from external edge strengths, depending on whether migration stocks remains within a community or lie between two communities. We then sum over, for each community, all intra-community migration edge strengths between the countries assigned to that community; and we also perform such sums for the inter-community edge strengths between pairs of countries that are assigned to different communities. In the resulting community adjacency matrices for each decade, the edge strengths that remain within communities appear on the main diagonal, and the edge strengths between communities appear off of the diagonal. We follow the same procedure for C^O and C^L. As Hanneman and Riddle (2011)

[10] Retrieved on 15 August 2014 from http://unstats.un.org/unsd/methods/m49/m49regin.htm

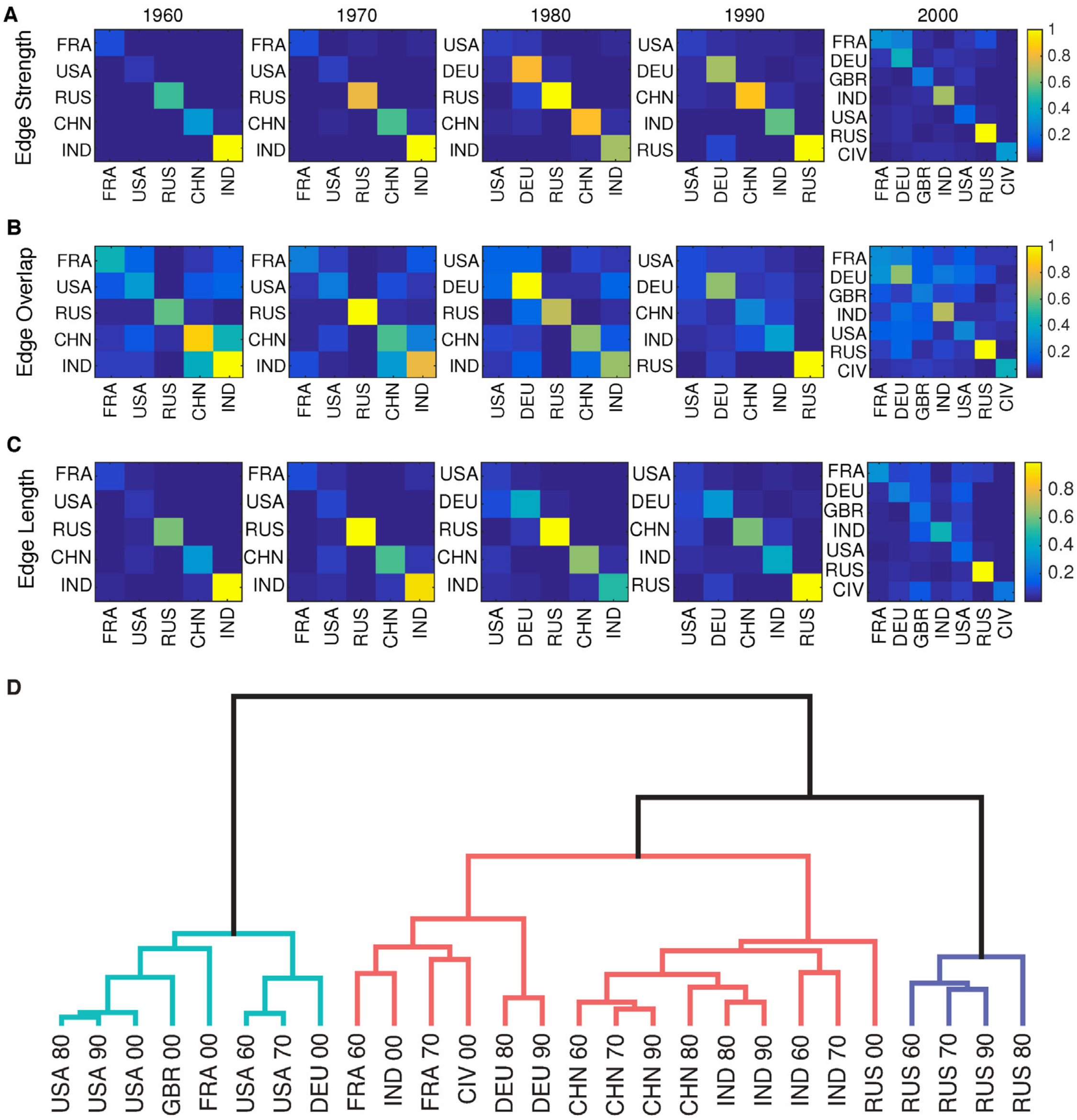

Fig. 4. Normalized community adjacency matrices for migration (A) edge strengths, (B) edge-neighborhood overlaps, and (C) edge lengths. Each column and row in the matrices indicates one of the communities in Fig. 2B. Intra-community migration edges appear on the main diagonal, and inter-community migration edges appear off of the main diagonal. The values range from low (in blue) to strong (in yellow). We exclude communities that consist of two or fewer countries. (D) Dendrogram of migration communities on the basis of E–I edge strength, E–I edge-neighborhood overlap, and E–I edge length for all 27 communities that we obtain by maximizing spatial modularity across the five decades. We use agglomerative hierarchical clustering to partition the 27 communities. Specifically, we employ Euclidian distance to determine pairwise (dis)similarities and then use average linkage clustering (Wasserman and Faust, 1994: 381) to sequentially group communities into a dendrogram. The color of the branches represents the three detected factions. (To intepret the comments about color, see the online version of this article.)

discussed, the propensity of an edge to occur within or between communities is constrained by the number of communities, their relative size, and network density. To ensure that the properties of international migration communities are not influenced too heavily by global network properties (e.g., density or number of communities), we normalize community adjacency matrices using a corresponding community matrix C^{mean} that records a corresponding mean intra-community and inter-community edge quantity. That is, we calculate $C^{\text{norm}} = C/C^{\text{mean}}$ for each time period and for edge strength, edge-neighborhood overlap, and edge length.

In Fig. 4A, we show that international migration communities have very different distributions of internal versus external edge strengths. The communities centered on India, Russia, and China have considerably larger internal edge strengths than those centered on the USA, GBR, and France. Further, the latter set of communities is more likely to exchange migration with other communities. Finally, there is a clear pattern of increasing inter-community edge strengths over the decades.

As expected, migration edges with large edge-neighborhood overlaps are more likely than those with small overlaps to be within communities (see Fig. 4B). Instances of large inter-community edge-neighborhood overlap are rare and typically involve geographically close communities (e.g., India and China, and Uganda and Ivory Coast). Similar to edge strength, edge-neighborhood overlap is distributed unevenly across international migration communities. For example, for all decades, the communities centered on Russia, Ivory Coast, and India have greater edge-neighborhood overlaps than those centered on the USA.

To evaluate the relationship between internal and external migration edge strength, edge-neighborhood overlap, and length, we compute E–I indices for the three diagnostics for each individual community in Fig. 4A–C. We then use the resulting indices—which we denote by EI_S, EI_O, and EI_L—to classify international migration communities into types with different characteristic patterns of local cohesion and global cohesion in the WMN. In Fig. 4D, we show a classification of international migration communities into three factions. We use a permutation-based ANOVA test (Borgatti et al., 2002) to evaluate alternative—specifically, two, four, and five—numbers of factions, and find (using 10,000 permutations) that a three-faction partitioning maximizes the ratio F of inter-faction variance to intra-faction variance in EI_S (we obtain $F_{2,24} \approx 62.9$), EI_O (with $F_{2,24} \approx 102$), and EI_L (with $F_{2,24} \approx 39.6$) at the $p < 0.001$ significance level.[11] In the resulting classification, we obtain (1) international migration communities centered on the USA and on France, Germany, and Great Britain in 2000; (2) communities associated with India and China, as well as communities that involve European countries (e.g., Germany and France), before 2000; and (3) communities centered on Russia before 2000.

The strength-of-weak-ties hypothesis (Granovetter, 1973) suggests that the overlap of node neighborhoods increases with edge strength, and such overlap is typically induced by proximity in social and geographic space. Applied to the WMN, the hypothesis suggests that two countries that are strongly connected to each other via migration stock are more likely to connect to common third countries, thereby forming a tightly-knit community. Conversely, edges that bridge communities are likely to be associated with weaker migration. As we show in Fig. 5, linear regression models fit to the E–I indices suggest that edge strength ($R^2 \approx 0.607$) and edge length ($R^2 \approx 0.681$) correlate strongly with the variation in edge-neighborhood overlap. International migration communities with larger internal edge strengths and edge lengths are likely to have high local cohesion, and vice versa. This pattern suggests a heterogeneous distribution of local and global cohesion across international migration communities.

4.4. Typology for migration communities

We define a typology of international migration communities based on their global and local cohesion.

4.4.1. "Local" migration communities

We say that a cluster of international migration communities with negative scores for E–I migration strength, overlap, and length indices are *local*. We find such a cluster that consists of four communities centered at Russia (see Fig. 4D). As we show in Fig. 5, local communities are characterized by strong local cohesion—i.e., densely clustered, strong, and relatively short-distance migration edges—but weak global cohesion (i.e., lack of weak, bridging ties across communities), resulting in tightly-knit migration interactions that are largely fragmented from the rest of the WMN. Local communities epitomize the view of international migration as "geographically discrete" and/or "geographically concentrated", as advanced in Abel et al. (2016), DeWaard et al. (2012), and Salt (1989). Given the structure of local communities, they are likely to channel regional migratory movements, while simultaneously providing very few opportunities for inter-community migration. Movements of people that originate from local communities are largely constrained to remain within communities due to the limited number of inter-community edges that allow migration to other communities.

[11] Partitions with two, four, and five factions tend to under represent variation in EI_O. However, apart from this limitation, four-faction and five-faction partitionings are also viable choices. Partitions with six or more factions yield groups with very few communities, and a two-faction partitioning has high intra-group variability.

4.4.2. "Global" migration communities

We say that international migration communities that occupy the positive end of the E–I migration edge strength, overlap, and length continuum are *global* communities. We find eight such communities (see Fig. 4D). In comparison to local communities, a characteristic feature of global communities is the preponderance of external bridging edges over internal edges, as reflected in the large EI_O. Consequently, global communities group countries that are likely to be connected to countries from different communities and also likely to have few migration edges to common third countries, thereby contributing to the global interconnectedness of the WMN. Another indication of the bridging nature of global communities is a large EI_L, which reflects the long distance of migration edges from and to other communities (see Fig. 5). Global international migration communities tend to provide better opportunities than other communities for both cross-community exchanges and cross-continental exchanges, as they often group noncontiguous countries and even countries from different continents.

4.4.3. "Glocal" migration communities

We refer to the international migration communities in the middle of the E–I migration edge strength, edge-neighborhood overlap, and edge length values as *glocal* communities. We find fifteen glocal communities (see Fig. 4D). Wellman (2002) used the term "glocalized" connectivity to refer to the simultaneous presence of strong local relationships and weak relationships that are global in geographic scope. Some glocal communities tend to resemble local communities with respect to their prevalent internal, strong migration edges, as indicated by the small and negative values of EI_S. Simultaneously, a substantial number of glocal communities have values of E–I edge-neighborhood overlap and, especially, E–I edge length that are comparable to the corresponding indices of global communities (see Fig. 5). The fact that glocal communities have longer edge lengths but smaller edge-neighborhood overlaps than local communities indicates that they are likely to channel strong migration between relatively distant regions. Examples of glocal communities include those that connect France and countries from North Africa in 1960 and 1970 and those that connect the Gulf States and South Asia. In contrast to global communities, which bridge various communities across the globe, the glocal communities are likely to channel migration between particular geographic regions.

4.5. Continuity and changes in international migration communities

Has the connectivity of the WMN changed over the latter half of the 20th century? A body of literature on international migration (Castles and Miller, 2009; Held et al., 1999; Vertovec, 2007) argued that large-scale migration patterns changed in the mid 1970s (after the 1973 oil crisis): novel origin–destination connections have arisen and numerous globe-spanning movements have occurred, and such movements often were smaller in magnitude than earlier movements that developed as a response to "prior contact", bilateral agreements, and proximity. To examine these propositions, we divide the period under study into two parts: before (1960–1970) and after (1990–2000) the hypothesized change in the mid 1970s. Migration stocks for 1980 include a mixture of movements before and after the hypothesized change, and we therefore exclude them from this comparison.

As Fig. 5 indicates, the bridging role of global communities has increased from the first two decades (1960–1970) to the last two decades (1990–2000) in our data, as reflected in the increasing E–I edge-neighborhood overlap (see Fig. 5.2A). Likewise, we observe a statistically significant increase in E–I edge strength and E–I edge length (see Figs. 5.2B and 5.2C, respectively). Based on these results,

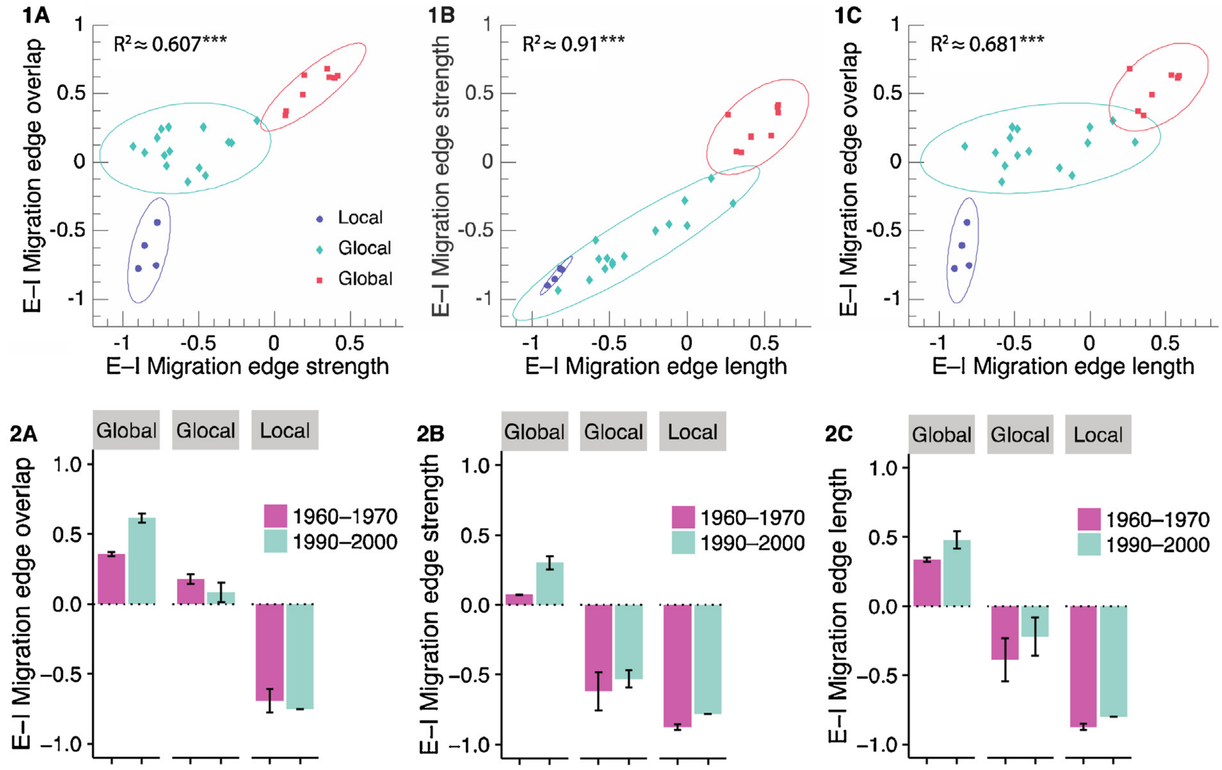

Fig. 5. A characterization of individual international migration communities based on the relationship between internal and external indices (E–I indices) for migration edge strengths, edge-neighborhood overlaps, and edge lengths. (1A–1C) Regression models examining relationships between the E–I indices for edge strength, edge-neighborhood overlap, and edge length. The ellipses indicate errors at the 95% confidence interval for the corresponding community type, and *** indicates that the p-value is $P < 0.001$. (2A–2C) ANOVA tests of mean differences in migration edge strength, overlap, and length across community types for two time periods (1960–1970 and 1990–2000). Error bars represent the 95% confidence interval.

we conclude that the global cohesion of the WMN has increased over time.

However, connectivity appears to be distributed unevenly in the WMN. Key spatial network properties of local communities and glocal communities have not changed significantly during the period 1960–2000. The spatial concentration and edge-neighborhood overlap of those communities in 1990–2000 were very similar to those in 1960–1970. The impact of distance shrinkage and the increase of weak edges between diverse origins and destinations are concentrated in global communities; they do not substantially impact other areas of the WMN. Therefore, the processes of increased global interconnectedness that we observe for the network as a whole are in fact local: they operate in some regions of the network but not in others.

5. Conclusions

In this study, we examined spatial network structures and dynamics of international movements of people worldwide using longitudinal migration-stock data. By operationalizing world migrations as a social–spatial network, we were able to identify not only spatially-induced migration groupings but also multilateral groupings of distant countries and more migration edges across groupings. Together, these overcome the fragmentation tendencies present in geographic proximity and thereby contribute to integration of the WMN. Thus, our spatial-network perspective helps adjudicate contrasting propositions in the literature about the structure of world migration.

When we consider the spatial community structure of the WMN as a whole, our findings provide evidence that the interconnectedness of world migration has increased moderately over the second half of the 20th century. This has manifested in the increasing movements that cut across international migration communities in a way that bridges noncontiguous countries, distinct regions, and continents, thereby expanding opportunity structures for migration over decades. Our finding sheds light on the observation that an increasing number of diverse origins have been involved in international migration since the 1970s (Castles and Miller, 2009; Vertovec, 2007). Although some of the novel migration connections were between countries that were already part of the same community, indicating the continuing importance of spatial constraints in certain regions of world migration, we also observed a moderate increase in the importance of inter-community migrations that bridge disconnected areas of origin and destination over time.

Our findings also suggest that while continental divisions of the world provided a somewhat useful approximation of migration groupings in 1960, since then, the preponderance of movements between continents over movements within continents has become more prominent over the decades. In 2000, there were equal numbers of movements between continents as within continents. Geographic regions (as defined by the UN Statistical Division) are even less informative than continents: there were more migrants outside than inside geographic regions for the whole period 1960–2000. Because continental and regional boundaries have become less instrumental than before in characterizing world migration as a whole, research in large-scale international migration would benefit from algorithmic methods for group discovery. This is the approach that we employ in the present paper. Methods to detect dense sets of nodes ("communities") in a network, when tailored to the nature of world migration, can recover useful "functional regions" (Ratti et al., 2010) that perpetuate different patterns of migration movements. Moreover, they can help provide a basis for forecasting future mobility patterns and thereby inform migration-policy debates.

Our findings about individual international migration communities indicate a substantial variability in community structure and dynamics. We developed a typology of three different categories of communities in the WMN that exhibit characteristic intra-community and inter-community connectivity, as reflected in dyadic (edge strength), network (edge-neighborhood overlap), and spatial (edge length) properties. "Global" communities have strong global cohesion, which manifests in the preponderance of long inter-community (and thus bridging) edges. "Local" communities, by contrast, exhibit strong local cohesion that is associated with the preponderance of strong intra-community over inter-community edges, edge-neighborhood overlaps, and short-distance movements. "Glocal" communities are characterized by glocal cohesion, in which significant internal edge strength coexists with relatively long-distance edges that typically connect two distinct geographic regions. The three community types provide very different migration opportunity structures. Global communities and glocal communities contribute, respectively, to world and cross-regional interconnectedness, with multilateral possibilities for migration across regions. In contrast, local communities are largely fragmented from the rest of the WMN in a way that traps movements within regional boundaries. Considered together, our findings point to the existence of a network structure that is heterogeneous in strength, clustering, and length of migration exchanges.

We found that heterogeneity is also encoded in the patterns of change. While the prevalence of bridging and long-distance edges in global international migration communities have increased significantly over time, changes in local and glocal communities have been less pronounced (and rarely are statistically significant).

Going back to the contrasting propositions from the international migration literature, which has argued either for increasing interconnectedness or for regional concentration of international migration, our findings suggest that migration interconnectedness has increased gradually among groups of countries while certain geographic regions have remained largely isolated from the dynamics of global interconnectedness. In the presence of heterogeneous processes of global and local cohesion, our results appear to support a skeptical argument that globalization has widened the gap between relatively constraint-free global mobility and local migrations that are trapped in bounded geographic regions (Hirst and Thompson, 1999; Wallerstein, 1974).

Our analysis can be extended in several ways. First, upon data availability, one can stratify the edges in the WMN by type of migration (e.g., highly-skilled professionals, workers, students, refugees, and family unification) and construct a multilayer network (Kivelä et al., 2014) in which countries are connected via multiple types of migration exchanges. Second, if one is considering a single type of migration exchange, then given the multilateral nature of current migration, one can explore the possibility of countries belonging to more than one community using approaches for discovering overlapping community structure (see, e.g., Gopalan and Blei (2013) for a scalable method). Third, understating of migration would improve if the flow of people is examined in conjunction with flows of information, goods, and capital. Recent research (e.g., Belyi et al., 2017) has examined some of these flows and may provide helpful insights to further examine global and local cohesion in a wide variety of flows. Finally, the ubiquity of online information in the public domain provides an opportunity to collect data about human mobility (e.g., geolocated career records in LinkedIn (e.g., State et al., 2014)) and thereby draw a map of local and global connectivity in world migration using self-reported data instead of administrative data. Our approach for investigating global and local cohesion in world migration can be extended to multiple movements and data sources, and it can thus shed light on emerging transnational patterns of migration interactions and possibilities.

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Appendix A. Supplementary material

Supplementary material associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.socnet.2017.06.003.

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Appendix A: Consensus Partitions

To identify robust communities (i.e., communities that do not change substantially from one run to another of a computational heuristic) in the WMN and ameliorate the issue of the numerous near-degeneracies (Good et al., 2010) in the modularity objective function, we employ a technique for finding consensus partitions (Bassett et al., 2013; Lancichinetti and Fortunato, 2012). As we discussed in the main text, we maximize multilayer modularity using both the LN null model (Leicht and Newman, 2008) and a spatial null model (Expert et al., 2011). For each of the two multilayer modularity maximizations, we use the same consensus technique, which involves the following steps (Bassett et al., 2013; Bazzi et al., 2016; Sarzynska et al., 2016). First, we perform 100 maximizations of multilayer modularity (Mucha et al., 2010) of the WMN using a Louvain-like heuristic (Jutla et al., 2011–2014) with an intralayer resolution-parameter value of $\gamma = 1$ for each layer and an interlayer resolution-parameter value of $\omega = 1$. Note that one maximization assigns each "node-layer" (i.e., a country at a specific time point) to a community. Second, from our 100 partitions, we construct a co-association matrix A^{assoc}, in which each off-diagonal entry is the number of times that a pair of node-layers is assigned to the same community. (The diagonal entries of A^{assoc} are 0.) Because there are N = 226 countries in each layer and $T = 5$ layers (from the censuses in 1960, 1970, 1980, 1990, and 2000), A^{assoc} is an $NT \times NT = 1130 \times 1130$ matrix.

Given the large number of possible pairwise associations in A^{assoc}, one needs to account for the probability that two node-layers are assigned to the same community by chance. To factor out random co-assignments, our community detection for A^{assoc} uses modularity maximization with the uniform null model $P_{ij}^{U} = \frac{2w}{NT(NT-1)}$ (Bassett et al., 2013; Sarzynska et al., 2016), where i and j index the node-layers and w is the total edge weight in the graph with adjacency matrix A^{assoc}. We employ a Louvain-like heuristic (Jutla et al., 2011–2014) to maximize modularity for A^{assoc} with $\gamma = 1$ and the null model P_{ij}^{U} to detect the consensus international migration communities that we presented in Fig. 2 in the main manuscript. In these consensus partitions, strongly associated countries in a given layer (i.e., countries that are often assigned to the same community in multilayer modularity maximization for a given time point) are likely to be part of the same international migration community in that layer.

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