# International environmental cooperation and climate change laws: A quantitative analysis

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## Statement of originality

I, Jianjian Gao, confirm that the research included within this thesis is my own work or that where it has been carried out in collaboration with or supported by others, this is duly acknowledged below, and my contribution is indicated. Previously published material is also acknowledged below.

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Details of collaboration and publications:

Chapter 3 has been published in Ecological Economics, a leading peer-review journal in the field of economics, and the preliminary is documented by World Bank.

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- **Jianjian Gao**, Caterina Gennaioli, Pietro Panzarasa. Regionalisation of international environmental cooperation: Evidence from community structure analysis (working paper).
- **Jianjian Gao**, Caterina Gennaioli, Pietro Panzarasa. European countries lie at the core of international environmental cooperation (working paper).

# Abstract

The increasing number of IEAs has induced a complex web of interdependent relationships among countries. This thesis mainly studies the international environmental cooperation network created by IEAs and countries' adoption of national climate change laws by combing theories and methods from network science, economic and political economics and international relations. Specifically, I will outline four projects concerned with IEAs and climate change laws. In the first project, I construct a statistically significant international environmental cooperation network among countries and study its emergency and evolution by investigating its structural properties. The results reveal that the popularity of environmental agreements led to the emergence of an environmental cooperation network and document how collaboration is accelerating. The second and third projects concern the meso-organisation of international environmental cooperation. Specifically, the second project studies the community structure of the environmental cooperation network. Community detection is conducted, and results show that environmental cooperation presents regionalisation. In the third project, I study the core-periphery structure of international environmental cooperation by investigating the nestedness and rich clubs arising from country-treaty relationships. Furthermore, the cooperation complexity is analysed based on methods from economic complexity to further assess country-treaty relationships. I develop a new measure to quantify the diversification of countries' commitment to environmental treaties. Results show that European countries lie at the core of international environmental cooperation with the highest diversification of commitment. In addition, countries' diversification of commitment is significantly correlated with environmental performance within countries. In the fourth project, I turn to national climate change laws to explore factors influencing the burst of countries' adoption behaviours. I show that scientific consensus, COPs, and natural disasters are significantly and positively associated with the burst of countries' adoption behaviours.

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# List of abbreviations

**ACES** American Clean Energy and Security Act

**BASIC** A group of the four major emerging economies, including Brazil, South Africa, India, and China

**CBD** Convention on Biological Diversity

**CCLW** Climate Change Laws of the World

**CIESIN** Center for International Earth Science Information Network

**CITES** Convention on International Trade in Endangered Species of Wild Fauna And Flora

**COPs** Conference of Parties

**DPI** Database of Political Institutions

**DRM** Disaster Risk Management

**ECOLEX** Global Portal to Environmental Law

**ENGOs** Environmental Non-governmental Organisations

**EPI** Environmental Performance Index

**FAO** Food and Agriculture Organisation of the United Nations

**GDP** Gross Domestic Product

**GHG** Greenhouse Gas

**G7** Canada, France, Germany, Italy, Japan, the United Kingdom and the United States

**IEA** International Environmental Agreement

**INDCs** Intended Nationally Determined Contributions

**IPCC** Intergovernmental Panel on Climate Change

**IPOs** Indigenous Peoples' Organisations

**IUCN** International Union for Conservation of Nature

**K-NNG** K-Nearest Neighbour Graph

**MARPOL** International Convention for the Prevention of Pollution from Ships

**MEA** Multilateral Environmental Agreement

**NGOs** Non-governmental Organisations

**NMI** Normalised Mutual Information

**NODF** Normalised Nested Overlap and Decreasing Fill

**SDGs** United Nations Sustainable Development Goals

**UN** United Nations

**UNCCD** the United Nations Convention to Combat Desertification

**UNCED** United Nations Conference on Environment and Development

**UNEP** United Nations Environment Programme

**UNFF** United Nations Forum on Forests

**UNFCCC** United Nations Framework Convention on Climate Change

**YOUNGOs** Youth Non-governmental Organisations

# Chapter 1

# Introduction

Global environmental governance involves efforts from different scales, including global, national and local. National interests will shape international negotiations while fulfilling international commitments requires political and policy changes at the domestic level (O'Neill, 2017).

At the global level, environmental treaties among different political jurisdictions play a crucial role in achieving the Sustainable Development Goals outlined in the 2030 Agenda (UNEP, 2016) and in addressing the global environmental changes which require the cooperation of a global set of actors. At the national level, national policies provide the legal basis to fulfil international commitments documented in environmental treaties.

Recent decades have witnessed a significant increase in the number of environmental treaties, up to a total of almost $2,000$ in 2015. The number of signatory countries has also increased constantly over time, from 6 in 1869 to 238 in 2015. A complex institutional system has emerged globally in the context of environmental policy, with different sets of countries participating in some treaties but not in others.

In addition, national policies pay increasing attention to climate change. The passage of national climate change laws and policies is accelerating, with over $1,800$ laws and policies in 198 jurisdictions at the end of 2019. Nearly all countries have issued climate change laws and policies, mainly covering carbon pricing schemes, energy policies, transport, forestry, and adaptation interventions. National climate legislation provides a legal basis for fighting climate change and thus constitutes an essential part of climate change governance (Eskander et al., 2021).

Recent years have seen an increasing interest in using techniques from complex systems to study global environmental governance (Kim, 2020; Orsini et al., 2020). Traditionally, methods for studying the international environmental agreement system have been based on econometric methods. Very few attempts have been documented to visually represent the structure of the system, making it difficult for us to analyse the interaction patterns between countries. Network science provides a novel and effective way to analyse complex systems and interactions among components by representing systems as networks in which vertices (or nodes) are joined by edges (or links).

Over the past two decades, there has been an explosion of interest in social network analysis among social scientists from psychology to economics (Borgatti et al., 2009). In the social sciences, the main assumption is that individuals are embedded in webs of social relations and interactions.

Social network analysis can date back to 1932 when Jacob Moreno suggested that the positions of the runaways in a social network mattered more (Moreno, 1934). The studies of the small-world effect conducted by Watts and Strogatz (1998) in 1998 and of the scale-free network by Barabási and Albert (1999) in 1999 have contributed to the development of network science which largely promotes the application of advanced quantitative methods from physics and applied mathematics to social network analysis. Various real-world networks have been extensively studied, including technological networks (e.g., the Internet, the power network) and social networks (e.g., the scientific collaboration network, the movie actor network). Social network analysis has become so popular among social researchers due to its ability to provide us with a more effective way to capture the underlying topological structure and dynamics of complex networks, as well as to analyse various phenomena unfolding in social systems, including synchronisation, diffusion and emergence (Newman, 2018).

## 1.1 Part I: A network analysis of international environmental cooperation

Many urgent environmental dilemmas require international collaboration. Sometimes cooperation involves a relatively limited number of parties (e.g., to manage a shared water body), and sometimes it requires broad coalitions of many nations (e.g., to address global threats like climate change).

Understanding how environmental coalitions have emerged and expanded is therefore an important question in international cooperation and global governance research. The literature has tackled the problem both theoretically and empirically, using, among others, the tools of game theory (e.g. Barrett, 2003, 2007; Battaglini and Harstad, 2016a; de Zeeuw, 2015; Harstad, 2016; O'Neill, 2017), international relations (e.g., Falkner, 2013b; Mitchell, 2002) and experimental economics (e.g., Barrett and Dannenberg, 2012; Milinski et al., 2006, 2008; Tavoni et al., 2011).

The subject of interest in these studies is typically a particular international environmental agreement (IEA). Researchers are interested in the political, game theoretic or behavioural dynamics that explain the emergence, design or effectiveness of a treaty (e.g., Barrett, 1994; Breitmeier et al., 2011; Young, 1999).

What tends to be overlooked by studies concerned with individual treaties is that, as a collective, IEAs have given rise to a dense network of environmental cooperation. Recent decades have witnessed a significant increase in the number of IEAs, reaching almost 2000 in 2015. The number of signatories had increased from 6 in 1869 (when there were fewer sovereign nations) to 238 in 2015, including not just nation-states but also international organisations, dependent territories, and sub-national entities. However, little is known about the macro-structure and the evolution of the system, and why countries can coordinate and reach an agreement so quickly in response to some environmental problems, and slowly in response to others, and not at all in response to others (Mitchell, 2003).

Here, I am interested in the network of cooperation these treaties create. While every environmental agreement has particular objectives, managing global environmental threats successfully depends on the synergies between multiple treaties and the resulting interaction between signatories. The effectiveness of cooperative ties between countries is affected not only by the countries' individual attributes (Mitchell, 2002) but also by the structure of the network connecting them (Kinne, 2013).

I apply network theories and methods to ECOLEX, one of the largest collections of data on IEAs, to better understand the structure and dynamics of global environmental cooperation. ECOLEX stands for "Global Portal to Environmental Law" which is constructed by three international organisations: the Food and Agriculture Organisation (FAO) of the United Nations, the International Union for Conservation of Nature (IUCN), and the United Nations Environment Programme (UNEP). ECOLEX aims to provide the most comprehensive global source of information on environmental law, including treaties, international soft-law and other non-binding policy and technical guidance documents, national legislation, judicial decisions, and law and policy literature (IUCN, 2017), and thus provides potential for users to perform quantitative analysis of the environmental laws.

In Chapter 3, I use network metrics to elucidate, with new quantitative evidence, some long-standing debates in the economics and political science of international environmental cooperation and offer topological corroboration for several conjectures supported so far, primarily by qualitative or preliminary correlational evidence.

## 1.2 Part II: Meso-organisation of international environmental cooperation

After obtaining the overall landscape of international environmental cooperation leveraging global measures in network science, the second part of my thesis concerns the meso-organisation of international environmental cooperation by extracting away from individual nodes. I first study the regionalisation of international environmental cooperation through community structure analysis in Chapter 5 and then attempt to quantify its hierarchical organisation by analysing nestedness and rich clubs in Chapter 6.

### 1.2.1 Regionalisation of international environmental cooperation: Evidence from community structure analysis

Regional environmental governance has drawn attention in recent decades (Balsiger and Debarbieux, 2011; Balsiger and VanDeveer, 2010, 2012), as the global cooperation stagnates (Balsiger and Debarbieux, 2011; Balsiger and Prys, 2016; Balsiger and VanDeveer, 2012; Conca, 2012). Cooperation at the regional level is considered a potentially effective scale to provide tailored measures to cover differences across regions (Balsiger and Prys, 2016) and overcome problems encountered by global cooperation (Balsiger and VanDeveer, 2012).

Regional cooperation has been defined differently according to either hard, material factors or social constructions (Balsiger and Prys, 2016). How to identify and define the boundaries of regions has been a topic of longstanding debate in the literature.

Regional environmental cooperation case studies can provide valuable empirical insights into the cooperative clusters. However, no matter how to define regions, case studies inevitably focus on a specific region or a specific theme, such as deforestation and river basins or seas, or a specific agreement, and consequently fail to reveal the overall landscape of the groupings of countries emerging in the case of coexistence of various environmental problems and the complex interaction among geography, politics, economics, and culture across the world.

To fill the gap, my study leverages the whole set of IEAs, not limited to regional ones, and goes beyond "potential regions" proposed by Balsiger and Prys (2016) by revealing systematically whether "potential clusters or communities" of shared interests exist. The primary assumption is the same as Balsiger and Prys (2016), namely that agreements can contribute to forming country groupings. Unlike these studies, however, my work systematically considers the whole set of agreements and focuses on groupings that emerge spontaneously. The focus on "potential clusters or communities" allows for the emergence of groupings at any level, regardless of whether previous institutions are in place or geography plays an important role. I can thus capture traditional regional cooperation that is constrained by geography as well as other forms of cooperation that are not limited to geography.

To this end, in Chapter 5, I turn to one important network property - the community structure. Communities, also called clusters or modules, are made up of highly interconnected nodes that are less connected to nodes in other communities. Communities are a way to coarse-grain the level of description of a network. I leverage techniques from network science to detect and analyse the community structure in the cooperation network constructed in Chapter 3.

### 1.2.2 European countries lie at the core of the international environmental cooperation

One of the characteristics of IEAs is that a country's participation in a treaty is totally voluntary (Battaglini and Harstad, 2016b). According to the statistics, the average number of countries per treaty was 32 in 2015, and over 75 countries have signed a few treaties (Carattini et al., 2023).

The rationale behind forming IEAs has been studied extensively. It is widely accepted that IEAs should be self-enforcing to play their roles fully (Barrett, 1994). In addition, other factors have been studied extensively to uncover the origins of IEAs. First, actors who decide whether to sign and implement IEAs are the main force that promotes the formation of IEAs (Congleton, 1992; Fredriksson and Gaston, 2000; Marchiori et al., 2017; Neumayer, 2002a). For instance, environmental problems powerful states are concerned about tend to receive international attention (Mitchell, 2003). In addition, interactions between politics, economics and the environment in an individual country can be vital to influence a country's decision (Mill, 1900; Neumayer, 2002b). An interplay of domestic environmental issues influences the decisions of states, the economic outcomes of action or inaction, and the perceptions of domestic political audiences. Another factor concerns states' influence (i.e., states influence each other in their decision at the international level) (Mitchell, 2003). Policy diffusion is one of the mechanisms to consider the mutual influence between countries (Jordan and Huitema, 2014a,b).

The country-treaty relations are not assigned randomly due to the influential factors introduced above. However, under the combined effect of different factors, the heterogeneity in membership of treaties and the consequent structural pattern of country-treaty interactions are rarely discussed. Some countries tend to sign treaties on certain environmental problems that need intensive attention in their own countries. For instance, countries with rich forest resources may manage to protect forests, e.g., Russia, Brazil, Canada and Indonesia (Heino et al., 2015; Riyanto et al., 2020). Or countries may focus on certain areas that are within their own political and economic capacity. After the Paris Agreement, China has put efforts into the mitigation of climate change by promoting renewable energy, nuclear power and energy conservation despite its high need for rapid economic development (Zheng et al., 2019). In this case, different clusters of countries are expected, with each cluster focusing on one specific area. However, some countries may go beyond their domestic environmental issues and aim to act as a leader in international environmental issues, such as France (Falkner, 2007). This case may give rise to a situation where some countries put their efforts into different kinds of environmental issues. Current research mainly uses case studies that cannot show an overall picture of the country-treaty interactions. My research aims to go beyond isolated cases and reveal the overall landscape of country-treaty relationships.

These research questions involve another metric in network science to quantify the meso-organisation of a network - nestedness. In a perfect nested network, the neighbourhood of a node with a smaller degree is contained in the neighbourhood of a node with a larger degree (Mariani et al., 2019). A nested structure in country-treaty relationships will have some countries signing multiple kinds of treaties and others only signing a subset of these treaties. Nestedness quantifies core-periphery structures where central and densely connected nodes form a core while non-central nodes are sparsely connected to constitute the periphery, which is connected to the core (Csermely et al., 2013). Different from a community structure, a core-periphery structure generally contains only one core, while a community structure tends to have multiple modules. The emergence of nestedness indicates a hierarchical organisation where the sequence of elements matters. For instance, the extinction sequence can be predicted by the nested distribution of species in fragmented habitats (Atmar and Patterson, 1993). In addition, evidence shows that nestedness plays an essential role in maintaining the stability and robustness of ecological (Bastolla et al., 2009) and socio-economic systems (Bustos et al., 2012).

Young (1996) defined nested institution to reveal institutional linkages. In his definition, the nested institution describes the establishment of protocols under wider framework conventions and efforts to replicate and implement those broader commitments established at the global level, both nationally and regionally. For instance, the United Nations Framework Convention on Climate Change (UNFCCC) is a global treaty that provides the foundation framework for regional or national provisions (Kuyper et al., 2018). Another example concerns the implementation of the Convention on Biological Diversity (CBD) in local territories, which requires national efforts. Yong's definition involves multiple levels of governance and coordination across different scales. This kind of nestedness might promote or hinder the coherence and consistency in the cooperation between countries depending on whether there is an effective mechanism for coordination and integration across different levels of governance.

Here, my study goes beyond the concept proposed by Yong Young (1996), and borrows the concept of nestedness in network science to characterise the nested structure of country-treaty relationships. Differently, the hierarchical structure indicated by the nestedness can not be explained by governance at different levels or scales. It arises as an overall landscape from the country-treaty relationships, and the sequence of countries in the structure matters.

Existing research rarely focuses on the hierarchical organisation of country-treaty interactions. Whether country-treaty interactions have a core-periphery structure, i.e., certain countries form a densely connected core while others are sparsely connected at the periphery, or no apparent cores exist, is still unknown. In Chapter 6, I first attempt to reveal the nestedness in country-treaty relationships to reveal the hierarchical structure and countries' commitment preferences hidden in the structure. The ranking of countries' commitment preferences will enable us to characterise countries' roles in the system. Then, I quantify the cooperative relationships among the central countries in the nested structure to reveal the impact of nestedness on the cooperation network among countries. Furthermore, I draw on techniques from economic complexity to systematically quantify the diversification of countries' environmental commitment and test its correlation with countries' environmental performance.

## 1.3 Part III: Climate change laws

Climate change has been one of the challenges facing humanity since the second half of 1800, just after the Industrial Revolution. Scientific knowledge about the greenhouse effect can date back over 100 years. However, climate change has only gradually received policy attention since the 1990s when few countries fulfilled their promise under the 1992 UNFCCC with domestic legislation (Fankhauser et al., 2014), with only 110 laws and policies passed from 1990 to 1999 directly or indirectly oriented to climate change (Eskander et al., 2021).

The Paris Agreement in 2015 documented a substantial shift in global climate change governance. The shift is from a top-down governance architecture, where a consensus of greenhouse gas reduction targets is negotiated, to a hybrid structure, where bottom-up national commitments are expected (Fankhauser et al., 2015; Iacobuta et al., 2018).

The passage of national climate change laws and policies is accelerating, with over $1,800$ laws and policies in 198 jurisdictions at the end of 2019 (Eskander et al., 2021). The prevalence of national climate change action gives rise to increasing academic interest. Existing research mainly constitutes two strands. One line concerns the development of climate change policies, tracking the process and attempting to reveal the causal factors behind the development in various countries (Eskander et al., 2021; Fankhauser et al., 2014, 2015, 2016; Kammerer and Namhata, 2018; Lachapelle and Paterson, 2013; Schoenefeld et al., 2022). Another strand explores the working mechanism and the impact of national climate policies through both case studies (Bang et al., 2015; Harrison and Sundstrom, 2010) and empirical analysis (Eskander and Fankhauser, 2020).

My study falls into the first strand and focuses on adopting national climate change laws. Existing research reveals that the passage of climate laws is influenced by both international factors and domestic factors (Eskander et al., 2021; Fankhauser et al., 2015, 2016; Kammerer and Namhata, 2018; Lachapelle and Paterson, 2013; Matisoff, 2008; Never and Betz, 2014; Schoenefeld et al., 2022). Empirical research tends to employ econometrics. Some use the absolute number of climate change policies adopted by each state in one year as dependent variables to study driving factors of policy adoption across countries (Fankhauser et al., 2015, 2016; Matisoff, 2008). Others focus on a specific international factor, policy diffusion, and employ event history analysis (Baldwin et al., 2019) or directed dyadic analysis. (Matisoff, 2008). Recently, network inference has been applied to infer the potential diffusion paths of climate change policies between countries, shedding new light on the diffusion process (Mandel et al., 2020; Vega and Mandel, 2018).

Yet until now, there has been no attempt to explain the dynamics of countries' adoption behaviours. Research on human behaviours has shown bursts of rapidly occurring events separated by long periods of inactivity (Goh and Barabási, 2008; Karsai et al., 2012; Vázquez et al., 2006). Inspired by the burst phenomenon in human behaviours, I focus on the dynamics of countries' adoption behaviours on climate change laws. According to Nachmany et al. (2014), countries pass a climate change law every 18 to 20 months on average. But no empirical analysis has been conducted to describe and explain the dynamics fully.

By studying the dynamics of countries' adoption of climate change laws, researchers and policymakers may expect to find several valuable insights. First, analysis of the dynamics of climate change laws can reveal trends in climate policy development over time, such as political priorities and shifts in the institutional framework for climate governance. In addition, changes in law frequency can reflect policy responses to significant climate events or crises, such as natural disasters, extreme weather events, or international agreements (e.g., the Kyoto Protocol) (Fankhauser et al., 2016). More importantly, an increase in laws related to specific climate science findings may demonstrate policymakers' efforts to align policy with the latest scientific knowledge on climate change (Grundmann, 2007; Siebenhüner, 2002). Moreover, an increase in climate laws may reflect public pressure and activism demanding action on climate change (O'brien et al., 2018; Roser-Renouf et al., 2014).

My research aims to fill this gap by studying the dynamics of countries' behaviours when adopting climate change policies and attempts to reveal relevant factors associated with the emergence of bursty in countries' adoption behaviours. To this end, I draw on the most comprehensive data set, the Climate Change Laws of the World. Instead of using the absolute number of policies adopted by a country in one year as the dependent variable, I use the time intervals between two consecutive adoption years. Various determinants of burst when adopting climate change laws are investigated based on econometrics techniques.

## 1.4 The structure of the thesis

As introduced above, my thesis mainly focuses on international environmental cooperation and national climate change laws. In Part I, I will first introduce the background concerned with social network analysis and IEAs in Chapter 2.1, and then present my first project on the topology and evolution of the international cooperation network in Chapter 3. In Part II, I will first introduce existing literature on regional environmental cooperation, roles of European countries, and meso-organisations in networks in Chapter 4, and then introduce two projects on community structures in Chapter 5 and nestedness and rich clubs in Chapter 6, respectively. In Part III, I will first present the theoretical background of climate change laws and then present one project investigating factors influencing countries' bursty behaviours when passing climate change laws. Finally, in Chapter 9, I will summarise the main findings, discuss the contributions to the literature, and outline the agenda of my future research.

# Part I: Network analysis of international environmental cooperation

# Chapter 2

# Literature review for Part I

Part I concerns the topological structure and evolution of international environmental cooperation through treaties. I leverage techniques from network science to quantify the structure of international environmental cooperation. This chapter will first introduce the basic ideas of social network analysis, and then existing research on IEAs.

## 2.1 Social network analysis

A network is a set of vertices and edges between them. In computer science, vertices and edges are called nodes and links; in sociology, they are referred to as actors and ties, respectively. Basic measures, such as the number of nodes and links, degree, strength, density, shortest path length, and clustering coefficient can provide fundamental information on the overall topological structure of a network. And centrality measures, betweenness centrality and closeness centrality can shed light on the node's position in a network. In addition, models of dynamical systems on networks provide effective methods to investigate various processes, including the communication of information or news among friends, trade between economic activities as well as the spread of diseases.

The structure of a network provides insights into its functioning as a system of interacting components (Jackson, 2010). Many important mechanisms that determine the likelihood of cooperation, such as shared interests, reputation, and the pursuit of common goals through the mitigation of self-interest (Dai et al., 2010; Hafner-Burton et al., 2009), are typically associated with common third-party ties. Further, agents in a certain position of a cooperation network may play an important role in maintaining its stability (Lozano et al., 2008), while also possibly benefiting from their particular position (Li and Schürhoff, 2019). As such, the network not only reflects existing cooperative relationships but also influences the costs and benefits of future cooperative attempts (Kinne, 2013).

My study is inspired by related literature, which applies social network analysis to wider international relations contexts, including trade, financial integration, and technology diffusion (e.g. Fagiolo et al., 2010; Hafner-Burton et al., 2009; Htwe et al., 2020; Kim and Shin, 2002; Schiavo et al., 2010; Smith and White, 1992; Vega and Mandel, 2018).

## 2.2 International environmental cooperation through IEAs

Several economic theories are in support of IEAs. Hardin (1968) characterised the environmental game among countries as a prisoner's dilemma that would induce the so-called "tragedy" of the common. The tragedy of the commons occurs because each individual seeks to maximise his own gain from the commons but takes no responsibility for the environmental protection. This leads to over-exploitation of resources. IEAs can overcome this problem by creating a framework for collective action. However, according to game theory, free riding may occur when some countries defect from the cooperation but enjoy the benefits others bring for free. IEAs have been widely adopted to reduce the likelihood of defection, as they can punish free-riding (Barrett, 1994). In addition, Chase (1994) leveraged Coase Theorem (Coase, 1960) and game theory and argued that IEAs can create an institutional framework that will fulfil the economic function of reducing transaction costs and achieving the most efficient resource allocation among participating countries. A typical example is the 1987 Montreal Protocol on Substances That Deplete the Ozone Layer [1] which reduced the transaction cost by providing a "structure that facilitates friendly, open, and cooperative relations.". Another example concerns the emission trading and carbon tax. Similarly, IEAs can create a framework to reduce transaction costs and ensure their implementation. Moreover, according to Ostrom (1990), self-governance and good institutional design can avoid the tragedy of commons. She emphasised that

[1] It was agreed in September 1987 and entered into force in January 1989.

IEAs should prioritise a decentralised and collective approach that engages users and communities to manage resources. By promoting community participation and emphasising the value of traditional knowledge and practices, IEAs can play their role in contributing to the sustainable development of people and the environment.

According to Mitchell (2003), an IEA "is an intergovernmental document intended as legally binding with a primary purpose of preventing or managing human impacts on natural resources". IEAs include multilateral agreements and bilateral agreements. An agreement between two countries is called a bilateral environmental agreement, and if it is cosigned by three or more countries, it is known as a multilateral environmental agreement (MEA). More specifically, IEAs can be "conventions, treaties, agreements, accords, or their non-English equivalents, and protocols and amendments" (Mitchell, 2003). One of the early representative treaties is the United Nations Framework Convention on Climate Change (UNFCCC) which was made available for signature at the Earth Summit held at Rio de Janeiro in June 1992 and entered into force in March 1994 after fifty countries had ratified the Convention. As a framework treaty, the UNFCCC stipulates principles and commitments to implement national policies to relieve climate change. By ratifying the UNFCCC, the Annex One countries aimed to reduce emissions individually or jointly to their 1990 levels by the year 2000 (Fredriksson and Gaston, 2000; Ostrom, 2009; Rayner and Jordan, 2013).

However, traditional methods for studying the international environmental agreement system are based on econometric methods, which cannot visually represent the structure of the system, making it difficult for us to analyse the interaction patterns between countries. New methods should be applied to uncover the structure and dynamics of the system. Social network analysis provides an effective way to analyse the complex system based on IEAs, by representing the complex system as a network in which countries are joint by links constructed based on IEA memberships.

Four studies, which my study complements, are worth highlighting. Kim (2013) examines a network of IEAs linked through citations and finds an international environmental governance system that is characterised by a cohesive polycentric legal structure. Hollway and Koskinen (2016) apply network analysis to the governance of global fisheries, using and identifying a high degree of social embeddedness in the system. Wagner (2016) uses a structural model of international negotiations to estimate the date when countries ratified the Montreal Protocol as well as the dynamics of trade agreements. Mitchell et al. (2020) discuss the potential, without yet exploiting it, of the International Environmental Agreements Data Base, a similar database to ECOLEX, to better understand the formation of IEAs.

# Chapter 3

# The topological structure and evolution of international environmental cooperation

## 3.1 Introduction

The breadth and depth of environmental cooperation through IEAs have been documented in information sources such as ECOLEX (IUCN, 2017) and the International Environmental Agreements Data Base (Mitchell, 2003; Mitchell et al., 2020). The main interest of such databases is often the classification and categorisation of different treaty types.

Here, I create an inter-temporal environmental cooperation network based on ECOLEX, where each node is a country that has signed IEAs and each link reflects the number of treaties that countries have co-signed. The data cover 546 environmental treaties agreed upon between 1948 and 2015. Each co-signed treaty is generally assigned the same weight, but I also introduce new ways to reflect the differing importance of treaties. Crucially, the global structure of the cooperation network is assessed against a properly constructed null model, which allows us to filter out connections that would be established simply by random expectation.

I derive four pertinent hypotheses from the IEA literature and test them using topological metrics that describe the structural landscape and evolution of international environmental cooperation.

The first hypothesis concerns the emergence and evolution of international environmental cooperation. I find that a statistically significant environmental cooperation network began to materialise in 1971, i.e., some countries share a statistically significant number of treaties than expected if the number of treaties of each country is kept but the country-treaty relationships are reshuffled, and reached stability in 1980. Before then, treaty links were too weak. Since then the network has grown steadily in size and strength, resulting in higher connectivity between signatory countries. Indeed, cooperation is accelerating: Treaty membership is associated with the faster ratification of subsequent IEAs. These results hold even when "retiring" treaties with low levels of ongoing activity, and when differentiating treaties by their importance. As such, the data support earlier findings on the pivotal role played by events like the 1972 UN Conference on the Human Environment in Stockholm, as posited in Falkner and Buzan (2019).

The second hypothesis concerns the ability of IEAs to foster policy cooperation. The literature sees IEAs as vehicles for engagement, which provide organisational structures, sustain a shared purpose, and engender trust (e.g., Bernauer et al., 2010; Carattini et al., 2019b; Meyer et al., 1997; Ostrom, 2009). My analysis quantifies how, through membership interconnections, environmental cooperation has become denser and more cohesive. The paths through which countries can reach each other have shortened, creating more effective platforms for policy coordination and knowledge diffusion. Again, these results hold when accounting for activity levels and the importance of treaties.

The third hypothesis concerns environmental leadership and its implication for network acceleration. I find that the environmental cooperation network, while global, has a noticeable European imprint. Initially, the United Kingdom and, more recently, France and Germany have been the most important network nodes, through which IEAs have been facilitated. They occupy these positions in their own right, rather than through membership in the European Union, which is itself a party to many IEAs. These findings support the view of international relations scholars such as Vogler and Stephan (2007) and Kelemen and Vogel (2010) who discuss the leadership role of European countries in (domestic and international) environmental issues. I further show that more central network positions are associated with an increased appetite for future cooperation, with central countries more ready to ratify new IEAs.

The fourth hypothesis concerns differences in international environmental cooperation by subject area. I find that international environmental coordination started with the management of fisheries and the sea but is now most intense on waste and hazardous substances. The networks on species, waste and natural resources have a hierarchical structure, which is absent in the networks on sea and fisheries and air and atmosphere. Despite its policy salience, the network of air and atmosphere treaties is comparatively less cohesive and intense. It is also the subject area where treaties negotiated under the auspices of the United Nations (such as those on climate change and transboundary air pollution) have the most impact on the topological properties of the network. The results speak to the "regime complexity" of global climate governance (Keohane and Victor, 2011; Meyer et al., 1997), and might explain the ambivalence towards the UN in much of the environmental governance literature (Biermann and Bauer, 2004; Ivanova, 2010; Mee, 2005).

The remainder of this chapter is organised as follows. Section 3.2 describes the data, and the construction of the environmental cooperation network and motivates the subsequent analysis with a set of descriptive statistics. The main results are contained in sections 3.3 to 3.6, each of which studies a different aspect of international environmental cooperation. Section 3.7 concludes.

## 3.2 Data and methodology

### 3.2.1 Environmental treaty data

I use global data on IEAs from ECOLEX (IUCN, 2017), which combines information on environmental laws and treaties from several sources. As in Mitchell (2003), the treaties included in the ECOLEX database are defined as *intergovernmental documents intended as legally binding with a primary stated purpose of preventing or managing human impacts on natural resources.* The documents include treaties, conventions, accords or modifications. In my study, for convenience, treaties refer to these legally binding documents. The official definition of international treaties originates from the Vienna Convention on The Law of Treaties (1969). The definition used here has been adapted to treaties on environmental matters. My sample comprises 546 environmental treaties signed over the period 1948-2015 by 200 countries.

The original ECOLEX database contains information on 1,998 environmental treaties signed by 238 parties between 1868 to 2015. I exclude 1,411 treaties on which important dates (e.g., on treaty ratification and entry into force) are missing. In addition, I focus on treaties signed by countries [1] and not by other parties such as international organisations, dependent territories and sub-state territories. Finally, I focus on the post-war period as the post–World War II period saw the rise of international environmental agreements (Battaglini and Harstad, 2016b). The 546 treaties are illustrative of the network as a whole and include the largest and most important global treaties.

For each treaty, I have information on signatory countries, subject areas, the date it was signed and the date it entered into force. The data also include country information on the dates of treaty ratification, acceptance or approval and the date of withdrawal, where applicable.

There is considerable thematic overlap, with many treaties covering multiple subject areas. Table 3.1 provides information on the number of subject areas different treaties cover. Whatever their scope, each treaty enters the network only once. However, IEAs covering more than one subject area are included in all the

[1] See Appendix A for the list of parties. According to ECOLEX, Taiwan, Hong Kong, and Kosovo are also included. In addition, Great Britain (GB) signed a treaty instead of the UK. Therefore, Great Britain (GB) is on the list.

subject-specific networks the treaty covers.

Table 3.1: Number of treaties with different numbers of subjects

| Number of subjects | Number of treaties |
|---|---|
| 1 | 302 |
| 2 | 222 |
| 3 | 26 |
| 4 | 24 |
| 5 | 5 |
| 6 | 2 |
| 7 | 2 |
| 9 | 3 |

Among other research questions, I am interested in the role of the United Nations as a platform for international cooperation. In support of this analysis, Table 3.2 lists the number of treaties supported by the UN directly or through UN agencies.

Table 3.2: Number of IEAs in the UN and UN agencies

| Number of treaties | Organisation name |
|---|---|
| 105 | United Nations (UN) |
| 47 | Food and Agriculture Organisation of the UN (FAO) |
| 45 | International Maritime Organisation (IMO) |
| 3 | International Labour Organisation (ILO) |
| 6 | UN Educational, Scientific and Cultural Organisation (UNESCO) |
| 3 | United Nations Environment Programme (UNEP) |

IEAs cover practically all aspects of regional or global environmental concerns (Fig. 3.1). In this study, I am interested in the network as a whole, although for some calculations I group IEAs into six categories: sea and fisheries, wild species and ecosystems, waste and hazardous substances, natural resources (e.g., water, cultivated plants, environment genes, food, forestry, land and soil, livestock, and mineral resources), air and atmosphere (e.g., air pollution, ozone layer depletion and climate change), and energy.

There is considerable overlap, with many treaties covering more than one subject area. For example, a large number of treaties on the seas also concern issues of waste (57 treaties), fisheries (38 treaties) or wild species and ecosystems (17 treaties). Independent of their scope, each treaty enters the network only once. However, treaties may be assigned to more than one subject area for the construction of subject-specific networks.

To understand the systemic properties of these treaties, I now turn to network analysis.

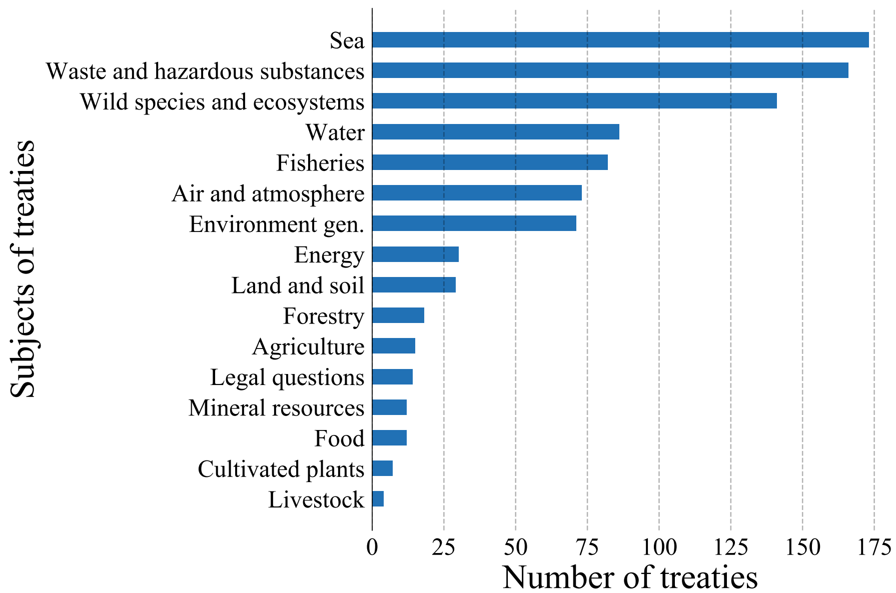
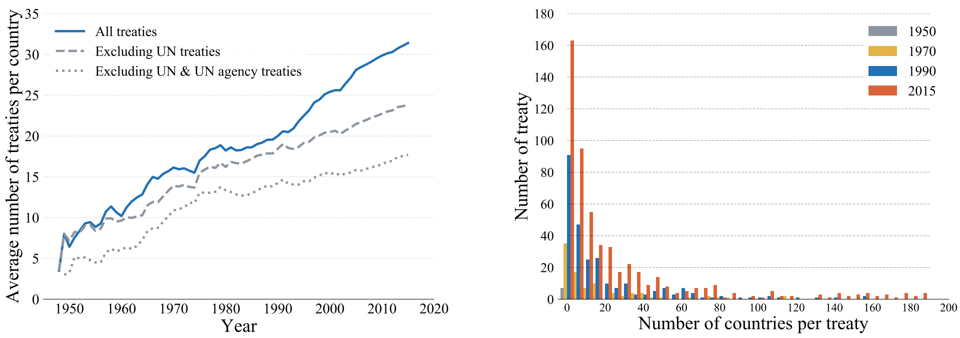



Figure 3.1: Cumulative frequency of treaties for different subjects in 2015

### 3.2.2 Growth in environmental treaties

This section provides a brief quantitative description of the raw country-treaty-year data on IEAs. The number of signatories per treaty and the number of treaties signed by each country is illustrated.

Over the period under scrutiny, the average number of signatory countries per treaty rose from 4 in 1948 to 31 in 2015 (Fig. 3.2, panel a). At the same time, the distribution of the number of signatories per treaty has become wider and more skewed (panel b). I have seen the emergence of global treaties that are signed by a large number of countries (>75 countries), [2] but also a significant increase in the number of treaties with fewer than 10 signatories, suggesting that formal cooperation on both regional and global environmental dilemmas has expanded over time.



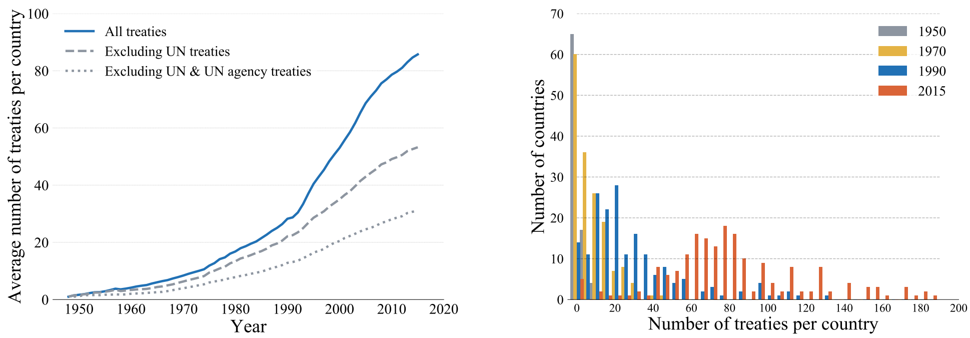

(a) Average number of countries per treaty

(b) Distribution of the number of countries per treaty in different years

Figure 3.2: Number of countries per treaty.

[2]The ten largest treaties by number of signatories, in decreasing order of size, are: Vienna Convention for the Protection of the Ozone Layer, Montreal Protocol on Substances that Deplete the Ozone Layer, Convention on Biological Diversity, United Nations Framework Convention on Climate Change, United Nations Convention to Combat Desertification in those Countries Experiencing Serious Drought and/or Desertification, particularly in Africa, Convention on the Prohibition of the Development, Production, Stockpiling and Use of Chemical Weapons and on their Destruction, Kyoto Protocol to the United Nations Framework Convention on Climate Change, United Nations Convention against Transnational Organised Crime, Basel Convention on the Control of Transboundary Movements of Hazardous Wastes and their Disposal, WHO Framework Convention on Tobacco Control (FCTC).

The number of treaties each country signs up to has gone up in parallel (Fig. 3.3). Growth was particularly fast between 1992 and 2008 when the average number of treaties per country grew from 30 to 76 (panel a). The average patterns mask some interesting heterogeneity (panel b). In the first part of the period under analysis, most countries tended to join only a small number of treaties, while a small number of very active countries signed up to a large number. Over time, the distribution becomes less skewed. The absolute number of treaties increases, but the peak decreases and moves to the right. In 1950, a few leading countries (France, the Netherlands, the United Kingdom and the United States) had signed over 10 treaties. In 1970 the lead group had expanded to also include Belgium, Denmark, Sweden, and Switzerland, each signing over 30 treaties. In 1990, a larger group of still mostly European countries had signed more than 90 treaties each and in 2015 they were signatories to over 190 treaties each.




(a) Average number of treaties per country

(b) Distribution of the number of treaties per country in different years

Figure 3.3: Number of treaties per country.

### 3.2.3 Network construction

This section introduces the method I use to convert the country-treaty-year data into a sequence of annual environmental cooperation networks. The bipartite networks and one-mode projection are introduced in detail. The bipartite null models and the procedure to perform the statistically validated projections are illustrated [3].

#### The bipartite networks

The raw data documents which country is a member of which treaty in a specific year. In network analysis, this type of data is called affiliation data. A broad range of affiliation data have been studied, such as women's attendance of events (Davis et al., 1941), corporate board memberships (Battiston and Catanzaro, 2004; Robins and Alexander, 2004), co-authorship data (Newman, 2001a,b), and actors-movies relations (Newman, 2001a; Watts and Strogatz, 1998). Co-membership of groups or events, such as countries' membership in IEAs, indicates social ties or in my case cooperative relationships among countries signing the same treaties (Borgatti and Halgin, 2011a).

In network analysis, affiliation data can be abstracted as a bipartite network. Also known as two-mode networks or affiliation networks, bipartite networks have two disjoint classes of nodes, participants and groups or events, and links connecting participants to groups or events (Latapy et al., 2008). Accordingly, I can represent the country-treaty relationships as a bipartite network in which, if a country signs

[3]The Python codes are available at https://github.com/jiaoyang2018/Cooperation-network-based-on-IEAs.

a treaty, a link is created between the country and the treaty, as shown in the left-hand panel of Fig. 3.4.

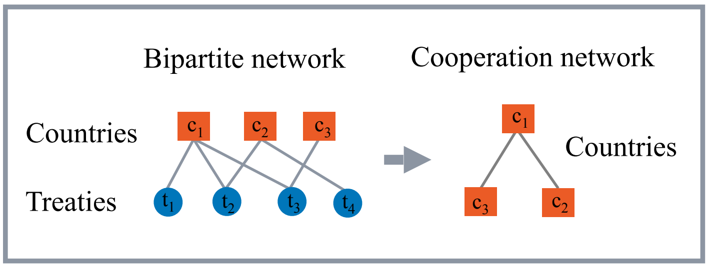



Figure 3.4: Network construction

### One-mode projections

The cooperative tie between two countries is defined as the co-affiliation with, or co-participation in, the same treaties. In other words, if two countries are signatories of the same treaty or treaties, there is a cooperative tie between them, as shown in the right-hand panel of Fig. 3.4. To obtain these cooperative ties, I need to project the bipartite network defined above onto a one-mode network using the country layer. In network science, this process is called one-mode projection and the resulting networks are called one-mode networks. I call the annual one-mode networks obtained through this process the environmental cooperation network or cooperation network for short.

Links are not just binary, i.e., either present or absent, but are characterised by their intensity or weight. Heterogeneity in the intensity of links encodes valuable network information (Barrat et al., 2004). I quantify the intensity of cooperation by assigning a weight to each link, which is proportional to the number of treaties two countries have co-signed and inversely proportional to the number of signatory countries involved in each common treaty (Newman, 2001b). The formula to calculate link weights is as follows:

$$w_{u,v} = \sum_k \frac{\delta_u^k \delta_v^k}{d_k - 1} \tag{3.1}$$

where $u$ and $v$ are countries, and $k$ is an IEA. The value $d_k$ is the degree of the IEA $k$ in the bipartite network, i.e., the number of signatories of the IEA, and $\delta_u^k$ is 1 if country $u$ is linked to IEA $k$ in the original bipartite graph, i.e., country $u$ is a signatory of IEA $k$, or 0 otherwise.

The intuition here is that two countries who co-sign a treaty together with many other countries have a less extensive cooperation relationship on average than two countries that are the sole signatories of a treaty. This implies that all else being equal, bilateral treaties contribute more to the intensity of cooperation between two countries than multilateral treaties. Here, I only consider the impact of treaty participation on cooperation intensity. In Section 3.3 and 3.4, the salience of treaties will be taken into account, as multilateral treaties might have more extensive influence, more resources, and more political clout and thus contribute more cooperation intensity, such as the Paris Agreement.

### Bipartite null models and statistically validated projections

To ensure that the cooperation network truly reflects the relationship between countries, I filter out any connections that might also be found in a random network where links are assigned by chance. That is, I remove any links that are not statistically significant. A variety of methods have been proposed to determine which links are significant (Latapy et al., 2008; Neal, 2014; Saracco et al., 2017; Serrano et al., 2009). Here I adopt the grand canonical algorithm proposed by Saracco et al. (2017), which can be used to obtain a statistically-validated projection of any binary, undirected, bipartite network. The general idea underpinning this method is that any two countries should be connected in the corresponding one-mode projection, i.e., the cooperation network, if, and only if, they co-signed a statistically significant number of treaties.

The algorithm can be applied through the following four steps. First, for each pair of countries, the number of co-signed treaties is computed. This can be regarded as a measure of the degree of similarity between the two countries.

The second step quantifies the statistical significance of the similarity between each pair of countries. The null hypothesis here is that the observed similarity between any two countries can be explained simply by chance, given the involvement of the two countries in various treaties. To test this hypothesis, an appropriate null model is needed.[4] Here, I adopt the bipartite partial configuration model. This model is part of the entropy-based exponential random graph (ERG) class of null models, and constrains only the degrees of the nodes in the layer of interest, i.e., in my case the number of treaties each country has signed (Park and Newman, 2004; Saracco et al., 2015b, 2017; Squartini and Garlaschelli, 2011).

More specifically, the partial configuration model generates a bipartite network in which each country has exactly the same degree (i.e., participation in the same number of treaties) as in the original bipartite network, but the connections between countries and treaties have been randomly reshuffled. Given two countries

[4]The Python code for this step can be obtained from `https://github.com/tsakim/bipcm`.

$c_i$ and $c_j$, the distribution describing the behaviour of each value of similarity between $c_i$ and $c_j$ is the Poisson–Binomial distribution. That is, the Poisson-Binomial distribution describes the probability that two given countries $c_i$ and $c_j$ co-sign $n^T_{c_i,c_j}$ treaties simply by chance, with $n^T_{c_i,c_j} = [0, ..., N_T]$, and where $N_T$ is the total number of treaties. Based on this bipartite partial configuration model, measuring the statistical significance of the observed value $n'^T_{c_c,c_j}$ thus implies calculating a $p-$value$_{c_i,c_j}$ on the Poisson–Binomial distribution, i.e., the probability that $c_i$ and $c_j$ co-sign a number of treaties greater than, or equal to, the $n'^T_{c_c,c_j}$ simply by chance. Notice that, as a one-tail statistical test, this approach would lead to establishing a link between any two countries if the observed number of co-signed treaties is "sufficiently large".

Third, once the $M$ $p-$values associated to each pair of countries have been calculated (where $M = \binom{N^C}{2}$ is the total number of possible pairs of countries and $N^C$ the total number of countries), I adopt a statistical procedure for simultaneously testing multiple hypotheses of similarities between pairs of countries. This is necessary to account for the lack of independence of similarities (and associated $p-$ values), since each observed link in the original bipartite network between a given country and a given treaty inevitably affects the number of common treaties that country co-signs with each of the remaining countries, and therefore the similarities of several pairs of countries. To account for this, I applied the so-called False Discovery Rate (FDR) procedure, which controls for the expected number of false "discoveries" (i.e., incorrectly-rejected null hypotheses, Benjamini and Hochberg 1995). To this end, I sort the $M$ $p-$values in increasing order and then identify the largest integer $\hat{i}$ such that $p-\text{value}_{\hat{i}} \leq \frac{\hat{i}\alpha}{M}$, where $\alpha$ is the single-test significance level, which here I set at 0.01.

As a final fourth step, I obtain a statistically-validated projection of the bipartite network by considering as statistically significantly similar only those pairs of countries $c_i$ and $c_j$ whose $p-\text{value}_{c_i,c_j} \leq p-\text{value}_{\hat{i}}$. Equivalently, this translates into rejecting the null hypotheses of observing by chance the similarities between countries when the corresponding $p-$values are smaller than the given FDR threshold. In this way, a link will be established only between pairs of countries that are sufficiently similar, i.e., that have co-signed a larger number of treaties than would be randomly expected. All my subsequent analyses will be based on such a statistically validated network projection.

### 3.2.4 Network analysis

I then use global network metrics to describe the topological structure of the resulting environmental cooperation network. The chosen metrics include measures of network size (cumulative frequency of nodes and links), connectivity (average degree, average strength), and social cohesion (density, shortest path length, number of components, and clustering coefficient). In addition, the roles of individual countries in the cooperation network are investigated through centrality measures, such as betweenness centrality and closeness centrality. Further intuitive explanations are provided in the application of the metrics below.

**Cumulative frequency of nodes and links.** The size of a network can be measured straightforwardly through the number of nodes and links it contains. In a dynamic setting, the growth in network size can be measured through cumulative distributions of nodes and links over time.

**Degree and strength.** The degree $k$ of a node is the number of links connected to it. In weighted networks, the metric of node degree is complemented by node strength, $s$, which is the sum of the weights of the links incident upon the node (Barrat et al., 2004). In the cooperation network, the degree of a country indicates the number of partners which this country cooperates with, while the strength accounts for the intensity of cooperation between this country and others. The average degree and average strength of a network are global variables of network connectivity. In contrast, the degree and strength of individual nodes are local measures of connectivity. A node with a higher degree is expected to have more access to information and to be more salient for communication activities in the network than nodes with lower degrees (Freeman, 1978; Hafner-Burton et al., 2009).

**Density.** The density of a network is the ratio between the actual number of links $m$ and the maximum possible number of links, i.e., $\binom{n}{2} = \frac{1}{2}n(n-1)$, where $n$ is the number of nodes in the network. Density ranges from 0, when no link is established, to 1, when all possible links have been established. In the cooperation network, density measures the portion of the potential cooperative connections that are actual connections through treaties. Thus, the network density can be seen as an indicator of cooperative cohesion among countries.

**Shortest path length.** For a binary network, the shortest path length $d_{ij}$ between node $i$ and node $j$ is the length of the path with the lowest number of links separating the two nodes (Newman, 2018). In weighted networks, shortest path lengths between nodes are traditionally measured through the algorithm proposed by Dijkstra (1959). In this case, weights indicate the cost of information transmission or resource flow, and distances are calculated as sums of the weights of the links traversed. Thus, the weighted shortest path length between any two nodes is the path with the least resistance in terms of exchange costs. However, in my study the weights of links do not represent the cost, but the intensity of cooperation between countries, and therefore we use the reciprocal of weights to identify weighted shorted paths using the Dijkstra's algorithm (Brandes, 2001; Newman, 2001b). Hence, in the network, the higher the weight of the link, the closer two countries are and the lower the cost of cooperation.

**Component.** A component is the largest subset of nodes in a network in which there exists at least one path between any pair of nodes. The components in a network organise the network into different isolated subgraphs, and the number of components in a network can therefore be used to assess the isolation of nodes. All else being equal, a network with more (and smaller) components is less cohesive, as countries only build cooperative ties within the same component. Conversely, a smaller number of (larger) components in the cooperation network indicates a higher level of network cohesion.

**Clustering coefficient.**Social capital refers to the "advantages that individuals or groups have because of their location in social structures (Burt, 2000)". Different from human capital which emphasises the impact of the capacity of individuals on success, social capital acknowledges the importance of connections the focal individual has. Different network structures may carry different kinds of social capital. Studies of the network sources of social capital have suggested that closed structures facilitate access to complex information, stimulate trust, sustain cooperation and promote social norms by enabling the enforcement of collective sanctions (Burt, 2000; Coleman, 1988). A better understanding of the role of social capital brought by closed structures in the cooperation network will enable policymakers to develop more effective strategies to promote collective actions. Traditionally, network closure is measured through the global and local clustering coefficients.

The global clustering coefficient of a network quantifies the level of *global connectivity* based on the density of triplets. A triplet can be defined as three nodes connected by either two (open triplet) or three (closed triplet) links. The global clustering coefficient measures the fraction of closed triplets over the total number of open and closed triplets, that is, the degree to which triplets in a network close up into triangles (Newman, 2018; Opsahl and Panzarasa, 2009). For example, in the context of international relations, it has been shown that countries that share bilateral agreements with the same third parties are more likely to form bilateral agreements themselves (Kinne, 2013).

To take the weights of links into consideration, I use a generalisation of the global clustering coefficient based on the values of triplets (Opsahl and Panzarasa, 2009):

$$C^w = \frac{\sum_{\text{closed triplets}} v_i}{\sum v_i} \tag{3.2}$$

Here, the value of a triplet $v_i$ is the arithmetic mean of the weights of the two links that make up the triplet. Note that the weight of the closing link of a triplet is not taken into account as the weighted coefficient is simply aimed at assessing the likelihood of the closing link, and not its strength.

Unlike the global clustering coefficient, the *local clustering coefficient* is defined for a single node and captures the connectivity of a node's local neighbourhood. In particular, it quantifies the tendency of a node's neighbours to be connected with each other.

The *weighted local clustering coefficient* is a generalisation of the coefficient that takes the weights of links into consideration (see Saramäki et al., 2007, for details on comparison of different methods). We rely on the method proposed by Onnela et al. (2005) to account for the intensity of cooperation between countries. This method is based on a node's subgraph intensity, defined as the geometric average of the weights of the links forming all closed triplets centred on the node, where each weight is normalised by the maximum weight globally found in the network.

In addition, in what follows we discuss findings based on an alternative method proposed by Barrat et al. (2004), according to which the contribution of each closed triplet centred on a node depends on the ratio of the average weight of the two links incident on the node to the average strength of the node (i.e., the node's strength divided by the node's degree). Hence, in this case local distributions of weights heavily affect the value of the weighted local clustering coefficient, while according to the former method proposed by Onnela et al. (2005) the coefficient depends on the distribution of weights across the whole network.

**Betweenness centrality.** Betweenness centrality was originally proposed by Freeman (1977) to measure the degree to which one node lies on the shortest paths between others. It is defined as:

$$C_{B,i} = \sum_{j,k} \frac{g^i_{j,k}}{g_{j,k}}, \tag{3.3}$$

where $g_{j,k}$ is the number of shortest paths between node $j$ and node $k$, and $g^i_{j,k}$ is the number of those paths passing through node $i$. If $j = k$, $g_{j,k} = 1$, and if $i \in j, k$, then $g^i_{j,k} = 0$.

Betweenness centrality quantifies the extent to which a node presides over indirect connections between all other nodes in a network (Burt, 2000). Hence, betweenness centrality is an indicator of the importance of nodes in participating in and controlling, the flow of critical resources in networks, such as the the spread of information, news, opportunities across various regions of a social system (Freeman, 1978). In international relations networks, a node with a high betweenness centrality has a high brokerage power over otherwise disconnected countries, and has therefore the potential to foster and facilitate cooperation between other countries (Hafner-Burton et al., 2009).

**Closeness centrality.** The *closeness centrality* of a node is defined as the inverse of the average shortest path length from the node to all other reachable nodes:

$$C_{C,i} = \frac{n-1}{\sum_j d_{ij}}, \tag{3.4}$$

where $n$ is the number of nodes reachable by node $i$, and $d_{ij}$ is the shortest path length between node $i$ and node $j$. In social networks, higher closeness centrality, i.e., the shorter average distance from other nodes, implies quicker communication at a lower cost (Freeman, 1978). Information from the most central nodes can spread out quickly and in the most cost-effective manner. Thus, in my study closeness centrality can be a proxy of the proximity of a country to other countries in the network based on existing cooperative connections, and consequently of the potential cost of sustaining cooperation with other countries.

## 3.3 The extent of cooperation

### 3.3.1 Overview

I first explore what the growth in IEAs means for the emergence and evolution of an environmental collaboration network. The 1972 UN Conference on the Human Environment in Stockholm has been described as the beginning of a systematic and potentially universal approach to international environmental policy-making (Falkner and Buzan, 2019). In the ensuing half-century global environmental cooperation has become all but ubiquitous (Mitchell, 2003). Intuitively, one would expect this proliferation of treaties to result in deeper and more intensive environmental cooperation.

The prominence of treaties negotiated under the auspices of the United Nations and UN agencies suggests that the UN played an important role in encouraging this trend. The suite of treaties agreed at the 1992 "Earth Summit" in Rio de Janeiro, in particular, have come to define global environmental cooperation in areas such as biodiversity (Convention on Biodiversity), climate change (UN Framework Convention on Climate Change) and desertification (Convention on Desertification). However, the literature is equivocal about the coordinating and catalytic role played by the UN, pointing out institutional shortcomings and arguing for a stronger anchoring body in global environmental governance (Biermann and Bauer, 2004; Ivanova, 2010; Mee, 2005).

Several reasons are attributable to the performance of the UN in environmental affairs. First, the authority of the UN to enforce environmental regulations and agreements depends on support from its member states, particularly powerful states, like the United States. As the UN relies on the voluntary engagement of its member states, the limited, voluntary financial resources tend to be a source of many of its challenges (Ivanova, 2010). Its real powers have weakened due to reduced budget allocations and increased earmarked funding (Mee, 2005). In addition, current institutions in the UN are fragmented with different agencies and bodies responsible for different aspects of the environment resulting in a very loosely and sometimes poorly coordinated network (Lodefalk and Whalley, 2002; Mee, 2005). Moreover, power imbalance within the UN can largely influence the decision-making process. Environmental issues concerned by powerful countries are more likely to be prioritised, and the demands of developing countries are marginalised (Mitchell, 2003).

These observations give rise to the following **hypothesis:** *Over the past 50 years, global environmental cooperation has become pervasive, covering virtually all countries. Indeed cooperation is accelerating. This trend has been aided by the UN and its agencies, but the UN is not the dominant platform for environmental cooperation.*

I test the hypothesis using metrics concerned with network size and connectivity. A straightforward way to measure the size of the environmental cooperation network is the number of nodes (countries) and links (through treaties) it contains, and more specifically the cumulative frequency of nodes and links over time. I use two metrics to measure the connectivity of the network, i.e., the average degree and the average strength. The average degree considers the number of partners with which each country cooperates, while the average strength describes the intensity of cooperation of a country with others (Barrat et al., 2004). I use the speed of treaty ratification as the measure of network acceleration.

I find that since the early 1970s countries have been integrated into a network of increasingly intensive environmental cooperation. The growing intensity of global environmental cooperation is reflected in the size of the network, which includes virtually all countries of the world, and a high level of connectivity (high average degree and node strength) between countries. I note that countries do occasionally withdraw from treaties, which weakens the network, but this is relatively rare. Treaty membership is associated with the faster ratification of subsequent IEAs, which suggests network acceleration.

The UN has been an important platform for, but not the main contributor to, the connectedness of the environmental cooperation network. Network properties remain similar with and without the inclusion of UN-sponsored treaties.

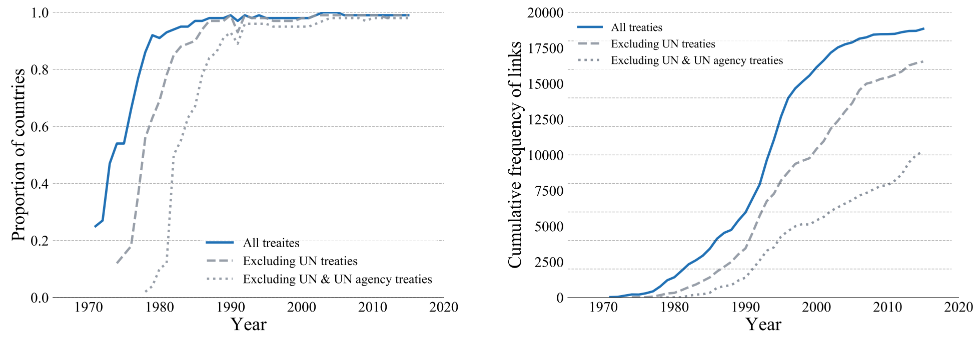
The results are robust to alternative calculations that factor in the level of activity under a treaty (by "retiring" dormant treaties) and the relative importance of treaties (as measured by number of media mentions and citations in other agreements). The results of these extensions are reported in Sections 3.3.4 and 3.3.5.

### 3.3.2 Network size

A first important observation when assessing the size of the environmental cooperation network is that a statistically significant network only appeared in 1971. From 1948 to 1970, the number of common treaties between any two countries is not significantly different from the number that would be obtained simply by chance, given the involvement of the two countries in the various treaties. That is, before 1970 no pair of countries managed to co-sign a larger number of treaties than would be randomly expected, thus preventing the emergence of statistically significant cooperation links.

However, since 1971 the cumulative frequency of network nodes and network links has grown steadily, both in absolute terms and relative to the number of nation states, which has also grown, as shown in Fig. 3.5. In the early 1970s many of the newly independent countries in the Global South began to engage with the international environmental treaties. The cooperation network became stable in the year 1980, when the growth rate in the number of nodes (countries) fell below 5%. These patterns are consistent with the views of international relations scholars like Falkner and Buzan (2019), who also date the beginning of international environmental cooperation to the 1970s.

The most rapid growth in network links occurred in the 1990s. During this period, 153 new treaties promoted cooperative ties among 192 countries. The growth in links levelled off around the year 2000, when the cumulative frequency of links almost reached the maximum possible.




(a) Cumulative frequency of nodes (b) Cumulative frequency of links

Figure 3.5: Cumulative frequency of nodes and links in country networks from 1971 to 2015.

I next investigate the role of the UN and its agencies[5] as a platform for international environmental cooperation. I do this by filtering out treaties negotiated under the auspices of the UN or a UN agency and reconstructing the network without them. The result suggests that the UN has had a notable impact on the network structure, particularly through its agencies, but it is not the dominant platform of international cooperation, as shown in Fig. 3.5a. The majority of countries remain engaged, even with the simulated removal of the UN treaties. The number of statistically significant cooperative links decreases without UN treaties, but remains substantial.

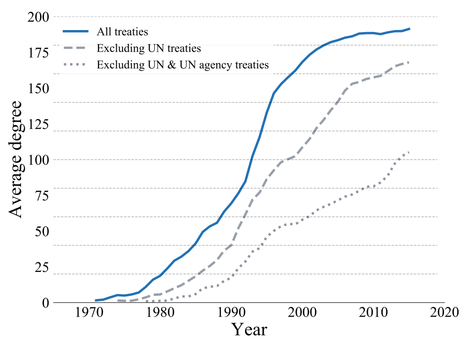
### 3.3.3 Connectivity

Over the period of interest, both the average degree and the average strength in the cooperation networks have increased greatly (panel a of Fig. 3.6 and 3.7).

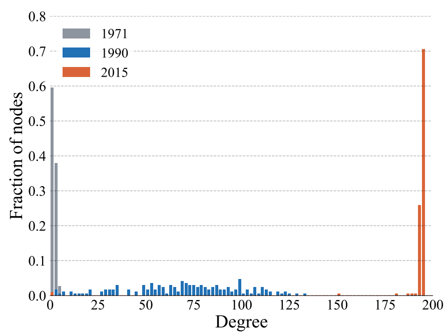
[5]The UN agencies investigated here include, based on the data provided by ECOLEX, Food and Agriculture Organization of the UN (FAO), International Maritime Organization (IMO), International Labour Organization (ILO), United Nations Educational, Scientific and Cultural Organization (UNESCO), United Nations Environment Programme (UNEP).

The growth in connectivity was particularly pronounced in the 1990s. During this period the degree distribution and strength distribution both widened (panel b), suggesting that the growth in connectivity was initially driven by a vanguard of particularly active countries that forged ahead. By 2015, the degree distribution had narrowed again as the laggards caught up and the average number of partner countries reached a maximum. However, the strength distribution continues to be wide. The cooperation network had reached a point in which connectivity did not depend on the average number of partners, but was constantly reinforced by the average intensity of cooperation among countries.

I again study the impact of the UN on this pattern by recalculating the metrics for a cooperation network without UN-sponsored treaties. The average degree of the network decreases notably in particular when treaties supported by UN agencies are excluded (Fig. 3.6, panel a). The exclusion of UN-sponsored treaties also reduces the number of common treaties between countries and consequently the average strength in the network. The effect is particularly pronounced in the second half of the study period (Fig. 3.7, panel a).

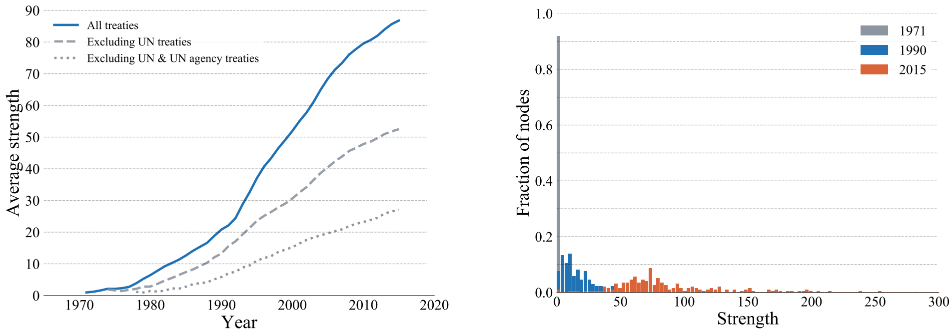



(a) Average degree




(b) Degree distribution

Figure 3.6: Average degree and degree distribution from 1971 to 2015.




(a) Average strength

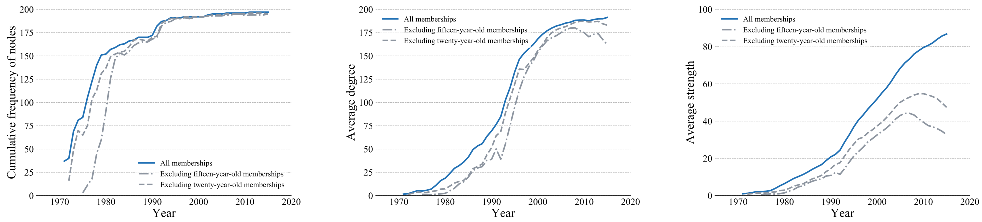
(b) Strength distribution

Figure 3.7: Average strength and strength distribution from 1971 to 2015.

### 3.3.4 Relationship between activity levels and the extent of cooperation

In this section, I analyse the possibility that some older treaties may be less dynamic and that the intensity of cooperation may therefore decrease over time.

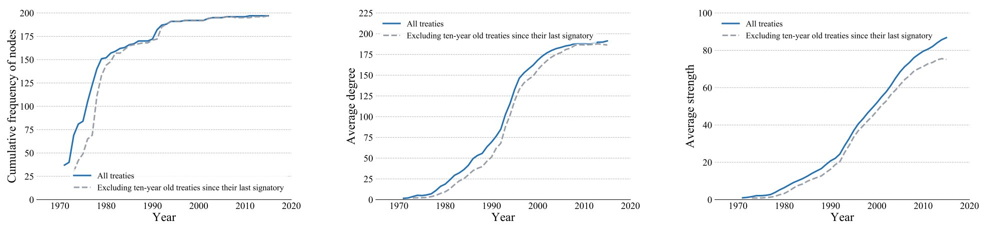
I employ two strategies to account for the level of activity in a treaty. First, I consider the age of the country-treaty relationships and retire older treaties automatically. I consider this to be a relatively extreme scenario that constitutes a lower bound of the extent of international cooperation. In the year of observation, country-treaty relationships which are at least 10 years old are removed from the sample when constructing the network. Following these amendments, I replicate my main results, as displayed in Fig. 3.8. It can be seen that the overall trends are similar, except for average strength, which declines toward the end of the period of interest as a growing number of treaties are retired.




(a) Number of nodes (b) Average degree (c) Average strength

Figure 3.8: Cooperation networks when removing old country-treaty relationships

Second, I use the date of the last new signatory as an indicator of treaty activity. In the year of observation, treaties with no new signatories over the past 10 years are removed from the network. The assumption is that treaties that attract new signatories remain active platforms of collaboration. This second scenario is less extreme than the first interpretation above, and as shown in Fig. 3.9, the main results are robust to this alternative approach.




(a) Number of nodes (b) Average degree (c) Average strength

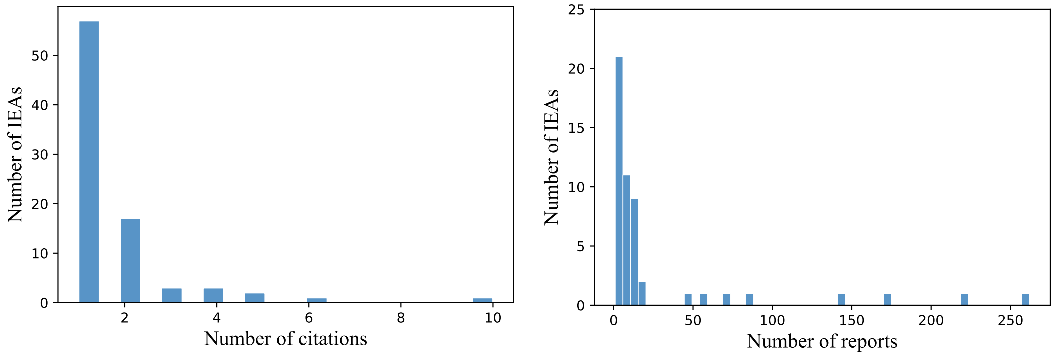
Figure 3.9: Cooperation networks when removing less active treaties

### 3.3.5 Relationship between treaty salience and the extent of cooperation

This section explores whether treaty salience has implications for international cooperation. I define treaty salience as the importance or relevance of a treaty in the context of international relations. Chayes and Chayes (1993) mentioned "political salience" in his study, but did not provide a definition. Here, treaty salience indicates how much attention and priority a specific treaty receives from the countries that are party to it, as well as from the international community as a whole. Factors that influence the salience of a treaty include its subject, the number of its member states, the level of enforcement and compliance and the degree of attention it receives from the media, the civil society, and other actors. Based on the factors, different proxies can be developed to measure the degree of salience, such as the number of states that have ratified the treaty, the amount of media coverage a treaty receives, the number of environmental organisations engaged in the treaty, and the number of domestic regulations or policies in countries to implement the treaty. In my study, I chose the media coverage as the proxy of treaty salience. The hypothesis is that IEAs on salient issues may be associated with higher levels of cooperation. I proceed in two ways.

First, I use citations (or cross-references) in other agreements as the measure of treaty importance. These data are available from Ecolex, and the approach is similar to Kim (2013). I conjecture that cited agreements have added value, in that subsequent agreements build on them. There are 84 treaties which have been cited at least once. The distribution of the number of citations is illustrated in Fig. 3.10a.

In addition, I collect data from the database Factiva on the media coverage of agreements in the *The New York Times*. I conjecture that continued media coverage over time is a sign that an agreement remains salient and keeps receiving attention. This is the case even if some of the coverage is critical of the agreement. There are 52 treaties that have featured in *The New York Times*, with 5 treaties reported on more than 100 times. The maximum number of reports is 1623 mentions for the Paris Agreement. The distribution of the number of reports is shown in Fig. 3.10b (excluding the Paris Agreement).




(a) Citations

(b) Reports

Figure 3.10: Distribution of the number of citations and the number of reports for agreements reported less than 300 times

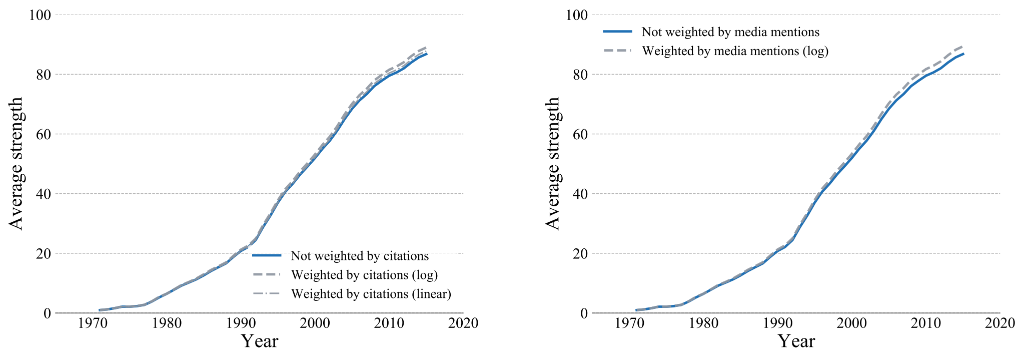
I incorporate the importance of citations and media reports into the analysis by revising the formula for calculating link weights. Specifically, I add a term $f(n)$ to Equation 3.1, where $f(n)$ is an increasing function of the number of citations $n_c$, or the number of media reports $n_r$. I consider both linear and logarithmic functions of citations, as shown in Equations 3.6 and 3.7, while for media coverage I only consider a logarithmic functional form.

$$w_{u,v} = \sum_k \frac{\delta_u^k \delta_v^k}{d_k - 1} f(n) \tag{3.5}$$

$$f(n) = n + 1 \tag{3.6}$$

$$f(n) = log(n + 1) + 1 \tag{3.7}$$

I then construct new cooperation networks using the revised formulas. In this case, the prominence of the Paris Agreement is considered through media reports. The Paris Agreement is a landmark in international cooperation on climate change. It was adopted by 196 Parties at the UN Climate Change Conference (COP21) in Paris, France, in 2015. It received extensive attention with 1623 mentions in media reports. In Equation 3.1, the contribution of the Paris Agreement to cooperation intensity between countries is relatively less than other treaties as almost every country signed it. Here, the influence of the Paris Agreement is enhanced by adding the additional term. The only metric that may potentially be affected by the revision is average strength, but Fig. 3.11 suggests that the patterns in country strength are, in fact, not notably different from those found in the original network. Although partial, the additional evidence provided in this section thus seems to rule out that the results are driven by cooperation on old or insignificant treaties.




(a) Citations (b) Reports

Figure 3.11: Average strength from 1971 to 2015 when considering salience of treaties.

### 3.3.6 Treaty membership and network acceleration

Past participation in IEAs may create more opportunities for future collaboration and increase a country's readiness to join new treaties when they become available. I explore this possibility by running a simple OLS regression [6] where I regress the speed at which a country joins new IEAs on the extent of past treaty membership. The regressions include a full set of fixed effects to control for unobserved characteristics at the country, time and treaty level, that might influence the speed of ratification of a new IEA. I then investigate whether the speed of ratification is associated with membership in treaties of a certain type, such as UN-sponsored treaties or important treaties with high media mentions or cross-citations.

In this section, I study whether past treaty membership is associated with faster collaboration in future treaties. I use simple regression analysis to explore the correlation between the cumulative number of treaties a country has joined at the time a new treaty becomes available and their readiness to join subsequent IEAs. I start by focusing on all treaties, to then study the role played by specific types of treaties. In particular, I consider salient treaties (as measured in the previous section, by the average number of media mentions and the average number of citations of past treaties), UN-sponsored and non-UN sponsored IEAs.

The dependent variable is the log of the speed of ratification, i.e., the time span (years) between the date of the availability of a treaty and the date a country ratifies the treaty. I estimate the following equation:

[6] Despite being in the spirit of some of the empirical methods for networks as discussed in, e.g., Chandrasekhar 2016 and De Paula 2020, this exercise does not consider the process of network formation nor represents a comprehensive analysis of the drivers of the speed of ratification. Therefore results can only be interpreted as suggestive.

$$log\Delta\left(t-t_a\right)_{i,j}=\beta_0+\beta_1 C_{i,t_a-1}+G_j+V_i+Z_t+e_{ijt} \tag{3.8}$$

$\Delta(t-t_a)_{ij}$ represents the number of years it takes to country $i$ to ratify or enforce treaty $j$, where $t$ indicates country $i$'s year of ratification or enforcement, and $t_a$ indicates the year the treaty becomes available. $C_i$ is the independent variable of interest of country $i$, the year before the treaty becomes available. $G_j$ is a treaty dummy, $V_i$ is a country dummy and $Z_t$ is a time of ratification or enforcement dummy. The inclusion of a full set of fixed effects allow us to control for unobserved characteristics at the country, time and treaty level, that might influence the speed of ratification of a new IEA.

Table 3.3 presents the results. Results in column 1, indicate that past treaty participation accelerates the speed at which a country joins the next available treaty. The following columns report results for specific types of treaties. All coefficients of interest are negative and significant, indicating that past participation in salient treaties is associated with quicker participation in subsequent IEAs. There are many factors that may be attributable to this phenomenon according to the literature on incentives of countries to ratify IEAs (Wangler et al., 2013). Past participation in IEAs has enabled countries to establish relatively comprehensive institutions and legal frameworks oriented to international environmental issues, including economic and political ones (Fredriksson et al., 2007; Neumayer, 2003b; Perrin and Bernauer, 2010; Roberts et al., 2004). Countries driven by previous IEAs engaged in technical capacity building to measure and monitor environmental indicators (Elliott and Breslin, 2011). In addition, past treaties may provide channels for countries to create ties to global scientific associations, intergovernmental organisations, or international environmental non-governmental organisations which favour more treaties in the future (Yamagata et al., 2017a). Past participation in both UN and non-UN-sponsored treaties seems to make countries more responsive to future cooperation opportunities, with participation in UN-sponsored treaties being slightly more effective. Yet, it is important to highlight that this evidence is only suggestive and cannot be interpreted as causal.

They suggest that past treaty membership is indeed associated with quicker participation in subsequent IEAs, with salient and UN-sponsored treaties playing a prominent role. I interpret this as a sign of network acceleration.

Table 3.3: Past treaty membership and speed of ratification of future IEAs

| | Speed of ratification | | | |
|---|---|---|---|---|
| Variables | 1 | 2 | 3 | 4 |
| Total number of IEAs | -0.00362*** | | | |
| | (0.000604) | | | |
| Average number of media mentions | | -0.0295* | | |
| | | (0.0157) | | |
| Average number of citations | | | -0.191* | |
| | | | (0.103) | |
| Cumulative number of UN IEAs | | | | -0.00441*** |
| | | | | (0.00130) |
| Cumulative number of non-UN IEAs | | | | -0.00280* |
| | | | | (0.00154) |
| Observations | 11913 | 11913 | 11913 | 11913 |
| Adjusted $R^2$ | 0.842 | 0.841 | 0.841 | 0.842 |
| Year FE | Yes | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes | Yes |
| Treaty FE | Yes | Yes | Yes | Yes |

Notes: The dependent variable is the log of the speed of ratification (years), i.e., the time span between the date of the availability of a treaty and the date of ratification in a country. In the first column, the independent variable is the total number of treaties a country is a member of till one year before the availability of a new treaty. Similarly, the independent variables in column 2 and column 3, are the average number of media mentions and the average number of citations of treaties a country is a member of. The two independent variables in column 4, are the total number of UN IEAs and non-UN IEAs, respectively, a country is a member of till one year before the availability of a new treaty. Standard errors clustered at the country level in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 3.4 The ease of collaboration

### 3.4.1 Overview

I next study what the proliferation of IEAs implies for the ability of countries to cooperate and the effectiveness with which knowledge and policy are diffused.

IEAs are both the result of environmental cooperation and a facilitator of such cooperation (Bernstein and Cashore, 2012). The shared objectives and agreed actions from environmental cooperation are frequently codified in an IEA, but the IEA then creates the basis for further cooperation by establishing relationships, providing platforms for engagement and setting up organisational structures to share the benefits of cooperation (e.g., Bernauer et al., 2010; Keohane, 1984; Meyer et al., 1997; Sauquet, 2014). Therefore, cooperation through IEAs may help to create trust among countries through ties established, which in turn facilitates subsequent cooperation as trust is key for dealing with both local and transnational environmental issues (Carattini et al., 2015, 2019b; Carattini and Löschel, 2021; Ostrom, 2009; Owen and Videras, 2008).

The environmental cooperation network further serves as an information network (Lazer, 2005), where easier information flows can facilitate both learning and imitation (or conditional cooperation). Both are crucial for policy diffusion in the context of transnational and global public goods. Several studies have shown that a shorter distance between nodes leads to the faster diffusion of information (Cheng et al., 2014; Goel et al., 2016; Newman, 2018; Zhang et al., 2016). As such IEAs may be an important driver of policy convergence (Busch et al., 2005;

Holzinger et al., 2008).

These observations lead to the following **hypothesis:** *The network of IEAs has promoted environmental cooperation, knowledge exchange and information diffusion by shortening the distance between countries and facilitating the emergence of tightly-knit communities and third-party relationships.*

I assess the facilitating functions of IEAs by studying the global and local cohesion of the environmental cooperation network. For the analysis of global cohesion, I refer to the concepts of components, network density, average shortest path length, and global and local clustering coefficient.

The number of components in a network can be used to gauge the degree of global cohesion across the network, i.e., a network with more components is less cohesive and more fragmented than a network with fewer components. The network density measures the portion of the potential cooperative connections that are actual connections based on co-signing of treaties.

The weighted shortest path between any two nodes is the path with the least resistance between them in terms of costs of communication, coordination and exchange (Brandes, 2001; Newman, 2018, 2001b). Thus the average weighted shortest distance describes the ease and cost of cooperation between countries as a result of their structural positions. All else being equal, a network with a small number of components, a high density and a small average shortest distance has a high level of global cohesion and low fragmentation.

It has been suggested that clustering fosters a sense of belonging to a shared group (Portes and Sensenbrenner, 1993), mutual trust, the enforcement of social norms, and the exchange of complex and proprietary information, which in turn facilitates coordination, cooperation, and collective action (Coleman, 1988). Clustering captures social cohesion both at the global and local levels. The global clustering coefficient detects the degree to which connected triads tend to close up into triangles across the network (Newman, 2018; Opsahl and Panzarasa, 2009). The local clustering coefficient captures the tendency of a node's neighbours to become connected themselves (see Barrat et al., 2004; Onnela et al., 2005; Saramäki et al., 2007, for details on the comparison of different methods). Both measures can be used to uncover closed structures as sources of social capital and in particular the tendency of collaboration to originate from tightly-knit communities (global level) and third-party relationships (local level).

My analysis shows that, over the past decades, the network of environmental cooperation has become denser, more cohesive, and has shorter distances between countries. Countries have become gradually less isolated when dealing with environmental problems. The network ended up consisting of just one component that connects all countries. The combination of high cohesion at both the global and local levels (high density, short path lengths and high clustering) creates a system that can be conducive to policy coordination and the diffusion and exchange of knowledge.

It is worth emphasising that the results on cohesiveness do not speak to the ambition of treaties, which I do not observe directly. To explore this aspect at least indirectly, I again turn to the alternative specifications that factor in activity levels and treaty importance, as introduced in Section 3.3 and Sections 3.3.4 and 3.3.5. The hypothesis is that active treaties which continue to attract signatories are particularly good platforms of collaboration and that significant treaties, which are cross-referenced or enjoy media attention, are especially powerful in facilitating cooperation and knowledge exchange. However, when recalculating the metrics to account for these treaty features, I find that the results are not sensitive to their presence. The ease of international environmental cooperation does not seem to be driven by particularly active or important treaties (see Sections 3.4.4 and 3.4.5 for details).

### 3.4.2 Cohesion

In the early 1970s, when statistically significant environmental cooperation links began to emerge, the network consisted of just 37 countries which formed as many as 12 components. Practically all of the components were regional groups (for example, there was a component of Middle-Eastern countries) and many were bilateral, consisting of just two nodes. The network was small and fragmented.

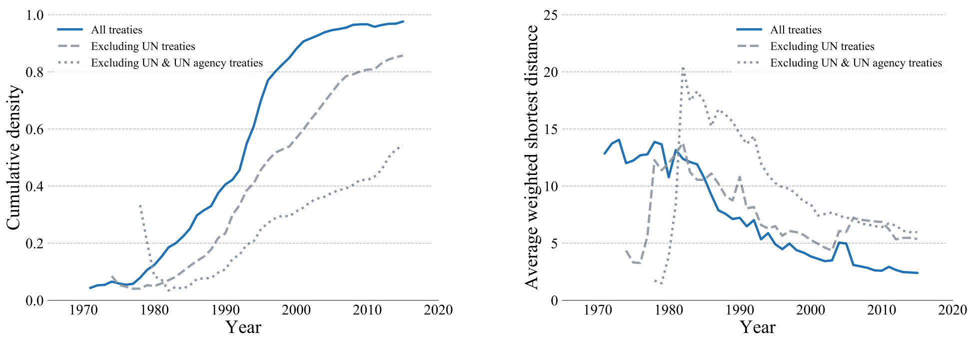
By the early 1980s, the cooperation network had grown to 157 countries which were integrated into a single component. New components formed in the late 1980s and early 1990s as the countries of Eastern Europe and the former Soviet Union started to engage in environmental cooperation. For example, in 1991, newly-independent Armenia, Azerbaijan, Georgia, Kazakhstan, Tajikistan, Latvia, and Uzbekistan joined the cooperation network as a separate component.

They were absorbed into the largest component in the following year when the network coalesced again into a single global component. Since 1992 every pair of countries (except Taiwan and later Hong Kong) has been able to reach each other through direct or indirect treaty-based connections.

The density of the cooperation network grew at a similar pace, increasing rapidly through the 1980s and 90s. At the start of this century, nearly every pair of countries had established a significant cooperation relationship (Fig. 3.12, panel a).

The average weighted shortest distance of the network stayed at a high level in the 1970s, reflecting the growing size of the largest network component, but has fallen steadily since (Fig. 3.12, panel b). The size of the largest network component remained stable throughout this period, encompassing some 95 percent of nodes. At the same time, new connections appeared and existing connections were strengthened through new treaties, which in turn fostered a reduction in average distances.

These results corroborate the view that the fall of the Soviet Union and the end of the Cold War in the early 1990s created the opportunity for new alliances, encouraging international cooperation and policy diffusion to occur outside the two hegemonic blocks (Yamagata et al., 2017b).




(a) Cumulative density (b) Average weighted shortest distance

Figure 3.12: Cumulative density and the average weighted shortest distance from 1971 to 2015.

The exclusion of UN and UN agency-sponsored treaties leads to a smaller density and a larger average weighted shortest distance, as shown in Fig. 3.12. Around 1980, the exclusion of UN-sponsored treaties leads to more components and a smaller fraction of countries belonging to the largest component, which results in a lower average shortest distance. However, even without the UN-sponsored treaties, the whole network remains connected from around 1990 to 2015.

Thus, the UN and its agencies have contributed to reducing the distance between countries and provided a framework for inter-state cooperation (in line with Meyer et al., 1997). As noted before, the UN agencies play a more important role in this process than the UN itself.

### 3.4.3 Clustering

The evolution of the global clustering coefficient of the network is shown in Fig. 3.13. Following a short blip in the 1970s, the clustering coefficient has grown rapidly and steadily through the 1980s and 1990s before levelling off at the beginning of this century. As such, the trend is comparable to that observed for the network size and connectivity metrics. It suggests that, as the cooperation network expanded and new links were created, third-party relationships (i.e., links between countries sharing partners) were formed simultaneously and at the same rate.

Many factors can promote the presence of common partners, such as geographic proximity, affiliation with related regional groups or organisations, a similar economic status, a shared history and trading relationships (Fagiolo et al., 2010;

Sauquet, 2014). The presence of common partners is likely to have promoted trust and helped countries establish deeper relationships. As I have observed with other network metrics, the overall trend of the global clustering coefficient changes significantly when both the UN and UN agency treaties are removed.

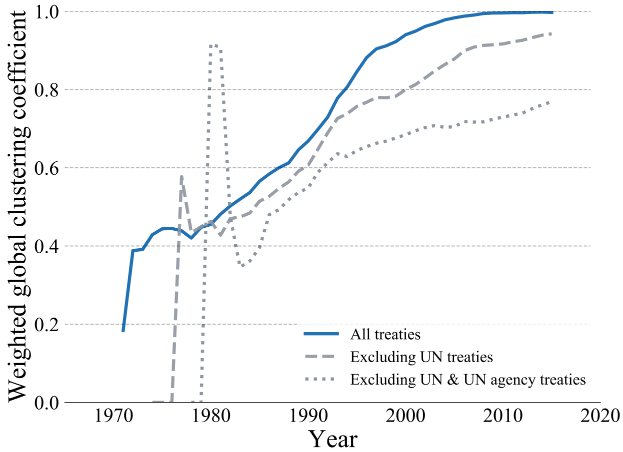
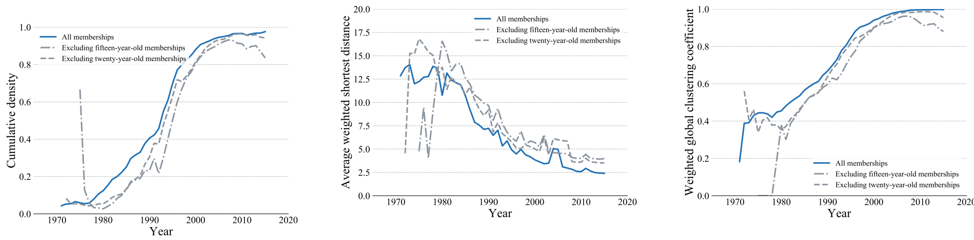



Figure 3.13: Global clustering coefficient from 1971 to 2015.

### 3.4.4 Relationship between activity levels and the ease of cooperation

In this section, I investigate if my results on the ease of collaboration are driven by older treaties or treaties which register little activity. The same strategies introduced in Section 3.3.4 are applied. As shown in Fig 3.14 and Fig 3.15, the level of activity under treaties does not affect my results on the ease of collaboration.

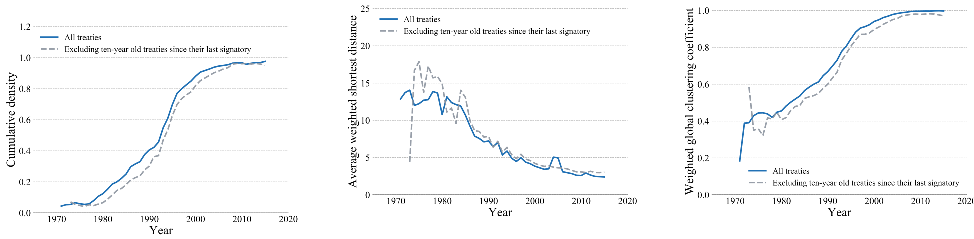



(a) Density

(b) Average weighted shortest distance

(c) Global clustering coefficient

Figure 3.14: Cooperation networks when removing old country-treaty relationships




(a) Density

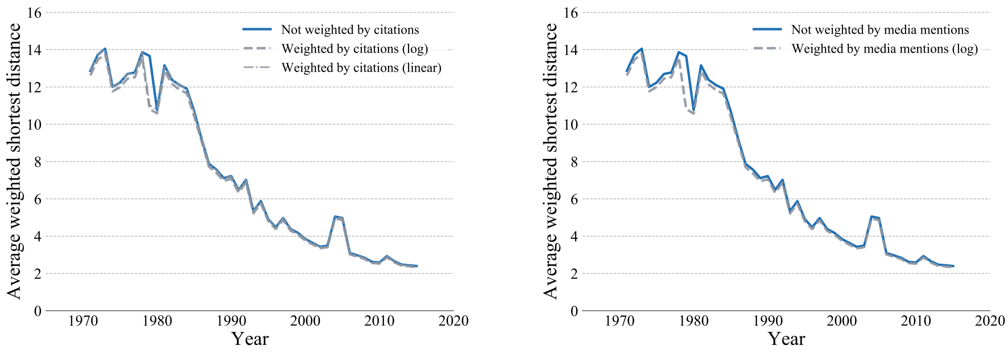
(b) Average weighted shortest distance

(c) Global clustering coefficient

Figure 3.15: Cooperation networks when removing less active treaties

### 3.4.5 Relationship between treaty salience and the ease of cooperation

Similar to the exercise performed in Section 3.3.5, I study the association between the salience of IEAs, as measured by media coverage or citations, and the ease of cooperation. The key metric affected by the alternative weighting strategy introduced in Section 3.3.5 is the shortest path length. However, Fig. 3.16 shows that the original results on the average shortest distance are robust to this alternative specification. The caveats expressed in Section 3.3.5 again apply.




(a) Citations (b) Reports

Figure 3.16: Average weighted shortest distance from 1971 to 2015 when considering salience of treaties.

## 3.5 The role of individual countries

### 3.5.1 Overview

I now turn to the positions of individual countries in the cooperation network. The role and motivations of different countries is an essential subject in the international relations literature, covering angles such as the influence of hegemons (Yamagata et al., 2017b) and the changing role of players like the United States (Falkner, 2005; Kelemen and Vogel, 2010) and Europe (Falkner, 2007; Kelemen 2010, p336; Vogler and Stephan, 2007). A widely held view is that the United States has not played the same dominant role in environmental cooperation as it has in other areas. Instead, international environmental leadership has been provided by the countries of Europe.

I express this observation through the following **hypothesis:** *The major European countries, and not the US, have persistently been the most important players in the* *environmental cooperation network. Their prominent position has, in turn, made it easier for European countries to engage in further environmental cooperation.*

To measure the role of individual countries in the network, I use the centrality metrics of node strength, betweenness centrality and closeness centrality. To assess the impact of central network positions on further environmental cooperation, I correlate centrality measures with the speed of subsequent treaty ratifications.

Node strength accounts for the intensity of cooperation of a country with others, while betweenness centrality measures the ability of a country to intermediate between others. In other words, betweenness centrality is an indicator of the importance of nodes in participating in networks and influencing the flow of critical resources, such as the spread of information and opportunities across various regions of a social system (Freeman, 1978). Closeness centrality measures the distance of a focal country to the other countries in the network. Higher closeness centrality, i.e., the shorter average distance from other nodes, implies quicker communication at a lower cost (Freeman, 1978), and consequently lower potential cost for further cooperation, based on existing treaty connections.

The analysis confirms that the network of environmental cooperation, while fundamentally global, has a noticeable European imprint. In terms of cooperation intensity, betweenness and closeness centrality, the network is heavily influenced by European countries, in particular, the United Kingdom and, more recently, France and Germany. European countries hold these positions in their own right rather than as members of the European Union.

The position of countries has remained relatively stable over time, although there are significant fluctuations. This is partly driven by the fact that a central network position is associated with an increased openness toward further environmental cooperation.

### 3.5.2 Centrality

I find a strong path dependence on the important role of individual countries in the cooperation network. The countries that topped the centrality rankings at the outset were broadly able to maintain their important positions. This stability is in contrast to other networks, where the centrality of individual nodes is often highly sensitive to changes in the network structure (in my case, the signing of new treaties).

I assess the stability of countries' network position over time by looking at the Kendall-Tau correlation coefficients of country rankings for different centrality measures. The Kendall-Tau coefficient measures the rank correlation for each centrality measure between time window $t$ and $t+1$. The starting point of the analysis is the year 1980 when the number of countries in the network begins to stabilise (see Fig. 3.5a above), and the rankings of countries are comparable.

I find a statistically significant and positive correlation between country rankings over time for each centrality measure. The path dependence is most pronounced in the case of strength and closeness centrality, with Kendall Tau coefficients of around 0.9. The positive correlation for betweenness centrality is lower but has solidified over time, from 0.65 to 0.85.

Within this stable overall pattern, it is possible to discern some notable trends for individual countries. While my methodology accentuates smaller countries, I am interested, in particular, in the network position of major economies. Fig. 3.17 shows the overall trends of the chosen metrics for 10 major economies: five members of the G7 (Germany, France, United Kingdom, Japan and the US), the four BASIC countries (Brazil, China, India and South Africa), and Russia. BASIC is the acronym that refers to a group of the four major emerging economies that have formed a bloc to cooperate on climate change issues, including Brazil, South Africa, India, and China. The term "BASIC" was first used in 2009 when they signed an agreement to act jointly at the Copenhagen climate summit, and have since then worked to define a common position on emission reductions and climate aid money. They face significant challenges and opportunities in their transition to low-carbon development. Therefore, they seek to balance their economic growth and environmental protection. BASIC countries advocate for the principle of "common but differentiated responsibilities," promote renewable energy and energy efficiency, and support other developing countries in terms of climate finance. BASIC countries have been influential in shaping global climate negotiations and outcomes (Hallding et al., 2013). The statistics are shown in terms of country rankings since I am interested in the relative position of countries rather than the actual centrality scores.

The strongest positions in the network are held by European countries, which have both high node strengths and centrality scores. For the past few years, France and Germany were ranked first and second with respect to all three centrality measures. This makes the two countries significant hubs in environmental cooperation, with a high cooperation intensity, significant brokerage power and, thanks to the short network distance to other countries, the ability to influence the cooperation network.

France and Germany are replacing the United Kingdom at the top of the rankings. The United Kingdom played a dominant network role in the 1980s and continues to be a hub in terms of cooperation intensity (node strength). It should be noted that the the 20th, the UK played a leading role in the formation of some IEAs, such as the Convention on International Trade in Endangered Species of Wild Fauna And Flora (CITES) [7] and the Montreal Protocol on Substances that Deplete the Ozone Layer. The UK was also one of the first countries to establish an environmental ministry, the Department of the Environment, in 1970 (Wilson, 2018). However, its position as a network broker (betweenness centrality) is waning.

The major European countries occupy these positions in their own right rather than through membership in the European Union. The EU as a body participates in 122 IEAs and sometimes negotiates as a block (most prominently perhaps in the international climate negotiations). However, including the EU as an additional network node does not alter the crucial position in the network of individual EU member states. Additional results, where I include the EU as a network participant in its own right, are reported in Section 3.5.3.

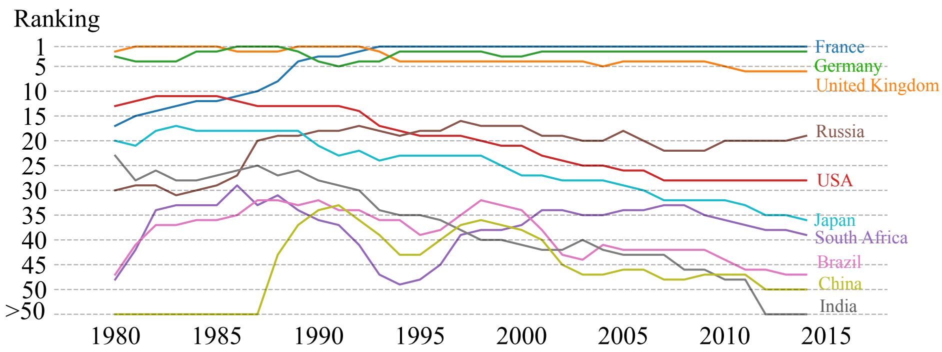
Reflecting its recent ambivalence to international environmental cooperation, the network centrality of the United States has decreased notably over the years. The United States still exerts considerable influence over the network but does not play the dominant role one might expect from a global superpower. The final G7 country, Japan, has also seen its influence wane.

[7] https://cites.org/eng

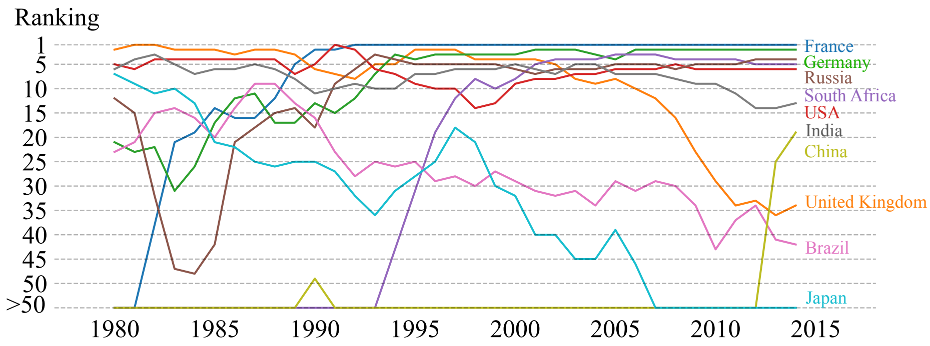
I further note the low centrality of most emerging markets to the cooperation network, including perhaps most notably China's. Until relatively recently, environmental issues were not high on the agenda of the Chinese government, either domestically or internationally, although this is starting to change, for example, with an increased domestic interest in air quality and a stronger international role in climate change (Green and Stern, 2015).

These rankings corroborate my hypothesis about the leadership role played by European countries rather than the traditional superpowers.

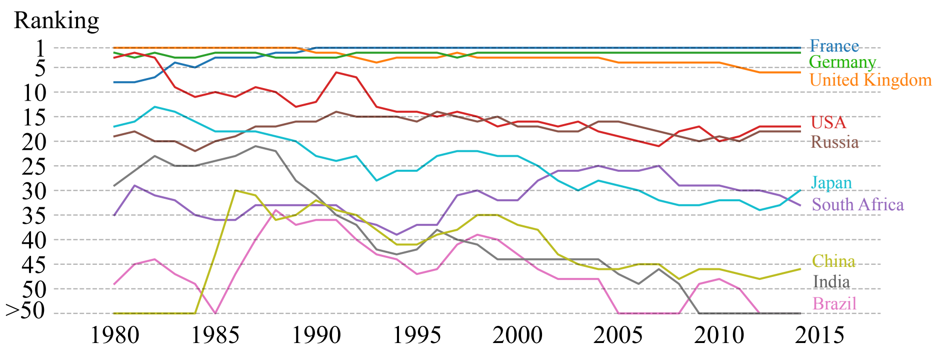
The rankings also speak to future prospects. The roles of different countries in the cooperation network are both a reflection of their past behaviours in international environmental politics and an indicator of future strengths or weaknesses when seeking international cooperation. In Section 3.5.4, I report results of a simple OLS regression similar to the one introduced in Section 3.3.6, where I regress the speed at which a country joins new IEAs on its centrality position. For all three centrality measures - node strength, betweenness centrality and closeness centrality - I find a significant negative correlation. The more central countries are to the network, the faster they join new treaties. This suggests that centrality is not only associated with influence over the current network but with an increased willingness to pursue further cooperation opportunities.




(a) Strength of countries




(b) Betweenness centrality of countries




(c) Closeness centrality of countries

Figure 3.17: Centrality measures. Country rankings from 1980 to 2015.

### 3.5.3 The role of the European Union

In this extension, I consider the role of the European Union in environmental cooperation. The EU is a signatory to several IEAs and EU members sometimes act as one negotiation team in international treaties (e.g., in the UNFCCC climate negotiations). Two interesting questions arise: i) to what extent is the EU as a whole an important player in the network in its own right and ii) how is the network position of EU member states influenced by the activities of the EU?

To explore these issues, I focus on the 122 IEAs which explicitly feature the EU as a signatory. In 65 of them the EU signed the agreement ahead of the majority of member states that were part of the block at the time (see Fig. 3.19). In addition, there are 5 agreements which only have the EU, but not individual member countries, as a signatory. I consider these 70 treaties as driven by the EU. They are assigned to the EU as an additional node in the cooperation network. The remaining 52 agreements, as well as any IEAs not signed by the EU, are assigned to individual member countries as before.

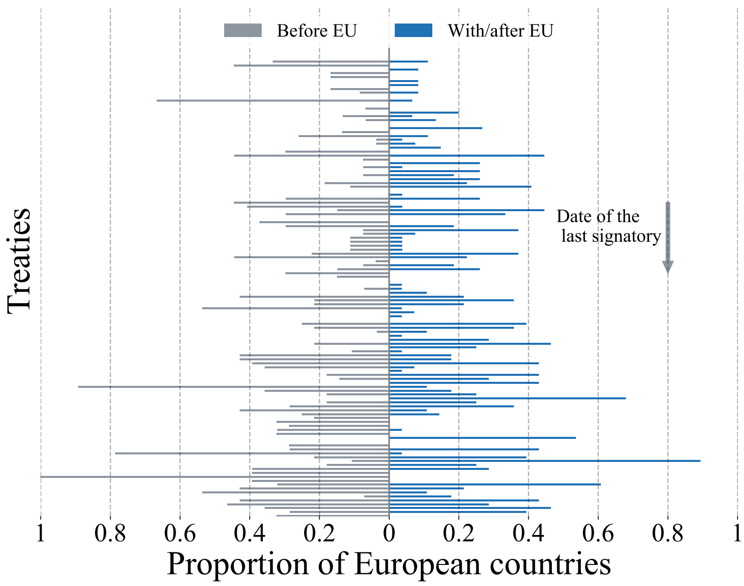
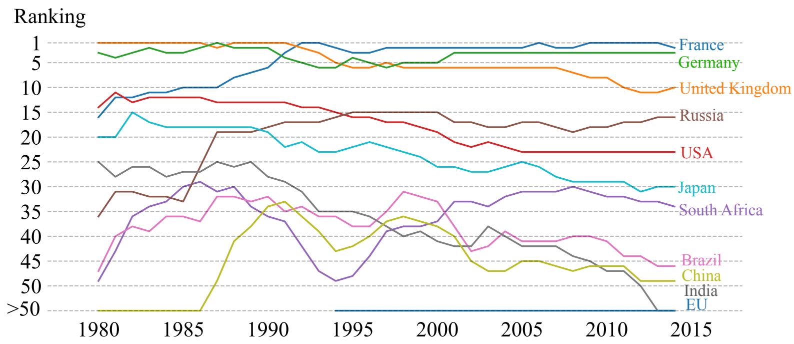
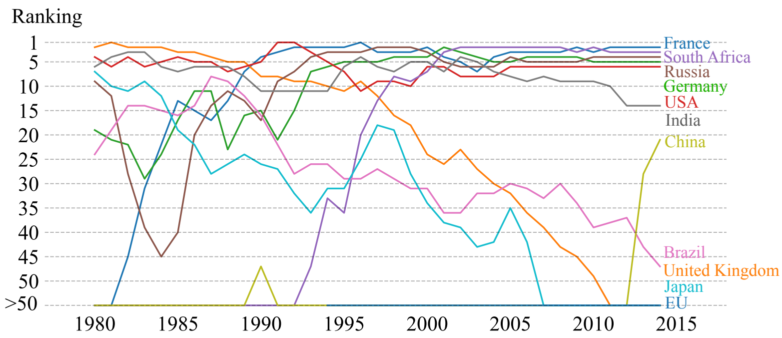


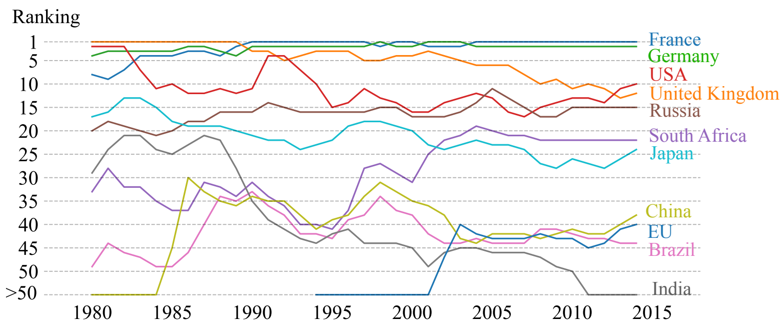

Figure 3.18: Proportion of European countries ratifying or enforcing IEAs before or with/after the EU. Each horizontal line corresponds to a treaty. The grey part of the line indicates the proportion of European member states for which a particular IEA is ratified or enters into force before the EU, while the blue part of the line indicates the proportion of member states for which the treaty is ratified or enters into force at the same time or after the EU. Treaties are sorted by the date of the last signatory.




(a) Strength




(b) Betweenness centrality




(c) Closeness centrality

Figure 3.19: Evolution of centrality measures of European countries and the EU.

Fig. 3.19 shows the strength and centrality rankings of different countries in the re-calculated network with the EU as an additional member. The results show that, although the EU acts as an important negotiator in some treaties, this does not change the important individual roles of major European countries, such as

France, Germany and the UK, in the cooperation network. However, two caveats are in order. First, it may be worth noting that the closeness centrality of the EU has increased over recent years, indicating an increasingly important role of the EU in the cooperation network. Second, my approach is based on what I observe in the data. That is, it is still possible that the EU plays an important role behind the scenes, then leaving it to member states to ratify IEAs.

### 3.5.4 Centrality measures and network acceleration

The centrality measures reported speak to the influence different countries have on the cooperation network. Here, I explore whether countries' position in the network also influences their own behaviour. In particular, I investigate the possibility of network acceleration, that is, whether a central position in the network is correlated with a higher speed in joining new IEAs.

I use the same method as introduced in Section 3.3.6. That is, I estimate equation 3.8 to determine the correlation between countries' centrality position in the network and their readiness to join subsequent IEAs. The dependent variable is again the log of the speed of ratification, i.e., the time span (years) between the date of the availability of a treaty and the date a country ratifies the treaty. The variable of interest is now the centrality ranking of countries in the year preceding the launch of a new agreement. I consider the ranking in strength, betweenness centrality and closeness centrality.

Table 3.4 reports the main set of results for the different centrality measures. All coefficients of interest are negative and significant, indicating that for each centrality measure, the higher a country is in the centrality ranking, the quicker the ratification of the next IEA.

Table 3.4: Centrality ranking and speed of ratification of future IEAs

| | Speed of ratification | | |
|---|---|---|---|
| Variables | 1 | 2 | 3 |
| Strength ranking | -0.00165*** | | |
| | (0.000294) | | |
| Betweenness ranking | | -0.000313** | |
| | | (0.000134) | |
| Closeness ranking | | | -0.00146*** |
| | | | (0.000285) |
| Observations | 11913 | 11913 | 11913 |
| Adjusted $R^2$ | 0.841 | 0.841 | 0.841 |
| Year FE | Yes | Yes | Yes |
| Country FE | Yes | Yes | Yes |
| Treaty FE | Yes | Yes | Yes |

Notes: The dependent variable is the log of the speed of ratification (years), i.e., the time span between the date of the availability of a treaty and the date of ratification in a country. The independent variable is the centrality ranking of countries (the higher the ranking, the large the value). Standard errors clustered at the country level in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

## 3.6 Differences across environmental issues

### 3.6.1 Overview

My final line of inquiry concerns the cooperation patterns among countries under different treaty subjects. Different environmental problems have attracted international attention at different times and with varying intensities. This reflects differences in the interplay between interests, political power and discourse within and between countries (Mitchell, 2003; Mitchell et al., 2020), as well as the distinct characteristics of different environmental problems (Falkner, 2013a; Meyer et al., 1997). For example, Keohane and Victor (2011) argues that intricate global problems like climate change give rise to more "regime complexity" than more straightforward issues.

Accordingly, I formulate and test the following **hypothesis:** *The dynamics of environmental cooperation are not uniform. Environmental cooperation has distinctly different network features depending on the subject area.*

I analyse environmental cooperation on different treaty subjects by constructing separate cooperation networks for the different categories of treaties introduced in section 3.2. I use the same metrics as in previous sections, with a focus on network size (number of nodes), connectivity (average degree, strength), and cohesion (density, weighted shortest distance, clustering coefficient). This allows us to describe in topological terms the regime complexity discussed in the international environmental governance literature.

The analysis confirms that environmental cooperation has distinctly different network features depending on the subject area. Specifically, I find that environmental coordination started with the management of marine resources (fisheries and the sea), but is now strongest in the area of waste and hazardous substances. The networks on species, waste and natural resources have a hierarchical structure, where a series of densely connected, small clusters combine into a less dense global network. This feature is absent in the networks on sea and fisheries and air and atmosphere. Despite the high policy salience of the topic, cooperation in the air and atmosphere network appears to be less intensive and the network is less cohesive. Finally, unlike the other networks, the air and atmosphere network is heavily shaped by UN-sponsored treaties.

### 3.6.2 Network properties by treaty subject

The topic-specific cooperation networks obtained statistical significance at different times. A statistically significant cooperation network first appeared in sea and fishery affairs in 1985, followed by natural resources in 1987 [8], waste and hazardous substances in 1990, wild species and ecosystems in 1994 and air and atmosphere in 2000. Based on the method, the cooperation network for energy treaties does not reach statistical significance, and I, therefore, do not analyse this network.

The topic-specific networks become statistically significant later than the overall network for methodological reasons. When treaties are divided into different categories, each category has a smaller number of treaties, relative to the number of countries. In some of the early country-treaty bipartite networks, the number of countries can be more than four times the number of treaties. When projecting onto the country layer to obtain the cooperation network, this makes it harder for the number of co-signed treaties between countries to be significantly different from the null model. My interest is therefore in the sequence in which topic networks become significant and not the specific dates.

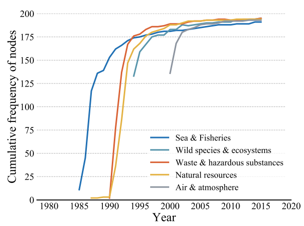
The different speed at which international cooperation occurred may reflect a number of factors, including the changing salience of different environmental

[8] For the category of natural resources, the volatile statistics in initial years are caused by the small number of countries in the network in the initial years.

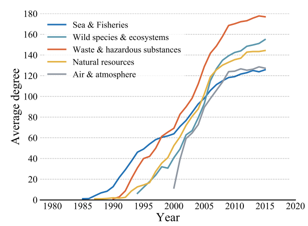
matters over time (e.g., the emergence of climate change as an issue in the 1990s), path dependency (the deepening of links in areas of long-standing cooperation) and potentially an initial focus on subjects where cooperation is easier (per Keohane and Victor, 2011).

However, by 2005 most countries had joined all five cooperation networks, suggesting that countries are now collaborating across the full range of environmental issues. In each subject area, nearly all the countries now form a single component.

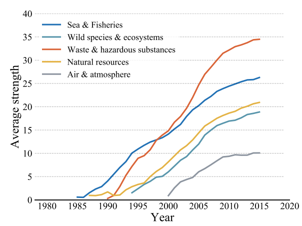
The relative growth in network size and connectivity is shown in Fig. 3.20. The cooperation network on waste and hazardous substances ranks first in terms of size (number of nodes), connectivity (average degree, average strength), and global cohesion (density, average weighted shortest distance and global clustering coefficient).



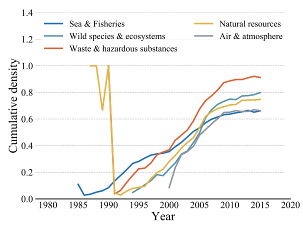

(a) Number of nodes



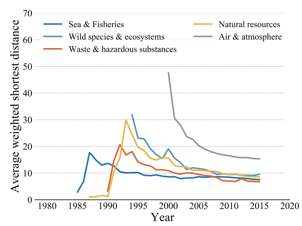

(b) Average degree



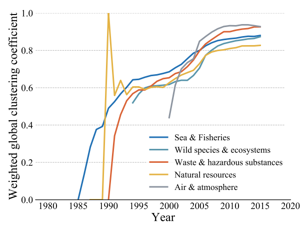

(c) Average strength




(d) Density



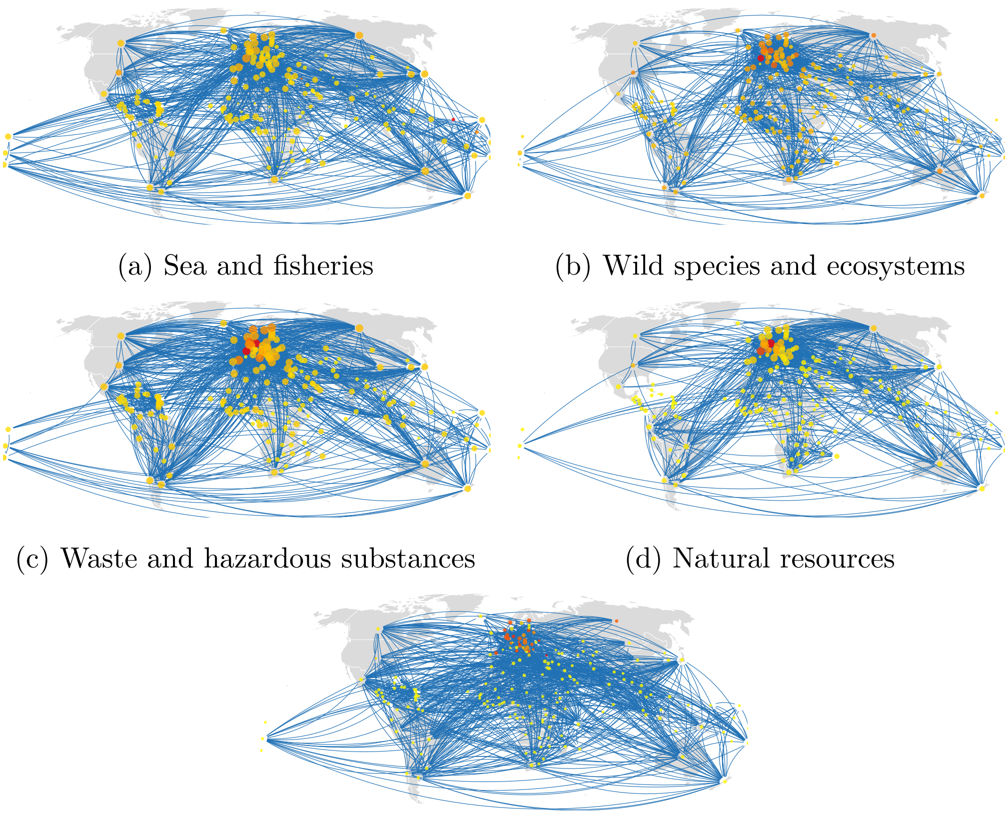

(e) Average weighted shortest distance




(f) Global clustering coefficient

Figure 3.20: Cooperation networks for different treaty subjects.

The cooperation network on air and atmosphere is worth a closer look. Although countries have a high average number of partners in this network, the average cooperation intensity is relatively low. This may be attributable to the fact that there are a number of high-profile treaties with near-global membership such as the 1985 Vienna Convention and the 1987 Montreal Protocol (which explains the high average degree) (Falkner et al., 2010; Parson, 2003). However, compared with other categories, the overall number of air and atmosphere treaties is relatively small (which explains the lower node strength). Moreover, the air and atmosphere network is characterised by a lower density and a higher average weighted shortest distance.



(a) Sea and fisheries

(b) Wild species and ecosystems

(c) Waste and hazardous substances

(d) Natural resources

(e) Air and atmosphere

Figure 3.21: Country networks for different treaty categories in 2015. For the sake of visualisation, the figure only shows the top 10 percent of links in terms of weight. The size of a node is proportional to its strength, and the colour of a node (red = stronger; yellow = weaker) reflects its weighted local clustering coefficient measured using the method proposed by Onnela et al. (2005).

Consistent with the prominence of global treaties, the cooperation relations on air and atmosphere are distributed evenly across the map and do not have an apparent core (Fig. 3.21). This is in contrast to most other subject areas, which have a prominent core located in Europe.

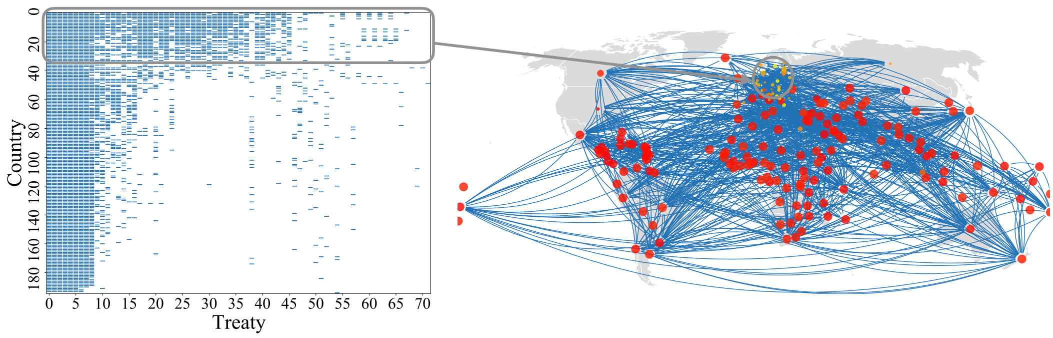
A further result of note concerns the role of the UN in air and atmosphere treaties. Unlike in the other categories, I cannot construct a statistically significant network when excluding UN-sponsored treaties. In other words, in the area of air and atmosphere, there are no statistically significant cooperation relationships among countries without the support of the UN. The results confirm that the UN has been an effective facilitator in promoting cooperation on issues such as ozone layer depletion, climate change, and air pollution.

### 3.6.3 Local clustering and node degree

It is instructive to look at the inter-relationship between different network metrics. I first focus on the correlation between unweighted local clustering and degree.

For the cooperation networks on species, waste, and natural resources, countries with a larger degree tend to have a smaller local clustering coefficient: there is a statistically significant and negative Pearson correlation coefficient between degree and local clustering coefficient. This is consistent with a hierarchical structure in which small clusters are densely connected and combine to form larger, but less dense, groups (Ravasz and Barabási, 2003). Similarly, when coping with these environmental issues, countries with a large number of partners are less involved in interconnected closed triplets.

In contrast, neither the cooperation network on sea and fisheries nor the network on air and atmosphere appears to have a hierarchical structure. In these networks, countries with a high local clustering coefficient also have a high degree: the Pearson correlation coefficient between the two metrics is statistically significant and positive.




(a) Bi-adjacency matrix of the bipartite country-treaty network

(b) Cooperation network

Figure 3.22: The cooperation network and the bi-adjacency matrix of the bipartite country-treaty network for air and atmosphere in 2015. In panel (a), the rows (countries) and the columns (treaties) of the bi-adjacency matrix have been sorted by degree. The figure highlights the group of few countries that signed many treaties and ended up with small values of degree and clustering. In panel (b), for the sake of visualisation, the country network only shows the top 10 percent of links in terms of weight. The size of a node is proportional to its degree, and the colour of a node reflects its unweighted local clustering coefficient (red = stronger; yellow = weaker).

The positive coefficient observed in the air and atmosphere network can be explained as follows. Countries fall into two distinct groups with different treaty-related behaviours. As shown in Fig. 3.22, the split can be visually detected from the bi-adjacency matrix of the bipartite country-treaty network, which depicts which countries have signed which air and atmosphere treaties. The rows (countries) and the columns (treaties) of the matrix have been sorted by degree, i.e., the number of treaties each country has signed up to, and the number of signatories each treaty has attracted, respectively.

This section explains the patterns on local clustering and node degree reported in Section 3.6.2. There I highlight that neither the cooperation network on air and atmosphere nor the network on sea and fisheries has the hierarchical structure of other subject-specific networks.

First, there is a large number of countries (from row 30 to row 190 in Fig. 3.22a) which have primarily signed large global treaties (e.g., on ozone layer depletion and climate change). In fact, there are some countries (e.g., Bahrain, Burundi, Palau, Uzbekistan, Turkmenistan) that have signed up only to large treaties. The number of common treaties between any two countries in this group tends to be large enough to pass the significance test and result in a statistically validated link between the two countries. This, in turn, results in a one-mode projection in which countries tend to have a high degree (large nodes in Fig. 3.22b) as they are connected to the many co-signatories of the large treaties, and at the same time a large local clustering coefficient (red nodes in Fig. 3.22b) as most of the co-signatories, they are connected to tend to be connected with each other (Ravasz and Barabási, 2003).

Second, there is a smaller group of countries which signed a much larger number of treaties (about the first 30 rows in the grey rectangle in Fig. 3.22a). On the one hand, the number of common treaties between these countries and others in the network is relatively small compared to the total number of treaties signed by these countries among themselves. This makes it less likely for countries in this group to form statistically significant links with countries in the former group. On the other hand, although these countries signed a large number of treaties, the number of common treaties between any two countries in this group is not, on average, sufficiently large to pass the significance test and to result in a statistically validated link. Notice that, as the number of treaties individually signed by any two countries increases, the number of common treaties co-signed by these two countries also needs to increase to pass the significance test. Therefore, countries in this second group tend to have a low degree as well as a small local clustering coefficient (small and yellow nodes in Fig. 3.22b).

To sum up, it is the distinctiveness of the treaty-related behaviours of countries dealing with air and atmosphere issues that can (at least partly) explain the non-hierarchical organisation of these countries and the unusual positive correlation between degree and clustering observed in this network.

### 3.6.4 Local clustering and node strength

I now turn to the correlation between the weighted local clustering coefficient and node strength. When clustering is computed through the method proposed by Onnela et al. (2005) (see Section 3.2), there is a statistically significant and positive correlation between the weighted local clustering coefficient and node strength for each treaty category. This implies that, when copying with environmental issues, countries characterised by many intense collaborative links tend to be connected with other countries that also collaborate with each other. That is, countries at the centre of strong triplets are more likely to be embedded in closed structures, rich in closed triangles than countries at the centre of weak triplets. This is clearly indicated by Fig. 3.21, where the larger nodes (i.e., with higher strength) tend to be closer to the red end of the colour spectrum (i.e, with higher weighted clustering).

The network on air and atmosphere again deserves special consideration. That network is characterised by a statistically significant and negative correlation between weighted local clustering coefficient and node degree. Combined with the previous finding on unweighted clustering and degree, this has a twofold implication: (i) when dealing with air and atmosphere countries with many collaborators tend to be included in many triangles (thus resulting in a positive correlation between unweighted clustering and degree); (ii) however, the weights of the collaborative links in these triangles tend to be relatively small (thus resulting in a negative correlation between weighted clustering and degree). Thus, on these issues of air and atmosphere it is the weaker triads that tend to close up into triangles. Once again, this finding can be explained by the fact that on these issues a very large number of countries tend to co-sign only a small number of very large and popular treaties (Newman, 2001b).

## 3.7 Discussion and conclusion

Global environmental governance has been the subject of academic scrutiny for some time. My study adds a novel angle to this debate by providing quantitative evidence from network analysis. I use network analysis to reveal the macrostructure of international environmental cooperation. Based on one of the largest collections of IEAs, I construct the cooperation network among countries based on country-treaty memberships. Cooperation intensity between any two countries is quantified by the link weight. Notably, the statistical significance of links is assessed by comparing them with random networks, i.e., there is a link between any two countries if, and only if, there is a significant number of treaties cosigned by these two countries. Then, the extent and the ease of cooperation are measured using global measures of networks, including the number of nodes, density, average degree, average strength, average shortest path length, etc. In addition, countries' positions in the cooperation network are quantified by centrality measures, and the correlation between countries' positions and their treaty ratification speed is investigated. The role of the UN and UN agencies is studied. Differences in the network structure across environmental subjects are compared. Moreover, treaty salience and memberships are considered to quantify link weights further, i.e., cooperation intensity.

### 3.7.1 Implications for research

Network analysis provides a systematic, quantitative analytical lens that can corroborate or refute the evidence from the existing literature, often of a qualitative nature. Network metrics can help to assess the structure and depth of environmental cooperation and flush out exciting patterns. The main findings are as follows:

Analysis of the size and connectivity of the cooperation network suggests that, over the past 50 years, global environmental cooperation has become pervasive, covering virtually all countries. Indeed cooperation is accelerating. This trend has been aided by the UN and its agencies, but the UN is not the dominant platform for environmental cooperation. The results are robust when considering the activity under a treaty and the relative importance of treaties. In addition, implications hold by studying the cohesion and clustering of the network that the cooperation network has a shorter distance between countries and facilitate the emergence of tightly-knit communities and third-party relationships. Furthermore, centrality measures suggest that European countries have persistently been the most critical players in the cooperation network. Finally, comparing the network structure of different environmental subjects indicates that the dynamics of environmental cooperation are not uniform, and the network structures are different across environmental subjects.

### 3.7.2 Implications for practice

Global environmental governance is vital to mitigate and adapt to environmental problems. IEAs are an essential part of global environmental governance to resolve collective problems. My research demonstrates the need to understand the macrostructure of international environmental cooperation as it will enable us to obtain insight into global environmental governance created by the existing IEAs. Any future reform by policymakers in the global environmental government should be based on the features of the cooperation network among countries. On the one hand, IEAs do foster policy cooperation, and thus countries can increase or strengthen cooperative relations by participating in treaties, thereby increasing their influence on the international stage. On the other hand, attention should be given to the function of the cooperation network created by IEAs. Countries' environmental leadership will facilitate IEAs. Therefore policymakers can target countries with a dominant position in the cooperation network, such as France and Germany, to promote more IEAs.

### 3.7.3 Limitations and future work

The analysis gives rise to a rich agenda for follow-up research. There are intriguing topological differences, for example, between environmental subject areas, which are worthy of further investigation. Other lines of enquiry could move from the predominantly global metrics used here to the meso level, investigating, for example, the tendency of the most well-connected countries to generate exclusive collaborative groups.

Another avenue for future research concerns the dynamic formation of the cooperation network. Pertinent techniques from the econometrics of networks (as reviewed in Chandrasekhar 2016 and De Paula 2020) could be used to identify the factors driving the formation of the cooperation network, which in my study, I take primarily as given.

The impact of the withdrawals from treaties on the cooperation network is also worth investigating. In my thesis, I only consider the impact of memberships of a treaty after withdrawals occur. As withdrawals are rare, countries's withdrawal from treaties will not violate the structure of the cooperation network. However, the withdrawal from a treaty may have substantial implications on not only the effectiveness and implementation of the treaty but also the trust and cooperation between countries and, furthermore, the passages of subsequent treaties. There are many examples to illustrate such implications. The most influential case is the withdrawal of the US from the Paris Agreement, a global treaty to reduce greenhouse gas emissions to tackle climate change. The withdrawal was completed on November 4th, 2020. The US is one of the largest greenhouse gas emitters and its withdrawal created concerns about the global community's ability to achieve the goals of the Paris Agreement. Moreover, Sælen et al. (2020); Zhang et al. (2017) argued that the US's withdrawal set a bad precedent for international climate cooperation as it disrupts the process of climate cooperation, damages the universality of the Paris Agreement and undermines the confidence of countries in climate change cooperation. Other examples include the withdrawal of Brazil from the United Nations Framework Convention on Climate Change (UNFCCC) in 2019, the withdrawal of Canada from the Kyoto Protocol in 2011 and the withdrawal of Russia from the Paris Agreement in 2020. All these withdrawals may weaken the influence of the treaty. Thus, future research may take into account the impact of the withdrawals on cooperation intensity between countries, i.e., link weights.

Another limitation concerns the categorisation of treaties. All the treaties are classified into six categories: sea and fisheries, wild species and ecosystems, waste and hazardous substances, natural resources (e.g., water, cultivated plants, environment genes, food, forestry, land and soil, livestock, and mineral resources), air and atmosphere (e.g., air pollution, ozone layer depletion and climate change), and energy. My classification is based on the degree of overlap between legal topics and common knowledge. However, other classification strategies can be applied to check the robustness of the differences in international cooperation across environmental issues. For instance, the treaties can be classified into climate change (e.g., UNFCCC, Kyoto Protocol and Paris Agreement), biodiversity and conservation (e.g., CBD), pollution (e.g., the International Convention for the Prevention of Pollution from Ships (MARPOL)), water resources (i.e., the Convention on the Protection and Use of Transboundary Watercourses and International Lakes), land and forest resources (i.e., the United Nations Convention to Combat Desertification (UNCCD) and the United Nations Forum on Forests (UNFF)) and sustainable development (i.e., the United Nations Sustainable Development Goals (SDGs)).

In addition, other research questions can be explored when the most recent data on IEAs can be obtained. My thesis is based on data from 1948 to 2015, which limits the research scope. For instance, in recent years, China has put more effort into environmental issues, especially climate change. As one of the largest greenhouse gas emitters, China has engaged in mitigation efforts since the Paris Agreement by developing renewable energy and nuclear power, capping coal consumption, and promoting energy conversation (Zheng et al., 2019). Thus, it is interesting to investigate whether the role of China in the cooperation network changed in recent years due to its efforts. Another question concerns the catalytic role of the Paris Agreement, signed in 2015. Whether the Paris Agreement has promoted more extensive international cooperation and, therefore, changed the structure of the cooperation network is still unknown.

Through judicious network design, network analysis can account for many of the rich historical, cultural, and economic links between countries and beyond joint treaty membership, potentially including soft power measures. More complex network methods could be further leveraged to construct and infer from these networks, such as the K-Nearest Neighbour Graph (K-NNG) construction (Dong et al., 2011).

### 3.7.4 Contribution to the literature

My study is part of the broader theoretical and conceptual literature in economics and political science on environmental governance and international environmental cooperation. Methodologically it relates most closely to a strand of empirical literature at the crossroad of economics and political science, which leverages large data sets on IEAs, such as the one I use, to identify empirical patterns of environmental cooperation.

My study in this chapter demonstrates the power of network analysis by testing topologically four hypotheses related to salient debates in political science, international relations and economics literature.

First, my study provides quantitative evidence of the network structure of international environmental cooperation. To my knowledge, this study is the first attempt to investigate the network structure of international environmental cooperation by quantifying cooperation intensity between countries based on country-treaty memberships in IEAs. Second, measures from network science are selected and applied to quantify features of international environmental cooperation, which will add more understanding of international environmental cooperation to existing literature. In addition, methodologically, I introduce the activity and the importance of IEAs to adjust the cooperation intensity between countries. Moreover, the association between network structures and future ratification is analysed.

My analysis also contributes to increasing interest in using techniques from complex systems to studying global environmental governance (Kim, 2020; Orsini et al., 2020) and has demonstrated that network analysis has the potential to become a powerful complement to the tools traditionally used in the study of global governance and international cooperation.

# Part II: Meso-organisation of international environmental cooperation

# Chapter 4

# Literature review for Part II

In Part II of my thesis, I will turn to the meso-organisation of international environmental cooperation. The analysis of meso-organisation will allow us to discover features of a system that might not arise from a local or global level. I focus on two topics in the existing literature on the organisational structure of international environmental cooperation - regional environmental cooperation and core players. This chapter will first review relevant literature on these two topics and then introduce the measures from network science to quantify the meso-organisation of the cooperation network.

## 4.1 Regional environmental cooperation

Various case studies have been performed. The book by Elliott and Breslin (2011) divided the world according to geographical regions and systematically summarised various aspects of environmental cooperation in each region, including political institutions, capacity building, and the role of states. Balsiger and Prys (2016) and Selin (2007, 2010) focused on social constructions and conducted case studies on different forms of regional environmental cooperation, including regional environmental agreements, under the auspices of global agreements or originating from existing regional organisations, such as the EU (Balsiger and VanDeveer, 2012). Especially, Balsiger and Prys (2016) defined “potential regions” by further categorising different forms of “regionality” based on regional agreement membership and spatial ambit, i.e., geographical application.

According to Balsiger and VanDeveer (2012), regional environmental cooperation takes different forms including regional environmental agreements, in the auspices of global agreements, or originating from existing regional organisations, such as the EU. For each form, specific cases are analysed (Balsiger and Prys, 2016; Selin, 2007, 2010). Especially, Balsiger and Prys (2016) sought to define regional agreements based on agreement membership and spatial ambit.

## 4.2 The role of European countries in international environmental cooperation

The most relevant studies on the hierarchical organisational structure of international environmental cooperation focus on the position shift between the United States and the European Union. It is commonly argued that the European Union and the United States shifted their positions in international environmental cooperation since the 1990s. In the late 1960s and early 1970s, the United States strongly supported international environmental cooperation. However, the European Union emerged as a global leader in international environmental cooperation in the 1990s, while the United States showed reluctance and even refused multiple multilateral environmental agreements (Kelemen and Vogel, 2010; Kelemen 2010, p336; Vogler, 2005). Other literature focuses on the contributions of powerful countries, such as France, Norway, Germany, the United States, etc (Falkner, 2005, 2007; Gullberg et al., 2014; Mitchell, 2003). The main argument is that the membership of powerful states might be why other states join the same IEA (Mitchell, 2003).

## 4.3 Community, nestedness, rich Clubs and economic Complexity

The meso-organisation of a system can be quantified by multiple measures (Csermely et al., 2013). I choose community structures, nestedness and rich clubs to quantify the meso-organisational structure of international environmental cooperation. Community structures represent groupings of nodes where nodes in the same group are densely connected. In contrast, nestedness and rich clubs are used to quantify the core-periphery structure of networks. A network tends to have multiple communities but usually only includes one core. Furthermore, I draw on techniques from economic complexity to identify more robust core players. This section will introduce the basic idea of each measure.

### 4.3.1 Community

Communities, also called clusters or modules, are an essential property in network science that characterises a network's mesoscopic structure by classifying nodes only according to the information encoded in the network topology (Fortunato, 2010). Community structure, at the intersection between the scale of nodes and that of the whole network, is an essential property of a network. Nodes in one community tend to possess common characteristics and/or play a similar role in the network (Fortunato, 2010). Typical examples include working or friendship groups in social networks, functional modules in brain networks (Crossley et al., 2013; van den Heuvel and Sporns, 2013) and metabolic networks (Guimera and Amaral, 2005), and communities of cities in worldwide air transportation network (Guimera et al., 2005). Communities in international relations represent potential communities of shared interests. A typical example is the World Trade Web (WTW) communities which have been explored extensively (Barigozzi et al., 2011; Fan et al., 2014; Piccardi and Tajoli, 2012; Saracco et al., 2017; Tzekina et al., 2008; Vandermarliere et al., 2018; Zhong et al., 2014).

Communities have multiple applications. First, community detection can help improve the efficiency of systems. For instance, identifying clusters of consumers with the same purchasing habits will enhance the efficiency of recommendation systems (Reddy et al., 2002). In addition, communities provide one way to classify nodes based on their roles within and across modules. Nodes sharing many links with the other group members occupy a central position in their modules and may have an essential function of control and stability within the group. In contrast, nodes at the boundaries between modules play an essential role in mediation and exchanges between different modules (Fortunato, 2010). In cooperation networks, central nodes are the key to maintaining the robustness of the cooperative behaviour (Lozano et al., 2008).

### 4.3.2 Nestedness

Nestedness characterises the hierarchical structure of systems that are neither randomly assembled nor organised into parallel communities according to specialisation (Bascompte et al., 2003). In nested interaction relations, the more specialist interacts only with proper subsets of units interacting with the more generalists (Mariani et al., 2019). This concept was first used to describe the species distribution pattern (Atmar and Patterson, 1993; Patterson and Atmar, 1986), e.g., species-islands networks, and then a variety of mutualistic networks (Ulrich et al., 2009) and socio-economic networks (Saavedra et al., 2009; Saracco et al., 2016). The sequence of elements in a nested structure contains crucial information. For instance, species-islands networks' nestedness reveals species' predictable extinction sequences of species (Atmar and Patterson, 1993). In a country-product network, the sequence of countries and products indicates the diversification and ubiquity, respectively (Saracco et al., 2016). In addition, nestedness reveals the distribution pattern of species or capacities, e.g., there is no product division across the world (Saracco et al., 2016).

Furthermore, the implications of nested structures provide new insights into the dynamics and functions of complex systems. For a mutualistic system, nestedness minimises competition and increases biodiversity (Bastolla et al., 2009), and vital contributors to network persistence are the most vulnerable to extinction

(Saavedra et al., 2011). Evidence also shows that nestedness contributes to the stability of the world trade network (Ermann and Shepelyansky, 2013), and the nested structure of the firm-location associations can predict the evolution of industrial systems (Bustos et al., 2012).

Nestedness is related to other network properties, such as degree distribution (Payrató-Borras et al., 2019), disassortativity (Jonhson et al., 2013) and modularity (Borge-Holthoefer et al., 2017). Here, I focus on another metric – rich clubs – and attempt to clarify that the nestedness in a bipartite network will promote the emergence of rich clubs in the one-mode projection.

### 4.3.3 Rich clubs

While community structure enables us to study the large-scale structure of a network by abstracting away from individual nodes, it may also cover up the significant influence of a system's "richest" elements. Indeed it has been suggested that there exist prominent actors that leverage their connections to gain and maintain control over resources in the network (Opsahl et al., 2008). In network science, these rich actors form the so-called rich clubs, which are subgroups of essential or influential nodes that preferentially interact with one another (Colizza et al., 2006) or monopolise the flow of resources among one another (Opsahl et al., 2008). The presence of the rich-club phenomenon divides a network into two parts: high-richness nodes with advantages and relatively low-richness nodes with disadvantages in terms of their positions in the partition (Ma and Mondragón, 2015). For example, Fagiolo et al. (2009) suggested that the 10 richest countries in terms of strength (i.e., total export volume) are responsible for about 40 per cent of the total trade flow among all countries. In addition, high-income countries constitute the core of the global trade and financial networks where they tend to cooperate more with each other and form tightly linked groups (Marrs et al., 2018; Minhas et al., 2017; Schiavo et al., 2010).

### 4.3.4 Economic complexity

The study of economic complexity has accelerated since the last decade. The most seminal contributions are the proposal of two metrics: relatedness (Hidalgo et al., 2007) and complexity (Hidalgo and Hausmann, 2009).

A network of relatedness between products, or product space, is constructed based on the proximity between products which quantifies the ability of a country to produce a product depending on its ability to produce other products. The product space reveals the path dependency of a country and can predict the development of goods in a specific country (Hidalgo and Hausmann, 2009).

Another metric is the economic complexity index which measures the availability, diversity and sophistication of the inputs in an economy by investigating the structure of the country-product bipartite network (Hidalgo, 2021). The metric of economic complexity was first defined by Hidalgo and Hausmann (2009). It was developed to quantify the complexity of a country's economic activities, i.e., labour division. Unlike traditional economic methods, which create new metrics by averaging other variables, this metric draws on dimensionality reduction techniques to aggregate a set of variables (Hidalgo, 2021). This metric has been widely applied. Evidence shows that this metric can be used to predict economic growth (Hidalgo and Hausmann, 2009), income inequality (Sadeghi et al., 2020), environmental sustainability (Rafique et al., 2022), and carbon emissions (Doğan et al., 2021).

# Chapter 5

# Regionalisation of international environmental cooperation: Evidence from community structure analysis

## 5.1 Introduction

The environmental collaboration network, which emerged in the early 1970s, can be defined as a network of cooperative relationships among countries based on co-signed IEAs (see Carattini et al., 2023, for more details). Here, I aim to uncover the community structure of the environmental cooperation network and thus reveal the inhomogeneity of the distribution of cooperative ties, with high concentrations of ties within special groups of countries and low concentrations between these groups. At the macro level, the cooperative ties between countries have become denser and more cohesive, and the distance between countries has become shorter, indicating a more cooperative relationship between countries. However, the mesoscopic organisation of the cooperation network, i.e., the modules or communities of the network, is still unknown.

Thus, questions arise naturally: whether cooperation clusters have emerged as the breadth and depth of environmental cooperation through IEAs increased over time, and whether the cooperation tended to be global (i.e., cooperative ties existed among any two countries with no prominent groupings) or regional (i.e., determined by geography or other socioeconomic factors).

I apply the toolkit from network science to detect potential communities to understand the functional organisation of state-led global environmental governance. Furthermore, the distribution of coalitions worldwide, the drivers behind the division, and the resulting function are also explored. The analysis provides quantitative evidence of cooperation coalitions in international environmental cooperation and global environmental governance. Mainly, our study provides topological evidence for regional cooperation from a systematic perspective rather than based on case studies in current economics and political science.

Precisely, I deploy the Louvain algorithm (Blondel et al., 2008) to detect potential communities in the environmental cooperation network. The algorithm identifies communities that are present compared with a null model. Countries are then divided into clusters representing the coalitions' current global environmental governance landscape. In addition, the roles of countries are investigated based on their patterns of inter-connections and intra-connections between communities, which allows us to identify bridges that not only play an essential role in mediation and exchanges between modules (Fortunato, 2010) but also promote a high level of cooperation (Lozano et al., 2008), as well as local hubs for the robustness of cooperation (Lozano et al., 2008). I then extend my analysis to reveal the contribution of geography to the current landscape and the characteristics and outcomes of community structures.

My work falls within the growing body of research now devoted to analysing regional environmental cooperation. However, methodologically, my research goes beyond case studies and regional constraints and leverages social network analysis and the whole set of IEAs to systematically reveal potential coalitions which might or might not confine to geography.

The chapter is structured as follows. Section 5.2 briefly introduces the data and the construction of the cooperation network, and then focuses on how to perform community detection and define countries' roles based on communities. The main results are shown in section 5.3. Finally, in section 5.4 I outline some implications of my findings and discuss future research directions.

## 5.2 Data and methodology

### 5.2.1 Data

I employ the data on IEAs from the ECOLEX database and, after data cleaning, obtain a final sample of 546 IEAs signed over the period 1948-2015 by 200 countries. According to the database, 393 treaties are defined as regional agreements while

147 are global ones (6 treaties have no information). In addition, according to Carattini et al. (2023), IEAs are classified into six categories which are sea and fisheries, wild species and ecosystems, waste and hazardous substances, natural resources (e.g., water, cultivated plants, environment genes, food, forestry, land and soil, livestock, and mineral resources), air and atmosphere (e.g., air pollution, ozone layer depletion, and climate change), and energy.

### 5.2.2 Methodology

Based on the data, I first construct a time sequence of bipartite networks (Latapy et al., 2008). These are two-mode networks where a link is established between a country and a treaty if the former has signed the latter. Second, I convert the bipartite network into one-mode projections to study cooperation networks among countries. The main assumption here is that co-participation can be seen as underlying social ties (Borgatti and Halgin, 2011b). Thus, a cooperative tie between two countries is defined as co-participation in the same treaty. That is, a link is established between any two countries if they have signed at least one common treaty. In addition, I quantify the intensity of cooperation between countries by assigning a weight to each link, which is proportional to the number of treaties two countries have co-signed and inversely proportional to the number of signatory countries involved in each common treaty Newman (2001c). The intuition here is that two countries that co-sign a treaty together with many other countries have a less extensive cooperation relationship on average than two countries that are the sole signatories of a treaty. This implies that all else being equal, bilateral treaties contribute more to the intensity of cooperation between two countries than multilateral treaties.

The final step concerns statistical validation, that is, identifying statistically significant links through comparison with an appropriate null model. I adopt the grand canonical algorithm proposed Saracco et al. (2017), which can be used to obtain a statistically-validated projection of any binary, undirected, bipartite network [1]. The general idea underpinning this method is that any two countries should be linked in the corresponding one-mode projection, i.e., the cooperation network, if, and only if, they co-signed a statistically significant number of treaties.

After obtaining the cooperation network, community detection is performed on the network, and the community-based roles of countries are analysed.

Communities, also called modules, are made up of highly interconnected nodes that are less connected to nodes in other communities. Communities are a way to coarse-grain the level of description of the network, which can not only identify underlying relationships or functionalities between nodes but also define nodes' role according to their positions in the community structure (Guimera and Amaral, 2005).

I adopt the Louvain algorithm (Blondel et al., 2008) to detect communities. Specifically, the Louvain algorithm is applied on each snapshot independently to detect static communities, and then for each snapshot the communities were matched with the communities detected on the previous one (Cazabet et al., 2014; Rossetti and Cazabet, 2018). This approach enables me to reveal the dynamics of communities, i.e., operations on communities: birth, growth, contraction, splitting, merging, and death (Palla et al., 2007). Although there are other approaches,

[1]The Python codes used in this study can be obtained from https://github.com/tsakim/bipcm

e.g., the Stochastic Block Models (SBM) (Peixoto, 2015), to directly detect communities on several snapshots at a time to resolve the problem of instability of the approach above, these approaches lack the capacity to handle operations on communities (Cazabet et al., 2014; Rossetti and Cazabet, 2018). A figurative sketch of a network with such a community structure is shown in Fig 5.1.

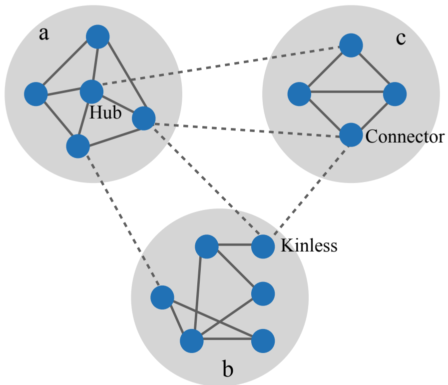



Figure 5.1: A figurative sketch of a network with community structure. This network has three communities (a, b, and c). A hub node, a connector node and a kinless node are also illustrated in the figure.

At each time step, the goodness of a partition is evaluated by optimising the modularity of the partition. This metric was first proposed by Newman and Girvan (2004) and gained popularity in community detection research. The modularity of a partition measures if there are more edges within communities than would be expected based on chance. Specifically, it quantifies the density of links within communities relative to what would be expected if edges were distributed uniformly at random (Newman, 2006; Newman and Girvan, 2004). In our case, I use the weighted version of the modularity, which considers the weights of network links. Modularity is a scalar value between $-1$ and 1. If the number of within-community links is equivalent to a random network, the modularity is 0. The larger the value, the stronger the community structure. A prominent community structure has modularity from about 0.3 to 0.7 (Newman and Girvan, 2004).

Furthermore, to compare community partitions, I use the normalised mutual information (NMI) measure (Danon et al., 2005; Meilă, 2007), a measure of similarity between two partitions, $P_A$, and $P_B$, based on information theory. It is calculated by

$$\mathrm{NMI}\left(P_A, P_B\right) = \frac{-2\sum_{i=1}^{C_A}\sum_{j=1}^{C_B} N_{ij}\log\left(\frac{N_{ij}N}{N_i N_j}\right)}{\sum_{i=1}^{C_A} N_i \log\left(\frac{N_i}{N}\right) + \sum_{j=1}^{C_B} N_j \log\left(\frac{N_j}{N}\right)} \tag{5.1}$$

where the number of communities in partition $P_A$ and $P_B$ are denoted by $C_A$ and $C_B$, respectively; $N_i$ is the number of nodes in community $i$ in partition $P_A$, and $N_j$ is the number of nodes in community $j$ in partition $P_B$; $N_{ij}$ denotes the number of nodes both in community $i$ in partition $P_A$ and in community $j$ in partition $P_B$. $NMI$ is between 0 and 1. The more similar the two partitions are, the larger $NMI$ is.

In addition, I investigate each country's role given a particular partition based on its pattern of inter-community and intra-community connections. Unlike other metrics that assign roles to individual nodes, such as node degree, closeness centrality, and betweenness centrality, community-based roles consider the underlying community structure in a network (Scripps et al., 2007; Wang et al., 2011). Specifically, nodes with a central position in their modules, also called local hubs, i.e., sharing a large number of links with the other group members, may have an essential role in maintaining stability within the group. Nodes acting as bridges between modules play an important role in mediation and exchanges between different communities (Fortunato, 2010). According to Lozano et al. (2008), local hubs are the critical nodes for the robustness of cooperative behaviour, and bridges with interconnectivity can promote a high level of cooperation.

I adopted two measures proposed by Guimera and Amaral (2005) to quantify countries' roles: module-hub score ($z$) [2] and participation coefficient ($P$). If $\kappa_i^s$ is the number of links of node $i$ to other nodes in its module $s$, $\bar{\kappa}_i^s$ is the average of $\kappa_i^s$ over all the nodes in $s$ and $\sigma_{\kappa_i^s}$ is the standard deviation of $\kappa_i^s$ in $s$ then:

$$z_i = \frac{\kappa_i^s - \bar{\kappa}_i^s}{\sigma_{\kappa_i^s}}$$

is the so-called $z$ -score. The local-hub score $z$ measures how well-connected node $i$ is to other nodes in the module.

The participation coefficient $P_i$ of node $i$ was proposed to quantify how the links of a node are uniformly distributed among all the modules. It is defined as:

$$P_i = 1 - \sum_{s=1}^{N_M} \left( \frac{\kappa_i^s}{k_i} \right)^2$$

where $\kappa_i^s$ is the number of links of node $i$ to nodes in module $s$, and $k_i$ is the total degree of node $i$. The participation coefficient of a node is therefore close to 1 if its links are uniformly distributed among all the modules and 0 if all its links are within its own module.

According to Guimera and Amaral (2005), I defined nodes with $z \geq 2.0$ as module

[2] It was originally called within-module degree, but I think it is more appropriate to call it module-hub score to highlight its meaning.

hubs and nodes with $z < 2.0$ as non-hubs. Non-hub nodes are divided into four different roles: ultra-peripheral nodes, that is, nodes with all their links within their module ($P \leq 0.05$); peripheral nodes, that is, nodes with most links within their module ($0.05 < P \leq 0.62$); non-hub connector nodes, that is, nodes with many links to other modules ($0.62 < P \leq 0.80$); and non-hub kinless nodes, that is, nodes with links homogeneously distributed among all modules ($P > 0.80$). Hub nodes are divided into three different roles: provincial hubs, that is, hub nodes with the vast majority of links within their module ($P \leq 0.30$); connector hubs, that is, hubs with many links to most of the other modules ($0.30 < P \leq 0.75$); and kinless hubs. that is, hubs with links homogeneously distributed among all modules ($P > 0.75$).

## 5.3 Results

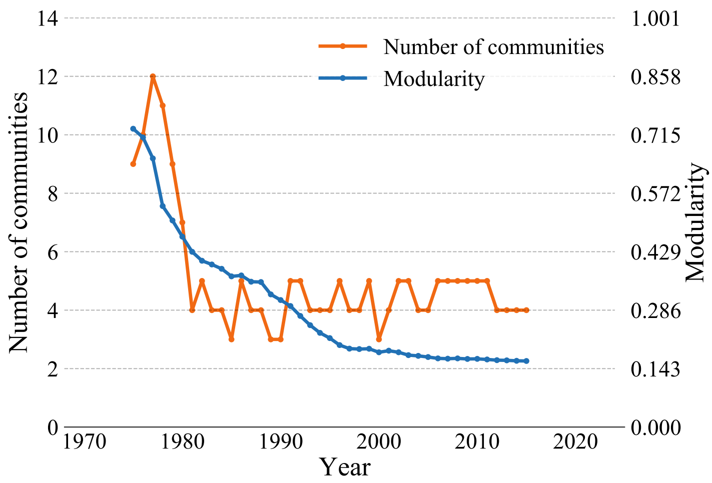
### 5.3.1 Emergence, evolution and consolidation of communities

I first aim to identify potential groupings of countries in their search for collective answers to common problems in a world of complex interdependence and reveal the contributions of IEAs to the division during the process. Here, I detect "potential groupings" of countries that cooperate intensively amongst themselves but have few cooperative ties with countries outside their group. The detection allows for the emergence of clusters based on cooperative ties among countries created by treaties, not constrained by other factors, such as spatial space and existing institutions like the EU. From a dynamic perspective, groupings' emergence, evolution, and consolidation are analysed with the breadth and depth of environmental cooperation through IEAs increasing over time.

Communities in network science can indeed represent this kind of grouping. In this section, the Louvain algorithm introduced in section 5.2.2 is used, and community detection is performed on the international environmental cooperation network constructed based on regional and global treaties to uncover the overarching division of countries in global environmental governance. The individual contribution of these two types of treaties will be studied in Section 5.3.3.

The cooperation network first appeared in 1971 with 37 countries forming 12 components. Since 1975, the most significant component occupies over 90% countries in the cooperation network. Thus, community detection is performed on networks from 1975 to 2015.

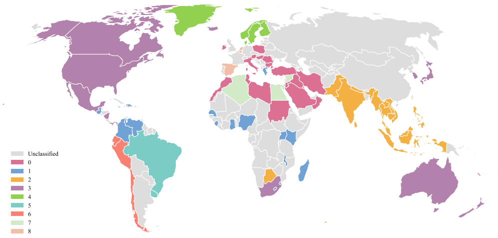
First, the evolution of the number of communities and the goodness of divisions, indicated by modularity in network science, are investigated. As shown in Fig. 5.2, the number of communities first decreased from 9 in 1975 to 4 in 1981 and then fluctuated around 4, indicating that countries are increasingly integrated into a system of global environmental governance. Modularity, a measure of the quality of a particular division, is above 0.25 from 1975 to 1993, indicating that there were prominent community structures compared with random networks, and countries formed distinct groupings. Afterwards, the increasing density of the network makes the division less prominent compared with random networks.



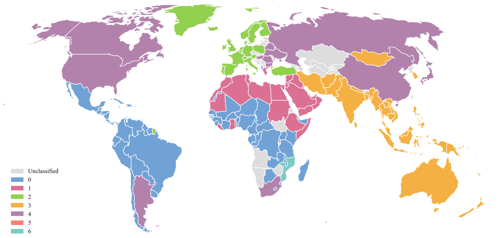

(a)

Figure 5.2: The number of communities and the modularity from 1975 to 2015

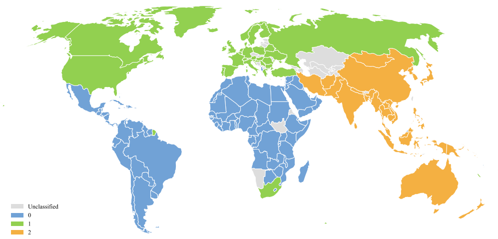
Then, I focus on the country groupings' emergence, evolution, and consolidation. The coloured world maps in Fig. 5.3 show the community distribution worldwide from 1975 to 2015. Countries belonging to the same community are associated with the same colour. The Sankey diagram in Fig. 5.4 allows us to visualise communities' birth, merging, growth, contraction, splitting, and death across different partitions over time (Palla et al., 2007). The number beside each rectangle represents the number of countries in the community, and the colour of each rectangle corresponds to the community colour in Fig. 5.3.



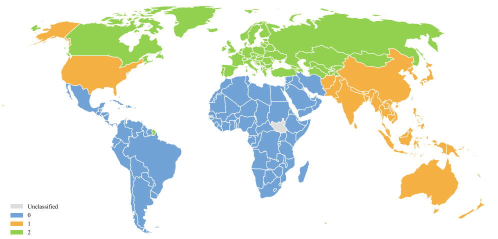
(a) 1975



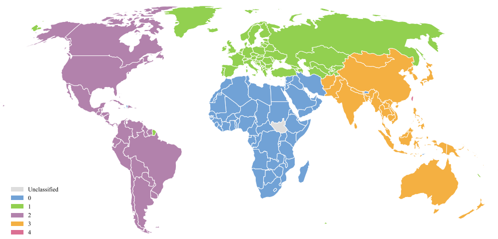
(b) 1980



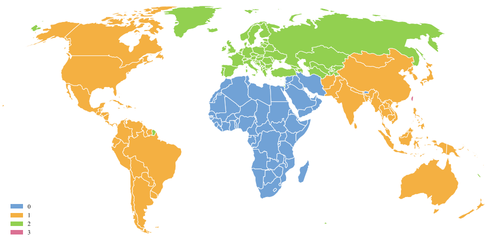
(c) 1990



(d) 2000



(e) 2010



(f) 2015

Figure 5.3: Communities in 1975, 1980, 1990, 2010 and 2015. Countries are coloured according to which community they belong to.

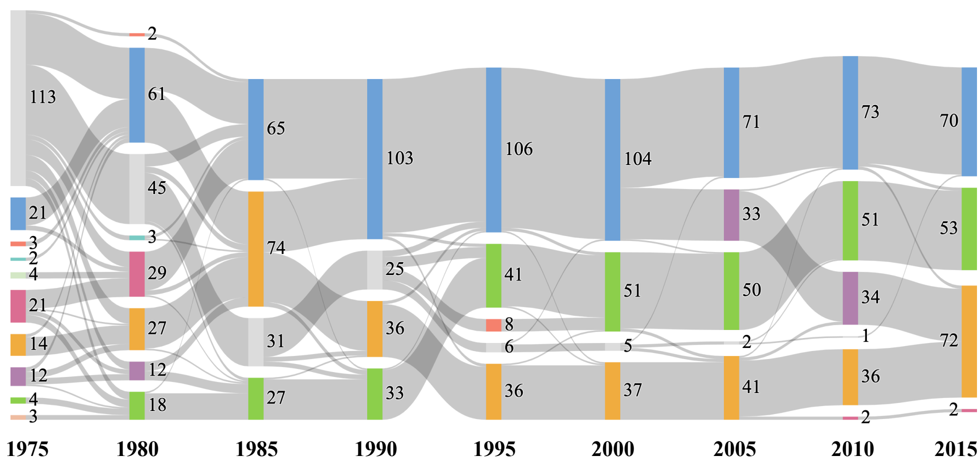



Figure 5.4: Sankey diagram of the evolution of country communities. The colour of each community corresponds to the colours in Fig. 5.3. The numbers indicate the size of each community.

In 1975, international environmental cooperation tended to be regional across continents, though varying degrees, especially in Southeast Asia, North America, and Western Asia.

Extensive regional environmental cooperation based on continents emerged after 2000, attributed to several historical membership changes across communities. First, the Soviet Union was combined with countries in North America (the USA and Canada) and Asia (China and Japan) around 1980, but since 2005 Russia and most European countries have formed a distinct community. Second, countries in Central Asia participated in the cooperation network as a distinct community in 1995 and were finally absorbed into the community dominated by European countries in 2000. Third, in 1980 China belonged to the community containing the Soviet Union and the USA. However, later, China cooperated more with Southeastern Asian countries and Australia. Forth, countries from Latin America separated from the community dominated by African countries in 2010. Finally, the USA and Canada first cooperated more with European countries from 1990 to 2000. Only around 2010 they cooperated more with countries in Latin America.

Until 2015, countries worldwide can be divided into three communities which correspond to Southeast Asia and America, Europe, and Africa [3]. Thus, visually the general trend of international environmental cooperation is toward regionalisation worldwide. Balsiger and Prys (2016) argues that many examples of regional environmental cooperation exist beyond North America and Europe. Here, our results provide new evidence of regional cooperation from a more systematic perspective.

[3]The community consisting of two countries is a component including Hong Kong and Taiwan

In addition, to quantify the stability of the whole process introduced above, I compare the partitions obtained at time $t$ and $t+\Delta t$ by computing the normalised mutual information (NMI) (see 5.2.2 for more details). The larger NMI is, the more stable the community structure is over time. As shown in Fig. 5.5, the community structure was increasingly stable over time despite some fluctuations ($\Delta t = 2$ years). The whole phase under observation can be divided into three stages corresponding to the emergence, evolution, and consolidation of regionalisation. These three stages are divided by two major changes happening around 1990 and 2005. Before the 1990s, the $NMI$ was around 0.6. In the 1990s and the early 2000s, the $NMI$ remained around 0.8, but afterwards, it remained at a high level, about 0.9. Thus, 1975-1990 period saw the emergence of regionalisation, which evolved and consolidated itself in 1990-2005 and 2005-2105, respectively.

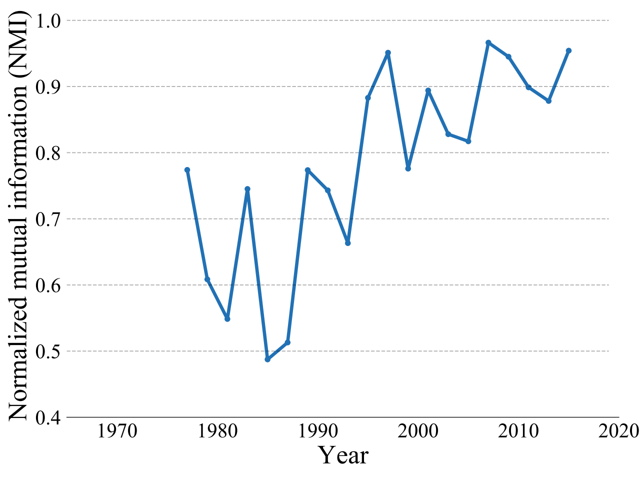



Figure 5.5: Normalised mutual information (NMI) when comparing the community structures obtained at time $t$ and $t + 2$ for $t = 1975, ..., 2015$.

### 5.3.2 Community-based roles of countries

Based on the analysis in section 5.3.1, international environmental cooperation tends to be regionally based on the cooperative ties created by IEAs. I next study the roles of countries within and across regions and uncover whether regions are constrained by regional powers or balanced from the topological perspective of the cooperation network.

I first focus on power distribution within regions and aim to identify critical powers. Regional governance may be constrained by regional powers or balanced with power distributed equally across member states. According to Elliott and Breslin (2011) great powers or hegemons within regions are vital actors in regional governance, as their attitude towards multilateralism in intra-regional diplomacy will influence the extent and nature of regional governance on environmental issues. Their function can be enhanced to some extent by community structures, as tightly-knit communities and third-party relationships with solid ties are essential for high-risk behaviours to diffuse (Easley and Kleinberg, 2010). This is particularly important for environmental cooperation in providing public goods with a high risk of free-riding. Thus, if one can identify critical actors within regions, and persuade them to facilitate and enhance regional governance, then more effective regional governance might be established based on the favourable tightly-knit communities.

Here, I quantify the within-region power of countries by the within-community strength of countries based on intra-community connections in each community. Specifically, for each country, the module-hub score $z$ (see section 5.2.2 for more details) is calculated. Intuitively, the module-hub score $z$ indicates how well-connected a country is to other countries in its region.

Then, I turn to bridges or connectors between regions. In network science, nodes acting as bridges between communities play an essential role in intermediating and exchanging resources and information between different communities (Fortunato, 2010). According to Kamal (2004) and Vannijnatten (2011), regionalisation starts with information-sharing among countries. Thus, at the early stage of regionalisation, countries acting as bridges between communities play an important role in facilitating the merging of small-scale regions into large-scale regions. In addition, the connectors can promote policy convergence across different regions, albeit the existence of difference among them (Elliott and Breslin, 2011).

The bridges or connectors can be quantified by the participation ratio $P$ (see section 5.2.2 for more details), which indicates how the links of a node are uniformly distributed among all the communities.

After obtaining the two metrics of countries, each country can be characterised by a role defined by its location on the zP-space (with $z$ as the y-axis and $P$ as the x-axis). Different roles can be detected, including module hubs, hub connectors, non-hub connectors, etc. (see section 5.2.2 for more details on defining different roles). Results are shown in Fig. 5.6.

Initially, there were no hub connectors, and most countries were non-hub marginal. In 1975, Hungary and the USA were local hubs in their community. In 1980, Ecuador was a hub-connector in the community dominated by Latin America and African countries. In 1980, Ecuador was a local hub in its community, and Tunisia, Nigeria, and Morocco were hub connectors. In addition, 24.3% of countries were non-hub connectors [4].

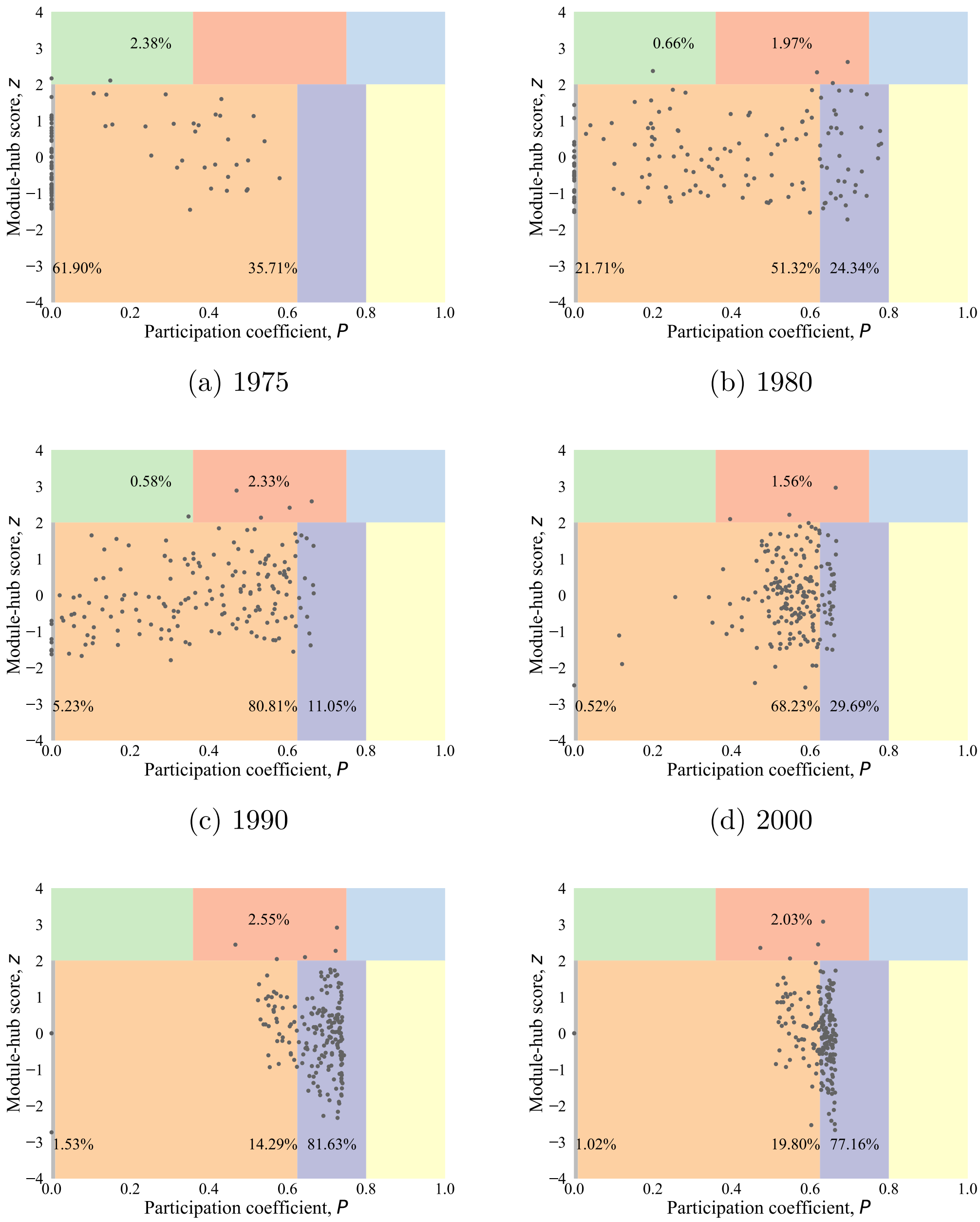
The 1990s saw Senegal as a local hub and a small portion of non-hub connectors, 11.05%. Egypt, Tunisia, and Nigeria were hub connectors in the community dominated by countries in Africa and Latin America, with Mexico, South Africa, Argentina, and Israel being the non-hub connectors. Australia was a hub connector among the Southeast Asian countries, with New Zealand, China, India, South Korea, Singapore, Mongolia, Japan, Afghanistan, North Korea, Lao, and Pakistan being non-hub connectors. Canada was a non-hub connector in its community.

In 2000, Australia, Panama, and Germany were their community hub connectors. Almost 30 per cent of countries were non-hub connectors. Since 2010, more countries have become non-hub connectors (81.63% in 2010; 77.16% in 2015), which means that countries in different modules interacted more with each other, which blurred the boundaries between communities. This would explain why the value of modularity was relatively small (below 0.20) between 2000 and 2015, as shown in Fig. 5.2. France became a hub connector in 2010, together with Australia, Germany, Tanzania, and Chile. In 2015, the hub connectors were Australia, the United States of America, Germany, and France. In addition, the majority of non-hub connectors since 2000 were from Africa, Asia, and America, not Europe, indicating that most European countries cooperated more with each other internally, and in the meantime, the connectors played a vital role in serving as a link between European community and the other communities.

[4] Canada, United States of America, Japan, Israel, Mexico, San Marino, Ghana, Cyprus, Bahamas, Korea, Dominican Republic, South Africa, Tunisia, China, Rwanda, Iran, Islamic, New Zealand, Argentina, Jordan, Senegal, Singapore, Romania, Brazil, Liberia, Chile, Morocco, Mauritius, Saint Vincent and the Grenadines, Panama, Seychelles, and Austria.

To sum up, some countries played an essential role in regional environmental governance given the module structure of the cooperation network. First, Australia has been a hub connector since 1990 in a community dominated by Southeast Asian countries. Second, Germany has developed a hub connector since 2000, and France became a hub connector in 2010, followed by the United States of America in 2015. Third, few European countries played the role of non-hub connectors; conversely, most of them cooperated more internally. On one hand, countries acting as hub connectors can serve as a platform to bring together countries within the same cooperation cluster and thus maintain the stability of the cooperation. On the other hand, they facilitate dialogue, knowledge sharing and coordination among different cooperation clusters, and therefore foster policy diffusion and convergence. In addition, I assess whether the power distribution in each community is centralised or balanced. To this end, the Gini coefficient of module-hub scores of countries in each community is calculated. Fig. 5.7 shows the evolution of the Gini coefficient for communities dominated by Asia, Europe and Central Asia, and Africa, respectively [5]. The Gini coefficient decreased over time for Asian (from above 0.35 to about 0.25) and African countries (from above 0.35 to about 0.22), while it stayed around 0.35 for European countries. The results indicate a more balanced power distribution across Asian and African counties, but a relatively less balanced distribution among European countries.

[5] I do not report the results for the Americas, as American countries formed a separate community only in the 2010s.




(a) 1975 (b) 1980

(c) 1990 (d) 2000

(e) 2010 (f) 2015

Figure 5.6: Roles of countries in the $zP$-space. The whole space is divided into seven parts. Each node in a network can be allocated to a part according to its module-hub score $z$ and its participation coefficient $P$. The proportion of nodes in different parts is indicated.

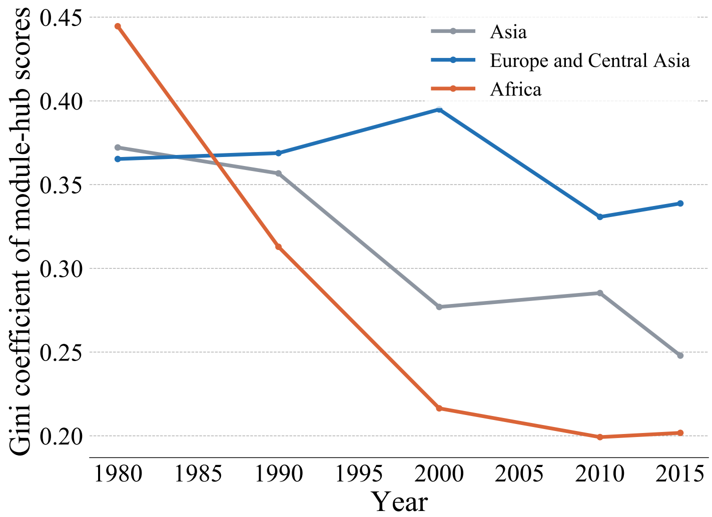



Figure 5.7: Gini coefficient of module-hub scores in Asia, Europe and Central Asia, and Africa.

### 5.3.3 Community structures and geography

The communities detected here are based on the cooperative ties created by IEAs, which are legally binding intergovernmental efforts oriented to reducing human impacts on the environment (Mitchell, 2003). Thus, the regions identified above are institutional construct corresponding to problem-solving or *de jure* "Regions" described by Balsiger and Debarbieux (2011). Compared with the problem setting or *de facto* "regions" (Balsiger and Debarbieux, 2011), I do not assume preexisting boundaries among communities. However, the regionalisation of international environmental cooperation implies the important role of geography in shaping its meso-organisation. According to Conca (2012), spatial proximity means great similarity in interests, norms, perceptions, and values among states, which facilities international cooperation. Thus, this section aims to quantify how geography contributes to forming problem-solving regions.

Before introducing the geographical factors, IEAs are first divided into global and regional ones to reveal the contribution made by these two types of IEAs to international environmental cooperation. According to the data sample, regional treaties are constrained to specific geographical regions, while global treaties are not. Our analysis is based on the 393 regional and 147 global treaties. Fig. 5.8 and Fig. 5.9 compare the difference between regional and global treaties in terms of the number of signatories and the distribution of signatories across continents. It can be seen that, on average, a global treaty tends to have more signatories than a regional one. Besides, the signatories of most regional treaties tend to be confined to a particular continent as opposed to the global treaties in which signatories distribute across different continents.

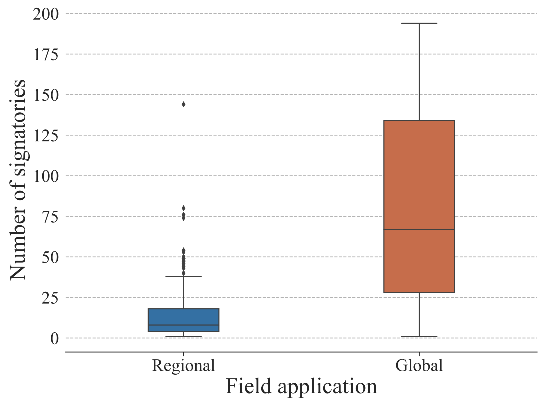



Figure 5.8: Boxplots of the number of signatories for regional and global treaties

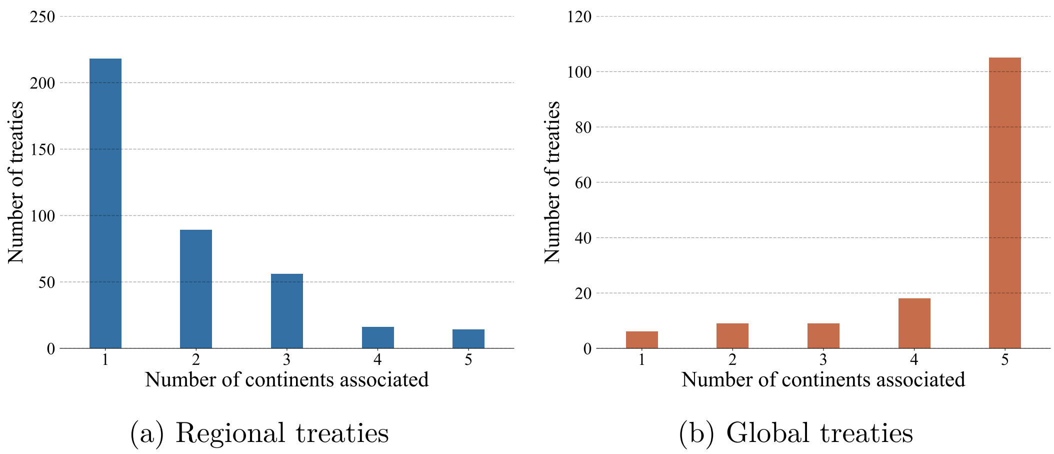
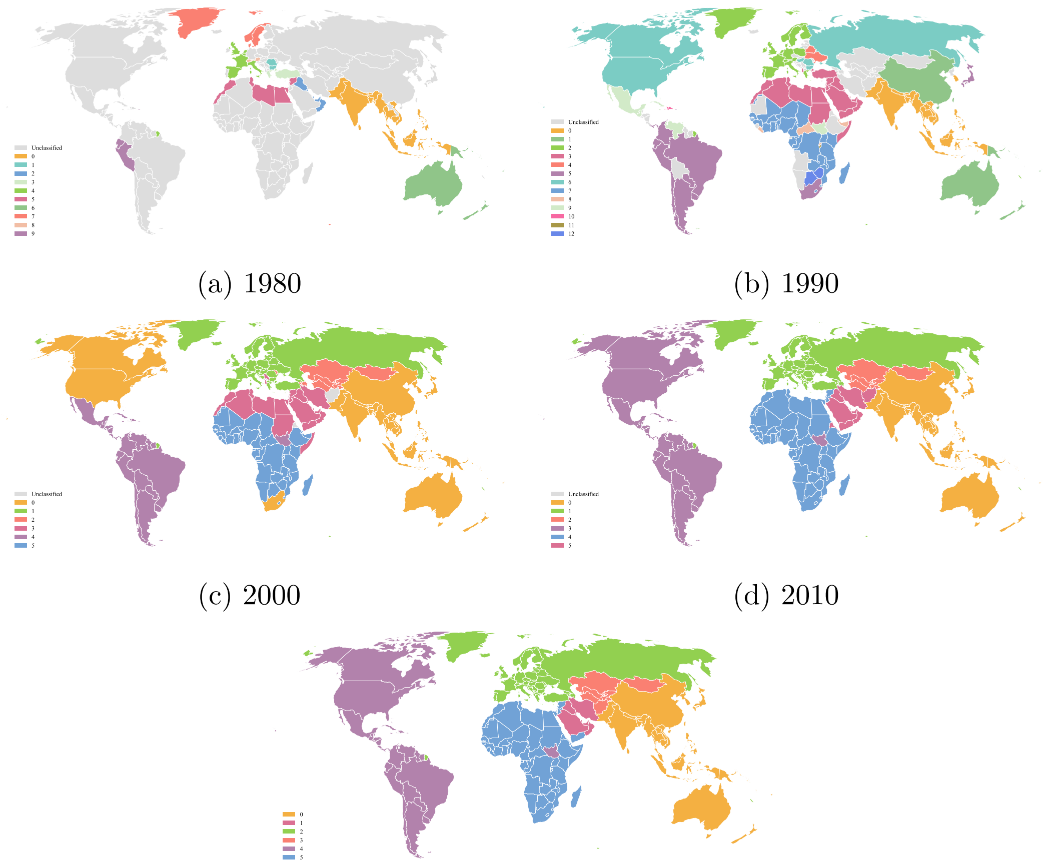



Figure 5.9: Distributions of treaties associated with different number of continents

Then, the environmental cooperation network is reconstructed based on regional and global treaties, respectively, and then community detection is performed on the reconstructed cooperation networks. Fig. 5.10 shows the community distribution based on regional treaties. The statistically significant cooperation network first appeared in 1977, and the partition was regional. In 2015, communities were mainly based on four continents, similar to the results of regional and global treaties. The USA and Canada cooperated more with the Soviet Union in 1990, then belonged to the community dominated by Southeastern Asian countries in 2000, and finally joined the community, including countries in Latin America in 2010. In addition, countries in Central Asia and West Asia have formed two distinct communities since 2000.



(a) 1980

(b) 1990

(c) 2000

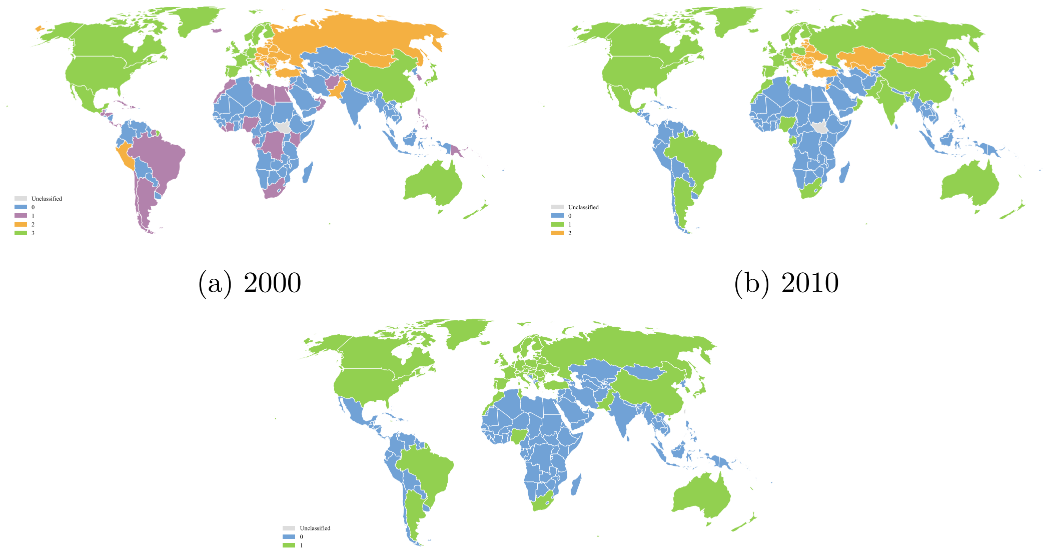
(d) 2010

(e) 2015

Figure 5.10: Communities in 1980, 1990, 2010 and 2015 based on regional IEAs. Countries are coloured according to which community they belong to.

Next, the cooperation network based on global treaties is constructed. The statistically significant cooperation network first appeared in 1996. Fig. 5.11 shows the results of the community detection. In general, international environmental cooperation based on global treaties shows a different pattern that is not constrained by geography. As shown in Fig. 5.11, although the number of communities was relatively large at the beginning of the formation of the international cooperation network, the number of communities was subsequently smaller than that based on regional treaties at the same time. Although there is local and regional cooperation in each community of varying degrees, especially among countries in Europe and Africa, the cooperation in each community is not confined to regions or continents.

In addition, it should be noted that large economies tended to cooperate, and less developed countries cooperated more.



(a) 2000

(b) 2010

(c) 2015

Figure 5.11: Communities in 2000, 2010 and 2015 based on regional IEAs. Countries are coloured according to which community they belong to.

Finally, I consider quantifying how geography contributes to forming cooperation communities. According to the coloured world maps in Fig. 5.3, 5.10 and 5.11 environmental cooperation is associated with geography to some extent. Visually, countries in the same region or continent tend to cooperate more, especially for cooperation contributed by regional treaties in Fig. 5.3 and 5.10. Then, I deploy the continental and macro-area geographical partitions as the benchmark [6], and compare the community structures with the continental and macro-area geographical partitions.

Here, I adopt the Normalised Mutual Information (NMI) measure to quantify the

[6] The sub-regions include Australia and New Zealand, Central Asia, Eastern Asia, Eastern Europe, Latin America and the Caribbean, Melanesia, Micronesia, Northern Africa, Northern America, Northern Europe, Polynesia, South-eastern Asia, Southern Asia, Southern Europe, Sub-Saharan Africa, Western Asia, and Western Europe. The continents observed are Africa, Americas, Asia, Europe, and Oceania.

similarity of the two partitions. Fig. 5.12 shows the results. The blue, orange and green lines are based on all the regional and global treaties, respectively. For each category, the solid and dotted lines refer to regions and continents as a benchmark, respectively. First, the general trend of the international environmental cooperation based on all IEAs is towards regionalisation, with the $NMI$ increasing gradually to around 0.6 after 2000 (blue lines). During this process, regional treaties contributed more to the general trend with a $NMI$ of around 0.7 (orange lines) in contrast to global treaties with a $NMI$ of around 0.2 (green lines). Cooperation based on regional environmental treaties and cooperation based on global environmental treaties are constrained by geography to different degrees. In addition, the degree to which the two kinds of cooperation are affected by geography shows different development trends. Cooperation among countries based on regional treaties is largely driven by geography from the beginning, while cooperation based on global treaties is increasingly geographically unconstrained. Finally, comparing the solid and dotted lines, it can be argued that before 2000 countries tended to cooperate with others in the same region, but afterwards, cooperation tended to be based on continents, which indicates broader integration based on geography.

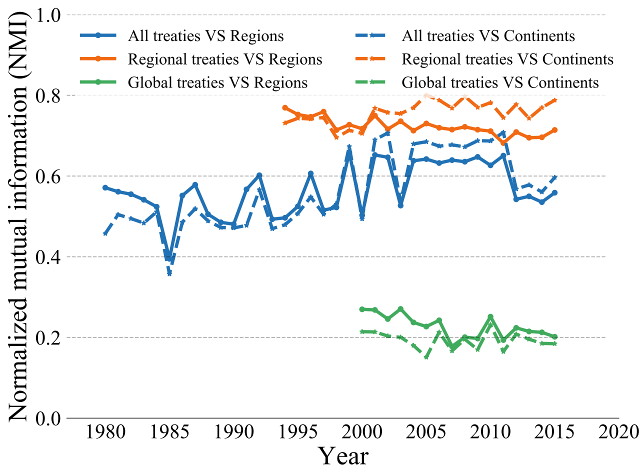



Figure 5.12: Normalised mutual informaiton ($NMI$) when comparing the community structures with continental and macro-area geographical partitions.

### 5.3.4 Characteristics and outcomes of regionalised cooperation

Regional environmental cooperation might be a solution in the context of the stagnation of global cooperation (Conca, 2012). It is believed that collective action can be more effective than action based on national measures alone, as the greater similarity of interests, norms, perceptions, and values at the regional level facilitates international cooperation. (Conca, 2012; Elliott and Breslin, 2011). From the perspective of institutionalism, Biermann and Bauer (2017) argues that regional organisations' and institutions' functions lie in three broad categories: knowledge brokers, negotiation facilitators, and capacity builders. Thus, I expect the communities detected in my study to perform all or part of the functions introduced above and act as more effective cooperation coalitions.

This section aims to reveal the differences across communities and the functions performed by each community. I focus on the year 2010 when distinct communities based on regions had formed (see Figs. 5.3 and 5.4).

First, the international environmental cooperation landscape within and across communities is investigated. Each community is taken as a block. The intra-community and inter-community cooperation intensity is calculated. Here, the intra-community cooperation intensity is the sum of link weights within each community, while the inter-community cooperation intensity between two communities is the sum of link weights between these two communities. Fig. 5.13 shows the induced graph of communities. Each node represents a community. The node size is proportional to the intra-community cooperation intensity, and the link width is proportional to the inter-community cooperation intensity. It can be seen that the community dominated by Europe and Central Asia has the most considerable intra-community cooperation intensity. African countries cooperated more with European and Central Asian countries than those in America and the rest of Asia. In addition, the cooperation intensity is relatively lower between countries in America and Asia.

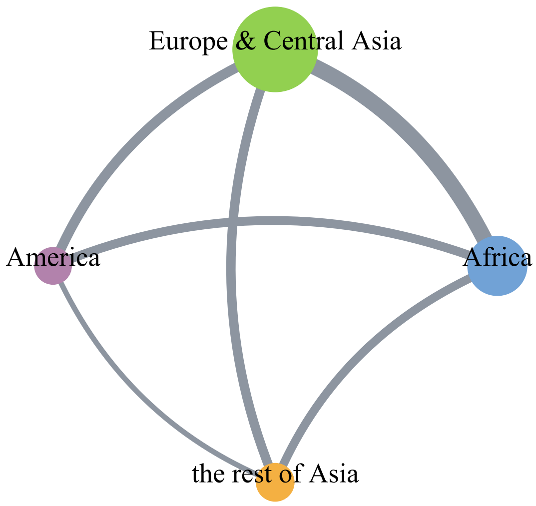
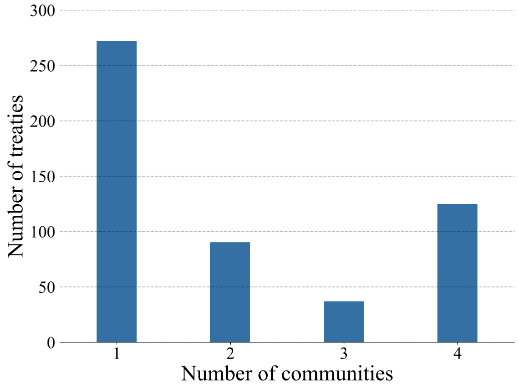


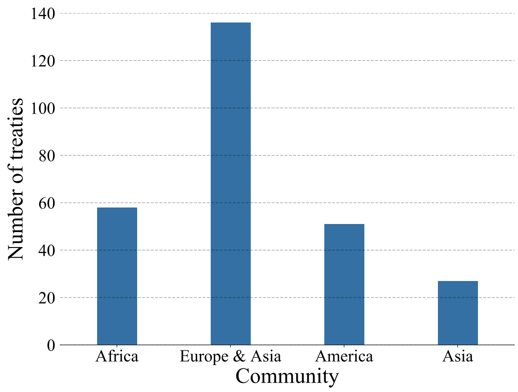

Figure 5.13: Induced graph of communities. Each node represents a community. The node size is proportional to the intra-community cooperation intensity, and the link width is proportional to the inter-community cooperation intensity.

Next, I turn to the role of communities in facilitating international environmental cooperation by investigating whether countries have a higher speed to ratify or enforce within-community treaties than inter-community treaties. The timing of ratifying international treaties of countries is an important measure to reflect the strength of countries' willingness to join a treaty (Fredriksson and Gaston, 2000; Wagner, 2016; Yamagata et al., 2017a). Multiple factors might influence the timing of countries joining certain treaties, including state power, financial situation, greenhouse gas emissions, etc (Fredriksson and Gaston, 2000; Wagner, 2016; Yamagata et al., 2017a).

To this end, I first identify treaties signed by countries from one, two, three, or four communities, as shown in panel (a) in Fig. 5.14. Over 250 treaties were signed within one community. Then, the number of within-community treaties for each community is counted, as shown in panel (b) in Fig. 5.14. The community dominated by countries from Europe and Central Asia had passed more within-community treaties.




(a) Number of treaties of which signatories are from one, two, three or four communities in 2010

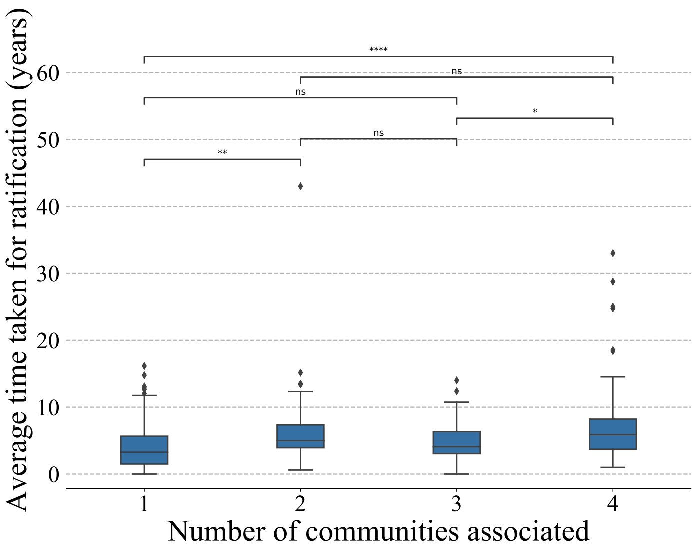



(b) Number of within-community treaties for each community in 2010

Figure 5.14: Number of treaties

Then, the time spans between the availability of a treaty and the ratification or entry into force in its signatories are calculated. According to (Balsiger and VanDeveer, 2010), "enhanced commonalities in a particular environmental challenge, greater familiarity with key actors, and the ability to tailor mitigating action to a smaller than global constituency" can benefit cooperation. Thus, I expect that the period of treaties with signatories from the same community is shorter than those with signatories from more than one community.

Panel (a) in Fig. 5.15 illustrates that the time span for treaties in one community is relatively shorter than those based on more than one community, indicating that IEAs based on regional cooperation can gain a quicker settlement. It can be argued that the communities detected here can serve as negotiation facilitators to speed up negotiations and shape environmental cooperation. On one hand, communities detected here are made up of highly interconnected countries, and the ties between them can provide social capital to facilitate communication and trust-building (Burt, 2000). This can be instrumental in negotiation processes to avoid or solve conflicts. On the other hand, the cooperation communities are based on geography, and thus, member states in the same community often have valuable local knowledge about their environment, ecosystems, and resource management. This knowledge can be crucial in negotiations to find sustainable solutions that consider the unique characteristics of the region (Ostrom, 1990). Moreover, indigenous and local communities often have deep cultural and spiritual connections to the environment. This cultural perspective can influence negotiations and promote a sense of responsibility for environmental stewardship.




(a) Time span of treaties associated to different number of communities

Figure 5.15: Time spans. Welch's t-test between any two groups is performed ($^{*}p < 0.1$, $^{**}p < 0.05$,$^{***}p < 0.01$)

In addition, different areas have different environmental protection capacities due to their economic development level and orientation to some environmental issues (Elliott and Breslin, 2011). I resort to the keywords of treaties that contain information on its instruments and environmental issues oriented to be solved and aim to gain insight into the institution building and environmental focus in each community based on existing IEAs.

To this end, I focus on keywords of within-community treaties, i.e., treaties associated with only one community. First, the number of keywords in each community is obtained. There are 198, 192, 140, and 88 keywords in communities dominated by Africa, Europe and Central Asia, America, and the rest of Asia, respectively. The number of treaties having it as a keyword for each keyword is counted. Results are shown in the word clouds in Fig. 5.16. The size of each word is proportional to its relative frequency in each community. First, communities based in Africa, Europe, and Central Asia played an important role in data collection and reporting, research, monitoring, and dispute settlement. Differently, treaties based in Africa mentioned education more, while those in Europe and Central Asia focused more on management and conservation. Second, treaties in America do not show specific orientations except for data collecting and reporting. Finally, the rest of Asia had fewer keywords than other communities indicating its lack of overall concern about the global environment. In addition, the Gini coefficient is calculated for each community based on the word frequency to assess the balance between each word. Communities dominated by Africa, Europe and Central Asia, America, and the rest of Asia have a Gini coefficient of 0.51, 0.53, 0.43, and 0.44, respectively. Thus, the communities dominated by Africa, Europe, and Central Asia are less balanced among different instruments and environmental issues, i.e., the distribution of power is heterogenous and there exist powers in regional environmental cooperation.


(a) Africa

(b) Europe and Central Asia

(c) America

(d) The rest of Asia

Figure 5.16: Word clouds for treaties within each community in 2010. The word size is proportional to its relative frequency in each community. Keywords with a shallow frequency are not displayed in the figures.

## 5.4 Discussion and conclusion

Regional environmental cooperation has received increasing attention over the last decade, as it indicates a potential scale to tackle problems encountered by global environmental cooperation in global environmental governance. In this Chapter, I conducted community structure analysis to uncover potential clusters of countries in international environmental cooperation. Community detection was performed on the cooperation network constructed in Chapter 3 from 1971 to 2015. The landscape and evolution of the community structure was analysed. In addition, power distribution within and across communities ass analysed based on inter-connections between and intra-connections.Furthermore, the characteristics and functions of different communities were studied.

### 5.4.1 Implications for research

Community structure analysis identifies potential groupings of countries in their search for collective answers to common problems solely based on the topological structure of the environmental cooperation network created by IEAs. 1975-1990 saw the emergence of regionalisation, which evolved and consolidated itself in 1990-2005 and 2005-2105, respectively. Specifically, extensive regional environmental cooperation based on continents emerged after 2000. Until 2015, countries worldwide could be divided into three communities: Southeast Asia and America, Europe, and Africa.

In addition, my study uncovers key regional powers and bridges. First, Australia has been a hub connector since 1990 in a community dominated by Southeast Asian countries. Second, Germany has developed a hub connector since 2000, and France became a hub connector in 2010, followed by the United States of America in 2015. Third, few European countries played the role of non-hub connectors; conversely, most of them cooperated more internally. Furthermore, results suggest a more balanced power distribution across Asian and African counties but a relatively less balanced distribution among European countries.

Furthermore, my study indicates that geography contributed to forming cooperation communities, and the communities detected here can serve as negotiation facilitators to speed up negotiations and shape environmental cooperation.

Finally, attention should be paid to the functions or outcomes of the community structure of the cooperation network. The average period between the availability of the treaty and the date of ratification in countries for treaties in one community is relatively shorter than those based on more than one community, indicating that IEAs based on regional cooperation can gain a quicker settlement. In addition, different areas show different environmental protection capacities and instruments. Africa, Europe, and Central Asia played an important role in data collection and reporting, but Africa focuses more on education while Europe and Central Asia pay more attention to management and conversation. In contrast, America does not show specific orientations. The rest of Asia indicates a lack of overall concern about the global environment.

### 5.4.2 Implications for practice

Regional environmental cooperation might be a more effective solution to global environmental problems. My study systematically shows the emergence of regionalisation, which gives a clear picture of the coalition of countries. In addition, policymakers can take full advantage of regions' role as cooperation facilitators to foster collaboration. My study also identifies powerful players within each region, and thus lobby can be conducted among these powers to promote policies within regions.

### 5.4.3 Limitations and future work

The analysis suggests several avenues for future theoretical and empirical research. First, other rationales behind the formation of regionalisation of environmental cooperation need to be studied besides the contribution of geography. One line of enquiry is about the relationship between problem-solving and problem-setting regions. The regions identified here are institutional constructs responding to problem-solving. To what extent problem-setting regions contribute to such a division needs to be investigated. In addition, the contribution of regional economic integration and security cooperation to the current landscape of the environmental cooperation groupings needs to be explored. One solution might be to compare the community structures in these three areas. Second, empirical evidence of the role of key players identified based on the community structure in facilitating knowledge diffusion and cooperation needs to be explored. The final avenue for future reseaarch is concerned with other metrics that can be used to characterise further the cooperation network's mesoscopic structure, such as rich clubs, assortativity and k-cores.

### 5.4.4 Contribution to the literature

This chapter provides quantitative evidence of the formation of regional environmental cooperation from a study of the community structure of the international environmental cooperation network from 1971 to 2015. To my knowledge, this is the first study to systematically and quantitatively reveal regionalisation in international environmental cooperation.

My study goes beyond conventional case studies used in current political science and environmental economics and enables me to reveal potential coalitions emerging from the complex interdependence through IEAs, and, furthermore, the contributions of IEAs to the current landscape. This chapter, therefore, makes a contribution to the study of regional cooperation and helps to identify a more efficient cooperation scale in global environmental governance.

# Chapter 6

# European countries lie at the core of the international environmental cooperation

## 6.1 Introduction

In this chapter, I investigate the core-periphery structure of international environmental cooperation. My study is still based on the whole set of IEAs documented in ECOLEX. The study starts from nestedness arising from the country-treaty relations based on IEAs to indicate its hierarchical organisation. The sequence of countries and treaties in the hierarchical structure are analysed, and core players are identified. Then, I attempt to reveal that the nested structure will induce a densely connected core in the cooperation network among countries by quantifying rich clubs. Furthermore, I borrow ideas from economic complexity and attempt to quantify the diversification of countries' environmental commitment and identify robust core players. In contrast to previous chapters, my study here attempts to uncover the overall hierarchical organisational structure of the country-treaty relationship.

First, I study the country-treaty relationship by investigating the country-treaty bipartite network from 1948 to 2015 and find that these networks are nested. This means that treaties ratified by countries with a smaller number of treaties are a subset of treaties in countries with a larger number of treaties. But, a subset of treaties is only ratified by countries with a larger number of treaties. The generalist will facilitate the formation of rarely ratified treaties.

Second, the evolution of nestedness is investigated. I calculate the normalised Nested Overlap and Decreasing Fill (NODF) to assess nestedness, which allows me to compare the nestedness in different years. The nestedness decreased gradually since 1965. In addition, the ranking of countries and treaties is relatively stable. European countries come out on top. The results are robust when exploiting nestedness temperature and excluding UN and/or UN agency treaties.

Third, I study the impact of the nestedness in the bipartite country-treaty network on the cooperation relationships between countries in the one-mode projection. The rich-club phenomenon is investigated with node strength as node richness. Countries ranking first in the nested country-treaty bipartite network form rich clubs in the one-mode cooperation network among countries. Thus, European countries tend to collaborate more in international environmental cooperation than with others outside Europe. The United States and Australia were not in the rich club after 2000.

Finally, starting from nestedness, I define two measures to indicate the diversification of countries committing to IEAs and the ubiquity of treaties being ratified – commitment diversification and ratification ubiquity – based on methods from economic complexity. Analysis shows that European countries have a higher level of commitment diversification. There is a significant correlation between commitment diversification and the environmental performance index, especially in the long term.

The remainder of this chapter is structured as follows. 6.2 introduces the data, networks' construction, and measures of interest. Main results are reported in sections 6.3, 6.4 and 6.5, which study nestedness, rich clubs and cooperation complexity, respectively. 6.6 concludes.

## 6.2 Data and methodology

### 6.2.1 Data

I employ the ECOLEX database, which contains IEAs from different sources. After data cleaning, I obtain a final sample of 546 IEAs signed from 1948-2015 by 200 countries. For each treaty, I have information on signatory countries, the process date information, the depositories, and the main subjects.

### 6.2.2 Methodology

Based on the data, I first construct a time sequence of bipartite networks connecting treaties to countries. Nestedness is studied on these bipartite networks. Then, by constructing a statistically significant one-mode projection of the bipartite networks, I obtained a time sequence of networks connecting countries that co-signed IEAs (Saracco et al., 2017). Weights are assigned to links in the country networks based on the method proposed by Newman (2001c). More details about constructing the bipartite and cooperation networks can be found in Carattini et al. (2019a). Here, I focus on two metrics: nestedness and rich clubs.

**Nestedness.** Nestedness has been studied extensively in ecological networks in the last decades. According to the formal definition given by Mariani et al. (2019), in a perfect nested network, the neighbourhood of a node with a smaller degree is contained in the neighbourhood of a node with a larger degree (see Figure 6.1 for an example). This concept applies to both the bipartite and unipartite networks. In this chapter, I focus on the nestedness of bipartite networks.

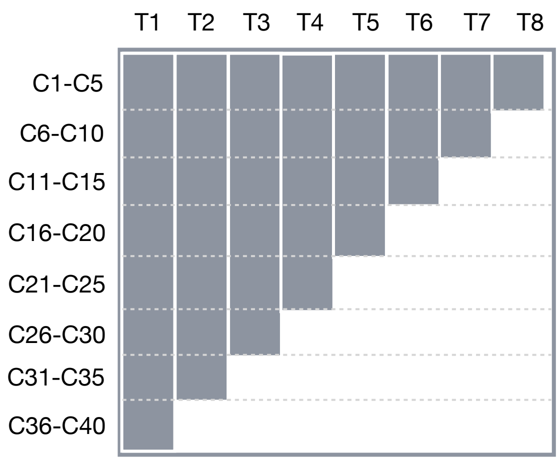



Figure 6.1: An example of a nested bipartite network. The rows are countries, and the columns are treaties.

There are various methods to quantify the extent of nestedness in a network (Mariani et al., 2019; Payrató-Borràs et al., 2020; Ulrich et al., 2009). The two most popular measures are the nestedness temperature and the NODF. The nestedness temperature was first proposed by Atmar and Patterson (1993) to quantify the nestedness in the distribution of species in fragmented habitats. This metric is distance-based by quantifying the deviation of a real matrix from a perfectly nested matrix. The most popular algorithm to perform the temperature computation is the BINMATNEST proposed by Rodríguez-Gironés and Santamaría (2006). Another widely-used metric is the NODF which attempts to measure nestedness by calculating how often neighbours of lower-degree nodes are also neighbours of larger-degree nodes (Almeida-Neto et al., 2008; Mariani et al., 2019).

As measures of nestedness are correlated with network properties, such as the network size, density, etc, the values of nestedness of different networks can not be compared with each other using nestedness measures, including the nestedness temperature and the NODF. To overcome this limitation, a commonly-used method is to calculate $z$-scores based on null models (Gotelli, 2000; Mariani et al., 2019; Ulrich et al., 2009). However, Song et al. (2017) pointed out that the $z$-score is also correlated with the network size, and thus proposed standardisation of the NODF, as shown in Equation 6.1. Evidence shows that the standardised metric is consistent across networks with different sizes and densities, indicating that it can be a reliable metric for comparing nestedness across different networks. This chapter mainly uses this normalised metric to quantify nestedness, while the nestedness temperature is used as a robustness check.

$$NODF_c = \frac{NODF_n}{C * log(S)} \tag{6.1}$$

where $NODF_n = NODF/max(NODF)$ and $max(NODF)$ is the maximum possible value of a network; $C$ is the network density, and $S$ is the geometric mean of plants and pollinators.

Hoeppke and Simmons (2021) developed highly-optimised algorithms in R to compute the $NODF_c$ and created a new package "maxnodf". This chapter will use functions in this package to obtain the normalised NODF.

**International environmental cooperation complexity.**

A matrix represents the country-treaty bipartite network $M$ where $M_{ct}$ equals 1 if country $c$ enforces or ratifies a treaty $t$; otherwise 0. Similarly, I define the commitment diversification of countries ($k_{\mathrm{c,N}}$) and the ratification ubiquity of treaties ($k_{\mathrm{t,N}}$) by calculating the following metrics:

$$k_{\mathrm{c,N}} = \frac{1}{k_{\mathrm{c,0}}} \sum_{p} M_{\mathrm{ct}} k_{\mathrm{t,N-1}} \tag{6.2}$$

$$k_{\mathrm{t,N}} = \frac{1}{k_{\mathrm{t,0}}} \sum_{c} M_{\mathrm{ct}} k_{\mathrm{c,N-1}} \tag{6.3}$$

for $N \geq 1$, and $k_{c,0}$ and $k_{t,0}$ represent the degree of countries and treaties in the bipartite network, respectively.

$$k_{\mathrm{c,0}} = \sum_{p} M_{\mathrm{pt}} \tag{6.4}$$

$$k_{\mathrm{t,0}} = \sum_{c} M_{\mathrm{ct}} \tag{6.5}$$

Through iteration, a vector $\vec{k}_c = (k_{c,0}, k_{c,1}, ...k_{c,N})$ is generated for each country, and a vector $\vec{k}_t = (k_{t,0}, k_{t,1}, ...k_{t,N})$ is generated for each treaty. The commitment diversification of countries can be measured by the even variables $(k_{c,0}, k_{c,2}, k_{c,4}, ...)$, while the odd variables indicate the ratification ubiquity of treaties ratified by countries. For products, the even variables $(k_{t,0}, k_{t,2}, k_{t,4}, ...)$ represent the ratification ubiquity of treaties, while the odd ones $(k_{t,1}, k_{t,3}, k_{t,5}, ...)$ quantify the commitment diversification of treaties' member countries.

**Rich clubs.** Rich clubs are subgroups of rich nodes that interact more with one another than expected by chance (Alstott et al., 2014; Colizza et al., 2006; Zhou and Mondragón, 2004). Node "richness" can be defined in terms of structural measures, e.g., the degree of nodes or other centrality measures, or non-structural measures, e.g., the node metadata such as social and technical information (Cinelli, 2019). All the nodes in the network can be ranked according to node "richness", and rich nodes are those whose richness exceeds a threshold $r$. Figure 6.2 shows an example with the richness defined as the node degree. The blue nodes form a rich club where each node has a degree larger than 3. In my study, I choose node degrees and node strengths as the structural measures, GDPs, total exports and imports, and energy imports and exports as the non-structural measures.

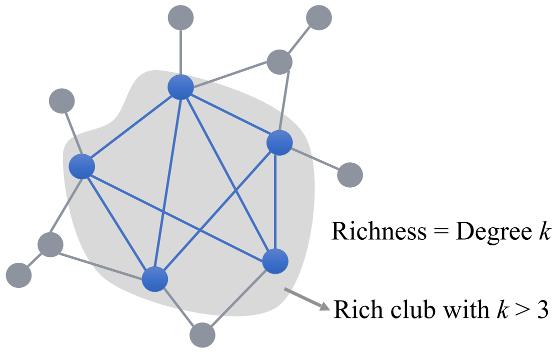



Figure 6.2: An example of a rich club. The richness is defined as node degree. Blue nodes form a rich club in which each node has a degree larger than 3.

I performed the topological (Cinelli, 2019; Zhou and Mondragón, 2004) and weighted rich-club analysis (Alstott et al., 2014; Opsahl et al., 2008) for the selected richness measures. The topological rich-club analysis examines the tendency of prominent elements to establish connections among themselves (Opsahl et al., 2008; Zhou and Mondragón, 2004). The topological rich-club coefficient is the ratio between the number of existing connections between the rich nodes and the number of maximum possible connections between them.

$$\phi(r) = \frac{2E_{>r}}{N_{>r}\left(N_{>r}-1\right)} \tag{6.6}$$

where $E_{>r}$ is the number of links between rich nodes, and $N_{>r}$ is the number of rich nodes in the rich club.

In addition, there is a heterogeneous distribution of resources among elements, and the prominent elements may gain and maintain control over resources in a system. The weighted rich-club coefficient evaluates the degree to which the prominent nodes in a network exchange among themselves the majority of the resources flowing within the network:

$$\phi^w(r) = \frac{W_{>r}}{\sum_{l=1}^{E_{>r}} w_l^{\text{rank}}} \tag{6.7}$$

where $w_l^{\text{rank}} \geq w_{l+1}^{\text{rank}}$ with $l = 1, 2...E$ are the ranked weights on the links, and $E$ is the total number of links. Equation 6.7 thus quantifies the fraction of weights shared by the prominent nodes compared with the total amount they could share if they were connected by the strongest links in the network (Opsahl et al., 2008).

Moreover, to assess the presence or absence of rich clubs, I obtained $1,000$ random networks and conducted statistical tests at the 5% significance level (Opsahl, 2009). A negative and significant weighted rich-club effect is present if $\phi(r)$ measured on the observed network falls into the left tail of the distribution measured on random networks, and a positive and significant effect is present if $\phi(r)$ falls into the right tail of the distribution. For the random network, the nodes in the rich club should be the same as in the observed network, so the distribution of richness $r$ should be maintained in random networks. In addition, main topological attributes, such as the degree distribution, should be preserved to make the null model comparable to the observed network (Opsahl et al., 2008). In analysing topological rich clubs, I use the configuration model, which keeps the degree distribution of nodes and reshuffles links. When coping with weighted rich club analysis, I exploit different random models, i.e., weight reshuffling, weight and link reshuffling, and weight local reshuffling. In particular, when richness is defined as node strengths, the weight of local reshuffling should be chosen to ensure that the ranking of node strength in the random network is the same as in the observed network.

## 6.3 Nestedness in the country-treaty bipartite network

I first explore what the ratification behaviours of countries mean for the organisational structure of international environmental cooperation. Countries' ratification behaviour is attributed to different factors and thus not random. The number of treaties across countries shows a heterogeneous distribution. Some treaties have over 100 signatories, while others only have several. In addition, different countries show different levels of concern for different environmental issues. Environmental issues which gain attention from powerful states tend to receive international attention (Mitchell, 2003). Whether different countries have their own preferences in signing treaties is still largely unknown.

To this end, I attempt to uncover the hierarchical structure in country-treaty relations by investigating nestedness in the country-treaty bipartite network. The nestedness matrices for the country-treaty bipartite network in specific years are presented. The normalised $NODF$ is calculated for the country-treaty bipartite network from 1948 to 2015.

The country-treaty bipartite network shows nestedness. Figures 6.4, 6.5 and 6.6 are the nestedness matrices for the country-treaty bipartite network in specific years. The rows represent the countries, while the columns indicate the treaties. Each grey rectangle indicates the presence of ratification. The algorithm sorts countries and treaties to maximise nestedness. The nestedness matrices show the hierarchical organisation of the country-treaty bipartite network where treaties ratified by countries with a smaller total number of treaties are also ratified by countries with a larger total number of treaties, but a subset of treaties are only ratified by countries with a larger total number of treaties, i.e., treaties on the top-right of the matrices. The results are robust when excluding UN and/or UN-agency treaties, as shown in Figures 6.5 and 6.6.

The normalised $NODF$ enables us to compare the nestedness across different years. Figure 6.3 shows the evolution of the normalised NODF for the country-treaty bipartite network with all the treaties, without UN treaties and without UN and UN agency treaties, respectively. The nestedness first increased from 1950 to 1965 and then gradually decreased.

Here, countries with a relatively larger number of treaty memberships have a higher commitment diversification, and treaties with a relatively larger number of signatories have a larger ratification ubiquity. Based on the hierarchical organisation, countries with a high commitment diversification support the existence of treaties with a low ratification ubiquity. Thus, countries with a high commitment diversification arising from such a nested network might play an important role in pioneering or driving more IEAs.

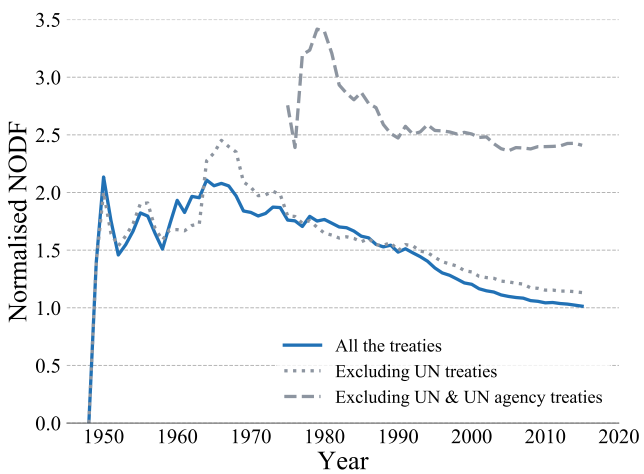
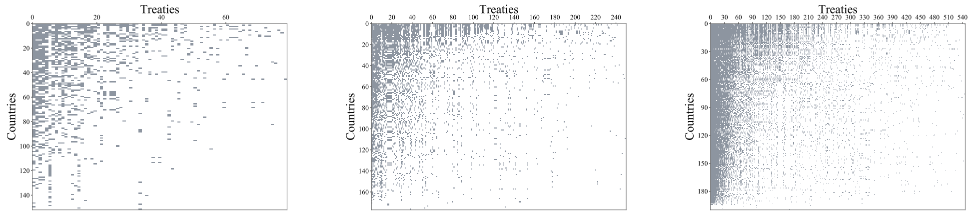
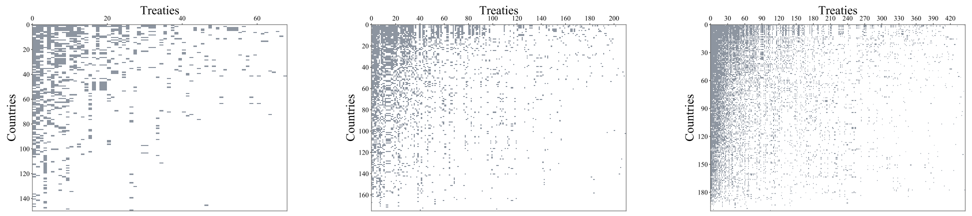



Figure 6.3: Normalised NODF from 1948 to 2015



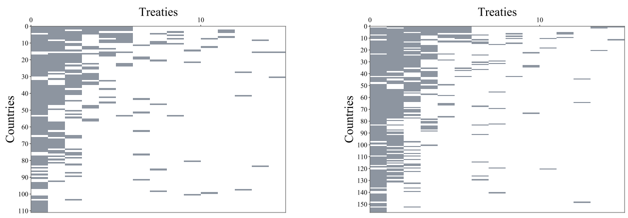

(a) 1970 (b) 1990 (c) 2015

Figure 6.4: Nestedness in the bipartite country-treaty network considering all the treaties. The rows represent the countries, while the columns indicate the treaties. Each grey rectangle indicates ratification. The algorithm sorts countries and treaties to maximise nestedness.




(a) 1970 (b) 1990 (c) 2015

Figure 6.5: Nestedness in the bipartite country-treaty network without the UN treaties. The rows represent the countries, while the columns indicate the treaties. Each grey rectangle indicates ratification. The algorithm sorts countries and treaties to maximise nestedness.




(a) 1990 (b) 2015

Figure 6.6: Nestedness in the bipartite country-treaty network without the UN and UN agency treaties. The rows represent the countries, while the columns indicate the treaties. Each grey rectangle indicates ratification. Countries and treaties are sorted by the algorithm to maximise nestedness.

Next, I analyse the rankings of countries and treaties in the nested bipartite network. Results show that the ranking of countries is relatively stable. The Kendall tau coefficient between the rankings in years $t$ and $t + 5$ is calculated.

The coefficient is around 0.8 whether or not the UN treaties are included. When excluding UN and UN-agency treaties, the coefficient first increased from 1980 to 2000 and then levels off at around 0.9. Thus, it can be argued that a certain set of countries kept having a higher commitment diversification and thus contributed more to maintaining treaties with a low ratification ubiquity.

Then, the composition of the set of countries contributing more to the ubiquity of treaties is analysed. Results indicate that European countries account for approximately 80% of the top 10% counties in terms of commitment diversification irrespective of whether the UN treaties were included (see Figure 6.8). When excluding UN and UN-agency treaties, European countries occupy around 40% of the top 10% countries. Results are robust when adopting the nestedness temperature to quantify nestedness (see Figure C.7). Thus, European countries contributed more to maintaining treaties with a low ratification ubiquity.

The ranking of treaties is also relatively stable in the matrices. This can be illustrated when the ranking of treaties is divided into five equal intervals, i.e., $0-20\%$, $20-40\%$, $40-60\%$, $60-80\%$, and $80-100\%$. Figure 6.9 shows the evolution of the ranking of the top 64 treaties from 1970 to 2015. Despite fluctuations, most treaties remained in an interval continuously. Some treaties might span adjacent intervals over the years, but rare treaties span all the intervals. It can be seen that the ratification ubiquity of different treaties is relatively stable.

The dominant role of European countries in global climate change discussions and actions can be attributed to several factors. First, European countries, especially those in Western Europe, were early industrialisers and significant contributors to historical greenhouse gas emissions. While their emissions per capita may be lower than those of China and the United States today, they have accumulated a substantial historical carbon debt (Rocha et al., 2015). This historical responsibility has made European nations keenly aware of their role in climate change and the need to take action. In addition, European countries have a strong tradition of environmental activism and awareness. Grassroots movements, NGOs, and civil society organisations have played a vital role in pushing for environmental protection and climate action. This activism has influenced public opinion and policy decisions. Another important factor concerns the EU's ambitious environmental policy. EU has made efforts to take on a leadership role in promoting international environmental agreements since the late 1980s (Kelemen 2010, p336). Its leadership arose as the combined effect of domestic politics and international regulatory competition. The institutional framework and technological innovations are also attributable. The European Union (EU) has developed one of the most comprehensive and ambitious institutional frameworks for addressing climate change. The EU Emissions Trading System (ETS), renewable energy targets, and other policies provide a structured approach to reducing emissions (Oberthür and Dupont, 2021; Teixidó et al., 2019). European countries have been leaders in developing and adopting clean energy and environmental technologies. Innovations in renewable energy, energy efficiency, and sustainable transportation have made Europe a hub for clean technology development and exports (Teixidó et al., 2019).

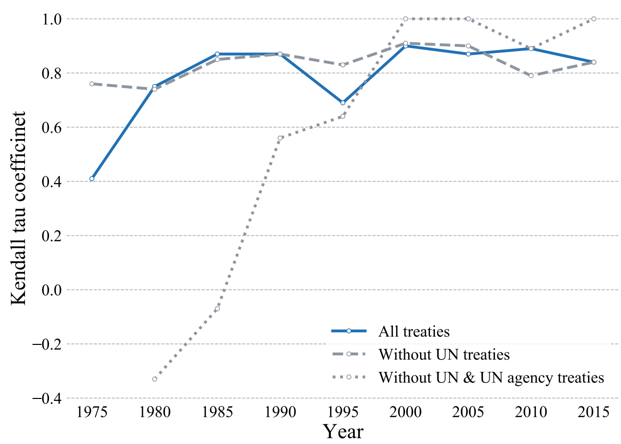



Figure 6.7: Correlation between rankings of countries in year $t$ and $t + 5$ based on the NODF. The Kendall tau coefficient is calculated.

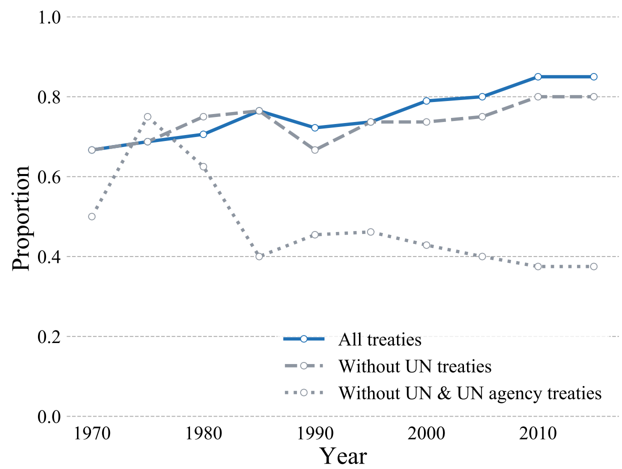



Figure 6.8: Proportion of European countries among the top 10% countries in each year based on NODF

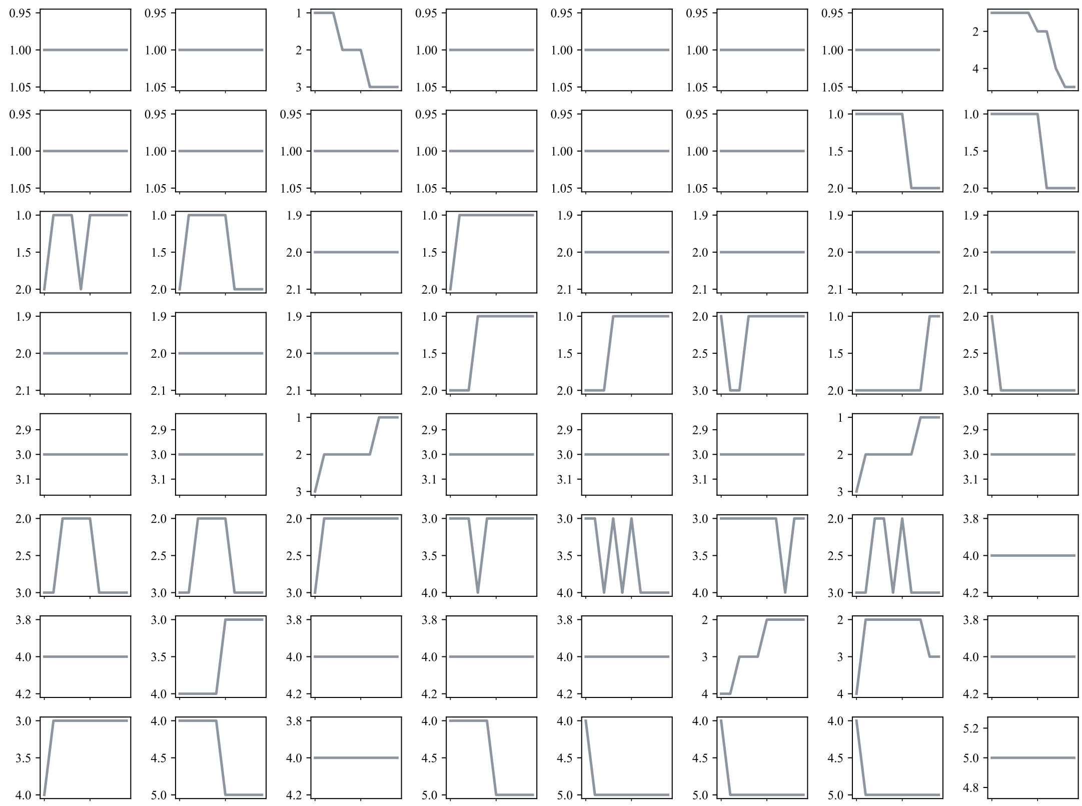


Figure 6.9: Ranking of the top 64 treaties based on the NODF from 1970 to 2015. The ranking of IEAs are divided into 5 equal intervals: $0-20\%$, $20-40\%$, $40-60\%$, $60-80\%$, $80-100\%$. The y-axis represents the five intervals. The x-axis indicates the years.

## 6.4 European countries form a rich club

In the above section, a hierarchical organisation is found in the bipartite country-treaty network indicated by the nestedness phenomenon. European countries show a more diverse commitment without specialising in a subset of treaties. What does this mean for the cooperation network obtained by projecting on the country layer of the bipartite network? In this section, I focus on the rich club in a network which classifies nodes in the network into a core and a periphery.

In the nested bipartite country-treaty network, countries are ordered by algorithms which attempt to maximise the nestedness. Normally, countries ratifying more treaties rank first. In the one-mode projection cooperation network, weights are assigned to links between countries according to the method proposed by Newman (2001c), which takes into account the number of treaties commonly ratified by two countries and the number of members in each treaty (see equation 3.1). The assumption here is that two countries who co-sign a treaty together with many other countries have a less extensive cooperation relationship on average than two countries that are the sole signatories of a treaty. Thus, link weights can quantify the cooperation intensity between countries. Mathematically, when link weights are assigned in this way, the strength of a country, i.e., the sum of weights of links incident on this country, is equal to the number of treaties ratified by this country (Newman, 2001c). Equation 6.8 clearly shows the relationship.

$$s_i = \sum_{j(\neq i)} w_{ij} = \sum_k \sum_{j(\neq i)} \frac{\delta_i^k \delta_j^k}{n_k - 1} = \sum_k \delta_i^k, \tag{6.8}$$

where $s_i$ is the strength of country $i$. $w_{ij}$ is the link weight between country $i$ and country $j$. $k$ indicates the number of treaties ratified by country $i$. $\delta_i^k$ equals 1 if country $i$ has ratified treaty $k$; 0, otherwise. $n_k$ is the number of member countries of treaty $k$.

Statistical validation is performed during the one-mode project, i.e., there is a link between two countries if and only if there is a statistically significant number of common treaties between these two countries. In this way, the non-significant links are removed. Thus, in my case, the strength of a country is only approximately equal to the number of treaties ratified by this country.

The country-treaty bipartite network shows nestedness where countries and treaties are sorted by algorithms to maximise nestedness (see Section 6.3). Normally, countries ratifying a larger number of treaties rank first and form the core in the bipartite country-treaty bipartite network. It has been discussed above that the number of treaties ratified by a country is approximately equal to its strength in the one-mode projection. Then, what are the positions of countries with the largest strength in the one-mode projection?

Here, I study the impact of the nestedness in the bipartite country-treaty network on the cooperation relationships between countries in the one-mode projection. Countries' strength, i.e., the number of treaties ratified by countries, is defined as node richness, and the rich-club phenomenon is investigated. In other words, I investigate whether countries with the highest cooperation intensity with others or with the largest number of treaties tend to form a rich club.

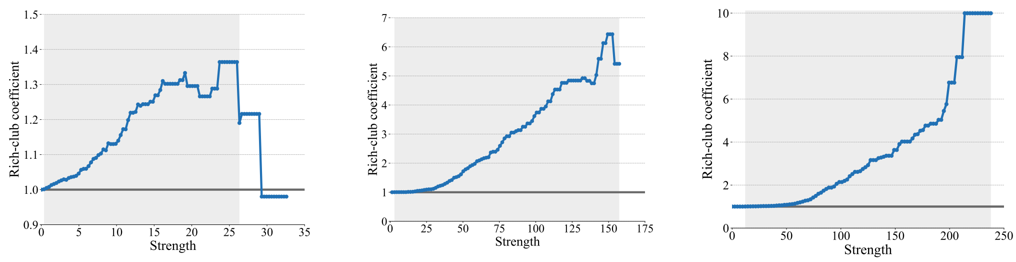
The statistical significance of the rich-club coefficient is evaluated by generating a series of random networks where the link weights of each country are reshuffled locally to keep the rankings of country strength. According to Figures 6.10, the rich-club coefficient is always statistically significantly greater than one, indicating that there is a rich-club phenomenon based on countries' strength [1]. In 1980, most of the top 10 per cent countries in terms of strength came from Europe, except Australia, the USA and Tunisia. Similarly, in 2000, the top 10 per cent countries, apart from Australia and Russian Federation, were all from Europe. Finally, in 2015, the top 10 per cent countries were all from Europe except the Russian Federation. Thus, European countries dominate the rich clubs (see the

[1] In 1980, only three countries have a strength larger than 27.0.

maps in Figure 6.11).

Intuitively, nodes with the highest strength naturally form a rich club in the one-mode projection due to the nestedness in the bipartite network when the link weights are assigned according to Newman (2001c). Take Figure 6.1 for example. Figure 6.1 shows a nestedness structure in the bipartite country-treaty network. When projecting on the country layer according to the method introduced in 6.2.2, there will be a complete network, i.e., there is a link between any pair of countries, as every country ratifies treaty $T1$. However, link weights differ across different sets of countries due to the hierarchical structure of the bipartite network. Specifically, treaty $T1$ contributes to the link weight between any pair of countries. In contrast, treaty $T2$ only contributes to the link weights of the first 35 countries. Treaty $T8$ only contributes to the link weights between the first 5 countries. Thus, links between countries ranking high have a larger weight due to the contribution of a larger number of treaties than those ranking low. Thus, countries ranking high naturally constitute a rich club when the richness is defined as the node strength. The nestedness in a bipartite network will lead to a rich club in the one-mode projection when the richness is defined as node strength.

I believe that the nestedness in the country-treaty relationships helps to promote the formation of rarely ratified treaties due to the existence of some generalist countries, such as France. To some extent, the nested structure of the country-treaty relationships promotes coherence and consistency in environmental policy and actions as countries ranking lower in the hierarchical structure just join treaties already signed by those ranking high. This is the positive aspect of the nestedness. However, as introduced in Section 4.3.3, rich clubs consist of prominent actors that leverage their connections to gain and maintain control over resources in the network (Opsahl et al., 2008). The rich club arising from the nestedness of country-treaty relationships indicate that countries in the rich club interact more with each other, which provides them with an advantageous position in the cooperation network to have more say in specifying the international environmental governance. Conversely, countries outside the rich club interact less with those in the rich club and among themselves. Thus, they may have a disadvantageous role when formulating international environmental regulations. To eliminate the negative impact of nestedness, it is essential to establish effective mechanisms for coordination and integration across the boundary of the rich club and give countries outside the rich club more access to express their environmental needs, especially when there are conflicting interests or priorities against countries in the rich club.




(a) 1980 (b) 2000 (c) 2015

Figure 6.10: Weighted rich club coefficient. The richness is defined as node strengths. The random networks are generated by keeping the strength distribution but reshuffling weights locally for each node across its outgoing links. The grey background indicates that the results are statistically significant when assessed against the null model. The significance level is 5%

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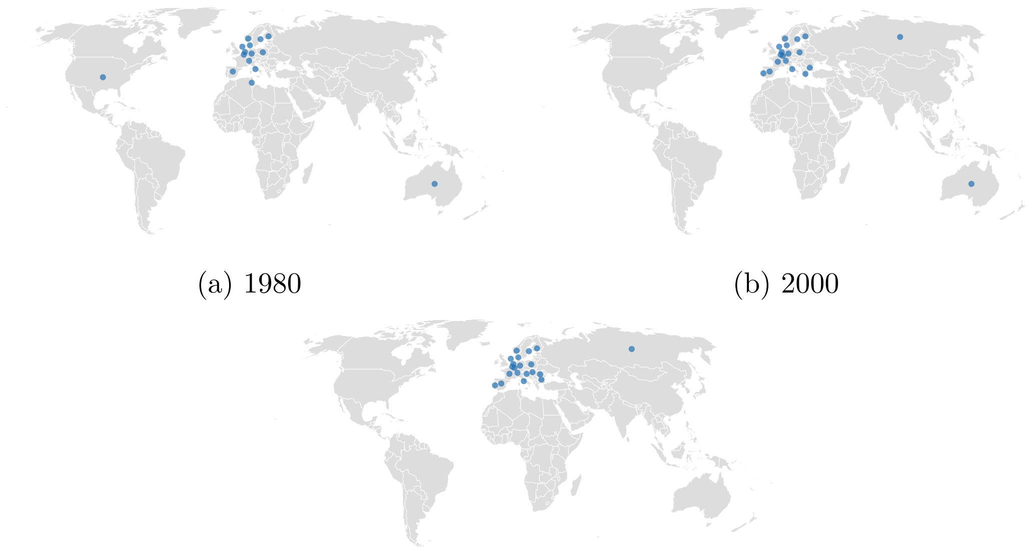


(a) 1980 (b) 2000

(c) 2015

Figure 6.11: Distribution of countries in the rich club across the world. Only the rich club formed by the top 10% countries is illustrated.

In addition, notably, in 1980, the USA was a member state of the rich club. Although it was also in the rich club from 1980 to 1998, since 1999, the USA was not in the rich club. This phenomenon is consistent with the "shift from the global environmental leader in the 1970s and 1980s to laggard and obstructionist in the 1990s and 2000s (Kelemen 2010, p336)".The US acted as a global environmental leader in the 1970s and 1980s. The US promoted the 1972 United Nations Conference on the Human Environment and was in support of the 1987 Montreal Protocol on Ozone Depleting Substances. Falkner (2005) also mentioned the widespread perception of the collapse of US environmental leadership since the early 1990s, as the US was opposite to key agreements at the United Nations Conference on Environment and Development (UNCED) in 1992. Similarly, from 1975 to 2005, Australia was a member state of the rich club, but afterwards, it was not.

## 6.5 Commitment diversification and ratification ubiquity

In section 6.3, it is found that the bipartite country-treaty network shows a nestedness structure where countries have different levels of commitment diversification across treaties. Countries have no specification to ratify treaties. In this section, I apply methods from economic complexity to quantify this type of diversification. Furthermore, the correlation between the metric of diversification and the EPI is investigated.

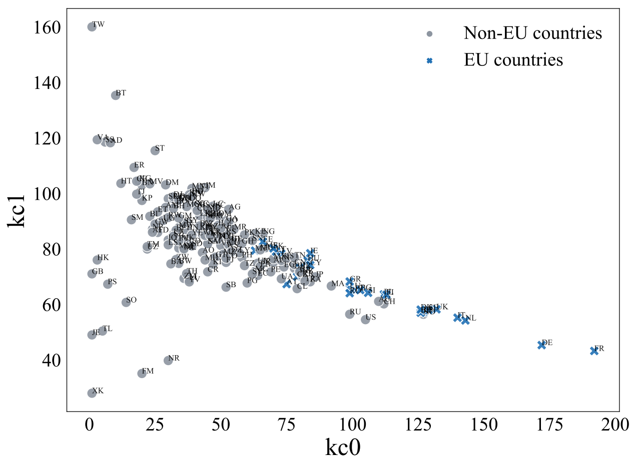



Figure 6.12: Commitment diversification of countries versus ratification ubiquity of treaties within countries. Only the results of $kc_0$ and $kc_1$ are illustrated. The blue crosses indicate European countries.

According to the methodology introduced in Section 6.2.2, the commitment diversification of countries and the ratification ubiquity of treaties are generated through iterations of equations 6.2 and 6.3 where the initial values are the country degree and the treaty degree in the bipartite network. Figure 6.12 shows the relationship between the commitment diversification of countries $k_{c,0}$ and the ratification ubiquity of treaties within a country $k_{c,1}$. Countries with a high commitment diversification tend to have a low ratification ubiquity of their treaties. European countries tend to have a larger commitment diversification compared with non-EU countries.

Figure 6.13 shows the ranking of countries according to the measure of commitment diversification of countries. When the commitment diversification is quantified by $k_{c,0}$, i.e., the degree of countries, there is an overlap between the rankings of multiple countries. As the iteration continues, the rankings of countries tend to stabilise and the overlap disappears. Especially, the rankings of most countries experience a dramatic change from $k_{c,0}$ to $k_{c,2}$. It should be noted that although France ranks first indicated by $k_{c,0}$, its ranking drops to $9th$ according to $k_{c,10}$. In addition, the USA ranks from the top 20 to outside the top 50. In contrast, Turkmenistan's (TM) ranking keeps rising from around $150th$ to around $60th$. EU countries consistently rank high through the iteration (see Figure 6.13 in which EU countries are highlighted in blue.). Thus, it can be argued that, in global environmental governance, EU countries have the highest commitment diversification.

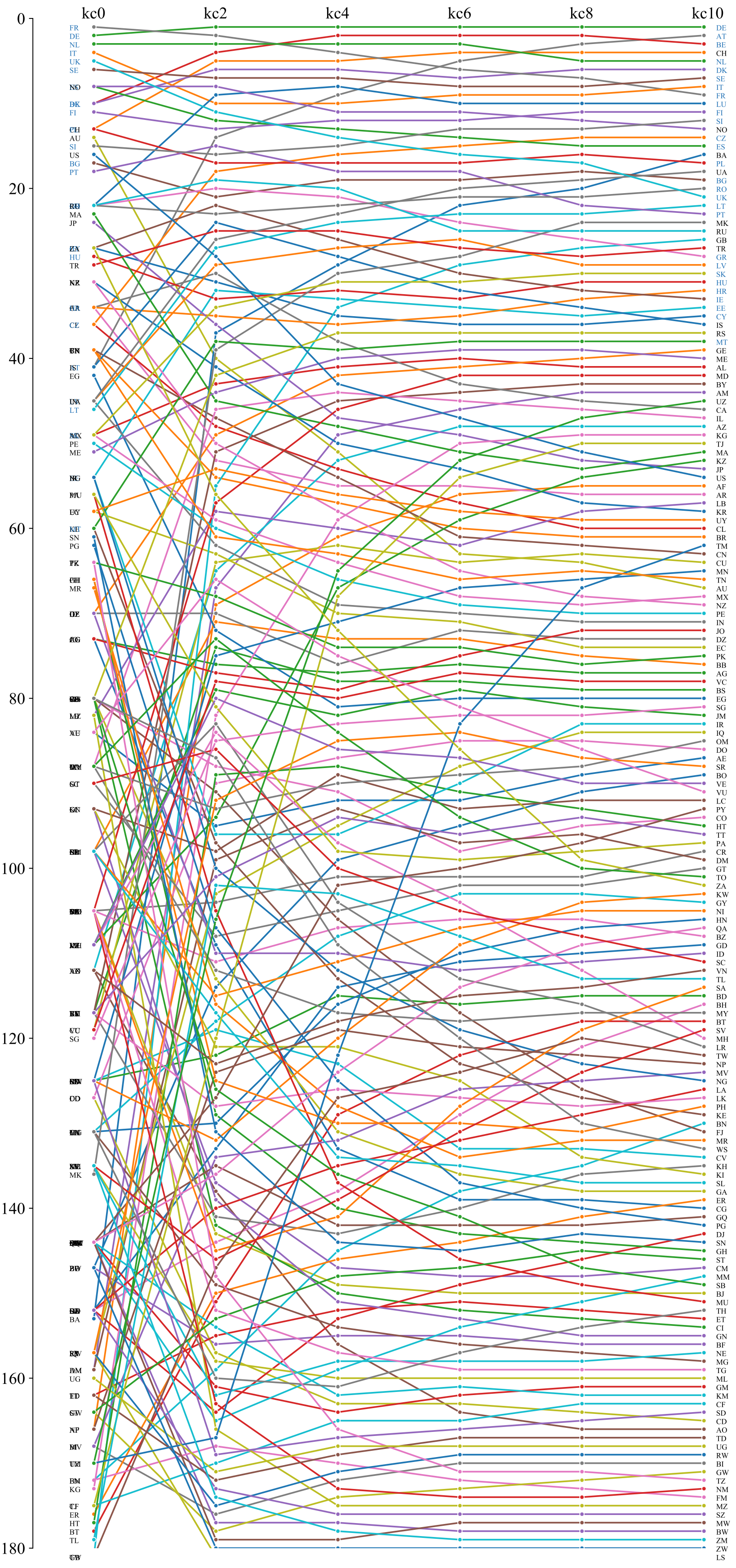



Figure 6.13: Ranking of countries based on the commitment diversification in 2015. EU countries are highlighted in blue.

Next, I study the correlation between the commitment diversification of countries and the environmental performance index within countries. To this end, I draw on the Environmental Performance Index (EPI) database developed by the Yale Center for Environmental Law and Policy and The Center for International Earth Science Information Network (CIESIN) at Columbia University's Earth Institute [2]. This database provides an EPI score for each country by combining a set of performance indicators, including environmental health, ecosystem vitality, nitrogen use efficiency, etc. I use the EPI in 2016, 2018 and 2020 to investigate the short and long-term impact of the commitment diversification of countries in 2015. To make the results comparable, $kc_0$, $kc_2$, $kc_4$, $kc_6$, $kc_8$ and $kc_{10}$ are normalised according to $\frac{kc_N - \bar{kc}}{std(kc_N)}$. Results are shown in Figures 6.14, 6.15 and 6.16.

Commitment diversification is correlated with the environmental performance index, especially in the long term. Pearson's correlation coefficient is larger than 0.6 for different $kc_N s$ when considering the EPI in 2016, 2018 and 2020. However, the initial value of the commitment diversification of countries $k_{c,0}$, i.e., the number of treaties ratified by countries, tends to be less correlated than those obtained by the iteration, i.e., $k_{c,2}...k_{c,10}$. Thus, the combined metrics of the commitment diversification of countries are more beneficial to reveal the correlation between treaties ratified by countries and countries' environmental performance index.

In addition, the long-term effects of the commitment diversification of countries are more pronounced, especially for those with a high commitment diversification. In Figure 6.14, as the commitment diversification increases, the increasing trend of the marginal effect of the commitment diversification on the EPI in 2016 slows

[2]The database of Environmental Performance Index (EPI) can be obtained at `https://epi.yale.edu/`

down. The correlation tends to be more linear, with a larger Pearson's correlation coefficient when the EPI in 2018 and 2020 is considered. Pearson's correlation coefficient is around 0.7 and 0.8 in 2018 and 2020, respectively. As European countries tend to have a higher commitment diversification, they will have a better environmental performance index, and the difference will become larger over time, even among EU countries.

Several factors may support the conclusion above. Diversification of environmental commitments means addressing a wide range of environmental issues and taking a comprehensive approach to environmental protection. This holistic approach can lead to better overall environmental performance. In addition, addressing multiple environmental challenges simultaneously can lead to synergistic effects. For example, policies that promote energy saving may not only reduce greenhouse gas emissions (climate change commitment) but also improve water-saving (water resource commitment) and reduce dependence on fossil fuels (energy security commitment) (Gu et al., 2014). Moreover, a diversified set of environmental commitments can make a country or organisation more resilient to environmental shocks and challenges (Hirons et al., 2020). Besides, high diversification indicates a high political will to tackle environmental issues, which will drive countries to pass more domestic regulations and policies to satisfy the commitments.

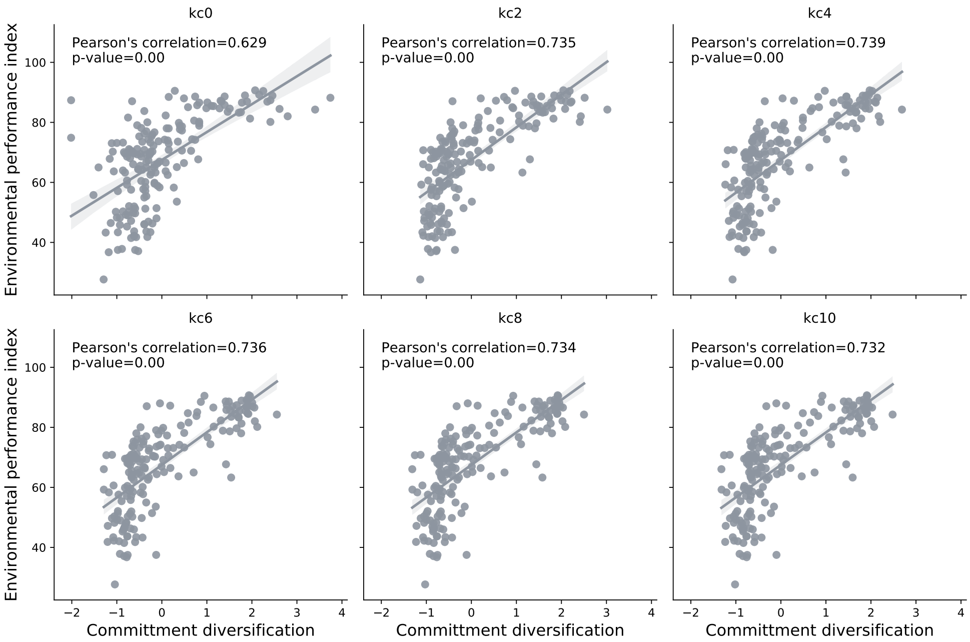



Figure 6.14: Correlation between the EPI in 2016 and the normalised commitment diversification of countries for $N = 0, 2, ..., 10$ in 2015.

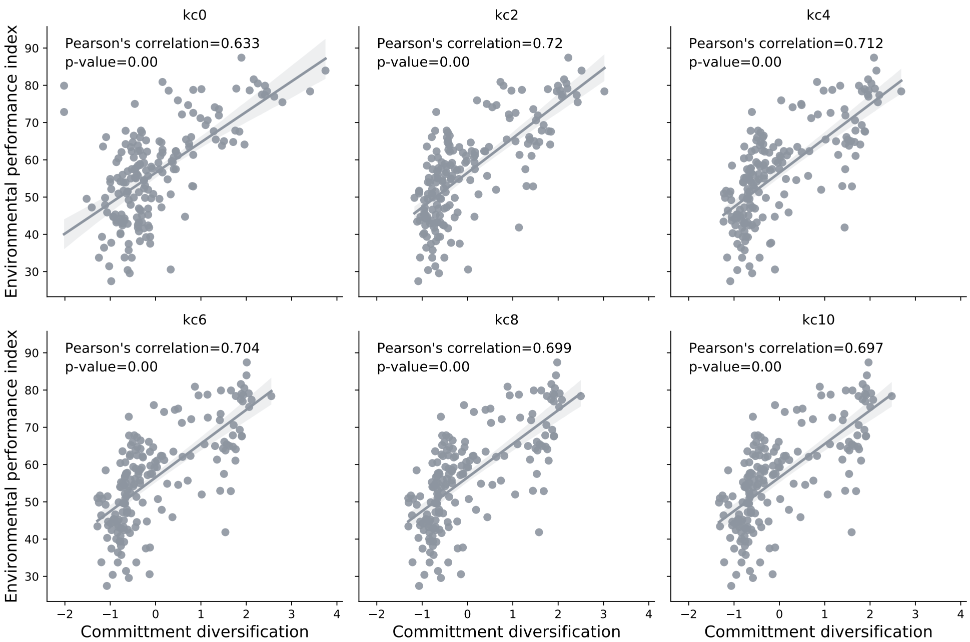



Figure 6.15: Correlation between the EPI in 2018 and the normalised commitment diversification of countries for $N = 0, 2, ..., 10$ in 2015.

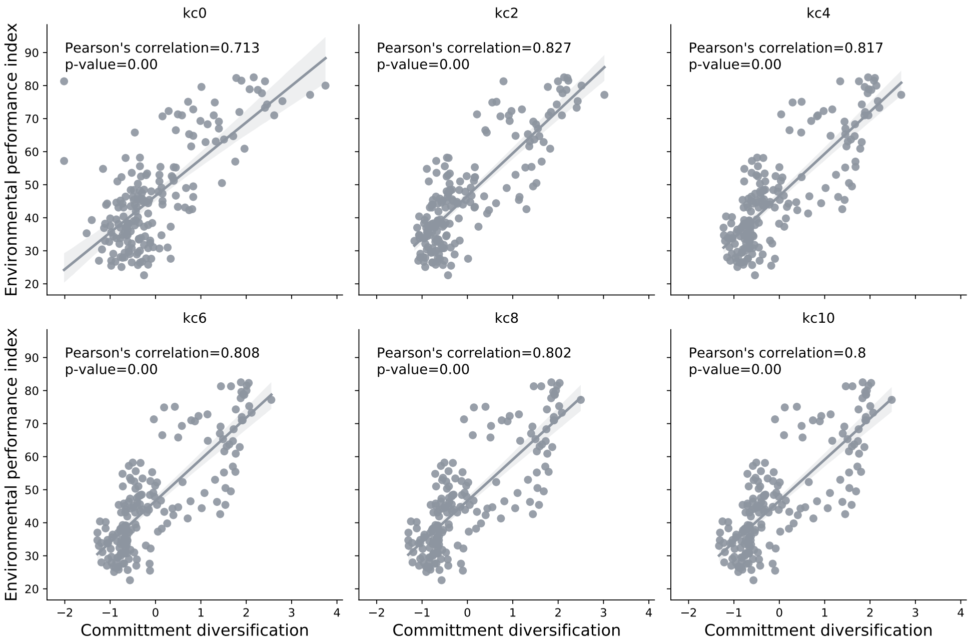



Figure 6.16: Correlation between the EPI in 2020 and the normalised commitment diversification of countries for $N = 0, 2, ..., 10$ in 2015.

## 6.6 Discussion and conclusion

Global environmental governance and international environmental cooperation have drawn attention in recent decades. However, the organisational structure of international environmental cooperation has been rarely discussed. To fill this gap, I investigated the nestedness of country-treaty relationships and rich clubs in cooperation among countries. Moreover, I borrowed methods from economic complexity to further analyse the nestedness in country-treaty relations. Commitment diversification and ratification ubiquity were calculated. A more robust ranking of countries in terms of commitment diversification was obtained.

### 6.6.1 Implications for research

European countries constitute the core of international environmental cooperation from the perspective of nestedness and rich clubs. The country-treaty relations demonstrate a nested structure where the more specialist ratifies only proper subsets of treaties ratified by the more generalist. Generalist countries thus facilitate the emergence of rarely-ratified treaties. Results show that European countries serve as the generalists, consistently indicating their pioneering roles in promoting IEAs. In addition, the nestedness in country-treaty relations inevitably induces rich clubs in the one-mode cooperation network among countries. In the rich clubs, European countries tend to collaborate more with one another than with other countries.

In addition, European countries have the highest commitment diversification. Moreover, there is a significant positive correlation between countries' EPIand commitment diversification, especially in the long term.

### 6.6.2 Implications for practice

My study deepens our understanding of the hierarchical organisation of international environmental cooperation. The features and the function of the hierarchical organisation should be considered to understand the status of countries' environmental commitment and assess the influence of existing IEAs on environmental performance. First, policymakers cannot ignore the contribution of European countries in promoting environmental treaties. European countries act as generalists who tend to ratify all kinds of treaties without specifying specific treaties, which to some extent, promotes rarely ratified treaties. In addition, better environmental performance is expected in countries with higher diversification of environmental commitment. This, to some extent, reveals the benefits of signing environmental treaties. Ratifying an IEA is a voluntary act of a state. My finding might encourage countries to enlarge their baskets of environmental commitment.

### 6.6.3 Limitations and future work

The analysis opens the path to further studies. A nontrivial question that deserves further investigation is the formation mechanism of the nested country-treaty network. Researchers reveal different formation mechanisms for nestedness in ecological, social and economic networks (Mariani et al., 2019). For instance, the capacity-based model can characterise the country-product export network (Falkner et al., 2010), and the competition model can represent the dynamics of the processes of countries' innovation and competition on the exports (Saracco et al., 2015a). Investigating the formation mechanism of the country-treaty ratification network can complement the previous studies by quantifying the importance of network structures for countries' ratification behaviours.

Another avenue for further research is the implications of countries' commitment diversification. More advanced methods can be used to explore the causality between countries' commitment diversification and environmental performance index.

### 6.6.4 Contribution to the literature

My study contributes to global environmental governance and international environmental cooperation literature by examining nestedness and rich clubs in international environmental cooperation through treaties.

I believe that the study on the country-treaty ratification network can shed new light on the structural foundations and cooperation complexity in global environmental governance, the landscape of countries' ratification behaviours, and the role that nestedness can play in enhancing or inhibiting environmental performance. My study unveils the nested structure and rich-club organisation of international environmental cooperation through IEAs, thus providing a key contribution to the emerging literature that applies network theory to international environmental cooperation.

# Part III: Climate change laws

# Chapter 7

# Literature review for Part III

In Part III, I will study the motivating factors of bursts of climate change policy adoptions. Policy adoption theory has been studied extensively. The internal determinants model explains policy adoption as a function of state characteristics, while the regional diffusion model considers the influence of neighbouring states' adoption behaviours. This Chapter will first review the literature on climate change laws, mainly on studies of motivations for adopting climate change laws. Then, the burst phenomenon in human behaviours is introduced to motivate my study.

## 7.1 Adoption of climate change laws

Literature on climate change laws has expanded dramatically in the last decade. In particular, the documentation of national climate action has become more systematic. Eskander et al. (2021) describes the evolution of climate change laws based on the most comprehensive data to date, i.e., the Climate Change Laws of the World (CCLW), and reveals that national legislation peaked around 2009 to 2014. National legislation is still accelerating, with 2280 climate laws in 198 jurisdictions at the end of 2020.

In addition, based on another database, the Climate Policy Database [1], Iacobuta et al. (2018) conducts a comprehensive review of national climate legislation and strategies for climate mitigation across 194 countries from 2007 to 2017, including both national climate legislation and strategies and targets on greenhouse gas (GHG) emissions, renewable energy and electricity, and energy efficiency. Both GHG reduction targets and renewable energy targets experienced a steady increase during the decade.

The prevalence of national climate legislation has prompted scholars and policymakers to further explore its drivers. Policy innovation can be influenced by motivations, resources, and obstacles to policy change. Specifically, environmental conditions and citizens' demands might motivate climate-related policy innovation. Resources might place constraints on policy innovation, including states' financial and geographic resources, such as solar radiation intensity. However, the national reliance on carbon-intensive industries might constitute obstacles.

For instance, Fankhauser et al. (2016) study the effect of international factors on the passage of climate change legislation through regression analysis based on panel data. Results indicate that policy diffusion is essential in promoting more climate change laws. The Kyoto Protocol [2] set legally binding emission targets

[1] The Climate Policy Database can be obtained at `https://climatepolicydatabase.org/`

[2] The Kyoto Protocol is an international treaty that was adopted in 1997 under the UN Framework Convention on Climate Change (UNFCCC). The treaty requires developed countries

for industrialised countries to be achieved between 2008 and 2012. Despite doubts about this protocol, it is seen as a breakthrough in climate change policy and is important for further policy process (Protocol, 1997). Fankhauser et al. (2016) found that binding obligations under the Kyoto Protocol tend to boost the passage of climate change laws in developed countries, but the effect was not present in developing countries. A parallel study is performed to explore the influence of domestic factors by Fankhauser et al. (2015). Existing legislation might hinder the passage of more laws, and the presence of a strategic "flagship law" tends to promote more legislation. In contrast, political orientation is less critical, with no difference in the number of laws passed by left-wing and right-wing governments. In addition, Eskander et al. (2021) explores countries' tendency to pursue climate policy in difficult economic times. The correlation between the number of climate change laws and the cyclical component of GDP is investigated. Results show that legislative activity decreases during recessions. But in more rigorous regression analysis, two factors- concern for the environment and green investment during a recession- might compete to entangle their effects (Fankhauser et al., 2015).

The existing empirical analysis mainly regresses the absolute number of laws adopted by a country in one year on different potential factors based on panel data (Fankhauser et al., 2015, 2016). The assumption is that the absolute number of policies measures regulatory activity and the intensity of policy activity in states.

Another avenue to explain the adoption of climate change policies focuses on the diffusion process. Scholars on public policy have long been interested in policy

to reduce greenhouse gas emissions by a specific amount to keep a global temperature rise this century well below 2 degrees Celsius above pre-industrial levels. It entered into form in 2005 and was initially signed by 192 countries.

diffusion, and have developed a variety of theories and models (see Jordan and Huitema (2014a,b) for an overview ). Policy diffusion can be defined as "the process whereby policy choices in one unit are influenced by policy choices in other units" (Gilardi, 2016; Maggetti and Gilardi, 2016). Thus, policy diffusion is characterised by interdependence. The main mechanisms of policy diffusion are learning, emulation and competition. And, alongside the different mechanisms, various indicators have been developed, including geographic proximity, joint membership, the success of the policy, structural equivalence, number of previous adopters, trade flows, etc. (Yamagata et al., 2017a).

Policy diffusion theories have been applied to climate change policies. Schoenefeld et al. (2022) reviews the literature on the diffusion of adaptation laws, indicating that four mechanisms are in place when explaining the diffusion of adaptation laws. The four mechanisms are "interests (linked with learning and competition), rights and duties (tied to coercion), ideology, and recognition (both connected with emulation)".

The primary empirical method has been event history analysis. For instance, Massey et al. (2014) restricts the study of the adoption and diffusion of climate change adaptation policies across 29 European countries and investigates its drivers and barriers. Results show that adaptation is primarily driven by internal factors. In addition, the international diffusion of carbon pricing policies has been explored through estimating semi-parametric Cox proportional hazard models revealing that the policy adoptions in one country increase the probability of subsequent adoption in the other country (Linsenmeier et al., 2022). However, when focusing on energy efficiency and renewable energy policies, regional diffusion does not explain policy innovation across countries (Matisoff, 2008). Thus, policy diffusion might only apply to a specific type of policy. These results are concerned with the effects of the percentage of neighbouring countries, i.e., countries sharing borders, who have already adopted the same policy on the adoption in the focal country.

Other empirical methods have also been applied to the study of the diffusion of climate change policies. Notably, Skovgaard et al. (2019) has employed cluster analysis and divides policies into five clusters: early adopters, North American sub-national entities, Chinese pilot provinces, second-wave developed polities, and second-wave developing policies. Findings suggest that domestic factors are more critical for early adopters. In addition, directed dyadic analysis has been used to study the diffusion of climate-related policies. For instance, Baldwin et al. (2019) used directed dyadic analysis to study renewable energy policy diffusion. This method creates a dyadic data set comprising all pairs of countries in each year, which allows us to observe the interaction between any couple of countries, thus providing opportunities to analyse relationships between individual countries. Developed and developing countries are more likely to emulate the policies of their political partners while developing countries prefer to mimic donors' policies.

## 7.2 Burstiness

The dynamics of human behaviours have interested researchers since the 20th century when a quantitative understanding of the call patterns of individuals is needed (Vázquez et al., 2006). Evidence shows that human behaviours are not randomly distributed in time but tend to present bursty dynamics in which intensified activities occur during a short time period followed by a long period of inactive (Karsai et al., 2018; Vázquez et al., 2006).For instance, when people respond to emails, high-priority tasks will be processed soon after their arrival, whereas low-priority items will have to wait until all higher-priority tasks are cleared (Barabasi, 2005). Web activities, including queries, messages or logging actions, also show bursty phenomenon (Radicchi, 2009). In addition, printing requests (Harder and Paczuski, 2006), and phone calls or face-to-face interactions (Zhao et al., 2011) illustrate burstiness. Identifying burstiness and the mechanism of its origin can help us better predict and control human behaviours.

Research on burstiness is multidisciplinary, involving knowledge from different disciplines, including physics, mathematics, network science, statistics and social science. Empirical research shows that these busty phenomena can be characterised by a non-Poissonian process with temporal heterogeneities on various temporal scales rather than by a Poisson process with a single temporal scale. Specifically, the distribution of inter-event times between two consecutive occurrences of a given type of an event is heterogeneous and follows a non-Poinssonian function, such as power law (Barabasi, 2005), log-normal (Mryglod et al., 2012) or stretched exponential (Bogachev and Bunde, 2009; Kleban and Clearwater, 2003). In contrast, other forms of human behaviours, e.g., call patterns of individuals, first-come-first-serve, are randomly distributed in time, and the inter-event times, also called waiting time, can be described by an exponential distribution (Barabasi, 2005; Panzarasa and Bonaventura, 2015; Vázquez et al., 2006).

In addition, human behaviours can transcend the individual level and present burstiness in different levels of organisational structures, including dyadic interactions and collective activities (Karsai et al., 2018). Different levels might influence each other, and the busty dynamics of collective actions may arise from individual activities and vice versa (Panzarasa and Bonaventura, 2015).

There are many factors that can explain the burstiness in human behaviours, including work patterns, human nature (sleep patterns), resource availability, etc. Different models are developed to characterise the features of burstiness based on different factors. Here, I only introduce some models for the individual level as my study focuses on individual country behaviours. The non-Poisson process might be driven by a queuing model driven by human decision-making. In this case, an individual faces multiple tasks and accomplishes them one by one according to their priorities (Vázquez et al., 2006). Another typical model is the memory-driven model, where the action sequence might be influenced by its previous mean activity, which is described by (Karsai et al., 2018).

Furthermore, beyond describing phenomena, bursty patterns might impact various dynamic processes taking place on them, such as information and disease diffusion (Vazquez et al., 2007) and resource allocations (Paxson and Floyd, 1995).

Burstiness can be employed to study the pattern of human behaviours when dealing with climate change, such as policy-making, energy consumption, and transportation schedules. A better understanding of the bursty phenomenon of human behaviours will enable policymakers to predict the potential emergence and to implement intervention to steer things in a positive direction.

# Chapter 8

# Climate change laws

## 8.1 Introduction

Existing research on adopting climate change laws mainly employs the count model, event history analysis and dyadic analysis to investigate drivers behind the adoption. The adoption is measured by the intensity of policy activities, i.e., the number of policies adopted by a country in one year, or a dummy variable indicating the status of whether to adopt or not. However, these studies overlook the dynamics of countries' adoption behaviours. Human behaviours show bursty dynamics characterised by intermittent increases and decreases in the activity or frequency of events (Karsai et al., 2018). According to Nachmany et al. (2014), countries pass a climate change law every 18 to 20 months on average. However, no empirical analysis has been conducted on the dynamics of adoptions. In fact, the passage of climate change laws tends to exhibit a pattern of sudden activity followed by a long period of inactivity. A typical example concerns the Paris

Agreement in 2015. Both before and after the agreement saw an increase in national commitments. In preparation for this agreement, countries submitted Intended Nationally Determined Contributions (INDCs) for addressing the climate change challenge after 2020 (Rogelj et al., 2016). When the Paris Agreement was ratified in 2015, only a handful of nations, such as Costa Rica, Bhutan, and Sweden, had established goals for achieving net-zero emissions reductions. However, in the five years following the adoption of the Paris Agreement, a growing number of countries have embraced similar objectives, with a surge in announcements of net-zero targets from significant greenhouse gas emitters in 2021 (Höhne et al., 2021; Victoria and Bob, 2017). Domestic factors may also be attributable to such a burst phenomenon at the national level. For instance, the Waxman-Markey bill, officially the American Clean Energy and Security Act of 2009 (ACES), aimed to place the "cap-and-trade" rule on the emissions from the electric power, industrial and transportation sectors. However, this bill faced significant opposition and was ultimately not implemented. Moreover, from that time on, these obstacles led to the stagnation of similar legislation (Murray, 2015).

To fill this gap, I computed the time intervals between consecutive adoption years and attempted to explain the origin of bursts. That is, I investigate whether a given country passes at least one law every year for several consecutive years, or whether laws tend to be passed within very short time intervals separated by long periods in which no law is passed.

My study is based on the Climate Change Laws of the World created by the Grantham Research Institute on Climate Change and the Environment at the London School of Economics. Until October 2021, this data set documents

2315 laws in 198 countries and areas covering mitigation and adaptation. The comprehensive data set provides the opportunity to investigate the dynamics of countries' adoption behaviours.

This chapter aims to identify key international and national factors that contribute to the emergence of a burst in the passage of climate change policies. I test six hypotheses based on existing theories and the Climate Change Laws of the World using regression analysis. My first hypothesis concerns the correlation between scientific assessment and the emergence of a burst in adopting climate change laws. To this end, I chose scientific assessment reports from the Intergovernmental Panel on Climate Change (IPCC) in 2001, 2007, and 2014 and created a dummy variable to test the correlation. 3 or 5 years lag effects are considered.

Second, a positive association between international pressure from the Conference of Parties (COPs) and a burst is expected. To test the hypothesis, I create a dummy variable indicating the occurrence of COP3 in Kyoto in 1997, COP15 in Copenhagen in 2009 and COP21 in Paris, and consider 3 or 5 years lag effects.

In addition, my third hypothesis concerns exposure to natural disasters. On one hand, exposure to natural disasters might change the beliefs of a changing climate and consequently force countries to react quickly to mitigate and adapt to climate change, depending on the type of disaster they experience (Osberghaus and Fugger, 2022; Sloggy et al., 2021). On the other hand, the enormous economic losses caused by natural disasters lead people to support policies for economic recovery rather than policies to address climate change. These two factors intertwine, making the impact of exposure to natural disasters unclear (Hallegatte et al., 2016) . I, therefore, formulate the third hypothesis to expect a positive or negative correlation between exposure to natural disasters and a burst. I draw on the International Disaster Database to test the hypothesis, and similarly, a 3 or 5 years lag is considered. Fourth, economic recessions might have a positive or negative correlation with the burst in adopting climate laws as two factors with opposite effects – concern for the environment and green investment during recessions – make the situation unclear. To test the hypothesis, I obtain business cycles by filtering out the trend of GDPs and create a dummy variable to indicate whether a period is during economic recoveries or recessions. Fifth, there is a debate on the influence of governments' political orientations on climate laws. My study aims to reveal whether bursts are expected under left-wing governments. Based on the Database of Political Institutions (DPI), I create an independent variable – the political orientation ratio, which is the ratio of the number of years with a left political orientation to the number of years of a period. My last hypothesis expects a positive correlation between new governments and a burst, as new governments might promote climate change policies at the early stages of the establishment to satisfy the public. To this end, I construct another explanatory variable to indicate the concurrence of new governments – the number of political orientation shifts.

The chapter is structured as follows. Section 8.2 introduces theories and hypotheses. Sections 8.3 and 8.4 describe the data and the empirical strategy I use to test the hypotheses. Section 8.5 discusses the results, and conclusions are drawn in Section 8.6.

## 8.2 Theory and hypotheses

Science plays a critical role in environmental issues because they tend to be global in scale and have long-term impacts. Responses must be provided with urgency (Jäger, 1998). Shackley and Wynne (1996) pointed out that understanding the dynamics of science and policy and their consequences is essential to exploit existing knowledge further to mitigate and adapt to climate change. Environmental assessment is critical in this case, as it connects science and policies. The Intergovernmental Panel on Climate Change (IPCC), established in 1988, is the most extensive integrated assessment. The IPCC produces assessment reports on the state of knowledge on climate change from scientific, technical and socioeconomic perspectives. The impacts and future risks are also indicated, and furthermore, suggestions are given to mitigate the process of climate change [1].

Till now six assessment reports have been issued since 1990. The Sixth Assessment Report assesses the impacts of climate change, including ecosystems, biodiversity, and human communities at global and regional levels. In addition, the vulnerabilities, capacities, and limits of the natural world and human societies to adapt to climate change are also reported.

Case studies on IPCC show that scientific assessments enable us to learn from experience, which facilitates the formation of more powerful institutions and provides support for decision-making (Siebenhüner, 2002). Bolin (1994) argued that the IPCC assessment promoted rapid progress in reaching a consensus with the UNFCCC. Thus, I expect bursts will follow the release of the IPCC in adopting

[1] https://www.ipcc.ch/

climate change policies. I chose the IPCC reports in 2001, 2007 and 2014 to study their impact on countries' adoption behaviours, and I hypothesise that

**Hypothesis** 1: *The release of scientific assessments by IPCC will correlate positively with the emergence of bursts in adopting climate change policies.*

The Conference of Parties (COPs) might help pressure countries to fulfil commitments through new domestic legislation. From the first conference held in 1995, COPs aim to review the implementation of the "Rio Convention", the UN Framework Convention on Climate Change (UNFCCC) (Rhodes, 2016). The UNFCCC entered into force on 21 March 1994 and formulated a framework to keep atmospheric concentrations of greenhouse gases (GHGs) at a low level. Key conferences, such as COP3 in Kyoto in 1997, COP15 in Copenhagen in 2009, and COP21 in Paris in 2015, and the international treaties that arose from the conferences require countries to contribute to reducing greenhouse gas emissions, although the conference in Copenhagen saw no agreement to the Kyoto Protocol. Although there is no compelling target amount for each country to reduce GHGs and even no penalty measures for the failure of fulfilment, countries may face severe criticisms if no commitment is met. To test the correlation between COPs and the burst in adopting climate change laws, I formulate the following hypothesis:

**Hypothesis** 2: *Binding obligations imposed by essential COPs positively correlate with bursts in adopting climate change laws.*

Another important factor influencing the burst in the adoption of climate change laws is natural disasters. Increasing scientific evidence shows that climate change will cause natural hazards. A study by Sobel et al. (2016) indicates that hurricane intensity will increase as climate change intensifies. Trenberth et al. (2014) also pointed out that once a drought occurs, global warming will lead to its faster spread and greater severity. Even worse, simulations indicate that increased temperatures will promote greater fire frequency in wetter, forested areas (Westerling and Bryant, 2008). These natural hazards may cause severe economic, environmental, and social consequences (Hallegatte et al., 2016).

Although there is extensive scientific evidence of the changing climate, if people's daily lives have not experienced significant impacts from climate change, they may harbour doubts about whether climate change is really occurring. Exposure to natural disasters might influence the attitude of individuals toward climate change which can directly influence public policy (Sloggy et al., 2021). Several studies have examined the linkage of exposure to natural disasters and public opinions on climate change. Sloggy et al. (2021) argued that exposure to certain types of natural disasters, e.g., hurricanes, would make people believe in the occurrence of climate change. Meanwhile, his study showed that exposure to fires and floods had no effect on peoples' opinions. Osberghaus and Fugger (2022) also found that exposure to floods might have no effects on beliefs about climate change by investigating peoples' attitude change after exposure to floods in Germany between 2012 and 2015. Other studies show that an increase in the probability that individuals support policies to protect the environment can be expected after exposure to droughts and heatwaves (Owen et al., 2012). However, economic factors might influence individuals' beliefs after exposure to natural disasters in an opposite direction. People may tend to support economic incentives for economic recovery rather than long-term climate change policy. For instance, Kahn and

Kotchen (2011) showed that states with higher unemployment rates decrease the probability that individuals believe climate change is occurring as well as that in supporting government actions to address climate change.

Based on existing literature, it is possible that there may or may not be a burst in the adoption of climate change laws after countries experience natural disasters. I test the following hypothesis based on the International Disaster Database and restrict it to climatological, hydrological and meteorological disasters.[2].

**Hypothesis** 3*a*: *Bursts in adopting climate change policies are positively correlated with exposure to natural disasters.*

**Hypothesis** 3*b*: *Bursts in the adoption of climate change policies are negatively correlated with exposure to natural disasters.*

In addition, countries tend to slow down the passage of climate change policies during recessions. Eskander et al. (2021) concludes that legislative activity decreases in times of economic difficulty. But in more rigorous regression analysis, two factors - concern for the environment and green investment during a recession - might compete with each other to entangle their effects (Fankhauser et al., 2015). Here, I obtain the cyclical component of GDP(constant US$) to measure the business cycle and attempt to test my fourth hypothesis:

**Hypothesis** 4*a*: *Bursts in the passage of climate change policies are negatively correlated with economic recessions.*

**Hypothesis** 4*b*: *Bursts in the passage of climate change policies are positively correlated with economic recessions.*

[2]the International Disaster Database can be obtained at https://www.emdat.be/

There is a debate on the preference of parties with different political orientations regarding climate change policies. Evidence shows that left-of-centre governments are more likely to pass legislation on environmental issues (Neumayer, 2003a). Regarding climate change, both Eskander et al. (2021) and Fankhauser et al. (2015) argue that the facts are not as widely believed, and governments on the left have not been as aggressive in making legislation as governments on the right. In their studies, the political orientation at a time point serves as an explanatory variable, but here my method allows me to focus on governments' political exposure during a time period. Thus, I construct one independent variable - political orientation ratio, based on the database of political institutions [3]. Specifically, the political orientation ratio is the ratio of the number of years with a left political orientation to the number of years of the time interval. This variable will be used to estimate whether the left-wing government is more inclined to legislate on climate change. Furthermore, if the left-wing and right-wing governments do not have apparent differences in preference, will the new government encourage climate change policies in the early stages of the establishment to satisfy public opinion? Existing research shows that electoral cycles impact policy legislation, as controversial measures are not beneficial for the election (List and Sturm, 2006). Fankhauser et al. (2015) argued that in democracies, climate laws are less likely to be passed before an election. Differently, I focus on new government shifts. To answer this question, I construct another independent variable - the number of political orientation shifts during two adoption years. The following two hypotheses are tested:

[3] The Database of Political Institutions (DPI) can be obtained at https://publications.iadb.org/en/database-political-institutions-2020-dpi2020

**Hypothesis** 5: *Left-wing governments are more inclined to pass climate change policies.*

**Hypothesis** 6: *New governments, whether left- or right-wing, are more inclined to pass climate change policies.*

## 8.3 Data

I use the Climate Change Laws of the World (CCLW) [4] to study the legislative behaviours of countries when coping with climate change. This data set is collected by the Grantham Research Institute at the LSE and the Sabin Center at Columbia Law School, and documents national-level climate change legislation and policies. All UN and UNFCCC parties, including the European Union, and several countries, regions, and territories that are not UN or UNFCCC members (e.g., Taiwan, Palestine, and Western Sahara) are included in the database. The data set includes climate change-related laws broadly, including "legal documents that address policy areas directly relevant to climate change mitigation, adaptation, loss, and damage or disaster risk management" (see Eskander et al., 2021, for more details). Till the end of 2020, this data set documents 2315 laws in 198 countries and areas [5]. However, this data set has some limitations. Due to resource limitations, such as language limitations, levels of media coverage, and expertise of researchers, the data set may not be comprehensive and accurate.

[4] Climate Change Laws of the World database is from Grantham Research Institute on Climate Change and the Environment and Sabin Center for Climate Change Law. Available at `climate-laws.org`.

[5] The statistics are based on the data set downloaded on 21st October 2021. The data set is being constantly updated, even for laws passed before 2021. I only consider the laws passed between 1st January 1990 and 31st December 2020.

In addition, the data set prioritises the most recent laws and policies and does not capture legislation at the sub-national level. Another limitation concerns the categorization of laws, as the categorization is done by individuals and has not been checked by other methods. Despite these limitations, the CCLW is one of the most comprehensive data sets of climate change legislation.

Here, I focus on laws adopted after 1990; since then, broad attention to resolving or mitigating climate change has been on the agenda worldwide. Thus, our final data set contains 2280 laws passed from 1990 to 2020. For each law, various information is documented in the data set, including the title, environmental issues, principal instruments, sectors, keywords, brief descriptions, the adoption timing, etc. All the climate change laws can be divided into four categories: adaptation, mitigation, disaster risk management (DRM), and loss and damage. There are different combinations between these four categories in the data set, as shown in Table 8.1. I focus on the 1723 laws with "mitigation" as a keyword, as shown in Table 8.2.

Table 8.1: Category combinations in the data set

| Category | Number of laws | Number of countries |
|---|---|---|
| Adaptation | 327 | 141 |
| Adaptation, DRM | 185 | 99 |
| Adaptation, DRM, Loss and damage | 4 | 4 |
| Adaptation, DRM, Mitigation | 62 | 43 |
| Adaptation, DRM, Mitigation, Loss and damage | 7 | 7 |
| Adaptation, Loss And Damage | 2 | 2 |
| Adaptation, Mitigation | 432 | 145 |
| Adaptation, Mitigation, Loss And Damage | 9 | 8 |
| DRM | 39 | 28 |
| DRM, Mitigation | 9 | 9 |
| Mitigation | 1204 | 189 |

Table 8.2: Statistics of laws

| Category | Number of laws | Number of countries |
|---|---|---|
| Mitigation | 1723 | 195 |
| Adaptation | 1028 | 182 |
| Loss and damage | 22 | 20 |
| DRM | 306 | 120 |

## 8.4 Methodology

I test the hypotheses using econometric techniques. The study is based on a data set of 1723 climate policies in 195 jurisdictions over 31 years, from 1990 to 2022. In what follows, I will introduce the dependent variables, independent variables, control variables, and the statistical model.

**Dependent variable**

I measure bursts of countries' legislation behaviours by computing the time interval between any two consecutive adoption years. For each country, each mitigation law is assigned to its adoption year. Then, all the adoption years are sorted in time, and the time intervals between any two adoption years are calculated. Finally, all time intervals across countries are created to obtain the data set. The final data set includes 974 observations which allow me to adopt a quantitative, statistical approach.

In the regression equation, $\mathbf{\Delta T}_{it_1t_2}$ indicates the time interval between the first adoption year $t_1$ and the second $t_2$ in the country $i$.

### Independent variable

**IPCC reports.** I define a dummy variable, $\mathbf{IPCC}_{it_1t_2}$. If an IPCC report, such as the TAR (2001), the AR4 (2007) and the AR5 (2014) [6], is released in year $t_0$, and the first and the second adoption years are $t_1$ and $t_2$, respectively, the dummy variable is equal to 1, if $t_0 \leq t_1$ and $t_2 \leq t_0 + 3$; 0 otherwise.

**COPs.** A dummy variable is defined as $\mathbf{COP}_{it_1t_2}$. If a COP, such as the COPs in Kyoto (1997), Copenhagen (2009) and Paris (2015), is held in year $t_0$, and the first and the second adoption years are $t_1$ and $t_2$, respectively, the dummy is equal to 1 if $t_0 \leq t_1$ and $t_2 \leq t_0 + 3$; 0 otherwise.

**Natural disasters.** I consider the impact of natural disasters by $\mathbf{Haza}_{it_1t_2}$. If at least one disaster event happens in year $t_0$, and the first and the second adoption years are $t_1$ and $t_2$, the dummy is equal to 1 if $t_0 \leq t_1$ and $t_2 \leq t_0 + 3$; 0 otherwise. In addition, the number of natural disasters is taken into account. As shown in Figure 8.1 there is a heterogeneous distribution of the number of natural disasters across all the observations.

[6] More details can be obtained at https://www.ipcc.ch/ar6-syr/

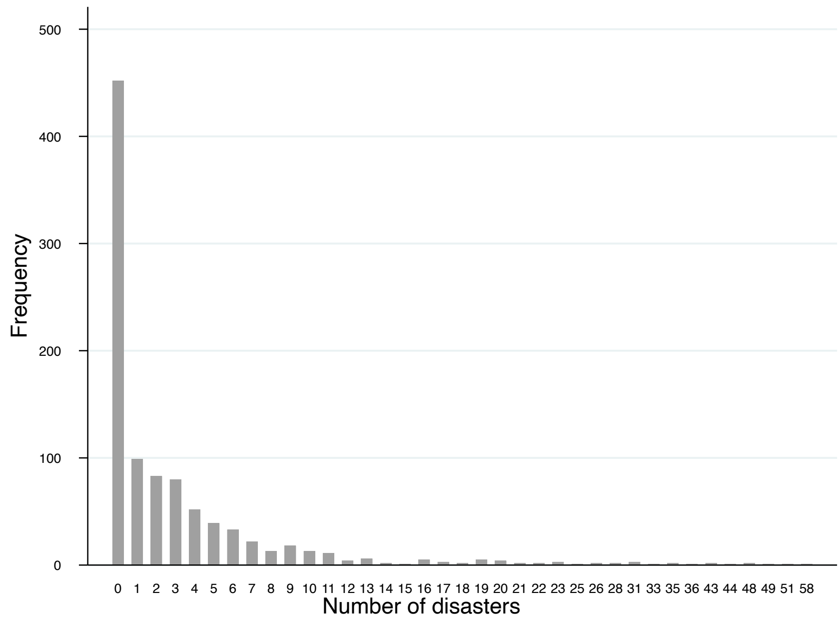



Figure 8.1: Distribution of the number of natural disasters across all time intervals.

**Business cycles.** The cyclical component of GDP(constant US$) [7] is a measure of the business cycle, computed through a Hodrick–Prescott filter [8]. After obtaining the cyclical component of the log of GDP, I calculate the difference between the two adoption years. A positive difference indicates a recovery period, while a negative difference represents a recession. Thus, $\mathbf{CYCLE}_{it_1}$ is a dummy variable which equals 1 during a recovery period and 0 in a recession.

**Political orientation ratio.** The ratio of the number of years with a left-wing political orientation to the total number of years $t_2 - t_1 + 1$ is indicated by $\mathbf{LEFTS}_{it_1t_2}$.

**Political orientation shifts.** The political orientation shifts are calculated by $\mathbf{ORIES}_{it_1t_2}$, the ratio of the number of political orientation shifts to the time

[7]The data on GDPs can be obtained at `https://data.worldbank.org/indicator/NY.GDP.MKTP.KD`

[8]Python codes can be obtained at `https://www.statsmodels.org/dev/generated/statsmodels.tsa.filters.hp_filter.hpfilter.html`

interval [9].

### Control variables

Here, I acknowledge the importance of control variables and introduce the necessary ones into my empirical analysis.

**Number of laws.** The number of laws $\mathbf{NUM}_{it_1}$ adopted by country $i$ at $t_1$ is used to control countries' tendency to adopt laws. The assumption is that laws that were passed early on have had a long and, therefore, more significant impact on climate policy (Eskander et al., 2021).

**GDP per capita.** The GDP per capita is used to control the economic status of countries. $\mathbf{GDPcap}_{it_1}$ indicates the log of real GDP per capita at $t_1$ [10].

**Democracy strength.** To control for the democracy strength at $t_1$, I use $\mathbf{DEMO}_{it_1}$, the Polity2 variable from Polity5, taking values $-10$ to 10 with higher values associated with better democracies [11]

**Average strength of the executive.** Evidence shows that more climate legislation can be expected in strong governments with a majority in parliament (Fankhauser et al., 2015). Here, I leverage the DPI and calculate the average strength of the executive during the time interval as a control variable. In the DPI, the power of the executive is equal to 1 if the executive's party controls the absolute majority of the legislative; 0 otherwise [12].

[9] The years without information about the political orientation are counted in the denominator

[10] The data can be obtained at `https://data.worldbank.org/indicator/NY.GDP.PCAP.CD.`

[11] The data of Polity5 can be obtained at `http://www.systemicpeace.org/inscrdata.html.`

[12] It is the *ALLHOUSE* variable in DPI.

Table 8.3: Descriptive Statistics

| Variables | (1) Observations | (2) Mean | (3) SD | (4) Min | (5) Max |
|---|---|---|---|---|---|
| Time interval | 974 | 2.616 | 2.548 | 1 | 22 |
| Number of laws | 974 | 1.434 | 0.868 | 1 | 9 |
| Log GDP per capita | 934 | 8.824 | 1.411 | 5.173 | 11.56 |
| Democracy strength | 379 | 5.781 | 5.669 | -10 | 10 |
| IPCC (3 years lag) | 974 | 0.156 | 0.363 | 0 | 1 |
| COPs (3 years lag) | 974 | 0.161 | 0.368 | 0 | 1 |
| Disasters (3 years lag) | 974 | 0.536 | 0.499 | 0 | 1 |
| Number of disasters (3 years lag) | 974 | 3.277 | 6.523 | 0 | 58 |
| Left orientation share | 895 | 0.313 | 0.435 | 0 | 1 |
| Orientation change frequency | 895 | 0.0423 | 0.163 | 0 | 1 |
| Average executive | 856 | 0.464 | 0.475 | 0 | 1 |
| Business cycle | 831 | 0.538 | 0.499 | 0 | 1 |

### Statistical model

The negative binomial fixed effect model with clustered standard errors at the country level is adopted, as the variance of the intervals is much larger than the mean. Here, $t$ indicates the focal year; $i$ represents country $i$; $t_1$ and $t_2$ denote the two consecutive adoption years. The country ($\theta_i$), year fixed effects ($\nu_t$) and a random error term ($\varepsilon_{it}$) are also included. The country and year-fixed effects capture country-specific features and evolving global factors such as an increased scientific consensus and environmental protection awareness. The regression equation is as follows:

$$\begin{aligned}\Delta \mathbf{T}_{it_1t_2} &= \alpha + \beta \mathbf{COP}_{it_1t_2} + \gamma \mathbf{IPCC}_{it_1t_2} + \lambda \mathbf{Haza}_{it_1t_2} + \delta \mathbf{CYCLE}_{it_1} \\ &+ \beta \mathbf{LEFTS}_{it_1t_2} + \eta \mathbf{ORIES}_{it_1t_2} + \psi \mathbf{NUM}_{it_1} + \xi \mathbf{GDPcap}_{it_1} + \chi \mathbf{DEMO}_{it_1} + \\ &\phi \mathbf{EXE}_{it_1t_2} + \theta_i + v_{t_1} + \varepsilon_{it_1}\end{aligned} \tag{8.1}$$

I estimate two models based on Equation 8.1: (a) a baseline model that only includes the control variables; (b) a model that includes all independent variables (control and independent variables of interest).

## 8.5 Regression results

In the negative binomial regression, the coefficients indicate the change in the difference in the logs of the expected value of the dependent variable when the independent variable changes by one unit and the other independent variables are kept constant. Here, I mainly comment on the sign and the significance of the coefficients.

Table 8.4 summarises the regression estimates from the negative binomial regression for different models. Despite the strong significance of the whole model, it is necessary to examine the individual parameter estimates of different models.

Model 1 only includes control variables, including the number of climate change laws in year $t_1$, average strength of the executive, and democracy strength. Although existing research shows correlations between these variables with adoptions of climate change laws. In my results, only the estimate of democracy strength is significant and indicates a negative correlation with time intervals.

In model 2 (Table 8.4, column 1), to test hypotheses 1, 2, 3, 4, 5 and 6, I regress the time intervals between any two consecutive adoption years in a country on the variables of interest, that is, the release of IPCC reports, the COPs, exposure to natural disasters, business cycles, left-wing political orientation ratio and political orientation shifts. First, the release of IPCC reports is negatively and significantly associated with time intervals. Thus, hypothesis 1 is supported. This finding suggests that releasing scientific reports can encourage countries to adopt climate laws consecutively, thus producing bursts of adoption activities. Second, the association between COPs and the time intervals is negative and significant, indicating that COPs can vastly decrease the interval between any two adoption years. Thus, Hypothesis 2 is supported. Third, the parameter estimate for the exposure to natural disasters is negative and significant, suggesting that bursts of laws in a country are associated with natural disasters. Hypothesis $3a$ is supported. Besides, the estimate for the business cycle is negative but only significant in model 3 when considering the number of natural disasters. This supports hypothesis $4a$, that is, bursts in adopting climate change laws are more likely to happen during periods of economic recovery. In addition, the coefficient of the left-wing political orientation ratio is positive but not significant, suggesting that more years in left-wing government are not correlated with climate change policies. Similarly, the estimate for political orientation shifts is not significant, showing no support for hypothesis 6.

In the next step, I extend the analysis to control for variations in the number of natural disasters. According to Figure 8.1, most observations have less than 5 natural disasters, but a small number of observations witness a large number of natural disasters, up to 58. Countries experiencing a more significant number of natural disasters may adopt laws more consecutively. Regression results show that an additional natural disaster decreases the time interval by 0.0338 years (Table 8.4, column 3).

In addition, I check for the long-term role of the release of IPCC reports, COPs and natural disasters with a lag of 5 years (Table 8.4, columns $4-5$). The regression coefficients of the release of IPCC reports and COPs become larger, indicating that IPCC reports and COPs have a stronger association with decreasing time intervals in the long term. However, the number of disasters tends to have a

Table 8.4: Analysis of climate legislation: Mitigation laws (years: 1990–2020). Model: Negative Binomial Fixed Effects

| | Time interval | | | | |
|---|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) | (5) |
| Number of laws | 0.0133 | 0.0195 | 0.0244 | 0.00596 | 0.0124 |
| | (0.0648) | (0.0431) | (0.0442) | (0.0328) | (0.0354) |
| Log GDP per capita | -0.167 | -0.284 | -0.535* | -0.156 | -0.593** |
| | (0.408) | (0.298) | (0.308) | (0.242) | (0.236) |
| Average strength of the executive | 0.0101 | 0.0262 | -0.0160 | 0.0276 | 0.0692 |
| | (0.161) | (0.108) | (0.128) | (0.0866) | (0.0925) |
| Democracy strength | -0.0575** | -0.0181 | -0.0238 | -0.0160 | -0.0247 |
| | (0.0226) | (0.0232) | (0.0202) | (0.0193) | (0.0244) |
| IPCC reports (3 years lag) | | -0.532*** | -0.796*** | | |
| | | (0.113) | (0.114) | | |
| COPs (3 years lag) | | -0.647*** | -1.071*** | | |
| | | (0.134) | (0.144) | | |
| Disaster (3 years lag) | | -0.819*** | | | |
| | | (0.0679) | | | |
| Business cycle | | -0.0313 | -0.119* | -0.0256 | -0.0535 |
| | | (0.0601) | (0.0704) | (0.0483) | (0.0551) |
| Left political orientation ratio | | 0.152 | 0.105 | 0.0631 | 0.0827 |
| | | (0.115) | (0.135) | (0.0891) | (0.109) |
| Political orientation shifts | | -0.159 | -0.110 | 0.0754 | 0.102 |
| | | (0.236) | (0.227) | (0.145) | (0.195) |
| Disaster number (3 years lag) | | | -0.0338*** | | |
| | | | (0.00914) | | |
| IPCC reports (5 years lag) | | | | -0.643*** | -0.911*** |
| | | | | (0.0784) | (0.0919) |
| COPs (5 years lag) | | | | -0.724*** | -0.937*** |
| | | | | (0.0892) | (0.0834) |
| Disaster (5 years lag) | | | | -0.769*** | |
| | | | | (0.0893) | |
| Disaster number (5 years lag) | | | | | -0.0120* |
| | | | | | (0.00668) |
| Observations | 350 | 321 | 321 | 321 | 321 |
| Pseudo $R^2$ | 0.179 | 0.288 | 0.260 | 0.303 | 0.282 |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |

Notes: The dependent variable is the time interval (years) between any two consecutive adoption years in a country. Model 1 is the baseline model, including only control variables. Model 2 includes independent variables of interest and control variables. Model 3 considers the number of natural disasters. Models $1-3$ consider three years lag. Models $4-5$ consider five years lag. Standard errors clustered at the country level are in parentheses.
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

stronger association in the short term as the coefficient decreases.

Table 8.5: Robustness check on the analysis of climate legislation using Poisson regression: Mitigation laws (years: 1990–2020)

| | Time interval | | | | |
|---|---|---|---|---|---|
| Variables | (1) | (2) | (3) | (4) | (5) |
| Number of laws | 0.0133 | 0.0195 | 0.0244 | 0.00596 | 0.0124 |
| | (0.0570) | (0.0363) | (0.0401) | (0.0292) | (0.0322) |
| Log GDP per capita | -0.167 | -0.284 | -0.535** | -0.156 | -0.593** |
| | (0.366) | (0.228) | (0.268) | (0.205) | (0.235) |
| Average strength of the executive | 0.0101 | 0.0262 | -0.0160 | 0.0276 | 0.0692 |
| | (0.126) | (0.0819) | (0.0971) | (0.0772) | (0.0802) |
| Democracy strength | -0.0575*** | -0.0181 | -0.0238 | -0.0160 | -0.0247 |
| | (0.0199) | (0.0194) | (0.0188) | (0.0153) | (0.0197) |
| IPCC reports (3 years lag) | | -0.532*** | -0.796*** | | |
| | | (0.0957) | (0.103) | | |
| COPs (3 years lag) | | -0.647*** | -1.071*** | | |
| | | (0.113) | (0.118) | | |
| Disaster (3 years lag) | | -0.819*** | | | |
| | | (0.0571) | | | |
| Business cycle | | -0.0313 | -0.119** | -0.0256 | -0.0535 |
| | | (0.0502) | (0.0584) | (0.0436) | (0.0493) |
| Left political orientation ratio | | 0.152* | 0.105 | 0.0631 | 0.0827 |
| | | (0.0815) | (0.0987) | (0.0793) | (0.0907) |
| Political orientation shifts | | -0.159 | -0.110 | 0.0754 | 0.102 |
| | | (0.197) | (0.215) | (0.130) | (0.161) |
| Disaster number (3 years lag) | | | -0.0338*** | | |
| | | | (0.00572) | | |
| IPCC reports (5 years lag) | | | | -0.643*** | -0.911*** |
| | | | | (0.0758) | (0.0750) |
| COPs (5 years lag) | | | | -0.724*** | -0.937*** |
| | | | | (0.0694) | (0.0704) |
| Disaster (5 years lag) | | | | -0.769*** | |
| | | | | (0.0675) | |
| Disaster number (5 years lag) | | | | | -0.0120*** |
| | | | | | (0.00420) |
| Observations | 350 | 321 | 321 | 321 | 321 |
| Pseudo $R^2$ | 0.237 | 0.339 | 0.313 | 0.354 | 0.333 |
| Country FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |

Notes: The dependent variable is the time interval (years) between any two consecutive adoption years in a country. Model 1 is the baseline model, including only control variables. Model 2 includes independent variables of interest and control variables. Model 3 considers the number of natural disasters. Models $1-3$ consider three years lag. Models $4-5$ consider five years lag. Robust standard errors are in parentheses.
$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

In my main results, I estimate Equation 8.1 through a negative binomial fixed-effects model. This count model is suitable since I am working on a count dependent variable, i.e., the number of years, which is over-dispersed, i.e., the mean is lower than the variance. I perform a robustness check to support the main results. I use the Poisson fixed-effects model, which is also suitable for analysing count data. Although a Poisson model is more suitable for count data without over-dispersion, a Poisson with robust standard errors can still offset some degree of over-dispersion. Thus, the robustness check is valuable. Results in Table 8.5 show that the main results are robust.

## 8.6 Discussion and conclusion

The global public goods nature of climate change requires international cooperation to mitigate climate change effectively. National climate change actions, as the legal base to fulfil the international commitment, have been experiencing an acceleration in the last decade. Recent research has focused on drivers (Eskander et al., 2021; Fankhauser et al., 2014, 2015, 2016; Kammerer and Namhata, 2018; Lachapelle and Paterson, 2013; Schoenefeld et al., 2022) and working mechanisms (Bang et al., 2015; Eskander and Fankhauser, 2020; Harrison and Sundstrom, 2010) of existing climate change policies.

In the existing literature on climate change laws, scholars have shown that national and international factors will influence the adoption of climate change policies. However, their research mainly focuses on the number of policies or the probability of adopting a policy using a count regression model or event history analysis. What is overlooked is the dynamics of countries' adoption behaviours. Motivated by the dynamic patterns in human beings' behaviours, my study attempts to reveal the factors that drive the emergence of bursts of adopting climate change laws.

My study is based on a comprehensive and updated data set of climate change policies covering 198 countries and areas. I focus on mitigation laws and test six hypotheses related to both national and international factors. I find that scientific assessment through IPCC reports is significantly and negatively associated with the time interval between any consecutive adoption years, thus promoting the emergence of the burst. Similarly, environmental commitment induced by COPs has a negative and significant correlation with the time interval. After the COPs, countries tend to pass policies in a short period. My third hypothesis concerns the impact of natural disasters. Results indicate a negative and significant correlation between the occurrence and the time interval. Results are robust when taking into account the number of natural disasters. Finally, my fourth hypothesis concerns the correlation between economic recession and the burst phenomenon. The negative estimates indicate that countries are reluctant to pass climate change policies during difficult times. But the relationship is not significant.

### 8.6.1 Implications for research

Results show that scientific assessment proxied by IPCC reports is positively and significantly associated with the emergence of bursts in countries when adopting mitigation laws. This suggests that after the release of IPCC reports, countries tend to pass climate change laws in a very short interval of time, and scientific assessment plays a vital role in policy-making. In addition, binding obligations imposed by COPs show a significant and positive correlation with bursts. Although the COPs do not force countries to reduce emissions, countries pass laws in a short time after the COPs. Another factor that has a positive and significant association with bursts is natural disasters. Coefficient estimates show that natural disasters are more correlated with policy bursts in the short term (three years) than in the long term (five years). These results hold implications for higher short-term impact of natural impacts. However, the business cycles seem not correlated with the bursty phenomenon. Similarly, political orientation appears to have no association with bursts. These weak correlations are consistent with existing research (Fankhauser et al., 2015).

### 8.6.2 Implications for practice

My findings provide several practical implications for policymakers. First, evidence shows that scientific assessment plays a vital role in policy-making through IPCC reports. Future studies may focus on the working mechanism of IPCC reports, i.e., whether knowledge of climate change, its causes, and potential impacts prompt countries to act or the extent to which the new policy follows the report's recommendations. In addition, COPs can act as catalysts in promoting climate policies. Thus, authorities and the public should monitor COPs more closely. Besides, policymakers should be aware that exposure to natural disasters tends to see an explosion in climate policies, and therefore take opportunities to promote legislation.

### 8.6.3 Limitations and future work

My study opens up avenues for future research. Whether the findings in my study still hold for different kinds of climate legislation, e.g., carbon price policies, adaptation policies, and energy policies, needs further investigation. In addition, my study does not consider interactions between countries. The emergence of policy bursts may be due to the influence of other countries, e.g., trade requires more sustainable standards.

Another interesting avenue goes beyond the frequency of climate change laws and concerns the burst of certain topics or content in climate change laws. The content analysis can be done by natural language processing (NLP) which is able to identify keywords, phrases, or topics that are frequently mentioned within a short period. In this way, we can monitor bursts of certain topics and reveal shifts in policy focus. These shifts may indicate policymakers' attempts to address emerging climate-related issues. In addition, examining the burst of specific content allows us to assess the potential impact of new laws and regulations. Moreover, climate science is continually evolving, and new research may highlight previously overlooked aspects of climate change. Bursting topics can indicate that lawmakers are adapting their policies to align with the latest scientific findings.

Other methodologies can be applied to study the bursty phenomenon in policy adoptions. Techniques from complex systems allow us to identify clusters of policies in time (Masuda and Lambiotte, 2016). Furthermore, countries are embedded in a complex cooperation network which will, in turn, impose influence on individual countries (Backstrom et al., 2006; Cha et al., 2009; González-Bailón et al., 2011; Romero et al., 2011). Thus, it is vital to reveal the impact of the network on policy adoption in each country.

In addition, future work can also be extended to study the impact of bursts in climate change laws on economics, politics and society. Whether such bursts can change individuals' perception of climate change and, furthermore, change individuals' daily behaviours can be studied. At the national level, it is worth revealing whether the sudden bursts promote institutional capacity building for climate change laws.

### 8.6.4 Contribution to the literature

I believe my results shed new light on an essential set of drivers of climate change policies and contribute to political economics on the dynamics of climate legislation. In my study, the dependent variable is the time interval between any two adoption years. This strategy has enabled me to study the association between relevant changes during the two adoption years and countries' adoption behaviours. Here, I studied the effect of left-wing orientation share and the orientation shift frequency between any two adoption years. Another novel aspect of my study is that, to my knowledge, it is the first empirical study that paves the way towards understanding the role that IPCC reports, COPs, and natural disasters play in the temporal patterns underpinning countries' adoption of climate change laws.

# Chapter 9

# Conclusion

## 9.1 Brief overview

Over the last few years, environmental issues have attracted more attention than ever due to recent phenomena, such as extreme weather, floods, fires, etc. Governments worldwide are actively seeking effective measures to deal with environmental degradation. Global environmental governance displays different scales from global to national and local (O'Neill, 2017). My thesis mainly focused on international environmental cooperation through treaties and national policies oriented to an urgent environmental problem - climate change. Existing research mainly employs international relations and political economics methodologies. In contrast, I apply network analysis to study the topological structure of international environmental cooperation. In addition, inspired by methods from complex systems, I developed a new dependent variable to study the bursty phenomenon in adopting climate change laws.

The first project was presented in Chapter 3. IEAs are part of global environmental governance. A complex network structure of IEAs has emerged as the total number of IEAs increased to almost 2000 in 2015. However, the macro-structure and the evolution of the system are still unknown. To fill this gap, I applied theories and methods of network analysis to one of the largest data sets of IEAs. Specifically, I constructed the cooperation network among countries by projecting the country-treaty bipartite network on its country layer. Notably, the statistical significance of each link between any two countries is assessed, i.e., there is a link between any two countries only if the number of common treaties of these two countries is statistically significant compared with null models. Furthermore, I assessed the extent and ease of cooperation by global measures of networks, including the number of nodes, average degree, average strength, density, average shortest path length, the number of components, and global clustering coefficient. Results show that the cooperation network becomes denser and more cohesive. In addition, countries' positions in the network are indicated by centrality measures, and results uncovered a noticeable European imprint where initially, the United Kingdom and, more recently, France and Germany have been the most critical players in brokering environmental cooperation. Besides, the role of the UN and the UN agencies have been investigated, and the cooperation networks of different subjects were compared. Moreover, I attempted to take into account treaty salience and treaty membership when quantifying the cooperation intensity between countries.

The second project was presented in Chapter 5. My study explored the community structure of international environmental cooperation to reveal potential clusters of countries. Community detection was performed on the cooperation network constructed in Chapter 3. The evolution of the community structure was analysed from 1975 to 2015. Results suggest that regionalisation emerged over time from international environmental cooperation. Furthermore, countries' positions in the network are further studied based on the interconnections between and the intra-connections within communities. In addition, results suggest that geography plays a vital role in shaping the landscape of the community structure. Moreover, I aimed to reveal the differences across communities and the functions performed by each community. Results suggest that communities detected can serve as negotiators to speed up negotiations and shape environmental cooperation.

Chapter 6 explored the core-periphery structure of international environmental co-operation. Specifically, I attempted to reveal the overall hierarchical organisational structure of the country-treaty relationship. The nestedness in the country-treaty bipartite network and rich clubs in the cooperation network among countries were analysed. The country-treaty bipartite network displays a nested structure, suggesting that generalists will facilitate the formation of rarely ratified treaties. In addition, countries ranking first in the nested structure form rich clubs in the one-mode cooperation network. Results suggest that European countries act as generalists and tend to collaborate more with each other in international environmental cooperation. Furthermore, based on the nestedness uncovered, I defined countries' commitment diversification and treaties' ratification ubiquity drawing on methods from economic complexity. European countries have a high level of commitment diversification, and countries' commitment diversification is significantly and positively associated with their environmental performance index.

My fourth project in Chapter 8 aimed to reveal potential factors associated with the burst in adopting climate change laws. To this end, I used the time interval between any consecutive adoption years as the dependent variable to assess the burst and test five hypotheses using negative binomial regression. Results suggest that scientific assessment released by IPCC, COPs and exposure to natural disasters are positively associated with the emergence of burst in adopting climate change laws on mitigation.

## 9.2 Contribution to the literature

My thesis is an interdisciplinary study, combining various theories and methods from different research domains, including environmental economics, political economics, international relations and network science. I developed an interdisciplinary approach to studying global environmental governance and international environmental cooperation. My study contributes to the increasing interest in applying theories and methods from complex systems to study global environmental governance.

Methodologically, my study is the first attempt to use network analysis to investigate international environmental cooperation through IEAs. Measures from network science were selected and developed to describe and quantify the characteristics of international environmental cooperation. Thus, the findings in my thesis provide new insights into the network structure of international environmental cooperation.

On the one hand, my research corroborates and provides evidence in favour of existing theories from a quantitative perspective. Regional environmental cooperation has been extensively studied by comparative analysis and case studies. In Chapter 5, the community structure analysis provided quantitative evidence to illustrate the emergence of regionalisation of environmental cooperation. On the other hand, my study provides new insights into international environmental cooperation and global environmental governance.

## 9.3 Future work

Based on the limitations of my study and new developments in network science, several studies can be conducted in the future. In what follows, I shall briefly outline a number of lines of inquiry.

### 9.3.1 Policy diffusion on the cooperation network

Based on the definition and mechanisms of policy diffusion, policy choices in one country are influenced by policy choices in other countries. According to Lazer (2005), the cooperation network based on IEAs can serve as an informational network that provides information diffusion channels. Thus, studies of how the cooperation network influences the adoption of climate change laws are of great value.

There are two kinds of diffusion models on networks - probabilistic and decision-based models (Easley et al., 2012; Gruhl et al., 2004). The probabilistic models lack a decision-making process and are sometimes random. They are used to simulate information propagation and epidemics. In contrast, in the decision-based models, nodes make decisions based on the pay-off benefits of adopting one strategy or the other. This kind of model is deployed to model diffusion of innovation which is complex diffusion and needs multiple exposures or enough benefits to trigger the diffusion process. Typical models include linear threshold models (Delre et al., 2007; Gomez-Rodriguez et al., 2012; Granovetter, 1978; Kempe et al., 2003; Montanari and Saberi, 2010; Talukder et al., 2019), cascade models (Kempe et al., 2003; Leskovec et al., 2007) and game-theoretic approaches (Blume and Durlauf, 2006; Montanari and Saberi, 2010).

Existing policy diffusion research assumes that other countries' influence on a certain country is the same. However, country-to-country influence is heterogeneous due to economic, political and historical factors. The heterogeneity can be represented by the international environmental cooperation network. Thus, according to the decision-based model, future work can concentrate on the diffusion of climate change laws on the cooperation network. Specifically, it is worth investigating whether a country will adopt a climate change law if the sum of the influence of its neighbour countries exceeds its individual threshold. In this way, one can analyse the influence of a country's neighbours who have already adopted a climate change law on the decision of the focal country.

### 9.3.2 Treaty network

Different networks may have to be constructed for different research questions. The network constructed here takes a country-based perspective. Country nodes are connected through treaty links. This is an obvious choice for an analysis interested in the international relations and political economy of environmental cooperation. Other research questions may require a treaty-based perspective, that is, a network in which the treaties are the nodes. In turn, these nodes could be linked through shared signatories (Böhmelt and Spilker, 2016; Kim, 2020), textual citations (Hollway and Koskinen, 2016; Kim, 2013), content similarity (Hollway and Koskinen, 2016), or geographic proximity (Hollway and Koskinen, 2016).

Another potential avenue of investigation is to use document embedding techniques. Word embedding has been an essential method for natural language processing (NLP) tasks in recent years (Almeida and Xexéo, 2019; Bakarov, 2018; Kusner et al., 2015). Its main function is to map words into numerical vector spaces, which can then be used for further studies. Indeed, any sequence of words can be converted to informative vector representations. Document embedding has a wide range of applications (Dai et al., 2015; Lau and Baldwin, 2016; Le and Mikolov, 2014). Inspired by these applications, future research may attempt to map treaties into numerical vector spaces and then leverage various measures of distance to quantify the similarity between pairs of treaties. Based on the results, a treaty network can be constructed using K-Nearest Neighbour Graph (K-NNG) construction (Dong et al., 2011). The relationship between treaties can then be studied.

### 9.3.3 High-order representation of international cooperation

My thesis captures the cooperation relationships through pairwise interactions among countries. However, international environmental cooperation displays group interactions with more than two countries ratifying each treaty. The cooperation network obtained by projecting on the country layer of the country-treaty bipartite network loses the group structure. High-order representations are needed to reflect group interactions in international cooperation.

Recently, high-order representations have been receiving increasing attention due to their powerful description of higher-order interactions in realistic systems, such as coauthor collaboration (Patania et al., 2017) and species interactions (Bairey et al., 2016). Typical methods include simplicial complexes and hypergraphs (Battiston et al., 2021, 2020; Lambiotte et al., 2019). In high-order representations, the elements are simplices or hyperlinks, each containing a set of more than two nodes. To my knowledge, high-order representations have not been applied to international cooperation. Inspired by the high-order representations, future research may draw on the data set of IEAs and techniques of high-order representations to study further the structure and mechanism of global governance and international cooperation.

### 9.3.4 Cooperation network of Non-Governmental Organisations (NGOs)

Non-governmental Organisations (NGOs) are part of the global environmental governance. Till 2015, more than 3000 NGOs had been accredited with official observer status by the UN, including ENGOs (environmental NGOs), IPOs (Indigenous Peoples' Organizations) and YOUNGOs (youth NGOs) (O'Neill, 2017).

In addressing climate change, while nations are the primary actors, due to the need for economic development, countries tend to lack the motivation to respond. International organisations, therefore, play a very important role in calibrating countries' behaviours. For instance, NGOs serve as observers at United Nations Framework Convention on Climate Change (UNFCCC) conferences, which enables non-state actors to play significant roles in international climate change negotiations (Pandey, 2015). Betsill and Corell (2001) summarised the main contributions of NGOs in the global climate change governance: "They (NGOs) try to raise public awareness of environmental issues; they lobby state decision-makers hoping to affect domestic and foreign policies related to the environment; they coordinate boycotts in efforts to alter corporate practices harmful to nature; they participate in international environmental negotiations; and they help monitor and implement international agreements." However, Pandey (2015) argued that although NGOs have done much as providers of scientific information and expertise in combating climate change, they have not fully fulfilled their contributions and suggested that NGOs should seek new and radical approaches to organise large-scale grassroots climate social movements and consequently better pressure governments domestically and internationally.

In such a context, the overall landscape of the cooperative relationships between NGOs may give us more insight into how to fulfil their contributions. The cooperation network based on the cooperative ties between NGOs can serve as a channel of information diffusion, which can benefit large-scale social movements. Key NGOs can also be identified by assigning each NGO a centrality score, such as the betweenness centrality and degree centrality. In addition, the Louvain algorithm can be used to detect potential clusters of NGOs, which will provide us with a big picture of fragmented or united cooperation relationships between NGOs. The identification of key hubs in each cluster and bridges between different clusters can also help to further enhance their contribution within their own cluster or between different clusters.

# Appendix A

# Appendix of Chapter 3

## List of countries

Table A.1: List of countries

| Party code | Name | Party code | Name | Party code | Name |
|---|---|---|---|---|---|
| AD | Andorra | BS | Bahamas | DM | Dominica |
| AE | United Arab Emirates | BT | Bhutan | DO | Dominican Republic |
| AF | Afghanistan | BW | Botswana | DZ | Algeria |
| AG | Antigua and Barbuda | BY | Belarus | EC | Ecuador |
| AL | Albania | BZ | Belize | EE | Estonia |
| AM | Armenia | CA | Canada | EG | Egypt |
| AO | Angola | CD | Congo, Dem. Rep. of | ER | Eritrea |
| AR | Argentina | CF | Central African Republic | ES | Spain |
| AT | Austria | CG | Congo | ET | Ethiopia |
| AU | Australia | CH | Switzerland | FI | Finland |
| AZ | Azerbaijan | CI | Côte d'Ivoire | FJ | Fiji |
| BA | Bosnia and Herzegovina | CL | Chile | FM | Micronesia, Fed. States |
| BB | Barbados | CM | Cameroon | FR | France |
| BD | Bangladesh | CN | China | GA | Gabon |
| BE | Belgium | CO | Colombia | GB | Great Britain |
| BF | Burkina Faso | CR | Costa Rica | GD | Grenada |
| BG | Bulgaria | CU | Cuba | GE | Georgia |
| BH | Bahrain | CV | Cape Verde | GH | Ghana |
| BI | Burundi | CY | Cyprus | GM | Gambia |
| BJ | Benin | CZ | Czech Republic | GN | Guinea |
| BN | Brunei Darussalam | DE | Germany | GQ | Equatorial Guinea |
| BO | Bolivia (Plurinational State of) | DJ | Djibouti | GR | Greece |
| BR | Brazil | DK | Denmark | GT | Guatemala |

Table A.2: List of countries (continued)

| Party code | Name | Party code | Name | Party code | Name |
|---|---|---|---|---|---|
| GW | Guinea-Bissau | MH | Marshall Islands | SK | Slovakia |
| GY | Guyana | MK | Macedonia, FYR | SL | Sierra Leone |
| HK | Hong Kong | ML | Mali | SM | San Marino |
| HN | Honduras | MM | Myanmar | SN | Senegal |
| HR | Croatia | MN | Mongolia | SO | Somalia |
| HT | Haiti | MR | Mauritania | SR | Suriname |
| HU | Hungary | MT | Malta | SS | South Sudan |
| ID | Indonesia | MU | Mauritius | ST | Sao Tome and Principe |
| IE | Ireland | MV | Maldives | SV | El Salvador |
| IL | Israel | MW | Malawi | SY | Syrian Arab Republic |
| IN | India | MX | Mexico | SZ | Swaziland |
| IQ | Iraq | MY | Malaysia | TD | Chad |
| IR | Iran, Islamic Republic of | MZ | Mozambique | TG | Togo |
| IS | Iceland | NE | Niger | TH | Thailand |
| IT | Italy | NG | Nigeria | TJ | Tajikistan |
| JE | Jersey | NI | Nicaragua | TL | Timor-Leste |
| JM | Jamaica | NL | Netherlands | TM | Turkmenistan |
| JO | Jordan | NM | Namibia | TN | Tunisia |
| JP | Japan | NO | Norway | TO | Tonga |
| KE | Kenya | NP | Nepal | TR | Turkey |
| KG | Kyrgyzstan | NR | Nauru | TT | Trinidad and Tobago |
| KH | Cambodia | NZ | New Zealand | TV | Tuvalu |
| KI | Kiribati | OM | Oman | TW | Taiwan |
| KM | Comoros | PA | Panama | TZ | Tanzania, Un. Rep. of |
| KN | Saint Kitts and Nevis | PE | Peru | UA | Ukraine |
| KP | Korea, Dem. People's Rep. | PG | Papua New Guinea | UG | Uganda |
| KR | Korea, Republic of | PH | Philippines | UK | United Kingdom |
| KW | Kuwait | PK | Pakistan | US | United States of America |
| KZ | Kazakhstan | PL | Poland | UY | Uruguay |
| LA | Lao, People's Dem. Rep. | PS | Palestinian Authority | UZ | Uzbekistan |
| LB | Lebanon | PT | Portugal | VA | Holy See |
| LC | Saint Lucia | PW | Palau | VC | Saint Vincent and the Grenadines |
| LI | Liechtenstein | PY | Paraguay | VE | Venezuela, Boliv. Rep. of |
| LK | Sri Lanka | QA | Qatar | VN | Viet Nam |
| LR | Liberia | RO | Romania | VU | Vanuatu |
| LS | Lesotho | RS | Serbia | WS | Samoa |
| LT | Lithuania | RU | Russian Federation | XK | Kosovo |
| LU | Luxembourg | RW | Rwanda | YE | Yemen |
| LV | Latvia | SA | Saudi Arabia | ZA | South Africa |
| LY | Libya | SB | Solomon Islands | ZM | Zambia |
| MA | Morocco | SC | Seychelles | ZW | Zimbabwe |
| MC | Monaco | SD | Sudan | | |
| MD | Moldova, Republic of | SE | Sweden | | |
| ME | Montenegro | SG | Singapore | | |
| MG | Madagascar | SI | Slovenia | | |

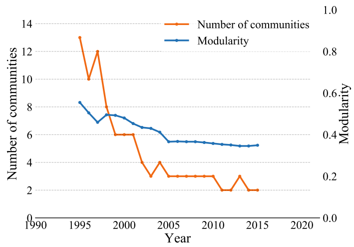
# Appendix B

# Appendix of Chapter 5

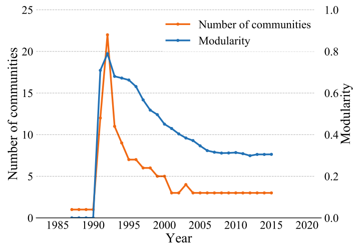
## Issue-oriented communities

The landscape of country groupings might be shaped by environmental issues. Different groupings may emerge in response to different environmental problems (Elliott and Breslin, 2011). Here, I study the community structure of the cooperation network for different subjects.

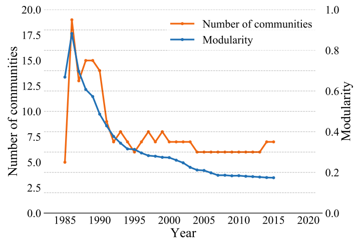
Similar to the cooperation network with all the treaties, the number of communities and the goodness of the division for different subjects decreased over time (see Figure B.1). Notably, the community structure's goodness remains high for air and energy, and resources above 0.3. In 2015, the number of communities for sea and species was 5 and 7, respectively, higher than the cooperation network for air and energy (2), resources (3) and waste (2). This might be due to the nature of environmental issues. Sea and species tend to be more regional or local problems, while the problems for air and energy, resources, and waste problems are more global.



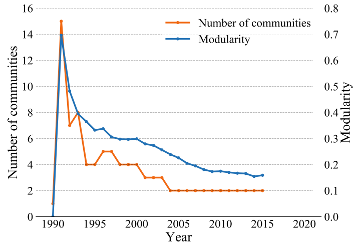

(a) Air and Energy



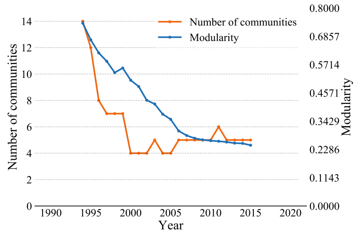

(b) Resource




(c) Sea

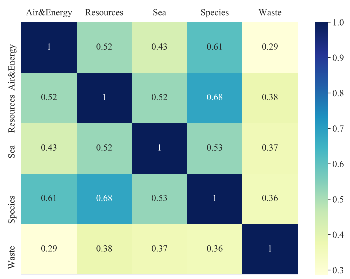



(d) Waste

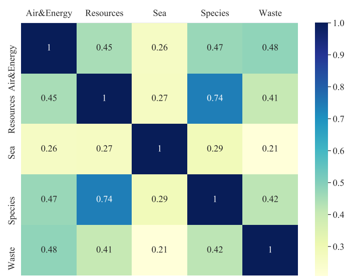



(e) Species

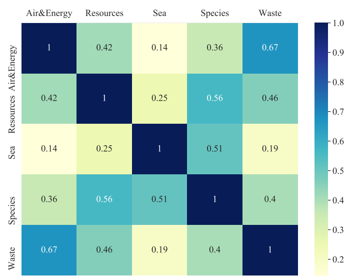
Figure B.1: Number of communities and modularity for different subjects in different years.




(a) 1995




(b) 2005




(c) 2015

Figure B.2: Heatmap of normalised mutual information ($NMI$) when comparing the community structures of different subjects with each other.

In addition, I compare the community structures of different subjects by computing the $NMI$ (see Chapter 5 for more details). Figure B.2 shows the heatmaps in 1995, 2005 and 2015. The similarity of the community structure for waste and air and energy gradually increased, from 0.29 in 1995 to 0.67 in 2015. Species and resources kept having a high level of similarity in their community structures with the $NMI$ above 0.55. Similarly, there is a big overlap between the community structures for resources and air and energy with the $NMI$ above 0.4. In contrast, the community structure for species was increasingly different from that for air and energy.

Furthermore, I assess the correlation between geography and community structures of different subjects through $NMI$. Figure B.3 shows that the community structure for sea and species were increasingly consistent with regions and continents. The $NMI$ for the sea has been around 0.6 since 2000, while for species, it increased up to 0.7. This might be decided by the regional features of the environmental problems for these two subjects. In contrast, the $NMI$ for air and energy, resources, and waste decreased gradually to below 0.5. The international cooperation in these three areas tended to be global, not constrained by geography.

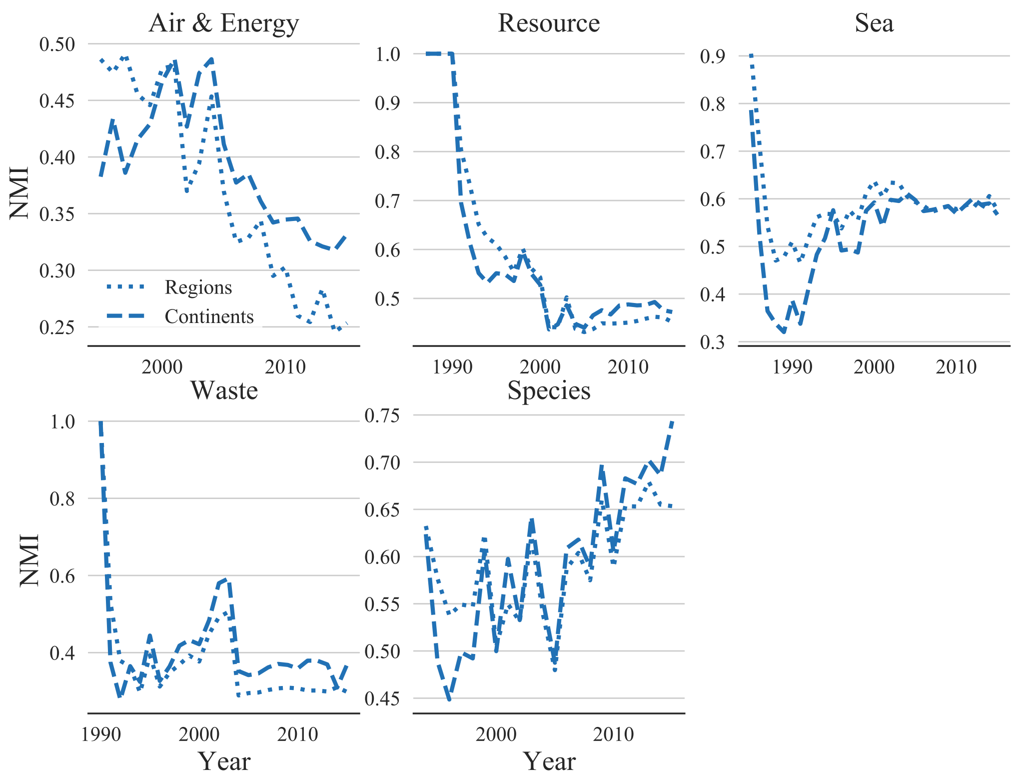



Figure B.3: Normalised mutual informaiton ($NMI$) when comparing the community structures of different subjects with continental and macro-area geographical partitions.

# Appendix C

# Appendix of Chapter 6

In this section, the robustness check of the nested structure in the country-treaty bipartite network discovered in Chapter 6 is performed by employing another algorithm to detect the nestedness. Specifically, the nestedness temperature is calculated. The method and explanations of the results are in Chapter 6.

## C.1 Nestedness based on nestedness temperature

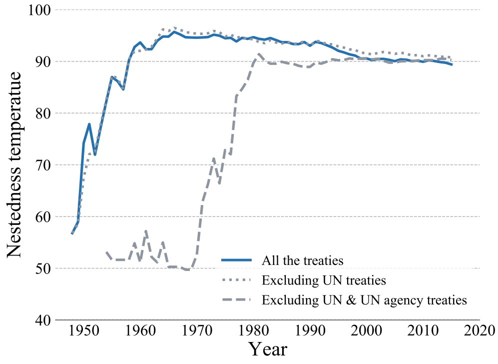
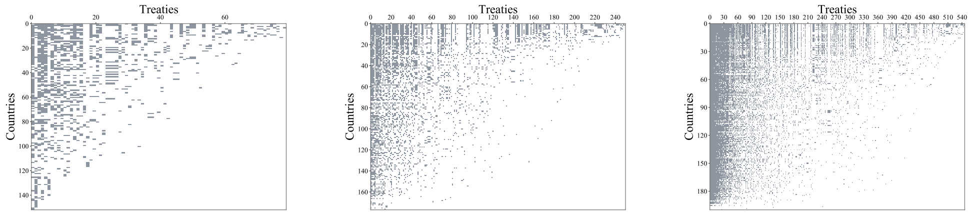
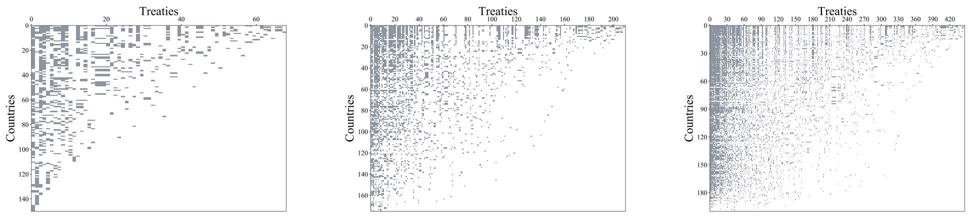



Figure C.1: Nestedness temperature from 1948 to 2015



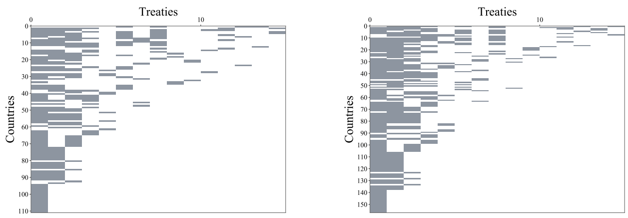

(a) 1970 (b) 1990 (c) 2015

Figure C.2: Nestedness in the bipartite country-treaty network considering all the treaties.




(a) 1970 (b) 1990 (c) 1990

Figure C.3: Nestedness in the bipartite country-treaty network exluding UN-sponsored treaties.




(a) 1990 (b) 2015

Figure C.4: Nestedness in the bipartite country-treaty network excluding UN and UN agency treaties.

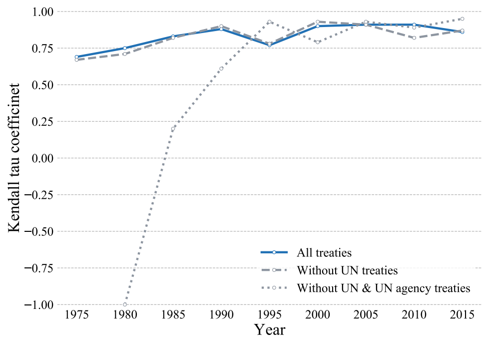



Figure C.5: Correlation between rankings of countries in year $t$ and $t + 5$ based on nestedness temperature. The Kendall tau coefficient is calculated.

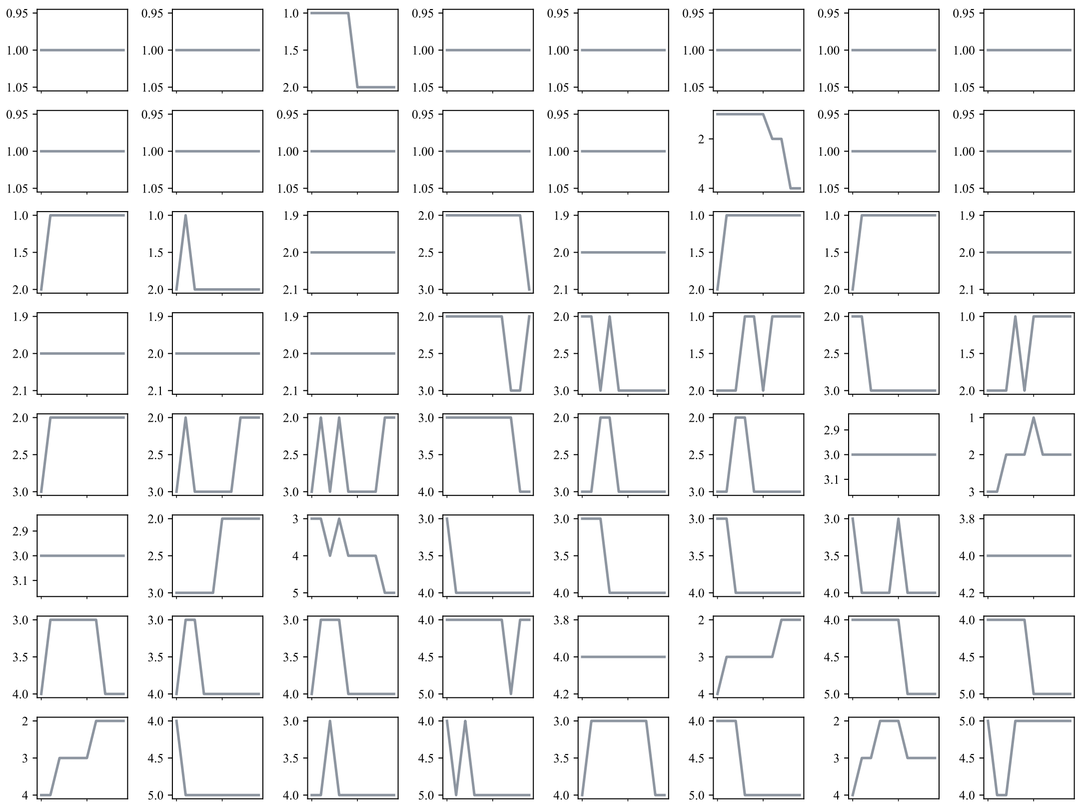


Figure C.6: Ranking of the top 64 treaties over years based on nestedness temperature. The ranking of IEAs are divieded into 5 equal parts: $0 - 20\%$, $20 - 40\%$,$40 - 60\%$,$60 - 80\%$,$80 - 100\%$. The y-axis represents the five parts. The x-aixi indicates the years.

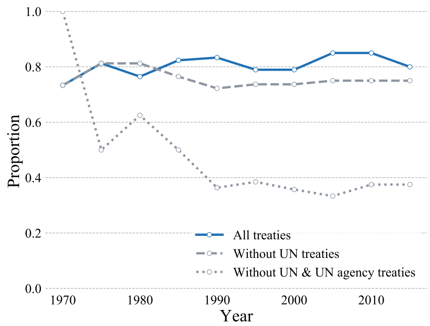



Figure C.7: Proportion of European countries among the top 10% countries in each year based on nestedness temperature

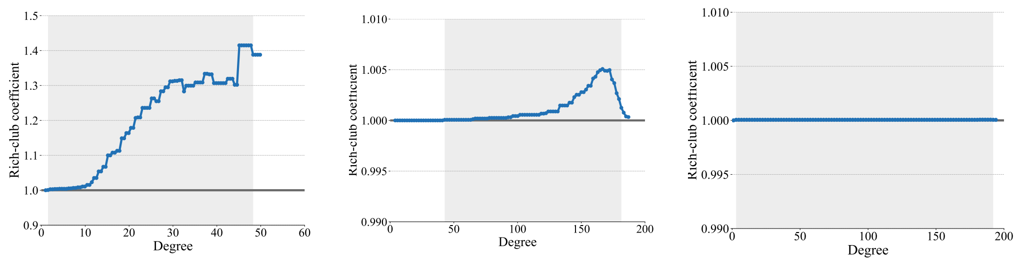
## C.2 Rich clubs

I detect rich clubs in Chapter 6 where the richness of nodes is defined as node strength. Here, I attempt to identify the presence of both the topological and weighted rich clubs when node richness is defined by other structural measures and non-structural measures. Specifically, I choose structural measures, node degrees, and non-structural measures - GDPs, imports and exports - as the richness parameters to detect the rich-club phenomenon.

### C.2.1 Rich clubs of the most connected countries

I first focus on the cooperative behaviours of countries with many partners. My previous study shows that small countries tend to have a large number of partners due to the fact that they cosigned many large treaties, i.e., treaties with a large number of signatories (Carattini et al., 2023). To study their cooperative behaviours, node degree is defined as the richness of countries. The topological rich-club coefficient is first calculated to quantify the extent to which they prefer to connect each other. Then the cooperation intensity is taken into consideration, and the weighted rich-club coefficient is calculated to quantify the extent to which they preferred to collaborate with each other.

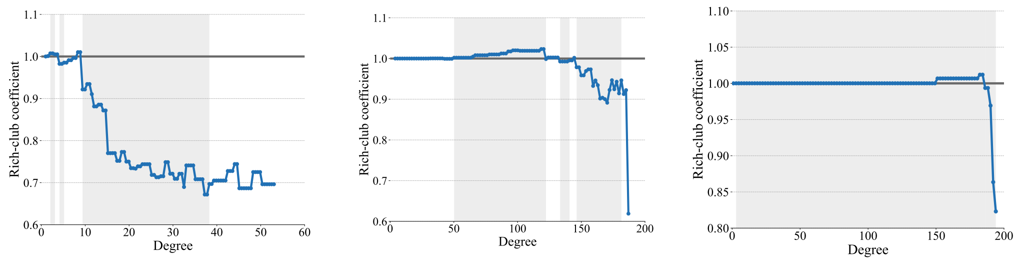
Fig. C.8 shows the results for the topological rich-club coefficient, which only considers the connections between countries and disregards the cooperation intensity. The rich-club coefficient is larger than 1.0 and positively significant. It can be argued that countries with a high degree (e.g., Ethiopia, Nigeria, Antigua and Barbuda, Malta, Mauritius) connected more with each other than expected in 1980 and 2000.




(a) 1980 (b) 2000 (c) 2015

Figure C.8: Topological rich club coefficient. The richness is defined as node degrees. The random networks are generated by the configuration model, which keeps the country's degree and reshuffles links across the network. The grey background indicates that the results are statistically significant when assessed against the null model.

However, when taking the cooperation intensity into account, countries with a high degree avoided each other, as shown in Fig. C.9. The rich-club coefficient is smaller than 1.0 and was statistically significant in 2000 and 2015. Based on the results above, it can be argued that although these small countries established cooperative relationships through large treaties, they cooperated less with each other than randomly expected.

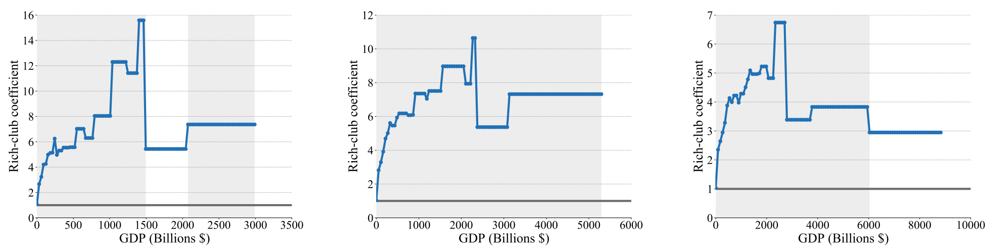



(a) 1980 (b) 2000 (c) 2015

Figure C.9: Weighted rich club coefficient. The richness is defined as node degrees. The random networks are generated by keeping the network topology but reshuffling weights across links. The grey background indicates that the results are statistically significant when assessed against the null model.

### C.2.2 Rich clubs of the largest economies

Next, I turn to non-structural measures to indicate countries' richness. First, the GDP is chosen to define the richness. As shown in Fig. C.10, there is a positive and significant rich club phenomenon in different years, indicating that large economies tended to collaborate with each other in addressing international environmental issues. The top ten countries in terms of GDPs in 2015 are the United States, Germany, Japan, France, Italy, China, Canada, India, Brazil and Australia. Only the USA and China have a GDP larger than 6000 billion dollars.

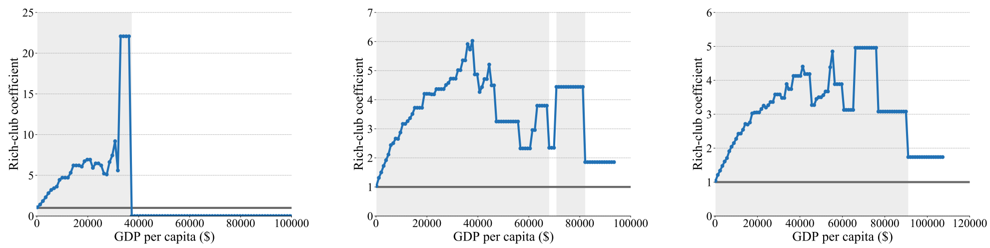



(a) 1980 (b) 2000 (c) 2015

Figure C.10: Weighted rich club coefficient. The richness is defined as the GDPs of countries. The random networks are generated by reshuffling links and weights across the network. The grey background indicates that the results are statistically significant when assessed against the null model.

### C.2.3 Rich clubs of countries with the highest GDP per capita

When the node richness is defined as GDP per capita, there is still a rich-club phenomenon. As shown in Fig. C.11, the rich-club coefficient is larger than one and statistically significant [1]. The top ten countries in 2015 are Monaco, Luxembourg, Norway, Switzerland, Ireland, Qatar, Denmark, Sweden, Australia and Singapore. These countries tended to cooperate with each other when singing IEAs to a larger extent than randomly expected.




(a) 1980 (b) 2000 (c) 2015

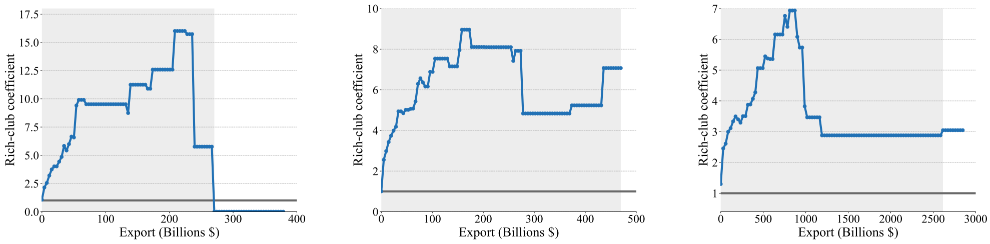
Figure C.11: Weighted rich club coefficient. The richness is defined as the GDP per capita of countries. The random networks are generated by reshuffling links and weights across the network. The grey background indicates that the results are statistically significant when assessed against the null model.

### C.2.4 Rich clubs of countries with the highest exports/imports

The rich-club phenomenon still holds when node richness is defined as export or import volumes. As shown in Fig. C.12 and C.13, the rich-club coefficient is

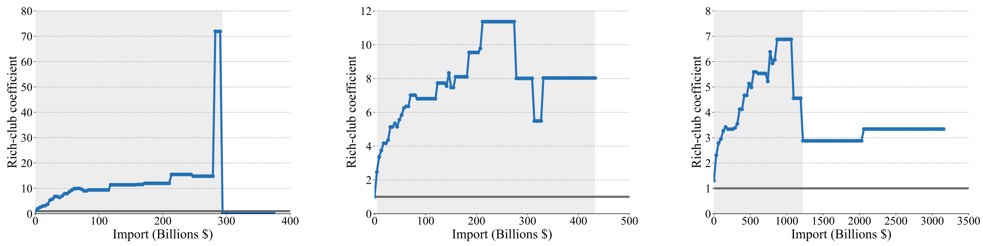
[1]In 2015, Monaco, Luxembourg and Norway had a GDP per capita larger than 90000 dollars; in 2000, Monaco, Luxembourg had a GDP per capita larger than 82000 dollars; in 1980, United Arab Emirates, Monaco, Switzerland and Norway had a GDP per capita larger than 37000 dollars.

always larger than one and statistically significant [2]. In 2015, the top ten countries in terms of exports were China, the United States of America, Germany, Japan, South Korea, Hong Kong, France, the United Kingdom, Italy and the Netherlands. And the top ten countries in terms of imports were the United States of America, China, Germany, the United Kingdom, Japan, France, Hong Kong, South Korea, Canada and Italy. These countries tended to sign IEAs with each other.




(a) 1980 (b) 2000 (c) 2015

Figure C.12: Weighted rich club coefficient. The richness is defined as the total exports of countries. The random networks are generated by reshuffling links and weights across the network. The grey background indicates that the results are statistically significant when assessed against the null model.




(a) 1980 (b) 2000 (c) 2015

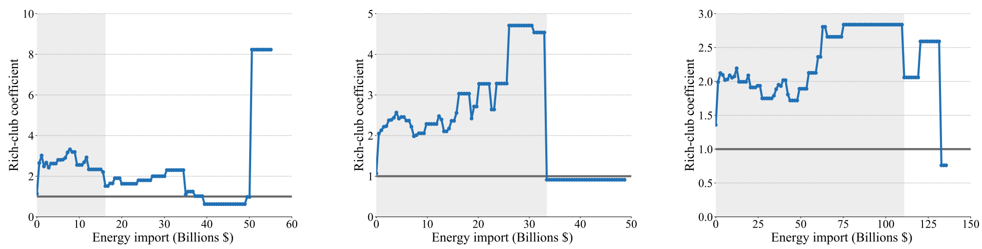
Figure C.13: Weighted rich club coefficient. The richness is defined as the total imports of countries. The random networks are generated by reshuffling links and weights across the network. The grey background indicates that the results are statistically significant when assessed against the null model.

[2]In 2015, only China and the USA had an export larger than 2600 billion dollars, and only the USA, China and Germany have an import larger than 1200 billion dollars.

### C.2.5 Rich clubs of countries with the highest energy exports/imports

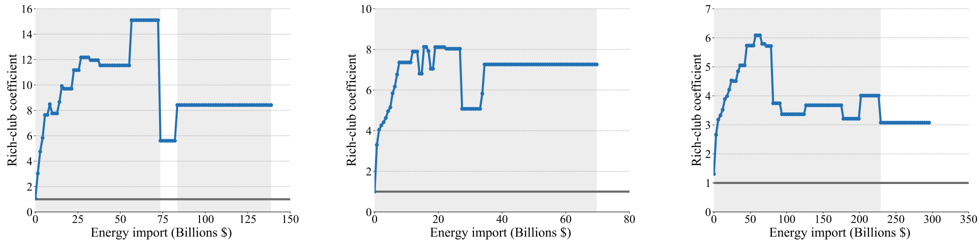
When node richness is defined as total energy exports, there was no significant rich-club phenomenon in 1980, but 2000 and 2015 saw a positive and significant rich-club phenomenon, as shown in Fig C.14. The top ten countries in terms of total energy exports (larger than 60 billion dollars) in 2015 were Russian Federation, Saudi Arabia, Canada, Qatar, Norway, Australia, the USA, Indonesia, Angola and Kazakhstan. It can be argued that these countries had a tendency to collaborate with each other when signing international environmental agreements.

Countries with the highest imports had a positive and significant rich-club phenomenon in different years.




(a) 1980 (b) 2000 (c) 2015

Figure C.14: Weighted rich club coefficient. The richness is defined as the energy exports of countries. Random networks are generated reshuffling links and weights across the network. The grey background indicates that the results are statistically significant when assessed against the null model.




(a) 1980 (b) 2000 (c) 2015

Figure C.15: Weighted rich club coefficient. The richness is defined as the energy imports of countries. Random networks are generated reshuffling links and weights across the network. The grey background indicates that the results are statistically significant when assessed against the null model.

# Appendix D

# Publications

## Journal publications

- Carattini, Stefano, Sam Fankhauser, **Jianjian Gao**, Caterina Gennaioli, and Pietro Panzarasa. What does network analysis teach us about international environmental cooperation?. Ecological Economics 205 (2023): 107670.
- Stefano Carattini, Sam Fankhauser, **Jianjian Gao**, Caterina Gennaioli, Pietro Panzarasa. The global network of environmental agreements: a preliminary analysis. Annual Bank Conference on Development Economics 2019, Washington, DC.

## Working papers

- **Jianjian Gao**, Caterina Gennaioli, Pietro Panzarasa. Regionalisation of international environmental cooperation: Evidence from community structure analysis. 2022.

- **Jianjian Gao**, Caterina Gennaioli, Pietro Panzarasa. European countries lie in the core of the international environmental cooperation. 2022.

# Appendix E

# Conference presentations

- Chapter 3 was presented in: *IC2S2 (2019)*, Poster.

  Jianjian Gao, Caterina Gennaioli, Pietro Panzarasa. Structure and evolution of the network of countries signing global environmental treaties. 5th International Conference on Computational Social Science, 2019, Netherlands.

- Chapter 3 was presented in: *IC2S2 (2020)*, Talk.

  Jianjian Gao, Stefano Carattini, Sam Fankhauser, Caterina Gennaioli, Pietro Panzarasa. Structure and Evolution of the International Environmental Cooperation Network. 6th International Conference on Computational Social Science, 2020, MA USA.

- Chapter 5 was presented in: *IC2S2 (2020)*, Poster; *NetSci (2020)*, Poster.

  Jianjian Gao, Caterina Gennaioli, Pietro Panzarasa. Communities and rich clubs in the international environmental cooperation network. International School and Conference on Network Science, NetSci, Sep 17-25, 2020, Roma, Italy.

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