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The Impact of Global Environmental Governance on Firm-level Innovation; Revisiting the Porter Hypothesis at the International Level.

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RESUME / ABSTRACT

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Bernhard Bieri
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Chapter 1

Introduction

In section 2, we review the existing literature on Porter's Hypothesis and the effect of policy certainty on innovation, and the emerging literature on the network analysis of the global environmental governance complex. In section 3, we define the computation of the two environmental governance network metrics that will proxy the effect of international policymaking on innovation. Furthermore, we will define our empirical strategy and provide the reader with descriptive statistics of the main variables of interest. In section 4, we present and discuss the results stemming from our empirical estimation. Finally, we wrap up in section 5 and provide pathways for further research in this up-and-coming field.

Chapter 2

Litterature Review

The present paper draws from three distinct but complementary strands of the literature on environmental policy. First and foremost, we ought to characterize what is known in the literature as the *Porter Hypothesis* and distinguish the different versions that have been devised over the years. We will thus strive to understand the impact of increased environmental regulations on both innovative activity of firms and on overall firm performance before completing the analysis by highlighting works that looked at the impact of the nature of environmental policy on firm-level innovation. The next strand of the literature relates to the concept of *policy certainty* which highlights the importance of designing policies that Finally, and most central to our contribution, lies the literature on *International Environmental Governance* and the related methodological advances to understand it within a network framework.

2.1 The Porter Hypothesis

Over three decades ago, the Porter Hypothesis (PH) challenged the conventional Panglossian economic thinking that enhanced environmental regulation would lead to a decrease in economic performance of firms due to the increased constraints imposed on the firm (Porter 1991). The main intuition behind the Panglossian doxa is that if it were profitable for firms to follow a more sustainable production path, they would do so in the absence of regulations. On the basis of case studies, Porter however argues that well designed, market-based, pollution preventing policies would lead firms to create products that are more resource efficient and thus competitive on the international market. An example of the latter could be the implementation of more stringent fuel consumption standards for cars. Porter thus advances that this increase in environmental stringency, would force domestic automobile companies to make more fuel efficient cars which in turn would increase the competitiveness of domestic cars in the world market.

Porter and Von der Linde later formalize his initial criticism in Porter and van der Linde (1995) where they outline six main causal links between increased environmental regulations and innovation or firm performance. First, they contend that "regulation signals companies about likely resource inefficiencies and potential technological improvements. Second, they argue that"regulation focused on information gathering can achieve major benefits [in terms of environmental performance and economic performance] by raising corporate awareness". Third, they mention that "environmental regulation reduces the"uncertainty that investments to address the environment will be valuable". Fourth, they advance that outside pressure, which includes the regulatory framework firms have to comply with, is able to overcome organizational inertia and motivate innovation. The fifth reason put forward by the authors is that "regulation levels the transitional playing field" in the sense that regulation ensures that companies do not gain an unfair advantage until new and improved technologies are proven. The sixth and final argument pertains to an important nuance between the effect of regulation on innovation and competitiveness of firms in that compliance costs arising from environmental regulations might not always be offset by benefits brought by product innovations. Crucially, Porter and Van der Linde contend that most benefits occurring from increased innovation will arise in the medium to the long term due to the required time span for the innovation to bear fruits. Hence the existence of a lag between the implementation of an environmental regulation and a signal on innovation or economic performance metrics of firms is to be expected.

Due to its unorthodox nature, the Porter Hypothesis generated a strong debate among economists during the late 1990's and the early 2000's (Jaffe, Peterson, et al. 1995). Ambec, Cohen, et al. (2013) provide a clear overview of the various arguments proponents used to defend the *PH*. They define a first set of studies which underlines the fact that firms are driven by individuals who might not satisfy the assumptions of rationality required for firms to be deemed profit-maximizers. Indeed, managerial risk-aversion, resistance to change (Aghion et al. 1997), and a combination of lacking information and the cognitive capabilities to process the latter (Gabel and Sinclair-Desgagné 2001) may cause a mismatch between the utility maximizing behaviors of the management and the firm as a whole. Akin to this principal agent issue, Ambec and Barla (2002) argue that managers may exhibit rent-seeking behavior by retaining private information on the true costs of technological innovations that would improve productivity and the environmental performance of the firm. This essentially follows the organizational inertia and learning effects put forward by Porter and van der Linde (1995) and outlined above.

A second strand of the theoretical literature explore the role of market failures beyond the pure environmental externalities generated by pollution and how increased environmental regulations could overcome them. Examples of this strand include situations where firms are first movers within international markets characterized by imperfect competition where domestic production may increase as a result of more stringent environmental regulation (Simpson and Bradford 1996). Another common market failure that could lead to the coexistence of the *PH* alongside profit-maximizing firms are information asymmetries between households and firms. The main idea here is that by setting industry standards or labels, firms are able to credibly communicate the environmental benefits of their products and overcome the asymmetry (Ambec and Barla 2007). Finally, the non-exclusive nature of R&D may lead to spillovers from the innovating firm to other firms in the industry. This may lead the economy to be in a bad equilibrium where firms invest too little in environmental technologies. If this is indeed the case, then regulations can level the playing field among firms and lead to a move to the higher, more R&D intensive equilibrium (Mohr 2002).

On the empirical front, much has been written to reinforce the initially very theoretical debate surrounding the Porter Hypothesis. To facilitate its analysis, Jaffe and Palmer (1997) divided the original hypothesis into three distinct ones. What is known as the "Strong Porter Hypothesis" (*SPH*) links environmental regulation to firm competitiveness. The "Weak Porter Hypothesis" (*WPH*) links regulation to innovation, and the "Narrow Porter Hypothesis" argues that flexible market-based regulations are more effective in generating innovation than stricter command-and-control policies[1].

The empirical literature analyzing the weak version of the Porter Hypothesis usually operationalizes innovation as R&D expenditures or through (aggregate or sector specific) patent counts. When instead analysing the strong version of the *PH* studies usually rely on firm profits. On the right hand side, the independent variable, environmental policy stringency, was initially proxied

[1]Since we will focus on the former two two hypotheses, we will not elaborate on the "narrow" hypothesis in this literature review.

by pollution abatement costs (Jaffe and Palmer 1997) or energy prices (Newell et al. 1999) before being more holistically estimated via the use of indicators such as the Environmental Policy Stringency (*EPS*) indicator developed by the OECD (Kruse et al. 2022) or national firm-level surveys such as the Community Innovation Survey[2] (Eurostat 2022). As we will outline more in detail in section 3 of the paper, we will take the modern approach and use the EPS index to proxy for environmental regulation stringency at the domestic level and patent counts and business R&D expenditures to proxy inventive activity of firms. The weak version of the Porter Hypothesis is found to be the most consistently verified hypothesis among the three as outlined in the meta-analysis by Cohen and Tubb (2018). The authors of the meta-analysis namely highlight the following points:

- Early studies tend to find a negative relationship between environmental stringency and innovation/competitiveness. More recent studies find a positive relationship between the two variables.
- Cross-country studies are more likely to find a positive link than firm-level studies. One possible reason for this can be found in the fact that innovative activity of upstream equipment manufacturers or new entrants may also respond to changes in the regulatory frameworks within an industry (Noailly and Smeets 2015; Sanyal and Ghosh 2013)[3].
- Studies incorporating a temporal lag between the change in regulation stringency and inventive or profitability outcomes are more likely to find a positive relationship. This echoes once again the original formulation of the Porter Hypothesis which states that while regulation may hurt short term competitiveness and productivity, the long term effects would be positive.

These findings will guide us in the elaboration of a panel model that will be outlined in more detail in section 3. Let us now turn our attention to the second strand of literature use to guide our empirical strategy and examine the impact of policy (un-)certainty on innovation.

[2]See Cohen and Tubb (2018) for a recent meta-analysis of the Porter Hypothesis and an outline of the different measures used.

[3]Furthermore, Cohen and Tubb (2018) note that "[t]o the extent that the Porter Hypothesis as originally formulated focused on the competitiveness of nations, this finding is of particular interest [. . .]". In other words, since the original *PH* focused on nations as the unit of analysis, it is natural to take this unit of analysis when empirically testing it.

2.2 The Role of Policy Certainty on the Innovative Behavior of Firms

While the empirical literature on the impact of policy certainty on innovation is more recent and less abundant than the one on the Porter Hypothesis, a number of papers have investigated it. The literature of the impact of policy certainty on innovative activity was derived from the one that links policy uncertainty and investments in tangible assets. Early theoretical contributions outline that non-reversible investments are often delayed or scrapped if firms experience regulatory uncertainty via an increase in the utility derived from the status-quo[4]. On the empirical front, Alesina and Perotti (1996) were the first to investigate this link with a cross-section analysis of over 70 countries. More specifically, they find that more unequal countries are more likely to be politically unstable and political instability in itself has an adverse effect on investments in tangible assets. Additional empirical evidence highlighting the negative effect of policy uncertainty was provided by Bloom, Bond, et al. (2007) who extend the analysis to a panel model, Julio and Yook (2012) who highlight a negative impact of being in an election year on firm investments, and Gulen and Ion (2016) who leverage the Economic Policy Uncertainty index developed by Baker et al. (2016) to describe a similar effect within a panel analysis.

This negative effect between policy uncertainty and tangible asset investments need not hold for intangible investments in R&D since the latter are different and are namely characterized by a long-term horizon and a fat tailed risk distribution[5]. Nevertheless, a growing game theoretical literature argues that short-term agreements are less conducive to investments in green R&D than long-term agreements due to the comparatively higher hold-up phenomenon when renegotiations are frequent (Harstad 2016). This phenomenon is mainly explained by the fact that countries that are more efficient in mitigating or abating emissions due to previous investments in the related technology will be asked to leverage their competitive advantage and bear the brunt of the emission reduction in negotiations. Bhattacharya et al. (2017) were the first to investigate the effect of policy uncertainty on innovation outcomes (i.e. patent quantities and citations) empirically. They extend the theoretical model proposed by Edmans (2009) on managerial myopia by adding economic uncertainty, a measure of policy state and a measure of policy uncertainty. Using this

[4]See Bernanke (1983) and Bloom, Draca, et al. (2016) for respectively a seminal and a recent theoretical model.
[5]This characteristic is a product of the trial and error nature of the R&D process where only a small subset of research endeavors are successful and profitable.

theoretical framework, they test whether the pure effect of country level policy orientation, as proxied by the Database of Political Institutions, and policy uncertainty, as proxied by the occurrence of election events, have an impact on firm-level innovation (Keefer 2012). Crucially, they are able to show that innovation is more affected by policy uncertainty than by policy itself. This leads to the conclusion that a politically stable environment is beneficial to R&D investments and confirms the findings of the game theoretical literature (Beccherle and Tirole 2011; Harstad 2016).

These studies are looking at the aggregate level effect between policy certainty and innovation. More recently however, newspaper indices on both climate policy uncertainty (**gavriilidisMeasuringClimatePolicy2** and on climate policy salience became available (**noaillyHeardNewsEnvironmental2021**). These indexes are both built by programmatically analyzing US newspaper articles over a given period to detect the co-occurrence of a given set of words[6]. **gavriilidisMeasuringClimatePolicy2021** used his index to show that increased policy uncertainty lead to a reduction of CO2 emissions. He further argues that, this might be due to either a decrease in energy consumption and a reduction in non-essential transport or an increase in the demand for renewable energy consumption and an associated increase in climate-friendly innovations. On the other `hand@noailly2021heard` were able to leverage their policy salience index to demonstrate a positive link between policy salience and the probability of cleantech startups receiving venture capital funding. While these indices are able to inform research on the link between environmental policy uncertainty/salience and innovative inputs and outcomes for the US, they cannot yet be used within a panel framework. Furthermore, these indices are symptomatic in that they capture perceptions of an aggregate policy environment. As both papers outline the aggregate sentiment as proxied by newspaper articles, they do not consider the root causes of this uncertainty or salience.

This underlines the importance of considering the potential variables which influence domestic environmental policy certainty and may reinforce innovative activity. This leads us to hypothesis that international commitments, in the form of the the participation in international environmental agreements, may reinforce the credibility of domestic environmental policy and thus increase the effect of environmental policy stringency on innovation. We will refer to this effect as the

[6]Both follow the methodology outlined in the Economic Policy Uncertainty index developed by Baker et al. (2016) and apply different keywords to the programmatic analysis of US newspapers.

indirect effect of international environmental governance on environmental innovation. The complementary *direct effects* of international environmental policy have been outlined in comparative studies within the international relations and political science literatures and will analyzed in more detail in the next subsection.

2.3 Assessing the Formation and the Effectiveness of International Environmental Governance

While the literature on global environmental governance does not specifically address the link between the participation rate of a country in the international governance complex and the rate of innovation of its firms, it offers insights in two main ways. First, an important strand investigates the drivers motivating countries in participating in international environmental treaties. A second complementary strand

explores the effect of international proximity and cooperation on environmental performance. We will analyse each strand in turn and focus on deriving the *direct effects* between the embeddedness of a country in the international environmental governance network and the innovation process to motivate our theoretical approach presented in the next chapter. The first strand of this literature leverages game theoretical or social network analysis methodologies to understand the formation of cooperative ties in the environmental governance network. The latter methodologies are of a particular relevance in our case since they acknowledge the interdependence of the cooperative tie formation process.

The initial methodological lens through which international environmental cooperation has been assessed is game theory. The main unit of analysis in early papers was often a single agreement such as the Montreal Protocol (Barrett 1994). More recent theoretical advances in the literature consider the participation in IEAs as a static or a dynamic game with repeated interactions between countries [beccherleRegionalInitiativesCost2011; harstadDynamicsClimateAgreements2016; Battaglini and Harstad (2016)].[7] The main conclusion of this strand that is of a particular interest to us is that long term agreements create a more certain policy environment and help reduce the uncertainty that surrounds investment in green R&D. However, although dynamic in nature, the aim of these models is to devise the characteristics of an effective prototypical

[7] The majority of the empirical evidence within the game theoretic literature comes from experimental economics. See e.g. Tavoni et al. (2011) and Barrett and Dannenberg (2012)

international environmental agreement. In other words, it does not consider the emergence of a *international environmental governance network*. This underlines the necessity of adopting a polycentric approach in the analysis of the *network* of environmental governance where agents interact at different levels (Ostrom 2009; Jordan et al. 2018) in a dynamic context. Social network analysis methods have thus been employed to understand the drivers of international cooperation within such a framework. The main benefits of using such an approach to analyse the emergence of cooperative ties is that these depend on both the *characteristics* of the agents that form them and the *structure* of the network they exist in. **kinneNetworkDynamicsEvolution2013** underlined that states are more likely to form bilateral cooperation ties if they share agreements with third parties[8].], if they sign more agreements overall, and if they exhibit similar characteristics with their bilateral partners. While Kinne examines a unimodal network of bilateral agreements between the end of the Second World War and 1980 due to data availability, Hollway and Koskinen (2016) further his analysis by examining the bipartite structure of network and highlight the importance of multilateral agreements in the process of triadic closure. While this first strand of the literature on the formation of environmental cooperation does not have a direct impact on the rates of innovation of countries, it is useful to understand the relevance of social network analysis as a mean to study the concurrent effects of the position of an agent in a network and their characteristics as opposed to the previously discussed game theoretical approach. Moving forward, we will therefore see the environmental governance complex as a network and highlight the effects of the topological attributes of countries on innovative inputs and outcomes.

The second strand of the literature on environmental governance grew from the fact that domestic policy is affected by *both* domestic and international factors (Drezner 2008; Hays 2009; Jahn 2016). As such, it investigates the *effects* of international environmental cooperation on country level variables such as environmental performance and innovation. This specific strand is surprisingly understudied and most evidence presented below either theoretical or qualitative. To our knowledge, the only attempt to investigate the link between the intensity of participation in the environmental governance complex quantitatively was provided by Jahn (2016) and is discussed below, after underlining a number of qualitative stylized facts on environmental cooperation.

[8]This confirms the triadic closure phenomenon highlighted by Granovetter Granovetter (1973)

The Stern review provides initial theoretical and qualitative insights into the ways increased international cooperation may facilitate eco-innovation (Stern et al. (2007), chapters 16 & 24). The main lens the review considers the link between international cooperation is one of portfolio management where cooperation is motivated by knowledge sharing[9], efficiency gains through the coordination of R&D portfolios and finally the pooling of risks which are a characteristic of the innovation process. In addition to this portfolio approach, they underline the importance of setting of international environmental standards which may reinforce domestic environmental regulation (Stern et al. (2007), chapter 24.6). In other words, Stern argues that international co-ordination on performance standards leads to larger markets being affected than if countries were to act in isolation which may lead the market to tip from one equilibirium to another due to a combination of network feedback effects, economies of scale or technological lock-in effects (See Barrett and Stavins (2003) for a discussion). These qualitative insights on R&D cooperation and international standard setting are not the only channels in which international environmental policy may affect innovation and environmental performance as we have outlined above in the previous subsection.

Jahn (2016) complements these insights with an analysis of the effect of supra-national factors such as the membership in international organizations, the membership in international treaties as well as more general effects such as globalization on multiple indices of environmental performance of OECD countries he constructed[10]. While Jahn's dependent variable is environmental performance, his central argument on the relevance of the *combination* of both national an international policy factors is nevertheless valuable in the context of this study as it highlights the rise of international environmental policymaking. The rising importance of international environmental cooperation has further been highlighted by Carattini et al. (2021) who illustrate it by using a network analysis approach to analyse the ECOLEX dataset(UNEP, IUCN, FAO 2022). The aim of their paper is to derive a set of stylized facts on the intertemporal evolution of the network of international agreements by constructing a "cooperation network" between states.[11] After constructing this cooperation network, Carattini et. al describe the evolution of the position

[9] To namely overcome the developed/developing divide and ensure a fair transition for developing countries where climate targets are met but not at the expense of the growth of developing countries.

[10] Other comparative analyses complement his findings: see e.g. Holzinger et al. (2008) and Bauer and Knill (2014).

[11] Section 3 provides the reader with more detail about the construction of such a cooperation network and in particular the theoretical implications associated with such a measure.

of states within this network. They narrow down their observations to the following four stylized facts:

1. "Meaningful environmental cooperation emerged in the late 1970's."
2. "Environmental cooperation has become closer, denser and more cohesive."
3. "The environmental cooperation network, while global has a noticeable European imprint."
4. International environmental cooperation started with fisheries agreements but the contemporary focus has shifted towards the management of waste and hazardous substances.

These stylized facts empirically confirm observations from the theoretical literature on international environmental agreements that highlight their growing importance (Jordan et al. 2018; Ostrom 2009).

In conjunction with the literature on policy certainty shown in the previous section, the increased importance of international environmental politics leads us to draw a model that investigates the concurrent effects of national and international environmental policies on the innovative behavior of firms. The aim of our paper is therefore to investigate whether or not the relative position[12] of a country in the global environmental governance network affects the different versions of the Porter Hypothesis. Now that the theoretical motivation of our study is set, let us outline our empirical strategy and data sources in the section that follows.

[12] In a topological sense.

Chapter 3

Methodology and Data

This section will outline the computation of a novel set of centrality measures which will be used in the subsequent analysis to proxy the relative importance of countries within the international environmental governance complex and account for the increasing importance of international policy to tackle environmental challenges. In what follows, we will describe the construction of the bipartite membership network of international agreements[1] and the extraction of a monopartite cooperation network which defines links between countries as the number of agreements that have been signed in common. We then statistically validate this projection by comparing the resulting observed one cooperation network with a null model. This process is also commonly known as *backbone extraction*. Finally, we describe the computation of two centrality indices that will proxy the intensity and the certainty of international policy as well as all other variables of interest. Let us however start by defining the empirical panel model that we will estimate in the next section before detailing the construction of its various coefficients.

3.1 The Empirical Models:

To analyse our unbalanced panel of OECD countries over the period of 1990 to 2015, we define the following regressions to investigate the *Weak Porter Hypothesis*.

```
\begin{align}
ln(BERD_{it}) = \beta_1 ln(\text{EPS}_{i,\ t-k}) + \beta_2 ln(\text{Strength}_{i,\ t-k}^{M}) +
\beta_3 ln(\text{Transitivity}_{i,\ t-k}^{M}) + \beta_4 ln(X_{it}) + \alpha_i + \delta_t + u_{it}
```

[1]Note that we interchangeably use bimodal and bipartite as adjectives to qualify the nature of the original membership network. The original network is both bimodal, since it has two different types of agreements, and bipartite since it does not have links between two nodes of the same type. (Borgatti 2009)

```
\\
ln(TPF_{it}) = \beta_1 ln(\text{EPS}_{i,\ t-k}) + \beta_2 ln(\text{Strength}_{i,\ t-k}^{M}) +
\beta_3 ln(\text{Transitivity}_{i,\ t-k}^{M}) + \beta_4 ln(X_{it}) + \alpha_i + \delta_t + u_{it}
\\
EnvPatShare_{it} = \beta_1 ln(\text{EPS}_{i,\ t-k}) + \beta_2 ln(\text{Strength}_{i,\ t-k}^{M}) +
\beta_3 ln(\text{Transitivity}_{i,\ t-k}^{M}) + \beta_4 ln(X_{it}) + \alpha_i + \delta_t + u_{it}
\end{align}
```

Where our three dependent variables are $BERD_{it}$, the business expenditures on R&D(OECD 2022a). This measures the *input* into the R&D process. TPF_{it} is the count of triadic family patents i.e. patents that have been granted by the three largest patent offices; the European Patent Office (EPO), the Japan Patent Office (JPO) and the United States Patent and Trademark Office (USPTO) (OECD 2022b). This measure proxies the *output* of the innovation process over both environmental and non environmental patents. Finally, we consider $EnvPatShare_{it} \in [0; 1]$ which measures the share of environmental patents over total patents by country (OECD 2022c).

On the RHS, $\text{EPS}_{i,\ t-k}$ is a proxy for national environmental policy stringency over the time period between 1990 and 2015 for OECD countries (Botta and Koluk 2014). $\text{Strength}_{i,\ t-k}^{M}$ and $\text{Transitivity}_{i,\ t-k}^{M}$ are indices characterizing the position of a country in the international environmental governance network. We compute these indices by using different *backbone extraction* methods M to ensure the robustness of our results. Furthermore, following Rubashkina et al. (2015) and Martínez-Zarzoso et al. (2019a), we make the hypothesis of a lagged effect of policy signals on innovation and productivity outcomes. Following both papers, we consider a lag structure of one and five years respectively. X_{it} is a vector of control variables including GDP per capita measures from the World Bank and import/export intensity measures to account for the economic integration of a given country in the global trade network[2](World Bank 2022). Finally, we add both country α_i and time fixed effects δ_t to capture the unobserved country and time level heterogeneity.

When moving on to the analysis of the *Strong Porter Hypothesis*, we define a similar panel model where our dependent variable is the growth of total factor productivity ΔTFP_{it}. This

[2]Note: All monetary variables have been standardized to 2015 USD PPP.

echoes the model run by **albrizioEnvironmentalPoliciesProductivity2017** who find a positive effect between the tightening of the EPS of a country and the growth of total factor productivity[3].

$$\Delta TFP_{it} = \beta_1 ln(\text{EPS}_{i,\ t-k}) + \beta_2 \text{Strength}^M_{i,\ t-k} + \beta_3 \text{Transitivity}^M_{i,\ t-k} + \beta_4 X_{it} + \alpha_i + \delta_t + u_{it}$$

We will begin by defining the construction of the Strength_{it} and the Transitivity_{it} measures of international governance before examining in more detail the EPS_{it} indicator and the various other dependent variables of innovation and productivity we succinctly described above.

3.2 Constructing International Environmental Cooperation Centrality Measures:

We leverage the ECOLEX dataset to construct country level measures of embeddedness in the international environmental cooperation network (UNEP, IUCN, FAO 2022)[4]. This dataset lists environmental agreements between two or more parties and the related membership actions over the period between 1868 and 2018 and contains over 25000 individual membership actions.[5] We follow Carattini et al. (2021) and retain agreements that were signed in the Post-war period starting in 1948. We retain 21270 individual membership actions after filtering out agreements signed before 1948. After further cleaning the data by excluding observations on which we do not have identifying information such as the date of the ratification of the agreement and the date of entry into force or the country which is the subject of the membership action, we retain 18878 individual membership actions that describe 521 individual international environmental agreements.

[3] Unlike **albrizioEnvironmentalPoliciesProductivity2017**, we consider the level of the EPS index to remain consistent with the Martínez-Zarzoso et al. (2019a) and the other estimations.

[4] To be more specific, we use a scraped version included in the `{manyenviron}` package (Hollway 2021) which was originally used in Sommer (2020)

[5] See Table 3.1 describing the structure of the dataset and displaying the first few observations.

Table 3.1: ECOLEX Dataset Head

ecolexID	treatyID	CountryID	Title	Beg	End	SignatureCountry	Rat	Force	DocType	GeogArea	Subject
TRE-001148	CBD_1992A	GIN	Convention On Biological Diversity	1992-06-12	NA	1992-06-12	1993-05-07	1993-12-29	M	G	Wild species & ecosystems
TRE-000557	CFAOUN_1948A	FJI	Constitution Of The Food And Agriculture Organization Of The United Nations	1948-01-01	NA	NA	NA	1948-01-01	M	G	Legal questions
TRE-000498	INTRMO_1948A	ARG	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1966-10-05	1966-10-05	M	G	Sea
TRE-000498	INTRMO_1948A	AUS	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1952-02-13	1958-03-17	M	G	Sea
TRE-000498	INTRMO_1948A	BEL	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1951-08-09	1958-03-17	M	G	Sea
TRE-000498	INTRMO_1948A	CHE	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1967-01-13	1967-01-13	M	G	Sea
TRE-000498	INTRMO_1948A	CHL	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1972-02-17	1972-02-17	M	G	Sea
TRE-000498	INTRMO_1948A	COL	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1974-11-19	1974-11-19	M	G	Sea
TRE-000498	INTRMO_1948A	ERI	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1958-03-17	1958-03-17	M	G	Sea
TRE-000498	INTRMO_1948A	FJI	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1959-04-21	1959-04-21	M	G	Sea
TRE-000498	INTRMO_1948A	GAB	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1952-04-09	1958-03-17	M	G	Sea
TRE-000498	INTRMO_1948A	GEO	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1949-02-14	1958-03-17	M	G	Sea
TRE-000498	INTRMO_1948A	GRD	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1958-12-31	1958-12-31	M	G	Sea
TRE-000498	INTRMO_1948A	IRL	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1959-01-06	1959-01-06	M	G	Sea
TRE-000498	INTRMO_1948A	IRN	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1951-02-26	1958-03-17	M	G	Sea
TRE-000498	INTRMO_1948A	JAM	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1957-01-28	1958-03-17	M	G	Sea
TRE-000498	INTRMO_1948A	LBR	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1966-05-03	1966-05-03	M	G	Sea
TRE-000498	INTRMO_1948A	NOR	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1949-03-31	1958-03-17	M	G	Sea
TRE-000498	INTRMO_1948A	PRT	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1960-03-16	1960-03-16	M	G	Sea
TRE-000498	INTRMO_1948A	PRY	Convention On The International Maritime Organization	1948-03-06	NA	1948-03-06	1976-03-17	1976-03-17	M	G	Sea

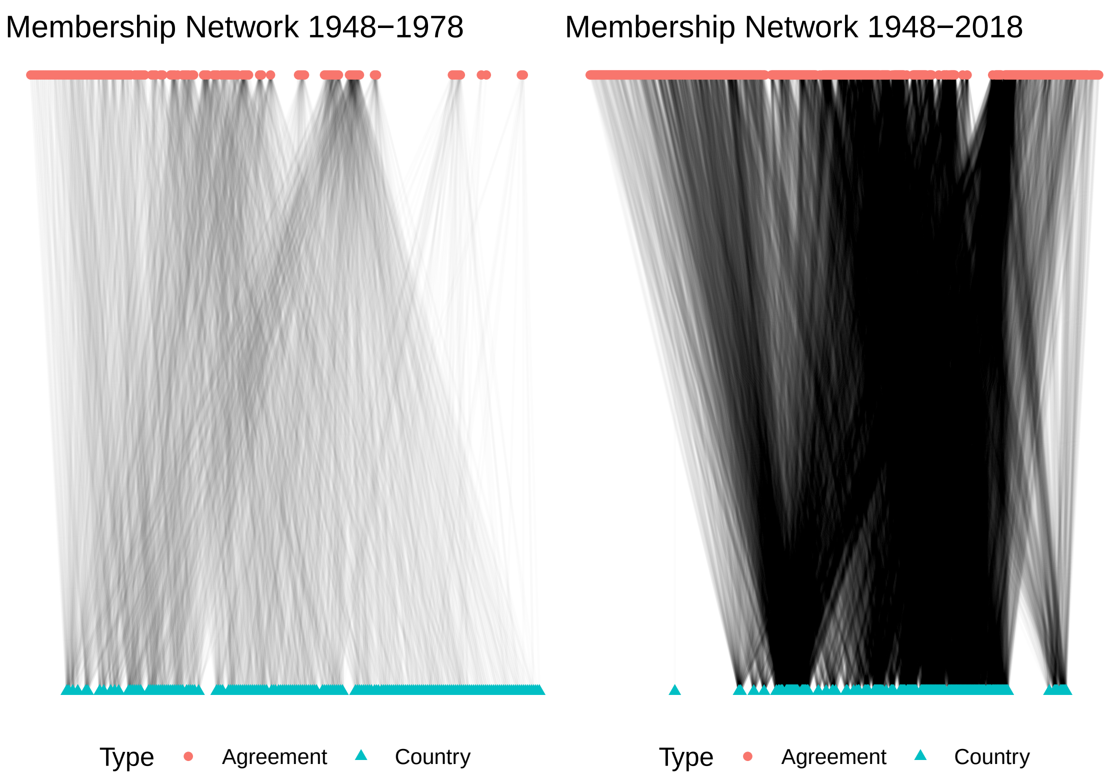
3.2.1 From a Bipartite Membership Network:

The ECOLEX dataset presented above in 3.1 can be visualized as an annual series of undirected, unweighted, bipartite/bimodal networks. This can be done in the form of a yearly incidence matrix $I^t_{C\times A}$ where each row corresponds to a country (an agent) and each column to a treaty (an artifact) (Latapy et al. 2008). The main theoretical difference between the two sets of nodes is that the former has agency over the links while the latter does not.[6] i^t_{ik} equals 1 if country i has ratified agreement k which entered into force during or before year t and 0 otherwise. A country can only be a member of a treaty once which implies that $i^t_{ik} \in \{0, 1\}$.

$$I^t_{ik} = \left.\overbrace{\begin{pmatrix} i_{1,1} & i_{1,2} & i_{1,3} & \dots & i_{1,A} \\ i_{2,1} & i_{2,2} & i_{2,3} & \dots & i_{2,A} \\ i_{3,1} & i_{3,2} & i_{3,3} & \dots & i_{3,A} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ i_{C,1} & i_{C,2} & i_{C,3} & \dots & i_{C,A} \end{pmatrix}}^{\text{Agreements}}\right\}\text{Countries}$$

We can also visualize the bipartite/bimodal membership network directly and distinguish agreements from countries. The network is depicted in @ref(fig:ECOLEX_bipartite_network) represents the membership network with all agreements that entered into force respectively during the period of 1948 and 1978 and 1948 and 2018. This shows that the network grew denser as agreements were signed, ratified and entered into force over time. To explore the intertemporal evolution of the structure of the network, we will divide this network and construct yearly snapshots of the membership graph whose incidence matrix we define as $I^t_{C\times A}$ which is one of the two standard methods used in social network analysis to account for the intertemporal evolution of a network (Everett and Borgatti 2013).

[6] This distinction will inform the choice of the backbone extraction algorithm as outlined below.



3.2.2 To a Monopartite Cooperation Network:

While we could further analyze this network directly, we will transform it into a more easily interpretable one mode network by using a projection and retaining only significant edges through a backbone extraction algorithm. We will thus broadly follow Carattini et al. (2021) while ensuring that our results are not contingent on the backbone extraction algorithm since the theoretical underpinnings of the latter are still somewhat unclear in empirical social network analysis (Neal et al. 2021).

We begin by creating a naive projection of the membership network. To perform this naive projection we multiply the yearly incidence matrix $I^t_{c\times a}$ defined above by its transposed $I^t_{A\times C}$ as follows:

$$I^t_{C\times A} I^t_{A\times C} = Adj^t_{C\times C}$$

Where $Adj^t_{c\times c}$ is the adjacency matrix of the projected cooperation network in which Adj^t_{ij} is the number of observed co-signed agreements between the two countries that entered into force in the interval $[1948; t]$. These weights capture the intensity of the environmental cooperation between two countries much like Newman (2001) captured collaboration within a bipartite network of scientific collaboration. Concurrently, it implies that bilateral treaties, ceteris paribus, carry a greater weight in the cooperation network than multilateral treaties. This is consistent with the heterogeneous role both play within the environmental governance network. As highlighted by Hollway and Koskinen (2016), bilateral treaties are akin to contracts between two parties while multilateral treaties serve “normative [. . .] law-making tools”. While both types may act as policy stringency signals, bilateral treaties carry more weight through their specific contractual nature hence developing a greater policy stringency signal for firms.

We cannot, however, directly analyze this cooperation network as the resulting *naive* monopartite network, depicted in the first panel of @ref(fig:ECOLEX_monopartite), still suffers from two issues. First, nodes with larger degrees in the original bipartite membership network (e.g. agreements with a larger number signatories or countries having signed a larger number of agreements) will bear stronger edges in the projected network. In other words, if *country A* and *country B* are bound by the same 5 agreements and have each signed 5 agreements in total, they are conceptually “closer” than *country C* and *country D* who share the membership in 10 agreements but have each signed a total of 50 agreements (Borgatti and Halgin 2011; Latapy et al. 2008; Neal 2014; Saracco, Straka, et al. 2017). However in the resulting one-mode projection, the latter will be weighted more than the former. The second issue relates to the fact that *naive* projections may lead to the emergence of spurious cliques in the projection that are due to a node with a single connection to the opposite layer in the original bipartite network (Saracco, Straka, et al. 2017). To solve these two common issues, we leverage what is known as a backbone extraction algorithm to retain only the statistically significant edges from the naive projection e.g. the edges that appear more frequently in the projection than expected by a given null model.

3.2.3 Correcting the Monopartite Cooperation Network:

We will use the following three distinct backbone extraction methods to ensure that our results are not the product of the choice of a particular extraction method alone. This is especially crucial since we do not have a “ground truth” or a counterfactual monoparite cooperation network to compare the corrected projection to. All three considered algorithms follow the same process in that they impose a constraint M on the original bipartite network and reshuffle the values of the incidence matrix $I_{C\times A}$.[7] In other words, we consider the set of all possible permutations of the original incidence matrix $I^t_{c\times a}$ containing the same countries and treaties and satisfying the constraint M. We call this set $\mathcal{I}^M$ which is consists of the individual permutated matrices I^*. The algorithm then constructs the one-mode projection of I^* as follows: $P^* = I^* \times [I^*]^T$ Recall that when performing the naive projection, we defined p_{ij} as the observed number of co-signed treaties between country i and country j. To decide whether an edge between i and j should be included in the backbone of the projected network, the algorithm compares the observed value p^t_{ij} to the simulated one in P^* which we call p^*_{ij}. We therefore define the following two-sided hypothesis test to characterize the presence (or absence) of a tie p^B_{ij} in the backbone P^B based on a significance level α.

$$p^B_{ij} = \begin{cases} 1 & \text{if } \Pr\left(p^*_{ij} \geq p_{ij}\right) < \frac{\alpha}{2} \\ 0 & \text{else} \end{cases}$$

As described in Neal et al. (2021), we use a two-tailed test since we would like to filter out both uncommonly small *and* uncommonly large collaborative ties in the projection. Neal (2022) point out that since we perform this hypothesis test for every non-null edge, we will inflate the Type-I error i.e. include too many false positives in our corrected graph. [8] Following Neal (2022), we therefore leverage the False Discovery Rate multiple test correction method which sorts the observed p-values in an increasing order before retaining all edges with a p-value satisfying P-value$_d \leq \frac{d}{m}\alpha$ where $d \in \{1, \ldots, e\}$ for all backbone extraction methods (Benjamini and Hochberg 1995).

Finally, this hypothesis test yields a binary correction matrix which informs us whether to keep a tie in the naive projection or not and thereby solves both issues of the naive projection described above. Now that we have a general understanding of the process of a backbone extraction algorithm, we turn to the following three subsections which will focus on the differences between the different algorithms that lie in the nature of the constraint they impose on the simulated networks. We will thus consider in turn the Fixed Row Model, the Fixed Degree Sequence Model, and the Stochastic Degree Sequence Model.

[7] We broadly follow the notation used in Neal et al. (2021) where each backbone extraction method is described in more detail. Furthermore, we abstract from superscript t to indicate the time period of the network as we apply the backbone extraction method to each temporal snapshot of the network.

[8] The significance level α defines the probability that a given edge is included in the backbone. Since we run this test over e edges, the probability that we detect at least one such false positive across our test equals $1-(1-\alpha)^e$ which is strictly increasing in the number of tests e.

Fixed Degree Sequence Model:

The Fixed Degree Sequence Model (FDSM) is a microcanonical backbone extraction method in that the constraint that it imposes on the set of possible permutations $\mathcal{I}^{FDSM}$ is satisfied *exactly*.[9] More specifically, the FDSM algorithm sets the degrees of each agent and each artifact to be equal to the degree sequences of the observed network. In our context, it implies that the row and column sums of the simulated I^*_{ik} are to be equal to those of the observed network I_{ik} under the FDSM algorithm.

$$I^*_{ik} = \begin{array}{c} \begin{pmatrix} 1 & 1 & 1 & \dots & 1 \\ 0 & 1 & 0 & \dots & 1 \\ 0 & 0 & 1 & \dots & 1 \\ 0 & 1 & 0 & \dots & 1 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 1 & 0 & \dots & 1 \end{pmatrix} \\ \begin{matrix} \sum_{i=1}^{C} i_{i1} & \sum_{i=1}^{C} i_{i2} & \sum_{i=1}^{C} i_{i3} & \dots & \sum_{i=1}^{C} i_{iA} \end{matrix} \end{array} \begin{matrix} \sum_{k=1}^{A} i_{1k} \\ \sum_{k=1}^{A} i_{2k} \\ \sum_{k=1}^{A} i_{3k} \\ \sum_{k=1}^{A} i_{4k} \\ \vdots \\ \sum_{k=1}^{A} i_{Ck} \end{matrix}$$

As Neal et al. (2021) point out, the main advantage of this method is that it is able to alleviate the two issues plaguing our *naive projection* outlined above by controlling for the vector of degrees. Intuitively, we retain the cooperative edges that occur more often than expected by the null model in the observed projection.[10] The main disadvantage of such an algorithm is that it is ill suited for large bipartite networks due the computational complexity of the algorithm (Neal et al. 2021). A set of alternative models has been developed to alleviate this computational issue, among which are the Fixed Row Model and the Stochastic Degree Sequence Model which we define below.

Fixed Row Model:

Like the FDSM, the Fixed Row Model (FRM) is also a microcanonical algorithm. However, the main difference is that it imposes the degree sequence constraint on the row sums of the incidence matrix only.[11] [12] That is, the degree of every *agent*/country is strictly controlled for, which implies that in all simulated networks, a country will be bound by the same number of

[9]This stands in opposition to canonical extraction algorithm that impose the constraint only *on average*.

[10]Vasques Filho and O'Neale (2020), degree sequences of the bipartite network are chiefly responsive for the structure of its monopartite projection.

[11]E.g.

$$\forall_{i\in\{1,\dots,C\}} \sum_{k=1}^{A} i_{ik} = \forall_{i\in\{1,\dots,C\}} \sum_{k=1}^{A} i^*_{ik}$$

[12]The FRM model is also sometimes referred to as the hypergeometric model (Tumminello et al. 2011).

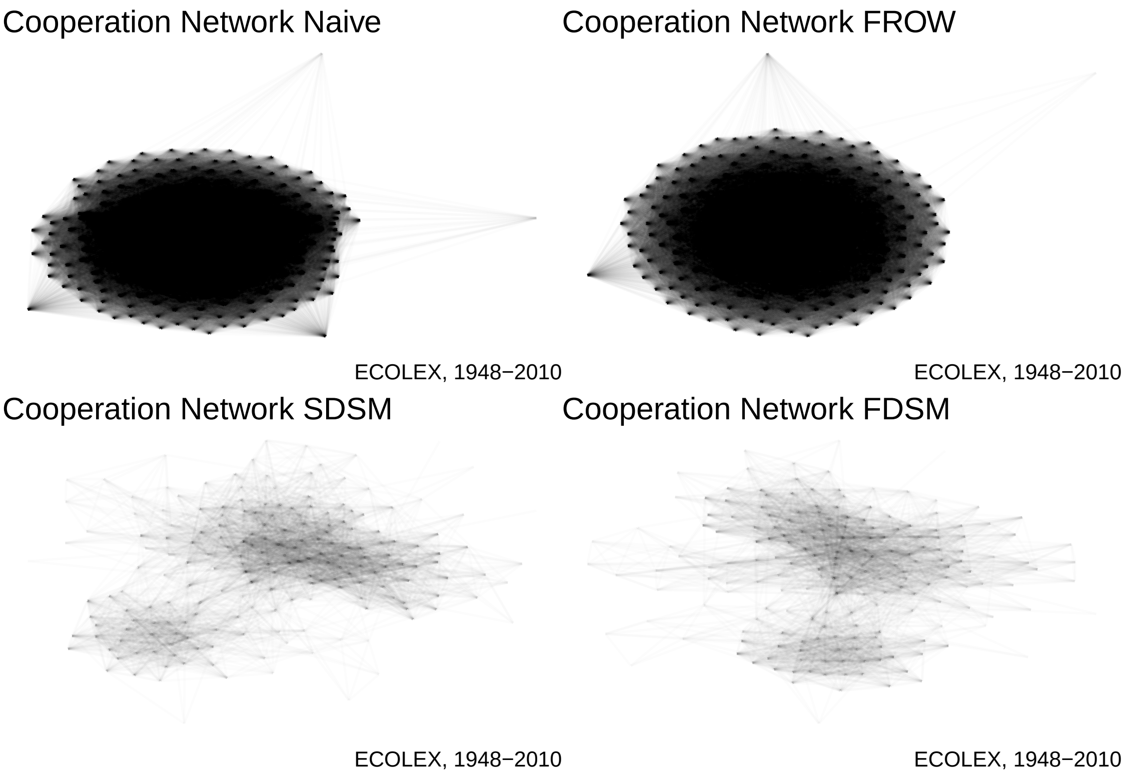
agreements than in the observed network. However, an agreement is free to have a different number of total signatories. This leads us to the reason why we are not considering the Fixed Column Model: agency. Recall that we previously defined two distinct sets of nodes depending on whether or not the nodes posses agency over the links they would like to create or dissolve. Since agreements do not have agency and are constructed through the will of countries, we constrain the latter's degree only. Carattini et al. (2021) applied the Bipartite Partial Configuration Model which is the canonical version of the FRM algorithm, to their membership network (Saracco, Straka, et al. 2017). This implies that the restriction imposed on the degree sequence of countries is only satisfied *on average* over all simulations. Since our membership network is small enough to be corrected by applying the more computationally intensive FRM algorithm, we follow the latter as it carries more information about the structure of the original bipartite network than the BiPCM algorithm (Saracco, Straka, et al. 2017).

Stochastic Degree Sequence Model:

The Stochastic Degree Sequence Model (SDSM) is a canonical algorithm that imposes a constraint on both the degree sequence of countries and on the degree sequence of agreements like the FDSM extraction method. However, the set of simulated networks satisfy this constraint only *on average*. In our case, this implies that the average number of member countries in a given international agreement k in the set of simulated networks is equal to the number of countries in the observed membership network. Conversely, it also implies that the average number of agreements signed by a given country i in the set of simulated networks is equal to the average number of agreements signed by country i in the observed network. Several methods exist to simulate networks satisfying this constraint which are compared in terms of accuracy and computational speed in Neal et al. (2021). The authors show that the Bipartite Configuration Model (BICM) is both the fastest and most accurate method to generate simulated network satisfying the average condition (Saracco, Straka, et al. 2017). We thus leverage it as our third and last backbone extraction model.

Comparing the Projections:

Before moving on to the definition of the various centrality measures we will use to measure the level of international embeddedness of countries within the network of international environmental agreements, we will compare the resulting corrected projections. We namely see that the correction of performed by the FROW backbone extraction process retains about 90 percent of the edges of the naive projection which leads to an overly dense network. We will therefore not consider it in the further analysis as it does not solve the two issues which we try to correct. This is consistent with Carattini et al. who mention that their BiPCM-corrected cooperation network's density is so high that almost every node is connected to each other (Carattini et al. 2021). On the other hand, both the SDSM and the FDSM retain on average about 15 percent of the most significant edges present in the naive projection. This ensures that we capture the true cooperative network and not a statistical artifact caused by the two issues we are trying to correct for. We will therefore compute the centrality scores on the basis of the latter two corrected networks.



3.2.4 Selecting and Computing Network Centrality Measures:

Now that we constructed and corrected the monopartite cooperation networks, we can characterize the topological position of a given country within the network and construct proxies for the *embeddedness* of a country in the international environmental governance complex. While there exist a multitude of centrality indices to characterize the position of a country and no unifying theoretical framework for defining it, we will consider the commonly used strength centrality measure and the eigenvector centrality measure which we will theoretically justify in turn.

Strength Centrality:

The strength of a node in an undirected and unweighted network measures the number of ties emanating from a node and weights them by their respective weights as follows:

$$s_i = \sum_{j=1}^{N} a_{ij} w_{ij}$$

Strength centrality echoes the proxy Jahn (2016) used to measure embeddedness in the international governance complex in that it captures the sum of cooperative ties of a given country within the weighted network of ties. Hence we expect that a country with a higher level of strength, ceteris paribus, will be more embedded in the international environmental agreement network. As stated in the previous chapter, we expect that this increased embeddedness leads to an increase in environmental innovation through both direct effects of the international policy framework and the indirect effects of a greater policy certainty. While we cannot distinguish both channels in this study, we expect that the node strength captures a relatively greater share of the direct effects of the increased embeddedness on innovation as it measures the quantity of agreement a country is bound by. The opposite can be said of the eigenvector centrality measure we define below.

Transitivity:

The weighted clustering coefficient extends the notion of embeddedness by computing the weighted proportion of triangles over connected triples that are centered on a given node (Barrat et al. 2004). On the illustration below, we see that the figure on the right is an open triple from the point of view of the orange node but not a triangle as opposed to the figure on the right. If we abstract from the weights, it is easy to see that the clustering coefficient, also known as transitivity, of the orange node on the left figure is equal to 1 while the transitivity of the orange node on the right hand side figure is 0.

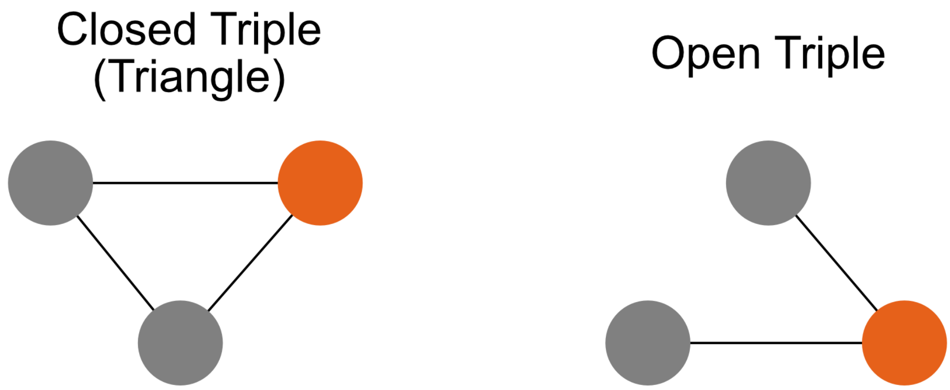


Figure 3.1: Transitivity

Mathematically, Barrat et al. (2004) define the weighted index as follows where w_{ij} is the weight of the link between node i and node j, a_{ij} is a binary variable indicating the presence of an edge between i and j, s_i is the strength of node i, and k_i is the node's degree.

$$c_i^w = \frac{1}{s_i\,(k_i - 1)} \sum_{j,h} \frac{(w_{ij} + w_{ih})}{2} a_{ij} a_{ih} a_{jh} \in [0; 1]$$

In our international cooperation network, we can interpret this coefficient as the local empirical reflection of closure which is a characteristic of a network where agents have a low level of information asymmetry with regards of the actions undertaken by each node over time (Coleman 1988). This facilitated monitoring favors the application of sanctions if an agent defects as well as the emergence of a virtuous cycle of trust and further cooperation (Burt 2000). This virtuous cycle echoes both arguments in sociology by Granovetter (1985) who posits that the cost of breaking a friends trust and therefore the friendship is greater when both agents have a friend in common since the betrayal may also affect one's relationship with the latter. This argument has been made concurrently in the field of economics and especially within the game theoretical analysis of repeated games (Tullock 1985) and within the empirical analysis of reputation in medieval trading (Greif 1989). The main insight in our case of international cooperation is therefore that countries with a higher transitivity index will have a higher cost of defecting. This in turn leads to a higher level of trust within the network, and crucially in our case, a higher level of economic policy certainty which we hypothesize is favorable to the process of green innovation.

3.3 Other variables:

3.3.1 Environmental Policy Stringency Index:

The Environmental Policy Stringency Index (EPS) is an index created by the OECD which measures the stringency of environmental policy at the country level during the period of 1990 to 2015 (Botta and Koluk 2014). As pointed out in the literature on environmental policy and innovation by Popp (2019), the

index is often used as an empirical proxy to measure environmental policy in the literature including in studies examining Porter's Hypothesis (Galeotti et al. 2020; Martínez-Zarzoso et al. 2019a). While we refer the reader to the original paper by Botta and Koluk (2014) for a detailed description of the construction of the index, we can summarize it as follows. The basis of the EPS index are individual indices of policy stringency such as emission taxes, trading schemes, environmental standards, and governmental R&D subsidies. These individual policy categories are then given a ranking on a Lickert scale between 0 and 6 before being aggregated into market and non-market based policies. These two subsets are then once again equally aggregated into the composite EPS index with equal weights which provides us with a reliable country level measure of aggregate domestic environmental policy. Overall, one can discern a positive trend in the stringency level over the considered period for every country indicating the implementation of more stringent environmental policies.

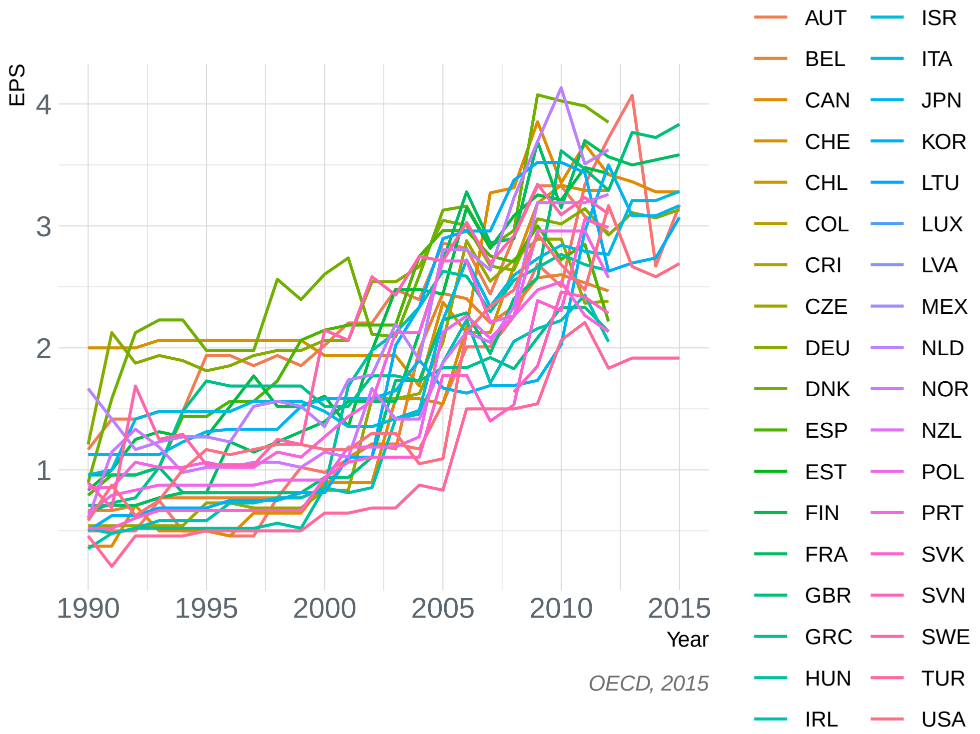


Figure 3.2: Environmental Policy Stringency 1990-2015

3.3.2 Innovation Measures:

We measure innovation, the first of our dependent variables, in two main ways. First, we consider the Business Expenditures on R&D (BERD) to capture the *input* side of the innovation process by using data from the OECD (OECD 2022a). We complement the insight from this analysis by using Triadic Patent Family (TFP) counts and Environmental Patent (EnvPat) counts to proxy the *outcome* of the research process (OECD 2022b; OECD 2022c). Both insights are complementary as Business Expenditures on R&D give a good approximation of the importance placed on the R&D process by firms while Triadic Family Patent counts and the country-level share of environmental patents allows us to examine the effect of environmental policy on the *outcomes* of inventive activity Popp (2019). A few caveats must be borne in mind when using patent counts as a proxy of innovative activity. First, as Martínez-Zarzoso et al. (2019a) point out using single country patent counts may lead to issues such as double counting of patents that are registered in multiple patent offices to gain worldwide protection. A related issue is that when using single patent counts is that one might capture low value innovations. We remedy both issues by considering the count of patent families as described by Martinez (2010b) rather than individual level patent counts. Finally, as pointed out by Popp (2019) and Martínez-Zarzoso et al. (2019a) national legislation and accountancy criteria of patents can bias the results. We will account for this heterogeneity by including country fixed effects in all our estimations. Overall, the combination of these innovation proxies will allow us to assess the *Weak Porter Hypothesis*. Let us now visualize the intertemporal evolution of all three innovation proxies.

Beginning with our business expenditure on R&D data (BERD), we identify a clear upward trend in the logged BERD indicating an increase of the level of expenditures on R&D across all countries. In addition, we note a considerable country-level heterogeneity with the top 3 countries being the United States, Japan and Germany.

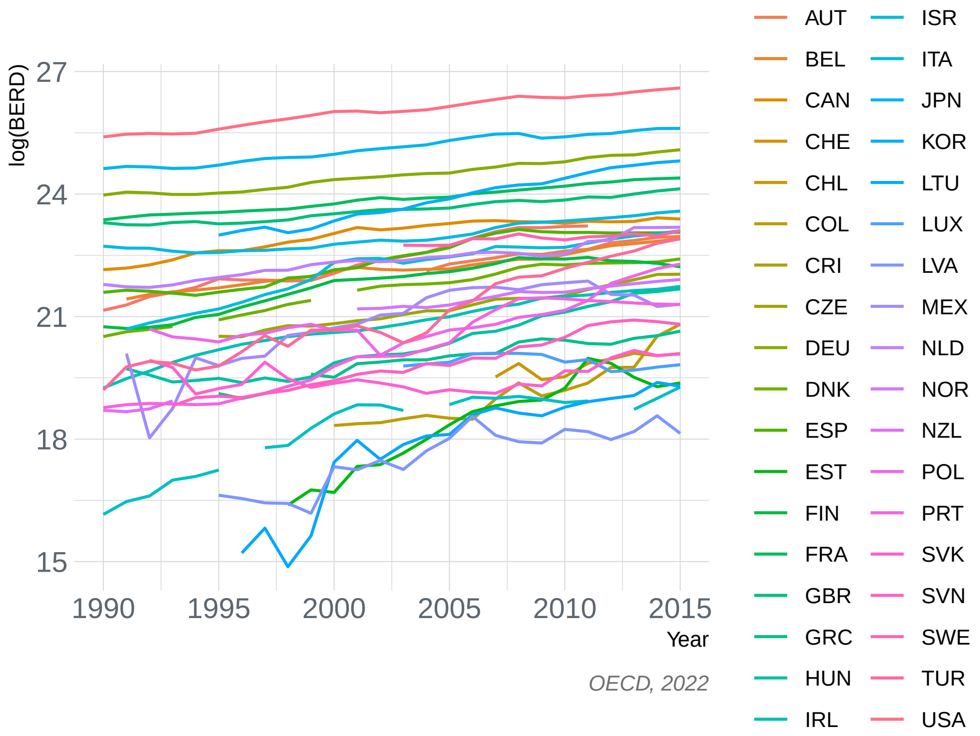


Figure 3.3: Business Expenditures in R&D 1990-2015

Triadic family patent counts show a similar pattern with respect to the country level heterogeneity. The top three countries are once again Japan, the United States and Germany. Note that while some countries, such as Japan and the US saw a marked increase in the yearly patent counts, most countries' counts remained relatively constant over time.

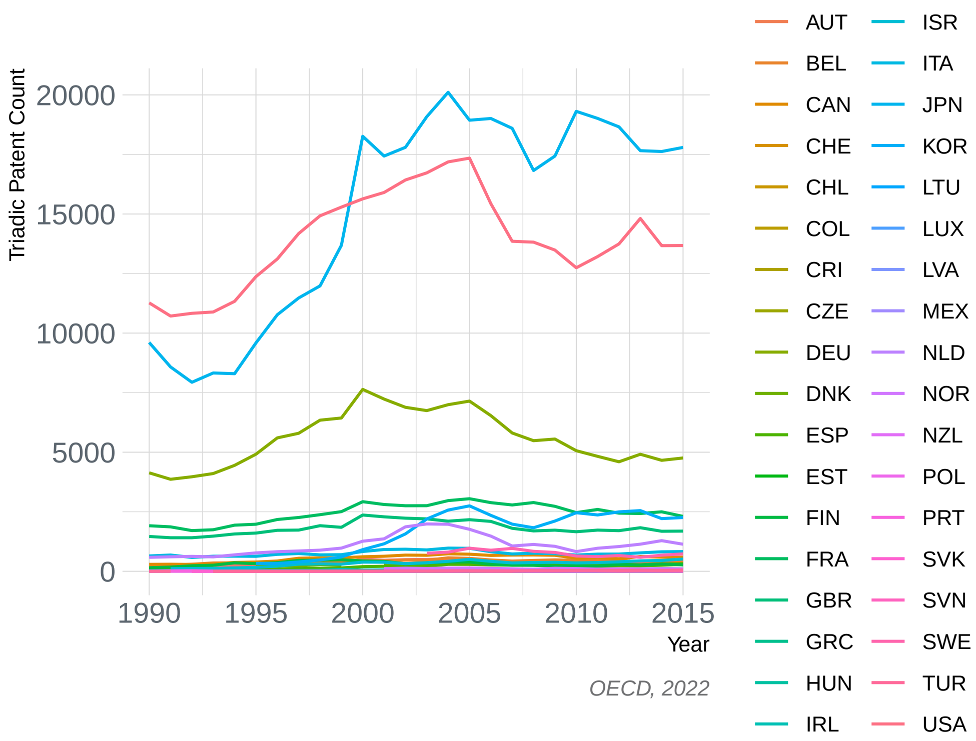


Figure 3.4: Triadic Patent Counts 1990-2015

Taking into account the share of *environmental* patents with respect to total patents allows us to refine our analysis by matching environmental policy to environmental patents. This link is key since environmental innovative activity should arguably be more strongly affected by environmental policy than other technologies. Using such an alternative estimation allows us to somewhat shield us from p-hacking claims as they are laid out by Bruns and Kalthaus (2020) in the case of solar energy policies and patents.

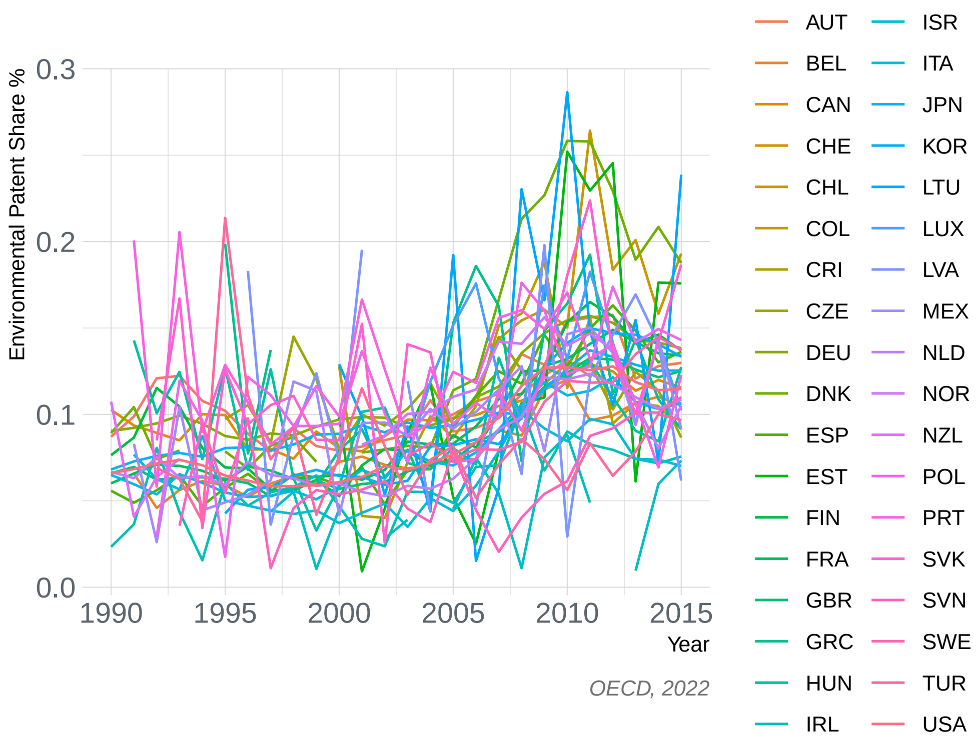


Figure 3.5: Environmental Patent Share 1990-2015

The *Strong Porter Hypothesis* we laid out in the previous chapter links environmental policy stringency and productivity or profits. We test this hypothesis by regressing total factor productivity on the independent domestic and international policy variables. To that effect, we will use the Total Factor Productivity index developed by the Vienna Institute for International Economic Studies (Stehrer 2022). We will follow Martínez-Zarzoso et al. (2019a) and use the "TFP0" decomposition of GDP based on capital stocks and hours worked only as defined below. Note that we use TFP growth rates instead of levels in this instance.

$$\Delta \ln Y = \Delta \ln TFP0 + \bar{s}_C \Delta \ln K + \bar{s}_L \Delta \ln H$$

Two features are salient from the graph below. First and foremost, we observe a form of growth rate convergence among OECD countries over the considered time period around 0% to 2.5% . A second prominent feature is the impact of the 2008 financial crisis which hit Greece particularly hard.

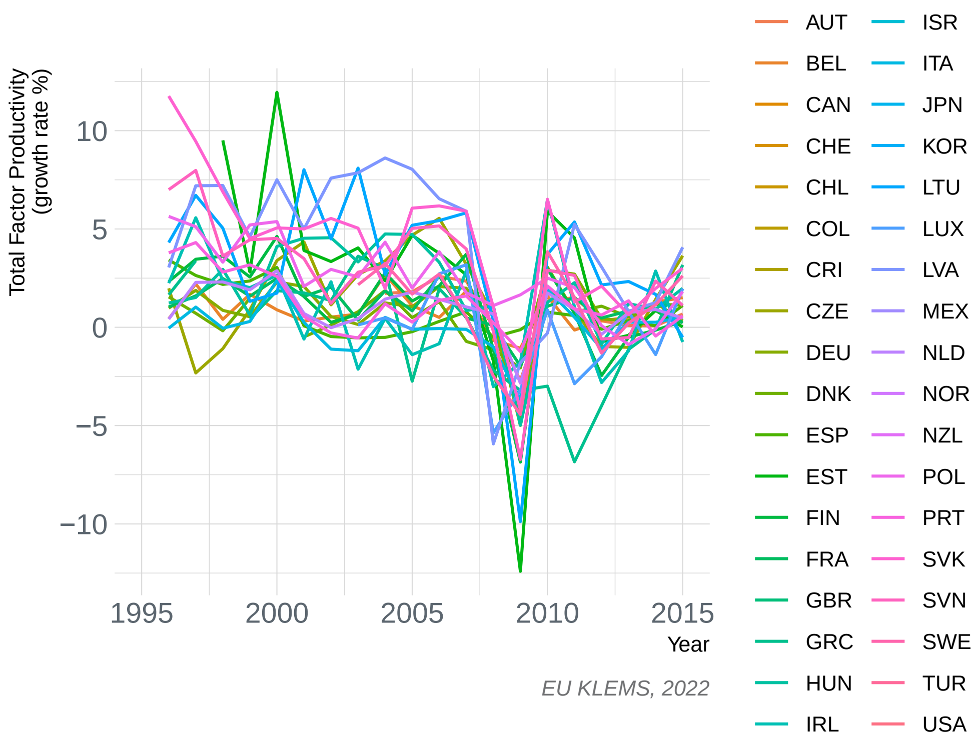


Figure 3.6: Total Factor Productivity 1990-2015

3.4 Correlations:

Before moving on to the results, let us consider the correlations between our variables of interest. The first four columns in of the correlogram 3.7 correspond to the correlations between the four dependent variables and the domestic and international policy variables. We examine the correlations of different lags and different specifications of the independent policy variables to ensure that our results are consistent across all specifications. We namely see that the business expenditure variable on R&D is positively correlated with all policy variables, both domestic and international as well as across lags and FDSM/SDSM specifications. Concurringly, the other innovation outcome proxies, Triadic Family Patent counts and the share of environmental patents, are also positively correlated with all policy measures. This evidence therefore seems to confirm the *Weak Porter Hypothesis*. On the other hand we see that the growth rate of total factor productivity (*TFP0*) seems to be weakly negatively correlated to our policy measures which indicates that the *Strong Porter Hypothesis* may not be verified in our case. Let us now move to the estimation of the empirical model defined in the beginning of this section in the next chapter to further investigate these correlations.

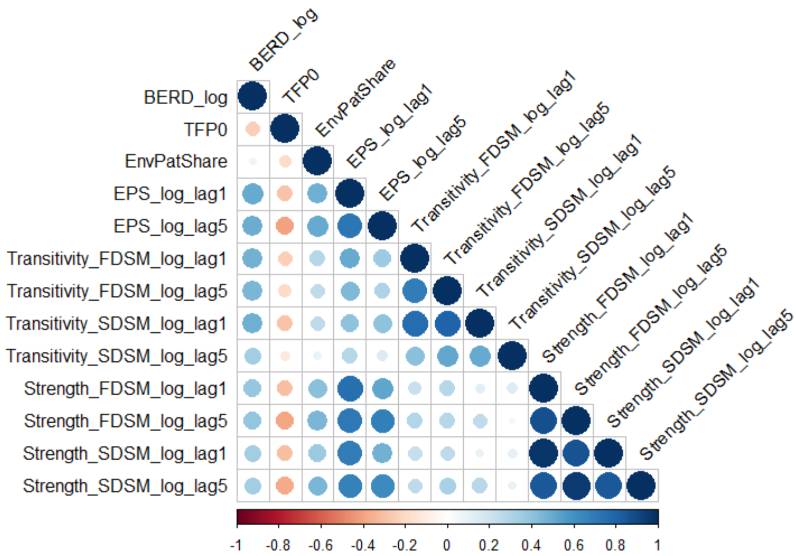


Figure 3.7: Correlations

Chapter 4

Results and Discussion

In this section, we will estimate the empirical model defined in the previous section across its multiple specifications while accounting for the backbone extraction method used as well as the lag structure of our policy variables. We will in turn describe and discuss the implications of our results for the *Weak Porter Hypothesis* and the *Strong Porter Hypothesis* before conducting various robustness checks.

4.1 Weak Porter Hypothesis:

Recall that the *WPH* links environmental policy stringency and innovation inputs and outcomes. We operationalized the former with BERD and Triadic Patent Counts and the share of environmental patents. We estimate the first two regressions with OLS while including fixed effects to account of unobserved country and time heterogeneity[1]. The third regression which uses the share of environmental patents as a dependent variable is estimated by using a fractional logit approach (QMLE) (Papke and Wooldridge 1996) and complements the analysis of the *WPH* by linking environmental regulation and environmental innovation.

4.1.1 One Year Lag:

Let us analyse the models including a one year lag of our policy variables by looking first at the first, second, fourth and fifth models which are testing the *WPH* for one year lagged policy variables. We will then examine the somewhat surprising results we observe with our environmental

[1] Patent counts may intuitively call for a Poisson regression. We follow Martínez-Zarzoso et al. (2019a) who use a standard OLS regression model since no observation bears the value 0. Hence, although our dependent variable is right tailed, we do not experience a "pure" zero inflation and transforming the data by log-linearizing it is sufficient.

patent share models. A one year lag is a relatively short period of time for policy stringency to take effect and translate into innovative outcomes. It is therefore unsurprising if we do not observe significant effects of domestic policy stringency on R&D investments and on patent counts in either of the two backbone extraction specifications. $Strength_{i,\ t-1}$, our first international policy variable, which measures the number of international agreements a country has signed at $t-1$ after undergoing the backbone extraction process $M \in \{FDSM; SDSM\}$ exhibits consistent point estimates across backbone extraction specifications. In model (5), we see that a 1 percent increase in the strength centrality of a country in the environmental cooperation network translates into a 0.15% increase in the number of triadic patents. $Transitivity_{i,\ t-1}$ which proxies the social capital of a given country within the environmental cooperation network also shows consistent positive point estimates in the second and fifth model investigating patents. The result in the fifth model shows that a 1% increase in the transitivity score will result in a 0.4% increase in subsequent triadic patenting activity. The crucial observation in these model is that the international policy variables supplant the the national index which shows the relevance of the international environmental governance network. Furthermore, transitivity or the building of closely knit triads of countries plays a relatively more important role than strength centrality in encouraging innovative output. On the innovation input side however, we do not observe significant effects of either international policy variable. Additionally the point estimates are not consistent across backbone extraction procedures and standard errors are relatively high. One additional observation we can derive from the comparison between the results of backbone extraction methods is that the standard errors are systematically bigger in the FDSM models for our international policy variables. This is mainly due to the fact that the stringency of the conditions imposed by the backbone extraction algorithm is greater in the FDSM case than in the SDSM case where more edges are statistically validated and retained in the corrected one-mode cooperation network. Overall, the point estimates found by Martínez-Zarzoso et al. (2019a) for the R&D expenditure model and the patent count model lie within the 95% confidence interval of our estimated coefficients which shows that our results are consistent with theirs although less precise. Moving on to the interpretation of the surprising results of the complementary analysis of the patent share of environmental technologies with respect to total patent counts, we find that all three policy variables exhibit a consistent negative effect on the share of environmental patents. These coefficients cannot however be interpreted as the previous double log models due to their non-linear nature. The average marginal effects in model 3 (FDSM) are: `EPS_FDSM_log_lag1`: -0.01012, `Strength_SDSM_log_lag1`: -0.01491, `Transitivity_SDSM_log_lag1` -0.03541 respectively. For model 5 (SDSM), they amount to: `EPS_SDSM_log_lag1`: \$ -0.0114\$, `Strength_SDSM_log_lag1`: -0.008402, `Transitivity_SDSM_log_lag1`: -0.01083. These marginal effects can be interpreted as the average marginal change of a 1% change in the policy variable on the share of environmental patents over total patents in a given country in a given year. The estimates for the domestic policy stringency indicator and the strength centrality are consistent across backbone extraction specifications and show a small negative effect. This is however not the case for our transitivity measure where the version computed on the FDSM-corrected network is larger than the one under the SDSM network. One possible explanation for this pattern can be found in the fact that the FDSM correction process is more likely to produce a high leverage transitivity scores since it retains fewer cooperative edges than the less restrictive SDSM correction. Overall we can however see that increased stringency, whether national or international seems to have a negative effect on the share of environmental patents. We also observe a large positive effect of GDP per capita under all specifications for both R&D expenditures, overall patent counts as well as environmental patents although the results are significant only in the first, second and fifth model. This is not surprising given that high value added processes such as R&D require both specialized human and physical capital which is found in wealthier countries. Curiously, Martínez-Zarzoso et al. (2019a) do not control for the GDP level but only for the level of international competitiveness. They proxy it by regressing the innovation metrics on export and import intensity[2]. We find that export intensity does not have a significant impact on R&D investments although it has a significant positive effect on the patent count. This partially shows a "learning-by-exporting" effect and echoes the argument put forward by **brunnermeierDeterminantsEnvironmentalInnovation2003** who argue that internationally competitive industries are more likely to innovate if foreign markets are already internationally competitive[3]. The impact of the ratio of import intensity on innovative activity is ambiguous

[2] The level of exports or imports over GDP in a given country and year.

[3] While their analysis focuses on sectoral innovation, we observe comparable effects that have been aggregated at the country level.

across our specifications. This result illustrates the continued theoretical debate on the effect of market concentration on innovative activity(**levinAppropriabilityOpportunityMarket1985**; **schumpeter1943capitalism**). This debate is further illustrated by the divergence between the results obtained by Rubashkina et al. (2015) and Martínez-Zarzoso et al. (2019a). The latter argue that the source of this divergence may be linked with the set of countries that are analyzed. In our case as well as in Rubashkina et al. (2015), the sample of considered countries is wider, more heterogeneous and less EU-centric and may thus lead to different conclusions on the impact of import and export intensity on innovative activity. Further empirical research is therefore needed to precisely assess the role of these two variables on innovative activity.

Overall, one can draw three main conclusions from the analysis of these one-year lagged policy measures. First, we cannot confirm the *WPH* on the basis of these results as the environmental policy stringency index which is not significant in either the R&D expenditure or the patent count model. This result is broadly consistent with Martínez-Zarzoso et al. (2019a). Second, we observe a positive effect of our international governance measures on patent counts. The point estimates are similar across backbone extraction process while being less precise in the FDSM case. Third, we observe somewhat heterogeneous results across backbone extraction specifications which shows the need of ensuring that our results are robust to the method used. This third observation shows that studies relying solely on one of method without being guided by theoretical considerations or computational barriers risk making wrong inferences with the resulting centrality indices. Let us now turn to the analysis of the models including the five year lagged policy variables.

4.1.2 Five Year Lag:

Much like in our analysis of the one year lag results presented in the previous subsection, we subset our analysis in two parts. We first consider the models describing the *WPH* before turning our attention to the complementary environmental patent share regressions.

Contrary to the results of the previous section with one year lags, we observe a positive and highly significant effect of our domestic environmental policy stringency index on R&D expenditures in both models. Since all policy variables are log-linearized, these coefficients are to be interpreted as the effect in percentage points of a 1% change in the independent variable. Thus, a 1 increase in the EPS index will lead to a 0.17% or 0.18% increase in business expenditures on

	FDSM			SDSM		
	R&D	Patents	Environmental Patents	R&D	Patents	Environmental Patents
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	Fractional Logit	OLS	OLS	Fractional Logit
ln EPS (t-1)	0.009	0.02	-0.12**	-0.02	-0.01	-0.13*
	(0.06)	(0.10)	(0.05)	(0.06)	(0.11)	(0.06)
ln Strength (t-1)	-0.01	0.09	-0.17***	0.10	0.15*	-0.10*
	(0.10)	(0.09)	(0.04)	(0.07)	(0.08)	(0.05)
ln Transitivity (t-1)	-0.08	0.43	-0.41**	0.32	0.40**	-0.12
	(0.21)	(0.35)	(0.17)	(0.20)	(0.18)	(0.14)
ln GDP/cap.	0.65*	2.0***	0.05	0.43	2.1***	0.09
	(0.32)	(0.34)	(0.21)	(0.35)	(0.36)	(0.22)
ln ExportIntensity	-0.03	0.66***	-0.10	0.003	0.69***	-0.28*
	(0.14)	(0.16)	(0.13)	(0.17)	(0.17)	(0.14)
ln ImportIntensity	0.38*	-0.84***	-0.23	0.25	-1.1***	-0.09
	(0.20)	(0.27)	(0.18)	(0.24)	(0.32)	(0.21)
Observations	551	550	550	466	466	466
Within R^2	0.0692	0.2285		0.0640	0.2740	
F-test	204.4	207.8		203.1	240.9	
Year fixed effects	✓	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓	✓

Newey West corrected standard errors. * significant 10%, ** significant 5%, *** significant 1%.

Table 4.1: Weak Porter Hypothesis; One Year Lag

R&D. These results are also in line with Martínez-Zarzoso et al. (2019a) who find a 0.13 point estimate in their study. On the other hand, unlike them, we do not find a positive effect of five-year lagged EPS when considering the specification with triadic patent counts as a dependent variable. Two facts may explain this divergence. First, Martínez-Zarzoso et al. (2019a) observe an effect of EPS that is one order of magnitude lower in the patent count specification than when considering R&D expenditures as a dependent variable and lies just outside the 95% confidence interval of our effect. A second cause for this inverse relationship could be due to larger set of countries that are considered in our study as well as the longer time frame. For these reasons, we find evidence for the *WPH* when considering the R&D expenditure model only and not our patent count specification. On the international policy side, we find that lagged strength centrality negatively affects R&D expenditures. This finding refutes our hypothesis that increased participation in environmental treaties would make the national policy environment more stringent. This result is robust across backbone extraction specifications and may be due to the lag selection process. Indeed, by taking the same lags than for domestic policy stringency, we implicitly make the hypothesis that these international policy signals operate in the same lag structure which may not be the case. Transitivity which can be interpreted as an indicator of policy certainty or international commitment shows positive point estimates across both specifications. While it is estimated more precisely and therefore significant in the SDSM setting only, we observe that increased transitivity increases R&D expenditures as well as patent counts. Crucially in this instance is that transitivity has a larger impact than the pure effect of lagged environmental policy stringency on R&D investments. This highlights the importance of a predictable policy environment when firms undertake innovation investments that are inherently risky and underlines the importance of meaningful international environmental cooperation to spur innovation. Our economic variables, although all positive, do no longer have a significant effect on R&D expenditures due to the reduction in point estimates rather than an increase in standard errors when compared to the results with the one-year lagged policy variables. On the other hand, the impact of all three economic variables is highly significant when we consider the number of triadic patent filings. We observe a similar pattern of results than under the previous one-year lagged specification in that GDP per capita positively impacts innovation outcomes like our proxy of international competitiveness; export intensity. We also see a negative effect of increased home competition on triadic patent counts which reinforces the Schumpeterian view that increased market concentration i.e. lower import penetration has a positive effect on innovation since the investment environment becomes less uncertain[4].

The models on the share of environmental patents complement this analysis allows us to test whether increased environmental policy stringency has had a relatively stronger impact on environmental innovation than aggregate innovation. Since we none of the policy coefficients are significant, we cannot conclude that five year lagged environmental policy increased the share of environmental patents with respect to total patents. Note that although our some coefficients are weakly significant, they are not consistently estimated across backbone model specifications and therefore cannot be interpreted safely.

We can once again derive three key insights from the regression of the innovation variables on the five-year lags of our policy variables. First, we see that the role of domestic environmental policy stringency as proxied by the EPS index has a higher effect than when we consider one year lags. This observation is consistent with Martínez-Zarzoso et al. (2019a) and verifies the *WPH* in the case of R&D expenditures. Second, we show that transitivity has a positive effect across all specifications and whose point estimates are larger than the pure effect of policy stringency. This

[4] As mentioned in the previous section, this result requires further research as we do not find concurring signs across the innovation input model (R&D expenditures) and the innovation output model (patents).

shows the importance of having a stable policy environment to reduce the policy risk associated with innovative investments which are already inherently risky. And finally, the third observation we highlight is that environmental innovation is affected in the same way as aggregate innovation by our policy variables since none is significant under both backbone extraction specifications. Let us now move on to the analysis of the *Strong Porter Hypothesis*.

	FDSM			SDSM		
	R&D	Patents	Environmental Patents	R&D	Patents	Environmental Patents
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	Fractional Logit	OLS	OLS	Fractional Logit
ln EPS (t-5)	0.17***	-0.11	2.3×10^{-5}	0.18***	-0.15**	0.05
	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)	(0.06)
ln Strength (t-5)	-0.11*	-0.03	-0.07*	-0.12**	-0.009	-0.01
	(0.07)	(0.07)	(0.03)	(0.05)	(0.06)	(0.04)
ln Transitivity (t-5)	0.37	0.04	-0.35	0.28*	0.61***	-0.18
	(0.24)	(0.28)	(0.29)	(0.14)	(0.17)	(0.12)
ln GDP per cap	0.41	2.3***	-0.03	0.24	2.1***	0.30
	(0.35)	(0.34)	(0.20)	(0.36)	(0.36)	(0.20)
ln ExportIntensity	0.19	0.70***	-0.12	0.25	0.74***	-0.40**
	(0.16)	(0.18)	(0.15)	(0.17)	(0.23)	(0.19)
ln ImportIntensity	0.29	-1.1***	-0.33*	0.18	-1.0***	-0.29
	(0.24)	(0.26)	(0.18)	(0.27)	(0.28)	(0.20)
Observations	513	512	510	422	421	419
Within R^2	0.0985	0.2580		0.0999	0.2858	
F-test	220.1	226.3		236.9	242.2	
Year fixed effects	✓	✓	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓	✓	✓

Newey West corrected standard errors. * significant 10%, ** significant 5%, *** significant 1%.

Table 4.2: Weak Porter Hypothesis; Five Year Lag

4.2 Strong Porter Hypothesis:

The *Strong Porter Hypothesis* assumes a positive link between environmental policy stringency and firm productivity as a direct result of the increased rates of innovation. We test this hypothesis by regressing the total factor productivity growth rate onto our policy proxies as well as our economic variables in the same lag and backbone extraction structures. Since the dependent variable is a growth rate and that our covariates are all log-linearized, the model can be interpreted in a similar way than the ones testing the *WPH* i.e. as the effect of a 1% change in growth rate percentage points. We draw two main conclusions from these models. First, we see that the one-year lag of the environmental policy stringency index has a positive and a significant effect on the growth rate of total factor productivity. Although seemingly confirming the strong version of the Porter Hypothesis, we should interpret these results with care as they are relatively large.

While they cannot be directly compared to the results Martínez-Zarzoso et al. (2019a) found due to the fact that their results considered an old *level* index of TFP of the EU KLEMS dataset (Stehrer 2022) and excluded the aftermath of the global financial crisis from their sample[5].

	TFP0			
Lag	lag = 1		lag = 5	
Model	FDSM	SDSM	FDSM	SDSM
	(1)	(2)	(3)	(4)
ln EPS	1.2**	1.1**	-0.53	-0.75
	(0.43)	(0.46)	(0.55)	(0.45)
ln Strength	-0.48	0.57	-0.69	-0.65**
	(0.74)	(1.1)	(0.42)	(0.29)
ln Transitivity	-3.0	-0.46	-0.83	-1.7
	(2.7)	(2.2)	(0.78)	(1.1)
ln GDP per cap	-5.8**	-6.2***	-2.9*	-3.3**
	(2.2)	(1.9)	(1.5)	(1.3)
ln ExportIntensity	-2.8	-3.5	-1.7	-1.6
	(2.3)	(2.1)	(1.6)	(1.5)
ln ImportIntensity	5.4*	5.9**	3.0	4.4**
	(2.8)	(2.7)	(2.0)	(1.9)
Observations	304	306	299	329
Within R^2	0.1059	0.1021	0.0837	0.1189
F-test	5.736	5.713	4.843	5.162
Year fixed effects	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓

Newey West corrected standard errors. * significant 10%, ** significant 5%, *** significant 1%.

Table 4.3: Strong Porter Hypothesis

4.3 Robustness Checks:

The first and most important robustness check we performed was to compute our network centrality indices following different backbone extraction methods to ensure that our results are not contingent on its choice as there exist no precise theoretical foundation that would motivate the choice of one backbone extraction method over another. This leads us to caution against the use of a *single* backbone extraction process to correct our bipartite networks as its choice may have consequences on the subsequent inferential process. This stands in contrast to Carattini et al. (2021) who derive stylized facts on the evolution of environmental cooperation by using a single BiPCM backbone extraction algorithm in their analysis. We therefore recommend both

[5] As one can see on the descriptive graph in chapter 3, the former was heavily impacted by the global financial crisis which reflects its sensitivity to business cycles (**vanbeverenTotalFactorProductivity2012**). We estimated all models with time fixed effects to account for these.

the elaboration of a theoretical justification for the selection the backbone extraction method as well as the use of various extraction methods to show the robustness of one's results[6].

More standard econometric checks were performed as well. Multicolinearity of our regressors was assessed by computing the VIF of each model. Non-spherical errors and autocorrelation were dealt with by using Newey-West corrected errors. Additionally, one might argue for the presence simultaneity issues whereby firms in less innovative countries may successfully dismantle environmental legislation[7]. Studies with lagged policy variables such as Rubashkina et al. (2015) , Martínez-Zarzoso et al. (2019a) and ours assuage these fears by pointing out that future firms cannot influence past environmental stringency states whether domestic or international.

Finally, we reestimated the models analyzing the *WPH* to ensure that our results were not solely driven by outlier countries. The US, Japan and Germany are the main drivers of global innovation and have both the largest levels of business expenditures on R&D as well as the largest patent counts[8].

[6]Recall that we excluded the fixed-column model from the backbone extraction model selection process due to the fact that agreements do not posses agency over how many countries join them. Therefore, it did not make theoretical sense to constrain their degree sequence.

[7]The opposite lobbying effect may equally be true.

[8]Results are presented in the appendix.

Chapter 5

Conclusion

Appendix:

Additional resources as well as all code files to replicate the present work can be found on its GitHub repository. The repository is currently private but feel free to reach out via email to get access.

All code files are located in the R/ folder and are labeled according to the order in which they should be executed. I.e. the first file to run would be the `0_Setup.R` file followed by the files in the `1_DataPreparation` folder. When executing the scripts, you might need to install/load particular versions of the loaded packages. These are indicated in comments next to the corresponding `library()` call in the corresponding file. If you have any specific questions regarding the replication of the thesis, please also feel free to reach out via email.

Below are the robustness checks for the two linear models testing the Weak Porter Hypothesis. These models have been reestimated following the exclusion of the United States, Japan and Germany which are three outlier countries in terms of innovation. We observe that results are robust to their exclusion.

Model	R&D	Patents	R&D	Patents
	FDSM		SDSM	
	(1)	(2)	(3)	(4)
ln EPS (t-1)	-0.04	-0.02	-0.05	-0.08
	(0.06)	(0.10)	(0.07)	(0.12)
ln Strength (t-1)	-0.05	0.06	0.08	0.15*
	(0.11)	(0.11)	(0.07)	(0.08)
ln Transitivity (t-1)	-0.13	0.74*	0.31	0.39**
	(0.28)	(0.42)	(0.22)	(0.18)
ln GDP per cap	0.49	1.9***	0.32	2.0***
	(0.35)	(0.37)	(0.37)	(0.37)
ln ExportIntensity	0.05	0.65***	0.10	0.73***
	(0.17)	(0.20)	(0.19)	(0.19)
ln ImportIntensity	0.39*	-0.73**	0.25	-1.0***
	(0.21)	(0.30)	(0.25)	(0.32)
Observations	478	477	421	421
Within R^2	0.0569	0.2302	0.0573	0.2776
F-test	118.0	137.5	139.0	173.7
Year fixed effects	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓

All models are estimated using Ordinary Least Squares. Newey-West corrected standard errors in parentheses. * significant 10%, ** significant 5%, *** significant 1%.

Table 5.1: Weak Porter Hypothesis without United States, Japan, and Germany

Model	R&D	Patents	R&D	Patents
	FDSM		SDSM	
	(1)	(2)	(3)	(4)
ln EPS (t-5)	0.16**	-0.14*	0.15**	-0.22***
	(0.06)	(0.08)	(0.06)	(0.07)
ln Strength (t-5)	-0.13	-0.03	-0.11**	0.008
	(0.07)	(0.08)	(0.05)	(0.06)
ln Transitivity (t-5)	0.48	0.12	0.29*	0.64***
	(0.30)	(0.35)	(0.15)	(0.17)
log(GDPCapita)	0.27	2.1***	0.20	2.1***
	(0.37)	(0.35)	(0.37)	(0.36)
log(ExportIntensity)	0.25	0.78***	0.30	0.84***
	(0.19)	(0.21)	(0.18)	(0.25)
log(ImportIntensity)	0.26	-1.1***	0.18	-1.0***
	(0.25)	(0.28)	(0.28)	(0.28)
Observations	452	451	385	384
Within R^2	0.0950	0.2630	0.0989	0.3055
F-test	133.9	153.5	167.5	180.5
Year fixed effects	✓	✓	✓	✓
Country fixed effects	✓	✓	✓	✓

All models are estimated using Ordinary Least Squares. Newey-West corrected standard errors in parentheses. * significant 10%, ** significant 5%, *** significant 1%.

Table 5.2: Weak Porter Hypothesis without United States, Japan, and Germany

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