The Relevance and Significance of Preferential Trade in the World Trade Network

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Abstract

In this paper we assess the impact of preferential trade agreements (PTAs) on the structure of world trade looking for communities in the world trade network (WTN), and allowing the presence of preferential trade patterns to emerge endogenously. The network analysis of the world trade system, modeling the international transactions among countries as links between nodes in a network, is a useful tool for studying the pattern of trade flows, their evolution over time, and the effects on world trade of a number of phenomena, including preferential trade agreements (PTAs). The finding of significant communities (as defined in network analysis) would imply that trading countries are organized in groups of preferential partners, e.g., on a regional basis. We use different approaches to analyze communities in the world trade network (WTN) between 1962 and 2008, but all methods agree in finding no evidence of a significant partition. A few weak communities emerge from the analysis, but they do not represent secluded groups of countries, as inter-communities linkages are also strong, supporting the view that the existing PTA are not strongly distorting the geography of trade patterns, at least at the aggregate level.

Keywords: Networks; communities; world trade; modularity; cluster analysis; Markov chains

JEL classification: D850, F100, F150, O190

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1 Introduction

Preferential Trade Agreements (PTAs) have been discussed in trade policy debates for a long time. Many works in the international trade literature show the increasing tendency of countries to sign preferential trade agreements, but there is no conclusive evidence on the actual effects of these treaties (Pomfret (2007); Baier and Bergstrand (2007)). Among the many still open issues, in particular on two points there is very little agreement in the literature: the actual impact of PTAs on the trade flows between members, and the possible distortion produced on trade flows with non-members. The first of these points has been addressed in the literature relying on the gravity model framework (see for example De Benedictis and Salvatici (2011)), but this approach raises a number of concerns on the endogeneity of the PTA dummy variable used (e.g. Baier and Bergstrand (2004); Baier et al. (2008)) and on the robustness of its conclusions. The second issue deals with the possibility that PTAs give rise to 'isolated' groups of countries, highly integrated among them, but separated from the rest of the world (i.e. possible 'stumbling blocs' on the way to multilateralism according to Bhagwati (1991)). The second issue was addressed mainly by building measures of regionalization of trade patterns, but all these indices have potential drawbacks (Iapadre (2004); De Lombaerde et al. (2011)), leaving open the discussion on the effects of PTA.

In this paper we address these issues using a different methodological approach, the network analysis of international trade flows. Among the many real-world networks studied in the literature, the World Trade Network (WTN) recently received increasing attention because of a number of interesting features. It is quite natural to represent international transactions among countries as a network, where countries are the nodes and the connecting edges are the international trade flows between them, giving rise to an intricate system of exchanges affecting all the countries. The specific economic motivations driving international trade flows shape this network, that consequently displays characteristics that are relevant for their economic implications, as well as for the network analysis in itself.

The aim of this paper is to study the possible existence of communities within the WTN to assess the impact of PTAs on the structure of world trade. Network analysis allows to examine the role of preferential trade not only on a bilateral basis, but considering the world trading system as a whole. The possible effects of trade creation and trade diversion are therefore fully taken into account, considering existing interdependencies for all countries. If the signed agreements signficantly affect the geographical pattern of trade flows, increasing trade between members and possibly reducing trade with non-members, community structures should emerge in the WTN. In fact, in general terms, a significant network community is a set of nodes with strong internal connections, much stronger than those with the remaining nodes of the network. What defines a community in this context are strong, above-average commercial ties (relative to the rest of the world) rather than imposed partitions of the network, or common individual characteristics of the nodes. Applying community analysis to the WTN should then discover - without pre-imposing any preferential link - groups of countries with privileged relationships, originated by geographical vicinity, common language or religion, traditional partnerships, and of course preferential trade agreements, if these agreements indeed affect trade. Instead, in a "globalized" or "multilateral" world, with no "exclusive" PTAs, we do not expect communities to be significant, as countries can be connected through trade to nearly any country in the world with similar ease.

So far, very few studies analyzed communities, or clustering, within the WTN (Reyes et al. (2009); Barigozzi et al. (2011); He and Deem (2010)), possibly because of the many open issues still existing in the methodologies for community analysis, making the intepretation of the results quite problematic (Fortunato (2010)). A direct reference to PTAs when looking for communities in the WTN is made by Reyes et al. (2009), using as a benchmark the groups of countries that signed regional trade agreements, and they find that over time the formation of communities follows an irregular pattern. Instead, He and Deem (2010) move from a peculiar definition of distance and clusters within the network to find that clustering declined over time, opposite to what would be expected observing the rising trend in preferential agreements. Barigozzi et al. (2011) examine the WTN considering sectoral trade flows, finding no clear time trend in communities formation. They observe heterogeneous communities structures in different sectors, even if it is impossible to compare the significance of the different communities. The above-mentioned studies define and detect communities in the WTN in distinct ways, but in all cases the main problem is that it is quite difficult to assess the significance of the partitions that emerge.

In this paper, we look for communities in the WTN in the period between 1962 and 2008, and we compare different methodologies to search for communities in networks, in order to verify the robustness of the results that we obtain. All the different methods applied here base the search for a community on the identification of a group of countries sharing a disproportionate amount of trade among them when compared with that they have with the rest of the world. Our analyses shed many doubts on the existence of communities in the WTN, as the results show that the network is not significantly splitted between different groups. Some "weak" communities emerge, but these groups of countries are not more connected among them than with the rest of the world to the extent of forming truly privileged or exclusive relationships.

2 The role of preferential trade

The number of existing trade agreements increased very rapidly since the 1990s, reaching almost 300 in 2011. Currently, all countries of the world are members of at least one trade agreement (with the only exception of Mongolia). According to the WTO (WTO (2011)), the value of trade between members of preferential trade agreements has grown faster than the world average in the past decades, increasing the share of PTA trade in world trade from 18% in 1990 to 35% in 2008. This remarkable increase, however, overstates the extent of trade that actually takes place on a preferential basis. The number and coverage of PTAs in fact is not fully conveying the effectiveness of these agreements in promoting trade among its members, and potentially diverting trade of non-members. What matters most is the actual preferential reduction in tariffs and other trade barriers put forth with a PTA, and in many ways, the multiplication of PTAs reduces the exclusivity of a trade agreement, possibly watering down its effects.

The eagerness of countries to form PTAs orginated a large body of literature trying to understand the causes and the effects of this phenomenon (Frankel (1998) is an example of the analyses undertaken when the current wave of regionalism began). At the basis of the interest both for economists and policy-makers are the potentially important welfare implications of such agreements, which can be positive or negative. Most concerns on the rapidly increasing number of PTAs are related to the extent that existing preferential arrangements might distort patterns of trade, a concern constantly present since the very beginning of the studies on PTAs in the 1950s. In spite of many modeling differences, most works agree in showing that the potential negative welfare effects depend on the trade diversion and the terms-of-trade distortions that can be created by such arrangements.

The crucial role of trade diversions is often neglected in the empirical work, as it is not easy to capture. A recent notable exception is Magee (2008), explicitely considering in a gravity equation not only the PTA effect, but also the effect of not partecipating to a PTA. In this work, the analysis is performed at the level of bilateral trade flows between countries, as the gravity framework suggests. This specification allows to conclude that the relevance of the diversion effects is very modest, but it does not consider more complex interactions between countries.[1] This is where the analysis of countries' blocs performed on the entire network of world trade can provide additional information.

3 Communities in the World Trade Network

3.1 The World Trade Network

The WTN is here modeled as a directed, weighted network composed of N nodes corresponding to countries ($\mathbb{N} = \{1, 2, \ldots, N\}$ is the set of nodes) and L edges connecting countries representing the trade flows among them. We denote by $W = [w_{ij}]$ the $N \times N$ *weight matrix*, where $w_{ij} \geq 0$ is the value of the trade flow from country i to country j. The *connectivity matrix* $A = [a_{ij}]$ is the $N \times N$ matrix where $a_{ij} = 1$ if $w_{ij} > 0$, i.e., if there exists the edge $i \to j$, and $a_{ij} = 0$ otherwise.

Data for our analysis come from the Direction of Trade Statistics published by the International Monetary Fund (IMF) and from the dataset made available by the Center for International Data at UC Davis, constructed from United Nations trade data by Feenstra et al. (2005), known as NBER-UN Trade Data. We use annual bilateral imports for the years 1962, 1965, 1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005 and 2008 (in the paper we mostly display results for the first and last year of our sample, but the full, detailed set of results is available from the authors). A number of important events affected the patterns of world trade in the period considered: the end of colonial links, changes in the exchange rate regime, removal of many barriers to trade, increasing role of emerging countries in the international markets, and - as mentioned - a rising trend in the number of PTAs signed. Our observation period stops before the outbreak of the financial crisis affected international trade, which was still growing by 15% in value in 2008 before the dramatic drop recorded in 2009.

We use directed aggregate flows received by an importing country from any given exporting country, measuring the value in U.S. dollars at current prices of all merchandise imported by a country from each partner country (import data are generally more reliable and complete than exports). Here we are not concerned with the change in prices over time, as we do not make any time series analysis, but we consider the existence of communities in each year separately (for other analyses of the WTN as a directed network see De Benedictis and Tajoli (2011); Barigozzi et al. (2011)).

[1] See Chen and Joshi (2010) on the importance of considering countries' interdependencies when analyzing PTAs.

The main topological properties observed by past analysis of the WTN are confirmed by this dataset, indicating that this network is *disassortative*, with a high *clustering* coefficient, and a number of *small-world properties* (Serrano and Boguñá (2003); Garlaschelli and Loffredo (2005); Serrano et al. (2007); Fagiolo et al. (2008)). In other words, in this network, countries with few trade links tend to be connected to countries with a large number of links, the trade partners of a given country are often trade partners themselves, and the average distance in terms of steps required to move from one node to another is small. These properties arise from the high heterogeity of countries as traders, from the presence of geographical distance or proximity, and from the structure of trade costs. The evolution of the WTN over time is slow, but it is in line with the so-called 'globalization' process, showing an increasing connectivity between nodes (De Benedictis and Tajoli (2011)).

Being the network directed, for each node i we distinguish between the in-degree $k_i^{in} = \sum_j a_{ji}$, the out-degree $k_i^{out} = \sum_j a_{ij}$, and the total degree $k_i = k_i^{in} + k_i^{out}$, and we denote the average degree by $\langle k \rangle = \sum_i k_i / N$. Analogously, we define the in-, out-, and total strength of node i as $s_i^{in} = \sum_j w_{ji}$, $s_i^{out} = \sum_j w_{ij}$, and $s_i = s_i^{in} + s_i^{out}$, respectively, and the total weight of the network edges as $w = \sum_{ij} w_{ij}$.

The network is *strongly connected* if, for every pair (i, j) of distinct nodes, there exists an oriented path from i to j (e.g., Barrat et al. (2008)). If the network is not connected, the set $\mathbb{N}$ of nodes can be partitioned in components $\mathbb{K}^1, \mathbb{K}^2, \ldots, \mathbb{K}^m$ having, without loss of generality, $N_1 \geq N_2 \geq \ldots \geq N_m > 0$ nodes, respectively ($\sum_i N_i = N$). Each component is a maximally strongly connected sub-network (i.e., it is strongly connected and it is not part of a larger connected sub-network). In our study, given the increase in international trade and in the number of trading partners for most countries, we will find that the largest component $\mathbb{K}^1$ is actually a *giant component*, i.e., it has a dimension N_1 which has the same order of magnitude as N and, on the other hand, it is much larger than all the other components. Network components can be identified by means of standard algorithms of graph analysis (Cormen et al. (2001)).[2] In 1962, the strongly connected component includes $N = 145$ countries, and it keeps slowly increasing until 1985 when it jumps to $N = 165$. From 1995 onward, the giant component is composed of $N = 180 - 182$ countries, including the new countries born from the disman-

[2]Even if the overall density of the WTN is high (density is given by $d = L/(N(N-1))$, i.e., the actual number of edges divided by their maximum allowable number), not all the countries in our sample are connected in every period. In fact, even if the cases in which a country does not trade at all are really exceptional, in our database a country can appear not connected in a given year for a number of reasons. For example, some countries did not report their data to the IMF in a given year.

tling of the former Soviet bloc. In the analysis of the following section we will consider the giant components only.

In our sample, the total value of world imports $w = \sum_{ij} w_{ij}$ increases from about 126 billion in 1962 to 15760 billion in 2008 (all amounts in U.S. dollars). The value of imports in our dataset represents approximately 95 per cent of total world imports in 2008 and slightly lower amounts in the previous years [3]. Not only the trade value but also the number of edges L registers a remarkable increase, passing from 7870 in 1962 to 21123 in 2008. The average in-strengh of each node also increases significantly, but average values in this network are not especially relevant, as nodes and edges (in our case, countries and trade flows) are very heterogeneous. For example, import flows span a range from 34 million for Tonga to 243 billion for the United States in 1980, and from 160 million to more than 2000 billion for the same two countries in 2008.

3.2 Searching for communities in the WTN

Consider now a directed, weighted, strongly connected network (or, if not connected, its giant component). Roughly speaking, a subset $\mathbb{C}_h \subset \mathbb{N}$ is called a *community* if the total weight of the edges internal to $\mathbb{C}_h$ is much larger than that of the edges connecting $\mathbb{C}_h$ to the rest of the network. In other words, community search in a network looks for non-random distributions of links between nodes, generating groups of nodes more tightly connected than the network average. In our WTN a community arises if a subset of countries is trading relatively more among them than with the rest of the world. This can occur for a number of reasons, but it is the effect that we expect to observe if a PTA is indeed promoting trade among its members, and trade within the PTA is indeed preferred to trade with the rest of the world, being more economically convenient.

The community analysis of a given network with nodes $\mathbb{N}$ consists therefore in finding the "best" partition $\mathbb{C}_1, \mathbb{C}_2, \ldots, \mathbb{C}_q$ (i.e., $\bigcup_h \mathbb{C}_h = \mathbb{N}$ and $\mathbb{C}_h \cap \mathbb{C}_k = \oslash$ for all h, k), according to some criteria (for simplicity, we do not consider possibly overlapping communities), or the "best" grouping of countries that are close trade partners. Despite a huge amount of contributions in the network analysis literature (Fortunato (2010)), there is not consensus, however, on formal criteria for defining communities and for testing their significance. This is why we will use four different approaches to analyze communities in the WTN.

[3] Our dataset does not cover all trade flows registered in a given year because some exchanges are covered by secrecy for security or similar reasons (e.g., arms trade) and the origin and/or destination of the flow are not recorded.

3.2.1 Modularity optimization

Finding the partition that maximizes a quality index called *modularity* is by far the most popular method for finding communities in a given network. Originally proposed by Newman and Girvan (2004); Newman (2006), this approach has found plenty of applications in diverse areas and has been extended in many directions Fortunato (2010).

In the case of a directed and weighted network, the modularity Q associated to the partition $\mathbb{C}_1, \mathbb{C}_2, \dots, \mathbb{C}_q$ is given by

$$Q = \frac{1}{w} \sum_{h=1}^{q} \sum_{i,j \in \mathbb{C}_h} \left[w_{ij} - \frac{s_i^{out} s_j^{in}}{w} \right], \tag{1}$$

which is the fraction of network weight internal to communities, minus the expected value of such fraction in a random network that has in common the in- and out-strengths with the original one (Arenas et al. (2007)).

Although the best partition (i.e., the one with $Q = Q_{\max}$) cannot be found by exhaustive search even in rather small networks, for computational reasons, many efficient algorithms are available for obtaining a presumably "close to optimal" solution (Fortunato (2010)). We use the aggregative, hierarchical method devised by Blondel et al. (2008), which is considered very effective both in terms of $Q_{\max}$ (i.e., in the capability of finding a partition with high modularity) and in computational requirements (Lancichinetti and Fortunato (2009)).

The results of modularity optimization for all the years of our WTN dataset are in Table 1 (see the Appendix for the composition of each community). In 1962 we obtain $q = 4$ communities with $Q_{\max} = 0.225$. The communities count 55, 44, and 22 countries, plus a very small community formed by only 4 countries. The largest communities essentially coincide with most of Europe and Africa, America, and Asia plus Oceania, respectively. This last community also includes UK and Ireland, still strongly linked to Commonwealth countries.

From 1970 onward, the results show $q = 3$ with a similar grouping of countries (possibly with the exception of African countries, that tend to become more scattered across communities), and with UK and Ireland shifting to the European community, following their membership of the EEC in 1973. In this case, we see in the change of the community composition the possible effect of joining a PTA.

The number of communities temporarily increases in 1995, when trade flows for the new countries formed by the dismantling of the Soviet bloc start to be recorded, and indeed one of the communities is formed essentially by this group. Over time, the strong ties between these countries loosen up, as they appear no longer as a separate group, but mostly in the large Europe-based community. In 2008 the communities contain 68, 66, and 47 countries, but the largest cluster is now associated to Asia/Oceania, confirming the rapidly increasing role of Asia in international trade. This clustering by continents is very much in line with the large body of literature showing that geographical proximity still matters for international trade and for the formation of trading blocs (e.g., Krugman (1991b), Egger (2008)).[4] A slightly larger modularity appears over time, reaching $Q_{\max} = 0.296$ in 2008, but this cannot be immediately seen as an increase in the relevance of our communities, as max modularity generally grows if the size of the graph increases.

A first check on the significance of these partitions, which appear very weak looking at the values of $Q_{\max}$, comes from filtering the original WTN. A well-known peculiarity of the WTN is the large value of its density in comparison to most real-world networks. In our dataset, d ranges from 0.37 in 1962 to 0.65 in 2008. Since the weights are extremely diversified, a large number of edges convey a very small import/export flow. It is reasonable to wonder whether this could be an obstacle to our analysis, in the sense that the actual communities could be concealed by the many scarcely significant inter-country connections. To assess this, we applied a filtering technique to the WTN to extract its "backbone", namely a set of truly significant edges. Besides the trivial threshold approach (which discards all weights below a fixed level), a few filtering methods have recently been proposed which are explicitly designed to deal with multi-scale weight distributions. We apply the method proposed in Serrano et al. (2007, 2009) where, in deriving the filtered network, only those edges are preserved which significantly deviate from a null model which assumes that the strength of each given node is uniformly distributed among its incident edges. More precisely, once a significance level $0 < \alpha < 1$ is set, an edge is preserved if the probability that its weight complies with the null hypothesis is less than α (a smaller α value is thus more selective). Therefore the method acts locally by analyzing each single node, and by discarding edges which do not carry a significant fraction of the node strength. Since the selection is done on a node-by-node basis, none of the edges (and none of the countries) is *a priori* discarded, which is instead the effect of trivially fixing a threshold.

We apply the filtering method to the WTN from 1962 to 2008, and we

[4] We also note that, in terms of the number q of communities, our results are qualitatively consistent with Barigozzi et al. (2011), where a value of q ranging from 2 to 4 is reported for the period 1992-2003 (no modularity value is reported, however, in that paper).

(a) original network

year	N	$\langle k_i^{in} \rangle$	$\langle s_i^{in} \rangle$	$Q_{\max}$	# comm.
1962	145	54.2	870	0.225	4 [55,44,42,4]
1965	145	64.4	1197	0.223	4 [48,43,40,14]
1970	150	74.1	1949	0.244	3 [51,50,49]
1975	151	80.8	5528	0.238	3 [75,40,36]
1980	151	76.9	12322	0.232	3 [75,42,34]
1985	165	69.2	11383	0.282	3 [70,64,31]
1990	163	78.7	20330	0.260	3 [74,70,19]
1995	182	92.7	26315	0.281	6 [77,73,18,8,4,2]
2000	180	106.7	34432	0.290	3 [76,61,43]
2005	181	113.6	56024	0.294	3 [70,65,46]
2008	181	116.7	87056	0.296	3 [68,66,47]

(b) filtered network

year	N	$\langle k_i^{in} \rangle$	$\langle s_i^{in} \rangle$	$Q_{\max}$	# comm.
1962	136	5.3	731	0.287	4 [44,40,39,13]
1965	141	6.0	983	0.288	4 [51,41,41,8]
1970	149	6.9	1618	0.302	4 [52,47,43,7]
1975	150	7.8	4553	0.296	3 [77,71,2]
1980	151	7.5	10009	0.287	4 [56,42,41,12]
1985	159	6.6	9449	0.349	4 [74,61,21,3]
1990	161	7.3	17298	0.312	4 [76,68,14,3]
1995	181	8.4	22338	0.341	6 [79,75,18,5,2,2]
2000	180	9.8	29545	0.341	3 [79,57,44]
2005	181	10.4	47759	0.348	5 [68,54,49,8,2]
2008	181	10.8	72534	0.360	3 [72,62,47]

Table 1: (a): World Trade network statistics in the 1962-2008 period, and the results of the max-modularity community analysis. (b): same as above, but for the *filtered* network. N: number of countries of the giant component; $\langle k_i^{in} \rangle$: average number of import partner countries; $\langle s_i^{in} \rangle$: average import value (million US dollars); $\langle k^{\rm sym} \rangle$: average number of partner countries; $\langle s_i^{\rm sym} \rangle$: average trade value (import + export, million US dollars); $Q_{\max}$: max modularity; # comm.: number of communities, and number of countries for each community (see the Appendix for the composition of each community).

present in panel (b) of Table 1 the results for $\alpha = 0.01$. Consistently with Serrano et al. (2007), we find that this α-level yields a reasonable trade-off between the simplification of the network (the number of edges is dramatically reduced to 10% or less) and the integrity of its important features (about 80% of the total weight is preserved, and practically all nodes remain connected). If the community analysis if then performed, however, the results obtained with the original and filtered networks are not very different. As expected, the maximal modularity is larger for filtered networks, but the dramatic decrease of the density does not give rise to a similar increase of $Q_{\max}$ nor to a structural redesign of the communities. In fact, we note that the newly appeared communities turn out to be very small and, although geographically meaningful (e.g., Kenya, Rwanda, and Uganda in 1990), they have scarce economical importance. We conclude that, while filtering is an essential tool for unveiling important network properties, it seems not crucial in community analysis because different weight scales are naturally treated within the definition of modularity (1).

The problem we face now is the significance of the obtained network partitions. Maximizing the modularity obviously yields some "best" partition, but this does not imply that the network is actually structured in significant clusters. In our analysis, what emerges in most cases is a partition of the WTN into three (almost continental) blocs, which is the number that many observers expected to emerge "naturally", but that was also seen as a welfare-minimizing situation (Krugman (1991a)). This could be a worrisome conclusion, but in fact what really matters for the welfare effects is the extent of intra-bloc preferences (Frankel et al. (1998)). If the three blocs are scarcely significant in terms of relevance of intra-bloc trade with respect to inter-bloc trade, welfare implications would be very different. This is why assessing the significance of the partitions is relevant.

Although a large value of $Q_{\max}$, *per se*, should reveal that the network has a modular organization (as it measures a kind of "dissimilarity" between the network and its randomizations), a large value of $Q_{\max}$ can even be obtained in random (i.e., Erdős-Rényi) networks, which instead are expected to have no community structure by construction Reichardt and Bornholdt (2006). In addition, the values of $Q_{\max}$ we obtain can hardly be considered to be large.[5] So, finding the partition that maximizes Q by no means concludes the community analysis of the network (Fortunato (2010)). For undirected, unweighted networks, some methods have been proposed for complementing

[5]For example, the values of $Q_{\max}$ for two synthetically generated benchmark networks, purposely built with a well-defined cluster structure in Piccardi and Tajoli (2011) have $Q_{\max} = 0.604$ and 0.861, respectively.

the max-modularity approach with a test of statistical significance. These methods, however, have some features that make their use problematic in our case. Firstly, the significance analysis is based on the modularity optimization of many instances of a random model or of a perturbed network, thus potentially it suffers of the same criticalities that affect the computation of $Q_{\max}$ (and of the associated partition) in the original network. Secondly, no straightforward extensions exist in the case of weighted, directed networks, for which the definition of randomized models and of suitable perturbation schemes is absolutely not trivial (see Zlatic et al. (2009); Piccardi et al. (2010) for some proposals). For these reasons, in the next sections we will move to completely different approaches for testing the existence and significance of communities in the WTN.

3.2.2 Cluster analysis

Standard data clustering is aimed at organizing objects into "homogeneous groups", trying to maximize at the same time the intra-group similarity and the inter-group dissimilarity. This needs defining a suitable *distance* among data. When we move to *graph clustering*, i.e., grouping the nodes of a network, which distance should be used is by no means obvious.

We adopt a notion of similarity/distance among nodes which is based on *random walks*. An N-state Markov chain can straightforwardly be associated to the N-node network by row-normalizing the weight matrix W, i.e., by letting the transition probability from i to j equal to

$$p_{ij} = \frac{w_{ij}}{\sum_j w_{ij}} = \frac{w_{ij}}{s_i^{out}}. \tag{2}$$

The resulting transition matrix $P = [p_{ij}]$ is a stochastic (or Markov) matrix, i.e., $0 \leq p_{ij} \leq 1$ for all i, j, and $\sum_j p_{ij} = 1$ for all i.[6]

It is important to note that modeling the WTN by (2) corresponds to moving from *absolute* to *relative* trade values, since the flow from i to j is now normalized by the total export flow from country i. This allows to control for countries' different economic weight, and the consequence is that communities, if any, will not necessarily be composed of groups of countries related by large trading, but instead by countries with privileged partnership,

[6] The study of many problems in network science benefits from some sort of Markov chain approach (e.g., epidemic spreading, navigation, etc. Barrat et al. (2008); Newman (2010)). Community analysis is one of them, and several contributions have already been published along this vein - we recall Pons and Latapy (2005); Rosvall and Bergstrom (2008); Steinhaeuser and Chawla (2010); Piccardi (2011) among others. See again Fortunato (2010) for a comparative survey.

namely whose trading is important in relative terms. As mentioned, this can be due to different factors, but certainly it should arise in presence of trade agreements that promote trade between members more than trade with non-members because they give rise to a preferential treatment. Since we expect such communities to be composed of a mixture of large and small economies (Whalley (1998); WTO (2011)), the use of relative trade values appears to be more appropriate, as absolute measures would *a priori* obscure the position of medium-small countries.

In defining a distance among nodes, we essentially adopt the approach of Steinhaeuser and Chawla (2010), where a T-step random walk is performed, in a Monte Carlo fashion, from each of the N network nodes. If the two nodes (i, j) are visited along the same walk, a similarity counter σ_{ij} is increased by 1. At the end, a *similarity matrix* $\Sigma = [\sigma_{ij}]$ is obtained which is used as a basis for agglomerative, hierarchical clustering. The rationale of the method is the following: if the number T of steps is limited, the random walker started from i will more likely visit nodes strongly connected to i, i.e., within the same community.

The distance $d_{ij} = d_{ji}$ between nodes (i, j) is defined by complementing the similarity and normalizing the results between 0 and 1:

$$d_{ij} = d_{ji} = 1 - \frac{\sigma_{ij} - \min \sigma_{ij}}{\max \sigma_{ij} - \min \sigma_{ij}}. \tag{3}$$

At this point, a standard hierarchical, aggregative cluster analysis is used to explore the possible existence of communities (Everitt et al. (2011)). More precisely, a binary cluster tree (dendrogram) is computed by initially defining N groups each containing a single node, and then by iteratively linking the two groups with minimal distance.[7]

The dendrograms obtained for the WTN in 1962, 1980, and 2008 (i.e., the two extremes of the time window of our dataset, plus and intermediate year) are displayed in Fig. 1 (the full set of dendrograms with the indication of the countries is available from the authors). In the dendrograms, each vertical line corresponds to a node (a country). Horizontal lines ("links") connect two groups of nodes, and the height of the link (as read on the y-axis) is the distance between the two groups.

A clear, visual indication of a clusterized network structure would be the existence of long vertical segments or, equivalently, of links (i.e., horizontal segments) whose height is largely different from the heights of the links below them. In fact, this situation arises when the distance between the two

[7] See Piccardi and Tajoli (2011) for the technical details on the derivation of the similarity matrix and the computation of these dendrograms.

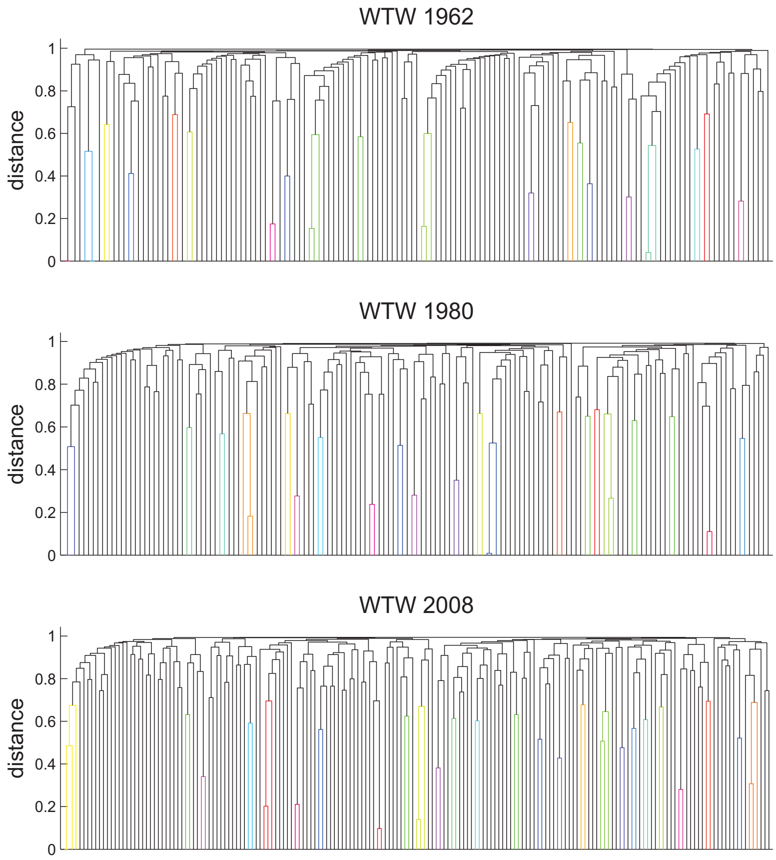

Figure 1: The dendrograms obtained by the hierarchical cluster analysis. From top to bottom: WTN in 1962, 1980, and 2008. Colors (other than black) denote groups of nodes whose distances are all not larger than 0.7.

groups joined by the link is much larger than the distance among the nodes forming the two groups - this exactly means that there are clusters in the network. The situation appears to be markedly different in the WTNs' dendrograms: no long vertical segment is shown and only few distinct groups appear, and they are mostly composed of few countries. Moreover, there seems to be no significant structural differences through the years, possibly with a diminishing visual distance between groups over time.

In all years, some expected patterns can be observed: United States and Canada form one of the closest pairs (actually in 5 cases over 7 their distance is zero, meaning they are the closest pair consistently with (3)); France is strongly connected to some of its former colonies; Germany is close to other European countries, and these large countries tend to fall in the left or central part of the dendrogram. Some of these links are very large both in absolute and in relative terms (e.g. between US and Canada), others are important in relative terms (e.g. over one third of the imports of New Caledonia come from France). Often very small countries are connected to much larger ones, confirming the disassortativity already observed in the WTN (Fagiolo et al. (2008)). These links tend to be small in absolute terms, given the small economic size of the countries, but they are very important in relative terms, as they show a strong preference for a given partner.

As pointed out above, the visual analysis of the dendrograms lead us to claim that the WTN, through the years, does not display a significant community structure. It is important to point out that this result is neither specific to our particular choice of node distance, nor to the choice of considering relative trade values.[8]

In summary, the results of the cluster analysis (although based on the visual evidence only) denote the absence of a strong evidence of the existence of a significant community structure in the WTN. This emerges both from the use of relative trade measures, a metric that appears to be more suited to a multi-scale network such as the WTN (it is actually consistent with the filtering technique described in Sec. 3.2.1), and from the adoption of a node distance based on absolute trade values. Together with the small modularity level (Sec. 3.2.1), this is a further clue of a mild community structure of the WTN.

[8]We repeated the hierarchical cluster analysis by using a different definition of distance, the one proposed by He and Deem (2010), relating country i to its direct neighbors through the *absolute* trade value w_{ij}. This led to exactly the same conclusion as above: the qualitative structure of the dendrograms is markedly different passing from the benchmarks to the WTN, denoting clusterization levels very strong for the formers but extremely mild for the latter.

3.2.3 Stability of partitions

A different approach for exploiting random walks in studying network communities has been devised by Delvenne et al. (2010), who introduced the concept of *stability* of a partition. As above, the rationale is that, in a strongly clusterized network, a random walker started in a community is likely to remain for quite a long time within that community, before leaving it to enter another community. Imagine that the walker emits a signal at each step, which has the same value as long as it remains within a community and changes when moving to another community. Then studying the persistence of this signal provides important information on the community structure of the network.[9]

A good, significant partition will have a stability measure r_t^H which remains large over a long time span, since the random walker has a high likelihood of remaining within the same community for long time. On the contrary, a rapidly decaying r_t^H denotes a scarcely significant partition, because the walker rapidly abandons the starting community.[10]

We compute the stability function r_t^H for all the WTWs of our dataset 1962-2008. In all instances, we consider the partition H obtained via modularity optimization (Sec. 3.2.1). The results are depicted in the upper panel of Fig. 2 (for readability, only the WTN curves for 1962, 1980 and 2008 are plotted, together with the curves of two benchmark clustered networks). These functions are, however, not easy to be compared, essentially for two reasons. First, the curves start from different values r_1^H. Second, the decay velocities are hardly comparable because of the different dimensions N of the networks. For these reasons, we normalize the curves along both axes and plot, in the lower part of Fig. 2, the normalized stability r_t^H/r_1^H with respect to the normalized time t/N. In this way the curves are directly comparable. The visual exam of the figure is probably sufficient to grasp the much more rapid decay, i.e. the much lower stability of partitions, of the WTNs with respect to two artificial benchmark networks, GN and LFR, built with

[9]Delvenne et al. (2010) propose a measure of the stability of a network partition based on the probability, evolving according to a Markov chain process, that the random walker is still within a given community after a infinitely large number of steps. See Delvenne et al. (2010); Piccardi and Tajoli (2011) for details on this stability measure.

[10]In Delvenne et al. (2010) r_t^H is actually proposed not only for testing the significance of a given partition but mainly as a tool for finding the "best" partition. If a pretty large number of "good" candidate partitions are derived, then the *graph stability* function $r_t = \max_H r_t^H$ puts in evidence, for each time instant t, which is the "optimal" partition according to the stability criterion. It is suggested in Delvenne et al. (2010) that the most relevant partitions are those which are optimal over long time windows.

a community structure.[11]

3.2.4 Persistence probabilities

The final search on the presence of significant communities in the WTN is performed by extracting another quantitative indicator, that we call the *persistence probability* of the communities. Starting from the N-state network, a given partition $\mathbb{C}_1, \mathbb{C}_2, \ldots, \mathbb{C}_q$ induces a q-state meta-network, where communities becomes meta-nodes. At this scale, the random walker can be described by the q-state *lumped* Markov chain (Kemeny and Snell (1976)) with stochastic matrix U.[12] Under appropriate assumptions, the entry u_{cd} of U is the probability that the random walker is at time $(t+1)$ in any of the nodes of community d, provided it is at time t in any of the nodes of community c. We define *persistence probability* of the community c the diagonal term u_{cc} of U. Large values of u_{cc} are expected for significant communities. In fact, the expected escape time from $\mathbb{C}_c$ is $\tau_c = (1-u_{cc})^{-1}$: the walker will spend long time within the same community if the weights of the internal edges are comparatively large with respect to those pointing outside. The analysis of the persistence probabilities induced on a network by a given partition has recently been proved to be an effective tool for testing the existence and significance of communities (Piccardi (2011)).

We compute the persistence probabilities u_{cc}, $c = 1, 2, \ldots, q$, of the WTNs in the 1962-2008 period for the partition corresponding to the maximum modularity (Sec. 3.2.1). The results are in Fig. 3, for the original and filtered WTNs, and for two benchmark networks characterized by built-in communities. It is evident from Fig. 3 that the u_{cc}-s of all the WTNs under scrutiny are smaller than those of the benchmarks, and in most cases much smaller. Actually, in all instances the entire range of the u_{cc}-s of the original WTNs is below the corresponding range of the benchmarks. If we then individually analyze each single community, we discover that most of them turn out to be scarcely significant, as revealed by the small persistence probability. From this point of view, the results are even worse for the filtered networks. From one side, removing several small-weight edges slightly increases the highest persistence probabilities. But, on the other side, the finer partition detected by the max-modularity approach pops up some small,

[11] The computation (via linear fitting) of the decay rate γ reinforces this impression: while the artificial networks have $\gamma = 23.3$ and 26.6, respectively, the WTNs in 1962, 1980 and 2008 are characterized by the much higher decay values 106.8, 100.3 and 97.6, respectively. Similar figures ($92.4 < \gamma < 109.4$) are obtained for the other years of the dataset, with no clear trend with respect to time.

[12] See Piccardi (2011) for details.

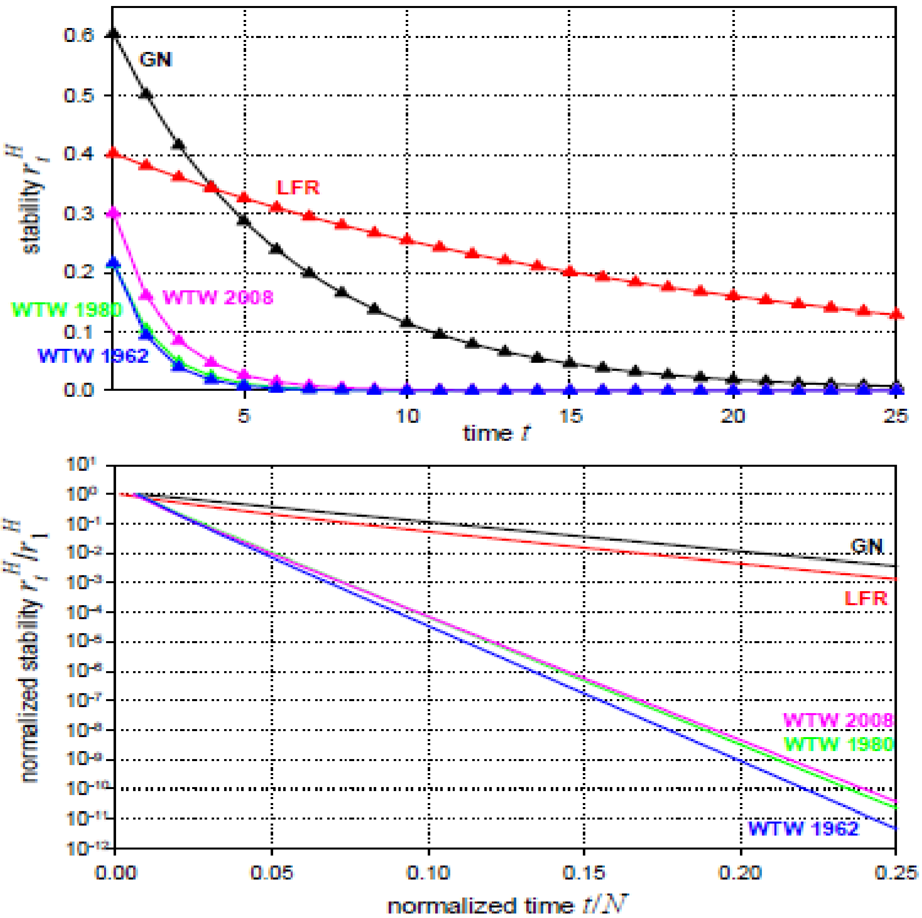

Figure 2: (Above: the stability functions r_t^H of the GN and LFR benchmark networks, and those of the World Trade network (WTN) in 1962, 1980, and 2008. For each network, we consider the partition H obtained via modularity optimization. Below: same as above, but the stability is normalized by the initial value r_1^H and the time axis is normalized, separately for each curve, by the number N of network nodes.

scarcely significant communities, as clearly highlighted by the larger number of small u_{cc}-s in the lower panel of Fig. 3.

Nonetheless, some important information is conveyed by the analysis of Fig. 3. Even if, in most instances, the partition of the WTN is scarcely significant as a whole, we notice that there is in each case (at least) one community with rather large persistence probability, both in absolute terms, and comparatively with respect to most of the other u_{cc}-s. It turns out that it is a large community which always includes the entire set of European countries, plus a number of minor non-European partners (partially varying from year to year), mainly from North Africa, Near East, and the Asian republics of the former USSR. Up to 1995, there is also another large community with high persistence probability, which includes the entire North America and most of Central and South America, plus China, Australia and many others. Since 2000, however, the community partition dictated by the max-modularity suggests a different arrangement, with North and South America in a community and China and Australia in another one. Notably, both these new communities have a definitely smaller persistence probabilities than before, denoting less exclusive intra-community partnerships. The evidence emerging from this analysis is partially in line with what can be expected looking at the existence of trade agreements between countries. Most European countries form the European Union (EU), the oldest and deeper custom union in the world, and the persistence of their ties is confirmed by the data. But this analysis also suggests that the EU is not a group of countries separated from to the rest of the world, and the observed community includes non-EU members, and the not-too-high persistence probability suggests that trade links with other countries are also important (in 2008, over one third of the European Union imports were coming from non-EU countries). The reported evidence also captures the new active role of China, which became a major player in many areas of the world, less dependent from the US market.

Overall, we can conclude that, as well as the other methods above presented, the use of stability functions and the evaluation of the persistence probabilities seem to confirm the absence of a strong clusterized structure in the WTN, when considered as a whole. However, the capability of the persistence probabilities of assessing the quality of each single community, differently from the other tools of analysis, puts forward the existence of some significant cluster of countries with privileged intra-community partnerships.

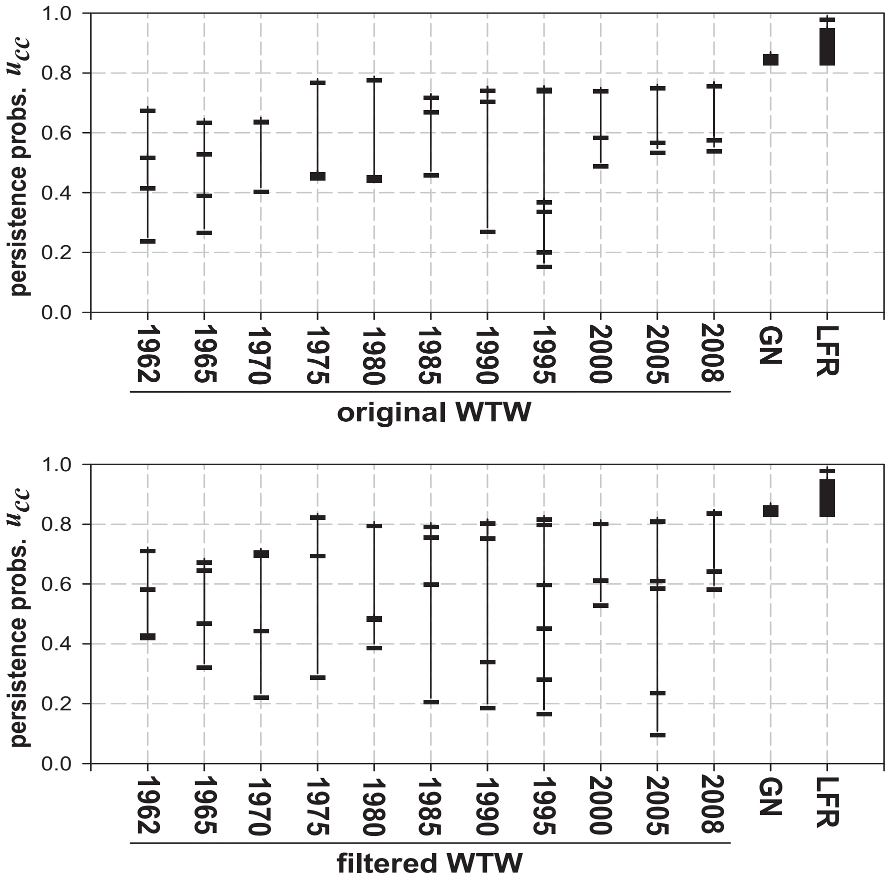

Figure 3: The persistence probabilities of the World Trade Network (WTN 1962-2008) and of the GN and LFR benchmark networks. The panels refer, respectively, to the original and filtered WTN, as defined in Sec. 3.2.1. For each network, we consider the q-community partition obtained via modularity optimization: the q horizontal dashes denote the values of the diagonal terms u_{cc} of the lumped Markov matrix U (vertical straight lines are for visual aid only).

4 Testing the significance of the PTA partition

In a world where international trade takes place according to well-defined preferential partnerships, we would expect to observe a world trading system formed by separated, clearly identified groups of countries, intensely trading within each group, and trading relatively less among each other. If PTAs indeed foster trade between members *and* discourage trade with non-members, significantly distorting trade flows, communities should emerge in the WTN. The evidence presented in the previous section indicates that the world trading system does not have such a structure. The communities analyzed, arising endogenously from the bilateral trade data, appear weak and scarcely significant in shaping the structure of world trade.

As a further test of the role of PTAs, we computed the indicator of *persistence probability* for the communities formed by the existing preferential trade agreements, rather than the ones suggested directly by the trade data, to test their significance within the WTN structure. The existing PTAs and the countries belonging to them were taken from the WTO database (WTO (2011)). Even if many countries are members of more than one trade agreement, and grant some kind of preferential treatment to different group of countries, the list used here includes only plurilateral preferential trade agreements regionally based, so that each country appears only in one group.[13] The PTAs considered are listed in Table 2, together with the respective persistence probabilities. The persistence probabilities were computed for the strongly connected component of the WTN in 2008.

From Table 2 it is possible to observe that most PTAs have a very low persistence probability, generally lower than the values found for the endogenous partitions, i.e. they do not form significant communities from the point of view of the network structure. If we were to choose a 0.5 threshold for the persistence probability to define a community (a situation in which for every member of the community, trade with a member of the same community is preferred - in probabilistic terms - to trade with a non-member at least half of the times), only the the EU would satisfy this criterion, and NAFTA would only come close, but stay below the threshold. Not surprisingly, the values for the African and Asian communities are generally extremely low: it is acknowledged that the trade agreements between these countries are not very effective. The EFTA displays the lowest value, as for its members trade

[13] According to these criteria, only four plurilateral agreements listed by the WTO are left out of our partition: the Asia-Pacific Trade Agreement, the Economic Cooperation Organization, the Pan-Arab Free Trade Area, and the Global System of Trade Preferences.

Communities formed by different PTA members in 2008

PTA	N	Persistence prob.
EU	27	0.6707
NAFTA	3	0.4595
ASEAN	10	0.2403
CACM	5	0.2022
CIS	8	0.1947
MERCOSUR	4	0.1507
ECOWAS	15	0.1219
CARICOM	13	0.1062
COMESA	17	0.0841
ANDEAN	4	0.0697
GCC	6	0.0626
SAFTA	6	0.0495
EFTA	3	0.0065
Others	60	0.3407

Table 2: Persistence probabilities of the communities in the WTN formed by the existing PTAs (see the Appendix for the composition of each community).

with other European countries is much more important. These results can be due to the fact that - as mentioned - many of these agreements are not exclusive. The EFTA countries in fact, even if not belonging to the EU, have trade agreements also with the EU.

In any case, the evidence confirms that the existing trade agreements forming PTAs are not giving rise to significant trade diversion, and they do not isolate the member countries from the rest of the world, as they limit the links of non-members to members in a very mild way. This result is fully in line with the previous results of the paper, that could hardly identify communities in the WTN without pre-imposing any partition. Overall, the results show that these trade agreements do not affect significantly the general structure of world trade as a whole.

5 Concluding remarks

In this paper we used different approaches to analyze communities in the WTN. These methods are actually able to identify communities in directed-weighted networks, but in the case of the WTN, all the four approaches led to similar conclusions: there is no significant evidence on the existence of a strong community structure in the WTN. The eligible communities found in the data are reasonable, but they are not very significant according to any of the criteria adopted. Even if there is not a single robust measure to identify communities in the WTN, the convergence of results from all the approaches strengthens the robustness of this conclusion. Also the significance of communities formed by the existing PTAs turns out to be very weak, confirming the general result.

The configuration of the WTN therefore supports the view that the growth of international trade linkages did not occur only within specific groups of countries and through the formation of PTAs. Even if countries select their trading partners, this selection is not following a strong or exclusive preferential structure. In this respect, the effects of the PTAs on trade patterns appear to be weak, and not introducing significant distortions in trade flows.

While globalization of trade in terms of aggregate flows is quite plausible, much stronger community ties can emerge considering trade in specific sectors, where the effect of removing trade barriers can be sizable. Future developments of this work could focus on trade flows between countries in particular commodities, using these aggregate results as a benchmark.

6 Appendix. Composition of the communities analyzed

PTAs

EU Community (27 nodes): 'Austria' 'Belgium' 'Bulgaria' 'Cyprus' 'Czech Republic' 'Denmark' 'Estonia' 'Finland' 'France' 'Germany' 'Greece' 'Hungary' 'Ireland' 'Italy' 'Latvia' 'Lithuania' 'Luxembourg' 'Malta' 'Netherlands' 'Poland' 'Portugal' 'Romania' 'Slovak Republic' 'Slovenia' 'Spain' 'Sweden' 'United Kingdom'

NAFTA community (3 nodes): 'Canada' 'Mexico' 'United States'

ASEAN community (10 nodes): 'Brunei Darussalam' 'Cambodia' 'Indonesia' 'Lao People's Democratic Republic' 'Malaysia' 'Myanmar' 'Philippines' 'Singapore' 'Thailand' 'Vietnam'

CACM community (5 nodes): 'Costa Rica' 'El Salvador' 'Guatemala' 'Honduras' 'Nicaragua'

CIS community (8 nodes): 'Armenia, Republic of' 'Azerbaijan, Republic of' 'Belarus' 'Georgia' 'Kazakhstan' 'Moldova' 'Russian Federation' 'Ukraine'

MERCOSUR community (4 nodes): 'Argentina' 'Brazil' 'Paraguay' 'Uruguay'

ECOWAS community (15 nodes): 'Benin' 'Burkina Faso' 'Cape Verde'

’Côte d’Ivoire’ ’Gambia, The’ ’Ghana’ ’Guinea’ ’Guinea-Bissau’ ’Liberia’ ’Mali’ ’Niger’ ’Nigeria’ ’Senegal’ ’Sierra Leone’ ’Togo’

CARICOM community (13 nodes): ’Bahamas, The’ ’Barbados’ ’Belize’ ’Dominica’ ’Grenada’ ’Guyana’ ’Haiti’ ’Jamaica’ ’St. Kitts and Nevis’ ’St. Lucia’ ’St. Vincent and the Grenadines’ ’Suriname’ ’Trinidad and Tobago’

COMESA community (17 nodes): ’Burundi’ ’Comoros’ ’Congo, Democratic Republic of’ ’Djibouti’ ’Egypt’ ’Ethiopia’ ’Kenya’ ’Libya’ ’Madagascar’ ’Malawi’ ’Mauritius’ ’Rwanda’ ’Seychelles’ ’Sudan’ ’Uganda’ ’Zambia’ ’Zimbabwe’

ANDEAN community (4 nodes): ’Bolivia’ ’Colombia’ ’Ecuador’ ’Peru’

GCC community (6 nodes): ’Bahrain, Kingdom of’ ’Kuwait’ ’Oman’ ’Qatar’ ’Saudi Arabia’ ’United Arab Emirates’

SAFTA community (6 nodes): ’Bangladesh’ ’India’ ’Maldives’ ’Nepal’ ’Pakistan’ ’Sri Lanka’

EFTA community (3 nodes): ’Iceland’ ’Norway’ ’Switzerland’

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