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RESEARCH ARTICLE

Does Human Migration Affect International Trade? Network Perspective

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Figures



Abstract

This paper explores the relationships between international human merchandise trade using a complex-network approach. We firstly c topological structure of worldwide networks of human migration an the period 1960–2000. Next, we ask whether pairs of countries that the migration network trade more. We show that: (i) the networks of migration and trade are strongly correlated, and such correlation c by country economic/demographic size and geographical distance international-migration network boosts bilateral trade; (iii) intensive centrality are more trade enhancing than their extensive counterpa suggest that bilateral trade between any two countries is not only a presence of migrants from either countries, but also by their relativ the complex web of corridors making up the network of internation;

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Introduction

Cross-border human migration and international trade account for mobility of people and goods across our planet, and their important relentlessly growing during the last waves of globalization [1]. Over 2010, for example, the share of total world exports over real-domes increased by 172%, whereas human migration, in terms of number more than doubled, with an estimated migrant population of more t

Despite in the last decades governments have kept reducing barriers proportionally lowering those to immigration, also the share of world population has increased by almost 20%. The extraordinary growth of human migration and trade did not occur only intensively, but also extensively. Intensive growth refers to increasing migration stocks over a fixed set of migration corridors, whereas extensive growth concerns the creation of new migration corridors. Over the period 1960–2000, the number of newly-created export corridors between countries exhibited a threefold increase. Similarly, simple back-of-the-envelope calculations on World Development Indicators (WDI) data [2], show that migration corridors almost doubled.

The intensive and extensive time evolution of international trade corridors has led, over the years, to an intricate web of relationships which has been recently investigated using a complex-network perspective. A feature of the existing works on migration and trade networks is that these two phenomena as they were completely independent [4–13]. The topological properties of the International-Trade Network (ITN) [8] and Migration Network (IMN) [11] have been separately investigated as if they were two fully disconnected layers of the same multigraph where countries represent the nodes and trade or migration links play the role of different interaction channels.

This paper tries to fill this gap and better understand, from a complex-network perspective, the correlation and causal links between migration and trade. Precisely, we address two related issues.

First, we compare the topological structure of the IMN and ITN and study how they are linked in the two layers of migration and trade networks, and what patterns do emerge between them. Note that our work focuses on a network perspective. See Ref. [14] for a complementary analysis that explores similar issues from a specific trade perspective. We also investigate the main determinants of the correlations. Not surprisingly, we find that economic and demographic variables, as well as geographical distance, play a key role in explaining differences between IMN-ITN topologies, similarly to what happens to bilateral trade and migration stocks.

Second, we study whether there exists any causal relationship between migration and trade. We are specifically interested in understanding if the relative population of countries in the IMN explains their bilateral trade. Note that a large part of the literature in economics has deeply explored the causal connections between migration and trade from a more standard econometric perspective. More specifically, there is quite a robust evidence suggesting that bilateral migration affects trade flows [15, 16]. As argued in Ref. [17], for example, trade between countries may be enhanced by the stock of immigrants present in either country or the other one. This is because migrants originating in j and present in i may foster imports of goods produced in their mother country (bilateral trade preference effect) or reduce import transaction costs thanks to the familiarity with both home- and host-country laws, habits, and regulations.

Such a *bilateral effect* only takes into account the *direct* impact of migrants from countries present in the other one to explain bilateral trade. However, trade between any two countries can be fostered not only by *direct effects*, but also through *indirect effects* conveyed by migrants coming from "third parties" [18–20]. More generally, the more any two countries are connected in the IMN, the larger the average number of third countries that they share as immigration flows, and the more likely the presence of strong third-party communities in both countries. This may further enhance trade via information effects. Moreover, it may happen that two countries are connected in the IMN (in both binary and weighted terms) even if they do not share a large number of overlapping third parties. In such a case, one may ask whether the environment engendered by the presence of many ethnic groups immigrating from non-overlapping origins can be trade enhancing—and if so, how?

Building on these ideas, we study if *indirect network effects* may play a role in explaining bilateral trade, beyond what we can explain through the *direct bilateral effect* hypothesis. Our hypothesis is that bilateral trade may increase the more the two countries are inwardly connected in the IMN. This may happen either because they share common immigration corridors or attract more immigrants from common origins because they are more inwardly connected (in both intensive and extensive terms). Expanding upon the existing literature, we fit gravity models of trade where country centrality is added as a new factor.

Our exercises strongly suggest that pairs of countries that are more inwardly connected in the IMN also trade more. Interestingly, we find that also inward third-party connections from corridors that are not shared by the two countries can be trade enhancing in addition to common inward ones.

We argue that this can be due to either learning processes of new preferences by migrants whose origins are not shared by the two countries (facilitated by an open and cosmopolitan environment) or by the presence of second-generation migrants belonging to the same ethnic group in both countries. Empirical evidence indicates that migration networks (in the sense of Ref. [18]) are condensed because they create linkages not only between pairs of countries that share a common destination of migration, but also among countries that are the destinations of migration flows from third (shared or non-shared) countries.

Finally, we test whether the migration-enhancing effect on bilateral trade can be explained from an extensive or an intensive form of centrality into the IMN. No previous literature only explores the impact of migration networks (in the sense of Ref. [18]) on intensive vs. extensive margins of trade. For example, Refs. [21, 22] find that migration networks increase trade on the intensive margin more than on its extensive one. However, no attempt is made to evaluate the relative importance of intensive forms of migration in affecting bilateral trade. In this paper, we test whether binary (extensive) vs. weighted (intensive) inward country centrality affects bilateral trade. We find that both forms of inward centrality separately affect bilateral trade. However, when one compares them directly, intensive inward centrality has a stronger effect on its extensive counterpart. Therefore, bilateral trade seems to be boosted by intensive inward centrality.

number of immigrants (both common and non-overlapping) than by corridors held by any two countries in the IMN.

Materials and Methods

Data and Definitions

Migration data employed in the paper come from the United Nations Database [23], which comprises, for each year $y = \{1960, 1970, 1980, 1990, 2000\}$, an origin-destination square matrix recording bilateral migration between countries. The generic element (i, j) of each matrix is equal to the stock of migrants (at the last completed census round) originating in country i and present in country j . Migrant status is consistently defined in terms of country of birth.

As to merchandise trade, we employ the dataset provided by Kristia Kourtellos, which contains bilateral export-import yearly figures for the period 1950–2000. We follow the flow of goods: rows represent exporting countries, where i is the origin and j is the destination, and columns represent importing countries. The generic bilateral element (i, j) thus records the value of exports from i to j in year y . Trade figures, which are originally expressed in current US dollars, are deflated to get real values.

We merged these two datasets by keeping, in each of the 5 years a sample of countries that were present also in trade data with at least one export flow. This results in 5 origin-destination $N^y \times N^y$ matrices, where $N^y = \{163, 183\}$. The sample of countries included explains more than 90% of the trade flows and migration stocks in each year.

We employ additional country-specific data such as real gross domestic product (GDP) and population (POP) and per-capita real gross-domestic product (rGDP) from Penn World Tables version 6.3 (<https://pwt.sas.upenn.edu>). We also use bilateral trade data, political and socio-economic data from the CEPII gravity dataset (see <https://www.cepii.fr/>). The latter includes information about between-country (great-circle distance (■)), contiguity (CONTIG, i.e. whether two countries share a common border), and preferential trade agreements (PTA), common language (COMLANG). These variables are mostly used to perform gravity-like exercises (more on this below).

We use trade and migration data to build a time sequence of 5 weighted migration-trade (multi) graphs describing both bilateral-migration stocks and trade flows. More precisely, we define the international migration-trade network (IMTN) as a directed weighted multigraph wherein between any two nodes (countries) there are at most four weighted-directed links, two of which describing bilateral migration and two concerning bilateral trade. Alternatively, we can think to the IMTN as a sequence of 2-layer weighted directed networks, the first layer representing the migration network (IMN) and the second the ITN. In both cases, the IMTN at each time $y = 1960, \dots, 2000$ is defined by the pair of $N^y \times N^y$ weight matrices (M^y, T^y) , where M^y and T^y define the weighted-directed International Migration Network (IMN) and the weighted-directed International Trade Network (ITN). The generic element of M^y represents the number of migrants m_{ij}^y originated in country i and present at year y in country j .

element of T^y records the value of exports t_{ij}^y from country i to country j .

Accordingly, we define the binary projection of the IMTN through the adjacency matrices (A_{My}, A_{Ty}) , where the generic element of A_{Xy} , $X \in \{M, T\}$, is one if and only if the correspondent entry in X^y is strictly positive (and zero otherwise).

Fig. 1 plots the undirected weighted version of the IMN (a) and of the ITN (b) in year 2000. In the figures, link directions are suppressed to attain a better visualization and only the top 5% of link weights are plotted. Link thickness is proportional to the total bilateral migrants ($m_{ijy} + m_{jiy}$) and the logs of total bilateral trade ($t_{ijy} + t_{jiy}$) respectively. To get a feel of migration and trade determinants, node size is proportional to the log of country population, while node color (from lighter to darker grey) represents logs of country rGDPpc (a measure of country income). The map allows one to appreciate some of the main general differences between the IMN and the ITN, e.g. the central role of Russia in the IMN (absent in the ITN) and the strong connections between the United States and South-Asian countries. Also, as expected, notice the widespread presence of low-income countries (beige color), while the most relevant trade connections occur between higher rGDPpc (red color).



Fig 1. The International-Migration Network (a) and the International-Trade Network (b) in year 2000.

The figure plots the undirected weighted version of the ITN and IMN in year 2000. Only the top 5% of bilateral link weights (total number of bilateral trade and total number of bilateral migrants) are drawn. Thickness of links in the plot is proportional to the link weights. Node size is proportional to the log of country population, while node color represents country income (rGDPpc), from beige (low-income countries) to red (high-income countries).

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Comparative-Network Analysis

We begin with comparing the topological properties of the two layers. We compute basic statistics [25] to describe connectivity and asymmetry in binary and weighted networks. More specifically, connectivity measures include: (i) network density; (ii) number of strongly and weakly connected components; (iii) average path length. As far as binary-network asymmetry is concerned, we evaluate bilateral density, defined as the share of existing directed links that are in the forward direction. Furthermore, we evaluate weighted asymmetry by computing the ir

[26].

We also study the extent to which the two layers of the IMTN display behavior by exploring whether link weights (m_{ij}, t_{ij}) are positively correlated. A simple way to visualize any existing relation is to scatter plot link weights (m_{ij}, t_{ij}) (on a log-log scale) in each year, where each dot represents, in the ordered pair of countries (i, j) for which either $m_{ij} > 0$ or $t_{ij} > 0$. If a pair of countries is a natural candidate for explaining it are economic and demographic variables (country rGDP and POP, respectively) and geographic distance d_{ij} between them. In particular, we rely on the well-known empirical success of the gravity model of migration and trade [27, 28], which states that bilateral trade flows (stocks) are well explained by a gravity-like equation involving country sizes (rGDP, POP, respectively) and, inversely, geographical distance. If this is the case, we expect that most of the variation in the cloud of points (m_{ij}, t_{ij}) can be explained by products of country sizes and smaller distances. We check this hypothesis by plotting each dot in the scatter plots a size proportional to the product of country sizes divided by country distance $(POP_i * POP_j / d_{ij})$, and a color scale (from blue to red) depending on the product of country rGDPs divided again by geographic distance $(rGDP_i * rGDP_j / d_{ij})$.

Next, we investigate matches and mismatches between ITN vs IMN. We want to assess, firstly, whether the presence/absence of directed links in the ITN is correlated with the presence/absence of trade channels. We do so by comparing adjacency matrices (A_M, A_T) and counting the percentage of total links present or missing links), and the share of IMN links (respectively, ITN links) present in the ITN (respectively, in the IMN). Secondly, we ask if geographic distances can explain matches and mismatches between binary strings. To answer this question, we assign in each year y all possible $N^y(N^y - 1)$ pair of countries to four possible cases as far as presence/absence of a link in the two networks is concerned, namely: (C_1) no link in both IMN and ITN; (C_2) link in ITN and no link in the IMN; (C_3) link in IMN and no link in the ITN; (C_4) link in both ITN and IMN. Then we set up a partition of all possible $N^y(N^y - 1)$ directed edges in four subsets (s_1, s_2, s_3, s_4) , where subset s_h contains all directed edges that belong to class C_h . We then compute, for each year separately, average and standard deviation of $q_{ij} = \log(rGDP_i) \cdot \log(rGDP_j)$ and $\log(d_{ij})$ over each separate subset s_h . The time-sequence of subsets $\{s_h\}$, where $h = 1, \dots, 4$ and $y = 1960, \dots, 2019$, is characterized by four coordinates, i.e. conditional average and standard deviation of q_{ij} and $\log(d_{ij})$ for each class C_h and year y . To simplify things, we collapse standard deviations of q_{ij} and $\log(d_{ij})$ into a single coordinate defined as the product of standard deviations of q_{ij} and $\log(d_{ij})$. The 20 subsets (number of classes times number of years) can then be plotted whose x- and y-axis feature the mean of q_{ij} and $\log(d_{ij})$, respectively. The points can then be characterized by a color representing its class, a size proportional to the product of standard deviations, and a label identifying the year. This visualization allow one to investigate if dots of different classes exhibit different patterns of matches and distance is concerned, and if dots of consecutive years are sufficiently different from each other once within-class conditional standard deviation is properly taken into account.

Finally, we study correlation patterns of node-network statistics bet

the IMTN in both their binary and weighted representations. For each compute node in- and out-degrees and strengths [29], average nearest degrees and strengths [30], binary and weighted clustering coefficient, number of binary and weighted node-centrality indicators, ranging from Page-Rank [35] centrality, to hubs and authority scores [36]. As in the literature [8, 11], we compute weighted statistics using the logs of link weights. We then ask whether countries that are more connected, clustered in the IMN layer are also more connected, clustered or central in the ITN layer, and whether country-size may drive any emerging correlation (e.g. countries that are more connected, clustered or central in both layers just because their size). We use information on country rGDP and POP to country-specific network indicators in scatter plots.

Panel Regressions

In addition to correlation patterns, we study whether network effects have a causal link going from migration to trade. We want to test if bilateral trade between two countries is enhanced the more: (i) these two countries share more connections with themselves (direct bilateral effect); (ii) they are jointly more central in the network (indirect effect); we aim to check if having more inward connections or receiving more migration leads to more bilateral trade. This can happen either from inward channels shared by both countries (common inward effect) or through non-overlapping ones (inward effect).

We explore these issues by performing a set of econometric exercises. We use a gravity-model of trade [27], expanded to take into account migration. Building on Ref. [37], we fit to our data a gravity model whose general form is

□

where ϵ_{ij} is the error term; α is a constant; $W_{ij} = t_{ij} + t_{ji}$ is total bilateral migration; δ_{iy} and δ_{jy} are country-time importer-exporter dummies controlling for all country-time variables such as rGDP and POP; more precisely, $\delta_{iy} = 1$ (resp. $\delta_{jy} = 1$) if country i is importer (resp. the exporter), and zero otherwise; β_{ij} is geographic features bilateral country dummies (CONTIG, COMLANG, PTA^y); and γ is migration-related network variables accounting for bilateral and common overlapping indirect effects. Results are robust to additional controls for religion, common colonial ties, and landlocking effects.

In the first battery of econometric exercises, we separately test five specifications to check for alternative hypotheses about how network effects affect bilateral trade. In the first one, we only control for baseline gravity-related variables (log(β_{ij}), CONTIG, COMLANG, PTA^y), i.e. W_{ij} does not appear. The second specification augments the first one by including in W_{ij} only total bilateral migration: $BIL_MIG_{ij} = \log(m_{ij}) + \log(m_{ji})$.

In the remaining three specifications, we add also network, common

overlapping, effects related to country inward centrality in the IMN. We compare the relationship between binary and weighted centrality indicators, to understand the role of extensive migration margins (i.e. the number of inward corridors) and intensive migration margins (i.e. the stock of immigrants). For the binary case, we employ country centrality *in-degree country centralization*, defined as:

□

where ind_{ij} is country in-degree (i.e. the number of inward links of country i from country j). Country in-degree centralization is highly and positively correlated with all other (binary and weighted) centrality indicators in the IMN (i.e. eigenvector-based inward centrality, etc.). For this reason, our results are quite robust to alternative centrality measures. We use inward corridors only because we expect inward migration to be more relevant in explaining bilateral trade rather than outward channels.

Since we employ importer-exporter time dummies, in the third specification we control for the log of the sum of country i and j in-degree centralization:

□

instead of the two separately.

Furthermore, we study the role of third-party (indirect) common and inward migration channels. To do so, the fourth specification features a control for the share of common in-neighbors of any given pairs of countries ($COMM_IN_{ij}$). In the fifth and final specification, we control for both $COMM_IN_{ij}$ and $NOTCOMM_IN_{ij}$, which captures inward channels that the two countries do not share ($NOTCOMM_IN_{ij}$ is computed dividing by N^j). In other words, given any two countries i and j , $NOTCOMM_IN_{ij}$ is the number of directed links pointing to i and j originating from third countries h that do not point to both i and j . The residual contribution accounts for the number of inward channels that originate from third countries k that only send migrants to either i or j .

In the weighted case, we explicitly consider link weights in the IMN (i.e. migration stocks). We then replace in Eq. (3) country in-degrees (ind_{ij}/N_j) with country in-strengths (ins_{ij}/V_j), where now we re-scale in-strength by the volume of the inward migration (i.e. the total sum of logged migrant stocks). We compute $COMM_IN_{ij}$ by summing up the number of commonly-shared inward channels. Similarly, $NOTCOMM_IN_{ij}$ is computed by summing up link weights over all inward links originated from third countries k that only send migrants to either i or j .

The second battery of econometric exercises aims at disentangling the relative importance of extensive vs. intensive forms of migration in enhancing bilateral trade. More precisely, we are interested in assessing whether trade between countries is boosted (if any) more by their *extensive* inward centrality (i.e., $IN_CENTRALIZATION$ using country in-degrees) or by their *intensive* inward centrality (i.e., $IN_STRENGTH$ using country in-strengths). In other words, we want to understand whether the role of explaining bilateral trade is country centrality in terms of the number

(*extensive* form of centrality in the IMN) or in terms of the stock of immigrants (intensive form of centrality in the IMN). To address this question, we estimate six additional specifications. In two of them, we include only the logs of extensive centrality, labeled as $\log(\text{IN_CENTR}_{ijy})_B$, or only the logs of intensive centrality, $\log(\text{IN_CENTR}_{ijy})_W$. In two additional specifications, we add the bilateral effect due to migrants, BIL_MIG_{ijy} . Finally, in the last two specifications, we add both extensive and intensive measures, again without or with the bilateral effect due to migrants and j .

Estimation of Eq. (1) can be plagued by endogeneity issues. Indeed, BIL_MIG_{ijy} is highly correlated with the explanatory variables due to a reverse-causal relationship between migration and migration corridors. This is true whenever we use BIL_MIG_{ijy} as a regressor. To address this problem, we augment the equation with *weighted* network-related variables. We use BIL_MIG_{ijy} as an instrument. This problem may be almost irrelevant in terms of binary network variables, as migration corridors are formed only in migration corridors only, as it is very unlikely that changes in bilateral migration destroy or form new links in the IMN. When link weights in the IMN are continuous, however, it may well be the case that changes in migration corridors also impact on migration stocks and in turn on country centrality. To address this issue, we employ a standard instrumental-variable (IV) approach. Borrowing from the literature, we set up an auxiliary streamlined gravity regression to instrument bilateral migration stocks, BIL_MIG_{ijy} . More formally, we use ordinary least-squares (OLS) to fit to the following specification:

□

where $(\delta_{iy}, \delta_{jy})$ are origin and destination country-time dummies and ϵ_{ijy} is a noise error. The specification in Eq. (4), as expected, is able to explain the variation in bilateral stocks. Furthermore, according to the F test (test of the null hypothesis that the employed instruments are valid).

Next, we use the predictions $\hat{\text{BIL_MIG}}_{ijy}$ of the model in Eq. (4) to replace BIL_MIG_{ijy} in the definition of BIL_MIG_{ijy} . Furthermore, in order to instrument BIL_MIG_{ijy} with $\hat{\text{BIL_MIG}}_{ijy}$, we employ $\hat{\text{BIL_MIG}}_{ijy}$ to build, in each year y , a predicted log-migration matrix $\log \hat{M}_{ijy} = \{\hat{\text{BIL_MIG}}_{ijy}\}$. Notice that since we use logs of BIL_MIG_{ijy} in Eq. (4), we only consider strictly-positive migration stocks, i.e. we only consider non-zero migration stocks. The predicted IMN weighted matrices are characterized by a binary property: they are exactly equal to the observed one in each year, i.e. $\hat{M}_{ijy} = M_{ijy}$. We use the predicted IMN weighted matrices to re-compute in the weighted case IN_CENTR_{ijy} and NOTCOMM_IN_{ijy} and use them as instrumented regressors in Eq. (1) using OLS. Similar results are obtained with Poisson pseudo maximum likelihood estimation [40].

Two remarks are in order. First, the presence of (serial) autocorrelation in the error term may bias the estimation and possibly inflate goodness-of-fit statistics. To check if this is the case, we have computed Wooldridge-Drukker statistics [41, 42] to test for the presence of autocorrelation in linear panel-data models. We report the p-value of the test in the regression tables for the null hypothesis of no autocorrelation in the

Second, our regression exercises may be affected by biases due to the towards-the-mean (RTM) effect. This may lead to, e.g., overestimation of short-distance links and underestimation of long-distance ones. Potential biases may be mitigated by the inclusion of dummy variables such as bordering or trade agreements, which we both include in all regression exercises. From a dynamic perspective, RTM effects on trade can be induced by fluctuations in exchange rates back to their normal (fundamental) levels, which we account for in our data and gravity exercises. Despite all that, the overall estimation results are difficult to quantitatively evaluate, and we leave this for future research.

Results and Discussion

ITN vs. IMN: Descriptive Statistics

We begin with a comparison between the topological properties of the two networks across time. Table 1 reports for the years 1960, 1980 and 2000 the descriptive statistics for both networks. We show only these three waves for the sake of simplicity. The 1990 to the Table does not add additional insights to our descriptive statistics as both networks are extremely dense. The ITN increased its density by the end of the period covered by our data, and became more dense than the IMN. The ITN is also more symmetric than the IMN, as testified by a larger percentage of reciprocated directed links. This is because a trade link is more likely to reciprocate than a migration corridor. This is true also when one considers the weights of the links: weighted asymmetry [26] is indeed larger in the IMN. The fact that countries tend to be more bilaterally balanced in trade than in migration is also reflected in the fact that both networks are always weakly and (almost) strongly-connected. The number of weakly connected components is always one and strongly connected components are achieved before year 2000 only because of the presence of one or two isolated and not connected countries, typically small and peripheral nations. Finally, as reported in Refs. [8, 11], the IMN features a more marked small-world property, with average path lengths smaller than in the ITN.


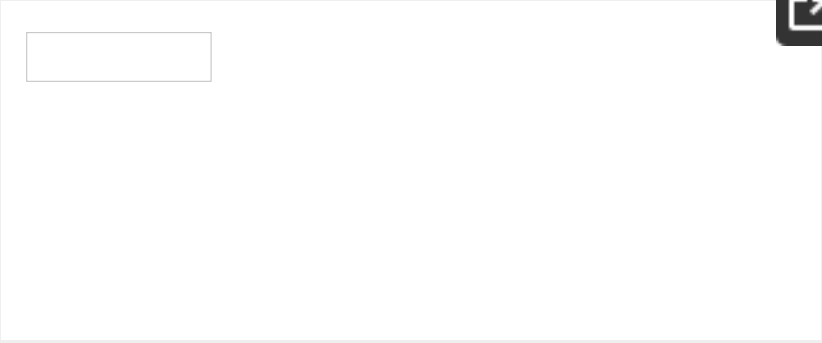


Table 1. IMN vs. ITN: Descriptive Network Statistics.
Note: SCC: Strongly connected components. WCC: Weakly connected components. APL: Average path length.
<https://doi.org/10.1371/journal.pone.0097331.t001>

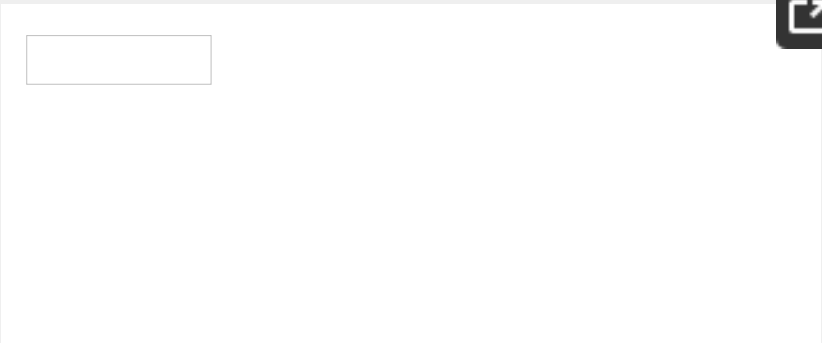
we shall explore in more details below in our regression exercises.



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Fig 3. IMN vs ITN: Comparison of binary structure.
Tot Matches: % of total matches (either missing or present links) of IMN links which are also present in the ITN. ITN Links in IMN: % are also present in the IMN.
<https://doi.org/10.1371/journal.pone.0097331.g003>

To see if real GDP and distances can also explain matches and mismatches in binary structures, we plot for each year the averages of the quantities $\log(rGDP_{iy}) - \log(rGDP_{jy})$ and $\log(\sigma_{ij})$, conditional to the four positions (with different colors), namely: (i) no link in both IMN and ITN (red); (ii) link in the IMN (green); (iii) link in IMN and no link in the ITN (blue); (iv) link in both (magenta), see Fig. 4. It is easy to see that a simultaneous absence of links is due to the combination of, respectively, low rGDPs and high distances. Furthermore, as expected, the IMN is more sensible to distances than the ITN: a link in the ITN that is not present in the IMN is typically associated with short distances. On the contrary, the ITN is more sensible to rGDP. Even at smaller distances, there is a difference: when the latter is small enough, links in the IMN are more likely to be present in the ITN. Note also that these results are very robust across time (all years are very close to each other) and display quite a good precision (cf. the small conditional dispersion, i.e. colored balls do not overlap). Similar findings are observed when rGDP is replaced by country population.

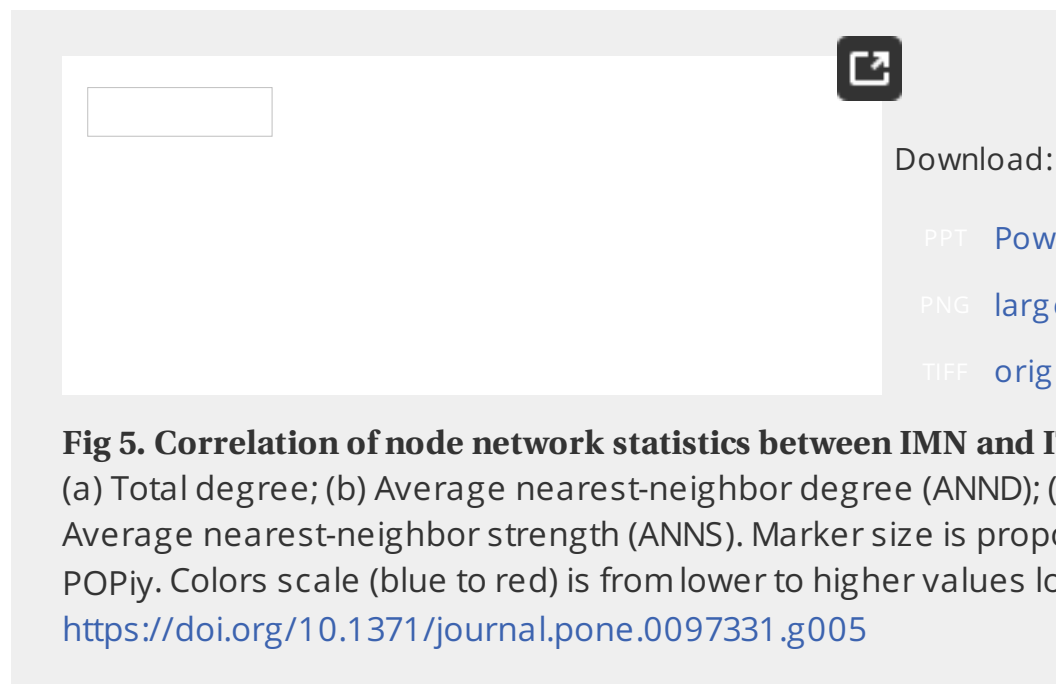


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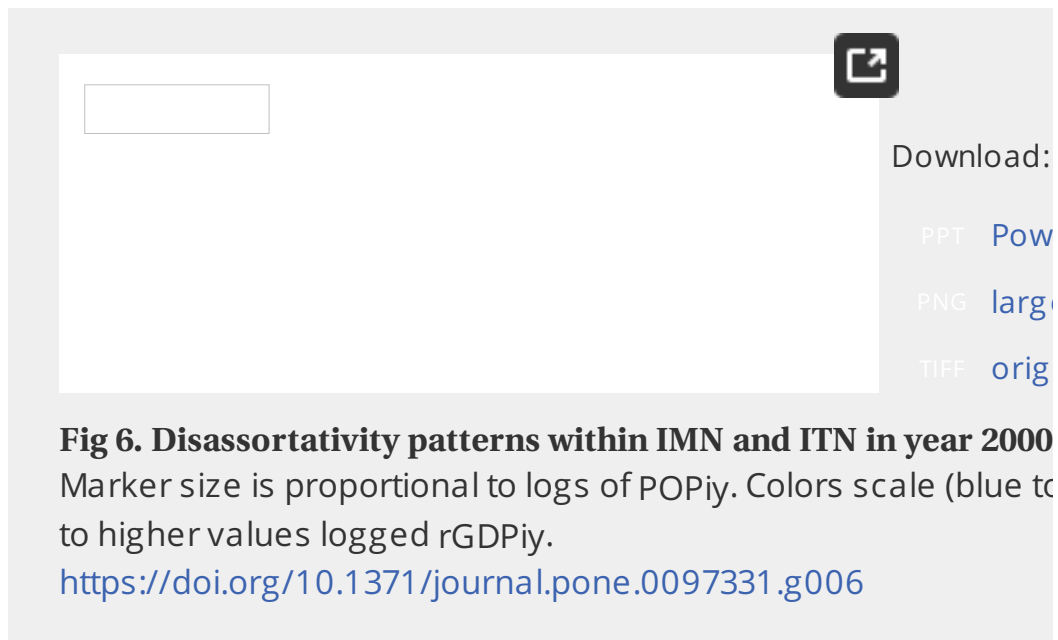
Fig 4. Scatter plot of average $\log(rGDP_{iy}) \cdot \log(rGDP_{jy})$ versus average $\log(\sigma_{ij})$ conditional on matches/mismatches between IMN vs ITN binary structures.
Colors: Red = Absence of link in both ITN and IMN. Green = No link in ITN, link in IMN. Blue = No link in ITN, link in IMN. Magenta = Link in both ITN and IMN.
The plot shows that the product of standard deviations of $\log(rGDP_{iy})$ and $\log(rGDP_{jy})$ is proportional to the product of standard deviations of $\log(\sigma_{ij})$, conditional to matches/mismatches between IMN vs ITN.

We now contrast ITN and IMN layers in terms of node network statistics. In brevity, we only show results related to: (i) total degree: the sum of all links of a node; (ii) total strength: sum of inward and outward link weights; (iii) total average nearest-neighbor degree (ANND) and strength (ANNS) degree (respectively, strength) of the neighbors of a node, no matter the links held by the node. Whereas total degree and ANND are computed for the IMTN, node strength and ANNS employ its weighted representation. For the whole range of network statistics that we have computed, in both binary/weighted clustering and centrality indicators.

Fig. 5 shows that both node degrees and strengths are positively correlated in the two layers, see panels (a) and (c). This means that if a country has more trade channels (respectively, trades more), it also carries more migration (respectively, holds larger immigrant/emigrant stocks). Again, this positive relation is mostly explained by country demographic and economic factors. We find that if a country trades with countries that either trade with many other countries (respectively, trade a lot), is also connected to countries that hold a lot of migration stocks, i.e. both ANND and ANNS are positively correlated in the two layers,



However, unlike what happens for degrees and strength, smaller levels of ANNS in the IMTN are associated to larger demographic and economic variables. To see why this is the case, we study binary and weighted disassortativity in the two IMTN layers. Fig. 6 scatter-plots node total degree (respectively, total strength), separately for ITN and IMN, and correlates this with country population and rGDP as in Fig. 5. As already known [8, 11, 41], both layers display a marked (binary and weighted) disassortative behavior: the most strongly connected nodes are weakly connected. However, larger levels of rGDP and POP also hold larger degrees and strengths. Countries with larger levels of ANND and ANNS are smaller, in both demographic and economic terms.



The fact that country size and geographical distance can explain the correlation between migration and trade link weights is not surprising given the well-known empirical success of the gravity model. What cannot be fully explained is the ability of the same variables to account for the correlation between migration and trade on the topological (binary and weighted) properties. Indeed, existing work on the gravity specification is not always able to replicate the topological properties of the trade network [45], especially at the binary level. Our results seem to suggest that the correlation picked up by country size and geographical distance is primarily on the IMN side, where a gravity specification attains a much better performance.

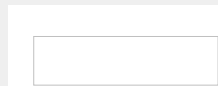
Does Migration Affect Trade?

In the preceding sections, we have explored the patterns of correlation between migration and trade layers of the ITMN and their determinants. We move now to assess if there exists any causal relationship between the IMN and the ITN. As we have seen when discussing the evidence on binary structures (see Fig. 3), the correlation between the ITN seems to be driven by existing migration corridors. More generally, if (as already found in several papers, see e.g. Ref. [17]) bilateral trade between countries i and j is boosted by the presence of migrants in i coming from j and vice versa (a bilateral effect). Furthermore, we want to understand if indirect network effects play a role in enhancing bilateral trade. Our main hypothesis is that bilateral trade is the more the two countries under consideration are inward central.

To test these hypotheses, we estimate Eq. (1) using our migration and trade data. We separately perform two sets of exercises, one when binary network centrality is considered and one when country centrality is measured using weighted centrality. In each exercise, we estimate the five specifications discussed above. On the right-hand side of the regression either BIL_MIG_{ij} or weighted centrality indicators appear, we instrument them using Eq. (4) and the procedure explained in the Methods section.

Regression results are reported in Tables 2 (binary centrality indicators) and 3 (weighted centrality indicators). The first two columns of Tables 2 and 3 obviously

reported for clarity and comparability sakes. Note first that all specifications show a high goodness of fit, as it always happens in empirical gravity estimation. The residuals of the regression specifications where we instrumented network variables are not correlated with the instruments, indicating that the latter are a good instrument. In addition, the addition of network statistics induces an increase in adjusted R^2 , although the adjusted R^2 values do not seem to be inflated by the presence of network variables. The reported p-values of Wooldridge-Drukker F-test [41, 42] lead on the null hypothesis of no autocorrelation. Similar p-values are obtained using the Wooldridge-Drukker autocorrelation test [46]. We argue that this may be due to the fact that we use yearly data, but waves at 10-year lags.



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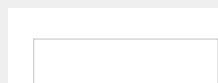
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Table 2. Gravity-model estimation with binary network variable

Full-sample (pooled) ordinary least-square (OLS) fit. Years $y = 1990-2009$.
Dependent variable: logs of total bilateral trade $\ln ijy = \ln tijy + \ln tjy$. Control variables for importer/exporter effects and constant included. Explanatory variables: See main text. WD (p-val): Wooldridge-Drukker F-test for autocorrelation in linear panel-data models (p-value) [41, 42]. Significance levels: * = 10%

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Table 3. Gravity-model estimation with weighted network variable

Full-sample (pooled) ordinary least-square (OLS) fit. Years $y = 1990-2009$.
Dependent variable: logs of total bilateral trade $\ln ijy = \ln tijy + \ln tjy$. Control variables for importer/exporter effects and constant included. Explanatory variables: See main text. WD (p-val): Wooldridge-Drukker F-test for autocorrelation in linear panel-data models (p-value) [41, 42]. Significance levels: * = 10%.

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The impact of distance, contiguity, common language and participation agreement are strong, significant, and signed in line with existing studies. Migration positively affects bilateral trade as expected, and its impact is positive no matter the chosen specification [37].

In both tables, columns (3)–(5) report regressions where country-neighboring indicators are accounted for. We find that the more total inward-migration immigrants a pair of country holds, the larger their bilateral trade, i.e. a positive and significant effect on trade in both extensive and intensive margins.


To check whether this is due to common vs non-overlapping in-neighboring channels, columns (4) and (5) report specifications where only $COMM_IN_{ij}$ or $NOTCOMM_IN_{ij}$ enter the model. Estimates suggest that: (i) common stocks of immigrants coming from common origins have a positive effect on trade; (ii) once one controls for common third-party effects (either by the number of non-overlapping channels or the stock of immigrants originating from common third parties) are also trade enhancing, even if with a smaller effect.

As a robustness check, notice that all the results hold true also if country exporter dummies are removed and replaced with country rGDPs. Similar results are obtained if we employ t_{ij} as dependent variable and we use as regressors country-centrality indicators (IN_CENTR_{ij} and IN_CENTR_{ij}). The positive effect on trade of $NOTCOMM_IN_{ij}$ is preserved when one controls for the regressions without $COMM_IN_{ij}$.

The foregoing evidence suggests that in addition to bilateral-migration between any two countries (i, j) may increase due to their binary connectivity in the IMN. This might happen via two related mechanisms: (i) countries holding more inward links or more immigrants are more likely to have an increasing number of inward corridors and/or immigrants coming from a larger number of third party migration origins $k \in (i, j)$ and therefore, thanks to consumption information effects, more bilateral trade [18–20]. Second, a smaller trade-enhancing effect can come from the presence in both countries of inward migration corridors that are however not shared by i and j and immigrants coming from such corridors. In other words, if countries i and j originated respectively from countries $I = \{i_1, \dots, i_m\}$ and $J = \{j_1, \dots, j_n\}$, the larger m and/or n , and the higher the stock of migrants originating from such corridors, the higher bilateral trade between the two countries. This second trade-enhancing effect can have a twofold explanation. On the one hand, more immigrants coming from overlapping migration channels, coupled with commonly-shared or cosmopolitan and inclusive environments in both countries, which include shared ethnic groups, learning processes about consumption patterns of immigrants, and therefore more bilateral trade. On the other hand, more immigrants arrived through non-overlapping inward migration channels, which increase a higher probability to find in both countries more second-generation migrants belonging to the same ethnic group. Indeed, our data record migrants according to their country of origin and not necessarily their ethnic origin. Therefore, it may be the case that h_i and h_j are not shared as inward channels by i and j respectively, but second-generation migrants belonging to the same ethnic group to

enhancing their bilateral trade. This effect cannot be entirely picked up by the extensive form of centrality and it can thus show up, as Tables 2 and 3 suggest, in the binary array of NOTCOMM_INijy.

Finally, we test whether bilateral trade is more enhanced by extensive forms of centrality in the migration network. We aim at disentangling that extensive country centrality (proxied by the number of inward corridors) and intensive country centrality (proxied by the total number of country-year corridors) are both boosting bilateral trade. We do so by running a second battery of regressions that include either $\log(\text{IN_CENTR}_{ijy})_B$ (to control for extensive inward centrality) or $\log(\text{IN_CENTR}_{ijy})_W$ (to control for intensive inward centrality), or both, along with the bilateral effect BIL_MIG_{ijy} . Results are presented in Table 4. Notice that the first two columns of Table 4 coincide, respectively, with the third and fourth columns of Tables 2 and 3. The next two columns report our findings for the specifications where only extensive (columns 1 and 2) or intensive centrality (columns 3 and 4) are included. As expected, both extensive and intensive inward centrality separately increase bilateral trade, independently on the presence or absence of a bilateral effect. However, when instead, display the case where extensive and intensive inward centrality are both considered in the regression. It is easy to see that extensive inward centrality explains almost completely its importance in explaining trade, whereas the effect of intensive centrality remains positive and statistically significant. This suggests that both forms of migration separately increase bilateral trade. However, intensive centrality in the IMN appears to outweigh extensive centrality. *Ceteris paribus*, a larger number of immigrants seems more important than holding more corridors.



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Table 4. Extensive vs. intensive forms of migration and bilateral trade. Gravity-model estimation. Full-sample (pooled) ordinary least-squares regression, $y = 1960, \dots, 2000$. Dependent variable: logs of total bilateral trade. Explanatory variables: $\log(\text{IN_CENTR}_{ijy})_B$ = country i and j in-degree centrality; $\log(\text{IN_CENTR}_{ijy})_W$ = country i and j in-strength (weighted degree) centrality. WD (p-val): Wooldridge-Drukker F-test for serial correlation in panel-data models (p-value) [41, 42]. Significance levels: *** = 1% level, ** = 5% level, * = 10% level. <https://doi.org/10.1371/journal.pone.0097331.t004>

Conclusions

This paper has explored the relationships between international migration and trade using a complex-network approach. More specifically, we have performed several exercises. First, we have investigated the patterns of correlation between migration and trade networks (IMN), comparing link weights, topological structures and node network centrality. We found that trade and migration networks are strongly correlated and this is mostly explained by country economic and demographic size and geographical proximity. Second, we have asked whether country centrality in the IMN can be predicted by trade. Expanding upon the existing economic literature, we have fit to the data a model of bilateral trade adding migration-network variables among the regressors. We found that for country inward centralization, and the number and intensity of overlapping inward migration channels. Our results indicate that the number of overlapping inward migration channels and the intensity of inward—both common and non-overlapping—migration are held by any two countries, the higher bilateral trade.

This suggests that migration networks (in the sense of Ref. [18]) work at the bilateral level, but they are also able to create linkages among countries. The centrality of destinations of migration flows from third (shared or non-shared) parties can provide evidence pointing towards a preponderance of intensive or extensive trade. Centrality in enhancing bilateral trade.

This work can be extended in several ways. First, one may explicitly include the geographic dimension in trade and migration data by using spatial econometric techniques in gravity regressions [47]. Indeed, the absence of serial correlation in trade and migration data (as documented by Wooldridge-Drukker tests) is likely due to the presence of autocorrelation at the spatial level (either in the dependent variable or in the disturbances). This may introduce spurious effects in gravity estimates. Second, one might go beyond a migration-trade network representation and study the network graph characterization of the macroeconomic network, where between countries there may exist many links, each representing a different type of bilateral interaction (i.e., trade, mobility, finance, foreign investment). This may lead to whether different layers display similar topological properties, and how these properties are correlated, or causally linked, between layers. Third, one may move towards a better understanding of how the properties of a network change over time, and how nodes behave and perform over time [48, 49]. Once possible endogenous factors are properly taken into account, this empirical research program may yield interesting insights on the importance of network structure in shaping the dynamics of the societies and economies where we live.

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Author Contributions

Conceived and designed the experiments: GF MM. Performed the experiments: GF MM. Analyzed the data: GF MM. Wrote the paper: GF MM.

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