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

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RESUME / ABSTRACT

This paper investigates the link between environmental policy stringency, innovation and firm competitiveness which is commonly known as the Porter Hypothesis in OECD countries between 1990 and 2015. Unlike previous studies, we consider the evolution of international environmental policy and extend the traditional domestic policy analysis by using a network analysis approach to understanding international environmental cooperation patterns over time. To investigate the relationship between international cooperation and innovation or firm competitiveness, we define two country-level measures of embeddedness in the international governance network; strength and transitivity. We find that domestic environmental policy stringency has a positive effect on innovation as proxied by R&D expenditures but not on patent counts. Furthermore, we find that social capital proxied by transitivity, which is conducive to a stable international policy environment positively affects innovation but not competitiveness. Finally, the impact of the cooperative intensity, proxied by strength is not consistent across specifications and is consistently smaller than the transitivity estimates. We thus find that the combination of stricter environmental policy measures and a stable international governance environment is conducive to innovation.

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Chapter 1

Introduction

Innovation is a key topic in the discussion surrounding environmental policy and the impact of the latter on the former has been the topic of a large body of research over the past few decades. This link becomes apparent when we consider the innovation required by the transition from a carbon-intensive energy production equilibrium to a decarbonized one which will be required by the middle of the century to achieve the ambitious environmental performance goals and attain net-zero emissions by 2050 in line with the objectives of the Paris Agreement (European Union 2020). The political environment is therefore central to firm-level decisions on resource allocation, strategic planning of innovation activities and *in fine* economic performance.

We investigate this link by extending what is known as the *Porter Hypothesis* in the environmental economics literature (Porter and van der Linde 1995). To empirically assess its validity, Jaffe and Palmer (1997) divided it into three distinct hypotheses: the *Weak Porter Hypothesis* (WPH), the *Strong Porter Hypothesis* (SPH), and the *Narrow Porter Hypothesis*. The weak version contends that increased environmental policy stringency stimulates firm-level innovation. The strong version goes one step further and argues that firm competitiveness is enhanced by increased environmental policy stringency. Finally, the narrow version posits that more flexible, market-based policies are more apt at spurring innovation and firm competitiveness than less flexible command-and-control measures.

While empirical studies examining these hypotheses considered domestic policy stringency as the main independent variable, we argue that one needs to account for the rise in international environmental policymaking that occurred over the past half-century and has likely had an increasingly important influence on firm-level innovation processes (Carattini et al. 2021). In this paper, we extend the standard model testing the Porter Hypothesis by constructing novel measures characterizing the evolution of international environmental cooperation. To achieve this, we conceptualize international cooperation as a bipartite membership network where countries are connected via their membership status in a given International Environmental Agreement (IEA). We then construct a yearly one-mode cooperation network and compute country-level measures describing the position of countries in the network. We define strength as the intensity of a country's involvement in the environmental governance network as well as transitivity which proxies the level of social capital or international policy certainty of a country in the network. We thus add these international policy covariates to the standard models testing the Porter Hypothesis and estimate them using an unbalanced panel of OECD countries over the period between 1990 and 2015 (Martínez-Zarzoso et al. 2019; Rubashkina et al. 2015).

The rest of this thesis is organized as follows. In section 2, we review the existing literature on Porter's Hypothesis, the effect of policy certainty on innovation, and the emerging literature on the network analysis of the international environmental governance network. In section 3, we define the computation of 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 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 the innovative activity of firms and on overall firm performance. The next strand of the literature relates to the concept of *policy certainty* which highlights the importance of maintaining a stable and predictable policy environment to decrease the risk inherent to innovative activity. Finally, and most central to our contribution, lies the literature on *International Environmental Governance*. We will notably review previous work conceptualizing it as a cooperative network.

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 the economic performance of firms due to the increased constraints imposed on the firm (Porter 1991). The central 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. However, based on case studies, Porter argues that well-designed, market-based, pollution-preventing policies would lead firms to create more resource-efficient products and thus be competitive in 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 1991).

Porter and Van 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 spur innovation. The fifth reason put forward by the authors is that "regulation levels the transitional playing field" because 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 essential nuance between the effect of regulation on innovation and the competitiveness of firms in that compliance costs arising from environmental regulations might not always be offset by the benefits brought by subsequent product innovations. Crucially, Porter and Van der Linde contend that most benefits from increased innovation will arise in the medium to the long term due to the required time span for the innovation to bear fruit. Hence, the existence of a lag between the implementation of environmental regulation and a signal on innovation or economic performance metrics of firms is to be expected[1].

Due to its unorthodox nature, the Porter Hypothesis generated an intense debate among economists during the late 1990s and the early 2000s (Jaffe, Peterson, et al. 1995). Ambec, Cohen, et al. (2013) provide a clear overview of the arguments proponents used to defend the *PH*. They define a first set of studies that underline 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

[1] A lag structure will therefore be taken into account in our empirical estimations.

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 actual costs of technological innovations that would improve productivity and the environmental performance of the firm. This essentially follows the organizational inertia and learning effects argument put forward by Porter and van der Linde (1995) that we outlined above.

A second strand of the theoretical literature explores 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 can 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 *ex-ante* 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 a 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*) relates environmental 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. Since we will focus on the former two hypotheses, we will not elaborate further on the Narrow hypothesis in this literature review.

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 considering the strong version of the *PH*, studies typically rely on firm profits or total factor productivity. On the right-hand side, environmental policy stringency was initially proxied 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*) index 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 for the inventive activity of firms. The weak version of the Porter Hypothesis is 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 medium to long-term effects would be positive.

These findings will guide us in the elaboration of the panel model that will be outlined in more detail in section 3. Before that, let us focus on the second strand of literature guiding 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 on 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 due to the relative 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 that subsequent political instability has an adverse impact 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 identify the 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.

However, note that the 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 assessing international environmental governance 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 reductions during the 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

[4]See Bernanke (1983) and Bloom, Draca, et al. (2016) for a seminal and a recent theoretical model respectively.

[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.

economic uncertainty, a measure of policy state, and an estimate of policy uncertainty. Using this 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). 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 benefits R&D investments and confirms the findings of the aforementioned game theoretical literature (Beccherle and Tirole 2011; Harstad 2016).

These studies look at the aggregate effect between policy certainty and innovation and do not analyze environmental innovation specifically. More recently, however, newspaper indices on climate policy uncertainty (Gavriilidis 2021) and climate policy salience became available (Noailly, Nowzohour, et al. 2021). 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]. Gavriilidis (2021) used his index to show that increased policy uncertainty leads 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 rise in climate-friendly innovations. On the other hand, Noailly, Nowzohour, et al. (2021) were able to leverage their policy salience index to identify a positive link between policy salience and the probability of cleantech startups receiving venture capital funding. While these indices can inform research on the link between environmental policy uncertainty/salience and innovative inputs and outcomes for the US. We cannot yet use them within a panel framework across multiple countries. Furthermore, these indices are symptomatic as they capture perceptions of an aggregate policy environment. As both papers outline the aggregate sentiment proxied by newspaper articles, they do not consider the root causes of this uncertainty or salience.

These studies underline the importance of considering the potential variables which influence domestic environmental policy certainty and may reinforce innovative activity. Thus they lead us to our hypothesis that international commitments, in the form of participation in international environmental agreements, may strengthen the credibility of domestic environmental policy and

[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.

thus increase the effect of domestic environmental policy stringency on innovation. We will refer to this credibility effect as the *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 be analyzed in more detail in the following subsection.

2.3 Assessing the Formation and the Effectiveness of International Environmental Governance

While the literature on global environmental governance does not explicitly 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 to participate in international environmental agreements. A second complementary strand explores the effect of international proximity and cooperation on environmental performance[7]. In turn, we will analyze each strand and focus on deriving potential *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 methods are particularly relevant in our case since they acknowledge the interdependence of the cooperative tie formation process. Early papers' main unit of analysis 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 (Beccherle and Tirole 2011; Harstad 2016; Battaglini and Harstad 2016)[8]. The main conclusion of this strand that is of particular interest to us is that long-term agreements create a more certain policy environment and help reduce the uncertainty that surrounding investment in green R&D. However, although dynamic, these models aim to devise the characteristics of an effective prototypical international environmental agreement. In other words,

[7]Environmental performance is different from economic performance as it relates to targets such as pollution abatement efforts.

[8]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)

it does not consider the emergence of an *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 in a dynamic context (Ostrom 2009; Jordan et al. 2018). Social network analysis methods have thus been employed to understand the drivers of international cooperation within such a framework. The main reason behind the use of such an approach to analyzing 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. Kinne (2013) underlined that states are more likely to develop bilateral cooperation ties if they share agreements with third parties[9].], 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 studying the bipartite structure of the global fisheries network and highlight the importance of multilateral environmental agreements by showing that sharing membership in a multilateral agreement is conducive of bilateral triadic closure. While this first strand of the literature on the formation of environmental cooperation does not highlight a direct link between embeddedness and the rates of innovation of countries, it is helpful to understand the relevance of social network analysis as a means 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 conceptualize the environmental governance complex as a network and highlight the effects of the topological attributes of individual countries on innovative inputs and outcomes as well as firm-level competitiveness over time.

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 is either theoretical or qualitative. To our knowledge, the only attempt to quantitatively investigate the link between the intensity of participation in the environmental governance complex was provided by Jahn (2016) and

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

is discussed below, after underlining a number of qualitative stylized facts on environmental cooperation.

The Stern Review provides initial theoretical and qualitative insights into how increased international cooperation may facilitate eco-innovation (Stern et al. (2007), chapters 16 & 24). The primary lens the Review considers the link between international cooperation and innovation is one of portfolio management, where cooperation is motivated by knowledge sharing[10], efficiency gains through the coordination of R&D portfolios, and finally the pooling of risks which are a crucial characteristic of the innovation process. In addition to this portfolio approach, the Review underlines the importance of setting international environmental standards which may reinforce domestic environmental regulation (Stern et al. (2007), chapter 24.6). In other words, Stern argues that international coordination 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 equilibrium to another due to a combination of network feedback effects, economies of scale or technological lock-in effects [11].

Jahn (2016) complements these qualitative insights with an analysis of the positive effect of supra-national factors such as the membership in international organizations, the membership in international environmental treaties, as well as more general effects such as globalization on multiple indices of the environmental performance of OECD countries he constructed[12]. While Jahn's dependent variable is environmental performance, his central argument on the relevance of the *combination* of national and 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 using a network analysis approach to analyze the ECOLEX dataset(UNEP, IUCN, FAO 2022). Their paper aims to derive a set of stylized facts on the intertemporal evolution of the network of international agreements by constructing a "cooperation network" between states[13] After constructing this cooperation network, Carattini et al. describe

[10] Namely to 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.

[11] See Barrett and Stavins (2003) for a discussion

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

[13] Section 3 provides the reader with more detail about the construction of such a cooperation network.

the evolution of the position of states within it. They narrow down their observations to the following four stylized facts:

1. "Meaningful environmental cooperation emerged in the late 1970s."
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 subsection, 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. Therefore, our paper aims to examine whether or not the relative position[14] 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 following section.

[14]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 centrality of countries within the international environmental governance complex and account for the increasing importance of international policy in tackling 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 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 we will estimate in the next section before detailing the construction of its various coefficients.

3.1 The Empirical Models

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

[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 nodes and bipartite since it does not have links between two nodes of the same type (Borgatti 2009).

$$
\begin{aligned}
ln(BERD_{it}) = \beta_1 ln(\text{EPS}_{i,\ t-k}) + \\
\beta_2 ln(\text{Strength}^M_{i,\ t-k}) + \beta_3 ln(\text{Transitivity}^M_{i,\ t-k}) + \\
\beta_4 ln(X_{it}) + \alpha_i + \delta_t + u_{it}
\end{aligned} \tag{3.1}
$$

$$
\begin{aligned}
ln(TPF_{it}) = \beta_1 ln(\text{EPS}_{i,\ t-k}) + \\
\beta_2 ln(\text{Strength}^M_{i,\ t-k}) + \beta_3 ln(\text{Transitivity}^M_{i,\ t-k}) + \\
\beta_4 ln(X_{it}) + \alpha_i + \delta_t + u_{it}
\end{aligned} \tag{3.2}
$$

$$
\begin{aligned}
EnvPatShare_{it} = \beta_1 ln(\text{EPS}_{i,\ t-k}) + \\
\beta_2 ln(\text{Strength}^M_{i,\ t-k}) + \beta_3 ln(\text{Transitivity}^M_{i,\ t-k}) + \\
\beta_4 ln(X_{it}) + \alpha_i + \delta_t + u_{it}
\end{aligned} \tag{3.3}
$$

Where the first of our three dependent variables is $BERD_{it}$, the business expenditures on R&D, which measures the *input* of the R&D process (OECD 2022a). TPF_{it} is the count of triadic family patents i.e. patents that have been granted by the three largest patent offices worldwide; 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). This last measure does not test the *WPH per se* but allows us to test whether environmental innovation is relatively more influenced by changes in domestic environmental policy stringency or our international policy measures.

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). $\text{Strength}^M_{i,\ t-k}$ and $\text{Transitivity}^M_{i,\ t-k}$ 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 which will be described below. Furthermore, following Rubashkina et al. (2015) and Martínez-Zarzoso et al. (2019), we make the hypothesis of a lagged effect of policy signals on innovation and productivity outcomes and consider a lag structure k of one and five years, respectively. X_{it} is a vector of control variables including, GDP per capita as well as import and export intensity measures from the World Bank to account for the economic integration of a given country in the global trade network and its relative competitiveness[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 in all specifications.

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 echoes the model run by Albrizio et al. (2017) who find a positive effect between the tightening of the EPS of a country and the growth of total factor productivity[3].

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

Now that we laid out an overview of the variables that we will consider in our empirical mode, we continue by defining the construction of the Strength_{it} and the Transitivity_{it} measures of international governance. We will subsequently examine the EPS_{it} indicator as well as 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

[2]Note: All monetary variables have been standardized to 2015 USD PPP.
[3]Unlike Albrizio et al. (2017), we consider the level of the EPS index to remain consistent with the Martínez-Zarzoso et al. (2019) and the other estimations and not its change.
[4]To be more specific, we use a scraped version included in the `{manyenviron}` package (Hollway 2021) which was initially used in Sommer (2020)
[5]See Table 3.1 describing the structure of the dataset and displaying the first few observations.

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.

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 $i^t_{ik} \in \{0, 1\}$.

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

We can also visualize the bipartite/bimodal membership network directly and distinguish agreements from countries. The network depicted in 3.1 represents the membership network with all agreements that entered into force between 1948 and 1978 and 1948 and 2018, respectively. This illustration 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 the most commonly used method in social network analysis to account for the intertemporal evolution of a network (Everett and Borgatti 2013).

3.2.2 To a Monopartite Cooperation Network

While we could further analyze this bipartite network directly, we will transform it into a more easily interpretable one-mode cooperation network. We do so by using a projection and retaining only statistically 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).

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

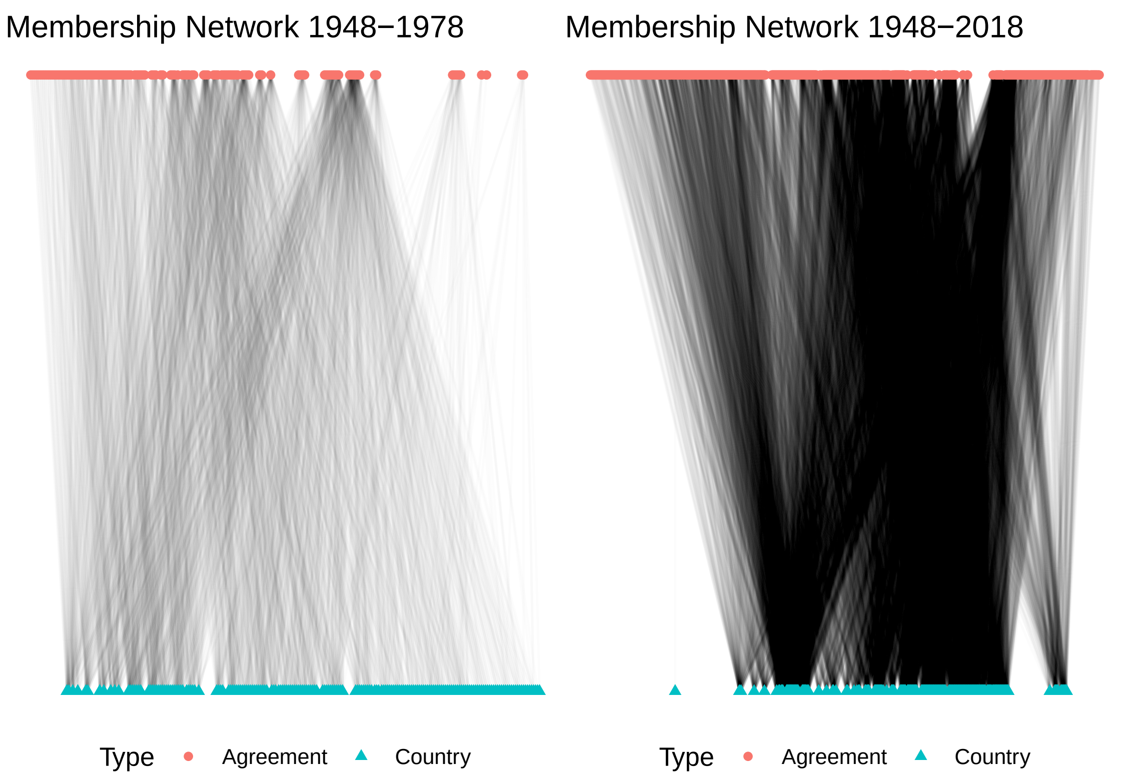

Figure 3.1: Bipartite Membership Network Snapshots

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 p^t_{ij} is the number of observed co-signed agreements between 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 the intensity of scientific collaboration within a bipartite network of scientists. Concurrently, it implies that bilateral treaties, ceteris paribus, carry a greater weight in the cooperation network than multilateral treaties, which 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 as "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 making them more relevant in our study.

We cannot, however, directly analyze this cooperation network as the resulting *naive* monopartite network, depicted in the first panel of 3.2, still suffers from two issues. First, nodes with larger degrees in the original bipartite membership network (e.g. agreements with a larger number of signatories or countries having signed a larger number of agreements) will intrinsically yield stronger edges in the projected network. In other words, if *country A* and *country B* are bound by the same five agreements and have each signed five agreements in total, they are conceptually "closer" than *country C* and *country D* who share the membership in ten 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 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 monopartite cooperation network to compare the corrected projection to. We, therefore, depart from Carattini et al. (2021) who consider only a single backbone extraction method. 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 consists of the individual permutated matrices I^*. The algorithm then constructs the one-mode projection of I^* as follows: $P^* =$

[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 network's time period as we apply the backbone extraction method to each temporal snapshot of the network.

$I^* \times [I^*]^T$. 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_{ij}^t 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_{ij}^B in the backbone P^B based on a significance level α.

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

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 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 backbone algorithms, which lie in the nature of the constraint they impose on the simulated networks. We will thus consider, in turn, the Fixed Row Model (FRM), the Fixed Degree Sequence Model (FDSM), and the Stochastic Degree Sequence Model (SDSM).

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

[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.

[9] This stands in opposition to canonical extraction algorithms that impose the constraint only *on average* over all simulated networks. This is done to speed up computation when dealing with vast networks.

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 bipartite network I_{ik} under the FDSM algorithm.

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

As Neal et al. (2021) point out, this methods main advantage is that it can alleviate the two issues plaguing our *naive projection* outlined above by controlling for the vector of degrees. As Vasques Filho and O'Neale (2020) point out, degree sequences of bipartite networks are chiefly responsive for the structure of their monopartite projections. The main disadvantage of such an algorithm is that it is ill-suited for large bipartite networks due to its computational complexity (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[10].

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. This implies that a country will be bound by the same number of agreements in all simulated networks as 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 possess 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

[10] We were fortunately still able to estimate the backbone via this method within about a day.

[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).

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). Furthermore, as we see in 3.2, the FRM is already too weakly constrained and does not solve the two issues of the naive projection. We, therefore, argue that the BiPCM algorithm would be ill-suited for our purpose. We now move to Stochastic Degree Sequence Model, the last backbone extraction algorithm we considered.

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 the degree sequence of agreements. However, the set of simulated networks satisfies this constraint only on the *average* of all simulated networks. This makes it very similar to the FDSM algorithm while imposing somewhat looser constraints. In other words, this implies that the average number of member countries of a given international agreement k in the set of simulated networks is equal to the number of member 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 number of agreements signed by country i in the observed network. Several methods exist to simulate networks satisfying this constraint. These are compared in terms of accuracy and computational speed in Neal et al. (2021). The authors show that the Bipartite Configuration Model (BICM) is the fastest and most accurate method to generate simulated networks satisfying the average condition specified above (Saracco, Straka, et al. 2017). Finally, given our bipartite network characteristics and the computational complexity of the FDSM algorithm, Neal et al. (2021) and Neal (2022) recommend the use of this algorithm over other solutions. 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 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. Therefore, we will not consider it in the further analysis as it does not solve the two issues we are trying 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 algorithms retain, on average, about 15 percent of the most significant edges present in the naive projection. This ensures that we capture the actual cooperative network and not a statistical artifact caused by the two issues we are trying to correct for. Furthermore, as we mentioned above, Neal et al. (2021) recommend the use of the SDSM extraction process given the bipartite membership network it was provided. We will, thus, compute the centrality scores on the basis of the latter two corrected networks.

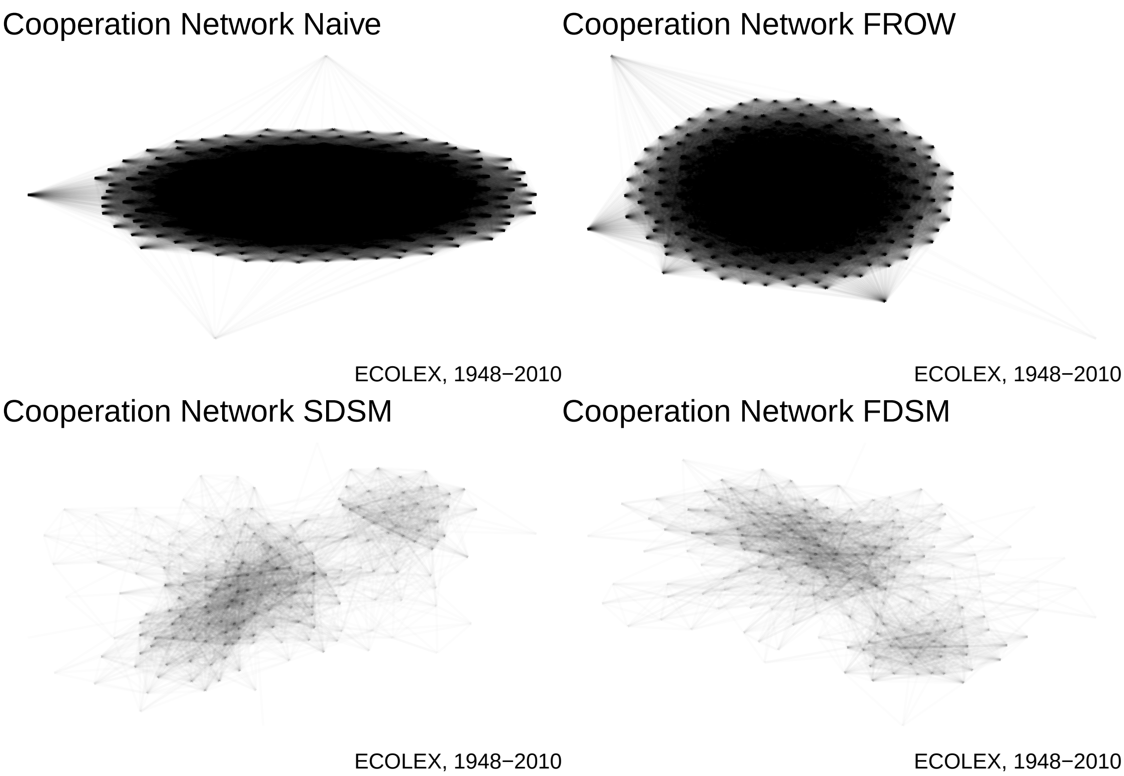

Figure 3.2: Comparing Backbone Extraction Methods

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. Thus, we construct proxies for the *embeddedness* of a country in the international environmental governance complex, which we hypothesize affect the rates of innovation and/or its competitiveness in direct and indirect ways. While there exists 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 transitivity or triadic closure measure, which we will describe 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 greater policy certainty. While we cannot formally distinguish both channels, it is reasonable to expect that the strength of a node captures a relatively greater share of the direct effects of the increased embeddedness on innovation as it measures the number of agreements a country is bound by. This measure can thus be interpreted as a measure for *international environmental stringency* and interpreted as a proxy for the *direct effects* of environmental governance on innovation and competitiveness. We will now extend our analysis by defining a proxy capturing the indirect effects of embeddedness within an international environmental collaboration network.

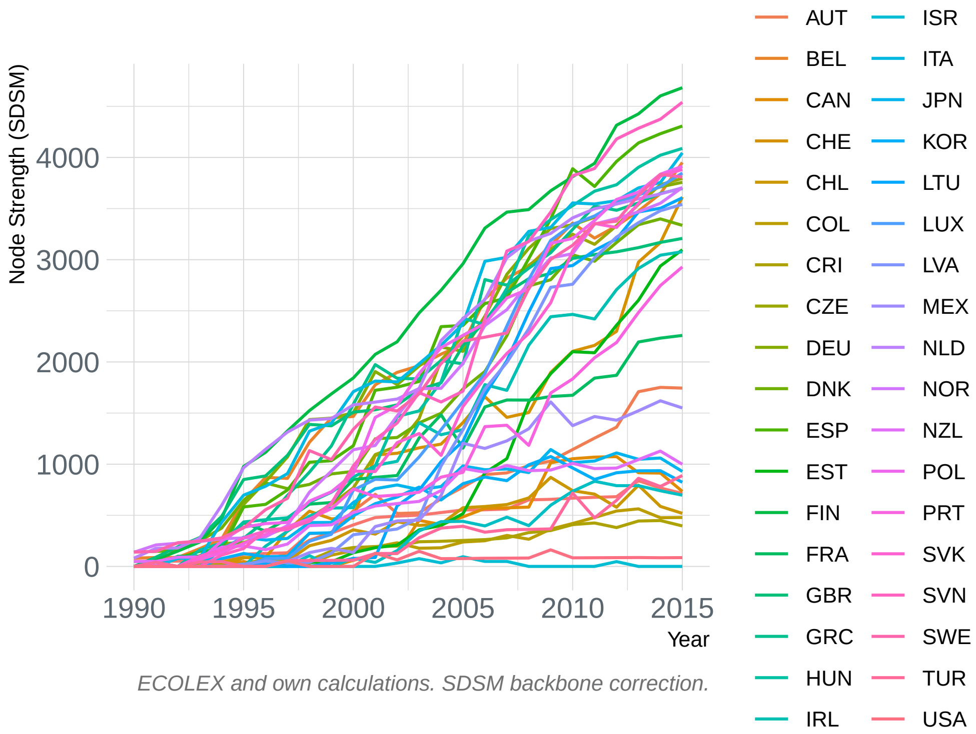

Figure 3.3: Strength 1990-2015

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). In the illustration below 3.4, 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 left. If we abstract from the weights, it is easy to see that the local transitivity coefficient, also known as triadic closure, of the orange node on the left figure is equal to 1, while the local transitivity of the orange node on the right-hand side figure is 0.

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.

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

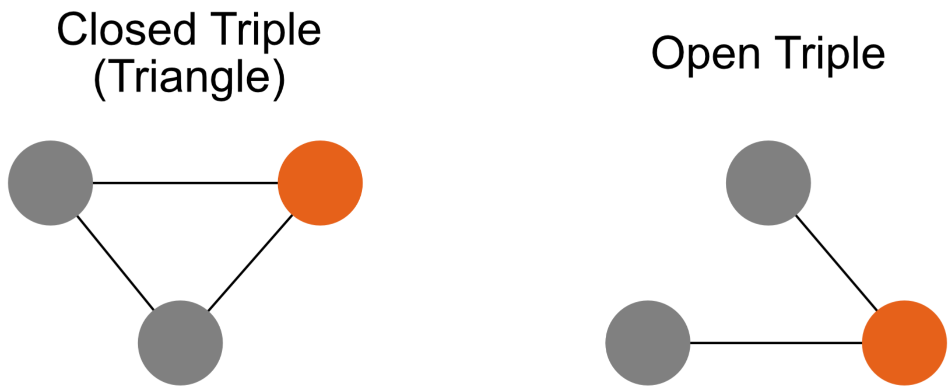

Figure 3.4: Transitivity

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 about the actions undertaken by each other 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 the sociological argument by Granovetter (1985) who posits that the cost of breaking a friend's 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 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). Thus, the central insight in our case of international cooperation is 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 innovation and competitiveness. Hence, this measure proxies the *indirect effects* that international embeddedness has on our dependent innovation and competitiveness variables.

Now that we have defined the computation of a novel set of measures characterizing interna-

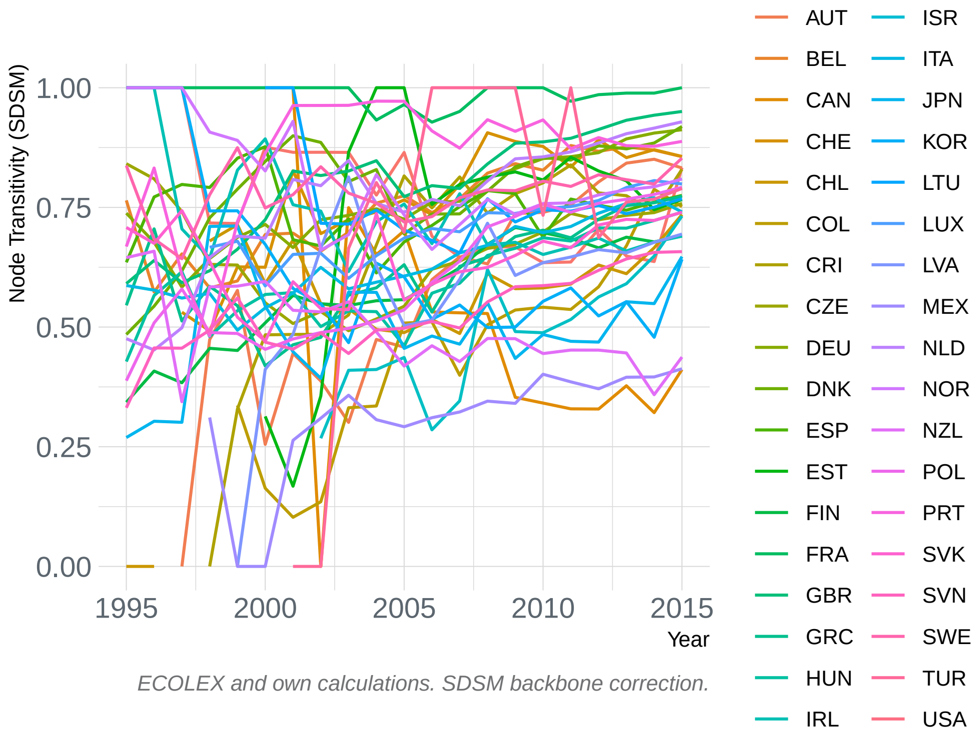

Figure 3.5: Transitivity 1995-2015

tional cooperation let us turn our attention to other, more standard variables that we include in our empirical analysis.

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 from 1990 to 2015 (Botta and Koluk 2014). As pointed out 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. 2019). 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 is constituted of individual indices of policy stringency such as emission taxes, trading schemes, environmental standards, and governmental R&D subsidies. These individual policy categories are then ranked 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 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 domestic environmental policies.

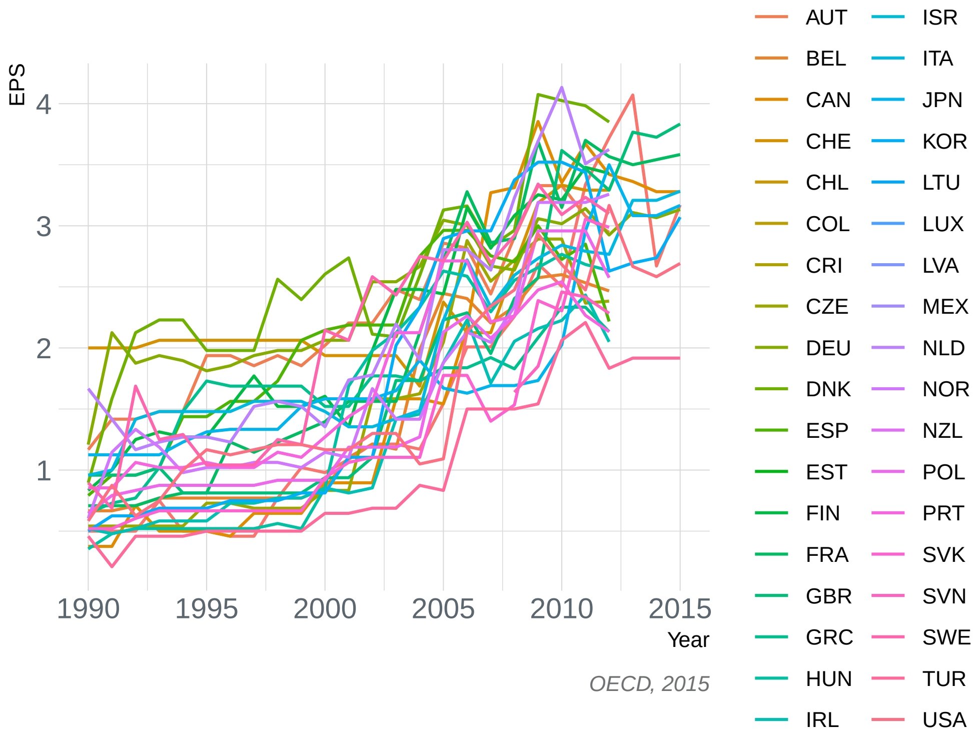

Figure 3.6: Environmental Policy Stringency 1990-2015

3.3.2 Innovation and Productivity 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. At the same time, Triadic Family Patent counts and the country-level share of environmental patents allow us to examine the effect of environmental policy on the *outcomes* of inventive activity (Popp 2019). However, a few caveats must be borne in mind when using patent counts as a proxy for innovative activity. First, as Martínez-Zarzoso et al. (2019) point out, using single country patent counts may lead to issues such as the double counting of patents registered in multiple patent offices. A related issue is that one might capture too many low-value innovations when using single patent office patent counts. In other words, if firms seek protection from multiple patent offices, it is likely to be for a valuable innovation due to the associated patenting costs. We remedy both issues by considering the count of *patent families* as described by Martinez (2010b) rather than individual patent office patent counts[13]. Finally, as pointed out by Popp (2019) and Martínez-Zarzoso et al. (2019) 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 in 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.

Triadic family patent counts show a similar pattern with respect to country-level heterogeneity. The top three countries are, once again, Japan, the United States, and Germany. 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.

Considering 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 intuitively be more strongly affected by environmental policy than other technologies.

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 growth on the independent domestic and international policy variables. To that effect, we will use the Total Factor Productivity growth developed by the Vienna Institute for International

[13] Triadic patent families are groups of similar patents that have been registered with the three main patent offices in the world: the USPTO, the Japanese Patent Office, and the European Patent Office

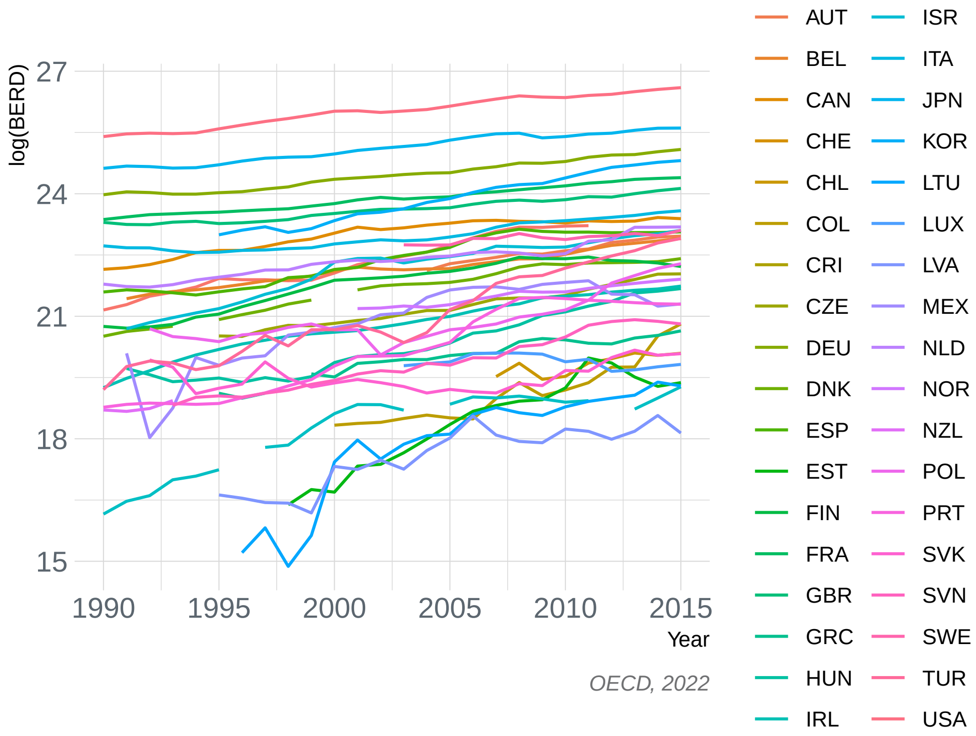

Figure 3.7: Business Expenditures in R&D 1990-2015

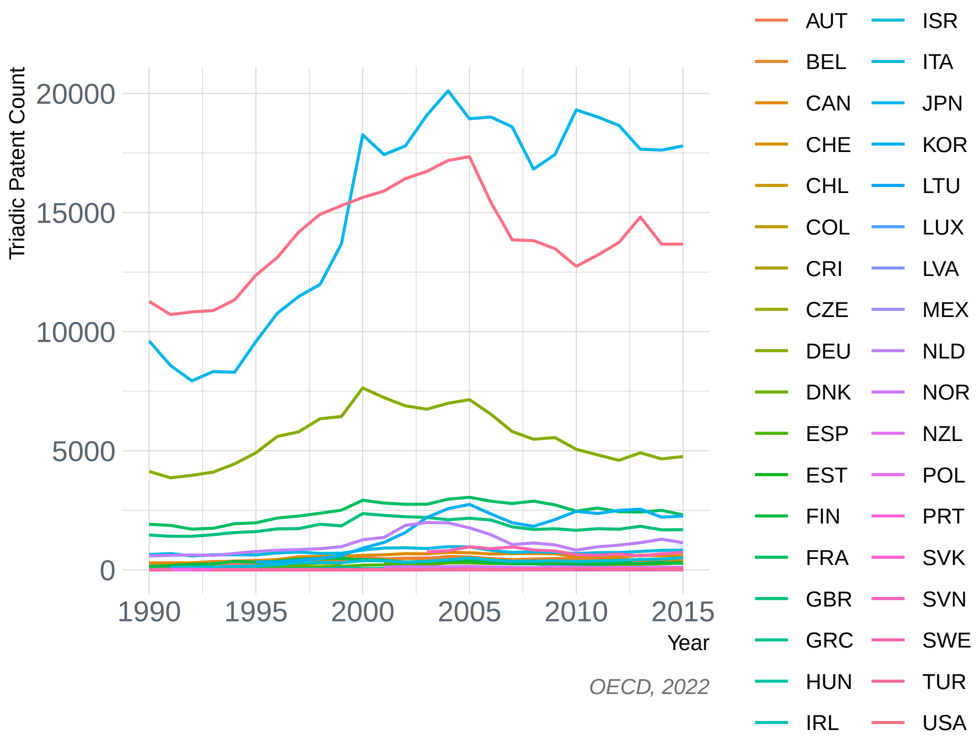

Figure 3.8: Triadic Patent Counts 1990-2015

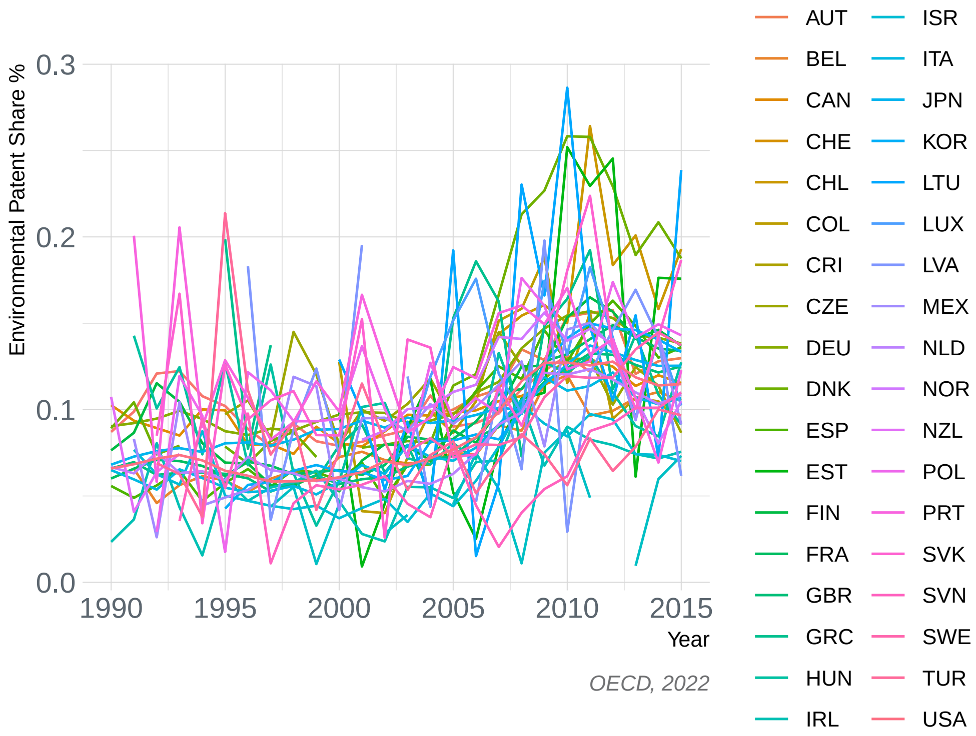

Figure 3.9: Environmental Patent Share 1990-2015

Economic Studies (Stehrer 2022). We will follow Martínez-Zarzoso et al. (2019) and use the "TFP0" decomposition of GDP based on capital stocks and hours worked only as defined below.

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

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 at around 0% to 2.5% where high-income countries tend to have a lower TFP growth rate than middle-income countries[14]. A second prominent feature is the impact of the 2008 financial crisis, which hit all countries' TFP growth hard. Although still more measured in the following years, the TFP growth rate recovered rapidly. Finally, note that we estimate this model from 1996 onward only due to data availability.

[14] Relative to OECD countries.

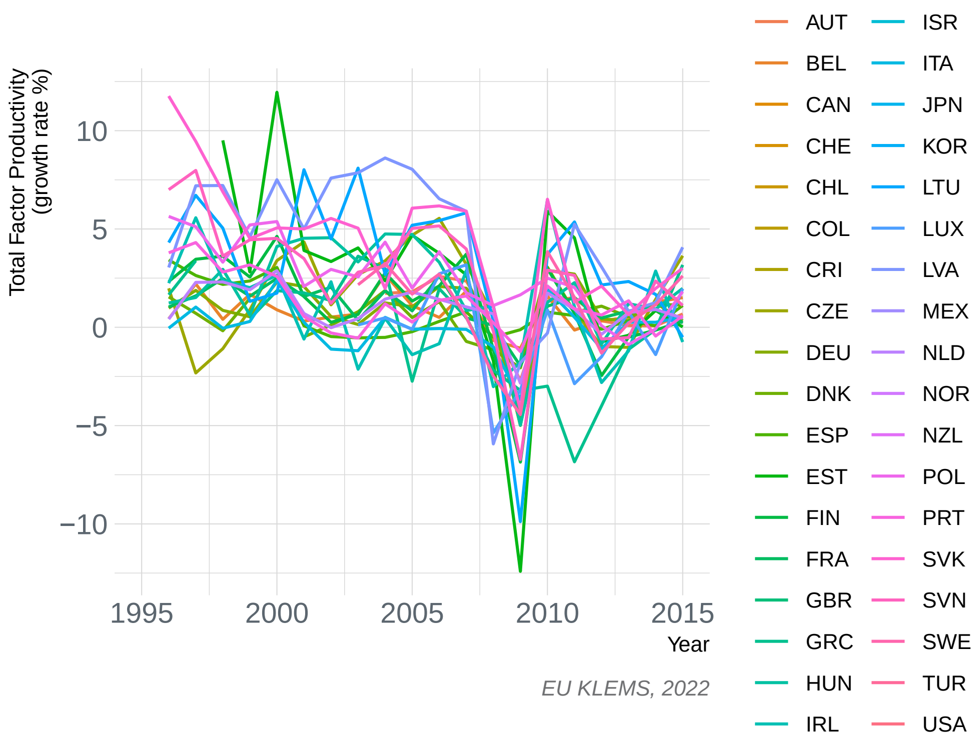

Figure 3.10: Total Factor Productivity 1996-2015

3.4 Correlations

Before moving on to the results, let us consider the correlations between our variables of interest. The first four columns in the correlogram 3.11 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, although less strongly. This evidence, therefore, yields the first hint for the confirmation of 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 seemingly suggesting that the *Strong Porter Hypothesis* may not be verified in our case. Let us now move on to the estimation of the empirical model defined in the beginning of this section at the next chapter to investigate these simple correlations further.

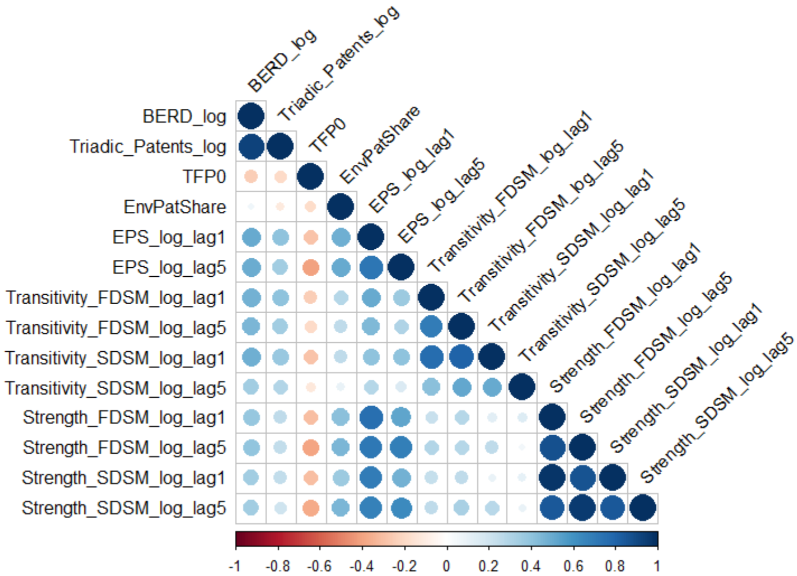

Figure 3.11: Correlations

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 latter with business expenditures on R&D (BERD) and triadic patent counts, respectively. We complement the analysis by looking at the share of environmental patents with respect to total patents to test the link between environmental policy and environmental innovation. We estimate the first two regressions with OLS while including fixed effects to account for unobserved country and time heterogeneity[1]. The third regression, which uses the share of environmental patents as a dependent variable, is estimated using a fractional logit approach (QMLE) (Papke and Wooldridge 1996). Let us now describe the results for our one-year lagged policy variables and our five-year lagged policy variables in turn.

4.1.1 One-year Lag:

Let us analyze the models including a one-year lag of our policy variables, by looking at the first, second, fourth, and fifth models, which are testing the *WPH* for one-year lagged policy variables.

[1]Patent counts may intuitively call for a Poisson regression. We follow Martínez-Zarzoso et al. (2019) 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.

We will subsequently examine the somewhat surprising complementary results we observe in our environmental patent share models. These results are described in table 4.1.

A one-year lag is a relatively short period of time for policy stringency to take effect and translate into innovative outcomes. Therefore, it is unsurprising if we do not observe significant effects of domestic policy stringency (EPS) on R&D investments and patent counts in either one of the specifications. Let us begin by analyzing the innovation output models i.e. the patent count models. $Strength_{i,\ t-1}$, 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 overall positive point estimates in the second and fifth model investigating patents, is although not always precisely estimated. 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 models is that the international policy variables supplant 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 within the one-year lag specifications.

On the innovation input side, however, we do not observe significant effects of either international policy variable on business expenditures on R&D. Additionally, the point estimates are inconsistent 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 tend to be 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. (2019) 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 consistently negative effect on the share of environmental patents. These coefficients cannot 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 domestic policy stringency indicator estimates 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 is that the FDSM correction process is more likely to produce high leverage transitivity scores since it retains fewer cooperative edges than the less restrictive SDSM correction and that our transitivity measure relies on the presence of three edges to exists as opposed to one in the case of strength centrality. However, we can see that, overall, increased stringency, whether national or international, seems to have a negative effect on the share of environmental patents, which goes against our initial hypothesis that environmental innovation would be more affected by policy variables than regular innovation. Recall that we found a negative correlation between triadic patent counts and the share of environmental patents, which partially hinted at this result[2]. Further empirical investigations are thus necessary to determine the cause of this surprising result.

Furthermore, we 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 only significant in the first, second and fifth models. This is not surprising given that high-value-added processes such as R&D require both specialized human and physical capital

[2] See figure 3.11

found in wealthier countries. Curiously, Martínez-Zarzoso et al. (2019) 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[3]. 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 Brunnermeier and Cohen (2003) who argue that internationally competitive industries are more likely to innovate if foreign markets are already internationally competitive[4]. The impact of the ratio of import intensity on innovative activity is ambiguous across our specifications. This result illustrates the continued theoretical debate on the effect of market concentration on innovative activity (Levin et al. 1985; Schumpeter 1943). The divergence between the results further illustrates this debate obtained by Rubashkina et al. (2015) and Martínez-Zarzoso et al. (2019). 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 about the impact of import and export intensity on innovative activity. Further empirical research is therefore needed to assess the role of these two variables on innovative activity precisely.

Overall, one can draw three main conclusions from the analysis of these one-year lagged policy measures. First, we cannot confirm the *WPH* based on these results as the environmental policy stringency index is insignificant in either the R&D expenditure or the patent count model. This result is broadly consistent with Martínez-Zarzoso et al. (2019). 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, which illustrates the positive impact of international environmental governance on innovation. Third, we observe somewhat heterogeneous results across backbone extraction specifications which shows the need to ensure that our results are robust to the method used. This third observation shows that studies relying solely on one method without being guided by theoretical considerations or computational

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

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

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.

	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

4.1.2 Five-year Lag:

Much like our analysis of the one-year lag results presented in the previous subsection, we subset our analysis into two parts. We first consider the models describing the *WPH* before turning our attention to the complementary environmental patent share regressions. All regressions assessing the *WPH* have been estimated with Ordinary Least Squares and include country and time fixed effects. The regressions evaluating the impact on the share of environmental patents have once again been estimated using a fractional logit regression via QMLE.

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 should 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 R&D. These results are in line with Martínez-Zarzoso et al. (2019) 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. (2019) 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. They partly explain this by measurement issues that plague this proxy. These may also affect our analysis. A second cause for this inverse relationship could be due to the 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 but not when considering 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 hypothesize that these international policy signals operate with the same lag structure which may not be the case. Further modeling efforts are therefore required to understand this surprising result better. 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, 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.

Although all positive, our economic variables 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 in the BERD specification. On the other hand, the impact of all three economic variables is highly significant when considering 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[5].

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

We can once again derive three critical 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. (2019) and verifies the *WPH* in the case of R&D expenditures. Second, we show that transitivity has a positive effect across all specifications. The point estimates of the effect of transitivity are larger than the pure effect of policy stringency. This shows the importance of having a stable policy environment to reduce the policy risk associated with innovative investments, which are already inherently risky and remains constant with our observations under the one-year lag specification. 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*.

[5] 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) which may be due to measurement errors in patent counts.

	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 and our economic covariates in the same lag and backbone extraction specifications than in the *WPH* model presented above. Since the dependent variable is a growth rate and our covariates are all log-linearized, the model can be interpreted similarly to the ones testing the *WPH* i.e. as the effect of a 1% change in the dependent variable on TFP growth rate in 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 significant effect on the total factor productivity growth rate. Although seemingly confirming the strong version of the Porter Hypothesis, we should interpret these results with care as they are relatively large. They cannot be directly compared to the results Martínez-Zarzoso et al. (2019) found because their results considered an older *level* index of TFP of the EU KLEMS dataset (Stehrer 2022) and excluded the aftermath of the global financial crisis from their sample[6]. Therefore, we are unable to confirm the *Strong Porter Hy-*

[6]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 (Van Beveren 2012). We estimated all models with time fixed effects to account for these.

pothesis as further research with these old level indicators is required to understand better these results[7]. The second observation one can derive from these results is that the international policy variables are not significant or consistently estimated across lags. Therefore, we cannot make an inferential claim on the nature of the relationship between the embeddedness of a country in the international environmental cooperation network and total factor productivity growth.

	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 in parentheses. * significant 10%, ** significant 5%, *** significant 1%.
Models are estimated from 1996-2015 due to data availability using OLS.

Table 4.3: Strong Porter Hypothesis

4.3 Robustness Checks:

The first and most crucial 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 exists no precise theoretical foundation that would motivate the choice of one backbone extraction method over another. This leads us to caution the reader against using a *single* backbone extraction process to correct bipartite networks as its choice may have consequences on the subsequent inferential process. This stands in contrast with 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. Therefore, we recommend both

[7] We were unsuccessful in replicating the results of Martínez-Zarzoso et al. (2019) due to data availability constraints of their version of the TFP index.

the elaboration of a theoretical justification for the selection of the backbone extraction method as well as the use of various extraction methods to show the robustness of one's results[8].

Additionally, standard econometric checks were performed as well. The potential 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 of simultaneity issues whereby firms in less innovative countries may successfully dismantle environmental legislation[9]. Studies with lagged policy variables such as Rubashkina et al. (2015) , Martínez-Zarzoso et al. (2019) , and ours assuage these fears by pointing out that future firms cannot influence past environmental stringency levels, 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 the largest levels of business expenditures on R&D and the largest patent counts[10]. The results are virtually identical than under the full sample showing that our results are robust to this test. Now that we have laid out the main results, discussed their implications, and tested their robustness, let us now conclude this study in the next chapter.

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

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

[10] Results are presented in the appendix.

Chapter 5

Conclusion

We conclude by highlighting the main contributions of the present work to the description of the intertemporal evolution of the international environmental collaboration network and, in particular, its impact as a policy signal encouraging innovation. We were able to consistently identify a positive impact of social capital proxied by transitivity on our measures of innovation. This effect is larger than the pure effect of domestic policy stringency, which underlines the importance of a stable international environmental governance environment to reduce the risk emanating from changing policies. It also shows that global environmental cooperation can take on such a risk-reducing role by being tightly knit, which would, in turn, favor future cooperation due to the building of trust among actors in the network, which may lead to a positive feedback loop. This contrasts with the results we obtained for strength centrality, which provided less consistent point estimates across lag and backbone specifications and are smaller overall than transitivity. Although less consistent, the fact that indirect effects of international environmental governance supplant direct effects resonates with Bhattacharya et al. (2017) who find that domestic policy uncertainty affects innovation rather than the domestic policy itself. Finally, we nuance this last point as we were able to confirm the weak version of the Porter Hypothesis in the R&D expenditures model within the five-year lag but not in the one-year lag specification, which is consistent with the results of Martínez-Zarzoso et al. (2019), Rubashkina et al. (2015), and Jaffe, Peterson, et al. (1995). We, therefore, conclude that a mix of stringent domestic policy associated with a stable, tightly knit position within the international environmental cooperation network is likely conducive to innovative activity.

5. Conclusion

Two main empirical puzzles remain that must be addressed in future research endeavors. First, we find that environmental innovation is less affected by environmental policy stringency in the short term than total innovation. This difference disappears in the five-year lag specification. This goes against our initial hypothesis that there would be a relatively stronger effect on environmental innovation. A sectoral level analysis linking research funding and innovation outputs to specific international policy would allow us to perform more precise estimations. Furthermore, we would be able to leverage the full richness of the Ecolex dataset used in this study by disaggregating international environmental agreements in specific sectors and matching them with the corresponding economic sector (UNEP, IUCN, FAO 2022). The second puzzle that remains to be addressed is the unusually high coefficient estimations for our environmental policy stringency proxy, as well as inconsistencies in the point estimates of the international policy variables across specifications in the model testing the strong version of the Porter Hypothesis. Hence, we cannot confidently confirm the latter, and further research to improve the econometric modeling is required.

Concurrently to these empirical findings, our study furthers the theoretical understanding of the implications behind the choice of a backbone extraction method to correct the weighted projections of bipartite networks. These choices are often key to correct inference, and when a choice between two algorithms cannot be theoretically justified, both should be considered to ensure robust inference. In our case, the main difference between the two algorithms that were retained on theoretical grounds is that the confidence intervals of our coefficient estimates tend to be larger in the model imposing harsher constraints on the set of simulated networks since it retained fewer edges in the corrected projection of the cooperation network. Since we might not have detected effects if we only reported a single backbone extraction method, we recommend that future research consider multiple theoretically founded extraction methods.

Therefore, we conclude on the empirical side that a combination of stringent domestic environmental policy and a position with a high level of social capital within the international environmental governance network are conducive to innovation. On the methodological side, we highlighted the importance of the careful choice of backbone extraction methods which need to be grounded in theory to ensure that inferential claims are robust to this choice.

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, one 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 (1 year lag)

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 (5 year lag)

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