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TRADE NETWORK AND ECONOMIC FLUCTUATIONS IN ASIA

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Trade networks and economic fluctuations in Asia

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Abstract

The paper presents a new methodology, based on tensor decomposition, to map dynamic trade networks and to assess their strength on spreading economic fluctuations at different periods of time in Asia. Using the monthly merchandise import and export data across 33 Asian economies, together with the US, EU and UK, we detect the modularity structure of the evolving network and we identify communities and central nodes inside each of them. Our findings show that data are well represented by two communities, in which the People's Republic of China and Japan play the major role. We then analyze the synchronisation between GDP growth and trade, and apply our model to the prediction of economic fluctuations. Our findings show that the model leads to an increase in predictive accuracy, as higher order interactions between countries are taken into account.

Keywords:

Asia, Trade Network; Tensor decomposition; Community detection.

JEL classification: G01, C58, C63.

1 Introduction

The global economy is evolving rapidly, with a complex and ever-changing picture. Despite a growing body of research on the globalization, our knowledge on its working forces and on its impacts on trade, the structure of economies, employment, incomes, and human capital are at best incomplete. What has been largely missing is a comprehensive and detailed picture

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of the dynamic network structure of the global economy. In the presence of flows of goods, services and capital across countries as well as intersectorial input-output linkages, microeconomic idiosyncratic shocks may lead to aggregate fluctuations (Acemoglu et al., 2012). The clear link between trade pattern and global business cycle indicates that trade networks provide a natural framework for us to understand the transmitting mechanism of economic shocks from one unit to another. The idea that sectoral interdependencies and trade relationships has an important influence on aggregate economic behavior has attracted increasing attentions in economics. Long Jr and Plosser (1983), Horvath (1998), Horvath (2000) and Acemoglu et al. (2012) show that the topology of the input-output network has a crucial role in determining the aggregate behavior of the system. If the network is significantly asymmetric, that is, if relatively few nodes play a predominant role as suppliers, then idiosyncratic shocks give rise to aggregate fluctuations. When the organization of production is dominated by a small number of key players supplying inputs to many different sectors, disruptions in these critical nodes can affect the global production system, determining losses in production and welfare (Acemoglu et al., 2012).

Our research uses the export and import of merchandise across Asian economies to map the dynamic trade network and its strength on spreading economic fluctuations at different periods of time. Moreover, we also take into account the main world economies including the United States, thereafter US, the European Union and the United Kingdom, as additional nodes in the network. Asia provides a compelling setting to study this issue due to two reasons. First, Asia is a region of growing global significance, currently accounting for around 30 percent of the global economy by most measures, e.g. production, trade, investment and finance (Dent, 2017). It is also a regional economy that has become increasingly integrated in various ways and, in particular, in a rising intra-regional trade. Indeed, despite the slowdown in global trade since 2011, the share of intra-Asian trade continues its growing trend and rose to 57.1 percent in 2015, up from an average of 55.8 percent during 2010-2014 (see Figure 1). By comparison, the shares of intra-regional trade flows within North America and Europe has fallen since the end of 1990s. This reflects a growing importance of the Asian trade network in the world economy.

FIGURE 1 ABOUT HERE

Moreover, the Asian trade network has undergone several stages of dynamic and significant transformation since the beginning of this century, mainly due to the rise of Peoples Republic of China (PRC) as the dominant supplier in wide-ranging manufacturing industries to both regional and global markets. This rapidly-evolving Asian production network can be highlighted by the dominant links of flows of manufacturing across borders. Figure 2 shows the typology of foreign value added embedded in bilateral manufactured exports from 2000 to 2015. The entire network was dispersed in 2000. The US was the core of both Asia-Pacific and north American communities while there is almost no connection between the European com-munity and Asia-Pacific community. In 2005, PRC became the new core of East Asia+ASEAN community while the US maintained its connections only with Canada and Mexico. The role of PRC in the Asia-Pacific community was more phenomenal in 2011 because it outsourced a large portion of foreign value added to other countries in the region. At the same time, the magnitude of connections was strengthened, with the US, PRC, Germany and Republic of Ko-rea being the main hubs. However, the network showed a recession in 2015 due to the rising tide of trade protection and the substitution of domestically produced intermediate inputs for imported intermediate inputs in major emerging developing economies like PRC (Degain et al., 2017).

FIGURE 2 ABOUT HERE

In a few words, the dense patterns of trade network and other forms of supply chain activ-ity have helped forge systemic economic interdependencies among Asian economies, that have been further augmented by developments in financial markets and industries, and strengthened regional infrastructure networks.

In this paper, we first identify the centrality and community structure of the Asian trade network. Understanding the structure of the trade network, and in particular determining which countries act as hubs in the network is important to understand the origin of aggregate fluctuations, so to inform policymakers on how to prepare for, and recover from, adverse shocks hitting the regional network. Not surprisingly, the research in network theory has dedicated a vast amount of effort to deal with this topic (Battiston et al., 2012). Various measures of centrality had been proposed in network theory (see Perra and Fortunato, 2008; Bonacich and Lloyd, 2001; Bonacich, 1972; Katz et al., 1973; Brin and Page, 2012; Kleinberg, 1999). These measures provide information on the position of each node relative to all the others. We use those based on counting the first neighbors of a node (degree centrality), as more intuitive to interpret, from an economic viewpoint. Our results indicate, in particular, the increasing importance of PRC in the Asian trade network, especially after 2000.

Studies that analyze the empirical characteristics of economic networks have systemically found the existence of a community structure (see Garratt et al., 2011, among others). The community structure reveals how a network is internally organized, and indicates the presence of special relationships between nodes, that may not be easily accessible from direct empirical tests. In other words, the community structure refers to the occurrence of groups of nodes that are more densely connected internally than with the rest of the network. A recent survey (Malliaros and Vazirgiannis, 2013) provides a broader definition of community structure as a set of nodes that share common or similar features together. The import-export networks, where links representing flows of goods are typical examples. Much of the focus in community detection algorithms has been devoted to identify disjoint communities. However, it is well known that nodes in a network are naturally characterized by multiple community memberships (Xie et al., 2013). In economic networks, it is very common for an institution to participate in more than one community, so that communities are often overlapped. Cao et al. (2013) propose a novel model to identify overlapping communities and central nodes, in case of static networks. In our context of international trade, adapting the model of Cao et al. (2013) to temporal networks can dynamically capture nodes systemic importance, thus revealing the most plausible areas of contagion and, thereby, enhancing our understanding of the system. Our results indicate that the Asian trade network can be decomposed into two over- lapping communities, with different countries inside each community playing the role of main importers or exporters.

In the paper we also investigate the relationships between trade and GDP growth. We first analyse the synchronization between business cycle and trade, by applying a Hidden Markov Model to the pairwise correalations between countries GDP growth and export levels. The increasing level of synchronization found in the data reinforces the idea that globalization has increased the interconnections between countries, making them more susceptible to global fluctuations. We then apply the proposed network model to the prediction of economic slowdowns or crisis. Our results show that the model leads to an important gain in predictive performance, which can be explained by the fact that the centrality measures at the basis of our model take into account not only first order trade interactions but also higher order interactions, ranking countries according to their influence on the whole network.

This research extends the existing research on trade network (Serrano and Bogu, 2003; Kali and Reyes, 2007; Barigozzi et al., 2010; De Benedictis et al., 2013 and Cepeda-Lopez et al.,

2017) and contributes to the economic and financial stability literature in several perspectives. We propose a network model, based on temporal trade data, to detect the modularity structure of an evolving weighted directed network. This helps to identify important nodes inside each community, tracking their common activity over time. To our knowledge, the paper is the first application of network modelling to capture the flow of merchandise through export and import across Asian economies, a region that is gaining increasing importance in the world trade.

From a methdological viewpoint, we present a novel method, based on import-export trade network tensor decomposition aimed at deriving centrality measures and, accordingly, rank countries in terms of their importance within their community. Communities can be thought as proxies of the most plausible areas of countries influence. Our method is based on the fact that a temporal network is naturally represented as a time-ordered sequence of adjacency matrices, each describing the state of the system at a given point in time. Adjacency matrices can be combined in a single mathematical object: a three-way tensor (Acar et al., 2005 and Kolda and Bader, 2006). While static networks have been extensively studied, few studies pioneered approaches to community detection in temporal networks (Gauvin et al, 2014) and, in particular, none of them addressed at the same time the issue of identifying communities and central nodes inside each community in dynamic networks. Our research fills this gap in the literature.

The paper is organized as follows: Section 2 presents the methodology; Section 3 describes the data and reports the main results; and section 4 concludes the paper.

2 Methodology

2.1 Tensor decomposition and community detection

A tensor is a multidimensional array. More formally, an N-way or N-th order tensor $\mathcal{X}$ is obtained from the product of N vector spaces, each of which has its own coordinate system.

The methodology described in this paper is based on a particular tensor decomposition technique, the so-called CP decomposition (named after the two most popular and general variants, CANDECOMP developed in Carrol and Chang (1970) and PARAFAC developed by Harshman (1970). It can be regarded as a generalization of the well known singular value decomposition (SVD) applied to tensors. If we focus on non-negative tensor decompositions (Cichocki et al., 2009), the methodology can be seen as a multidimensional extension of the HITS algorithm (Kleinberg, 1999), which provides two attributes for each node: an authority score and a hub score.

Authority measures prestige: the nodes that many other nodes point to are called authorities. A node having a high number of nodes pointing to it has a high authority value and this qualifies its role as a source of information. On the contrary, a hub is an actor referring to many authorities and its score measures acquaintance. In our context, countries with high authority score are systemically important importers while those having high hub scores are systemically important exporters. If we assign to each node a centrality score proportional to the sum of the scores of its neighbors, centrality results from a node having many neighbors, or from having some central neighbors, or both. Thus, two players will be ranked differently as hubs, even if they export the same volume, depending on the behavior of their importers: the algorithm will rank higher those that export to the most systemically important importer. The same happens for the authority score with respect to the importers: two players that import the same volume will be ranked differently, depending on the importance of the exporter they import from.

When a temporal dimension is included in the tensor, the CP decomposition provides a further score related to the temporal evolution of the activity level of countries over time. The value of the activity pattern in a time span is related to both hub and authority scores of all the players involved in the transactions that occur during a certain period of time.

The calculation of the hub, authority and time scores of different countries in the network provides the key elements of a decomposition that projects a tensor in a lower dimensional space, similarly to what happens in the well known principal components algorithm. As in the latter, scores can be employed to group countries into clusters, or "communities" consisting of countries that are "close" in the projected space.

To partition countries into communities we propose to employ a soft partition scheme, which does not classify a country node exclusively into one community, as in hard partition schemes but, rather, let a country belong to all communities, with different membership probabilities calculated by the model.

The detection of communities from the available tensor data requires the extraction of lower-dimensional components, which can be achieved by means of the CP decomposition. Solving this problem consists in finding the R rank-1 tensors that best approximate the tensor $\mathcal{X}$.

More formally, assuming the number of communities is fixed at R, let $\mathcal{X} \in \mathbb{R}^{I \times I \times K}$ be the third-order ultimate tensor. Our goal is to compute a CP decomposition with R components that best approximates $\mathcal{X}$, that is, to find

$$\min_{\widehat{\mathcal{X}}} \left\| \mathcal{X} - \widehat{\mathcal{X}} \right\| \quad \text{with} \quad \widehat{\mathcal{X}} = [\sigma; \mathbf{U}, \mathbf{V}, \mathbf{W}] = \sum_{r=1}^{R} \sigma_r \mathbf{u}_r \circ \mathbf{v}_r \circ \mathbf{w}_r \tag{1}$$

where R is a positive integer and $\mathbf{V} \in \mathbb{R}^{I \times R}$, $\mathbf{U} \in \mathbb{R}^{I \times R}$, $\mathbf{W} \in \mathbb{R}^{K \times R}$ and $\sigma = \|\mathbf{V}\| \, \|\mathbf{U}\| \, \|\mathbf{W}\|$.

Since data are non negative, representing flows of goods between importers and exporters, Pecora and Spelta (2017) have solved the above problem applying a non-negative tensor decomposition. Thus, for $r = 1, .., R$, we can obtain non negative hub, authority and activity pattern vectors $\mathbf{u}_r \geq 0$, $\mathbf{v}_r \geq 0$, and $\mathbf{w}_r \geq 0$. This is customarily used to achieve a purely additive representation of the tensor in terms of components, which greatly simplifies the interpretation of the resulting decomposition (Lee and Seung, 1999). We refer to Pecora and Spelta (2017) for further technical details.

From an interpretational viewpoint, we remark that the number R of components is chosen on the basis of the desired level of detail: a low number of components allows a better representation but may lead to loss of information, whereas a high number of components may lead to a better fit, but faces the risk of a complex interpretation.

It is straightforward to interpret $u_{ir} v_{ir} w_{kr}$ as the contribution, in terms of model fitting, of the r-th community to the edge $\mathcal{X}_{ijk}$. In other words, the interaction $\hat{\mathcal{X}}_{ijk} = \sum_{r=1}^{R} \hat{\mathcal{X}}_{ijk}^{r} = \sum_{r=1}^{R} u_{:r} v_{:r} w_{:r}$ between nodes i and j at time k is the result of the sum of their participation in the same communities (Psorakis et al., 2011; Mankad and Michailidis, 2013). Therefore, $\hat{\mathcal{X}}$ is a summation of R tensors and each $\hat{\mathcal{X}}^{r}$ denotes the number of pairwise interactions in the context of community r at time k. Thus $\hat{\mathcal{X}}$ is an approximation of the original tensor $\mathcal{X}$. In order to assign nodes to the communities, we first average over time the sub-tensor representing each community $\hat{\mathcal{X}}^{r}$ obtaining a matrix $\hat{\mathbf{X}}^{r} = \frac{1}{K} \sum_{k=1}^{K} \mathbf{X}_k$; then we calculate for each node its strength for every $\hat{\mathbf{X}}^{r}$ and we stack this measure in a matrix $\mathbf{D}^{I \times R}$ where each element d_{ir} represents the weighted degree centrality of node i in community r. Normalizing each row of $\mathbf{D}$ by $\delta_r = \sum_{r=1}^{R} d_{:r}$ we obtain the soft partition solution of the so-called degree membership: $a_{ir} = d_{ir}/\delta_r$. Such an edge decomposition can then be used also to assign nodes to communities according to a hard partition scheme, that is, assigning each node to the community in which it has the highest impact in terms of strength.

An important issue that arises in computing a CP decomposition is the choice of the number of rank-one components. Most procedures fit multiple CP decompositions with different number of components until a “good” enough one is found. Theoretically, if the data are noise-free and we have a procedure for calculating the CP decomposition with a given number of components, then the computation can be made for $R = 1, 2, 3, ...$ components and stopped at the first value of R that gives a fit of 100 percent. But, in practice, there are many problems with this procedure. When the data are noisy (as it is frequently the case), the model fit cannot determine the rank in any case; instead, Bro and Kiers (2003) proposed the Core Consistency Diagnostic (CORCONDIA) to compare different numbers of components, and this is the method we employ here.

Once the number of communities is determined, the tensor decomposition technique can be applied to assign countries to the different communities. The factor matrices $\mathbf{U}, \mathbf{V}, \mathbf{W}$ all have R columns, each one corresponding to the hub, authority and time activity pattern vector of one community. The matrix element u_{ir} indicates the export systemic importance of country i into community r. Similarly v_{ir} describes the import systemic importance of country i into community r. The element w_{kr}, on the other hand, associates each component r to the time intervals k that it spans, and the matrix values for a given component indicate the activity level of that community as a function of time (index k), i.e., its temporal activity pattern. The outer product $u_{:r}v_{:r}w_{:r}$ approximate the sub-tensor representing the spatiotemporal connections inside the r-th community $\hat{\mathcal{X}}^r$. The normalized strength $a_{ir} = d_{ir}/\delta_r$, computed over the time averaged matrix $\hat{\mathbf{X}}^r$ represents the degree of membership of country i in community r.

We remark that the assignment of countries to communities is probabilistic, that is, individual nodes can be members of different communities, with different weights. In this way, the non-negative factorization of the temporal network can naturally capture overlapping communities.

2.2 Tensor decomposition, synchronisation and crisis prediction

Tensor decomposition and community detection can be helpful to detect synchronicity in growth and trade patterns of different countries. Synchronicity refers to the relationship between the state of the system and the state of a set of exogenous variables that may affect it.

The relationship between trade and business cycle has been widely investigated and a range of empirical studies have found that country pairs that trade more with each other experience higher business cycle synchronization (see for instance Frankel and Rose, 1996; Frenkel and Rose, 1998). These papers, however, do not control for common global shocks, that could potentially drive the trade-business cycle relationship. When the latter are taken into account, the relationship becomes insignificant (see e.g. Kalemli-Ozcan et al., 2013).

To overcome this problem, we propose a Hidden Markov Model for the synchronisation between trade volumes and GDP growth rates, on top of the community detection model previously described.

A Hidden Markov Model (HMM) first assumes that an observation at time t is generated by some process, whose state S_t is hidden to the observer. Secondly, it assumes that the states of the hidden process satisfy the Markov property. Taken together, these Markov properties means that the joint distribution of a sequence of states and observation can be factorized as:

$$P(S_{1:T}, Y_{1:T}) = P(S_1)P(Y_1|S_1)\prod_{t=2}^{T} P(S_t|S_{t-1})P(S_t|Y_t) \tag{2}$$

To define a probability distribution over sequences of observations, all that is left to specify is a probability distribution over the initial state $P(S_1)$, the KxK state transition matrix defining $P(S_t|S_{t-1})$ and the output model defining $P(Y_t|S_t)$. HMMs usually assume that the state transition matrices and output models are not dependent on t, or in other words, the model is time invariant (except for the initial state). If the observables are discrete taking on one of the L values, the output can be fully specified by a KxL observation (or emission) matrix.

We remark that, to estimate the transition matrices from the observed sequence of emissions, given initial model state and emission, we use the Baum-Welch algorithm (Durbin, 1998).

A high level of trade and GDP growth synchronisation suggests that trade data may be employed to predict economic crisis and slowdowns.

The macroprudential policy frameworks (see e.g. Rhu et al., 2011; Brockmeijet et al., 2011), encourage the development of instruments targeting systemic risk. The operationalisation of those indicators requires the identification of early warning signals (EWS), aimed at predicting economic crisis, that could serve as the basis for the activation of macroprudential policies.

Early warning indicators of economic crisis were based, in the early stage, on cross-country ordinary regressions which provide a set of variables that explain the difference in the severity of the crisis faced by various countries (see e.g. Rose and Spiegel, 2012). However, few papers have addressed the issue that linkages between institutions themselves are the primary sources of crisis, and meaningful predictors of their intensity. Among them, Chinazzi et al. (2013) and Giudici et al. (2017) are the first trying to explore this important issue.

In line with the previous developments, we provide a method to evaluate the improvement in the prediction of economic fluctuations by using our proposed trade network model. Specifically, and without loss of generality we can define a country to be in a state of crisis when its GDP growth rate is less than a given threshld. We then compare the prediction on economic slowdown obtained by using the net exports (out-strength minus in-strength: $\hat{NX}_{cn,k}$) estimated by the model: $\hat{\mathcal{X}}$ with the predictions obtained using the empirical net exports (not "mediated" by the model: $NX_{cn,k}$): $\mathcal{X}$. In formulae:

$$\hat{NX}_{cn,k} = \sum_j \hat{\mathcal{X}}_{cn,j,k} - \sum_i \hat{\mathcal{X}}_{i,cn,k} \tag{3}$$

$$NX_{cn,k} = \sum_j \mathcal{X}_{cn,j,k} - \sum_i \mathcal{X}_{i,cn,k}, \tag{4}$$

We claim that our model-mediated net export produces a better predictive indicator, with respect to its empirical counterpart. To test our claim we briefly recall how to measure and compare predictive accuracy, in the context of early warning signaling.

The predictive power of two competing measures can be evaluated on the basis of the likelihood that the indicators are able to correctly signal the upcoming economic slowdown or crisis, while at the same time not issuing too many false alarms.

When a signal is produced (the value of the indicator is greater than a specified threshold) it is classified as correct if the economic slowdown or crisis follow within a specified time horizon (we employ a three-month) and it is classified as false otherwise. When a signal is not produced (the value of the indicator is smaller than a specified threshold), it is classified as correct when the economic slowdown or crisis does not follow, and as false if the economic slowdown or crisis materializes. The true positive rate (TPR) is defined as the ratio of correctly predicted crisis. The false positive ratio (FPR), on the contrary, is the fraction of signals wrongly issued. On the basis of the TPR and of the FPR one can compute the Receiver Operating Characteristic (ROC) curve plotting the TPR against the FPR, for different levels of the threshold. The predictive accuracy of a signal can then be measured by the Area Under the ROC Curve (AUROC), which ranges between 0 and 1, with hogher values corresponding to higher predictive accuracy.

3 Data and results

Although the world input-output table provides detailed breakdown information on the use of products according to their origin, either by a domestic industry or by a foreign industry, it covers only 43 countries among which only nine Asian and Pacific economies are included. To have a complete picture on Asian trade network, we hence turn to use International Monetary Fund (IMF)s Direction Of Trade Statistics (DOTS) . IMF provides data on the country and area distribution of its member countries monthly merchandise exports and imports as reported by themselves or by their partners. The value of export is reported on a Free On Board (FOB) basis while the value of import is reported on the basis of Cost Insurance and Freight (CIF). The data in our sample are expressed in million of dollars and cover 33 Asian economies, together with the main world economies including the US, the European Union and the United Kingdom, as additional nodes in the network. The long and wide coverage of IMF data allow us to map the evolution of Asian trade network and forecast the economic fluctuations associated with this network.

3.1 The evolution of the Asian trade network

We first employ some preliminary graphs to describe the evolution of the Asian trade network over time. Figure 3 shows the change, over the considered time period, of the density of Asian trade network with two indicators: the number of links between countries (in percentage over the total possible links) and the percentage of links that are reciprocated.

FIGURE 3 ABOUT HERE

Figure 3 shows that, in line with the increasing openness and intra-regional integration of Asian economies, the number of import/export links across countries have increased considerably, and are usually reciprocated: if there is an import link between the two economies, there is also an export link between them. Note also that the network becomes very dense after the year 2000, with 90% of all possible links being presented in the network, of which about 80% are reciprocated, indicating the full trade connectedness in Asia. This echoes the growing importance of intra-regional trade plotted in Figure 1.

To better understand how the network changes over time, Figure 4 exhibits four network representations of the most important import/export links, for the years of 2000, 2005, 2011, and 2015. These four years are chosen so as to make a comparison between the network constructed by the gross trade data with that by GVC data reflected in Figure 2. The width of each link is proportional to the corresponding trade volume.

FIGURE 4 ABOUT HERE

Figure 4 shows that the trade network in Asia becomes increasingly dense, reciprocal and clustered during this period of time, which is consistent with what we observe in Figure 2. Moreover, the visualization reveals the concentration of trade network around a few countries in all periods. In 2000, the most important export links shows that there are two main sub networks: the Asia-Pacific one, centered around the US, and the European one, centered around Germany. In 2005, PRC clearly emerges as a third center, for the Asian countries, and its role is magnified in 2011. This is consistent with the fact that PRC surpassed Germany as the second exporter since 2009-2010. In 2015 the three sub networks are confirmed, but export trade volumes decreased due to the change in world trade dynamics during and after the global financial crisis (Chora and Manovab, 2012; World Bank, 2009), as already observed in Figure 2. Overall, a notable feature observed across Figure 4 is the increasing interconnections of the network and the rise in the role of PRC as a central player in the network. All these stylized facts suggest the structure of the network reflected by the gross trade is comparable to that depicted by GVC data embedded in the World Input Output Table, confirming the robustness of our conclusions.

We further explore the trade partnership embedded in the network with two indicators of degree and strength in Figure 5. The out-degree counts the number of out-going links (export) originated from a country to its trade partners while the in-degree measures the number of in-coming links to this country (import). Similarly, the out-strength gauges the amount of export originated from a country to all its partners while the in-strength computes the amount of import flow into this country. In Figure 5, the top panel plots the in and out degree and while the bottom panel depicts the in and out strength, averaged over the sample period, for each country.

FIGURE 5 ABOUT HERE

From Figure 5 (top) we note that on average, Japan, India, Pakistan, Thailand and PRC have the largest number of in-degree while Japan, PRC, India and Singapore have the largest number of out-degree, indicating the high level of openness of these countries. More generally, the in-degree (import) is lower than the out-degree (export) for most countries. This means that countries, on average, export to a large set of other countries while import is more concentrated. From Figure 5 (bottom) we note that the Asian countries with the largest average strength are, as expected, PRC and Japan, followed by Hong Kong, China, Republic of Korea and Singapore, together with non-Asian countries of EU and US. Comparing in-strength with out-strength, all countries are quite unbalanced, with Asian countries more export oriented, and US and EU countries more import oriented.

Note that the summary of network representation in Figure 5 is averaged over time. To give a representation of the time dynamics, Figure 6 shows how the degree of each country has evolved over time, and Figure 7 does the same, in terms of strength.

FIGURE 6 ABOUT HERE

FIGURE 7 ABOUT HERE

The in- and out-degree figures suggest that most countries display a considerable increase in the number of trading partners, reflecting the remarkable globalization process achieved by Asian countries in the last few decades. However, the distribution of the strength is skewed towards the large economies of PRC, Japan, EU and US. Note that, while the degree measures increase over time, the strength measures show a substantial decrease for most countries during the 1997 Asian crisis and the 2008 global financial crisis (GFC). However, while PRC maintains its growing trend in both import and export even after the crisis, the trade volume of Japan declines after the GFC.

To complete the description of the Asian trade network, Table 1 summarizes the main network statistics for each country, aggregated over time: the In and Out degrees, corresponding to Figure 5, the In and Out Strength corresponding to Figure 6, the community membership probabilities corresponding to Figure 9. It also contains the hub and authority scores of each country in each community, which will be described in Figures 10 and 10.

TABLE 1 ABOUT HERE

3.2 The community structure of the Asian trade network

Having seen the most important descriptive statistics of the trade network, we now move to the detection of the relevant communities inside it. We apply the CP decomposition, introduced in Section 2.1, to our available trade data, represent them in tensor form and, consequently, obtain hub, authority and time scores, on the basis of which countries with similar scores can be grouped into homogeneous communities, according to the proposed soft partition algorithm.

To choose the number of communities to partition the countries, we applied the CORe CONsistency DIAgnostic (CORCONDIA) procedure, which guarantees a good balance between model parsimony and goodness of fit. We find that two community factors explain approximately 88 percent of the original data variability and, in addition, pass very well the test diagnostic. This suggest that our data can be very well described by two communities.

Figure 8 shows the probability for a country of belonging to one of the two communities that are detected in the network over all time.

FIGURE 8 ABOUT HERE

From Figure 8 we find that Community 1 has high weights in importer countries, such as the US and the European Union, whereas Community 2 has high weights in exporter countries, such as Republic of Korea and Oil producing countries of Bahrain, Iran, Kuwait, Omen, Saudi Arabia, and Yemen. Note that both PRC and Japan have similar weights in the two communities, with Community 1 prevailing for Japan, and Community 2 for PRC. We remark that Figure 8 shows a fuzzy assignment (soft partition) of each country along the two communities. However, a crisp assignment (hard partition) can be directly inferred from Figure 8, choosing the community for which each country has the maximum degree of membership. Doing so, Japan would be attributed to Community 1 and PRC to Community 2.

To further illustrate the structural difference of the two communities, we not only evaluate the probability of each country belonging to either community but also, inside each community, compute the relative weight of each country. To this end, Figure 9 displays the hub and the authority scores, in each of the two communities, for each country. The hub score in the top panel translates into the importance of a country in terms of export in each community.

FIGURE 9 ABOUT HERE

From Figure 9 PRC exhibits the highest weight in Community 1, while Hong Kong, China, the US, Republic of Korea, the European Union and Japan and Republic of Korea (in decreasing order) play the role of main exporters in the Community 2. The authority score displayed in the middle panel reflects the importance of a country in each community in terms of import. It displays that the roles of the different countries are overturned, with respect to the hub scores. PRC imports mainly from Community 2, while US, the European Union, Hong Kong, China, Japan and Republic of Korea mainly import from Community 1.

The observed dual role of the countries in two communities can be interpreted in terms of a global value chain: countries import from one community and export to the other, indicating that they are connected through a strong production network. In particular, what we find suggests two complementary network communities in the global value chain: in Community 1, PRC exports to Hong Kong, China, Republic of Korea, Japan, the US and the European Union. In Community 2, PRC imports from the same countries. The first community may be explained with the role of PRC as a supplier of intermediate goods to Hong Kong, China, Japan and Japan, which will eventually export final goods to the rest of the world. The second community with the role of PRC as importer of final goods from the other countries, with its large share of the worlds population.

We remark that, with a hard partitioning, these conclusions would not have been obtained. The bottom panel of Figure 9 reports the activity pattern of each community over time. It indicates that the activity of Community 2 exceeded that of Community 1 until 2002. However, Community 1 became more active thereafter. This finding is likely to be driven by the PRCs accession to WTO in the end of 2001, which dramatically increased the countrys export to the rest of the world. Note also that, during the 2008-2009 crisis, the importance of Community 1 shrinked, possibly due to a reduction in the demand of intermediate goods.

It is critical to assess how trade communities evolve over time. This is especially important in the light of the obvious structural changes of the Asian trade network we observe in the previous sub-section. To this aim, we repeatedly apply the community detection model, separately for each of the time period considered. Figure 10 presents the results.

FIGURE 10 ABOUT HERE

Comparing Figure 10 with Figure 9, we note that, while the role of Western countries, importers in the first community and exporters in the second, is stable over time, the last two decades emphasize the growing role of PRC, which substitutes Japan as leading exporter in Community 1 and leading importer in Community 2., consistent with the pattern displayed in Figure 9. Hong Kong, China and Republic of Korea, instead, maintain their role over time, although with a varying weights.

3.3 The Asian trade network synchronization

We now evaluate the synchronization of the trade network with the business cycle. We select a list of $C = 8$ countries, the largest ones in terms of GDP. For each country we measure two variables: the GDP growth rate, available on a quarterly basis, and the net export volumes, the difference between total exports and imports, available on a monthly basis. This leads to a total of 16 variables, indexed by time. We then fix rolling time windows of three years and, for each of them (t) we calculate the matrix of correlations between the corresponding series, leading to a $16X16$ matrix that describes pairwise synchronisations, between GDP and export volumes, both within and between countries, for period t. For each time period we then measure the number of synchronisation events, that is, the number of pairwise correlations that exceeds a threshold value (we consider 0.80 as a reference value). This count can be described as the time emission of the Hidden Markov model. We then assume that such emissions are generated by an underlying synchronisation categorical variable, with H unobserved states. We take H be equal to three hidden levels, and interpret them as indicating low, medium and high levels of synchronization. From an econometric viewpoint, hidden levels can be interpreted as regime switching states. The time evolution of the emission variable, which is the realization of a discrete process over time, is presented in Figure 11, together with the corresponding variation over time. In particular, the top panel illustrates the evolution over time of the emissions (the synchro- nisations events) both in absolute value (blue dots) and as a percentage over the considered 120 possible different pairs (red line). The bottom panel presents the first differences of the emission counts.

FIGURE 11 ABOUT HERE

Figure 11 clearly shows that synchronisation starts to increase in the 1990s, decreases sharply during the GFC, bounces back thereafter, but finally, falls. Moving on, from a descriptive to an inferential context, we assume that the emissions are the observed realizations of an underlying and unobserved discrete stochastic process, with three hidden states of low, medium and high. Using a Hidden Markov model, we can thus estimate, at each time point, what is the most likely level of synchronisation, among the three possible ones. Figure 12 shows, for each time point, the evolution of the estimate level.

FIGURE 12 ABOUT HERE

The estimation shows an increase in the level of synchronization over time, moving from an initial low level, to a medium one in the 1980s, and to a high level with the new millennium. However, it reverts to a medium state in the last few years, in correspondence with the slow down in world trade.

We further verify whether synchronisation is affected by community membership. To this end, we perform the previous HMM analysis separately in each of the two communities. Figure 13 plots, for each time point, the estimated level of synchronisation, separately for each community.

FIGURE 13 ABOUT HERE

Figure 13 indicates that the evolution of the estimated synchronisation is similar in the two communities, confirming the general pattern we identified in the previous subsection.

3.4 Predicting GDP growth with the tensor network model

We use the trade network to predict the economic fluctuations for major Asian countries. Specifically, we test whether the model-mediated net exports produce better anticipatory signals for the occurrence of fluctuations than the signal produced by the observed (empirical) net exports. We focus the predictive assessment, without loss of generality, on four countries: PRC, Japan, Republic of Korea and Thailand. Based on the historical GDP growth record, we set a threshold value of 8% for PRC, 0% for Japan and Thailand and 2% for Republic of Korea respectively. The occurrence of an economic crisis (or slowdown) will be identified if their GDP growth rates fall below the thresholds. To quantify the improvement in predictive accuracy due to our model, with respect to the empirical counterpart, we compare, for any given threshold value, whether the detection of a signal exceeding the threshold is followed by the occurrence of a slowdown event three months later, from which a ROC curve can be derived.

Figure 14 shows, for each country, four different figures: (a) the GDP growth rate (red) together with the model-mediated net exports (blue); (b) the GDP growth rate (red) together with the empirical net exports; (c) the ROC curve measuring the predictive power for the model mediated net exports; and (d) the ROC curve measuring the predictive power for the empirical net exports. For all countries, the yellow bars indicate the economic crisis or slowdown periods, defined according to the previously defined threshold. Finally, for each country we also report the correlation between the GDP growth and the net export series, either model mediated or empirical.

FIGURE 14 ABOUT HERE

We start interpreting Figure 14 from the top left figures for PRC. The crisis bars are concentrated around the Asian crisis of 1997, the global financial crisis of 2007-2008 and the countrys recent slowdown. Both the model mediated and the empirical net exports are positively correlated with the GDP growth, showing that the trade surplus is positively correlated with GDP growth, as expected. However, the model mediated net exports display a higher correlation with the GDP growth, by about 11 percent points, pointing towards a better predictive capability of our model. This is confirmed by the fact that the model-mediated net exports show a better performance in predicting GDP crisis, with respect to its empirical counterpart: its AUROC is equal to 0.91 against 0.81. In a word, the model-mediated net exports produce a better crisis predictive signal, both in terms of a higher true positive rate and a lower false positive rate.

The top right panel of Figure 14 displays the prediction results for Japan. Although trade is not a good predictive measure of GDP growth, the model-mediated net exports produce a better early warning signal. The AUROC is equal to 0.53 against 0.41. The results for Thailand are similar to those for Japan. The results for Republic of Korea are instead similar to those for PRC, with trade being a good predictor for GDP growth, confirming that the model-mediated net exports produce a more informative signal, with respect to their empirical counterparts.

Overall, from an interpretational viewpoint, the forecasting superiority of the model- mediated net exports can be explained by the fact that the model purifies data from noise. Moreover, hub and authority measures are feedback centralities, that take into account not only first order trade interactions (as the empirical measure) but also higher order interactions.

4 Conclusions

This paper presents a new methodology to map the dynamic trade network and to assess its strength on spreading economic fluctuations at different periods of time in Asia. We not only enrich the existing researches on trade networks but also contribute to the ecoomic and financial stability literature in two main directions.

From an econometric viewpoint, we present a novel method, based on import-export trade network tensor decomposition and community detection, to derive centrality measures and, accordingly, rank countries in terms of their importance within their community. From an economic viewpoint, we present the first application of network modelling to trade between Asian countries, a region that is increasingly integrated and gaining growing importance in the world. The proposed model well describes interregional interaction between Asian countries and is consistent with the literature findings. Two trade communities are detected: the first may be explained with the role of PRC as a supplier of intermediate goods to Hong Kong, China, Japan and Japan, which will eventually export final goods to the rest of the world; the second with the role of PRC as importer of final goods from the other countries.

Our research also reveals that GDP and trade relationships display an increasing level of synchronization through time, which has decreased in recent times, consistently with the reduction in world trade. Finally, when applied to the prediction of economic slowdown, our proposed model well predicts the GDP growth of countries whose economies largely depends on trade, such as PRC. The model overperforms standard models as it correctly takes high order interactions between countries into account.

From a policy making perspective, our research provides, on one hand, a better understanding of trade networks between Asian countries and, on the other hand, it supplies predictive tools that can be employed, in an early warning context, to monitor and mitigate economic slowdowns, that depend on trade networks.

Future research may involve, from an applied viewpoint, extending the model to other world regions and, from a methodological viewpoint, extending the model to the consideration of multi-layer networks, in which each layer describes a different sector of the economy.

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Table 1: Main network summary measures, for each country, averaged over time: In degree, Out degree, In Strength, Out Strength, Community 1 membership probability, Community 2 membership probability, Community 1 Hub weight, Community 2 Hub weight, Community 1 Authority weight, Community 2 Authority weight.

Countries	In Degree	Out Degree	In Strength.	Out Strength	Comm.1 Memb.	Comm.2 Memb.	Comm.1 Hub	Comm. 2 Hub	Comm.1 Auth	Comm.2 Auth
Azerbaijan	9,644	8,396	100,157	262,280	0,756	0,244	0,005	0,000	0,000	0,002
Bahrain	20,696	18,197	394,930	188,318	0,291	0,709	0,001	0,001	0,001	0,003
Bangladesh	18,125	18,954	617,394	393,233	0,868	0,132	0,007	0.000	0,006	0,002
Brunei	14,503	11,974	123,983	257,029	0,479	0,521	0,001	0,001	0,001	0,001
Cambodia	12,606	12,726	219,119	115,625	0,808	0,192	0,002	0,000	0,002	0,001
PRC	21,781	24,244	22.199,821	29.641,006	0,488	0,512	0,433	0,003	0,000	0,451
HongKong	23,373	26,688	11.253,800	10.654,282	0,488	0,512	0,035	0,189	0,151	0,007
India	25,035	28,780	5.558,220	4.012,179	0,535	0,465	0,044	0,010	0,027	0,052
Indonesia	21,620	23,073	3.125,992	3.653,396	0,518	0,482	0,023	0,020	0,020	0,021
Iran	21,273	20,252	1.439,920	1.672,614	0,374	0,626	0,007	0,017	0,008	0,008
Japan	29,197	30,720	17.387,311	20.902,809	0,523	0,477	0,146	0,103	0,081	0,104
Jordan	21,159	18,262	386,656	105,548	0,381	0,619	0,001	0,000	0,002	0,004
Kazakhstan	10,403	11,103	408,486	833,265	0,678	0,323	0,014	0,005	0,005	0,004
Republic of Korea	23,313	20,325	9.110,661	6.603,894	0,237	0,763	0,002	0,130	0,059	0,065
Kuwait	22,388	19,615	643,147	1.502,975	0,416	0,584	0,010	0,009	0,002	0,007
Lao PDR	7,975	8,651	91,514	51,534	0,490	0,510	0,000	0,001	0,001	0,000
Lebanon	19,748	16,944	376,414	54,713	0,143	0,857	0,000	0,000	0,001	0,006
Macau	11,825	10,458	145,440	71,862	0,662	0,338	0,000	0,000	0,002	0,001
Malaysia	22,078	24,499	4.613,119	4.902,115	0,495	0,506	0,033	0,026	0,024	0,032
Myanmar	16,332	19,222	270,909	173,960	0,668	0,333	0,000	0,002	0,004	0,000
Oman	18,932	17,490	525,008	718,933	0,117	0,884	0,001	0,012	0,001	0,005
Pakistan	24,610	27,113	1.024,378	539,528	0,702	0,298	0,006	0,001	0,007	0,004
Philippines	21,459	23,109	2.007,102	1.487,067	0,563	0,437	0,013	0,006	0,013	0,014
Qatar	19,001	17,425	473,466	1.443,486	0,387	0,613	0,010	0,010	0,001	0,007
SaudiArabia	22,242	21,648	2.864,508	6.293,021	0,365	0,635	0,038	0,045	0,008	0,035
Singapore	23,893	25,045	7.365,139	7.624,116	0,428	0,573	0,048	0,038	0,027	0,064
SriLanka	18,374	19,130	324,204	243,319	0,706	0,294	0,003	0,000	0,001	0,002
Syria	20,522	15,974	251,049	208,132	0,581	0,419	0,002	0,000	0,001	0,002
Tajikistan	7,615	5,923	48,285	16,923	0,841	0,159	0,000	0,000	0,001	0,000
Thailand	23,944	26,793	4.132,148	4.092,076	0,489	0,511	0,031	0,021	0,022	0,033
UAE	17,001	17,094	3.089,506	3.318,525	0,355	0,645	0,014	0,016	0,015	0,036
Viet Nam	18,555	15,596	2.078,210	1.768,388	0,646	0,354	0,023	0,011	0,024	0,015
Yemen	13,015	11,386	182,215	127,989	0,313	0,687	0,000	0,001	0,001	0,001
European Union	23,606	25,016	19.010,592	16.409,477	0,568	0,432	0,022	0,183	0,218	0,000
United Kingdom	22,584	24,616	2.999,618	2.125,468	0,660	0,340	0,004	0,016	0,032	0,002
US	22,445	24,433	19.994,524	12.367,863	0,654	0,346	0,022	0,123	0,234	0,013

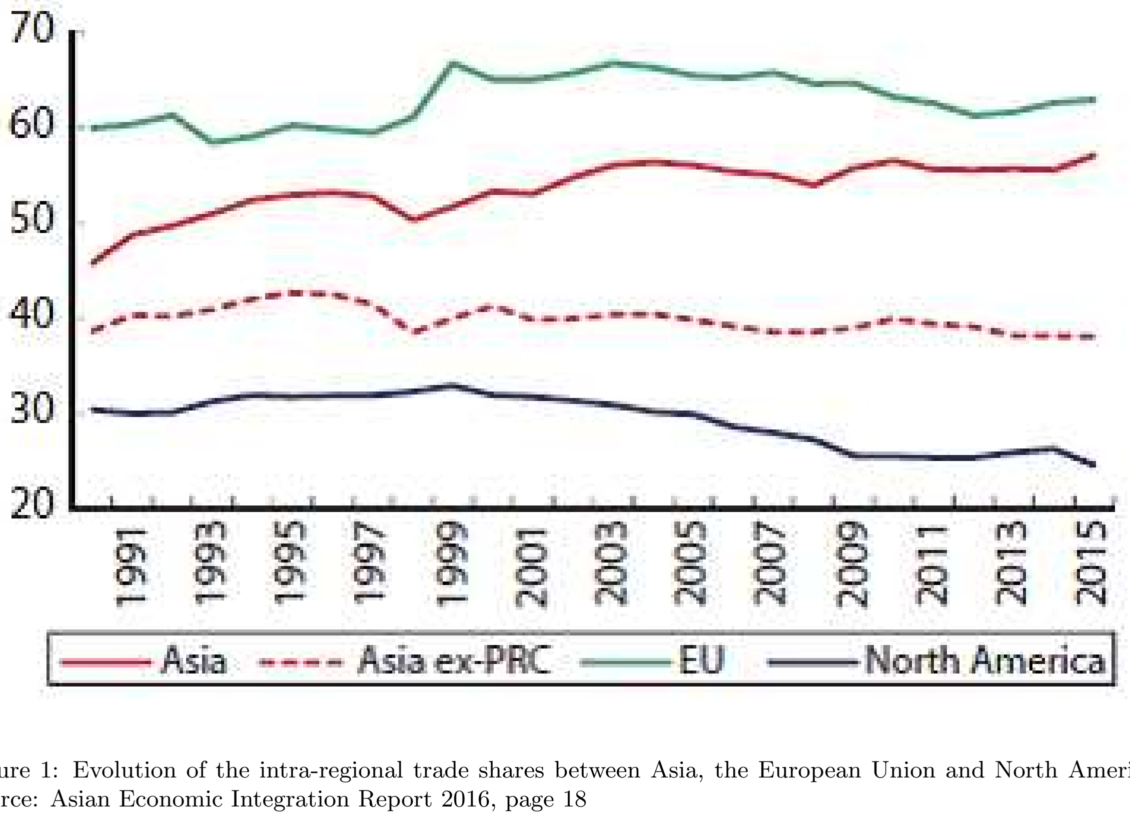

Figure 1: Evolution of the intra-regional trade shares between Asia, the European Union and North America. Source: Asian Economic Integration Report 2016, page 18

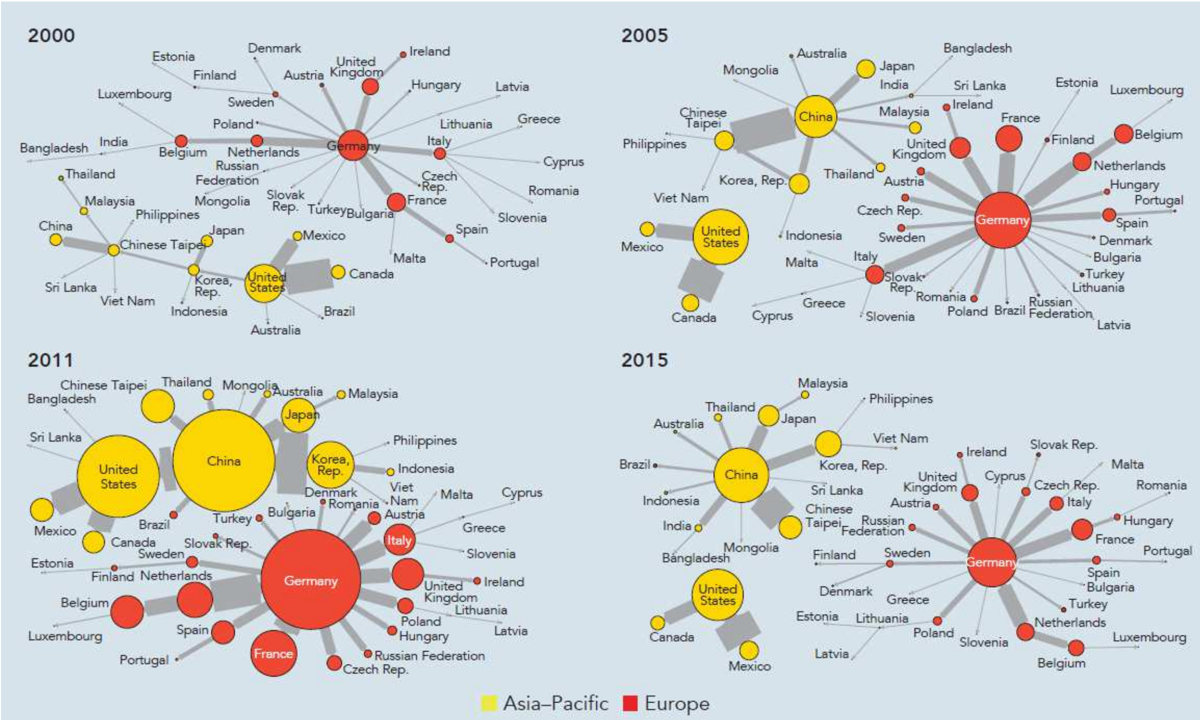

Figure 2: Networks of bilateral manufactured exports, in 2000, 2005, 2011, 2015. Source: Global Value Chain Development Report 2017, page 51

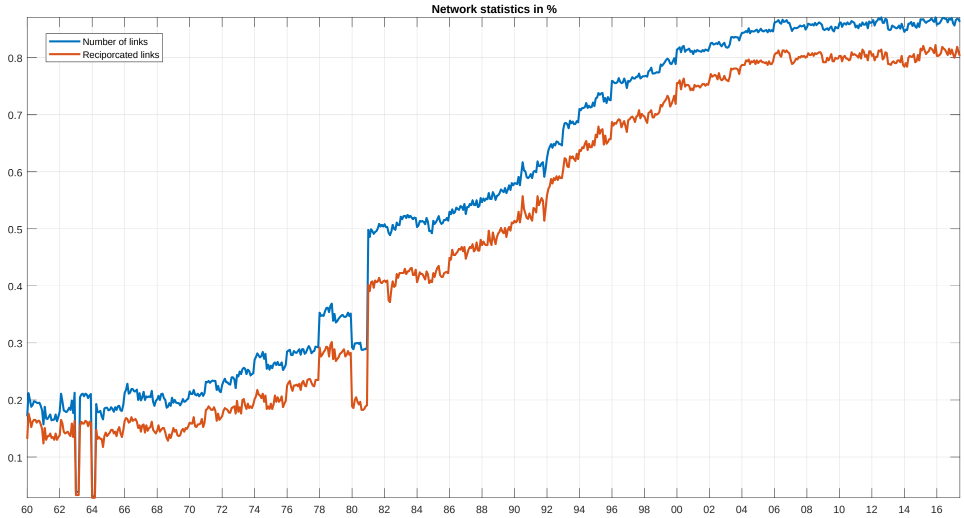

Figure 3: Number of trade links and number of reciprocated links, in percentage, along time.

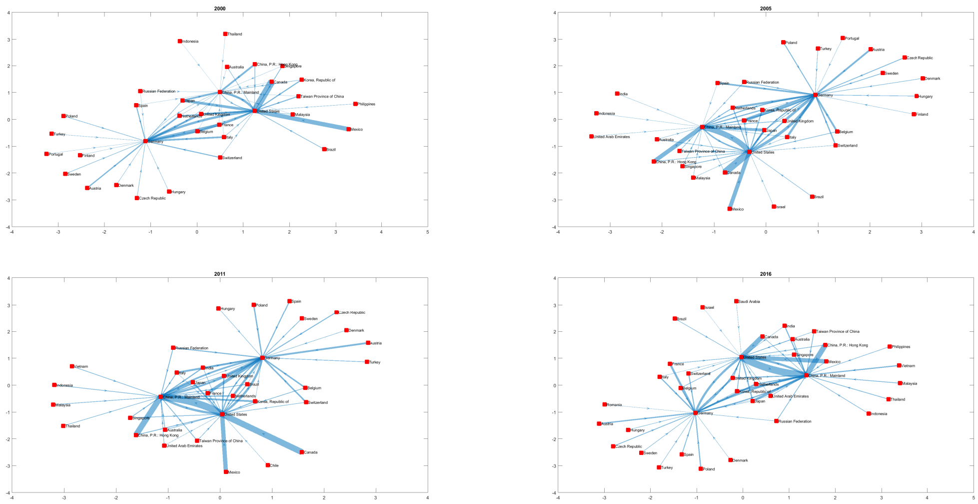

Figure 4: The recent evolution of Asian trade: the most important import-export trade links in 2000, 2005, 2011 and 2015 (reading clockwise). The width of each link is proportional to the corresponding trade volume.

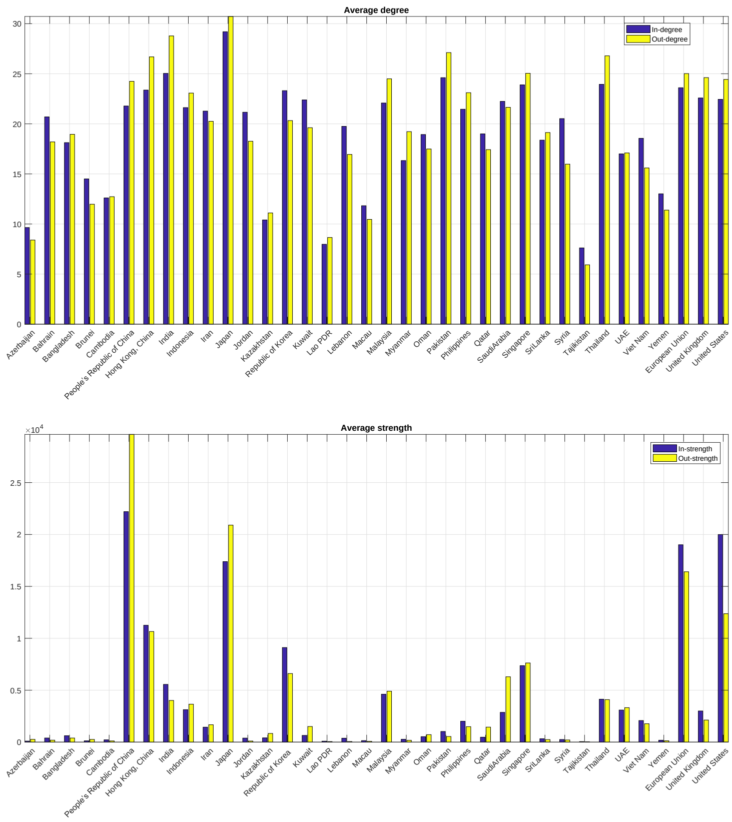

Figure 5: Asian countries trade: average degree (top) and average strength (bottom) of each country, both In (import) and Out (export). The degree is measured by the number of links, the strength by trade amount, in millions of US dollars.

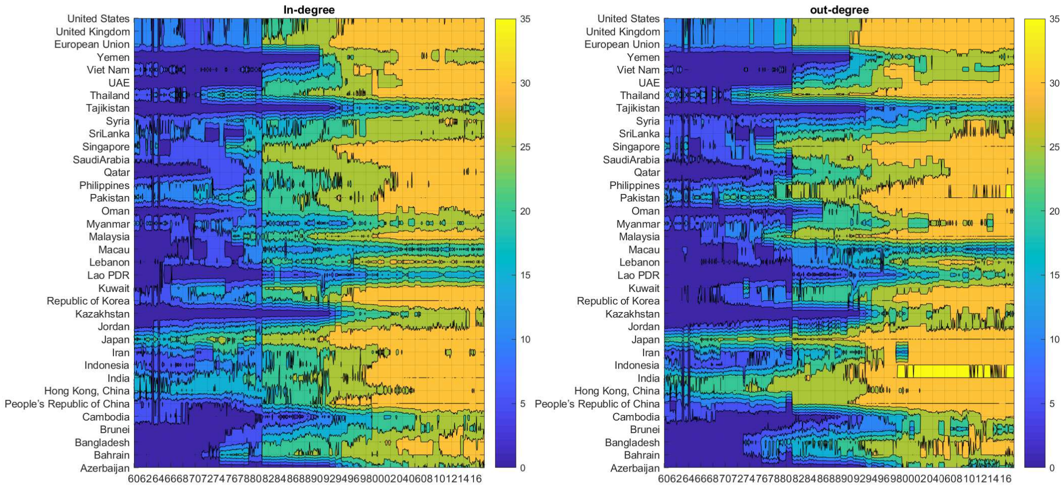

Figure 6: Asian countries trade: evolution of country In and Out degrees over time

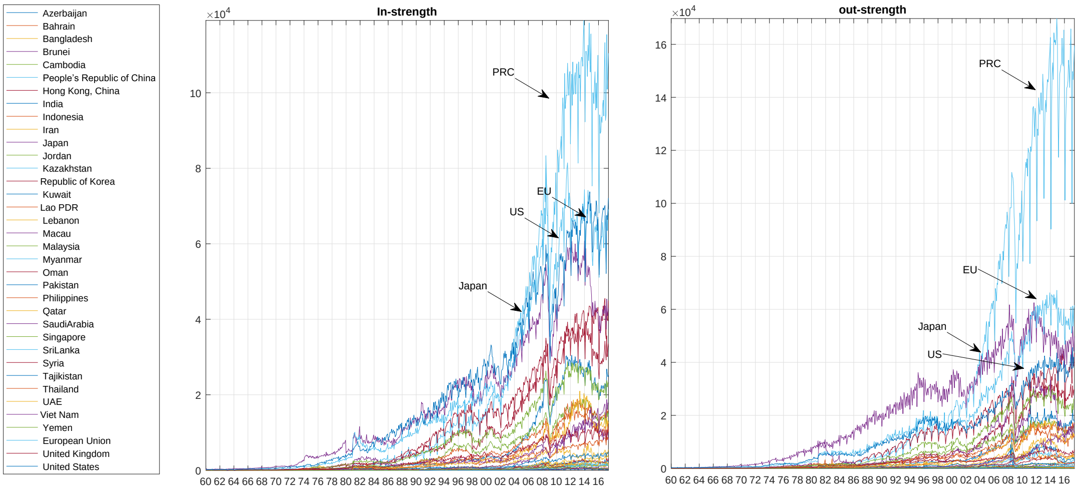

Figure 7: Asian countries trade: evolution of country In and Out strength over time

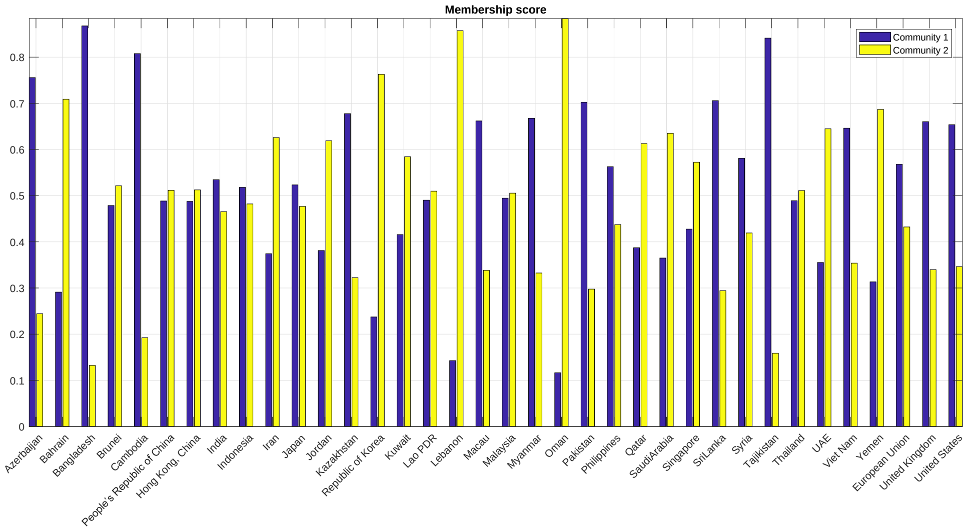

Figure 8: Community memberships: for each country, the probability of belonging to one of the two identified communities

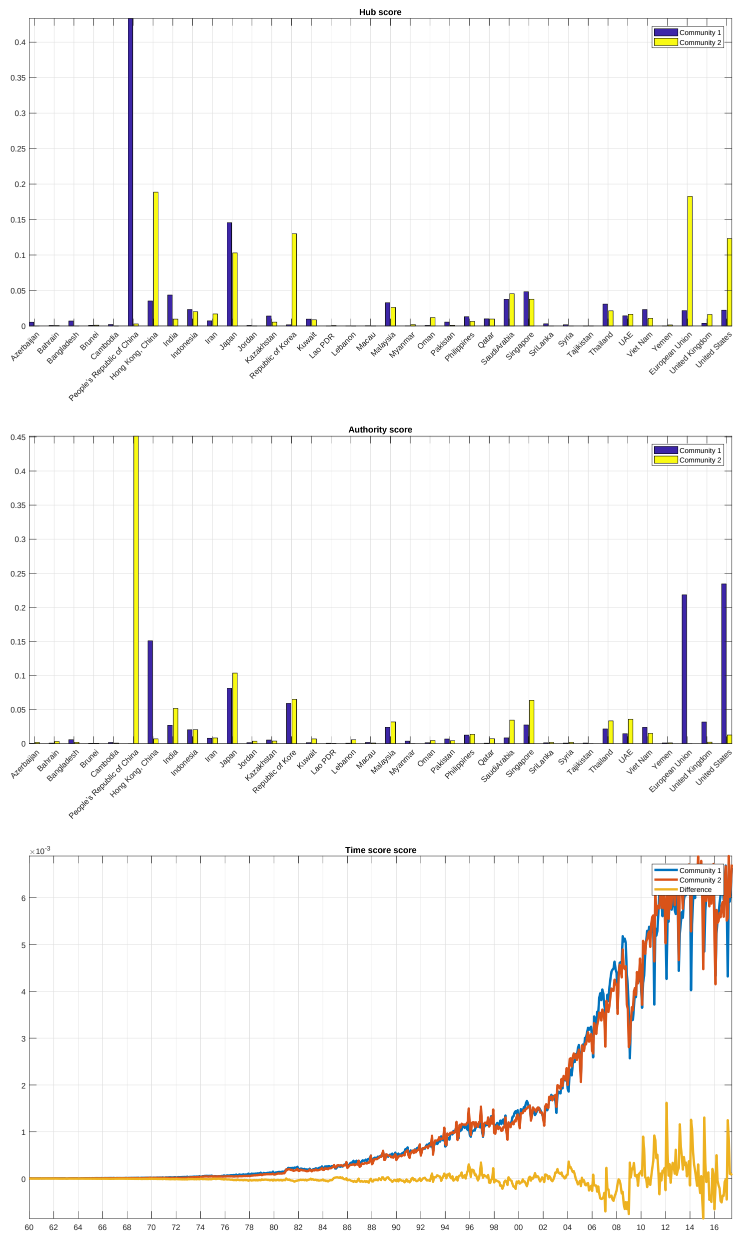

Figure 9: Community hub, authority and time scores (reading from top to bottom)

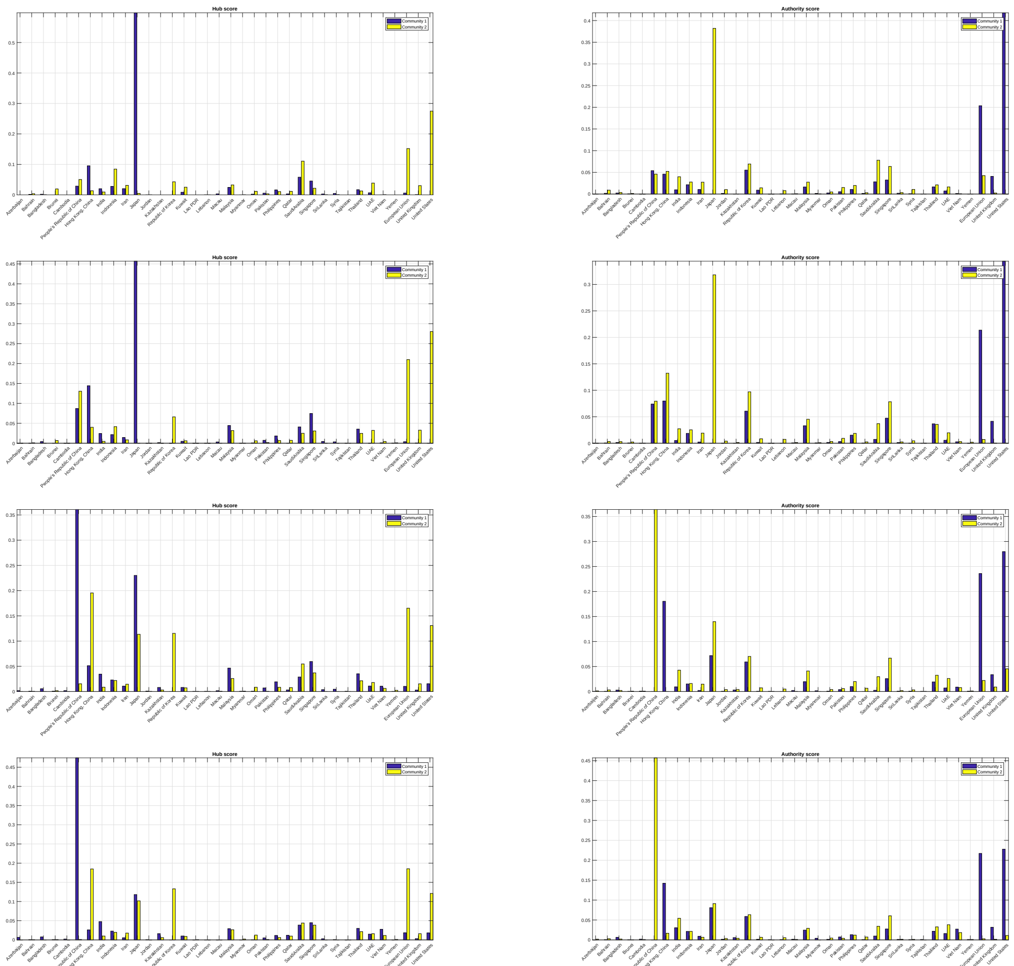

Figure 10: Evolution of communities over time: hubs and authority scores in the two communities, for the periods 1978-1987 (top two figures), 1988-1997 (second row figures), 1998-2007 (third row figures), 2008-2017 (bottom figures).

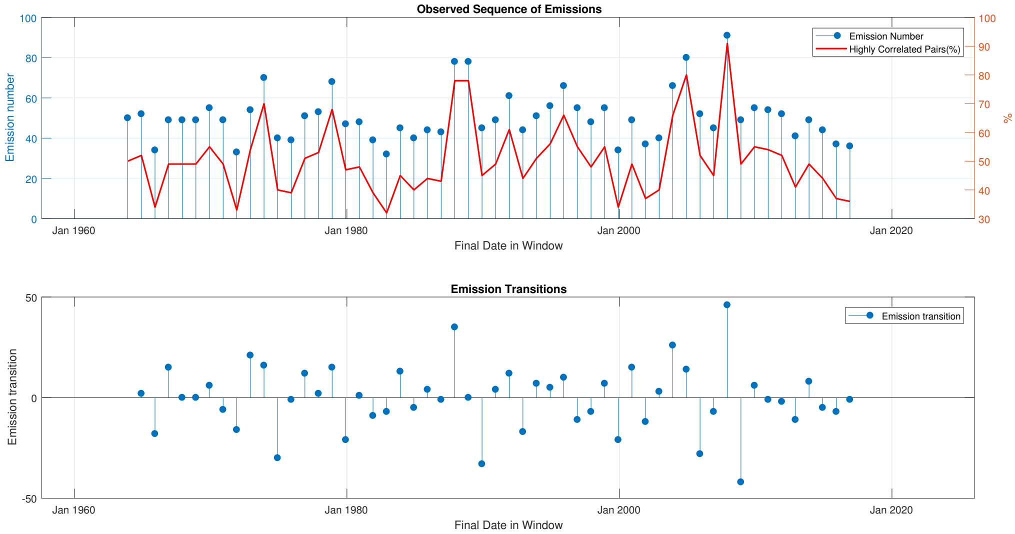

Figure 11: The observed synchronisation events (emissions): the number of pairwise correlations greater than 0.8, among the sixteen considered variables, two per country: GDP growth and Net exports, for the largest eight countries.

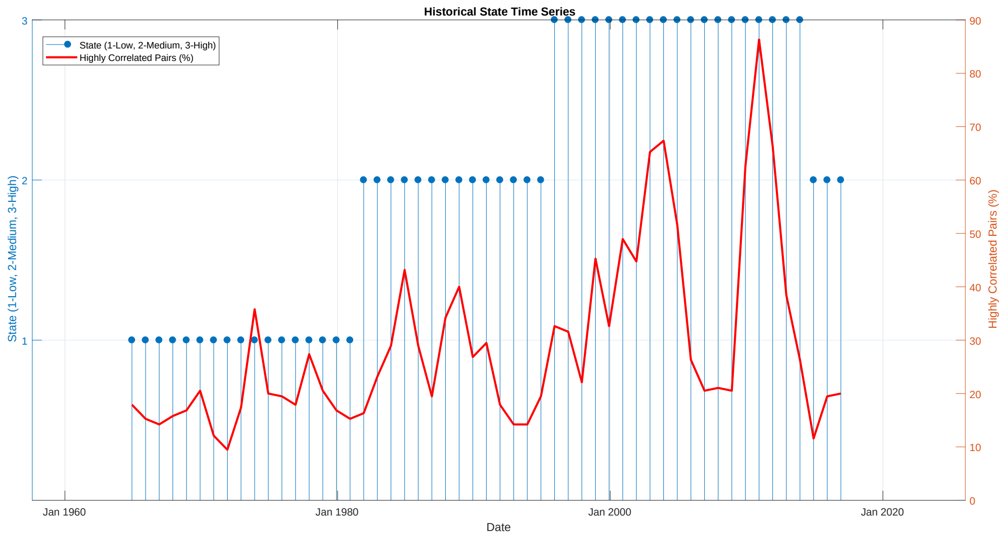

Figure 12: Estimated synchronization level, along time.

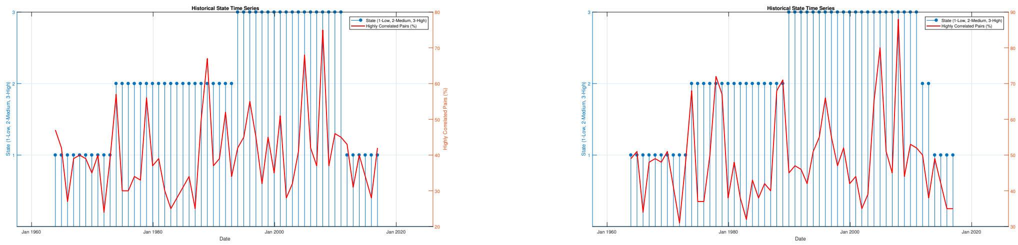

Figure 13: Estimated synchronisation level along time, for each community. Left panel: community 1. Right panel: community 2.

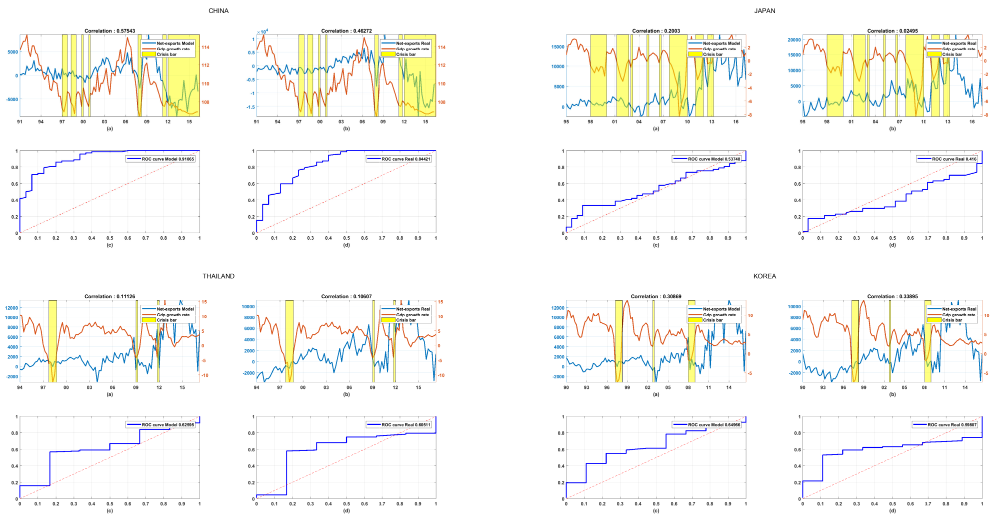

Figure 14: PRC, Japan, Thailand and Republic of Korea GDP growth rate along with estimated net exports, model mediated (panel a) and empirical (panel b) together with ROC curve and AUC value, corresponding to the model mediated net exports (panel c) and empirical net exports (panel d)