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Autocatalytic networks, Trade and Structural Changes in Emerging Economies

Arnaud Persenda

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THÈSE DE DOCTORAT

Réseaux autocatalytiques, commerce international et changements structurels dans les économies émergentes

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du grade de docteur en sciences
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d'Université Côte d'Azur**

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Réseaux autocatalytiques, commerce international et changements structurels dans les économies émergentes

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Réseaux autocatalytiques, commerce international et changements structurels dans les économies émergentes

Dans cette thèse, j'explore deux changements structurels majeurs : la croissance des liens input-output (IO) internationaux et l'émergence d'industries vertes, en portant une attention spécifique aux économies émergentes. Ces transformations structurelles modifient la dynamique des activités économiques et influencent par conséquent le processus d'industrialisation d'une nation. J'étudie comment ces changements s'accompagnent de structures industrielles caractérisées par des effets de feedback. L'accumulation de feedback loops déclenche des mécanismes de causalité cumulative, qui influencent fortement la dynamique des industries dans les économies émergentes. L'étude des cycles dans les liens input-output (IO) est réalisée en y appliquant pour la première fois le cadre des réseaux autocatalytiques (ACS), initialement introduite par Jain et Krishna (1998) pour analyser les écosystèmes biologiques mais applicable de manière plus large aux systèmes socio-économiques. A notre connaissance, cette recherche est pionnière dans l'utilisation des ACS pour examiner les transformations des liaisons IO au cours du développement. Ma thèse comprend trois études de cas qui serviront de base pour les trois chapitres : (i) l'émergence des industries chinoises comme centre du réseau de production mondial ; (ii) les changements dans la structure des liens IO des nations post-socialistes; (iii) la croissance conjointe des industries vertes et non vertes dans les économies émergentes. Dans la première étude, je revisite l'émergence de la Chine au cœur du commerce mondial. Je modélise l'économie mondiale sous la forme d'un réseau inter-industrie basé sur les données WIOD couvrant la période 2000-2014, j'identifie deux points clés dans le développement de la Chine : d'abord, l'année 2005, lorsqu'un ACS local chinois se connecte à l'unique ACS mondial, révélant la complémentarité entre les cycles domestiques et internationaux ; ensuite, l'année 2013, lorsque les industries américaines ont commencé à être reléguées à la périphérie de l'ACS mondial, révélant une nouvelle rivalité potentielle entre ces deux grandes économies. Dans la seconde étude, j'étudie les changements dans les liens IO au sein et entre les nations post-socialistes sur la

période 1990 à 2021. J’analyse les différences dans l’évolution des flux d’inputs domestiques et internationaux entre nations qui ont rejoint l’Union Européenne (CEEU) et celles qui sont restées dans la sphère d’influence russe et ont rejoint la Communauté des États Indépendants (CEI). Je modélise un réseau IO basé sur les données EORA. Je détecte également différentes tendances au sein des deux groupes de pays. Les pays du CEEU sont plus intégrés dans les chaînes de valeur globales, tandis que les pays de la CEI sont en général plus autarciques. Dans la troisième étude, j’étudie la probabilité pour un pays d’acquérir de nouvelles capacités productives dans des biens verts et non verts ainsi que les externalités en termes de perspectives de diversification qui en découlent. Je modélise un réseau dans lequel les nœuds sont des produits et les liens représentent la probabilité qu’un produit “catalyse” un autre produit quelques années plus tard. Ce réseau utilise la base de données BACI qui répertorie tous les flux commerciaux bilatéraux au niveau 6 digits sur la période de 1990 à 2021. Je constate que les biens verts ont tendance à offrir moins d’opportunités de diversification que les biens non verts. Je trouve également que les capacités productives non vertes pourraient servir de tremplin pour le développement des industries vertes. De manière générale, nous espérons, par ce travail, contribuer au débat en cours sur la gestion de l’équilibre délicat entre le développement économique et la protection de l’environnement.

Mots clés: Analyse de réseaux, Complexité économique, Réseaux économiques, Analyse entrée-sortie, Commerce international, Développement économique, Croissance économique, Changement structurel

Autocatalytic Networks, Trade and Structural Changes in Emerging Economies

In this PhD thesis, I explore two key structural changes: the growth of international Input-Output (IO) linkages and the rise of green industries, while putting a special emphasis on emerging economies. These structural transformations alter the dynamics of economic activities, subsequently influencing a nation's industrialization process. I aim to investigate how these structural changes are characterized by industrial configurations that create feedback loop effects. Multiple overlapping feedback loops trigger cumulative causation mechanisms, which strongly influence the dynamics of industries in emerging economies. The study of cyclical patterns is conducted by applying and extending a novel, promising framework, the Autocatalytic Set (ACS) framework, introduced by Jain and Krishna in 1998. Initially conceptualized for ecosystem dynamics but found to have broader applicability in socio-economic systems, this research pioneers the use of ACS theory to scrutinize structural transformations and economic development. It is the first time that an ACS framework is applied to international Input-Output (IO) networks. My investigation encompasses three case studies which will be the basis for the three chapters: (i) the emergence of Chinese industries as the center of the global production network; (ii) the configuration and changes of input linkages of post-Socialist nations; (iii) the co-evolutionary growth of green and non-green industries in emerging economies. In the first study, I revisit the emergence of China as a dominant player in the world economy. By applying an ACS detection algorithm to a World Input-Output Network built from the WIOD database covering the 2000-2014 period, I identify two key turning points in China's development: first, the year 2005, when a Chinese local ACS branched into a global ACS, revealing the complementarity between domestic and international cycles; second, the year 2013, when US industries began to be pushed to the periphery of the global ACS, revealing a potential rivalry between these two large economies. In the second study, I describe the changes in input linkages in post-Socialist economies between 1990 and 2021. I analyze the differences in the evolution of both domestic and international input linkages between post-Socialist countries that joined the Euro-

pean Union (CEEU) and those that remained in the Russian sphere of influence and joined the Commonwealth of Independent States (CIS). This analysis has been performed by examining the IO network based on the EORA database. From this chapter, I detect different patterns within both groups of countries. EU countries tend to partake in more international linkages, while CIS countries tend to be more self-reliant. In the third study, I investigate how likely a country is to acquire new capabilities in producing green or non-green products. I also examine the externalities in terms of diversification prospects that arise from acquiring new capabilities in green goods. For this purpose, I define a directed network in which nodes are products and links represent the probability that one product “catalyzes” another product a few years later. This network relies on the BACI database, which lists all bilateral trade flows at the 6-digit level over the period 1990-2021. I first observe that green products tend to provide fewer diversification opportunities than non-green products. I also find that non-green capabilities might serve as a stepping stone for the development of green industries. In summary, this dissertation offers an innovative examination of inter-industry linkages through the lens of networks with cyclical structures. Hopefully, it contributes to better understand the delicate trade-off between economic development and environmental care.

Keywords: Network Analysis, Economic Complexity, Economic Networks, Input-Output Analysis, International Trade, Economic Development, Economic Growth, Structural Change

“L’Université Côte d’Azur n’entend donner aucune approbation ni improbation
aux opinions émises dans cette thèse. Ces opinions doivent être considérées
comme propres à leur auteur.”

À ma famille.

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Arnaud

*“Performance drives success, but when performance can’t be measured, networks
drive success.”*

Albert-László Barabási

The Formula: The Five Laws Behind Why People Succeed

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1 General Introduction

The main challenge of the 21st century is to promote shared prosperity while protecting the environment. This challenge, which concerns both developed and developing countries, cannot be addressed without profound and directed structural changes in their economies. These changes may require two key dynamics: the acquisition of new technologies and capabilities for the creation of new industries, and the movement of resources from traditional industries to newer ones.

Understanding both of these processes is therefore important for steering economies toward better economic perspectives. For emerging countries, compared to developed ones, these structural changes hold even greater significance, as these processes are required steps for achieving prosperity.

To be specific, the types of industries located in a country heavily influence its development prospects. Hausmann et al. (2007) and Rodrik (2013) show that the structure of production, such as the share of manufacturing in the economy and the types of goods exported, greatly influences a country's ability to converge to higher levels of development. However, many countries today are still limited in their industrialization prospects by their economic specialization (see in particular Hausmann and Klinger, 2007; Hidalgo, 2009). For what concerns more specifically green industries in developing countries, the situation is even more critical, as most of these countries lack the required technologies to achieve green industrialization (Rodrik, 2014).

In developing countries, the emergence of new industries is less about inventing new economic activities and more about testing whether industries that exist abroad can be successfully implemented locally. The concept of Self-Discovery, outlined in Hausmann and Rodrik (2003), describes the process entrepreneurs, including foreign actors, undergo when initiating new activities in a country. According to this theory, the actual profitability and costs of a new venture in a

country (acquiring skilled labor, establishing a supply chain, finding customers, etc.) are only known ex-post, after their implementation. In case of failure, the entrepreneur absorbs the full cost, while success leads to shared knowledge of an existing comparative advantage for the country in a given industry. This knowledge can spur industry growth as potential producers establish competing firms.

The expansion of these emerging industries might be constrained by several factors, some of which are domestic and others are foreign. Among the domestic factors is inter-industry competition. A new industry must compete with other existing domestic industries for resources, such as financial resources and skilled workers. Among the international factors is international intra-industry competition, which means becoming competitive compared to other foreign industries both domestically and abroad.

As previously stated, emerging industries compete against established industries for capital and labor. Consequently, offering higher capital and labor remuneration could be a vital strategy to draw more resources to infant industries (Lewis, 1954). This shift is crucial for channeling resources away from traditional, less productive sectors to more productive ones, such as manufacturing.

Other factors exist that can hinder a country's industrial development process. For instance, Auty and Warhurst (1993) introduced the concept of the "Resource Curse" to describe the situation where developing nations, specialized in natural resource exports, experience low growth in other industries. The Resource Curse can be explained by a phenomenon known as Dutch Disease. This phenomenon occurs when a surge in a resource's value attracts significant foreign investment in that industry, causing an influx of foreign currency that appreciates the national currency. This appreciation makes the country's exports more expensive and imports cheaper, posing challenges to the manufacturing and agricultural sectors as they compete with cheaper imports and face reduced global competitiveness. Consequently, capital and labor shift toward the booming industry, making the economy less diversified and more reliant on a single industry's performance, thereby increasing vulnerability. Additionally, the sudden influx of wealth in one industry can discourage investment in other economic sectors, leading to inflated property and service costs (Sachs and Warner, 2001).

In their quest for economic growth, industries in developing countries also com-

pete against established foreign industries for market shares, both abroad and domestically. There is imperfect competition between infant and established industries due to increasing returns to scale and, more broadly, advantages in terms of technology, capital, and market access. This makes it difficult for emerging industries to gain a foothold even in their domestic markets (see for instance Krugman, 1987; Rodrik, 1988). In this configuration, firms from domestic industries can suffer from direct competition with foreign firms from more established industries (Aghion et al., 2021), which in turn can reduce the growth of these industries. In this context, countries can decide to protect their domestic industries to gain the required size or competitive advantage needed to compete with foreign firms.

Inter-industry relationships within a country, as well as across countries, may involve not only competition but also complementarities. There are two types of complementarities: vertical and horizontal. Vertical complementarities correspond to the complementarities between industries that operate at different stages of the same production chain. For instance, there is a vertical complementarity between the production of cars and the production of wheels. An increase in the production of cars leads to an increase in the demand for wheels, and reciprocally, an increase in the production of wheels, or a reduction in wheel prices, decreases the prices of cars.

Complementarities occur in international relationships as well as between domestic industries. Regarding international complementarities, Lall and Albaladejo (2004), which studied China's competitive threat in Eastern Asia in the '90s, finds that Chinese and Japanese industries were in competition for low-technology products but complementary in the production of high-technology products. Aghion et al. (2021) finds similar results, at the firm level, concerning the related subject of the China shock in France. Aghion et al. (2021) finds that French firms experience a negative impact from Chinese exports to the French market when both French and Chinese industries produce the same output. On the other hand, French firms benefit from Chinese exports when Chinese industries provide them with inputs. These examples highlight the existence of international complementarities between industries that participate in the same supply chain through input linkages. At the domestic level, Jones (2011a) and Jones (2011b) highlight the role of intermediate linkages for industry productivity by modeling how input linkages,

as well as more broadly, inter-industry complementarities, create a multiplier effect that increases the productivity of a given industry. Moreover, Bartelme and Gorodnichenko (2015) finds a positive correlation between the density in Input-Output linkages, proxied by the average output multiplier, and a country's worker productivity. This idea is closely linked to the seminal concept already advocated in Young (1928) about the increasing returns from the division of labor between industries.

Horizontal complementarities refer to the complementarities that arise between industries requiring a common, non-rival good to operate. For instance, the fishing industry and the shipping industry both rely on well-maintained ports and harbors. Investing in port infrastructure to improve the fishing industry can also enhance efficiency for other users of the port, such as the shipping industry. This concept also applies to more intangible goods like skills and capabilities. For example, the finance industry and the insurance industry both rely on workers with similar skill sets, such as risk analysis. An increase in the number of workers with the required skills in finance can expand the pool of potential workers in insurance. While the literature on knowledge spillovers is vast, in the context of industrial development, we will be interested in how knowledge from different industries can be combined to create new industries.

Hausmann and Klinger (2007)'s capability theory of development emphasizes the importance of "capabilities" in the development process. Capabilities consist of knowledge, skills, and technologies that enable a country to produce specific goods and services. According to this theory, production capabilities are often non-tradable and difficult to move across borders, making them a unique asset for each country. The production process is based on the combination of specific capabilities. The more diverse the set of capabilities a country possesses, the larger the number of possible combinations of capabilities will be. This diverse set of capabilities can create a more complex set of combinations, which will lead to the emergence of more sophisticated goods. In other words, each new capability leads to increasing returns, both in the number of possible combinations and in the complexity of those combinations. Hausmann and Klinger (2007) and Hidalgo et al. (2007) show that an industry is more likely to acquire new production capabilities if the country already has related capabilities.

The capability dimension establishes a crucial structure of relationships between products, with strong implications for industrial policies. A country is more likely to start producing a new good if this good is related to another domestic production. On the contrary, it is more challenging for a country to enter an industry if it doesn't have the required supply chain. Both of these phenomena can create path dependency in the industrialization process, in which coherence both in terms of supply chains and capabilities constrains the industrial development of countries.

Economists have developed a number of tools for mapping inter-industry relatedness, with the aim of understanding the structure of relationships between industries, and across countries. This thesis will focus on the interpretation of these tools and the development of new ones to understand the consequences of these complementarities. The tools used in this thesis will be based on three main frameworks: the *Input-Output* (IO) framework, the *Economic Complexity* (EC) framework, and the *Autocatalytic Set* (ACS) framework.

The IO framework is the oldest one in the economic literature. Introduced by Leontief (1936), it uses data on inter-industry linkages to measure the contribution of each industry to other ones. This simplified model of inter-industry trade has provided a series of useful tools to study the interdependencies between industries. The most well-known of these tools is the Leontief inverse, which measures the input requirement in industry i generated by the production of one unit of output in industry j . This approach has been widely used to understand the process of economic development and the role that linkages play in it. This literature has found new vitality with the emergence of Global Multi-Region Input-Output (GMRIO) databases such as the World Input-Output Database (WIOD) and the EORA database that will be used in this Thesis. These databases provide information on the interdependencies between economic agents from multiple countries, making them especially relevant for understanding the role of international linkages in economic development.

In this thesis we will study trade data with an Economic Complexity approach (EC). Introduced by Hausmann and Klinger (2006), it focuses on modeling complementarities between economic activities. This framework is used to study how the set of capabilities influences the likelihood of the emergence of new activities in

a given territory. One advantage of this approach is its high level of disaggregation (usually at the product level, generally in 4-digit or 6-digit codes), which makes possible detailed analysis of structural changes. For example, the probability of two goods being co-exported by the same country can be explained by the use of similar capabilities for both productions.

Finally, we use a third framework, the ACS framework. Introduced by Jain and Krishna (1998), this framework serves as a kind of third pillar in this thesis, as it complements and extends the two frameworks of IO data and EC, putting an emphasis on cyclical structures of economic relationships. The ACS framework builds on the same idea of relatedness and complementarities of industries or products and extends the analysis in two directions: first, it provides a mathematical set of metrics for evaluating the degree of presence of cyclical structures in a network; second, it offers a dynamic explanation of change based on the idea of circular cumulative causation, through the metaphor of “catalytic” links between economic entities.

The concept of circular cumulative causation, introduced in (Myrdal et al., 1944), is an economic theory that describes a self-reinforcing process based on feedback loops, in which economic events and outcomes build upon each other, leading to growth or decline in a cyclical manner. In this framework, initial advantages or disadvantages in sectors like technology, industry, or human capital can lead to a series of events that either amplify these advantages or exacerbate disadvantages. For example, an initial investment in a particular industry can attract more capital, skilled labor, and technological advancements, which in turn make the industry even more competitive and attractive for further investments. This creates a virtuous cycle of growth and development. Conversely, a lack of initial investment can lead to a vicious cycle of decline. Circular cumulative causation is often used to explain various economic phenomena including regional development disparities, uneven industry growth, or income inequality.

Circular cumulative causation mechanisms have been theorized as solutions to the multiple “chicken and egg” problems that arise during the development process. For instance, emerging economies struggle to establish complex production due to the absence of specialized inputs. Reciprocally, industries that could provide these specialized inputs are not incentivized to emerge because of the limited market

size (Matsuyama, 1995).

Acquiring a critical mass of support industries can initiate a circular mechanism in which an increase in the division of labor leads to the creation of more specialized inputs. These inputs can then be utilized by other industries, thereby facilitating the emergence of new industries in a cumulative process (Matsuyama, 1995). Another process, highlighted by Hirschman (1958), known as unbalanced growth theory, suggests that if the state promotes the emergence of an industry, it creates demand for that industry's inputs. The industries supplying those inputs will experience increased profits, attracting new actors to the market. Both of these cyclical mechanisms offer solutions to the coordination challenges between emerging industries and their suppliers.

Another example is the need for specific capabilities to create new industries; however, to acquire these capabilities, a developing country must already have the relevant industries in place (Hausmann et al., 2013). These circular dependencies can constrain the growth of new industries in developing countries. The solution proposed by Hausmann et al. (2013) involves the acquisition of related goods. Since countries can produce only the goods for which they have the required capabilities, diversification toward products requiring similar capabilities is feasible. As countries transition from one set of related goods to another, they can acquire new capabilities and, consequently, produce more complex goods.

Originating in biology, the ACS framework models processes where complementarities between species, in the context of natural selection, lead to the emergence of self-sustaining clusters of species, similar to circular cumulative causation phenomena. Jain and Krishna present a model in which agents are species connected by their catalyzation relationships (for example, predation relationships). The presence of a catalyzer species improves the fitness of its predator. To model the process of evolution, the species with the lowest fitness is forced to evolve and adopt new catalyzing relationships (preys and predators).

The main point of interest lies in the dynamics of the model. (i) The model starts with a random set of relationships. (ii) Over time, cyclical relationships emerge and create clusters (ACS) in which species have a higher level of fitness. There is increasing selective pressure for unrelated species to form links with members of the set to benefit from the positive feedback loop that occurs within the

ACS. Slowly, every species starts to become increasingly reliant on the set and its members. (iii) This can lead to situations in which the species with the lowest fitness are ACS members. The mutation of these members, who are sometimes key species, can lead to crises in which large clusters of species are disconnected from the ACS. (iv) Over time, a cyclical trend of consolidation of the ACS followed by periods of crisis emerges.

Although the ACS framework was first proposed as an explanation for self-organization in chemical and biological systems, it is very relevant for describing structural change in economic systems as well. The original idea of ACS is to model catalytic effects between species, which can lead to the emergence of self-sustaining clusters of species in the context of natural selection. The same mechanism provides a meaningful context in which economic complementarities have an effect on economic performance through the system of links of their relationships (see in particular Jain and Krishna, 2002a; Matutinović, 2005; 2020).

In this context, economic agents can be firms or industries connected by industrial or technological complementarities. This model can provide insights into the emergence of industrial clusters in developing countries. Industries in developing countries would receive strong incentives to become increasingly reliant on the wealthiest industry (or cluster of industries) in the country, even if this industry (or cluster of industries) is not conducive to long-run growth. This framework has been applied to several economic networks to understand the effects of feedback on trade (Bakker et al., 2014) and on innovation (see for instance König et al., 2011; Napolitano et al., 2018), but it has yet to be used on IO networks and Product Spaces to understand their effects on structural change and growth.

The IO, EC, and ACS frameworks have in common the extensive use of network tools. The use of network tools in the IO framework is rather recent. The availability of reliable IO data has led to the emergence of data-driven approaches such as the network approach. While our datasets are too broad to capture heterogeneity at the level of individual industries, plants, or firms, they offer the advantage of capturing economy-wide effects of resource reallocation. This framework provides a bird's-eye view that studies confined to the manufacturing sector cannot provide. Moreover, our broad scope allows for a more extensive comparison across a diverse range of developing countries. As such, our work should be considered

as a complement to studies that focus on plant- or firm-level IO linkages (see for instance Di Giovanni et al., 2018; Bernard et al., 2019).

This approach, applied to Global Multi-Region IO relationships, has provided more information on the general structure of global production networks (see Carvalho, 2013; Cerina et al., 2015), the international spreading of shocks through industries (Li et al., 2014), and the role of each industry in it (see Cerina et al., 2015; Tsekeris, 2017). This approach is especially relevant due to the network nature of international supply chains.

The EC methodology is based on network methodologies (see for instance Hausmann and Klinger, 2006; 2007; Neffke and Svensson Henning, 2008; Zaccaria et al., 2014; Joyez and Laffineur, 2022). The technological complementarities between products (or industries) are modeled using network modeling. The resulting network is the Product Space or the Industry Space in which industries or goods are connected by their relatedness. Mapping the goods produced by countries and the goods using similar capabilities based on the network provides important insights into the opportunities for diversification of each production.

Finally, the ACS approach is also based on network theory. It comes with a series of mathematical tools to detect the Autocatalytic Sets in networks based on positive complementarities such as the IO network and the Product Space. It also provides tools to measure the strength of the positive feedback loop occurring in each of the ACSs. In this thesis, we contribute to the economic development literature by focusing on modeling the network aspects of structural change and long-run growth issues.

More specifically, we focus on the relative dynamics of domestic and international inter-industry linkages in the course of economic development in the era of global value chains (GVC). We will concentrate on two case studies: the emergence of China's domestic industries in the global production network and the changes in input linkages in post-Socialist economies since the end of the Soviet Union. Both of these case studies provide insights into how changes in the structure of the IO network can lead to changes in the performance of domestic industries.

A series of empirical papers have shown that the structure of the IO network affects the growth and competitiveness of firms, industries, and countries. Several studies have demonstrated that specific structures in production networks can

generate divergence in performance between different entities. This difference in performance has been studied at the firm level (Muscolo et al., 2018) and at the country level (Bakker et al., 2014). Furthermore, Criscuolo et al. (2017) has shown that firms located in central industries in IO networks have higher productivity when they are far from the technological frontier. This last paper provides encouraging hints that the position of an industry within the structure of the IO network can create a diverging pattern of performance, partly explained by the industry's position in the GVC.

This thesis focuses on the idea that specific structures in the IO network can create circular cumulative causation mechanisms that favor the growth of industries and countries. The structures we study in this thesis are cycles in the production network. For example, in a given industries A and B, a cycle occurs when Industry A sells its output to Industry B, which in turn sells its output back to Industry A (Sonis et al., 1993). The existence of such bilateral IO relationships can enhance industry performance by encouraging cooperation between industries, such as information sharing on production processes or economic opportunities, or the establishment of more favorable contracts. Another effect could be a more localized transmission of positive and negative shocks in the network (for example industry failure or price reduction). A shock occurring in Industry A will be transmitted to Industry B, which will then transmit it back to Industry A. This will continue back and forth until the shock dies out (see for instance Zhu et al., 2014; McNerney et al., 2022).

The ACS framework is particularly relevant for the study of economic development. Indeed, the general structure of the IO network is highly influenced by the level of development (Boehm, 2015). As a country becomes more developed and therefore diversified, it transitions from reliance on extractive and agricultural sectors to more manufacturing and service sectors and increases the number of domestic linkages in the economy. GVC-led development also leads to an increase in international trading relationships between domestic and foreign industries. Such 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.

To summarize, this thesis is an empirical application of the theoretical framework of Jain and Krishna on the international IO network and the Product Space

to better understand the processes of cumulative circular causation that occur in the course of development. Through this approach, we primarily aim to reveal new stylized facts about structural change in emerging economies. While the results are mostly descriptive, they provide several stylized facts about the evolution of the relationship between industries that occur through the development process.

Chapter 2 studies the evolving position of China's industries in the World Input-Output Network. In this paper, we revisit China's emergence as a dominant player in the world economy using the innovative concept of Autocatalytic Sets (ACS) introduced by Jain and Krishna (1998). Specifically, we apply an ACS detection algorithm to a World Input-Output Network built from the WIOD database covering the 2000-2014 period. From this exercise, we identify two key turning points in the course of China's development: First, 2005, when a Chinese densifying local ACS branched to a Global ACS, revealing the complementarity between domestic and international cycles in China's development; Second, 2013, when US industries started to be pushed to the periphery of the Global ACS, revealing a new rivalry between these two large economies.

Chapter 3 studies the changes in input linkages in post-Socialist economies between 1990 and 2021. We analyze the differences in the evolution of input shares between post-Socialist countries that joined the European Union (CEEU countries) and those that remained in the Russian sphere of influence and joined the Commonwealth of Independent States (CIS). This is done by analyzing an Input-Output network based on the EORA database. From this chapter, we detect different patterns between both groups of countries. CEEU countries tend to partake more in international linkages, while CIS countries tend to be more self-reliant.

Finally, using a Directed Product Space, Chapter 4 studies the best diversification strategy for developing countries to gain comparative advantages in green products. Green goods are products necessary to reach sustainable development targets. Since they present many benefits, we discuss the question of why every country doesn't produce them. Using the Economic Complexity (EC) framework, we study how likely a country can start their production. We also study the externalities in terms of diversification prospects that arise from producing and exporting green goods. For this purpose, we define a directed network in which nodes

are products and links are the probability of a product to catalyze another one several years later. This network relies on the BACI database, which encompasses bilateral trade flows at the 6-digit level; we assess the autocatalytic structure of product adoption by identifying clusters of self-reinforcing products. We show that green goods are less prone to self-reinforcement compared to their non-green counterparts and offer fewer avenues for economic diversification. We also find that the impact of diversification varies across countries, suggesting that a one-size-fits-all approach to fostering green goods production may not be effective.

2 The Rise of China in the Global Production Network: What Can Autocatalytic Sets Teach Us ?

2.1 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, it is not easy to understand what is unique in the success story of the Chinese economy. One could explain the rise of China as a direct consequence of its openness to world markets. However, several other developing countries joined the WTO during the same period, but 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. On the other hand, success stories of small economies that also managed to industrialize through their access to global production networks also exist, as for example the so-called East Asian Dragons¹ of the '70s and the

This chapter is based on a paper co-authored with Flora Bellone and Paolo Zeppini.

¹This group of countries refers to South Korea, Singapore, Taiwan, and Hong Kong.

'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 Product Space and industry structure 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). However, none of these earlier contributions explore the underlying mechanisms that have driven the dynamics of the Chinese industries.

In order to delve deeper into the Chinese economic miracle, this chapter proposes 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 of trade are particularly important as they can drive the processes of cumulative causation in economic activities. To develop this idea, we use the framework of Autocatalytic networks proposed by Jain and Krishna (1998). Autocatalytic sets are defined as a subset of the network where each node has an incoming link from at least one node belonging to the same set. Autocatalytic Sets (ACSs) exploit and generalize cyclical structures in a network. Jain and Krishna (1998) propose a model of network formation where ACSs form endogenously within a selective evolutionary process, resulting in successful self-sustaining structures. In this chapter, we apply this framework to a World Input-Output Network (WION) that we construct from the second release of the World Input-Output Database (WIOD), covering the period 2000-2014.

With this novel methodology, specific attention is devoted to the evolution of Chinese industries within both local and global autocatalytic structures in the WION. More specifically, our approach allows to observe how each ACS is structured and how 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 key 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 American industries were pushed to the Periphery of the 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 US industries in the early 2010s. This could be spotted in our analysis through the lens of autocatalytic networks.

Section 2.2 presents an overview of the relevant literature. Section 2.3 introduces our database and Section 2.4 describes our methodology. Section 2.5 discusses our main findings and Section 2.6 concludes.

2.2 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).

When China officially joined the WTO in 2001, it was already a significant trade player. However, Chinese industries were not yet the unique and 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 trade and production networks offers new insights into the Chinese miracle by examining the evolving position of this country in the world economy through the lens of network analysis. Zhu et al. (2014) apply network analysis to the International Trade Network (ITN) based on the CEPII BACI Database and find a strong evolution of the Chinese position in the network between 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 American community in 2002-2004 and finally reemerged with China as its Core between 2005 and 2011.

However, this aggregation at the country level cannot model the complex in-

dustrial dynamics that have occurred during China’s development. The evolution of Chinese industrial development can be further scrutinized at a lower level of aggregation. Using Input-Output networks can highlight the change in the position of each Chinese industry in global value chains and its impact on the structure of its economy.

The recently made available GMRIO databases² have helped deepen our understanding of changes in the world economy and China’s new role. These databases can be transformed into a network model of the world economy, such as the World Input-Output Network (WION) introduced in Carvalho (2013) and formalized in Cerina et al. (2015), based on the WIOD provided by the Groningen Growth Development Center (GGDC). The WION is a network in which each node is a Country-Industry (CI), and each flow represents the size of the input flow from one industry to another. Since the WIOD was the first GMRIO database to provide consistent yearly time series for each flow, it became possible to analyze the evolution of individual country-industries in the network between 1995 and 2011.

In this framework, Li et al. (2014) develop a cascading failure tolerance analysis to rank the relative economic importance of countries and industries. The methodology consists in measuring the resulting cascading effect of an income-reducing shock to a specific node, defined as a CI, on the other nodes of the world production network. The methodology allows for the ranking of industries and countries by averaging the scores of all industries in a given country.³ The rise of China’s manufacturing industries is reflected in this measure. On average, the rank of Chinese manufacturing industries surpassed that of their American coun-

²These datasets have been used for research on various issues involving the Chinese economy, but not necessarily on the specific issue we are interested in, namely understanding what has been unique in China’s outward-oriented growth strategy. 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 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). More recently, these GMRIO databases have been used to shed light on the propagation of shocks across the world economy through IO relationships.

³Specifically, a tolerance threshold p is set such that if a given CI receives an income reduction p' greater than the threshold level, the node will fail and cut all of its national and international transactions. The methodology measures how many remaining nodes are left at any given threshold depending on the removed node, and identifies for each industry the value pc , which the threshold p must take, at which the removal of the node leaves only 30% of the nodes active in the rest of the network. The higher the value of pc , the greater the impact on the world economy if the industry disappears. At the aggregate level, the pc measure is defined as the average pc of the industries of a given country.

terparts as early as 2003, and it has continued to rise since, while the USA rank kept declining.

Recent studies have used a network approach to analyze the WIOD, such as Cerina et al. (2015). While their exploration does not specifically focus on China, it allows for tracking the emergence of Chinese industries. They compute three other relevant indicators: the PageRank centrality measure, the community core-ness measure, and the Laumas method of backward linkages⁴, for each node of their WION over the period 1995 to 2011. According to these alternative measures, while dominant nodes are mostly American and Japanese industries over the studied period, some Chinese industries begin to appear in these rankings from 2011. In particular, the Chinese construction industry dominates the Laumas and core-ness rankings.

Zhu et al. (2015) introduces a Global Value Trees framework to model each CI supply chain as a tree, with the CI serving as the root. 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, the Chinese textile industry has, on average, increased its number of intermediaries with most other countries' industries, while China's electrical equipment industry has seen a decrease.

Amador and Cabral (2017) further 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 earlier findings by Zhu et al. (2014). 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.

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

⁴PageRank centrality is a variant of Eigenvector centrality that solves the problem of overvaluation of nodes at the Periphery. Community core-ness measure is based on cluster computations, with clusters being defined as communities of nodes that trade more with each other than with the rest of the network. Finally, the Laumas method of backward linkages, based on the Leontief inverse, highlights the direct and indirect dependence of each node relative to the final demand.

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.

Finally, Adarov (2021), focusing on Information and Communication Technologies (ICT) industries, shows that a structural transformation occurred in the relative importance of countries in these industries, 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

2.3 Data

In this research, we use the WIOD, which 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.⁶ 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 2016 WIOD release as it is the most relevant one for investigating the rise of China in the Global Production Network (GPN) following its entry into the World Trade Organization (WTO) in 2000.

⁵These 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).

⁶For 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).

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 A.1 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 countries and industries covered by the WIOD are presented in the Appendix.

The structure of the WIOD is illustrated in Figure 2.1, 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. To illustrate how to read the WIOD tables, let us consider the example of the first cell of Figure 2.1. Here, the value 1 indicates a flow of \$1 million worth of “goods and services” sold by Industry 1, *Crop and animal production industry*, in Australia (AUS-r1) to the same industry in Austria (AUT-c1).⁷

In this chapter, 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 dynamics and aggregate

⁷The industry codes in the first column of Figure 2.1, from A01 to U, broadly follow the 3-digit ISIC rev. 4 industrial classifications. The letters *r* and *c*, which precede the WIOD industry codes in column 4 and row 4 respectively, serve to identify the selling or row *r* and the buying or column *c* industries.

economic growth.⁸

Figure 2.1: Structure of the World Input-Output Table

		Intermediates use												Consommation finale												
		A01	...	U	A01	...	U	A01	...	U	...	U	CONS_h	CONS_np	CONS	GFC	INVEN	...	CONS	...	GO					
		Crop and animal production...	...	Activities of extraterritorial	Crop and animal	...	Activities of extraterritorial	Crop and animal	...	Activities of extraterritorial	...	Final consumption expenditure by households	Final consumption expenditure by non-profit organisations	Final consumption expenditure by private households	Gross fixed capital formation	Changes in inventories and valuables	...	Final consumption expenditure by households	...	Total output						
		AUS	AUT	ROW	AUS	AUS	AUS	AUS	AUS	...	ROW	...	TOT													
		c1	...	c56	c1	...	c56	c1	...	c56	c57	c58	c59	c60	c61	...	c57	...	c62							
supplier industry	A01	Crop and animal production...	r1	1																						
																							
	U	Activities of extraterritorial	AUS	r56	Inter-industry flows												Final demand									
																						
	A01	Crop and animal production...	r1																							
																						
U	Activities of extraterritorial	AUT	r56																							
...																							
A01	Crop and animal production...	r1																								
...																							
U	Activities of extraterritorial	ROW	r56																							
ll_fob	Total intermediate consumption	TOT	r65																							
TXSP	taxes less subsidies on products	TOT	r66																							
EXP_ad	Diff fob adjustments on exports	TOT	r67	Supplementary informations												Supplementary information										
PURR	Direct purchases abroad by residents	TOT	r68																							
PURNF	Purchases on the domestic territory by non-residents	TOT	r69																							
VA	Value added at basic prices	TOT	r70																							
IntTTM	International Transport Margins	TOT	r71																							
GO	Output at basic prices	TOT	r73																							

Note: The value 1 indicates a flow of \$1 million worth of “goods and services” sold by Industry 1, Crop and animal production industry, in Australia (AUS-r1) to the same industry in Austria (AUT-c1). The industry codes in the first column of Figure 2.1, from A01 to U, broadly follow the 3-digit ISIC rev. 4 industrial classifications. r stand for row and c stand for column.

2.4 Methodology

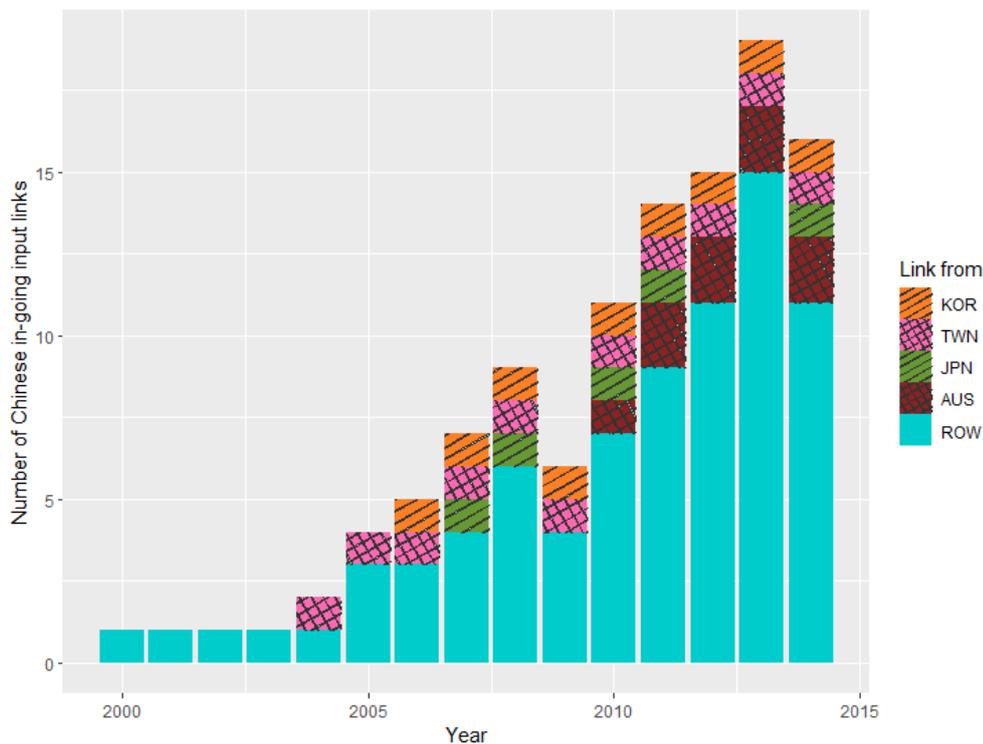
2.4.1 Building the WION

Turning to the application of our methodology to the WIOD, we proceed as follows. First, in the same manner as Cerina et al. (2015), we build a WION in which the nodes are CIs and the (directed) edges represent the amount of goods and services flowing from any supplying CI to any buying CI. In a second step, we filter the raw

⁸A possible extension of this research could involve 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.

WION to highlight the most important flows and run our ACS detection algorithm on the filtered WION. Filtering is a necessary step to identify meaningful ACSs because, as previously shown by the literature, our raw WION is characterized by high density, high degree distribution, and low hierarchy. Taken together, these features make detecting small sets of strongly connected nodes unlikely, as all nodes are connected to all other nodes by a directed path. The raw network is connected by flows with both large and small values.

Figure 2.2: Distribution of ingoing links to China, across the countries of origin, in the filtered World Input-Output Network



Note: Count of the number of linkages worth more than \$10 billion.

Since our interest lies in the evolution of communities of nodes that exchange the largest flows, we therefore set a filtering threshold value such that any input flow below this value is discarded from the network. As a benchmark filtering threshold value, we take the value of \$10 billion. Flows above \$10 billion are then given a value of 1 in the network, and flows below \$10 billion are given a value of 0 and therefore not displayed in the network.⁹ As a result, we obtain a binary

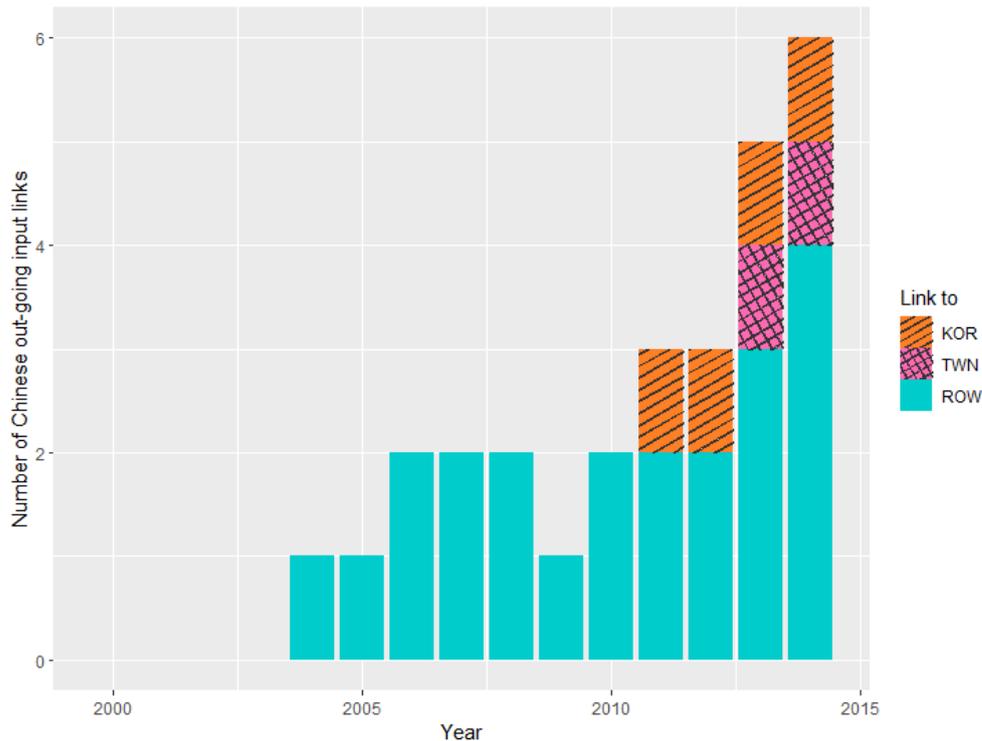
⁹Note that this procedure turns our WION into a binary network similar to the first J&K model (Jain and Krishna, 1998). In the second J&K model (Jain and Krishna, 2001), a weighted network is considered, which allows extending the theoretical results found in the first model to this more general setting.

network of 0's and 1's, which represents the adjacency matrix of CIs in the global economy.

In Section 2.5.3, we explore the sensitivity of our key findings to changes in the filtering threshold value. To describe China's position within our filtered WION, we present the numbers of ingoing and outgoing input links between Chinese industries and their main trade partners over our period of investigation.

Observing the distribution of ingoing links to China, across the countries of destination, reveals interesting facts. The main observation is the increase in ingoing links to China, primarily driven by the rising number of flows greater than \$10 billion from the "Rest of the World" (RoW) region. This increase in the number of flows larger than \$10 billion from the RoW Industry mainly originates from the *Mining and quarrying* Industry (ROW4). This shows the extent to which China extracts resources from the RoW countries to fuel its industries.

Figure 2.3: Distribution of outgoing links from China, across the countries of destination, in the filtered World Input-Output Network

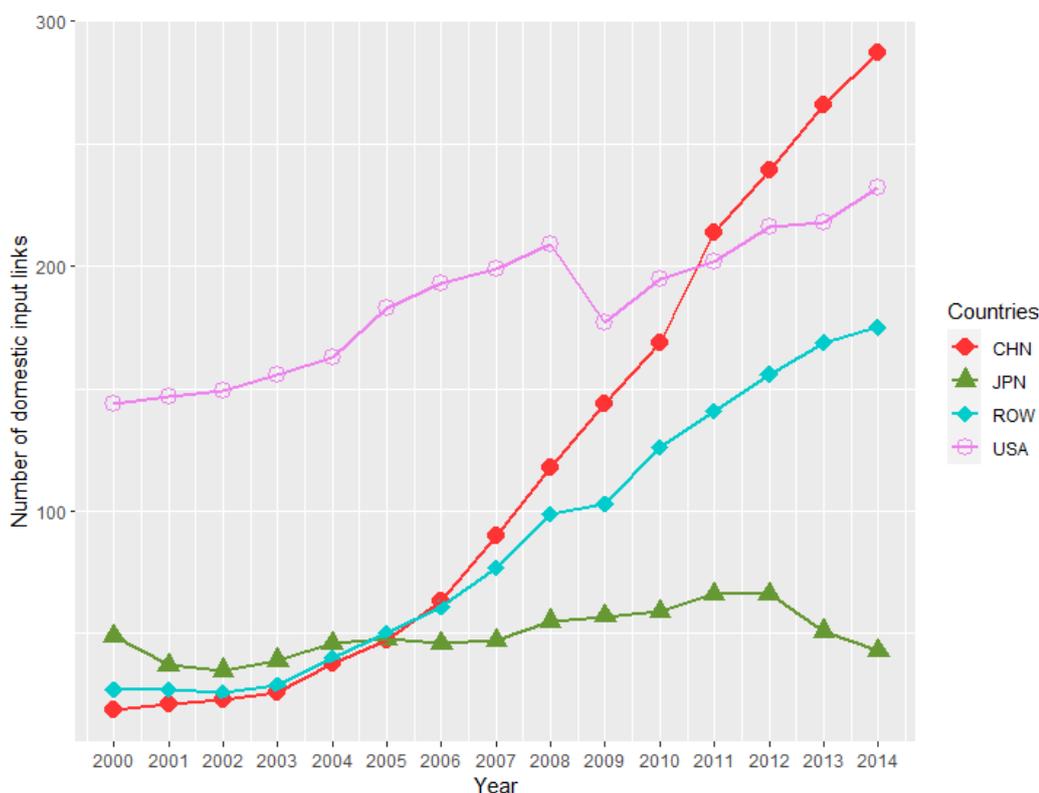


Note: Count of the number of linkages worth more than \$10 billion.

The outgoing links from China tell a similar story. The increase in outgoing links from China is driven by the rising number of flows greater than \$10 billion to the RoW region. Another stylized fact is the lower number of large outgoing

flows compared to ingoing flows. Similarly, the number of partners receiving large flows is also lower. Korea and Taiwan are the only countries receiving large flows from China. The increasing density of outgoing and ingoing links for China denotes, first, the economic growth of this country and, second, China's positioning as a trade partner with countries other than the traditional big economies. Overall, both graphs show a strong regional influence in the origin and destination of Chinese input flows, as well as the absence of US industries as direct origin or destination of Chinese input flows.

Figure 2.4: Number of domestic input linkages for key countries

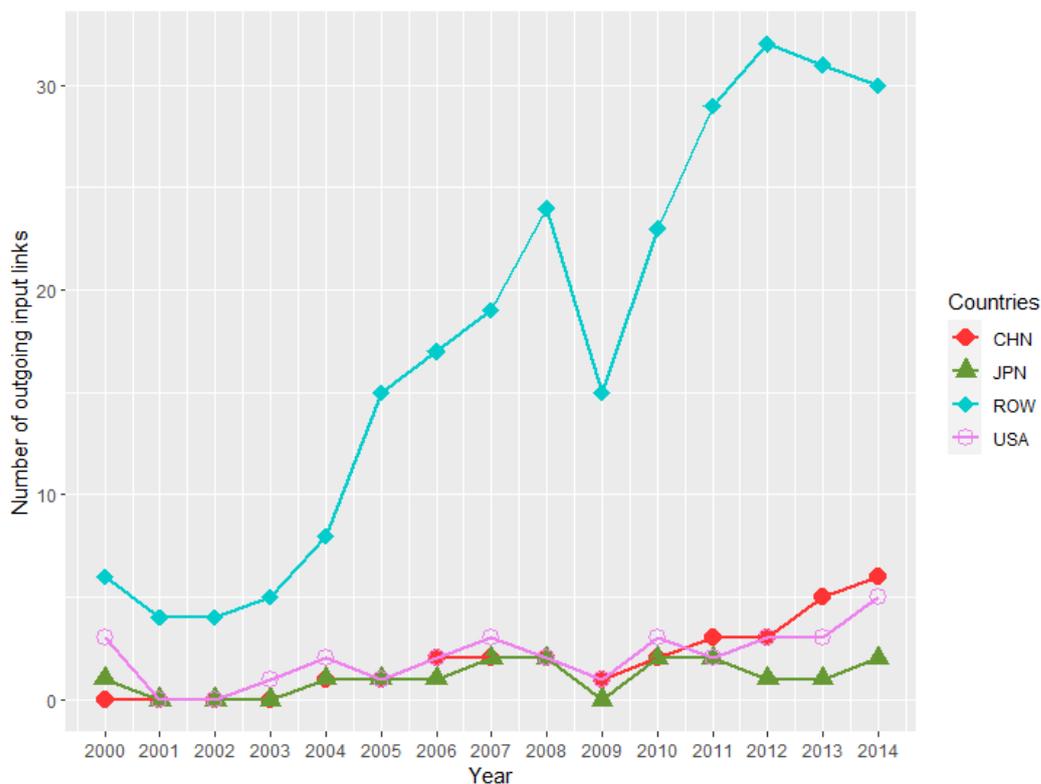


Note: Count of the number of linkages worth more than \$10 billion.

Figure 2.4 displays the evolution of the number of links over time for China, Japan, the USA, and the RoW Region. The evolution of the number of domestic input flows valued at more than \$10 billion reveals that the 15 years between 2000 and 2014 are characterized by an increase in the size of Chinese domestic flows. The number of domestic flows in China exhibited monotonous growth throughout the period. Similarly, the RoW Region also experienced an increase in the size of its inter-industry linkages. The USA saw an increase in the size of its domestic input flows as well, with the number of flows exceeding \$10 billion remaining stable

throughout the period, except for 2008 and 2009. Concerning Japan, the number of flows valued at more than \$10 billion remained stable during the period.

Figure 2.5: Number of outgoing input linkages for key countries

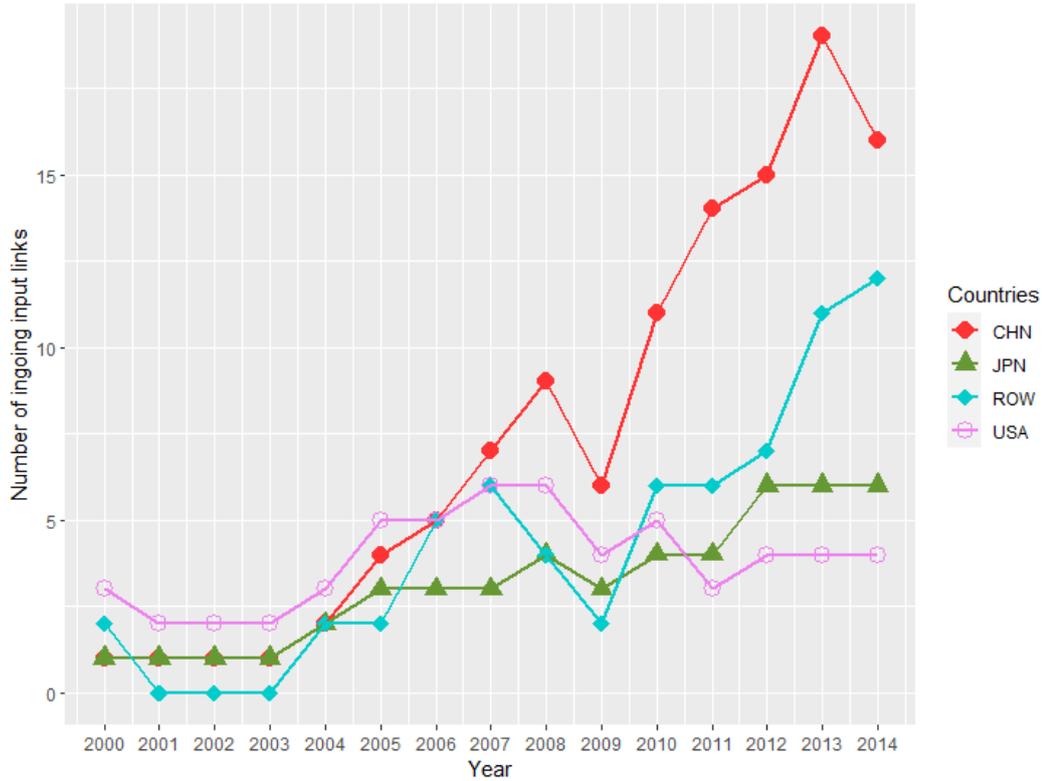


Note: Count of the number of linkages worth more than \$10 billion.

Figure 2.5 displays the evolution of the number of export flows valued at more than \$10 billion for China, Japan, the USA, and the RoW Region. This evolution illustrates that one of the main changes in terms of international export flows is the increase in both the size and number of aggregate export flows from the RoW Region. Japan remained stable throughout the entire period. While China and the USA gradually increased the number of flows valued at more than \$10 billion, China reached 6 large export flows in the last year. This increase in exports from the RoW *Mining and quarrying* industry (ROW4) is mirrored in Figure 2.6 by the increase in imports from China.

Figure 2.6 displays a similar indicator but for import flows worth more than \$10 billion for China, Japan, the USA and the RoW region. In terms of import flows, the picture is different, as most countries represented increased the number of import flows worth more than \$10 billion. While most countries increased their overall number of flows, except for the USA, China was the country with the

Figure 2.6: Number of ingoing input linkages for key countries



Note: Count of the number of linkages worth more than \$10 billion.

largest increase in large incoming input flows, followed by the RoW region.

2.4.2 Detecting the Autocatalytic Sets in the WION

In this section, we briefly summarize the analytical framework of Jain and Krishna (1998) and explain how we apply this framework to identify Autocatalytic Sets (ACSs) within the World Input-Output Network (WION) that we construct from the WIOD. As explained in the introduction, ACSs are defined as a subset of the network where each node has an incoming link from at least one node belonging to the same set of nodes. ACSs exploit and generalize cyclical structures in a network.

We then present some key characteristics of the ACSs found in the original J&K model. In Jain and Krishna (1998), nodes represent species of a population, each characterized by a fitness level that evolves based on the catalytic effect of incoming links. Over a longer time scale, the population is reshuffled, with low-fitness species removed and replaced by new species. This reshuffling event involves

not only the deletion of nodes but also of their links, with the links of the new nodes distributed randomly. This process then has a selection bias, or drift, which endogenously shapes the network structure. In particular, the process gives rise to the emergence of ACSs, which results in self-sustaining structures where nodes catalyze each other. Networks involving at least one ACS are characterized by three subsets of nodes:

- (i) A subset of self-reinforcing nodes, the so-called ACS “Core”, that serves as the “engine” of the ACS. Each member contributes to the fitness of the other members of the Core and benefits from the contributions of other Core members. This circular causation process of contributing and benefiting to the community increases the growth regime of the set members.
- (ii) A subset of nodes that only receive flows directly or indirectly from the Core, the so-called ACS “Periphery”. This subset corresponds to nodes that benefit from but do not contribute to the preservation and growth of the ACS. This position is associated with growth in fitness but not as much as the Core nodes.
- (iii) The rest of the network nodes that are neither part of the ACS Core nor Periphery and do not benefit from its catalytic properties.

To detect ACSs, we follow a methodology presented in Jain and Krishna (2002a) and Napolitano et al. (2018). First, we identify irreducible subgraphs within the directed network¹⁰. We proceed by relying on the Perron-Frobenius theorem to analyze the adjacency matrix version of the irreducible subgraphs. In the adjacency matrix version of these subgraphs, supplier industries are rows and client industries are columns. 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.¹¹

¹⁰An 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.

¹¹More 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 2.1: Autocatalytic Sets detected in the World Input-Output Network ranked by size, by year

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

Note: The Global ACS is mostly composed of a consistent set of countries. ACSs labeled 2 to 5 represent additional autocatalytic sets identified annually, ranked by size from largest to smallest. It's important to note that the composition of these smaller ACSs may vary from one year to the next.

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.

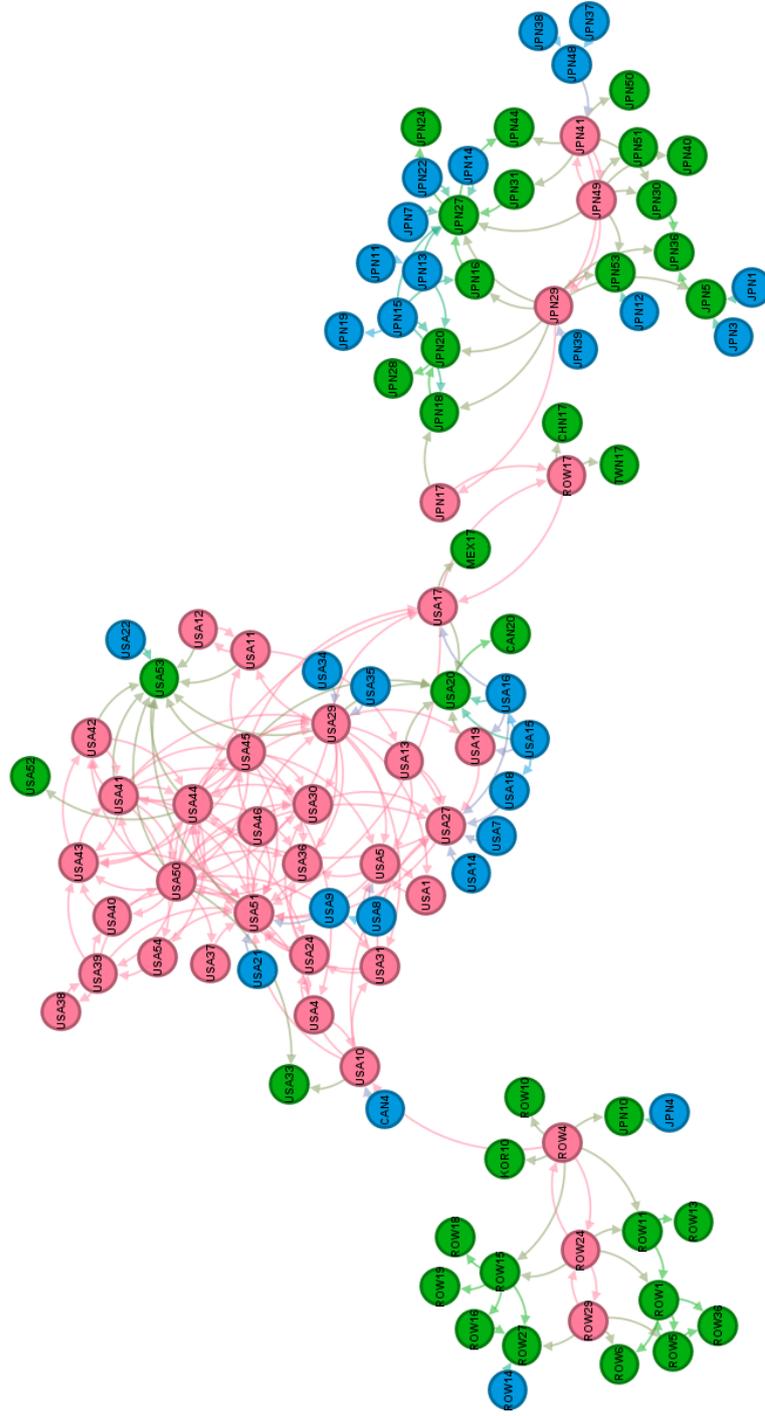
The distinction between Core and Periphery is rooted in the network structure. The Core is primarily characterized by cycles, where each member both receives and sends at least one flow from a node within the Core. These cycles generate multiple feedback loops, concentrating economic activities among Core members. On the other hand, the Periphery consists of nodes that are catalyzed by the Core but do not reciprocate the flow. These peripheral nodes are akin to parasites, benefiting from the economic activities within the Core without contributing to it.

Theoretically, this method can detect multiple ACSs in a given network. When applied to the WION, this methodology identifies one large ACS and a few smaller ones. Table 2.1 illustrates this feature, which holds for every year of observation. This table ranks the ACSs found in the WION for each year of observation by size, measured by the number of countries and industries. Each year, a large international ACS is detected, while all other ACSs involve only a few industries in a single country. We will refer to the former as the Global ACS and the latter as the local ACSs. Note that local ACSs are few; depending on the year of observation, the number of local ACSs ranges from 1 to 5.¹²

Table 2.1 provides some 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 countries in the Global ACS 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. The number of industries in the Global ACS exhibits the same pattern; it oscillates between 49 and 73 from 2000 to 2004 and then steadily increases from 113 to 174 between 2005 and 2014.

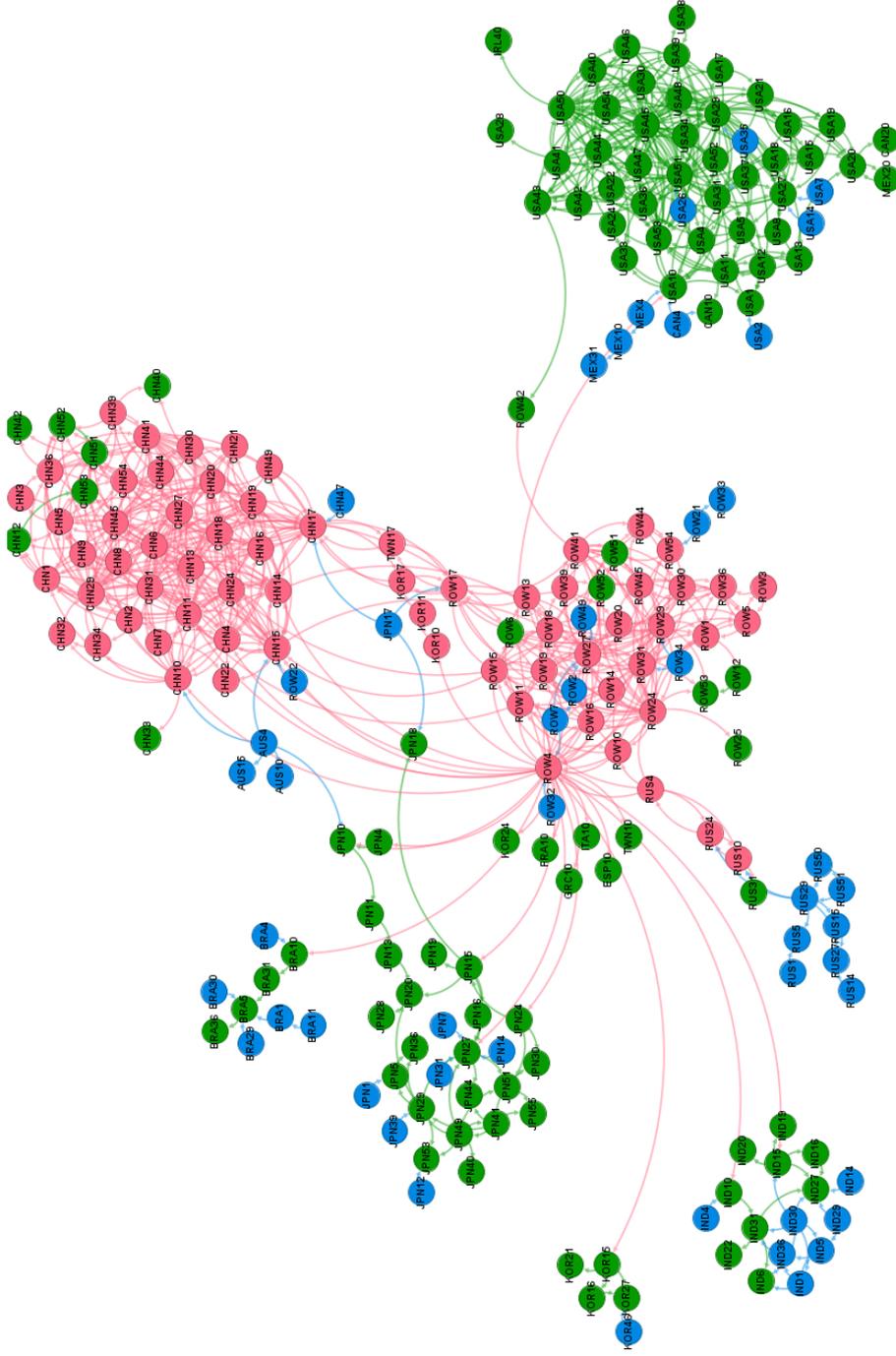
¹²In the robustness check section, we investigate the sensitivity of this pattern to a change in our filtering threshold value.

Figure 2.7: The Global Autocatalytic Set in the World Input-Output Network, in 2000



Note: The Network visualization is conducted using the force-directed algorithm ForceAtlas2 (Jacomy et al., 2014). The nodes in red correspond to Core industries. The nodes in green correspond to the Periphery. The nodes in blue are not in the ACSs.

Figure 2.8: The Global Autocatalytic Set in the World Input-Output Network, in 2014



Note: Only the subgraph containing the Global ACS is displayed. The Network visualization is conducted using the force-directed algorithm ForceAtlas2 (Jacomy et al., 2014). The nodes in red correspond to Core industries. The nodes in blue correspond to the Periphery. The nodes in blue are not in the ACSs.

Figures 2.7 and 2.8 display the Global ACS for the years 2000 and 2014. We notice that the Global ACS is composed of multiple components, each with their own Core. In 2000, for instance, there are three components: one mainly composed of US industries, one for Japan, and one mainly composed of RoW industries. While most of the trade occurs within each component, they feed into each other, making up the Global ACS.

Between 2000 and 2014, there have been dramatic changes in the position of China in the WION. How did China move from being outside of the Global ACS in 2000 to being at its Core in 2014? What were the dynamics of the US industries? The rest of the chapter answers these questions regarding how this change at the center of international trade occurred.

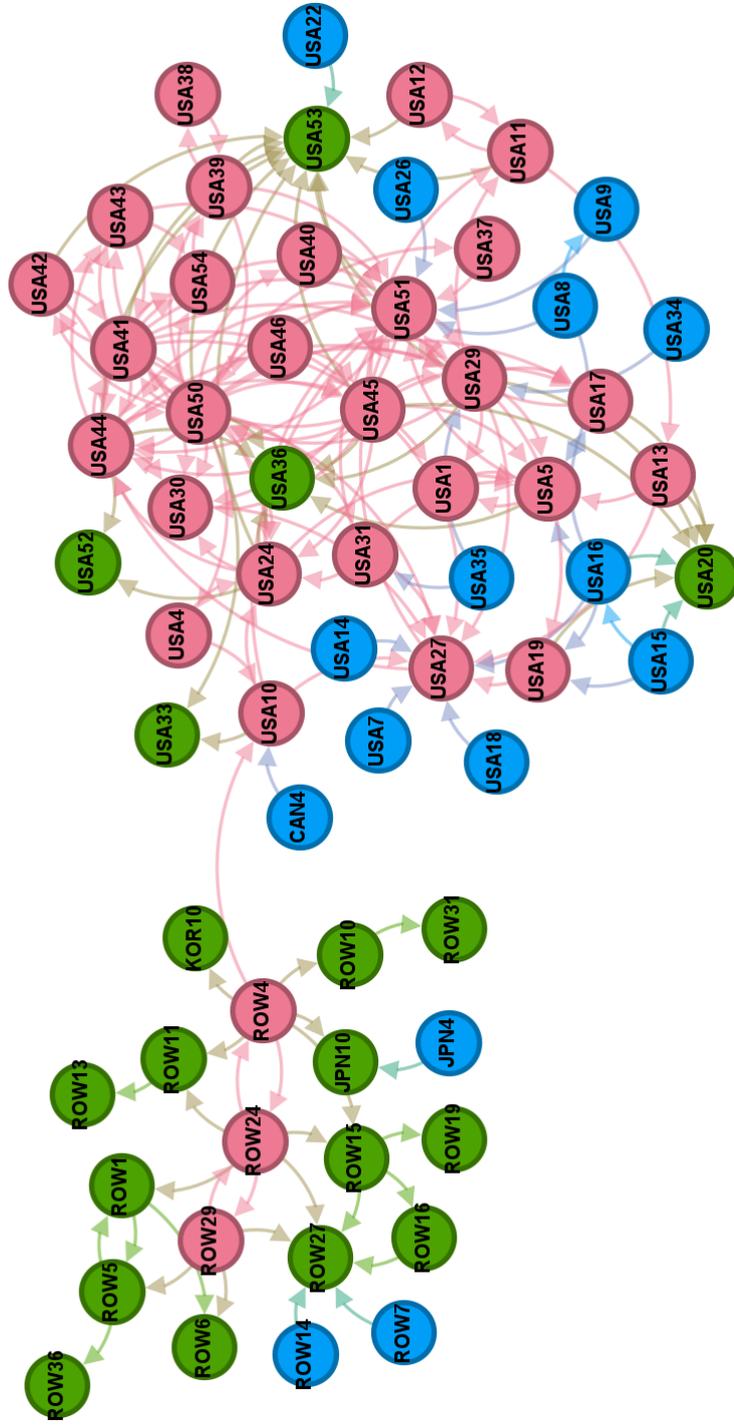
2.5 Results

In this section, we first describe how Chinese industries have evolved from outside to within the Global ACS over the period 2000 to 2014 and identify 2005 as a key turning point when a densifying Chinese local ACS branched into the Global ACS. Second, we compare the dynamics of Chinese industries to those of US industries and reveal a peripheralization pattern of US industries starting from 2013.

2.5.1 The evolving position of Chinese industries from local ACS to the global one

To describe the evolution of the position of Chinese industries within the ACSs detected in the WION over time, we first examine the position of Chinese industries in the year immediately following the year of observation, that is, the year 2001, when China entered the WTO. Figures 2.9 and 2.10 report the Global ACS and the Chinese local ACS, respectively, for 2001.

Figure 2.9: The Global Autocatalytic Set in the World Input-Output Network, in 2001



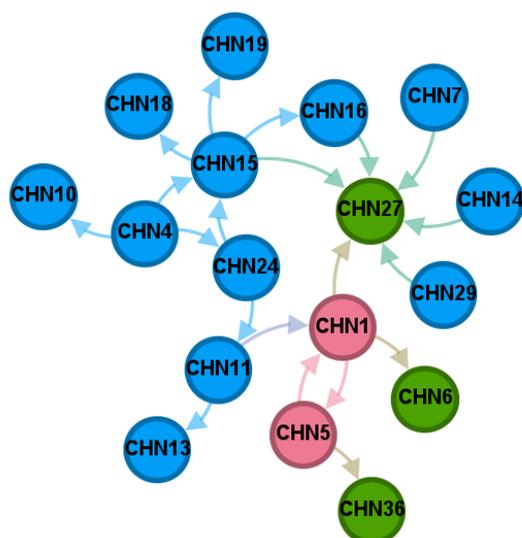
Note: Only the subgraph containing the Global ACS is displayed. The Network visualization is conducted using the force-directed algorithm ForceAtlas2 (Jacomy et al., 2014). The nodes in red correspond to Core industries. The nodes in green correspond to the ACS. The nodes in blue are not in the ACS.

Here, each link is directed from a selling CI to a buying CI. The first noticeable feature of the ACS structure of the WION in 2001 is that no Chinese industries appear in the Global ACS, except one: the Chinese *Computer and electronic* industry (CHN17), which receives a large input flow from its RoW counterpart industry (ROW17). In turn, the ROW17 industry is a Core industry in the Global ACS through its bilateral connection with the Core USA17 industry.

However, as shown in Figure 2.10, a few other Chinese industries form a Core of a local ACS in 2000. This Chinese local ACS is made of 5 traditional industries, 2 Core ones, namely the *Crop and animal production* industry (CHN1) and *Agrofood* industry (CHN5) and 3 peripheral ones, namely the *Textile* industry (CHN6), the *Accomodation and food services* industry (CHN36) and *Construction* (CHN27).

Fig 2.11 displays the Global ACS for the year 2001. At the core of the Global ACS, US industries are the most numerous ones with a few RoW industries completing the picture. The cluster of Core US industries is connected to the RoW cluster by primary industries linkages. Specifically, the Core *Mining and quarrying* industry (ROW4) is a key supplier of the Core *Manufacture of Coke and refined petroleum products* industry (USA10).

Figure 2.10: The Chinese local Autocatalytic Set in the World Input-Output Network, in 2001



The few other CIs that show up in the Global ACS in 2001 are all peripheral industries as for instance the Japanese and the Korean *Manufacture of coke and refined petroleum products* industry (JPN10, KOR10).

In the following years, the size of the Chinese local ACS increased, revealing a more complex structure over time and including new circular relationships combining agriculture-related industries to other heavy and light manufacturing industries. This is illustrated in Figure 2.11 which represents both the Chinese local ACS and the Global ACS detected in the 2004 WION.

In the Chinese local ACS, Core industries now include *Manufacture of coke and petroleum products* (CNH10), *Chemicals and chemical products* (CHN11), *Mining and quarrying* (CHN4), *Electricity & gas* (CHN24), *Rubber & plastic products* (CHN13) and *Computer and electronics* (CHN17) still connected by bilateral flows to their counterpart Taiwanese and RoW industries (ROW17 and TWN17). Twelve other Chinese industries are in the Periphery of this local ACS. We find among these industries the above-mentioned agro-related and construction industries (CHN1, CHN5, CHN36, CHN27). Also more complex light industries join the previously mentioned *Textile* industry in the Periphery of the Chinese local ACS. Those new industries include the *Fabricated metal products* industry (CHN16), the *Motor vehicles* industry (CHN20), the *Land transport* (CHN31) and the *Retail trade* (CHN30) and the *Basic metals* industry (CHN15).

On the other hand, the Global ACS is still dominated by Core US industries. Interestingly, the Core of the Global ACS no longer includes the US *computer and electronics* industry (USA17). Core US industries are still connected to a few Core RoW ones through IO linkages to primary industries (ROW10, ROW4) and to *Basic metals* (ROW15). In the 2004 Global ACS, it is also noticeable that Japanese industries are all positioned outside of the Core in the Periphery of the ACS. The *peripheralization* of the Japanese industries is a phenomenon that has been documented earlier in the literature. Through the lens of autocatalytic sets, it appears that this phenomenon started right after China's accession to the WTO. Indeed, from 2001 onwards, no Japanese industry appears in the Core of the Global ACS anymore.

The Chinese economy's branching to the Global ACS occurred in 2005 through very specific industry linkages, as illustrated in Figure 2.12. In this figure, 19 other Chinese industries appear, all as peripheral nodes. After some Chinese industries appeared in the Periphery of the Global ACS, their numbers kept increasing over the subsequent years. In the years following China's branching to the Global ACS,

Figure 2.11: The Chinese local Autocatalytic Set and the Global Autocatalytic Set in the World Input-Output Network, in 2004

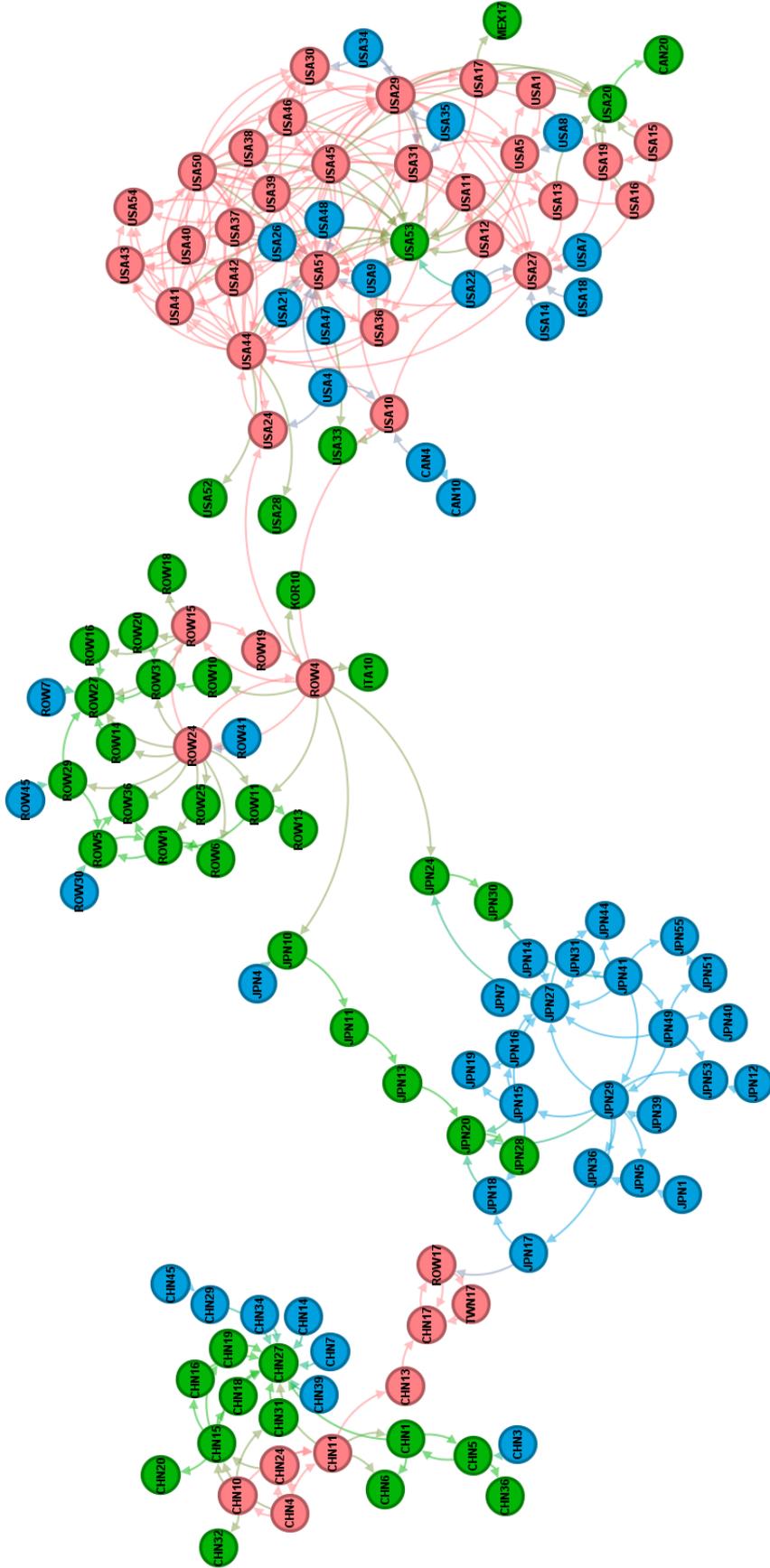
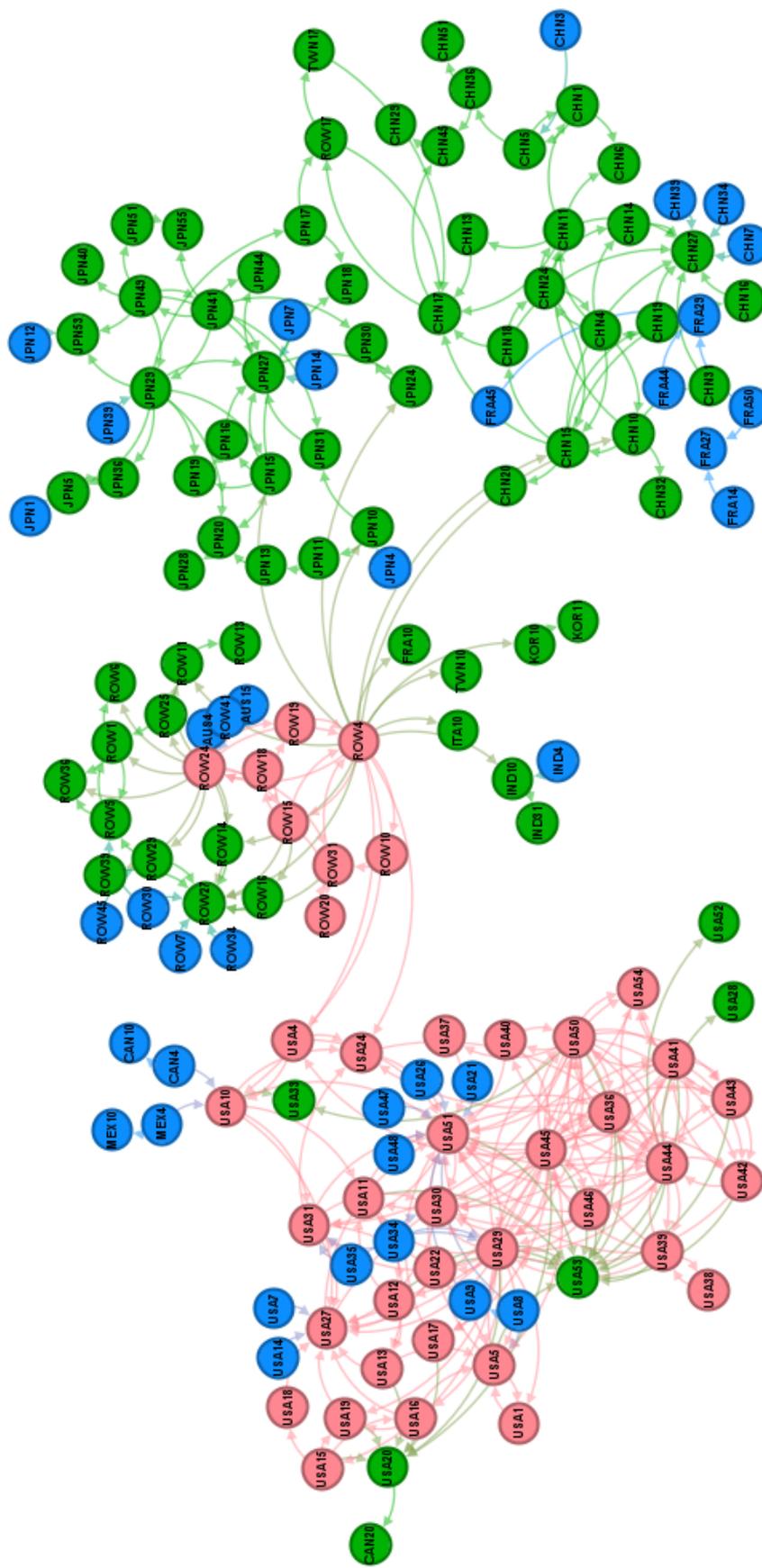
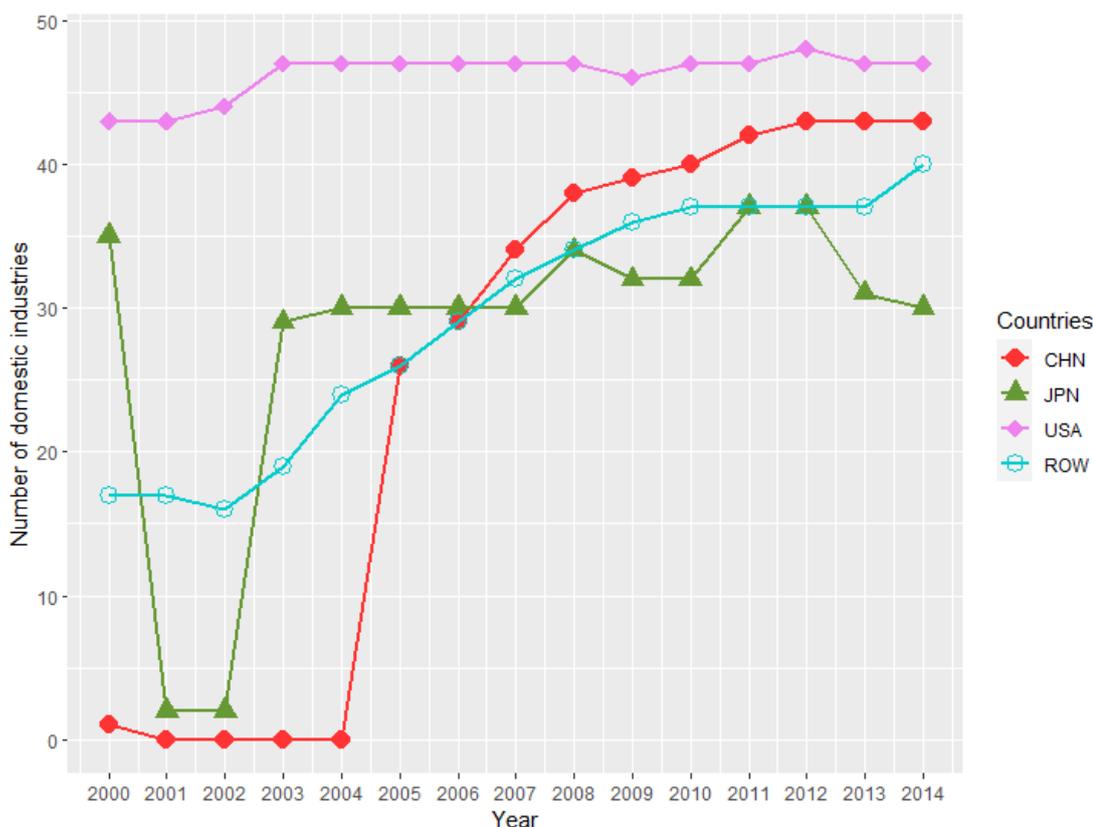


Figure 2.12: The Global Autocatalytic Set in the World Input-Output Network, in 2005



both Chinese intra-national flows and international flows between China and the RoW strengthened. What the ACS approach shows is that part of the success of China’s internationalization process comes from how this country transforms its local circular causation industrial relationships into global ones by branching its industries into global production networks.

Figure 2.13: Composition of the Global Autocatalytic Set in the World Input-Output Network



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

Our main interest lies in the role of economies, especially China, within the trade network. For this reason, we examine in detail the positions of countries within the autocatalytic structure of the WION. Figure 2.13 reports the number of domestic industries in China, Japan, the USA, and the RoW within the Global ACS. Several dynamics are evident. The number of American industries in the ACS remains stable over time, positioning the USA as the country with the highest count of industries in the set. Japanese industries disappear from the ACS in 2001 and 2002 but subsequently stabilize with approximately 30 industries. Both China and the RoW experience an increase in size. China enters the Global ACS in 2005

and rises to become the country with the highest number of CIs in the Global ACS by 2014.

2.5.2 The relative position of Chinese and American industries within the Global ACS

We now turn to a description of the relative positions of Chinese and American industries within the Global ACS and 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 2.15 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 US 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 US 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 US industry and a Core RoW industry concerns primary resources; specifically, it is a flow from the *Mining and quarrying* industry (ROW4) to the US *Manufacture of coke and refined petroleum products* industry (USA10). Overall, since 2013, the US economy appears to be a more isolated, self-sustained part of the Global ACS compared to the Chinese economy.

Figure 2.15: The Global Autocatalytic Set in the World Input-Output Network, in 2013

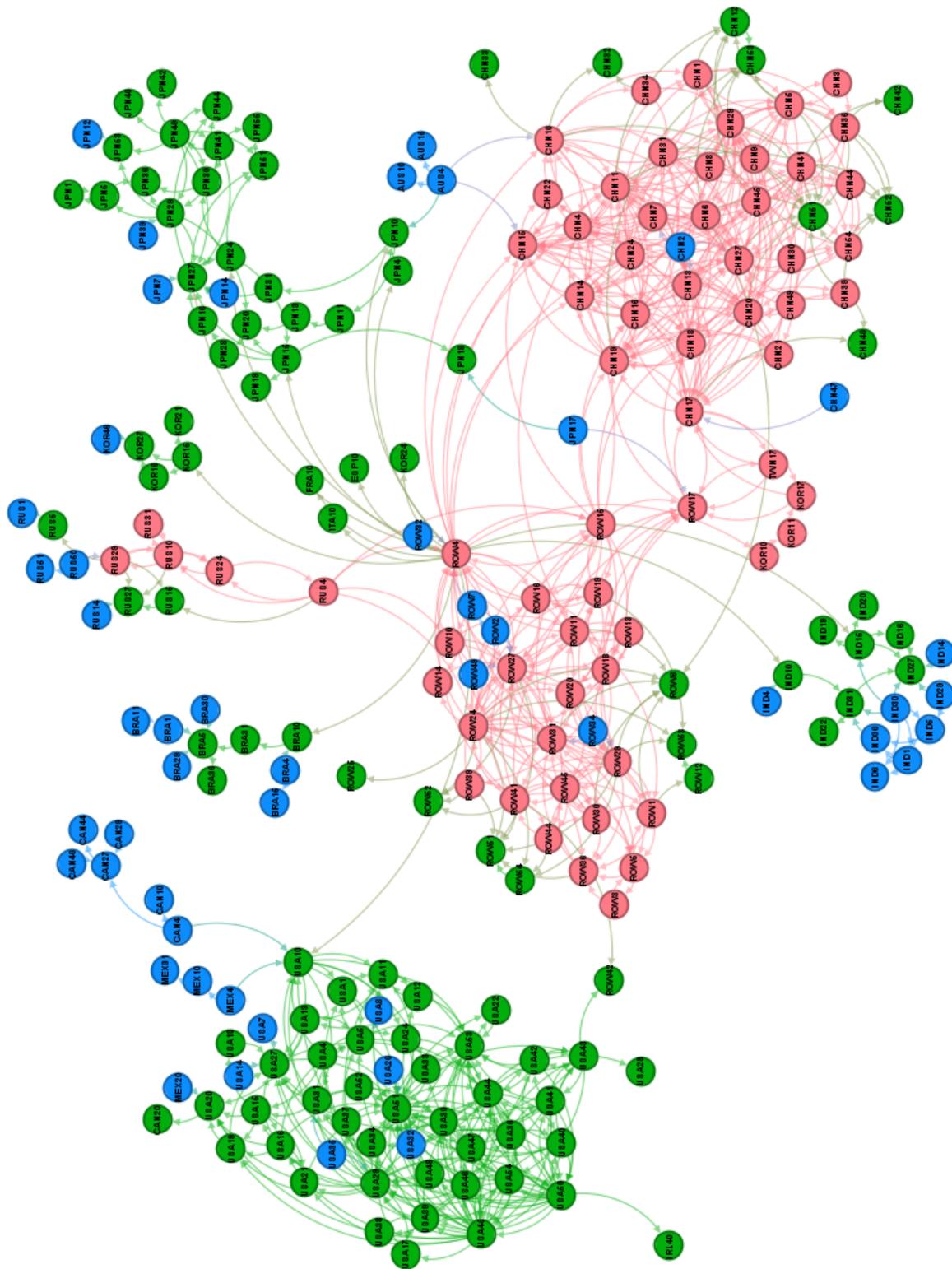
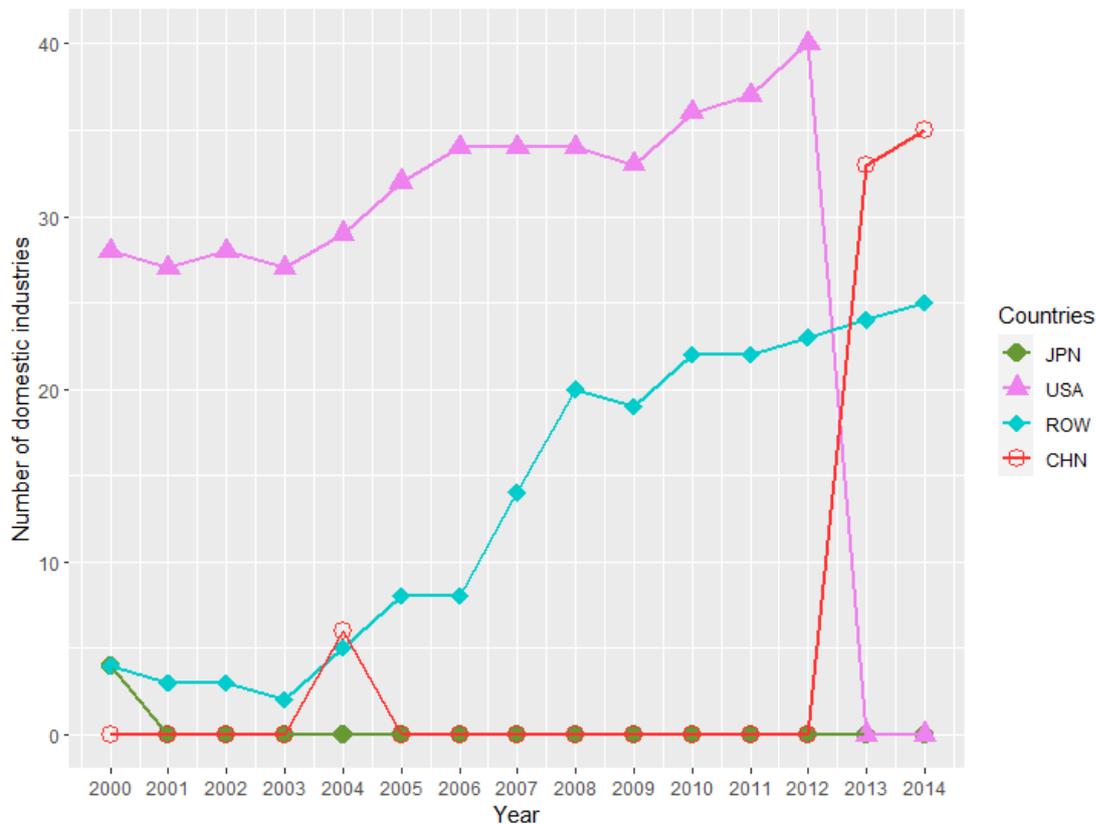


Figure 2.14: Composition of the Core of the Global Autocatalytic Set in the World Input-Output Network



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

When examining the positions of these countries' industries in the Core of the ACS, as reported in Figure 2.14, only the USA, the RoW, and China remain as significant members of the set. The RoW has expanded over time, growing from about 4 industries to roughly 25. The USA maintained its dominance in the ACS until 2012. Although China briefly entered the Core in 2004, it disappeared until 2013. Upon its return to the Core of the Global ACS in 2013, China becomes a dominant member of the set, supplanting the USA.

2.5.3 Sensitivity of our analysis to changes in the filtering threshold value

In this section, we explore the sensitivity of our ACS detection algorithm and of our key findings, to changes in the filtering threshold value used to filter the WION. We start by investigating how the number of detected ACSs changes with

the level of filtering threshold value.

Figure 2.16: Number of Autocatalytic Sets by the World Input-Output Network Filtering Threshold Values

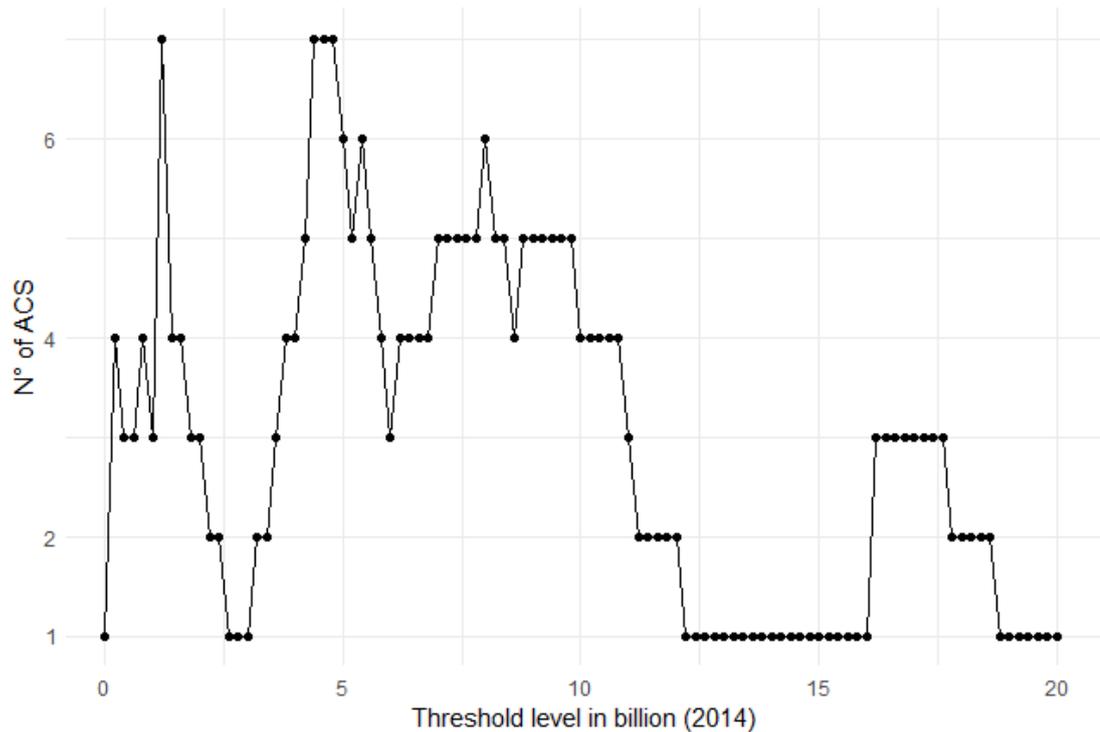


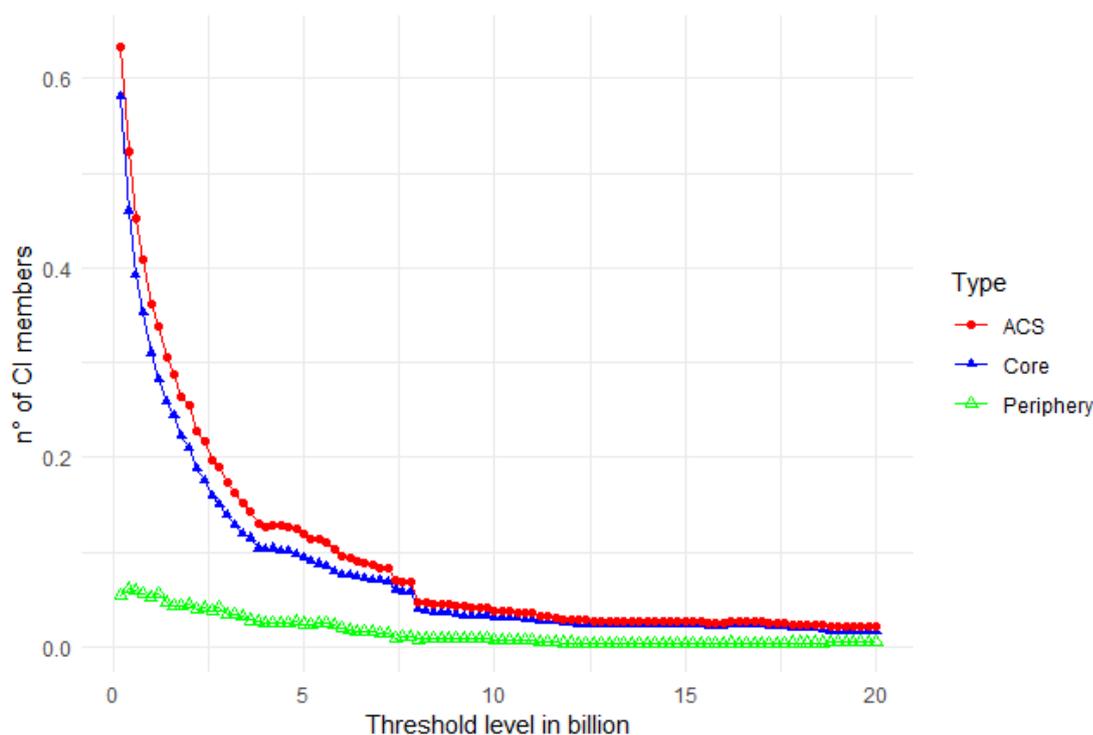
Figure 2.16 reports the number of ACSs as a function of the filtering threshold value used to filter the WION. Each time the number of ACSs increases, it indicates that a larger ACS has split when the filtering threshold value is raised. Conversely, when the number of ACSs decreases, it signifies that one or more crucial links have been removed, affecting the structure of one or more ACSs.

Without filtering (filtering threshold value set at zero), the WION is a complete network, which amounts to a trivial case of one ACS encompassing all CIs. When we introduce a filtering threshold value, this ACS splits into several smaller ACSs, initially increasing their number. The pattern is non-monotonic, however, because another effect occurs: as the filtering threshold value rises, the filtering process becomes more selective, and crucial links for the existence of an ACS may be severed. This is how ACSs may disappear. The maximum number of 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.

In particular, we observe a significant drop in the number of ACSs above a \$2 billion filtering threshold value, reaching a count of one ACS. After this point,

the effect of ACSs breaking becomes dominant again. The interplay of these two effects explains the oscillations in their numbers until a maximum of seven ACSs is reached at a filtering threshold value of \$4.75 billion. Beyond this value, the secondary effect of severing essential ACS links takes over, reducing the number of ACSs to just three at a filtering threshold value of \$6 billion. The count then rises to six ACSs around the \$7.75 billion mark, only to decline to one at \$12.25 billion. For values above this, the number of ACSs fluctuates between 1 and 3. Although not shown in the graph, beyond the \$20 billion filtering threshold value, the count remains at a single ACS.

Figure 2.17: Relative size of the Autocatalytic Set’s Core and Periphery as a function of the filtering threshold value, in 2014



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

So far, we have focused on the number of ACSs. A complementary and equally important aspect is the ACSs’ aggregate size. We explore this dimension by evaluating the ratio of the number of CIs in any ACS to the total number of CIs in the filtered WION. This ratio essentially serves as a “participation” rate or relative size of the ACSs, which measures the autocatalytic nature of the WION.

In Figure 2.17, we plot this aggregate ACS’s relative size for different levels of the filtering threshold value. The aggregate Core and Periphery are also included.

For low values of the filtering threshold value, up to about \$12.5 billion in trade flows, the overall size of ACSs decreases due to CIs being removed from them. There is a break around the \$7.5 billion filtering threshold value, where part of the ACS becomes disconnected. The relationship between the number of CI members and the filtering threshold value level is mainly driven by the number of CIs located in Cores. Peripheries show a slow downward curve following the increase in the filtering threshold value.

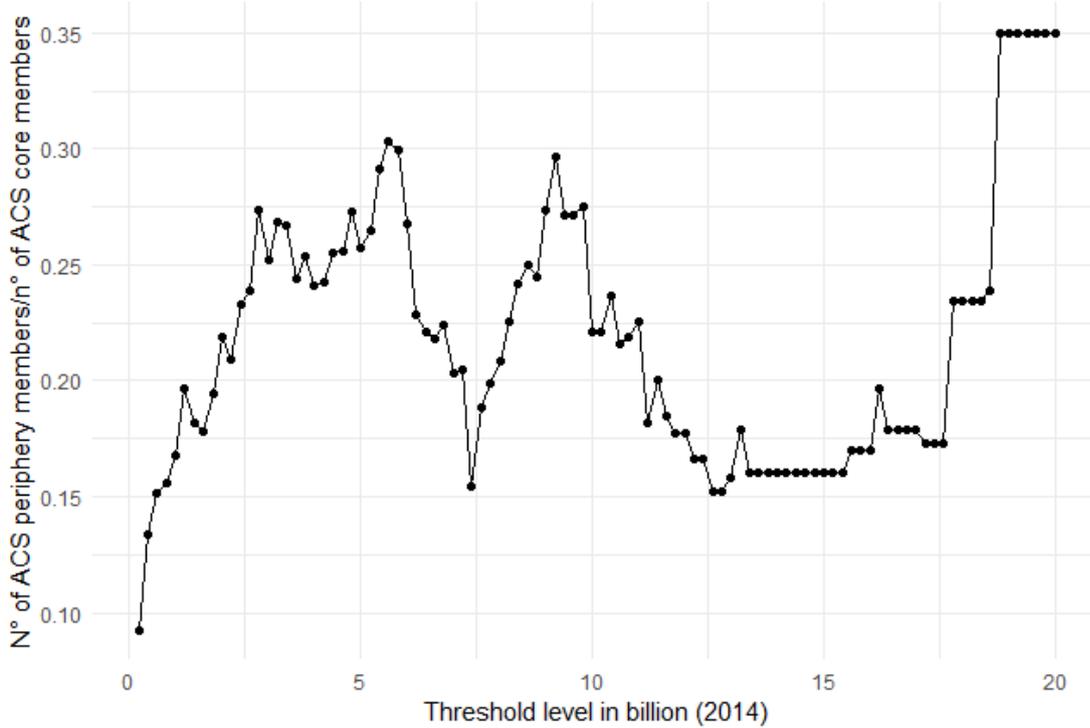
An intriguing observation emerges in the pattern of the ACSs' size above the \$7.5 billion filtering threshold: here, we note only a slow downward change in the number of industries belonging to an ACS. This suggests that filtering occurring at higher thresholds is robust and structurally significant to the WION. The downward trend of the participation rate confirms that when the screening is weaker, most CIs are members of an ACS. Conversely, when the screening is stronger, fewer CIs are part of an ACS. This result aligns with what we have observed above in terms of the number of ACSs: when considering thresholds from \$10 billion to \$20 billion, the number of ACSs decreases, but not the aggregate number of CIs belonging to an ACS. This finding complements another interesting result about the internal structure of ACSs, specifically the relative size of the Periphery of ACSs.

Finally, we have computed the ratio between the aggregate number of CIs belonging to the Periphery and the number of CIs belonging to the Cores of all ACSs. A ratio equal to 1 indicates that peripheries and cores are equally large in terms of the number of CIs. The same applies to Figure 2.18, which illustrates this ratio as a function of the filtering threshold value, extending up to \$20 billion. It is noticeable how the relative size of the peripheries expands at the expense of the cores of the ACSs on multiple occasions. Three notable peaks in the relative size of the Periphery can be observed: the first is around the \$6 billion level, the second around the \$10 billion level, and the third around the \$20 billion mark. Beyond the \$20 billion level, the ratio stabilizes and remains roughly constant.

Figure 2.18 displays the ratio of Periphery size to Core size across a wide range of thresholds. Two filtering threshold values are identified as local optima. The first local optimum occurs at 5.6 billion, where the value of the ratio is approximately 0.3. The second local optimum is found at 9.2 billion, with the ratio also around

0.3. Finally, within the range depicted, there is a plateau representing the global maximum, reached at 18.8 billion. At this level, the ratio stands at 0.35.

Figure 2.18: Relative size of the Periphery compared to the Core depending filtering threshold value in the World Input-Output Network, in 2014



Note: The aggregate measures of Core and Periphery sizes are calculated by summing up the sizes of all cores and peripheries, respectively. An upward shift in the ratio corresponds to an increase in the relative size of the Periphery compared to the Core. Conversely, a downward trend in the ratio signifies a decrease in the relative size of the Periphery.

In the second part of this section, we investigate to what extent our 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 varying filtering threshold values, as demonstrated in Table 2.2.

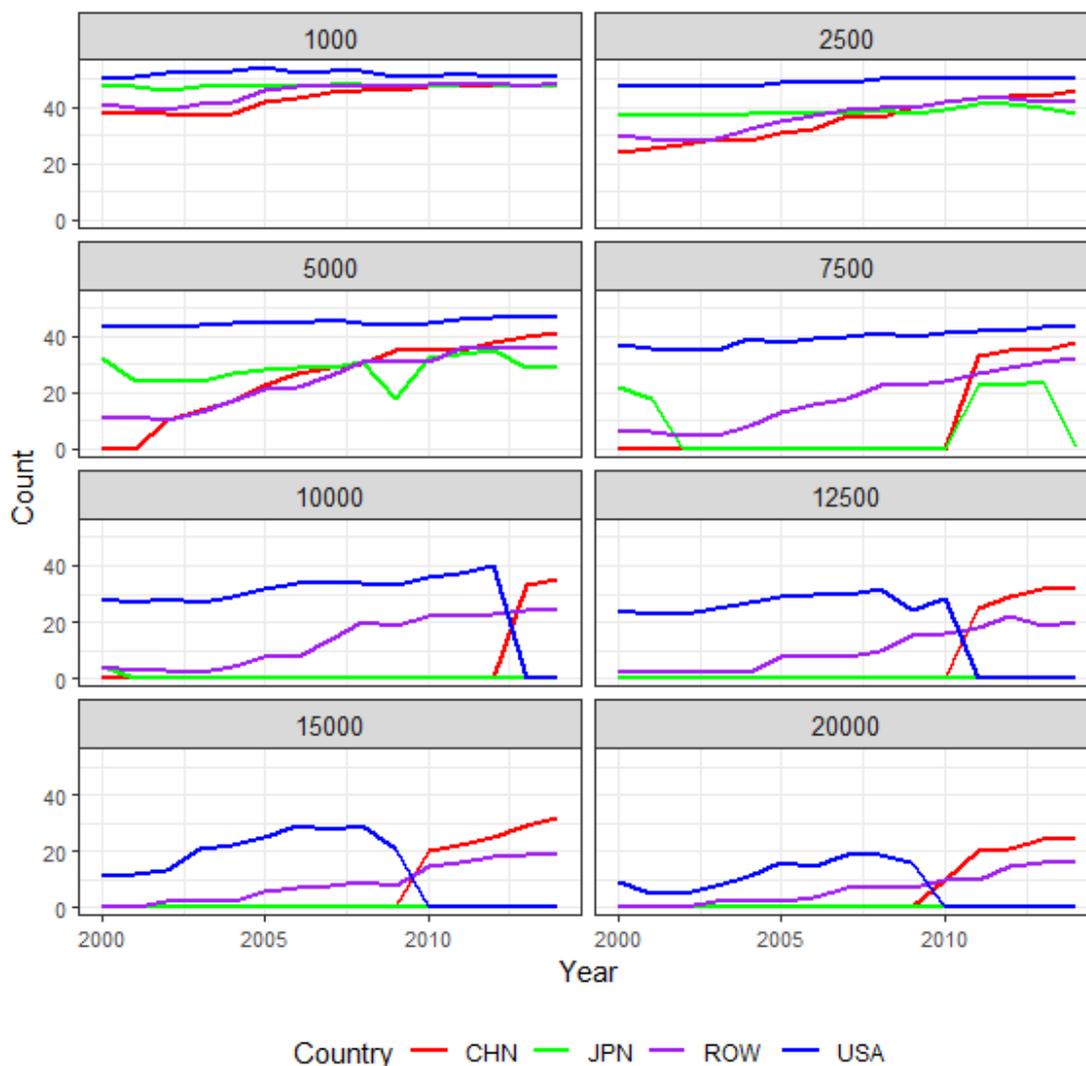
This table traces the trajectory of Chinese industries, illustrating their progression from being outside the ACS to becoming part of the local ACS, and ultimately joining the Global ACS. This transition is analyzed across a range of predefined filtering threshold values. Notably, at thresholds below \$10 billion, China consistently features as a member of the Global ACS. However, it is at these higher filtering threshold values that the aforementioned distinctive shift occurs.

Table 2.2: Is China part of the Global or local Autocatalytic Set, by filtering threshold value?

	1	2.5	5	7.5	10	12.5	15	20
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	Local ACS	Local ACS	Local ACS				
2005	Global ACS	Local ACS	Local ACS	Local ACS				
2006	Global ACS	Global ACS	Local ACS	Local ACS				
2007	Global ACS	Global ACS	Global ACS	Global ACS				
2008	Global ACS	Global ACS	Global ACS	Global ACS				
2009	Global ACS	Global ACS	Global ACS	Global ACS				
2010	Global ACS	Global ACS	Global ACS	Global ACS				
2011	Global ACS	Global ACS	Global ACS	Global ACS				
2012	Global ACS	Global ACS	Global ACS	Global ACS				
2013	Global ACS	Global ACS	Global ACS	Global ACS				
2014	Global ACS	Global ACS	Global ACS	Global ACS				

Note: filtering threshold values are expressed in billion 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.*

Figure 2.19: Evolution of Core membership in the World Input-Output Network by filtering threshold value and year



Note: Each graph represents a different filtering threshold value in thousand USD

Our second claim is that the evolution of some key Chinese industries within the Global ACS has been accompanied by a peripheralization of both Japanese and USA industries. In Figure 2.19, we trace the evolving numbers of industries in the Core of the Global ACS for the USA, Japan, China, and the RoW over a range of thresholds. We are going to discuss this figure to illustrate the relative position of China versus Japan and then China versus USA.

Let's start with the China-Japan. Up to the 7500 filtering threshold values: Until this point, Japan enjoys a robust position within the Core. However, even within this range (1000 to 7500), there's a clear rise of China as it progressively catches up and in the last years overtake Japan as the biggest Asian ACS member.

Beyond the 7500 threshold: Japan has a limited presence in the Core. Meanwhile, as the filtering threshold value rises, Chinese industries join the Core of the ACS in later years. This delineation underscores the shifting dynamics of the global industrial framework, with China appearing as a main player, especially at high filtering threshold values.

We now turn to the scenario for the USA. Figure 2.19 also provides compelling evidence for our claim regarding the shifting positioning of China and the USA within the Core of the Global ACS. The figure reveals two distinct dynamics, characterized by the filtering threshold value: Up to the 7500 filtering threshold value, the USA retains its dominant position in the Core of Global industries. Its leadership at these levels is consistent, underscoring the historical strength of American industries. In contrast, at thresholds exceeding 7500, a marked transformation occurs. The USA's presence in the Core diminishes in the last years. The Core shifts toward China and the Rest of the World region, emerging as the predominant forces in the Core. Their growth, especially China's, signifies a new alignment in Global industries, with China becoming the primary member of both the Core and ACS.

This pattern offers a striking illustration of China's ascent to prominence within the global industrial landscape. It also highlights a relative decoupling of the USA from the RoW, reinforcing the complex interplay of forces that shape the global industrial Core.

2.6 Conclusion

In this chapter, we applied the ACS framework to the WIOD to describe the changing position of Chinese industries after its accession to the WTO. By focusing only on the strongest inter-industry flows, those above \$10 billion, we found evidence of the existence of an isolated cluster of industries from China. This cluster contains an ACS, which is a group of self-reinforcing industries. The size of this structure has increased over time, due to the densification of Chinese domestic linkages. At the same time, China has increased its volume of trade both with its regional partners and, even more so, with the RoW (Rest of the World) region.

We also described the existence of a large international cluster of CI. This

cluster is built around a multinational ACS, referred to as the Global ACS, which is primarily dominated by American industries. The general structures of these ACSs (both the Global one and the local Chinese one) have been detected in the WIOD for various filtering threshold values. We have shown that this framework can be useful for detecting communities where economic activities are concentrated in the WIOD. It enables economists to observe the evolving positions of domestic industries within these communities.

Our main findings can be summarized as follows: The WION comprises one main global and several local autocatalytic structures. The exact number of ACSs detected depends crucially on the filtering threshold value used to filter the WION.

The expansion of its local ACS served as a preliminary step before some key China succeeds 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. Precisely, the number of Chinese industries in the local ACS increased from 5 in 2000 to 15 in 2004. Then, once this group of industries branched into the Global ACS through a key industry, namely the *Computer, electronic, and optical products* industry (CHN17), the number of Chinese industries belonging to the Global ACS steadily increased from 17 in 2005 to about 40 in 2014. Overall, the dynamics of Chinese industries, first within the local ACS and then within the Global ACS, offer new insights into how local and global autocatalytic structures complement each other in the course of the industrial development of an emerging economy.

Japanese industries tend to reposition themselves at the Periphery of the Global ACS over the period 2000-2014. The emergence and then strengthening of Chinese industries as Core industries in the Global ACS has been accompanied by a decoupling of the positioning of USA industries towards the RoW industries. In the mid-2010s, the USA economy appears as a more isolated part of the Global ACS than in the early 2000s.

Although the research in this chapter has remained purely descriptive, we showed that the concept of autocatalytic structures is a promising one to shed light on the patterns of economic development at the age of global value chains. In particular, this concept reveals that the development of local circular causation cycles has been a prerequisite to the successful branching of the Chinese economy

onto global trade. In particular, this phenomenon is an example of the structural change experienced by an emerging economy, namely China, which has succeeded in expanding its industrial base rather than specializing in a limited number of primary resources or agriculture-related industries.

Interestingly enough, the local ACS that expanded before the branching of the Chinese economy onto global value chains is one with strong IO relationships across different agriculture-related industries and also across themselves and key heavy and light manufacturing industries (*Electricity and gas, Textile, Motor vehicles, Chemicals, Basic metals, and Fabricated metals, Petroleum products, Rubber and plastics*). This finding echoes an earlier 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. Recently, new multi-sectoral general equilibrium models comforted this view by demonstrating that, under non-homothetic preferences, trade liberalization policy was precisely what could make an emerging economy efficiently reallocate resources out of agricultural industries for the benefit of the expansion of manufacturing industries (see in particular Matsuyama, 1992; Teignier, 2018). In opposition to this view, some 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 institutionalist-oriented view on a study case of the South Korean growth miracle). As regards this earlier debate, our chapter is more supportive of the latter view rather than the former one.

For further research directly following the work of this chapter, we envisage two main avenues. First, we want to enlarge our descriptive analysis to other emerging economies, in order to confirm the pattern we found about the complementary role of local and Global ACSs in the course of outward-oriented growth dynamics. We plan to mobilize the recently released long-run WIOD database¹³ in order to explore further the existence of both local and Global ACSs in the dynamics of emerging countries which industrialized in the second half of the 20th century. We expect to reveal a similar pattern to the one we found for China in the early 21st Century. Second, we could replicate our study on alternative GRMIO databases to

¹³This database has been released by GGDC in March 2022.

test further the robustness of our key findings. A good candidate for that purpose would be the EORA database. This database has the advantage to cover more individual countries as compared to the aggregated RoW of the WIOD. Also, the EORA database covers the most recent period of time, although access to the last years is not free.¹⁴ We didn't choose the EORA database for our baseline investigations because the industry classification of the EORA database is far less detailed than the one of the WIOD. However, as aggregates, agriculture-related industries can be differentiated from heavy and light manufacturing industries in the EORA database, and then we could be able to explore further their complementarity in the course of development.

¹⁴Access to the EORA database is free for the years covering the period from 1990 to 2016. The years 2017 to 2021 are only available under costly licensing agreements.

3 Changes in Post-Socialist Industrial Linkages: A Network Approach

3.1 Introduction

Three decades have passed since the curtain fell on the Eastern bloc and the dissolution of the Soviet Union, leading to profound economic and political transformations in the Eurasian continent. Both Europe and Asia have grappled with the economic and geopolitical aftershocks triggered by these changes. The countries that emerged from the vestiges of post-Socialist rule, spanning from the Baltics to the Steppes, are tirelessly working to bridge the gap created by structural economic disparities with their more advanced neighbors in Europe and Asia.

All post-Socialist republics have faced tension between a reliance on historic partners and new international integration forces. This tension can be summarized as follows: On one hand, most post-Socialist countries still overly rely on Russian industries, especially its energy sector; this fact was very true in the wake of the invasion of Ukraine. On the other hand, Central and Eastern European industries' integration into German supply chains has led to the emergence of cutting-edge, export-oriented manufacturing industries in some of these countries. Finally, and more recently, there has been new tension towards integration into the international network coming from China, through its "Belt and Road" Initiative strategy in Central Asia. These three integration forces, respectively led by Russia, Germany, and China, have not balanced in the same way in each post-Socialist country, leading to a variety of transition patterns in those countries.

Our aim in this chapter is to document the variety of transition patterns by

exploring the evolution of the production network in former socialist countries. As former socialist countries transition from a planned economic structure and embrace the institutional frameworks of a market economy, it catalyzes shifts in industrial dynamics, which in turn influence the inter-industry flow of inputs. These alterations impact both domestic and regional linkages. This analysis highlights the differences between two groups of countries that underwent distinct economic and political transformations. These groups can be identified based on their political affiliations: the group of Central and Eastern European Union (CEEU) countries, which consists of post-Socialist republics that later joined the European Union, and the group associated with the Commonwealth of Independent States (CIS), a regional intergovernmental organization formed in Eurasia under the leadership of Russia, following the dissolution of the Soviet Union. The detailed list of countries is in Table 3.1.

Comparing the CEEU and CIS-affiliated countries offers rich ground for understanding the divergent paths that nations can take following significant political and economic upheavals. The CEEU countries, having embraced the European Union's regulatory frameworks and market dynamics, present a case of closer integration with the Western economic sphere, characterized by adherence to democratic norms, market liberalization, and a focus on innovation-driven growth. Conversely, the CIS countries, retaining a more centralized approach to governance and economic management, offer insights into a different kind of resilience and adaptation. This last group is also marked by higher political instability.

As highlighted before, the economic trajectories of these post-Socialist countries have been varied. Despite their common historical legacies and the initial implementation of similar liberalization policies, divergences in trajectories have emerged. These divergences can be attributed to their endowment and reliance on national resources, their integration into global markets, the establishment of new liberal institutions, and influence from foreign countries. This divergence makes these nations a compelling case study for understanding the complexities of industrial development within the unique socio-political landscape of post-Socialist transformation.

This chapter explores the evolution of production networks in those former socialist countries, scrutinizing their transformation through the lens of Input-

Output (IO) linkages, more precisely, the change in their input linkages. For that purpose we use the EORA database. The changes in the post-Socialist production network are influenced by several forces: the structural change that emerges from a transition from a planned economy to a market-based economy; the establishment of new supply chains due to the formation of new political borders; the adoption of industrialization strategies to establish new production chains; and finally, the tendency of those countries to balance between the economic spheres of influence of Germany, Russia, and China. These different forces have led to deep transformations in the domestic, regional, and international flows of post-Socialist countries.

This study aligns with a growing body of literature that investigates economic dynamics through the lens of IO data (see Carvalho, 2013; Cerina et al., 2015; Tsekeris, 2017; Mundt, 2021). This collection of works employs network methodology to model the interconnections between industries and countries. The benefits of network approaches to understanding industrial dynamics are manifold. First, they allow pinpointing the Core industries in any region of a network. Second, they model the propagation of shocks within the IO network, such as the spreading of innovation, propagation of default, or supply shocks. Lastly, they can outline the feedback loops between an industry's position in the network and its economic dynamics. In earlier literature, this approach has been especially useful to shed light on the global economy's increasing vulnerability to disruptions in Chinese industries (Li et al., 2014) and to understand the economic repercussions of events like Brexit (Giammetti et al., 2020).

This chapter is the first attempt, to the best of our knowledge, to model the input linkages in post-Socialist countries, especially over a large time span of 30 years. This chapter also provides network statistics to comprehend the evolving structure of post-Socialist linkages. More broadly, analyzing the alterations in linkages during economic development in developing countries is important to understand how the structure of the Global Value Chain (GVC) influences a Country-Industry (CI)'s behavior. This is especially relevant due to the peculiar nature of the structural changes from a planned economy to a market economy. The substantial domestic and international restructuring presents an ideal environment to study the effects of the changes in linkages that occur through economic development.

Another contribution of this chapter is that, alongside traditional network metrics, I apply the Autocatalytic Set (ACS) framework to a regional IO network. Introduced by Jain and Krishna (1998), this framework provides a lens to study cumulative circular causation within a directed network. Similarly to its application on the World Input-Output Network in Chapter 2, when applied to the network based on post-Socialist IO linkages, the framework reveals a network structure, called ACS, based on overlapping feedback loops. The position of post-Socialist countries within the ACS makes them more affected by the positive and negative feedback loops that can occur within the production network.

The remainder of the chapter is structured as follows: Section 3.2 delves into the development of post-Socialist regions. Section 3.3 presents the EORA dataset and outlines the methodology employed in this study, Section 3.4 presents the findings, and Section 3.5 offers conclusions and closing remarks.

3.2 A brief history of post-socialist structural change and development

This section discusses how post-Socialist countries have developed after the fall of the Berlin Wall. The end of the Cold War brought an end to planned economies and therefore necessitated economic reforms. These countries have endured the challenges of economic transition, including soaring inflation, partial de-industrialization, breakdowns in supply chains, massive emigration of the qualified workforce, and the breakdown of Soviet-era welfare systems.

Most post-Socialist countries were pressured to implement a series of liberal reforms. This series of reforms included a reduction of public expenditure, the end of price control, financial and trade liberalization, privatization of state enterprises, the elimination of barriers to Foreign Direct Investments (FDI), tax reforms, securing property rights, and the creation of democratic institutions. In some countries, these reforms have been implemented thoroughly, mainly in the post-Socialist countries that aimed for and achieved their accession to the EU. In other countries, the implementation did not occur or was limited, for example, in Central Asia or in Russia.

The rapid economic shifts (including the cessation of subsidies and the imple-

mentation of liberalization reforms) coupled with political transformations (such as the emergence of national borders and border conflicts) have precipitated a significant decline in industrial output.

In Central and Eastern Europe (Bulgaria, Czechia, Estonia, Croatia, Hungary, Lithuania, Latvia, Poland, Slovakia, Slovenia, and Romania), the fast implementation of liberalization reforms initially caused multiple declines in many outputs that led to the bankruptcy of many large public companies in key sectors of the economy such as agriculture, light manufacturing, or heavy manufacturing. State-controlled industries were privatized, placing them directly in competition with more established and productive foreign firms (see Berend, 2009; Pavlínek, 2015).¹

In the Ex-USSR countries (Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Russia, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan), these disruptions of economic activities were coupled with changes in political borders. These countries found themselves cut off from both their supply chains and their former markets, ending up ill-equipped to compete in the newly established market conditions. Similarly, major industries lost economic support, such as subsidies, from Moscow. These difficulties in adapting to the new market conditions were aggravated by the fact that several skilled Russian nationals moved back to Russia, further increasing the lack of human capital in those countries (see Spechler, 2008; Batsaikhan and Dabrowski, 2017).

After these initial years of disruption for all post-Socialist countries, different nations pursued very diverse strategies to reestablish a production structure. Two main strategies were established, each subsequently influencing the production structure in those countries.

The first strategy was an FDI-driven development strategy. The goal of this strategy is the implementation of a series of liberal reforms in order to attract capital from foreign investors. This strategy aims to attract three types of investments: (i) Market-seeking investment involves multinational companies that target a country because they want to supply its market with goods or services. (ii) Labor-seeking investment involves companies that aim to exploit skilled, low

¹Stiglitz (2000) explains that an incremental strategy, instead of shock therapy, would have been better to ensure the economic well-being of Eastern European economies.

labor costs in proximity to larger markets. This type of investment is focused on relocating labor-intensive processes. It was achieved by taking over existing companies, outsourcing, or by making “greenfield” investments, which means setting up new factories. (iii) “Complementary specialization” seeking investment. The interest here is to benefit from the increasing quantity of key components produced in a locality. While many companies were originally interested in labor-seeking investment, the concentration of factories has created dense local supply chains in high-technology sectors such as automotive, pharmaceutical, electrical machinery, computer equipment, telecommunications equipment, or optical instruments, which has made some post-Socialist countries even more attractive for foreign companies (see Berend, 2009; Jürgens and Krzywdzinski, 2009).

The second strategy consists of driving development by using the wealth generated by natural resources. In several resource-rich countries, a distinct strategy emerged that uses natural resource production as a catalyst for development. This strategy aims to capitalize on the exportation of natural resources like oil, natural gas, cotton, aluminum, or gold. Leveraging natural resources offers numerous advantages. Capturing profits from natural resource exports, either through export taxes or state-owned monopolies, furnishes a substantial income stream for governments. These financial resources can be directed into social programs (e.g., education or healthcare), infrastructure development, or subsidies for other economic activities like agriculture or energy.

In this context, I identify three groups among the post-Socialist countries with converging characteristics.

Table 3.1: Countries groups within the post-Socialist republics

CIS-affiliated countries		EU-affiliated countries		Western Balkans	
ARM	Armenia	BGR	Bulgaria	ALB	Albania
AZE	Azerbaijan	CZE	Czechia	BIH	Bosnia and Herzegovina
BLR	Belarus	EST	Estonia	MNE	Montenegro
GEO	Georgia	HRV	Croatia	SRB	Serbia
KAZ	Kazakhstan	HUN	Hungary	MKD	North Macedonia
KGZ	Kyrgyzstan	LTU	Lithuania		
MDA	Moldova	LVA	Latvia		
TJK	Tajikistan	POL	Poland		
TKM	Turkmenistan	SVK	Slovakia		
UKR	Ukraine	SVN	Slovenia		
UZB	Uzbekistan	ROU	Romania		

The first group, the Central and Eastern European Union (CEEU) countries, is composed of post-Socialist republics that later joined the European Union. CEEU countries have principally applied the first strategy. Their transition involved substantial economic restructuring and integration into Western markets. The success of this strategy has been attested in the CEEU countries by their accession to the European Union (EU). Attracting FDI was expected to drive the catching-up process of those economies. As theorized in Rosenstein-Rodan (1943), CEEU countries were expected to modernize part of their industries by attracting FDIs through their insertion in the international division of labor. Many domestic companies, including strategic companies, were bought by Western companies such as Carrefour, Deutsche Telekom, Société Générale. In the car industry, the Czech company Škoda was bought by Volkswagen and the Romanian company Dacia was bought by Renault.

Some of these countries, such as Czechia, Hungary, or Poland, managed to benefit from complementary specialization-seeking investment. Several multinational companies (especially in the automotive industry) have made greenfield investments to process capital-intensive tasks or upgrade existing facilities. For example, Nexen, a South Korean tire producer, set up a facility with an investment of 829 million euros in 2018 in Žatec, Czechia, which will serve as the main production base in Europe to supply local car assembly plants (see Berend, 2009; Jürgens and Krzywdzinski, 2009).

The large amount of FDI has led to an increasing participation in Global Value Chains (GVCs) of CEEU countries. Over time, CEEU countries have specialized in downstream sectors, while Western Europe² (WE) has retained activities with high value-added, such as design, engineering, research and development (R/D), and non-standardized tasks, as well as financing functions. This has created an industrial sector dependent on Western European capital and innovation facilities (Epstein, 2019). This over-reliance on FDI has rendered CEEU countries vulnerable to external economic shocks. The 2007 financial crisis led to a stagnation in the quantity of capital-intensive FDI inflows into manufacturing. However, there was

²Western Europe is defined in this chapter as the group of European countries that were not communist countries during the Cold War, namely Andorra, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Liechtenstein, Luxembourg, Malta, Monaco, Netherlands, Norway, Portugal, San Marino, Spain, Sweden, Switzerland, and the United Kingdom.

no sign of disinvestment or capital exit from these countries (see Medve-Bálint, 2015; Pavlínek, 2015) after the economic crisis. Both Medve-Bálint (2015) and Pavlínek (2015) also show evidence of an increase in FDI in the business and service sector, and a consolidation of existing investments.

The second group includes countries that became members or associate members of the Commonwealth of Independent States (CIS), a regional intergovernmental organization formed in Eurasia after the dissolution of the Soviet Union. While Turkmenistan has never been a full member, it was included in this group due to its status as an associate member and its active participation in the organization. It should be noted that Ukraine ceased its participation in the CIS in 2014 due to the invasion of Crimea and Donbass and formally left the organization in 2018. Similarly, Georgia, a former CIS member, withdrew from the association in 2008 following the Russo-Georgian War.³

This second group has had more diverse trajectories. The strategy that has been more prevalent in CIS-affiliated countries has been the second strategy. A significant challenge with this approach is the economy's heavy dependence on the international price of these resources. For example, an increase in oil prices has bolstered finances in Kazakhstan. Conversely, a decrease in the price of cotton and gold led to a balance of payments crisis in Uzbekistan (Spechler, 2007). Another drawback is the emergence of an economy dependent on a limited number of industries. For instance, the surge in revenues from natural resources in Kazakhstan caused an appreciation of the local currency, rendering other sectors such as manufacturing or agriculture less competitive (Spechler, 2008). This strategy can reduce the incentive for implementing necessary reforms, particularly in countries plagued by poor institutional practices. Factors such as weak contract enforcement, corruption in project approval, and non-transparent policies can diminish FDI in industries outside of energy, tourism, and agriculture.

In order to have a point of reference for comparing CEEU and CIS countries, I consider a third group consisting of countries that have not joined either the EU or the CIS. All of these countries are located in the Balkans and will therefore be referred to as the Western Balkans (WB). With the exception of Albania,

³During the study period, countries including Armenia, Azerbaijan, Georgia, Tajikistan, the former Yugoslav republic, and Ukraine underwent military conflicts, which notably hindered the success of their economic transition.

these countries were once part of the Yugoslav republics and have endured several years of conflict. Currently, they are candidates for EU membership but remain unaffiliated with both the EU and the CIS. This unaffiliated status provides a unique perspective. As EU candidates, they aim to comply with EU regulations and aspire to follow the first strategy; however, they have yet to meet all the requirements for EU integration. Analyzing these countries can offer additional insights into the specific characteristics that have led other countries to succeed in their applications. At the same time, as remnants of the disintegrated Yugoslavia, their evolution can be compared to that of the former members of the USSR.

Finally, a significant factor in understanding the changes in regional linkages in post-Socialist countries is the growing role of China through the “Belt and Road” Initiative, also known as the New Silk Road. This initiative represents China’s ambitious plan to revive the ancient Silk Road, which once flourished as a trade route through Central Asia. The “Belt and Road” Initiative is designed to enhance infrastructure across Central Asia, South Asia, and Europe. Every Central Asian nation, except Turkmenistan, has joined the Asian Infrastructure Investment Bank to help finance the project. As a result, trade between China and Central Asia has now eclipsed trade with Russia, with commodities being the primary focus. In particular, China’s investment in Kazakhstan’s energy sector reached \$21 billion in 2015, surpassing Russia’s investment which declined to \$12.7 billion. China has also actively engaged in constructing oil and gas pipelines, roads, and railways, significantly increasing its influence in the region. This engagement led to an almost tenfold rise in oil imports from Kazakhstan from 2005 to 2008 and rendered Turkmenistan nearly entirely reliant on China for natural gas exports. The ongoing railway and infrastructure developments further underscore China’s commitment to reinvigorating the age-old trade route (Batsaikhan and Dabrowski, 2017).

In the following sections, I investigate the changes in domestic, regional, and international input linkages of these countries, with the aim of better understanding the diversity of transition patterns among post-Socialist nations.

3.3 Methodology

In this section, I outline the approach used in this chapter. I begin by describing the database, and then discuss the multiple tools I apply for the study of IO linkages and structures in post-Socialist countries.

3.3.1 Data

In this chapter, I use the EORA 26 database, which provides data on inter-industry linkage values across 26 industries and 187 countries from 1990 to 2021 (Lenzen et al., 2013). Compared to the WIOD used in Chapter 2, the EORA database offers a longer time coverage and a larger country coverage but less detailed industry coverage. Table B.1, in the Appendix, lists the industry coverage. The lower industry count compared to the WIOD is a trade-off for a larger country coverage. This high number of countries was facilitated by a different statistical approach. Contrary to the WIOD, which relies mainly on Supply and Use Tables and on IO data provided by official statistical authorities, allowing for more fine-grained measurement of input linkages, EORA relies on a more diverse set of sources to reconstitute the IO data of developing countries.

Thanks to its extensive country coverage, it enables the examination of shifts in inter-industry linkages throughout all post-Socialist countries in Europe and Central Asia. More specifically, I focus on the countries from the three groups I defined earlier in Section 3.2: countries affiliated with the EU (CEEU), countries affiliated with the Commonwealth of Independent States (CIS), and countries that did not join either political association, all of which are located in the Balkans and therefore will be referred to as the Western Balkan (WB). Table 3.1 lists the countries studied and their respective groups.

By comparing these three groups, the study aims to offer a comprehensive understanding of the global value chain's evolution in the Eurasian post-Socialist era. These countries are studied alongside Germany and Russia. While not the subject of this analysis, China is included in this analysis due to its increasingly central influence in the Eurasian region.

It is important to highlight how the database handles the independence processes that occurred during the study's 31-year timeframe. Several post-Socialist

countries underwent dissolution: the Soviet Union dissolved on December 26, 1991; Yugoslavia disintegrated between 1991 and 1992; and Serbia and Montenegro separated in 2006. The EORA database uses existing data, such as export data, Supply and Use Tables, and official IO data to infer the missing IO tables of the database. When a specific year is lacking, estimates are extrapolated based on the output size of each CI and the closest available IO sources chronologically. For countries that faced instability in their early years, national IO tables are primarily available for years following their independence. The number of countries remains constant in the database, accounting for each UN member country by 2021 that emerged from the breakup of Czechoslovakia, the USSR, and Yugoslavia as separate entities.

3.3.2 The empirical approach

The analysis of the evolution of post-Socialist republics' input linkages is conducted using an extensive set of measurements. This set can be divided into two groups: the first group concerns measures of change in input linkages; the second group focuses on conducting a network analysis of the Post-Socialist Production Network (PSPN). In this subsection, I provide a detailed description of the tools used for these two approaches.

To analyze changes in input linkages, I first focus on characterizing the specialization of CEE and CIS-affiliated countries. To this end, I provide a measure of Revealed Industry Specialization (RIS), adapted from the Revealed Comparative Advantage of Balassa (1965), to observe the evolution of the size of each industry located in post-Socialist countries compared to their world average. Subsequently, I identify the sources of inputs for these industries. To quantify the use of foreign inputs, I calculate the proportion of foreign inputs in each CI's input share. Conversely, to identify which domestic sectors are most used in the country, I assess the intensity of domestic utilization of each sector. Following this, I evaluate the stability of these flows over the decades (1990, 2000, 2010, 2020) using a Pearson correlation index.

For the network analysis, I initially construct a model of the PSPN, where nodes represent post-Socialist industries and links signify intermediary input flows. I then apply a comprehensive array of network statistics to characterize the PSPN. Subsequently, I subset this network to facilitate comparisons among different groups of

countries (CEEU, CIS, and the WB). This analysis is complemented by community detection using Neumann’s community detection algorithm. Finally, I employ the ACS algorithm to identify a Core-Periphery structure within the PSPN. At various stages of the investigation, Chinese industries are included to assess their influence on post-Socialist industries. The remainder of this subsection delves deeper into the tools employed in the analysis.

Measuring the Revealed Industry Specialization of countries

The RCA, or Revealed Comparative Advantage, introduced by Balassa (1965), is a measure used to calculate the relative advantage or disadvantage of a country in the export of a class of goods or services, as evidenced by its trade flows. This index helps in identifying the potential sectors where a country has a comparative advantage, thereby guiding policymakers and researchers in understanding the dynamics of international linkages. It is extensively used in economic research, especially in studies related to trade and competitiveness.

In this chapter, I adapt this formula in order to measure the share of an industry in a country’s total production compared to the world average. Both the production of intermediary inputs and the production of final goods and services are included. I name these indices as RIS. The formula for calculating RIS is given by:

$$RIS_{ai} = \frac{(Prod_{ai}/Prod_a)}{(Prod_{gi}/Prod_g)} \quad (3.1)$$

where RIS_{ai} is the Revealed Industrial Specialization of country a in industry i , $Prod_{ai}$ is the total output of industry i in country a , $Prod_a$ is the total output of country a , $Prod_{gi}$ is the total output of industry i worldwide, and $Prod_g$ is the total worldwide output.

The interpretation of the RIS index is as follows:

- $RIS_{ai} > 1$: Industry i is oversized in country a ’s economy compared to the world average.
- $RIS_{ai} = 1$: Industry i in country a has the same proportion in country a ’s economy as in the world average.

- $RIS_{ai} < 1$: Industry i is undersized in country a 's economy compared to the world average.

In this context, the RIS assesses a country's specialization (via the share of a specific industry in the country's total output) relative to the world specialization (via the share of the same industry in the world's total output).

Measuring the intensity of use of foreign inputs

Using IO data, I provide the share of foreign inputs in the total inputs of each CI. The aim of this tool is to measure the intensity of the use of foreign inputs. I compare the results for the years 1990 and 2021.

$$Use\ of\ foreign\ input_{bj} = \frac{\sum_a \sum_i Flow_{bj}^{ai}}{\sum_c \sum_k Flow_{bj}^{ck}} \quad (3.2)$$

With $a \neq b$. Where $\{a, b, c\}$ are indices for countries and $\{i, j, k\}$ are indices for industries. $Flow_{bj}^{ai}$ denotes the flow of intermediary inputs from CI_{ai} to CI_{bj} . $\sum_a \sum_i Flow_{bj}^{ai}$ is the sum of inputs from foreign countries bought by CI_{bj} . $\sum_c \sum_k Flow_{bj}^{ck}$ represents the total input purchased by CI_{bj} .

Measuring the intensity of use of domestic inputs

In this chapter, I adopt an approach similar to Boehm (2018), who compares the importance of each sector in an economy to the input shares of other sectors across a broad range of countries. The main result here is that these values correlate with the country's level of development.

Following this approach, I aggregate the 26 industries into 4 sectors (Agriculture and Fishing, Manufacturing, Mining and Energy, and Service).⁴ Contrary to Boehm (2018), I separate *Agriculture* and *mining* sectors due to their significance in the post-Socialist region.

⁴**Agriculture and fishing:** Agriculture, Fishing. **Mining and Energy:** Mining and quarrying, Electricity, gas and Water. **Service:** Construction, Maintenance and repair, Wholesale trade, Retail trade, Hotels and restaurants, Transport, Post and telecommunications, Financial intermediation and business activities, Public administration, Education, Health and other services, Private households. **Manufacturing:** Food & beverages, Textiles and wearing apparel, Wood and paper, Petroleum, Chemical and non-metallic mineral products, Metal products, Electrical and machinery, Transport equipment, Other manufacturing, Recycling.

I then measure the average output of a domestic sector of the economy used by other domestic sectors. Intra-sector linkages are not accounted for in this analysis. More precisely, the average domestic use of a sector's output by other sectors is measured as:

$$Domestic\ Use_{au} = \frac{1}{3} \sum_w \left(\frac{Flow_{aw}^{au}}{\sum_b \sum_v Flow_{aw}^{bv}} \right) \quad (3.3)$$

With $w \neq u$ since I look only at the use of the output of one sector in other domestic sector. $\{u, v, w\}$ are indices for economic sectors. This equation represents the average domestic use of the sector u in the country a . It is calculated as the average share of inputs from sector au in the total inputs of other domestic sectors. $Flow_{aw}^{au}$ represents the flow of goods, services, or other economic activities from sector aw to sector au . $\sum_b \sum_v Flow_{aw}^{bv}$ represents the total input of sector aw .

Measuring the stability of input linkages

I employ the Pearson correlation as a statistical measure of temporal stability of linkages in post-Socialist countries. The Pearson correlation coefficient serves as a robust metric for quantifying the linear relationship between the sizes of specific linkages at two distinct points in time. A coefficient close to 1 indicates a strong positive correlation, suggesting that the size of a given linkage has remained relatively stable over the observed period. Conversely, a coefficient near -1 would indicate a strong negative correlation, signaling a significant change in the size of the input share. A coefficient around zero would denote the absence of any linear correlation, implying that the size of the input share at one point in time is not predictive of its size at a subsequent point in time.

To increase the amount of information provided by our analysis, I categorize the linkages into three distinct types: domestic linkages (flows from a domestic selling industry to a domestic buying industry), regional outgoing linkages (flows from a domestic selling industry to a foreign industry located in post-Socialist countries), and regional incoming linkages (flows from a foreign selling industry to a domestic buying industry in post-Socialist countries). This categorization allows the isolation and examination of the temporal correlation of each type of linkage

independently.

In summary, the application of Pearson correlation in this context serves multiple purposes. It not only quantifies the strength and direction of the temporal relationship between linkage sizes but also facilitates comparative analyses across different types of linkages and geographical regions.

Building the Post-Socialist Production Network

The Global Production Network (GPN) approaches Input-Output inter-linkages from a network perspective where nodes are CI, i.e., the association of an industry and the country where this industry is present. Directed links represent input linkages between two producers. A link from CI_A to CI_B represents a flow of intermediate inputs from the selling industry CI_A to the buying industry CI_B .

Similarly, the PSPN is a subset of the GPN where nodes represent post-Socialist industries, such as the Polish *Construction* or the Uzbek *Agriculture* industry. Links between each node represent flow input linkages. Contrary to the WION presented in Chapter 2, focused only on the strongest flows, the PSPN is modeled as a weighted network. Having a weighted network allows for accounting for the heterogeneity in the size of IO inputs by including both strong and small linkages.

In this chapter, the weights are based on input share and therefore reflect how much a CI_A contributes to another CI_B 's total input. Using input share eases the comparison of input linkages from different countries and industries by making them comparable.

Network modeling serves as the most effective framework for modeling cumulative phenomena that may arise within post-Socialist IO linkages. Here are some examples of network effects that can be captured using the PSPN:

- The first network effect is that since CI_A is a major supplier to CI_B , the growth in demand for inputs by CI_B can partly be absorbed by CI_A . This can also create an upward chain reaction where the growth of CI_B 's economic activity increases the economic activity upstream within CI_B 's supply chain.
- The second network effect is that if CI_A fails to deliver its output to industry CI_B , CI_B will face some difficulty in fulfilling their commitments too. This

can create a chain reaction, but this time downward, where multiple nodes fail to deliver their inputs to the subsequent nodes, leading to a cascade of failures downstream.

- The third network effect is that since CI_A is a major supplier to CI_B , if CI_A can reduce its prices, this reduction will benefit CI_B . In turn, CI_B can lower its prices to benefit its customers, thereby initiating another downstream chain reaction.

To define the input share, I employ the following equation:

$$Input\ share_{bj}^{ai} = \frac{Flow_{bj}^{ai}}{\sum_c \sum_k Flow_{bj}^{ck}} \quad (3.4)$$

Where $\{a, b, c\}$ are indices for countries and $\{i, j, k\}$ are indices for industries. $Flow_{bj}^{ai}$ denotes the flow of intermediary inputs from CI_{ai} to CI_{bj} . $\sum_c \sum_k Flow_{bj}^{ck}$ represents the total input purchased by CI_{bj} . Consequently, Input share $_{bj}^{ai}$ serves as a measure of the proportion of CI_{ai} 's inputs in CI_{bj} 's total input. Therefore, in this chapter, flows in the PSPN correspond to the share of a CI in the total input of a receiving CI.

Network analysis

In the PSPN, I apply standard network metrics to Eastern Bloc countries for the pivotal years of 1990, 2000, 2010, and 2021. The tools used are described in Table 3.2. Each tool can provide additional information about the characteristics of the linkages in the Eastern bloc.

Furthermore, the metrics of completeness and reciprocity provide insights into the overall structure and reciprocity of the network, indicating the extent to which the network is interconnected and the nature of relationships between different nodes.

The average clustering coefficient and assortativity in degree further enhance this analysis by offering insights into the clustering patterns and the tendency of nodes to connect with similar nodes within the network. These metrics can offer clues into the underlying structures and patterns within the network.

I conduct this analysis at three thresholds: 10%, 0.1%, and 0.01%. Links corresponding to input shares with a value lower than the filtering threshold value are deleted. The first filtering threshold value corresponds to the 0.1% threshold. This is the lowest threshold and excludes the smallest links in the network. The second filtering threshold value corresponds to the 1% threshold. This filtering threshold includes both large and medium-sized flows. The third filtering threshold value corresponds to the 10% threshold and includes only the large flows. Differences in the metric results at various filtering threshold values help identify the characteristics of each type of flow (small-sized flows, medium-sized flows, and large-sized flows). Moreover, I conduct this analysis for the years 1990, 2000, 2010, and 2021. This allows for a temporal analysis, facilitating a deeper understanding of the evolution of this network over time.

Table 3.2: Summary of network metrics

Metric	Definition
Degree	It refers to the number of edges connected to a node. The in-degree counts the number of incoming edges to the node, while the out-degree counts the number of outgoing edges from the node.
Completeness	It refers to the ratio of the actual number of edges in the network to the maximum possible number of edges. It is a measure of network density and indicates how interconnected nodes are within the network. A completeness value of 1 would mean that every node is connected to every other node, forming a fully connected network. Lower values indicate sparser networks with fewer connections relative to the maximum possible.
Reciprocity	It refers to the proportion of mutual connections between nodes in a directed network. It measures the likelihood that if node A is connected to node B , then node B is also connected to node A . A higher reciprocity value indicates a greater prevalence of mutual or bidirectional relationships within the network.
Average Clustering Coefficient	It is the mean of the clustering coefficients of all nodes in a network. The clustering coefficient of a single node measures the likelihood that its neighbors are also connected to each other, forming a “cluster”.
Assortativity in Degree	It measures the tendency of nodes with similar degrees to be connected to each other. A positive assortativity value indicates that high-degree nodes are more likely to be connected to other high-degree nodes, and low-degree nodes to other low-degree nodes. A negative value suggests that high-degree nodes are more likely to be connected to low-degree nodes, and vice versa.

Community detection algorithm

I proceed with the use of a community detection algorithm. Community detection algorithms are network tools designed to identify clusters of nodes that trade more with each other than would be expected in a network with random links. They can detect whether input linkages are organized into domestic clusters, sub-regional clusters, or clusters that span the post-Socialist region.

When applied to the PSPN, these tools can provide additional information about which nodes are more likely to be affected by the behavior of another node. As previously stated, a PSPN based on input share has several implications for the effects of one CI on another CI. These implications include direct and indirect effects, both upward and downward. In this context, applying community detection provides an estimation of the clusters where these upward and downward effects are likely to occur.

The community detection algorithm applied in this paper is the Leading Eigenvector method introduced in Newman (2006). The Leading Eigenvector method exploits the eigenvectors of the modularity matrix of the network. The method aims to maximize “modularity”, a metric that quantifies the density of links within communities compared to links between different communities. In simple terms, it tries to find groups of nodes that are more densely connected with each other than with nodes outside the group.

Contrary to more well-known community detection algorithms, such as the Louvain and the Fast Greedy methods, which are tailored for undirected networks, the Newman method can be applied to directed networks such as the production network.

Detecting the Autocatalytic Sets

The last empirical tool used to study input linkages in post-Socialist countries is based on the so-called Autocatalytic Sets (ACS) framework. Introduced in Jain and Krishna (1998) and formalized in Jain and Krishna (2002a), this framework is used to detect network structures that favor Circular Cumulative Causation. These network structures are called ACSs and are based on multiple overlapping

feedback loops. Applied to a directed network, the ACS framework reveals Core-Periphery structures in which some nodes are more impacted by the positive and negative feedback loops that occur in the network. In this chapter, mirroring the approach taken in Chapter 2, I detect which CIs are part of an ACS.

The ACS is defined as a set of nodes where each member receives at least one link from another member of the set. In other words, the ACS is defined as a set of CIs in which each set member is dependent on another set member for its inputs. More precisely, the ACS detection algorithm identifies one ACS by sub-graph based on the corresponding eigenvalue. A node is part of the ACS if its eigenvalue is equal to the Perron–Frobenius eigenvalue, which is the highest eigenvalue. The ACS therefore corresponds to the set of nodes in which there is the highest amount of feedback loops between its members.

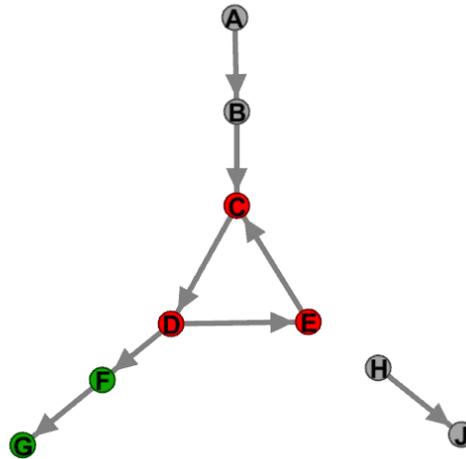
Just as in Chapter 2, the ACS represents a concentration of economic activity, with additional implications brought about by the usage of input share as a link weight. As previously stated, there are three network effects that can be inferred from the network. The first is the network effect in which the growth in downstream sectors can increase the economic activity of the upstream sector. The second is the network effect in which a CI’s failure to deliver its inputs propagates downstream. The last network effect is the propagation of price reductions downstream.

Returning to our examples of network effects, the ACS captures the two downstream effects. ACS members are therefore the group of nodes in which failure in one part of the set is more likely to propagate to the other set members. ACS members are also the group of nodes in which price reductions from within the set are more likely to accumulate.

The ACS detection algorithm identifies three groups of nodes, depending on their position in the overall structure of the network and therefore how much they benefit from the ACS: the Core of the ACS (red), the Periphery of the ACS (green), and the Unrelated nodes. Figure 3.1 provides a description of the ACS structure.

The Core (in red) is primarily characterized by cycles ($C \rightarrow D \rightarrow E \rightarrow C$), where each member both receives and sends at least one flow within the core. These cycles concentrate economic activities among Core members, and also create multiple feedback loops. For instance, C ’s failure to deliver input to D reduces the

Figure 3.1: Description of the Autocatalytic Set



input that D can provide, which impacts E , which will further reduce the amount of input that C can provide. In the same vein, if C reduces the price of its output, D can be more price-competitive and can lower the price of its output for E , which can do the same for C , further increasing the price competitiveness of other Core members.

The Periphery (in green) is composed of nodes that receive a significant portion of their inputs from the Core but do not reciprocate the flow. Members of the Periphery are both direct F and indirect G customers of the Core members. These CIs are affected by events that occur in the Core while having a limited effect on the Core.

To identify the ACS, I follow a process similar to that outlined in Chapter 2. Given that the PSPN is a fully connected network, it is necessary to filter the network by selecting only the strongest links. In the context of this chapter, I determine the strongest links by establishing a minimum filtering threshold value for the input shares. This filtering threshold value preserves only the strongest links. A large value of the input share for an industry suggests a high reliance on external inputs and greater participation in inter-industry and intra-industry linkages. Concerning the choice of the filtering threshold value, I identify a range of values within which the autocatalytic structure can be identified. If the filtering threshold value is too high, it deletes all links in the filtered network. If the filtering threshold value is too low, the filtered network preserves most links, including those that are too small to be relevant. In this study, I select the 1% filtering threshold

value. However, for comparison, other filtering threshold values are discussed (10% and 0.1%).

I apply the Perron-Frobenius theorem, as described, to detect a Core-Periphery structure within the filtered PSPN. I am using a methodology described in Jain and Krishna (2002a) and Napolitano et al. (2018), based on the Perron-Frobenius theorem. This methodology is discussed in detail in Section 2.4.2 of Chapter 2.

3.4 Results

The results section is organized into two parts. Firstly, I present and discuss the changes in IO domestic linkages within each post-Socialist economy. Secondly, I explore the changes in input linkages across all post-Socialist economies, plus Germany, Russia, and China.

3.4.1 Results on the analysis of input linkages

Identifying the industry specialization of post socialist countries

Post-Socialist countries underwent significant changes in the 30 years since their transition from socialism. I start with a brief summary of the evolution of the specialization of each of the post-Socialist countries by comparing the Revealed Industry Specialization (RIS) index, as explained in the methodological section. A country with a RIS greater than 1 in a given industry indicates that the industry's share in the total output of a country is oversized compared to its share in the global economy. Conversely, a RIS lower than 1 means that the industry's share of output is undersized relative to its share in the global economy. Detailed tables reflecting these RISs for the years 1990 and 2021 are depicted in Figures 3.3 and 3.4, respectively. Figures for the years 2000 and 2010 can be found in the Appendix, specifically in Figures B.2 and B.3.

I begin by describing the RIS outlook in 1990 and 2021, before discussing the changes that occurred over time in a few selected industries. In 1990, one year before the dissolution of the Soviet Union, most socialist countries had RIS greater than 1 in the *Agriculture* (1), *Electricity, gas, and water* (13), and *Transport* (19) industries.

Table 3.3: Post-Socialist countries' Revealed Industry Specialization, in 1990

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	
1990	0.318	0.063	0.762	0.848	0.715	0.945	0.703	0.965	0.949	1.111	1.064	0.177	1.171	0.763	0.427	1.162	1.509	0.835	1.084	0.706	1.256	0.901	1.423	0.003	0.003	0.2	5.349
DEU	2.677	10.394	2.048	2.197	0.773	0.506	1.181	0.908	1.183	0.1	1.892	4.668	0.659	0.941	0.219	0.35	0.971	0.006	1.548	0.477	0.466	0	1.721	0	0	0	0.033
BGR	2.841	0.736	1.003	0.88	0.93	0.824	0.842	0.858	0.816	0.771	0.961	1.561	2.756	0.473	0.31	1.01	0.864	1.07	1.137	1.857	0.992	0.865	0.862	0.909	0.966	0.66	0.011
HRV	0.882	0.61	0.782	0.701	0.856	0.781	0.722	0.555	0.715	0.689	1.123	1.066	1.383	0.644	0.385	1.422	1.17	1.594	1.028	1.529	1.143	1.844	1.395	1.211	0.674	0.013	0.013
CZE	0.654	0.172	1.163	1.098	1.491	1.023	0.988	1.291	1.032	1.376	1.645	1.176	2.655	0.952	3.108	1.039	0.607	0.831	1.605	0.808	0.835	0.569	0.769	0.034	0.865	0.004	0.004
EST	1.027	1.641	1.078	1.446	1.796	1.306	0.332	0.384	0.351	0.158	1.83	0.088	2.271	0.973	3.067	1.328	1.529	1.109	2.81	1.193	0.891	0.979	1.15	0.119	0.926	1.603	
HUN	1.136	0.109	0.497	1.47	1.222	0.855	0.809	0.737	0.906	0.66	0.815	0.375	2.005	0.688	3.328	1.114	1.274	0.897	1.302	1.186	0.937	0.99	1.14	0.023	1.97	1.321	
LVA	1.478	2.355	0.319	1.986	1.717	1.24	0.23	0.366	0.176	0.172	0.672	0.487	2.752	0.936	4.133	1.746	2.517	0.943	2.869	1.447	0.503	0.909	1.193	0.124	1.63	0.327	
LTU	1.082	0.766	0.618	2.082	2.075	0.958	0.741	0.185	0.255	0.122	0.992	1.627	2.173	0.835	3.635	1.295	2.19	0.675	1.749	1.131	0.558	1.407	1.191	0.618	2.554	8.913	
POL	1.132	0.255	1.682	1.491	1.212	1.063	0.744	0.945	0.439	0.537	1.424	0.324	1.89	1.043	4.72	1.326	1.615	0.641	1.847	0.948	0.92	0.762	0.949	2.935	1.167	2.089	
ROU	2.537	0.061	2.493	2.258	1.558	0.677	0.761	0.839	0.33	0.429	1.366	0.033	3.417	0.729	0.683	1.079	0.876	0.954	1.847	1.353	0.642	0.596	0.899	0.031	0.004	3.55	
SVK	1.015	0.058	0.544	1.359	0.922	0.855	0.905	0.917	0.562	0.88	0.754	0.382	3.839	0.885	1.819	1.073	1.659	0.708	1.618	0.739	0.75	1.201	1.175	0.027	0.412	0.054	
SVN	0.607	0.073	0.669	0.994	2.064	1.366	0.657	1.301	0.795	0.688	1.524	0.77	1.307	1.101	3.851	1.021	1.547	1.276	1.347	0.883	0.865	0.815	1.097	0.2	0.987	0.21	
ARM	2.045	0.224	0.173	1.154	0.935	1.668	1.812	1.76	1.716	1.737	0.301	0.393	0.294	1.62	0.005	0.715	0	0.321	0.262	0.613	0.123	0.96	0.375	0.001	0	0	
AZE	1.632	0.598	2.078	1.127	0.751	1.421	1.39	1.237	1.273	1.295	1.404	0.792	1.991	0.602	0.184	0.806	0.831	1.013	0.898	1.302	0.66	0.603	0.719	0.623	0.417	0.055	
BLR	0.768	3.949	2.127	0.49	2.278	0.961	2.581	1.008	0.713	0.219	1.022	4.106	0.885	0.3	1.433	0.857	3.917	0.434	1.16	0.588	0.426	0.307	0.361	6.966	13.812	4.075	
GEO	3.154	0.427	1.172	2.514	0.419	0.535	0.55	0.368	0.247	0.247	0.251	0.412	1.554	1.04	0.333	0.108	1.809	0.939	1.74	1.682	0.601	1.487	1.17	0.78	6.296	0.032	
KAZ	3.246	13.56	2.492	1.97	3.042	0.224	0.799	1.001	0.322	0.049	1.018	0.926	1.321	1.802	0.141	0.225	0.625	0.02	1.917	0.695	0.476	0.158	0.717	0.171	12.015	0.006	
KGZ	7.032	0.185	5.621	1.927	2.271	0.175	0.411	1.03	0.148	0.411	0.534	0.875	1.985	0.587	0.02	0.032	0.089	0.235	0.998	0.418	0.346	1.552	1.078	0.011	0.806	0.086	
MDA	2.433	13.234	2.595	1.679	2.418	0.817	0.355	0.802	0.439	0.616	2.79	12.239	2.15	0.422	4.634	0.875	1.715	1.168	0.988	1.298	0.29	0.977	0.527	24.385	9.188	7.887	
TJK	1.111	1.433	1.515	0.803	0.617	0.928	0.809	0.811	0.702	0.709	1.302	1.996	1.41	0.532	0.504	1.071	1.035	1.419	1.375	1.863	1.539	0.589	0.956	1.461	1.14	0.159	
TKM	0.672	0.759	1.85	0.818	0.612	0.726	0.679	0.519	0.725	0.763	1.213	1.376	0.901	0.759	0.393	0.987	1.243	1.455	1.114	1.832	1.374	1.356	1.324	1.651	0.663	0.07	
UKR	2.978	12.439	3.459	2.551	3.253	0.302	0.702	1.512	0.93	0.22	2.009	2.059	0.902	0.718	0.136	0.217	0.602	0.021	1.182	0.531	0.454	0.158	0.69	0.252	17.756	0.003	
UZB	3.634	17.24	1.074	2.245	7.899	0.106	0.53	0.468	0.264	0.019	1.502	1.497	1.093	1.101	0.17	0.271	0.752	0.024	1.308	0.572	0.458	0.169	1.05	0.167	11.755	0.019	
ALB	2.286	2.046	1.743	0.754	0.709	0.56	0.471	0.349	0.501	0.445	0.915	0.427	1.667	0.95	0.544	1.629	1.527	2.246	1.639	1.421	0.946	1.234	1.043	1.913	0.683	0.162	
BIH	0.521	0.913	1.496	0.723	0.537	0.643	0.549	0.447	0.593	0.627	0.966	1.495	1.406	0.715	0.386	1.077	1.255	1.517	1.383	1.723	1.498	1.549	1.384	1.44	0.675	0.046	
MKD	2.445	0.199	1.916	1.521	2.6	0.445	0.516	0.825	0.138	0.102	0.272	0.742	1.869	0.992	7.292	0.861	1.536	1.028	1.506	1.96	0.695	1.439	0.985	0.34	0.424	0.26	
MNE	1.153	1.346	1.797	0.763	0.354	0.638	0.524	0.431	0.528	0.57	0.933	1.805	1.828	0.63	0.499	1.225	1.319	1.623	1.497	1.982	1.246	1.58	1.362	1.638	0.798	0.196	
SRB	0.958	0.913	1.089	0.607	0.303	0.497	0.437	0.336	0.469	0.534	0.773	0.966	1.227	0.564	0.401	0.947	1.206	1.417	1.067	1.443	1.151	3.215	1.926	1.599	0.625	0.011	

Note: Green cells represent the instance in which an industry in a country is oversized compared to the share of this industry in the world economy. A value lower than 1 means that the industry is undersized compared to the share of this industry in the world economy. The industry codes used in this table are the one displayed in Table B.1.

Table 3.4: Post-Socialist countries' Revealed Industry Specialization, in 2021

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
DEU	0.318	0.033	0.162	0.631	1.056	0.914	1.277	1.101	2.171	0.7	0.419	0.9	0.693	0.29	0.979	0.662	0.537	1.102	0.861	1.178	0.946	1.284	0.005	0.164	5.979	
RUS	1.684	3.151	1.46	1.372	0.344	0.908	1.696	1.796	0.871	0.015	1.288	2.04	1.13	1.052	0.798	1.236	2.746	0.012	1.454	0.01	0.535	0.378	0.777	0	0.001	0.021
BGR	1.368	0.383	0.435	0.893	1.286	1.16	1.024	1.04	0.964	0.699	0.848	0.733	2.372	0.888	0.428	1.584	0.78	1.523	1.425	1.704	0.759	1.105	0.656	0.782	0.347	0.026
HRV	0.84	0.776	0.512	0.72	1.102	1.408	1.096	0.641	0.946	0.752	1.081	0.634	1.343	1.073	0.55	1.911	1.09	1.323	0.841	1.368	0.907	0.868	0.901	0.261	0.025	
CZE	0.901	0.071	0.512	1.272	1.04	1.575	1.045	1.374	1.092	1.652	1.369	1.019	2.097	1.197	4.382	1.158	0.5	0.804	1.124	0.795	0.897	0.426	0.474	0.035	0.34	0.01
EST	1.209	0.842	0.449	1.166	1.667	2.573	0.487	0.533	0.712	0.408	1.651	0.093	1.487	0.913	3.558	1.491	0.968	0.722	2.21	1.199	0.851	0.975	0.78	0.309	0.287	1.932
HUN	1.441	0.051	0.177	1.49	1.021	1.255	0.953	0.809	1.582	1.325	0.69	0.258	1.185	0.668	3.131	1.086	0.952	0.794	0.998	1.009	0.829	0.942	0.814	0.012	0.648	1.809
LVA	1.136	0.399	0.294	1.806	2.294	1.793	0.891	0.226	0.403	0.182	1.177	1.057	1.34	0.805	4.275	1.606	1.747	0.511	1.636	1.161	0.522	1.001	0.886	0.608	0.952	10.921
POL	1.313	0.135	0.709	1.526	0.894	1.662	0.872	1.016	0.565	1.081	1.126	0.27	1.284	1.177	5.538	1.497	1.246	0.517	1.14	0.976	0.836	0.796	0.831	1.985	0.412	1.649
ROU	2.736	0.043	0.916	2.151	1.492	1.04	0.848	0.962	0.412	0.667	1.04	0.075	2.245	0.884	0.721	1.144	0.804	0.754	1.117	1.165	0.662	0.867	0.831	0.014	0.001	4.831
SVK	1.132	0.014	0.239	1.036	0.872	1.657	1.143	1.527	0.773	1.741	0.758	0.354	3.077	0.98	1.903	1.127	0.846	0.655	1.32	0.811	0.737	0.864	0.687	0.02	0.263	0.018
SVN	0.711	0.06	0.265	1.057	1.625	2.104	0.892	1.508	1.084	1.167	1.352	0.628	0.814	1.126	4.334	1.112	1.432	0.996	0.99	0.885	0.743	0.839	0.875	0.178	0.35	0.359
ARM	3.509	1.589	1.141	1.144	0.409	0.741	0.475	0.657	0.604	0.501	0.855	2.3	1.534	1.541	1.143	1.403	1.364	0.695	0.717	1.338	0.876	1.234	0.867	3.195	0.148	0.306
AZE	1.741	0.429	6.477	0.628	0.276	0.744	0.642	0.417	0.505	0.46	0.646	0.325	3.653	1.315	0.524	1.37	1.166	1.058	0.761	1.528	0.769	0.996	0.562	1.111	0.28	0.077
BLR	2.407	0.638	0.523	0.812	1.293	1.243	1.624	1.046	1.967	0.104	0.359	1.125	0.325	1.023	0.415	1.693	0.71	0.189	2.054	0.895	0.383	0.901	1.055	1.47	0.486	0.406
GEO	2.574	0.249	0.73	2.196	0.339	0.83	0.741	0.827	0.808	0.567	0.316	0.409	1.021	1.262	0.491	0.622	1.779	0.835	1.491	1.238	0.572	1.656	0.681	0.865	1.991	0.35
KAZ	4.377	8.91	6.018	2.218	2.684	0.272	0.734	1.519	0.301	0.064	0.751	0.557	1.904	0.941	0.149	0.23	0.512	0.025	1.412	0.585	0.405	0.134	0.383	0.074	2.362	0.014
XGZ	8.409	0.078	2.205	2.103	2.011	0.442	0.695	1.184	0.201	0.543	0.595	0.77	1.652	0.904	0.029	0.046	0.102	0.37	0.97	0.519	0.397	1.103	0.659	0.013	0.427	0.332
MDA	4.276	4.557	0.653	2.337	1.812	0.654	0.244	0.721	0.414	0.402	1.028	3.233	1.727	0.662	2.421	1.714	0.217	1.023	1.151	2.437	0.667	0.844	0.68	9.168	0.26	0.379
TJK	2.783	0.947	0.313	0.812	0.473	1.118	0.814	0.561	0.777	0.802	0.706	0.715	0.512	0.895	0.415	1.199	1.122	1.093	0.811	2.101	1.409	0.885	0.746	0.951	0.201	0.031
TKM	0.909	0.513	0.69	0.948	0.597	1.051	0.724	0.506	0.843	0.932	1.017	0.808	0.538	1.111	0.669	1.532	1.518	1.515	0.809	2.043	0.881	1.17	1.479	1.952	0.463	0.053
UKR	3.392	6.904	2.193	2.564	2.08	0.406	0.801	1.531	0.842	0.212	2.376	0.951	2.172	0.349	0.513	0.794	1.765	0.024	1.282	0.632	0.522	0.102	0.38	0.075	2.418	0.01
UZB	5.527	12.658	0.866	2.329	6.135	0.192	0.723	0.568	0.379	0.042	1.225	0.98	1.137	1.223	0.194	0.3	0.667	0.024	0.817	0.506	0.43	0.184	0.674	0.099	3.174	0.051
ALB	3.379	2.105	0.721	0.604	0.803	0.837	0.506	0.416	0.545	0.471	0.886	0.474	1.387	2.351	0.824	1.525	1.214	1.213	0.847	1.191	0.799	1.35	0.724	2.322	0.229	0.134
BIH	1.951	0.884	0.936	0.797	1.304	1.455	0.753	0.715	0.858	0.793	1.031	0.991	1.671	0.806	0.69	1.603	1.254	1.309	0.783	1.345	0.899	1.574	0.806	1.644	0.285	0.111
MKD	3.283	0.111	1.105	1.556	2.089	0.773	0.834	1.272	0.226	0.174	0.358	0.766	1.268	1.201	9.532	1.022	1.129	0.855	1.065	1.514	0.649	1.289	0.625	0.644	0.136	0.415
MNE	1.288	1.893	0.797	1.238	0.371	0.826	0.355	0.442	0.341	0.493	0.932	2.601	3.225	0.958	2.062	2.26	1.338	2.175	1.979	1.646	0.529	1.609	0.745	6.864	0.734	1.031
SRB	1.751	1.591	0.641	1.057	0.426	1.238	0.708	0.791	0.675	0.677	0.86	1.135	4.692	0.724	0.775	1.373	0.965	1.549	1.616	1.284	0.641	1.246	0.697	2.596	0.546	0.258

Note: Green cells represent the instance in which an industry in a country is oversized compared to the share of this industry in the world economy. A value lower than 1 means that the industry is undersized compared to the share of this industry in the world economy. The industry codes used in this table are the one displayed in Table B.1.

The WB countries are characterized by a lower RIS compared to other groups in the *Food and beverages* (4) industry but outperformed the others in the *Financial intermediation and business activities* (21), and *Public administration* (22) industries. Both the CIS-affiliated countries and the WB countries had higher RIS in the *Mining and quarrying* (3) industry compared to the CEEU countries. Overall, the CIS countries tend to have larger *Mining and quarrying* (3) industries than the other groups, with Kyrgyzstan as a leader with a RIS of 5.62 in this specific industry.

The CEEU and the WB countries are characterized by larger RIS in *Wholesale trade* (16) and *Retail trade* (17) industries. The CEEU countries are significantly more numerous in having a $RIS > 1$ than the other groups in the *Maintenance and repair* (15) and *Wholesale trade* (16) industries. On the other hand, CIS-affiliated countries outperform the other groups in the *Agriculture* (1), *Fishing* (2), *Mining and quarrying* (3), and *Textiles and wearing apparel* (5) industries due to the large values of the RIS of those countries. *Maintenance and repair* (15) is the industry in which the CEEU countries had the largest RIS. However, in 1990, most countries had undersized *Petroleum, chemical and non-metallic mineral products* (7), *Metal products* (8), *Electrical and machinery* (9), *Transport equipment* (10), and *Construction* (14) industries.

30 years later, post-Socialist countries maintained a RIS larger than 1 in the *Agriculture* (1), *Electricity, gas, and water* (13), and *Transport* (19) industries. In 2000, Kazakhstan overtook Uzbekistan and is shown to have the largest *Mining and quarrying* (3) industry share in the region. Kazakhstan was replaced by Azerbaijan in 2021. Notably, Kyrgyzstan's *Agriculture* (1) industry share represents 7 times the world average, while the second one in the region, Uzbekistan, has a RIS of 3.6. Kyrgyzstan's *Agriculture* (1) RIS values remained high throughout the entire period. Over time, both the Kazakh and the Moldovan agriculture industries increased their RIS indexes, reaching the second and third spots in 2021.

Concerning the *Transport equipment* industry, the only post-Socialist countries in 1990 with a $RIS > 1$ were Czechia in the CEEU sub-region and Armenia and Azerbaijan in the CIS sub-region. Starting from the 2000 table, it was confined to only CEEU countries such as Czechia, Hungary, Slovakia, and Slovenia. Poland was added to this group in the 2021 table.

In 2000, most CEEU countries with a $RIS > 1$ preserved their oversized *Wholesale trade* (16) industries. At the same time, they increased their number of industries with a $RIS > 1$ in the *Textiles and wearing apparel* (5), *Wood and paper* (6), and *Post and telecommunications* (20) industries. Concerning CIS-affiliated countries, RIS values tend to be larger than those of their CEEU and Balkan counterparts in the *Fishing* (2), *Mining and quarrying* (3), and *Textiles and wearing apparel* (5) industries. Finally, the WB countries tend to have a similar specialization by having a RIS in generally the same industries, namely *Mining and quarrying* (3), *Retail trade* (17), *Hotels and restaurants* (18), *Post and telecommunication* (20), *Public administration* (22), and *Education, health and other services* (23) industries.

I conclude by presenting the Pearson correlation ⁵ of RISs across the reference years 1990, 2000, 2010, and 2021 (see Table 3.5). The biggest change in Pearson correlation occurred between 1990 and 2000, with a value of 0.78. In the subsequent years, its value was 0.9 between 2000 and 2010, and 0.86 between 2010 and 2021. The overall Pearson correlation index for the changes in RIS between 1990 and 2021 is 0.67. While the correlation remain positive and therefore the post-Socialist countries specialization remained partly explained by the specialization adopted under the planned economy, the transition to market economy and even more so the change in political borders seems to have a strong influence in industry specialization. This is shown by the fact that for CEEU, CIS and WB countries the biggest change occurred in the first decade.

Table 3.5: Pearson correlation across Revealed Industry Specialization by region and decades

	All countries	CEEU	CIS	WB
1990-2000	0.784	0.891	0.769	0.834
2000-2010	0.898	0.966	0.887	0.919
2010-2021	0.858	0.966	0.861	0.879
1990-2021	0.670	0.890	0.683	0.732

Note: A pearson correlation by country version can be found in the Appendix in Table B.4

⁵The Pearson correlation measures the linear correlation between two lists. It is bounded between -1 for perfect anti-correlation and 1 for perfect correlation.

Among all three groups of countries, the CIS-affiliated countries underwent the most significant changes in RIS indices. These changes primarily occurred during the period from 1990 to 2000. Despite facing similar hardships, such as gaining independence, alterations in supply chains, and enduring military conflicts for two decades, the Balkan countries have maintained a more stable specialization. This observation can imply that the industries in the former Yugoslav countries were less dependent on each other, and therefore suffered less disruption. The CEEU countries constitute the group that has maintained the most stable specialization.

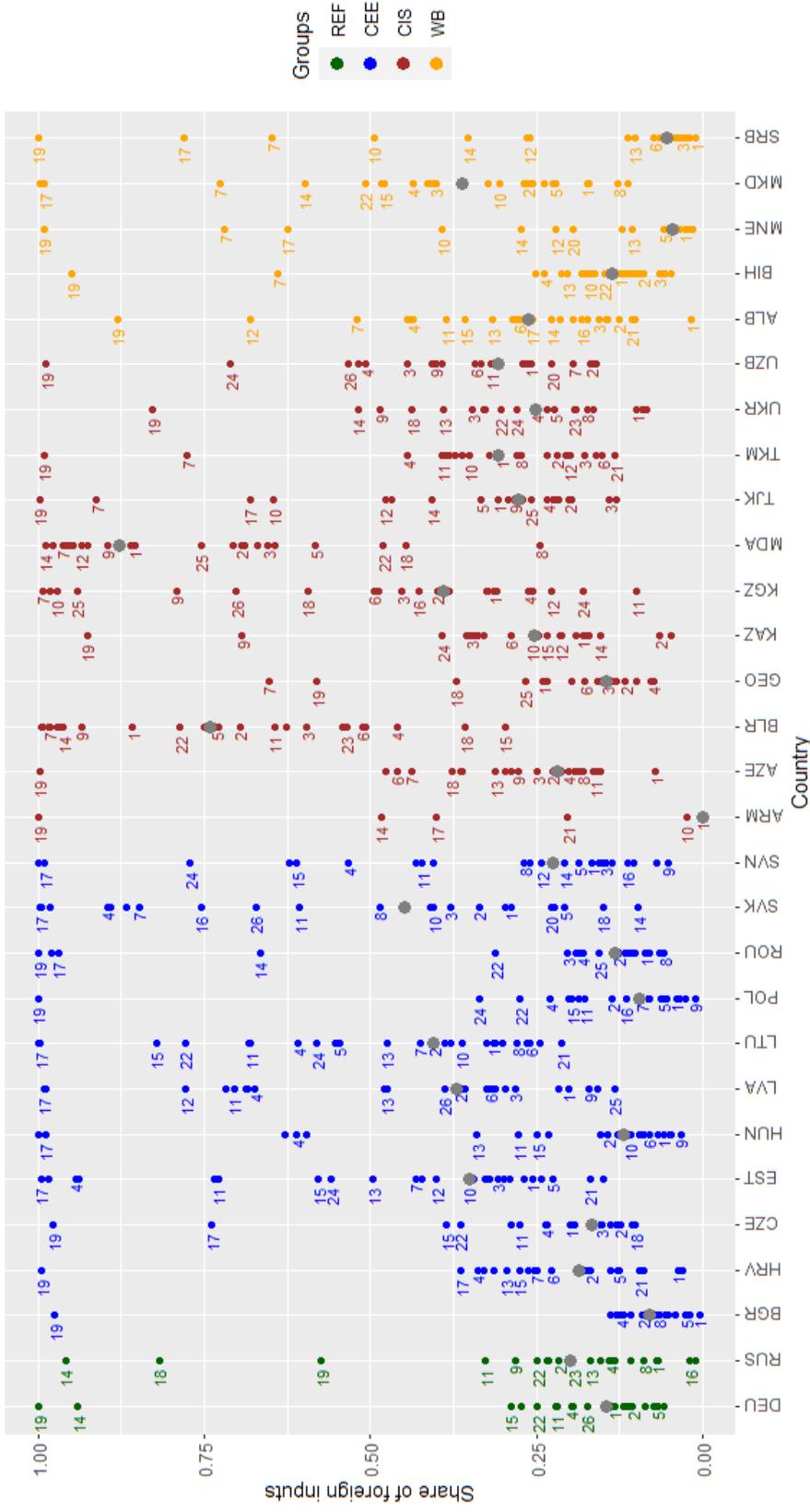
As shown by the country version of the previous table found in the Appendix in Table B.4, the change in RIS is not necessarily correlated with changes in political borders. Among the CEEU countries, the country with the lowest Pearson correlation, between 1990 and 2000 but also throughout the whole 3 decades, is Bulgaria, even though it had stable political borders during the period. Similarly, the countries with the most stable RIS Pearson correlation, between 1990 and 2000 but also throughout the whole 3 decades, were Latvia and Lithuania, despite their separation from the USSR. However, the most stable countries in the first decade are Turkmenistan and Kyrgyzstan in the CIS.

Changes in the sources of inputs by industry

I first examine the extent to which post-Socialist countries rely on domestic inputs rather than foreign ones. I begin by displaying Figure 3.2 and Figure 3.3. These figures display the proportion of foreign inputs used by each industry in a given country. If this proportion exceeds 0.5, it indicates that over 50% of the inputs used in a given industry are sourced from abroad. The gray point represents the median value among each input share of imports. To facilitate comparison, the differences in the share of foreign inputs between 1990 and 2021 are provided in the Appendix, in Figure B.1.

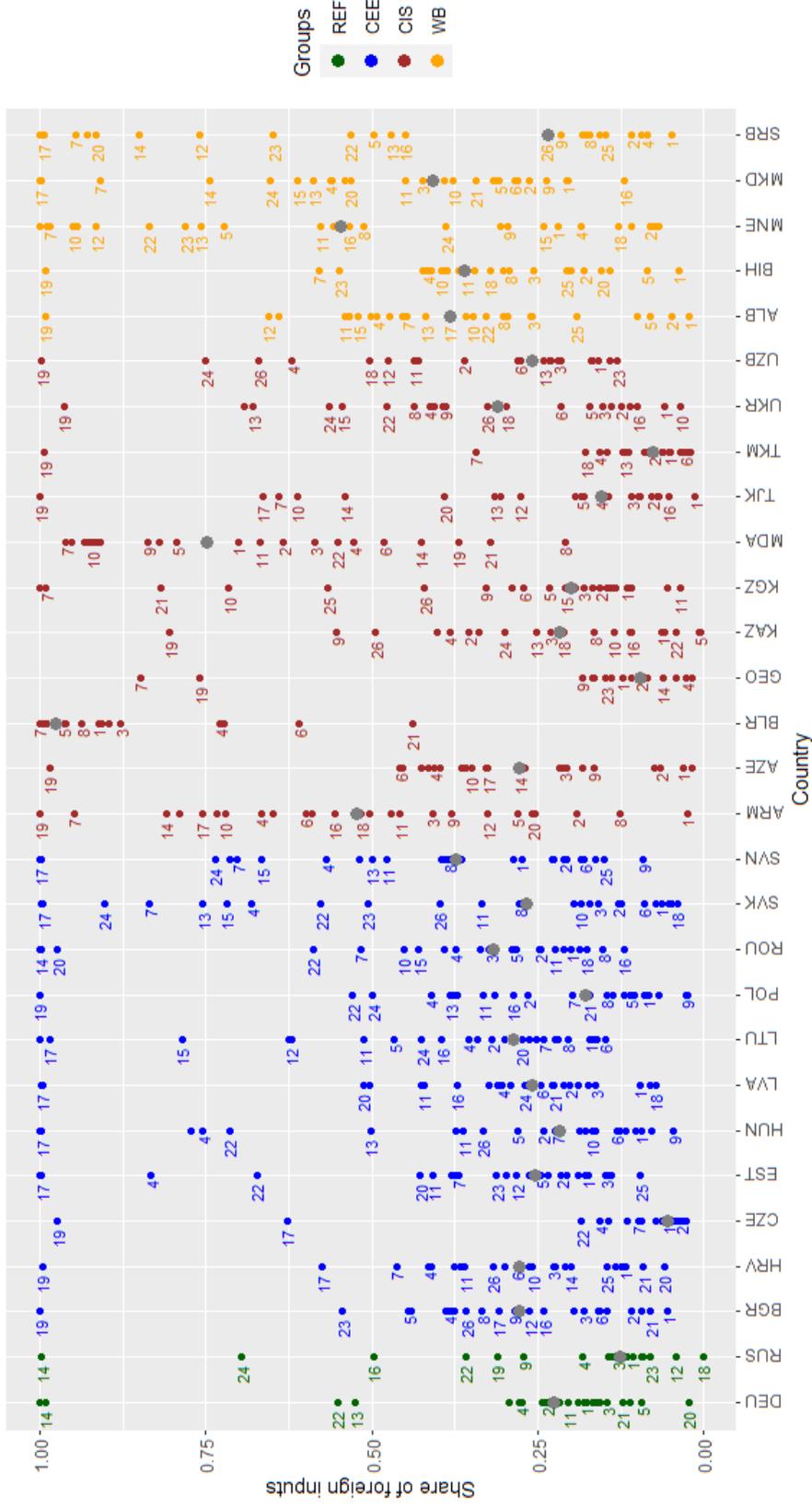
A recurring theme throughout most of our analysis is that CIS-affiliated countries experience higher variance compared to other groups, reflecting a broader range of trajectories than in the other two groups. The CIS group exhibits the greatest heterogeneity between countries. In 1990, Moldova and Belarus were highly dependent on foreign inputs, having respectively 88% and 74% of their in-

Figure 3.2: Share of foreign inputs in domestic industries, in 1990



Note: This share is computed using the total world value of input, not only those that come from post-Socialist countries. The numbers are Id numbers of the industries. The gray nodes correspond to the median value of the ratio.

Figure 3.3: Share of foreign inputs in domestic industries, in 2021



Note: This share is computed using the total world value of input, not only those that come from post-Socialist countries. The numbers are Id numbers of the industries. The gray nodes correspond to the median value of the ratio.

puts coming from abroad. This group also includes Armenia, which had the lowest level with 0.02% of its inputs coming from abroad. In 2021, Armenia increased its reliance on foreign inputs to achieve a median value of 52%, while Belarus increased to a value of 97% in its use of foreign inputs. Conversely, Moldova maintained a high dependence on foreign inputs while reducing its ratio from 88% in 1990 to about 74% in 2021. Despite strong variation between CIS countries, the average median value remained at 34% in both 1990 and 2021, indicating that increases in some countries were compensated by decreases in others. The countries that increased their reliance were Armenia and Belarus, and the countries that decreased were Georgia, Kyrgyzstan, Moldova, Tajikistan, and Turkmenistan.

CEEU countries, however, are more concentrated towards the lower bound (below 50%). The share of imported inputs has remained stable over time, rising from an average median value of 23% in 1990 to over 25% in 2021. This stability in average median value hides multiple shifts between CEE countries. Bulgaria, Croatia, Hungary, Poland, Romania, and Slovenia have increased in their use of foreign inputs between 1990 and 2021. While Czechia, Estonia, Latvia, Lithuania, and Slovakia have also increased in their use of foreign inputs.

WB countries have followed a different trend, increasing their average share of foreign inputs from 17% in 1990 to reaching an average median value of 38% in 2021. All WB countries increased in their use of foreign inputs.

The intensity of domestic inputs by sector

I continue the analysis by examining the extent to which post-Socialist countries vary in their use of domestic inputs. Boehm (2018) study the distribution of the size of domestic input shares across industries and sectors in developing countries. They find that input shares are correlated with development. Developing countries generally exhibit higher domestic shares of input originating from the *Agriculture and mining* sector and lower domestic shares of input originating from the *Manufacturing* sector. The relationship between services and development, however, follows a U-shaped pattern: domestic input shares in services are high for low-income countries, decrease for middle-income countries, and then reach intermediate levels for high-income countries.

Figure 3.4: Average Domestic Use of *Agriculture and fishing* sector, in 1990

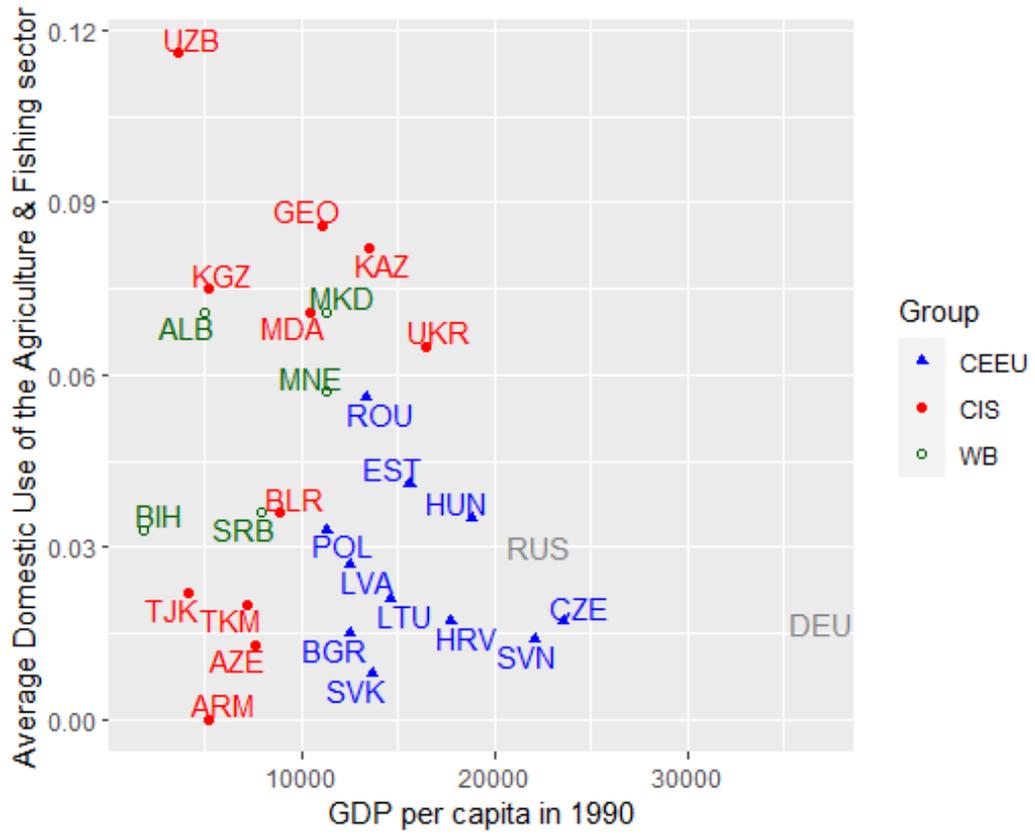
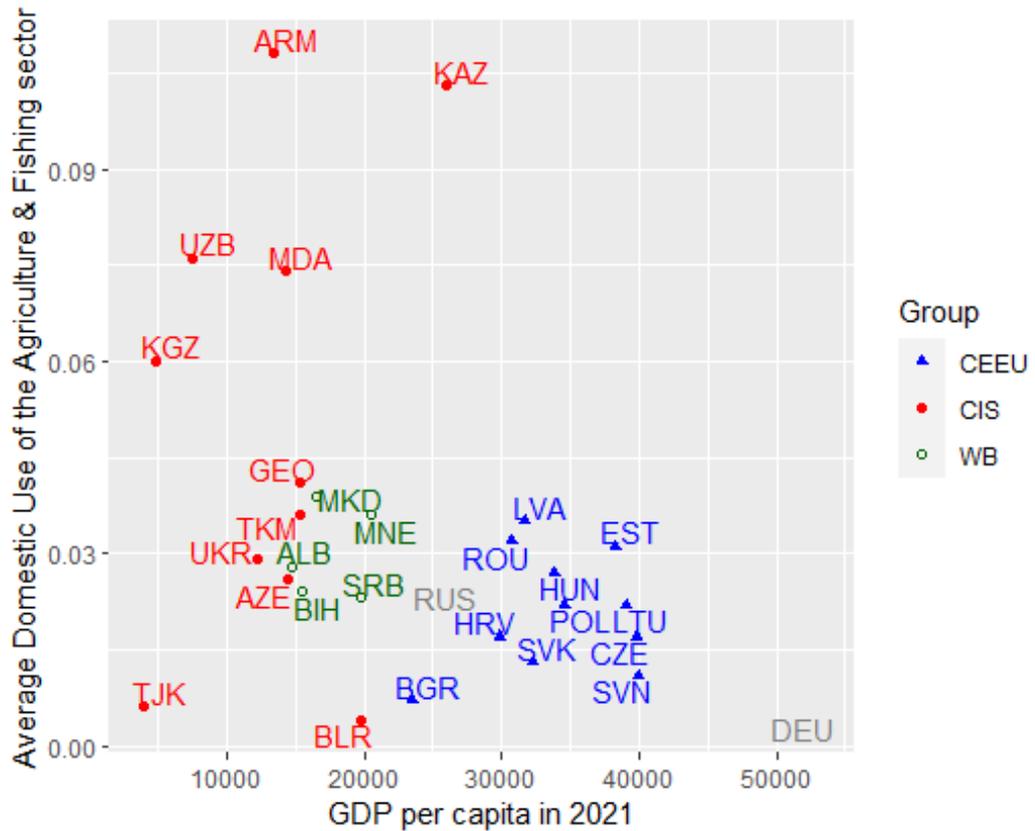


Figure 3.5: Average Domestic Use of the *Agriculture and fishing* sector, in 2021



In the following results, I discuss whether these findings also hold for post-Socialist countries. Figures 3.4 and 3.5 provide the average domestic use for the *Agriculture and fishing* sector for the years 1990 and 2021, respectively. Figures 3.8 and 3.9 provide the average domestic use for the *Manufacturing* sector for the years 1990 and 2021. Figures 3.6 and 3.7 provide the average domestic use for the *Mining and energy* sector for the years 1990 and 2021. Figures 3.10 and 3.11 provide the average domestic use for the *Services* sector for the years 1990 and 2021. Each of these values is plotted against the country's respective GDP per capita in PPP terms. The detailed list of coefficients for the years 1990, 2000, 2010, and 2021 is provided in the Appendix, specifically in Figures B.5, B.6, B.7 and B.8.

I begin with the *Agriculture and fishing* sector. Among post-Socialist countries, low GDP levels are associated with high variance in the use of the domestic *Agriculture and fishing* sector. High GDP levels are associated with low use of the domestic *Agriculture and fishing* sector. CEEU countries, being the wealthiest among the three groups, exhibit low use of their *Agriculture and fishing* sector. This usage decreases as they become wealthier in subsequent decades. WB countries are characterized by moderate use of their domestic *Agriculture and fishing* sector, which also decreases over time as they become wealthier.

CIS countries exhibit high heterogeneity in their use of their domestic *Agriculture and fishing* sectors. In 1990, two groups emerge among CIS countries. The first group has high use of their domestic *Agriculture and fishing* sector, including Uzbekistan, Georgia, Kazakhstan, Kyrgyzstan, Moldova, and Ukraine. The second group has low use of their domestic *Agriculture and fishing* sector and is composed of Belarus, Tajikistan, Turkmenistan, Azerbaijan, and Armenia. In 2021, the groups mostly remained the same, with two notable exceptions: Ukraine, which started in 1990 with high use of their domestic *Agriculture and fishing* sector, decreased to low use in 2021. Armenia, which started in 1990 with low use of their domestic *Agriculture and fishing* sector, became, along with Kazakhstan, the biggest user of their domestic *Agriculture and fishing* sector in the region, overtaking Uzbekistan.

Figure 3.6: Average Domestic Use of the *Mining and energy* sector, in 1990

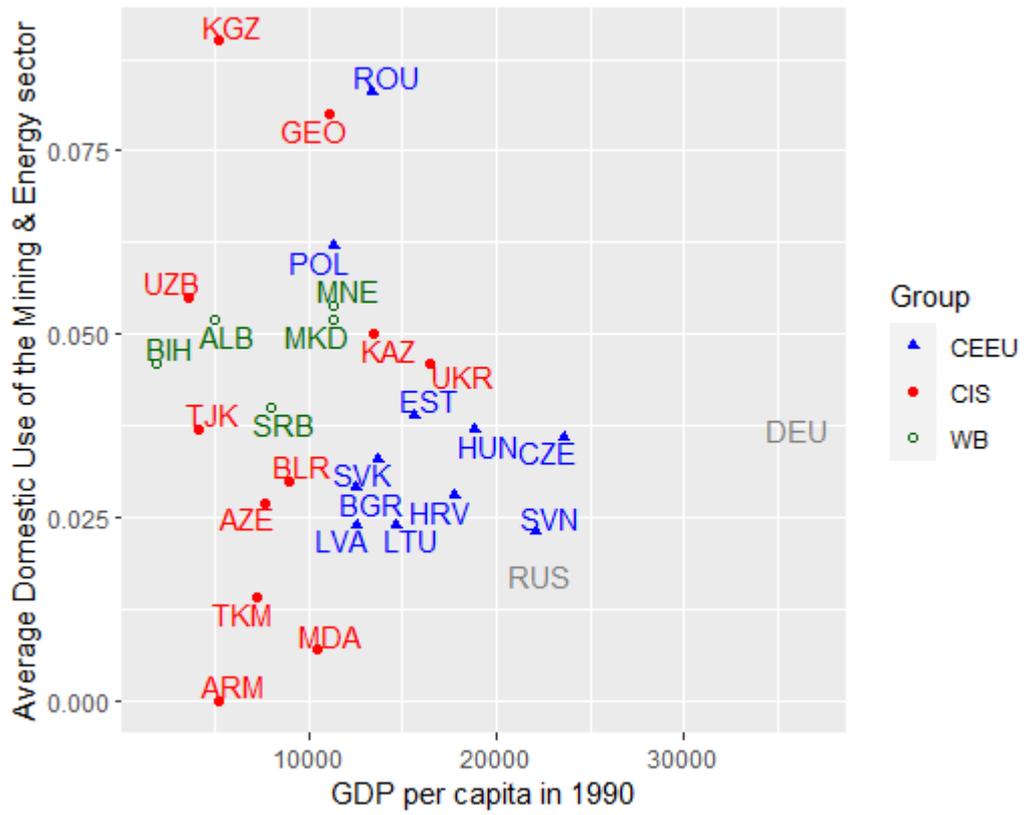
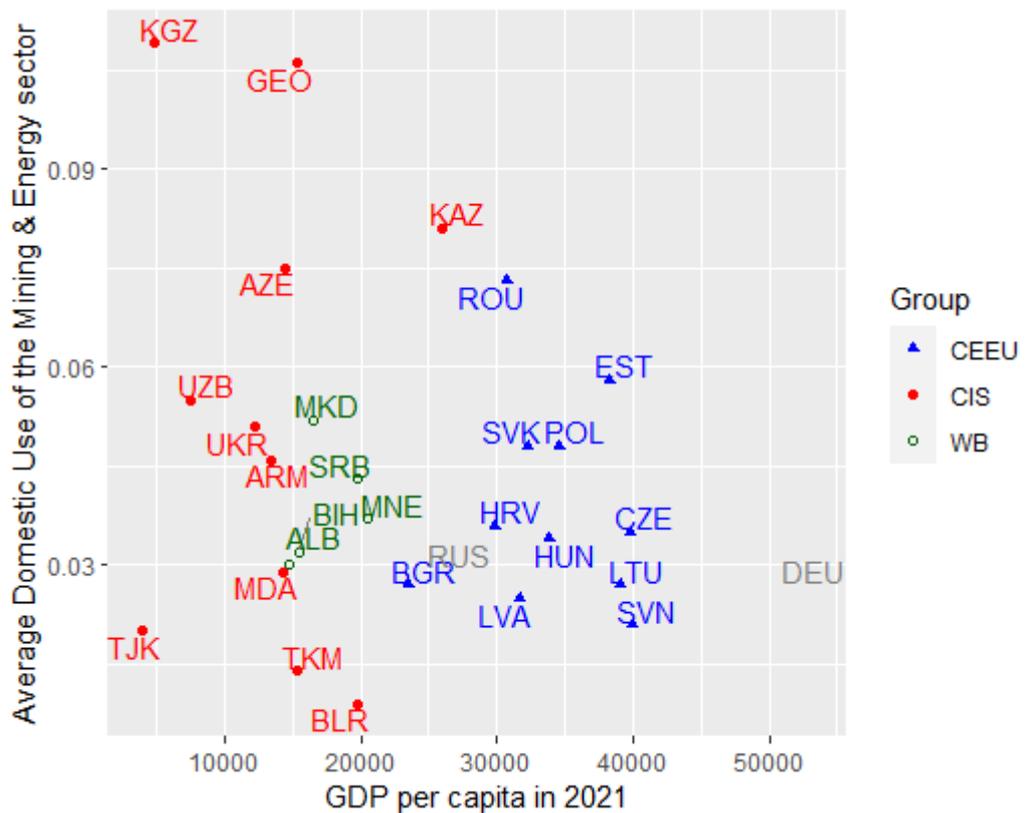


Figure 3.7: Average Domestic Use of the *Mining and energy* sector, in 2021



I continue with the *Mining and energy* sector. Post-Socialist countries with low GDP exhibit higher variance in their use of the *Mining and energy* sector, ranking among both the highest and lowest users of the sector. As these countries become wealthier, they converge toward a middle point, approximately at 0.04.

CEEU displays higher heterogeneity in this sector. In 1990, most CEEU countries have moderate use of their *Mining and energy* sector; however, Romania and Poland stand out with high use of this sector. Romania ranked second in its use in 1990. In 2021, Romania remained a high user but was overtaken by many CIS countries, while Poland reached a level similar to other CEEU countries. WB countries have medium use of their *Mining and energy* sector, similar to most of the CEEU countries.

CIS remains the most heterogeneous group, but they have also changed significantly over time. In 1990, the countries with the highest use of their *Mining and energy* sector are Kyrgyzstan, Georgia, and Uzbekistan. Armenia and Moldova had the lowest values among all the post-Socialist countries. In 2021, the ranking among CIS countries changed significantly, with Kyrgyzstan and Georgia at the top, followed by Kazakhstan and Azerbaijan, which both jumped to second place. The lowest-ranked are also CIS countries; in 2021, the spot is taken by Belarus and Turkmenistan.

A low reliance on domestic inputs in this scenario may point to either a scarcity of natural resources within the country or a preference for importing these resources from abroad. Both factors contribute to reduced use of domestic sectors.

I move on to the *Manufacturing* sector. Post-Socialist countries with low GDP per capita exhibit higher variance in domestic *Manufacturing* sector use. This group includes both the highest and lowest users for both years. Richer countries show lower variance and tend to converge toward a medium level compared to other post-Socialist countries.

CEEU countries have medium, compared to other post-Socialist countries, use of their domestic *Manufacturing* sector. There are a few outliers. Hungary in 1990 had one of the strongest domestic uses of their supply chain among all post-Socialist countries. In 2021, Czechia had a similar level to Hungary.

Figure 3.8: Average Domestic Use of the *Manufacturing* sector, in 1990

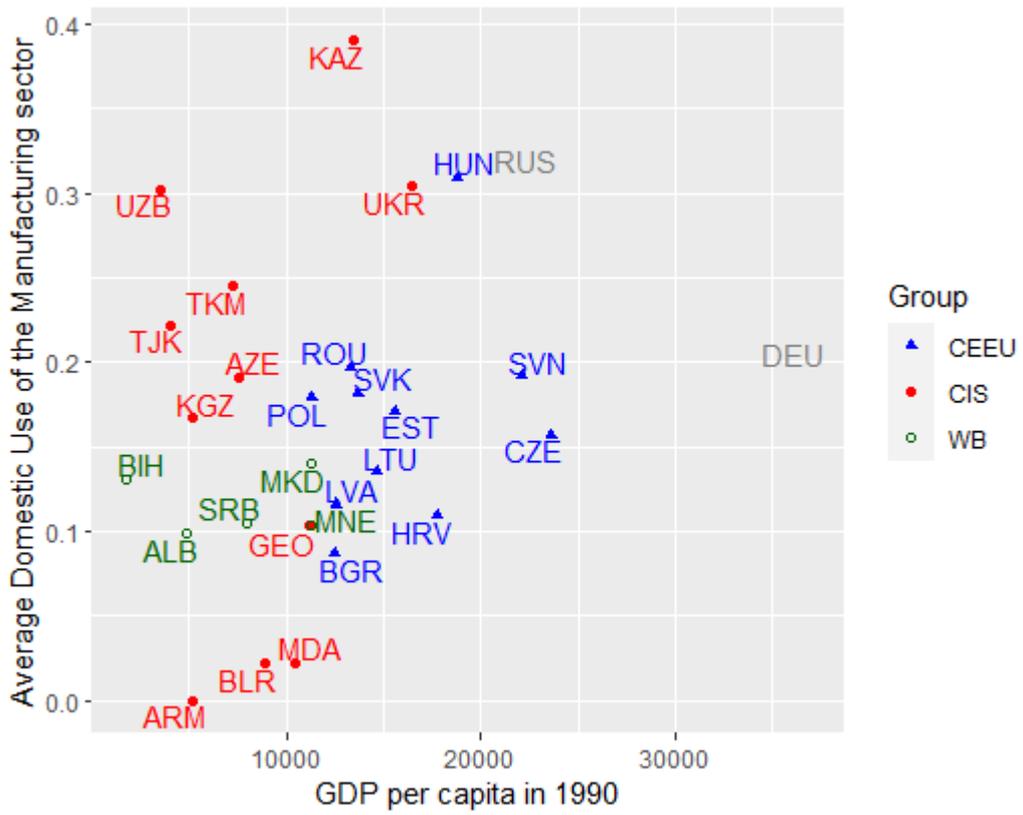
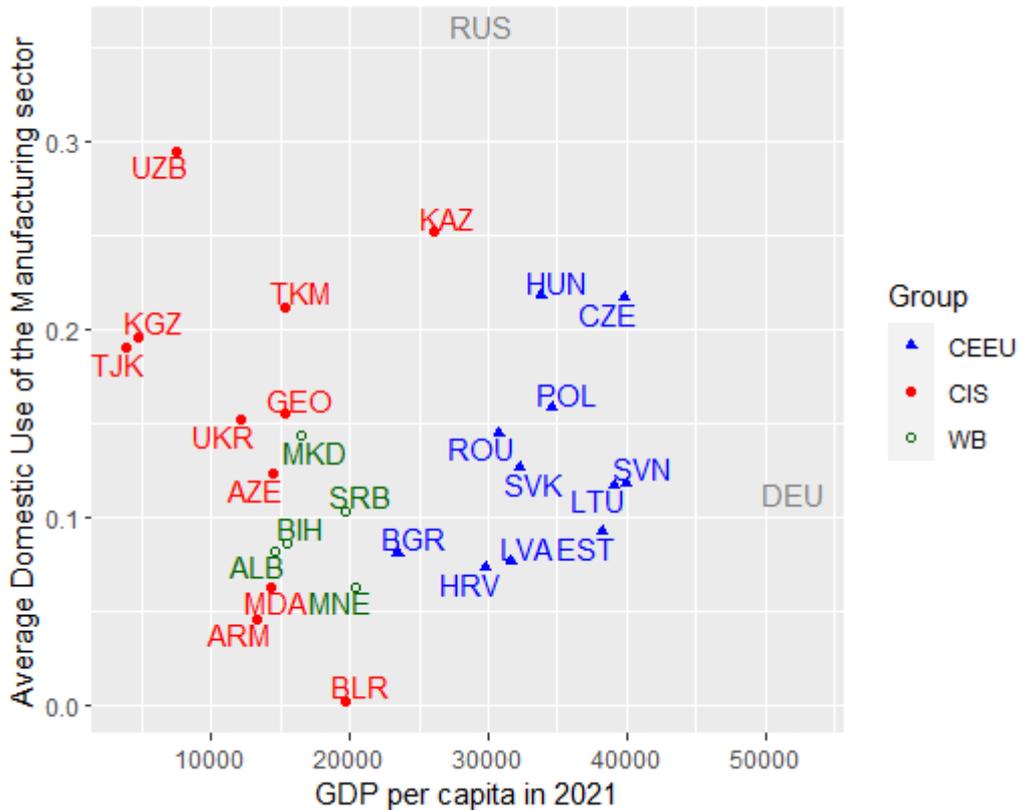


Figure 3.9: Average Domestic Use of the *Manufacturing* sector, in 2021



WB countries have a similar low level of use of their domestic manufacturing sector. On average, the WB use of their domestic *Manufacturing* sector is lower than CEEU countries. CIS countries have the strongest and lowest average domestic use of their domestic *Manufacturing* sectors. In 1990, it included Kazakhstan, which was the highest user in 1990, after Russia. It also includes Uzbekistan and Ukraine, which have average use of the *Manufacturing* sector similar to Hungary and Russia. Armenia, Belarus, and Moldova were the post-Socialist countries with the lowest use of their domestic *Manufacturing* sectors.

The absence of Germany from the top positions may seem unexpected; however, this could be explained by the intricate network linkages in Eastern Europe, which lessen the reliance on domestic sectors alone. This is shown by the strong decrease in average domestic use of the *Manufacturing* sector in Germany.

I conclude by examining the average domestic use of the *Service* sector. The U-shape described by Boehm (2018) does not seem to be evident among post-Socialist countries during this period. This could suggest that post-Socialist countries have reached the point where GDP per capita starts to be positively correlated with higher use of the domestic *Service* sector. There is high diversity in use among countries with low GDP per capita, and a convergence toward high use of the domestic *Service* sector is observed for countries with high GDP per capita.

CEEU and WB, in 1990, tend to have higher average use of their domestic *Service* sectors. In 2021, both groups diverged; the use of the domestic *Service* sector in CEEU countries increased on average, and decreased in WB countries.

CIS countries exhibit high heterogeneity. Most members of this group have low average use of their domestic *Service* sectors compared to other post-Socialist countries. However, Tajikistan, Turkmenistan, and Georgia in 1990 had higher average domestic *Service* sectors than most other post-Socialist countries. In 2021, this group of high users of their domestic *Service* sectors is joined by Azerbaijan.

Lastly, the *Service* sector exhibits a U-shaped relationship with the level of development, as cited in Boehm (2018). The top five users of domestic *Service* inputs include Turkmenistan, Latvia, Georgia, Poland, and Estonia. On the contrary, Ukraine and Belarus recorded the lowest use in this category in 2021.

Figure 3.10: Average Domestic Use of the *Service* sector, in 1990

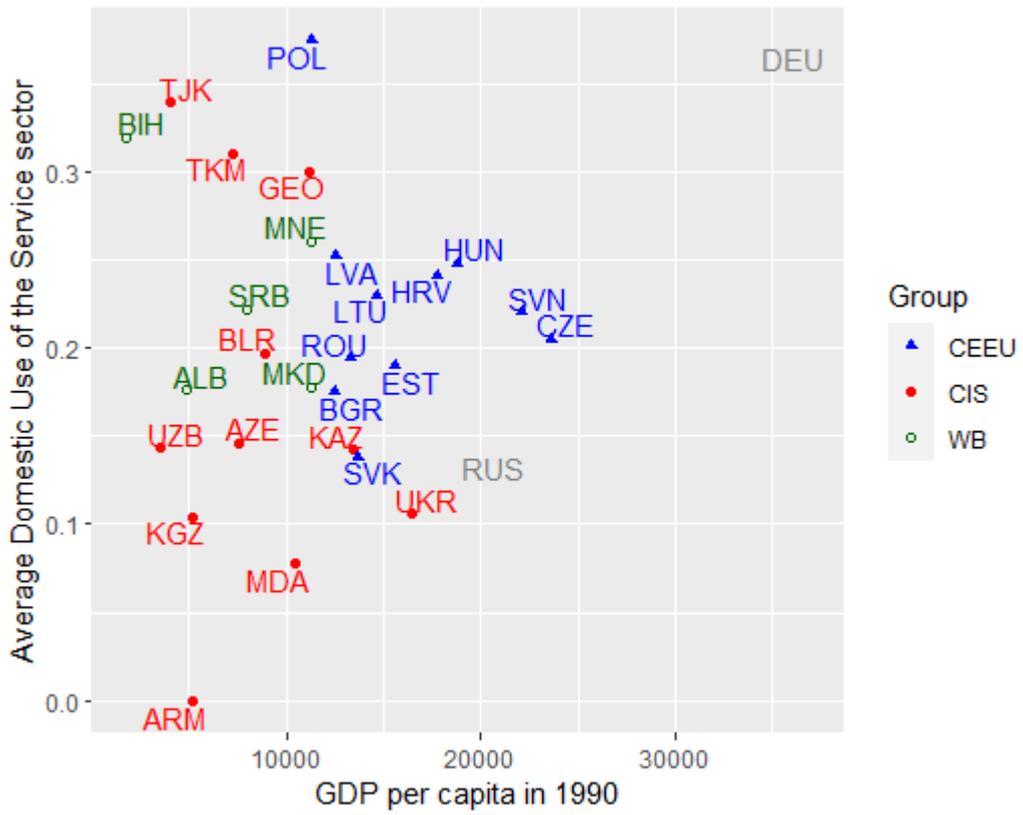
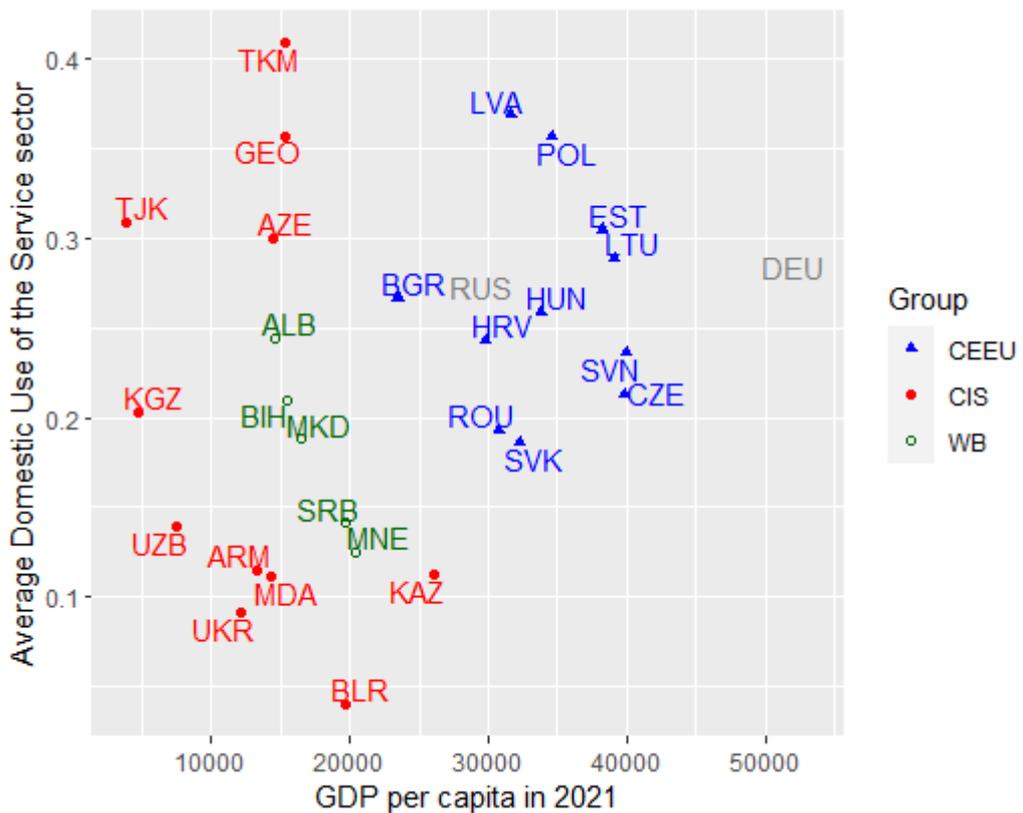


Figure 3.11: Average Domestic Use of the *Service* sector, in 2021



Armenia has undergone a notable transformation, moving from a situation in 1990 where they used few domestic inputs from all its four sectors to a situation in 2021 where they make significant use (more than 10 percent on average) of their own domestic inputs in both the *Agriculture and fishing* and *Service* sectors. Belarus transitioned from moderate input use of its domestic *Agriculture and fishing* and *Manufacturing* sectors in 1990 to the lowest input use of both sectors in 2000, 2010, and 2021.

In every period surveyed, countries in CEEU tend to exhibit more uniformity in the sectors they use. The *Agriculture* and *Mining and quarrying* sectors tend to have higher use in CIS-affiliated countries, even though this group also includes some countries with the lowest overall use. Moreover, CIS-affiliated countries include countries that are highly self-reliant but also other countries that rely more on international supply chains.

Stability of the size of input linkages

I conclude by assessing the extent to which the size of the linkages has changed over time. I apply the Pearson correlation to the list of linkages to determine whether the size of the flow between two industries in a given year correlates with the size of the same flow ten years later. The Pearson correlation index is bounded between -1, indicating negative correlation, and 1, indicating positive correlation.

The list of flows has been subsetted into three types of input linkages: domestic linkages (flows from a domestic selling industry to a domestic buying industry), regional outgoing linkages (flows from a domestic selling industry to a foreign industry located in post-Socialist countries), and regional incoming linkages (flows from a selling foreign industry to a domestic buying industry located in post-Socialist countries). The aim is to measure for each country the amount of change in input linkages that occurred over the 30 years of the post-Socialist period.

Among the three types of linkages, domestic linkages are the most stable. Across all three periods, the average Pearson correlation for domestic linkages is higher than for the other two types of flows, indicating fewer changes in domestic linkages compared to foreign linkages. However, there are some notable exceptions.

Table 3.6: Pearson correlation of Input-Output linkages by flow type

		Domestic flows			Regional outgoing flows			Regional ingoing flows			
Name		90-00	00-10	10-20	90-00	00-10	10-20	90-00	00-10	10-20	Mean
Ref:	DEU	0.94	0.994	0.936	0.945	0.923	0.986	0.88	0.743	0.963	0.923
	RUS	0.651	0.994	0.813	0.924	0.956	0.943	0.749	0.733	0.944	0.856
CEEU countries	BGR	0.92	0.985	0.942	0.983	0.988	0.969	0.928	0.824	0.937	0.942
	HRV	0.942	0.979	0.888	0.9	0.984	0.918	0.933	0.949	0.938	0.937
	CZE	0.997	0.946	0.996	0.977	0.983	0.989	0.908	0.85	0.959	0.956
	EST	0.936	0.986	0.994	0.942	0.988	0.97	0.971	0.957	0.961	0.967
	HUN	0.974	0.989	0.994	0.922	0.949	0.976	0.971	0.942	0.967	0.965
	LVA	0.926	0.973	0.997	0.958	0.982	0.985	0.958	0.938	0.96	0.964
	LTU	0.978	0.98	0.99	0.957	0.986	0.991	0.97	0.973	0.976	0.978
	POL	0.983	0.985	0.998	0.883	0.951	0.946	0.98	0.956	0.981	0.963
	ROU	0.992	0.988	0.981	0.869	0.905	0.957	0.926	0.919	0.948	0.943
	SVK	0.893	0.985	0.996	0.933	0.861	0.967	0.939	0.886	0.962	0.936
	SVN	0.99	0.991	0.995	0.968	0.944	0.955	0.992	0.895	0.99	0.969
CIS countries	ARM	0.367	0.955	0.768	0.537	0.865	0.822	0.104	0.969	0.944	0.703
	AZE	0.751	0.973	0.908	0.766	0.968	0.977	0.886	0.951	0.951	0.903
	BLR	0.403	0.926	0.7	0.423	0.484	0.991	0.812	0.922	0.918	0.731
	GEO	0.966	0.987	0.959	0.644	0.937	0.907	0.909	0.898	0.886	0.899
	KAZ	0.876	0.997	0.97	0.881	0.855	0.964	0.932	0.995	0.911	0.931
	KGZ	0.989	0.987	0.986	0.69	0.832	0.928	0.786	0.922	0.942	0.896
	MDA	0.314	0.868	0.598	0.85	0.6	0.868	0.907	0.264	0.891	0.685
	TJK	0.944	0.995	0.891	0.544	0.596	0.63	0.916	0.909	0.97	0.822
	TKM	0.962	0.94	0.994	0.978	0.93	0.908	0.909	0.697	0.968	0.919
	UKR	0.981	0.974	0.791	0.852	0.864	0.926	0.941	0.959	0.872	0.907
	UZB	0.972	0.97	0.996	0.662	0.941	0.808	0.816	0.891	0.954	0.89
W. Balkan countries	ALB	0.827	0.988	0.924	0.534	0.739	0.561	0.959	0.885	0.965	0.820
	BIH	0.975	0.987	0.855	0.461	0.96	0.864	0.943	0.944	0.933	0.880
	MNE	0.97	0.957	0.783	0.892	0.815	0.886	0.807	0.629	0.8	0.838
	SRB	0.965	0.971	0.91	0.878	0.712	0.683	0.633	0.816	0.616	0.798
	MKD	0.994	0.988	0.993	0.888	0.941	0.904	0.948	0.96	0.934	0.95
	Mean	0.875	0.974	0.915	0.815	0.877	0.902	0.873	0.868	0.929	0.892

Domestic linkages may exhibit greater stability due to their reduced exposure to international market fluctuations, whereas regional linkages may be more susceptible to geopolitical shifts or changes in global demand.

Unsurprisingly, the period that saw the end of the Soviet Union, between 1990 and 2000, experienced the most significant changes. During this time, both domestic and foreign linkages had lower Pearson correlations. The average Pearson value for domestic linkages was 0.875 between 1990 and 2000, which is significantly lower than for the other two periods of domestic linkages.

The countries with the lowest correlation between their domestic linkages in 1990 and in 2000 are CIS-affiliated countries, especially Moldova (0.314), Armenia (0.367), Belarus (0.403), and Russia (0.651). Factors such as the separation of GVCs between multiple countries, the end of governmental contracts, and the cessation of subsidies contributed to changes in domestic Input-Output linkages.

Domestic linkages remained mostly stable between 2000 and 2010, with Moldova having the lowest Pearson correlation at 0.868. In the last decade, the value of the domestic linkages Pearson correlation decreased, with the lowest values occurring in Moldova (0.598), Belarus (0.7), Armenia (0.768), and Ukraine (0.791).

While Moldova, Belarus, and Armenia faced many changes in their domestic linkages throughout the three decades, Ukraine remained mostly stable with a relatively low amount of change for the first two decades before having its Pearson correlation on domestic linkages drop from 0.974 to 0.791 in the last decade. In the case of Ukraine, this change could be attributed to the Russian invasion of Crimea and Donbass, but two other countries, Bosnia and Herzegovina and Montenegro, underwent similar changes without facing similar hardships.

Regarding regional outgoing linkages, 1990-2000 remained the period with the most change, driven mainly by a group of countries. Those with the most significant changes in outgoing linkages during this period include Belarus (0.423), Bosnia (0.461), Albania (0.534), Armenia (0.537), and Azerbaijan (0.544). Over the three decades, the countries with the most changes in outgoing input flow values were Tajikistan (average Pearson correlation of 0.59), followed by Albania (0.611) and Belarus (0.632).

Concerning, Regional ingoing linkages in 1990-2000 the average Pearson correlation in ingoing input flows (0.872) was lower than for domestic linkages (0.875).

Some values stand out, such as Armenia, which saw the most changes in regional ingoing linkages in 1990-2000 with a Pearson correlation of 0.104. Moldova had the second most significant change in value between 2000 and 2011 (0.264).

The countries with the lowest average Pearson correlations were Moldova (0.685), Armenia (0.703), Belarus (0.731), and Serbia (0.798). In contrast, the most stable countries over the entire period were Lithuania (0.978), Slovenia (0.969), Hungary (0.965), Latvia (0.964), Poland (0.963), and North Macedonia (0.95).

3.4.2 Network analysis

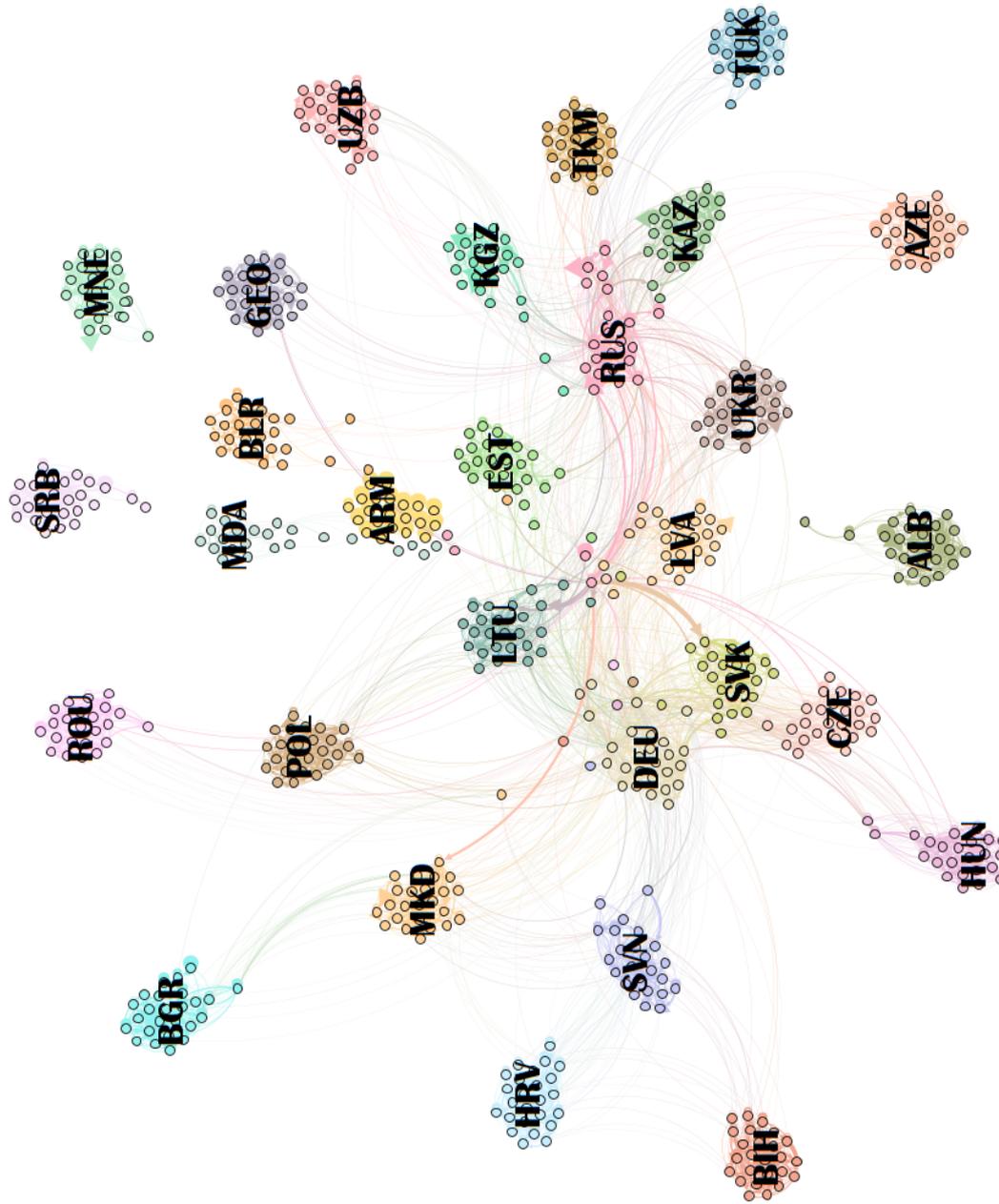
This subsection focuses on the application of network analysis to post-Socialist countries. I introduce the PSPN, a directed network where nodes represent CIs and links indicate the share of input from a producer CI in a buyer CI's total inputs.

The Post-Socialist Production Network

Figures 3.12 and 3.13 illustrate the network modeling for the years 1990 and 2021, respectively. Additional visualizations for the years 2000 and 2010 are available in Figures B.2 and B.3. Due to China's growing significance in the region, supplementary modeling that includes China is also provided for the first and last years in Figures 3.14 and 3.15.

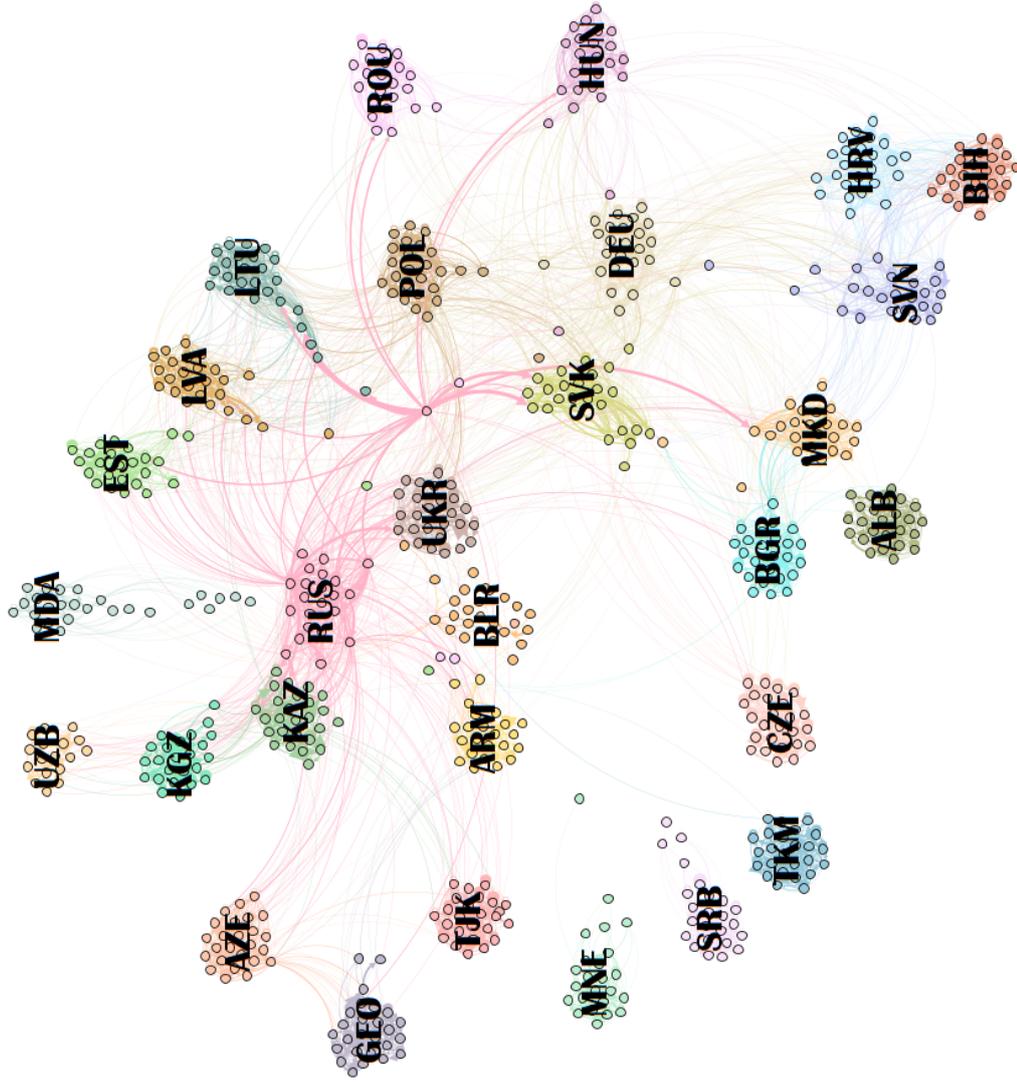
As expected from our previous findings, input flows are more substantial within national boundaries than across them. In the network, this phenomenon appears as clusters of domestic industries. The PSPN that I have identified reveals a hierarchy among countries, with Germany and Russia emerging as central hubs. Specifically, most countries direct their outward linkages toward these hubs. This configuration aligns with the gravity model of trade, which explains that countries tend to trade more extensively with neighboring nations, especially when one or both partners are of significant size.

Figure 3.12: The filtered Post-Socialist Production Network, in 1990



Note: Figures 3.12 and 3.13 represent the network visualization of the filtered Post Socialist Production Network (PSPN). In these figures, nodes symbolize Country Industries (CIs), and links represent IO relationships from the supplier to the buyer. Only the flows that account for at least 1% of input shares are displayed. The nodes are color-coded by country, and the positions of the CIs within the PSPN are determined using the ForceAtlas algorithm.

Figure 3.13: The filtered Post-Socialist Production Network, in 2021



Note: Figures 3.12 and 3.13 represent the network visualization of the filtered Post Socialist Production Network (PSPN). In these figures, nodes symbolize Country Industries (CIs), and links represent IO relationships from the supplier to the buyer. Only the flows that account for at least 1% of input shares are displayed. The nodes are color-coded by country, and the positions of the CIs within the PSPN are determined using the ForceAtlas algorithm.

This hub structure has consequences: On the positive side, it fosters efficiency and specialization. Different CI nodes focus on specific sectors where they hold comparative advantages and rely on the hubs, Russia or Germany, for other inputs. Some CIs serve primarily as suppliers of raw materials or low-value-added manufactured products to the industries in the hubs. In return, these hubs can provide products with higher value-added, for example, in manufacturing.

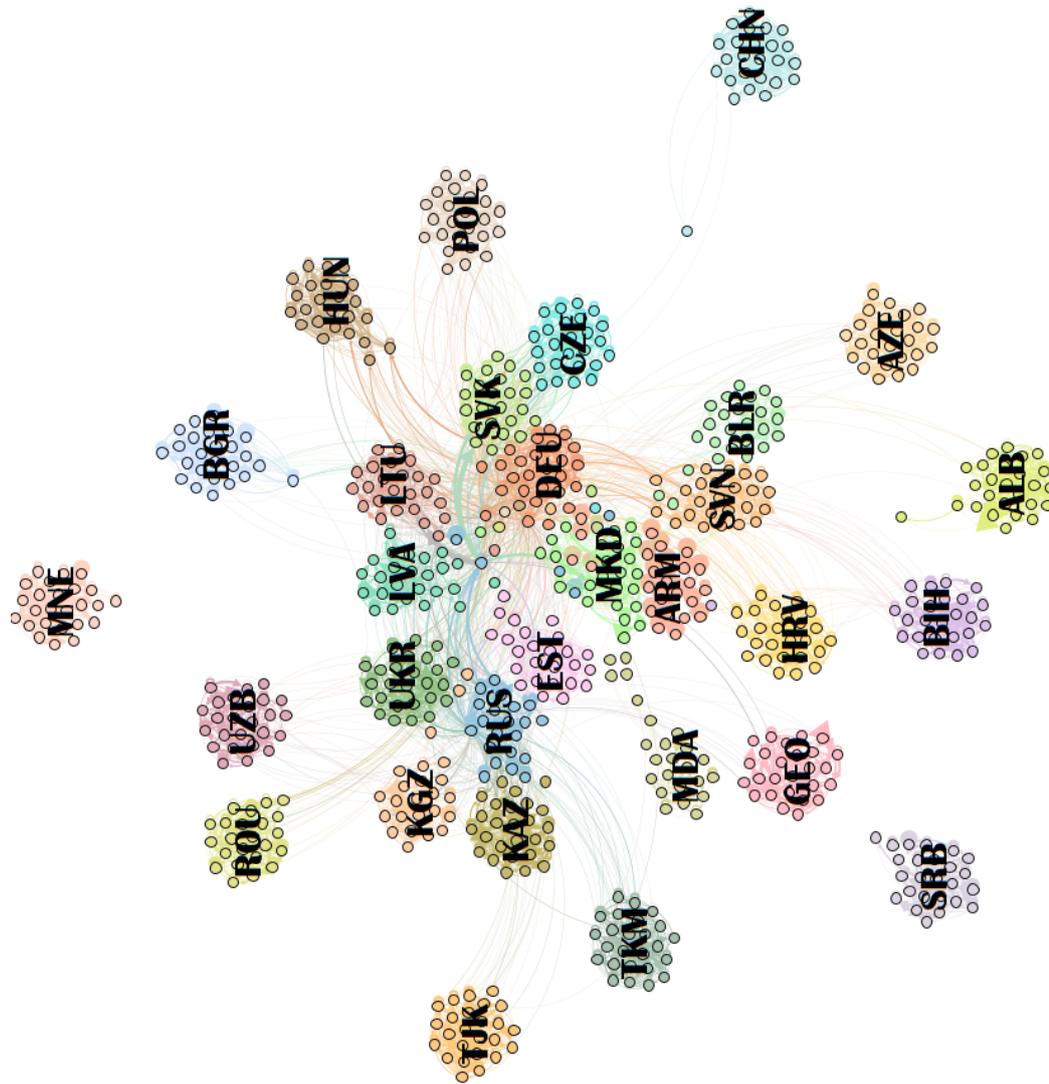
On the flip side, Germany and Russia can exert significant control over the network, influencing the economic activities and policies of other countries in the block. At the same time, the network may be vulnerable to economic shocks affecting Germany and Russia, as disruptions in these hubs could cause ripple effects throughout the network.

A few countries, while adhering to the Hub and Spoke structure, also develop industry linkages with their neighboring countries. Among these countries are the Baltic states, which are part of the CEEU countries, and maintain extensive inter-industry linkages with the two hub countries, Russia and Germany, as well as with each other.

Already in 1990, at the end of the Cold War, Germany had become the hub for the socialist countries that would later join the EU. Similarly, Russia played a central role in the eastern part of the PSPN and continues to do so until 2021, the year preceding the invasion of Ukraine. For example, several linkages have persisted despite the pre-existing conflict in the Donbass region.

For a more comprehensive understanding of regional dynamics, I have included China in the network representations for the years 1990 and 2021, as depicted in Figures 3.14 and 3.15. This inclusion emphasizes the growing influence of Chinese industries, which have evolved from a loosely connected cluster into a prominent hub, particularly linked to Germany and the CEEU countries, including Poland, Romania, and Hungary.

Figure 3.14: The filtered Post-Socialist Production Network, in 1990 (China included)



Note: Figures 3.12 and 3.13 represent the network visualization of the filtered Post Socialist Production Network (PSPN). In these figures, nodes symbolize Country Industries (CIs), and links represent IO relationships from the supplier to the buyer. Only the flows that account for at least 1% of input shares are displayed. The nodes are color-coded by country, and the positions of the CIs within the PSPN are determined using the ForceAtlas algorithm.

Network analysis of the Post-Socialist Production Network

In this section, I describe the general structure of the Post-Socialist Production Network (PSPN) using various network metrics, as detailed in Table 3.7. I present these metrics for the years 1990 and 2021 at three filtering threshold values: 10%, 1%, and 0.1%. As previously stated, the variation in metric values across different filtering thresholds helps to identify the characteristics of each type of flow (small-sized, medium-sized, and large-sized).

The discussion of the network analysis is organized as follows. First, I analyze the results of each indicator for the PSPN, taking into account the different flow sizes by comparing the same metrics across thresholds. Second, I evaluate how each metric stacks up against the corresponding measure for Western Europe and the GPN. Lastly, I examine the differences in network metrics between the post-Socialist sub-regions, specifically focusing on the CEEU and CIS sub-regions.

The network metrics of the PSPN are compared to those of the Western European region. More specifically, I subset the GPN to capture the input linkages between industries in Western Europe, defined as countries that were not communist during the Cold War (micro-states are excluded). This group is composed of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. The resulting network is referred to as the Western European Production Network (WEPN), which serves as a reference point for comparing the metrics of the PSPN. Additionally, the network metrics of the PSPN are compared to those applied to the entire GPN, encompassing the 189 countries and territories in the EORA database.

I begin with Table 3.7, which provides the network metrics for the PSPN, the WEPN, and the GPN. First, I compare the metrics across different filtering threshold values to understand the variations in patterns for linkages corresponding to small, medium, and large input shares. Subsequently, I compare these metrics between regions.

Table 3.7: Network metrics by region

PSPN	1990			2000			2021		
Filter	10%	1%	0.1%	10%	1%	0.1%	10%	1%	0.1%
Link	1312	7809	20689	1310	7971	21807	1186	8024	24892
Avg. out degree	1.74	10.357	27.439	1.737	10.572	28.922	1.573	10.642	33.013
Completeness	0.002	0.014	0.036	0.002	0.014	0.038	0.002	0.014	0.044
Reciprocity	0.049	0.348	0.424	0.06	0.366	0.415	0.06	0.346	0.377
Avg. Cluster. Coeff.	0.372	0.654	0.606	0.448	0.659	0.596	0.344	0.631	0.531
Deg. Assort.	-0.124	-0.022	-0.058	-0.17	-0.028	-0.069	-0.196	0.011	-0.054
WEPN	1990			2000			2021		
Filter	10%	1%	0.1%	10%	1%	0.1%	10%	1%	0.1%
Link	870	5755	19376	818	5828	20698	832	5379	18419
Avg. out degree	1.968	13.02	43.837	1.851	13.186	46.828	1.882	12.17	41.672
Completeness	0.004	0.029	0.099	0.004	0.03	0.106	0.004	0.028	0.094
Reciprocity	0.073	0.341	0.383	0.066	0.329	0.374	0.067	0.331	0.391
Avg. Cluster. Coeff.	0.47	0.582	0.566	0.445	0.567	0.568	0.561	0.597	0.543
Deg. Assort.	-0.251	-0.015	-0.121	-0.218	-0.02	-0.133	-0.258	-0.044	-0.105
GPN	1990			2000			2021		
Filter	10%	1%	0.1%	10%	1%	0.1%	10%	1%	0.1%
Link	9227	58618	259325	9452	58580	259941	8308	60633	308041
Avg. out degree	1.878	11.929	52.773	1.923	11.921	52.898	1.691	12.339	62.686
Completeness	0	0.002	0.011	0	0.002	0.011	0	0.003	0.013
Reciprocity	0.041	0.342	0.244	0.042	0.35	0.252	0.042	0.294	0.207
Avg. Cluster. Coeff.	0.471	0.639	0.51	0.536	0.653	0.517	0.414	0.572	0.458
Deg. Assort.	-0.252	-0.018	-0.174	-0.258	-0.008	-0.16	-0.193	-0.037	-0.173

Note: The Western European Production Network (WEPN) corresponds to the regional Production Network for Western Europe and is composed of Austria, Belgium, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom. This creates a second network based on regional linkages, on which we apply the given network metrics. The Global Production Network (GPN) includes all the countries in the EORA database.

The first metric is the number of links in the network. The number of large input shares, indicated by the 10% filtering threshold value, is stable around 1310

between 1990 and 2000, and decreases afterward, reaching 1186 in 2021. The number of medium input shares, indicated by the difference between the 10% filtering threshold value and the 1% filtering threshold value, is steadily increasing from 6497 in 1990 to 6651 in 2000 and 6838 in 2021. The number of small input shares, indicated by the difference between the 1% filtering threshold value and the 0.1% filtering threshold value, is steadily increasing from 12880 in 1990 to 13836 in 2000 and 16868 in 2021. Most of the input shares in the network are therefore of small size. These results also show that there is an overall reduction in the number of large input shares, which might explain part of the increase in the number of medium input shares. This increase is also explained by the increase in the size of small input shares. These changes could be the result of a shift from a centrally-planned economy to a market-oriented economy.

This increase in the number of input shares is further explored by examining the evolution of the Completeness index. The Completeness index measures the difference between the actual number of links in a network and the theoretical maximum number of links that could exist in that network. It is bounded between 1, where all possible edges exist, and 0, where no links exist in the network. In the PSPN, the Completeness index is close to 0 at all levels of filtering threshold values. This suggests that, after removing all marginal input shares, the PSPN remains a sparse network with low levels of interconnection among the CIs.

The value of the Completeness index remains stable over time for both the large input shares and the medium input shares, as evidenced by the stability in the three decades of the metric for the 10% filtering threshold value and the 1% filtering threshold value. However, the steady increase in the completeness index for the 0.1% filtering threshold value, from 0.036 in 1990 to 0.44 in 2021, indicates a densification of the network for small input shares. In other words, it means that there is an increase in small input shares between CIs that were not connected before.

To confirm this previous finding, I calculate the average clustering coefficient. The clustering coefficient quantifies the likelihood that the neighbors of a node are also connected to each other. In this context, it measures the probability that the trading partners (either buyers or sellers) of a CI are also engaged in trade with each other. The average clustering coefficient is bounded between 0 and 1, where

0 signifies no clustering and 1 signifies complete clustering.

The values of the average clustering coefficient for the 1% filtering threshold value, ranging between 0.631 and 0.654, and for the 0.1% filtering threshold value, ranging between 0.606 and 0.531, are higher than those for the 10% filtering threshold value, which range between 0.372 and 0.448. This suggests that large input shares are less likely to be structured in clusters compared to smaller input shares. Specifically, the probability that a partner of a CI exists within the same cluster, at this 10% filtering threshold value, lies only around 30% to 40%.

For the large input shares at the 10% filtering threshold value, there is an increase in the average clustering coefficient between 1990 and 2000. Knowing that at the same time there was a decrease in the number of large linkages, this implies that the large linkages that remained are with CIs that were already trading. As previously stated, domestic linkages correspond to most of these large input shares. This could mean a reduction in the number of large international input shares. Between 2000 and 2021, however, there is an increase in the average clustering coefficient at the 10% filtering threshold value, indicating a reversal of the previously stated trend. Since the decrease in the number of large input shares also occurs during this period, this implies that the reduction of these large input shares occurred within clusters.

When accounting for both large and medium input shares at the 1% filtering threshold value, the value of the average clustering coefficient remains relatively stable. However, when employing the 0.1% filtering threshold value and including smaller input shares into the linkages, a decrease in the average clustering coefficient is observed. This lends further support to the hypothesis that there is a shift toward more globalized, smaller supply chains at the expense of localized domestic clusters.

The next indicator studied is the average reciprocity, which measures the probability that a link in one direction is matched with a link in the opposite direction. In more economic terms, it corresponds to the probability that a seller to a CI is also a buyer for that CI. This value is bounded between 1, in which every buyer is also a seller, and 0, in which no partnerships are reciprocated. Higher reciprocity suggests more balanced trade relationships between CI, which could be a sign of a more stable economic environment. Having a value close to 0 indicates

a strong hierarchy among CIs. This is precisely the case for the strongest flows, as indicated by the 10% filtering threshold value, where the average reciprocity ranges between 0.04 and 0.06. At the 1% filtering threshold value, or in other words, when medium input linkages are included, the average reciprocity increases to approximately 0.65. This suggests an imbalance in the relationships within the network.

To further investigate this imbalance, assortativity in degree is employed. This metric measures the degree of homophily in the network, or in simpler terms, the tendency of a CI with numerous partners to prefer a CI with a similar number of partners. The values of assortativity in degree at nearly every filtering threshold value are negative, indicating that CIs with a high number of partners prefer CIs with a smaller number of partners (and vice versa). This heterophily is stronger when only the large input linkages are accounted for at the 10% filtering threshold value. This reinforces the previous result that there is a strong hierarchy at this filtering threshold value. This hierarchy is reinforced over time, as shown by the increasing values of assortativity in degree.

When accounting for both large and medium input shares, stability in assortativity in degree is observed between 1990 and 2000. However, the year 2021 displays a positive assortativity in degree that is not observed when accounting for smaller input shares. This indicates that in 2021, medium input shares were more characterized by homophily, while smaller input shares were more characterized by heterophily.

The next step is to compare the metrics of the PSPN with the same metrics in the WEPN and the GPN. The average out-degree in post-Socialist countries is lower than in the WEPN and the GPN. The average out-degree indicates that nodes are less connected in post-Socialist countries compared to their WE counterparts and also less connected compared to the world average. The higher connectiveness in the WEPN is also reflected by the difference in completeness between the WEPN and the PSPN; the WEPN is denser than the PSPN.

For the other metrics, the differences are less clear-cut and are better analyzed by comparing within thresholds for large input shares, medium input shares, and small input shares. Large input shares in the PSPN have a lower average reciprocity compared to the WEPN in 1990. This indicates that the WEPN has

developed more balanced input linkages. However, the average reciprocity in both the PSPN and the WEPN converges over time. Both regions have stronger average reciprocity compared to the GPN. The average clustering coefficient shows that the large input shares in the PSPN are less clustered than in the WEPN and the GPN. The large flows in the post-Socialist region are therefore more clustered than in the two other networks. This difference disappears in 2000; during this year, the average clustering coefficient in the PSPN and the WEPN are similar. And in the last year, the difference between the PSPN and the WEPN reemerges. Finally, based on the average reciprocity, CIs with many linkages in the PSPN are more likely to be connected to CIs with low input sizes. This tendency is lower than in the WEPN and the GPN.

Including medium flows at the 1% filtering threshold value: The average reciprocity of the PSPN remains similar to that of the WEPN for the entire period studied. At this level of threshold, the PSPN is closer to the GPN in terms of clustering. Both are stronger than in the WEPN. This is true for all the years studied. Finally, the assortativity in degree is negative in 1990 and 2000, with heterophily stronger than in the other two networks; however, this trend changes in 2021 and reaches a positive value, indicating homophily in 2021.

Including small flows at the 0.1% filtering threshold value: the Reciprocity and the average clustering coefficient tend to be higher in the PSPN than in the two other regions. However, like in the 1% filtering threshold value, there is a convergence with the WEPN over time. Finally, in terms of assortativity in degree, the PSPN is characterized as heterophilic; however, its heterophily is smaller compared to the two other regions.

Comparing the network metrics for CEEU and CIS countries

I turn our attention to a comparative analysis of indicators between the CEEU and CIS sub-regions. These two sub-regions within the post-Socialist region are notably distinct yet similar in size. The comparison of network metrics between the CEEU and the CIS reveals distinct patterns in the CI interactions. In the CEEU, the number of directed links and the average out-degree both higher compared to the CIS. This higher metric value in the CEEU suggests that CIs in this region have

more interconnected supply chains, possibly indicating a more complex economic network or more robust trade relationships.

Table 3.8: Network metrics by country group

CEEU	1990			2000			2021		
Filter	10%	1%	0.1%	10%	1%	0.1%	10%	1%	0.1%
Link	547	3592	8637	531	3640	9039	508	3593	9578
Avg. out degree	1.753	11.513	27.683	1.702	11.667	28.971	1.628	11.516	30.699
Completeness	0.006	0.037	0.089	0.005	0.037	0.093	0.005	0.037	0.098
Reciprocity	0.066	0.359	0.486	0.058	0.364	0.479	0.067	0.377	0.478
Avg. Cluster. Coeff.	0.319	0.663	0.646	0.355	0.652	0.636	0.328	0.639	0.599
Deg. Assort.	-0.104	-0.065	-0.067	-0.124	-0.074	-0.08	-0.191	-0.02	-0.055
CIS	1990			2000			2021		
Filter	10%	1%	0.1%	10%	1%	0.1%	10%	1%	0.1%
Link	487	2648	6695	509	2756	7266	486	2877	7828
Avg. out degree	1.561	8.487	21.458	1.631	8.833	23.288	1.558	9.221	25.09
Completeness	0.005	0.027	0.069	0.005	0.028	0.075	0.005	0.03	0.08
Reciprocity	0.049	0.321	0.435	0.08	0.352	0.41	0.052	0.327	0.401
Avg. Cluster. Coeff.	0.367	0.655	0.627	0.473	0.67	0.623	0.384	0.643	0.591
Deg. Assort.	-0.085	0.04	-0.055	-0.191	0.009	-0.117	-0.17	0.002	-0.067

Note: In the PSPN, the linkages between members of the CEEU and between members of the CIS have been extracted. This creates two networks based on subregional linkages, on which we apply our network analysis.

The Completeness values for the CEEU and the CIS are higher than those previously observed in the PSPN. Given that Completeness measures the difference between the actual number of links and the theoretical maximum number of links, the observed increase suggests that a substantial number of the “missing” links in the PSPN were between the CEEU and the CIS. This observation reinforces the finding that the majority of linkages within the PSPN tend to occur between neighboring CIs.

I continue the analysis by examining differences between thresholds, aiming to understand the distinct characteristics of large, medium, and small input shares.

At the 10% filtering threshold value, which accounts only for large input shares,

the Completeness values are remarkably similar between the CEEU and CIS sub-regions. This indicates that the networks in both regions have a comparable proportion of actual links to the maximum possible number of links among CI.

The Reciprocity indices of the two regions exhibit a mirrored trend. In 1990, CEEU countries have higher Reciprocity values than those in the CIS, suggesting more balanced reciprocal relationships. This Reciprocity value in the CEEU diminishes between 1990 and 2000 but rebounds from 2000 to 2021. Conversely, Reciprocity in CIS countries increases from 1990 to 2000, even surpassing the CEEU, before experiencing a decline thereafter.

When it comes to the Average Clustering Coefficient, CIS countries outperform their CEEU counterparts, indicating that CIs in this region are more clustered, potentially signaling more integrated or localized production networks.

Lastly, Assortativity in Degree is negative for both regions at this specific filtering threshold. Despite this commonality, the trends differ. In CEEU countries, heterophily gradually increases over time, indicating a growing tendency of CI to connect with dissimilar CIs. Conversely, in CIS countries, the negative Assortativity value doubles between 1990 and 2000, followed by a decrease in negative Assortativity from 2000 to 2021.

At the 1% filtering threshold value, which incorporates medium input shares, the network metrics between CEEU and CIS countries delineate distinct economic behaviors. Firstly, the completeness in CEEU remaining constant at 0.037 suggests economic stability and entrenched trading partnerships within the network. In contrast, the CIS's slow increase in completeness from 0.27 in 1990 to 0.3 in 2021 indicates an ongoing process of economic integration, though still lagging behind the CEEU's robust network connectivity. Secondly, the gradual increase in reciprocity in CEEU, from 0.359 in 1990 to 0.377 in 2021, implies a trend towards more balanced and equitable economic relationships. Conversely, the reciprocity in CIS fluctuates, peaking at 0.357 in 2000 before declining to 0.324 in 2021. This trend implies that there was a tendency toward a more balanced relationship in 2000; however, it did not remain over time.

Regarding the Average Clustering Coefficient, the slight decline in CEEU from 0.663 to 0.636 suggests a modest increase in flows involving CIs outside of established clusters. This could indicate a gradual rise in international input shares of

medium size. In contrast, the CIS follows a trend similar to that of reciprocity. It initially experiences an increase from 0.655 to 0.67, but subsequently drops below CEEU levels. This implies that economic linkages or clusters in the CIS are short-lived and do not sustain over the long term.

Finally, the Assortativity in Degree provides insights into the network structure. Negative values in CEEU indicate heterophily, suggesting a diversified economic portfolio where CIs are more open to engaging with a variety of trading partners. Conversely, the shift towards positive Assortativity in the CIS, particularly when medium-sized flows are included, suggests a growing homophily. This preference for trading within similar economic structures could potentially limit both innovation and economic diversification.

At the 0.1% filtering threshold value, which includes small input shares, several interesting economic trends are observed. Firstly, the completeness levels increase in both CEEU and CIS regions, rising from 0.089 in 1990 to 0.098 in 2021 in CEEU. This increase suggests that the economic network is becoming denser with more small-scale linkages, possibly signifying greater economic diversification.

Secondly, reciprocity levels decline in both regions: CEEU falls from 0.486 in 1990 to 0.478 in 2021, and CIS drops from 0.435 in 1990 to 0.401 in 2021. The sustained higher reciprocity levels in CEEU compared to CIS might indicate more balanced IO relationships within the CEEU network.

In terms of the Average Clustering Coefficient, both regions also experience a decrease in values. For CEEU, the coefficient drops from 0.646 in 1990 to 0.599 in 2021, and for CIS, it declines from 0.627 in 1990 to 0.591 in 2021. These declines could indicate a reduction in local clustering and a potential shift towards more globalized trading patterns, as lower clustering coefficients often signify less tightly-knit economic circles.

Lastly, assortativity in degree remains negative for both regions throughout the three years analyzed. Both regions show an increase between 1990 and 2000 and a decrease between 2000 and 2021.

Community detection analysis of the Post-Socialist Production Network

To gain a deeper understanding of the emerging clusters within the network, I employ a community detection algorithm to identify groups of CIs that exchange more extensively with each other. For this purpose, I apply Newman’s modularity-based clustering method to the PSPN. This method aims to find groups of CIs that are more densely connected with each other than with nodes outside the group. This approach is particularly useful for revealing the underlying community structure in complex networks. Given China’s significant influence in the steppe and Eastern Europe, its inclusion is important for comprehensively capturing the complexities of community interdependencies in this context. Although I tested both the Fast Greedy and Louvain methods, neither detected any apparent or coherent international communities, identifying primarily national clusters instead. The results of this application for the years 1990, 2000, 2010, and 2021 are displayed in Figures 3.16, 3.17, 3.18, and 3.19, respectively.

Figure 3.16: Newman community detection in 1990

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
ALB	1	1	3	1	1	1	1	3	3	3	3	1	1	1	1	1	1	1	3	3	1	3	1	1	1	3
ARM	8	12	7	8	14	8	8	13	8	8	8	7	8	8	8	8	8	8	8	8	8	8	8	8	8	16
AZE	4	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	18
BLR	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	18
BIH	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
BGR	16	16	9	16	9	16	16	16	16	16	16	16	16	16	16	9	9	16	16	16	9	9	16	16	9	16
CHN	6	6	6	6	6	6	6	6	6	6	6	20	6	6	6	6	6	6	6	6	6	6	6	6	6	16
HRV	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	18
CZE	19	19	19	19	27	19	19	19	19	19	19	19	19	19	19	19	19	19	19	3	19	19	19	19	19	19
EST	19	19	19	19	19	19	19	19	19	19	19	18	19	19	19	19	19	19	19	19	19	19	19	19	18	19
GEO	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18
DEU	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	18
HUN	28	28	28	28	28	28	28	28	28	19	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	19
KAZ	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25
KGZ	26	18	26	26	26	26	26	26	26	26	26	26	26	26	26	26	25	26	26	26	26	26	26	26	26	18
LVA	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	18	19
LTU	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	18	19
MNE	22	16	16	15	22	16	22	22	22	16	16	16	22	22	16	22	22	16	22	16	22	15	22	16	22	22
POL	19	19	19	19	19	19	19	3	3	19	19	19	19	19	19	19	19	19	3	3	19	19	19	18	19	19
MDA	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	11	16
ROU	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19
RUS	27	27	27	27	27	27	27	27	27	27	27	18	27	27	27	27	27	27	27	27	27	27	27	27	18	27
SRB	25	25	25	25	25	25	25	25	25	5	25	25	25	25	25	25	25	25	25	19	25	25	25	18	18	25
SVK	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	16
SVN	19	16	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	16
TJK	30	19	30	30	30	30	30	30	30	19	30	19	30	30	19	30	30	30	30	30	30	30	30	30	18	30
MKD	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	21	18
TKM	24	20	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	18
UKR	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	19	20	20	20	20	20	20	20
UZB	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	18

Note: Columns correspond to industries and rows correspond to countries. Each number represents a cluster number. CIs that share the same number are part of the same cluster.

Figure 3.17: Newman community detection, in 2000

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	
ALB	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	6	
ARM	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	6	
AZE	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	18	6	
BLR	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	6	
BIH	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	27	
BGR	4	25	4	23	23	23	9	23	23	23	25	25	23	23	25	23	23	23	23	4	23	23	23	4	4	25	
CHN	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	6	
HRV	12	12	27	12	27	12	27	27	27	27	27	15	12	12	27	27	27	27	27	27	27	27	27	6	27	6	
CZE	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	6	6	27	
EST	20	20	20	20	21	20	20	20	21	20	20	12	20	20	20	20	20	20	20	20	20	20	20	6	20	21	
GEO	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	19	
DEU	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	6	
HUN	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	27	6	27	27	
KAZ	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	6	
KGZ	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	23	6	
LVA	17	17	17	21	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	17	6	17	14	
LTU	14	14	14	14	21	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	6	14	21	
MNE	23	6	6	26	26	23	23	23	23	6	6	6	23	23	6	23	23	6	23	23	23	6	23	6	6	6	
POL	11	11	27	11	27	11	11	27	27	27	11	11	27	11	11	11	27	11	11	11	11	11	27	6	11	27	
MDA	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	6	
ROU	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	16	27	
RUS	22	22	22	22	22	22	22	22	22	22	22	6	22	22	22	22	22	22	22	22	22	22	22	22	6	27	
SRB	5	5	12	5	23	5	5	5	5	23	5	5	5	5	5	5	5	5	5	5	23	5	23	5	6	23	
SVK	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	6	
SVN	12	12	12	7	12	12	27	27	27	27	12	12	12	12	12	12	12	12	12	12	12	12	12	6	12	6	
TJK	29	29	29	27	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	29	6	29	27
MKD	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	24	6	
TKM	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	6	
UKR	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	6	
UZB	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	

Figure 3.18: Newman community detection, in 2010

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
ALB	1	6	1	1	1	1	1	1	6	6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	3
ARM	5	31	31	5	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	31	3
AZE	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
BLR	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	38
BIH	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	38
BGR	3	3	3	3	3	3	28	3	3	3	3	29	28	3	29	3	3	3	3	3	3	3	3	3	3	3
CHN	16	16	16	16	16	16	16	16	16	16	16	21	16	16	16	16	16	16	16	16	16	16	16	16	16	4
HRV	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	15	4
CZE	24	24	24	22	27	24	24	24	26	24	24	24	24	24	24	24	24	24	24	24	24	24	24	4	4	15
EST	37	37	37	37	37	37	37	37	37	37	37	29	37	37	37	37	37	37	37	29	29	37	37	3	37	28
GEO	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41	41
DEU	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	13	38
HUN	26	26	26	26	26	26	26	26	26	24	26	26	26	26	26	26	26	26	26	26	26	26	7	26	26	24
KAZ	30	30	30	30	30	30	34	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30	30
KGZ	34	29	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34	3
LVA	39	39	28	39	39	39	28	39	39	39	39	28	39	39	39	39	39	39	39	23	39	39	39	39	39	28
LTU	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	40	38	40	28
MNE	33	33	33	20	33	33	33	33	33	33	33	33	33	33	33	33	4	33	33	33	20	33	33	33	33	33
POL	10	10	10	10	27	10	28	10	10	10	17	10	10	10	10	10	10	10	10	10	10	10	10	10	10	24
MDA	11	4	11	11	18	11	11	11	11	11	18	4	11	11	4	11	11	11	11	11	11	11	11	3	16	3
ROU	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	25	24
RUS	27	27	27	27	27	27	27	27	27	27	27	16	27	27	27	27	27	27	27	27	27	27	27	27	29	28
SRB	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	28	7	28	28
SVK	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	14	4
SVN	15	4	28	15	15	15	28	15	15	15	15	15	15	15	15	15	15	15	28	15	15	15	15	29	15	29
TJK	12	22	12	12	16	12	26	12	26	24	24	12	12	12	12	12	12	12	12	12	12	12	12	29	26	24
MKD	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	35	3
TKM	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32	32	3
UKR	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
UZB	36	36	36	4	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36	36

Figure 3.19: Newman community detection, in 2021

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	
ALB	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
ARM	1	1	1	1	1	1	1	1	3	3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
AZE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
BLR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
BIH	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
BGR	1	1	1	1	1	4	3	3	3	1	1	1	3	1	1	1	1	3	1	5	7	3	1	1	1	1	
CHN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
HRV	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
CZE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
EST	9	9	9	9	9	9	9	9	9	9	9	9	4	9	9	9	9	9	9	9	9	9	9	9	1	9	4
GEO	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
DEU	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
HUN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
KAZ	11	11	14	11	11	11	11	11	11	3	11	11	11	3	11	11	11	3	11	11	11	11	11	11	11	11	6
KGZ	13	1	13	13	13	13	13	13	13	13	13	13	13	13	10	13	10	13	13	13	13	13	13	13	13	13	1
LVA	8	4	4	8	8	4	4	8	4	4	4	4	4	4	4	4	4	4	4	1	1	4	4	1	4	4	
LTU	8	8	8	8	8	8	8	8	8	8	8	8	4	8	8	8	8	8	8	8	8	8	8	1	8	4	
MNE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
POL	1	1	6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
MDA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
ROU	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
RUS	1	1	1	1	1	1	1	1	1	1	1	1	14	1	1	1	1	1	1	1	1	1	1	1	1	14	
SRB	10	3	4	10	3	3	3	3	4	4	3	3	4	4	4	4	4	4	4	4	4	4	1	4	1	4	
SVK	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
SVN	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
TJK	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	
MKD	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12	1
TKM	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2
UKR	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3	1
UZB	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	10	1

The Newman Clustering Method approach reveals multiple large clusters. In 1990, the largest community was cluster 19, corresponding to industries from CEEU countries, namely Croatia, Czechia, Estonia, Latvia, Lithuania, Poland, Romania, and Slovakia. These Eastern European countries would later join the EU. The existence of this cluster shows the extent to which CEEU countries were already exchanging before the end of the Soviet Union. It shows that those countries were already trading more with each other than with the rest of the network. Notably, the Baltic countries, despite being part of the USSR at that time, Estonia, Latvia, and Lithuania, were also part of this group. This indicates that those countries were less connected in terms of linkages to the rest of the USSR. It also indicates that Baltic countries were already more connected to the other CEEU countries. Most other countries' industries were at that time organized into domestic clusters.

This community was the largest in 1990, but there were other transnational communities, such as cluster 3, composed of Belarusian industries, a third of the Albanian industries, the Polish *Metal products* (8), *Electrical and machinery* (9), *Post and telecommunications* (20), and *Financial intermediation and business ac-*

tivities (21), and the Czech *Transport* (19) industry. Another example is cluster 25 with Serbia and Kazakhstan.

In the year 2000, the large cluster broke down into smaller communities. Most countries were in domestic clusters. The largest cluster was cluster 27, composed of most Croatian, Czech, Hungarian, and Polish industries, along with some Slovenian industries. The industries in Croatia and Slovenia that aren't part of cluster 27 are mostly in cluster 12. Those smaller CEEU clusters organized into groups of neighboring countries show the emergence of new regional value chains. Bulgaria, Kyrgyzstan, and a few industries from Montenegro and Serbia are part of cluster 23. Serbian and Kazakh industries remained in the same cluster.

The year 2010 witnessed the formation of up to 41 clusters, with no large cluster emerging. A few notable exceptions: Ukraine, previously in a single-country cluster, is part of cluster 3 with Bulgaria. Croatia and Slovenia form a separate cluster 15.

In 2021, most industries were within one cluster, cluster 1. This new cluster showcases an increase in the integration in the whole post-Socialist Region. The countries without a majority of industries in cluster 1 were Estonia, Latvia (cluster 4 and cluster 8), Lithuania (cluster 8), Kazakhstan, Kyrgyzstan, Serbia, North Macedonia, Turkmenistan, Ukraine, and Uzbekistan.

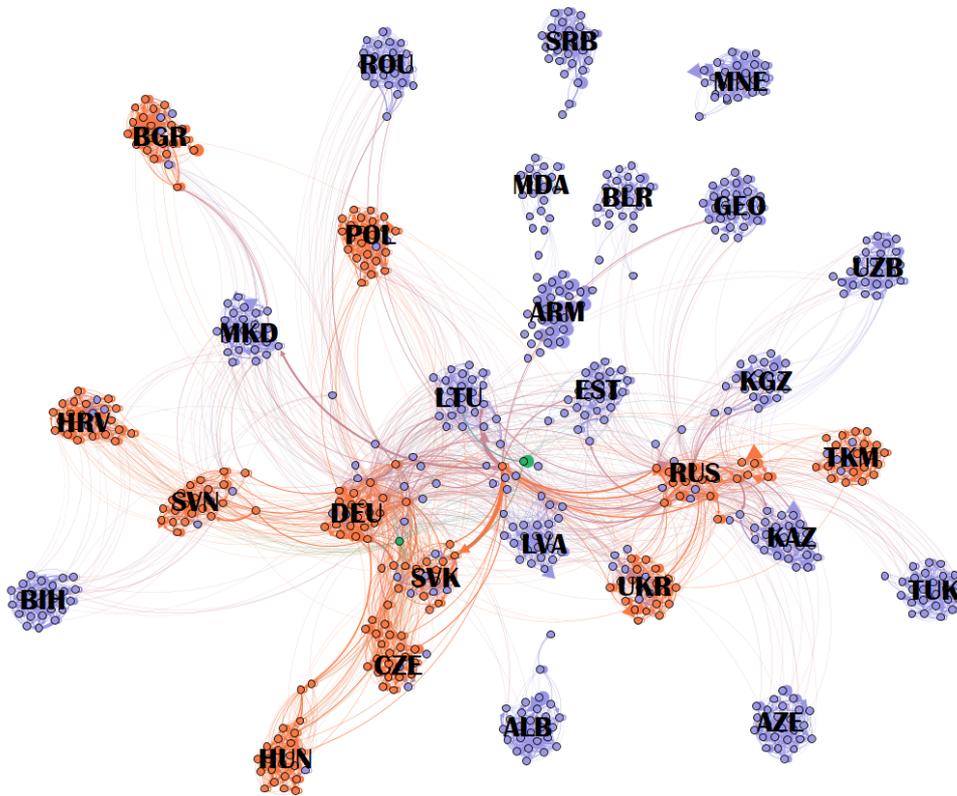
I have observed that CIS countries are more likely to form domestic clusters compared to their CEEU counterparts. This observation reinforces the finding that CEEU countries are more interconnected than CIS countries. The latter appear to be less integrated into regional supply chains. While China, Germany, and Russia serve as hub countries, their industries tend to trade more with each other than with other industries, resulting in their isolation within their own national clusters.

Autocatalytic Sets in the Post-Socialist Production Network

I conclude by adding the perspective of autocatalytic structures into this empirical analysis. I begin by applying the ACS detection algorithm to identify ACS structures within the PSPN. As previously described, ACSs are sets of CIs in which each member has at least one other member within the set serving as a supplier.

The position of an industry in the ACS is important. Cores benefit from

Figure 3.20: Autocatalytic Set in the filtered Post-Socialist Production Network, in 1990 (1%)



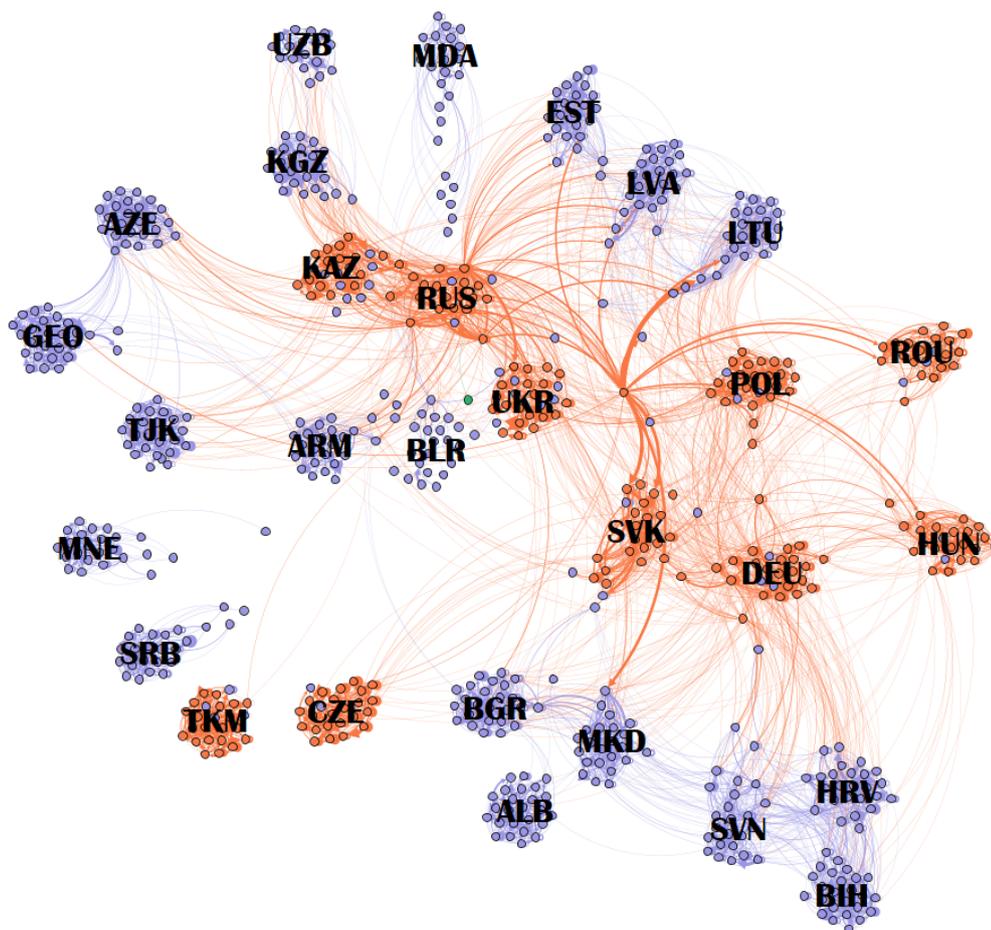
Figures 3.20 and 3.21 overlay the ACS position on the filtered PSPN. Nodes are CIs belonging to a post-Socialist country. Links represent input shares that exceed the 1% filtering threshold value. CIs in orange are Core members, CIs in green are Periphery members, and CIs in purple are non-ACS members. Network visualization is based on the ForceAtlas force-directed algorithm Jacomy et al. (2014).

feedback loops as they function both as customers and suppliers within the core. Additionally, they benefit either directly or indirectly from the growth of other ACS members, as they are direct or indirect customers. On the other hand, Peripheral nodes are direct or indirect customers of core nodes but do not benefit from feedback loops.

Figures 3.20 and 3.21 display the results of applying the ACS detection algorithm to the filtered PSPN for the years 1990 and 2021. Figures for the years 2000 and 2010 can be found in the Appendix (see Figure B).

The algorithm reveals a single large ACS for each year. This global ACS is composed of multiple industries located in various countries. I note that ACS membership varies more among industries from different countries than among industries within the same country. Consequently, there are countries where the majority of industries are part of the ACS, and others where most industries are

Figure 3.21: Autocatalytic Set in the filtered PSPN, in 2021 (1%)



Figures 3.20 and 3.21 overlay the ACS position on the filtered PSPN. Nodes are CIs belonging to a post-Socialist country. Links represent input shares that exceed the 1% filtering threshold value. CIs in orange are Core members, CIs in green are Periphery members, and CIs in purple are non-ACS members. Network visualization is based on the ForceAtlas force-directed algorithm Jacomy et al. (2014).

not included in the set. Another observation is that only a few industries are located in the periphery.

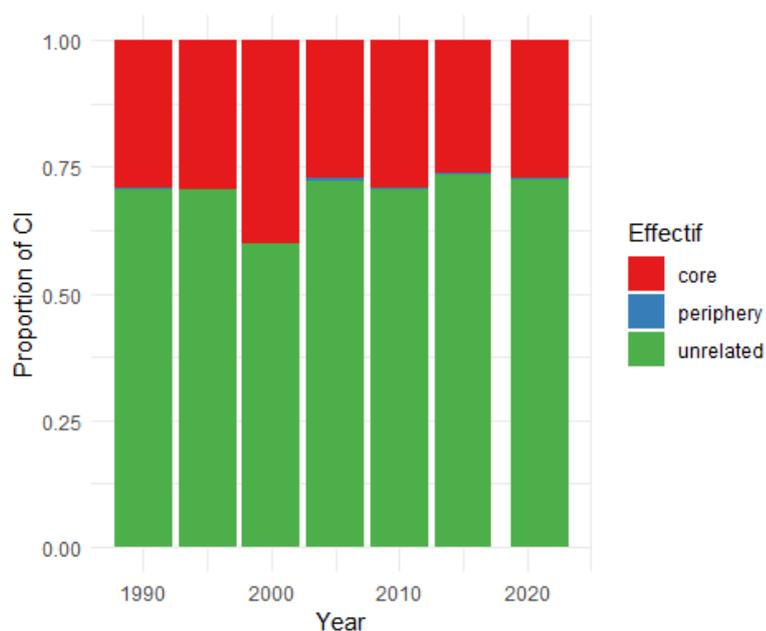
Regarding membership, the ACS includes Bulgaria, Czechia, Croatia, Germany, Hungary, Poland, Russia, Slovakia, Slovenia, Turkmenistan, and Ukraine. This set encompasses both CEEU and CIS countries, and notably incorporates Germany and Russia. In the year 2000, Bosnia and Herzegovina, Kazakhstan, Romania, and Uzbekistan joined the ACS. By 2010, Bulgaria, Croatia, Slovenia, and Uzbekistan had exited the ACS. In 2021, Bosnia and Herzegovina also departed from the ACS. This indicates that some CIs within the ACS have maintained their membership throughout the years studied. These CIs include Germany, Czechia,

Russia, Poland, and Hungary.

I apply the algorithm to the PSPN, which includes Chinese industries, for the years 1990 and 2021. These results are depicted in Figures B.6 and B.7, both of which can be found in the Appendix. The outcomes differ significantly. The primary ACS identified is not in Europe but within the Chinese domestic network, a finding that holds true for both 1990 and 2021.

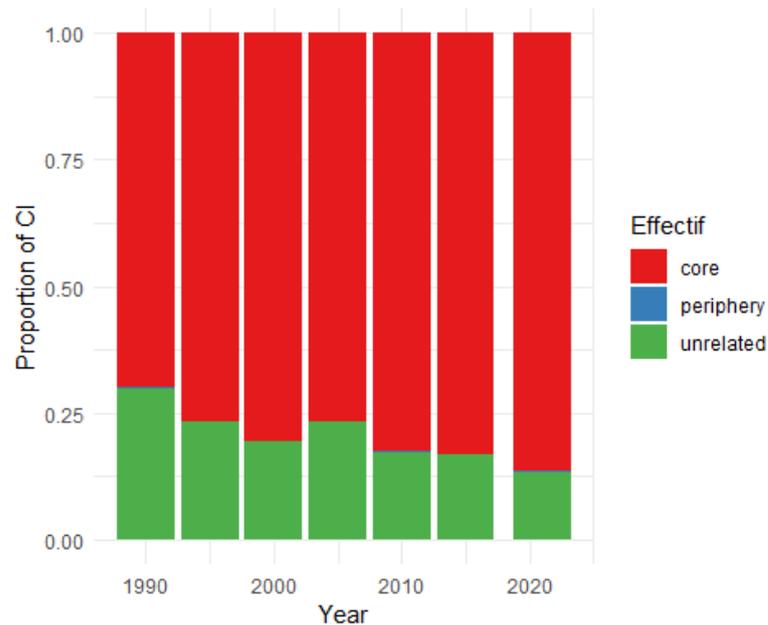
The displayed ACS corresponds to the dominant ACS in the network, representing the ACS with the highest eigenvalue. The first implication is that the multi-country ACS previously displayed in the filtered PSPN is only loosely connected to the Chinese ACS. This indicates a significant separation between the economic activities in China and Europe. The second implication is that the number of feedback loops within the Chinese domestic production network exceeds that within the PSPN. Consequently, Chinese industries are more reliant on their domestic inputs compared to industries in any other post-Socialist countries. The third implication is that, since no European countries are part of the ACS with China, it implies that European industries do not engage in any feedback loop with Chinese industries.

Figure 3.22: Autocatalytic Set Core and Periphery nodes, for a filtering threshold value of 1%



I continue our ACS analysis by examining the evolution of the ACS in the filtered PSPN, excluding China. Figure 3.22 shows the distribution of Core and

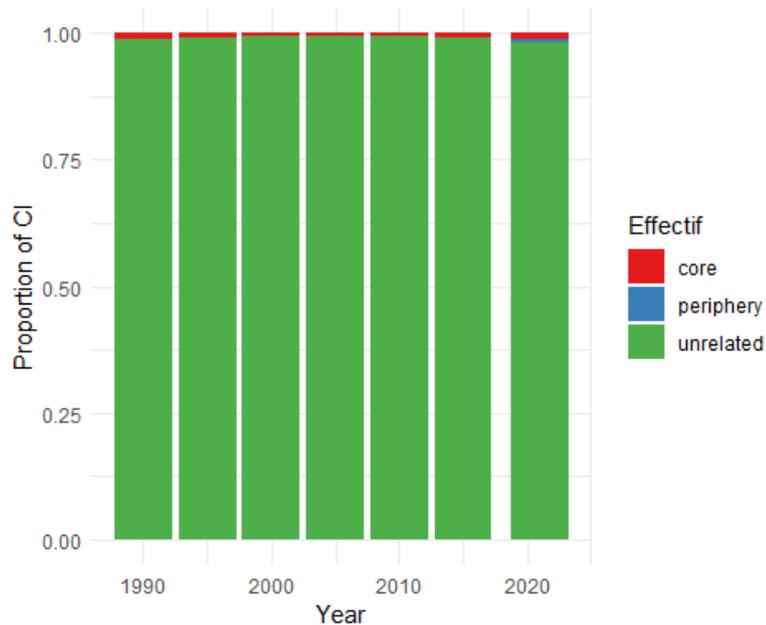
Figure 3.23: Autocatalytic Set Core and Periphery nodes, for a filtering threshold value of 0.1%



Peripheral industries within the ACS detected in the PSPN when filtered with a 1% threshold. Notably, the majority of nodes are not part of the ACS at this threshold. From 1990 to 2021, the size of the Core has remained relatively stable, while the Periphery is almost negligible. Similarly, Figure 3.23 displays the Core-Periphery distribution at the 0.01% filtering threshold. At this level, virtually all nodes are part of the ACS. In this case, the ACS is not only more prominent but also exhibits an increasing size over time; most nodes are part of the Core. Most nodes within the ACS at this threshold are actually part of the Core, and their numbers have been increasing. On the other hand, Figure 3.24 illustrates the distribution at a more exclusive 10% filtering threshold. At this level, most nodes are outside of the ACS, indicating an absence of a Core-Periphery structure.

Table 3.9 and 3.10 describe the distribution of CIs from our three different groups within the ACS detected in the PSPN filtered at the 1% filtering threshold value, respectively, for the years 1990 and 2021. The filtering threshold value of 1% is particularly useful for tracking the evolution of post-Socialist industries within the ACS. In 1990, CEEU industries were predominantly located in the Core, with half of them being Core members and the remainder in the Periphery. In contrast, a large majority of industries from the CIS, 82% to be exact, were not part of the ACS. Industries in the Western Balkans were uniformly excluded from the ACS.

Figure 3.24: Autocatalytic Set Core and Periphery nodes, for a filtering threshold value of 10%



In 2021, a notable shift is observed. The number of industries from CIS countries that belong to the Core of the ACS increased from 54 to 76, meaning that now 24% of CIS industries are part of the ACS. Meanwhile, industries from CEEU countries continue to dominate the Core of the ACS, and the Periphery remains almost negligible in both years.

This temporal evolution is captured in Figure 3.25, which plots the proportion of CEEU and CIS industries in the ACS at five-year intervals from 1990 to 2021. The graph reveals a gradual increase in CIS representation within the ACS from 1990 to 2010, followed by a decline in 2015 and 2021.

Table 3.9: Number of Country-Industries in the Autocatalytic Set by country group, in 1990

1990	Core	Periphery	unrelated	Sum
CEEU	166	1	145	312
CIS	54	1	257	312
WB	0	0	130	130
Sum	220	2	532	754
CEEU	0.532	0.003	0.465	1
CIS	0.173	0.003	0.824	1
WB	0	0	1	1
Sum	0.292	0.003	0.706	1

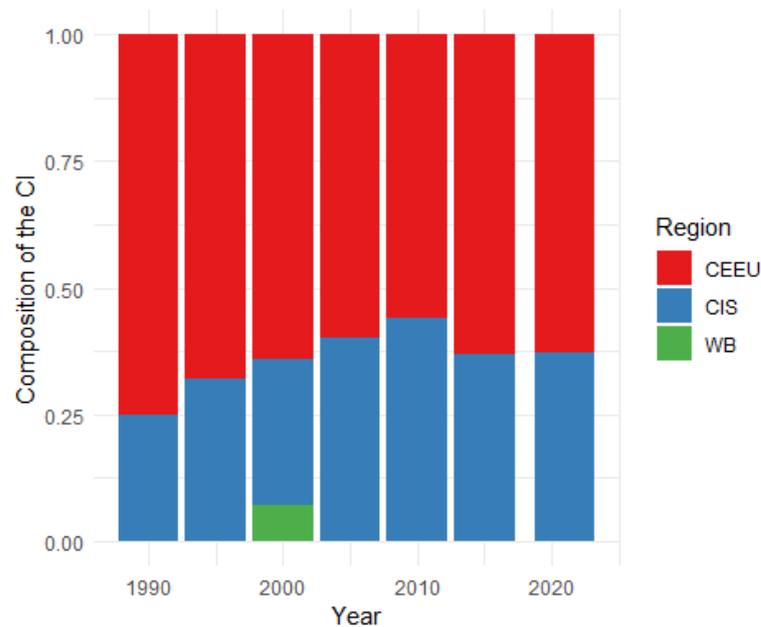
Note:PSPN filtered at the 1 % threshold value

Table 3.10: Number of Country-Industries in the Autocatalytic Set by country group, in 2021

2021	Core	Periphery	unrelated	Sum
CEEU	129	0	183	312
CIS	76	1	235	312
WB	0	0	130	130
Sum	205	1	548	754
CEEU	0.413	0	0.587	1
CIS	0.244	0.003	0.753	1
WB	0	0	1	1
Sum	0.272	0.001	0.727	1

Note:PSPN filtered at the 1 % threshold value

Figure 3.25: Composition of the Autocatalytic Set by country group



3.5 Conclusion

In this chapter, I conducted a comprehensive analysis of transformations in the production network in the post-Socialist region. Using the EORA 26 database, I examined the evolution of input linkages across industries in these countries.

Our research reveals substantial differences between the two primary sub-groups of post-Socialist countries: those that have become members of the EU, known as Central and Eastern European Union (CEEU) countries, and those that are affiliated with the EU's Eurasian counterpart, the Commonwealth of Indepen-

dent States (CIS).

Using Pearson correlation to measure changes in industrial total output and changes in industry linkages, I observed relative stability in linkages in CEEU countries compared to those in CIS countries. Conversely, the less stable nature of linkages in CIS countries could reflect the economic uncertainties and changes these nations have undergone. Structural change was more pronounced in countries affiliated with the CIS, as both the value of their Revealed Industrial Specialization and their linkages experienced significant fluctuations in the initial decade following the dissolution of the Soviet Union, before stabilizing.

While CEEU countries appear to be converging in their characteristics, perhaps influenced by shared economic policies or the stabilizing effect of EU membership for some, CIS countries are diverging. This divergence could be a legacy of the varied economic trajectories these countries have taken post-Soviet Union, each adapting to its own set of local and international pressures. For example, CIS countries display a wide spectrum of development trajectories. On one end, there are nations like Moldova and Belarus, which are heavily dependent on international linkages, particularly with Russia. On the other end, there are countries like Armenia in 1990, and Georgia and Turkmenistan in 2021, that exhibit minimal reliance on foreign inputs. CEEU countries, on the other hand, demonstrate high engagement with their service sector. The diminished reliance on their domestic manufacturing sectors can be attributed to higher participation in Global Value Chains.

Regarding the network structure of linkages, once the weakest links in the PSPN are filtered out, a hub-and-spoke structure emerges. While Germany and Russia have maintained their central roles as hubs, the inclusion of China in the network signals the emergence of a new hub. In the network, China appears to be primarily and increasingly connected to Germany and Eastern Europe. I also observe the development of regional flows between neighboring countries. This latter observation aligns with the results of the community detection algorithms, where industries are predominantly clustered within national boundaries, with the exception of a cluster primarily composed of CEEU industries. In later stages, the majority of the network becomes part of a single cluster.

The ACS detection highlighted two main points. Firstly, a Core-Periphery

structure exists in the PSPN, where the Core is primarily constituted from CEEU industries, Germany, and Russia. Secondly, there is a noticeable absence of a well-defined Periphery structure in the network.

The prominence of CEEU countries in the ACS indicates a higher concentration of economic activity within these nations, which could be both an asset and a liability. On the one hand, this concentration may enable these countries to benefit more substantially from positive network effects, such as increased economic activity in downstream sectors positively impacting upstream sectors. On the other hand, they are also more vulnerable to negative network effects, where a failure in one part of the set could propagate more widely within the network.

Contrastingly, the lesser presence of CIS countries in the ACS suggests a more fragmented and less interdependent economic structure. While this may offer some insulation from systemic risks, it also means these countries might not fully capitalize on the benefits of positive feedback loops within the network. The high variance and heterogeneity observed in CIS countries' input linkages could be reflective of this less cohesive network structure, which may require a different set of policy interventions.

Overall, CEEU countries tend to showcase more robust and efficient production networks, indicative of a more integrated and diversified economic structure. This might reflect the successful economic restructuring and integration into Western markets that these nations have experienced.

In summary, our study provides a multi-faceted view of the evolving production networks in post-Socialist countries. It highlights the successes and challenges these countries face as they navigate their paths in the post-Soviet era. As new economic realities set in, understanding these complex network structures becomes increasingly crucial for policymakers, industry leaders, and researchers alike.

Future research could focus on the implications of these network structures for economic policy and resilience, offering more targeted recommendations for sustainable development of post-Socialist Countries.

To conclude, after 30 years of post-Soviet development, no post-Socialist countries have reached the Western European level of development. CEEU countries are the only ones in the process of catching up. This convergence process has been facilitated by the accumulation of capital, the import of technologies, and the

exchange of know-how through FDI and the importation of capital goods. However, fully converging to Western European levels of income will require a shift from labor-intensive productions to an innovative and technologically advanced economy.

4 Autocatalytic Networks and the Green Economy

4.1 Introduction

The vision of “green growth” has become the dominant policy response to climate change, being supported by international organizations such as OCDE (2011), United Nations (2012) and World Bank (2012). The main idea is to achieve global economic growth with at the same time reaching environmental targets. However, the scientific debate is still open about the compatibility between economic growth and curbing climate change by keeping the global temperature rise below $2^{\circ}C$ as stated in the Paris agreement (UNFCCC, 2015). Part of the literature argue that we can maintain a global economic growth within planetary boundaries (see Capasso et al., 2019, for a summary), while others remain skeptical about the feasibility of this goal (Jackson, 2009; Hickel, 2018; Hickel and Kallis, 2020).

Policy intervention is a key factor in the debate on how to achieve climate goals. Indeed, from a theoretical perspective, environmental and technology externalities should be addressed by adequate public policies (Jaffe et al., 2005; Fischer and Newell, 2008; Popp et al., 2009; Acemoglu et al., 2012). Besides allowing faster transition and preventing environmental disasters, Green Industrial Policies (GIP) are gaining popularity as they support national competitiveness and job creation (Fankhauser et al., 2013; Rodrik, 2014). Furthermore, the notion of “green growth” sheds new light on aspects of structural change (see Savona and Ciarli, 2019, for a review) that affects greenhouse gas emissions.

This chapter is based on a paper co-authored with Alexandre Ruiz.

Those GIP relies on the use of the so-called green goods. Green goods are products or technologies that contribute to environmental sustainability through one or more of the following ways: reducing pollution, promoting resource efficiency, supporting environmental monitoring and protection, enhancing energy management, finally also facilitating sustainable end use or disposal.

Our chapter adds to this line of research by investigating the interdependencies between green and non-green industries. By using a Product Space modeling, we will model four distinct cases that underpin the interdependence between both types of industries. The first case pertains to the potential for polluting sectors to appear as a result of gaining production capabilities in a green sector. The second case involves a situation in which gaining production capabilities in a non-green sector augments the probability of a green sector's emergence. The third case delves into instances where at least two sectors, one green and one non-green are mutually reinforcing each other, leading to the development of positive feedback loops that mutually benefit both sectors. Finally, the fourth case examines situations where feedback loops occurs within green sectors or within non-green sectors.

These dynamic interactions shape the economic and environmental landscape, and their understanding is crucial for policy making and industrial strategy. A crucial issue that has been overlooked by the literature is that green products are seldom completely green, as green industries are not isolated but are instead embedded in a value chain together with several other industries of more or less environmental impact. Our paper addresses this point by investigating the interdependencies between green and non-green industries.

Green goods are mostly supplied by industrialized countries. If developing countries want to ride the wave of green growth, they need to foster their own production capabilities. Such production bolsters environmental protection and resilience against climate change, a concern that is increasingly significant for many low and middle-income nations. This is even more true since some of those low and middle-income nations have limited access to international resources and supply chains. Moreover, engaging in the production of green goods often necessitates the adoption and mastery of advanced technologies. This encourages local innovation and technical skill development and catalyzes the transfer of technology

from high-income to lower-income countries, thus promoting broader economic and social development. Finally, producing green goods domestically reduces import dependence, improving trade balance and economic resilience.

A burgeoning literature has developed within the GIP literature that aims to uncover empirical stylized facts on industrial capabilities (i.e. inputs, technologies and tacit knowledge needed to produce a specific good), competitiveness, and environmental performance. Based on the economic complexity framework Hidalgo et al. (2007), and Hidalgo and Hausmann (2009), this literature uses a country's export portfolio to extract several insights on a country's production capabilities. Some of those insights include (i) level of sophistication of the good exported by the country, (ii) level of sophistication of a country's production system and (iii) diversification prospect at the product level.

Applied to green industrial development, this framework shows that GIP are more effective if the country has the right capabilities (Huberty and Zachmann, 2011). Barbieri et al. (2023) show that new green technologies are often the recombination of existing technologies, including non-green ones. Recently, Fraccascia et al. (2018), Lapatinas et al. (2019), Mealy and Teytelboym (2020) and Romero and Gramkow (2021) have provided strong evidence that economic sophistication contributes to high capabilities in environmentally friendly production, or green goods, and reduces greenhouse gas emissions.

The contribution of this chapter is twofold. First, following methods introduced by Napolitano et al. (2018) we create a Directed Product Space providing a dynamic and empirical overview of the positive externalities between each product produced by a given country. There is a positive externality between two goods when the production of one good significantly increases the probability to start producing the other good years later. Our results suggest that green goods are, on average, less likely to create production capabilities in other goods compared to non-green goods over time. Second, following Jain and Krishna (2002a), we classify goods according to their importance in the Product Space by using a network approach based on the key concept of autocatalytic set, which aims to capture and classify how products benefit and contribute to each other. More precisely we divide the Product Space into the Core, where there is a strong self-reinforcing cyclical catalytic structure, the Periphery, which is a set of products catalyzed

by the Core but that doesn't catalyze it back, and the rest of the network. On the basis of this classification, we show that the structure of the autocatalytic set (ACS) is relatively stable over time, allowing the identification of patterns in the reinforcement between green goods and other non-green and green products. Based on those two contributions we derive some key industrial policies.

The rest of the chapter is organized as follows: Section 4.2 presents our literature background. Section 4.3 describes the methodological framework and the data. In section 4.4 we discuss the results. Section 4.5 concludes.

4.2 Literature background: Theory and empirics

A greener economy relies on specific technologies, some of which are embedded into green goods. Green goods are defined as products essential for sustainable development. Understanding how to foster the emergence of the industries necessary to produce those green goods is therefore important. In this chapter, we aim to uncover the underlying mechanisms that constrain the ability of some countries to gain production capabilities in environmental products. We also investigate if those mechanisms can explain situations in which investing in green industries can lead to the emergence of more polluting industries. To answer this question we rely on the theoretical framework from Hausmann's Capability Theory. This framework emphasizes that a country's economic growth and diversification process is driven by its existing capabilities (see Hausmann et al., 2013). To produce a given good a country requires the combination of a specific set of capabilities. Capabilities in this context are non-tradable inputs necessary for the production process. Those capabilities include infrastructure (cargo airports, container port, railroads, pipelines, or high-speed internet), resources (oil reserve or arable lands), institutions (laws, property rights, or education), or collective knowledge (see Ortiz-Ospina and Beltekian, 2018).

Countries have different sets of capabilities. Some countries have a large set of capabilities and are therefore able to create many combinations of capabilities including some sophisticated products that require a large set of capabilities. Some other countries have a small set of capabilities and cannot produce the most complex goods. Following this approach, we make the assumption that a country

only make the products for which it has all the required capabilities. To start the production of environmental goods, a country must therefore acquire the required capabilities. Capability accumulation is a necessary step toward economic development and green industrial development. Decision makers must, however, be aware that on the path to the acquisition of the capabilities for environmental goods, it may also acquire the capabilities for polluting industries. Indeed, acquiring those capabilities could reduce the cost for the establishment of polluting industries and increase the likelihood of their emergence. Reciprocally, the capabilities used to produce sophisticated green goods might be found in less sophisticated industries. A country might need to acquire production capabilities in those simpler productions first to gain the capabilities of the more sophisticated products later.

This theory suggests that countries should leverage their existing strengths and capabilities to create environmentally friendly products. For example, if a country has a strong manufacturing sector with expertise in producing a large set of turbines, it could build upon that capability to develop a manufacturing industry in wind turbines. Similarly, if a country has a skilled workforce in a specific sector such as the textile industry, it could use that expertise to develop greener alternatives.

The aim of this chapter is to model these interconnections between green and non-green goods. Introduced in Hausmann and Klinger (2006), “product relatedness” models the interrelation between products based on their probability of co-occurrence in a country’s export basket. Formally, goods a and b are related if both products are likely to be exported together. The Hausmann’s Product Space is explained in detail in the Section C.2.1 of the Appendix. Thus, exporting a is expected to increase the probability of exporting b and vice versa. The “Product Space” is the network modeling of this list of pairwise interrelations (see Hausmann and Klinger, 2006; Hidalgo and Hausmann, 2009). The Product Space is defined as a network model in which nodes are products and links are their relatedness. Their main contribution to this literature has been to model product relatedness in order to understand economic development. Hausmann and Klinger (2006) contributes to the more general industry relatedness literature (see Teece et al., 1994) by introducing the question of economic development and regional

product diversification.

To have an accurate measure of what a country produces, we follow the literature by relying on export data as a proxy. They have several advantages (i) they cover most countries, (ii) they provide a reliable and extensive list of goods produced and (iii) these databases are produced over a large time span. This broad coverage is useful to measure production capabilities for most countries and territories, including those that doesn't have reliable production statistics. More specifically, in the context of product and industry literature space, the use of trade data is a trade-off between data availability and data coverage. The use of export data consists of observing only a small subset of global economic activity which are the goods exported by a small group of competitive firms. However, the wide coverage, the standardization and the high level of disaggregation make it one of the best proxies to study industrial development, especially since it includes extensive information on low-income countries that may not have reliable production statistics.

Hausmann and Klinger (2006) contribution was to model those relatedness relationships into a network called the Product Space. In this network, nodes are products and links are the probability of two products to be co-exported.¹

In Hausmann's Product Space, there isn't an explicit explanation of how goods relate to each other. Moreover, links measure proximity between one good to the other as a proxy for shared capabilities. However, this model doesn't offer a way to determine if the existence of a particular product increases the likelihood of another product's presence. Such relationship should exist. According to Hausmann Capability Theory a good is produced when a country has all the required capabilities. Products differ in they required capabilities and therefore some good require more capabilities than others. The more capabilities a product requires, the more sophisticated it is. Therefore some good can be the recombination of capabilities used in other products. In consequence, if a product a requires the capabilities (A, C, D) and the product b requires the capabilities (A, B, C, D) . A

¹The authors rely on the uncomtrade database (Feenstra et al., 2005) in order to model the evolution of the Product Space from 1962 to 2000 at Standard International Trade Classification (Revision 4) at the 4-digit level. The proximity between good a and b is the minimum between the number of co-exportation of good a and b normalized by the ubiquity of good a (the number of countries that export the good a (with a RCA > 1)) and the number coexportation of good a and b normalized by the ubiquity of good b .

country that produces b is likely already producing the product a as it has all the required capabilities. If it is not the case, the country can easily start producing a in the short term. On the other hand, building the capabilities of the good a can be useful in order to reach the product b . For policy-makers, having this information on the hierarchy among products is crucial in order to devise efficient diversification policies.

Several attempts have been made to establish relationships between economic activities, both at the industry and product level.² “The earliest Directed Product Space, constructed using export data, is the “taxonomy matrix”, as proposed by Zaccaria et al. (2014). This network operates on the principle that the production of certain goods is prerequisite for the production of others. To do so the authors calculate the increase in the statistical probability that a good a will be produced based on the presence of good b . The resulting matrix is the taxonomy matrix. Additionally, to the taxonomy matrix, Zaccaria et al. (2014) introduce another matrix. The assist matrix which quantifies the number of times the production of a good b in time t leads to the emergence of good a in time $t + \delta$ ³ While the taxonomy matrix is estimated at a single year of trade data, the assist matrix is estimated by comparing multiple periods.

A similar approach to the assist matrix was made by Quan et al. (2017). In their article, the authors have created a directed network for which the links are the conditional probability of exporting good a given that a country exports good b in t years. In this paper they also estimate separately the probability of going from a to b and from b to a .

Another important contribution is from the work of Pugliese et al. (2019), who scrutinized the diversification process within the technology network by creating a directed space using a one-step process. More specifically, they build a network of patents. In their paper for every couple of patent classes, they counted the number of times a patent class a has become active in a region r that is already active, for some time, in the patent class b . This sum is normalized by the ubiquity⁴ level

²For an earlier instance of this attempt see: Teece et al. (1994) and Neffke and Henning (2013)

³ δ is a time difference to allow the creation of new production capabilities and therefore the exportation of new goods.

⁴The number of regions active in patent class a

of the patent class and the level of diversification⁵ a . δ corresponds to the time lag. One of its other contributions is to assess a link significance by comparing the probability of a link to exist compared to multiple random network (null network) of similar parameters (patent class ubiquity and regional diversification). The multiple random networks are generated from a null model based on the bipartite configuration model from Saracco et al. (2015). This creates a robust directed space that can help better understand the real interdependence between technologies. More specifically, instead of tacking the strongest links, which is commonly done in the literature, it will detect links that are less strong but statistically significant.

Further enriching this body of literature, Napolitano et al. (2018) delved into the autocatalytic structure of the technology network by investigating the dynamics of Autocatalytic Sets (ACS) over time. The ACS is a subset of nodes within the directed network such that each node receive at least one catalytic link from other members of the set. The ACS framework introduced by Jain and Krishna (1998) and formalized in Jain and Krishna (2002a) describes the process of emergence of evolving complex network structures in ecosystem networks. The author discerned varying dynamics within the catalytic network, noting that the Core of the ACS demonstrated a higher growth over nodes at the Periphery or outside the set. The authors also noted the expanding nature of the ACS over time, suggesting that research intensity in the ACS can influence the distribution of links and increase the probability of the emergence of a new link towards a previously unrelated node. A similar process was detected in the patent network in Napolitano et al. (2018). They found that patent class in the Core and have a higher growth. They also found an increasing reliance from the nodes in the Periphery and outside of the set on Core technologies, namely Computer science.

Closer to our interest, Cunzo et al. (2022) use an approach similar in spirit to the directed patent spaces from Napolitano et al. (2018) and Pugliese et al. (2019) to investigate the empirical relationship between green technologies and industrial production. The study uses patent data as a proxy for green innovation and export data as a proxy for industrial production. A bipartite directed network is constructed to track the influence of green technological development on industrial production, based on time-lagged co-exportation of green technologies and prod-

⁵the number of patent classes active in the region r

ucts in countries' industrial and technological specialization profiles. The network links are then refined using a maximum entropy null model. The study finds a strong connection between green technologies and the export of products associated with the processing of raw materials, crucial for climate change mitigation and adaptation technologies. The results also suggest increasing importance of more complex green technologies and high-tech products in the network over time, indicating the growing significance of these elements in green economic growth. This work contributes to our understanding of how green technology innovation is integrated into industrial production and evolves over time.

We also link this literature to another body of literature which is the green complexity literature, introduced in Hamwey et al. (2013). This contribution proposes a green Product Space methodology to identify export strengths of countries in green markets. This model identifies green products for which a country is likely to be globally competitive based on the performance of related products. This method, illustrated with the Brazil's study case, provides a fundamental tool to support "green growth" and sustainable development.

The goal of this literature is to use the economic complexity approach in order to understand the process of path dependency in a country specialization and its effect on green good adoption (see Talebzadehhosseini et al., 2019; Talebzadehhosseini and Garibay, 2021). It also helps to tailor green economic policies by knowing which green industries are easier to be started (see Fraccascia et al., 2018; Barbieri et al., 2022; Alhaddad et al., 2023; Müller and Eichhammer, 2023). Ferraz et al. (2021) provides a broader review of the literature, identifying research gaps in integrating environmental and social sustainability considerations in economic diversification and complexity studies. The authors call for more intersections between economic complexity research, "green growth" policy research, and studies on diversification in less developed regions. In this literature, our main contribution will be to study the positive feedback loops between green and non-green economic activities through the process of industrialization.

4.3 Data and method

4.3.1 Data

In our analysis, export data are used to construct a proxy of countries' production capabilities, a method widely followed in the literature, as explained in the previous section. The database is extracted from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII). The Base pour l'Analyse du Commerce International (BACI) Dataset, referenced by Gaulier et al. (2008), is a comprehensive data set focused on international trade. It encompasses an extensive catalog of over 5000 products, each denoted with a unique 6-digit identifier. This data set meticulously logs the annual aggregated value⁶ of product flow from one country to another, thus providing a comprehensive overview of international trade patterns. Moreover, it also includes detailed information about both the country of origin and the destination for all bilateral transactions, thereby covering a global spectrum of approximately 200 countries.

Another advantage of this database is its reliance on the Harmonized System. The Harmonized System or HS is a standardized product nomenclature used by custom authorities. Administered by the World Custom Organization, they provide a list of traded goods. This list is updated regularly. Exporter's report and importer's report of the same flow are linked and the reliability of each reporter is assessed. Based on this assessment, an accurate estimation of countries export value has been computed by the CEPII. We use the version of the database that relies on the HS 92 nomenclature which covers every year between 1995 and 2021.

4.3.2 Green goods classification

Classifying green goods is a complex task. There isn't any international consensus on which goods are considered as environmental. To create such list many studies have been conducted by working groups of the Organisation for Economic Co-operation and Development (Sauvage, 2014, OECD) as well as by works during negotiations for trade and tariff purposes by the World Trade Organization (WTO, 2011) and the Asia-Pacific Economic Cooperation (APEC, 2012) to create

⁶The value is estimated at current USD.

such a list. In this chapter we use the Combined List of Environmental Goods (CLEG) used by the OECD introduced in Sauvage (2014). This list has been chosen for multiple reason: It is independent from trade negotiations and their mercantilist influences (see Balineau and De Melo, 2013; de Melo and Solleder, 2017). Negotiated environmental product lists, such as the WTO list, exclude some goods that have a clear environmental content and include other goods on which the environmental aspect can be debated. The CLEG contains 248 environmental goods at the 6-digit level following the HS 07 nomenclature and can be divided further according to their environmental aspect. The CLEG list goes through several checks to ensure its environmental content including insights from Environmental Business International Inc. (EBI)⁷ and from the OECD.

The CLEG list's main downside is the multiple end-use of some of its goods. Those goods can therefore also be used for non-environmental purposes.⁸ The categories of environmental goods in the CLEG database are the following ones:

- Air pollution control
- Cleaner or more resource-efficient technologies and products
- Environmentally preferable products based on end use or disposal characteristics
- Heat and energy management
- Environmental monitoring, analysis and assessment equipment
- Natural resources protection
- Noise and vibration abatement
- Renewable energy plant
- Management of solid and hazardous waste and recycling systems
- Clean up or remediation of soil and water
- Waste water management and potable water treatment

Using publicly available correspondence tables⁹, we transformed the data from

⁷Environmental Business International Inc. (EBI) is a publishing and research company that generates strategic market intelligence on emerging opportunities in the Environmental Industry and the Climate Change Industry (Environmental Business International inc., 2023)

⁸Green goods can be classed in two categories. Goods for Environmental Management (GEM) defined as products (and services) that reduce environmental risk and minimize pollution and resource use. Those goods are generally considered as multiple end use. Which includes pollution management and resource management. Environmentally Preferable Products (EPPs) which are products that produce fewer environmental damages either in production, use, or disposal. Those goods are generally considered as single end use.

⁹Those correspondence tables between HS 2007 to HS 1992 can be found on:

HS 2007 to HS 1992 to ensure compatibility with the trade data. It is worth noting that no goods were omitted from the original classification, but a total of 24 goods had changes in their assigned HS codes.

4.3.3 Building the Directed Product Space

We construct a directed network of products by taking inspiration from the method used by Napolitano et al. (2018) in their study of a directed network of technological fields. In our framework, the nodes of the network are the products, and the network edges are ‘catalyzing’ relationships: a product is connected to one another if the presence of the first product in a country’s export basket at the time t increases the probability of the emergence of the second good in the same country’s export basket at the time $t + \delta$.

An implicit assumption is made using trade data: a good is exported only if that country masters the production capabilities of that good. However, in order to filter out the countries that export only a marginal quantity of a good, and therefore, avoiding a situation in which every country has production capabilities in every good, the literature on the Product Space (also the one on Industry space and on the Technology space) relies heavily on the concept of revealed comparative advantage of Bena Balassa (Balassa, 1965).

$$RCA_{cp} = \frac{(X_{cp} / \sum_p X_{cp})}{(\sum_c X_{cp} / \sum_c \sum_p X_{cp})} \quad (4.1)$$

X_{cp} corresponds to the value of the export of the product p by the country c . The RCA index measures the share of the export of a given good in the countries’ export basket ($X_{cp} / \sum_p X_{cp}$) compared to the world share of the same good over the world total export ($\sum_c X_{cp} / \sum_c \sum_p X_{cp}$). Having a $RCA > 1$ implies being better at exporting a good than most countries.

The fundamental concept of comparative advantage suggests that a country has an interest in specializing in a narrow subset of goods, even though it could potentially produce a broader range of goods. By contrast, Capability Theory explains why countries specialize far less than what is predicted by comparative advantage theory. Countries are expected to export, or at least produce, all the

<https://unstats.un.org/unsd/classifications/Econ>

goods for which they have the required capabilities. It is therefore important to understand that the RCA index captures a notion of specialization not present in Hausmann’s Capability Theory.

This approach has some conceptual limitations. It is not able to discriminate between instances where certain countries are unable to produce a specific product because they lack capabilities and instances where countries fail to reach a significant level of export for these goods due to market forces or a lack of competitiveness. However, in this methodology, we use this RCA concept not to reveal a competitive advantage but simply to measure the existence of production capabilities.¹⁰

Eq. 4.1 allows to construct the Country-Product Matrix (M_{cp}) which gives us the level of competitiveness for all exports of every country. To model the catalytic links between each exports for which the country is competitive, we model the export basket as a Directed Product Space. The adjacency matrix of our network is defined as follows:

$$M_{cp} = \begin{cases} 1 & \text{if } RCA_{cp} > 1 \\ 0 & \text{otherwise} \end{cases} \quad (4.2)$$

This is a binary matrix that has a value of 1 if a country has a $RCA > 1$ in the exportation of a given good and 0 otherwise. The ‘ubiquity’ of a product is defined as follows:

$$u_p = \sum_c M_{cp} \quad (4.3)$$

This corresponds to the number of countries that export the good with a $RCA > 1$. Likewise Eq. 4.4 defines the diversification of a country which is the number of good exported by the country c .

$$d_c = \sum_p M_{cp} \quad (4.4)$$

Finally, we define the probability that a product p favors the emergence of a product p' as follows.

¹⁰Not present in this thesis, our following step for the publication will be to confirm our results by doing a robustness check with a lower RCA threshold.

$$B_{pp'}(t, t + \delta) = \frac{1}{u_p(t)} \sum_c \frac{M_{cp}(t)M_{cp'}(t + \delta)}{d_c(t + \delta)} \quad (4.5)$$

This probability measure consists of the product between the Mcp at time t and the Mcp matrix at time $t + \delta$.¹¹ This matrix is normalized by the ubiquity of each product u_p and the diversification of each country d_c .

Eq. 4.5 is a Directed Product Space. The Undirected Product Space described in Pugliese et al. (2019), has similar characteristics to a Directed Product Space, this is the network representation of the stronger probability of exporting the good a δ years later if the good b is exported by a country c in year t .

4.3.4 Assessing link significance

The adjacency matrix just defined expresses the probability of catalyzation between all pairs of good. A high value for the catalyzation of the product b by the product a means that if the product a is in the export basket of a country in time t it is highly likely to find product b in the export basket at time $t + \delta$. Likewise a probability of 0 implies that when the product a is exported at time t the product b is never found in the export basket in time $t + \delta$.

The next step is to discriminate between the instances in which a product catalyzes another and the instances in which both products happens to be coincidentally produced by the same type of countries. We therefore filter out the links for which a co-exportation can be coincidental. A high level of co-exportation between goods can occur for three reasons: (i) Some products have a high co-exportation rate because they are exported by most countries (high ubiquity). (ii) Some products have a high co-exportation rate because they are produced by a few highly industrialized and diversified countries. (iii) Some products have a high co-exportation because they are based on the same capabilities or because they are complementary.

To select only links that are economically relevant (and correspond to (iii)), we follow the methodology presented in Napolitano et al. (2018) and Pugliese et al. (2019). For each link we measure its likelihood to emerge due to coincidental

¹¹The result is a product by product matrix which corresponds to a inter-temporal matrix of co-exportation. In this matrix, the higher is the value of an entry, the higher will be the amount of co-exportation.

reasons. This is done by comparing the co-exportation probability (of a product in time t and another product in time $t + \delta$) in the empirical network with the co-exportation probability in 1000 random networks. If the co-exportation of two goods occurs a significant amount of time in the random network then the catalyzing link is considered as economically non-relevant. More precisely, we assess the significance of each link depending on the frequency of its occurrence in 1000 Directed Product Space with randomized $M_{cp}(t)$ and $M_{cp}(t+\delta)$ matrices. Those M_{cp} matrices are generated using a null model. This null model is based on the bipartite configuration model presented in Saracco et al. (2015) and can generate a randomized binary matrix with specific degree distribution. It is used to create binary matrices in which countries have on average the same diversity d_c and products have on average the same ubiquity u_p as in the original M_{cp} matrices. A first null model is used to randomly generate 1000 binary matrices that display the same average degree distribution than the original $M_{cp}(t)$. Another null model is used to generate 1000 null matrices for $M_{cp}(t + \delta)$. Those two sets of null matrices are used to create 1000 randomized Directed Product Spaces (null network).

The following step is to test the empirical Directed Product Space against the 1000 of randomly generated counterparts. The significance of a link, therefore, depends on its number of occurrences in the 1000 null networks. We select a threshold of the number of occurrences over which the link will be discarded. This threshold will be our p-value. Only links that are statistically significant depending on the selected p-value are considered as economically relevant.

In this chapter, we have selected a significance level of 0.1%. Comparing individually each link's p-value to our significance level creates an issue called the multiple comparison problem. This problem arises when an analysis involving multiple statistical test is made. Running this high number of tests increases the probability of making false positive errors Colquhoun (2014). To accurately control for the proportion of false positives simultaneously for all links, we adjust the confidence level. This is done by applying the false-discovery-rate correction procedure from Benjamini and Hochberg (1995) to maintain the overall significance level at 0.1%.

We convert our filtered network into a binary format, where a link represents a significant catalyzation relationship, and the absence of a link indicates a lack

of significant catalyzation connection.

4.3.5 Detecting Autocatalytic Sets in the Directed Product Space

We apply the Autocatalytic set (ACS) framework to understand the multiple feedback loop effects that occur within the Product Space. The application of the Autocatalytic set framework on the Directed Product Space will provide new information on the positive feedback loop effect between the different exports of a country. This is especially relevant to understand the interdependencies between green goods and exports that can be negative for the environment.

To detect Autocatalytic Sets (ACS) we utilize a methodology detailed in Jain and Krishna (2002a) and Napolitano et al. (2018), based on the Perron-Frobenius theorem. This approach involves representing the Directed Product Space as an adjacency matrix, which is binary, indicating the presence (1) or absence (0) of a link. This binary structure makes the adjacency matrix non-negative.

The Perron-Frobenius theorem guarantees that for all non-negative matrices there exist a real positive eigenvalue which is the largest of all other eigenvalues. This eigenvalue, the Perron-Frobenius eigenvalue (PFe), signifies the presence of closed directed paths or feedback loops within the graph. When the PFe exceeds 1, we have an ACS, indicating that certain goods are part of self-reinforcing sets, benefiting from these feedback loops. The PFe value also suggests the growth speed due to the feedback: the larger the PFe, the faster the anticipated growth.

Nodes forming part of an ACS can be identified through the corresponding eigenvector of the matrix. If an eigenvector element is non-zero, its related node is part of an ACS. For more information see the methodology section 2.4.2 in the chapter 2 .

4.4 Results

We start by highlighting some stylized facts about which country produces green goods and at which stage of development. Figure 4.1 is a map that displays the number of green products exported (with $RCA > 1$) per country.

Figure 4.1: World map of diversification level in green products



Note: Areas with lighter green are characterized by higher green products diversification

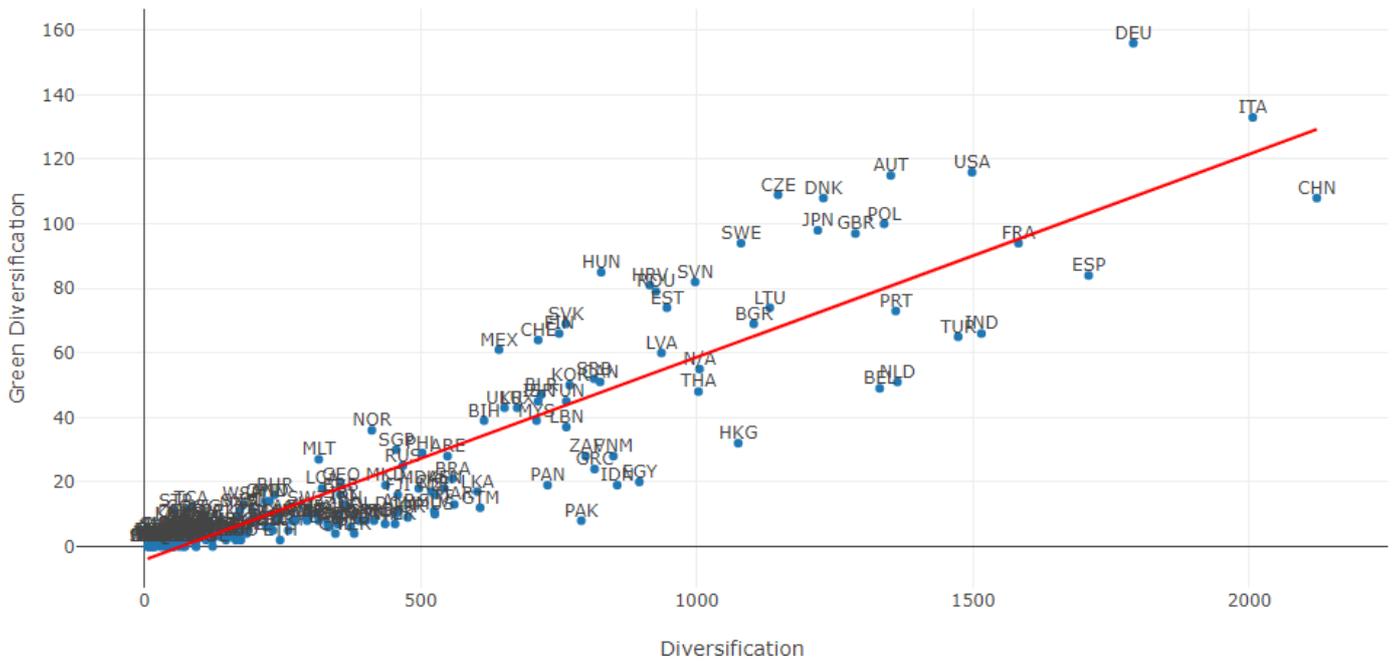
This map shows that the production of green good is not evenly distributed. Green goods are mainly produced by developed countries in North America, Europe and East Asia. This geographical representation underscores a disparity, revealing that emerging economies are laggard in the export of green products.

Given that underdeveloped and developing countries are likely to bear the brunt of climate change's adverse effects, and considering their limited capacity to influence climate change due to insufficient institutional and technological capabilities to curb GHG emissions, it becomes imperative for these nations to expand their production of green goods. Doing so would enable them to formulate more effective policies tailored to their specific needs and constraints.

This is reinforced by the two following figures. First, we plot in Figure 4.2 the number of green goods exported by a country against its level of diversification. Second, we plot in Figure 4.3, by comparing the number of green goods exported by a country against a measure of a country's industrial sophistication. This index based on the work of Tacchella et al. (2013) is a sophistication indicator for both products and countries. Each product is given a value based on its complexity level,

which is essentially determined by the complexity of the capabilities required to produce these goods. Countries are assigned a value according to their ability to export products that necessitate a complex combination of capabilities. For more information, see Section C.2.2 of the Appendix.

Figure 4.2: Green goods diversification index versus total product diversification index



Both graphs show a positive linear correlation between the level of green diversification and the level of industrial development. From an economic perspective, this suggests that production capacity and market dynamics of environmentally sustainable goods can be a by-product of a country’s economic progress. The acquisition of capabilities in the production of green goods seems to be obtained in a similar way as for other goods in the course of industrialization. Countries with a stronger capacity to produce complex products will be able to access more complex green goods categories. Leaders in the production of green goods are also those capable of producing other goods, such as Germany, Italy, China, and the United States, showing the complementary in the development of production capabilities.

of the network, which corresponds to 2641 of the 4647 products in the database. All the other products are isolated nodes, which are not displayed in the figure.

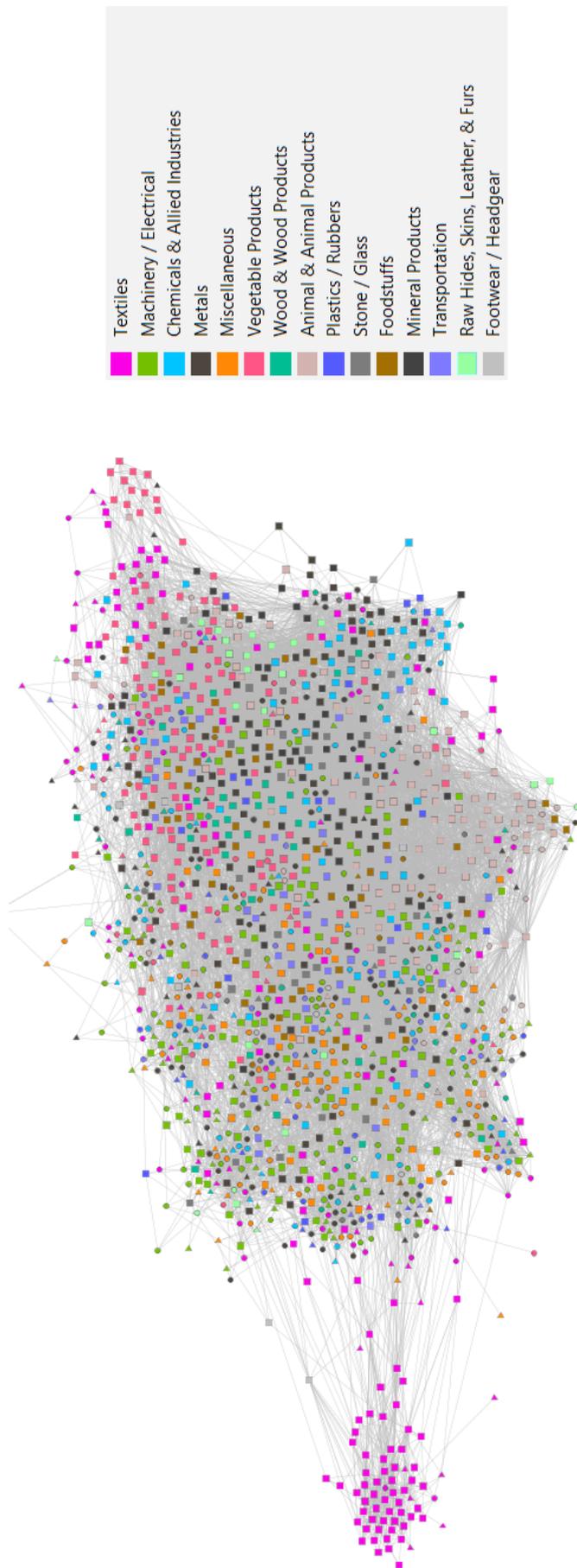
Figure 4.4 displays two interconnected subgraphs. The smaller subgraph on the left consists entirely of textile products and lacks any green goods for the period 2017-2019. A second, more diverse subgraph is visible on the right, featuring a large variety of industries. Out of the 4647 products listed in BACI for the years 2017-2019, 2641 belong to the Directed Product Space, accounting for 56.8% of the total. Within this Directed Product Space, products in the ACS members make up 1886 items (or 40.5%), while the non-ACS members account for 755 items (or 16.2%). Among the ACS members, 1028 are identified as Core products (22.1%), and 858 are identified as peripheral products (18.4%).

The observation that a majority of nodes within the Directed Product Space are also part of the ACS is not inconsequential. This suggests that the structure of the Directed Product Space is influenced by the ACS framework. The ACS is defined as a set of nodes where each member receives at least one link from another member within the set. Core members are specifically those ACS members that send a link to other Core members. Nodes not included in the Directed Product Space are generally either without links or have only a few links. This group of 2006 products represent less than the majority. Only the nodes represented organize themselves into clusters. Most nodes receive at least one link from other ACS members, and the majority of ACS members are classified as Core. Figure 4.5 illustrates the ACS within the Directed Product Space.

Another observation concerns the dispersion of green goods within the main subgraph. In this context, green goods are distributed homogeneously across the Directed Product Space, with the exception of the textile industry. This pattern is attributable to the nature of the CLEG classification for green goods, which is based on their potential use in sustainable transition processes rather than any inherent product quality. More precisely, green goods are not defined by a specific set of capabilities or technologies. Instead, they encompass a diverse range of specific applications, some of which may contribute to sustainable development.

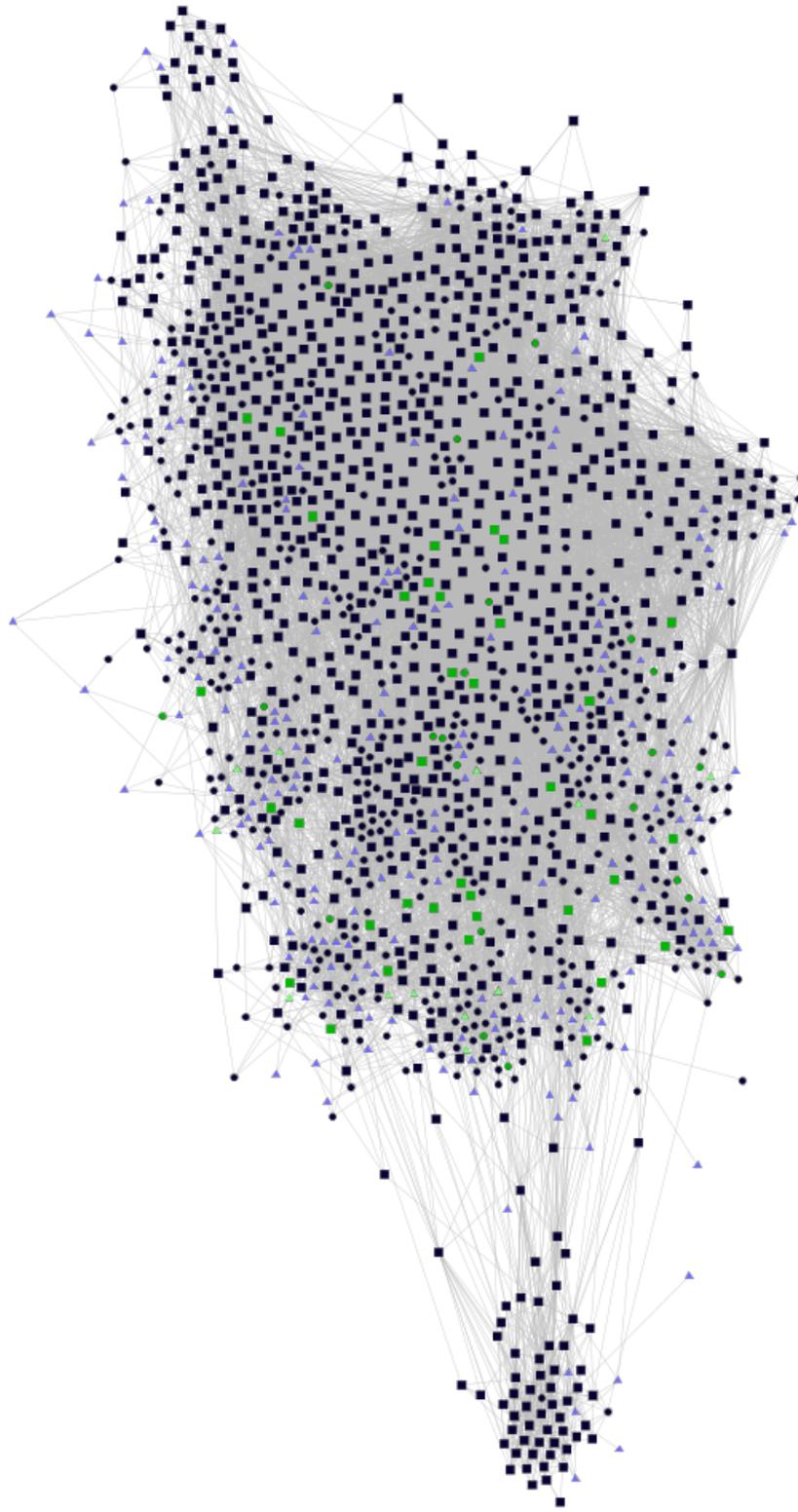
This has multiple implications for policy-making. First, the absence of specific clusters where green goods are concentrated suggests that there is no singular set of capabilities that can optimize the path toward producing these goods. As a re-

Figure 4.4: The Directed Product Space, period 2017-2019



Note: The figure represents the Directed Product Space for the period 2017-2019. Each node corresponds to a specific exported good, while the links between nodes indicate catalyzation relationships among these goods. The colors are used to differentiate various sectors of the economy. Only nodes that are connected through links are displayed in the visualization. The network visualization was generated using the ForceAtlas2 force-directed algorithm (Jacomy et al., 2014). For better comprehension, it is recommended to view this figure in color.

Figure 4.5: Green goods and autocatalytic set in the Directed Product Space, period 2017-2019



Note: The figure illustrates the positioning of green goods and Autocatalytic Sets (ACS) within the Directed Product Space for the period 2017-2019. Green nodes represent green goods (Dark green corresponds to ACS members and light green corresponds to non-ACS members). Black nodes are non-green ACS members. Blue nodes are non-green non-ACS nodes. The shape of the node conveys information about the position in the ACS: square nodes are the Core, round nodes are the Periphery, and triangle nodes are outside of the ACS. For better comprehension, it is advisable to view this figure in color. Only nodes that are connected are displayed in the visualization.

sult, the development of green goods will require the acquisition of a diverse set of capabilities, each tailored to a specific green good. Second, the products most similar to green goods in terms of capability requirements are often non-green goods. This suggests that gaining a comparative advantage in the production and export of non-green goods could be a useful stepping stone toward acquiring the capabilities needed for green goods. Lastly, countries may find it beneficial to prioritize the development of green goods that are closely related to products they already export, thereby leveraging existing capabilities for sustainable development.

This creates a direct connection between industrial development and the export of green products. Enhancing industrialization levels in developing countries is essential for increasing the number of nations capable of producing green goods. In this scenario, the concept of leapfrogging becomes particularly relevant. It offers these countries the opportunity to skip certain phases of industrial development, enabling quicker adoption of green technologies (leapfrogging).

The Directed Product Space serves as a roadmap in this context, indicating which products can be leapfrogged and which cannot, based on a country's existing export portfolio. This approach could accelerate the transition to sustainable practices and simultaneously boost export capabilities in green goods.

4.4.2 Green and non-green interactions in the Directed Product Space

In this subsection, we explore the complex interactions between the development of green and non-green products, specifically examining their catalytic relationships within the network. By analyzing these network interactions, we aim to discern the extent to which the growth of green and non-green industries is interconnected. Specifically, we investigate whether the development of a green industry is likely to stimulate the growth of a non-green industry, and conversely.

Table 4.1 displays a summary of the links between green and non-green good in the network. It quantifies the pairwise catalyzation relationship between green and non-green.

Table 4.1: Contingency table summarizing the type of good at the origin and destination of a link.

From/To	Number of links			% of ingoing link			% of outgoing link		
	Green	Non-green	Total	Green	Non-green	Total	Green	Non-green	Total
Green	46	630	676	6.8%	93.2%	100%	2.95%	5.24%	3.04%
Non-green	832	20702	21534	3.86%	96.14%	100%	97.05%	94.76%	96.96%
Total	878	21332	22210	3.95%	96.05%	100%	100%	100%	100%

Note: period 2017-2019. The number of links is the number of catalytic relationship from a category to another. % of ingoing link measures the share of green and non-green that catalyze each given category. % of outgoing link measure the share of green and non-green catalyzed by each category.

From Table 4.1, it can be inferred that in the Directed Product Space for the period 2017-2019, green goods are more likely to act as catalysts for non-green goods, as evidenced by 93% of outgoing links from green goods being directed towards non-green products. Similarly, green goods are also more likely to be catalyzed by non-green goods. It is observed that an overwhelming 97.05% of ingoing links going towards green goods are originating from non-green goods. What the data essentially suggests is a complex interdependence between green and non-green goods, where non-green goods appear to be instrumental in fostering the growth of green industries.

To help policy makers better understand the complex choices between different types of goods, we have provided a comparison of the centrality of green goods and non-green goods in the Appendix (see Section C.4 of the Appendix). This comparison shows that non-green goods have a higher centrality than green goods. It also shows that green goods receive less catalytic effects than other products. This reinforces the idea that specific industrial policies are necessary to orient the industrialization process towards green products, even when the capabilities are present.

We will now focus on the interdependency between the green and the non-green goods. More specifically we will investigate the positive feedback loop that occurs within the Product Space between the export of those two types of products. Consider, for instance, the feedback loop between product 840810 (*Engines: for marine propulsion, compression-ignition internal combustion piston engines diesel or semi-diesel engines*) and product 560811 (*Twine, cordage or rope: fish-*

ing nets, made up, of man-made textile materials). The former is the non-green good used as inputs for motorboats and, the later, the green good is a twine that have a higher rate of recyclability, durability, reduced environmental impact and responsible disposal.

While this study doesn't make assumptions about the reasons behind catalysis, it is reasonable to deduce in this case that a nation with a robust shipbuilding industry would likely support both an engine and a twine industry. Consequently, the growth of one industry could potentially stimulate the growth of the other, forming a mutually beneficial loop.

The next part will generalize the study of those feedback loops and their effect on the catalyzation of green products. We examine the autocatalytic cycles in Figures 4.6 and 4.7, which account for instance when green and non-green goods are part of a feedback loop within the network. It is interesting to note that only a small fraction of green products are part of these cycles with other green goods. This could be ascribed to the diverse nature of manufacturing processes, and uses associated with these green goods.

Figure 4.6: Green and non-green goods membership of a two-node cycles in the Directed Product Space

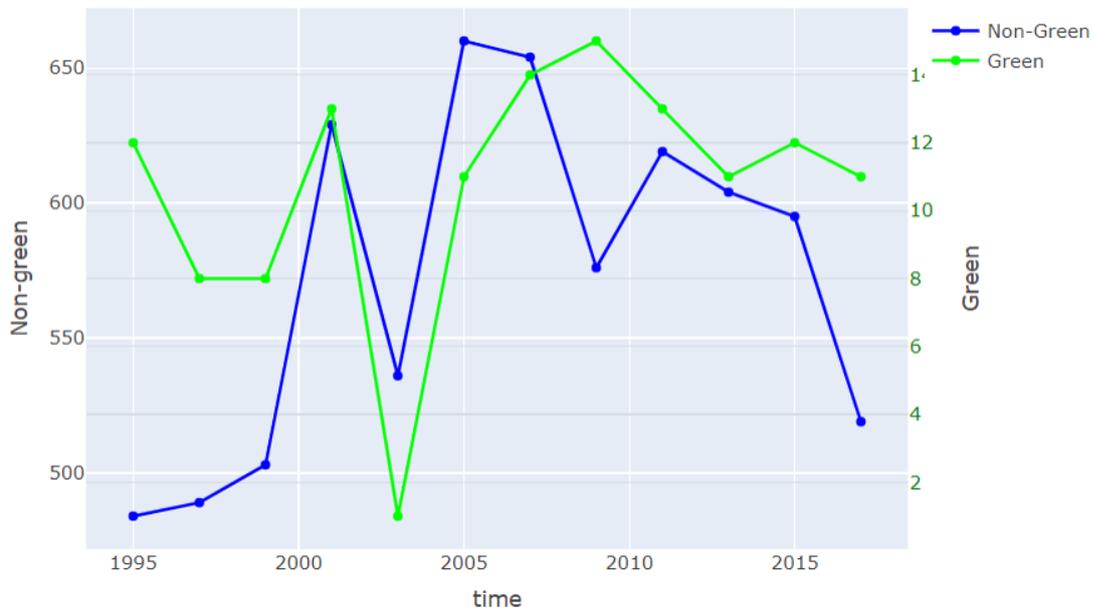


Figure 4.7: Green and non-green goods membership of a three-node cycles in the Directed Product Space

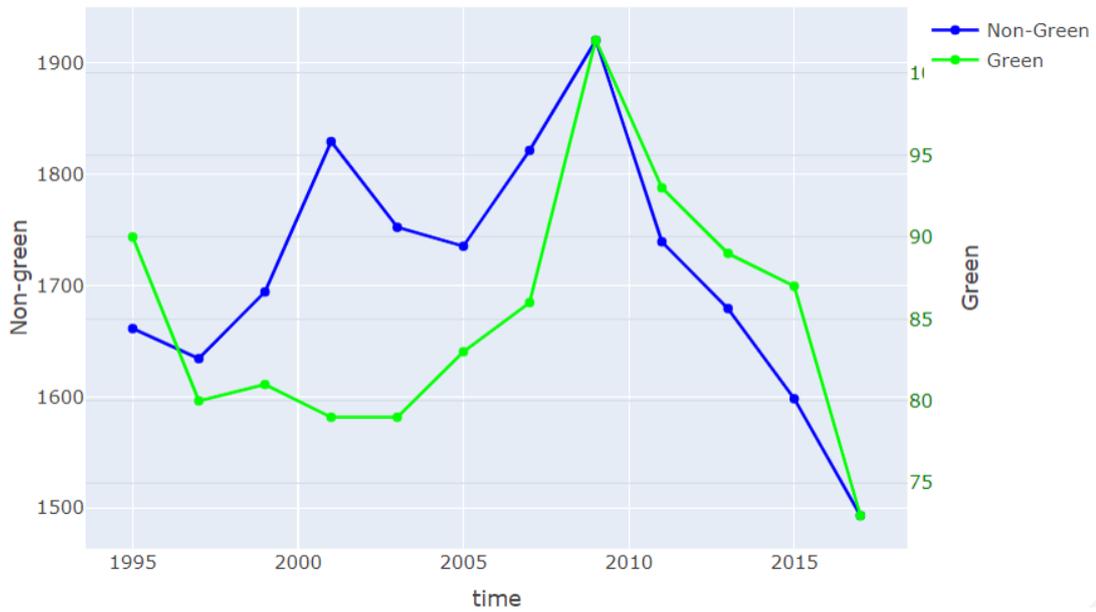
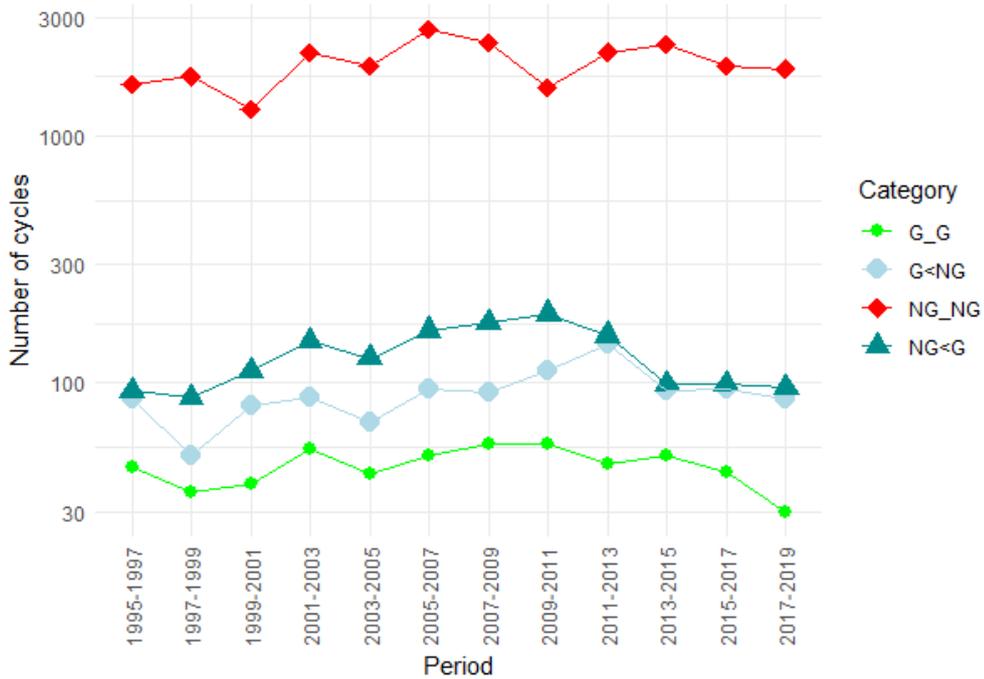


Figure 4.8: Number of two-node cycles by product type



Note: We separate the cycles that involve both green and non-green products into two groups, depending on which of the green or non-green goods emerges first. To do so, we use the *PRODY* index, which is an indicator corresponding to the weighted average of the GDP per capita of the countries that export a given good. In this context, it is used as a proxy to measure the level of development at which a good is likely to appear in an export basket. $G < NG$ means that the green good has a lower *PRODY* than the non-green good, while $NG < G$ means that the non-green good has a lower *PRODY* than the green good. The source for the GDP per capita is CEPII (2023).

Given the broad spectrum of technologies they originate from, green goods do not necessarily share common capability requirements. However, they are inclined to form connections with other product types within the same industry or those based on similar technologies, most of which are non-green goods.

Figure 4.8 illustrates the evolution of the number of two-node cycles that exist among green goods, non-green goods, and cycles involving one green and one non-green good. The quantity of autocatalytic cycles containing only green goods is notably low. This underscores the concept that a significant portion of green goods' growth may be catalyzed through interactions between green and non-green goods. Most two-node cycles involving green goods are two-node cycles between a green and a non-green good.

Concerning the cycles that involve both green and non-green goods, they are separated into two groups depending on which of the green or non-green goods emerges first. To do so, we use the PRODY index, which is an indicator corresponding to the weighted average of the GDP per capita of the countries that export a given good (see Section C.2.3 of the Appendix, for details on the construction of this index). In essence, we examine which product is likely to emerge first in the development process. The results reveal that for every year between 1997 and 2011, in two-node cycles involving both green and non-green goods, the non-green good is more likely to be the first to emerge and hence catalyze the growth of the other green good. However, the years following this period display a convergence in the number of two-node cycles.

One limitation of these counts is that the cycles are often not standalone, but rather frequently overlap with each other. Some products are part of multiple cycles, resulting in a cumulative effect of these cycles. To address this and account for such cumulative cycles, the subsequent subsection will implement an Autocatalytic Set (ACS) approach.

4.4.3 Autocatalytic Sets, green goods and Product Space

4.4.3.1 The Structure of the ACS

In this section, we delve deeper into the analysis of product cycles by employing the Autocatalytic Set (ACS) approach, which allows us to account for overlapping cycles. The economic implications of the ACS in the Product Space for economic development are important.

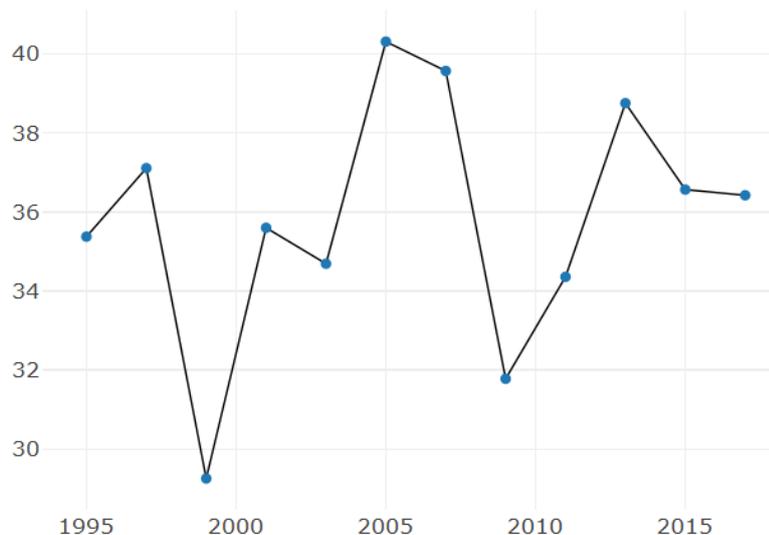
The ACS encompasses all the products that can be catalyzed by other members of the set. Products that are ACS members are more likely to benefit from a boost in their exports if the country has a comparative advantage in the exports of other products. Exporting a product from the ACS, and especially from the Core, implies the ability to leverage its structure in order to guide the country's diversification process. The more goods from the set that are produced, the stronger the effects will be from multiple overlapping feedback loops, and the more potent the ACS catalyzation effects will become.

It is therefore crucial for a developing country, which lacks resources, to leverage the ACS to benefit from a boost in its industrialization. Utilizing the ACS structure to develop green industries is also feasible. The structure of the network can provide multiple catalyzing effects for the development of green products. As a country increases the number of products in which it has a comparative advantage within the set, it becomes easier for that country to develop green products. Conversely, as a country increases the number of green products in the set, it is more likely to adopt other non-green products within the set. Understanding the position of green products within the set is essential for comprehending the link between diversification and green product adoption in developing countries.

We will first describe the ACS in the Product Space and then consider the role of green products within this set. One way to measure the autocatalytic feedback loop present within the network is through the strongest eigenvalue of the network, known as the Perron-Frobenius eigenvalue (PFe). An eigenvalue surpassing 1 is indicative of the existence of ACS. The magnitude of this eigenvalue reflects the autocatalytic strength of the network – the larger the value, the stronger the autocatalytic effect. As depicted in Figure 4.9, the PFe in our network exhibits fluctuations over time. It decreases from 1995 to 1999, rises till 2005, drops again

until 2010, and finally ascends, reaching 36 in 2017.

Figure 4.9: Perron-Frobenius eigenvalue



Note: The Perron-Frobenius eigenvalue indicates the amount of feedback loops within the directed product network. A rise in this value signifies an increase in the number of cycles in the network.

Considering the network's complexity, it is interesting to observe how the size and composition of the Core evolve over time. Figure 4.10 portrays the changing composition of products within the Core and Periphery of the autocatalytic structure. We observe fluctuations over time across each product class; however, the total number of nodes remains relatively stable.

Table 4.2 analyzes the evolution of ACS membership over time using the Pearson correlation¹², all the correlation values are above zero. This indicates a positive relationship from one ACS membership to the next. More specifically, ACS membership in one period is positively correlated with ACS membership in the preceding period, yielding an average correlation of around 0.35. When we focus specifically on Core membership, we observe an even stronger correlation over time, around 0.59, indicating a stronger level of stability in the Core relative to the overall ACS.

¹²The Pearson correlation is a statistical measure that gauges the strength and direction of the linear relationship between two variables, ranging from -1 to 1. A value of -1 signifies a perfect negative correlation, 0 denotes no correlation, and 1 signifies a perfect positive correlation.

Figure 4.10: Relative share of nodes in the Core, Periphery and the rest

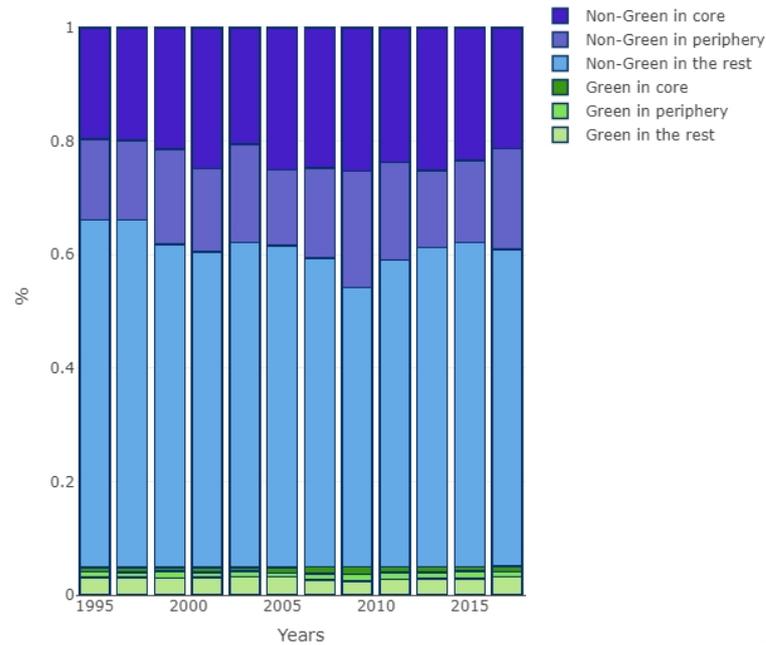


Table 4.2: Pearson correlation of product's ACS and Core membership between periods, from 1995 to 2019

First period	Second period	ACS	Core
1995-1997	1997-1999	0.32	0.58
1997-1999	1999-2001	0.33	0.59
1999-2001	2001-2003	0.32	0.59
2001-2003	2003-2005	0.36	0.58
2003-2005	2005-2007	0.35	0.60
2005-2007	2007-2009	0.39	0.62
2007-2009	2009-2011	0.34	0.58
2009-2011	2011-2013	0.34	0.59
2011-2013	2013-2015	0.38	0.62
2013-2015	2015-2017	0.42	0.64
2015-2017	2017-2019	0.38	0.61
2017-2019	1995-1997	0.29	0.44

Note: The membership of a product in an Autocatalytic Set is represented by a binary list, with a value of 1 indicating inclusion and 0 indicating exclusion. These lists are standardized to include only the products that are present in every year (i.e., the common denominator; 4635 goods). Subsequently, a Pearson correlation is computed for all pairs of products in the list. This process is performed for both the Core and the ACS.

Table 4.3: Contingency table for Autocatalytic Set membership

		2017-2019				Total
		Non-ACS		ACS		
1995-1997		Observed	frequency	Observed	frequency	
	Non-ACS	2078	0.70	889	0.30	2967
	ACS	671	0.40	997	0.60	1668
	Total	2749	0.59	1886	0.41	4635

Note: observation corresponds to the number of products from each of the categories in 1995-1997 and where they are in 2017-2019. Frequency is the share of products, from each category in 1995-1997, that goes into the ACS and non-ACS categories of 2017-2019.

Products that are part of the ACS during the initial period of 1995-1997 exhibit a probability of approximately 60% to persist as members of the ACS during the final period of 2017-2019. Conversely, products that are not part of the ACS in the first period have a higher probability of around 70% to continue to remain outside the ACS in the last period. Furthermore, the likelihood of ACS members exiting from the set is approximately 40%, whereas non-ACS products have a probability of about 30% to enter the set during the specified time frame.

Table 4.4: Contingency table for Core membership

		2017-2019				Total
		Non-core		Core		
1995-1997		Observation	Frequency	Observation	Frequency	
	Non-Core	3205	0.87	467	0.13	3672
	Core	402	0.42	561	0.58	963
	Total	3607	0.78	1028	0.22	4635

Note: observation corresponds to the number of products from each of the categories in 1995-1997 and where they are in 2017-2019. Frequency is the share of products, from each category in 1995-1997, that goes into the Core and non-core categories of 2017-2019.

Those results are reinforced for Core nodes. Products that are part of the Core during the initial period exhibit a probability of approximately 58% to persist as members of the Core during the final period. Conversely, products that are not part of the Core of the first period have a higher probability of around 87% to continue to remain outside the Core in the last period. Furthermore, the likelihood

of Core members exiting from the set is approximately 42%, whereas non-core products have a probability of about 13% to enter the set during the specified time frame. This remarkable stability in the autocatalytic structure has significant environmental policy implications. Particularly, it emphasizes the concept that introducing more green goods into the ACS may not be a feasible strategy, given the robust stability of the network.

In Table 4.5, we show the total number and the distribution of green and non-green products for the period 2017-2019. The non-green goods tend to be in the Core, while green goods are more likely to be in the Periphery.

Table 4.5: Average distribution of products across the Core, Periphery and non-Autocatalytic Set members, from 1995 to 2019

	Mean number of product			Share of the product typology		
	Non-green	Green	Total	Non-green	Green	Total
Core	1127.83	44.67	1172.50	24%	18%	24%
Periphery	779.25	51.00	830.25	17%	21%	17%
non-ACS	2774.92	145.92	920.83	59%	60%	59%
Total	4682	241.58	4923.58	100%	100%	100%

As shown in Table 4.2, we find a strong correlation between nodes belonging to the Core over time, indicating that more than half of the products owned by the Core are relevant drivers of catalyzation over the period analyzed. This reinforces the idea that green good are less likely to be the driver of the diversification process. Therefore, a combination of green and non-green goods is necessary to optimize the process of diversification while also striving towards environmental sustainability.

4.4.3.2 Measuring the effect of the ACS on export volume

As established previously, a country can rely on non-green goods to gain the required capabilities to produce specific green goods. This final subsection aims to establish whether belonging to an ACS, and therefore benefiting from its multiple feedback loops, can increase a country's ability to export a given good.

ACS is defined differently in this subsection. In the previous sections, the ACS detection algorithm was applied to the global network. In this subsection,

the ACS detection algorithm is applied to a subset of the network, namely the domestic Product Space.

The domestic Product Space is a subset of the Product Space. A country's domestic Product Space is therefore based on the following elements: Nodes are products that are exported by the country with a RCA greater than 1. A link exists when the node at the origin of the catalyzing relationship and the node at the destination of the catalyzing relationship are exported with a RCA greater than 1. This network represents the multiple feedback loops that reinforce goods already produced by a given country. In other words, the network structure among products is the same; however, we highlight the products that these countries are currently exporting and the catalyzing relationships between exported goods.

To gain deeper insight into the implications of the local ACS, we have mapped the positions of each of the BRICS countries (Brazil, Russia, India, China, South Africa) within the Directed Product Space. The result of this exercise is presented in Section C.5 of the Appendix.

The hypothesis we aim to validate in this section is whether the ACS detected in the domestic Product Space reinforces a country's level of export of a given product. If this effect is real, it means that having clusters of related industries in the country is important for the export of a good. The economic implications would lead us away from the idea of an optimal strategy to acquire specific capabilities, and instead toward creating policies to maintain a cluster of industries related to the given green good. If the structure has no impact, then the ACS should not exhibit significantly higher values of RCA in the network. Similarly, goods in the Core and the Periphery should not exhibit significantly higher values either.

We therefore apply the ACS detection algorithm to the domestic Product Space. It provides us with multiple indicators that are country-specific and product-specific. ACSlocal measures whether a product is part of the local ACS of a country. Corelocal and Perilocal indicate whether the product is part of the Core or the Periphery of the ACS of that given country.

We then use a log-log fixed-effect model to measure this effect. Our dependent variable is the export level of a country in a given good at the 6-digit level. To test the importance of belonging to an ACS, we estimated the following four equations:

$$\begin{aligned} \log(Exp_{c,p,t}) = & \alpha_1 ACSlocal_{c,p,t} + \alpha_2 Maxprox_{c,p,t} \\ & + \alpha_3 \log(GDP_{c,p,t}) + \epsilon_t \end{aligned} \quad (4.6)$$

$$\begin{aligned} \log(Exp_{c,p,t}) = & \alpha_1 Corelocal_{c,p,t} + \alpha_2 Perilocal_{c,p,t} \\ & + \alpha_2 Maxprox_{c,p,t} + \alpha_3 \log(GDP_{c,p,t}) + \epsilon_t \end{aligned} \quad (4.7)$$

Equation 4.6 expresses the volume of export of a good as a function of its position as a local ACS member within the Directed Product Space of a country ($ACSlocal_{c,p,t}$), the similarity that the product has with other goods in the country's export basket ($Maxprox_{c,p,t}$), and the size of this country's economy ($\log(GDP_{c,p,t})$). Equation 4.7 is the same equation but separates $ACSlocal_{c,p,t}$ into two other variables, $Corelocal_{c,p,t}$ and $Perilocal_{c,p,t}$.

$$\begin{aligned} \log(Exp_{c,p,t}) = & \alpha_1 ACSlocal_{c,p,t} + \alpha_2 Maxprox_{c,p,t} \\ & + \alpha_3 \log(GDP_{c,p,t}) + \alpha_4 \log(Neighborprox_{c,p,t}) \\ & + \alpha_5 Sophistication_{p,t} + \alpha_6 \log(pop_{c,t}) \\ & + \alpha_7 \log(RCA_{c,p,t}) + \alpha_8 Green_p + \epsilon_t \end{aligned} \quad (4.8)$$

$$\begin{aligned} \log(Exp_{c,p,t}) = & \alpha_1 Corelocal_{c,p,t} + \alpha_2 Perilocal_{c,p,t} \\ & + \alpha_2 Maxprox_{c,p,t} + \alpha_3 \log(GDP_{c,t}) \\ & + \alpha_4 \log(Neighborprox_{c,p,t}) + \alpha_5 Sophistication_{p,t} \\ & + \alpha_6 \log(pop_{c,t}) + \alpha_7 \log(RCA_{c,p,t}) \\ & + \alpha_8 Green_p + \epsilon_t \end{aligned} \quad (4.9)$$

Equation 4.8 and Equation 4.9 take the previous equations and add additional variables. $Maxprox_{c,p,t}$ and $Neighborprox_{c,p,t}$ are measures of a country's opportunity to export a good based on other goods exported by the country and its neighbor. $Green_p$ and $Sophistication_{p,t}$ provide information on a product's characteristics. $\log(FDI_{c,t})$, $\log(pop_{c,t})$ and $Tradeopenness_{c,p,t}$ provide information on

the country's characteristics. All variables are described in the Appendix in Table C.2.

The panel regression has been applied to all goods and to two subgroups, only the green goods, and only the non-green goods. Table 4.6 provides the results of these regressions. Belonging to the ACS has a significantly positive effect on the level of exports. In the shorter form of the equation, the effect of being part of the ACS is stronger than in its long-form version. The long-form equation captures effects that the short-form misses; additional variables measuring the sophistication of the good, the proximity of the good to the export basket of neighboring countries, and the country's current RCA level all explain parts of this effect. Moreover, products in the Core exhibit higher export levels than those in the Periphery, but only in the short version. Surprisingly, once the additional variables are added, the effect is reversed, as the Periphery exhibits higher levels of exports than the Core. Both, however, have a significant positive effect on export levels.

Finally, $GDP_{c,t}$ has a positive effect on exports. A country also has a higher chance of exporting a given product if the country's neighbors are already producers of that good. The RCA level of the country also has a positive effect on the level of exports of the good. The sophistication and population size have a negative effect on the export level of the good. It is worth noting that green goods display higher exports than non-green goods.

Each model includes a high number of observations (over 2.5 million) for the version with all observations included. The green goods subgroup includes around 160,000 observations. Each model demonstrates strong explanatory power in its long form. For all observations, the R2 value corresponds to 0.58. The model has the strongest explanatory power in the green goods subgroup, with an R2 value of 0.679. The F-statistics are also highly significant, indicating the overall validity of each model.

Table 4.6: Regression

	<i>Dependent variable: log(exp)</i>												
	All goods			Green goods			Non-green goods						
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(4)
ACStlocal	2.509*** (0.005)		0.248*** (0.005)	2.082*** (0.025)		0.179*** (0.022)	2.552*** (0.006)		0.253*** (0.005)				
Corelocal		2.644*** (0.007)		0.200*** (0.006)		2.204*** (0.043)		0.078** (0.036)			2.701*** (0.007)		0.211*** (0.006)
Perilocal		2.289*** (0.009)		0.318*** (0.007)		2.019*** (0.031)		0.229*** (0.026)			2.299*** (0.009)		0.318*** (0.007)
maxprox	6.775*** (0.015)	6.753*** (0.015)	2.223*** (0.013)	10.230*** (0.061)	10.238*** (0.061)	4.063*** (0.055)	6.569*** (0.015)	6.544*** (0.015)	2.114*** (0.013)				2.119*** (0.013)
log(real_gdp)	0.747*** (0.001)	0.749*** (0.001)	0.643*** (0.001)	0.865*** (0.003)	0.865*** (0.003)	0.754*** (0.004)	0.742*** (0.001)	0.744*** (0.001)	0.633*** (0.001)				0.632*** (0.001)
log(Neighborprox)			0.442*** (0.002)	0.442*** (0.002)		0.232*** (0.007)		0.232*** (0.007)			0.450*** (0.002)		0.450*** (0.002)
Sophistication			0.268*** (0.001)	0.268*** (0.001)		0.259*** (0.003)		0.259*** (0.003)			0.268*** (0.001)		0.268*** (0.001)
log(pop)			-0.099*** (0.001)	-0.099*** (0.001)		-0.159*** (0.004)		-0.159*** (0.004)			-0.093*** (0.001)		-0.093*** (0.001)
log(RCA)			1.697*** (0.002)	1.699*** (0.002)		2.050*** (0.010)		2.051*** (0.010)			1.682*** (0.002)		1.684*** (0.002)
Green			0.974*** (0.005)	0.972*** (0.005)									
Observations	2,540,199	2,540,199	2,500,444	163,065	163,065	160,001	2,377,134	2,377,134	2,340,443	2,377,134	2,340,443	2,340,443	2,340,443
R ²	0.358	0.359	0.580	0.506	0.506	0.679	0.353	0.353	0.573	0.353	0.353	0.573	0.573
Adjusted R ²	0.358	0.359	0.580	0.506	0.506	0.679	0.353	0.353	0.573	0.353	0.353	0.573	0.573
F Statistic	473,010.800***	355,194.000***	431,764.000***	55,569.300***	55,569.300***	48,248.180***	42,221.890***	432,337.200***	448,488.100***	432,337.200***	324,778.500***	448,488.100***	392,468.300***
df	3; 2540185	4; 2540184	8; 2500425	9; 2500424	3; 163051	4; 163050	7; 159983	8; 159982	3; 2377119	4; 2377120	7; 2340425	8; 2340424	8; 2340424

*p<0.1; **p<0.05; ***p<0.01

To sum up, having a product within a country's ACS is positively correlated with a higher value of exports. It is therefore important to consider having a cluster of domestic industries instead of focusing on a single green industry. This domestic cluster of industries is important as they provide catalyzing feedback loops. Contrary to the framework presented in Jain and Krishna (1998), the Periphery has a stronger positive effect than the Core in terms of the size of exports.

Finally, when comparing the two subgroups, the effect of the ACS for green goods export is weaker than its effect for non-green goods export. This is true both as an aggregate value and when separated between Core and Periphery. This reinforces the idea that the catalyzation effect is lower for green goods than in non-green goods. The significativity of the effect, however, remains high both for green and non-green goods.

4.5 Concluding remarks

In conclusion, the global imperative of addressing climate change poses significant challenges, especially for developing countries most adversely impacted by its effects. The domestic manufacturing of environmental products is important to reinforce the ability of developing countries to create tailored policies to address climate change. Nevertheless, considerable obstacles persist, predominantly in the shape of constrained financial and technological assets, insufficient infrastructure, and a lack of skilled workforce.

This chapter has investigated a specific type of constraint that affects the set of capabilities of a given country. To do so, we have modeled the inter-industry relationships in the form of a Directed Product Space. In this Directed Product Space, we have identified environmental products. Furthermore, we have described the position of these green goods in the network, comparing their direct and indirect catalyzation power with their non-green good counterparts. We have also analyzed the cycles in the network, especially those that include both green and non-green goods. Finally, we have accounted for the multiple overlapping cycles in the network by modeling the ACS.

We showed that green goods benefit from fewer self-reinforcing effects than

their non-green counterparts. This effect translates into a lower impact of the ACS on export levels. This implies that green industrial policies are necessary to facilitate the emergence of green products. Indeed, our results suggest that left to their own devices, non-green products will be preferred by market forces. We also showed that green goods provide fewer opportunities for diversification compared to other products. Governments in developing countries that prioritize economic development may be less interested in the adoption of green products. Therefore, several incentives should be created by the international community to push for the development of green goods in developing countries.

We also described the interaction between green and non-green goods. Green goods are more likely to be in a feedback loop with non-green goods than with other green goods. When this occurs, the non-green good is more likely to emerge first and initiate this positive feedback loop.

There are three main avenues of research following this paper. First, additional research needs to be done to understand why peripheral nodes have a stronger catalytic effect on exports than those in the Core, as they are supposed to receive fewer feedback loops than in the Core. Second, this paper studies the relationship between green and non-green goods. Measuring the relationship between goods that have a negative effect on the environment and green goods can improve policymakers' choices between two industries. Lastly, more research is needed to investigate whether economic development takes precedence over the development of green goods. Such research can be conducted by simulating the evolution of a country's export basket within the Directed Product Space.

The challenge lies in striking a balance between fostering green product development and encouraging economic diversification. To address this, we propose a multi-faceted approach. The adoption of green products should be integrated into a broader industrialization strategy, rather than focusing solely on the optimal path toward green goods adoption. A more strategic approach might be to identify a cluster of industries for specialization and subsequently encourage the adoption of related green industries. More precisely, developing countries should aim to diversify their industries as a means to acquire a large set of capabilities.

In countries that have the required capabilities for the development of green industries, policies should be set to enhance incentives for both policymakers and

businesses to promote the growth of green industries. This could include rewarding sustainable practices, providing subsidies for green product development, or implementing mechanisms to provide monetary and non-monetary support to foster green industry development. This compensation could be dispensed at various levels: national politicians might drive domestic incentives, while international players like institutions or foreign countries could provide external investment. This holistic approach could foster sustainable development without compromising the broader goal of industrial diversification.

Our research also underscores the complexity of the transition to sustainability, which cannot be achieved by merely substituting non-green goods with green ones. With the insights gained from our analysis, we hope to contribute to the ongoing discourse on managing the delicate balance between economic development and environmental care, and inspire further research in addressing the multifaceted challenges of sustainability.

5 General Conclusion

This research has focused on two pivotal aspects of structural change particularly relevant for developing nations. First, it examined the transition toward a diversified and industrialized production network, essential for boosting economic output, creating jobs, and improving living standards. Second, it explored the adoption of green industries, crucial for mitigating the adverse effects of industrialization on the environment.

These structural changes were examined through the lens of inter-industry complementarities, based on three frameworks. Vertical complementarities were studied using an Input-Output framework, which described the linkages between industries both domestically and internationally. Horizontal complementarities were modeled using the Economic Complexity framework, which measured industry relatedness based on their use of common capabilities. Finally, the novel Autocatalytic Set (ACS) framework was employed in this thesis to describe how complementarities between industries and products could create autocatalytic structures that influenced structural changes.

The novel combination of analytical frameworks proposed in this Thesis was applied to three case studies that exemplified the important challenges facing developing countries. Each case study was the subject of a separate chapter in the thesis. Firstly, I examined the emergence of Chinese industries as the center of the global production network. Secondly, I explored changes in the domestic and international input linkages within and across post-Socialist nations. And lastly, I investigated the symbiotic growth of green and non-green industries in emerging economies.

In Chapter 2, I modeled Input-Output linkages as a network using the World Input-Output Database, focused solely on the strongest linkages, and highlighted the existence of Core-Periphery structures within the World Input-Output Net-

work. More precisely, I found that the World Input-Output Network consisted of one main Global ACS and several local ACSs. The Global ACS comprised industries from a wide range of countries. The exact number of ACSs detected depended crucially on the filtering threshold value used to select the strongest linkages. Across all these thresholds, the following trend was observed: China initially started as an isolated ACS, then densified its domestic linkages, and later branched into the Global ACS. At the \$10 billion filtering threshold value, China's local ACS joined the Global ACS in 2005 and dominated the Core in 2013. This model also captured two other phenomena: the peripheralization of Japanese industries and the shift from an ACS Core based on American industries to one based on industries from China and an aggregated Rest of the World industry.

In Chapter 3, we study of production networks in post-Socialist countries, we identified a number of meaningful trends. The first was the instability of linkages between 1990 and 2000, especially among Commonwealth members. This instability was stronger than that experienced by ex-Yugoslav countries facing similar situations. Countries affiliated with the CEEU had more stable linkages. CEEU countries also had a more integrated production network compared to CIS countries, primarily with other European Union members. CIS countries were more diverse; for example, Moldova and Belarus were heavily dependent on international linkages, particularly with Russia, while countries like Kazakhstan were more self-sufficient, with production systems clustered within national boundaries.

By applying the ACS detection algorithm to the production network of post-Socialist countries, I identified one ACS composed mainly of a Core but with almost no Periphery. The Core primarily consisted of CEEU industries along with Germany and Russia. This regional production network was organized as a hub-and-spoke structure, with Germany and Russia serving as hubs for their respective spheres, namely CEEU and CIS. China showed a densification of its trade, mainly with CEEU countries and Germany.

In Chapter 4, I studied the emergence of green industries in developing countries, focusing particularly on the catalytic relationships between green and non-green products. Using the BACI database, I modeled a directed network in which nodes represented products, and links represented catalytic relationships measured as the probability of one product catalyzing the production of another product.

I used the OECD's green product classification to identify green products in this network. In this setting, I examined the interactions between green and non-green products through pairwise relationships. I applied the ACS detection algorithm in two respects: first, to detect the Core-Periphery structure in the Product Space network; second, to identify ACSs within the catalytic relationships of goods exported by a country.

Through the analysis of the Directed Product Space, I found that green goods received fewer direct catalytic links than their non-green counterparts. They were also characterized by a lower amount of feedback loops; if they were in a feedback loop with another good, it was more likely to be with a non-green good than with another green good. In these feedback loops, non-green goods were more likely to appear first in the development process and initiate the positive feedback loop. Green goods were less likely to be part of the ACS compared to non-green goods. At the country level, ACS membership was correlated with higher export quantities. Finally, green goods in ACSs had lower catalytic effects than non-green goods.

The main contribution of this thesis was to propose a novel analytical and empirical framework for detecting and measuring the extent of cyclical feedback loops in trade networks and, from a broader perspective, to provide a general quantitative framework for studying processes of cumulative causation in the economy. In particular, the thesis provided several proofs of concept for the use of the ACS framework by studying mechanisms of cumulative causation within economic development processes. We outlined how countries navigated two cyclical dependency problems: The first was the circular dependency that arose when an industry could not expand due to a lack of appropriate linkages. The second circular dependency involved an industry's need for capabilities, which can only emerge through learning by doing. The solutions discussed in this thesis involved catalyzation processes that emerged from complementarities between industries and between products.

Through the case studies of China and post-Socialist countries, the thesis showed how nations could overcome the lack of suppliers of intermediary goods to achieve more complex production. We discussed how China leveraged its geographical proximity to Japan, Korea, and Taiwan to become a producer in the

high-technology sector of manufacturing computers, electronics, and optical products. Similarly, Central and Eastern European countries used their physical proximity to Western Europe and Germany to produce in another high-technology sector, the automotive industry. In both cases, this led to increasing returns to scale, which in turn led to a growing number of new foreign-oriented industries. However, the thesis also showed that while CEE countries became increasingly dependent on international input linkages, China primarily focused on densifying the linkages between its domestic industries. This fact highlighted complementarities more than substitutability of domestic and international linkages. Through the last case study of complementarity between green and non-green products, the thesis also contributed to showing how countries leverage existing production capabilities to acquire the necessary capabilities for producing subsequent goods.

The thesis represents a first step into the promising, novel empirical approach of the ACS model applied to trade networks. ACSs touch on a variety of economic factors and involve a set of multiple overlapping feedback loops, of which trade relationships are just one layer. Processes of cumulative causation encompass several mechanisms, both positive and negative, that extend beyond production networks. New avenues of research involve complementing the ACS framework with additional economic factors such as markets, worker mobility, and capital movement.

Another important extension is to directly tackle pressing themes of environmental and resource economics through the lens of ACS. Examples include resource scarcity, energy markets, and the environmental public “bad” resulting from instances of climate change. Some of these themes have implications for development economics. Resource scarcity and climate change are currently driving both skilled and unskilled workers from the Global South to migrate to the Global North. This influx of population in northern countries is likely to generate economies of scale, expand local demand, and stimulate innovation and specialization, thereby reinforcing the economies of the North. This migration pattern, often referred to as brain drain, shifts skilled labor from underdeveloped regions to wealthier areas, exacerbating existing regional imbalances (Matutinović, 2020).

Moreover, the study of international capital flows between sectors can offer insights into the relationship between industries in wealthier economies and those in

less developed economies. This analysis can reveal another type of self-sustaining cycle: the cyclical relationship between industries in a developed economy that provide capital to industries in developing economies. In return, these latter industries can supply their output to the developed economy. This relationship captures both the outsourcing dynamics between a developed country and its subsidiaries in low-cost countries, as well as the extractive relationships where developed economies finance resource extraction in resource-rich countries. This can be accomplished by examining a multi-layered network in which multiple types of flows overlap.

On the methodological side, an important and promising extension of the model in this thesis is an autocatalytic network with negative links. In particular, different forms of competition or resource scarcity can give rise to the inhibitory effects that one industry can have on another (Jain and Krishna, 2001). Extending the ACS framework with inhibitory relationships within inter-industry networks can further elucidate the economic constraints that some countries face in terms of development.

The challenge of how to address resource scarcity in an overpopulated world is becoming ever more crucial. Jain and Krishna (2002b) show how the same model where ACS structures form out of catalytic effects in intertwined cycles can reach a point where growth is constrained by the limited amount of resources that can be added to the network. In that critical scenario, the network is prone to collapse when the removal of a link triggers a cascade of cycle breaks.

In the context of economic phenomena, as described in Matutinović (2020), autocatalytic phenomena do not imply infinite growth. Autocatalytic cycles are constrained by the scarcity imposed by planetary biophysical boundaries. This suggests that while economic growth has long been viewed as a solution to mitigate inequalities between developed and developing economies, there is no indication that in an era of increased scarcity of resources, further economic growth can be simultaneously achieved at the mutual benefit of all countries.

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A Appendix for Chapter 2

Table A.1: 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 A.2: 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 Appendix for Chapter 3

Table B.1: Industry coverage in EORA 26

Industry code	Industry name
1	Agriculture
2	Fishing
3	Mining and Quarrying
4	Food & Beverages
5	Textiles and Wearing Apparel
6	Wood and Paper
7	Petroleum, Chemical and Non-Metallic Mineral Products
8	Metal Products
9	Electrical and Machinery
10	Transport Equipment
11	Other Manufacturing
12	Recycling
13	Electricity, Gas and Water
14	Construction
15	Maintenance and Repair
16	Wholesale Trade
17	Retail Trade
18	Hotels and Restaurants
19	Transport
20	Post and Telecommunications
21	Financial Intermediation and Business Activities
22	Public Administration
23	Education, Health and Other Services
24	Private Households
25	Others
26	Re-export & Re-import

Table B.2: Post-Socialist countries' Revealed Industry Specialization, in 2000

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
2000	2.753	0.869	1.112	0.922	0.589	0.86	0.76	0.947	0.945	0.66	0.878	1.776	1.032	0.773	0.437	1.095	1.095	1.25	0.925	1.288	0.98	1.045	1.065	1.217	0.496	0.066
DEU	1.434	0.588	2.662	0.849	0.479	0.876	0.866	0.726	0.85	0.709	0.953	0.49	1.353	0.913	0.364	1.065	0.92	1.072	0.97	1.439	1.044	1.233	0.998	0.87	0.554	0.024
BLR	0.819	1.77	1.179	1.373	7.445	2.497	2.962	2.917	2.362	0.349	1.294	4.294	0.673	0.234	0.752	0.6	1.128	0.275	0.879	0.35	0.15	0.102	0.143	1.4	0.877	0.313
GEO	4.959	0.354	1.279	2.738	0.483	0.868	0.911	0.715	0.434	0.369	0.365	0.486	1.477	1.889	0.34	0.137	1.504	0.688	1.495	1.262	0.447	0.762	0.739	0.444	3.474	0.032
KAZ	6.313	14.325	6.977	2.698	4.002	0.292	0.901	2.154	0.42	0.073	0.835	0.596	1.028	1.098	0.112	0.187	0.409	0.025	1.632	0.518	0.337	0.114	0.409	0.063	4.735	0.021
KGZ	12.017	0.229	4.99	2.096	3.042	0.257	0.651	2.105	0.318	0.454	0.493	0.657	2.48	0.653	0.022	0.037	0.08	0.165	0.944	0.325	0.252	0.895	0.572	0.009	0.644	0.081
MDA	3.343	7.542	1.263	3.487	7.454	0.99	0.602	2.831	0.902	0.59	1.945	5.869	0.851	0.348	2.616	0.798	0.986	0.732	1.146	0.769	0.155	0.275	0.246	8.378	2.341	2.31
TKM	1.481	0.942	0.717	1.002	2.21	0.956	0.888	1.085	0.709	0.672	0.889	1.39	0.967	0.583	0.497	1.121	1.003	1.091	1.036	1.312	1.216	0.728	0.94	1.181	0.741	0.118
TKM	0.86	0.457	1.212	0.818	0.932	0.93	0.914	0.747	0.892	0.83	0.926	0.828	0.761	0.912	0.361	1.043	0.902	1.079	0.903	1.354	0.38	1.177	1.042	0.917	0.515	0.028
UKR	4.888	11.063	3.598	2.931	3.56	0.541	1.13	2.915	1.316	0.31	1.534	1.364	0.969	0.755	0.112	0.186	0.408	0.022	1.069	0.38	0.316	0.11	0.41	0.109	8.177	0.004
UZB	6.243	15.868	0.77	2.761	9.061	0.16	0.788	0.679	0.331	0.046	1.227	1.008	0.924	1.46	0.146	0.243	0.531	0.02	1.139	0.465	0.328	0.156	0.767	0.087	6.474	0.013
ALB	1.282	0.797	0.949	0.791	0.932	0.81	0.712	0.611	0.764	0.631	0.929	0.378	1.057	1.184	0.407	1.197	1.112	1.398	1.279	1.313	1.028	1.255	1.041	1.039	0.502	0.034
BIH	0.705	0.614	0.995	0.793	1.086	0.965	0.778	0.747	0.807	0.724	0.894	0.84	0.923	0.883	0.363	1.054	0.953	1.175	1.062	1.284	1.161	1.42	1.118	0.919	0.489	0.022
MKD	4.318	0.185	1.582	1.737	3.256	0.702	0.825	1.558	0.216	0.251	0.302	0.584	1.516	1.296	0.947	0.847	1.048	0.817	1.353	1.45	0.503	1.052	0.623	0.112	0.242	0.186
MNE	1.487	1.072	0.936	0.849	0.413	0.875	0.717	0.678	0.727	0.761	0.879	1.55	1.157	0.838	0.504	1.178	1.012	1.247	1.04	1.378	1.036	1.511	1.178	1.251	0.623	0.153
SRB	2.874	0.667	0.702	0.866	0.414	1.019	0.861	0.793	0.807	0.735	0.833	0.516	1.279	0.78	0.369	1.092	0.979	1.19	0.92	1.323	0.971	1.292	1.107	0.832	0.532	0.014

Note: Green cells represent the instance in which an industry in a country is oversized compared to the share of this industry in the world economy. A value lower than 1 means that the industry is undersized compared to the share of this industry in the world economy. The industry code used in this table are the one displayed in B.1.

Table B.3: Post-Socialist countries' Revealed Industry Specialization, in 2010

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	
2010																											
DEU	0.371	0.04	0.163	0.716	0.385	1.105	0.953	1.322	1.193	2.112	0.689	0.415	0.834	0.673	0.344	1.063	0.951	0.535	0.934	0.761	1.09	0.795	1.172	0.003	0.179	5.923	
RUS	1.754	3.393	1.474	1.355	0.38	0.769	1.48	1.587	0.864	0.014	1.186	1.945	1.06	1.128	0.811	1.407	2.883	0.015	1.833	0.012	0.522	0.302	0.89	0	0.001	0.025	
BGR	1.308	0.405	0.509	0.814	1.341	1.046	0.89	0.912	0.932	0.698	0.885	0.866	1.429	1.105	0.398	1.518	0.814	1.156	0.946	1.643	1.016	1.131	0.9	0.79	0.457	0.011	
HRV	0.984	0.521	0.417	0.721	0.804	1.097	0.821	0.587	0.863	0.733	0.938	0.686	1.439	1.398	0.383	1.672	0.888	1.354	0.888	1.303	0.984	0.984	1.626	1.1	0.809	0.379	0.008
CZE	0.903	0.11	0.531	1.097	1.291	1.483	1.11	1.428	1.345	1.699	1.332	0.748	1.745	1.267	3.124	1.099	0.469	0.682	1.255	0.697	0.706	0.628	0.674	0.04	0.449	0.01	
EST	1.307	0.879	0.442	1.228	1.922	2.439	0.471	0.54	0.769	0.365	1.766	0.069	1.378	1.159	2.932	1.437	0.847	0.735	2.551	1.143	0.777	0.901	0.806	0.148	0.383	1.492	
HUN	1.48	0.054	0.18	1.487	1.282	1.167	0.918	0.811	1.725	1.391	0.739	0.227	1.231	0.798	2.825	1.061	0.865	0.715	0.953	0.934	0.794	0.897	0.868	0.005	0.92	1.384	
LVA	1.806	1.162	0.307	1.875	1.717	2.157	0.322	0.545	0.32	0.204	0.589	0.355	1.763	1.354	3.825	2.013	1.631	0.776	2.186	1.301	0.526	0.981	0.961	0.115	0.772	0.157	
LTU	1.437	0.495	0.324	2.014	2.523	1.572	0.948	0.222	0.392	0.166	1.108	0.992	1.508	0.959	3.476	1.507	1.642	0.546	1.503	1.014	0.477	1.145	0.908	0.449	1.348	7.878	
POL	1.657	0.159	0.779	1.627	0.895	1.477	0.798	0.916	0.512	0.87	1.071	0.244	1.347	1.455	4.804	1.459	1.341	0.558	1.081	0.834	0.802	0.814	0.831	2.492	0.652	1.024	
ROU	3.525	0.045	1.065	2.322	1.711	0.979	0.805	0.928	0.414	0.614	1.072	0.044	2.4	1.004	0.618	1.095	0.676	0.798	1.326	1.118	0.532	0.735	0.851	0.006	0.001	3.428	
SVK	1.369	0.01	0.251	1.156	0.938	1.457	1.063	1.403	0.818	1.706	0.741	0.321	2.989	1.259	1.63	1.184	0.939	0.575	1.437	0.712	0.652	0.872	0.653	0.009	0.294	0.005	
SVN	0.786	0.052	0.284	0.981	1.855	1.892	0.833	1.497	1.086	1.135	1.376	0.58	0.857	1.387	3.496	1.068	1.139	1.023	1.048	0.737	0.709	0.906	0.961	0.099	0.479	0.2	
ARM	2.833	0.412	1.1	0.826	0.331	0.589	0.438	0.495	0.593	0.431	0.652	1.602	1.514	2.529	0.458	1.198	1.104	0.604	0.89	1.455	0.949	1.034	1.018	0.955	0.163	0.105	
AZE	1.318	0.499	1.764	0.704	0.328	0.699	0.587	0.396	0.629	0.525	0.718	0.416	1.278	1.209	0.412	1.289	1.097	1.179	0.897	1.558	1.29	1.464	1.104	1.109	0.461	0.029	
BLR	0.765	2.14	0.78	1.128	4.8	2.236	2.131	1.704	1.913	0.35	1.349	4.319	0.619	0.291	1.473	0.878	2.027	0.411	0.815	0.569	0.219	0.201	0.206	4.065	2.79	1.464	
GEO	3.412	0.217	0.864	2.526	0.385	0.793	0.739	0.776	0.372	0.537	0.227	0.298	1.108	1.424	0.355	0.327	1.429	0.823	1.781	1.262	0.502	1.7	0.809	0.444	2.99	0.093	
KAZ	4.877	10.269	5.098	2.304	3.179	0.255	0.697	1.372	0.351	0.065	0.782	0.565	1.007	1.337	0.131	0.227	0.464	0.026	1.883	0.66	0.391	0.137	0.483	0.08	4.094	0.01	
KGZ	10.386	0.048	2.502	1.966	2.092	0.337	0.566	1.188	0.205	0.481	0.544	0.714	1.902	0.867	0.022	0.038	0.078	0.25	1.046	0.448	0.304	1.098	0.73	0.009	0.479	0.111	
MDA	2.077	9.517	1.295	1.942	3.427	1.283	0.453	1.114	0.604	0.76	2.451	8.507	1.343	0.667	4.822	1.11	0.708	1.223	0.983	1.407	0.363	0.794	0.529	17.96	2.387	2.518	
TJK	1.499	0.785	0.365	0.865	0.832	1.023	0.79	0.672	0.784	0.77	0.767	1.129	0.579	0.585	0.53	1.148	1.023	1.155	0.911	1.581	1.507	0.866	1.044	1.483	0.369	0.099	
TKM	0.722	0.616	1.84	0.76	0.789	0.955	0.74	0.54	0.811	0.793	0.946	0.862	0.582	0.925	0.498	1.157	0.957	1.183	0.92	1.562	1.328	1.198	1.116	1.415	0.494	0.085	
UKR	3.073	6.454	3.042	1.979	2.185	0.363	0.761	1.59	0.858	0.19	1.265	1.135	2.723	0.381	0.516	0.895	1.835	0.02	1.354	0.637	0.528	0.1	0.491	0.101	5.214	0.004	
UZB	5.214	12.019	0.582	2.552	7.625	0.166	0.666	0.472	0.322	0.031	1.188	0.975	0.786	1.608	0.163	0.283	0.581	0.025	1.104	0.531	0.385	0.171	0.815	0.095	4.899	0.023	
ALB	1.329	0.766	0.646	0.667	0.711	0.675	0.457	0.355	0.585	0.476	0.779	0.288	0.937	2.257	0.498	1.448	1.2	1.561	1.23	1.357	1.03	1.41	1.064	1.321	0.373	0.059	
BIH	1.624	0.746	0.747	0.784	1.033	1.01	0.616	0.542	0.75	0.673	0.86	0.869	1.367	0.982	0.439	1.3	1.043	1.35	0.959	1.243	1.05	1.714	1.182	1.173	0.393	0.035	
MKD	3.582	0.084	1.063	1.616	2.314	0.683	0.717	1.232	0.199	0.131	0.306	0.629	1.329	1.37	7.842	0.989	1.12	0.902	1.286	1.621	0.586	1.232	0.693	0.232	0.185	0.227	
MNE	1.321	1.539	0.819	0.791	0.38	0.764	0.433	0.385	0.492	0.549	0.909	1.855	1.374	1.128	1.004	2.101	1.175	1.858	1.097	1.664	0.976	1.646	1.196	2.67	0.739	0.287	
SRB	1.677	0.997	0.593	0.867	0.4	1.033	0.697	0.576	0.743	0.701	0.883	0.846	2.194	0.874	0.579	1.394	1.13	1.433	0.834	1.334	1.008	1.443	1.18	1.396	0.545	0.025	

Note: Green cells represent the instance in which an industry in a country is oversized compared to the share of this industry in the world economy. A value lower than 1 means that the industry is undersized compared to the share of this industry in the world economy. The industry code used in this table are the one displayed in B.1.

Table B.4: Pearson correlation between RIS list, by country and by decades

		1990-2000	2000-2010	2010-2021	1990-2021
Ref.	Germany	0.960926	0.992983	0.99667	0.948841
	Russia	0.801894	0.960613	0.989908	0.719777
EU-affiliated countries	Bulgaria	0.644795	0.625241	0.886083	0.715381
	Croatia	0.776287	0.794481	0.924051	0.742583
	Czechia	0.891687	0.969221	0.962286	0.892898
	Estonia	0.837244	0.961129	0.969801	0.824105
	Hungary	0.797228	0.973215	0.975143	0.791249
	Latvia	0.897808	0.97411	0.979346	0.839177
	Lithuania	0.967799	0.990804	0.988805	0.966222
	Poland	0.900543	0.980769	0.969928	0.901487
	Romania	0.89955	0.983868	0.942084	0.868961
	Slovakia	0.837806	0.98186	0.9845	0.853888
	Slovenia	0.89419	0.974432	0.977376	0.920255
CIS-affiliated countries	Armenia	0.240962	0.740661	0.721913	0.013195
	Azerbaijan	0.713465	0.856748	0.674139	0.645157
	Belarus	0.111503	0.803744	0.216794	-0.09086
	Georgia	0.825191	0.947134	0.958294	0.782955
	Kazakhstan	0.838534	0.995706	0.976284	0.7534
	Kyrgyzstan	0.945678	0.981005	0.997542	0.894259
	Moldova	0.778086	0.837175	0.897455	0.797168
	Tajikistan	0.415704	0.617569	0.815482	0.343606
	Turkmenistan	0.953686	0.997742	0.984702	0.907455
Western Balkans	Ukraine	0.779909	0.869922	0.696285	0.690615
	Uzbekistan	0.901486	0.944536	0.912628	0.675159
	Albania	0.750295	0.864345	0.703964	0.729604
	Bosnia and H	0.764469	0.785971	0.883705	0.430609
	Montenegro	0.943817	0.976816	0.988685	0.963377
	N. Macedonia	0.841501	0.783586	0.809129	0.523171
	Serbia	0.405942	0.735931	0.804085	0.321379

Table B.5: Average contribution of a domestic sector to the total input of other domestic sectors, in 1990

	1990	Agriculture and Fishing	Manufacture	Mining and Energy	Service
Ref:	Germany	0.014	0.214	0.039	0.373
	Russia	0.033	0.31	0.015	0.141
EU affiliated countries	Bulgaria	0.015	0.087	0.029	0.175
	Croatia	0.017	0.109	0.028	0.241
	Czechia	0.017	0.157	0.036	0.205
	Estonia	0.041	0.171	0.039	0.19
	Hungary	0.035	0.309	0.037	0.248
	Latvia	0.027	0.116	0.024	0.252
	Lithuania	0.021	0.135	0.024	0.23
	Poland	0.033	0.179	0.062	0.374
	Romania	0.056	0.197	0.083	0.194
	Slovakia	0.008	0.182	0.033	0.138
	Slovenia	0.014	0.192	0.023	0.22
CIS affiliated countries	Armenia	0	0	0	0
	Azerbaijan	0.013	0.191	0.027	0.146
	Belarus	0.036	0.022	0.03	0.197
	Georgia	0.086	0.104	0.08	0.3
	Kazakhstan	0.082	0.39	0.05	0.142
	Kyrgyzstan	0.075	0.167	0.09	0.104
	Moldova	0.071	0.022	0.007	0.078
	Tajikistan	0.022	0.222	0.037	0.339
	Turkmenistan	0.02	0.245	0.014	0.31
	Ukraine	0.065	0.304	0.046	0.106
	Uzbekistan	0.116	0.302	0.055	0.143
Western Balkan	Albania	0.071	0.099	0.052	0.176
	Bosnia and H.	0.033	0.131	0.046	0.319
	Montenegro	0.057	0.104	0.054	0.26
	N. Macedonia	0.071	0.14	0.052	0.178
	Serbia	0.036	0.105	0.04	0.222

Table B.6: Average contribution of a domestic sector to the total input of other domestic sectors, in 2000

	2000	Agriculture and Fishing	Manufacture	Mining and Energy	Service
Ref:	Germany	0.01	0.175	0.026	0.425
	Russia	0.024	0.379	0.035	0.256
EU countries	Bulgaria	0.01	0.127	0.026	0.353
	Croatia	0.016	0.124	0.027	0.319
	Czechia	0.014	0.152	0.032	0.18
	Estonia	0.031	0.114	0.037	0.263
	Hungary	0.023	0.239	0.032	0.202
	Latvia	0.025	0.109	0.031	0.346
	Lithuania	0.028	0.125	0.029	0.288
	Poland	0.028	0.188	0.057	0.336
	Romania	0.047	0.169	0.078	0.184
	Slovakia	0.012	0.139	0.042	0.166
	Slovenia	0.014	0.169	0.022	0.219
CIS countries	Armenia	0.024	0.112	0.023	0.285
	Azerbaijan	0.014	0.149	0.027	0.298
	Belarus	0.002	0.004	0.038	0.086
	Georgia	0.064	0.112	0.068	0.353
	Kazakhstan	0.083	0.218	0.061	0.092
	Kyrgyzstan	0.065	0.136	0.134	0.128
	Moldova	0.007	0.021	0.016	0.067
	Tajikistan	0.011	0.185	0.038	0.442
	Turkmenistan	0.009	0.215	0.02	0.406
	Ukraine	0.056	0.281	0.053	0.111
	Uzbekistan	0.132	0.333	0.059	0.204
Western Balkan	Albania	0.022	0.124	0.037	0.295
	Bosnia and H.	0.019	0.14	0.032	0.394
	Montenegro	0.031	0.121	0.039	0.318
	Serbia	0.025	0.136	0.033	0.276
	N. Macedonia	0.062	0.159	0.051	0.193

Note: Each cell represents the quantity of output from a specific domestic sector that is used by other sectors within the economy. It is quantified as the average share of that domestic sector's output serving as an input for other domestic sectors.

Table B.7: Average contribution of a domestic sector to the total input of other domestic sectors, in 2010

	2010	Agriculture and Fishing	Manufacture	Mining and Energy	Service
Ref:	Germany	0.006	0.101	0.025	0.325
	Russia	0.024	0.355	0.035	0.264
CEEU countries	Bulgaria	0.011	0.095	0.034	0.289
	Croatia	0.015	0.106	0.03	0.251
	Czechia	0.014	0.135	0.032	0.185
	Estonia	0.031	0.103	0.041	0.257
	Hungary	0.021	0.213	0.032	0.206
	Latvia	0.024	0.095	0.03	0.32
	Lithuania	0.022	0.108	0.027	0.243
	Poland	0.026	0.177	0.054	0.333
	Romania	0.049	0.156	0.074	0.169
	Slovakia	0.011	0.131	0.042	0.16
	Slovenia	0.012	0.143	0.021	0.215
CIS countries	Armenia	0.072	0.063	0.055	0.186
	Azerbaijan	0.03	0.131	0.036	0.375
	Belarus	0.006	0.002	0.016	0.064
	Georgia	0.041	0.131	0.08	0.281
	Kazakhstan	0.108	0.253	0.079	0.12
	Kyrgyzstan	0.066	0.149	0.099	0.119
	Moldova	0.021	0.059	0.015	0.058
	Tajikistan	0.009	0.163	0.018	0.295
	Turkmenistan	0.012	0.243	0.013	0.373
	Ukraine	0.03	0.124	0.105	0.087
	Uzbekistan	0.123	0.33	0.054	0.192
Western Balkan	Albania	0.034	0.084	0.035	0.238
	Bosnia and H.	0.03	0.102	0.039	0.224
	Montenegro	0.051	0.08	0.043	0.177
	Serbia	0.028	0.132	0.039	0.186
	N. Macedonia	0.057	0.163	0.056	0.186

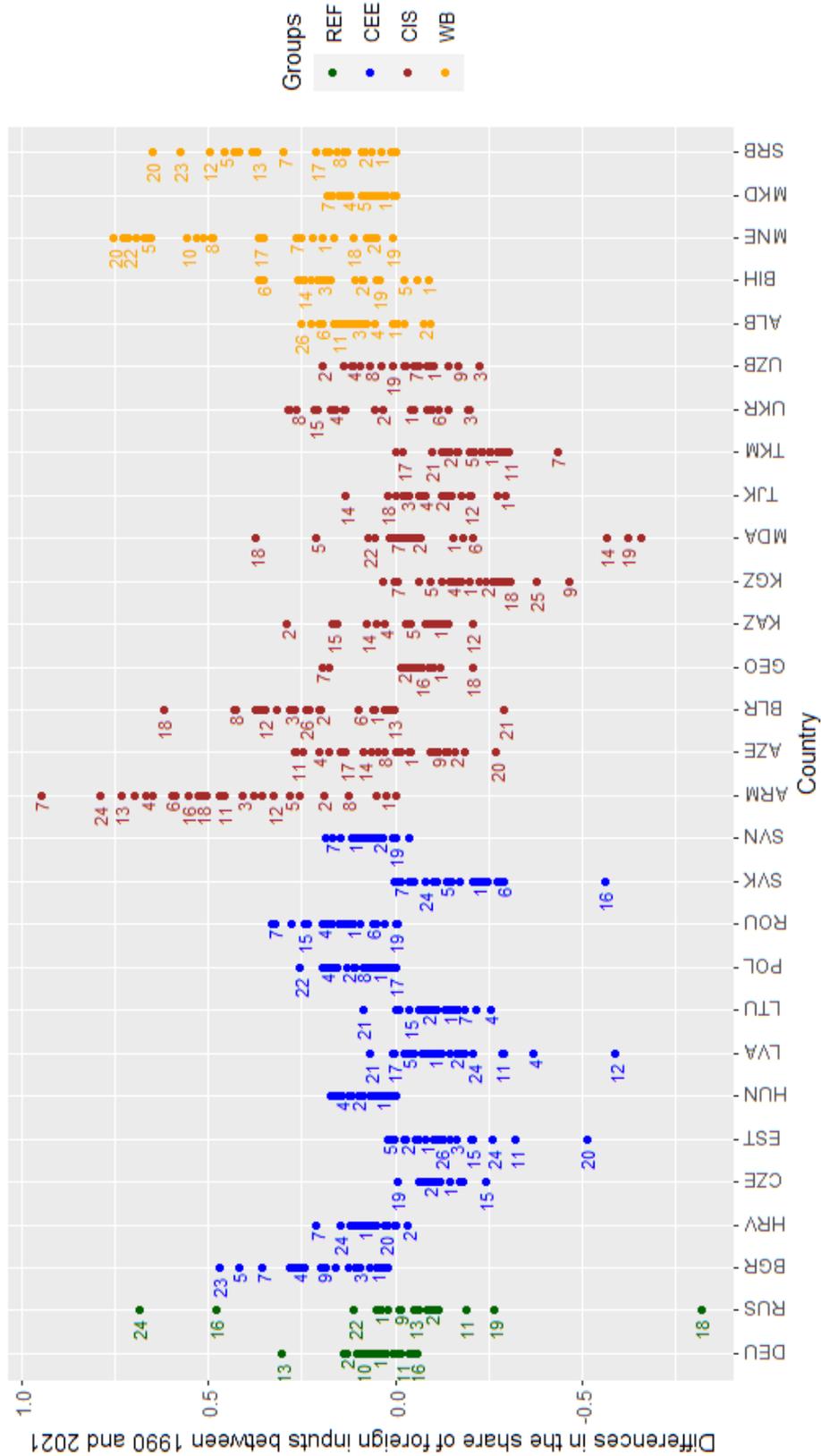
Note: Each cell represents the quantity of output from a specific domestic sector that is used by other sectors within the economy. It is quantified as the average share of that domestic sector's output serving as an input for other domestic sectors.

Table B.8: Average contribution of a domestic sector to the total input of other domestic sectors, in 2021

	2021	Agriculture and Fishing	Manufacture	Mining and Energy	Service
Ref:	Germany	0.005	0.121	0.027	0.293
	Russia	0.024	0.354	0.034	0.265
CEEU countries	Bulgaria	0.007	0.081	0.027	0.267
	Croatia	0.017	0.073	0.036	0.243
	Czechia	0.017	0.217	0.035	0.213
	Estonia	0.031	0.092	0.058	0.305
	Hungary	0.027	0.218	0.034	0.259
	Latvia	0.035	0.076	0.025	0.369
	Lithuania	0.022	0.117	0.027	0.289
	Poland	0.022	0.158	0.048	0.357
	Romania	0.032	0.145	0.073	0.193
	Slovakia	0.013	0.126	0.048	0.186
	Slovenia	0.011	0.118	0.021	0.236
CIS countries	Armenia	0.108	0.046	0.046	0.115
	Azerbaijan	0.026	0.123	0.075	0.3
	Belarus	0.004	0.002	0.009	0.04
	Georgia	0.041	0.155	0.106	0.357
	Kazakhstan	0.103	0.252	0.081	0.112
	Kyrgyzstan	0.06	0.196	0.109	0.203
	Moldova	0.074	0.063	0.029	0.111
	Tajikistan	0.006	0.19	0.02	0.309
	Turkmenistan	0.036	0.212	0.014	0.409
	Ukraine	0.029	0.152	0.051	0.091
	Uzbekistan	0.076	0.295	0.055	0.139
Western Balkan	Albania	0.028	0.082	0.03	0.244
	Bosnia and H.	0.024	0.086	0.032	0.21
	Montenegro	0.036	0.063	0.037	0.125
	Serbia	0.023	0.103	0.043	0.141
	N. Macedonia	0.039	0.143	0.052	0.188

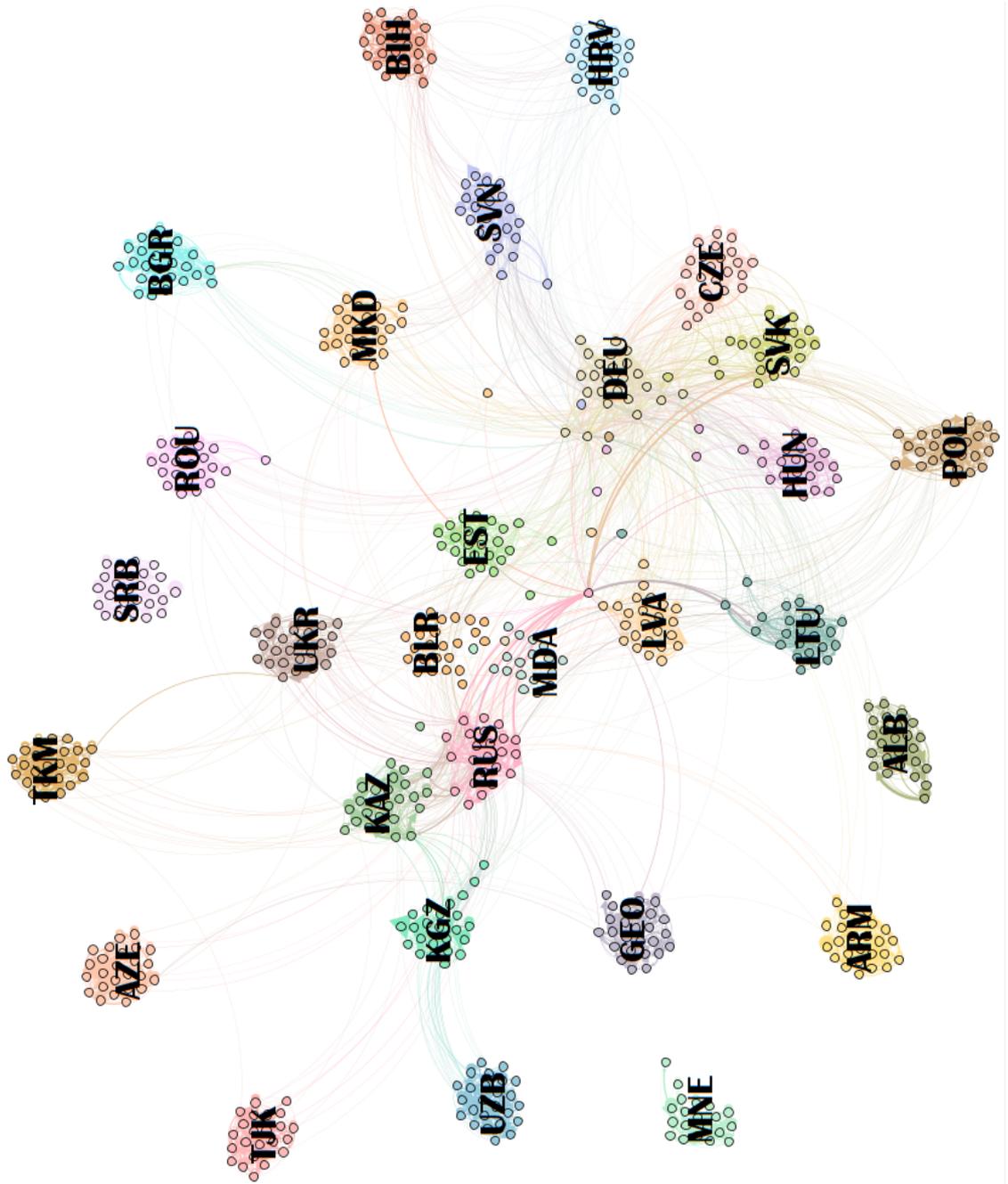
Note: Each cell represents the quantity of output from a specific domestic sector that is used by other sectors within the economy. It is quantified as the average share of that domestic sector's output serving as an input for other domestic sectors.

Figure B.1: Differences in the share of foreign inputs between 1990 and 2021



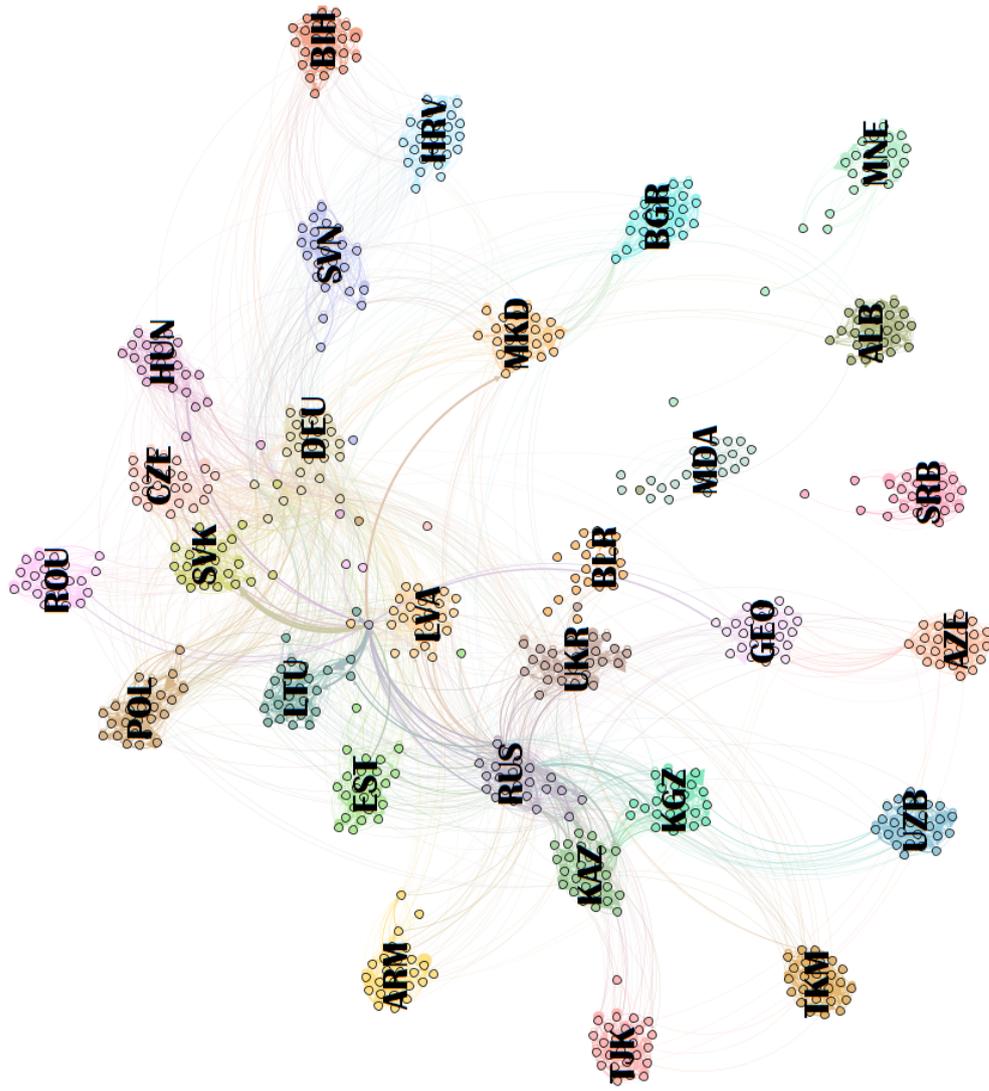
Note: The share of foreign inputs from 1990 has been subtracted from the same share from 2021. If the value of this difference is superior to 0, there is an increase in the share. If its value is inferior 0, there is a decrease in the share.

Figure B.2: The filtered Post-Socialist Production Network, in 2000



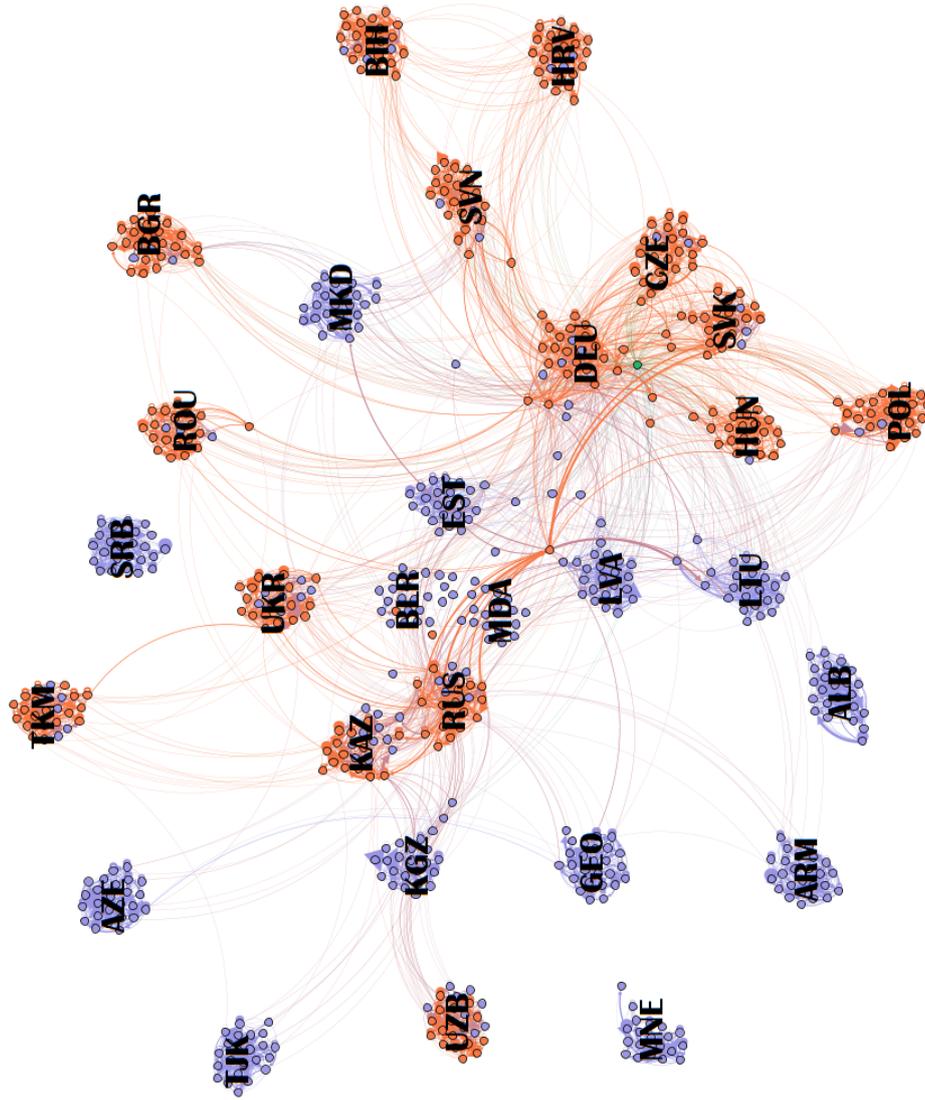
Note: Nodes are CIs belonging to a Post-Socialist country; links represent input shares that exceed the 1% filtering threshold value. Each color corresponds to a country. Network visualization is based on the ForceAtlas force-directed algorithm. Jacomy et al. (2014).

Figure B.3: The filtered Post-Socialist Production Network, in 2010



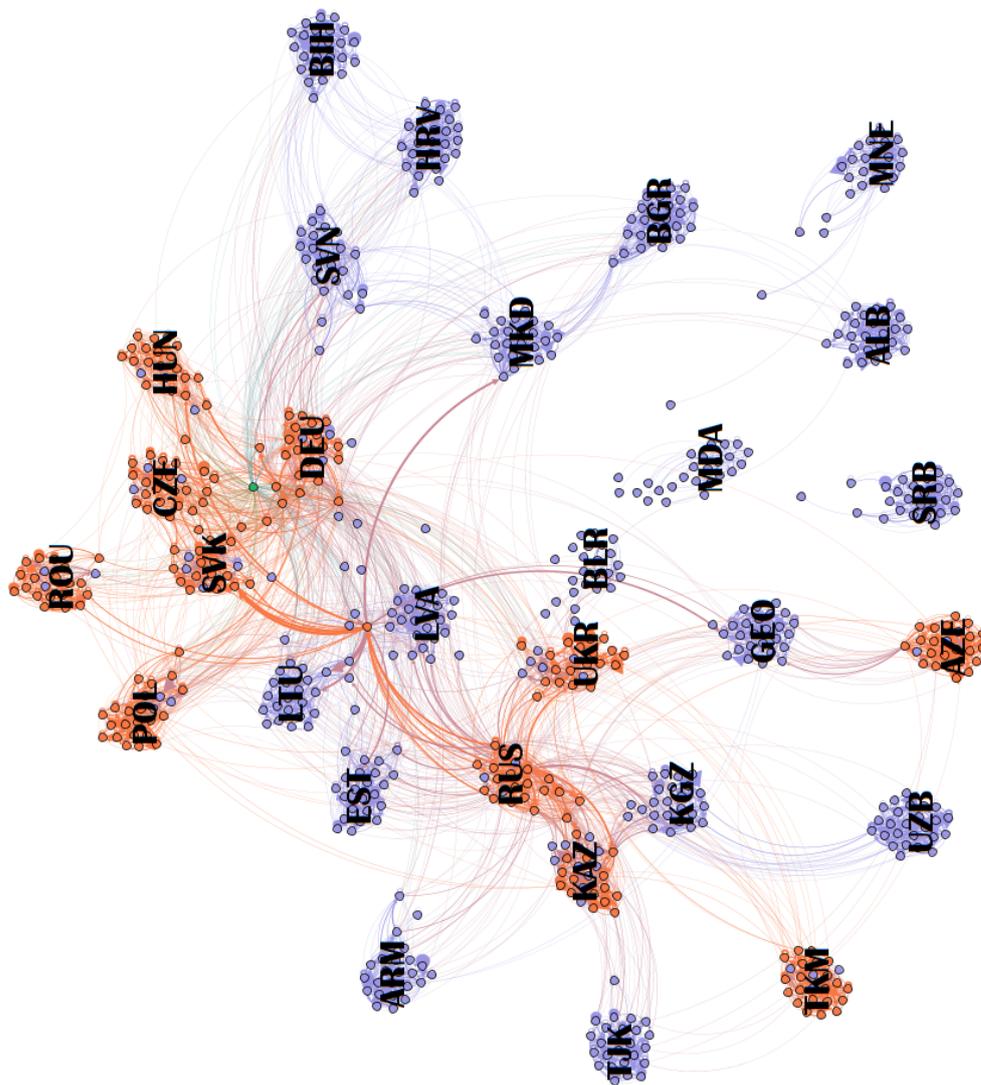
Note: Nodes are CIs belonging to a Post-Socialist country; links represent input shares that exceed the 1% filtering threshold value. Each color corresponds to a country. Network visualization is based on the ForceAtlas force-directed algorithm Jacomy et al. (2014).

Figure B.4: ACS in the filtered Post-Socialist Production Network, in 2000 (1%)



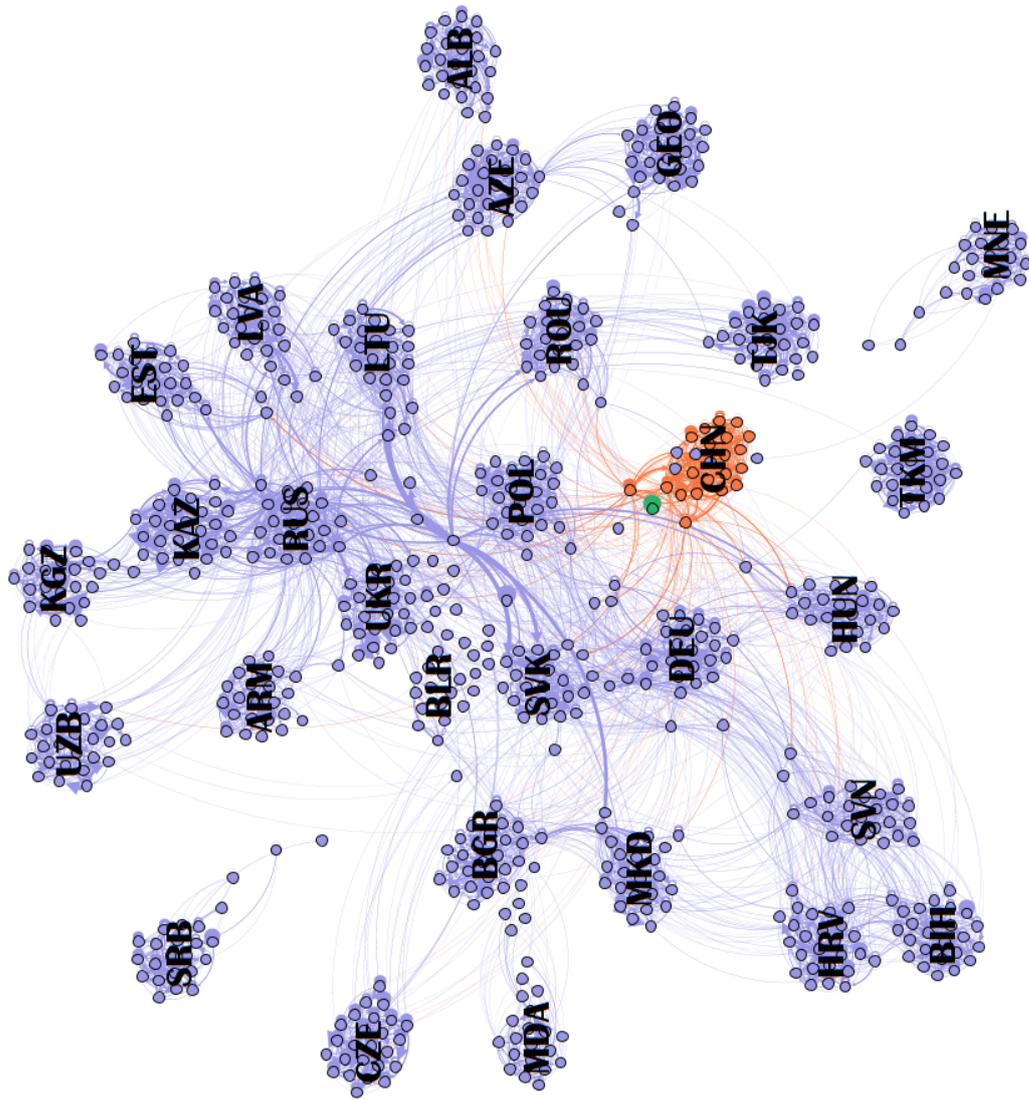
Note: Nodes are CIs belonging to a Post-Socialist country. Links represent input shares that exceed the 1% filtering threshold value. CIs in orange are Core members, CIs in green are Periphery members, and CIs in purple are non-ACS members. Network visualization is based on the ForceAtlas force-directed algorithm Jacomy et al. (2014).

Figure B.5: ACS in the filtered Post-Socialist Production Network, in 2010 (1%)



Note: Nodes are CIs belonging to a Post-Socialist country. Links represent input shares that exceed the 1% filtering threshold value. CIs in orange are Core members, CIs in green are Periphery members, and CIs in purple are non-ACS members. Network visualization is based on the ForceAtlas force-directed algorithm Jacomy et al. (2014).

Figure B.7: ACS in the filtered Post-Socialist Production Network in 2021 with China (1%)



Note: Nodes are CIs belonging to a Post-Socialist country; China is included. Links represent input shares that exceed the 1% filtering threshold value. CIs in orange are Core members, CIs in green are Periphery members, and CIs in purple are non-ACS members. Network visualization is based on the ForceAtlas force-directed algorithm Jacomy et al. (2014).

C Appendix for Chapter 4

C.1 Additional Tables

Table C.1: Number of green and non-green goods in each HS92 2-digit category

Sectors	Non-green	Green
Animal & Animal Products	194	0
Chemicals & Allied Industries	759	1
Foodstuffs	181	0
Footwear / Headgear	55	0
Machinery / Electrical	659	105
Metals	563	25
Mineral Products	151	0
Miscellaneous	338	49
Plastics / Rubbers	182	7
Raw Hides, Skins, Leather, & Furs	74	0
Stone / Glass	176	12
Textiles	800	9
Transportation	95	37
Vegetable Products	323	0
Wood & Wood Products	225	3

Table C.2: Variable list

Variable name	Type	Definition	Source
$Export_{c,p,t}$	Continuous	Value of export of the product (p) by country (c) at time (t)	BACI database
$ACSlocal_{c,p,t}$	Binary	Dummy variable indicating whether a product (p) is part of the local ACS of the country (c) at time (t)	Calculation of the authors
$Corelocal_{c,p,t}$	Binary	Dummy variable showing if a product is in the core of the local ACS of the country (c) at time (t)	Calculation of the authors
$Perilocal_{c,p,t}$	Binary	Dummy variable showing if a product is in the periphery of the local ACS of the country (c) at time (t)	Calculation of the authors
$Maxprox_{c,p,t}$	Continuous	Proximity between a given product (p) and the nearest product exported by the same country (c) at time (t)	Calculation of the authors
$Green_p$	Binary	Dummy variable equal to 1 if the product is "green" and 0 otherwise.	CLEG
$Neighborprox_{c,p,t}$	Continuous	Average proximity at time (t) between a given product (p) and all the other goods exported by the geographical neighbors of the country (c)	Calculation of the authors
$Sophistication_{p,t}$	Continuous	Measure of a product sophistication based on Fitness-complexity method by Tacchella et al. (2013)	Calculation of the authors
$Realgdp_{c,t}$	Continuous	GDP PPP of the country (c) at time (t)	CHELEM database
$pop_{c,p,t}$	Continuous	Population of the country (c) at time (t).	CHELEM database
$RCA_{c,p,t}$	Continuous	RCA of the country (c) in the production of the product (p) at the time (t)	Calculation of the authors

Note: The proximity matrices are based on the proximity network introduced by Hausmann and Kingger (2006) see Appendix C.2.1

C.2 Formula

C.2.1 Hausmann's Undirected Product Space

The Product Space, as introduced by Hausmann and Klinger (2006), is a network representation of the set of products exported by different countries. Each product is a node in the network, and the edges between nodes represent the probability of two goods being exported by the same country, or in other words, the conditional probability that, given a country exports one product, it also exports the other.

The proximity measure between two products p and p' , based on the $M_{c,p}$, is then computed as the minimum of the conditional probabilities that, given a country has comparative advantage in product p , it also has a comparative advantage in product p' , and vice versa.

$$\phi_{pp'} = \min \left\{ \frac{\sum_c M_{cp} M_{cp'}}{\sum_c M_{cp}}, \frac{\sum_c M_{cp} M_{cp'}}{\sum_c M_{cp'}} \right\} \quad (\text{S1})$$

The higher is the value of $\phi_{pp'}$ the higher is the probability of p and p' to be co-exported. Based on the probability of co-exportation of a good, the proximity index serves as a proxy for the similarity in terms of capability requirements between two products.

C.2.2 Sophistication Index

The Sophistication Index originating from Tacchella et al. (2013), serves as a measure of sophistication for both products and countries. The product sophistication serves as a proxy for the diversity of capabilities required for producing a given good. This complexity requires advanced technologies, specialized skills, infrastructure, or an advanced division of labor.

Similarly, country sophistication measures a country's ability to export sophisticated products. This ability is correlated with the country's technological advancement and division of labor, as it demonstrates that the country has a large set of capabilities that it can combine to produce complex goods.

The Sophistication Index, therefore, is a valuable tool for measuring a country's comparative advantage and potential for economic growth. For a detailed explanation of the Sophistication Index, see (Tacchella et al., 2013).

$$\begin{cases} \tilde{F}_c^n = \sum_p M_{cp} Q_{cp}^{(n-1)} \\ \tilde{Q}_p^n = \frac{1}{\sum_c M_{cp} \frac{1}{F_{cp}^{(n-1)}}} \end{cases} \quad (\text{S2})$$

$$\begin{cases} F_c^n = \frac{\tilde{F}_c^n}{\langle \tilde{F}_c^n \rangle} \\ Q_p^n = \frac{\tilde{Q}_p^n}{\langle \tilde{Q}_p^n \rangle} \end{cases} \quad (\text{S3})$$

The Fitness-Complexity algorithm proposed by Tacchella et al. is an iterative method that quantifies the sophistication of countries and the complexity of products.

Here's a breakdown of the symbols in the equation:

- F_c^n : The sophistication of country c at the n -th iteration of the algorithm.
- Q_p^n : The complexity of product p at the n -th iteration of the algorithm.
- M_{cp} : A binary matrix where $M_{cp} = 1$ if country c has a revealed comparative advantage (RCA) in product p , and $M_{cp} = 0$ otherwise.
- \tilde{F}_c^n and \tilde{Q}_p^n : The raw (unnormalized) sophistication of country c and complexity of product p at the n -th iteration.
- $\langle \tilde{F}_c^n \rangle$ and $\langle \tilde{Q}_p^n \rangle$: The average raw sophistication and complexity across all countries and products, respectively, at the n -th iteration.

The algorithm operates as follows:

1. In the first set of equations, \tilde{F}_c^n is computed as the sum of the complexities of the products that country c has an RCA in, and \tilde{Q}_p^n is the reciprocal of the sum of reciprocals of the sophistications of the countries that have an RCA in product p .
2. In the second set of equations, the raw sophistication and complexity values are normalized by dividing each by their respective averages, to get F_c^n and Q_p^n .
3. This process is iterated until the values of F_c^n and Q_p^n diverge.

The intuition behind this algorithm is to calculate the sophistication of a country by looking at the complexities of the products it exports, and to estimate the complexity of a product by considering the sophistication of the countries that export it. A high sophistication score indicates that a country can produce a

diverse set of complex products, while a high complexity score suggests that a product is made by a small number of highly fit countries.

C.2.3 PRODY index

The PRODY index is designed as a proxy to estimate the level of economic development, or more specifically, the GDP per capita, at which a particular good emerges within a country’s export basket (Hausmann et al., 2007). It achieves this by calculating the weighted average GDP per capita of all countries that export the said product. The weights are determined based on each country’s Revealed Comparative Advantage (RCA), a concept introduced by Balassa (1965), which is a measure of a country’s relative advantage or disadvantage in exporting certain goods.

In essence, the PRODY indicator provides insights into the economic sophistication of a product in the global market. A high PRODY value suggests that the product is primarily exported by countries with high GDP per capita, implying that the production of such goods might require advanced technologies, high-level skills, or substantial infrastructure that are typically found in more developed economies. Conversely, a lower PRODY value may be associated with products exported by less developed countries, potentially reflecting goods that require less complex capabilities for their production.

$$PRODY_k = \sum_j \frac{(x_{jk}/X_j)}{\sum_j (x_{jk}/X_j)} Y_j \quad (S4)$$

It computes the expected income level or GDP per capita associated with a particular product, k . j denotes a specific country in the set of all countries. x_{jk} is the export value of product k by country j . X_j is the total export value of country j . Y_j is the GDP per capita of country j . The weight assigned to each country’s GDP per capita (Y_j) in calculating the PRODY value is the Revealed Comparative Advantage (RCA) of country j in exporting product k .

The intuition behind this formula is to give more weight to the GDP per capita of countries that have a higher RCA in the particular product. The PRODY indicator, therefore, reflects the income level of the countries that are relatively more successful or competitive in exporting product k .

C.3 Network analysis

Table C.3: Network metrics of the Directed Product Space

Years	1995-1997	2001-2003	2011-2013	2017-2019
Edge	25094	28615	26244	22210
Node	2821	3054	2933	2641
Product	5015	5003	4878	4647
Average out-degree	5.004	5.72	5.38	4.779
Average shortest path	3.922	4	4.122	4.123
Maximum degree	246	250	275	268
Maximum out-degree	131	133	138	142
Maximum in-degree	118	123	137	126
Diameter	12	11	12	11
Completeness	0.001	0.001	0.001	0.001
Reciprocity	0.146	0.171	0.192	0.186
Average clustering coeff	0.175	0.185	0.192	0.181
Assortativity in degree	0.256	0.231	0.258	0.26

In this section of the appendix, we provide a network analysis of the general structure of the Product Space. The general structure of the network yields important information on the dynamics of the network and the prospects for diversification for a country.

Table C.3 presents the general characteristics of the Product Spaces for a few specific periods that are representative of the period studied: (1995-1997), (2001-2003), (2011-2013), and (2017-2019). Comparing the number of nodes in the network with the number of products within BACI shows that half of the products are scattered nodes without significant links.

Since the Product Space is a network, its structure can be analyzed through standard network analysis. Our analysis includes the following network metrics: average out-degree, average shortest path, maximum degree, diameter, completeness, reciprocity, average clustering coefficient, and assortativity.

A link represents the number of catalyzing relationships in the network. If the catalyzation is reciprocal, it will be considered as two separate links. The probability

of a catalyzing effect being reciprocal is between 14% and 19%. Nodes correspond to the number of products that are connected to at least one other node.

Using a 0.1% significance level, only around 22210 to 28615 links remain. The completeness index, which is the ratio between the number of links and the total possible number of links, is 0.001 and remains the same throughout the period. This level of completeness indicates that the network is sparse.

The number of edges follows two trends: an increase during the first two periods from 25094 in the period 1995-1997 to 28615 in the period 2001-2003, followed by a decrease to 22210 in the period 2017-2019. This suggests that the network initially increased the number of catalytic relationships and then decreased them in the last two periods. This trend aligns with the evolution of the total number of connected products in the network.

The average out-degree represents the mean count of outgoing links from each node, equating to the average number of different products that a given product catalyzes. On average, a product catalyzes 4 to 6 goods. However, the number of catalyzed goods can vary significantly. The maximum out-degree refers to the node with the highest degree of connectivity; in this network, that value is 142 goods.

While many links have been filtered, the average clustering coefficient, which is the probability of two neighbors of a node also being connected, ranges between 10% and 20% depending on the year. This suggests that some nodes have few or no outgoing links, while others are in a dense region of the network. Both the reciprocity rate and the clustering coefficient indicate that multiple feedback loop effects can occur due to the network's clustered structure.

The assortativity in degree, which is the likelihood of a node being connected to another node with a similar number of connections, shows that goods with multiple connections are more likely to connect with other highly connected nodes. Negative assortativity implies that more connected nodes are likely to connect with nodes that have fewer connections.

Both the average shortest path and the network's diameter¹ indicate that relatively few steps of catalyzed products are needed to connect all the connected products in the network. Overall, the network appears to be relatively stable over time, with

¹The diameter of a network is the longest shortest possible path in the network.

similar measures for most of the analyzed features across the four time periods.

C.4 Comparing green and non-green Centrality in the Directed Product Space

We continue our analysis by comparing the relative importance of green goods in the network. Table C.4 provides a comparison of network centrality statistics for green and non-green nodes. We will interpret these centrality scores and discuss their economic implications for the development of green products as well as their impact on further diversification.

Table C.4: T-test comparing the average centrality between green and non-green goods

Average centrality	Non-green product	Green product	P-value	
In-degree	8.48	6.85	0.09	*
Out-degree	8.56	5.28	5.29e-05	***
Betweenness	3365.41	2016.23	0.004	***
Closeness	0.35	0.28	0.001	***
Eigenvector (upstream)	0.03	0.008	9.21e-17	***
PageRank (upstream)	0.0003	0.0002	3.00e-11	***
Eigenvector (downstream)	0.04	0.02	0.04	**
PageRank (downstream)	0.0003	0.0002	2.25e-06	***

*Note: 128 green products and 2513 non-green products between 2017 and 2019. Only the nodes connected within the network is considered in this analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.*

First, the out-degree centrality measures the number of outgoing connections from a node in a network, indicating the number of products catalyzed by a given product. Non-green goods have higher out-degree centrality on average, playing a significant role in the diversification process. Conversely, the lower average out-degree centrality of green goods signifies fewer diversification opportunities.

When considering indirect connections, similar results are observed. A similar pattern is found in Closeness centrality². Closeness centrality measures the product's average distance to all other reachable goods. On average, non-green goods are

²Corresponding to the inverse of the sum of distances from a node to all other reachable nodes

closer to other goods, indicating better prospects for diversification compared to green goods. However, this can vary considerably from one product to another. Some green goods have higher centrality than some brown goods.

In-degree centrality counts the number of goods that catalyze a specific good. Higher in-degree centrality for non-green goods indicates that they are more likely to be catalyzed by other goods in the network.

Betweenness centrality measures the importance of a node in a network. It quantifies how often a node lies on the shortest path between other nodes. Goods with higher betweenness centrality play a key role in the development process, serving as necessary paths for the adoption of a wide range of products. Non-green products have higher betweenness scores compared to their green counterparts, making them more crucial for the development of new industries.

Eigenvector centrality and PageRank centrality measure the importance of a node based on the centrality of its neighbors. These measures assign relative scores to all nodes in the network, considering not only the number of connections but also the importance of connected nodes. The main difference between the two is that PageRank centrality includes a dampening factor that reduces the influence of distant nodes.

Upstream eigenvector centrality and upstream PageRank centrality gauge the importance of nodes based on the importance of their catalyzing goods. Higher scores indicate that these goods are more likely to be catalyzed due to the network structure. The difference in average upstream centrality measures shows that non-green goods are catalyzed by more important nodes. Reciprocally, downstream eigenvector centrality and downstream PageRank centrality measure the importance of green goods based on the centrality of the goods they catalyze. The difference in average downstream centrality measures shows that non-green goods are more likely to catalyze important goods in the long run.

The network centrality measures illustrate two key aspects of green goods' position in the Directed Product Space. First, green goods offer fewer diversification opportunities on average compared to non-green counterparts. This presents a trade-off for resource-limited countries when selecting industries for investment. Second, green goods are less frequently catalyzed within the Directed Product Space, indicating challenges to their incorporation into existing industry frameworks or supply

chains.

C.5 BRICS countries position in the Directed Product Space

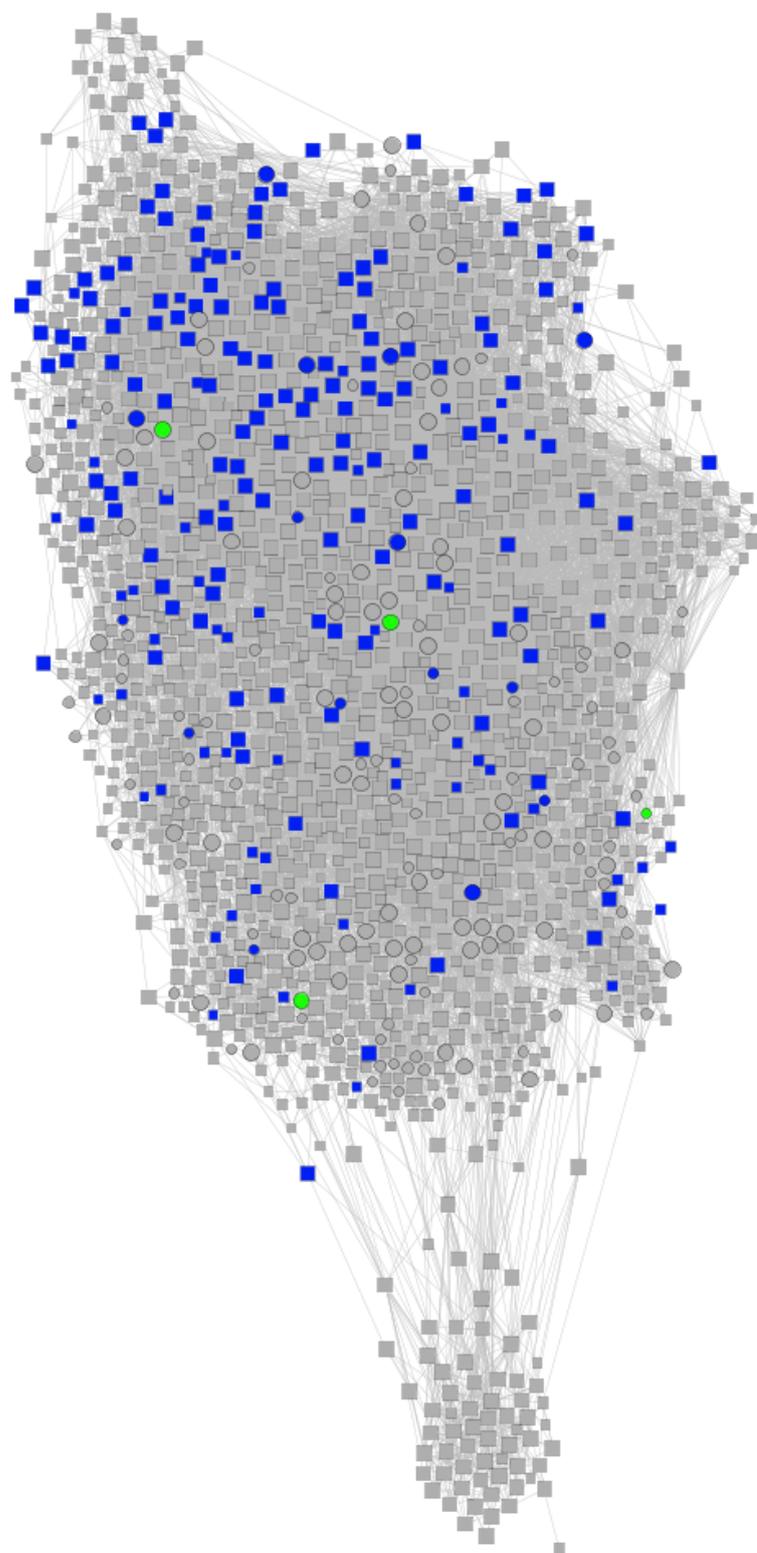
In line with previous findings on the Product Space, each country's position within the Directed Product Space highlights its industrial specialization.

Starting with Russia, two patterns describe its position within the Directed Product Space. The first pattern comprises isolated nodes, and the second consists of nodes concentrated into a cluster. These clustered nodes receive stronger positive feedback loops than the isolated nodes, reinforcing Russia's specialization and its position in the exportation of extractive industries. This reinforcing pattern also increases the likelihood of developing green goods related to its specialization. For the years 2017-2019, only two green products are displayed in the network.

India is a highly diversified country with a diverse array of goods, giving it a strong advantage in catalyzing a diverse range of green goods. China bears similarities to India, having a large variety of exports which affords it the ability to diversify toward many green goods. However, its specialization in normal goods differs, with a tendency toward more complex goods.

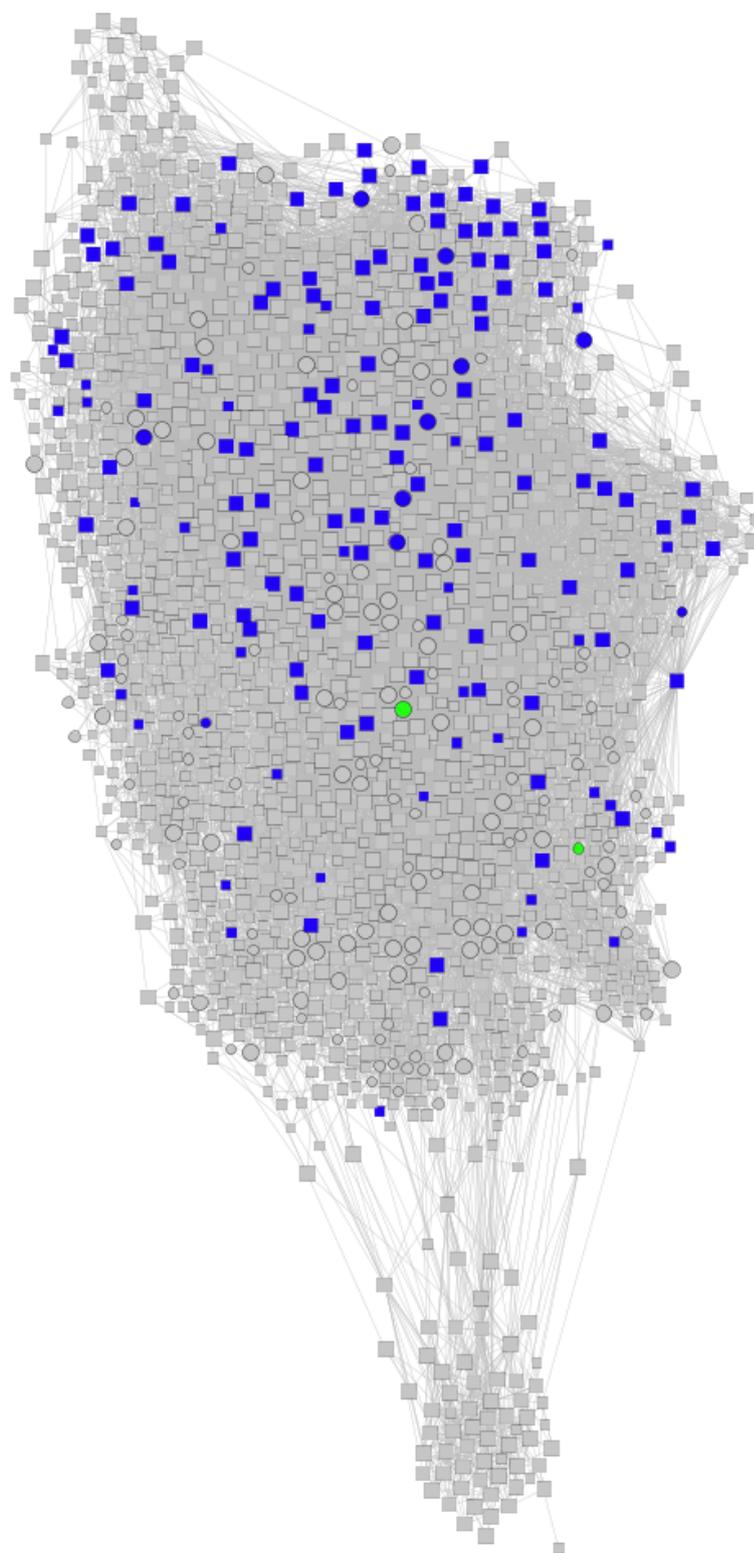
In comparison to other BRICS countries, the goods exported from Brazil are scattered in the network. This scattering can reduce the number of positive feedback loops that reinforce the production of goods, especially green goods. South Africa's position in the ACS resembles that of Russia, featuring both unconnected nodes in the ACS and a group of nodes organized into clusters.

Figure C.1: Brazilian Product Space and Autocatalytic Set



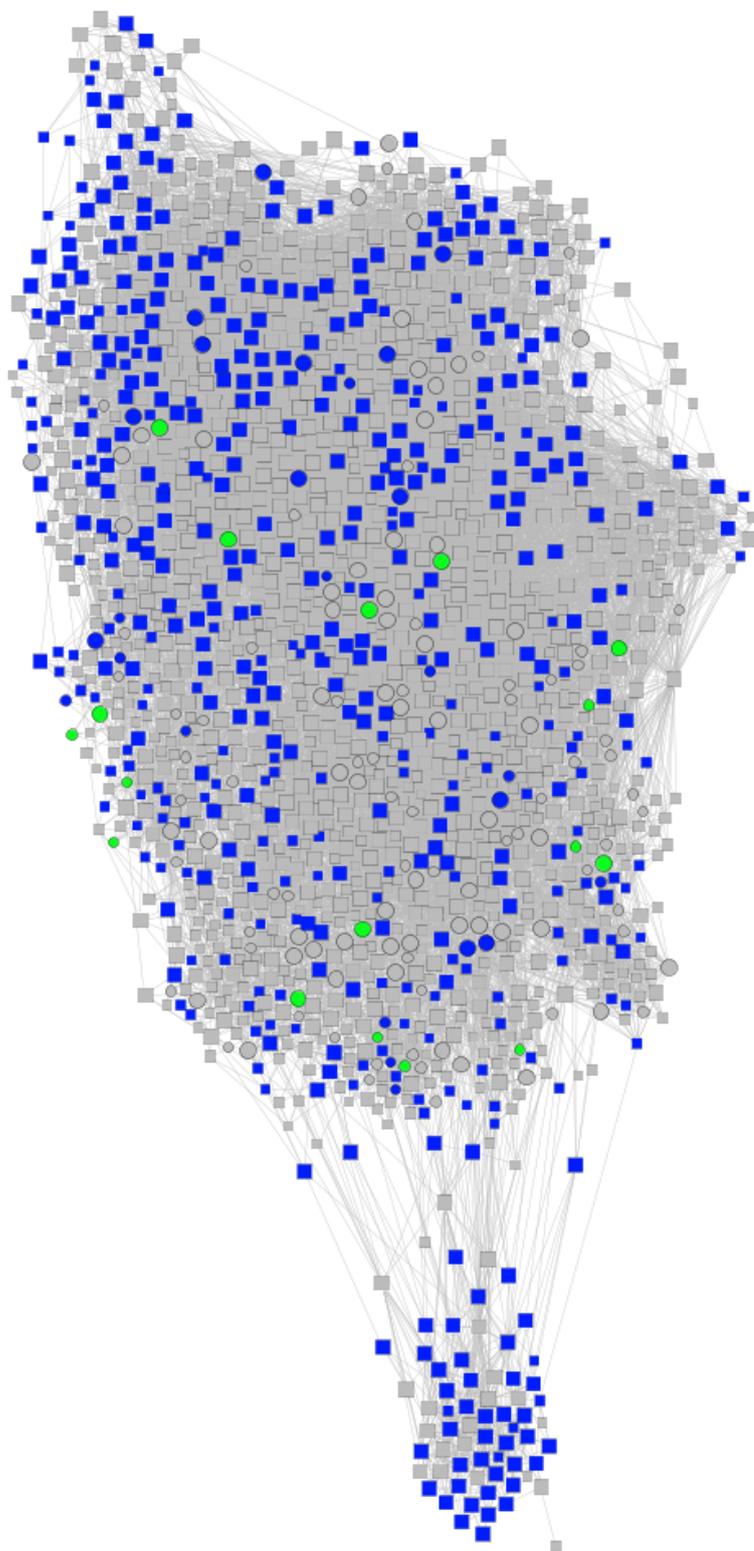
Note: We model the Brazilian Product Space as a network in which nodes represent products exported by Brazil with an $RCA > 1$, and links signify catalytic relations as represented in the Global Product Space. On this network, we apply the ACS detection algorithm to model the Brazilian Autocatalytic Set. Blue = Non-green products, Green = Green products, Gray = Products exported with an $RCA < 1$.

Figure C.2: Russian Product Space and Autocatalytic Set



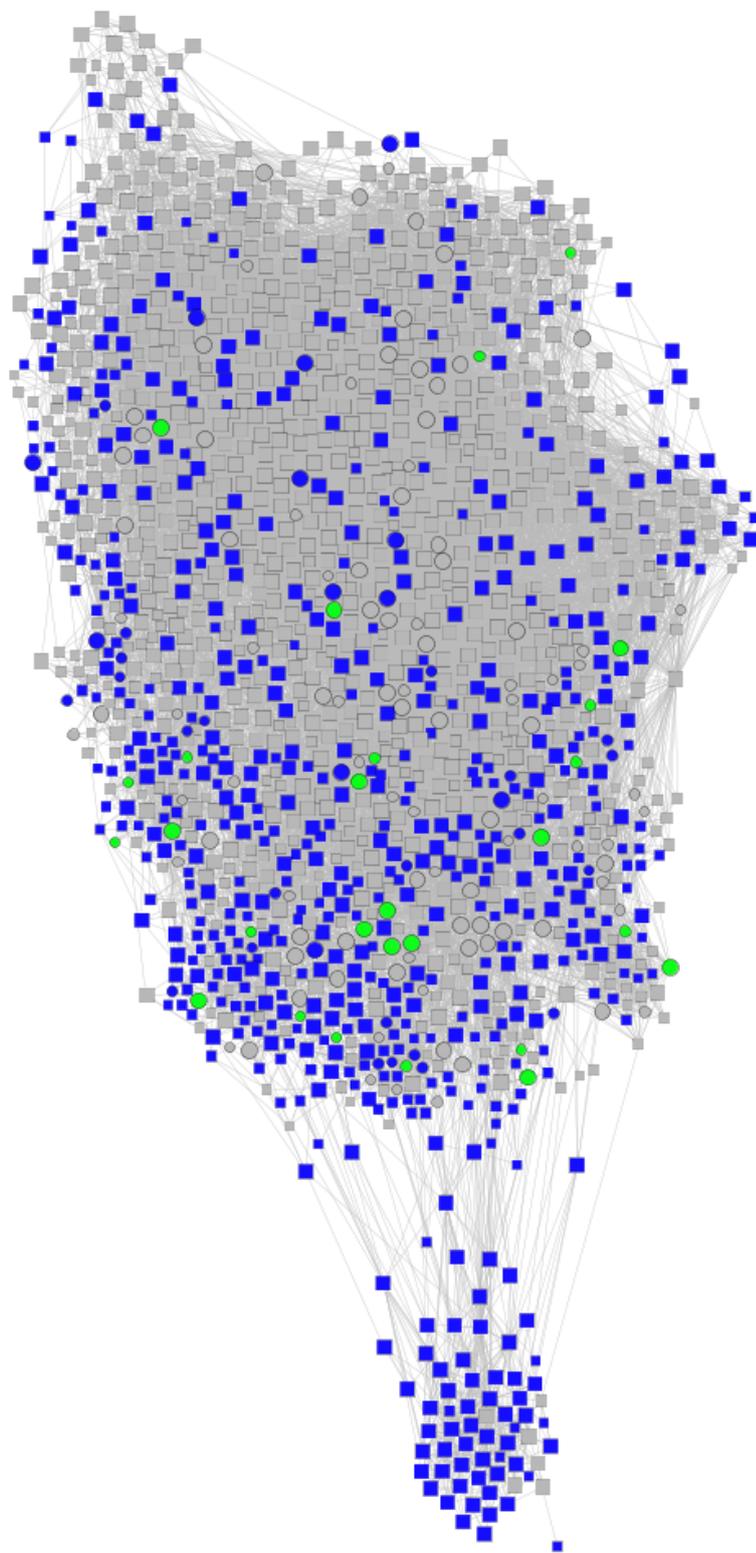
Note: We model the Russian Product Space as a network in which nodes represent products exported by Russia with an $RCA > 1$, and links signify catalytic relations as represented in the Global Product Space. On this network, we apply the ACS detection algorithm to model the Russian Autocatalytic Set. Blue = Non-green products, Green = Green products, Gray = Products exported with an $RCA < 1$

Figure C.3: Indian Product Space and Autocatalytic Set



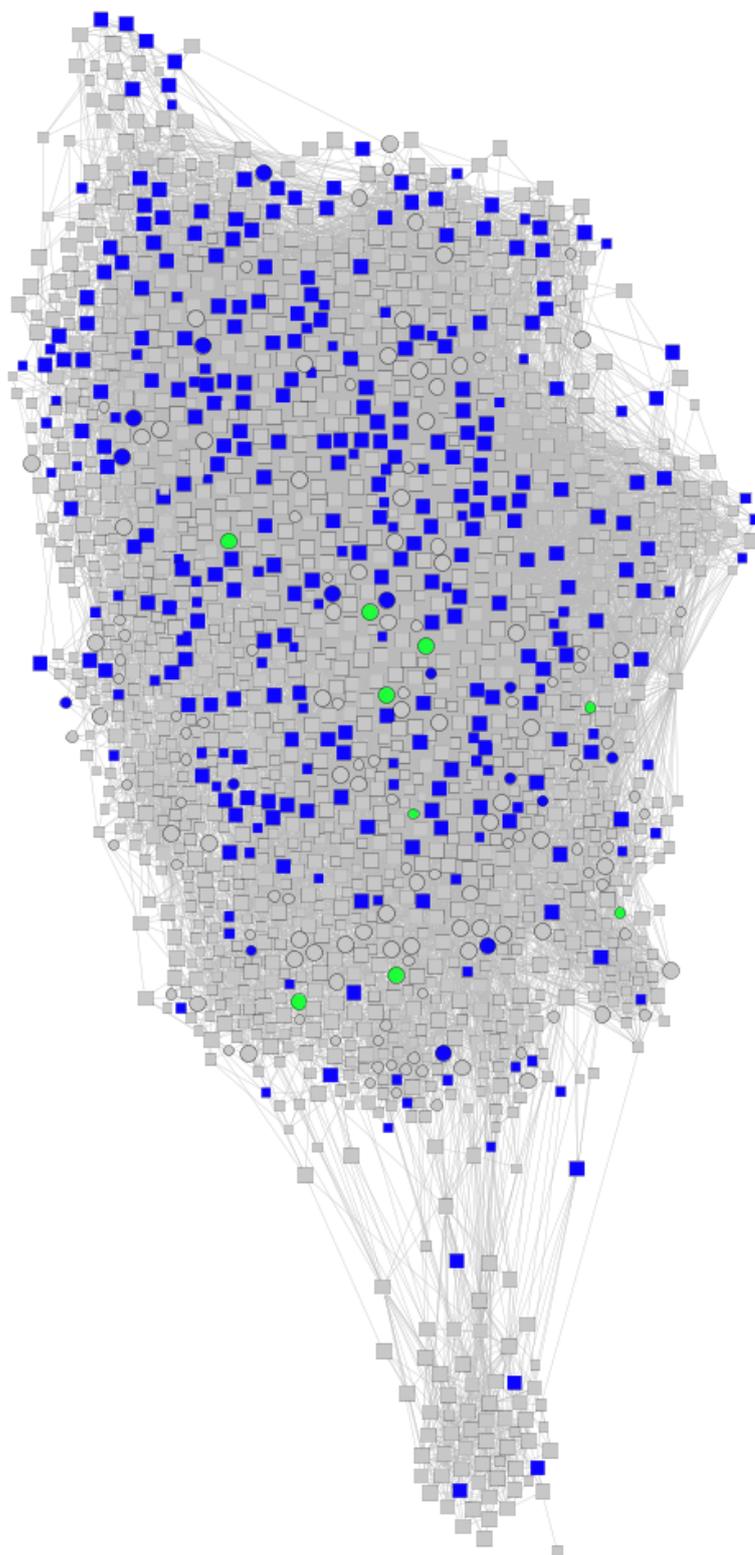
Note: We model the Indian Product Space as a network in which nodes represent products exported by India with an $RCA > 1$, and links signify catalytic relations as represented in the Global Product Space. On this network, we apply the ACS detection algorithm to model the Indian Autocatalytic Set. Blue = Non-green products, Green = Green products, Gray = Products exported with an $RCA < 1$.

Figure C.4: Chinese Product Space and Autocatalytic Set



Note: We model the Chinese Product Space as a network in which nodes represent products exported by China with an $RCA > 1$, and links signify catalytic relations as represented in the Global Product Space. On this network, we apply the ACS detection algorithm to model the Chinese Autocatalytic Set. Blue = Non-green products, Green = Green products, Gray = Products exported with an $RCA < 1$.

Figure C.5: South African Product Space and Autocatalytic Set



Note: We model the South African Product Space as a network in which nodes represent products exported by South Africa with an $RCA > 1$, and links signify catalytic relations as represented in the Global Product Space. On this network, we apply the ACS detection algorithm to model the South African Autocatalytic Set. Blue = Non-green products, Green = Green products, Gray = Products exported with an $RCA < 1$.

Titre: Réseaux autocatalytiques, commerce international et changements structurels dans les économies émergentes

Résumé:

Dans cette thèse, j'explore deux changements structurels majeurs : la croissance des liens input-output (IO) internationaux et l'émergence d'industries vertes, en portant une attention spécifique aux économies émergentes. J'étudie comment ces changements s'accompagnent de configurations industrielles créant des effets de feedback. J'utilise des techniques de modélisation de réseau en incorporant un cadre, initialement conceptualisé pour la dynamique des écosystèmes, le cadre des réseaux Autocatalytiques, introduit par Jain et Krishna en 1998. Ma thèse est pionnière dans l'utilisation de ce cadre pour examiner les transformations structurelles au sein des réseaux IO. Elle est construite autour de trois études de cas : (i) l'émergence des industries chinoises comme centre du réseau de production mondial ; (ii) les changements dans les liens IO au sein et entre les nations post-socialistes; (iii) la croissance jointe des industries vertes et non vertes dans les économies émergentes.

Mots clés: Analyse de réseaux, Complexité économique, Réseaux économiques, Analyse entrée-sortie, Commerce international, Développement économique, Croissance économique, Changement structurel

Title: Autocatalytic networks, Trade and Structural Changes in Emerging Economies

Abstract:

In this PhD thesis, I explore two key structural changes: the growth of international Input-Output (IO) linkages and the rise of green industries, while putting a special emphasis on emerging economies. I investigate how these structural changes are characterised by industrial configurations that create feedback loop effects. I employ network modeling techniques within the framework of autocatalytic networks introduced by Jain and Krishna (1998). To the best of my knowledge, this research is the first attempt to use the autocatalytic networks lens to scrutinize structural transformations within international IO networks. My investigation encompasses three case studies which will be the basis for the three chapters: (i) the emergence of Chinese industries as the center of the global production network; (ii) the changes of input linkages within and across post-Socialist nations; (iii) the co-evolutionary growth of green and non-green industries in emerging economies.

Keywords: Network Analysis, Economic Complexity, Economic Networks, Input-Output Analysis, International Trade, Economic Development, Economic Growth, Structural Change

