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The network of global migration 1990-2013.
Using ERGMs to test theories of migration between countries.

Introduction

Global migration has an impact on receiving as well as sending countries and attracts high attention both in scientific research and public debates. It is thus important to get better informed insight into causes of migration between countries. Out- or inflow of migrants create a network between countries and bind them "socially" together. But what are the basic determinants of migration between countries? Why do people migrate from one country to another? Why do they choose specific destinations? The present paper focuses on *geographic*, *demographic*, *economic, religious*, *linguistic* and *historical* factors of migration between countries. It is a new approach in migration research to take a global perspective, to statistically control various factors against each other in a comprehensive model, and also to control for statistical non-independence of dyads in networks. Are global migration flows directed from poor to richer countries or from the Global South to the North? Are there effects of spatial distance, area size or demographic trends on migration, as expected according to demographic and geographic theories? Do we find effects of language and religion as well as historical path dependencies due to colonization? And, more importantly, does the social network paradigm lead to new insight into statistical non-independence and embeddedness of two country-dyads into a wider "social" environment?

Global migration results from a multi-factorial constellation of determinants statistical models should account for. Social network analysis provides methods to control for the embeddedness of dyads into the surrounding *network structure*. If Spain attracts immigrants from Morocco, and sends at the same time migrants to Germany, migrants might be also pulled from Morocco to Germany, indicating an underlying hierarchy of attractiveness and pull-factors.

Using data from the UN Migration Wallpaper on 202 countries for the years 1990, 2000, 2010 and 2013, this paper investigates global migration patterns from a social network perspective by using methods of temporal and cross-sectional exponential random graph modelling (ERGM). The focus is on *factors* triggering global migration, so each country will be equally treated as a vertex in the network, regardless of its population size. According to the measurement of migration suggested in this paper models are neither dominated by large countries nor by extraordinarily high migration flows between particular country-dyads. If a country-dyad is in the highest quartile of the migration measure's distribution, a migration flow from ego to alter will be regarded as being relevant, and will thus constitute a tie in a binary network. In addition, the analysis will be also extended to valued networks of different *intensities* of a migration flow.

Theories of migration

Over the history of migration research different theories have been developed to explain migration flows between spatial units. *Spatial distance* and *population size* are crucial factors in the early theories. Together, these two components make up the *gravity model*: the higher the mass of two objects and the smaller the distance between them, the stronger are the forces pulling them together. In this case, these forces trigger migration flows between them (Boyle et al. 1998). Spatial proximity might facilitate also **(<- p. 20)** back-and-forth migration, as highlighted in theories of *immigrant transnationalism* (Jaworsky and Levitt 2007), since travel time, monetary costs and cultural differences increase with increasing spatial distance.

A migration flow from the *South* to the *North* is often assumed (Collier 2013; Castles et al. 2014), but it is an open question whether a general effect of *South* or *North* location exists net of economic differences. According to the *neoclassical theory*, migration results from disequilibrium in the global distribution of income and wealth (Massey 1998; Castles et al. 2014). Rational individuals try to maximise their benefit and decide to migrate to richer countries. As a result, the supply of labour in the richer regions increases and wages decrease, which would, in the long run, lead to a convergence of regions in wealth and income. Even though this mechanism rarely exists in a pure form, basically due to border control and immigration policies, it motivates the hypothesis of a global migration flow from poor to rich countries. But opportunities for out-migration can be restricted as well, as it was the case in the socialist countries in Central-Eastern Europe. Today, global mass communication brings information about wealthy lifestyles into each lodge and yurt; the extreme inequalities between countries are now globally visible. Given that, non-forced migration is often also driven by relative deprivation rather than by objective needs (Czaika and de Haas 2011), so that comparatively well-off persons in the Global South invest in illegal migration e.g. to the US or Europe.

Another branch in migration theory focuses on the *evolution of migration systems* (Castles et al. 2014). In history, waves of immigration such as from Europe to the US in the 19th century created diaspora-groups which boosted a further inflow via chain-migration. The *classic immigration countries* attract more immigrants from a wide range of sending countries simply due to the fact that, on average, the size of diaspora groups is already large. More importantly, the experience with immigration and the absorption of "strangers" evolved over decades, even centuries. It is "… part of the myth of nation-building" (Castles et al. 2014: 20), which is why countries such as New Zealand, Canada and the US are regarded as being tolerant and open and are still attractive to immigrants.

Migration flows between countries can also result from *homophily* in the dominant *religion* and *language*. Homophily is a central concept in social network theory, usually applied in studies on network ties between persons (Kadushin 2012). Taking the expected costs of acculturation into account (Esser 2010), immigrants might decide to move to countries where languages, but also basic behavioural standards, are assumed to be similar to those in the country of origin. Religious ideas are related to fundamental attitudes, values, norms and conduct of life (Windzio and Wingens 2014). Conversion, relaxing a religious commitment or even to apostatise is unthinkable in some religious groups. If two countries have the same dominant religion, conflicts e.g. due to children's affinity to assimilate towards secular norms or to convert are unlikely. Hence, if two countries are part of the same religion, the decision to migrate might be less costly. Religious doctrines can be even directly related to migration, such as variants of the *hijra* concept in Islam (Masud 1990). *Hijra* means "to migrate" or "to depart" and refers to the migration of the early Islamic community from Mecca to Medina in order to escape from a "territory of disbelieve". Over the centuries Islamic scholars elaborated different interpretations of *hijra*, e.g. as being obligatory when the religious life of the community is repressed by non-Muslim forces, but also to propagate Islam in other countries (Masud 1990: 43). The latter interpretation would imply that countries with a dominantly Muslim population send migrants non-Muslim countries.

Cultural characteristics such as religion and language sometimes gain *hegemonic* dominance. Hegemony implies that power is concentrated on one or a limited number of actors (Vögtle and Windzio 2016). In history, some countries became expansive by imperialistic politics, and thereby also their *languages*, as important vehicles for the diffusion of power, became hegemonic, e.g. Latin in ancient Europe or Arabic in Asia and Northern Africa during the Umayyad Caliphate since 661. The origin of English's and Spanish's hegemony is their colonial history. Still today, powerful nation-states such as the US influence the world-culture through all kinds of cultural media, so that English becomes a lingua franca. Potential migrants have a basic knowledge of these languages, so the costs of migration decrease, which is also the case when languages are similar between country of origin and destination, that is, if languages belong to the same branch in the classification of languages.

One of the driving forces of migration is *population density* (Durkheim 1965: chp. 2, I), the number of persons divided by the country's area size. Densely populated countries show intensified competition for housing space, but also on labour markets. In the 1950s, the Turkish government was highly interested in sending migrants to European countries, e.g. the Netherlands and Germany, because of Turkey's increasing population (Boyle et al. 1998: 59p).

If a country B attracts migrants from a county C, and B sends migrants to another country A, also C and A might be linked by migration if migrants from C expect opportunities in the even more attractive alternative A. If such a hierarchy in attractiveness exists between countries, it should be captured by effects of triadic closure in subnetworks, which usually occur in friendship networks (Windzio 2015). Analysing such kind of statistical non-dependency is unique to the social network approach. Effects of e.g. triadic closure can provide insight into hierarchies of attractiveness resulting from unobserved factors. These hierarchies are not only due to differences in economic performance and welfare, but possibly also due to the countries' "social models" (Collier 2013), namely the institutions and regulations guiding actors' expectations and behaviour. Social models correspond with safety, order and economic performance (North 1990). However, these dimensions of place utility (Wolpert 1965) are difficult to measure in a global data set and the research design should attempt at controlling them as unobserved factors (see below).

Existing research based on different designs

Migration research should ideally be based on data on migration decisions at the level of individual actors or households. Excellent studies have been conducted e.g. on Mexican-US migration (Massey and Espinosa 1997), and on migration from Poland to Germany (Massey et al. 2008). However, in fact they are *case studies* of country-dyads, and often focus on moving back and forth in a transnational social space between two or more countries (Jaworsky and Levitt 2007), or on one sending and one receiving country (e.g. Mexico and the U.S. or Poland and Germany) (Massey et al. 2008). An individual-level global migration survey is hardly conceivable. Studies based on aggregate data, in contrast, do not allow conclusions about migration decisions at the micro level, but can reveal in which world regions migration flows are most intensive. This intensity strongly depends on population size, so absolute numbers of migrants should be used as a dependent variable for descriptive purposes (Abel and Sander 2014). If the focus is on the *factors causing* migration, however, or on links between two countries by high diaspora populations, relative frequencies should be used. Based on global data on the foreign-born population in the receiving countries, causes of migration can be analysed on a global scale. Data on global migration is provided by the UN population division and the World Bank. For instance, the UN (2014: 6) ranks country-dyads according to the population born in a sending country living in a receiving country. Czaika and Haas (2013) draw on **(<- p. 21)** the Global Bilateral Migration Database (GBMD) and challenge the common view that migration has increased over the last decades. They decomposed trends in global migration into *intensity*, *spread* and *distance* of migration, and came to the result that there was no acceleration at a global level, but new migration hubs emerged in Asia, the Gulf and in Europe.

Using the same data, Özden et al. (2011) showed an increase in global migration in absolute terms. When the former Soviet Union and India are controlled, however, migration between the Global South (formerly termed “developing countries”) turned out to be rather stable from 1960 to 2000. Moreover, in relative as well as in absolute terms, migration from the Global South into developed countries shows the largest growth during this period. Albeit the share of female immigrants has considerably increased during this period, global migration is still male dominated (Özden et al. 2011). *Within* the new EU member states migrants are particularly attracted by countries that opened access to their labour markets (Palmer and Pytliková 2015).

New tools for generating migration plots have been recently developed, arranging nodes region-wise in a circle. The “thickness” of lines between nodes represents the intensity of the migration flow, e.g. the absolute number of migrants (Sander et al. 2014: 9). These studies provide important insight into patterns and trends of global migration. While such a tool gives evidence on the *absolute numbers* of migrants, it should not be used to analyse *causes* of migration, since absolute numbers are dominated by population size, e.g. by a large flow between Latin and North America (Abel and Sander 2014).

Using historical data on rural-urban migration in northern France during the industrial revolution in the 19th century, Lemercier and Rosental relied on social network analysis in order to identify typical routes either into the metropolis or between different rural areas (Lemercier and Rosental 2010). They found significant effects of spatial distance between communes, of their population size, of similarity in language and triadic substructures, and also a tendency to homophily in language, socio-economic and political factors. Desmarais and Canmer (2012) applied a generalization of exponential random graph models for valued networks (Krivitsky 2012) to inter-state migration within the U.S. Their results show effects of transitive and cyclic triads similar to friendship networks (Desmarais and Cranmer 2012). Until now, however, there is no analysis of *global* migration which combines geographic, demographic, economic as well as religion and language effects in one model, and simultaneously controls for network-structural effects, which could indicate a significant influence of hierarchies of attractiveness between countries due to unobserved characteristics.

Data and methods

Migration data

The UN "Migration Wallpaper" is based on data of global migration patterns between all available countries. The data includes information on the total *migrant stock* at mid-year for the years 1990, 2000, 2010 and 2013 by country of origin. Immigrants are defined as persons who are not born in the respective country. Since it is known how many are born in a particular sending country, a directed network of global migration can be created: the measurement of global migration indicates the stock of population born in country A and now living in country B. For the analysis at hand, the original matrix has been transposed so that rows identify sending countries and columns receiving countries. Each cell represents the absolute number of emigrants from the sending country (now in the row) to the receiving country.

Dependent variable

The "population sent-to-alter / population at home" ratio (*S*ent-*H*ome *R*atio, SHR) is the share of emigrants from a sending country at the overall population in the sending country at time *t*. The SHR in each cell was used to compute the distribution of mean shares of emigrants over the whole matrix. Each dyad-specific SHR has been related to this distribution in order to define a threshold between "low" and "high" SHRs: quartiles from the SHR distribution identify discrete categories of migration *intensity*. If a particular cell of the matrix falls into the highest quartile, a *relevant* directed migration flow has been identified with the value 1, and 0 otherwise. In addition, quartiles have been used as a count variable measuring the intensity of migration ties for valued network models.

ERGMs for ties in the network of global migration

Migration between two countries is analysed as part of a set of *nodes* (countries) and *arcs* (directed arrows between nodes). Exponential random graph models (ERGMs)(Lusher et al. 2013) will be used to explain why an empirically given network out of a huge set of possible networks has an increased probability of being observed. Explanatory variables are covariate effects, in this case node or dyadic characteristics of countries, but also structural effects of network embeddedness. Taking these network-structural effects into account is a great benefit of applying ERGMs in the analysis of global migration patterns. Structural effects are e.g. in- and out-degree, geometrically weighted edge-wise shared partners (`gwesp`) and cyclical effects (Lusher et al. 2013). From the perspective of a particular dyad *i* and *j*, edge-wise shared partners count the number of shared partners where the respective dyad *i* and *j* is closed.

Figure 1: edge-wise shared partners in directed networks

edge-wise shared partners (`gwesp`)

(see Lusher et al. 2013, p. 70)

In directed networks `gwesp` is a measure of transitive closure, often interpreted as a social hierarchy e.g. in friendship networks (Windzio 2015). If *i* is a friend of *j* due to *j's* friendship with *k*, *k* ranks high because she determines friendships among others. A similar logic is applicable to networks of global migration: if country *i* sends a relevant share of its population to country *k*, because the latter is an attractive destination, but at the same time there is considerable migration from *k* to *j*, it should be also attractive to migrate from *i* to *j*. With regard to economic performance and welfare such hierarchies could be captured by appropriate measurements, such as GDP per capita. But there might be also unobserved hierarchies of *place utility* (Wolpert 1965). In addition, it is unlikely that migration follows a circular pattern among three or more countries', so cyclic triplets should occur less often in the empirical network of global migration compared with a random network.

Since the migration data covers four time-points (1990, 2000, 2010 and 2013) the modelling approach should also take the longitudinal character of this data into account. This will be done in a first step by applying a temporal ERGM (TERGM)(Leifeld et al. 2016). The standard cross-sectional ERGM predicts the probability of observing a given network by a vector of statistics $\mathbf{h}$ of the network *N* (e.g. counts of transitive triads or actor or dyadic attributes) and their coefficients $\boldsymbol{\theta}$. The normalizing constant $c(\boldsymbol{\theta})$ represents the odds of other networks which could be created by the given set of nodes.

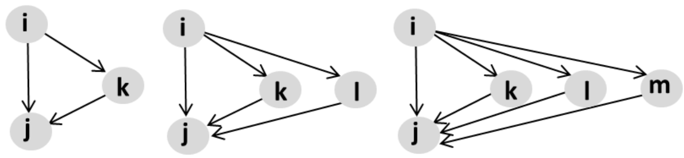
$$P(N,\boldsymbol{\theta}) = \frac{\exp(\boldsymbol{\theta}'\mathbf{h}(N))}{c(\boldsymbol{\theta}')}$$

nodes *arcs*

gwesp

i *j*

i *j*



gwesp

gwesp

i *j* *j's*

k *k*

i

k

k *j*

i *j*

place utility

among three or more countries'

h *N*

$\boldsymbol{\theta}$ c $\boldsymbol{\theta}$

$$P(N,\boldsymbol{\theta}) = \frac{\exp(\boldsymbol{\theta}'\mathbf{h}(N))}{c(\boldsymbol{\theta}')}$$

In the longitudinal case with $K \in \{0,1,\ldots,t\text{-}1\}$ measurements of network N the temporal ERGM estimates the probability of N^t **(<- p. 22)** conditional on the observed network at previous measurement occasions, that is, on statistics of the lagged networks N^{t-K}.

$$P(N^t \mid N^{t-K},\ldots,N^{t-1},\boldsymbol{\theta}) = \frac{\exp(\boldsymbol{\theta}'\mathbf{h}(N^t, N^{t-1},\ldots,N^{t-K}))}{c(\boldsymbol{\theta}', N^{t-K},\ldots,N^{t-1})}$$

Under the assumption that networks occurring earlier in the time-series are independent of later outcomes, the probability of observing the networks within a given window of observation can be estimated by taking the product of the time-specific probabilities, so that the outcome of interest is the joint probability $P(N^{K+1},\ldots, N^t|N^1,\ldots, N^K, \boldsymbol{\theta})$. The TERGM allows estimating different variants of how lagged networks affect the current state as a "memory". First, *positive auto-regression* includes a term for edge persistence (ones), while the stability of the zeros (non-edges) is ignored. Secondly, *dyadic stability* extends the former approach also to non-edges. One counts the number of dyads where the respective outcome remains either one or zero. Finally, *edge innovation* counts the number of newly created edges between t-1 and t (Leifeld et al. 2016).

Sensitivity and robustness of the TERGM will be checked by also estimating separate cross-sectional ERGMs. Likewise, the models allow for time-specific effects of each covariate and network-structural effect.

Explanatory variables

Existing theories on migration focus on geographic, demographic, economic, historical and cultural factors. In the present study, countries in the *Northern* and *Southern hemisphere* have not been defined according to the equator as a boundary, because many countries with a high emigration potential, for instance Mexico, Algeria or Mali, would fall in the *Northern* category. Instead, the 40s° degree of latitude has been defined as a separating line. Information on longitudes and latitudes has been used also for computing the approximate *distance between countries*. In most cases centroid distances have been applied. In case of Russia the reference point has been shifted somewhat to the east, where the population density is considerably higher. Approximate distances of locations on the globe are computed using angles and radian measures:

$$angle = \arccos(\sin(lat_A) \bullet \sin(lat_B) + \cos(lat_A) \bullet \cos(lat_A) \bullet \cos(lon_B - lon_A))$$
$$\text{distance} = angle / 360^0 \bullet 40{,}000 km$$

The classification of *world regions* given in the UN migration wallpaper data has been used.[1] For each country, information on *area size* has been collected from the English

[1] These UN world regions are 1. East Asia & Pacific; 2. Europe & Central Asia; 3. Latin America & Caribbean; 4. Middle East & North Africa; 5. North America; 6. South Asia; 7. Sub-Saharan Africa

version of Wikipedia. Wikipedia has been also used for getting information on the *former communist* and *socialist Eastern Block*, and to collect information on a country's *dominant religion* as well as its status as a *former colony* or a former *colonial power*. Whether information drawn from Wikipedia should be used for scientific purposes or not is a controversial issue. Wikipedia is an open system where anybody can participate. The community can correct and further develop the entries, but there is no systematic reviewing process. Obviously, any entries related to ideologies or issues of group identity should be regarded with suspicion. Scientific information, in contrast, can be highly reliable in Wikipedia, as demonstrated by Kräenbring et al. (2014) who compared pharmacological information on drugs between Wikipedia and textbooks. Regarding data on countries, a large international community, international organizations, but also officials of the respective countries can check and correct the data, so it can be assumed that it is rather accurate as well. Nonetheless, the data has been cross-checked using information from the 1999 edition of Geographica (Martin and Penny 1999), which showed indeed a good accordance of these characteristics with Wikipedia.

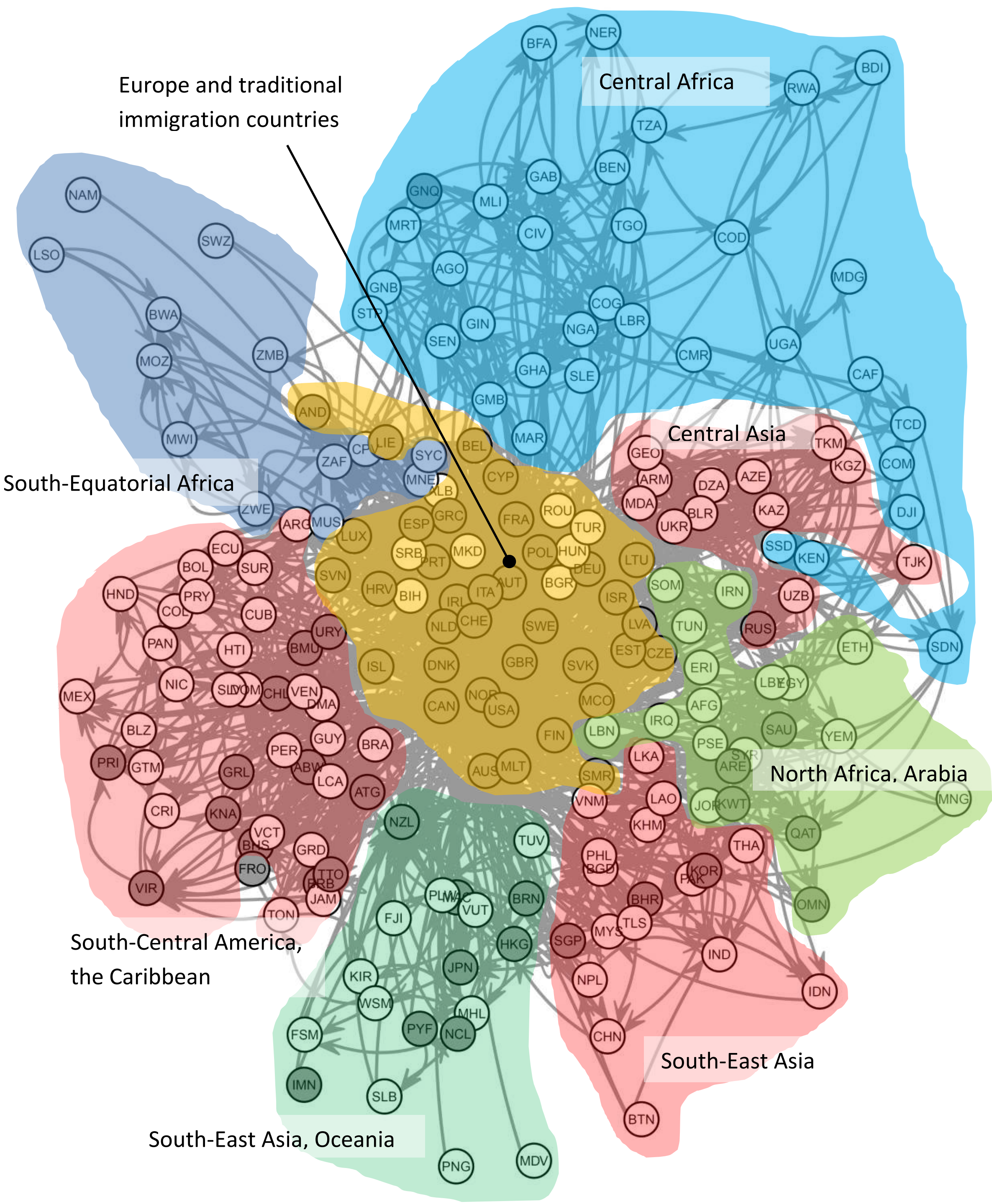
As a time-varying characteristic the *size of a country's population* is available in the World Development Indicators Database provided by the World Bank. This information has been also used to compute country-specific population growth for each t minus 10 years. The same data set includes time varying information about the *GDP per capita*. To classify a country's *dominant language* the Ethnologue database has been used (https://www.ethnologue.com/). There are many more languages than countries in the world, and the assignment of one dominant language to each country considerably reduces their number. Languages are grouped at different hierarchical levels. For instance, there are 6 branches at level I, in which the branch of the Indo-European family comprises more than 400 languages spoken by nearly 3 billion people in more than 70 countries in Europe, Asia and America. In the following analysis the level II classification has been used, which is more differentiated with 33 categories, while at the same time the linguistic similarity of languages within categories is much higher. To give an example: the dominant language in Brazil is Portuguese, which is an Indo-European language (level I) and belongs together with 45 other languages to the "Italic" sub-branch at level II.

Descriptive statistics on time-constant and time-varying covariates are shown in Table A1 (appendix), and a list of countries is given in Table A2 (appendix).

Results

Figure 2 is a fruchterman-reingold spring-embedder visualization of the network of global migration in the year 2013. There is considerable regional clustering in the graph, which does not substantially change over the years.

Figure 2: Network of global migration ties 2013



In the center of this graph we find Europe and the traditional immigration countries, which are densely connected internally, but also have ties to all other regions in the world – which is why the algorithm pulled this group into the center. Here we also find most high-income countries, defined by GDP per capita of at least $12,276 according to the

World Bank (nodes are colored in grey).[2] Interestingly, Africa is divided in a South-Equatorial and a Central-African cluster, but some African countries such as to Tunisia, Libya and Egypt fall into the cluster "North Africa, Arabia". This graph reveals thus not only regional clustering, but also indicates **(<- p. 23)** homophily with regard to language and religion. Subsequently, more insight into the determinants of ties in the global migration network will be provided by multivariate models for networks.

Table 1 shows four temporal exponential random graph models (TERGM) (Leifeld et al. 2016), where all four networks have been pooled. There is no time-dependence in model 1. In models 2-4 the estimation is conditional on the networks at t-K, which is why the first measurement occasion (the observed network in 1990) is not regarded as an outcome. Model 2 estimates a "memory" in terms of *stability* of dyads, regardless of whether there is a 0 or a 1. Model 3 estimates a memory in terms of the tendency to establish new ties between t and t-1 (*innovation*). Finally, *autoregression* in model 4 captures the effect of ones in the lagged dependent networks on the network at t.

Overall, covariate effects are similar across models, but in some cases there are notable differences. Effects of `gwesp` (positive) and cyclic triplets (negative) are significant, indicating a hierarchical pattern of triadic closure. However, the effect of cyclic triplets is not significant in model 1. There is a negative effect of *distance* in all models, while the effect of *area size* on in-degree is positive. Moreover, the effect of *North* on in-degree is negative, which is also true for the effect of *South* on out-degree, except for models 2 and 4, where *South* on out-degree is not significant. Also *same region* shows significant effects only in models 1 and 3, which are in this **(<- p. 24)** case positive. Taken together, results are in line with the geographic hypotheses on the negative effect of distance, but clearly contradict the hypothesis of South-North migration.

Effects of demographic factors are consistent across all four models: in line with the gravity hypothesis population *size* has a positive effect on in-degree and a negative effect on out-degree. Population *density* shows a negative effect on in-degree and a positive effect on out-degree: a high density corresponds with competition for scarce resources and thereby increases prices. Also in line with the gravity hypothesis is the negative effect of population growth on out-degree.

We find a positive effect of GDP on in-degree, as well as a negative effect on out-degree: richer countries receive immigrants from many different countries, while they send emigrants only to few other countries. Moreover, there is a positive effect of "former socialist" on out-degree, which can be interpreted as the relief of a migration potential after 1990 – recall that the network in 1990 is not an outcome in the TERGM. Regarding religion and language, there is a positive effect of homophily in the *language family*, whereas effects of homophily regarding the *dominant religion* are inconsistent.

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[2] "As of 1 July 2011 low-income economies are those that had average incomes of $1,005 or less in 2010; lower-middle-income economies had average incomes of $1,006 to $3,975; upper-middle-income economies had average incomes of $3,976 to $12,275; and high-income had average incomes of $12,276 or more" (World Bank, http://data.worldbank.org/news/2010-GNI-income-classifications , last access March, 2nd, 2016).

Table 1: Ties in the network of global migration 1990-2013, temporal ERGMs for binary ties, N=202

	(1) no time dep.	(2) stability	(3) innovation	(4) auto-regression
edges	-3.858***	-2.230***	-4.037***	-5.751***
network structure				
GWESP (alpha=0.693)	0.939***	0.490***	0.895***	0.490***
cyclic triplets	-0.055n.s.	-0.204***	-0.256***	-0.204***
GW outdegree (alpha=(0.2))	2.413***	1.302***	2.314***	1.302***
GW indegree (alpha=(0.5))	-1.887***	-1.599***	-2.075***	-1.599***
geography				
distance(km/1000)	-0.219***	-0.143***	-0.220***	-0.143***
IND. North, lat.>40	-0.482***	-0.417***	-0.529***	-0.417***
OUTD. South, lat.<=40	-0.106***	0.019n.s.	-0.116***	0.019n.s.
same region	0.784***	0.424n.s.	0.721***	0.424n.s.
IND. area size (1000 km2)	0.0001***	0.00003***	0.0002***	0.00003***
demography				
IND. pop. size (mio.)	0.0006***	0.0007***	0.0007***	0.0007***
OUT. pop. size (mio.)	-0.003***	-0.001***	-0.004***	-0.001***
IND. pop. density	-0.321***	-0.248***	-0.337***	-0.248***
OUTD. pop. density	0.167***	0.125***	0.178***	0. 125***
OUTD. pop. growth (t – 10 years)	-1.423***	-1.483***	-1.581***	-1.483***
economy				
IND. GDP/cap.	0.069***	0.068***	0.078***	0.068***
OUTD. GDP/cap.	-0.031***	-0.015***	-0.032***	-0.015***
OUTD. former socialist	0.333***	0.782***	0.367***	0.782***
religion				
Christ=>Christ	reference	reference	reference	reference
Islam=>Christ	-0.290***	-0.235***	-0.317***	-0.235***
other/no=>Christ	0.134***	-0.123n.s.	0.130***	-0.123n.s.
Christ=>Islam	0.204***	-0.382***	0.316***	-0.382***
Islam=>Islam	0.377***	-0.080n.s.	0.376***	-0.083n.s.
other/no=>Islam	0.247***	-0.296n.s.	0.237***	-0.296n.s.
Christ=>other/no	0.022n.s.	0.144n.s.	-0.015n.s.	0.144n.s.
Islam=>other/no	0.038n.s.	-0.081***	0.103n.s.	-0.081***
other/no=>other/no	0.493***	0.514***	0.407***	0.514n.s.
language				
same language-family (lev. 2)	0.743***	0.280***	0.746***	0.280***
IND. English	1.101***	1.141***	1.172***	1.141***
IND. Spanish	0.227***	0.292***	0.224***	0.292***
IND. Arabic	-0.839***	-0.150***	-0.873***	-0.150***
hist. path dependency				
OUTD. former colony	0.375***	0.323***	0.399***	0.323***
IND. former colonial power	0.616***	0.704n.s.	0.725***	0.704n.s.
time-related edge covariates				
delayed reciprocity	-	0.579***	1.482***	0.579***
memory	-	3.521***	20.147***	7.042***

see the appendix for fit of autoregressive model (4)

Compared with the reference group of two dominantly Christian countries, the effect of ”Islam→Christ” is negative, while the effect of ”Christ→Islam” is positive in models 1 and 3, but negative and insignificant in models 2 and 4. In addition, also the effects of ”Islam→Islam” and ”Islam→other/no” are inconsistent. One reason for this inconsistency could be the multicollinearity of dominant religion and language (Arabic and Islam). If these models are estimated without the language effects, however, the results did not change considerably (table not shown here).

Indeed, *English* and *Spanish* seem to be hegemonic languages, since they correspond with positive effects on in-degree. The effect of English is, as expected, much stronger. In contrast, *Arabic* has a negative effect on in-degree, so it does not seem to be a hegemonic language with regard to ties in the global migration network.

Finally, we find a positive effect of *former colony* on out-degree, whereas the effect of *former colonial power* on in-degree is positive, but significant only in models 1 and 3. At the bottom of table 1 we find strong and highly significant effects of each memory term, while there are also positive effects of delayed reciprocity: there is a tendency to reciprocate a tie at *t* that was only unidirectional at *t-1* (Leifeld et al. 2016). This could indicate a tendency to form a migration system, where persons born as second generation immigrants **(<- p. 25)** in the receiving country before *t-1* tend to migrate to their parents' country of origin at time *t*. In contrast to the other three models, model 4 fits quite well and has thus a higher credibility (see below and appendix A3).

To check the robustness of the longitudinal approach, Table 2 presents results of four cross-sectional ERGMs, separately for each year 1990, 2000, 2010 and 2013, which account for edge-wise shared partners, cyclic triplets (could not be estimated for year 1990) as well as geometrically weighted in- and out-degree. In the years 2000, 2010 and 2013 there is a positive effect of edge-wise shared partners (`gwesp`), whereas the effect of cyclic triplets is negative. In other words, transitive closure occurs more often and cyclic triadic patterns less often in our empirical networks then in a comparable random network. According to the `gwesp` effect, we again find a hierarchy of attractiveness of countries from the migrants' point of view for reasons not observed in the data. Net of the observed factors, a country C sends emigrants to the more attractive country B, and country B sends its own emigrants to country A, because for some reasons the living conditions in the latter are regarded as being more attractive than in the former. Consequently, C also sends emigrants to A because the difference in attractiveness between C and A is even higher than between B and A, so A > B > C. Since a variety of covariates has been controlled in these models, this hierarchy of attractiveness results from unobserved factors, so that the network-structural effects could be regarded also as "nuisance" parameters. While there is no effect of in-degree, the positive effect of out-degree is strong and highly significant. Effects in- and out-degree are difficult to interpret, so this will be left open in this study.

Many of our geographic, demographic, economic, religious, linguistic and historical factors show effects in line with the expectations. We find a highly significant, robust and negative effect of *spatial distance* as an edge-covariate in all four years, which is in line with gravity models. Again, the effects of *North* on in-degree or *South* on out-degree are negative, but the effect of *South* is insignificant. Hence, the *South-North* migration flow should be regarded as a metaphor of the huge global economic inequalities.[3] If two countries belong to the same category in the regional classification (*same region*) used by the United Nations (see footnote 1) it becomes more likely that they have a tie in the network of global migration. Moreover, we also find the expected effect of a country's area size on in-degree: the larger the area, the higher is the number of ingoing arcs.

Regarding the *demographic* determinants, we find that countries with a large population tend to have a higher in-degree, but fewer outgoing ties, which holds for all years. In line with the gravity model, population size is not a push effect, but rather an attractor. In all four years density has a significant negative effect on in-degree and a positive effect on out-degree. Under the assumption that land prices and rents are high in densely populated countries, and the competition for economic opportunities is tight, this result is not surprising.

[3] This effect does not gain in significance if we exclude differences in GDP from the model.

Table 2: Ties in the network of global migration 1990-2013, cross-sectional ERGMs for binary ties, N=202

	network 1990 (1)	network 2000 (2)	network 2010 (3)	network 2013 (4)
edges	-4.558***	-4.754***	-4.662***	-4.678***
network structure				
GWESP (alpha=0.4;0.3)	1.508***	1.568***	1.554***	1.603***
cyclic triplets	-	-0.299***	-0.213***	-0.282***
GW outdegree (alpha=(0.4))+	7.211***	3.516***	3.424***	2.933**
GW indegree (alpha=(0.5))	0.190	0.065	0.147	0.199
geography				
distance(km)	-0.0002***	-0.0002***	-0.0002***	-0.0002***
IND. North, lat.>40	-0.441***	-0.139*	-0.239***	-0.194**
OUTD. South, lat.<=40	-0.174	0.004	-0.093	-0.088
same region	0.911***	1.014***	1.027***	1.015***
IND. area size (1000 km2)	0.0002***	0.0001***	0.0001***	0.0001***
demography				
IND. pop. size (mio.)	0.001***	0.001*	0.001***	0.001***
OUT. pop. size (mio.)	-0.008***	-0.004***	-0.003***	-0.003***
IND. pop. density	-0.332***	-0.222**	-0.275***	-0.268***
OUTD. pop. density	0.175***	0.080***	0.080***	0.073***
OUTD. pop. growth (t – 10 years)	-1.760***	-1.189***	-0.961***	-1.071***
economy				
IND. GDP/cap.	0.050***	0.028***	0.025***	0.022***
OUTD. GDP/cap.	-0.030***	-0.009**	-0.007**	-0.005*
OUTD. former socialist	-0.056	0.084	0.261***	0.266**
religion				
Christ=>Christ	ref.	ref.	ref.	ref.
Islam=>Christ	-0.129	-0.300***	-0.303***	-0.313***
other/no=>Christ	0.284*	0.148	0.205	0.206
Christ=>Islam	0.065	-0.124	-0.162	-0.223*
Islam=>Islam	0.554***	0.302***	0.375***	0.363***
other/no=>Islam	0.463*	0.178	0.144	0.118
Christ=>other/no	-0.229	-0.263	-0.176	-0.264
Islam=>other/no	-0.026	-0.152	-0.257	-0.267
other/no=>other/no	0.566*	0.490	0.425*	0.422
language				
same language-family (lev. 2)	0.775***	0.717***	0.709***	0.697***
IND. English	0.682***	0.792***	0.917***	0.906***
IND. Spanish	0.241**	0.217*	0.222**	0.175
IND. Arabic	-0.542***	-0.462***	-0.442***	-0.495***
hist. path dependency				
OUTD. former colony	0.377***	0.362***	0.365***	0.380***
IND. former colonial power	0.502***	0.558***	0.807***	0.801***
Akaike Inf. Crit.	8,216.182	8,272.289	8,643.760	8,473.843
Bayesian Inf. Crit.	8,483.141	8,547.859	8,919.330	8,749.413

+ alpha 1990=0.5 sig.: *p<0.05; **p<0.01; ***p<0.001

According to the results, also *population growth* should be regarded as a gravity factor when population density is controlled: the more a population grows the less out-degree we observe in a country. In addition, the higher the GDP per capita, the higher the in-degree and the lower the out-degree a country has, which is in line with the expectation of economic theories.

Interestingly, we do not find an effect of *former socialist* countries in the year 1990. From the year 2010 onwards, however, the positive effect on out-degree remains significant if we control for the network effects.

Compared with the reference group Christ=>Christ we find a negative effect in the category Islam=>Christ from the year 2000 onwards, also in the conditional model. In contrast, there is a positive effect in the year 1990 in the category other/no => Islam, which vanishes in the subsequent years, whereas the effect of Islam=>Islam is positive in all four years. Accordingly, again, migration from Muslim to Christian countries is definitely not the dominant pattern in the *global migration network*. Interestingly, there seems to be a high density in the global migration subnetwork within the group of dominantly Muslim countries, which is in line with the religious homophily hypothesis, rather than with the *Hijra* doctrine of global propagation of Islam in combination with outmigration (Masud 1990).

Based on the level II classification of Ethnologue the propensity of having a tie in the global migration network is strongly increased if two countries share the same level II language-family. Again we find strong and highly significant positive effects of English language on in-degree in all four years, while the positive effect of Spanish on in-degree loses significance in model 4 (2013). In contrast, the effect of Arabic on in- degree is negative in all four years. Again, it should be kept in mind that Arabic language is positively correlated with Islam as the dominant religion, so there might be some multicollinearity in these effects.

As an effect of historical path dependency, having been a former colony has a significant and positive effect on out-degree in all four years, while having been a colonial power has positive effects on in-degree. The British Commonwealth, for instance, is closely linked to several other countries by immigration flows, e.g. from India, Pakistan and Jamaica. But why should former colonies have more out-degree? If there was only one colonial power in a country, only one link in the global migration network should have resulted from the historical heritage. Yet, several former colonies underwent changes in the colonial power over history. In today's Rwanda, for instance, the German colonial rule has been replaced with Belgian colonial government during the First World War. The succession of different colonial powers in some countries could be an explanation of this effect. Another explanation could be that migrants started out going to their former colonizing country (for example Moroccans went to France), but over time scattered to the surrounding countries (e.g. Netherlands or Belgium). Finally, it could indicate a general fact that countries exploited by colonial powers in the past trend to be *emi*gration countries today, maybe because they had not the appropriate resources to develop economically functional “social models” (Collier 2013).

Even though the effects are well in line with existing theoretical arguments, it could be argued that the dichotomization of the SHR by setting the highest quartile to 1 is somewhat arbitrary and ignores differences in the *intensity* of the migration flow. For this reason, models for valued relations based on count data (Krivitsky 2012) have been estimated (Table 3). Quartiles of the SHR provide categorical information on the intensity of a tie. A similar approach has been applied in a recent study on student mobility in a network of 41 countries (Vögtle and Windzio 2016), which is one of the few studies analysing international migration networks using ERGMs for valued relations. The negative effect of *non-zero* in Table 3 indicates that the share of zeros is higher than we would expect according to the Poisson distribution. The effect of *transitive* weights is highly significant and positive in all four models and indicates again a tendency towards transitive closure. There are negative effects of *distance* and positive effects of *same region*, while the effect of *GDP per capita* on in-degree is positive.

Table 3: Ties in the network of global migration 1990-2013, ERGMs for valued ties, N=202

	network ties 1990 (1)	network ties 2000 (2)	network ties 2010 (3)	network ties 2013 (4)
sum	-1.713***	-1.690***	-1.800***	-1.854***
non-zero	-1.672***	-1.697***	-1.486***	-1.524***
transitiveweights.min.max.min	0.765***	0.794***	0.694***	0.776***
distance(km)	-0.0001***	-0.0001***	-0.0001***	-0.0001***
same region	0.706***	0.726***	0.717***	0.753***
IND. GDP/cap.	0.034***	0.025***	0.021***	0.019***
IND. pop. density	-0.214***	-0.162***	-0.182***	-0.184***
OUTD. pop. density	-0.004	-0.004	0.004	-0.000
OUTD. pop. growth (t – 10 years)	-0.632***	-0.426***	-0.492***	-0.518***
OUTD. former socialist	0.089**	0.071	0.139***	0.127***
same language-familiy (level 2)	0.457***	0.399***	0.465***	0.485***
IND. English	0.083	0.121*	0.157***	0.085
IND. Spanish	0.110	0.006	0.033	0.009
IND. Arabic	0.150***	0.046	0.129*	0.174*
OUTD. former colony	0.055	0.031	0.047	0.012
IND. former colonial power	0.360***	0.296***	0.357***	0.302***
Akaike Inf. Crit.	-39,273.5	-38,484.1	-38,656.6	-38,597.0
Bayesian Inf. Crit.	-39,135.8	-38,346.3	-38,518.8	-38,459.2

Note: *p<0.05; **p<0.01; ***p<0.001; models converged only once

Both the density and the growth in population size show negative effects on out-degree, whereas *former socialist* countries have more out-degree than expected in all years, except for the year 2000. Again we find robust and significantly positive effects of *same language family*, but the effect of *hegemonic* **(<- p. 26)** languages differs from the binary ERGMs in Tables 1 and 2. An important difference is that in the valued models the combinations of dominant religions could not be estimated due to convergence problems. Given that, the effect of Arabic language on in-degree tends to be positive. Arabic is not a hegemonic language in the network of global migration, but *if* there is an ingoing tie, countries with Arabic as a dominant language tend to host comparatively *high* shares of alter's emigrants. Finally, we also find significant positive effects of former colonial power on in-degree in all four years, whereas the effect of former colony on out-degree is not significant. Results presented in Table 3 are preliminary because they do not include the same set of covariates as in the binary ERGMs in Tables 1 and 2. The simplification was necessary – otherwise the models did not converge. Moreover, each model converged only once, but not twice, even though the coefficients of previous model runs have been included as starting values in subsequent runs. The results could be unstable (which was not the case in these estimations) and should be interpreted with caution. Nevertheless, social network analysis as a paradigm for the analysis of global migration patterns is not limited to binary networks, but can be also used to analyse the intensity of migration flows.

Table A3 (appendix) shows the model fit of the auto-regression TERGM model in Table 1. It shows a good good fit with respect to all network statistics, except for geographic distance, which are at least satisfyingly represented by the model-based simulated networks. Also the ROC and PR curves show a very good performance: deviance from the reference lines (light red/ diagonal from lower left to upper right, and light blue/horizontal) show how well the estimated model performs compared with a null model. Also the community structure predicted from the model is highly similar to the empirical data. In contrast, yearly specific model fits of the cross-sectional ERGMs from Table 2 are far from being perfect for minimum geodesic distance and edgewise shared partners. Probably one could improve the model fit by increasing the alpha of the `gwesp` parameter, but this led to problems with model convergence. Irrespective of the worse fit of the ERGMs compared with the TERGM, both models lead to similar and robust results.

Summary and conclusion

Until now most migration studies do not simultaneously combine and control *geographic*, *demographic*, *economic, religious, linguistic*, as well as *historical* determinants of migration between countries in one model. There are only a few studies to date, if any at all, that simultaneously combine and statistically control various factors in a network model to explain global migration. Another distinctive feature of this study is that the assumption of statistical **(<- p. 27)** independence of ties between dyads was relaxed. Social network analysis, and ERGMs in particular, can capture the embeddedness of social processes. Also longitudinal models and models for valued data have been estimated. According to the empirical results, the effect of edge-wise shared partners can be interpreted as a transitive hierarchy of attractiveness, which results from unobserved characteristics. Consequently, structural effects should be included as they account for unobserved factors.

Overall, results are in line with what has been expected according to existing theories. Regarding *geographic* factors, there is a negative effect of distance between two countries. At the same time, location in the same region and area size (on in-degree) show positive effects. Ties in the migration network are directed from countries with small and mid-sized populations to countries with large populations, whereas the population density has a negative effect on in-degree and a positive effect on out-degree. In line with gravity theory, population growth has a negative effect on out-degree. Results are also in line with economic theories: migration is clearly directed from poor to rich countries. The breakdown of the iron curtain had no effect in the year 1990, whereas the effect became generally significant from 2010 onwards, also in the valued-tie models in Table 3. R*eligion* and *language* are of particular importance as well. The combination of two Muslim countries shows a positive effect on having a tie in the migration network, compared with the reference group of two Christian countries. Furthermore, there is homophily with regard to language-families (here at level II in the Ethnologue database), but language is also a hegemonic factor. Finally, while former colonies have a higher out-degree than expected, the same is true for the in-degree of former colonial powers.

Albeit the models for valued relations have been simplified in order to make the estimation possible, many results remain stable if we also account for the *intensity* of a migration tie. This holds for geographic and economic effects and also, basically, for the demographic density effect, which is highly significant and negative on in-degree. In the simplified valued model also Arabic appears as a hegemonic language which predicts the *intensity* of migration flows, but this probably also results from the fact that the same dominant religion (Islam) could not enter the model.

The global perspective on explaining international migration is a unique feature in current migration research. Future research should also include factors such as interstate armed conflicts, civil war and the (dis-)functionality of social models (Collier 2013). The latter, for instance, could be measured by homicide rates, which strongly differ between countries (UNODC 2014). In addition, also effects of natural disasters and climate change should be analysed. The same is true for the effects of colonial linkages, which should be analysed also as a dyadic factor of networks, and not just as effects on in- and outdegree. Furthermore, the analysis should be extended to actual *flows* of migrants, instead of *stocks* of persons born in a different country.

A further weakness of this study is the imperfect fit of some models. One could argue that under the assumption of a non-correlation of predictors and the error term results are unbiased. However, depending on network types, structural factors can be strong and if model specifications do not appropriately account for these dependencies, the assumption of non-correlation between predictors and the error term becomes virtually heroic, so that it is very likely that the estimates will be biased.

If the overall set of structural mechanisms in a particular network is unknown, which currently is the case in the network of global migration, or the appropriate network statistics are not yet implemented, it will be difficult to estimate a well-fitting model. Future research should also analyse the idiosyncratic forms of structural effects in global migration networks, and provide new terms for the ERGM. Accounting for network-structural factors produces significant and robust effects, in this case particularly of out-degree, cyclic triplets and `gwesp`. Moreover, the fact that many effects are in line with theoretical reasoning suggests that these models do indeed capture patterns of social reality, even though they do not represent the complete underlying network generating processes. For this reason, the analyses presented in this paper should be regarded as a starting point in the analysis of global migration networks. **(<- p. 28)**

Appendix

Table A1: Descriptive Statistics of actor attributes, N= 202

	mean	standard deviation	min	max
geography				
North, lat.>40	0.198	0.399	0	1
South, lat.<=40	0.802	0.399	0	1
area size (1000 km2)	666.246	1874.009	0.002	17,098.24
demography				
pop. size (mio.) 1990	25.712	103.864	0.009	1135.185
pop. size (mio.) 2000	29.733	118.893	0.009	1262.645
pop. size (mio.) 2010	33.571	130.926	0.010	1337.705
pop. size (mio.) 2013	34.755	134.339	0.010	1357.380
pop. density 1990	0.286	1.388	0.000	14.719
pop. density 2000	0.330	1.589	0.000	16.041
pop. density 2010	0.386	1.881	0.000	18.423
pop. density 2013	0.402	1.961	0.000	18.916
pop. growth 1980-1990	0.222	0.173	-0.119	1.130
pop. growth 1990-2000	0.174	0.147	-0.153	0.756
pop. growth 2000-2010	0.176	0.220	-0.115	1.947
pop. growth 2003-2013	0.174	0.233	-0.134	2.285
GDP/cap. 1990 (1000 USD)	6.182	10.295	0.098	84.290
GDP/cap. 2000 (1000 USD)	7.906	12.582	0.125	82.537
GDP/cap. 2010 (1000 USD)	13.901	20.503	0.145	145.230
GDP/cap. 2013 (1000 USD)	15.749	23.248	0.145	159.753
former socialist	0.144	0.352	0	1
religion				
Christ	0.639	0.482	0	1
Islam	0.252	0.436	0	1
other/no	0.109	0.312	0	1
language				
English	0.109	0.312	0	1
Spanish	0.099	0.299	0	1
Arabic	0.089	0.286	0	1
historical path dependency				
former colony	0.634	0.483	0	1
former colonial power	0.025	0.156	0	1

Table A2: N=202 countries

Afghanistan	Albania	Algeria
Andorra	Angola	Antigua_and_Barbuda
Argentina	Armenia	Aruba
Australia	Austria	Azerbaijan
Bahamas	Bahrain	Bangladesh
Barbados	Belarus	Belgium
Belize	Benin	Bermuda
Bhutan	Bolivia	Bosnia_and_Herzegovi
Botswana	Brazil	Brunei_Darussalam
Bulgaria	Burkina_Faso	Burundi
Cambodia	Cameroon	Canada
Cape_Verde	Central_African_Republic	Chad
Chile	China	China_Hong_Kong
China_Macao	Colombia	Comoros
Congo	Costa_Rica	Cote_d_Ivoire
Croatia	Cuba	Cyprus
Czech_Republic	Democratic_Republic_of_Congo	Denmark
Djibouti	Dominica	Dominican_Republic
Ecuador	Egypt	El_Salvador
Equatorial_Guinea	Eritrea	Estonia
Ethiopia	Faeroe_Islands	Fiji
Finland	France	French_Polynesia
Gabon	Gambia	Georgia
Germany	Ghana	Greece
Greenland	Grenada	Guatemala
Guinea	Guinea_Bissau	Guyana
Haiti	Honduras	Hungary
Iceland	India	Indonesia
Iran	Iraq	Ireland
Isle_of_Man	Israel	Italy
Jamaica	Japan	Jordan
Kazakhstan	Kenya	Kiribati
Kuwait	Kyrgyzstan	Lao
Latvia	Lebanon	Lesotho
Liberia	Libya	Liechtenstein
Lithuania	Luxembourg	Macedonia
Madagascar	Malawi	Malaysia
Maldives	Mali	Malta
Marshall_Islands	Mauritania	Mauritius
Mexico	Micronesia	Moldova
Monaco	Mongolia	Montenegro
Morocco	Mozambique	Namibia
Nepal	Netherlands	New_Caledonia
New_Zealand	Nicaragua	Niger
Nigeria	Norway	Oman
Pakistan	Palau	Palestine
Panama	Papua_New_Guinea	Paraguay
Peru	Philippines	Poland
Portugal	Puerto_Rico	Qatar
Republic_of_Korea	Romania	Russian_Federation
Rwanda	Saint_Kitts_and_Nevis	Saint_Lucia
Saint_Vincent_and_Grenadines	Samoa	San_Marino
Sao_Tome_and_Principe	Saudi_Arabia	Senegal
Serbia	Seychelles	Sierra_Leone
Singapore	Slovakia	Slovenia
Solomon_Islands	Somalia	South_Africa
South_Sudan	Spain	Sri_Lanka
Sudan	Suriname	Swaziland

Sweden	Switzerland	Syria
Tajikistan	Tanzania	Thailand
Timor_Leste	Togo	Tonga
Trinidad_and_Tobago	Tunisia	Turkey
Turkmenistan	Tuvalu	USA
Uganda	Ukraine	United_Arab_Emirates
United_Kingdom	United_States_Virgin_Islands	Uruguay
Uzbekistan	Vanuatu	Venezuela
Vietnam	Yemen	Zambia
Zimbabwe		

Table A3: Diagnostics, model fit for the binary TERGM (Table 1, autoregression, model (4)).

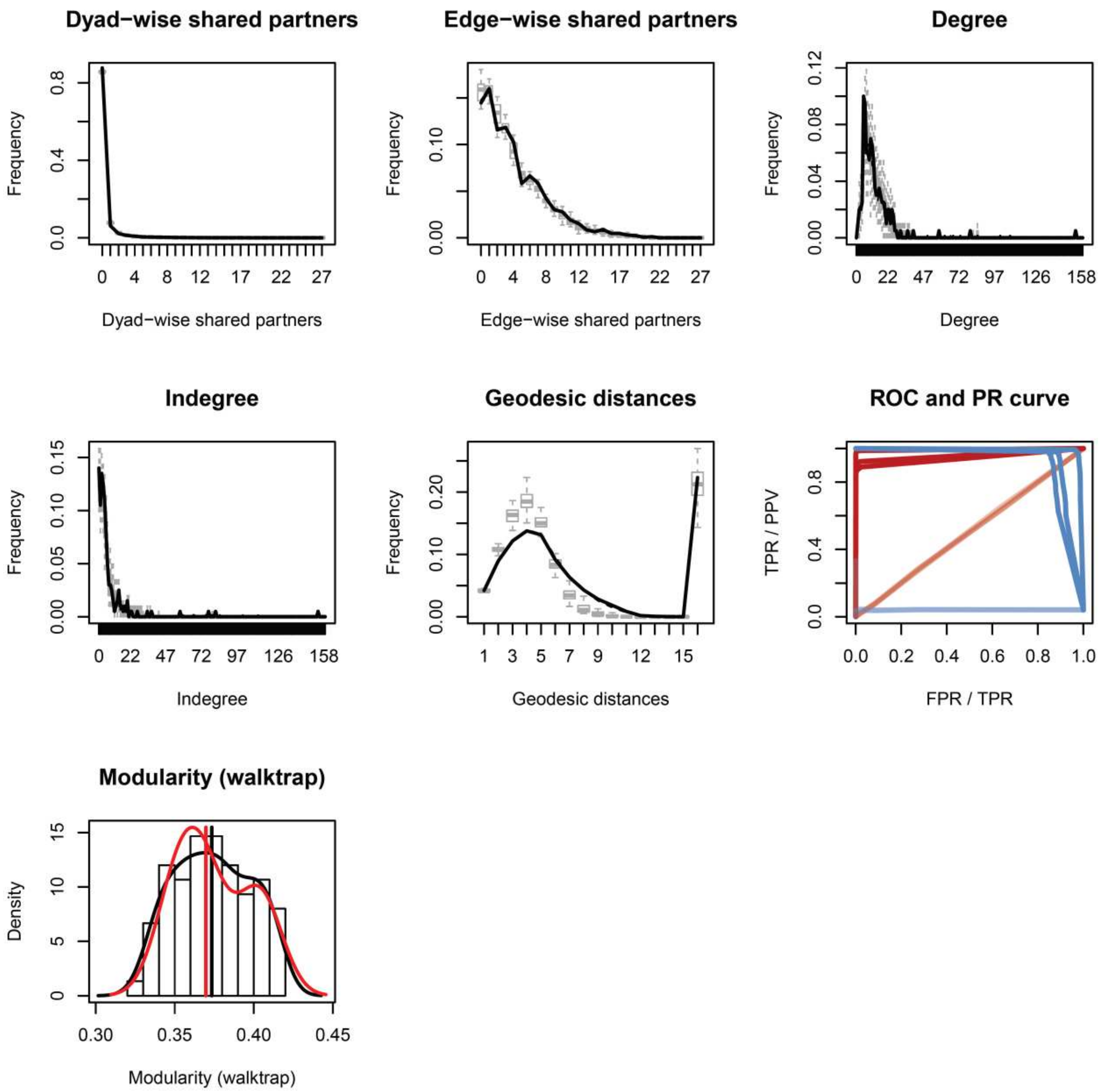
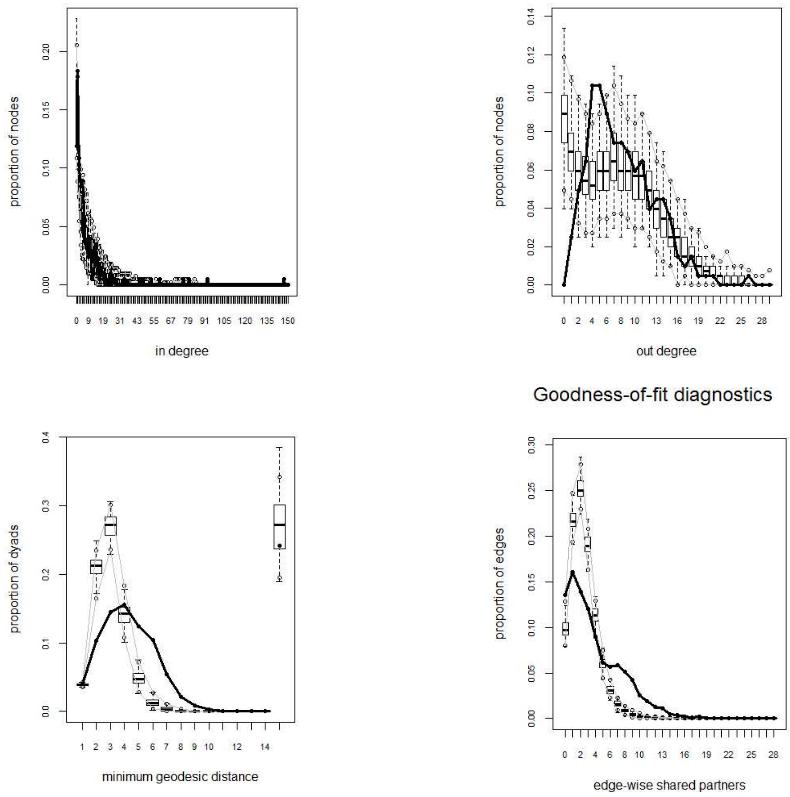
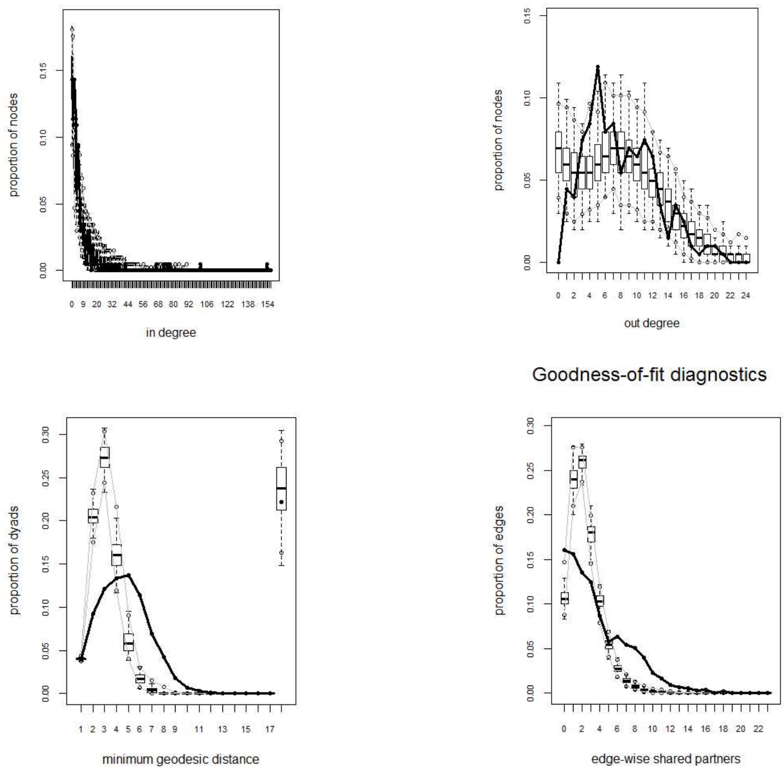


Table A4: Diagnostics, model fit for the binary ERGMs, Table 2

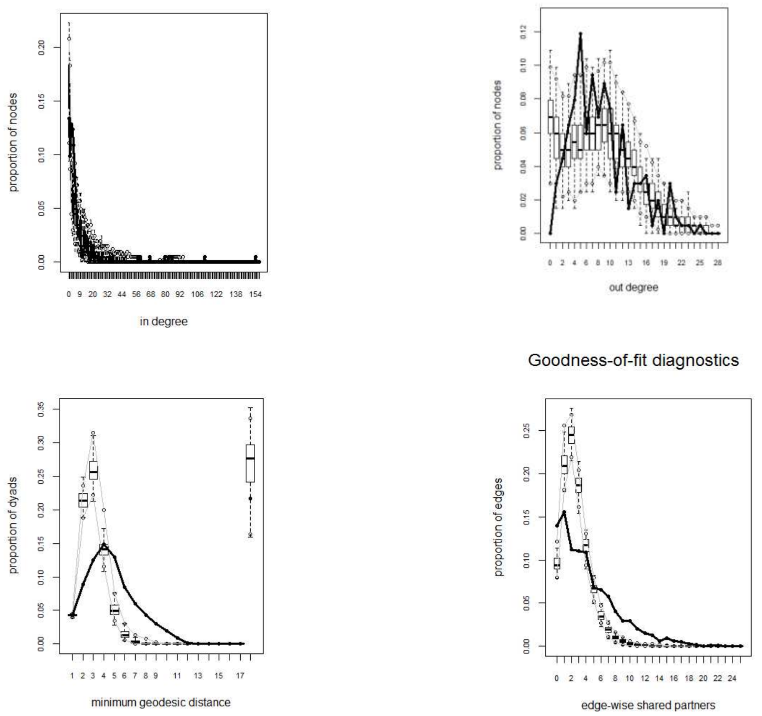
1990


proportion of nodes
in degree
proportion of nodes
out degree
Goodness-of-fit diagnostics
proportion of dyads
minimum geodesic distance
proportion of edges
edge-wise shared partners

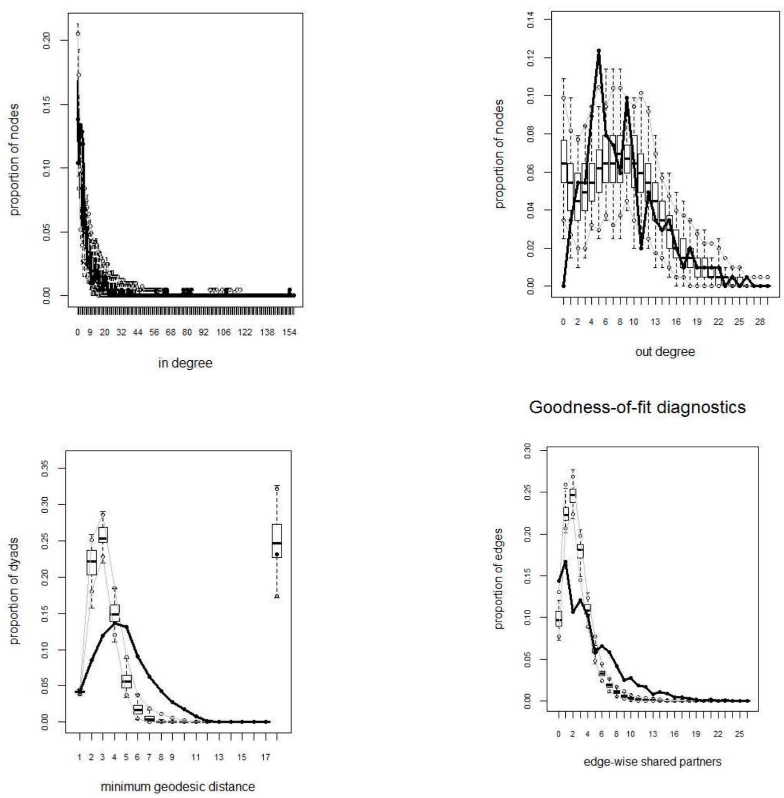
2000


proportion of nodes
in degree
proportion of nodes
out degree
Goodness-of-fit diagnostics
proportion of dyads
minimum geodesic distance
proportion of edges
edge-wise shared partners

2010



2013



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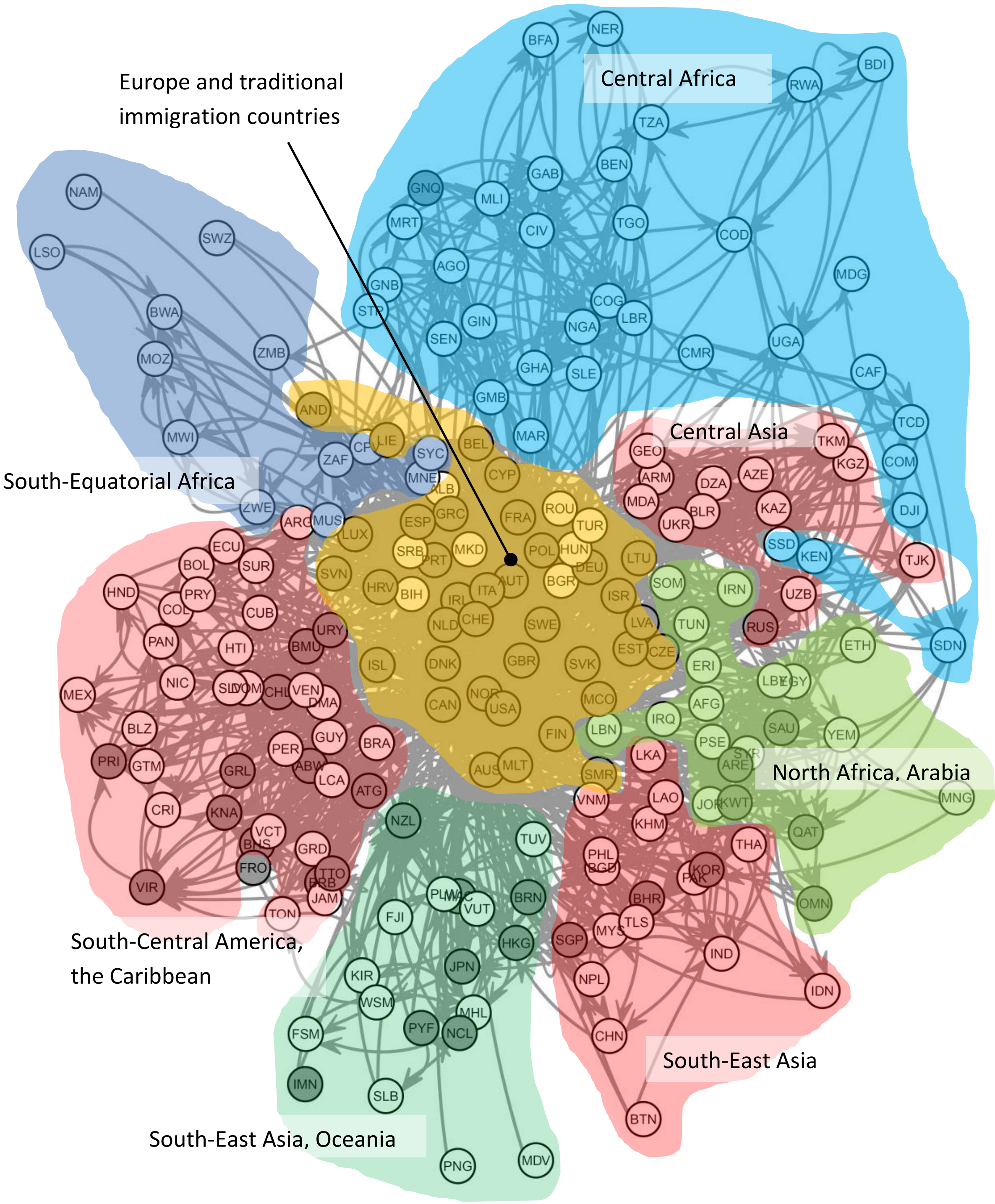
Europe and traditional immigration countries
Central Africa
South-Equatorial Africa
Central Asia
North Africa, Arabia
South-Central America, the Caribbean
South-East Asia
South-East Asia, Oceania

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