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Global dynamics of international migration systems across South–South, North–North, and North–South flows, 1990–2015

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Abstract

Evidence from 184 countries over the span of 25 years is gathered and analyzed to understand North–North, South–South, and North–South international migration flows. Conceptually, the analysis borrows from network theory and Migration Systems Theory (MST) to develop a model to characterize the structure and evolution of international migration flows. Methodologically, the Stochastic Actor-oriented Model of network dynamics is used to jointly model the three types of flows under analysis. Results show that endogenous network effects at the monadic, dyadic, and triadic levels of analysis are relevant to understand the emergence and evolution of migration flows. The findings also show that a core set of non-network covariates, suggested by MST as key drivers of migration flows, does not always explain migration dynamics in the systems under analysis in a consistent fashion; thus, suggesting the existence of important levels of heterogeneity inherent to these three types of flows. Finally, evidence related to the role of political instability and countries' care deficits is also discussed as part of the analysis. Overall, the results highlight the importance of analyzing flows across the globe beyond typically studied migratory corridors (e.g., North–South flows) or regions (e.g., Europe).

Keywords: International migration, Migration Systems Theory, Social networks, Stochastic Actor-oriented Model, Global North, Global South

Introduction

Scholarly work on international migration overwhelmingly focuses on movements from the Global South to the Global North (Freier and Holloway 2019). However, some of the best evidence available to date clearly suggests that about a third of all international migratory movements take place between countries in the Global South (Abel and Sander 2014). This paper aims to answer calls to investigate migration flows beyond South-to-North flows (Nawyn 2016; Kim and Cohen 2010; Cerrutti and Parrado 2015). It does so by jointly analyzing the dynamics of South–South, North–North, and North–South flows around the globe over the span of 25 years.

The international migration literature is also usually restrictive in that it exhibits a disproportionate emphasis on large bilateral—i.e., dyadic—migratory exchanges, and in

that it typically focuses on only one destination or sending country at a time (Massey et al. 1990; Garip 2016; Menjívar 2006; Leal 2014; Steinmann 2019). A key assumption of this paper is that moving from studies of bilateral migration flows to truly multilateral studies is vital to further develop migration theory and empirics (Fawcett 1989; Abel and Sander 2014; Leal et al. 2019a; DeWaard and Ha 2019). By using state-of-the-art estimations of place-to-place international migration flows (Azose and Raftery 2019), this paper carries out a world-wide analysis of the emergence and evolution of migration flows beyond North-to-South flows and beyond specific dyadic flows. It does so by leveraging one comprehensive, and distinctly relational, theoretical framework: Migration Systems Theory (MST) (Mabogunje 1970; Fawcett 1989; Zlotnik 1992; de Haas 2010; DeWaard et al. 2012; Bakewell 2014; Windzio et al. 2019).

Even though some of the initial empirical studies of migration systems based on MST aimed to be global (Zlotnik 1992), recent analyses in the MST literature have heavily focused only on North–North flows (Nogel 1994; DeWaard et al. 2012; Windzio et al. 2019). Using newly available data and analytical techniques, this study carries out a network-based analysis using MST that goes beyond North–North flows. Critically, by moving away from exclusively studying either North–South or North–North flows, this paper shows how factors like income, political instability, care deficits, or cultural similarity can have different impacts on the emergence and evolution of flows between and within the Global South and the Global North.

Methodologically, this study relies on the Stochastic Actor-oriented Model (SAOM) of network dynamics to characterize the evolution of international migration flows over time. Given the global scope of this paper, the set of migration flows under analysis here can be conceptualized as a bounded network. In other words, this study embraces the fact that migratory exchanges can be modeled as *international migration networks*, that is, social networks comprised of migration flows (i.e., ties or edges) between countries (i.e., nodes or vertices) (Nogel 1994; Bakewell 2014; Windzio 2018; Windzio et al. 2019).¹

Theory

Migration Systems Theory (MST)

In what is typically considered the first explicit statement of MST, Mabogunje (1970) highlights that migration systems are entities that emerge from *regular* patterns of flows of people/migrants between localities across space and time. Even though Mabogunje (1970) did not have international migration but internal urban–rural migration in mind, the idea of focusing on the system of emergent regularities or patterns exhibited by flows of people remains a major theoretical insight. In a classic review of international migration theories, Massey et al. (1993) pointed out that theoretical frameworks from an ample variety of traditions—from institutional theories to world systems approaches—agree on the idea that international migratory exchanges do exhibit a high degree of stability that allows for the emergence, and study, of identifiable structures (i.e., migration systems). The empirical identification of such structures, with a special emphasis on

¹ In graph theory, nodes represent *actors* (e.g., countries) and ties represents *relationships* between actors (e.g., migratory exchanges between countries).

their geographic organization, is a key endeavor of MST (Mabogunje 1970; Zlotnik 1992; DeWaard et al. 2012; DeWaard and Ha 2019).

A key analytical advantage of focusing on migration systems, rather than on specific dyadic flows or selected destination/sending countries, is that any given flow in the system is examined in the context of the (relational) structure that exists between all other flows (Fawcett 1989; Nogel 1994; Windzio et al. 2019). This insight is critical because it fully introduces into the analysis the relational dependencies that define any network. Put simply, here it is assumed that there are network structures at the monadic (e.g., in and outdegree distributions), dyadic (e.g., mutual dyads), and triadic (e.g., transitive triangles) levels of analysis that can plausibly contribute to explain the empirical relational patterns observed in migration systems.

Research on international migration typically has lacked large-scale (e.g., global) data needed to fully bring network structures into the analysis in the context of other traditional explanatory factors behind the emergence and stability of migratory exchanges. For example, migration research regarding the importance of country-level differences in income (Greenwood and McDowell 1991) or of cultural similarity (Kim and Cohen 2010) typically has not integrated the network structure of flows as a relevant factor into the analysis. Since this paper explicitly takes into account key network structures, it incorporates the idea that any purported mechanism behind the emergence and stability of migration flows (e.g., countries' cultural similarity) must also consider the network structure in which flows are embedded.

Beyond the role of network structure per se, a consistent finding in MST's theoretical and empirical work suggests that migration systems are highly hierarchical (Fawcett 1989; Zlotnik 1992; DeWaard et al. 2012; Windzio et al. 2019; see also Massey et al. 1993; Windzio 2018). Examples of the hierarchical nature of migratory exchanges are not hard to find outside the MST tradition: from the "brain drain" of top-level professionals, to the existence of "global diasporas" (Banerjee et al. 2019; Cohen 2008). Social network theory suggests that an effective way to uncover the existence of global hierarchical networks is by means of analyzing their (local) triadic patterns (Davis 1970); or by analyzing *success-breeds-success dynamics*² (van de Rijt et al. 2014) through the modeling of inequalities in the distribution of indegrees³ (Snijders et al. 2010). Thus, network structures cannot only be used to avoid the misspecification of non-network effects as indicated in the paragraph above, but also to explicitly model key properties of migration systems suggested by theory.

The literature that focuses on the study of the structure of migration networks as described above represents one, admittedly small, segment of MST as a whole. Some MST theorists have labeled this approach as *MST's abstract systems form* (Bakewell 2014). Starting with the work of Fawcett (1989), other forms of MST highlight the existence of 'nonpeople' linkages between countries (Fawcett 1989) as key drivers behind the emergence of migration flows. Fawcett (1989) classified these nonpeople linkages into three analytic categories. First, *tangible linkages* focus on the flow of money and goods

² This is more generally known as the Matthew effect of accumulated advantage (Merton 1968).

³ Indegree refers to the number of nodes (e.g., countries) *from* which a given node receives ties (e.g., flows). Outdegree refers to the number of nodes *to* which a given node sends ties.

between localities (Greenwood and McDowell 1991). Second, *relational linkages* refer to shared culture and history between localities (Kim and Cohen 2010; Roll and Leal 2010a). Third, *regulatory linkages* are related to geographic propinquity and shared membership in supranational organizations (DeWaard et al. 2012). Virtually the same classification scheme, with slightly different labels, is offered by Zlotnik (1992). A key contribution of this study is to evaluate how these three drivers of international migration proposed by MST might vary across three different types of migratory corridors (South–South flows, North–North flows, and North–South flows), above and beyond network structure.

Migratory dynamics in the North and South

North–North flows

Several of the most recent large-scale analyses of migratory dynamics that use MST study North–North migration in Europe (Nogel 1994; DeWaard et al. 2012; DeWaard and Ha 2019; Windzio et al. 2019). In terms of regulatory linkages, earlier research on geographic propinquity by Nogel (1994) finds that sharing a border is not predictive of migratory movements, while recent research by Windzio et al. (2019) finds a positive association in this regard using a larger sample of European countries. Similarly, DeWaard et al. (2012) report that increases in geographic distance between European countries are negatively associated with, and that shared region is positively associated with, the size of flows. Still within the realm of regulatory linkages, but this time seen as shared co-membership in supranational organizations and congruent state policies, Windzio et al. (2019) do not find consistent results regarding the effect of time of access to the European Union (EU), or the opening of domestic labor markets, on the emergence of flows in Europe. However, DeWaard et al. (2012) do find a positive effect of the time of countries' accession to the EU on the size of flows. Unlike Windzio et al. (2019), DeWaard et al. (2012) do not explicitly control for network structure in their analysis.

Both DeWaard et al. (2012) and Nogel (1994) find no relationship between language similarity, understood as a proxy for relational linkages, and migratory movements. Interestingly, Windzio et al. (2019) do not test for relational linkages in their study. Instead, Windzio et al. (2019) explicitly test for the role of network topology, finding a positive tendency towards transitivity and a negative tendency towards cyclicity when predicting the *size* of flows. This is critical since the combination of transitivity and (anti) cyclicity is known to be a blueprint of hierarchical relational systems (Davis 1970; Chase 1980; Kitts et al. 2017). Even though DeWaard et al. (2012) did not model network topology, they do report the existence of a clear core/periphery structure in the European migration system, a finding that goes in tandem with the idea that migration systems are highly hierarchical entities. Finally, in terms of tangible linkages, DeWaard et al. (2012) find no effect of GDP on the size of flows in Europe. Similarly, Windzio et al. (2019) find no consistent effect of GDP on either the existence of flows or their size.

South–South flows

When compared to North–North migration flows, there is reason to believe that South–South flows might respond differently to classic drivers of migration such as MST's tangible, regulatory, and relational linkages. For instance, in terms of the geographic

component of regulatory linkages, South–South flows are known to primarily take place between neighboring countries (Dumont et al. 2010; Freier and Holloway 2019), partially due to the fact that, unlike migrants from the Global North, migrants from the Global South do not always have the financial resources to migrate across long distances. Unlike North–North flows, tangible linkages in terms of income differentials between countries are known to be key drivers of South–South migration. For instance, the literature on South–South migration in Latin America during the second half of the twentieth century suggests that increasing levels of inequality in economic well-being between countries fueled migration across the region to middle-income countries such as Venezuela or Argentina (Pellegrino 1995, 2003; Durand and Massey 2010; Cerrutti and Parrado 2015).

The importance of political factors, which are highlighted by some MST theorists (Jennissen 2007), is also likely to play out differently outside the world of North–North flows. In the case of South–South flows specifically, flows of refugees are known to be a distinctive characteristic of South–South migratory exchanges. Indeed, 86% of the world's refugees under the United Nations High Commissioner for Refugees (UNHCR) command migrated to countries in the Global South in 2015 (UNHCR 2015). This speaks about the importance of political (in)stability, and political factors more generally, to understand South–South flows. The case of Venezuela in recent years clearly exemplifies the relevance of political instability in South–South flows since the vast majority of new Venezuelan migrants are known to have migrated primarily to neighboring Colombia (UNHCR 2018; World Bank Group 2018).

South–North flows

According to Abel and Sander (2014), some of the most prominent South-to-North migratory corridors are composed of large flows from: (a) Western Africa to Western Europe; (b) Latin America to North America and Southern Europe, and; (c) South Asia and Southeast Asia mostly to North America, and to a lesser extent, to Europe. South-to-North flows are thus correlated with cultural affinity, that is, relational linkages in the form of a shared colonial past (Pedersen et al. 2008; Roll and Leal 2010b). The role of tangible linkages, such as wage differentials between sending and receiving countries, is also a defining feature of South-to-North flows (Greenwood and McDowell 1991; Zlotnik 1992; Pedersen et al. 2008).

Empirically speaking, North-to-South migration flows are both relatively small and uncommon when compared to South-to-North flows (Abel and Sander 2014). The largest North-to-South corridor in the world takes place between North America and Latin America and the Caribbean (Azose and Raftery 2019). *Migrants of privilege*, both from the US and Canada, are known to live as retirees in countries like Mexico (Croucher 2009) or Ecuador (Hayes 2014). The distinctive role played by relational linkages (e.g., colonial past) and tangible linkages (e.g., differences in wages and costs of living between countries) in North–South exchanges suggest that North–South flows (both South-to-North and North-to-South) are analytically and empirically distinct from both South–South and North–North flows. This makes the main contribution of this study, namely, the comparison of the determinants of North–North, South–South, and North–South flows worthwhile.

Materials and methods

Methods: the Stochastic Actor-oriented Model (SAOM)

The SAOM is designed to perform inferential analyses of the stochastic processes governing the evolution of network dynamics as if these dynamics were (theoretically) driven by actors' actions (Snijders et al. 2010; Snijders 2001; Ripley et al. 2020).⁴ The model assumes that discrete unobserved opportunities for network change, also known as *micro steps* (Snijders 1996; Snijders et al. 2010), happen in continuous time between empirically observed data points or waves. The first wave of data is not modeled but conditioned upon, which means that there must be at least two waves of data in order to use the SAOM (Snijders et al. 2010). Parameters are estimated using the method of moments implemented by means of computer simulation in the RSiena software (Ripley et al. 2017). Since the SAOM assumes that ties represent enduring states changing throughout a series of micro steps, the evolving network is understood to be the outcome of a continuous time Markov process (Snijders et al. 2010; Snijders 2001).

The network opportunities for change in the SAOM happen at a speed controlled by a network rate function. At each micro step, only one randomly selected node (e.g., a country) is deemed the opportunity for change (Snijders 1996; Snijders et al. 2010; Snijders 2001). In this paper, the network rate function is assumed to be constant across nodes, which means that the opportunities for change do not depend on nodes' attributes (e.g., their indegree).⁵ The SAOM further assumes that only one type of change—either sending a new flow, deleting an existing flow, or doing nothing—, can happen at any given micro step (Steglich et al. 2010). A discrete (multinomial) choice function is used to probabilistically evaluate the relative likelihood of these three mutually exclusive possibilities (Snijders et al. 2010; Steglich et al. 2010). This choice function is known as the *network objective function*. This function governs the network processes being modeled. Once successfully estimated, the individual parameter values obtained in the context of this choice function will characterize the role of each effect (e.g., reciprocity) in the contribution to an accurate reproduction of the network dynamics observed in the data.

More formally, let x be a variable under evaluation for change. Then, $f_i(\beta, x)$ is the objective function of node i , applied to x using parameter β . The likelihood that node i moves to state a of variable x (x^a), given other states in x is given by:

$$\frac{\exp(f_i(\beta, x^a))}{\sum_{x' \in X} \exp(f_i(\beta, x'))}$$

where X is the set of all possible states of x .

Continuing with a node-oriented interpretation of the model, when given the opportunity for bringing change, the selected node is assumed to “myopically” strive for higher values of their objective function in a stochastic fashion (Snijders 2005). This is said to be a myopic decision-making process because the node is subject to the restrictions

⁴ Actors in the SAOM can be any type of social actor, from social animals and humans to countries. Equivalently, these social actors can be simply defined as the nodes in a given social network.

⁵ This follows the recommendation by Ripley et al. (2020) according to which a constant rate function should be used as a default. To be sure, rate functions do not have a substantive interpretation, they control the rate at which the networks under analysis change during the estimation of the model's coefficients.

imposed by the current state of the “world” (e.g., the state of the migration network at a given micro step).⁶ It is because of this rather natural node-oriented interpretation of the SAOM that it can easily be in direct communication with other actor-oriented modeling approaches such as agent-based models or Relational Event History models.⁷ The specific network objective function of the SAOM used in this paper is determined by three theoretically distinct types of effects (details on these covariates and their measurement are provided below, their ordering does not indicate order of operation in the model):

- 1 Network endogenous effects (e.g., outdegree, reciprocity, indegree popularity)
- 2 MST linkages (e.g., regulatory, relational, and tangible linkages).
- 3 Other effects (e.g., political instability, old-age dependency ratio).

In this paper, the three networks under analysis were jointly fit in one overarching model by declaring the three networks as mutually exclusive (or ‘disjoint’ in SAOM parlance, see Ripley et al. 2020). The convergence t-ratio for each of the parameters under analysis, and the overall maximum convergence ratio for the entire model, always fulfilled the thresholds for good convergence established in the specialized literature (Ripley et al. 2020).⁸

Data and measures

Dependent variable(s)

This paper focuses on a key dimension of migration flows, namely, the *diversity* of flows, that is, which countries are and are not connected in a migration network; as opposed to the *intensity* of flows, that is, the size of the flows in a migration network. This important theoretical distinction between the diversity versus the intensity of migration flows is commonly used in the migration literature (Czaika and de Haas 2014; Arango 2000; DeWaard and Ha 2019). Recent formal work in the context of the MST tradition has shown that both the diversity and the intensity of flows provide complementary, yet unique insights to understand migration systems (DeWaard and Ha 2019).

⁶ In the standard version of the SAOM (e.g. Snijders et al. 2010)—which is the one used in this paper—nodes cannot coordinate to change their ties in a given micro step. Only ego is under control of what to do regarding their out-going ties. All the information needed to make a decision is assumed to be available to ego in the context of a given micro step. It is also assumed that, in a given micro step, ego has full information about their, and all other actors’, attributes, as well as about the current state of the network.

⁷ Following Butts (2017), actor-oriented models—such as SOAM, Relational Event History models, Dynamic Network Actor models, or agent-based models—are all part of a family of models that can be expressed in terms of the actions of individual agents. Agents (e.g., countries) are autonomous entities with unique attributes that follow a set of rules (e.g., the network objective function), and that adapt to changes in the environment, including the actions of other agents towards them (i.e., receiving a migration flow). Even though it is tempting to humanize agents, they do not need to be human, they can be animals, organizations, states, et cetera (e.g., Kitts et al. 2016).

⁸ All models were estimated with RSiena version 1.2–23. The method of moments was used with five phase 2 sub-phases. The (default) score function with 5,000 phase 3 iterations was used to calculate standard errors. The overall maximum convergence ratio for all models was always below 0.17, and the absolute value of the t-ratios for all coefficients in all models, were always below 0.1. These two metrics suggest excellent model convergence that meets the standards to publish results (Ripley et al. 2020). Except for the (GWDSP) in-stars and mixed-stars (more details on these two effects are in Sect. 3.2.2. in the article), no evidence of collinearity was found in the reported models since the absolute value of the correlations between the estimated parameters in a given model were always below 0.95 (Ripley et al. 2020). As recommended by Ripley et al. (2020), to ensure that the collinearity between the (GWDSP) in-stars and mixed-stars did not pose a threat to our findings, each model discussed in this paper was ran twice with different seeds to evaluate how robust/consistent the standard errors were. Since results were virtually identical across the different runs, it is warranted to conclude that collinearity did not drive the results.

The original migration flow data used in this paper were estimated by Azose and Raftery (2019) based on UN bilateral migrant stock data (United Nations 2015). Put simply, these flow data are weighted and directed matrices in which the ij th cell represents the intensity (i.e., size or weight) of the flow (i.e., tie or edge) from country i to country j . This effectively means that in this study migration flows are modeled as directed ties linking nodes representing countries. The Azose and Raftery (2019) data cover the period 1990 to 2015 by intervals of 5 years; thus, resulting in a time-series of 5 weighted migration networks: 1990–1995; 1995–2000; 2000–2005; 2005–2010; and 2010–2015.

To study which sending and receiving countries are (and are not) connected through migratory exchanges (i.e., to study the diversity of the system) flows were binarized. This means that the actual migration networks under analysis were not weighted directed networks representing the intensity/size of flows, but *binary* directed networks representing the diversity of flows. These binary networks are the dependent variables under analysis. Again, in the MST tradition, DeWaard and Ha (2019) have formally and empirically shown that studying the diversity and the intensity of flows provides unique information to understand the dynamics of migration systems (see also Czaika and de Haas 2014; Bell et al. 2002).

The binarization of the original weighted networks follows the insights of Michael Windzio by using a threshold based on flows' size in order to retain the largest, most "relevant," flows in the system (Windzio 2018: 22; see also Windzio et al. 2019). This is theoretically warranted since MST theorists have long advocated that the structure and dynamics of migration systems are more evidently observed among the largest flows in the system (Zlotnik 1992; Fawcett 1989), which suggests that studying flows of smaller sizes will probably provide weaker signals regarding the operation of MST linkages as drivers of migration. Studying how MST can be used to effectively model migration flows of different sizes is thus both beyond the scope of this paper and an important avenue for future research. To be sure, using a threshold to binarize and study naturally weighted networks through inferential methods is also common outside the migration literature (Faust and Skvoretz 2002; Fowler 2006; Cranmer and Desmarais 2011).

In order to binarize migration flows in each one of the 15 networks under analysis (5 time periods \times 3 types of flows—i.e., North–North; South–South; North–South),⁹ all flows in the first three quartiles of the distribution of flows arranged by size were coded as a 0 (i.e., as non-existing flows), whereas all flows in the upper quartile were considered *relevant* migration flows and thus coded as a 1 (i.e., as existing flows). In practice, this means that this paper focuses on the *diversity* exhibited among the largest migratory corridors in the context of South–South, North–North, and North–South exchanges. A total of 184 countries around the globe had complete data on all relevant covariates and were thus included in the analysis. More schematically, the binarization rules that created the 15 migration networks under analysis can be described as follows:

⁹ More explicitly, the 15 networks under analysis can be viewed as belonging to **three** time-series (one for North–North flows, one for South–South flows, and one for North–South flows) with **five** waves each (1990–1995, 1995–2000, 2000–2005, 2005–2010, 2010–2015).

- *North–North migration network* $_t = 1$ for all flows which size is in the upper quartile of the distribution of flows between countries in the Global North at time t ; 0 otherwise.
- *South–South migration network* $_t = 1$ for all flows which size is in the upper quartile of the distribution of flows between countries in the Global South at time t ; 0 otherwise.
- *North–South migration network* $_t = 1$ for all flows which size is in the upper quartile of the distribution of flows from countries in the Global North to countries in the Global South (and vice versa) at time t ; 0 otherwise.

Covariates

MST linkages. First, as put by DeWaard et al. (2012: 1324), regulatory linkages “include geographic isolation, typically measured by country contiguity or shared region (Pedersen et al. 2008), as well as economic and political memberships.” As a result, two dyadic time-invariant measures of geographic propinquity are used here: **sharing a border** (yes = 1; no = 0), and **same geographic region** (yes = 1; no = 0). The information on borders and regions was compiled by the *Centre d’Etudes Prospectives et d’Informations Internationales* (CEPII) (Mayer and Zignago 2011). The classification of countries by region used in this article can be found in Additional file 1: Appendix A. In terms of co-membership in supranational organizations, a time-variant dyadic measure of **shared membership in International Organizations** (IGO) is used here. The original data set was developed by the *Correlates of War project* (Pevehouse et al. 2019). In this study we limited the analysis to 16 IGOs capable of generating relatively congruent trade policies among their members.¹⁰ The focus on trade relations is consistent with MST theory since it suggests that trade is a key dimension of state to state relations and, therefore, constitutes a macro-level correlate of international migration (Fawcett 1989; Nogel 1994; DeWaard et al. 2012). Descriptive statistics for all MST covariates are reported in Additional file 1: Appendix B and links to all original data sources and code to reproduce the analysis are available in Additional file 1: Appendix C.




Second, in terms of tangible linkages, and following previous work in the MST literature, data on GDP were used to capture the effect of (economic) well-being in both origin and destination countries (DeWaard et al. 2012; see also Greenwood and McDowell 1991). The main effect of (logged) **GDP** on both inflows (indegree) and outflows (outdegree) are included in the analysis as time-varying node-level covariates. GDP for each year between 1990 and 2015 was taken from the UN Statistics Division data portal (United Nations Statistics Division 2019b). Because migration flow data are aggregated in 5-year intervals, GDP was computed as the average (logged) GDP of a country between the first and last year in a given 5-year interval. Finally, in terms of relational linkages, **shared official language** (yes = 1; no = 0) was used as a time-invariant dyadic

¹⁰ We looked at IGOs that focused on trade relations and that were not directly part of the UN since most countries belong to the UN. The following IGOs were included in analysis: Andean Community, Arab Maghreb Union, Asia–Pacific Economic Cooperation, Association of Southeast Asian Nations, Caribbean Community, Economic Community of West African States, Eurasian Economic Community/ Eurasian Economic Union, Euro Free Trade Association, European Union, Gulf Cooperation Council, North American Free Trade Association, MERCOSUR, Central American Integration System, Common Market for East and South Africa, Southern African Development Community.

covariate to measure cultural similarity between countries (DeWaard et al 2012; see also Kim and Cohen 2010). Information on countries' official languages was taken from the CEPII's data set referenced above.

Network endogenous covariates. Several different measures were used to model the network structure of migration flows. First, a covariate to model **outdegree** was included in the analysis to account for the baseline probability of observing ties/flows. A covariate to account for **dyadic reciprocity** was also included. Incorporating these two parameters is a standard practice in the inferential study of cross-sectional and longitudinal social networks, including internal and international migration networks (Snijders et al 2010; Goodreau et al. 2009; Windzio et al 2019; Windzio 2018; Desmarais and Cranmer 2012). A mathematical and visual representation of all network statistics used here is reported in Table 1.

Second, inequalities in the distribution of in and outdegrees were also explicitly modeled. Here it was especially important to model self-reinforcing disparities in indegrees (i.e., inflows) by including a term to account for **indegree popularity** (Snijders et al. 2010), that is, the tendency for a country to attract inflows due to the inflows it currently has. This term models cumulative advantage or success-breeds-success dynamics (van de Rijt et al. 2014) in the distribution of indegrees; an inequality-generating process akin to the well-known concepts of the Matthew effect (Merton 1968) or preferential attachment (Bárabasi and Albert 1999). Substantively, a positive coefficient for indegree popularity would suggest the existence of a hierarchical system that gives rise to very popular nodes or *hubs*. Following Snijders et al. (2010), for completeness both **outdegree popularity** (i.e., the tendency of a country to attract inflows as a function of its existing outflows) and **outdegree activity** (i.e., the tendency of a country to send outflows as a function of its existing outflows) were also modeled in order to maximize the chances of obtaining a non-spurious indegree popularity effect.

Finally, to account for basic triadic processes, network configurations consistent with transitive and cyclic tendencies were also modeled. In this context, **transitive triads** (i.e., the 030T triad in the triad census of Davis and Leinhardt (1972), graphically: ) and **cyclic triads** (i.e., the 030C triad in the triad census, graphically: ) were included in the model. Research in social networks suggests that finding both a positive tendency towards transitivity *and* a negative tendency towards cyclicity is a structural signature of the existence of hierarchical local (i.e., triadic) tendencies in the formation of a given network (Davis 1970; Davis and Leinhardt 1972; Chase 1980; Robins 2015; Kitts et al. 2017). A term to control for the existence of dyadic reciprocity (i.e., an anti-hierarchical tendency) *within* transitive triads was also included. As suggested by Block (2015) this can be done by including a term to account for **transitive reciprocated triads** (i.e., the 120C triad in the triad census, graphically: .



Critically, closed triangles such as cyclic triads or transitive triads are actually impossible to form in North–South exchanges (e.g., the hypothetical open triangle Colombia → Spain; Spain → Venezuela cannot be closed by the flow Venezuela → Colombia because this last flow is not a North–South flow). Therefore, **in-stars** (i.e., the 021U triad in the triad census, graphically: ) and **mixed-stars** (i.e., the 021C triad in the triad census, graphically: ) were included instead in order to model triadic tendencies in North–South flows. As recommended in the specialized literature (Hunter 2007;

Table 1 Network effects included in the Stochastic Actor-oriented Models

Network effect	Equation	Visual representation
Outdegree	$\sum_j x_{ij}$	
Dyadic reciprocity	$\sum_j x_{ij}x_{ji}$	
Indegree popularity (sqrt)	$\sum_j x_{ij}\sqrt{x_{+j}}$	
Outdegree popularity (sqrt)	$\sum_j x_{ij}\sqrt{x_{j+}}$	
Outdegree activity (sqrt)	$(x_{i+})^{1.5}$	
Transitive triads	$\sum_{j,h} x_{ih}x_{ij}x_{jh}$	
Cyclic triads	$\sum_{j,h} x_{ij}x_{jh}x_{hi}$	
Transitive reciprocated triads	$\sum_{j,h} x_{hi}x_{ih}x_{ij}x_{jh}$	
GWDSP—mixed-stars	$\sum_{h=1;h\neq i}^n e^{\alpha} \left\{ 1 - (1 - e^{-\alpha}) \sum_{j=1}^n x_{ij}x_{jh} \right\}$	
GWDSP—in-stars	$\sum_{h=1;h\neq i}^n e^{\alpha} \left\{ 1 - (1 - e^{-\alpha}) \sum_{j=1}^n x_{ij}x_{hj} \right\}$	

A dotted line represents the creation of a new tie, based on the existing structure of the network as represented by the solid lines
i represents Ego, *j* represents an Alter, and *h* represents an Alter different from *j*

x_{ij} = 1 if the ordered pair $i \rightarrow j$ exists (x_{ij} = 0 otherwise)

α represents a tuning parameter that may range from 0 to ∞ . As recommend by Snijders et al. (2006), α was fixed at 0.69 to model decreasing marginal returns to indirect connections

Replacing an index (e.g., *j*) by a + denotes summation over that index

Snijders et al. 2006; Ripley et al. 2020), these star effects were modeled using a geometrically weighted dyadwise shared partners (GWDSP) function to improve model convergence (see Table 1 for a graphical and mathematical representation).

Other covariates. To account for political (in)stability a time-invariant node-level covariate that measures the yearly average number of **coups d'état** a country endured during the years under analysis is included. This information was taken from the coups d'état database created by the *Center for Systemic Peace* (Center for Systematic Peace 2019) and was computed as the total number of coups a country experienced divided by the total number of years under analysis. Even though this is an admittedly raw proxy for political instability, other prominent data sets such as the *Major Episodes of Political Violence Database*—which includes a wider range of measures of political upheaval due to political and ethnic conflict—was not available for all countries under analysis. The main effect of (logged) **population size** on both inflows and outflows was also included, and was gathered from UN population estimates available on the UN population database (United Nations 2019a). Population size was included as the average population a country had during a given 5-year interval in the same way that average GDP was computed. Finally, the main effect of countries' **old-age dependency ratio** on both inflows and outflows was also included in the models. This information was also taken from the UN population database (United Nations 2019b) and it is calculated as the ratio of total population 65 years old or older to total population aged 15–64 years old. The literature on *global care chains* clearly suggests that countries with a surplus of relatively young people, especially women, can be expected to send large outflows to countries with care deficits, that is, countries with a surplus of people in need of care, such as relatively older people (Hochschild 2000; Misra et al. 2006; Malhotra et al. 2016).

Results

Descriptive results



The size of the North–North, South–South, and North–South networks analyzed here is different because they are restricted to flows between countries that belong to a given global sociopolitical region (e.g., North countries such as Japan cannot be part of South–South migratory exchanges). The smallest networks are the North–North networks, which have 49 nodes in them. The South–South networks are much larger, with 135 nodes; the North–South networks are the largest because they include all countries (i.e., 184 nodes). All the descriptive statistics for the networks discussed below are available in Table 2.

All networks have relatively large levels of (indegree) Centralization.¹¹ On average across time intervals, the North–North networks have a Centralization of 0.58, South–South networks exhibit a Centralization of 0.60, and North–South networks have a Centralization of 0.54. The fact that these networks are relatively Centralized indicates the existence of very popular nodes or hubs that attract a sizeable number of flows to them. Research shows the existence of hubs is a defining feature of migration systems (Windzio et al. 2019; DeWaard et al. 2012; Zlotnik 1992).

¹¹ Formally, following the notation of Wasserman and Faust (1994), Centralization (C^*), or graph centrality, is defined as:
$$C^* = \sum_{i \in V} \left| \max_{v \in V} (C(v)) - C(i) \right|$$

$$C^* = \sum_{i \in V} \left| \max_{v \in V} (C(v)) - C(i) \right|$$
 Where $(C(v)) - C(i)$ is the difference between largest value and all other values, taken pairwise between actors. This value is then summed for all comparisons to represent a graph-level measure of centrality.

There are important differences in mean indegree¹² and outdegree¹³ across the three types of networks, yet notable stability within each type of network across time. A relevant feature of these distributions are their relatively large standard deviations. This is especially pronounced for the distribution of indegrees in North–South networks since in that context the standard deviation of nodes' indegrees is larger than their mean indegree across all five time periods (see Table 2). This is not entirely surprising given that, by definition, hubs create long (right) tails in the distributions that describe nodes' degrees. This is a known feature of North–South flows and North–North flows since countries such as the United States are a major pole of attraction of migration flows in those systems (Zlotnik 1992; Leal et al. 2019a; Abel and Sanders 2014; Windzio et al. 2019).

Information regarding the distribution of relevant triads for each network shows notable differences in the number of transitive triads (030T) versus cyclic triads (030C). Again, for reasons explained in the “Materials and methods” section, transitive triads and cyclic triads can only emerge in South–South and North–North flows. Triadic structures can be used to describe the tendencies to observe equitable or unequitable patterns of migratory exchange *beyond* bilateral flows (Windzio 2018). Indeed, on the one hand, here it is posited that cyclic triads topologically conform to equitable chain-like migratory exchange patterns (i.e., each country in the triad sends a flow out and each country also receives one flow back, graphically ). On the other hand, here it is argued that transitive triads conform to unequitable patterns of exchange (i.e., one country in the triad receives two flows yet sends out none back, one country sends two flows and receives none, and one country sends and receives one flow, graphically ). Empirically, the ratio of cyclic triads to transitive triads clearly suggests the low prevalence of equitable triadic structures (i.e., cyclical triads) vis-à-vis unequitable structures (i.e., transitive triads). More specifically, on average across all periods for both North–North and South–South flows, cyclic triads are always less than 0.008 times as likely to be observed in the data as transitive triads are.

Inferential results

The analysis of the SAOM results is presented in two sections. Following Lewis and Kaufman (2018), in the first section, a ‘pooled’ model is described in detail. This model represents the network dynamics of North–North, South–South, and North–South networks over *all* time intervals. Given that, by definition, pooling all time intervals in one model will lead to underreporting potential peculiarities taking place at specific points in time, in a second section ‘transition period’ models are presented in order to describe the changes between each consecutive pair of time intervals (e.g., 2000–2005 to 2005–2010). The period models are thus more temporally accurate, yet less encompassing (Lewis and Kaufman 2018).

¹² Formally, mean indegree is defined as: $\bar{d}_I = \frac{\sum_{i=1}^g d_i(n_i)}{g}$ $\bar{d}_I = \frac{\sum_{i=1}^g d_i(n_i)}{g}$. Where d_i is defined as the number of incoming ties for a node, n_i is the focal node (i.e., Ego), and g is the total number of nodes. It represents a mean of the incoming ties for nodes in a network.

¹³ Formally, mean outdegree is defined as: $\bar{d}_O = \frac{\sum_{i=1}^g d_O(n_i)}{g}$ $\bar{d}_O = \frac{\sum_{i=1}^g d_O(n_i)}{g}$. Where d_O is defined as the number of outgoing ties for a node, n_i is the focal node (i.e., Ego), and g is the total number of nodes. It represents a mean of the outgoing ties for nodes in a network.

Table 2 Network descriptive statistics for migration flows, 1990–2015 (binarized data)

	1990–1995	1995–2000	2000–2005	2005–2010	2010–2015
<i>North–North flows</i>					
Density	0.248	0.248	0.248	0.249	0.249
Centralization (indegree)	0.640	0.619	0.597	0.533	0.533
Mean in-degree (std. dev)	11.92 (10.22)	11.99 (9.81)	11.92 (9.99)	11.94 (8.95)	11.96 (9.22)
Mean out-degree (std. dev)	11.92 (7.83)	11.90 (8.84)	11.92 (9.28)	11.94 (9.74)	11.96 (9.38)
Number of nodes	49	49	49	49	49
Number of isolates	0	1	2	1	0
Dyad census					
Number of mutual dyads	219	223	233	233	246
Number of asymmetric dyads	146	137	118	119	94
Number of null dyads	811	816	825	824	836
Relevant triads					
Number of transitive triads (030T)	39	42	28	36	22
Number of 021U triads	283	209	213	89	95
Number of cyclic triangles (030C)	0	0	1	0	0
Number of 021C triads	150	181	120	136	74
Number of trans. rec. triads (120C)	37	39	42	38	34
<i>South–South flows</i>					
Density	0.265	0.264	0.258	0.268	0.254
Centralization (indegree)	0.627	0.486	0.634	0.647	0.594
Mean in-degree (std. dev)	35.57 (22.02)	35.34 (22.46)	34.63 (21.69)	35.98 (22.16)	34 (21.98)
Mean out-degree (std. dev)	35.57 (22.23)	35.34 (21.48)	34.63 (20.37)	35.98 (21.85)	34 (20.82)
Number of nodes	135	135	135	135	135
Number of isolates	0	0	0	0	0
Dyad census					
Number of mutual dyads	1760	1794	1819	1872	1952
Number of asymmetric dyads	1282	1183	1037	1113	686
Number of null dyads	6003	6068	6189	6060	6407
Relevant triads					
Number of transitive triads (030T)	2049	1345	1232	1490	322
Number of 021U triads	5863	6758	5890	5209	3738
Number of cyclic triangles (030C)	21	5	8	7	0
Number of 021C triads	2937	2250	2072	1739	412
Number of trans. rec. triads (120C)	1114	946	949	927	439
<i>North–South flows</i>					
Density	0.098	0.098	0.098	0.097	0.097
Centralization (indegree)	0.517	0.561	0.528	0.539	0.523
Mean in-degree (std. dev)	17.86 (21.23)	17.87 (23.32)	17.85 (23.25)	17.83 (22.32)	17.83 (22.51)
Mean out-degree (std. dev)	17.86 (18.42)	17.87 (17.15)	17.85 (17.50)	17.83 (18.37)	17.83 (18.21)
Number of nodes	184	184	184	184	184
Number of isolates	1	1	2	0	1
Dyad census					
Number of mutual dyads	1200	1202	1222	1260	1322
Number of asymmetric dyads	887	884	840	760	637
Number of null dyads	14,749	14,750	14,774	14,816	14,877
Relevant triads					
Number of transitive triads (030T)	–	–	–	–	–
Number of 021U triads	6958	10,661	9330	6595	5714
Number of cyclic triangles (030C)	–	–	–	–	–
Number of 021C triads	4129	2439	1818	1782	980
Number of trans. rec. triads (120C)	–	–	–	–	–

Migration flows included here are those in the top quartile of flows arranged by size in each migration network

Goodness-of-fit (GOF) measures are available at the bottom of Tables 3 and 4 in the form of a p value based on Monte Carlo Mahalanobis distance tests (Lospinoso and Snijders 2019; see also Lewis and Kaufman 2018). In a nutshell, these p values indicate the likelihood that a set of *simulated networks* generated under each one of the estimated models—with their corresponding parameter values—are able to recover key empirical features of the networks under analysis, in this case the observed distribution of inflows (indegree) and outflows (outdegree) (for a similar GOF approach in the Exponential Random Graph Model literature see Goodreau et al. 2009). Therefore, under this simulated-based GOF framework, better fit is signaled by large p values since that indicates that the indegree and outdegree distributions of the simulated networks are statistically indistinguishable from the observed indegree and outdegree distributions of the networks each model aims to fit.

In general, it is discouraged to use models with p values equal to 0 (Ripley et al. 2020: 60). Among the 24 p values computed for the single period models (i.e., 4 transition periods \times 3 network types \times 2 global properties [indegree and outdegree distribution]), no p values were equal to 0, three were below 0.05 and none were below 0.02. Given that the same parameters are used across all 4 single period models, this suggests that these parameters consistently fit well the observed networks in all individual periods. The complexity of the pooled model is reflected in lower overall fit—which is to be expected (Lewis and Kaufman 2018)—with two p values being equal to 0. Since the single period models and the pooled model have the exact same set of covariates and, with some minor exceptions discussed in detail below, the values and direction of all coefficients are consistent across all models, this indicates that the set of coefficients used here can be reliably used to describe the evolution of the migration networks under analysis.

Pooled model

Endogenous network effects The outdegree effect is consistently and negatively associated with the emergence of flows in the three migration systems under analysis (see Table 3). Observing a negative coefficient for outdegree is a typical feature of social networks since it indicates the existence of a low baseline probability for tie formation, that is, it reflects the fact that social networks tend to be sparse (Lusher et al. 2013). An equally fundamental network process model here is that of dyadic reciprocity. The results in this regard are also highly consistent since reciprocity is positively and significantly associated with the emergence of flows across all three networks. The coefficient for reciprocity is larger in same-status flows (i.e., North–North flows and South–South flows) than in different-status flows (i.e., North–South flows). This is consistent with the literature that suggests that dyadic reciprocity is typically low among different-status actors (Granados and Knoke 2013; Leal et al. 2019b).

The findings also suggest the existence of success-breeds-success dynamics as demonstrated by the positive and statistically significant indegree popularity effect found in all three networks. This indicates strong reinforcing inequalities in the distribution of inflows where popular nodes or hubs tend to become even more popular over time (Snijders et al. 2010). This is consistent with the robust evidence suggesting the existence of

Table 3 Pooled SAOM to investigate international migration flows by the global South/North divide (1990–2015)

	North–North networks Estimate (S.E.)	South–South networks Estimate (S.E.)	North–South networks Estimate (S.E.)
Rate parameters			
Period 1	4.116 (0.436)	18.569 (0.700)	10.324 (0.442)
Period 2	5.533 (0.562)	18.120 (0.701)	9.324 (0.418)
Period 3	4.088 (0.439)	10.557 (0.405)	5.011 (0.249)
Period 4	4.383 (0.468)	12.605 (0.484)	5.272 (0.256)
Network endogenous effects			
Outdegree	− 4.280*** (0.377)	− 2.557*** (0.156)	− 4.815*** (0.106)
Reciprocity	2.787*** (0.235)	3.101*** (0.106)	1.955*** (0.055)
Transitive triads (030T)	0.120*** (0.021)	0.053*** (0.003)	–
Transitive recipr. triads (120C)	− 0.108*** (0.032)	− 0.037*** (0.005)	–
Cyclic triads (030C)	0.004 (0.042)	0.026*** (0.007)	–
GWDSF mixed-star	–	–	− 0.078*** (0.010)
GWDSF in-star	–	–	0.053*** (0.008)
Indegree—popularity (sqrt)	0.852*** (0.141)	0.600*** (0.032)	0.520*** (0.028)
Outdegree—popularity (sqrt)	− 0.717*** (0.180)	− 0.883*** (0.050)	− 0.154*** (0.032)
Outdegree—activity (sqrt)	0.236*** (0.051)	0.099*** (0.015)	0.222*** (0.012)
MST linkages			
Common language	0.785*** (0.208)	0.335*** (0.035)	0.607*** (0.058)
Contiguous border	0.960*** (0.169)	1.688*** (0.204)	1.235*** (0.292)
Same region	0.107 (0.111)	0.603*** (0.045)	1.052*** (0.103)
Shared IGO	0.137 (0.124)	0.371*** (0.051)	0.288*** (0.095)
GDP—inflows	− 0.028 (0.044)	0.142*** (0.018)	− 0.004 (0.020)
GDP—outflows	0.029 (0.041)	− 0.170*** (0.021)	− 0.027 (0.019)
Other controls			
Old age dependency—inflows	0.009 (0.010)	0.002 (0.006)	0.003 (0.004)
Old age dependency—outflows	− 0.026*** (0.009)	− 0.015** (0.006)	− 0.015*** (0.004)
Population—inflows	0.181** (0.077)	0.055*** (0.015)	0.092*** (0.019)
Population—outflows	0.122 (0.063)	0.037** (0.015)	0.162*** (0.018)
Coups—inflows	0.632 (− 2.634)	− 0.636*** (0.148)	0.233 (0.298)

Table 3 (continued)

	North–North networks Estimate (S.E.)	South–South networks Estimate (S.E.)	North–South networks Estimate (S.E.)
Coups—outflows	− 1.651 (2.524)	0.146 (0.142)	− 0.017 (0.205)
Goodness of fit			
Indegree or inflows	0.896	0	0.044
Outdegree or outflows	0.067	0.026	0

* $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed tests)

preferential attachment dynamics in social and technological networks (de Solla Price 1976; Bárabasi and Albert 1999).

Both North–North and South–South flows exhibit a tendency in favor of the emergence of hierarchical-like triangles (i.e., positive transitive triads effect) and a tendency against reciprocity within triads (i.e., negative transitive reciprocated triads effect). Both of these tendencies are stronger in North–North flows than in South–South flows. This is perhaps related to the fact that South–South flows lack extremely popular hubs such as those observed in North–North flows (e.g., the US, Germany, or the UK). The presence of such hubs would likely make many of the triads in which they are involved hierarchical since, by definition, hubs tend to receive substantially more inflows than outflows; thus, making migratory exchanges unequal.¹⁴ Evidence of the hierarchical nature of North–North migration systems, and of the role of hubs such as the UK and Germany in that context, has been reported before in the MST literature (Windzio et al. 2019; DeWaard et al. 2012). There is also evidence of a positive tendency for the formation of cyclic triads in South–South flows, which suggests the presence of local antihierarchical forces among migratory exchanges within the Global South. Again, it is possible that this is related to the lack of prominent hubs in South–South flows. Finally, although highly indirect, the results also suggest the prevalence of hierarchical triadic migratory patterns in North–South flows. On the one hand, there is a negative tendency to observe (GWDSP) mixed-stars, which suggest an overall negative correlation between receiving and sending out flows in North–South triads. On the other hand, the evidence also suggests a significant and positive tendency to observe (GWDSP) in-stars in North–South triads, that is, open triangles where the central node receives two flows.

MST linkages. Regulatory linkages are typically understood in the MST literature as modeling both geographic propinquity and shared membership in supranational organizations (DeWaard et al. 2012). In terms of geographic propinquity, this paper uses both a measure of country contiguity and a membership-based measure of shared geographic region. As expected, both variables consistently suggest that geographic propinquity is positively associated with the emergence of flows in all the networks under analysis. However, the extent to which geographic propinquity matters varies between the three migration networks. On the one hand, shared region seems to matter less for

¹⁴ Further indirect evidence in this regard comes from the size of the indegree popularity effect since this coefficient is much larger in North–North flows ($\beta = 0.852$, $p < .001$) than in the South–South flows ($\beta = 0.600$, $p < .001$). This suggests that hubs in North–North migration networks attract more flows than hubs in South–South migration networks.

Table 4 Single transition period SAOMs to investigate international migration flows by the global South/North divide (1990–2015)

	Transition period 1: 1990–1995 to 2000–2005		Transition period 2: 1995–2000 to 2000–2010		Transition period 3: 2000–2005 to 2005–2015		Transition period 4: 2005–2010 to 2010–2015					
	North–North network	South–South network	North–North network	South–South network	North–North network	South–South network	North–North network	South–South network				
	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)				
Rate parameter	4.003 (0.421)	9.308 (0.400)	5.250 (0.521)	17.500 (0.736)	9.465 (0.436)	3.859 (0.423)	10.657 (0.439)	5.084 (0.267)	4.272 (0.475)	12.350 (0.488)	5.202 (0.266)	
<i>Network endogenous effects</i>												
Outdegree	− 5.951*** (0.986)	− 4.822*** (0.209)	− 4.979*** (0.710)	− 1.926*** (0.319)	− 4.739*** (0.194)	− 2.672*** (0.825)	− 2.392*** (0.388)	− 5.616*** (0.346)	− 4.245*** (0.874)	− 4.744*** (0.462)	− 4.99*** (0.260)	
Reciprocity	2.264*** (0.496)	1.813*** (0.114)	2.699*** (0.483)	2.839*** (0.211)	1.824*** (0.100)	3.047*** (0.535)	2.838*** (0.173)	1.990*** (0.123)	3.587*** (0.543)	4.235*** (0.292)	2.593*** (0.141)	
Transitive triads (030T)	0.133*** (0.041)	−	0.093* (0.041)	0.048*** (0.005)	−	0.172*** (0.048)	0.072*** (0.007)	−	0.104 (0.053)	0.019* (0.008)	−	
Tran. recipr. tri. (120C)	− 0.086 (0.073)	−	− 0.104 (0.065)	− 0.026*** (0.009)	−	− 0.125 (0.064)	− 0.031*** (0.009)	−	− 0.157* (0.068)	− 0.055*** (0.011)	−	
Cyclic triads (030C)	− 0.086 (0.110)	−	0.009 (0.076)	0.028* (0.014)	−	− 0.072 (0.082)	− 0.027 (0.014)	−	0.174 (0.102)	0.114*** (0.023)	−	
GWDSF mixed-star	−	− 0.104*** (0.020)	−	−	− 0.044** (0.019)	−	−	− 0.042 (0.023)	−	−	− 0.130*** (0.0268)	
GWDSF in-star	−	0.080*** (0.018)	−	−	0.023 (0.015)	−	−	0.032 (0.019)	−	−	0.086*** (0.024)	
Indegree—popularity	0.605 (0.353)	0.450*** (0.052)	0.997*** (0.266)	0.662*** (0.066)	0.462*** (0.049)	0.605 (0.326)	0.495*** (0.049)	0.706*** (0.071)	1.162*** (0.324)	0.755*** (0.087)	0.421*** (0.086)	
Outdegree—popularity	− 0.247 (0.483)	− 0.156* (0.068)	− 0.687* (0.315)	− 0.957*** (0.097)	− 0.107 (0.055)	− 0.731 (0.416)	− 0.693*** (0.097)	− 0.285*** (0.073)	− 1.190*** (0.382)	− 0.935*** (0.110)	− 0.027 (0.093)	
Outdegree—activity	0.380*** (0.128)	0.192*** (0.023)	0.355*** (0.010)	0.026 (0.028)	0.237*** (0.023)	0.091 (0.121)	0.092*** (0.034)	0.333*** (0.046)	0.122 (0.132)	0.166*** (0.042)	0.198*** (0.029)	

Table 4 (continued)

	Transition period 1: 1990–1995–2000		Transition period 2: 1995–2000 to 2000–2005		Transition period 3: 2000–2005 to 2005–2010		Transition period 4: 2005–2010 to 2010–2015				
	North–North network	South–South network	North–North network	South–South network	North–North network	South–South network	North–North network	South–South network			
	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)			
<i>MST linkages</i>											
Common language	0.381 (0.459)	0.397*** (0.066)	1.387*** (0.426)	0.378*** (0.065)	0.669*** (0.101)	0.815 (0.438)	0.350*** (0.077)	0.629*** (0.138)	0.714 (0.434)	0.219*** (0.084)	0.446*** (0.145)
Contiguous border	1.551*** (0.353)	1.925*** (0.398)	1.162*** (0.331)	1.566*** (0.364)	1.344** (0.531)	0.725 (0.384)	1.624*** (0.458)	1.468* (0.678)	0.516 (0.367)	1.674*** (0.447)	1.219 (0.766)
Same region	0.325 (0.224)	0.567*** (0.080)	-0.154 (0.242)	0.679*** (0.086)	0.928*** (0.181)	0.041 (0.277)	0.627*** (0.106)	1.153*** (0.257)	0.329 (0.225)	0.626*** (0.105)	1.251*** (0.262)
Shared IGO	0.423 (0.494)	0.761*** (0.141)	0.143 (0.315)	0.1545 (0.092)	0.159 (0.320)	0.122 (0.314)	0.252** (0.103)	0.373 (0.311)	0.132 (0.198)	0.552*** (0.115)	0.212 (0.129)
GDP – inflows	0.105 (0.111)	0.333*** (0.036)	-0.151 (0.088)	0.033 (0.034)	-0.109*** (0.036)	-0.034 (0.098)	0.051 (0.048)	-0.123* (0.054)	0.081 (0.115)	0.241*** (0.041)	0.085 (0.057)
GDP—out-flows	0.132 (0.101)	-0.148*** (0.036)	0.115 (0.082)	-0.121*** (0.043)	0.017 (0.035)	0.079 (0.102)	-0.020 (0.043)	-0.024 (0.046)	-0.353*** (0.126)	-0.237*** (0.059)	-0.032 (0.047)
<i>Other controls</i>											
Old age dep.—inflows	-0.008 (0.024)	0.016 (0.010)	0.044* (0.022)	-0.044*** (0.012)	0.024*** (0.007)	0.011 (0.020)	0.023* (0.011)	-0.029*** (0.009)	-0.005 (0.019)	0.034*** (0.010)	0.013 (0.008)
Old age dep.—out-flows	-0.002 (0.023)	-0.046*** (0.011)	-0.0224 (0.018)	0.007 (0.011)	-0.043*** (0.007)	-0.051* (0.023)	0.029* (0.011)	0.010 (0.011)	-0.024 (0.023)	-0.132*** (0.025)	-0.017 (0.009)
Population—inflows	-0.011 (0.191)	-0.052* (0.026)	0.344*** (0.132)	0.132*** (0.032)	0.189*** (0.034)	0.193 (0.162)	0.099*** (0.035)	0.105** (0.045)	0.137 (0.174)	-0.046 (0.034)	0.015 (0.049)

Table 4 (continued)

	Transition period 1: 1990–1995 to 1995–2000		Transition period 2: 1995–2000 to 2000–2005		Transition period 3: 2000–2005 to 2005–2010		Transition period 4: 2005–2010 to 2010–2015		
	North–North network	South–South network	North–North network	South–South network	North–North network	South–South network	North–North network	South–South network	
	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	Estimate (S.E)	
Population—outflows	0.058 (0.135)	0.049 (0.026)	0.248*** (0.039)	0.089*** (0.033)	0.272 (0.156)	−0.021 (0.031)	0.492** (0.210)	−0.132*** (0.052)	0.143*** (0.046)
Coups—inflows	−0.123 (6.051)	−1.374*** (0.266)	−1.316** (0.551)	0.232 (0.303)	5.030 (5.328)	−0.931*** (0.348)	−4.546 (6.185)	−0.192 (0.360)	1.746** (0.730)
Coups—outflows	−0.265 (5.349)	0.217 (0.263)	0.362 (0.404)	0.293 (0.265)	−6.936 (6.082)	0.483 (0.311)	−13.114 (7.674)	−0.224 (0.433)	0.073 (0.507)
Goodness of fit									
Indegree or inflows	0.680	0.040	0.564	0.212	0.824	0.369	0.884	0.134	0.188
Outdegree or outflows	0.836	0.304	0.024	0.224	0.732	0.445	0.282	0.924	0.237

p* < .05; *p* < .01; ****p* < .001 (two-tailed tests)

North–North flows ($\beta=0.107$, n.s.), more for South–South flows ($\beta=0.603$, $p<0.001$), and even more for North–South flows ($\beta=1.052$, $p<0.001$). In this regard, it is known that a substantial amount of North–South flows does tend to be directed from countries in the Global South to countries in the Global North located in the same region, yet these countries are typically not strictly contiguous to one another (e.g., El Salvador and the US in the Americas or Turkey and Germany in Europe). On the other hand, strict geographic contiguity seems to matter less for North–North flows ($\beta=0.960$, $p<0.001$), more for North–South flows ($\beta=1.235$, $p<0.001$), and even more for South–South flows ($\beta=1.688$, $p<0.001$). Supporting evidence in this regard in the migration literature suggests that, especially in times of crisis, large flows from the Global South tend to be directed to other geographically close Global South countries, not necessarily to Global North countries (UNHCR 2015; World Bank Group 2018).

Still within the world of regulatory linkages, co-membership in supranational organizations is roughly equally important for both North–South flows ($\beta=0.288$, $p<0.001$) and South–South flows ($\beta=0.371$, $p<0.001$), while it is not significantly associated with the emergence of flows in the North–North network ($\beta=0.137$, n.s.). The latter result is not surprising since most countries in the Global North belong to virtually the same Intergovernmental Organizations (IGOs), what Greenhill and Lupu (2017) call the *European/Northern IGO cluster*. This makes the co-membership in supranational organizations almost a constant for North–North flows. Similarly, after controlling for network structure, Windzio et al. (2019) did not find consistent effects regarding the timing of joining the European Union—understood as a proxy for regulatory linkages—on the existence of North–North flows in Europe. The results reported here point out in the same direction.

In terms of relational linkages, that is, the role of shared culture and history, results are in the expected direction since in all three migration networks sharing an official language is significantly and positively associated with the emergence of migration flows. The overall positive effect of language similarity on the existence of flows is consistent with existing empirical evidence (Kim and Cohen 2010; Spörlein 2015; Windzio 2018). Interestingly, the size of the coefficient for language similarity suggests that a shared culture and history is relatively more important to predict North–North flows ($\beta=0.785$, $p<0.001$), than North–South flows ($\beta=0.607$, $p<0.001$) or South–South flows ($\beta=0.335$, $p<0.001$).

In light of the results reported above regarding the role of geographic propinquity, the findings indicate that relational linkages might be relatively more important to predict North–North flows, while regulatory linkages might be more important to predict North–South flows and South–South flows. To be sure, as predicted by MST, both regulatory linkages and relational linkages are key to understand migration patterns across the three migration networks under analysis. Yet, when comparing results across the three migration networks the findings suggest that, *ceteris paribus*, North–North flows are better predicted by cultural distance, whereas North–South flows and South–South flows are better predicted by geographic distance. Existent evidence goes in tandem with this conclusion. On the one hand, Kim and Cohen (2010) report that a proxy for cultural similarity, namely, the existence of colonial linkages, is relatively more influential than geographic distance when predicting outflows between 13 Global North countries. On the other hand, Spörlein (2015) studies destination choices of Latin American migrants

moving to either other Latin American countries (i.e., South–South migration) or to North American countries (i.e., North–South migration), and reports that geographic distance is relatively more influential than cultural distance when predicting emigration decisions in this context.

Following DeWaard et al. (2012), the role of tangible linkages was measured through the main effect of GDP on both inflows and outflows. Perhaps unsurprisingly, the effect of GDP for North–North flows, which by definition are flows between relatively rich countries, is not significantly associated with countries inflows or outflows. This finding coincides with evidence in the context of North–North flows in Europe reported by DeWaard et al. (2012) and Windzio et al. (2019). This same qualitative pattern is observed in the context of North–South flows. This result likely emerges because people from countries in the Global North have an underlying low baseline probability to migrate to the Global South, even when the economic performance of countries in the Global South is relatively favorable. Yet, there is evidence suggesting that retirees from the Global North that go to live in the Global South might be an exception to this pattern (Croucher 2009; Hayes 2014; Benson 2013). The mirror image of this situation is found among South–South flows where increases in GDP are positively and significantly associated with receiving flows ($\beta = 0.142, p < 0.001$), as well as negatively and significantly associated with sending out flows ($\beta = -0.170, p < 0.001$). These results are generally consistent with the South–South migration literature (Pellegrino 1995, 2003; Cerrutti and Parrado 2015).

Other covariates. In terms of political instability, the only coefficient that reaches statistical significance is the negative effect of coups on countries' likelihood to receive inflows in South–South networks ($\beta = -0.636, p < 0.001$). The fact that this measure only achieved statistical significance in the South–South networks is indeed consistent with the literature, which suggest that political instability is a key driver of South–South flows more than of North–South flows (or North–North flows) (UNHCR 2015,2018; World Bank Group 2018). An interesting and consistent result across all three networks under analysis is that old-age dependency ratio—i.e., countries' care deficits—is significantly and negatively related to countries' tendency to send out flows. This is, admittedly highly indirect, evidence in favor of the *global care chains* argument, which suggests that countries with a relative surplus of older (younger) people can be expected to send less (more) migrants—specially migrant women—to countries with a relative surplus of younger (older) people (Hochschild 2000; Misra et al. 2006; Malhotra et al. 2016). This is, to the best of our knowledge, the first time that some evidence consistent with the global care chains argument is reported in an inferential and truly global analysis of North–North, South–South, and North–South migration flows. Fully testing the global care chains argument is beyond the scope of this paper as it will require, among other things, global flow data disaggregated by gender (e.g., Malhotra et al. 2016). Finally, in tandem with the broader migration literature, and the literature on gravity models in particular (DeWaard et al. 2012; Kim and Cohen 2010), population size is significantly and positively related with both sending and receiving flows across the three networks under analysis, except for the effect of population size on outflows in North–North flows, where the evidence is only marginally significant ($\beta = 0.122, p < 0.1$).

Single period models

A series of single period models was estimated for each transition period to evaluate if the findings described in the pooled model are driven by idiosyncratic features of any single period (Lewis and Kaufman 2018). In that context, Table 4 presents the same set of coefficients used in the pooled model in Table 3, but this time estimated on a single period basis. Overall, the findings discussed in the pooled model are robust to this period-by-period analysis, with three minor exceptions noted below.

Among all 236 coefficients tested across all four transition periods and presented in Table 4, only three significant coefficient switched direction when compared to the significant coefficients reported in the pooled model. This is the case of the effect of old-age dependency ratio on outflows in transition period 3 (2000–2005 to 2005–2010) for South–South networks. In that particular period, this coefficient emerged as positive and significant ($\beta=0.029$, $p<0.05$), yet in all the other single period models the effect was negative and significant or not significant. In the pooled model the effect was negative and significant ($\beta=-0.015$, $p<0.01$). The second case is the effect of population size on inflows for South–South flows in transition period 1 (1990–1995 to 1995–2000), which emerged as negative and significant in period 1 ($\beta=-0.052$, $p<0.05$), yet in all the other single period models the effect was positive and significant or not significant. In the pooled model the effect was positive and significant ($\beta=0.055$, $p<0.001$). The third and last case is the effect of population size on outflows for South–South flows in transition period 4 (2005–2010 to 2010–2015), which emerged as negative and significant in this particular period ($\beta=-0.132$, $p<0.01$), yet in all the other single period models the effect was positive and significant or not significant. In the pooled model the effect was positive and significant ($\beta=0.037$, $p<0.01$). Critically, since none of these three discrepancies are related to the key predictors analyzed here, namely, MST linkages and network endogenous effects, the single period models show that the pooled model reported in Table 3 is highly robust to time heterogeneity issues.

Conclusion

This paper carried out an analysis of North–North, South–South, and North–South migration flows over the span of 25 years using Migration Systems Theory (MST) as a guiding theoretical framework. The data used here allow for the incorporation of the vast majority of countries in the world into the analysis. Given the relational nature of MST, migration networks were modeled as social networks comprised of countries (nodes or vertices) connected through migration flows (ties or edges). The Stochastic Actor-oriented Model (SAOM) of network dynamics was used to model network endogenous (e.g., reciprocity) and exogenous (e.g., MST linkages) covariates that can explain the emergence and evolution of flows in the three types of networks under analysis.

Several findings are worth highlighting. First, network effects were found to be consistently important to model migration flows. More specifically, the network patterns modeled here show that, above and beyond dyadic reciprocity and outdegree, migration networks are hierarchical both in terms of their triadic structure and in terms of the distribution of their indegrees. The evidence also shows that even though dyadic reciprocity exists in all three systems, it is weaker between countries of different status (i.e., North–South flows) than among countries of similar status (i.e., North–North flows

and South–South flows). Taken together, the results suggest that in order to understand an international migration system, special attention should be paid to the endogenous network dynamics that characterize its (unequal) structure. Future work should further explore the connection between network processes and migration flows. For instance, it would be important to understand if the network effects described above are also detectable in regional analysis since most of MST's recent theoretical and empirical developments are based on the European case. It would be important to see if other regions of the world such as the Americas, Africa, or Asia exhibit similar network patterns and structures.

Second, evidence suggests that North–North flows, North–South flows, and South–South flows can respond differently to the influence of MST linkages. This is a most relevant conclusion that, to the best of our knowledge, has not been reported in previous MST studies. In terms of relational linkages, cultural distance (i.e., sharing a common language) appears to be more relevant for North–North flows than for either South–South flows or North–South flows. Conversely, sharing a border, understood as a proxy for regulatory linkages, is more relevant for North–South flows and South–South flows than for North–North flows. Still within the realm of geography, regulatory linkages measured as sharing the same region, are not significantly associated with North–North flows, yet they are a significant predictor of South–South flows and North–South flows. The same is true for the last indicator of regulatory linkages included in the analysis, namely, co-membership in IGOs.

Finally, in terms of tangible linkages, (economic) well-being measured through countries' GDP is associated with a lower probability to send out flows in South–South networks. As suggested by the MST literature (e.g., DeWaard et al. 2012; Windzio et al. 2019), GDP is not a predictor of either sending or receiving flows in North–North migration networks. The above results are a reminder that it is unlikely that a set of covariates such as MST's linkages will predict flows consistently and in the same direction across a set of heterogeneous migration (sub)systems. In this context, a key limitation of this study is that flows modeled here are the largest ones in each of the three systems under analysis. It is important that future work on the MST tradition evaluates the role of linkages as predictive devices of medium- and small-sized flows.

Third, beyond MST linkages, the results provide indirect yet provocative support of a key prediction based on the idea of global care chains, namely, the hypothesis that countries with care deficits are less likely to send out flows. This is, as mentioned previously, the first time that some evidence in favor of the global care chains argument is found in a truly global analysis of North–North, South–South, and North–South flows. Finally, the evidence also supports the idea that political instability might be more relevant to predict South–South flows than North–South flows (or North–North flows). This finding is supported by existing empirical evidence (e.g., UNHCR 2015), yet not sufficiently highlighted in the current literature, which overwhelmingly focuses on North–South flows and North–North flows. This finding should also be further explored in future research given that the proxy for political instability used here (coups d'état) by no means covers the spectrum of political events that can signal political instability. In general, however, this article suggests that explicitly taking into account the geopolitical nature of migration flows (i.e., North–North, South–South, North–South) is critical to make sense not

only of the role of political instability, but also of the role of most major correlates of migratory dynamics.

Supplementary information

Supplementary information accompanies this paper at <https://doi.org/10.1007/s41109-020-00322-x>.

Additional file 1: Appendices that include standardized country codes, Non-Network descriptive statistics, data sources, and the R code used to generate our results.

Abbreviations

CEPII: Centre d'Etudes Prospectives et d'Informations Internationales; GDP: Gross domestic product; GWDSP: Geometrically weighted dyadwise shared partners; IGO: International organizations; MST: Migration Systems Theory; SAOM: Stochastic Actor-oriented Model; UN: United Nations; UNHCR: United Nations High Commissioner for Refugees.

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Author's contributions

DL conceived and designed the study; DL and NH estimated the models; DL analyzed the results; DL and NH wrote the paper. All authors read and approved the final manuscript.

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Availability of data and materials

Links to the datasets used in our analysis are included in Additional file 1: Appendix C. The same information is provided below. The R objects on which the results are based are available from the corresponding author upon request. The code to reproduce the statistical analyses is available in Additional file 1: Appendix C. Coordinates of War code list: <https://correlatesofwar.org/data-sets/cow-country-codes>. Original migration flow data: <https://www.pnas.org/content/suppl/2018/12/18/1722334116.DCSupplemental>. Original population estimates per county: <https://population.un.org/wpp/Download/Standard/Population/>. Original data on shared borders (compiled by CEPII, can be downloaded from link): https://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=6. Original data on country-to-country distances (compiled by CEPII, can be downloaded from link): https://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=6. Original data on official language and colonial past (compiled by CEPII, can be downloaded from link): https://www.cepii.fr/CEPII/en/bdd_modele/presentation.asp?id=6. Original coups d'état data (compiled by the Center for Systematic Peace, can be downloaded from link): <https://www.systemicpeace.org/inscrdata.html>. Original UN GDP data: <https://data.un.org/Data.aspx?q=GDP+per+capita&d=SNAAMA&f=grID%3a101%3bcurrID%3aUSD%3bpcFlag%3a1>. Original UN Old/Young Dependency Ratio data: <https://population.un.org/wpp/Download/Standard/Population/>. Original supra-national organizations data: <https://correlatesofwar.org/data-sets/IGOs>

Competing interests

The authors declare that they have no competing interests.

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