THE RISE OF CHINA IN THE GLOBAL PRODUCTION NETWORK: WHAT CAN AUTOCATALYTIC SETS TEACH US?

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The Rise of China in the Global Production Network: What can Autocatalytic Sets teach us?

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Abstract

In this paper we revisit the emergence of China as a dominant player within the world economy by using the innovative framework of autocatalytic networks. Specifically, we build and apply an autocatalylic sets detection algorithm to a world input-output (IO) network built from the WIOD database, covering the 2000-2014 period. From this analysis, we identify two key turning points in the course of China development: First, the year 2005, when a Chinese densifying local autocatalytic set branched to a global one, unraveling the complementarity between domestic and international cyclical IO connections in the course of China development. Second, the year 2013, when key Chinese industries replace their U.S. counterparts at the core of the global autocatalytic set, revealing an economic rivalry between these two large economies specifically for their role and position in the global production network.

Keywords: Autocatalytic networks, Trade, Input-Output tables, China.

JEL codes: F63, O14, 053, D57.

1 Introduction

Two decades after its accession to the World Trade Organization (WTO), China has become one of its most prominent members. With the reform process started by Deng Xiaoping, China successfully transitioned from a protectionist country to an outward-oriented open economy, and Chinese integration into the global economy has become one of the main drivers of its economic development.

However, from conventional economic growth and trade models, the reasons behind the unique success story of the Chinese economy are not clear. One could explain the rise of China as a direct consequence of its openness to world markets. But several other developing countries joined the WTO during the same period, and hardly any of them exhibited the same successful industrialization and technological catching-up pattern as China did. Others could emphasize the unique size advantage of the Chinese economy. However, other large outward-oriented emerging countries such as India, Indonesia, or Brazil have not been as successful as China[1]. On the other hand, success stories of small economies that also managed to industrialize through their access to global production networks exist, as for example the so-called East Asian Dragons[2] in the '70s and the '80s.

On the empirical side, the increasing availability of international trade data, and the recent releases of various Global Multi-Regional Input-Output (GMRIO) datasets allow for scrutinizing in more detail the specific dynamics of the Chinese industry structure and product space over the last decades. In this vein, some earlier contributions have already highlighted the rise of China within trade networks and global value chains (see in particular Zhu et al., 2014; Li et al., 2014; Baldwin and Lopez-Gonzalez, 2015; Cerina et al., 2015; Amador and Cabral, 2017; Xiao et al., 2020; Adarov, 2021; Coquidé et al., 2023; Pu et al., 2023) that will be reviewed in details in the next section). While this literature has already provided fascinating new stylised facts about the dynamics of Chinese industries within the world trade and production productions, none of these earlier contributions has explored yet the underlying mechanisms that have driven the China miracle emphasising its intrinsic rival nature as we do in this paper.

In order to delve deeper into the Chinese economic miracle, we propose an exploration of the dynamics of Chinese national and international Input-Output (IO) relationships, based on the concept of circular causation mechanisms. Specifically, our working hypothesis is that cyclical structures in

[1] For example, Torres Mazzi et al. (2021) questions the beneficial effect of global value chains expansion on the Brazilian economy emphasizing the absence of positive impact on the performance of Brazilian exporting firms.

[2] This group of countries refers to South Korea, Singapore, Taiwan, and Hong Kong.

industry linkages are particularly beneficial, as they can drive the processes of cumulative causation that sustain the expansion of economic activities. To develop this idea in a objective and systematic fashion, we use the framework of autocatalytic networks proposed by Jain and Krishna (1998) (J&K1998 afterwards) and further developed in Jain and Krishna (2001) and Jain and Krishna (2002b). We apply this innovative framework to a multi-regional multi-industry network that we construct from the second release of the World Input-Output Database (WIOD) provided by the Groningen Growth Development Center (GGDC) and covering the period 2000-2014.

Our network display all directed input linkages from any selling industry to any buying industry covered by our database. We then identify cyclical structures in our directed world input-output network (WION) and devote a lot of attention to the evolution of Chinese industries within both local and global autocatalytic structures in this WION. More specifically, our approach allows to detect several Autocatalytic Sets (ACSs afterwards) and to trace how various industries are linked within each set and across them. It thus provides a new perspective on the shifting position of Chinese industries, emphasizing the local and global industrial linkages that have served as stepping stones for China's industrial development post-WTO accession, and how these two types of linkages complement each other.

Our main results are as follows. First, we show that the WION is characterized by one global ACS and several local ones. The unique global ACS is made of both intra-country and inter-country IO relationships, while the local ones are mainly based on domestic IO relationships. Second, we show that some key Chinese industries were part of an isolated local ACS which densified continuously between 2000 and 2004 and then, in 2005, a group of Chinese industries branched themselves to the global ACS. This result offers new insights on how local and global production networks complement each other in the industrial development of an emerging economy. Third, we identify another key turning point in the course of China's development: the year 2013, when Chinese industries moved from the periphery to the core of the global ACS, while U.S. industries experienced an opposite move from the core to the periphery of the global ACS. This last stylized fact is new to the literature. Specifically, while some earlier contributions emphasize the peripheralization of Japanese industries that occurred in the late 2000s as a consequence of the strengthening positions of Chinese industries in global production networks (Li et al., 2014), none has yet identified the peripheralization pattern of U.S. industries in the early 2010s. This could be spotted in our analysis through the lens of autocatalytic networks.

The rest of the paper is organized as follows. In Section 2, we present an overview of the relevant empirical literature while in Section 3, we present our theoretical framework grounded into auto-catalytic networks. Section 4 introduces our database. In Section 4.1 we describe our methodology. Section 5 discusses our main findings while Section 6 tests their robustness. We present our concluding remarks and avenues for further research in Section 7.

2 Literature review

A large body of literature has already explored China's economic rise, which began in the '80s. This literature agreed on the fact that the radical shift in China's international trade policy after Mao's death in 1976 has been crucial to its growth miracle. For instance, Wang (2008) describes two major features of the Chinese economy before Deng Xiaoping's rise to power. The first is the high level of isolation of the Chinese economy, due to an active inward policy aimed at self-reliance and independence from the Socialist world. The second feature is the extreme concentration of Chinese industries engaged in international trade, limited to a small number of specialized state-owned industries.

This period of isolation ended with Deng Xiaoping's "open-door" policy, established in 1978. China adopted an economic strategy focused on diversifying its trading partners. There was a gradual decentralization of the economic system and an end to the central planning policy. Companies were allowed to receive foreign investment to boost their exports, and, on the import side, tariff and non-tariff barriers were drastically reduced throughout the '80s and '90s. Unlike other developing countries that opened their economies to trade during the same period, China succeeded in aligning its trade policy with its own industrialization strategy. Specifically, what China exported proved crucial for its industrialization and technological catching-up dynamics (Rodrik, 2006). For an overview of the policies and institutions that have shaped this industrialization process, see Huang et al. (2017).

When China officially joined the WTO in 2001, it was already a significant trade player. However, Chinese industries were not yet the central nodes in global value chains (GVCs) that they have since become. The expansion of GVCs began in the mid-'90s, spurred by the new opportunities for international division of labor offered by the digital revolution (Baldwin, 2012 and 2017). The question then arises: why did Chinese industries benefit so much from this new trend? Certainly, relatively low labor costs are part of the answer. However, they cannot be the full explanation, as many other developing countries also had low wages, but hardly any of them succeeded in attracting the production stages of foreign multinationals as China did (Baldwin and Lopez-Gonzalez, 2015).

The emerging literature on network applied to trade and production networks offers new understanding on the pattern of trade and development. For instance, De Benedictis and Tajoli (2011) introduce the International Trade Network (ITN) by applying network modelling to international trade data. The ITN is a network in which each node is a country, and each flow represents the size of the export flow from one country to another. On the other side, Carvalho (2013)) introduce several production networks using input-output data at the local, national and international level. Among these networks lies the World Input-Output Network (WION) in which each node is a couple Country-Industry (CI), and each flow represents the size of the input flow from one CI to another. Both these approaches, based on either the ITN or the WION, provide new insights into the Chinese miracle by examining the evolving position of this country in the world economy through the lens of network analysis[3] .

Starting with trade networks, Zhu et al. (2014) find a strong evolution of the Chinese position in the ITN built from the CEPII BACI Database over the period 1995 and 2011. They apply community detection and community core detection algorithms to the ITN to analyze both global dynamics, through the evolution of communities over time, and regional dynamics, recording the evolution of the core of each of those communities. Several communities were detected, including an Asia-Oceania community that was initially led by Japan until its integration into the U.S. community in 2002-2004 and finally reemerged with China as its core between 2005 and 2011. However, aggregated data at the country level does not allow to tackle the complex industrial dynamics that have occurred during China's development.

More recently, Coquidé et al. (2023), building a ITN from the United Nations Comtrade database covering the 2010–2020 period in order to study a mathematical model of influence battle of three currencies, namely, the US dollar, the euro, and an hypothetical BRICS currency. In this model, a country trade preference for one of the three currencies is exclusively determined by a multiplicative factor based on trade flows between countries and their relative weights in the global international trade. Under this restrictive framework, they show that, as early as 2012 about 58% of countries

[3]ITN and WION have extensively been used in research about the propagation of shocks. For instance, a large body of literature has developed around what is called the *China Shock* after Autor et al. (2016). Part of this literature specifically uses GMRIO databases to measure the extent to which product and factor markets in high-wage countries have been impacted by the rise of Chinese manufacturing industries (see for instance Feenstra and Sasahara, 2018; Szymczak and Wolszczak-Derlacz, 2019). Our own research departs from this line of inquiry as our primary concern is about long-run development.

would have preferred to trade with the hypothetical BRICS currency, 23% with the euro and 19% with the US dollar. Interestingly, they also find that while the African continent is fragmented in 2010 between the influence of the three currencies, in 2019 almost all African countries come under the influence of the hypothetical BRICS currency. As China takes the largest part of the BRICS trade flows around the world, we interpret these results as providing some interesting empirical background to our own investigation about the rise of China in the international input-output network and the potential rivalry between China and some other large economies, primarily the U.S. one, for gaining key positions in the global production network.

On the side of production networks, Cerina et al. (2015) build a WION from the first release of WIOD covering the 1995-2011 period. While their exploration does not specifically focus on China, it allows for tracking the emergence of Chinese industries. In this earlier contribution, four centrality measures were computed for each CI: the Eigenvector centrality of backward linkage, the PageRank centrality, the Community coreness and the Laumas method of backward linkages[4]. According to each of these alternative measures, while dominant nodes are mostly U.S. and Japanese industries over the studied period, some Chinese industries begin to position high in these rankings from 2011 as for instance, the Chinese *Construction* industry.

As a companion paper of the previous one, Zhu et al. (2015) introduces a Global Value Trees framework to model each CI supply chain as a tree, with the supplying CIs being the roots. This framework allows for the visualization of the position and prevalence of a specific CI within the supply chains of other country-industries. The study reveals changing dynamics in the position of Chinese industries within these chains, such as shifts in the average number of intermediaries between Chinese industries and those of other countries. For example, this average number of intermediaries has increased for the Chinese *Textile* industry but decreased for the Chinese *Electrical equipment* industry.

[4] The Eigenvector centrality of backward linkages assesses a node's influence based on its connections to other influential nodes across the entire network. A strong Eigenvector centrality of backward linkages implies being supplied by the most influential CIs in the whole WION (Dietzenbacher, 1992). The PageRank centrality is a variant of Eigenvector centrality where a node's influence is determined by being downstream of the influential nodes among neighboring nodes. This is measured by introducing a dampening effect, reducing the contribution of nodes that are farther away in the network (Page et al., 1999).The Community coreness evaluates a node's centrality based on its importance within the multiple communities within the WWION, which are communities of CIs that trade more frequently among themselves than with the rest of the network (De Leo et al., 2013). finally, the Laumas method of backward linkages, grounded in the Leontief inverse, emphasizes the direct and indirect dependencies of each node on the final demand (Laumas, 1976).

More recently, Xiao et al. (2020) investigates the changes in topology and structure of Global Value Chains networks depending on the perspective, supply or demand, taken. They use the Asian Development Bank (ADB)'s multiregional Input-Output tables, which cover 62 economies and 35 sectors from 2000 to 2017, and show that the central role of China in the World Economy has especially strengthened on the demand side after its accession to the WTO. More specifically, they find that most of China's final demand used to be satisfied by its domestic suppliers in the early 2000s. However, the relative importance of imports for its final demand has continuously increased since. Because of this and the rapid rise in purchasing power, China is now an important point of demand in value-added embodied in traded final goods for several other countries.

Production networks have also be used to describe the change in the center of gravity in the world economy over the past two decades. In particular, Amador and Cabral (2017) show that the emergence of Chinese manufacturing industries as central supply nodes in global production networks has come at the expense of Japanese ones, comforting the earlier findings by Zhu et al. (2014). More specifically, in the last year of observation of the first release of WIOD, namely 2011, China had become part of the inner core of the value-added network in the world economy, partially replacing Japan. Focusing on Information and Communication Technologies (ICT) industries, Adarov (2021) further shows that a structural transformation occurred in the relative importance of countries, resulting in greater concentration of core activities in China. More specifically, the growing concentration of core ICT activities in China has been accompanied by the diminishing centrality, in the related global value chains networks, of ICT industries in a range of industrialized countries, most notably Ireland, Finland, Japan, South Korea, and the United States.[5] Finally, Pu et al. (2023) applies complex network analysis on a WION built from the EORA Database in order to shed new light on the production networks developing along the Belt and Road Initiative. The scope of their study is limited to Asian countries and Central and Eastern European countries. They find evidence of a core-periphery structure, with China, Russia, and Thailand as core countries.

Overall, while these previous contributions already point some rivalries between China and other economies either on a regional scale or for some specific industries like ICT, none of them make a general claim about the competing dynamics of China and the United State within the World

[5] These findings are based on the multi-country Input-Output database developed by the Vienna Institute for International Economic Studies (WIIW), which covers the period 2005–2018 (see Reiter et al. (2021) for more details on this database).

production network as we do in our paper based on the new stylised facts that the auto-catalytic network approach allows us to reveal.

3 Theoretical background

In this section, we present the framework of autocatalytic networks from Jain and Krishna (1998, 2001, 2002a), and we explain why this framework can serve as a guide for our empirical investigation about the rise of China in the global production network.

The original contribution of Jain and Krishna (1998) is a model of directed network formation, where autocatalytic sets form endogenously within a selective evolutionary process, resulting in self-sustaining structures. In this model, nodes represent species of a population, while directed links represent catalytic (let say 'beneficial') effects of a species onto another. Each node (species) is characterized by a fitness level that measures its 'performance', and that evolves based on the catalytic effect of incoming links. This is the so-called fast dynamics of the network in this model. Beside this, over a longer time scale, the population is reshuffled, with low-fitness species removed and replaced by new species, with random fitness levels, and connected at random. The crucial point of this model is that a reshuffling event involves not only the deletion of nodes but also of their links, and then a modification of the network topological structure. In particular, we must notice how this process has a selection bias, or drift, which endogenously shapes the network structure while determining a growth process of the overall average fitness.

The main result of Jain and Krishna (1998) is the emergence of *autocatylic sets* of nodes (ACSs), defined as those nodes that have at least one incoming link originating from a node that also belongs to the set. ACSs are self-sustaining structures where nodes catalyze each other. To illustrate this approach, we present in Figure 1 a simple directed network made of 9 nodes (A,B,C,D,E,F,G,H,I) in which one ACS can be detected.

More specifically, our simple network features one ACS made of 5 nodes (C,D,E,F,G) that can be further partitioned in two subsets of nodes:

- (i)The *core* made of 3 nodes {C,D,E} colored in red, each featuring both incoming and outgoing catalytic links with other nodes of the subset. This subset of self-reinforcing nodes serves as the 'engine' of the ACS. Each member contributes to the fitness of other members of the core, and at the same time benefits from other members. In larger networks, the core is made of multiple intertwined cycles. This circular structure induces multiple positive feedback

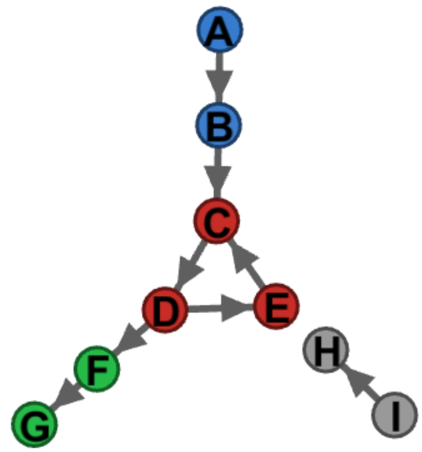

Figure 1: An exemple of an autocatalytic structure in a directed network

loops within the core. An implication of this structure is that each node is important to the fitness of all others, directly or indirectly. The removal of any node has a strong negative effect on the overall fitness, and also on the topological structure of the core.

- (ii) The *periphery* made of 2 nodes {F,G} colored in green, each receiving flows directly or indirectly from the core, but none having outgoing links to members of the core. This subset corresponds to nodes that benefit from but do not contribute to the preservation and growth of the ACS. This set is characterised by growth in fitness but is not useful to the growth of the system. Put differently, nodes in the periphery can be removed without any macroscopic effect on the rest of the network.

All other nodes of the network, namely {A,B,H,I} neither belong to the core nor to the periphery of the ACS. Among these remaining nodes, we further colored in blue the set of nodes {A,B}, that feed directly or indirectly some of the ACS nodes but do not receive any incoming links from them, and in grey the set of nodes that are strictly not connected to the ACS. According to Jain and Krishna (1998) framework, none of these nodes, whatever their color, are impacting the dynamics of the network as they are excluded by the fitness growth process of the ACS. This means that the removal of or shock on any of these nodes would be harmless for the rest of the network. The color discrimination, blue or grey, is only made for the sake of readability of our illustrations in the results section. Indeed, in our figures, we will usually fully abstract from the grey nodes while we will keep the blue ones to materialize country-industries that are not part of any ACS.

Various socio-economic systems with a network structure can be studied with the lens of this auto-catalytic framework (Napolitano et al., 2018). The closest application to our own study case is Bakker et al. (2014) which investigate the formation of autocatalytic cycles in a trade network built from United Nations ComTrade data. This paper proposes a set of variables that represent the participation of countries in autocatalytic trade cycles, and shows positive relationships between these variables and a variety of economic outcomes including trade flows, innovation, and economic growth. Interestingly, they also show that the relationship changes with autocatalytic trade cycle sizes, categories of goods and time scales.

In our application to the world input-output network (WION), the autocatalytic approach allows to uncover a number of interesting economic patterns. Firstly, we can search for ACSs in the WION, and study the evolution of ACSs over the period of data covered by the database. Secondly, we can trace the position of specific countries and industries in the global ACSs landscape. It is also noteworthy to consider that in the core of the ACSs that are detected in the WION, each node will both located upstream and downstream in the supply chain of other core members. This implies that a CI in the core is indirectly its own supplier and buyer at the same time, through connections of order higher than two. Consequently, core nodes create feedback loops that ultimately co-influence their economic performance. The existence of feedback loops within the network of buyer-supplier relationships creates incentives for cooperation between industries. This cooperation can materialize in pecuniary or technological externalities. Whatever the underlying mechanisms, the cyclical IO relationships can drive growth through cumulative causation.

The above mentioned features make the auto-catalytic theoretical framework a particularly relevant one for studying economic development. Indeed, as a country becomes more developed and therefore diversified, it transitions from reliance on extractive and agricultural sectors to manufacturing and service sectors, and at the same time witnesses an increase of the number of domestic linkages in its economy. GVC-led development also leads to an increase in international trading relationships between domestic and foreign industries. An increase in international trade creates a change in the IO structure of developing countries and creates co-movement between local industries and foreign industries.

In this research, we apply this framework to better understand the success story of the Chinese economy since its accession WTO. Conventional wisdom tells this success is one of a large economy opening to trade at a time when international transaction costs had become low enough to allow massive reallocation of production activities from high-wage countries towards low-wage countries.

Our approach rather emphasises the importance of domestic inter-industry linkage and cumulative causation mechanisms. We will see how the densifying of Chinese domestic inter-industry linkages preceded the expansion of Chinese industries in the global production network and then further accompanied it. This means that as China advanced in producing more complex goods and services, it also needed to develop more intricate domestic supply chains among a growing number of domestic industries.

This is not to say that in our approach trade openness is not an important part of the success story of the Chinese economy. On the contrary, key cyclical international input linkages will also play their part in driving the growth of Chinese industries. Still, our autocatalytic approach brings something new to the picture by emphasising a "zero-sum" aspect of this international contribution to the success story of the Chinese economy. It does so because it allows to visualize the emerging competition between China and the U.S. in the establishment of similarly intricate production structures and in particular the kind of race for the integration of foreign industries into one's own network of domestic production linkages that started to be at play between these two large economies in the late 2000's. In other words, autocatalytic networks provide a unique tool to gather information on the state of competition for gaining key positions in the network of economic trade at the global level. As we will see, a clear transition happened in the structure of the core of the largest ACS detectable in the WION, and this switch occurred at the benefice of Chinese industries and at the expense of both Japanese and U.S. ones[6].

[6]. Interestingly, this "zero-sum" aspect of open growth strategies fuelled by cumulative causation was also emphasised byLucas (1993), sketching a model of economic miracle that could fit the success story of the East Asian Dragons in the 70's and 80's.

4 Data and Methodology

4.1 The database

The WIOD is the outcome of a joint effort by a consortium of 11 research institutions led by GGDC and funded by the European Commission. It has become one of the most widely used GMRIO databases in the literature on global trade and production networks.[7] More specifically, WIOD is available in two successive releases. The first release, which occurred in 2013, covers the years between 1995 and 2011, while the second release, which occurred in 2016, covers the period 2000-2014. In this work, we use the most recent WIOD release.

One of the key advantages of WIOD over other available GMRIO databases is that it provides consistent annual time series over a large panel of country-industries and a detailed level of industry classification. In terms of country coverage, the WIOD 2016 release covers 43 countries, including all members of the European Union, some OECD countries, and especially those that play a large part in the global production system, such as the United States, Australia, or Japan, and large emerging countries such as Brazil, Russia, India, Indonesia, and, of course, China. Smaller emerging or developing economies are also included in the WIOD, but most of the time not individually, but rather aggregated in a Rest of the World (RoW) region (See Table 3 in the Appendix for the list of countries covered by the WIOD). In terms of industry coverage, the WIOD 2016 release covers 58 industries, which broadly follows the International Standard Industrial Classification (ISIC Rev.3), although some WIOD industry codes result from the aggregation of multiple 3-digit industry codes in the ISIC classification. The complete lists of industries covered by the WIOD are presented in the Appendix.

The structure of the WIOD is illustrated in Figure 2, with its three main sections identified by three colors: (i) the first section in green provides information on inter-industry flows, which will be the focus of our work; (ii) the second section in gray provides information on flows from industries to the final sectors of each country; (iii) the third section in blue provides supplementary information on each Country-Industry, most importantly their total value added and their factor endowments. In this research, we exclusively use the information from the first section of the WIOD, as our focus is on the autocatalytic properties of some global and local production systems and on how the Chinese economy took advantage of these autocatalytic structures to foster both its industrial

[7] For an exhaustive list of the empirical literature that uses WIOD data, references can be found on the WIOD webpage, www.wiod.org, while details about the construction of the database are in Timmer et al. (2015).

dynamics and aggregate economic growth.[8]

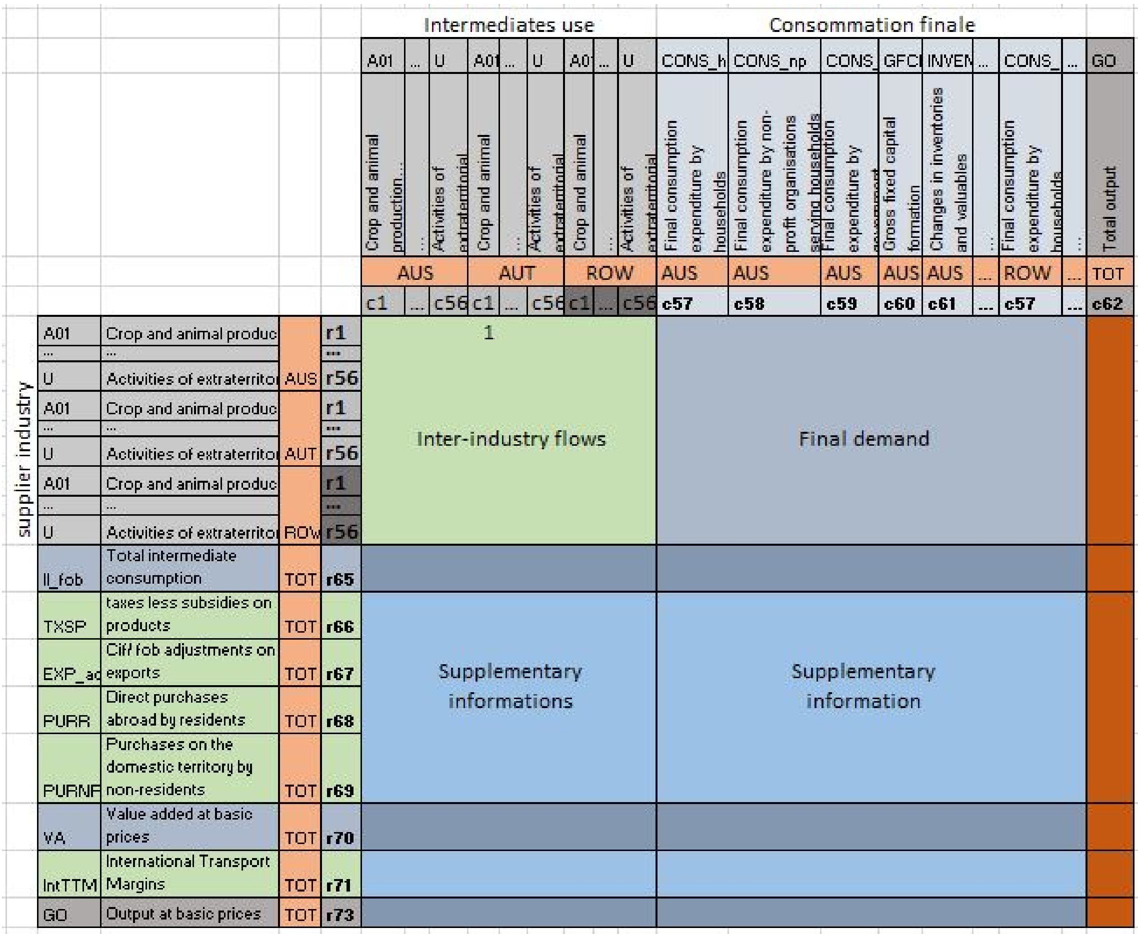

Figure 2: Structure of the World Input-Output Database (WIOD)

Note: The industry codes in the first column, from A01 to U, broadly follow the 3-digit ISIC rev. 4 industrial classifications. r stands for row and c stands for column. In the first raw, the value 1 indicates a flow of \$1 million worth of “goods and services” sold by the *Crop and animal production* industry in Australia (AUS-r1) to the counterpart industry in Austria (AUT-c1).

In what follows we explain how we built a directed input-output network from the WIOD data. We illustrate this process also presenting some meaningful descriptive statistics about the distribution and time evolution of incoming and outgoing flows to Chinese industries. We then explain the detection algorithm we implemented for the identification of ACSs in the network. We illustrate this second step with Figures of the largest ACSs found respectively for the initial and final years of our period of observation, namely 2000 and 2014.

[8] A possible extension of this research could consist in exploring cumulative causation mechanisms involving the interplay between the final demand sectors and the supply side of the WION. This is left for future research.

4.2 Building the WION

Following Cerina et al. (2015), we have constructed a raw WION for each year available, i.e. a spectrum of fifteen WIONs from 2000 to 2014. This evolving WION is made of all country-industries (CIs) couples as the nodes of the network, while the (directed) edges are defined by all reported values of goods and services flowing from any supplying CI to any buying CI. Considering both the country and industry coverages of the WIOD, our yearly raw WION is made of 2464 nodes (44 countries * 56 industries). As shown by the earlier literature, the raw WION is characterized by a high density of links, with a relatively large average of the degree distribution, and low hierarchy. Taken together, these features make it unlikely to detect small sets of strongly connected nodes, as all nodes are connected to all other nodes by a directed path. We have then filtered the raw WION, keeping only the largest flows. This filtering step is a necessary one before running our ACS detection algorithm in order to uncover meaningful cyclical structures. As a benchmark filtering threshold value, we chose an arbitrary absolute value of $10 billion. In Section 6, we test the sensitivity of our analysis to changes in the filtering threshold value, in order to warrant that our key results hare robust to the filtering process. Once the filter is applied, all flows above this threshold value are set to the value 1 (existing link), while all flows below the threshold are set to 0 (no link). This filtering step then turns our WION into a binary network of 0's and 1's, which represents the adjacency matrix of CIs in the global economy[9].

As a first application of our methodology, we study the position of China in the filtered WION by counting the numbers of (filtered) incoming and outgoing input links between Chinese and non-Chinese industries. We repeat this exercise for each year of observation and display the results in Figures 3 and 4 respectively for incoming and outgoing input linkages.

[9] Note that this binary network is similar to the first J&K model (Jain and Krishna, 1998). In the second version of the J&K model (Jain and Krishna, 2001), a weighted network is considered, which allows extending the theoretical results found in the first model to a more general setting.

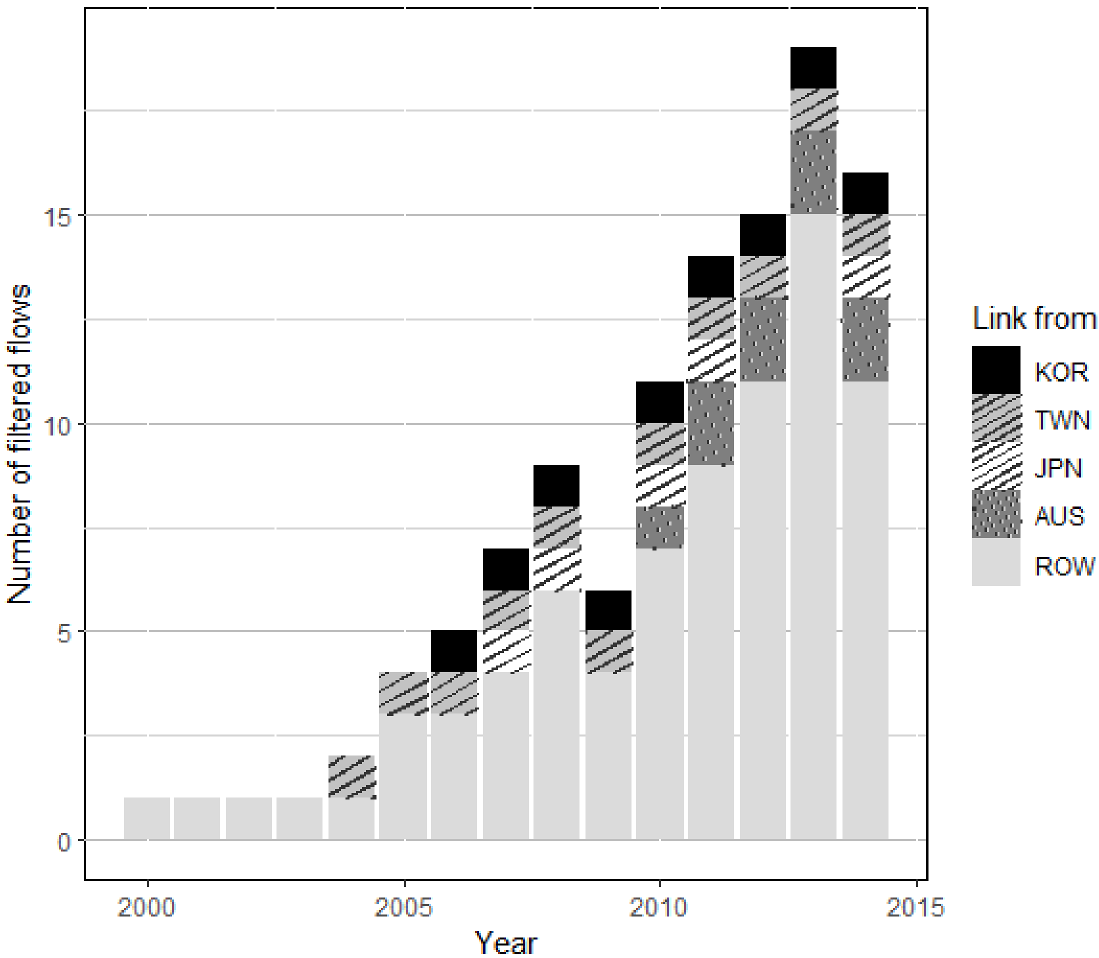

Figure 3: Chinese incoming input linkages, by provenance

Note: This figure counts the number of incoming input linkages above the 10$ billion threshold, and shows their provenance.

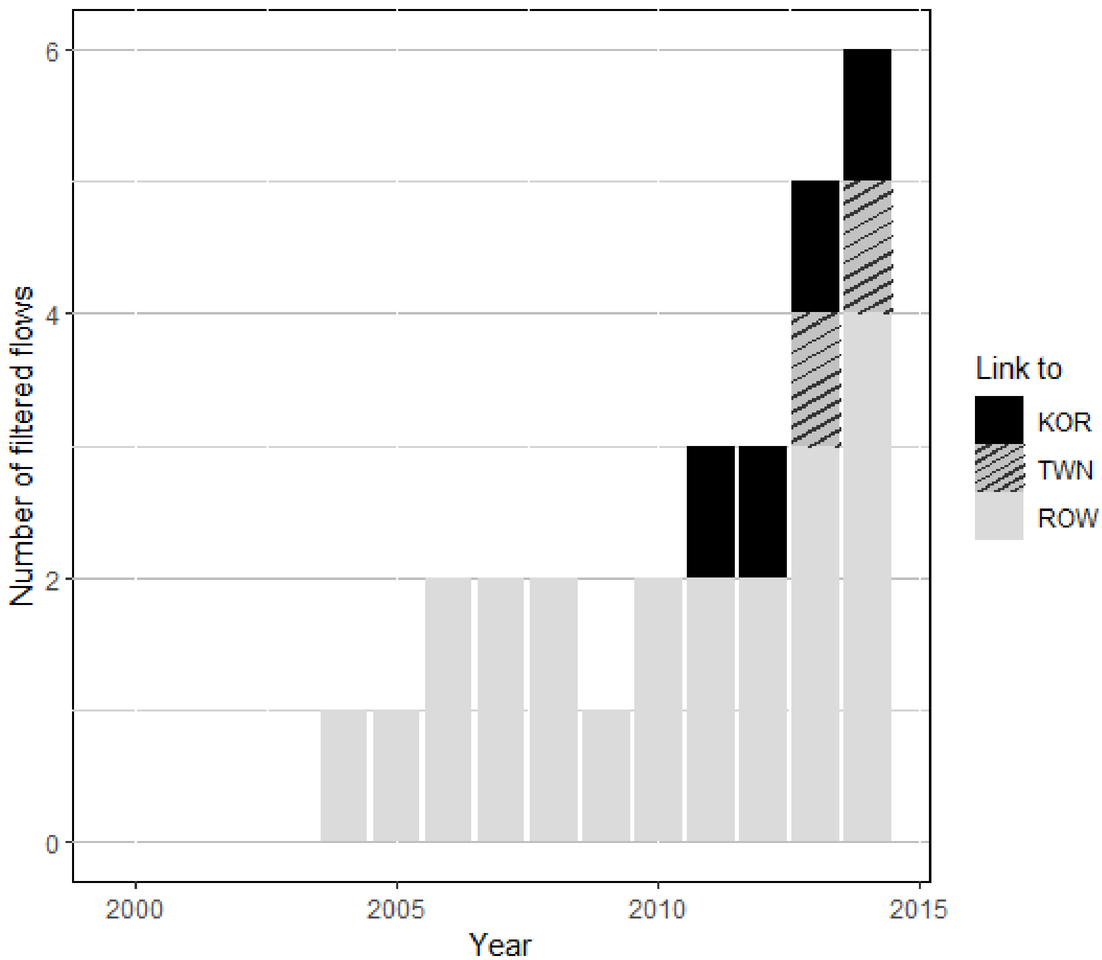

Figure 4: Chinese outgoing input linkages, by destination

Note: This figure counts the number of outgoing input linkages above the 10$ billion threshold, and shows their destinations.

Observing first the distribution of incoming large input flows to China (Figure 3), the most striking feature is that the U.S. industries never appear to be direct suppliers of such flows to the Chinese industries. By contrast, the RoW region is the most important and dynamic origin of inputs sourcing for Chinese industries. From 2004, South Korea, Taiwan, Japan and Australia, became 3 other key input sourcing origins for China. However, none of these countries reach the importance of the RoW region [10]. Turning to the distribution of outgoing input flows (Figure 4), our statistics again reveal strong linkages between China and the RoW region. From 2011, only two

[10] This trend is primarily driven by primary resources linkages with for instance the largest inputs flowing from the RoW *Mining and quarrying* Industry (ROW4) to the Chinese industries . This shows the extent to which China extracts resources from the RoW countries to fuel its industries.

other countries appear as key destinations of large Chinese input flows, namely South Korea and Taiwan. Overall, both figures show the potentiality of key production cycles involving Chinese and RoW industries[11], and enlighten, by contrast, the absence of large direct input linkages between U.S. and Chinese industries.

As the WION encompasses both international *and* domestic input linkages, we further show what our filtering process brings as regards the dynamics of domestic input linkages. In Figure 5 we display the time evolution of the filtered domestic linkages for China, and we compare this time series to its counterparts in Japan, in U.S., and in the RoW region.

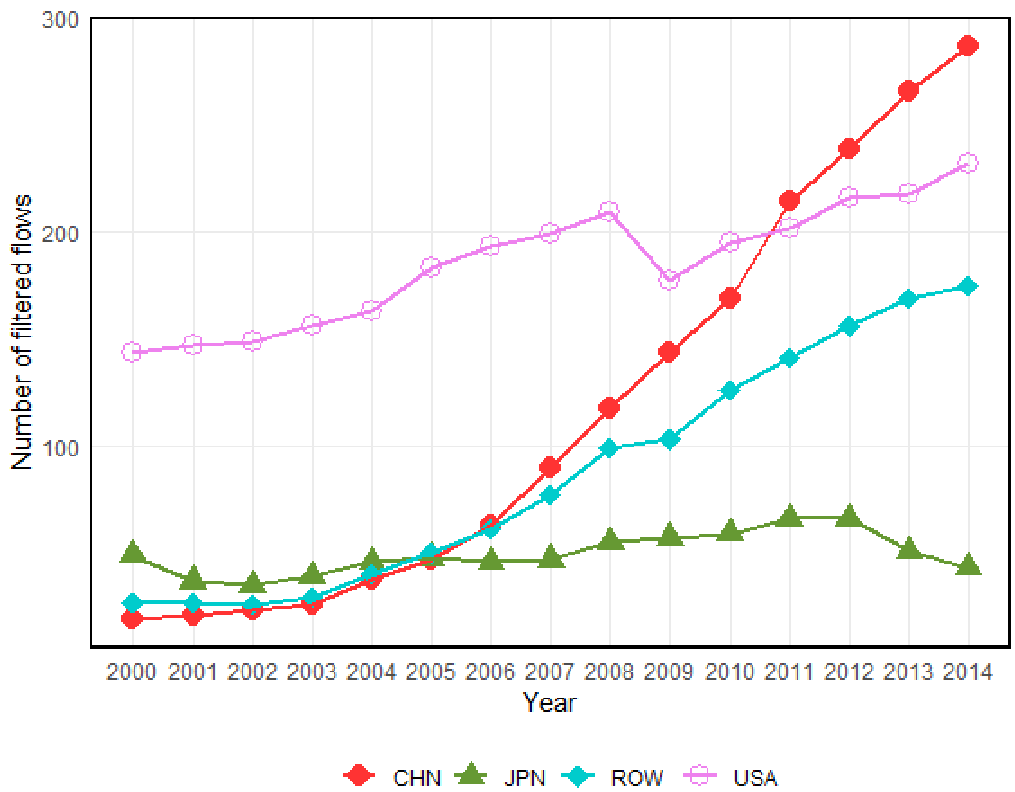

Figure 5: Domestic input linkages, cross-country comparisons

Note: This figure counts the number of large domestic input linkages for each of our country of interest. Large flows means flows greater than of equal to 10$ billion.

This comparative analysis reveals that Chinese domestic input flows experience a tremendous increase over the period of observation. While less than 20 large domestic flows could be recorded for China in the filtered WIONs of the early 2000's, this number reaches almost 300 in the 2014

[11] This increasing interconnection between China's economy and other developing countries has already been stressed for specific sectors, as for instance for the agricultural sector (see Gu et al., 2016).

filtered WION. The RoW region experiments a similar increasing trend of their intra-regional input linkages at amuch slower pace than China. Interestingly, in comparison with China, the RoW region started with a slightly higher number of large intra-regional inputs flows (about 25 in the early 2000s). HOwever, it ended up with half of the number recorded for China (about 150 domestic flows in the 2014 filtered WION). Compared to China and the RoW, the most contrasting pattern is the one of Japan with a relatively low and stable number of domestic flows in the filtered WION, averaging 50. As for the U.S., its pattern is unique as this country displays the largest domestic input linkages in the early 2000's (around 150 flows in the filtered WIONs) and still increase them over the period of investigation. However, from the early 2010's, large U.S. domestic input linkages became less numerous than their Chinese counterparts.

4.3 Detecting Autocatalytic Sets in the WION

We have developed an algorithm to detect ACSs in a binary directed network, adopting a procedure that is similar to the one used by Jain and Krishna (2002a) and Napolitano et al. (2018). The algorithm works as follows. First, we identify irreducible subgraphs within the directed binary network.[12] In the adjacency matrix version of these subgraphs, supplier industries are rows and client industries are columns. Secondly, we calculate the Perron-Frobenius eigenvector of irreducible subgraphs. According to the Perron-Frobenius theorem, for a positive (or irreducible) matrix, there exists a unique, real, and positive eigenvalue that is greater than or equal to the absolute value of any other eigenvalue of the matrix. Moreover, the associated eigenvector has strictly positive components.[13] On each irreducible subgraph, we detect the Perron-Frobenius eigenvalue (PFe) and its associated Perron-Frobenius eigenvector. The PFe can be interpreted as the amount of feedback loop occurring in the filtered network. A cycle exists in the graph if the PFe is greater than 0. An increase in the PFe means an increase in the amount of feedback in the filtered WION. The Perron-Frobenius eigenvector will be used to identify ACS members. If the Perron-Frobenius eigenvector has a value different from 0 then its corresponding CIs are part of an ACS.

[12] An irreducible subgraph is a maximal subgraph such that there exists a directed path between any pair of nodes in the subgraph. This means that every node in the subgraph can be reached from every other node in the subgraph by following directed edges.

[13] More formally: If A is an $n \times n$ (square) positive matrix (all its elements are positive real numbers), then there exists a unique and positive eigenvalue λ, called the Perron-Frobenius eigenvalue, such that $\lambda \geq |\lambda_i|$ for all eigenvalues λ_i of A. The eigenvector associated with the Perron-Frobenius eigenvalue has strictly positive components (i.e., its elements are all positive real numbers). This eigenvector is called the Perron-Frobenius eigenvector.

Table 1: Autocatalytic Sets detected in the filtetred WION, by size and by year

	ACS 1		ACS 2		ACS 3		ACS 4		ACS 5	
Nb. of	Nodes	Countries	Nodes	Countries	Nodes	Countries	Nodes	Countries	Nodes	Countries
2000	73	8	5	1	3	1				
2001	49	4	5	1						
2002	47	3	14	1						
2003	54	5	15	1	3	1				
2004	64	7	20	3	3	1				
2005	113	10	4	1	3	1				
2006	118	11	7	1						
2007	117	11	8	1	4	1				
2008	142	12	9	1	5	2				
2009	129	10	8	1	4	1				
2010	148	12	8	1	4	1	3	1		
2011	167	14	10	1	9	2	6	1	3	1
2012	179	16	9	1	6	1	3	1		
2013	174	14	10	1	6	1	3	1	3	1
2014	174	16	10	1	6	1	3	1		

Note: ACS stands for autocatalytic set. the size of each ACS found in the filtered WION is characterized by two metrics: number of nodes (country-industries) and number of different countries that it covers. The autocatalytic sets are ranked by size meaning that ACS 1 is the largest set found in the filtered WION in a given year, while ACS 2 is the second largest and so on.

Theoretically, this methodology can detect multiple ACSs in a given network. When applied to our filtered WION, it indeed identifies at least 2 ACSs in any given year of observation. This is shown in Table 1 which displays all the ACSs that we detected. More precisely, this table ranks by size the ACSs found in the filtered WION for each year of observation. The size of the ACS is measured by the number of nodes (i.e. country-industries). We also count, for each ACS, how many different countries have at least one industry in that ACS. Specifically, Table 1 must be read as follows. In 2000 (first raw), 3 different ACSs are detected in the WION : the largest one (ACS1) is composed of 73 different industries belonging to 8 different countries; the second largest one (ACS2) is made of 5 different industries belonging to a single country; the smallest one (ACS3) is made of 5 different industries belonging to a single country.

A notable result of the analysis reported in Table 1 is the presence, in each year, of a unique large international Autocatalytic Set (ACS 1), next to which all other detected ACSs involve only a few industries. We will refer to the large ACS as the *global ACS*, and to the smaller ACSs as *local ACSs*. Notice that local ACSs are always a few, the number of which ranging from 1 to 5 depending on the year of observation[14].

Table 1 provides additional interesting findings about each of the two types of ACS. Considering first the global ACS, it reveals a tendency for this autocatalytic structure to enlarge over our period of observation. The number of nodes included in this global ACS oscillates between 49 and 73 from 2000 to 2004 and then steadily increases from 113 to 174 between 2005 and 2014. The variety of countries taking part in the global ACS shows a similar pattern: it oscillates between 3 and 8 in the earlier period, i.e., from 2000 to 2004, and increases from 10 to 16 between 2005 and 2014. Considering next the local ACSs, an interesting feature it that they are almost exclusively made of domestic input-output cycles. Among the 34 local ACS that we detected in the filtered WION, in whole over our period of investigation, only 3 cover more than 1 country.

Our methodology further discriminates between the *core* and the *periphery* of each of the detected ACSs as the identification of core and peripheral nodes is rooted in our detection algorithm. To illustrate that, we display in Figure 6 the composition of the global and local ACSs for the initial year of observation, namely 2000. Recall that, for this specific year, our algorithm detects three ACS, one global and two local ones. Figure 6 further shows that the core of the global ACS is composed of three main components. The largest component is made of U.S. industries, while the

[14] In the robustness check of Section 6, we investigate the sensitivity of this pattern to a change in the filtering threshold value.

two other components are respectively made of a few Asian industries (mainly Japanese ones) and a few RoW industries. While most of the cycles can be found within each component, the three core components are interconnected through two key cyclical input-output relationships. The first one involves *Petroleum* and *Mining and Quarrying* industries while the second one involves *Computer and electronics* industries.

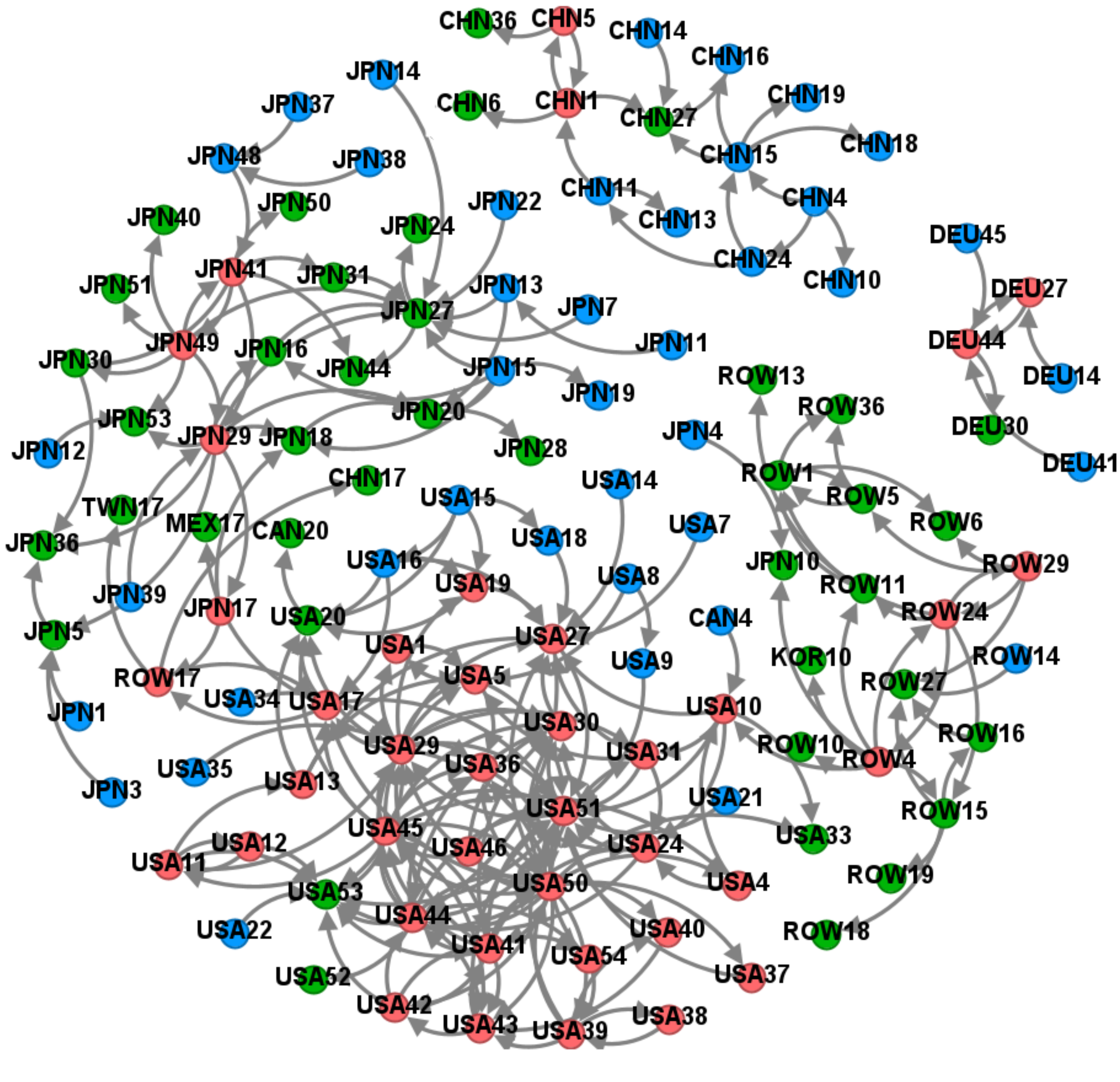

Figure 6: Autocatalytic Sets detected in the filtered World Input-Output Network of year 2000.

Note: The Network visualization is conducted using the force-directed algorithm ForceAtlas2 (Jacomy et al., 2014). The red nodes are Industry-Countries in the core of a ACS. The green nodes are the Periphery of the ACS. The nodes in blue are Industry-Countries connected to ACSs only by outgoing links, and are not part of a ACS.

Regarding the local ACSs detected for year 2000, one is exclusively made of Chinese industries with two core industries, *Mining and Quarrying* (CHN4) and *AgroFood* (CHN5) and 3 peripheral ones, *Construction* (CHN27) *Textile* (CHN6), and *Accommodation and food services* (CHN36). The other local ACS is composed of German industries with two main industries, *Real Estate* (DEU44) and *Construction* (DEU27), and a peripheral one, *Retail Trade* (DEU30) [15].

The most noticeable feature of the global ACS that emerged from Figure 6 is that U.S. industries dominates the core of the international production network in 2000. U.S. industries are not only strongly interconnected among themselves, they also have key connections with some peripheral manufacturing Canadian and Mexican industries, and some core primary and manufacturing RoW and Asian industries.

However, as we will see in the next section, this feature of the global ACS dramatically changed over our period of investigation. Significant shifts in the ACS landscape occured, with the rise of Chinese industries emerging as the primary driving force behind these profound structural transformations. The questions we specifically address concern the pathway of Chinese industries from this starting point, and most importantly after the accession of China to WTO in 2001. Through the lens of ACS, we are able to uncover the roots of major shifts, and also how the changing position of Chinese industries has impacted the positionning of their U.S. counterparts.

5 Results

This section presents the result of our inquiry focusing on the position of China in the evolving ACS map detected in the global production network across the years from 2000 to 2014. We obtained two main results from our analysis. First, the evidence that Chinese industries have moved from outside to inside the Global ACS over the period 2000 to 2014. We identify year 2005 as a key turning point when a densifying Chinese local ACS branched into the Global ACS. Second, by comparing the dynamics of Chinese industries with US industries, we observe a pattern of peripheralization of the latter, beginning in year 2013.

[15] This is a noticeable feature of our methodology that, except for a few German ones, European industries are virtually absent from our detected ACSs. This feature comes from the fact that individual European countries are not large enough to appear in our filtered network which displays on purpose only the largest flows. However, as our main focus is on the comparative positioning of Chinese and U.S. industries we do not see this feature as an undesirable one for this research. A further extension of our methodology would be necessary for addressing a similar comparative analysis of the positioning of Chinese and European industries.

5.1 The evolving position of Chinese industries in the ACS landscape

The development of Chinese industries within the ACSs detected in the WION begins a few years after China's accession to the WTO, in 2001. In particular, year 2004 stands out as the most interesting one to illustrate how the local Chinese ACS has densified in the early 2000's.

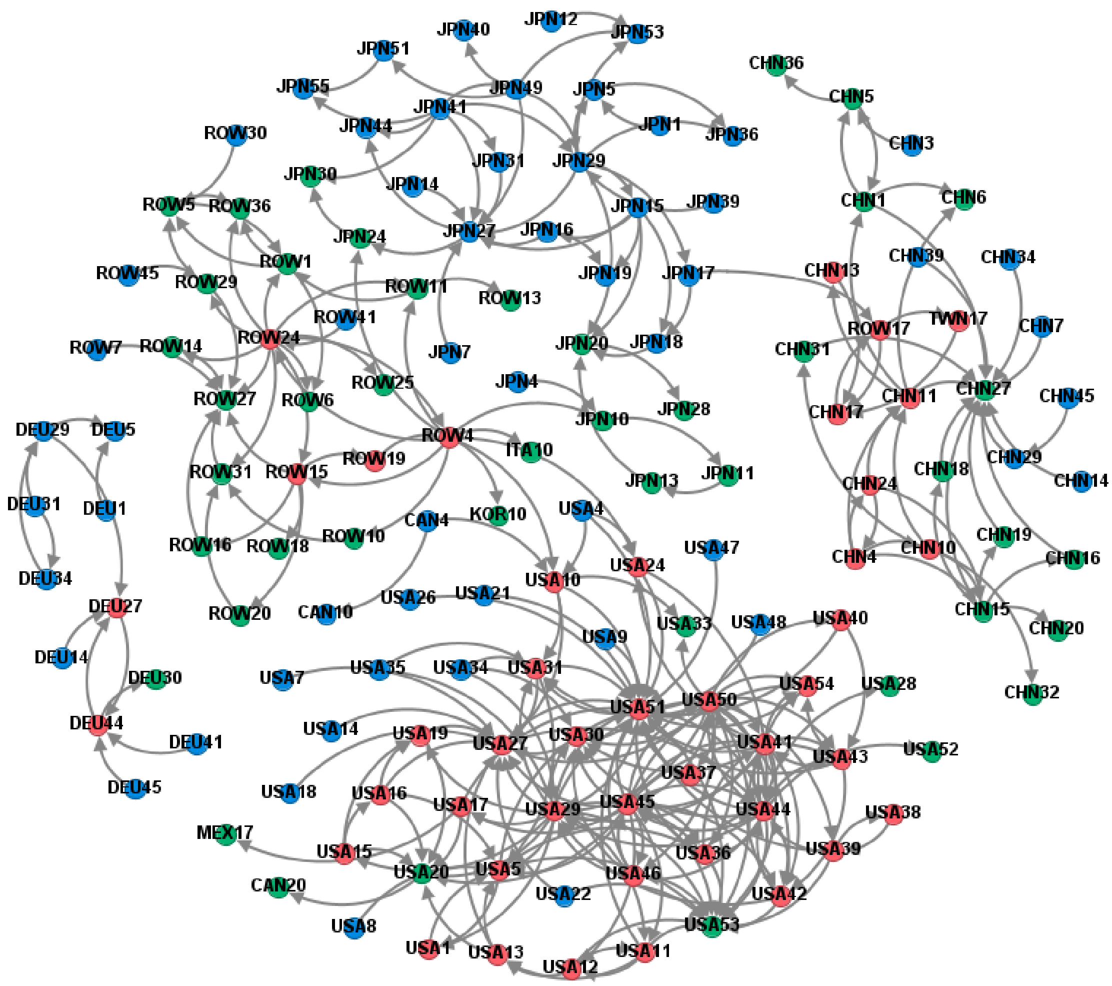

Figure 7: Autocatalytic Sets detected in the filtered World Input-Output Network of year 2004

Note: The red nodes are Industry-Countries in the core of a ACS. The green nodes are the Periphery of the ACS. The nodes in blue are Industry-Countries connected to ACSs only by outgoing links, and are not part of a ACS.

Figure 7 illustrates the ACS detected in the WION in year 2004, and distinguishes Industry-Countries nodes belonging to the core (in red) and to the periphery (in green). This autocatalytic structure is similar to the one of year 2000, with one crucial difference: the huge densification of the local Chinese ACS. The general picture remains one where US industries dominate the global production network with some key connections with RoW industries. The German ACS detected in 2000 is still present and remains very stable (same core and peripheral nodes). The key difference of the ACS structure in 2004 is the total change of the Chinese local ACS compared to its 2000 outlook. First, the Chinese ACS is much larger and diversified, being now composed of eight core industries (compared to only 2 industries in 2000) and 11 peripheral industries (compared to 3 in 2000). Moreover, among the core nodes, a more diverse set of manufacturing industries has replaced the single *Agrifood* industry of 2000. In this new set of core nodes, a new set of industries appears now, such as Rubber&Plastics (CHN11) *Chemicals* (CHN13), *Computer&Electronics* (CHN17) along with two energy related industries, *Petroleum Products* (CHN10), and *Electricity & Gaz* (CHN24). Thirdly, the local Chinese ACS is no more exclusively made of domestic industries. Two foreign industries of *Computer &Electronics* are now part of the local Chinese ACS, Taiwan (TWN17) and RoW (ROW17). It is noteworthy to observe the shift in China's position within the ACS landscape, particularly at a time when previous literature has documented a structural change in the geography of the Computer & Electronic industry in the early 2000s favouring Asia.

What are the implications of these results, provided by the lens of autocatalytic networks? First, our findings shed new light on a long lasting debate in the development literature which questions whether agriculture and manufacturing are complementary or competing industries in the course of economic development. Traditionally, economists advocate that they are rather competing as resources need to be reallocated outside agriculture towards manufacturing for the industrialization take-off to take place (see in particular Matsuyama, 1992; Teignier, 2018). In opposition to this view, other economists emphasize the complementary role of the expansion of both agriculture and manufacturing industries in the course of economic catching-up (see for instance Kay, 2002) which defends this view on a study case of the South Korean growth miracle). As regards this earlier debate, our findings are more supportive of the latter view as they show that the local Chinese ACS that expanded in the early 2000's featured strong IO relationships across different agriculture-related industries and also between them and key heavy and light manufacturing industries.

A second lesson is that key Computer & Electronic industries changed location within the ACS landscape in the early 2000's. This change could mean a shift of cumulative causation mechanisms from core U.S. industries in the late 90's towards Chinese industries in the mid 2000s. Overall, these changes show that the Chinese production network strongly reinforced locally before one could detect any branching of Chinese industries to the core of the global production network.

Year 2005 witnesses the branching of the Chinese economy to the Global ACS. This event occurs through the establishment of specific industry linkages, as illustrated in Figure 8. Here nineteen Chinese industries all figure as peripheral nodes of the global ACS. At first sight, Figure 8 could be interpreted as supporting the conventional wisdom according to which China entered a U.S. dominated global production network without threatening the core position of the U.S. economy. However, our claim is that this conventional wisdom hide some competing forces that were already at work before 2005 and that are inherent to cumulative causation mechanisms. These competing forces are particularly well exemplified by the repositioning of some key Asian *Computer &Electronics* industries towards China even before Chinese industries branched to the core of the global production network.

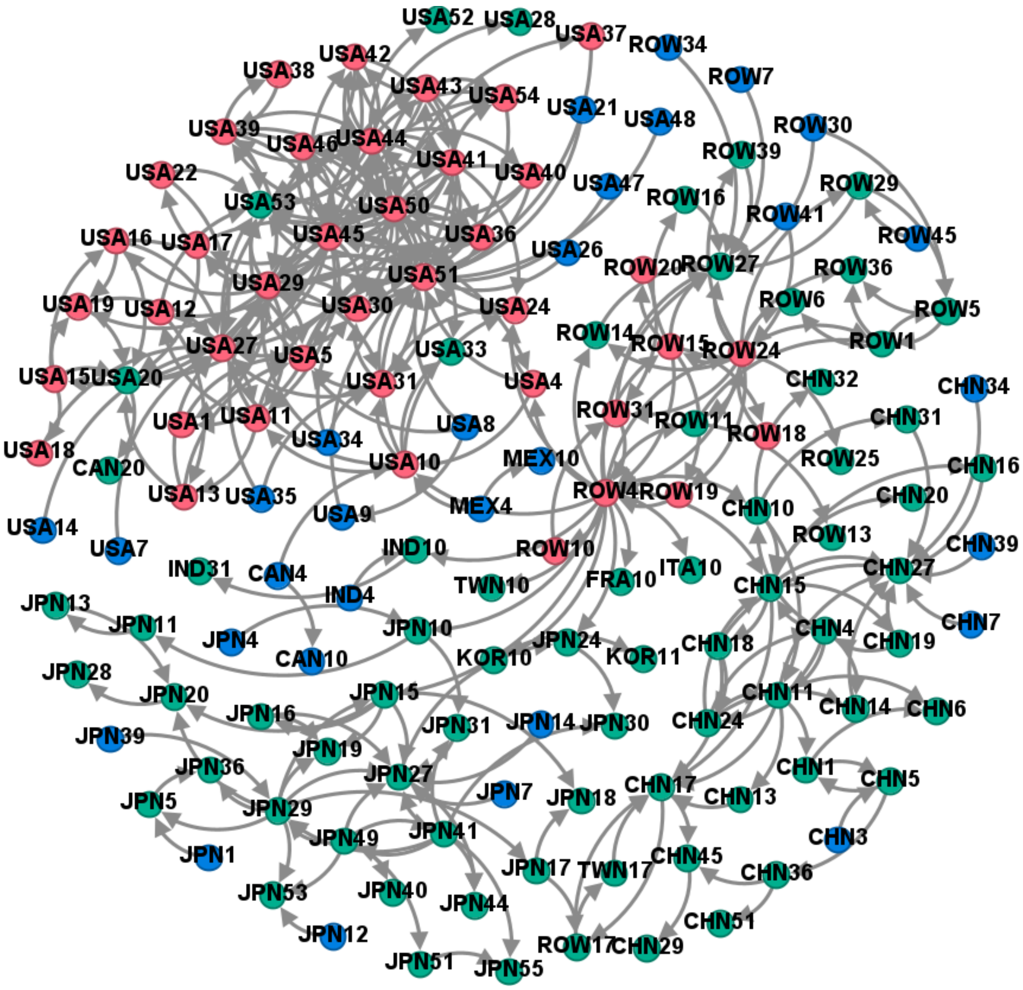

Figure 8: The Global Autocatalytic Set in the 2005 WION

Note: The red nodes are Industry-Countries in the core of a ACS. The green nodes are the Periphery of the ACS. The nodes in blue are Industry-Countries connected to ACSs only by outgoing links, and are not part of a ACS.

After the branching of the Chinese economy to the periphery of the global Production network, the number of Chinese industries included in the Global ACS kept increasing over the following years. This is illustrated in Figure 9, which allows to compare over time the number of domestic industries in China, Japan, the USA, and the RoW that take part in the Global ACS. This figure suggests a number of interesting observations. First, the number of American industries in the ACS remains the stable over time, positioning the US economy as the country with the highest count of industries in the Global ACS all along our period of observation. At the other extreme, the faith of Japanese industries is more chaotic with the disappearance of Japan from the global ACS in 2001 and 2002, a rather stabilized number of approximately 30 industries afterwards and a decreasing trend from 2012. In contrast, Both China and the RoW experience an increasing trend of the number of their industries belonging to the Global ACS. As already pointed out, China entered the Global ACS in 2005 and became the country with the highest number of industries after the U.S. by 2014.

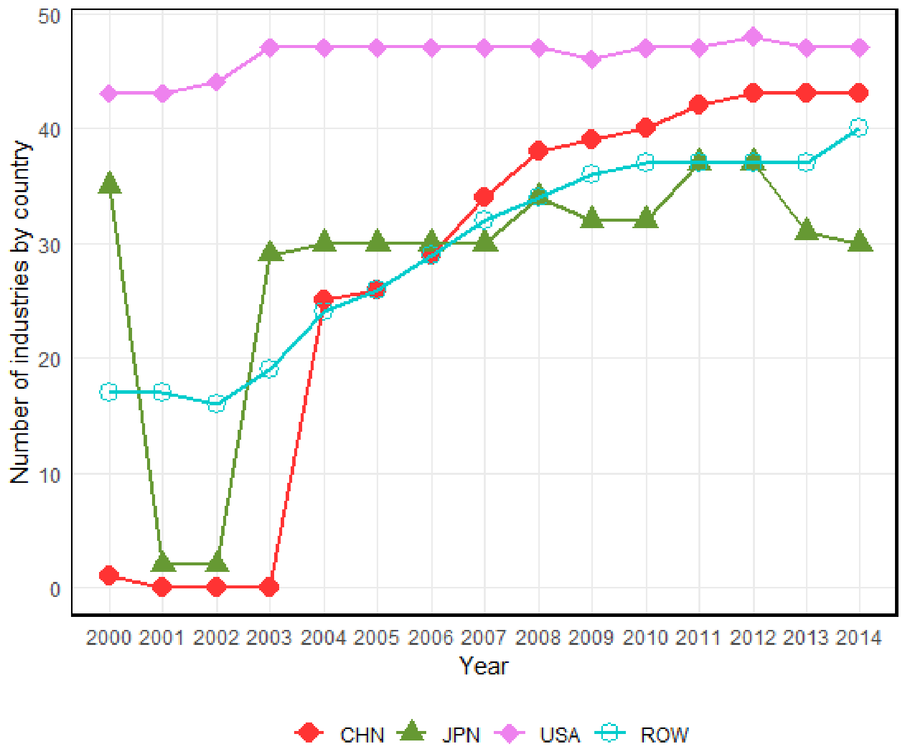

Figure 9: Comparative dynamics of Chinese industries in the global ACS, 2000-2014

Note: The vertical axis reports the number of domestic industries in the Global ACS from year 2000 to year 2014.

A conventional reading of Figure 9 would tell that the rise of China in the global production network could have occurred at the expense of the Japanese Economy but not at the expense of the U.S. Economy. And indeed, the earlier literature already pointed out how Japanese industries have been kicked out of central positions in both regional (Asian) and global production networks at the benefice of their Chinese counterparts.

Instead, the autocatalytic approach unveils a rather different story. The ACS evolving structure shows the success of China's internationalization process not as a simple move of China joining the technologically advanced and US dominated global production network, but as the profound structural change of a large economy transforming its local circular industrial relationships into global ones, by branching its industries to the periphery of the global production network rather than directly to the its US dominated core. To back this claim, in the next section we investigate further how the geography of key cyclical production relationships changed after the China's branching to the Global ACS.

5.2 The relative position of Chinese and U.S. industries within the global ACS

The identification of autocatalytic structures in the WION suggests to look specifically into the competitive dynamics of Chinese and American industries within the Global ACS, and to study their evolution over time. Compared to US industries, which continuously occupy the core of the Global ACS from 2000 to 2012 inclusive, Chinese industries remained in the periphery of that ACS for many years after joining it in 2005. However, a turning point occurs in 2013. From this year onward, Chinese industries began to occupy the core of the Global ACS, while American industries were pushed into its periphery.

Figure 10 illustrates this new feature of the global ACS, as observed in the 2013 WION. This figure also shows that Chinese industries are more strongly connected to RoW industries compared to U.S. industries. There are two possible and potentially complementary explanations for the strong linkages between core Chinese industries and core RoW industries in the 2013 global ACS. The first is that the Chinese productive system is strongly integrated regionally and receives large input flows from smaller developing countries that are part of the RoW. The second explanation is that China extracts more resources from the RoW than the U.S. does. To explore this issue further, one can examine the industry codes involved in the China-RoW linkages. It appears that China is primarily connected to the RoW through the *Manufacture of computer, electronic and optical products* industry (ROW17), which supports the first explanation. The single linkage between a core U.S. industry and a core RoW industry concerns primary resources; specifically, it is a flow from the *Mining and quarrying* industry (ROW4) to the U.S. *Manufacture of coke and refined petroleum products* industry (USA10).

An additional interesting feature of the 2013 WION is that, along with Chinese and ROW industries, a small set of industries from other countries enter (or re-inter) in the core of the global ACS now dominated by China. Among those industries are the *Computer & electronics* from Taiwan (TWN17) and Korea (KOR17). We can also note the core linkages between the Korean

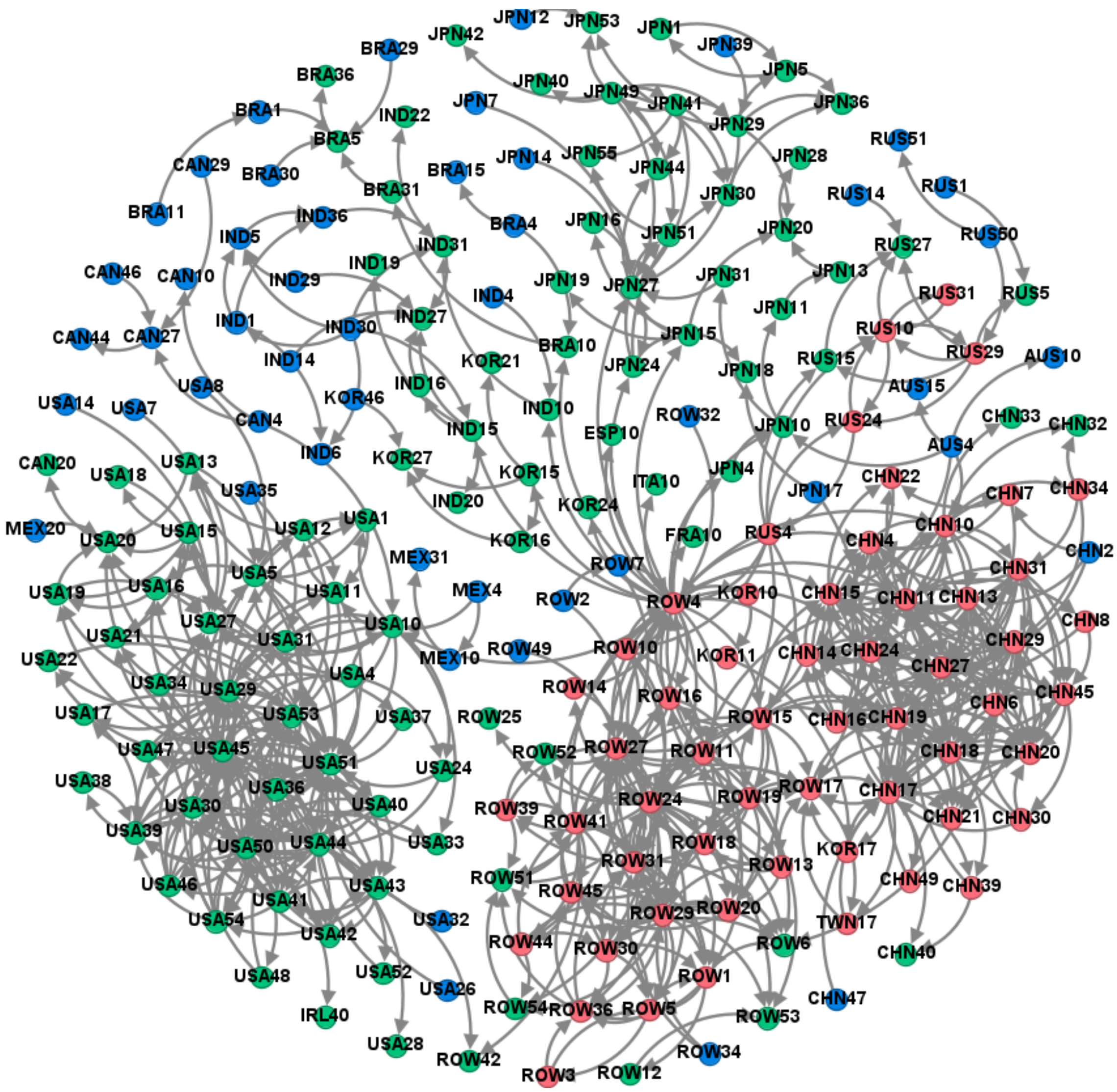

Figure 10: The Global Autocatalytic Set in the World Input-Output Network of 2013

Note: The red nodes are Industry-Countries in the core of a ACS. The green nodes are the Periphery of the ACS. The nodes in blue are Industry-Countries connected to ACSs only by outgoing links, and are not part of a ACS.

petrochemical industries (KOR10 and KOR11) and Chinese industries. Finally, we can observe an increasing part of Russian natural resource extracting and supplying industries[16] in this China dominated global ACS.

Overall, since 2013, the U.S. economy appears to be a more isolated, self-sustained part of the global ACS compared to the Chinese economy. By contrast, Chinese intra-national flows and

[16] *Mining and quarrying* (RUS4), *Manufacture of coke and refined petroleum products* (RUS10), *Wholesale trade, except of motor vehicles and motorcycles* (RUS29), and *Land transport and transport via pipelines* (RUS31)

international flows, especially the ones towards and from the RoW, dramatically strengthened in the periphery of the global production network. To make even stronger our claim that 2013 is a turning point in the World production network, we plot in Figure 11 the evolution of the relative position of China, the U.S., Japan and the RoW within the core of the global auto-catalytic set.

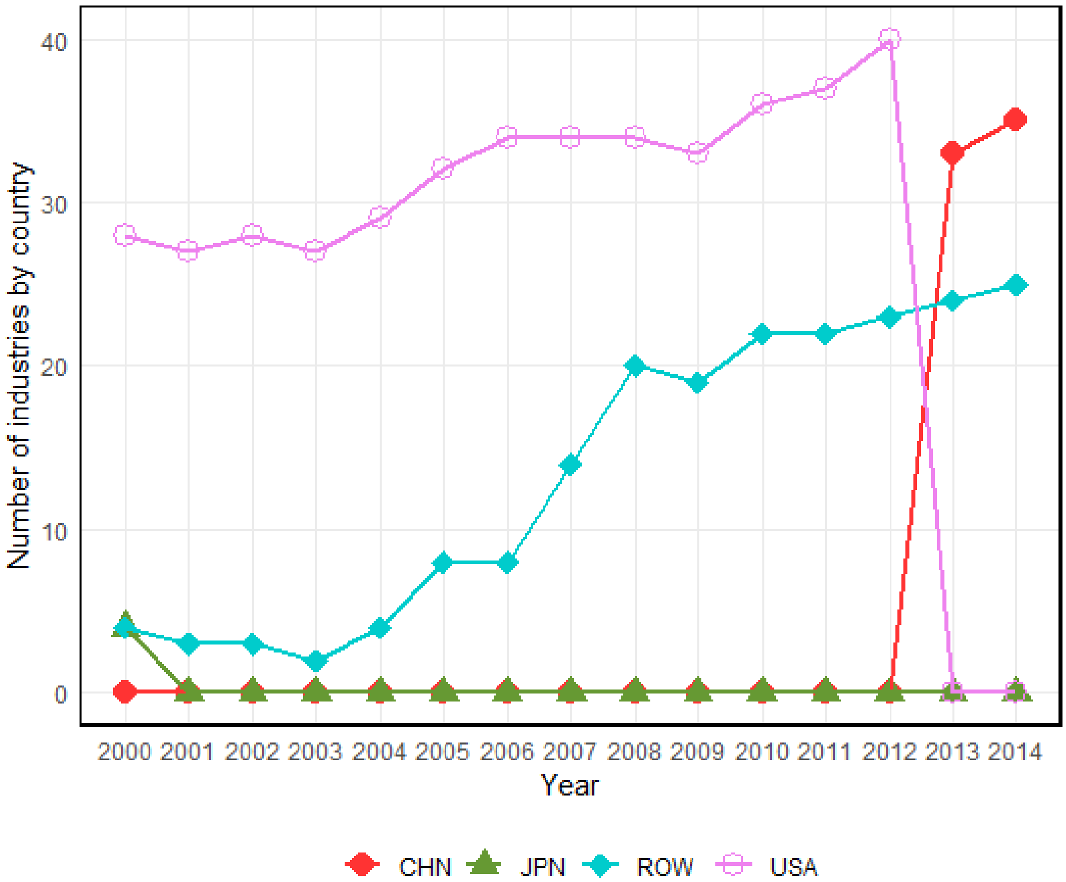

Figure 11: Composition of the core of the Global Autocatalytic Set in the World Input-Output Network

Note: The vertical axis reports the number of domestic industries in the core from year 2000 to year 2014.

Figure 11 presents the evolution of a geographical composition of the ACS core from 2000 until 2014, with the main countries involved. In particular, the figure illustrates the competitive dynamics of US and Chinese industries in the global production network. As long as the Us industries dominate the core of the Global ACS, i.e. from 2000 to 2012, Chinese ones remain confined to its periphery. As soon as Chinese industries populate the core on the global ACS, i.e. in 2013 and 2014, US. industries re-positioned themselves on its periphery. Interestingly, the upward trend in the number of RoW industries belonging to the core of the global ACS exhibits no rupture in 2013. This finding reinforces our view that the reversal of the position of Chinese and US industries is not damaging for the RoW, whose industries pursue their development while changing their key partnerships.

6 Robustness checks

In this section we explore the sensitivity of the ACS detection algorithm and perform a robustness check of our main findings. The main dimension of analysis is the threshold value used to filter the links of the WION. We start by investigating how the number and structure of the detected ACSs depend on the filtering threshold value of input-output flows. Secondly, we investigate whether, and to what extent, the choice of the threshold value affects the two main turning points of the evolutionary dynamics of ACS structures, namely years 2005 and 2013.

6.1 Sensitivity of the ACS detection algorithm

The number of ACSs that can be detected in the WION is strongly sensitive to the filtering threshold value of input-output flows. This is clearly evident from Figure 12, which reports the number of ACSs detected in the 2014 WION as a function of the threshold. The main feature of this figure is a non-monotonic pattern that reveals a kind of 'resonant' mechanism of autocatalytic structures in the WION. In other words, the WION appears to present a 'characteristic' range of flows values where the autocatalytic structure is most evident. This fact provides the main guidance in the identification of ACSs in the network. Without any filtering (threshold value set to zero), the identification algorithm only detects one global ACS. When all links are considered, the WION is a complete network, which amounts to a trivial case of one ACS encompassing all CIs. On the other hand, when the threshold is set large enough, only few links remain, and the resulting network is sparse, without any structure. In between these two limits, a number of ACS emerge, revealing the autocatalytic structure of the WION.

At the start of a filtering process, as the value of the filter is raised, the least important input flows are removed, while whose with a flow value greater than the filter are retained. This selection process has two opposite effects on the ACS detection. On the one hand, a higher threshold value makes the existence of a link between 2 nodes less likely. It is therefore possible that a large ACS

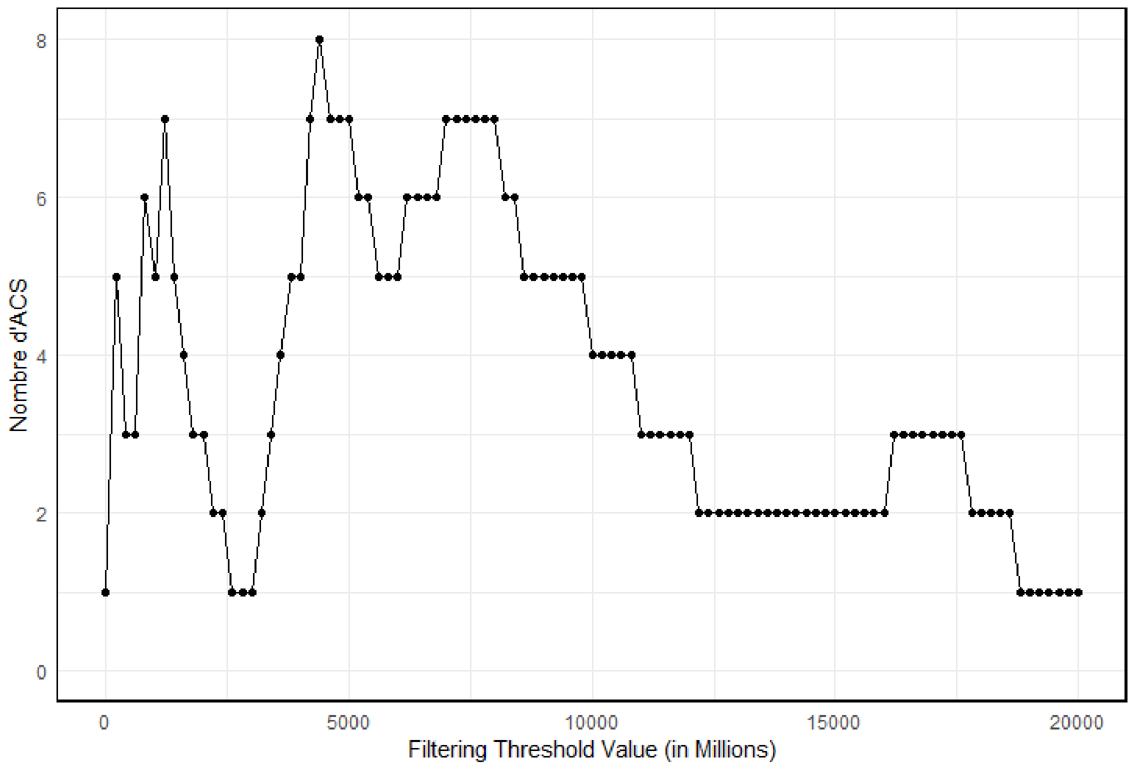

Figure 12: Number of detected ACSs by filtering Threshold Value, 2014

that could be detected for a lower threshold value splits up into 2 smaller ACSs after some links have been broken. This effect is certainly the one that explains the passage from 1 single ACS detected to a maximum of 7 ACS detected when the filter value increases from 0 to 2.5 billion.

For relatively large values of the filtering threshold, another effect occurs, which works in the opposite direction, reducing rather than increasing the number of ACS detected in the WION. Specifically, as the filter value increases, more and more links are removed, and the likelihood of detecting cycles decreases reducing both the number and the size of ACSs than can be detected. This counterbalancing effect makes that the number of ACSs that can be detected in the WION is a non monotonic function of the filtering threshold value. The maximum number of detected ACSs is reached twice: first around the \$1.25 billion filtering threshold value and a second time around the \$4.75 billion filtering threshold value. Eventually, the second effect dominates and for high enough filtering threshold value, i.e above \$18 billion, only one single ACS can be detected.

The effect of the filtering threshold is further illustrated in Figure 13, where we plot the aggregate number of country-industries (nodes) which are part of any ACS, as a function of the filtering threshold value. In this figure, we disentangle core and peripheral nodes of ACSs, so as to evaluate

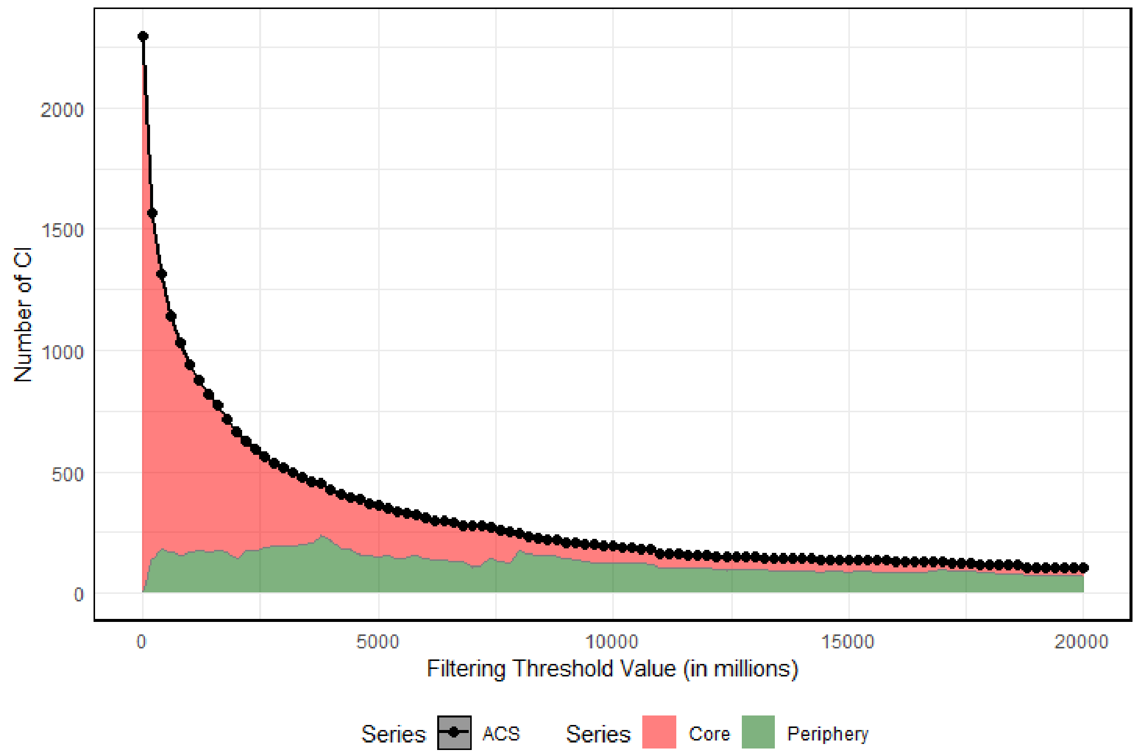

Figure 13: Aggregate number of core and peripheral ACS nodes by filtering threshold value, 2014

Note: The aggregate measures of Core and Periphery sizes are calculated by summing up the sizes of all cores and peripheries, respectively.

how their relative size depends on the level of the threshold.

First, perhaps unsurprisingly, the aggregate number of Country-Industries which are part of a ACS is a monotonic decreasing function of the filtering threshold value: considering that without filtering the WION is a large fully connected ACS, the number of nodes belonging to this one, or to the ones that emerge with increasing the filter, can only decrease, because nodes are only lost, as the threshold becomes lager. More specifically, core nodes become more and more scarce with a larger threshold. Importantly, some of them are reassigned as peripheral nodes. At the same time, some links of peripheral nodes are severed too, and disappear from ACSs. This means that we observe again counterbalancing effects at play in the autocatalytic structure of the WION, this time involving specifically the periphery of ACSs. The net result is a non-monotonic pattern of the size of the periphery (green area in Figure 13): there is a sharp increase for low values of the threshold, followed by a much slower increase up to about 4000 millions of dollars, and then a slow decline. This means that at low threshold values there are more nodes 'recruited' than lost by the periphery of ACSs. This is the emergence of the autocatalytic structure of the WION, where meaningful ACSs are characterised by relatively small cores and larger peripheries (see the graphs reported in Figures 7, 8 and 10).

Figure 14 illustrates the relative proportion of core and periphery in the WION as a function of the filtering threshold value, again for year 2014. Overall, the core proportion decreases, while the

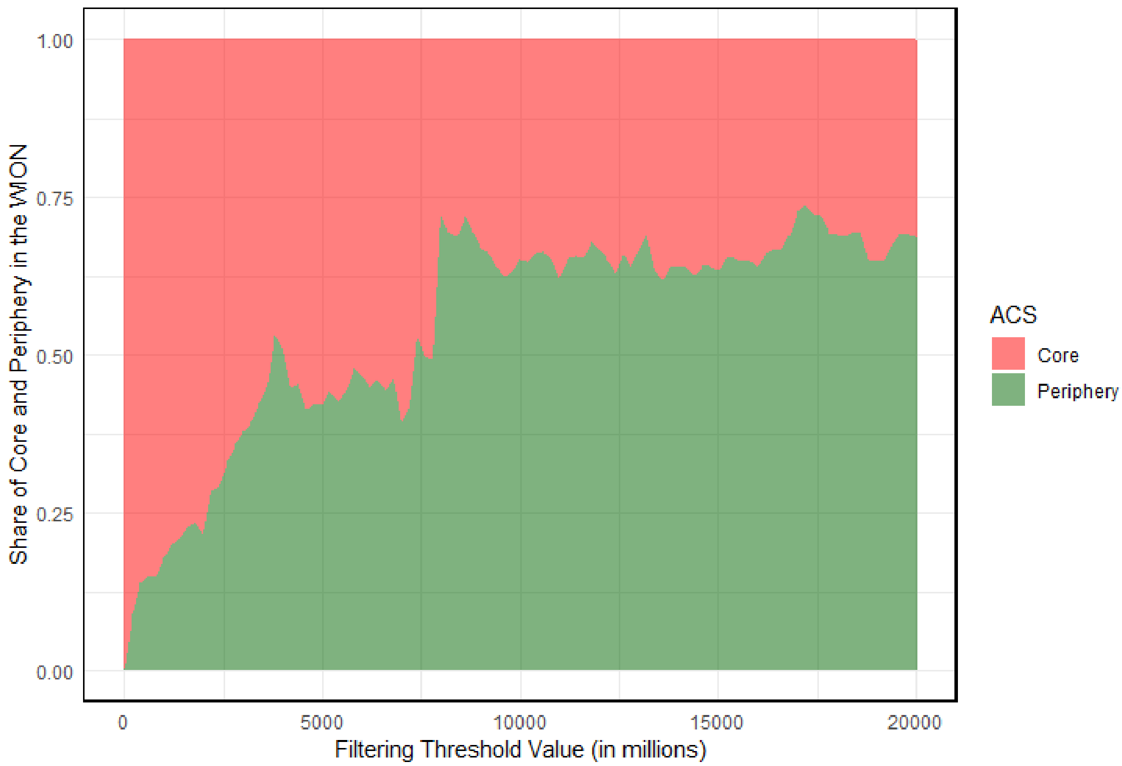

Figure 14: Share of Core and Periphery in the WION by filtering threshold value, 2014

proportion of the periphery increases. More specifically, core and periphery proportions attain a seemingly stable level at a threshold of about 8000 million dollars, above which the composition of ACSs ramains more or less constant, with a 30% of nodes in the core, and 70% in the periphery. This empirical observation is mostly useful for determining the threshold value to use in our analysis: the value of 10 billions already belongs to the stable proportion of core and periphery of the ACS (Figure 13), but still is characterised by relatively many ACSs (Figure 12).

To conclude, the structure of the WION in the threshold range where the auto-catalytic structure is mostly evident (resonant) is characterised by one single global and large ACS and few local and smaller ACSs. Beyond the 10 billions threshold, only the size of the global ACS and the demography of the local ones change with increasing further the threshold value, but not the overall proportion of core and periphery.

6.2 Robustness check of main findings

In the second part of this section we investigate to what extent the main findings about the dynamics of Chinese industries within ACSs are robust to changes in the WION filtering threshold value.

Our first claim is that a selection of Chinese industries started to expand within a local ACS, before China became a major player in the Global ACS. This trend remains consistent across a large range of filtering threshold values, as demonstrated in Table 2. This table traces the trajectory of Chinese industries, illustrating their progression from being part of a local ACS, and ultimately joining the Global ACS. This transition is analyzed across a range of predefined filtering threshold values. Notably, at thresholds below the $10 billion filtering value, no transition occurs. China consistently shows up as a member of the Global ACS. However, above the $10 billion filtering value and for all subsequent filtering threshold values, the aforementioned distinctive shift occurs. The shift occurs in 2005 only for the $10 billion filtering value. For higher values, the shift always occurs but in slightly later years namely in 2006 and 2007.

Our second claim is that the evolution of Chinese industries within the Global ACS has been accompanied by a peripheralization not only of Japanese industries but also of U.S. ones. To test the robustness of this claim to changes in this filtering threshold value, we trace in Figure 15, the evolving numbers of US, Japanese, Chinese, and RoW industries in the core of the Global ACS for a large range of filtering threshold values.

Up to the filtering threshold value of $ 7.5 billion, Japan enjoys a robust position within the core of the global ACS. However, even within this range of $1 to $ 7.5 billion, China clearly exhibit a chatching-up and then leap-frogging pattern as China systematically become the biggest Asian member of the global ACS in our last years of observation. Beyond the $ 7.5 billion threshold value, Japan no more appear in the core of the global ACS while Chinese industries always join the core of the global ACS at some point between 2009 and 2013. Interestingly, the higher is the filtering threshold value, the sooner Chinese industries enter in the core of the global ACS. This delineation underscores the shifting dynamics of the global production network framework, with China appearing as a main player, especially at high filtering threshold values.

Figure 15 provides compelling evidence for our claim regarding the shifting positioning of China and the US within the core of the Global ACS. On that respect, the figure reveals two distinct

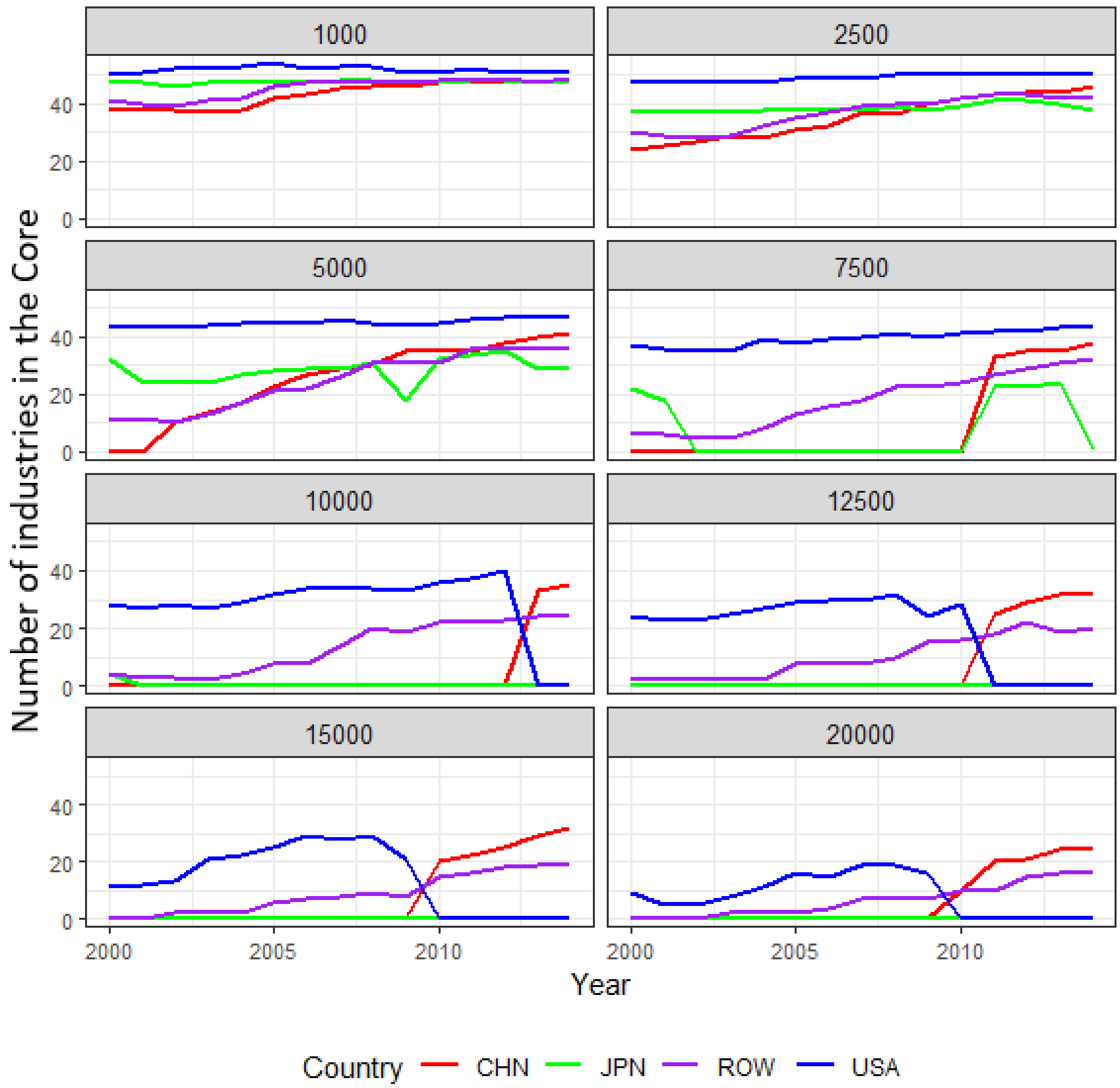

Figure 15: Relative position of countries within the core of the global ACS, by filtering threshold value and by year

dynamics, once again delineated by the filtering threshold value of $ 7.5 billion. Up to this value, the US exhibits a dominant position in the core of the global ACS over the whole period of observation. China catches up but never leap-frogs. In contrast, beyond this value, a structural shift occurs. China takes over the U.S at the domoinant player in the core of the ACS. This shift occurs at the end of the 00's or at the beginning of the 10's depending on the threshold value. Interestingly, the RoW industries strengthens their position in the core of the global ACS in all scenarios. This pattern offers a striking illustration that the China's ascent to prominence within the global production

Table 2: Is China part of the global or local Autocatalytic Set, by filtering threshold value?

	1000	2500	5000	7500	10000	12500	15000	20000
2000	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS*	Local ACS	0	0
2001	Global ACS	Global ACS	Global ACS	Global ACS	Local ACS	Local ACS	0	0
2002	Global ACS	Global ACS	Global ACS	Global ACS	Local ACS	Local ACS	Local ACS	0
2003	Global ACS	Global ACS	Global ACS	Global ACS	Local ACS	Local ACS	Local ACS	0
2004	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Local ACS	Local ACS	Local ACS
2005	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Local ACS	Local ACS	Local ACS
2006	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Local ACS	Local ACS
2007	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS
2008	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS
2009	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS
2010	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS
2011	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS
2012	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS
2013	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS
2014	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS	Global ACS

Note: filtering threshold values are expressed in million dollars. $10 billions correspond to our benchmark year. (*) At the benchmark year there is only one chinese industry in the global ACS the rest of the chinese industries are in the local ACS.

network did not occurred at the expenses of the RoW industries. By contrast, it highlights a relative decoupling of the US from the RoW.

7 Conclusion

In this article, we propose the innovative framework of analysis represented by auto-catalytic sets to describe the evolution of Chinese industries in the world Input-Output network, namely after its accession to the WTO. By focusing on the strongest inter-industry flows, a complex network structure of intertwined cycles emerges. In particular we present the evidence of an isolated cluster of industries from China which form a local ACS, the size of which increased over time, due to the densification of Chinese domestic linkages. In agreement with the literature, the autocatalytic sets approach reveals the existence of a large international cluster of industries primarily dominated by U.S industries. In this framework, this cluster forms a large multi-national autocatalytic structure, named as the global ACS.

As a novel contribution to the literature, this framework of analysis unveils new features of the ascent of China within the global production network. First, we show that the expansion of the Chinese local ACS served as a preliminary step before key Chinese industries succeed in branching into the Global ACS. More specifically, a Chinese local ACS continuously densified between 2000 and 2004, with the year 2005 marking the branching of the Chinese local ACS into the global one.

Second, the comparative analysis of Chinese, Japanese and American industries in the global production network reveals that U.S industries re-positioned themselves towards the periphery of the Global ACS in the early 2010s. In the mid-2010s they become more densely linked to the RoW industries. Overall, the US economy becomes a more isolated part of the Global ACS, compared to the early 2000s, while the relationships between China and the RoW is reinforced, and Chinese industries move to form the new core of the global ACS from 2013 onwards.

Although the research in this article has remained purely descriptive, our findings showcase the potential of autocatalytic sets as a promising framework to shed new light on the determinant of economic development and economic rivalries at the age of global value chains. From the view point on an emerging economy, this approach teaches us that the development of local circular causation cycles could be a prerequisite to the successful branching onto global trade as exemplified by the structural change experienced by China, which has succeeded in expanding its industrial base rather than specializing in a limited number of primary resources or agriculture-related industries.

From the view point on an advanced economy, the concept of auto-catalytic networks is also useful to reveal potential rivalries between them and the emerging economies, rivalries that have been overlooked by traditional approaches of economic development.

We envisage two main avenues for future research as a follow up of this paper. First, we suggest the extension of a descriptive analysis to other emerging economies, with the aim to confirm the patterns observed for Chine industries, and especially to validate the complementary role of local and global ACSs in the course of outward-oriented growth dynamics. Within this research line, we can extend the data with the recently released long-run WIOD database[17], in order to explore further the existence of local and global ACSs in the dynamics of emerging countries, which went through the industrialisation process in the second half of the 20th century. This analysis could reveal a pattern similar to the one observed for China in the early 21st Century. A second possibility is to replicate the present study on alternative GRMIO databases, with the objective to test further the robustness of key findings. A good candidate for this research is the latest version of the *ICIO* database recently released by the OECD.[18]

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[17]This database has been released by GGDC in March 2022.
[18]This database has been released by in November 2023.

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A Appendix

Table 3: Country coverage of the World Input-Output Database

Id	Country ISO 3	Name	Id	Country ISO 3	Name
1	AUS	Australia	23	IRL	Ireland
2	AUT	Austria	24	ITA	Italy
3	BEL	Belgium	25	JPN	Japan
4	BGR	Bulgaria	26	KOR	Republic of Korea
5	BRA	Brazil	27	LTU	Lithuania
6	CAN	Canada	28	LUX	Luxembourg
7	CHE	Switzerland	29	LVA	Latvia
8	CHN	China, People's Rep.	30	MEX	Mexico
9	CYP	Cyprus	31	MLT	Malta
10	CZE	Czech Republic	32	NLD	Netherlands
11	DEU	Germany	33	NOR	Norway
12	DNK	Denmark	34	POL	Poland
13	ESP	Spain	35	PRT	Portugal
14	EST	Estonia	36	ROU	Romania
15	FIN	Finland	37	RUS	Russian Federation
16	FRA	France	38	SVK	Slovakia
17	GBR	United Kingdom	39	SVN	Slovenia
18	GRC	Greece	40	SWE	Sweden
19	HRV	Croatia	41	TUR	Turkey
20	HUN	Hungary	42	TWN	Taiwan
21	IDN	Indonesia	43	USA	United States
22	IND	India	44	ROW	Rest of the World

Table 4: Industry coverage of the WIOD

Industry code	Industry name
1	Crop and animal production, hunting and related service activities
2	Forestry and logging
3	Fishing and aquaculture
4	Mining and quarrying
5	Manufacture of food products, beverages and tobacco products
6	Manufacture of textiles, wearing apparel and leather products
7	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
8	Manufacture of paper and paper products
9	Printing and reproduction of recorded media
10	Manufacture of coke and refined petroleum products
11	Manufacture of chemicals and chemical products
12	Manufacture of basic pharmaceutical products and pharmaceutical preparations
13	Manufacture of rubber and plastic products
14	Manufacture of other non-metallic mineral products
15	Manufacture of basic metals
16	Manufacture of fabricated metal products, except machinery and equipment
17	Manufacture of computer, electronic and optical products
18	Manufacture of electrical equipment
19	Manufacture of machinery and equipment n.e.c.
20	Manufacture of motor vehicles, trailers and semi-trailers
21	Manufacture of other transport equipment
22	Manufacture of furniture; other manufacturing
23	Repair and installation of machinery and equipment
24	Electricity, gas, steam and air conditioning supply
25	Water collection, treatment and supply
26	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services
27	Construction
28	Wholesale and retail trade and repair of motor vehicles and motorcycles
29	Wholesale trade, except of motor vehicles and motorcycles

Industry code	Industry name
30	Retail trade, except of motor vehicles and motorcycles
31	Land transport and transport via pipelines
32	Water transport
33	Air transport
34	Warehousing and support activities for transportation
35	Postal and courier activities
36	Accommodation and food service activities
37	Publishing activities
38	Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities
39	Telecommunications
40	Computer programming, consultancy and related activities;information service activities
41	Financial service activities, except insurance and pension funding
42	Insurance, reinsurance and pension funding, except compulsory social security
43	Activities auxiliary to financial services and insurance activities
44	Real estate activities
45	Legal and accounting activities;activities of head offices; management consultancy activities
46	Architectural and engineering activities; technical testing and analysis
47	Scientific research and development
48	Advertising and market research
49	Other professional, scientific and technical activities; veterinary activities
50	Administrative and support service activities
51	Public administration and defence; compulsory social security
52	Education
53	Human health and social work activities
54	Other service activities
55	Activities of households as employers; undifferentiated goods & services-producing activities of households for own use
56	Activities of extraterritorial organizations and bodies

B Declarations of interest

Declarations of interest: none

C Data statement

The data that support the findings of this study are openly available from

https://dataverse.nl/dataset.xhtml?persistentId=doi:10.34894/PJ2M1C

Notes

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