Three Essays on Environmental Economics

by

Asrafuzzaman

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Abstract

In the era of globalization, countries are adopting different environmental policies to mitigate the adverse impact of climate change. A better understanding of how these policies shape firms' decisions and impact innovation and the environment will help policymakers make informed decisions. The thesis aims to study firms' decisions regarding FDI and exports as countries introduce emission taxes and the link between innovation, environmental policy, and emissions.

The first chapter theoretically studies the firms' choice between FDI and export in a model with two countries, where each country has a single firm producing a polluting good that is subject to a per-unit emission tax. We consider a three-stage game theoretic model with both *ex ante* and *ex post* emission tax. In the case of *ex ante* emission tax, the government sets an emission tax, then firms decide between export and FDI and finally, firms choose their production level. In the *ex-post* case, firms choose between FDI and export first, and then the government decides its emission tax level, followed by the firm's production decision.

In the first case, when taxes are determined in the initial stage of the game, if the fixed cost of FDI is sufficiently high, both firms opt for exporting. However, if the fixed cost of FDI is sufficiently low, firms choose both FDI and exporting. For intermediate fixed costs, the decision between FDI and exporting depends on the level of emission taxes and tariffs. In the second case, with *ex post* emission taxes, anticipating that countries will set higher emission taxes if both firms engage in FDI, only one-way FDI from either country occurs in equilibrium.

The rest of the thesis examines the relationship between innovation, environmental stringency, and emissions. In doing so, the second chapter provides a comprehensive review of the recent literature that uses patent data with a specific emphasis on recent trends. This chapter also introduces the concepts and datasets used in the following two empirical chapters that use patent data, particularly green patent data, as well as new measures of environmental stringency. Furthermore, the second chapter also explores recent trends in green patent applications and environmental stringency.

The third and fourth chapters attempt to answer empirical questions using concepts introduced in the second chapter, using patent data from PATSTAT. In the third chapter, we investigate whether environmental policy stringency induces green innovation in OECD countries, the weak version of the Porter hypothesis. We use green patents to proxy innovation, while the newly introduced environmental stringency index proxies environmental stringency.

Some of the main empirical findings are as follows. First, we do not find evidence of the weak version of the Porter hypothesis. Rather, our results suggest the presence of the technology lock-in hypothesis. Second, we find that cumulative knowledge of green technology significantly increases the likelihood of having more green innovation. This is consistent with the path dependence of green innovation and the importance of knowledge accumulation for future innovation.

The fourth chapter studies whether green patents help reduce carbon dioxide (CO_2) and other Greenhouse Gas (GHG) emissions. The main findings show that increasing the number of green patents is not associated with a reduction in CO_2 emissions. This could be due to the rebound effect, which is discussed in energy economics. The rebound effect occurs when the savings from improved energy efficiency are offset by changes in an individual's behaviour.

Preface

This dissertation comprises a literature chapter, two empirical articles, and a theoretical article. The theoretical article, titled "Foreign Direct Investment, Export, and Emission Tax," is a collaborative work with my supervisor, Professor Corinne Langinier, and committee member, Professor Amrita Ray Chaudhuri. I was primarily responsible for the initial model development and drafting of the manuscript, while co-authors contributed to the motivation, development of the extended model, and manuscript editing. The other two articles are single-authored, though my supervisor provided valuable suggestions and comments at every stage. No part of this thesis has been previously published.

Dedication

In memory of my father, thank you, Abbu.

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Contents

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List of Acronyms

CCMT	Climate Change Mitigation Technology
CCUS	Carbon Capture, Utilisation and Storage
CPC	Cooperative Patent Classification
DTC	Directed Technological Change
EKC	Environmental Kuznet Curve
EPO	European Patent Office
EPS	Environmental Policy Stringency
EST	Environmentally Sustainable Technologies
EU	European Union
FDI	Foreign Direct Investment
GHG	Greenhouse Gases
GMM	Generalized Method of Moments
IPC	International Patent Classification
IPCC	Intergovernmental Panel on Climate Change
JPO	Japanese Patent Office
OECD	Organisation for Economic Co-operation and Development
PACE	Pollution Abatement Costs and Expenditures
PATSTAT	Worldwide Patent Statistical Database
PCT	Patent Cooperation Treaty
PHH	Pollution Haven Hypothesis
R&D	Research and Development
USPTO	United States Patent and Trademark Office
WDI	World Development Indicator
WIPO	World Intellectual Property Office

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Introduction

The adverse effects of climate change are now increasingly evident. In the twenty-first century, global Greenhouse Gas (GHG) emissions have consistently increased compared to three previous decades, intensifying climate change (Crippa et al., 2021). As a result, countries are implementing different environmental policies to mitigate the adverse effects of climate change.

Environmental policies in one country can have significant implications for other countries (Babiker et al., 2003; Schwerhoff et al., 2018), leading to potential environmental imbalances due to discrepancies in emission taxes. Consequently, firms may respond to policy changes through actions such as exporting and Foreign Direct Investment (FDI), which will affect emission levels. These decisions might be influenced by *ex ante* or *ex post* policies. Firms from strict environmental standard countries might shift their dirty plants to lax environmental standards countries, known as Pollution Haven Hypothesis (PHH). However, empirical studies testing PHH provide mixed results; some support the hypothesis (Gray, 2002; Xing and Kolstad, 2002; Zhang and Fu, 2008; Aliyu, 2005), while others do not find sufficient evidence (Eskeland and Harrison, 2003; Shen, 2008; Fabry and Zenghi, 2002). The choice of using FDI or export might depend on regulation, innovation, market size, and import tariff (Dong et al., 2012). It is essential to understand why a firm from one country will choose to export or use FDI to sell its dirty product in another country, with most likely different environmental policies.

In the first chapter, we develop a game-theoretic model of two asymmetric countries where each country has a single firm. We assume that one country is a developed country with cleaner technology while the other country is a developing country with relatively dirty technology. We consider a three-stage game in which, in the first stage, each country's government chooses an emission tax level (*ex ante*) that firms observe. In the second stage, each firm decides whether to export or use FDI to enter the other country's market. In the third stage, both firms compete in quantities in the countries where they operate. Our goal is to understand under what conditions firms decide between the option of FDI and export to enter the other country's market. A firm might decide differently if they choose FDI and export in the game's first stage. So, we also analyze the case of *ex post* emission tax, where the government chooses its tax in the second stage. We assume that emissions are local and that emitters must pay emission tax on output. Unlike the other studies, we consider both *ex ante* or *ex post* emission tax scenarios. Our results suggest that in the *ex ante* emission tax scenario, both firms might engage in FDI, while in the *ex post* scenario, only one-way FDI will occur in equilibrium.

However, stricter environmental policies might provide firms with an incentive to innovate and invest in greener technologies to comply with environmental regulations. It is generally considered that strict environmental regulations would increase production costs and, thus, reduce competitiveness (Rauscher, 2005). Porter (1990, 1991) refuted this idea by using the examples of Europe and Japan. This is known as the Porter hypothesis, which suggests that strict environmental regulations can lead to innovations and increased efficiency, which can ultimately result in economic benefits for companies and society as a whole. Proponents of strict environmental regulations laud Porter's hypothesis. Two versions of the Porter Hypothesis (PH) have been explored in the literature: the strong and the weak versions. The strong version assumes that environmental regulations will increase competitiveness, while the weak version hypothesizes that strict environmental regulations will increase innovation. However, the theoretical foundation of the Porter hypothesis can be challenged on the grounds of rationality and competitive markets (Rauscher, 2005).

In competitive markets, profit-maximizing firms would choose Environmentally Sustainable Technologies (ESTs) if it is economically feasible and profitable compared to traditional dirty technologies. Empirical evidence for Porter's hypothesis is mixed (Rauscher, 2005; Ambec et al., 2013). Thus, it is important to understand how the stringency of environmental policies will affect the incentive to innovate.

In 2014, the OECD developed the Environmental Policy Stringency (EPS) index to measure the strictness of environmental policies, taking into account both market-based and non-market-based instruments. In 2022, a new EPS version was released, adding support policies for green innovation to the existing market-based and non-market-based instruments. The EPS index is country-specific and allows for international comparisons of environmental policy strictness. Environmental stringency is determined by the extent to which environmental policies place a price on behavior that is harmful to the environment.

In the second chapter, we survey the recent trends and literature on green patents, and in the third chapter, we study whether environmental policy stringency induces green innovation for OECD countries, which is the weak version of the Porter hypothesis. The number of green patents started to increase in the early 1990s, and this trend continued until the early 2010s. We use the new version of the EPS to proxy environmental policy stringency and the count of granted green patents from the Worldwide Patent Statistical Database (PATSTAT) maintained by the European Patent Office (EPO) as a proxy for green innovation. We contributed to the literature by using the newly available EPS index, disaggregated patent data from PATSTAT, and a pre-sample mean of the patent to represent country-level fixed effect in a panel count data model. We do not find evidence for the weak version of the Porter hypothesis, which is consistent with the findings of other researchers (Ambec et al., 2013; Brunnermeier and Cohen, 2003). This result might be due to the technological lock-in effect, which states that existing inefficient technology might remain prevalent because of widespread adoption, as outlined by

Foxon (2002) and Pantaleone and Fazioli (2022). In addition, incremental change in environmental policy might not spur green innovation (Gerlagh et al., 2022).

Rather than trying to avoid complying with strict environmental policies in their countries, firms could comply with them by investing in environmentally efficient technologies. Green technologies, or ESTs, help protect and improve the environment. If properly implemented, green policies and technologies can boost productivity and spur growth and jobs (OECD, 2017). A new technology can be protected by a patent, which grants its owner a temporary monopoly right for their invention. As patent applications are usually filed early in the research process (Griliches, 1998), the patent count could represent the output of the innovative activity of a country (Popp, 2019). In addition, patent data is highly disaggregated; thus, patent counts are widely used to proxy innovation (Albino et al., 2014; Popp et al., 2011, 2019; Raiser et al., 2017). The adoption of ESTs might reduce carbon dioxide (CO_2) emissions and mitigate the adverse effects of climate change. For example, the use of an electric vehicle or the adoption of wind and solar-generated energy could curb emissions. From 1990 to 2010, green patents grew sixfold, whereas the growth of all other patents was only twofold (Haščič and Migotto, 2015). It is important to understand whether green innovation has a positive impact on emission levels. In the fourth chapter, we empirically investigate whether the surge in green patents has an impact on CO_2 and other greenhouse gas emissions.

We utilize data from the PATSTAT maintained by the EPO to proxy innovation in green technologies. To measure innovation, we use the stock of knowledge instead of a simple patent count, as suggested by Popp et al. (2011), since knowledge diffusion takes time and decays over time. In order to investigate the impact of human activities and green innovation on the environment, we adopted the Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) framework. We use pooled OLS and panel fixed effect model, and since CO_2 emissions are dynamic and can be influenced by previous periods, as a robustness check, we use a dynamic panel data model within the STIRPAT framework. We find that green patents are not associated with the reduction of CO_2 emissions for OECD countries, and a strong rebound effect may contribute to this outcome that is also consistent with previous literature (Weina et al., 2016; Vélez-Henao et al., 2020).

Chapter 1

Foreign Direct Investment, Export, and Emission Tax

1.1 Introduction

The liberalization of economic policies and trade has enhanced economic prosperity in the twenty-first century. Foreign Direct Investment (FDI) and international trade have become essential vehicles of globalization. According to the United Nations Conference on Trade and Development (UNCTAD), FDI inflow into developing countries represented 47% of total FDI in 2017. Increasing FDI flows into developing countries have initiated a substantial debate about the interaction between FDI and environmental regulations. Domestic regulations can influence FDI flows, as firms may seek to avoid stringent environmental regulations. FDI also has an impact on the host country's pollution. The presence of Multinational Companies (MNCs) in developing countries may reduce local environmental standards below suboptimal levels, known as the 'race to the bottom' or 'regulatory chill effect' (Dong et al., 2012). For instance, Chinese provinces compete intensely for foreign capital and promise preferential treatment to potential foreign investors (Esty and Mendelsohn, 1995).

Several studies have highlighted the problem of pollution leakage, a reduction in pollution in developed countries at the cost of increasing pollution in developing countries (Baylis et al., 2014; Golombeck and Hoel, 2004). Environmental literature also delves into the Pollution Haven Hypothesis (PHH), which is based on trade theory. It predicts that more stringent environmental policies (e.g., emission tax) shift pollution-intensive production toward low abatement cost regions (Gray, 2002). According to the World Investment Report 2023, the total global FDI was 1.3 trillion USD in 2022. In Africa, FDI fell back to the 2019 level of USD 45 billion after reaching unusually high in 2022; FDI inflows in developing Asia were flat at USD 662 billion, while flows to Latin America and the Caribbean increased by 51 percent (UNCTAD, 2023). FDI flows might impact the global environment due to transboundary pollution (Dong et al., 2012). In 2023, overall trade growth was 1.0 percent; after the robust increase of 5.3 percent in 2022. For the world as a whole, the trade-to-GDP ratio was 62.56% in 2023 and developing countries have the highest trade-to-GDP ratio. MNCs were responsible for more than half of the world's exports in 2014 (OECD, 2020). Additionally, FDI is no longer a one-way flow from developed to developing countries. From 2003 to 2014, the Chinese FDI flow grew from 28.5 billion to 1231.2 billion (Lin, 2016). In 2005, only 10% of Fortune Global MNCs were from an emerging market; however, in 2015, this increased to 40% (Casanova and Miroux, 2016). MNCs can choose between exports and FDI to serve foreign markets.

A manufacturing plant established by an MNC, either in its home country for domestic market and export or in a foreign country through FDI, will generate emissions in the form of GHGs. Emissions could be transboundary or local; in the case of transboundary pollution, no country can evade the consequences. To curb emissions, governments can take different measures, such as implementing emission taxes or environmental standards. However, firms might respond to these measures by deciding where to locate their plant to serve foreign markets; they can either export or use Foreign Direct Investment (FDI).

Despite the importance of FDI and export in today's economy and environment, its relationship with environmental policies (e.g., pollution tax) has not been extensively discussed theoretically in the existing literature. In addition, as more and more countries implement carbon tax policies, policymakers should have a clear idea of the implications of carbon tax on FDI and exports. We develop a theoretical model to investigate how firms choose between FDI and export in response to pollution tax implemented by governments.

In this paper, we consider a two-country model to investigate firms' FDI decisions and the consequent pollution impact. The two countries are asymmetric: one has a higher demand, lower marginal cost of production, and cleaner technology, and it represents a developed country, while the other represents a developing country. Each country has a single firm that produces a polluting product and must pay a per unit emission tax. Pollution damage is assumed to be local to the country where emissions occur. Each firm produces locally to sell in its domestic market. It can also sell its product in the foreign market either by exporting or via FDI. The latter involves setting up and operating a production facility in the foreign country. While exporting involves paying a per unit tariff, FDI involves a fixed cost to set up a firm in the foreign country. This tradeoff is further complicated by each country strategically setting emission taxes.

Our main contribution to the related literature is to examine how the timing of setting the emission taxes affects the above trade-offs. While most of the previous literature assumes that countries set the emission taxes before firms make their FDI decisions, we also consider the case where the countries set the emission taxes after firms make their FDI decisions. The timing of setting taxes is expected to change firms' decisions. For instance, Laffont and Tirole (1996) show that, in equilibrium, firms' R&D decisions change depending on the timing of tax implementation.

When taxes are set *ex ante*, our results are in line with the previous literature. When the fixed cost of setting up a firm in the foreign country is sufficiently high, each firm chooses to produce in its own country and export to the other. When the fixed cost of setting up a firm in the foreign country is sufficiently low, each firm chooses to produce in its own country to serve its domestic market and also engage in FDI by setting up a production facility in the other country to serve the foreign market. For intermediate values of the fixed cost, the outcome depends on the tariff level and the emission taxes set by each country. For higher tariff levels, the tariff-jumping effect induces firms to engage in FDI rather than exporting. When the emission tax of one country is higher than that of the other, the firm in the country with the higher tax engages in FDI in order to avoid paying the tax in its own country, while the firm in the country with the lower tax chooses to export to avoid paying the tax in the foreign country. In equilibrium, we find that the firm in the developed country engages in FDI but the firm in the developing country does not. Moreover, when such FDI occurs, emission shifts away from the developed to the developing country. When taxes are set *ex post*, there are three main departures from the case where taxes are set *ex ante*. First, even if the fixed cost is low, both firms never engage in FDI simultaneously in equilibrium. Second, unlike in the case where taxes are set *ex ante*, it is possible that the firm in the developing country engages in FDI while the firm in the developed country does not, in line with recent evidence. These differences occur because in the *ex ante* case, the equilibrium taxes are sometimes restricted to corner solutions, whereas in the *ex post* case, we always derive interior solutions. That is, in the *ex ante* case, countries are restricted by the fact that firms may change their FDI decisions based on their choice of tax level, whereas in the *ex post* case, since FDI decisions are already fixed, countries can achieve the unconstrained maximum while choosing taxes given the prevailing FDI structure. In the *ex post* case, foreseeing that countries will set higher emission taxes if both firms engage in FDI, firms avoid this scenario. Our findings thus suggest that in a world where governments are unable to commit to taxes a priori, two-way FDI (i.e., FDI from developed and developing countries simultaneously) is discouraged. However, one-way FDI could occur in either direction (i.e., either from the developed to developing or from the developing to developed country), unlike in the *ex ante* case where FDI only flows from the developed to developing country in equilibrium. Another important departure from the *ex ante* case is regarding the re-distribution of emissions across countries induced by FDI. While in the *ex ante* case, there is an unambiguous increase in emissions in a country when its firm switches from operating a foreign production facility to becoming a local firm that exports, in the *ex post* case, this does not hold. This is because, in the *ex post* case as opposed to the *ex ante* case, the emission tax rate is higher when the firm is local rather than when the firm engages in FDI since a local firm that exports emits more pollution than a firm that serves only the domestic market. Thus, while we are able to retrieve the standard intuitive results in line with the previous literature when we consider *ex ante* tax setting, we show that the results change significantly when taxes are set after FDI decisions have been taken.

The structure of the chapter is as follows: Section 2 presents a brief literature review. The model is introduced in Section 3. Section 4 presents the Cournot competition, which represents the last stage of the game. In Section 5, we solve the game in the first scenario, when both countries choose *ex ante* their level of emission taxes. Section 6 deals with the second scenario when the countries choose *ex post* their emission taxes. In Section 7, we compare the findings of both scenarios before concluding in Section 8.

1.2 Related Literature

To investigate firms' choice between FDI and export, we explore three strands of literature that study firms' location choices. The first one covers the Pollution Haven Hypothesis (PHH). The second strand of literature studies environmental economics and international trade economics, which studies firms' location choices. Finally, the third one covers firms' location choices from the perspective of environmental economics and industrial organization.

The first strand of literature has extensively studied the Pollution Haven Hypothesis (PHH), which predicts that more stringent environmental policies will increase compliance costs and, over time, shift pollution-intensive production toward low abatement cost regions, creating pollution havens and causing policy-induced pollution leakage (Baylis et al., 2014). However, empirical evidence of PHH is mixed. Earlier studies did not find significant evidence of the PHH (Dean et al., 1992; Grossman and Krueger, 1991; Repetto, 1995). For instance, Grossman and Krueger (1991) have used a computable general equilibrium model to study the effect of the introduction of the North American Free Trade Agreement (NAFTA) on pollution in Mexico. They found little evidence of PHH in export-oriented industries as trade liberalization shifted Mexican specialization in sectors that cause less than average amount of environmental damage.

On the other hand, later contributions found evidence of PHH (Gray, 2002; Xing and Kolstad, 2002; Zhang and Fu, 2008; Kellenberg, 2009). Such evidence could be industry-specific (i.e., the furniture industry), as it requires the use of toxic chemicals for paints and varnishes (Gray, 2002). Lax environmental regulations in a host country seem to be a significant determinant of FDI from the U.S. firms in heavily polluting industries (chemical and primary metal), and is insignificant in less polluting industries (electrical and food industry) (Xing and Kolstad, 2002). Using a panel dataset of Chinese provinces from 1998 to 2002, Zhang and Fu (2008) found that foreign firms prefer to set up plants in regions with relatively weak environmental regulations. Environmental policies seem to be an essential determinant for FDI flow from firms of OECD countries to less developed countries (Aliyu, 2005). Eskeland and Harrison (2003) found that the relationship between FDI and pollution intensity depends on the pollutant. Using Chinese provincial data from 1993 to 2002, Shi (2008) did not find evidence of PHH for most pollutants.

In the framework of the PHH hypothesis, some contributions have also studied the location choice of plants by Multi-National Companies (MNCs) depending on environmental regulations, even though most of these studies failed to find evidence of PHH (Letchumanan and Kodama, 2000). By using U.S. International Trade Commission's Chinese Customs data from 1995 to 2007, Dean et al. (2009) found that equity joint ventures funded by industrialized countries are not significantly attracted by countries with weak environmental standards, regardless of the pollution intensity of the industry. In the case of FDI from German firms to 163 destination countries for six manufacturing industries from 1995 to 2003, strong support for the PHH was only found in the chemical industry (Wagner and Timmins, 2009). Cherniwchan et al. (2017) found evidence of a negative impact of tighter environmental regulations on net export in polluting sectors, which supports the Pollution Haven Effect (PHE), not to be confused with the Pollution Haven Hypothesis (PHH). Due to stringent environmental policies, PHE is defined as an adverse effect in comparative advantage.

The second stream of literature has contributions in international trade and environmental economics that also explore the firms' choice between export and FDI. A firm's characteristics might determine whether the firm will choose to serve the domestic market, a foreign market, or both. Empirical evidence from U.S. plants and 52 countries that import the most from the United States in the year 1992 suggest that only a small portion of firms engage in exporting activities, and these exporting firms are generally more efficient and larger than non-exporting firms Cherniwchan et al. (2017). In a seminal work, Melitz (2003) developed a dynamic theoretical model of heterogeneous firms to trace the impact of international trade and trade-induced reallocation within an industry. Using Dixit and Stiglitz's (1977) model of monopolistic competition, Melitz (2003) extended Krugman's (1980) trade model that incorporates firm-level productivity differences. Melitz's model was able to explain empirical evidence of the characteristics of exporting firms found by Bernard et al. (2003).

According to the proximity-concentration trade-off theory, firms decide to serve foreign markets by exporting if the economies of scale from a single production plant in the home country outweigh the transportation cost. The international trade literature has used proximity-concentration trade-off theory to extensively study firms' choice between FDI and export. Using MNC sales data from the U.S. Bureau of Economic Analysis (BEA) for 1989, Brainard (1993) found that a firm's choice between FDI and export depends on transportation costs, fixed plant costs, and returns on the plant. Dijkstra et al. (2011) ignore the strategic influence of foreign firms and assume a duopoly market structure in the home country. They find that an increase in a per unit of output environmental tax can encourage an efficient foreign firm to change its supply method from exporting to FDI if environmental tax increases the cost of the domestic firm by at least twice that of the foreign firm. In a theoretical model, Elliot and Zhou (2013) found that if a domestic firm is in its infancy, greater stringency in environmental standards can lead to a strategic increase in capital inflows through FDI substituting export. Smith et al. (1986) show that when the demand is large enough to cover the fixed cost of setting up a plant for either domestic or foreign firms, but it is too small to allow either foreign or domestic firms to break even as a duopolist, the domestic firm will choose to stay out if the foreign firm enters. If a firm sets up a brand new plant abroad, it is called greenfield FDI, whereas cross-border acquisition involves buying an existing business in another country. In a theoretical study, Nocke and Yeaple (2008) found that more efficient firms choose greenfield FDI over cross-border acquisitions. In equilibrium, greenfield FDI exhibits a one-way flow, where high-production-cost countries set up plants in low-production-cost countries. On the contrary, FDI in the form of cross-border acquisition flows in both ways (Nocke and Yeaple, 2008).

Helpman et al. (2004) used the concept of heterogeneous firms to determine a firm's choice between export and FDI in the framework of the proximity-concentration hypothesis. They focus on horizontal FDI, where firms undertake the same production activities in multiple countries. Horizontal FDI helps to avoid transportation costs and import taxes but loses the advantage of economies of scale. In contrast, vertical FDI occurs when firms fragment different steps of the production process in different countries. In the multicountry multisector model, heterogenous firms choose between horizontal FDI and export to serve other markets. To test the model, Helpman et al. (2004) used U.S. export and sales data from 52 manufacturing industries and 38 importing countries for the year 1994. They found that, in equilibrium, no firms engage in both activities for the same foreign market, and only efficient firms can afford international operations. FDI will surpass exports if there is more heterogeneity in firms. The model also predicts that the least productive firms will only serve the domestic market but that relatively more productive firms export and that the most productive firms engage in FDI. This result is consistent with Bernard et al. (2003). They also found evidence of the proximity-concentration hypothesis.

To delve into the relationship between international trade and green growth, Copeland (2012) reviews the challenges and opportunities of green growth. Significant public commitment to subsidize R&D would be needed to move the economy to a greener growth path (Acemoglu et al., 2019). If pollution is generated by consumption, then tightening environmental standards is unlikely to reduce global competitiveness. Copeland (2012) summarized the literature on the PHH and showed that there is little or no evidence that the pollution-intensive industry is systematically migrating to jurisdictions with weak environmental policies. Other factors, such as labour productivity, capital abundance, and proximity to markets, are more important in determining plant location and output. There is also considerable evidence of the 'lock-in' effect for technologies. There are often long lags in adopting new technologies caused by factors such as the skill set of workers, network effects, and infrastructure (Copeland, 2012).

Copeland and Taylor (1994) developed a two-country general equilibrium static trade model between developed and developing countries where environmental policy differences are caused by income and that induce international trade. They found that higher-income countries choose stronger environmental protections and specialize in producing relatively clean goods. They have also isolated the effects of international trade's scale, composition, and technique on pollution and showed that free trade increases world pollution. On the contrary, income effects can lead to the adoption of cleaner production techniques. As developed countries choose a higher pollution tax, all the pollution-intensive industries move to developing countries. There are opposite arguments for freer trade. On one hand, free trade might lead to job loss and wage cuts; environmentalists oppose the view but are skeptical about the transfer of pollution. On the other hand, economists argue that the income effect boosted by freer trade will increase the demand for environmental quality and, thus, reduce the pollution level (Copeland and Taylor, 2001). Income gains can significantly impact some types of pollution emissions (Grossman and Krueger, 1993). The pre-trade world income distribution is crucial as it determines how trade will affect the environment. If the world distribution of income is highly skewed, then free trade harms the global environment, but if countries have relatively similar incomes, then free trade has no adverse effect on the environment (Copeland and Taylor, 2001).

The third strand of the literature is from the industrial organization literature that studies firms' choice between FDI and export. In a seminal work, Markusen et al. (1993) developed a two-firm, two-region, and three-product model where both polluting firms can choose the locations of their plants, with one homogeneous product produced in both regions. The firms face imperfect competition and exhibit increasing returns to scale at the plant level. They discussed the shortcomings of environmental policy analysis that examines the impact of different policy instruments on firms' decisions, as the assumptions of perfect competition and constant returns to scale are often violated. FDI and trade under imperfect competition can be complicated because firms may change the location and number of their plants, thus making the reaction curves in a Cournot model discontinuous. A small change in environmental policy may cause firms to alter their location choices, leading to significant discontinuous changes in pollution and welfare levels in the concerned countries (Markusen et al., 1993). In a later study, Markusen et al. (1995) extended the model and considered the strategic interaction of governments. The authors consider an imperfectly competitive firm with three options: plants in both regions, a plant in only one of the regions, or not produce at all. In addition, there is also a competitive firm in both regions that does not pollute. High set-up costs exclude entry by new firms. The model developed by Markusen et al. (1995) becomes complex with several options and assumptions; thus, the authors use a numerical example to derive some results. They show that if the disutility of pollution is high, then the two regions will compete by increasing their environmental taxes until the polluting firm is driven out of the market; otherwise, the regions will undercut each other's pollution tax rates to attract firms.

Strategic interactions between countries or states play an important role in determining firms' choice of FDI or export, given environmental policies. Indeed, U.S. states strategically decide their environmental policies based on the policies in adjacent states (Fredriksson and Millimet, 2002). In cross-country settings, Kellenberg (2009) found evidence of PHH by considering strategically determined environmental, trade, and intellectual property rights policies. In the case of bilateral FDI with identical firms and countries, where firms undertake FDI to avoid transportation costs, FDI does not give rise to pollution (De Santis and Stähler, 2009). However, the choice of FDI or export depends on regulation, innovation, market size, and import tariff (Dong et al., 2012).

The literature on international trade and industrial organization has looked into firms' decisions between export and FDI from a different perspective. While the international trade literature has mainly examined the validity of the concentration-proximity hypothesis, the industrial organization literature uses a game theoretic approach. In the market share game approach, firms choose their location to attain a market share before the governments set environmental policies. On the other hand, governments set policies (e.g., pollution tax levels) before firms choose their plant location in the race to the bottom game approach. Some studies that considered the market share game have ignored trade costs (Hoel, 1997; Ulph and Valentini, 2001). Therefore, they cannot study the case where FDI is a substitute for trade, as the existence of an equilibrium with horizontal FDI requires positive trade costs. Many studies also used the race to the bottom game (Ikefuji et al., 2016; Motta and Thisse, 1994; Ulph, 1996; Rauscher, 1995; Beladi et al., 1999). Most of these papers conclude that governments set too low standards or taxes in equilibrium, hence the name of the game "race to the bottom" in the literature. Ulph (1996) allows for strategic behaviour by both firms and governments and finds that firms are incentivized to behave strategically if the government strategically determines the emission tax. However, Ulph (1996) shows that the total welfare is lower if firms and governments act strategically. Ikefuji et al. (2016) used an oligopolistic market structure in a three-stage race to the bottom game. Following Markusen et al. (1993), Motta and Thisse (1994) assumed that the government unilaterally sets environmental policies in the country where the firms are initially located. They also assumed that one production unit generates one unit of pollution as a joint product.

As developing countries generally compete for FDI, MNCs and countries respond strategically to any change in environmental policies. Thus, a study of choice between FDI and export should investigate the strategic interactions in a game-theoretic framework Dong et al. (2012). Besides, firms and governments have more incentive to behave strategically in the case of emission taxes compared to standards (Ulph, 1996). After the 1970s, market-based instruments (i.e., emission taxes) have become more popular among policymakers (Li and Shi, 2012). Thus, we should have an insight into the impact of emission taxes on firms' location choices.

We use the industrial organization framework to theoretically examine firms' choice between FDI and export in a two-country framework. We assume that each country has a single firm to focus on strategic interaction. In the first timing, we consider that in the first stage, the government of each country chooses a level of emission tax that the firms observe. Each country has one firm that produces a polluting good in its own country. In the second stage, each firm decides whether to export or use FDI to enter the other country's market. In the third stage, both firms compete in quantities in the two countries. Unlike the study of Markusen et al. (1993), we use the partial equilibrium framework, and instead of emission standards used in Dong et al. (2012), we use emission taxes. In addition, our model incorporates different pollution levels generated from production and, unlike Ikefuji et al. (2016), firms keep their home plant even if they serve foreign markets by FDI.

1.3 The Model

We consider a three-period model with two countries: a developed country (country 1) and a developing country (country 2). Each country has one firm, and both firms compete in quantity. The firms differ in polluting production technologies: firm 1 in country 1 has a cleaner technology than firm 2 in country 2. When producing the same output, firm 1 pollutes less than firm 2.

Each firm serves its domestic market and can also decide to enter the other market through export or FDI. While an exporting firm produces in its own country and then exports to the other country, a firm that decides to enter the other market through FDI will build a new plant in the other country and, thus, will produce in the other country. Each firm decides to be either a national firm (which produces for the domestic market and exports to the other country) or a multinational firm (which produces for the domestic market and serves the other market through FDI). If firms decide to serve the other market through FDI, they must pay a fixed cost, F, associated with building a new plant. If firms decide to export, they must pay import taxes and transportation costs when they export. We lump them together for simplicity, and thus, we denote T as the import tax per unit of exported goods.

Each firm in each country faces a linear inverse demand function. The inverse demand of firm i in country k when firm j is also producing with $i, j = 1, 2$ and $i \neq j$ and $k = 1, 2$ is

$$p_{ik}(q_i, q_j) = \alpha_k - q_i - q_j,$$

where q_i and q_j are the quantities sold by firms i and j (in country k). The intercept α_k is country-specific as demands can differ depending on the country. We assume that consumers know when a product is cleaner.

Each firm has a marginal cost c_i, where $c_1 \leq c_2$.[1] Each firm i generates an

[1] We assume that firm 1 in country 1 has a lower marginal cost than firm 2 in country 2 as it might be more efficient.

emission γ_i per unit of output q_i for $i = 1, 2$. As firm 1 has a cleaner technology, we have that $\gamma_1 < \gamma_2$. Emissions cause damage to the country where production occurs. Thus, if firm i produces output q_i, it generates a damage $\gamma_i q_i$, for $i = 1, 2$. In addition, we assume that both countries are large enough $\alpha_k >> c_i$, for $i = 1, 2$ and $k = 1, 2$ such that output are non-negative. In each country, the emission tax rate is τ_k, endogenously determined by each country's government. Both countries simultaneously choose their emission tax levels.

We consider different timings of setting the emission tax and compare them. More specifically, we consider two scenarios. In scenario 1, we consider *ex ante* choice of emission taxes, where firms take as given emission taxes when choosing between FDI and export. In scenario 2, we consider *ex post* choice of emission taxes, where governments take as given firms' FDI decisions when setting emission taxes.

Scenario 1: *ex ante* taxes

1. Both countries' governments simultaneously choose their emission tax levels, τ_1 and τ_2.
2. Both firms observe these tax levels. Each firm then chooses to be a national firm (domestic and export) or a multinational firm (domestic and FDI). Both firms make their decision simultaneously.
3. Given the competition in each country, both firms simultaneously choose their quantity in each country they serve.

We solve the game by backward induction. For a given tax τ_k, for each country $k = 1, 2$ and for any given choice of being national or multinational for each firm, we determine the Cournot equilibrium in the last stage of the game. There are four possible configurations: *i*) both firms are national firms; *ii*) firm 1 is a national firm and firm 2 is a multinational firm; *iii*) firm 1 is a multinational firm and firm 2 is national firm; *iv*) both firms are multinational firms. To summarize, in the third stage of the game, there are four possibilities: $(N, N), (N, M), (M, N), (M, M)$ where N stands for the national firm, and M stands for the multinational firm. Thus, (N, N) means that firm 1 in country 1 is a national firm and that firm 2 in country 2 is also a national firm. Thus, both firms also export to the other country. Then, in the second stage of the game, each firm decides to be a national or a multinational firm for any given tax τ_k for each country k. Finally, in the first stage, anticipating whether firms will be national or multinational, the governments simultaneously decide their tax levels.

Scenario 2: *ex post* taxes

1. Each firm chooses to be a national firm (domestic and export) or a multinational firm (domestic and FDI). Both firms make their decision simultaneously.
2. Both countries' governments observe the firms' decisions, and they simultaneously choose their emission tax levels, τ_1 and τ_2.
3. Given the competition in each country, both firms simultaneously choose their quantity in each country they serve.

We solve the game by backward induction. We determine the Cournot equilibrium in the last stage of the game for any given choice of being national or multinational for each firm and for a given tax choice of τ_k for each country $k = 1, 2$. In the second stage of the game, for each possible choice of being national or multinational for the firms, both governments decide simultaneously their emission tax levels. Finally, in the first stage, anticipating the level of emission taxes that will be chosen in the second stage, both firms choose whether to be national or multinational.

We first discuss the equilibria under the four FDI-export scenarios. By backward induction, we start by solving the game's third stage in both timing scenarios

(Cournot competition). Then, we consider the first timing (*ex ante* choice of emission taxes) and solve that game: we determine whether the firms choose to be national or multinational before determining the optimal emission taxes. Second, we consider the second timing (*ex post* choice of emission taxes): we determine the optimal emission taxes and whether the firms choose to be national or multinational.

1.4 Cournot Competition

We note that the third stage of the model is common to both scenarios 1 and 2, i.e., firms' output choices are independent of the timing of emission taxes. We consider, in turn, the four possible configurations: both firms are national firms, (N, N); firm 1 is a national firm and firm 2 is a multinational firm, (N, M); firm 1 is a multinational firm and firm 2 is a national firm, (M, N); and both firms are multinational firms, (M, M).

1.4.1 Both Firms are National Firms

In the first scenario (N, N), both firms are national firms (both produce domestically and export in the other country) and, thus, there is no FDI. The profit function of firm 1, is

$$\pi_1^{NN} = \underbrace{(\alpha_1 - q_1^D - q_2^E - c_1 - \tau_1\gamma_1)q_1^D}_{(I)} + \underbrace{(\alpha_2 - q_1^E - q_2^D - c_1 - \tau_1\gamma_1 - T)q_1^E}_{(II)}, \quad (1.1)$$

where the superscript NN denotes that both firms are national. In profit function (1.1), q_1^D represents the output of the national firm 1 in its domestic market (denoted by superscript D), q_1^E represents the output of the national firm 1 in the export market where the superscript E denotes export, τ_1 is the emission tax in country 1,

T is the transportation cost per unit of exported output, and c_1 is the marginal cost of firm 1. The first term (I) in (1) represents firm 1's profit in its domestic market, and the second term (II) represents its profit from exporting. In its domestic market, firm 1 competes with firm 2, which is an exporting firm. Firm 1 also operates in country 2 as it exports q_1^E, and thus faces competition from firm 2 (which is a domestic firm in its own country). As the production process is polluting, each firm pays a tax bill in its domestic country where it produces. Thus, firm 1 pays the emission tax $\tau_1\gamma_1(q_1^D + q_1^E)$. Recall that firm 1 produces the cleaner good while firm 2 produces the polluting good.

Similarly, firm 2's profit function is

$$\pi_2^{NN} = (\alpha_2 - q_2^D - q_1^E - c_2 - \tau_2\gamma_2)q_2^D + (\alpha_1 - q_2^E - q_1^D - c_2 - \tau_2\gamma_2 - T)q_2^E. \quad (1.2)$$

Each firm i chooses (q_i^D, q_i^E) that maximizes π_i^{NN} for $i, j = 1, 2$ and $i \neq j$. Solving the two maximization problems, we obtain the following equilibrium output levels of firms 1 and 2 for the domestic (D) and export (E) markets

$$q_{1NN}^D = \frac{\alpha_1 - 2(c_1 + \tau_1\gamma_1) + (c_2 + \tau_2\gamma_2 + T)}{3}, \quad (1.3)$$

$$q_{1NN}^E = \frac{\alpha_2 - 2(c_1 + \tau_1\gamma_1 + T) + (c_2 + \tau_2\gamma_2)}{3}, \quad (1.4)$$

$$q_{2NN}^D = \frac{\alpha_2 - 2(c_2 + \tau_2\gamma_2) + (c_1 + \tau_1\gamma_1 + T)}{3}, \quad (1.5)$$

and

$$q_{2NN}^E = \frac{\alpha_1 - 2(c_2 + \tau_2\gamma_2 + T) + (c_1 + \tau_1\gamma_1)}{3}. \quad (1.6)$$

These quantities are positive for given τ_1 and τ_2 not too large (we assume that the countries do not want to prevent exports by choosing a tax too large), and T

such that $T < \overline{T}$ where

$$\overline{T} \equiv \frac{1}{2} min\{\alpha_1 - 2(c_2 + \tau_2\gamma_2) + (c_1 + \tau_1\gamma_1), \alpha_2 - 2(c_1 + \tau_1\gamma_1) + (c_2 + \tau_2\gamma_2)\}. \quad (1.7)$$

An increase in the emission tax in country 1, τ_1, (respectively, in country 2, τ_2) decreases firm 1's export quantity, q^E_{1NN}, and firm 1's domestic production, q^D_{1NN} (resp., q^E_{2NN} and q^D_{2NN}) while it increases q^E_{2NN} and q^D_{2NN} (resp., q^E_{1NN} and q^D_{1NN}). Thus, an increase in the emission tax in country 1 leads to more exports from firm 2, which has a more polluting technology. This is consistent with the pollution haven effect: increasing the stringency of environmental policies increases imports of pollution-intensive goods.

An increase in the transportation cost T reduces the quantities of exports, q^E_{1NN} and q^E_{2NN}, and increases the domestic quantities, q^D_{1NN} and q^D_{2NN}. Similar to the standard Cournot duopoly model, the output for the domestic market, q^D_{iNN}, and export market, q^E_{iNN}, for $i = 1, 2$ will increase with its rival's marginal cost, c_j, for $j = 1, 2$ and $j \neq i$ and decrease with own marginal cost, c_i.

If we further assume that $\alpha_1 = \alpha_2 = \alpha$, we have that $q^E_{2NN} > q^E_{1NN}$ if $c_1 + \tau_1\gamma_1 > c_2 + \tau_2\gamma_2$, or if the marginal cost of firm 1 is higher than the marginal cost of firm 2. This is a pollution haven effect: if $\tau_2 << \tau_1$, there will be more exports from the country with a lower emission tax, τ_2, than the one with a higher emission tax, τ_1.

We also have that $q^D_{iNN} > q^E_{iNN}$ for $i = 1, 2$ as long as $T > 0$.

Substituting quantities (1.3), (1.4), (1.5) and (1.7) into profit functions (1.1) and (1.2), we obtain firm 1's equilibrium profit

$$\pi_1^{NN} = \left(q^D_{1NN}\right)^2 + \left(q^E_{1NN}\right)^2,$$

and firm 2's equilibrium profit

$$\pi_2^{NN} = \left(q_{2NN}^D\right)^2 + \left(q_{2NN}^E\right)^2.$$

1.4.2 One Firm is a National Firm and another Firm is a Multinational Firm

In the second scenario (N, M), firm 1 is a national firm and firm 2 is a multinational one. Thus, firm 1 operates in its domestic market and exports in the other country, while firm 2 has production plants in both its home country and the other country as it uses FDI to produce in the other country. While firm 1 faces the emission tax of its domestic country as a national firm, firm 2 faces the emission tax of its domestic country for its domestic production and the emission tax of the foreign country for its production in the other country. In addition, FDI has a fixed cost, F, and there is a per unit import tariff, T, in case of export. The profit functions of firms 1 and 2 are

$$\pi_1^{NM} = \underbrace{(\alpha_1 - q_1^D - q_2^F - c_1 - \tau_1\gamma_1)q_1^D}_{(I)} + \underbrace{(\alpha_2 - q_1^E - q_2^D - c_1 - \tau_1\gamma_1 - T)q_1^E}_{(II)}, \quad (1.8)$$

$$\pi_2^{NM} = \underbrace{(\alpha_2 - q_2^D - q_1^E - c_2 - \tau_2\gamma_2)q_2^D}_{(I)} + \underbrace{(\alpha_1 - q_2^F - q_1^D - c_2 - \tau_1\gamma_2)q_2^F - F}_{(II)}, \quad (1.9)$$

where the superscript NM in the profit function of each firm represents that firm 1 is a national firm (N), and firm 2 is a multinational firm (M). The first part (I) of profit functions (1.8) and (1.9) represents the profit from the domestic market, and the second part (II) represents the profit from the foreign market. Quantities q_1^D and q_1^E represent the output of firm 1 in its domestic market and in country 2 (as firm 1 exports in country 2), and quantities q_2^D and q_2^F represent the output of firm 2 in its domestic market and in country 1 (as firm 2 produces in country 1 through FDI), where the superscript F stands for FDI. Firm 1 is a national firm, so it faces domestic emission taxes τ_1. As firm 2 has plants in both countries, it faces emission tax τ_2 in its domestic market and τ_1 in the foreign market. Thus, for the emission level $\gamma_2 q_2^D$ in its domestic market, firm 2 pays $\tau_2\gamma_2 q_2^D$, and for the emission level $\gamma_2 q_2^F$ in the foreign market, firm 2 pays $\tau_1\gamma_2 q_2^F$.

Firm 1 chooses (q_1^D, q_1^E) that maximizes π_1^{NM}, and firm 2 chooses (q_2^D, q_2^F) that maximizes π_2^{NM} such that we obtain the following equilibrium quantities

$$q_{1NM}^D = \frac{\alpha_1 - 2(c_1 + \tau_1\gamma_1) + (c_2 + \tau_1\gamma_2)}{3}. \tag{1.10}$$

$$q_{1NM}^E = q_{1NN}^E, \tag{1.11}$$

$$q_{2NM}^D = q_{2NN}^D, \tag{1.12}$$

$$q_{2NM}^F = \frac{\alpha_1 - 2(c_2 + \tau_1\gamma_2) + (c_1 + \tau_1\gamma_1)}{3}. \tag{1.13}$$

Quantities are positive as long as the taxes are not too large. As a national firm, firm 1's exported quantity, q_{1NM}^E, increases with the foreign emission tax, τ_2, and firm 2's production cost, c_2, and it decreases with its own marginal cost, c_1, the emission tax, τ_1, and the transportation cost, T. Similarly, firm 1's domestic produced quantity q_{1NM}^D increases with firm 2's marginal cost, c_2, and decreases with its own marginal cost, c_1, and the emission tax, τ_1. Firm 2's production for its domestic market increases with firm 1's marginal cost, c_1, the emission tax, τ_1, and the transport cost, T, while it decreases with its own marginal cost, c_2, and the emission tax, τ_2. On the other hand, firm 2's production q_{2NM}^F in country 1 through FDI decreases with its own marginal cost, c_2, and increases with firm 1's marginal cost, c_1.

Substituting quantities (1.10), (1.11), (1.12), and (1.13) into the profit functions (1.8) and (1.9) of firms 1 and 2, we obtain the equilibrium profits for firms 1 and 2 when firm 1 is the national firm and firm 2 is the multinational firm

$$\pi_1^{NM} = \left(q_{1NM}^D\right)^2 + \left(q_{1NM}^E\right)^2,$$

and

$$\pi_2^{NM} = \left(q_{2NM}^D\right)^2 + \left(q_{2NM}^F\right)^2 - F.$$

Firm 2 will decide to be a multinational firm if $\pi_2^{NM} \geq 0$, or equivalently, if $F \leq (q_{2NN}^D)^2 + (q_{2NM}^F)^2$. Thus, if F is too large, it will be too costly for firm 2 to install an infrastructure in country 1.

In the third scenario (M, N), firm 1 is now a multinational firm and firm 2 is a national firm such that firm 1 has production plants in its home country, as well as in the other country (through FDI), and firm 2 operates in its domestic market and exports in the other country. While firm 1 faces the emission tax of its domestic country for its domestic production and the emission tax of the foreign country for its production from FDI, firm 2 faces the emission tax of its domestic country as a national firm. In addition, FDI has a fixed cost, F, and there is a per-unit transportation cost, T, in the case of export. The equilibrium profit functions of firms 1 and 2 are

$$\pi_1^{MN} = \left(q_{1MN}^D\right)^2 + \left(q_{1MN}^F\right)^2 - F,$$

and

$$\pi_2^{MN} = \left(q_{2MN}^D\right)^2 + \left(q_{2MN}^E\right)^2,$$

where the equilibrium quantities are

$$q_{1MN}^D = q_{1NN}^D, \tag{1.14}$$

$$q_{1MN}^F = \frac{\alpha_2 - 2(c_1 + \tau_2\gamma_1) + (c_2 + \tau_2\gamma_2)}{3}, \tag{1.15}$$

$$q_{2MN}^D = \frac{\alpha_2 - 2(c_2 + \tau_2\gamma_2) + (c_1 + \tau_2\gamma_1)}{3}, \tag{1.16}$$

$$q_{2MN}^E = q_{2NN}^E. \tag{1.17}$$

Quantities are positive as long as the taxes are not too large.

Firm 1 will decide to be a multinational firm if $\pi_1^{MN} \geq 0$, or equivalently, if $F \leq (q_{1NN}^D)^2 + (q_{1MN}^F)^2$. Thus, if F is too large, it will be too costly for firm 1 to install infrastructure in country 2.

1.4.3 Both Firms are Multinational Firms

In the last scenario (M, M), as both firms serve their domestic markets and are engaged in the other market through FDI (and install plants in the other country), firm 1's profit function is

$$\pi_1^{MM} = \underbrace{(\alpha_1 - q_1^D - q_2^F - c_1 - \tau_1\gamma_1)q_1^D}_{(I)} + \underbrace{(\alpha_2 - q_1^F - q_2^D - c_1 - \tau_2\gamma_1)q_1^F - F}_{(II)}, \tag{1.18}$$

and firm 2's profit function is

$$\pi_2^{MM} = \underbrace{(\alpha_2 - q_2^D - q_1^F - c_2 - \tau_2\gamma_2)q_2^D}_{(I)} + \underbrace{(\alpha_1 - q_2^F - q_1^D - c_2 - \tau_1\gamma_2)q_2^F - F}_{(II)}, \tag{1.19}$$

where the first part (I) represents the domestic market and the second part (II) represents the profit in the other country. Both firms have plants in each country, so they must pay domestic and foreign emission taxes. Firm 1 (respectively, firm 2) will pay the domestic emission tax τ_1 (resp., τ_2) for its domestic emission $\gamma_1 q_{1MM}^D$ (resp., $\gamma_2 q_{2MM}^D$) and the foreign emission tax τ_2 (resp., τ_1) for the emission generated in the other country, $\gamma_1 q_{1MM}^F$ (resp., $\gamma_2 q_{2MM}^F$). The equilibrium outputs of the multinational firms 1 and 2, for the domestic and the foreign markets, are

$$q^D_{1MM} = q^D_{1NM}, \tag{1.20}$$

$$q^F_{1MM} = q^F_{1MN}, \tag{1.21}$$

$$q^D_{2MM} = q^D_{2MN}, \tag{1.22}$$

$$q^F_{2MM} = q^F_{2NM}. \tag{1.23}$$

By substituting the quantity levels (1.20), (1.21), (1.22) and (1.23) into the profit function (1.18) and (1.19), we obtain firm 1 and firm 2's equilibrium profit functions

$$\pi_1^{MM} = \left(q^D_{1NM}\right)^2 + \left(q^F_{1MN}\right)^2 - F,$$

$$\pi_2^{MM} = \left(q^D_{2MN}\right)^2 + \left(q^F_{2NM}\right)^2 - F.$$

Both firms decide to become multinational only if $\pi_1^{MM} \geq 0$ and $\pi_2^{MM} \geq 0$ or, equivalently, if $F \leq (q^D_{1NM})^2 + (q^F_{1MN})^2$ and $F \leq (q^D_{2MN})^2 + (q^F_{2NM})^2$. The incentive to become multinational rather than exporting arises due to the tariff-jumping effect whereby a firm can avoid paying a tariff on export by becoming a multinational.

1.5 Scenario 1: *Ex ante* Choice of Emission Taxes

We first consider the timing in which the countries choose *ex ante* their emission tax levels. We start with the analysis of the firms' decisions to become national or multinational (second stage of the game) before calculating the equilibrium emission tax levels (first stage of the game).

1.5.1 Equilibrium: National or Multinational

In the second stage of the game, for any tax levels τ_1 and τ_2, each firm must decide whether to be a national firm (produces domestically and exports), or a multinational firm (produces domestically and uses FDI to get into the other market).

We first show that it is a dominant strategy for firm 1 to be a national firm if $F > f_1(T, \tau_1, \tau_2)$ where

$$f_1(T, \tau_1, \tau_2) \equiv (q_{1MN}^F)^2 - (q_{1NN}^E)^2, \tag{1.24}$$

and that it is a dominant strategy for firm 2 to be a national firm if $F > f_2(T, \tau_1, \tau_2)$ where

$$f_2(T, \tau_1, \tau_2) \equiv (q_{2NM}^F)^2 - (q_{2NN}^E)^2. \tag{1.25}$$

All the proofs are relegated in the Appendix (see Appendix A1). We show that $f_1(T, \tau_1, \tau_2)$ and $f_2(T, \tau_1, \tau_2)$ are increasing and concave functions of T. We also show that when a firm decides to become a multinational, its profit is always positive. We summarize our findings in the following Proposition.

Proposition 1. *For any $F \geq 0$, $\tau_1 \geq 0$, and $\tau_2 \geq 0$,*

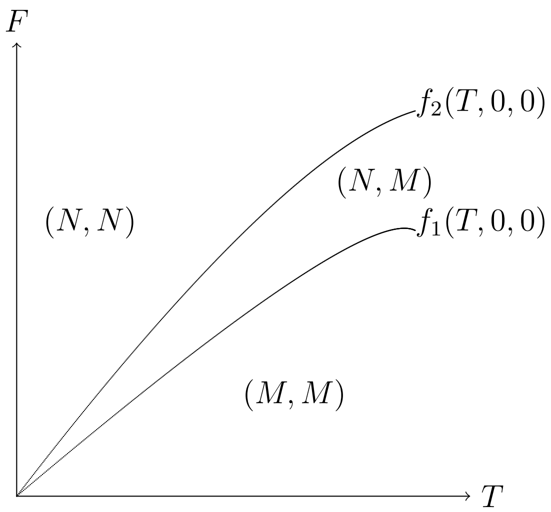
- *If $F \geq \max\{f_1(T, \tau_1, \tau_2), f_2(T, \tau_1, \tau_2)\}$, there is a unique Nash equilibrium (N, N) in which both firms choose to be national firms;*
- *If $F < \min\{f_1(T, \tau_1, \tau_2), f_2(T, \tau_1, \tau_2)\}$, there is a unique Nash equilibrium (M, M) in which both firms choose to be multinational;*
- *if $f_2(T, \tau_1, \tau_2) < F < f_1(T, \tau_1, \tau_2)$, there is a unique Nash equilibrium (M, N) in which firm 1 chooses to be a multinational and firm 2 chooses to be a national*

firm

- *if* $f_1(T, \tau_1, \tau_2) < F < f_2(T, \tau_1, \tau_2)$*, there is a unique Nash equilibrium* (N, M) *in which firm* 2 *chooses to be a multinational and firm* 1 *chooses to be a national.*

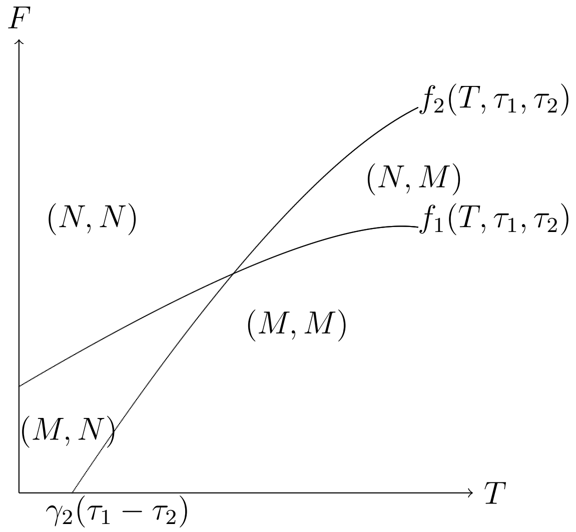
Imagine first that the countries do not set emission taxes so that $\tau_1 = \tau_2 = 0$. In Figure 1.1, we represent the different areas in a graph (T, F) for $\tau_1 = \tau_2 = 0$ and when $\alpha_1 \geq \alpha_2$. For a given T, as F increases to a large value, both firms prefer to be national, (N, N), as it is too costly to enter the other country with FDI. For a given F, as T increases, both firms decide to be multinational, (M, M), in line with the tariff jumping effect.

Figure 1.1: Nash Equilibria for $\tau_1 = \tau_2 = 0$



In Figure 1.2, we represent the different areas in a graph (T, F) for a given τ_1 and τ_2 with $\tau_1 > \tau_2$ and $\alpha_1 \geq \alpha_2$. For a relatively low T, as F increases, we go from a regime where firms initially choose to be multinational (as the cost F is relatively small) to a regime where firm 1 is a multinational firm while firm 2 decides to be a national firm. As F increases further, both firms are better off when they are national.

Figure 1.2: Nash Equilibria for $\tau_1 > \tau_2$



We show that $f_1(T, \tau_1, \tau_2)$ increases (respectively, decreases) as τ_1 (respectively, τ_2) increases and $f_2(T, \tau_1, \tau_2)$ decreases (respectively, increases) as τ_1 (respectively, τ_2) increases. Thus, as the emission tax in the country 1, τ_1, increases, the area where firm 1 is a multinational and firm 2 is a national firm expands. As τ_1 increases, firm 1 has a greater incentive to avoid paying emission tax in country 1, by relocating production to country 2. On the contrary, when τ_2 increases, this area shrinks.

1.5.2 Optimal Emission Tax in Country 1

In this subsection, for tractability, we consider the case where only country 1 chooses its optimal emission tax level while country 2 does not set any emission tax level, such that $\tau_2 = 0$. In other words, we assume that country 2 does not set an emission tax. We consider, in turn, the four possible subgame equilibria: (N, N), (N, M), (M, N) and (M, M) before calculating the optimal emission levels. In the next section, we determine the optimal emission tax levels when both countries simultaneously determine their emission tax levels.

1.5.2.1 Welfare and Optimal Emission Tax

In the subgame equilibrium (N, N), both firms choose to be national firms: they produce in their domestic country and export in the foreign country. The total welfare in country 1 is the sum of firm 1's profit, the consumers' surplus, and the tax revenue minus the emission generated by the production in country 1. Therefore, the total welfare in country 1 is

$$W_1^{NN} = \underbrace{\pi_1^{NN}}_{\text{profit}} + \underbrace{\frac{(q_{1NN}^D + q_{2NN}^E)^2}{2}}_{\text{consumers' surplus}} - \underbrace{\gamma_1(q_{1NN}^D + q_{1NN}^E)}_{\text{emission}} + \underbrace{\tau_1\gamma_1(q_{1NN}^D + q_{1NN}^E)}_{\text{tax revenue}}.$$

Country 1 chooses τ_1 that solves

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{NN} \\ \text{s.t.} & q_{iNN}^D \geq 0 \quad \text{for } i = 1, 2 \\ & q_{iNN}^E \geq 0 \\ & F \geq \max\{f_1(T, \tau_1, 0), f_2(T, \tau_1, 0)\} \end{cases}$$

where $f_1(T, \tau_1, 0)$ and $f_2(T, \tau_1, 0)$ are defined by (1.24) and (1.25). We find that there are values of T and F for which there is an interior solution (see Appendix A.2 for the details of the calculations) such that the optimal emission tax level is

$$\tau_1^{NN} = \frac{5c_1 - c_2 + 2T - 3\alpha_1 - \alpha_2 + 12\gamma_1}{7\gamma_1}.$$

For the constraints to be satisfied, we must have that $F \geq F_C^{NN} = \max\{f_1(T, \tau_1^{NN}, 0)$ $, f_2(T, \tau_1^{NN}, 0)\}$ and $T \leq T^{NN}$ (the latter condition ensures that all the quantities are positive) where

$$f_1(T,\tau_1^{NN},0) = -\frac{4\left(5c_1 - c_2 + 9T - 3\alpha_1 - \alpha_2 + 12\gamma_1\right)}{21}\frac{\left(19c_1 - 8c_2 + 9T - 3\alpha_1 - 8\alpha_2 + 12\gamma_1\right)}{21},$$

$$f_2(T,\tau_1^{NN},0) = \frac{4T\left(12c_1 - 15c_2 - 5T + 4\alpha_1 - \alpha_2 + 12\gamma_1\right)}{63},$$

and

$$T^{NN} = \frac{2\alpha_1 + 3\alpha_2 - 8\gamma_1 - 8c_1 + 3c_2}{6}.$$

If $T > T^{NN}$, firm 1 does not export anymore and $q_{1NN}^E = 0$.

For small values of F, the solution is no longer an interior solution but a corner solution such that τ_{1C} satisfied $F = f_1(T,\tau_{1C},0)$ where

$$\tau_{1C} = \frac{-2T+\alpha_2-2c_1+c_2-\sqrt{-9F+\alpha_2^2+4c_1^2+c_2^2-4\alpha_2c_1+2\alpha_2c_2-4c_1c_2}}{2\gamma_1}.$$

We also check that the condition $F > f_2(T,\tau_{1C},0)$ is satisfied (for the details of the calculation, see Appendix A.2). Thus, depending on the values of T and F, if $\tau_{1C} \geq \tau_1^{NN}$, the interior solution prevails; otherwise, if $\tau_{1C} < \tau_1^{NN}$, it is a corner corner solution, τ_{1C}. Therefore, in this case (N,N), the optimal emission tax level is

$$\tau_1^{NN*} = min\{\tau_1^{NN}, \tau_{1C}\}. \tag{1.26}$$

In the subgame equilibrium (M,N), firm 1 decides to be a multinational firm and firm 2 a national firm, such that firm 1 has production plants in its home country 1 and uses FDI in the other country, in which case it also produces in the other country 2. Therefore, the total welfare in country 1 is

$$W_1^{MN} = \pi_1^{MN} + \frac{(q_{1MN}^D + q_{2MN}^E)^2}{2} - \gamma_1 q_{1MN}^D + \tau_1 \gamma_1 q_{1MN}^D.$$

Country 1 chooses τ_1 that solves

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{MN} \\ \text{s.t.} & q_{iMN}^D \geq 0 \quad \text{for } i = 1, 2 \\ & q_{1MN}^F \geq 0,\ q_{2MN}^E \geq 0 \\ & F \leq f_1(T, \tau_1, 0) \\ & F \geq f_2(T, \tau_1, 0) \end{cases}$$

There are values of T and F for which there is an interior solution, and therefore, the optimal emission tax level is

$$\tau_1^{MN} = \frac{c_1 - \alpha_1 + 2\gamma_1}{\gamma_1}.$$

In order for the constraints to be satisfied, we must have that $f_2(T, \tau_1^{MN}, 0) < F < f_1(T, \tau_1^{MN}, 0)$ and $T \leq T^{MN}$ (the latter condition ensures that all the quantities are positive) where

$$f_1(T, \tau_1^{MN}, 0) = -\frac{4}{9}(c_1 + T - \alpha_1 + 2\gamma_1)(3c_1 - c_2 + T - \alpha_1 - \alpha_2 + 2\gamma_1),$$

$$f_2(T, \tau_1^{MN}, 0) = -\frac{4}{9}(T^2 + 2(c_1 - c_2 + \gamma_1)(\gamma_2 \frac{c_1 - \alpha_1 + 2\gamma_1}{\gamma_1} - T) - (\gamma_2 \frac{c_1 - \alpha_1 + 2\gamma_1}{\gamma_1})^2)$$

$$T^{MN} = \gamma_1 + c_1 - c_2.$$

If $T > T^{MN}$, firm 2 does not export anymore and $q_{2MN}^E = 0$.

For values of T and F that do not satisfy the constraints (for low values of T and F), the solution is no longer an interior solution but a corner solution such that

τ_{12C} satisfied $F \geq f_1(T, \tau_{12C}, 0)$, and $F = f_2(T, \tau_{12C}, 0)$ where

$$\tau_{12C} = \frac{T\gamma_1 - c_1\gamma_2 + 2c_2\gamma_2 - \alpha_1\gamma_2 + \sqrt{-(9F + 4T(-c_1 + 2c_2 + T - \alpha_1))(\gamma_1 - \gamma_2)\gamma_2 + (T\gamma_1 - (c_1 - 2c_2 + \alpha_1)\gamma_2)^2}}{2(\gamma_1 - \gamma_2)\gamma_2}.$$

For higher values of T and F, the corner solution is τ_{1C}. Therefore, depending on the values of T and F, if $\tau_{1C} > \tau_1^{MN}$ the solution is the corner solution, τ_{1C}; if $\tau_{12C} > \tau_1^{MN}$ the solution is the corner solution, τ_{12C}; and if $\tau_{MN} \geq \tau_1^{1C}$ or $\tau_{MN} \geq \tau_1^{12C}$ the solution is the interior solution τ_1^{MN}. Overall, the optimal emission tax level is

$$\tau_1^{MN*} = max\{\tau_1^{MN}, \tau_{1C}, \tau_{12C}\}. \tag{1.27}$$

In the subgame equilibrium (N, M), firm 1 decides to be a national firm and firm 2 a multinational firm, such that firm 2 has production plants in its home country 2 and uses FDI in the other country, in which case it also produces in the other country 1. Thus, the emission in country 1 comes from firm 1 that is producing domestically (for the domestic market and to export), and from firm 2 that has a production facility in country 1 and thus pollutes in country 1. However, country 1 gets tax revenue from its domestic firm, firm 1, and from firm 2 as well. Therefore, the total welfare in country 1 is

$$W_1^{NM} = \underbrace{\pi_1^{NM}}_{\text{profit}} + \underbrace{\frac{(q_{1NM}^D + q_{2NM}^F)^2}{2}}_{\text{consumers' surplus}} - \underbrace{[\gamma_1(q_{1NM}^D + q_{1NM}^E) + \gamma_2 q_{2NM}^F]}_{\text{emission}} + \underbrace{\tau_1\gamma_1(q_{1NM}^D + q_{1NM}^E) + \tau_1\gamma_2 q_{2NM}^F}_{\text{tax revenue}},$$

Country 1 chooses τ_1 that solves

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{NM} \\ \text{s.t.} & q_{iNM}^D \geq 0 \quad \text{for } i = 1,2 \\ & q_{1NM}^E \geq 0,\ q_{2NM}^F \geq 0 \\ & F \geq f_1(T, \tau_1, 0) \\ & F \leq f_2(T, \tau_1, 0) \end{cases}$$

We show that there are no interior solutions that simultaneously satisfy all the constraints (see Appendix A.2).

In the subgame equilibrium (M, M), both firms decide to be multinational firms, such that each firm has production plants in its home country and uses FDI in the other country, in which case it also produces in the other country. Therefore, the total welfare in country 1 is

$$W_1^{MM} = \pi_1^{MM} + \frac{(q_{1M}^D + q_{2M}^F)^2}{2} - \gamma_1 q_{1M}^D - \gamma_2 q_{2M}^F + \tau_1(\gamma_1 q_{1M}^D + \gamma_2 q_{2M}^F).$$

Country 1 chooses τ_1 that solves

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{MM} \\ \text{s.t.} & q_{iMM}^D \geq 0 \quad \text{for } i = 1,2 \\ & q_{1MM}^F \geq 0,\ q_{2MM}^E \geq 0 \\ & F \leq \min\{f_1(T, \tau_1, 0), f_2(T, \tau_1, 0)\} \end{cases}$$

There are values of T and F for which there is an interior solution so that the optimal emission tax level is

$$\tau_1^{MM} = \frac{\gamma_1(c_1 - \alpha_1) + 2(\gamma_1)^2 + \gamma_2(\alpha_1 - c_2) - 2\gamma_1\gamma_2 + 2(\gamma_2)^2}{(\gamma_1)^2 - 2\gamma_1\gamma_2 + 3(\gamma_2)^2}.$$

For the constraints to be satisfied, we must have that $F \leq \min\{f_1(T, \tau_1^{MM}, 0), f_2(T, \tau_1^{MM}, 0)\}$

which represents a very small area that requires a very large T. Overall, depending on the values of T and F, the optimal emission tax level is

$$\tau_1^{MM*} = min\{\tau_1^{MM}, \tau_{1C}\}.$$

As country 1 chooses its level of emission tax first, it will choose the tax level that maximizes its total welfare, i.e., $max\{W_1^{NN}, W_1^{MN}, W_1^{NM}, W_1^{MM}\}$. We represent country 1's total welfare as a function of the tax τ_1 in Figures 3 and 4. We assume that T is not too large $T < min\{T^{NN}, T^{MN}\}$, such that all quantities are positive, which excludes the case where (M, M) is a solution. Starting with a large value of F, we show that country 1 offers τ_1^{NN*}, which is the optimal level of tax that maximizes the total welfare (see Figure 3). For smaller values of F, country 1 is better off choosing the optimal tax level τ_1^{MN*} (=τ_{1C}) as shown in Figure 4.

Figure 1.3: Total welfare in Country 1 for large F when $\tau_2 = 0$

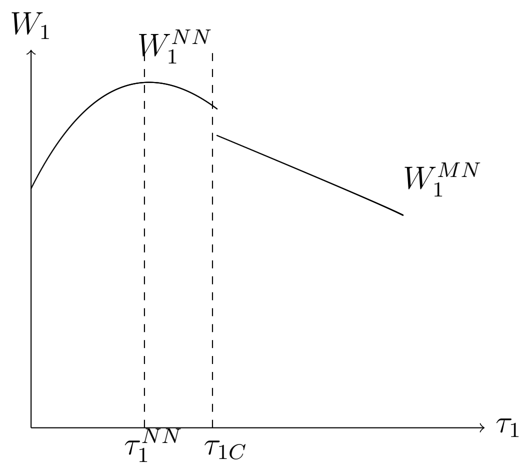
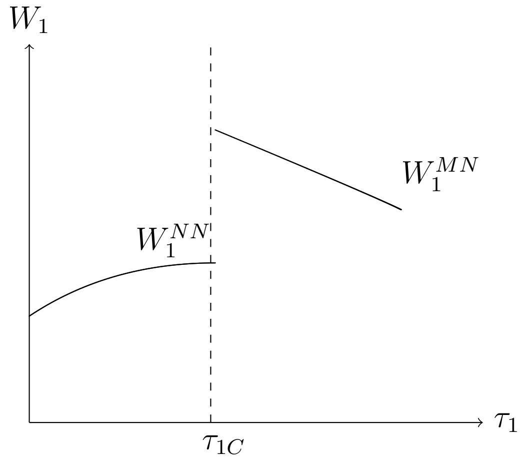


Figure 1.4: Total welfare in Country 1 for small and intermediate F when $\tau_2 = 0$



We summarize these findings in the following Proposition.

Proposition 2. *When $\tau_2 = 0$, if $T < min\{T^{NN}, T^{MN}\}$,*

- *for large values of F, $F \geq F_C^{NN}$, the subgame perfect Nash equilibrium is τ_1^{NN*}, and both firms choose to be national (N, N);*
- *for smaller values of F, $F < F_C^{NN}$, the subgame perfect Nash equilibrium is τ_1^{MN*}, and firm 1 decides to be a multinational while firm 2 decides to be a national (M, N).*

Thus, when F is relatively small, firm 1 is better off being a multinational firm and firm 2 is a national firm. As $\tau_1^{MN*} > \tau_2 = 0$, by being a multinational firm, firm 1's tax bill is reduced as it only pays a tax in its domestic country for its domestic production, and the tax bill of firm 2 is null. When F increases, it becomes too costly to be a multinational for firm 1; thus, both are national firms.

1.5.2.2 Equilibrium Emission Levels

We now calculate the emission levels in both countries depending on the equilibrium, which depends on the value of F. When F is large, $F \geq F_C^{NN}$, the equilibrium is such that both firms decide to be national (N, N), and the optimal tax level is τ_1^{NN*} as defined by (1.26). Thus, the emission levels in countries 1 and 2 are

$$\begin{aligned} e_1^{NN*} &= \gamma_1[q_{1NN}^D(\tau_1^{NN*}) + q_{1NN}^E(\tau_1^{NN*})], \\ \text{and} \quad e_2^{NN*} &= \gamma_2[q_{2NN}^D(\tau_1^{NN*}) + q_{2NN}^E(\tau_1^{NN*})]. \end{aligned}$$

For large values of F, the optimal tax level is the interior solution τ_1^{NN}, which does not depend on F. Therefore, $\partial e_1^{NN*}/\partial F = 0$ and $\partial e_2^{NN*}/\partial F = 0$.

When F is smaller, $F < F_C^{NN}$, the equilibrium is such that firm 1 decides to be multinational and firm 2 to be a national (M, N), and the optimal emission tax is τ_1^{MN*} as defined by (1.27). Thus, the emission levels in countries 1 and 2 are

$$\begin{aligned} e_1^{MN*} &= \gamma_1 q_{1MN}^D(\tau_1^{MN*}), \\ \text{and} \quad e_2^{MN*} &= \gamma_2[q_{2MN}^D(\tau_1^{MN*}) + q_{2MN}^E(\tau_1^{MN*})] + \gamma_1 q_{1MN}^F(\tau_1^{MN*}). \end{aligned}$$

In this case, the optimal solution is the corner solution τ_{1C}, where $\partial\tau_{1C}/\partial F > 0$. Thus

$$\frac{\partial e_1^{MN*}}{\partial F} = \gamma_1 \frac{\partial q_{1MN}^D}{\partial \tau_1} \frac{\partial \tau_{1C}}{\partial F} < 0,$$

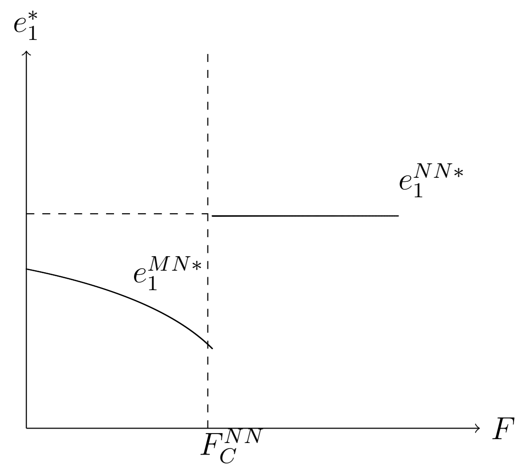
and

$$\frac{\partial e_2^{MN*}}{\partial F} = \gamma_2 \frac{\partial q_{2MN}^E}{\partial \tau_1} \frac{\partial \tau_{1C}}{\partial F} > 0.$$

We also calculate that $\partial^2\tau_{1C}/\partial F^2 > 0$, so that $\partial^2 e_1^{MN*}/\partial F^2 < 0$ and $\partial^2 e_2^{MN*}/\partial F^2 > 0$. Furthermore, evaluated at $F = 0$, we show that $e_1^{MN*} < e_1^{NN*}$. Indeed, $e_1^{MN*} < e_1^{NN*}$ is equivalent to having $q_{1NN}^D(\tau_1^{MN}) - q_{1NN}^D(\tau_1^{NN}) < q_{1NN}^E(\tau_1^{NN})$ which is always satisfied as $q_{1NN}^D(\tau_1^{MN}) - q_{1NN}^D(\tau_1^{NN}) < 0$. We also show that $e_2^{MN*} > e_2^{NN*}$.

In Figure 1.5, we represent the optimal emission level in country 1 as a function of F. For low values of F, the equilibrium is (M, N) such that firm 1 chooses to be a multinational and firm 2 a national firm, and the optimal tax is τ_1^{MN*}. As per Figure 1.5, the optimal value is $\tau_1^{MN*} = \tau_{1C}$, which is increasing with F. As F increases, the emission tax increases and, thus, the quantity q^D_{1MN} decreases. Thus, the emission level in country 1 decreases. As F increases further, we go from the equilibrium (M,N) to (N,N) in which both firms choose to be national firms. The emission level jumps upward as firm 1 now produces in country 1 both for its domestic and foreign markets. As firm 1 produces in country 1 for its domestic market, its overall production is lower, and thus it does not pollute as much as when firm 1 produces in country 1 for both markets.

Figure 1.5: Optimal emission level in Country 1 when $\tau_2 = 0$



We summarize these findings in the following Proposition.

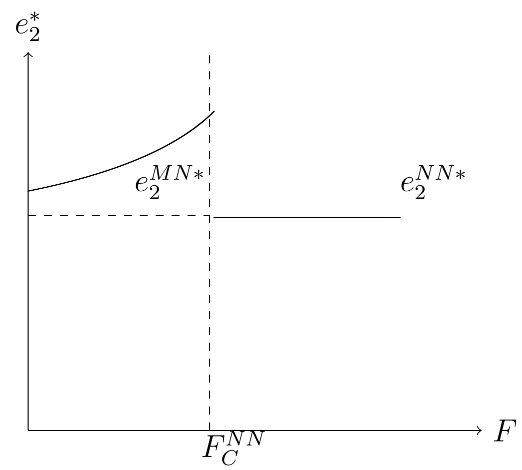
Proposition 3. *When $\tau_2 = 0$ and country 1 chooses optimally its emission tax level, country 1's emission is a non-monotonic function of the FDI fixed cost F. Initially, the emission level decreases as F increases. There is a discontinuity at F_C^{NN}, where the emission increases and becomes constant.*

Even though the emission tax decreases in the area (N,N), the optimal emission level increases. This is because, for low values of F, the equilibrium is in the area (M,N), where the emission in country 1 is due to the production of firm 1 in its own country as firm 1 is doing FDI in country 2 and, thus, produces in country 2. However, as F increases, firm 1 produces only in country 1 and exports in country

2 such that firm 1 produces more in country 1, which leads to more emissions even though the tax is smaller.

In Figure 1.6, we represent the optimal emission level in country 2 as a function of F. Initially, as F is small, the emission level in country 2 is increasing with F in the equilibrium (M, N). Indeed, as F increases, the emission $\tau_1^{MN*} = \tau_{1C}$ increases, which increases q_{2MN}^E. As F increases further, there is a jump downward when we reach a different equilibrium (N, N). Firm 1 does not produce in country 2 anymore, and the emission in country 2 is only due to the production of firm 2.

Figure 1.6: Optimal emission level in Country 2 when $\tau_2 = 0$



The policy implication is that if the developed country's firm does FDI, that is firm 1 sets up a multinational in country 2, this reduces emission in country 1 but increases emission in country 2 as shown by Figures 5 and 6, in line with the pollution leakage effect noted in the related literature.

1.5.3 Equilibrium Emission Taxes in both Countries

We now relax the assumption that country 2 does not set an emission tax. In the game's first stage, each country chooses its emission tax level by maximizing its total welfare function. We consider, in turn, the four possible equilibrium scenarios in the second stage: (N, N), (N, M), (M, N) and (M, M). Then, we calculate the optimal emission levels.

1.5.3.1 Welfare and Equilibrium Emission Taxes

If, in the second stage, in equilibrium, both firms choose to be national firms (N, N), they both produce in their domestic country and export to the foreign country. Therefore, the total welfare in country 1 is

$$W_1^{NN} = \underbrace{\pi_1^{NN}}_{\text{profit}} + \underbrace{\frac{(q_{1NN}^D + q_{2NN}^E)^2}{2}}_{\text{consumers' surplus}} - \underbrace{\gamma_1(q_{1NN}^D + q_{1NN}^E)}_{\text{emission}} + \underbrace{\tau_1\gamma_1(q_{1NN}^D + q_{1NN}^E)}_{\text{tax revenue}}.$$

Similarly, country 2's total welfare is

$$W_2^{NN} = \pi_2^{NN} + \frac{(q_{2NN}^D + q_{1NN}^E)^2}{2} - \gamma_2(q_{2NN}^D + q_{2NN}^E) + \tau_2\gamma_2(q_{2NN}^D + q_{2NN}^E).$$

Each country k chooses τ_k that maximizes W_k^{NN} for $k = 1, 2$. Similarly to the previous section, these optimization programs have constraints: all the quantities need to be positive and $F \geq \max\{f_1(T, \tau_1, \tau_2), f_2(T, \tau_1, \tau_2)\}$ (For the detail of the calculation, see Appendix A3). When all the constraints are satisfied, we calculate the first-order condition for each country, which gives us the best response function for each country to the tax level of the other country, $\tau_1(\tau_2)$ and $\tau_2(\tau_1)$. These best response functions are downward sloping, i.e., the taxes are strategic substitutes (See Appendix A3). If one country increases its tax level, the other country reduces its tax level. Solving for the equilibrium levels of emission tax, if there exist interior solutions, we find the following equilibrium tax levels

$$\tau_1^{NN} = \frac{3(3c_1 - c_2 + T) - 5\alpha_1 - \alpha_2 - 3(\gamma_2 - 7\gamma_1)}{12\gamma_1}, \tag{1.28}$$

and

$$\tau_2^{NN} = \frac{3(3c_2 - c_1 + T) - \alpha_1 - 5\alpha_2 + 3(7\gamma_2 - \gamma_1)}{12\gamma_2}. \tag{1.29}$$

As we assume that $c_1 \leq c_2$, $\gamma_1 < \gamma_2$, and $\alpha_1 \geq \alpha_2$, we find that $\tau_1^{NN} < \tau_2^{NN}$ as $3(c_2 - c_1) + 6(\gamma_2 - \gamma_1) + \alpha_1 - \alpha_2 > 0$, which is always satisfied. This finding is surprising as country 1 (developed country) will set a lower level of emission tax than country 2 (developed country). This is due to the fact that we assume that the firm producing in the developed country is more efficient ($c_1 \leq c_2$), and has a less polluting technology than firm 2.

Thus, if in the second stage, in equilibrium, both firms choose to be national, in the first stage, both countries choose the tax levels τ_1^{NN} and τ_2^{NN}. However, all the constraints need to be satisfied: $F \geq F_{NN} = \max\{f_1(T, \tau_1^{NN}, \tau_2^{NN}), f_2(T, \tau_1^{NN}, \tau_2^{NN})\}$ and all the quantities in equilibrium must be positive, which is satisfied if $T < T_{NN}$ where

$$T_{NN} = \frac{1}{3}(3c_1 - 5c_2 + \alpha_1 + \alpha_2 + 3\gamma_1 - 5\gamma_2). \tag{1.30}$$

We thus find that there exists an equilibrium τ_1^{NN} and τ_2^{NN} for values of T and F such that $T < T_{NN}$ and $F \geq F_{NN}$. Therefore, the optimal welfare functions in equilibrium in countries 1 and 2 are $W_1^{NN}(\tau_1^{NN}, \tau_2^{NN})$ and $W_2^{NN}(\tau_1^{NN}, \tau_2^{NN})$, where $W_1^{NN} > W_2^{NN}$ as long as $T < T_{NN}$ and $F \geq F_{NN}$.

There are other (corner) solutions when the parameters are such that one constraint is not satisfied, as shown in Figure A.5 in Appendix A3. In that case, there might be several corner solutions, as explained in the Appendix A3. We denote $(\tau_1^{NN*}, \tau_1^{NN*})$ the equilibrium emission levels of tax. Sometimes, the corner solution can yield a higher level of welfare than when the government changes its tax level to induce a different FDI decision. We later check which of these two solutions yields higher welfare when characterizing equilibrium taxes.

In the subgame equilibrium (N, M), firm 1 decides to be a national firm and firm 2 a multinational firm, such that firm 2 has production plants in its home country 2 and uses FDI in the other country, in which case it also produces in the other country 1. Therefore, the total welfare in country 1 is

$$W_1^{NM} = \underbrace{\pi_1^{NM}}_{\text{profit}} + \underbrace{\frac{(q_{1NM}^D + q_{2NM}^F)^2}{2}}_{\text{consumers' surplus}} - \underbrace{[\gamma_1(q_{1NM}^D + q_{1NM}^E) + \gamma_2 q_{2NM}^F]}_{\text{emission}} + \underbrace{\tau_1\gamma_1(q_{1NM}^D + q_{1NM}^E) + \tau_1\gamma_2 q_{2NM}^F}_{\text{tax revenue}},$$

and the total welfare in country 2 is

$$W_2^{NM} = \underbrace{\pi_2^{NM}}_{\text{profit}} + \underbrace{\frac{(q_{2NM}^D + q_{1NM}^E)^2}{2}}_{\text{consumers' surplus}} - \underbrace{\gamma_2 q_{2NM}^D}_{\text{emission}} + \underbrace{\tau_2\gamma_2 q_{2NM}^D}_{\text{tax revenue}}.$$

Country k chooses τ_k that maximizes W_k^{NM} for $k = 1, 2$. All the constraints must be satisfied: quantities must be positive, and $f_1(T, \tau_1, \tau_2) < F < f_2(T, \tau_1, \tau_2)$. However, we find that the conditions are not satisfied simultaneously (see Appendix A3). Indeed, we cannot have positive quantities and the conditions on f_1 and f_2 satisfied simultaneously. Therefore, at least one constraint will bind, and thus the solution will not be interior anymore. We find that country 1 chooses an emission tax level τ_{1C}^{NM} such that $f_2(T, \tau_{1C}^{NM}, \tau_2^{NM}) = F$ and country 2 chooses

$$\tau_2^{NM} = \frac{c_2 - \alpha_2 + 2\gamma_2}{\gamma_2},$$

which does not depend on τ_1. We have that $\tau_2^{NM} \geq 0$, if $2\gamma_2 \geq \alpha_2 - c_2$. The constraint $f_2(T, \tau_{1C}^{NM}, \tau_2^{NM}) = F$ binds, and all the quantities are positive. We verify that there are values of T and F such that $F > f_1(T, \tau_{1C}^{NM}, \tau_2^{NM})$. The resulting tax level τ_{1C}^{NM} is smaller than the tax that would have been determined optimally in the absence of any constraint. Thus, the optimal total welfare in countries 1 and 2 are $W_1^{NM}(\tau_{1C}^{NM}, \tau_2^{NM})$ and $W_2^{NM}(\tau_{1C}^{NM}, \tau_2^{NM})$.

In the subgame equilibrium (M, N), firm 1 decides to be a multinational firm and firm 2 a national firm, such that firm 1 has production plants in its home country 1 and uses FDI in the other country, in which case it also produces in the other country 2. Therefore, the total welfare in country 1 is

$$W_1^{MN} = \pi_1^{MN} + \frac{(q_{1MN}^D + q_{2MN}^E)^2}{2} - \gamma_1 q_{1MN}^D + \tau_1 \gamma_1 q_{1MN}^D,$$

and the total welfare in country 2 is

$$W_2^{MN} = \pi_2^{MN} + \frac{(q_{2N}^D + q_{1M}^F)^2}{2} - \gamma_2(q_{2N}^D + q_{2N}^E) - \gamma_1 q_{1M}^F + \tau_2\gamma_2(q_{2N}^D + q_{2N}^E) + \tau_2\gamma_1 q_{1M}^F.$$

Country k chooses τ_k that maximizes W_k^{MN} for $k = 1, 2$. All the constraints must be satisfied: quantities must be positive, and $f_2(T, \tau_1, \tau_2) < F < f_1(T, \tau_1, \tau_2)$. In that case, again, the conditions are not satisfied: we cannot have positive quantities and the conditions on f_1 and f_2 satisfied simultaneously. We find that

$$\tau_1^{MN} = \frac{c_1 - \alpha_1 + 2\gamma_1}{\gamma_1},$$

which does not depend on τ_2, and country 2 chooses τ_{2C}^{MN} such that $f_1(T, \tau_1^{MN}, \tau_{2C}^{MN}) = F$. We thus need to verify that at τ_{2C}^{MN} all the quantities are positive and $F < f_1(T, \tau_1^{MN}, \tau_{2C}^{MN})$. We find that there are values of T and F such that $F > f_2(T, \tau_1^{MN}, \tau_{2C}^{MN})$ and all quantities are positive. Thus, the optimal total welfare in countries 1 and 2 are $W_1^{MN}(\tau_1^{MN}, \tau_{2C}^{MN})$ and $W_2^{MN}(\tau_1^{MN}, \tau_{2C}^{MN})$.

In the subgame equilibrium (M, M), both firms decide to be multinational firms, such that each firm has production plants in its home country and uses FDI in the other country, in which case it also produces in the other country. Therefore, the total welfare in country 1 is

$$W_1^{MM} = \pi_1^{MM} + \frac{(q_{1M}^D + q_{2M}^F)^2}{2} - \gamma_1 q_{1M}^D - \gamma_2 q_{2M}^F + \tau_1(\gamma_1 q_{1M}^D + \gamma_2 q_{2M}^F),$$

and the total welfare in country 2 is

$$W_2^{MM} = \pi_2^{MM} + \frac{(q_{2M}^D + q_{1M}^F)^2}{2} - \gamma_2 q_{2M}^D - \gamma_1 q_{1M}^F + \tau_2(\gamma_2 q_{2M}^D + \gamma_1 q_{1M}^F).$$

Country k chooses τ_k that maximizes W_k^{MN} for $k = 1, 2$. All the constraints must be satisfied: quantities must be positive, and $F < f_1(T, \tau_1, \tau_2)$ and $F < f_2(T, \tau_1, \tau_2)$. When all the constraints are satisfied, we calculate the first-order conditions for each country, which yield the equilibrium emission tax levels

$$\tau_1^{MM} = \frac{-\gamma_1(\alpha_1 - c_1) + \gamma_2(\alpha_1 - c_2) + (\gamma_1)^2 + (\gamma_2)^2 + (\gamma_1 - \gamma_2)^2}{(\gamma_1)^2 - 2\gamma_1\gamma_2 + 3(\gamma_2)^2},$$

$$\tau_2^{MM} = \frac{-\gamma_2(\alpha_2 - c_2) + \gamma_1(\alpha_2 - c_1) + (\gamma_1)^2 + (\gamma_2)^2 + (\gamma_1 - \gamma_2)^2}{3(\gamma_1)^2 - 2\gamma_1\gamma_2 + (\gamma_2)^2}.$$

These equilibrium emission tax levels are such that $\tau_1^{MM} < \tau_2^{MM}$. The equilibrium quantities are always positive, and there are values of T and F such that $F < f_1(T, \tau_1^{MM}, \tau_2^{MM})$ and $F < f_2(T, \tau_1^{MM}, \tau_2^{MM})$. Thus, the optimal total welfare in countries 1 and 2 are $W_1^{MM}(\tau_1^{MM}, \tau_2^{MM})$ and $W_2^{MM}(\tau_1^{MM}, \tau_2^{MM})$.

There exist values of F such that the constraints are not satisfied. Therefore, we calculate that there values τ_{1C}^{MM} and τ_{2C}^{MM} are such that $f_1(T, \tau_{1C}^{MM}, \tau_{2C}^{MM}) = F$, where $\tau_{1C}^{MM} > \tau_1^{MM}$ and $\tau_{2C}^{MM} < \tau_2^{MM}$.

In the first period, each country chooses its emission tax level, which is the best response to the other country's emission tax level. What complicates the analysis is that depending on the tax values and the parameters of the model, we go from one area to another. For instance, if country 2 chooses τ_2^{NN}, to find the best response of country 1, we need to take into account the fact that if country 1 lowers its tax level, both firms will choose to be in area (N, M) where firm 1 is a national and firm 2 is a multinational, in which case country 1 will get W_1^{NM} and no longer W_1^{NN}. These changes create discontinuities in the best response functions for both countries, which makes it hard to analyze.

We find that for large values of F, and any values of T, the unique equilibrium is $(\tau_1^{NN}, \tau_2^{NN})$ (see Appendix A3 for the detail of the calculation). For smaller values of F, initially, the tax levels in equilibrium correspond to a corner solution $(\tau_{1C}^{NN}, \tau_{2C}^{NN})$. As F decreases further, we find that another equilibrium is achieved $(\tau_{1C}^{MN}), \tau_{2C}^{MN}$. Finally, for very small values of F and relatively large values of T, we find that the equilibrium is $(\tau_1^{MM}, \tau_2^{MM})$. We summarise these findings in the following Proposition.

Proposition 4. *If* $T < T_{NN}$*,*

- *for large values of* F*, the subgame perfect Nash equilibrium is* $(\tau_1^{NN}, \tau_2^{NN})$*, and both firms choose to be national* (N, N)*;*

- *for intermediate values of* F*, and relatively small* T*, the subgame perfect Nash equilibrium is* $(\tau_{1C}^{NN}, \tau_{2C}^{NN})$*, and both firms choose to be national* (N, N)*;*

- *for smaller values of* F*, and relatively small* T*, the subgame perfect Nash equilibrium is* $(\tau_{1C}^{MN}, \tau_{2C}^{MN})$*, and firm 1 decides to be a multinational while firm 2 decides to be a national* (M, N)*;*

- *for very small values of* F*, and relatively large* T*, the subgame perfect Nash equilibrium is* $(\tau_1^{MM}, \tau_2^{MM})$*, and both firms 1 decide to be multinational firms* (M, M)*.*

We now calculate the emission levels in both countries depending on the equilibrium, which depends on the value of F.

1.5.3.2 Equilibrium Emission Levels

Depending on the values of F, there are different equilibrium emission levels as per Proposition 4. Thus, country 1's equilibrium emission levels are

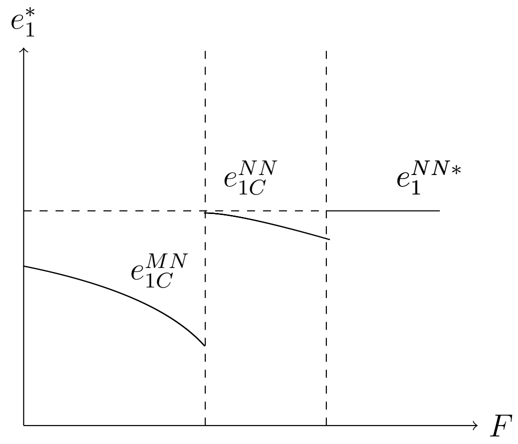
$$e_1^* = \begin{cases} e_1^{MN} = \gamma_1 q_{1MN}^D(\tau_{1C}^{MN}, \tau_{2C}^{MN}) & \text{for very small } F \\ e_{1C}^{NN} = \gamma_1 \left[q_{1NN}^D(\tau_{1C}^{NN}, \tau_{2C}^{NN}) + q_{1NN}^E(\tau_{1C}^{NN}, \tau_{2C}^{NN})\right] & \text{for intermediate } F \\ e_1^{NN} = \gamma_1 \left[q_{1NN}^D(\tau_1^{NN}, \tau_2^{NN}) + q_{1NN}^E(\tau_1^{NN}, \tau_2^{NN})\right] & \text{for large } F \end{cases}$$

and country 2's equilibrium emission levels are

$$e_2^* = \begin{cases} e_2^{MN} = \gamma_2 \left[q_{2MN}^D(\tau_{1C}^{MN}, \tau_{2C}^{MN}) + q_{2MN}^E(\tau_{1C}^{MN}, \tau_{2C}^{MN}) \right. & \\ \quad \left. +\gamma_1 q_{1MN}^F(\tau_{1C}^{MN}, \tau_{2C}^{MN})\right] & \text{for very small } F \\ e_{2C}^{NN} = \gamma_2 \left[q_{2NN}^D(\tau_{1C}^{NN}, \tau_{2C}^{NN}) + q_{2NN}^E(\tau_{1C}^{NN}, \tau_{2C}^{NN})\right] & \text{for intermediate } F \\ e_2^{NN} = \gamma_2 \left[q_{2NN}^D(\tau_1^{NN}, \tau_2^{NN}) + q_{2NN}^E(\tau_1^{NN}, \tau_2^{NN})\right] & \text{for large } F \end{cases}$$

In Figure 1.7, we represent the optimal emission level in country 1 as a function of F. Initially, as F is small, the emission level in country 1 is decreasing with F in the constrained equilibrium (M, N). Indeed, as F increases, the emission τ_{1C}^{MN} increases, which decreases q_{1MN}^D. As F increases further, there is a jump upward when we reach a different constrained equilibrium (N, N). Firm 1 does not produce in country 2 anymore, and thus the emission in country 1 is due to the domestic production as well as the exported production of firm 1. However, as firm 1 produces less than in the non-constrained equilibrium, the emission level is smaller than in the non-constrained case and decreases with F. As F increases further, the equilibrium becomes non-constrained such that the emission is independent of F.

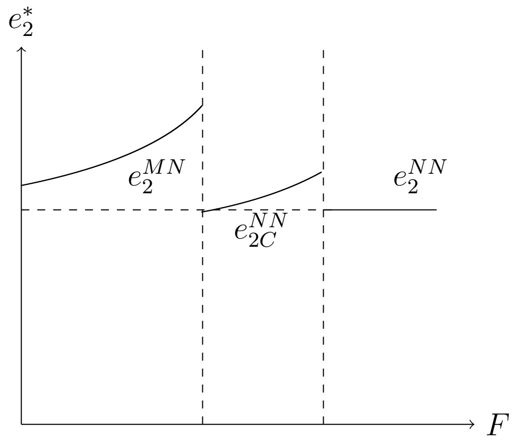
Figure 1.7: Optimal emission level in Country 1



Proposition 5. *Country 1's emission is a non-monotonic function of the FDI fixed cost F. Initially, the emission level decreases as F increases. There is a discontinuity where the emission jumps up before it decreases. Eventually, there is another increase where the emission tax becomes constant.*

In Figure 1.8, we represent the optimal emission level in the country 2 as a function of F. Initially, for low values of F, the emission level in country 2 increases with F in the constrained equilibrium (M, N). Indeed, as F increases, the emission τ_{2C}^{MN} decreases, which increases q_{2MN}^{D}. As F increases further, there is a jump downward when we reach a different constrained equilibrium (N, N). Firm 1 does not produce in country 2 anymore, and thus the emission in country 2 is reduced. As F increases further, the equilibrium becomes non-constrained such that the emission is independent of F.

Figure 1.8: Optimal emission level in Country 2



1.6 Scenario 2: *Ex Post* Choice of Emission Taxes

We now consider that the timing is changed such that the government of each country chooses its level of emission *ex post* once both firms have decided to be national or multinational firms. By backward induction, we start with the choice of the quantities. The Cournot equilibrium quantities are identical to the previous timing case for given decisions to be national or multinational and for given tax levels (Section 4). Then, given that firms have decided to be national or multinational, both countries determine their emission tax levels, which are also similar to the (unconstrained) tax levels determined in the previous section (Section 5). Finally, in the first stage of the game, when firms must decide whether to be national or multinational, they anticipate correctly the tax level that the countries will choose in the second period. We detail these decisions in the next subsection.

1.6.1 Equilibrium Emission Taxes

If both firms decide to be national firms, (N, N), both countries simultaneously choose their emission taxes τ_1^{NN} and τ_2^{NN} as defined by (1.28) and (1.29). The payoffs of firms 1 and 2 are $\pi_1^{NN}(\tau_1^{NN}, \tau_2^{NN})$ and $\pi_2^{NN}(\tau_1^{NN}, \tau_2^{NN})$. If firm 1 decides to be a national firm and firm 2 becomes a multinational firm, both countries choose their emission taxes τ_1^{NM} and τ_2^{NM} and both firms get $\pi_1^{NM}(\tau_1^{NM}, \tau_2^{NM})$ and $\pi_2^{NM}(\tau_1^{NM}, \tau_2^{NM})$. On the other hand, if firm 1 decides to be a multinational firm and firm 2 a national firm, both countries choose their emission taxes τ_1^{MN} and τ_2^{MN} and both firms get $\pi_1^{MN}(\tau_1^{MN}, \tau_2^{MN})$ and $\pi_2^{MN}(\tau_1^{MN}, \tau_2^{MN})$. Lastly, if both firms decide to be multinational firms, both countries choose their emission taxes τ_1^{MM} and τ_2^{MM} and both firms get $\pi_1^{MM}(\tau_1^{MM}, \tau_2^{MM})$ and $\pi_2^{MM}(\tau_1^{MM}, \tau_2^{MM})$.

We now solve the first stage of the game, when both firms decide whether to be national or multinational firms.

1.6.2 National or Multinational Decisions

Given that firm 2 is a national firm, firm 1 will prefer to be a national firm if $\pi_1^{NN}(\tau_1^{NN}, \tau_2^{NN}) > \pi_1^{MN}(\tau_1^{MN}, \tau_2^{MN})$ or, equivalently, if $F > f_{1NN}(T)$ where

$$f_{1NN}(T) \equiv \left(q_{1MN}^{D}(\tau_1^{MN}, \tau_2^{MN})\right)^2 - \left(q_{1NN}^{D}(\tau_1^{NN}, \tau_2^{NN})\right)^2 + \left(q_{1MN}^{F}(\tau_2^{MN})\right)^2 - \left(q_{1NN}^{E}(\tau_1^{NN}, \tau_2^{NN})\right)^2.$$

Given that firm 2 is a multinational firm, firm 1 will prefer to be a multinational firm if $\pi_1^{MM}(\tau_1^{MM}, \tau_2^{MM}) > \pi_1^{NM}(\tau_1^{NM}, \tau_2^{NM})$ or, equivalently, if $F < f_{1MM}(T)$ where

$$f_{1MM}(T) \equiv \left(q_{1MM}^{D}(\tau_1^{MM}, \tau_2^{MM})\right)^2 - \left(q_{1NM}^{D}(\tau_1^{NM}, \tau_2^{NM})\right)^2 + \left(q_{1MM}^{F}(\tau_2^{MM})\right)^2 - \left(q_{1NM}^{E}(\tau_1^{NM}, \tau_2^{NM})\right)^2.$$

Given that firm 1 is a national firm, firm 2 will prefer to be a national firm if

$\pi_2^{NN}(\tau_1^{NN},\tau_2^{NN}) > \pi_2^{NM}(\tau_1^{NM},\tau_2^{NM})$ or, equivalently, if $F > f_{2NN}(T)$ where

$$f_{2NN}(T) \equiv \left(q_{2NM}^D(\tau_1^{NM},\tau_2^{NM})\right)^2 - \left(q_{2NN}^D(\tau_1^{NN},\tau_2^{NN})\right)^2 + \left(q_{2NM}^F(\tau_2^{NM})\right)^2 - \left(q_{2NN}^E(\tau_1^{NN},\tau_2^{NN})\right)^2.$$

Given that firm 1 is a multinational firm, firm 2 will prefer to be a multinational firm if $\pi_2^{MM}(\tau_1^{MM},\tau_2^{MM}) > \pi_2^{MN}(\tau_1^{MN},\tau_2^{MN})$ or, equivalently, if $F < f_{2MM}(T)$ where

$$f_{2MM}(T) \equiv \left(q_{2MM}^D(\tau_1^{MM},\tau_2^{MM})\right)^2 - \left(q_{2MN}^D(\tau_1^{MN},\tau_2^{MN})\right)^2 + \left(q_{2MM}^F(\tau_2^{MM})\right)^2 - \left(q_{2MN}^E(\tau_1^{MN},\tau_2^{MN})\right)^2.$$

We show that $f_{1NN}(T)$, $f_{2NN}(T)$, $f_{1MM}(T)$ and $f_{2MM}(T)$ are concave functions (all the proofs are relegated in Appendix A4). We also show that when a firm decides to become a multinational, its profit is always positive, and all quantities are positive in equilibrium. We summarize these findings in the following Proposition.

Proposition 6. *For any $F \geq 0$,*

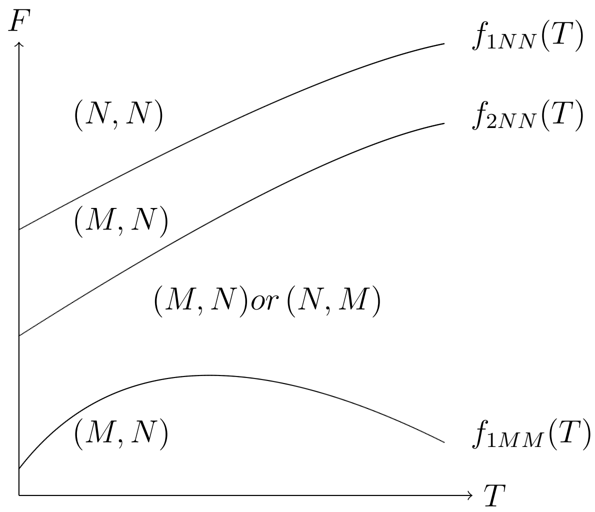
- *If $F \geq f_{1NN}(T)$, there is a unique Nash equilibrium (N,N) in which both firms choose to be national firms;*
- *If $f_{2NN}(T) < F < f_{1NN}(T)$, and if $f_{2MM}(T) < F < f_{1MM}(T)$ there is a unique Nash equilibrium (M,N) in which firm 1 chooses to be a multinational and firm 2 chooses to be a national;*
- *if $f_{1MM}(T) < F < f_{2NN}(T)$, there are two Nash equilibrium (N,M) in which firm 2 chooses to be a multinational and firm 1 chooses to be a national and (M,N) in which firm 1 chooses to be a multinational and firm 2 chooses to be a national.*

There would be an equilibrium (M,M) if $F < f_{2MM}(T)$. However, we show that $f_{2MM}(T) < 0$ is always satisfied so that there is no equilibrium in which both firms choose to be multinational.

The third bullet of Proposition (6) is a novel result. In contrast to the *ex ante* case scenario, firm 2 from the developing country can engage in FDI when firm 1 does not when taxes are set *ex post*. This is novel also in relation to the existing literature on FDI which typically concludes that the more efficient firms are the ones to engage in FDI Nocke and Yeaple (2008). This also explains the observation that in recent years firms from developing countries such as India and China have engaged in more outward FDI.

Figure 1.9 represents the different areas in a graph (T, F). This graph represents the case where $\alpha_1 \geq \alpha_2$. The function $f_{2MM}(T) < 0$ so that there is no equilibrium in which both firms choose to be multinational. For intermediate values of T and F, we have multiple equilibria: either firm 1 is a multinational and firm 2 is a national firm, or firm 1 is a national firm and firm 2 is a multinational firm.

Figure 1.9: Subgame Perfect Equilibrium in Scenario 2



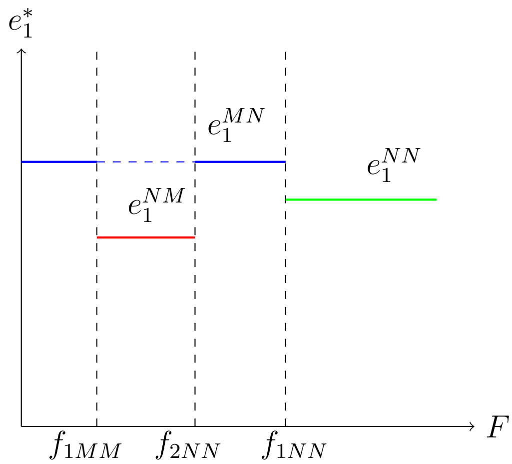
1.6.3 Equilibrium Emission Levels

For a given T, the equilibrium emission level for country k where $k = 1, 2$ is

$$
e_k^* = \begin{cases} e_k^{MN} & \text{for } F < f_{1MM} \\ e_k^{NM} \text{ or } e_k^{MN} & \text{for } f_{1MM} < F < f_{2NN} \\ e_k^{MN} & \text{for } f_{2NN} \leq F < f_{1NN} \\ e_k^{NN} & \text{for } F \geq f_{1NN} \end{cases}
$$

In Figure 1.10, we represent the equilibrium emission tax levels for country 1 in function of F for a given level of T.

Figure 1.10: Equilibrium Emission level in Country 1

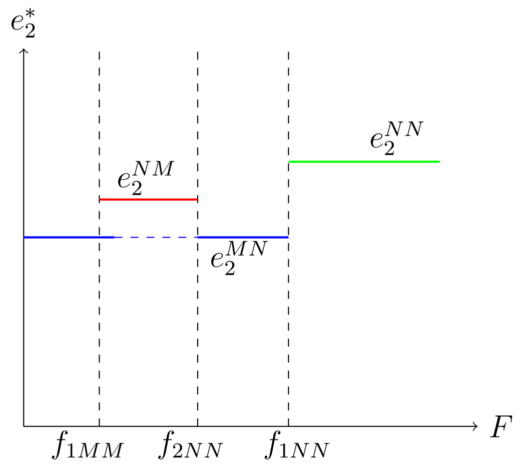


Emission taxes vary depending on the area. Indeed, we show that, in equilibrium, $\tau_1^{NM} > \tau_1^{NN} > \tau_1^{MN}$. When firm 1 is a national firm and firm 2 is a multinational firm, country 1 has an incentive to increase its tax level as the tax bill will also be borne by a foreign firm. This order of equilibrium taxes explains the discontinuities in the equilibrium emission levels. When firm 1 is a national firm and firm 2 a multinational firm, the tax is much higher than when firm 1 is a multinational firm, $\tau_1^{NM} > \tau_1^{MN}$, and thus, the quantities produced are smaller which reduces the total emission. When firm 1 is a multinational firm, the tax is smaller, so that firm 1 can produce more in its domestic country, which raises the emission level. We summarize these findings in the following Proposition.

Proposition 7. *When countries set ex post their emission tax levels, country 1's* *emission is a non-monotonic function of the FDI fixed cost F. Initially, the emission level is at a relatively large level when firm 1 is a multinational firm. There might be a discontinuity where the emission jumps down when firm 1 decides to be a national firm. There might be another jump up to the previous level, and eventually, the emission level is reduced.*

In Figure 1.11, we represent the equilibrium emission tax levels for country 2 in function of F for a given level of T. The emission level in the area (M, N)

Figure 1.11: Equilibrium Emission level in Country 2



In equilibrium, $\tau_2^{MN} > \tau_2^{NN} > \tau_2^{NM}$, so that country 2's emission level in the area (M, N) is the smallest one. Initially, for low values of F, the emission level is low as the equilibrium tax is high. As F increases, there might be a jump up, as the equilibrium tax decreases. Eventually, the emission increases.

1.7 Comparison: *ex ante* or *ex post* emission taxes

When taxes are defined *ex ante*, both countries can not always set the tax levels at their unconstrained optimal levels. Indeed, since the firms' decisions depend on the tax levels, countries must choose corner solutions. However, when tax levels are determined *ex post*, countries will always choose the optimal levels such that we have interior solutions, based on what firms choose initially. Overall, even though there are parameter values (low F and large T) for which both firms might decide to be multinational in the *ex ante* emission tax choice, they will never choose to be both multinational in the *ex post* emission tax choice. Furthermore, there are parameter values for which firm 1 decides to be a national while firm 2 decides to be a multinational firm in the *ex post* choice, which will never occur when taxes are chosen *ex ante*. Therefore, equilibrium emission taxes will be different in the two different scenarios. When choosing the emission taxes *ex ante*, countries are constrained to reduce their tax levels, which leads to lower emission levels for low values of F. We summarize these findings in the following Proposition.

Proposition 8. *For low values of F, the emission levels are overall lower when the emission taxes are chosen ex ante rather than ex post.*

The timing of the choice of the emission taxes does matter, as it will a have different impact on the emission levels.

1.8 Conclusion

This chapter contributes to the literature on the relationship between environmental regulation and plant location within an open economy context by examining how the timing of setting the emission taxes affects firms' FDI decisions. More specifically, we compare the case where countries set the emission taxes before firms make their FDI decisions, which is in line with most of the previous literature, to the case where countries set the emission taxes after firms make their FDI decisions. Our setup may be summarized as a two country model with a developed and a developing country. We consider two firms, each of which endogenously decides the number and location of production facilities. Each firm produces a polluting product and must pay a per unit emission tax. Pollution damage is assumed to be local to the country where emissions occur. The trade-off facing the firms is whether to pay a per unit tariff and export or to pay a fixed cost to set up a firm in a foreign country. Moreover, firms have an incentive to set up the plant in the country with a lower emission tax. We retrieve results in line with the previous literature when taxes are set *ex ante*. The lower the fixed cost of setting up a firm in the foreign country, the greater the likelihood of firms engaging in FDI. In equilibrium, we find that the firm in the developed country engages in FDI but the firm in the developing country does not, given the choices of the emission tax levels of each country. Moreover, when such FDI occurs, emission shifts away from the developed to the developing country. When taxes are set *ex post*, foreseeing that countries will set higher emission taxes if both firms engage in FDI, firms avoid this scenario. Our findings thus suggest that in a world where governments are unable to commit to taxes a priori, two-way FDI (i.e., FDI from developed and developing countries simultaneously) is discouraged. However, one-way FDI could occur in either direction (i.e., either from the developed to developing or from the developing to developed country), unlike in the *ex ante* case where FDI only flows from the developed to developing country in equilibrium. Another important departure from the *ex ante* case is regarding the re-distribution of emissions across countries induced by FDI. While in the *ex ante* case there is an unambiguous increase in emissions in a country when its firm switches from operating a foreign production facility to becoming a local firm that exports, in the *ex post* case this does not hold. This is because, in the *ex post* case as opposed to the *ex ante* case, the emission tax rate is higher when the firm is local rather than when the firm engages in FDI since a local firm that exports emits more pollution than a firm that serves only the domestic market. Thus, while we are able to retrieve the standard intuitive results in line with the previous literature when we consider *ex ante* tax setting, we show that the results change significantly when taxes are set after FDI decisions have been taken. A possible avenue to explore in future research would be to consider transboundary pollution (such as greenhouse gas emissions) instead of local pollution. This is expected to change the results since the equilibrium taxes would be set at a different level in both cases (i.e., *ex ante* and *ex post* tax setting cases) as each country will care about emissions in the other country.

Chapter 2

Green Patents and Environmental Policy Stringency

2.1 Introduction

This brief chapter introduces the concepts and datasets used in the following two empirical chapters that use patent data, particularly green patent data, as well as new measures of environmental stringency. These two chapters focus on green innovation; the research question of the former is to understand whether stronger environmental policies stimulate green innovation, and the latter focuses on the impact of green innovation on emissions.

Innovation is one of the drivers of growth because it creates new opportunities and improves efficiency. However, due to the public good nature of knowledge, innovators may not have sufficient incentives to innovate if they cannot protect their innovation with some kind of right. A patent gives its holder a temporary monopoly right, which lasts for a maximum of 20 years in most jurisdictions. In return for this temporary exclusive right, the patent holder must provide detailed information about his innovation. To be patentable, an innovation must meet the patentability requirements: novelty, inventive step (or non-obviousness), and applicability.

The patent application process is generally similar across countries (Eckert and Langinier, 2014). An innovator files a patent application either at a national patent office or through an international organization (e.g., the European Patent Office and the World Intellectual Property Organization). If an innovator plans to file a patent with multiple patent offices, a patent application filed through an international organization helps the applicant secure a priority date[1] for all countries.

Patent applications undergo a rigorous examination to ensure the invention is patentable, and the application process requires applicants to pay substantial fees, which can also deter lower-quality patent applications (Rassenfosse and Jaffe, 2017). When applying for a patent in different countries, innovators typically encounter four main types of costs: filing fees paid to the patent office, legal fees for the services of a patent attorney, drafting and illustration fees for preparing the necessary documents and drawings, and maintenance fees to keep the patent in force once granted. Patent fees are highly variable, with fees at the EPO being among the highest, and they increase with the patent's age (Rassenfosse et al., 2013).

Environmental innovation can help mitigate the adverse effects of climate change. A patent granted for an environmental innovation that ensures sustainability or reduces the adverse environmental impact is called a green patent. Green patents cover a wide range of technologies, including renewable energy, clean transportation, waste reduction and recycling, sustainable agriculture, etc. They can help mitigate adverse environmental impacts by reducing emissions or increasing energy efficiency. Green patents have different names in the literature, i.e., eco-patents, environmental patents, clean energy patents, and Environmentally Sustainable Technology (EST) patents.

The environmental economics literature has used different measures (i.e., R&D expenditure, number of scientific personnel, and patent count) to proxy innovation. As an output indicator, economists prefer patents as a measure of innovation. Patent

[1] Priority date refers to the earliest filing date in a family of patent applications.

data are classified according to industry and are readily available. Even though using a patent as a proxy for innovation has some drawbacks (e.g., the use of trade secrets instead of patents and concerns about patent quality), it is one of the most reliable and available measures to proxy innovation.

Countries enacted new laws and standards (e.g., carbon tax and emission trading schemes) to protect the environment, and different international protocols (e.g., Kyoto Protocol 1997 and Paris Agreement 2016) were signed. Stringent environmental policies put a price on polluting or environmentally harmful behaviour. Countries generally choose from a spectrum of environmental policies. Thus, cross-country comparisons of environmental policies are challenging.

To address this issue, Botta and Koźluk (2014) developed an index for the Organisation for Economic Co-operation and Development (OECD) known as the Environmental Policy Stringency (hereafter EPS14) index. The EPS14 allows the evaluation of different countries' policies over time on a scale from zero to six, where higher scores indicate tougher regulations. Kruse et al. (2022) enhanced and widened this EPS coverage with an updated version; we refer to it as EPS21. It covers data collected between 1990 and 2020 across forty countries, including thirty-four OECD member states focusing primarily on climate change control measures alongside air pollution mitigation strategies represented through thirteen distinct instruments or tools.

The paper is structured as follows: Section 2 begins with a brief history of green patents and explains their different classifications. Section 3 presents recent trends in green patents and the Environmental Policy Stringency (EPS) index. In Section 4, we delve into recent research that has utilized green patents. Finally, Section 5 concludes the chapter.

2.2 A Brief History of Green Patents Classification

Three methods are available to identify green patents based on code classification: ENV-TECH, developed by OECD; IPC Green Inventory, developed by the World Intellectual Property Organization (WIPO); and Y classification scheme, developed by the European Patent Office (EPO). However, of these three methods, only EPO classification offers a consolidated class (Y-class) determined by a field expert that specifically identifies green patents.

In 2006, the OECD Compendium of Patent Statistics proposed a methodology for classifying environmental technology patents into six categories based on International Patent Classification (IPC) classes[2] and keywords. However, this methodology relied on researchers to determine which IPC or Cooperative Patent Classification (CPC)[3] classes to include and which keywords to select. Since 2010, three reputable organizations have developed new strategies to facilitate the search for green technology patents. WIPO, in collaboration with the United Nations Framework Convention on Climate Change (UNFCCC) and the Intergovernmental Panel on Climate Change (IPCC), created the IPC Green Inventory list, which collected IPC codes and keywords related to Environmental Sound Technologies (ESTs). The European Patent Office (EPO) also developed a new classification scheme in 2012, called the Y02/Y04S scheme specifically designed to identify climate change mitigation technologies (CCMTs). In 2015, the OECD released patent search strategies for nine environment-related technologies (ENV-TECH) using various IPC classes.

Keyword searches are limited by language usage, while manual selection is not fea-

[2]IPC is a hierarchical patent categorization method utilized in over 100 countries to classify patents uniformly. It was established as part of the Strasbourg Agreement, one of several treaties overseen by the WIPO.

[3]Cooperative Patent categorization (CPC) is a collaboration between the United States Patent and Trademark Office (USPTO) and the European Patent Office (EPO), in which the offices have agreed to unify their existing categorization systems.

sible due to cost, terms, and technological expertise constraints. On the other hand, utilizing classification codes is considered the most efficient approach since it is based on the detailed knowledge of patent examiners and is necessary for handling large patent datasets. In the past, the absence of a single classification for sustainable technologies has made it difficult to search for patent documents related to sustainable energy. To address this issue, the EPO has created a dedicated classification scheme for CCMTs, which allows relevant patent publications to be tagged and classified separately within the CPC. In addition, the CPC has replaced the European CLAssification (ECLA) scheme, which included the Y classification specifically for sustainable energy. The Y-class is devoted to green technologies and is backed by formalized algorithms to search and detect. Experts at EPO created these algorithms, periodically re-run them, and can automatically identify and tag new documents that satisfy the search criteria (Angelucci et al., 2018). As a result, Y codes are appended to the existing classifications, and retroactive inclusion is also feasible.

The CPC Y class has an additional advantage in terms of its level of disaggregation. Unlike the IPC Green Inventory and ENV-TECH, which provide aggregate-level data and require manual retrieval to obtain information on specific green technologies, the CPC Y class data is highly disaggregated. Any patent information about a particular green technology can be retrieved using tagged CPC Y subclasses. The Y02 categories cover all technologies in developed sectors across several IPC/ECLA categories, allowing for precise results to be obtained using a single code. That demonstrates the advantage of using the Y class.

Table 2.1: Classification of Y02 Class Patents

Patent Class	Technology
Y	General identification of new technological developments; general identification of cross-sectional technologies spanning over several sections of the IPC;
Y02	Technologies or Applications for Mitigation or Adaptation Against Climate Change
Y02A	Technologies for Adaptation to Climate Change
Y02B	Climate Change Mitigation Technologies Related to Buildings, e.g. Housing, House Appliances or Related End-User Applications
Y02C	Capture, Storage, Sequestration or Disposal of Greenhouse Gases (GHG)
Y02D	Climate Change Mitigation Technologies In Information And Communication Technologies (ICT), i.e. Information and Communication Technologies Aiming at The Reduction of Their Own Energy Use
Y02E	Reduction Of Greenhouse Gas (GHG) Emissions Related to Energy Generation, Transmission Or Distribution
Y02P	Climate Change Mitigation Technologies in The Production or Processing of Goods
Y02T	Climate Change Mitigation Technologies Related to Transportation
Y02W	Climate Change Mitigation Technologies Related to Wastewater Treatment or Waste Management

Sources: USPTO and EPO

2.3 Green Patents Trend

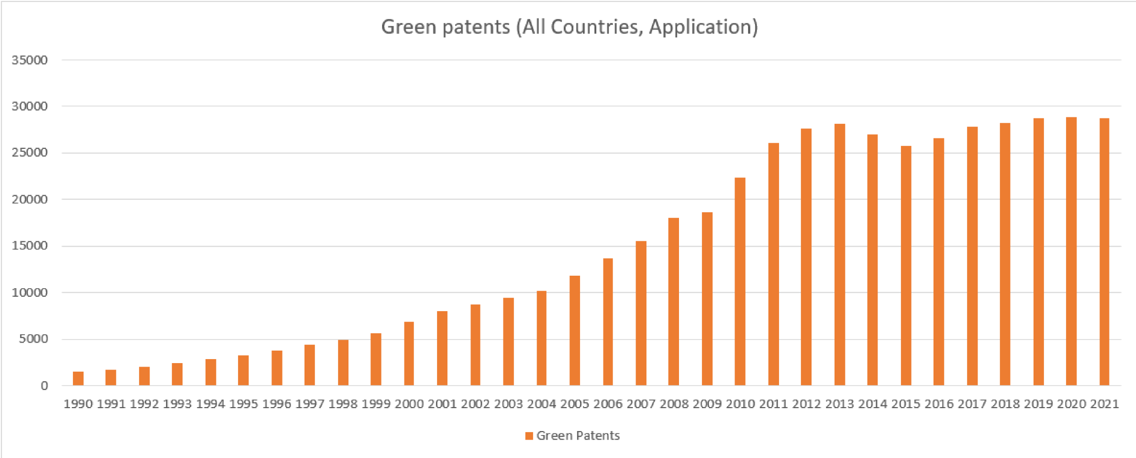
Green patents have been steadily growing since the early 2000s. Since 1990, the number of granted green patents has increased exponentially, though growth slowed after 2013 (Probst et al., 2021). Figure 2.1 shows trends of environment-related technologies in all countries, drawing data from the OECD database[4] up to the year 2021. Two prominent trends emerge that warrant attention. Firstly, a continuous surge in patenting activities was observed for green technology from 1990 to the early 2010s, signifying a period of significant growth and innovation in the green technology sector. However, in the years after 2014, patenting activities slowed down. This decline has sparked interest among researchers who have hypothesized multiple potential factors accounting for the decrease in green patents. Some of these suggested reasons include the reduction in fossil fuel prices, the shale gas exploration boom, the slow diffusion of existing green technologies, and the relatively low cost

[4] https://stats.oecd.org/index.aspx?queryid=22009#

associated with emissions (Acemoglu et al., 2023; Probst et al., 2021; Calel and Dechezleprêtre 2016; Popp 2002). Economists argue the importance of transitional energy sources on the path to the complete adoption of green energy (Gursan and de Gooyert, 2021). However, transitional energy sources (i.e., natural gas) might have a long-term negative impact on green innovation and emissions, even though in the short term, natural gas generally reduces emissions (Acemoglu et al., 2023). In a recent paper, Acemoglu et al. (2023) argue that the shale gas boom helped the environment in the short run by substituting coal, which outweighed the rebound effect. Nevertheless, in the long run, the natural gas boom reallocates scarce research inputs away from renewable fossil fuels and reduces green innovation. The study provides evidence of the U.S. shale gas boom and the electricity sector's reduction of green patent applications.

However, when exploring green patents in more detail, we turn to the PATSTAT dataset, which gives us more specific information about different types of green technologies. For our analysis, we focus on the data PATSTAT published in 2019. It is worth mentioning that it takes an average of three years for a patent to be granted from the filing date until its issuance (Demey and Golzio, 2020). Therefore, starting from Figure 2.3, we use the PATSTAT data until 2016, which allows us to include all the patents that have been granted up to that point and give us a better overall picture of patents in the green technology field over time.

Figure 2.1: Environment Related Technologies (World, with duplicate)



Source: OECD database

The graph represented in Figure 2.1 displays the yearly progression of green patents from 1990 to 2021. The data was collected from the OECD database for ESTs. We have used the patent granted under the Patent Cooperation Treaty (PCT)[5] to ensure patent quality. Indeed, PCT applications are considered high-value because in a single application, expenses, it provides a unified procedure, includes an international search and optional preliminary examination, allowing extended decision time for filing in specific countries and enhancing the perceived value of the invention.

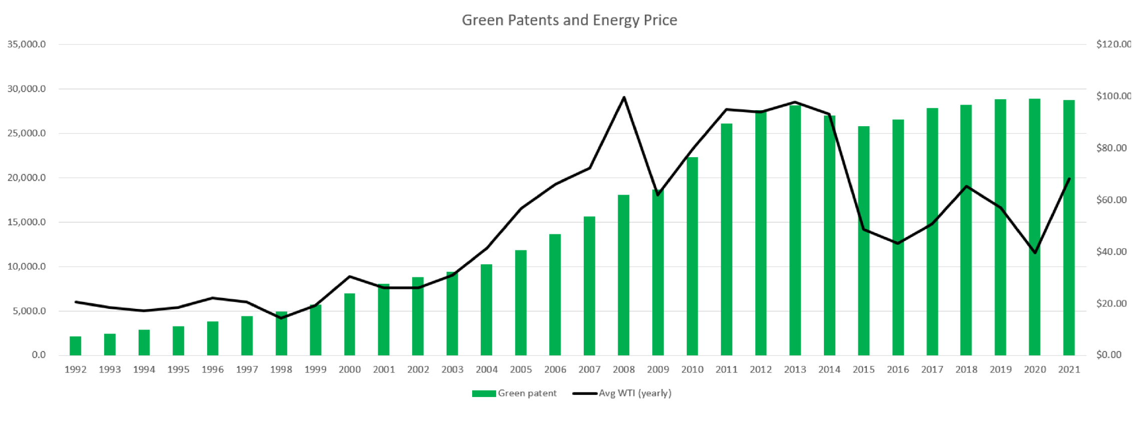
The count of green patents exhibits a consistent upward trajectory, doubling from 1990 to 1995. During this period, the number of green patents experienced a substantial surge, soaring from 1475 to 3229 patents. Relative to the number of green patents in 1990, there was a significant 370% increase by the year 2000. Following a rapid increase, the growth of green patents slowed at the peak of the global financial crisis in 2008-09. Post-2010, there was a gradual and steady resurgence in green patents, which peaked in 2013. However, starting in 2017, a discernible decline in the count of green patents began to emerge. Ultimately, by 2019, the number of

[5]The PCT is an international patent law treaty signed in 1970. It provides a unified procedure for filing patent applications to get precedence in each of its contracting countries.

green patents levelled off and demonstrated a steady trend till 2021. In 2021, green patents showed a noteworthy 19-fold upsurge compared to the levels observed in 1990.

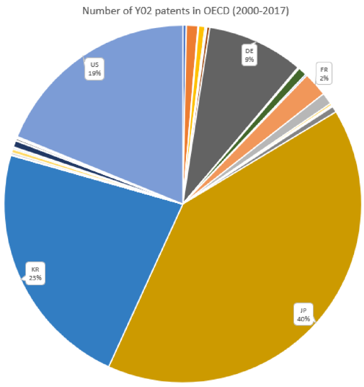
Figure 2.2 presents trends in green patents and energy prices. Previous studies (Probst et al., 2021; Popp, 2002) have found that energy prices have a positive impact on green innovation. Energy prices positively influence the number of green patents. The energy price was represented by the yearly average of West Texas Intermediate (WTI), and green innovation was represented by green patent applications through PCT. Figure 2.2 indicates a strong correlation between energy prices and green patent applications. The correlation coefficient between green patent applications and WTI prices is high at 0.78.

Figure 2.2: Green Patents and Energy Price



Sources: OECD patent database, Federal Reserve Bank

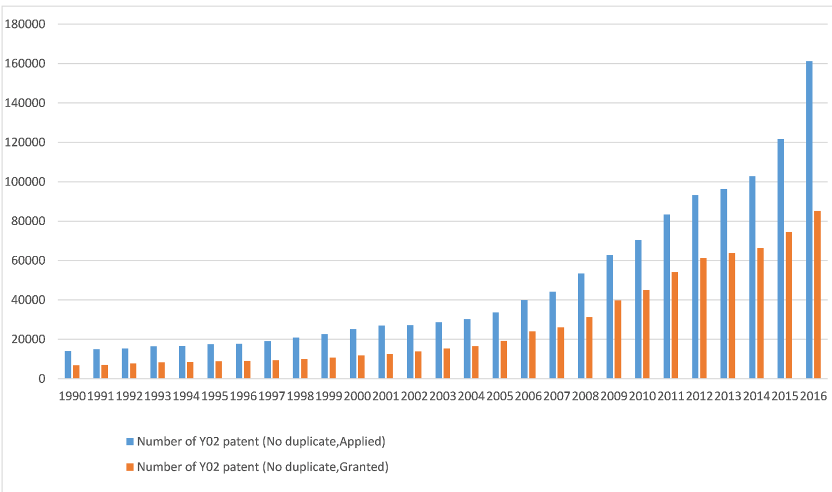
Figure 2.3: Green Patents in Different Countries



Source: PATSTAT

We can see from Figure 2.3 that the top twelve innovative nations provide roughly 90% of worldwide innovations, indicating that innovation is highly concentrated. Japan, the U.S., and Germany appear as the leading pioneers in a variety of technologies (Dechezleprêtre et al., 2011). The same holds true for green innovation. The Y02 patents in OECD countries from 2000 to 2017 are highly concentrated in the U.S., Japan, Korea, and Germany. Japan is at the top with 40% green patents in that period, followed by the Republic of Korea (23%), the U.S. (19%), and Germany (9%).

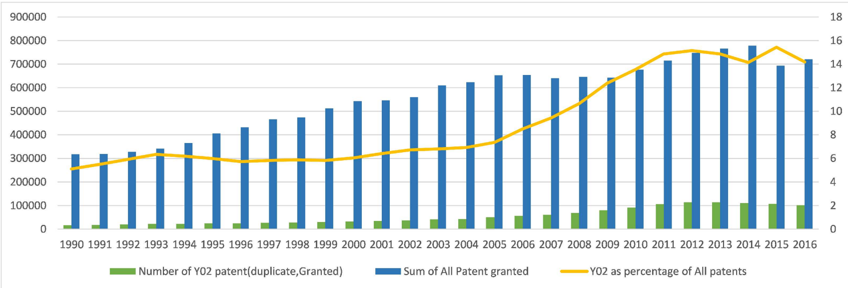
Figure 2.4: Unique Applied and Granted Y02 Patents



Source: PATSTAT

PATSTAT provides in-depth information. Figure 2.4 provides information about applied and granted green patents from 1990 to 2016. On average, in OECD countries, 55% of applied green patents were granted. The data further reveals that the range of granted green patents in relation to the total number of applied patents, fluctuated between 47% and 66% over the years.

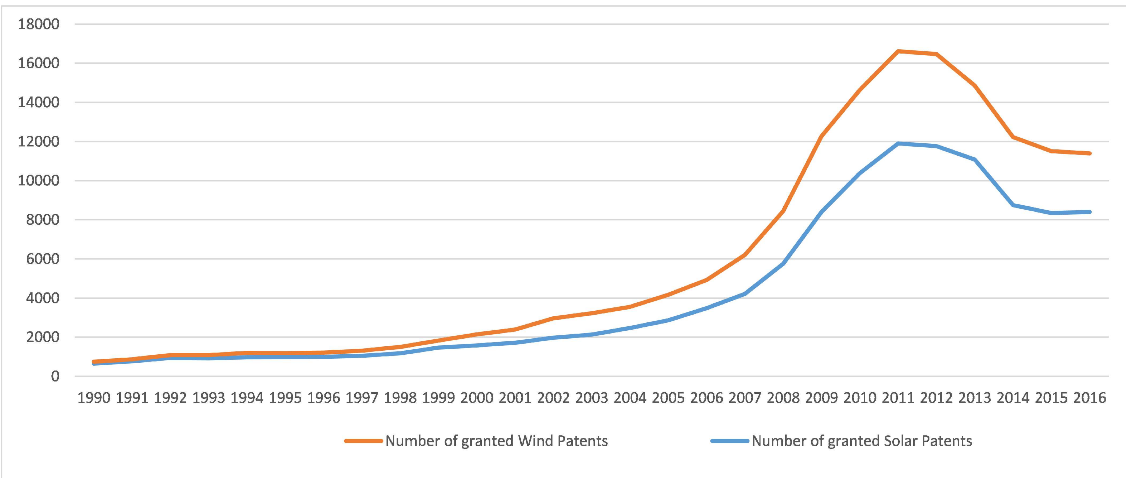
Figure 2.5: Y02 Patents as a Percentage of all Patents



Source: PATSTAT

Figure 2.5 illustrates the total number of granted patents and the corresponding count of green patents. In 1990, green patents represented 5.11% of total patents and maintained this range until 2003, fluctuating between 5% and 7%. Starting in 2004, there was a notable increase in green patents relative to the overall total of patents, peaking at 15.43% in 2015.

Figure 2.6: Granted Wind and Solar Patents

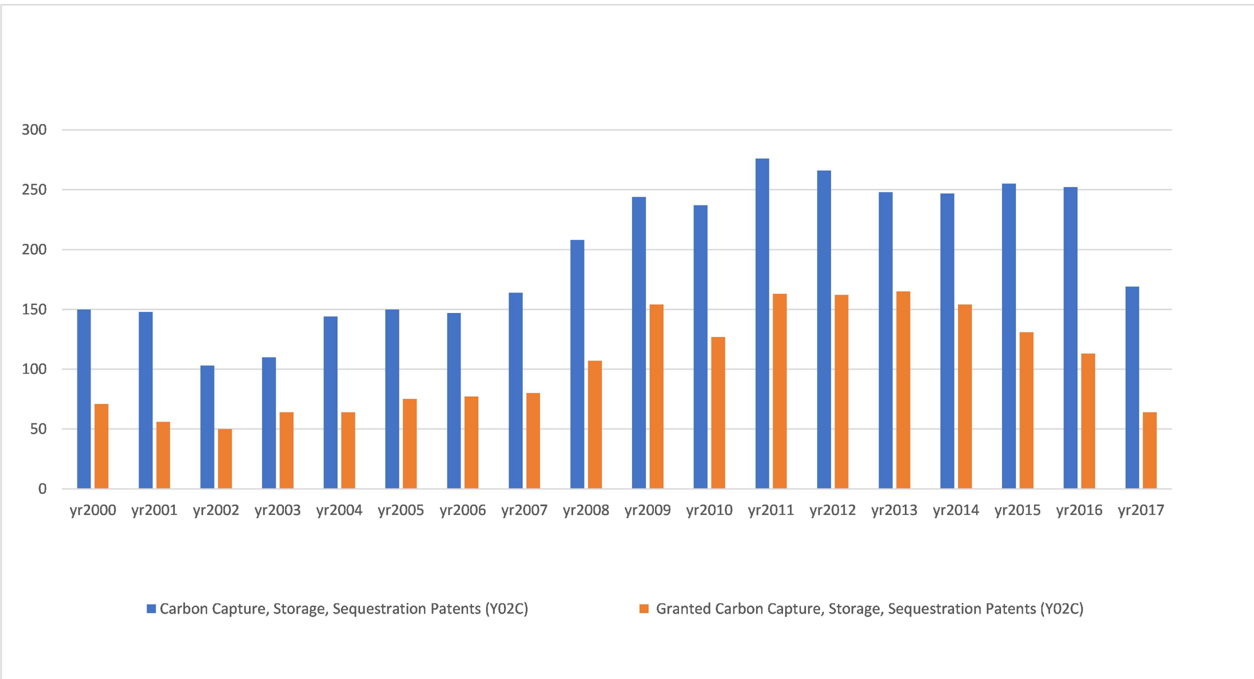


Source: PATSTAT

Wind and solar power are gaining popularity among renewable energy sources as costs decrease. Thus, we look into wind and solar patents trends in Figure 2.6. The wind and solar energy patents follow a similar pattern. In 1990, only 649 solar energy and 99 wind energy patents were granted. Wind and solar energy patents gained steadily up to 2004, reaching 1077 and 2470 patents, respectively. The number of wind and solar energy patents increased after that, reaching an all-time high in 2011 to 4714 patents and 11908 patents, respectively. After declining in 2012-2013, both wind and solar energy patents became steady.

The decrease in green patents in early 2010 is not ubiquitous; some emerging technologies thrived even though general green patenting declined. Two such technologies are green transport (hybrid and electric vehicles, battery technologies) and Carbon Capture, Utilization and Storage (CCUS) technologies. Figure 2.7 represents the number of CCUS patents doubled from 1990 to 2016.

Figure 2.7: CCUS Patents

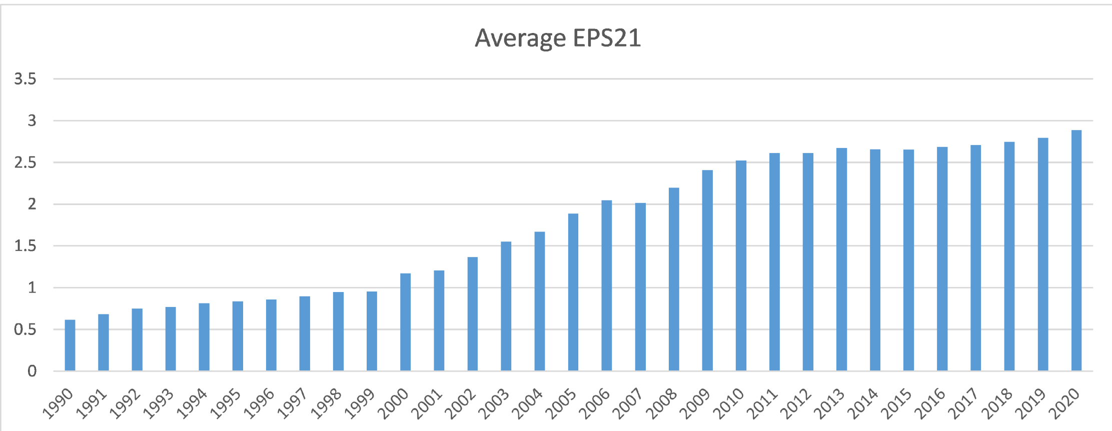


Source: PATSTAT

2.4 Environmental Policy Stringency (EPS) Index

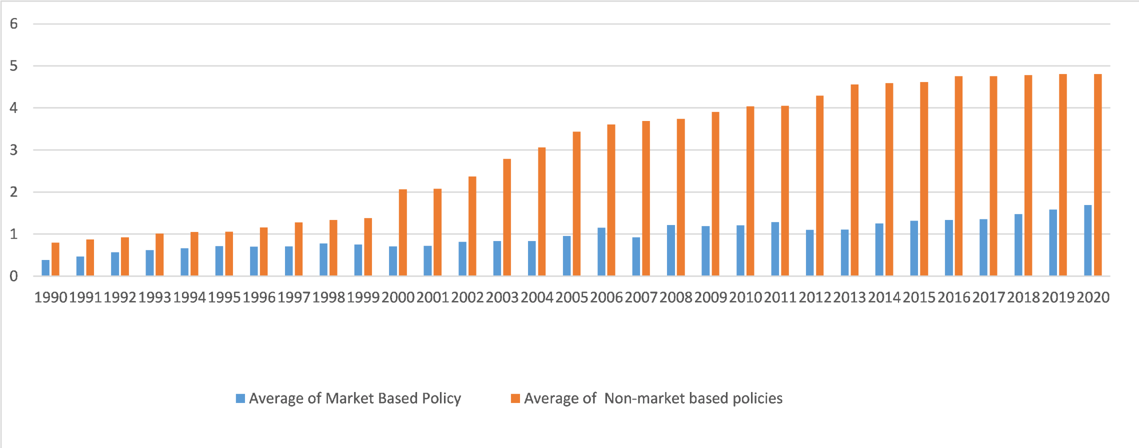
OECD first developed EPS in 2014. Since then, it has been extensively used in the environmental economics literature as a proxy for environmental stringency. One of the advantages of EPS is that it covers 40 countries and 13 policy instruments for over three decades. The updated EPS index was introduced in 2021, which includes both market-based and non-market-based as well as technology support policies. OECD countries have increased their environmental stringency significantly since 1990. From Figure 2.9 and Figure 2.10, we see that the EPS index more than doubled (+138%) since 2000 and jumped from 1.3 to 3.1. The EPS index had an average annual growth rate of 6.8% between 1990 and 2000 and a higher growth rate of 8% between 2000 and 2010. However, in the most recent decade, the growth in policy stringency has slowed down, with an average annual growth rate of only 1.1% between 2010 and 2020. The EPS levelled off between 2010 and 2015. It increased since 2015 to reach a score of 3.1 in 2020. Since 1990, market-based policy has grown faster than non-market-based policy.

Figure 2.8: Average EPS21



Source: OECD

Figure 2.9: Market and Non-Market Based Policy



Source: OECD

2.5 Recent Research Using Green Patents

The concept of sustainable development is the precursor concept of green innovation. The term "sustainable development" was first used by the International Union for Conservation of Nature (IUCN) in 1980 (Dresner, 2012; Schiederig et al., 2012). Green innovation or green patents can support the path to sustainable development. Schiederig et al., (2012) find that the terms "green innovation," "sustainable innovation," "environmental innovation," and "ecological innovation" were used in the literature interchangeably, and there were little differences in the definitions. They also found that academic studies of green innovation from an economic point of view started in the 1990s. The present section of this chapter builds upon the comprehensive literature review of Popp et al. (2010) and Popp (2019) and emphasizes more on recent literature.

Earlier studies have used pollution abatement costs and expenditures (PACE) to measure environmental stringency. Lanjouw and Mody (1996) studied environmental protection over the 1970s and 1980s. They analyzed how innovation measured by green patents responded to pollution abatement costs and expenditures (PACE).

They found that abatement costs increased green patenting in the U.S., Japan, Germany, and 14 other countries. For U.S. industries from 1974 to 1991, Jaffe and Palmer (1997) found that PACE has increased R&D spending, but it does not induce green patenting. In a similar study for the U.S. industry, Brunneimer and Cohen (2003) used a panel data model to analyze how regulatory standards impact PACE. They found that PACE has a small positive effect on environmental patents, but regulation enforcement does not affect innovation. In a similar study of the Japanese industry, Hamamoto (2006) used R&D expenditure as a proxy of innovation, and he found that PACE indeed increased R&D expenditure and also had a positive impact on the growth rate of total factor productivity. In a paper on international innovation and diffusion of air pollution control technologies for the U.S., Japan, and Germany. Popp (2016) finds that inventors respond to environmental regulatory pressure in their own country but not to foreign environmental regulations. Haščič et al. (2008) investigate if PACE drives innovation for five environmental technologies: air pollution, water pollution, waste disposal, noise protection, and environmental monitoring. They find that private-sector PACE increased environmental innovation for a panel of 16 countries between 1985 and 2004, while the public sector did not.

Measuring environmental stringency has always been difficult. Challenges of stringency measures come from multi-dimensionality, simultaneity, industrial composition, and novelty of pollution (Brunel & Levinson, 2016). In other words, a single indicator can not easily represent stringency and might suffer an endogeneity problem. In addition, industry structures are generally different, where newer types of pollution might get stringent regulatory standards. In addition, PACE is generally derived from survey questions, which are increasingly demanding for environmental managers to answer. According to Brunel and Levinson (2016), this problem can be addressed by using directly comparable stringency measures (i.e., EPS index), natural experiments, and instrumental variables.

In examining the relationship between environmental policy on innovation, Porter (1991) hypothesized that strong environmental regulation can promote efficiency and foster innovations that boost competitiveness, known as the Porter hypothesis. This hypothesis has garnered extensive attention among researchers (Porter and Van der Linde, 1995; Popp, 2006; Rauscher, 2005; Johnstone, Haščič, and Popp, 2010; Zhang, 2021) as economists argued that a profit-maximizing firm would choose sustainable technology if feasible (Rauscher, 2005). However, empirical evidence is mixed (Rauscher, 2005; Ambec et al., 2013; Cohen and Tubb, 2018) as researchers argue Porter's hypothesis might be industry or country specific.

Another strand of literature investigates the nexus between innovation and environmental policy instruments that use patents as a proxy for innovation. Empirical studies on the linkage between innovation and policy instruments follow the idea of induced innovation (Hicks, 1932; Binswanger & Ruttan, 1978). The idea is that a profit-maximizing firm innovates new technologies in response to changes in the relative price of polluting factors of production. Acemoglu (2002) has started a new paradigm of induced innovation in environmental economics that brings forth new studies in that field (e.g., Acemoglu et al., 2012; Aghion et al., 2016; Lemoine, 2017).

Johnstone et al. (2010) study the effect of environmental policies on renewable energy innovation. The study found that environmental policy has a significant positive impact on green patents, and targeted policy has a robust impact on the patents in the targeted sector. In addition, flexible environmental regulations lead to better and higher-quality innovation (Johnstone et al., 2008). This suggests that an environment that allows for more flexibility in meeting environmental regulations encourages innovation in this area. Crabb and Johnson (2010) used monthly data from the automotive sector from 1980 to 1999 and found that increased oil prices positively influence innovation, with an estimated elasticity of 0.238 between oil prices and energy-efficient automotive patents. Aghion et al. (2016) have also used data from the auto industry and took into account automotive-related patents of both clean and dirty technologies. They find that higher fuel prices have a more significant impact on clean (e.g., electric and hybrid vehicles) technology patents than gray (e.g., energy efficiency) technology patents.

In addition, technological innovation was also influenced in the year with higher gasoline prices (Knittel, 2011); on the contrary, Crabb and Johnson (2010) have found no such effect. Gugler et al. (2024) compared environmental taxes, regulation, and R&D subsidies for a set of countries, and they find that R&D subsidies for renewables have a more significant effect on rejuvenating green innovation. Chen et al. (2021) investigated the impact of the emission trading scheme in China and found that it significantly reduced the number of green patents, and companies prefer to reduce output rather than increase green technological innovation to achieve their emission reduction targets. Similarly, Zhang et al. (2022) find that carbon emissions trading inhibits green technology innovation in China.

Innovation is also impacted by the easiness of change. Noailly (2012) studies the impact of different energy-saving policies on innovation, and she found that policies have a robust effect on easily replaceable technologies (e.g., boilers and lighting) but generally have no effect in the short-run for harder to change technologies (e.g., insulation). The impact of innovation is a continuous process. Thus, innovation works as a knowledge stock that decays over time and also takes time to diffuse (Popp, 2002). Verdolini and Galeotti (2011) used the knowledge stock for a panel of 17 countries and found that a 10% increase in domestic green knowledge increases patenting by 3%, and a 10% increase in foreign green knowledge increases patenting by 9.6%. On the other hand, firms with substantial non-green knowledge bases may find it difficult to switch to green innovation when market conditions change (Stucki & Woerter, 2017).

Policy structures can also affect innovation. Policies that use market-based mechanisms are known as market-based policies (e.g., the U.S. SO_2 market or the European Union's Emission Trading System for CO_2). On the other hand, command-and-control policies or non-market-based policies set standards. While market-based policies are flexible and generally provide greater incentives for innovation, non-market-based policies penalize polluters but do not provide rewards, and economists prefer market-based policies to bring forward more innovation.

Johnstone et al. (2010) compare market and non-market-based policies and find that direct investment incentives are effective in supporting newer innovations (e.g., solar and waste-to-energy technologies). Market-based policies generally perform better than non-market-based policies (Fabrizi et al., 2018). However, strict penalties and enforcement can help bring better results from non-market-based policies (Klemetsen et al., 2018). De Santis and Lasinio (2016) find that the implementation of more stringent environmental policies regulated by market forces did not deteriorate competitiveness within EU member countries. They also found that non-market-driven actions negatively affect competitiveness while market-based policies (i.e., ETS, environmental taxes), in particular, positively impact productivity growth for EU economies.

In the long run, price-based policies perform better than quantity-based policies as firms invest more in cost reduction (Kim et al., 2017). Johnstone, Haščič and Popp (2010) find that environmental policies have an effect on innovation in renewable energy, as measured by applications for green patents submitted to the European Patent Office (EPO). Nicolli and Vona (2016) used data from 19 EU countries and find that feed-in tariffs increased patenting in solar photovoltaic technology. Dechezleprêtre and Glachant (2013) found similar results for wind energy.

2.6 Conclusion

This chapter explained recent trends in green patents and the EPS index, as well as recent literature on different measures of environmental innovation, specifically green patents. Patents are not a perfect proxy for innovation, but as an output measure, they are the best available proxy that can be identified at the technology level. Recently, countries have stepped up their efforts to avoid the adverse impacts of climate change, and different strands of literature delve into different aspects of policy measures. However, measuring the effects of policy is challenging, given the impact of the spillover effect and the presence of market failure. Nonetheless, the literature in this area is becoming more abundant, even though some studies have weaker identification strategies (i.e., PACE). The literature also distinguished between market-based and non-market-based environmental policies. The consensus in the literature is that a flexible policy measure generally helps spur innovation with few exceptions, as the impact could be industry specific.

Chapter 3

Does Environmental Stringency Increases Innovation? Evidence from the Environmental Policy Stringency (EPS) index

3.1 Introduction

The consequences of climate change are well documented (IPCC, 2018). To mitigate the adverse impact of climate change, countries are enacting new laws and standards, such as carbon tax and emission trading schemes. Countries choose different environmental policies, and in general, policies vary widely. Therefore, comparing environmental policies across countries is always challenging. To overcome these difficulties, the Environmental Policy Stringency (henceforth EPS14) index was formulated by Botta and Koźluk (2014) in a policy paper of the Organisation for Economic Co-operation and Development (OECD). EPS14 allows to compare policies across countries and time. The index is scored on a 0 to 6 scale, where 6 denotes the most stringent policies. Kruse et al. (2022) updated the index and broadened the environmental policy coverage in 2022. The updated OECD Environmental Policy Stringency (henceforth EPS21) index covers 1990 to 2020, 40 countries (including 34 OECD countries), and 13 policy instruments, focusing primarily on climate change and air pollution policies.

The EPS14 covers market-based (MB) and non-market-based (NMB) policies. Some examples of market-based policies are taxes, permits, and certificates. On the other hand, emission limits or standards are regarded as non-market-based policies. The EPS21 has three sub-indices compared to the two sub-indices in the EPS14. The technology support policy is the new sub-index in the EPS21, along with MB and NMB indices. Technology support policies are further divided into upstream support policies (i.e., Research and Development (R&D) support) and downstream support policies (i.e., Feed-in Tariffs (FIT) and auctions). Kruse et al. (2022) find that the average stringency for OECD countries has increased in the past three decades. However, the path varies across countries and time. Over the past two decades and on average across the OECD, the stringency of NMB instruments has increased the most in absolute terms, followed by technology support and MB policies.

The linkage between environmental policy stringency and innovation has received increasing attention from researchers and policymakers in the last thirty years. In a seminal article, Porter (1991) argued that a well-designed environmental policy could enhance competitiveness and increase productivity. The literature has investigated two versions of the Porter Hypothesis (henceforth PH): the strong and the weak. While the strong version focuses on the relationship between environmental regulation and proxies of competitiveness, the weak version investigates the relationship between environmental regulation and innovation.

The weak version of the PH postulates that an increase in environmental policy stringency will cause a spur in green technological innovation. The empirical evidence for both weak and strong versions of Porter's hypothesis is mixed (Ambec et al., 2013). In the first significant review of the Porter hypothesis, Jaffe et al. (1995) find relatively little evidence that environmental policies lead to significant losses in competitiveness. Jaffe and Palmer (1997) find a positive link between regulation (proxied by pollution abatement cost) and R&D expenditures in U.S. manufacturing sectors, but not between regulation and patent applications. However, innovation proxied by green patents can be spurred by environmental regulation (Popp, 2006; Johnstone, Haščič , and Popp, 2010). On the contrary, environmental regulations, like air pollution regulations significantly increased the age of fossil-fueled steam in U.S. electric utilities from 1969-83. Environmental regulations limiting sulphur dioxide (SO2) slowed productivity growth in the U.S. in the 1970s by 43 percent (Gollop and Roberts, 1983).

Technological innovation can be measured by R&D expenditure, number of scientific personnel, and patent count. While R&D expenditure is an input measure, the patent count is an output measure. Economists are generally interested in output measures as input measures such as R&D expenditure might not produce any output (Popp, 2019). Hall et al. (1986) state that patents measure something "above and beyond R&D inputs, a creation of an underlying knowledge stock". In addition, R&D expenditure data are only available in aggregated forms.

On the other hand, patent data are highly disaggregated and readily available, though not always in a convenient form. Using patent count as a measure of the invention has some drawbacks. First, many inventors do not patent their inventions; they value trade secrets to protect their new technology. Secondly, the same patent in different offices could increase the chance of double counting. Lastly, patents vary in quality. Despite those drawbacks, patent statistics have long been considered a valuable indicator of invention and technology transfer across borders (Dechezleprêtre et al., 2011; Haščič and Migotto, 2015). Furthermore, Dechezleprêtre et al. (2010) and Popp (2006) have used green patent count to measure Environmentally Sustainable Technologies (ESTs) invention.

Technological change is not a random or exogenous process but is directed or influenced by certain economic, social, and political factors. On the one hand, stringent environmental policies increase demand for new efficient technologies. This essence is captured by the Directed Technological Change (DTC) model, which has a long history in the growth model. Hicks (1932) shows that the relative price of factors can induce innovation. Acemoglu (1998, 2002) developed the seminal DTC model to explain the skill-biased technological change in the last century. In the late 1990s, the DTC model made its way into environmental economics with Acemoglu et al. (2012)'s framework. Environmental policy can impact technological change by setting standards and regulations that require businesses to develop and adopt more sustainable and environmentally friendly technologies. For example, stricter emission standards may drive companies to invest in new technologies that reduce their carbon footprint. At the same time, incentives for renewable energy sources may encourage the development of new renewable technologies. Dechezleprêtre and Hemous (2022) summarize the literature on DTC models in the context of environmental economics. The literature on Environmental DTC (EDTC) argues that policies need both carrot and stick elements to accelerate innovation. Acemoglu et al. (2012) find that an optimal mix of a carbon tax and research subsidy is needed to accelerate innovation. The EPS14 data set only included market-based and non-market-based policies, but EPS21 also included subsidies in the index. On the other hand, adoption of new technology can be hindered by the inertia of adopting clean technologies, as firms are tied to dirty technology. This is known as the lock-in effect, where widespread inefficient technology, e.g., a QWERTY keyboard, persists even if more efficient technology is available. This might happen if inefficient technology adoption is already widespread and new technologies are too costly.

The research question addressed in this chapter is the following. Given environmental policy changes, we examine whether environmental policy stringency induces green innovation, the weak version of the Porter hypothesis. We use EPS21 to proxy environmental policy stringency and green patents collected from the Worldwide Patent Statistical Database (PATSTAT) maintained by the European Patent Office (EPO) to proxy green innovation. The present chapter makes three contributions to the literature. First, this study uses EPS21, which includes emission tax, standards, and subsidies. The earlier literature used the EPS14, which only included emission tax and standard. By using EPS21, the study can also empirically test the environmental DTC model, which argues that a combination of carbon tax and subsidy is required for innovation. Second, in this study we use different green technologies patented in a given country from the global patent database (PATSTAT). The PATSTAT contained bibliographical records of 100 million patents from more than 100 countries. Data recorded in PATSTAT is highly disaggregated and can be differentiated according to technology and country. The third contribution is the estimation methodology: we use a count data model with a pre-sample mean of patents to represent country-level fixed effect.

The findings are the following. In relation to our primary variable of interest, namely the EPS index, we find that environmental stringency is not associated with green innovation. This finding remains robust across diverse technology selections, depreciation rates, lag periods, and econometric specifications. These results align with previous findings (Brunnermeier and Cohen, 2003; Calel and Dechezleprêtre, 2016). However, it is essential to note that these results do not necessarily imply that stringent environmental regulations universally impede overall innovation. The lock-in effect also might play a role, where existing inefficient technology dominates because of the scale effect. The effects of stringent policies may vary at different stages of the innovation process, warranting further investigation and analysis.

The structure of the chapter is as follows. We begin with a thorough review of the literature in Section 2, encompassing an examination of the Porter hypothesis and technology lock-in hypothesis. Section 3 provides a comprehensive explanation of the EPS index and measure of innovation. Data sources are presented in Section 4 to ensure transparency and reliability. The estimation technique, consisting of the theoretical background, empirical strategy, and knowledge stocks, is outlined in Section 5. Descriptive statistics are presented in Section 6. The results are discussed in Section 7. In Section 8, we conduct a robustness check by employing alternative specifications, including different depreciation rates, changes in lag periods, and alternative econometric models. Finally, Section 9 offers a concluding analysis of the chapter, summarizing the main findings and implications derived from the study.

3.2 Related Literature

There is a persistent question among environmental economists and policymakers about the extent of the spillover impact of environmental policies on the economy. Spillover effects of environmental policies encompass unintended consequences that ripple through economies and societies beyond their primary goals. Positive spillovers may arise, such as technological innovation, job creation, improved public health, and resource efficiency. We survey four strands of literature related to our research question. The first strand of literature focuses on directed technological change (DTC). The second strand is on the empirical evidence of Porter's hypothesis. The third one deals with environmental policy and green innovation, which is a more recent literature that gained momentum after the 2000s. Finally, the fourth strand of literature describes the technological lock-in hypothesis that analyzes and explains the persistence of old technology.

In the first strand of literature, Acemoglu (2002) develop a DTC model to solve problems in macroeconomics, development economics, labour economics, and international trade, where technical change is biased towards particular factors. Later, the DTC model was extended to the field of environmental economics (Acemoglu et al., 2012; Acemoglu et al., 2014; Calel and Dechezleprêtre, 2016). In his seminal paper, Acemoglu (2002) argues that technological progress does not solely depend on exogenous factors and shows that endogenous factors can determine technological progress. He incorporates market size along with prices as factors biasing the equilibrium direction of technical change and demonstrates that institutions and incentives play a crucial role in determining the path of technological innovation. The environmental DTC model introduces endogenous and directed technical change in a growth model with environmental constraints (Acemoglu et al., 2012). The authors show that a carbon tax promotes innovation in clean energy-augmenting technologies when the two inputs, namely clean and dirty technologies, are substitutes. The paper extends the concept of "induced innovation" in environmental economics, where environmental policies create economic incentives for firms to develop and adopt cleaner technologies and environmental regulations might act as a catalyst for technological change toward EST. In an extension of his seminal paper, Acemoglu et al. (2014) study environmental DTC in a North–South model framework. The study finds that an optimal policy requires global policy coordination, with the implementation of research subsidies and carbon taxes in both the North and South. In addition, a unilateral policy by the North might also be beneficial. Acemoglu et al. (2016) extend the model by calibrating the firm dynamics model with clean and dirty innovation. They find that in the case of an existing advanced dirty technology, the gap between dirty and clean technologies discourages research efforts directed toward clean technologies. An optimal combination of carbon taxes and research subsidies encourages innovation in green technologies. In recent decades, OECD countries have implemented various policy measures to reduce the environmental impact of economic activities. However, the effect of these policies on technological innovation patterns is not certain. While private incentives for eco-friendly innovations may have some influence, public policies often play a crucial role in creating a demand for innovation in environmentally related technologies. The effectiveness of these policies may differ depending on the country, type of pollutants, and time period (Calel and Dechezleprêtre, 2016).

In his seminal contribution, Hicks (1932) proposed the "induced innovation hypothesis" which suggests that changes in the prices of inputs can motivate firms to invent new production methods to reduce the use of relatively expensive factors of production. In the context of public policy, this means that governments can influence firms' incentives to seek improvements in production technology by affecting input prices or changing the costs associated with the use of environmental resources. Since markets often fail to assign a value to environmental resources, government's intervention largely determines the price of many environmental assets. The severity of regulation impacts the change in costs of pollution, which, in turn, influences incentives for firms to innovate and reduce the use of these factors.

In empirical studies, researchers have used various proxies to measure the impact of environmental regulation on technological innovation. These proxies include macroeconomic or sectoral Pollution Abatement and Control Expenditure (PACE), frequency of inspection visits, parameterization of policy types, and survey-based measures that capture the perceptions of the regulated community. While theoretical work supports the idea that environmental regulations provide incentives for technological improvements, there is limited empirical evidence on the relationship between the severity of environmental policy and innovative behavior. Nevertheless, there is a growing body of empirical literature that supports the idea that environmental policies do lead to technological innovation.

In the second and third strands of literature, we cover the Porter hypothesis and the impact of environmental policy on innovation. After the seminal work by Porter (1991), the hypothesis was extensively tested in the empirical literature (Porter and Van der Linde, 1995; Popp, 2006; Rauscher, 2005; Johnstone, Haščič, and Popp, 2010; Zhang, 2021). According to the Porter hypothesis, strong environmental regulation can promote efficiency and foster innovations that boost competitiveness. In environmental economics, the hypothesis is a widely discussed idea. It was introduced in 1991 by the economist Michael Porter and has since been the subject of numerous empirical research and theoretical assessments. Regarding rationality and competitive marketplaces, the Porter hypothesis's theoretical basis might be questioned (Rauscher, 2005). Profit-maximizing firms in a competitive market will choose clean technologies if they are economically feasible and lucrative compared to existing dirty technologies. Empirical evidence of Porter's hypothesis is conflicting (Rauscher, 2005; Ambec et al., 2013; Cohen and Tubb, 2018). Jaffe and Palmer (1997) analyze the manufacturing industry in the U.S. and find a positive impact of abatement costs on R&D expenditure but little evidence of a connection between compliance costs and patent applications. Other studies, such as those by Kneller and Manderson (2012) and Lanjouw and Mody (1996), have also found support for the weak version of the Porter hypothesis, indicating that environmental regulation encourages innovation. However, Brunnermeier and Cohen (2003) discovered that higher monitoring and reinforcement of controls on existing regulations do not promote environmental innovation in the U.S. manufacturing industry.

Additional studies have explored the relationship between environmental regulations and various aspects of innovation, such as pollution control equipment deployment in electric production plants in Japan, Germany, and the U.S. (Popp, 2006). It was concluded that innovation might be influenced by the strictness of environmental regulations in a particular country. In the manufacturing industry, Carrion-Flores and Innes (2010) find that environmental policies had an impact on innovation, resulting in a decrease in emissions. Johnstone et al. (2010) study the impact of environmental policies on technological innovation in the renewable energy sector and find evidence supporting the weaker version of the Porter hypothesis.

The literature has analyzed a wide variety of environmental policies, i.e., the European Union Emissions Trading System (ETS), Electric Vehicle (EV) subsidy, policy stringency, emission tax, and its impact on innovation (Calel and Dechezleprêtre, 2016; Zhang, 2022; Grégoire-Zawilski and Popp, 2022). De Santis and Lasinio (2016) find that stricter market-based environmental policies did not reduce the competitiveness in the EU member economies. However, the non-market-based policy has an adverse effect. Market-based policies (i.e., ETS, environmental taxes), in particular, positively impacted productivity growth for EU economies. Hassan and Rousseliere (2022) have investigated the impact of stringent environmental policy proxied by EPS14 on the environmental innovation of 27 OECD countries proxied by the number of patent applications from the OECD database. They use a dynamic panel data method and find that environmental policy stringency increased environmental innovation. In addition, the NMB policy has a more positive impact on environmental innovation than the MB policy. The mixed results of the Porter hypothesis can be attributed to slow adoption of clean technologies.

The concept of technological lock-in was first introduced by David (1985) and was further developed by Arthur (1989) as a phenomenon that can be explained by the inertia in innovation and the predominance of existing technologies. According to the technology lock-in hypothesis, any policy intervention in the earlier stages of innovation can hinder future innovation and result in the lock-in of existing technologies. David (1985) uses the classic example of the QWERTY keyboard to illustrate how old and inefficient technologies can survive due to network effects. The technological lock-in effect is also strengthened by increasing returns. The presence of increasing returns creates a cumulative effect by increasing the profitability of innovation as the number of adopters increases (Abrahamson and Rosenkopf, 1997). Arthur (1994) distinguishes four types of increasing returns: scale economies, learning effects, adaptive expectations, and network economies. Scale economies occur when technology has high fixed costs and comparatively small marginal costs. Learning effects occur with learning-by-doing, reducing production costs and improving product quality. Adaptive expectations arise as increasing adoption reduces uncertainty, and both users and producers become increasingly confident about the current technology's quality, performance, and longevity. The amplification of a technology is characterized by network effects, as its widespread use by more users makes the technology more convenient.

The literature on green innovation also addresses the hypothesis of lock-in technology. Pantaleone and Fazioli (2022) analyze hydrogen energy patenting activity for 52 countries over six years and find significant evidence of lock-in effects on fossil fuel policies. Additionally, their study confirms the path dependency of green innovation. Foxon (2002) examines the role of technological and institutional lock-in as barriers to more sustainable innovation. He argues that carbon-based energy systems form a techno-institutional entity that can lock in existing technology, a phenomenon known as "carbon lock-in". Unruh (2000) introduces the term "carbon lock-in" to describe how industrial economies have become locked to fossil fuel-based energy systems during a technical and institutional co-evolution driven by path-dependent increasing returns to scale. Carbon lock-in is a typical example of technological lock-in (Unruh, 2000).

Seto et al. (2016) outline the types and causes of carbon lock-in, including the scale, magnitude, and longevity of the effects and their policy implications. They identify three forms of carbon lock-in and describe how they co-evolve: (a) infrastructure and technology, (b) institutional, and (c) behavioural. These three forms of carbon lock-in generally interact and are responsible for inertia in carbon emissions reduction. The infrastructure and technology form of carbon lock-in is associated with technologies and facilities that emit CO_2 directly or indirectly, and difficult to switch to clean technology. Governance, institutions, and decision-making cause the institutional lock-in that influences energy-related production and consumption, ultimately determining energy supply and demand. Behavioural lock-in is determined by behaviours, habits, and norms associated with the demand for energy-related goods and services. Corporations may choose to engage in incremental innovation instead of disruptive innovation, as it allows for the continued exploitation of their existing knowledge base, leading to increased profitability. Thus, major energy firms tend to advocate for carbon capture and storage technologies rather than investing in renewable energy sources to maintain profitability within the industry (Noailly, 2022). Acemoglu et al. (2019) find that when the cost of coal increases, firms are more likely to choose shale gas instead of renewable energy sources. In 2016, fossil fuel energy investment was around 60 % of total global investment in energy supply (IEA, 2017). To overcome technology and carbon lock-in, well-designed policies, radical green innovation, and cost advantage are needed (Unruh, 2002; Seto et al., 2016).

To summarize, the Porter hypothesis continues to spark debates in economics, with ongoing discussions centered around the impact of strict environmental regulations on different types of innovation and the effectiveness of market-based and non-market-based approaches in environmental policy. The Porter and technology lock-in hypotheses might work in different directions, implying that environmental policy stringency's net impact on innovation is uncertain. On the one hand, policy stringency can promote green innovation, but on the other hand, it may result in the lock-in of earlier innovation for an extended period. This highlights the complexity of the relationship between environmental policy stringency and green innovation and could work either way. Recent studies have found a positive correlation between tighter environmental regulations and the number of patent applications. However, most of these studies have looked at innovation as a whole rather than specifically focusing on environmental innovation. Furthermore, the majority of empirical research has been carried out at the firm or industry level, with only a limited number of cross-country analyses.

To address the gaps in the literature, this chapter aims to examine the macroeconomic-level relationship between environmental policy stringency and environmental innovation using a panel dataset of OECD countries.

3.3 Environmental Policy Stringency (EPS) Index and Innovation

3.3.1 Environmental Policy Stringency (EPS) Index

Climate change has posed an unprecedented challenge to the planet and its biodiversity. Countries and stakeholders are implementing different environmental policies to slow down the adverse impact of climate change. There is a general consensus in the literature that climate policies are becoming increasingly stringent (Kruse et al., 2022). However, a reliable measure must be used to compare environmental policies across countries and time (OECD, 2016). In 2014, the OECD developed a new quantitative measure of environmental policy stringency (EPS), which is a “composite index, derived through the aggregation of information on selected environmental policy instruments, primarily related to climate and air pollution” (OECD, 2016). OECD defined stringency as the “... strength of the environmental policy signal – the explicit or implicit cost of environmentally harmful behaviour, for example, pollution”. The stringency of environmental policies can change the landscape of competitiveness and innovation (hypothesized by the Pollution Haven hypothesis[1] and Porter hypothesis) among different countries and firms. Botta and Koźluk (2014) develop a composite index by converting quantitative and qualitative information contained in different laws and regulations of the energy sector into a comparable country-specific measure of environmental policy stringency (EPS). The EPS14 included fifteen instruments for the energy sector and three instruments for economy-wide indicators for 24 OECD countries. These instruments are presented in Table 3.1 and Table 3.2, where Table 3.1 represents instruments and weights in the energy sector and Table 3.2 represents the economy as a whole.

[1]According to the Pollution Haven hypothesis, corporations would want to escape the costs of rigorous environmental laws (and high-energy prices) by locating manufacturing in nations with laxer environmental standards.

The aggregation procedure for both energy and broader indicators involves two steps. In the first step, instrument-specific indicators (e.g., taxes on SOx, NOx, and CO_2) are combined into mid-level indicators based on their type (e.g., environmental taxes). In the second step, the resulting mid-level indicators are classified into two broad categories: Market Based (MB) instruments and Non-Market-Based (NMB) instruments. MB instruments aim to solve the market failure of environmental externalities by either adding the cost of production or consumption activities through taxes or charges or by setting property rights and creating a market for environmental services (OECD, 2007). Some examples of market-based instruments are taxes and certificates, EU ETS, and Feed-in Tariffs (FITs). NMB instruments are command and control policies that influence behaviour by imposing obligations or offering non-financial incentives (e.g., standards). It is possible to use and combine sub-components in various ways, such as creating "stick" and "carrot" versions of the indicators. The "stick" version represents policies that punish environmentally harmful activities (e.g., taxes on pollutants), while the "carrot" version represents policies that incentivize environmentally friendly actions (e.g., subsidies).

Table 3.1: Structure of the energy sector indicator in the EPS14

	Instruments	Indicators
Market Based Policies (MBP) (1/2)	Taxes and Certificates (1/3)	CO_2
		NOx
		SOx
	Trading Schemes (1/3)	CO_2
		Renewable Energy Certificates
		Energy efficiency certificates
	Feed-in tariffs (FITS) (1/3)	Solar
		Wind
Non-Market Based Policies (NMBP) (1/2)	Standards (1/2)	ELVEmission Limit Value (ELV) for Nitrogen Oxides (NOx)
		ELV for Sulphur Oxides (SOx)
		ELV for for Particulate Matter (PMx)
		Sulphur Content Limit for Diesel
	R&D Subsides (1/2)	Government R&D expenditure on renewable energy

Source: Botta and Koźluk (2014)

Table 3.2: Structure of the extended (economy-wide) indicator in the EPS14

	Instruments	Indicators
Market Based Policies (MBP) (1/2)	Taxes and Certificates (1/4)	CO_2
		NOx
		SOx
	Trading Schemes (1/4)	CO_2
		Renewable Energy Certificates
		Energy efficiency certificates
	FITs (1/4)	Solar
		Wind
	DRS (1/4)	Deposit and Refund Scheme
Non-Market Based Policies (NMBP) (1/2)	Standards (1/2)	ELV for Nitrogen Oxides (NOx)
		ELV for Sulphur Oxides (SOx)
		ELV for for Particulate Matter (PMx)
		Sulphur Content Limit for Diesel
	R&D Subsides (1/2)	Government R&D expenditure on renewable energy

Source: Botta and Koźluk (2014)

Kruse et al. (2022) updated the EPS14 to include forty countries from 1990 to 2000. The structure and aggregation of EPS21 were revised in comparison to EPS14. To ensure consistency across time, changes were applied to the complete time series from 1990. The EPS21 consists of three equally weighted sub-indices, which respectively group MB (e.g., taxes, permits, and certificates), NMB (e.g., performance standards), and technology support policies. As presented in Table 3.1 and

3.2, technology support policies are further divided into upstream and downstream measures. Upstream technology support measures, such as public R&D expenditures, encourage and finance the development of clean technologies. Downstream technology support policies, such as renewable energy support policies, incentivize the adoption of specific technologies.

The EPS21 presented in Table 3.3, includes a separate sub-index for technology support because subsidies for R&D and FITs differ from the MB and NMB policies. The new index excludes two policy instruments from the previous version of the index, Deposit and refund Schemes and White Certificates (also known as energy efficiency certificates), due to limited data availability and concerns about data quality.

Table 3.3: The 2021 Environmental Policy Stringency Index

	Instruments	Indicators
Market Based Policies (MBP) (1/3)	Taxes and Certificates	CO_2 Certificates (1/6)
		Renewable Energy Certificates (1/6)
		CO_2 tax (1/6)
		Nitrogen Oxides (NOx) Tax (1/6)
		Sulphur Oxides (SOx) Tax (1/6)
		Fuel Tax (Diesel) (1/6)
Non-Market Based Policies (NMBP) (1/3)	Performance Standards	ELV for Nitrogen Oxides (NOx) (1/4)
		ELV for Sulphur Oxides (SOx) (1/4)
		ELV for for Particulate Matter (PM) (1/4)
		Sulphur Content Limit for Diesel (1/4)
Technology Support (1/3)	Upstream Support (1/2)	R&D Expenditure
	Adoption Support (1/2)	Adoption support for Solar (1/2)
		Adoption support for Wind (1/2)

Source: Kruse et al.(2022); Index weight in the parenthesis

3.3.2 Measure of innovation

Technological innovation enhances efficiency and productivity. But, measuring and comparing innovation across time and country is always been a challenge. The value of a measure depends on the reliability and availability of data. The way to measure and quantify innovation has always been a contentious issue. The literature on innovation uses several methods to assess innovation. One approach involves input from experts in their respective domains to identify and quantify significant innovations. However, it suffers from subjectivity and potential bias. In addition, the unavailability of data on a large scale impedes using experts' feedback due the possibility of bias. Another commonly used indicator for innovation or technological progress is research and development (R&D) expenditure or the number of people employed in the R&D sector. Nonetheless, R&D expenditure serves as an input rather than a direct measure of the output, and economists generally prefer output measures (Nagaoka et al., 2010).

Patent count is an output measure that can be easily calculated due to data availability. Thus, patent statistics are an excellent proxy for the measure of innovation (Nagaoka et al., 2010; Hall and Jaffe, 2012). Nevertheless, like any other proxy, the patent count has its drawbacks. Not all inventions are patented; rather, some inventors depend on trade secrets (i.e., Coca-Cola, WD-40), even though it is possible to copy a trade secret (Fontana et al., 2013). However, patent protection lasts a maximum of 20 years, while trade secrets might last indefinitely.

In addition, all patents are not equal; they vary in terms of value and usability. Harhoff et al. (1999), Gambardella, Harhoff, and Verspagen (2008), and Dechezleprêtre et al. (2011) find that patent values are highly skewed. Webster and Jensen (2011) find that less than half of patents see commercialization and mass production. Furthermore, Nagaoka and Walsh (2009) conducted a survey involving 3,700 inventors holding triadic[2] patents. Their findings reveal that approximately 60 percent of these inventions were successfully commercialized. Additionally, Amesse et al. (1991) surveyed 374 individual inventors from Canada and found that 43.3 percent of them generated positive revenues from their inventions, with approximately half being profitable.

Hanel (2008) finds that pioneering innovators patent more frequently. On the

[2]Triadic patents are a set of patents filed at three of these major patent offices: the European Patent Office (EPO), the Japan Patent Office (JPO) and the United States Patent and Trademark Office (USPTO)

other hand, firms that patent infrequently tend to be followers in a new field. He also finds that firms that protect their innovations are more likely to increase their profits than those that do not. The use of patent data as a means to assess innovation offers several advantages. Firstly, patents serve as a more accurate metric than commonly employed proxies (i.e., R&D expenditure), as they indirectly measure the output of the innovation process rather than its inputs, such as R&D expenditures or the number of researchers involved. Secondly, patent data provide comprehensive and detailed information about the disaggregated technology. Lastly, the requirement for an invention to be eligible for patent protection necessitates its marketability and potential for industrial application, and patenting is costly. Thus, a patent indicates that the inventor anticipates economic benefits stemming from their invention.

Therefore, considering the advantages of using patent counts as a measure of innovation compared to other metrics, we have adopted patent counts as a proxy for innovation. However, since patents are an imperfect proxy for innovation and their values can vary, we also consider patents that have been filed in multiple patent offices.

3.4 Data Sources

We use patent data from PATSTAT, environmental stringency data from the OECD, and other control variables data from the World Bank, OECD, and the International Energy Agency (IEA). One contribution of this chapter is that it uses disaggregated data from the Worldwide Patent Statistical Database (PATSTAT) to proxy innovation. PATSTAT, maintained by the European Patent Office (EPO), contains bibliographical data related to more than 100 million patent documents from leading industrialized and developing countries. Patents are divided into different categories or classes to represent different technologies. The Cooperative Patent Classification

(CPC) is an extension of the International Patent Classification (IPC) and is jointly managed by the EPO and the US Patent and Trademark Office. It is divided into nine sections, A-H and Y, which in turn are subdivided into classes, sub-classes, groups, and sub-groups. There are approximately 250,000 classification entries.

The Y02 CPC patent class covers selected technologies that control, reduce or prevent anthropogenic emissions of greenhouse gases (GHG) in the framework of the Kyoto Protocol and the Paris Agreement and technologies that allow adapting to the adverse effects of climate change. Y02 includes climate change adaptation technologies (CPC class Y02A) and Climate Change Mitigation Technology (CCMT) technologies. The patent data is used to calculate new variables, such as knowledge stock, which is explained in the methodology and descriptive statistics section.

Government R&D budgets for renewable are collected from the International Energy Agency (IEA). In our baseline model, we include patent applications that are eventually granted in at least one patent office. Subsequently, we use both the Y02 patent and the CCMT patent separately to see if the result differs. Finally, data on control variables, i.e., GDP and net FDI inflow, are collected from the World Bank. It would be ideal to use different energy prices for different technologies. However, since comprehensive data are unavailable for all technologies being considered, we are using the International Energy Agency's (IEA) real index for end-use energy prices in the industry sector as a proxy.

Our sample includes 34 countries: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Türkiye, the United Kingdom, and the United States. We use data from 1990 as EPS21 starts from 1990. In addition, even though EPS21 covers the year 2020, our data set contains data up to 2016, as, on average, it takes 3 years for a patent to be granted from the date of application. The descriptive statistics and data section (Section 3.6) contains more information about patents by year and country.

3.5 Estimation

3.5.1 Theoretical Background

Griliches (1998) identified the importance of demand and supply factors that impact innovation. The demand side consists of factors representing macro shifts in aggregate demand, population, exchange rates, and relative factor prices. The supply side includes scientific and technological breakthroughs that make further innovation more profitable.

According to Griliches (1998) and Verdolini and Galeotti (2011), the demand and supply factors impacting innovation can be written as follows:

$$TI_t = f(Z_t^D, Z_t^S),$$

where TI_t denotes Technological Innovation at date t, Z_t denotes the vector of either demand (D) or supply (S) determinants at time t.

The supply factors are generally embodied as technological capacity, i.e., innovation activity needed for further invention. The number of already existing patents in a given technology and other related technologies serves as a proxy of innovative activity. R&D in the given technology also impacts the supply of that technology. R&D refers to the process of creating new products, processes, or technologies. It is a key element of the innovation process, as it involves the generation of new ideas, testing and developing prototypes, and refining and optimizing final products or processes. R&D can significantly impact a country's innovation rate because it provides the resources and expertise needed to develop and commercialize new technologies and products. It can also build a country's knowledge base and technological capabilities, creating a strong foundation for future innovation.

Thus, supply factors can be represented as

$$Z_t^S = g(K_{t-i}^{own}, K_{t-i}^{other}, R\&D_{t-i}),$$

where $t - i$ represents lagged variables, K^{own} represents the stock of knowledge in the given industry, K^{other} represents the stock of knowledge in the other related industry, and $R\&D$ represents R&D cost in the given industry. The likelihood of innovation in a given technology is proxied by knowledge stocks in that technology and other related technologies.

For the demand side, we consider three factors: environmental policy, energy price expectation, and the state of the economy. First, environmental policy can impact the rate of innovation by setting standards and regulations that require businesses to develop and adopt new technologies and processes that are more sustainable and environmentally friendly. For example, stricter emission standards may drive firms to invest and innovate in new technologies that reduce their carbon footprint. At the same time, incentives for renewable energy sources may encourage the development of new renewable technologies. In addition, environmental policy can create new market opportunities for innovative products and technologies. For example, adopting policies that support using renewable energy sources may create demand for new renewable energy technologies, such as solar panels or wind turbines. We use $EPS21$ to proxy environment-related policies.

Second, the expected energy price P_t^E influences the adoption of new technologies. High energy prices can incentivize firms and individuals to invest in and adopt technologies that are more energy efficient or that use alternative energy sources.

Third, the state of the economy can be captured by lagged Gross Domestic Product

(GDP^E) and lagged Foreign Direct Investment (FDI^E) inflow. GDP is a measure of an economy's total size and strength. It represents the entire value of all commodities and services produced inside a nation during a specified time, often a year. As a result, GDP may be an effective predictor of a country's economic status, and strong economic conditions frequently promote innovation since firms may have greater resources and incentives to invest in R&D when the economy is robust. For example, during economic growth, firms may have more revenues and profits, allowing them to invest in new technologies and processes. FDI can take the form of capital investments, such as the construction of new factories or the acquisition of existing businesses. It can involve the transfer of technology or other intellectual property, which might positively impact innovation in several ways. FDI can bring new technologies and expertise into a country. It can also create new opportunities for local businesses to collaborate with foreign companies, promoting the exchange of ideas and knowledge transfer. It can stimulate competition within a domestic market, leading to increased innovation as businesses seek to differentiate themselves from their competitors.

Thus, demand factors can be represented as

$$Z_t^D = h(EPS21, P_t^E, GDP^E, FDI^E).$$

We can summarize the technological innovation function as

$$TI_t = f(EPS21, P_t^E, GDP^E, FDI^E, K_{t-i}^{own}, K_{t-i}^{other}, R\&D_{t-i}).$$

The weak version of Porter hypothesis's states a positive impact of EPS21 on innovation. However, evidence from empirical literature is mixed. In the present study, our variables of interest are the stringency index and innovation, and we also control for other demand and supply factors of the innovation.

3.5.2 Empirical Strategy

This study empirically investigates the impact of stringent environmental policy on green innovation in different technological fields. In line with EDTC, we use both demand-pull and technological-push effects in our analysis. We use country-level patent data to measure green innovation. Our data includes 34 OECD countries for the period 1990-2016. Our dependent variable is a count of granted green Y02 patent applications filed in country i in year t. As patents vary in quality, the literature generally suggests not to consider the number of applied patent applications.

Previous studies take into consideration granted patents (Noailly and Smeets, 2015), granted triadic patents[3] (Aghion et al., 2016; Lazkano et al., 2017; Rosendaal and Vollebergh, 2021), or patents granted in more than one patent office to eliminate low-quality patents. Granted patents undergo a rigorous examination process by patent offices to ensure that they meet the necessary legal and technical requirements for a patent. This includes evaluating the invention's novelty, non-obviousness, and usefulness. In our baseline model, we consider granted patents to ensure the patents' quality. We also include triadic patents and patents granted in more than one country to ensure high-value patents. As our dependent variable is a count of patents, our baseline model uses pseudo-maximum-likelihood Poisson regression,

$$gpatents_{it} = exp(\beta_0 + \beta_1\ EPS_{it-2} + \beta_2\ log\ KG_{it-2} + \beta_3\ log\ KP_{it-2} + \beta_4\ X_{it-2} + a_i + y_t + u_{it}),$$

where $gpatents$ is the count of green patents, EPS is the environmental stringency index, KG is the knowledge stock in green patents, KP is the knowledge stock of all patents, and X is the vector of control variables (Subsection 3.5.1). To represent country-level fixed effects, a_i, our main specification uses the pre-sample mean of patents, which requires only a weak exogeneity of the explanatory variables. Lastly,

[3]Patent applications filed at the United States Patent Office (USPTO), European Patent Office (EPO), and Japanese Patent Office

y_t represents year fixed effects. The right-hand side variables are lagged by two years to avoid reverse causality (Gregoire-Zawilski and Popp, 2023), and we use different lag periods in the robustness check.

Patent data model literature extensively uses count data models as patent data are count in nature (Popp, 2019; Dechezleprêtre and Glachant, 2014; Dechezleprêtre et al., 2021). With more than 52% of patent counts in two digits in our dataset, we use a Poisson specification (in the robustness check, we also use a panel fixed effect model). Our estimate encounters a difficulty. Strict exogeneity does not hold since the knowledge stocks are functions of lagged dependent variables. The usual Poisson fixed effects model may result in biased results in such circumstances. As such, our main specification uses the pre-sample mean of patenting activity to proxy for country fixed effects (e.g., Blundell et al., 1995; Noailly and Smeets, 2015; Rosendaal and Vollebergh, 2021). Patents in green technology gained momentum at the start of the 1990s. Thus, we have constructed the pre-sample mean for the years 1990 to 1999.

3.5.3 Knowledge Stocks

We calculate the knowledge stock for granted green technology patents and all granted patents. We also construct knowledge stocks for Climate Change Mitigation Technology (CCMT), solar, and wind technology. We use the perpetual inventory approach, which accounts for continuous knowledge creation by patents, developed by Cockburn and Griliches (1988) and Peri (2005), to determine the patent knowledge stock. The perpetual inventory approach has been used widely in the literature (Martinez-Zarzoso et al., 2019; Aghion et al., 2016; Dechezleprêtre et al., 2015; Verdolini and Galeotti, 2011). We calculate knowledge stocks using patents granted in each country for different technologies, i.e., solar, CCMT, and wind. These stocks represent the nation's prior patenting experience and serve as the foundation for knowledge supporting future innovation. The knowledge stock is defined as

$$K_{it} = (1 - \gamma)K_{it-1} + P_{it},$$

where K_{it} is the knowledge stock, γ is the depreciation rate of knowledge, and P_{it} is the successful patent applications for the given technology.

We calculate knowledge stock for green patents (KG), all patents (KP), and other related technologies i.e., solar, CCMT, and wind. There is no consensus on the depreciation rate of R&D and patents. Some studies that estimate the depreciation of patents are presented in Table 3.4, and they vary widely from 1% to 25%. Generally, patents in the established industry demonstrate lower depreciation, while newer industry suffers from high depreciation in patents.

Table 3.4: Literature on Depreciation Rate

Author	Indicator	Model	Rate
Liu et al. (2020)	Applied Patents	Solar Patent Citation	0.20-0.23
Rassenfosse and Jaffe (2018)	Applied Patents	Revenue	0.02-0.07
	Granted Patents		0.01-0.05
Bessen (2008)	Granted Patents	Patents Renewal	0.13-0.27
Deng (2007)	Granted Patents	Patents Renewal	0.06-0.11
Park et al., (2006)	Granted Patents	Patent Citation	0.13
Lanjouw (1998)	Granted Patents	Patents Renewal	0.02-0.06
Pakes (1986)	Granted Patents	Patents Renewal	0.11–0.19
Pakes and Schankerman (1984)	Granted Patents	Patents Renewal	0.25

The literature on innovation has presented different assumptions regarding the depreciation rate of knowledge stocks. Some studies have suggested a rate of 0.10

(Verdolini and Galeotti, 2011; Wurlod and Noailly, 2018), while others have proposed a rate of 0.15 (Dechezleprêtre et al., 2015). In the baseline case, we have used a 15 percent depreciation rate. We use different depreciation rates in the robustness check to calculate the sensitivity of the depreciation rate.

3.6 Descriptive Statistics

The descriptive statistics of the main variables in the analysis are presented in Table 3.5. The table shows a wide range of values for the CCMT patent variable. Table 3.6 displays the number of patents by country to provide further insights about the concentration of green patents. Only six countries have an average patent count exceeding three digits. Additionally, Table 3.7 shows the frequency distribution of CCMT patents. Out of all observations, 11.94% have a value of zero, 41% are below 50, and 52% are below 100.

Table 3.5: Descriptive Statistics

Variable	N	Mean	SD	Min	Max
CCMT Patents	578	1104.46	2928.57	0	19713
EPS21	578	2.33	1.02	0	4.22
All Knowledge Stock	578	72090.5	199642.9	0	1491316
CCMT Knowledge Stock	578	4885.16	13597.3	0	96393.4

Table 3.6: CCMT Patents by Country

Country	N	Mean	SD	Min	Max
Australia	17	1018.35	371.74	458	1586
Austria	17	862.29	604.98	100	1491
Belgium	17	3.941	12.29	0	51
Canada	17	1055.29	383.53	194	1574
Chile	17	.059	0.24	0	1
Czech Republic	17	79.41	28.62	47	139
Denmark	17	477.41	193.32	159	829
Estonia	17	6.471	4.46	1	19
Finland	17	72.64	20.89	37	112
France	17	884.11	303.90	389	1360
Germany	17	1824.58	532.07	811	2860
Greece	17	38	32.78	10	143
Hungary	17	17.529	14.98	1	51
Iceland	17	1.588	2.293	0	8
Ireland	17	3.294	3.584	0	10
Israel	17	110.529	47.21	53	189
Italy	17	55.706	105.70	0	312
Japan	17	9282.17	3063.48	3976	14069
Korea	17	6162.52	2821.39	1781	10557

Table 3.6: (contd)					
Luxembourg	17	9.235	4.86	2	17
Mexico	17	412.23	170.12	32	680
Netherlands	17	118.94	23.27	84	167
New Zealand	17	0	0.00	0	0
Norway	17	97.29	24.95	41	127
Poland	17	247.64	142.27	86	487
Portugal	17	138.23	79.42	1	216
Slovak Republic	17	20.94	11.95	4	40
Slovenia	17	8.706	2.88	3	14
Spain	17	1258.41	397.71	400	1813
Sweden	17	90.706	17.45	67	127
Switzerland	17	31.05	15.92	5	66
Türkiye	17	26.29	13.68	4	44
United Kingdom	17	382.23	97.82	211	563
United States	17	12753.76	4487.09	6746	19713

Table 3.7: CCMT Patent Frequency

CCMT Granted Patents	Frequency	Percent	Cumulative Frequency
0	69	11.94	11.94
51	2	0.35	41.35
100	2	0.35	52.77
999	1	0.17	80.62
19713	1	0.17	100
Total	578	100	

3.7 Results and Discussion

Our baseline result is presented in Table 3.8. We use Poisson regression and consider the number of granted CCMT patents in the OECD countries as our dependent variable. To control for country-level unobservable heterogeneity, we use the country's average annual count of patents in the pre-sample period to proxy for fixed effects. We have four regression models in Table 3.8, where the EPS21 index is our primary explanatory variable in the first Specification (Specification I). The following Specifications (II, III, IV) use sub-indices market-based, non-market-based, and technology support policies as the explanatory variables, respectively, to investigate if the impact of different policies differs.

Table 3.8: Poisson Models with Robust Standard Errors; OECD Countries
Dependent Variable: CCMT Patents

Variables	I	II	III	IV
EPS21	- 0.122***			
	(0.04)			
Market Based Policy		0.065		
		(0.07)		
Non-Market Based Policy			-0.189	
			(0.034)	
Technology Support Policy				-0.068***
				(0.23)
Knowledge Stock- CCMT	1.37**	1.38**	1.40**	1.21**
	(.65)	(0.67)	(0.66)	(0.60)
Knowledge Stock- All	-0.337	-0.391	-0.40	-0.19
Patents	(0.44)	(0.44)	(0.44)	(0.409)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-9800.81	-10041.58	-10064.23	-9627.49

All variables are lagged by 2 time periods. Regressions started in 2000 and end in 2016.
Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The results of the empirical analysis of the environmental policy stringency variables do not provide any evidence in support of the Porter hypothesis but instead suggests the presence of the technology lock-in hypothesis. A one-unit increase in the EPS21 index is associated with a 12.2% decrease in the number of granted CCMT patents, which is both statistically significant and economically substantial . This suggests that more stringent environmental policies discourage innovators from obtaining more patents. Market-based policy increases CCMT patenting, but the result is statistically insignificant. On the contrary, non-market-based policy's impact is negative and statistically insignificant. Technology support policies reduce

CCMT patenting, and the result is statistically significant. One-unit increase in the technology support policies index is associated with a 6.8% decrease in the number of granted CCMT patents. Environmental policies could have been formalized after an area of technology has matured and only confirmed existing practices by the industry actors.

Additionally, it is possible that environmental policies are not stringent enough to promote green innovation. The European Union Emissions Trading System (EU ETS) is one example. EU ETS is one of the largest emission trading systems in the world. It was launched in 2005 and covers about 45% of the European Union's greenhouse gas emissions from various sectors such as power generation, manufacturing, and aviation. Environmental economists have pointed out that the carbon pricing by the EU ETS was too low compared to the social cost of carbon (Gerlagh et al., 2022). Calel and Dechezleprêtre (2016) find that EU ETS has not affected patenting beyond the set of regulated companies. Furthermore, emissions reductions in the EU ETS have primarily come from operational changes, such as fuel switching, rather than technological changes. Gregoire-Zawilski and Popp (2022) study the impact of technology standards on grid modernization technologies. They find that standards have a negative effect on patenting activity, suggesting the locking-in of technology.

The second set of results is related to knowledge stocks. The countries with prior CCMT patenting experience have a positive impact on future CCMT patenting. The impact of CCMT knowledge on CCMT patenting is statistically significant too. A 1% increase in CCMT knowledge stock will increase CCMT patents by 1.37%. Interestingly, the impact of all patent knowledge stock on CCMT patenting is negative, but it is not statistically significant. These findings suggest the existence of path dependency in green technology, wherein more substantial exposure to green patenting leads to an increase in future green patenting. Additionally, the negative and statistically significant coefficients on all patent knowledge stocks may indicate some degree of crowding out of green innovation due to competition from other technologies.

Table 3.9: Poisson Models with Robust Standard Errors; OECD Countries
Dependent Variable: Number of Y02 Patents

Variables	I	II	III	IV
EPS21	-0.13***			
	(0.043)			
Market Based Policy		0.093		
		(0.071)		
Non-Market Based Policy			-0.035	
			(0.033)	
Technology Support Policy				-0.07***
				(0.19)
Knowledge Stock- Y02	1.58**	1.62**	1.69**	1.41**
	(0.69)	(0.70)	(0.69)	(0.66)
Knowledge Stock- All Patent	-0.485	-0.589	-0.624*	-0.332
	(0.475)	(0.474)	(0.467)	(0.454)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-11368.89	-11903.04	-11670.30	-11204.12

All variables are lagged by two time periods. Regressions started in 2000 and end in 2016.
Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.9 explores the relationship between environmental policies and patenting in the Y02 patent class rather than the CCMT patents used in the previous case. This analysis reveals that the direction and significance of the variables remain unchanged. Specifically, it is found that a one-unit increase in the EPS21 index, which measures the stringency of environmental policies, leads to a 13% decrease in the number of granted Y02 patents. This effect is statistically significant and economically substantial, suggesting that stricter environmental policies discourage innovation in the Y02 patent class. Additionally, market-based policies are found to have a positive but statistically insignificant impact on Y02 patenting. In contrast, the effect of non-market-based policies is found to be negative and statistically insignificant. Furthermore, technology support policies have a negative and statistically significant impact on Y02 patenting, with a one-unit increase in the technology support policies index leading to a 7% decrease in the number of granted Y02 patents.

Table 3.10: Poisson Models with Robust Standard Errors; G7 Countries
Dependent Variable: Number of Climate Change Mitigation Technology (CCMT) patents

Variables	I	II	III	IV
EPS21	-0.32***			
	(0.032)			
Market Based Policy		-0.144*		
		(0.08)		
Non-Market Based Policy			-0.043*	
			(0.022)	
Technology Support Policy				-0.135***
				(0.01)
Knowledge Stock- CCMT	2.28***	2.39**	2.44***	1.72***
	(0.64)	(.99)	(0.93)	(0.649)
Knowledge Stock- All	-1.34***	-1.36*	-1.48**	-0.764*
Patents	(0.40)	(0.75)	(0.715)	(0.41)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-3193.72	-3737.01	-3762.367	-3184.02

All variables are lagged by 2 time periods. Regressions start in 2000 and end in 2016.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.11: Poisson Models with Robust Standard Errors; G7 countries
Dependent Variable: Number of Y02 patents

Variables	I	II	III	IV
EPS21	-0.34***			
	(0.03)			
Market Based Policy		-0.154**		
		(0.078)		
Non-Market Based Policy			-0.05**	
			(0.021)	
Technology Support Policy				-0.14***
				(0.01)
Knowledge Stock- Y02	2.33***	2.45**	2.51***	1.79***
	(0.62)	(0.966)	(0.916)	(0.640)
Knowledge Stock- All Patents	-1.37***	-1.39*	-1.53**	-0.803*
	(0.407)	(0.743)	(0.721)	(0.428)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-3540.21	-4217.14	-4240.40	-3560.59

All variables are lagged by two time periods. Regressions started in 2000 and end in 2016.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Tables 3.10 and 3.11 report the results for the G7 countries, the world's most industrialized and economically developed nations. The G7 countries include Canada, France, Germany, Italy, Japan, the United Kingdom, and the United States. The impact of policy stringency on patenting for OECD countries is robust. Specifically, it is observed that a one-unit increase in the EPS21 index corresponds to a 32% decrease in the number of granted CCMT patents and a 34% decrease in the number of Y02 patents. Market-based, non-market-based, and technology support policies are found to have a negative and statistically significant impact on both CCMT and Y02 patents. These findings suggest a technology lock-in effect among the G7 countries. Additionally, it is observed that the knowledge stocks of CCMT and Y02 patents positively influence future green patents; however, the knowledge stock of all patents is found to have a negative but not statistically significant crowding-out effect on green patents.

Table 3.12: Poisson Models with Robust Standard Errors; Top 4 Countries
Dependent Variable: CCMT patents

Variables	I	II	III	IV
EPS21	- 0.091**			
	(0.04)			
Market Based Policy		0.168***		
		(0.06)		
Non-Market Based Policy			-0.054***	
			(0.01)	
Technology Support Policy				-0.043***
				(0.012)
Knowledge Stock- CCMT	0.33	0.249	0.292	-0.11
	(0.92)	(0.71)	(0.78)	(0.90)
Knowledge Stock- All	0.62	0.313	0.3404	0.739
Patents	(0.76)	(0.549)	(0.64)	(0.74)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-1919.78	-1915.86	-1956.14	-1901.98

All variables are lagged by 2 time periods. Regressions start in 2000 and end in 2016.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.13: Poisson Models with Robust Standard Errors; Top 4 countries
Dependent Variable: Y02 patents

Variables	I	II	III	IV
EPS21	- 0.11**			
	(0.04)			
Market Based Policy		0.18***		
		(0.06)		
Non-Market Based Policy			-0.064***	
			(0.01)	
Technology Support Policy				-0.051***
				(0.012)
Knowledge Stock- Y02	-0.084	0.263	0.238	-0.22
	(0.89)	(0.62)	(0.73)	(0.886)
Knowledge Stock- All Patents	0.71	0.282	0.37	0.831
	(0.73)	(0.488)	(0.58)	(0.73)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-2203.19	-2232.51	-2262.44	-2183.14

All variables are lagged by 2 time periods. Regressions start in 2000 and end in 2016.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Green patents are highly concentrated in top industrialized countries (Leon et al., 2023). In our dataset, more than three-quarters of green technologies are concentrated in the U.S., Japan, Korea, and Germany. Tables 3.12 and 3.13 present the results of the top four countries for CCMT and Y02 patents. The result confirms our previous findings. For the top four countries, environmental stringency reduces both CCMT and Y02 patents. But, as the literature suggests (Tand et al., 2020; Acemoglu et al., 2012; Aghion et al., 2016), the market-based policy helps spur both CCMT and Y02 innovation, and the result is statistically significant.

We also investigate solar technology (Y02E 10/4) and wind technology (Y02E 10/7) to determine if environmental stringency influences these specific green technologies. Table 3.14 represents the results of solar technology patents for OECD countries. An increase in the EPS21 index reduces granted patents, but the result is statistically insignificant. Interestingly, non-market-based policies increase solar patents, and the result is statistically significant at a 10% level. Furthermore, the impact of the knowledge stock of solar patents and of all patents on solar technology patenting is found to be statistically insignificant. However, it is found that the CCMT knowledge stock has a positive and statistically significant impact on solar technology patenting.

Table 3.14: Poisson Models with Robust Standard Errors; OECD Countries
Dependent Variable: Number of Granted Solar Patents

Variables	I	II	III	IV
EPS21	-0.033 (0.094)			
Market Based Policy		-0.026 (0.059)		
Non-Market Based Policy			0.083* (0.048)	
Technology Support Policy				-0.04 (0.034)
Knowledge Stock- Solar	0.003 (0.355)	0.011 (0.340)	-0.036 (0.355)	0.023 (0.360)
Knowledge Stock- CCMT	1.325** (0.527)	1.61** (0.51)	1.12** (0.529)	1.20** (0.496)
Knowledge Stock- All Patents	-0.363 (0.365)	-0.614* (0.343)	-0.169 (0.398)	-0.259 (0.341)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-1911.707	-2098.797	-1891.39	-1894.99

All variables are lagged by 2 time periods. Regressions started in 2000 and end in 2016.
Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.15 represents the results of wind technology patents for OECD countries. An increase in the EPS21 index reduces granted patents, and the result is statistically significant. Interestingly, the non-market-based policy increases wind patents, but the result is statistically insignificant. Furthermore, the impact of the knowledge stock of wind patents and all patents on wind technology patenting is found to be statistically insignificant. However, it is found that the CCMT knowledge stock has a positive and statistically significant impact on wind technology patenting in the first model.

Table 3.15: Poisson Models with Robust Standard Errors; OECD Countries
Dependent Variable: Number of Granted Wind Patents

Variables	I	II	III	IV
EPS21	-0.11**			
	(0.053)			
Market Based Policy		-0.189**		
		(0.072)		
Non-Market Based Policy			0.0005	
			(0.04)	
Technology Support Policy				-0.023
				(0.023)
Knowledge Stock- Wind	0.238	0.285	0.426	0.292
	(0.227)	(0.232)	(0.464)	(0.227)
Knowledge Stock- CCMT	0.976*	0.876	0.627	0.773
	(0.547)	(0.584)	(0.90)	(0.533)
Knowledge Stock- All Patents	-0.14	-0.06	-0.05	-0.02
	(0.310)	(0.347)	(0.40)	(.297)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-1332.393	-1324.1574	-1513.421	-1338.055

All variables are lagged by 2 time periods. Regressions started in 2000 and ended in 2016.
Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.8 Robustness Check

We need to confirm that the conclusions presented in this study are not determined by our choices, particularly the assumptions made about the depreciation rate of knowledge stocks, lag periods, and model choice. The first two robustness checks used our main specification: the Poisson model with robust standard errors with the average pre-sample mean of the dependent variable to proxy for firm fixed effects and year dummies. The third robustness check deals with the model choice.

3.8.1 Depreciation Rate

The choice of depreciation rate has been discussed in Subsection 3.5.3 and Table 3.4. As mentioned, the innovation literature presents depreciation rates ranging from 1% to 25%. In our baseline model, we use a 15% depreciation rate. Tables 3.16 to 3.19 compare the results of using a high depreciation rate (20%) and a low depreciation rate (10%) for granted CCMT patents and Y02 patents of OECD countries. The use of both high and low depreciation rates does not result in substantive changes compared to the results obtained from the baseline model.

Table 3.16: Low Depreciation Rate (10%); OECD Countries; Dependent Variable: Granted CCMT Patents

Variables	I	II	III	IV
EPS21	- 0.115**			
	(0.05)			
Market Based Policy		0.069		
		(0.07)		
Non-Market Based Policy			-0.161	
			(0.034)	
Technology Support Policy				-0.067**
				(0.22)
Knowledge Stock- CCMT	1.48**	1.49**	1.52**	1.31**
	(0.678)	(0.735)	(0.72)	(0.665)
Knowledge Stock- All Patents	-0.395	-0.461	-0.46	-0.233
	(0.45)	(0.494)	(0.49)	(0.456)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-10270.50	-10220.87	-10253.58	-9836.34

All variables are lagged by 2 time periods. Regressions started in 2000 and ended in 2016. Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.17: High Depreciation Rate (20%); OECD Countries; Dependent Variable: Granted CCMT Patents

Variables	I	II	III	IV
EPS21	- 0.129**			
	(0.044)			
Market Based Policy		0.061		
		(0.07)		
Non-Market Based Policy			-0.021	
			(0.034)	
Technology Support Policy				-0.070**
				(0.22)
Knowledge Stock- CCMT	1.28**	1.26**	1.30**	1.12**
	(0.603)	(0.617)	(0.61)	(0.556)
Knowledge Stock- All Patents	-0.286	-0.328	-0.344	-0.15
	(0.40)	(0.402)	(0.40)	(0.373)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-9612.23	-9888.44	-9902.45	-9441.17

All variables are lagged by 2 time periods. Regressions started in 2000 and ended in 2016. Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.18: Low Depreciation Rate (10%); OECD Countries; Dependent Variable: Number of Granted Y02 Patents

Variables	I	II	III	IV
EPS21	-0.12**			
	(0.043)			
Market Based Policy		0.098		
		(0.072)		
Non-Market Based Policy			-0.032	
			(0.033)	
Technology Support Policy				-0.068***
				(0.20)
Knowledge Stock- Y02	1.70**	1.78**	1.82**	1.52**
	(0.78)	(0.78)	(0.76)	(0.725)
Knowledge Stock- All Patent	-0.544	-0.682	-0.691	-0.376
	(0.53)	(0.543)	(0.519)	(0.50)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-11643.13	-11871.96	-11919.54	-11469.02

All variables are lagged by 2 time periods. Regressions started in 2000 and ended in 2016. Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.19: High Depreciation Rate (20%); OECD Countries; Dependent Variable: Number of Granted Y02 Patents

Variables	I	II	III	IV
EPS21	-0.137**			
	(0.043)			
Market Based Policy		0.090		
		(0.071)		
Non-Market Based Policy			-0.038	
			(0.033)	
Technology Support Policy				-0.072***
				(0.019)
Knowledge Stock- Y02	1.47**	1.52**	1.58**	1.31**
	(0.637)	(0.66)	(0.64)	(0.605)
Knowledge Stock- All Patent	-0.431	-0.536	-0.56	-0.289
	(0.433)	(0.443)	(0.427)	(0.415)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-11129.22	-11450.46	-11460.01	-10970.04

All variables are lagged by 2 time periods. Regressions started in 2000 and ended in 2016.
Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.8.2 Lag Period

We use a two-year lag for independent variables in the baseline model to avoid reverse causality. To assess the sensitivity of the results, a one-year lag was utilized in Table 3.20, and a three-year lag was employed in Table 3.20. The utilization of a one-year lag resulted in minimal modifications to the results, except for the sign of the non-market-based policy; however, this impact was not statistically significant. In contrast, the use of a three-year lag resulted in a similar sign as the two-year lag in the baseline model. The level of statistical significance for EPS21 and CCMT knowledge stock was altered.

Table 3.20: Robustness check with One-year lag; OECD Countries
Dependent Variable: Granted CCMT Patents

Variables	I	II	III	IV
EPS21	- 0.017			
	(0.03)			
Market Based Policy		0.057		
		(0.065)		
Non-Market Based Policy			0.010	
			(0.021)	
Technology Support Policy				-0.019
				(0.016)
Knowledge Stock- CCMT	1.59***	1.61***	1.85**	1.55***
	(0.475)	(0.483)	(0.496)	(0.434)
Knowledge Stock- All Patents	-0.318	-0.349	-0.304	-0.27
	(0.321)	(0.321)	(0.327)	(0.279)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-8664.36	-8374.40	-8400.59	-8630.09

All variables are lagged by 1 time periods. Regressions started in 2000 and ended in 2016.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3.21: Robustness check with a three-year lag; OECD Countries
Dependent Variable: Granted CCMT patents

Variables	I	II	III	IV
EPS21	- 0.152**			
	(0.063)			
Market Based Policy		0.141		
		(0.101)		
Non-Market Based Policy			-0.030	
			(0.04)	
Technology Support Policy				-0.095***
				(0.032)
Knowledge Stock- CCMT	1.39*	1.46*	1.45*	1.24*
	(0.748)	(0.766)	(0.77)	(0.728)
Knowledge Stock- All Patents	-0.584	-0.727	-0.673	-0.43
	(0.494)	(0.508)	(0.512)	(0.496)
Pre-sample Mean	Yes	Yes	Yes	Yes
Time Effect	Yes	Yes	Yes	Yes
Log-Likelihood	-11231.49	-11168.34	-11308.42	-10638.95

All variables are lagged by 3 time periods. Regressions started in 2000 and ended in 2016.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.8.3 Panel Fixed Effect Model

In the baseline model, we use the count data model. However, our data is skewed, and some countries (i.e., the U.S., Japan, Korea, and Germany) have a higher number of granted patents. Thus, we can test the robustness of our model selection by using a continuous data model, i.e., a panel fixed effect model. Table 3.22 shows a robustness check using the panel fixed effect model. The sign for EPS21, non-market-based policy and technology support policy remains the same compared to our baseline model in Table 3.8. Nevertheless, coefficients are statistically insignificant. It shows that our results are robust to using alternative measurements and models.

Table 3.22: Fixed Effect Models with Robust Standard Errors; OECD Countries
Dependent Variable: CCMT patents

Variables	I	II	III	IV
EPS21	- 259.78 (512.93)			
Market Based Policy		-28.54 (333.25)		
Non-Market Based Policy			-68.70 (114.81)	
Technology Support Policy				-115.67 (250.38)
Knowledge Stock- CCMT	151.18 (516.40)	181.57 (506.63)	179.05 (523.63)	168.71 (495.66)
Knowledge Stock- All Patents	599.94 (462.07)	550.50 (438.98)	577.92 (460.96)	545.70 (427.00)
Time Effect	Yes	Yes	Yes	Yes

All variables are lagged by 2 time periods. Regressions start in 2000 and end in 2016.
Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3.9 Conclusion

In this chapter, our goal is to understand the impact of environmental policy stringency on green (i.e., renewable energy technologies) innovation using data from 34 OECD countries from 2000 to 2016. Policymakers choose environmental policies that are more stringent to direct technical progress in climate change mitigation technologies. We survey the related literature, EPS index, and measure of innovation and show that the results are mixed. The weak version of the Porter hypothesis predicts that a more stringent environmental policy will induce more green innovation, while the technology lock-in hypothesis predicts the converse: with strict environmental policy, there will be less green innovation. The literature also discusses the fact that any incremental change in environmental policy might not induce more green innovation.

In the baseline model, we use Poisson regression, where our dependent variable is the count of both Y02 and CCMT patents. Then, to check the sensitivity of our result, we use different depreciate rates and lag periods as well as a different specification (panel fixed effect model). We show that too strict environmental policies are associated with green patenting activity, and the result holds true for all specifications. We suspect that this is due to a technology lock-in effect. Nevertheless, this does not always indicate that strict environmental policies harm overall innovation. Stringent policies may have distinct consequences at various steps of the innovation process. For example, while strict environmental policies may slow down patenting activities, it is possible that they will speed up technology implementation.

Chapter 4

Environmentally Sustainable Technologies and Emissions

4.1 Introduction

Climate change can be linked to extreme and unusual weather events. A global average temperature increase of 1.5 °C could potentially cause a loss of 20-30% of the world's biodiversity, resulting in catastrophic and irreversible consequences (IPCC, 2018). The greenhouse gases (GHG), particularly carbon dioxide (CO_2), are the primary drivers of global warming and climate change (Conference Board of Canada, 2013; Yazdi and Shakouri, 2018), and CO_2 emissions account for around 75% of global GHG emissions. Over the last three decades, CO_2 emissions have surged by 58% on a global scale (EEA, 2017).

Different international protocols (e.g., Kyoto Protocol 1997, and Paris Agreement 2016) was signed to help reduce GHG emissions and mitigate climate change's consequences. In December 1997, the Kyoto Protocol was adopted in Japan and set a GHG emissions reduction target for signatory countries during the first commitment period of 2008–2012. There are currently 192 signatory parties to the Kyoto Protocol, and it aims to reduce GHG emissions (i.e., CO_2) emissions, to a level that would prevent dangerous anthropogenic (human-made) interference with the climate. The Paris Agreement's environmental goal was to keep the increase in global average temperature below 2 °C compared to pre-industrial levels, and gradually limit the increase to 1.5 °C.

Innovating in new energy-efficient technologies is one way to mitigate emissions and slow down the increase in global average temperature. Thus, technological innovation could help improve the effectiveness of the Kyoto Protocol in terms of GHG mitigation (Kim, 2021). Among these innovations, Environmentally Sustainable Technologies (ESTs) could help reduce the amount of CO_2 in the atmosphere (Álvarez-Herránz et al., 2017). The United Nations Environment Programme (UNEP) defines ESTs as "Technologies that have the potential for significantly improve environmental performance relative to other technologies." In the literature, the term EST is interchangeably used as environmentally sound technology, green technology, clean technology, and environment-related technology. ESTs can protect the environment, mitigate pollution, and recycle waste and used products.

In developed countries, governments actively support EST inventions to mitigate the problem of negative externalities resulting from emissions and market failures related to EST Research and Development (R&D) due to their public good characteristics. OECD countries spent a considerable amount on R&D. In 2019, the total R&D expenditures represented 2.48% of total GDP in OECD countries, while military expenditure was 2.27% of GDP (OECD, 2020).

R&D expenditures create new knowledge and novel products or processes. However, an inventor needs an incentive to pursue new ideas and innovation. A patent is a temporary right awarded to an inventor to exclusively make, use, or sell the invention. A patent that protects inventions for technologies that are environmentally friendly, sustainable, or promote clean energy, is called a green patent and encourages and protect innovation in developing new environmental technologies and products that can help mitigate environmental damage or promote sustainable practices.

EST patenting activities have gained momentum in the last decades. In OECD countries, 7.11% of total patents were EST patents in 2000, which increased to 13.35% in 2013 and flattened to 11.66% in 2017 (OECD, 2021). Several countries (e.g., Australia, Canada, Israel, Japan, Korea, the United Kingdom, and the United States) implemented a fast-track patent application system for ESTs, which reduces the duration of the examination process compared to the regular patent granting system (Dechezleprêtre, 2013). USPTO started a new climate change mitigation pilot program in 2022, effective until 2027, or the date when a total of 4,000 applications were granted a special status under this program. Fast-tracking patent systems accelerated the diffusion of technological knowledge in green technologies. Nevertheless, it seems that only a small percentage of EST patent applications have been processed using this system (Dechezleprêtre, 2013).

Developed countries have launched initiatives to curb environmental pollution, i.e., signing environmental treaties, fast-tracking patent systems, pilot programs, solar and electric vehicle subsidies, carbon tax, and permits. However, to the best of our knowledge, no robust study has been conducted in OECD countries to analyze the relationship between EST patents and carbon emissions using micro patent data from PATSTAT. In this chapter, our goal is to bridge this gap by investigating whether ESTs impact CO_2 emissions in OECD countries using data from PATSTAT.

We investigate whether there is a relationship between green patents and a reduction in emissions that include CO_2 and other greenhouse gases (GHG), using data from PATSTAT maintained by the European Patent Office (EPO). We use the patent count of ESTs to proxy innovation in green technologies. In addition, as innovation is a flow variable, we use stocks of knowledge (Popp et al., 2011) calculated from the number of total patents in order to measure innovation. We find that green patents do not decrease CO_2 emissions. The findings are consistent across specifications. On the other hand, green knowledge stock displays a positive and significant impact on carbon dioxide emissions. Additionally, GDP and population both positively impact CO_2 emissions, implying that increases in either variable lead emissions to grow.

The contributions of our analysis to the literature are as follows. First, this study uses the PATSTAT database maintained by EPO. PATSTAT is a rich database containing over 100 million patents from over 100 patent offices, and it follows the Cooperative Patent Classification (CPC) system. CPC is an updated system of the International Patent Classification (IPC) system. It is jointly managed by the EPO and the U.S. Patent and Trademark Office. It is divided into nine sections, A-H and Y, which in turn are sub-divided into classes, sub-classes, groups and sub-groups. There are approximately 250,000 classification entries. EPO has classified Y02 patents as technologies or applications for mitigation or adaptation against climate change. We use both Y02 and CCMT as measures of innovation because Y02 encompasses an array of environmental innovations, including adaptation technology. At the same time, CCMT concentrates on mitigation technology, which might strongly influence emissions. Second, this study incorporates the STochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model, which can explain anthropogenic environmental impacts as a multiplicative function of population, affluence, and technology, as the theoretical foundation of the relationship between environmental innovation and emissions. Third, we use knowledge stock instead of simple patent count. The advantage of knowledge stock is that it can take into account the dynamic of innovation. Our analysis would overcome the drawbacks of using total patents or the number of scientific personnel by using only environmental-related patents to proxy for environmental inventions.

The chapter is organized as follows. We begin with an extensive review of the literature in section 2. Section 3 explains the methodology used in this analysis. Data sources are presented in section 4 to ensure transparency and reliability. The results are discussed in section 5. In section 6, we conduct a robustness check by employing alternative econometric models. Finally, in section 7, we offer a concluding remarks.

4.2 Related Literature

Climate change and ESTs have been widely analyzed in the last decades (Cheng et al., 2017). In the literature, R&D expenditure, the number of scientific personnel and patent count have been widely used to measure EST inventions. However, these proxies have some severe limitations. Although R&D expenditure is an input measure, the number of patents serves as an output measure. Economists often focus on output measures because input measures, such as R&D spending, may not always result in tangible outcomes (Popp, 2019). According to Hall et al. (1986), patents measure something "above and beyond R&D inputs, creation of an underlying knowledge stock." Moreover, R&D expenditure data is typically available only in aggregated formats, whereas patent data is highly detailed and accessible despite sometimes being inconvenient to use. There are certain limitations to using patent counts as a metric for invention, i.e., many inventors use trade secrets to protect their new technologies. In addition, as patents can be granted in different patent offices, this might lead to double counting. Also, patents vary in quality. Despite those drawbacks, patent statistics have long been viewed as a valuable indicator of invention (Dechezleprêtre et al., 2011; Haščič and Migotto, 2015; Dechezleprêtre et al., 2010; Popp, 2006).

To analyze the effects of human activities on the natural environment, the literature frequently adopts the Incidence, Population, Affluence, Technology (IPAT) framework or the STochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model. The IPAT equation (I = PAT) posits that the incidence of pollution is influenced by factors such as population size, level of affluence, and the extent of technological advancement. Though the IPAT model offers insights into how human activities contribute to the environment, it has some limitations. It assumes a linear relationship between variables and is unsuitable for empirical testing. Dietz and Rosa (1997) formulated an econometrically testable stochastic version of the IPAT equation known as the STIRPAT model. Human activity has contributed to pollution from the start of industrialization. The general idea of anthropogenic environmental impacts is a multiplicative function of population, affluence, and technology. Recently, scholars have extended the STIRPAT model to include environmental invention as a proxy for technology (Weina et al., 2016). The literature does provide mixed results. Some studies show that for different Chinese provinces, green patents that are oriented toward carbon-free technologies can significantly help lower CO_2 levels (Wang et al., 2012). On the other hand, Weina et al. (2016) used a STIRPAT framework to investigate the relationship between green technologies (measured by green patents) and CO_2 emissions for different provinces in Italy. They found that green technologies have not significantly promoted environmental protection, although they significantly improved environmental productivity (CO_2/value addition).

Among other factors, CO_2 emissions can be affected by economies of scale, population, industrial structure, energy consumption structure, energy efficiency, energy intensity, and the level of technology and management (Kaya, 1989). The literature has no consensus on whether new technologies could reduce carbon dioxide emissions. Sagar and Holdren (2002) and Sun et al. (2008) reported a significant role of energy technology innovation in reducing carbon dioxide emissions. On the other hand, Chuzhi and Xianjin (2008) and Ze-yuan and Jiang (2006) did not find any significant impact of energy-efficient technology on carbon dioxide emissions in the context of China. Some studies also investigated the impact of technological change at the sectoral level. Carrión-Flores and Innes (2010) investigated 127 U.S. manufacturing industries and found a negative and significant bidirectional linkage between toxic air pollution and environmental innovation. Lee and Min (2015) examined the impact of green R&D investments on environmental and financial performances in

Japanese manufacturing firms and showed that green R&D reduces carbon emissions and increases firms' financial performance. Public R&D expenditures on green technology increase energy efficiency but fail to reduce carbon intensity due to an insignificant link between R&D expenditure and carbon factor (Garrone and Grilli, 2010).

Green innovation can help reduce emissions, but it is highly concentrated in developed countries. Just four countries (Japan, the United States, Germany, and China) account for more than 60% of all patent families and international PCT patent applications in green energy technologies (León et al., 2018). Japan, the United States, and Germany are the top inventor countries for most green technologies. With 37 percent of the world's inventions, Japan's performance is particularly impressive. Japan ranks first in all technology fields, except for marine energy, where it is second and accounts for over 50 percent of the world's inventions in electric and hybrid, waste, and lighting. The data on public R&D investment for low-carbon technologies confirm the strong leadership of Japan, which in 2004 spent $US 220 million, significantly more than public R&D spending in the same year by the United States. ($ U.S. 70 million) and the E.U. ($ U.S. 50 million) combined (Dechezleprêtre et al., 2011).

There is no consensus on the impact of green innovation on emissions in empirical studies. Nevertheless, an increasing amount of recent studies highlight the relationship between green innovation and emissions. Wurlod and Noailly (2016) investigated the impact of green innovation on energy intensity in 14 industrial sectors of 18 OECD countries over the 1975-2005 period. They found a negative impact of green patenting on energy intensity. The effect of environmental innovation on the absolute level of CO_2 emissions is more inconclusive. Carrion-Flores and Innes (2010) used a simultaneous panel data model of 127 manufacturing industries from 1989 to 2004. They found that tightened pollution targets have an impact on the cost-saving benefit of innovation activity, and environmental innovation is an essential driver of reductions of toxic emissions in U.S. manufacturing industries. Shahbaz et al. (2018) studied the role of FDI, financial development, and energy innovations in environmental degradation in France. The authors found significant evidence that energy research innovation reduces CO_2 emissions. Fethi and Rahuma (2019) tested the Environmental Kuznet Curve (EKC) for 20 oil-exporting countries, including Kuwait, Saudi Arabia, and the UAE. They used the dynamic seemingly unrelated cointegrating regression and panel causality test to test the relationship among GDP, CO_2, energy consumption, and eco-innovation for 2007–2016. The results show that EST negatively affects CO_2 emissions.

Tnani (2018) investigated the relationship between innovation, economic growth, and CO_2 emissions between 1990 and 2014. For the leading countries in the field of innovation (Canada, China, France, Germany, India, Italy, Japan, the Republic of Korea, Spain, Switzerland, the United Kingdom, and the United States), the study found that CO_2 emissions being affected positively by population size and prices of photovoltaic systems and negatively by environmental taxes, high-technology exports, R&D spending, and innovation. Xu and Lin (2018) investigated the impact of the high-tech industry on CO_2 emissions in China between 1999 to 2015. They found that the high-tech industry was effective in reducing CO_2 emissions and promoting the transformation of the low-carbon economy. Erdogan et al. (2020) investigate the effects of innovation on carbon emissions on a sectorial basis for fourteen countries in the G20 between 1991 and 2017. They found that while an increase in innovation in the industrial sector leads to a reduction in carbon emissions, an increase in innovation in the construction sector increases carbon emissions.

A recent stream of literature has used complex econometrics methods to study the impact of innovation on emissions. Ganda (2019) has used the system General Methods of Moments (GMM) to investigate how innovation and technological investment affected CO_2 emissions between 2000 and 2014 in OECD countries. He has used data from the OECD database and the World Bank. They have found that while renewable energy consumption and R&D expenditure have a statistically significant negative relationship with carbon emission, the number of patent families has a statistically positive relationship with carbon emission. Többelmann and Wendler (2020) use difference GMM to investigate the relationship between environmental innovation and CO_2 emissions between 1992 and 2014 for 27 European Union (EU) countries. They used the environmental patent count defined by OECD and WIPO to proxy environmental innovation. They found that environmental innovation reduced CO_2 emissions, but general innovative activities did not.

Mensah et al. (2018) investigated the impact of innovation on CO_2 emissions for 28 OCED countries from 1990 to 2014. They found that innovation plays an important role in the mitigation of CO_2 emissions in most OECD countries, while the per capita GDP has a positive impact on emissions. Mensah et al. (2018) used the STIRPAT model, the economic-EKC growth model, and the innovation-EKC model. They have exclusively used data from the World Development Indicator (WDI). To measure the degree of environmental invention, they have used patents (more precisely, patent applications by residents and non-residents) per capita. This is a clear departure from the previous literature (Popp, 2006; Popp et al., 2011; Weina et al., 2016). Technologies need time to diffuse, and new technologies replace older technologies over time. Thus, some studies have used knowledge stock instead of the number of patents in a specific year as a proxy for innovation (Popp, 2006; Popp et al., 2011). For OECD countries, as less than 12% of total patents are green patents, the total patent count (or per capita patent) can not represent environmental invention. In addition, most studies only used aggregate-level patent data to represent environmental innovation that does not represent the true extent of green innovation.

4.3 Methodology

The methodology used in this chapter is based on Dietz and Rosa (1994), who developed a stochastic framework to allow inferences in the Incidence, Population, Affluence, Technology (IPAT) model. This stochastic model (STIRPAT), adopted in this chapter, also makes it possible to add other influential factors to analyze their influence on environmental performances. According to the STIRPAT model, environmental incidence (pollution) depends stochastically on population, affluence, and technology. Shi (2003) studied the impact of population change on CO_2 emissions in 93 countries during the period between 1975 and 1996. He found that changes in the global population are more than proportionally associated with increased CO_2 emissions. Transport and residential energy consumption vary according to age group and household size (Liddle, 2004; Prskawetz et al., 2004).

On the other hand, Zhu et al. (2016) found that for the Association of Southeast Asian Nations (ASEAN) countries, economic growth and population size has a negative effect on emissions in high-emitting countries. Scientists and economists have developed Integrated Assessment Models (IAM) to understand how human development and societal choices interact with and affect the natural world in the course of climate change. IAM of the Intergovernmental Panel on Climate Change (IPCC) uses the Kaya identity that is derived from the IPAT model. The Kaya identity is a mathematical formula that expresses the total emission level of the greenhouse gas carbon dioxide as the product of four factors: human population, GDP per capita, energy intensity, and carbon intensity. Fan et al. (2006) analyzed the impact of population, affluence, and technology on the total CO_2 emissions of countries at different income levels during the period 1975–2000. They found that global economic growth has the most significant impact on CO_2 emissions.

The basic STIRPAT model can be written as

$$I_{it} = aP^b_{i,t}A^c_{i,t}T^d_{i,t}e_{i,t}, \tag{4.1}$$

where I, P, A, and T represent environmental impact, population, affluence and technology. The constant a represents a scale of the model. Superscripts b, c, and d are the elasticity of population, affluence and technology, respectively. Subscript i represents the country, and subscript t represents the time. The term e is the error term and represents the random variables not observable or controllable in the model. In the logarithm form, we have,

$$lnI_{it} = a + b(lnP_{i,t}) + c(lnA_{i,t}) + d(lnT_{i,t}) + e_{i,t}, \tag{4.2}$$

The STIRPAT model considers institutional and economic factors that impact the environment. In addition, population, affluence, and technology can be decomposed into various factors (Rosa and Dietz, 1998). We use a modified STIRPAT framework to analyze the impact of innovation (proxied by patents) on environmental performance. However, the impact of the invention is not instantaneous, and technologies have become obsolete with time. To account for these issues, Popp et al. (2011) consider patents as the stock of past knowledge. Therefore, following Popp et al. (2011), we use the knowledge stocks to proxy technology (T) in the STIRPAT framework. Our models the following

$$ln(co_2)_{i,t} = \alpha_t + \mu_i + \beta_1 ln(grn\_stock)_{i,t} + \beta_2 ln(pop)_{i,t}, + \beta_3 ln(pcgdp)_{i,t} + \varepsilon_{i,t}, \tag{4.3}$$

where the subscript i represents the country, t represents the time, CO_2 is emissions, α_t is year fixed effect, μ_i is the country fixed effect, ε_{it} is the stochastic error term, grn_stock is the knowledge stock of ESTs defined below, pop is the population, and pcgdp is the per-capita GDP. Per-capita GDP represents affluence in the STIRPAT model. Following Popp et al. (2011), we use the equation below to derive the environmental patent stock by discounting green patents,

$$(grn\_stock)_{i,t} = \sum_{s=0}^{\infty} e^{-\beta_1(s)}(1 - e^{-\beta_2(s+1)})PAT_{i,t-s}, \tag{4.4}$$

where PAT denotes the number of granted green patents, s denotes the number of years before the current year, β_1 denotes the decay rate, and β_2 denotes the knowledge diffusion rate. Knowledge becomes obsolete over time, which can be taken into account by the decay rate, and knowledge also takes time spread, which can be taken into account by the diffusion rate We assume the rate of knowledge decay rate (β_1) is 0.10, and the rate of knowledge diffusion (β_2) is 0.25, in line with Popp (2001). The resulting knowledge stock varies by country and technology and would account for the diffusion of new technologies and the decay of older technologies. Green knowledge stock is a cumulative variable; thus, it should be greater than the patent count. Following Popp et al. (2011), year-fixed effects were included in all the specifications to account for the tendency of knowledge stock to grow over time.

4.4 Data

The present study focuses on the impact of green technology on CO_2 emissions in OECD countries. We construct panel data for the period from 2000 to 2016. In 2020, the OECD had 37 member countries. Seven countries became OECD members after 2000 (Chile, Estonia, Israel, and Slovenia in 2010; Latvia in 2016; Lithuania in 2018; Columbia in 2020). Thus, our panel dataset consists of 30 OECD countries for the period from 2000 to 2016. To measure grn_stock, we use data from PATSTAT maintained by EPO. PATSTAT data has four components. The first component is PATSTAT raw (patent) data, representing the bibliographic information from patent documents. Much raw data is extracted from the EPO's master bibliographic database. The second component is the legal event data for PATSTAT. This contains information on legal events that occurred during the life of a patent. The third one is the PATSTAT online extension. This database contains additional tables and attributes that are either derived from PATSTAT raw data or additional data taken from freely available sources. The last one is the European Patent Register for PATSTAT. This database contains bibliographic, legal, and procedural information on published European patent applications and on published patent applications according to the PCT[1] for which the EPO is a designated office.

Patents are categorized into classes depending on the type of technology. The Y02 Cooperative Patent Classification (CPC) patent class covers technologies that cover climate change, specifically those that control, reduce or prevent GHG emissions as defined in the framework of the Kyoto Protocol and the Paris Agreement and technologies that enable adaptation to the adverse effects of climate change. We extracted patent data of the Y02 class from PATSTAT. However, it is also well-established that the value of a patent varies widely. One way to capture high-value patents is to consider patents filed in multiple patent office (Popp et al., 2011). Thus, we consider all Y02 and patents filed in more than multiple patent offices. Among the Y02 class, there are several sub-classes. Y02A is a subsection of the broader Y02 classification, which represents climate change adaptation technology. Thus, we also consider Climate Change Mitigation Technology (CCMT), which contains the Y02 classification except for Y02A to take into account the technologies that were designed to reduce emissions. Data on CO_2 emissions, population, and GDP are collected from the World Bank database known as the World Development Indicator (WDI). Table 4.1 describes the variables.

[1]The Patent Cooperation Treaty (PCT) is an international treaty with more than 150 Contracting States. The PCT makes it possible to seek patent protection for an invention simultaneously in many countries by filing a single "international" patent application instead of filing several separate national or regional patent applications.

Table 4.1: Detailed description of variables

Variable	Name	Unit	Source
co_2	CO_2 emissions	CO_2 emissions (kg)	The Global Carbon Project and World Bank
grn_stock	Environmental sustainable technology stock	Calculated	PATSTAT and Author's calculation
pop	Population ages 15-64, total	Population ages 15-64, total	World Development Indicators (WDI)
$pcgdp$	Per capita GDP	GDP per capita (2010 constant USD)	World Development Indicators (WDI)

4.5 Empirical Results

Table 4.2 below presents regression results obtained from estimating the model in Eq. (4.3) using high-value unique granted CCMT patents. In specification I, we used the pooled OLS regression model as a baseline model. In contrast, in specification II, we employ a fixed effect panel data model. In Table 4.3, we have considered all granted Y02 patents.

Table 4.2: Pooled OLS and Fixed Effect Panel Data Model Regression Results with Robust Standard Errors (High value unique granted CCMT patents).

Model	I	II
	Pooled OLS	FE
Dep. Var.	Ln(CO_2)	Ln(CO_2)
Log (grn_stock)	0.06***	0.042
	(0.01)	(0.037)
Log(pcgdp)	0.336***	0.71***
	(0.03)	(0.17)
Log(popln)	0.969***	1.31***
	(0.014)	(0.37)
Time-effects	Yes	Yes
Observations	506	506

Regressions start in 2000 and end in 2016.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.3: Pooled OLS and Fixed Effect Panel Data Model Regression Results with Robust Standard Errors (Granted Y02 Patents).

Model Dep. Var.	I Pooled OLS Ln(CO_2)	II FE Ln(CO_2)
Log (grn_stock)	0.09***	0.002
	(0.009)	(0.020)
Log(pcgdp)	0.27***	0.67***
	(0.029)	(0.17)
Log(popln)	0.916***	1.53***
	(0.017)	(0.35)
Time-effects	Yes	Yes
Observations	506	506

Regressions start in 2000 and end in 2016.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In both specifications (pooled OLS model and FE model) in Table 4.2, we find that green patents is associated with an increase in CO_2 emissions. The results obtained from our baseline model demonstrate that variables such as green patents, GDP, and population exhibit a statistically significant influence on CO_2 emissions. Notably, our primary variable of interest, green knowledge stock, displays a positive and significant impact on CO_2 emissions. Specifically, in specification I, the the coefficient for the green patent stock is estimated to be 0.06, suggesting that a 1% increase in green patent stock is associated with a 0.06% increase in CO_2 emissions. In specification II, the coefficient is 0.04, indicating that a 1% increase in green patent stock is associated with a 0.04% increase in CO_2 emissions, but the result is not statistically significant.

The findings for GDP and population reveal that both GDP and population positively impact CO_2 emissions, implying that an increase in either variable leads to an increase in emissions. The effect of the population is substantially larger, twice as large as the effect of GDP. This suggests that the population is more strongly connected to CO_2 emissions. Our result indicates that a 1% increase in per capita GDP will increase emissions by 0.33% in Specification I and 0.71% in Specification II. For population, the result is, respectively, 0.96% and 1.31%. The result does not change significantly if we consider all Y02 patents instead of only CCMT patents. Results from Table 4.3 show that a 1% increase in green patent stock for all granted Y02 patents is associated with a 0.002% increase in CO_2 emissions, but this is not statistically significant.

In the literature, evidence similar to our findings exists. Braungardt et al. (2016) demonstrate that even though green innovations are generally considered an essential element of a green growth strategy, the impact on climate goals has been subjected to debate due to the existence of the rebound effect. Wang et al. (2012) find that energy technology patents do not play a significant role in reducing China's CO_2 emissions, and energy patents with free-carbon technologies contribute to CO_2 emission reduction only in the eastern area of China. Weina et al. (2016) find that green innovations improve environmental productivity in Italy but do not play a significant role in CO_2 emission reduction.

4.6 Robustness Check

As a robustness check, we first consider the dynamic nature of emissions. CO_2 emissions of the current period might be impacted by the emissions from the last period (Többelmann and Wendler, 2020). Production technology in the economy changes gradually over time, which might be responsible for the time dependence of CO_2 (Ibrahim and Law, 2014). Thus, we used a dynamic panel data approach to check the sensitivity of our result. The modified specification can be written as

$$\ln(\mathrm{CO}_2)_{i,t} = \alpha_t + \mu_i + \gamma_1 \ln(\mathrm{CO}_2)_{i,t-1} + \beta_1(\mathrm{grn\_stock})_{i,t} + \sum_{j=1}^{k} \delta_j X_{ji,t} + \varepsilon_{i,t} \quad (4.5)$$

where $ln(co_2)_{i,t-1}$ is the lagged dependent variable of country i in period t, $lnX_{i,t}$ is the set of control variables in the framework of the STIRPAT model. To estimate the above equation with Fixed-Effects (FE) estimator, the lagged explanatory variable ($ln(co_2)_{i,t-1}$) will be correlated with the error terms, which violates the strict exogenity assumption of the FE estimator. Thus, estimators using the FE model will be inconsistent, which is called Nickell's bias. According to Nickell (1981), FE estimators of dynamic panel data are biased and inconsistent. In order to deal with inconsistent estimators and endogeneity problems, we can use the instrumental variable (IV) estimation method, and the earlier lag of the dependent variable (i.e., first difference or level of second difference) can be used as an instrument (Anderson and Hsiao, 1982). However, IVs should be specified and defined. Thus, this method might be consistent but inefficient as it can only use some available moment conditions (Arellano and Bond, 1991).

This problem can be solved by using a Generalized Method of Moments (GMM) estimators proposed by Arellano and Bover (1995) and Blundell and Bond (1998). The GMM approach deals with this inherent endogeneity by transforming the data to remove the fixed effects and solve difference and level equations as a system. The standard approach applies the first difference transformation as follows,

$$\Delta \ln(\mathrm{CO}_2)_{i,t} = \Delta\alpha_t + \gamma_1 \Delta \ln(\mathrm{CO}_2)_{i,t-1} + \beta_1 \Delta(\mathrm{grn\_stock})_{i,t} + \sum_{j=1}^{k} \delta_j \Delta X_{ji,t} + \Delta\varepsilon_{i,t}. \quad (4.6)$$

Removing the fixed effects introduces auto-correlation between the lag difference of dependent variables and the error term, both of which have a term dated $(t-1)$. We can use an IV to solve this problem as first-differenced variables can be instrumented by their own lags. Those are highly correlated with the lagged variables but not correlated with the error term. Thus, the strictly exogenous variables are instrumented by themselves and the endogenous or predetermined by their lagged levels. The Arellano–Bond estimator sets up a generalized method of moments (GMM) problem in which the model is specified as a system of equations, one per time period, where the instruments applicable to each equation differ. Before we proceed, we need to check the validity of the instruments and the identification.

The original GMM estimation technique is known as difference GMM, while the new expanded technique is known as system GMM. We can only use GMM when $N > T$, where N is the number of countries and T is the number of years. In our case, N is 30, and T is 17. If the number of time-period is small and time series are persistent, then system GMM performs better than difference GMM and improves the estimation by minimizing the finite sample bias (Bond et al., 2001; Arellano, 2003; Baltigi, 2008). The system GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998) combine the standard set of moment conditions in first- differences with lagged levels as instruments, with an additional set of moment conditions derived from the equation in levels.

We first need to check the theoretical consistency of the chosen model. According to Roodman (2009), GMM estimation for the coefficient of the lag dependent variable (LDV) should fall in between the coefficients of pooled OLS (upward bias) and fixed effects estimator (downward bias). In Table 4.4, we present the results of OLS, FE, and GMM estimations with different specifications. The first and second regressions represent OLS and FE estimations, respectively. All the remaining regressions are GMM estimations in different control variables scenarios. The coefficients of LDV are between the OLS and the FE estimators. The soundness of instruments in the system GMM is tested using first and second-order autocorrelation in the error term. The AR(1) and AR(2) autocorrelation tests indicate the validity of the model specification used in the study. In addition, the Hansen test supports the use of the instruments. In Table 4.4, we have considered only high-value unique patents to derive grn_stock. The table records three models, OLS, FE and GMM are represented in Specification I, specification II, and Specification III, respectively. Specification III indicates that a 10 percent increase in high-value green stock will increase CO_2 by 0.02 percent, although the result is not statistically significant. In Table 4.5, we use all Y02 patents as the primary explanatory variable instead of unique CCMT high-value patents. In specification III (GMM) in Tables 4.4 and 4.5, we did not find any significant role of green patents in reducing CO_2.

Table 4.4: Pooled OLS, FE and system GMM regression results (High value unique granted CCMT patents).

Model	I	II	III
	OLS	FE	GMM
Dep. Var.	Ln(CO_2)	Ln(CO_2)	Ln(CO_2)
Lag of Log(CO_2)	0.99***	0.766***	0.96***
	(0.006)	(0.04)	(0.06)
Log (grn_stock)	0.0007	0.011	0.002
	(0.001)	(0.015)	(0.004)
Log(pcgdp)	-0.003	0.265***	0.006
	(0.004)	(0.061)	(0.022)
Log(popln)	0.001	0.212	0.03
	(0.007)	(0.143)	(0.061)
AB test for AR(1) in FD			-4.12***
AB test for AR(2) in FD			-1.18
Hansen test			1.68
Time-effects	Yes	Yes	Yes
Observations	476	476	476

Regressions start in 2000 and end in 2016.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.5: All Green Patents (Y02)

Model	1	2	3
	OLS	FE	GMM
Dep. Var.	Ln(CO_2)	Ln(CO_2)	Ln(CO_2)
Lag of Log(CO_2)	0.99***	0.766***	0.95***
	(0.007)	(0.057)	(0.65)
Log (grn_stock)	0.0009	-0.004	0.005
	(0.001)	(0.012)	(0.008)
Log(pcgdp)	-0.003	0.245***	0.005
	(0.005)	(0.076)	(0.018)
Log(popln)	0.002	0.178	0.034
	(0.007)	(0.133)	(0.057)
AB test for AR(1) in FD			-4.16***
AB test for AR(2) in FD			-1.18
Hansen test			1.53
Time-effects	Yes	Yes	Yes
Observations	476	476	476

Regressions start in 2000 and end in 2016.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In the second robustness check, we use different diffusion and decay rates. We have used decay and diffusion rates that are standard in the literature studying technological impact (Popp et al., 2011). In the baseline case of diffusion (β_2) is 0.25, and decay (β_1) is 0.10. In the case of cross-border, diffusion could be slower, while it would be faster within a country. From Table 4.6, we find that the result does not change with slower or faster diffusion.

Table 4.6: Green Stock Sensitivity

Dep. Var. Ln(CO_2)	Base decay=0.10 diffusion=0.25	Slow decay=0.10 diffusion=0.10	Fast decay=0.10 diffusion=0.50
Log (grn_stock)	0.042	0.042	0.042
	(0.037)	(0.037)	(0.037)
Log(pcgdp)	0.71***	0.71***	0.71***
	(0.17)	(0.17)	(0.17)
Log(popln)	1.31***	1.31***	1.31***
	(0.37)	(0.37)	(0.37)
Time-effects	Yes	Yes	Yes
Observations	506	506	506

Regressions start in 2000 and end in 2016.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In the third robustness check, we test the sensitivity of the dependent variable. Greenhouse gases (GHG) absorb and re-emit heat. The main GHGs in the atmosphere are water vapour, carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) and ozone. Thus in In Table 4.7, we use GHG as the dependent variable instead of CO_2. The data on GHG emissions retrieved from World Development Indicators (WDI), World Bank which is available up to 2012. We find that using the 2two specifications, the sign of the coefficient does not change if we consider GHG instead of CO_2.

Table 4.7: GHG as Dependent Variable

	I	II
Model	Pooled OLS	FE
Dep. Var.	Ln(GHG)	Ln(GHG)
Log (grn_stock)	0.108***	0.021
	(0.015)	(0.043)
Log(pcgdp)	0.303***	0.548***
	(0.0299)	(0.139)
Log(popln)	0.867***	1.09*
	(0.017)	(0.41)
Time-effects	Yes	Yes
Observations	390	390

Regressions start in 2000 and end in 2012.

Robust standard errors in the parenthesis. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.7 Conclusion

In this chapter, we analyze the determinants that may impact CO_2 emissions based on the STIRPAT framework. We use a dataset covering 30 OECD countries from 2000 to 2016. In our baseline model, we use pooled OLS and panel fixed effect models. The primary findings indicate that an increase in the stock of green patents has not reduced CO_2 emissions. To validate the results of the baseline model, we use the GMM model to take into account the dynamic nature of pollution. In addition, we also use different diffusion to check the sensitivity of our results. But, even with different specifications in the robustness check, our main results do not change. This outcome may be attributed to the rebound effect, a phenomenon identified in the energy economics literature, where changes in human behavior offset energy efficiency savings. Recent studies have shown strong evidence of a significant rebound effect, as documented in Linn (2016), Stapleton et al. (2016), and Zhang et al. (2017). The rebound effect can have a profound impact on environmental policy forecasts, potentially altering them by up to 300% (Vélez-Henao et al., 2020). The impact of the rebound effect on emissions is left for future research.

Concluding Remarks

In this dissertation, we focus on two themes related to environmental economics. In the first theme, we develop a theoretical model to investigate firms' responses to emission taxes in a two-country framework. In the second theme, we analyze innovation, environmental policies, and emissions. We provide a brief survey of the historical trend of green patents and recent environmental economics literature that uses green patents. Using the PATSTAT database, we then empirically analyze the impact of environmental policy stringency on green innovation. Lastly, we empirically study the relationship between green patents and emissions.

In the first chapter, we develop a theoretical model of two asymmetric countries to investigate firms' choice between FDI and export in the presence of emission tax. We use a three-stage model in two scenarios. In the first scenario, we consider the *ex ante* choice of emission taxes, where firms take emission taxes as given when choosing between FDI and export. The timing is the following: the government chooses the tax levels, then firms decide to export or do FDI, and lastly, firms produce. In the second scenario, we consider the *ex post* choice of emission taxes, where governments take firms' FDI or export decisions as given when setting emission taxes, and then firms make production decisions. We contribute to the literature by considering both scenarios and contrasting the outcomes.

Some of the results of the first chapter are similar to the existing literature. In the first scenario, where taxes are determined in the first stage of the game, if the fixed cost of FDI is sufficiently high, both firms choose export. However, if the fixed cost of FDI is sufficiently low, firms choose both FDI and export. In the case of intermediate fixed costs, the choice between FDI and export is determined by the level of emission taxes and tariffs. In the second scenario, for *ex post* emission taxes, anticipating that countries will set higher emission taxes if both firms engage in FDI, only one-way FDI from either country take place in equilibrium.

The second chapter reviews related literature on green patents, environmental policy, and emissions. It also briefly surveys the recent trends in green patenting in OECD countries. In the early 1990s, the number of green patents increased rapidly and grew till the early 2010s and then slowed down. The review of the literature reveals mixed results of the impact of environmental policy stringency on green innovation as it varies across countries and industries.

The third chapter studies whether environmental policy stringency induces green innovation, the weak version of the Porter hypothesis. We use the EPS21 index to measure environmental stringency and the Y02 patent from PATSTAT to proxy green innovation. As the green patent number is a count variable, we use a count data model with a pre-sample mean of the patents to represent country-level fixed effect. We also use an alternative continuous data model to check the sensitivity. We find that environmental stringency does not induce green innovation, and this finding remains robust across diverse technology selections, depreciation rates, lag periods, and econometric specifications. However, it is important to understand that these findings do not imply stringent environmental regulations universally hinder overall innovation. The technology lock-in effect, where existing inefficient technology prevails due to scale effects, may also contribute. The impact of stringent policies may differ at various stages of the innovation process, warranting further investigation and analysis.

In the fourth chapter, we analyze whether granted green patents reduce emissions that include CO_2 and other greenhouse gases (GHG). Similar to the previous chapter, we use patent count from PATSTAT to proxy environmental innovation.

As innovation is a flow variable, we use stocks of knowledge calculated from the number of total green patents in order to measure innovation. We use panel data from 30 OECD countries for the period from 2000 to 2016 and use the STIRPAT model. We find that green patents do not decrease CO_2 emissions, and our findings are consistent across specifications. However, as expected, green knowledge stock displays a positive and significant impact on CO_2 emissions. GDP and population both positively impact CO_2 emissions, implying that increases in either variable lead emissions to grow. This outcome of the relationship between green patents and CO_2 emission can be attributed to the rebound effect, a phenomenon identified in the energy economics literature, where changes in human behaviour offset energy efficiency savings. Recent studies have shown strong evidence of a significant rebound effect as much as 300%.

This thesis contributes to the literature in several aspects. In the first chapter, we use both *ex ante* and *ex post* emission taxes, and the contrasting result of firms' choices could help formulate effective policies. In the third and fourth chapters, we use the PATSTAT database to extract disaggregated green patent data to measure green innovation. Furthermore, we used the updated EPS index, which includes market-based, non-market-based, and technology support policies. Instead of using the number of patents as an explanatory variable, we use knowledge stock due to the dynamic nature of patents.

Future studies could consider transboundary emissions, as in the first chapter, we only consider local pollution. A theoretical model with transboundary emissions might change our findings since the equilibrium taxes would be set at a different level in both cases. In the third chapter, modelling or quantifying technological lock-in effects to extend the study of the relationship between environmental policy stringency and innovation might be interesting. Similarly, in the fourth chapter, quantifying the rebound effect, a phenomenon identified in the energy economics literature, where changes in human behaviour offset energy efficiency savings, can help understand the impact of the rebound effect on emissions.

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Appendix

A1. Nash Equilibrium: Multinational or National

We first show that it is a dominant strategy for firm 1 to be a national firm if $F > f_1(T, \tau_1, \tau_2)$.

Proof. It is a dominant strategy if, for any strategy of firm 2, firm 1 always chooses N. Thus, we show that $\pi_1^{NN} > \pi_1^{MN}$ and $\pi_1^{NM} > \pi_1^{MM}$ are always satisfied when $F > f_1(T, \tau_1, \tau_2)$. Indeed, $\pi_1^{NN} > \pi_1^{MN}$ if $(q_{1NN}^D)^2 + (q_{1NN}^E)^2 > (q_{1NN}^D)^2 + (q_{1MN}^F)^2 - F$ or, equivalently, if $F > f_1(T, \tau_1, \tau_2) \equiv (q_{1MN}^F)^2 - (q_{1NN}^E)^2$. Furthermore, $\pi_1^{NM} > \pi_1^{MM}$ if $(q_{1NM}^D)^2 + (q_{1NN}^E)^2 > (q_{1NM}^D)^2 + (q_{1MN}^F)^2 - F$ or, equivalently, if $F > f_1(T, \tau_1, \tau_2)$. Therefore, if $F > f_1(T, \tau_1, \tau_2)$, we have $\pi_1^{NN} > \pi_1^{MN}$ and $\pi_1^{NM} > \pi_1^{MM}$, and thus it is a dominant strategy for firm 1 to be a national firm. $\square$

It is a dominant strategy for firm 2 to be a national firm if $F > f_2(T, \tau_1, \tau_2)$.

Proof. It is a dominant strategy if for any strategy of firm 1, firm 2 always chooses N. Thus, we show that $\pi_2^{NN} > \pi_2^{NM}$ and $\pi_2^{MN} > \pi_2^{MM}$ are always satisfied when $F > f_2(T, \tau_1, \tau_2)$. Indeed, $\pi_2^{NN} > \pi_2^{NM}$ if $(q_{2NN}^D)^2 + (q_{2NN}^E)^2 > (q_{2NN}^D)^2 + (q_{2NM}^F)^2 - F$ or, equivalently, if $F > f_2(T, \tau_1, \tau_2) \equiv (q_{2NM}^F)^2 - (q_{2NN}^E)^2$. Furthermore, $\pi_2^{MN} > \pi_2^{MM}$ if $(q_{2MN}^D)^2 + (q_{2NN}^E)^2 > (q_{2MN}^D)^2 + (q_{2NM}^F)^2 - F$ or, equivalently, if $F > f_2(T, \tau_1, \tau_2)$. Thus, if $F > f_2(T, \tau_1, \tau_2)$, we have $\pi_2^{NN} > \pi_2^{NM}$ and $\pi_2^{MN} > \pi_2^{MM}$, and therefore it is a dominant strategy for firm 2 to be a national firm. $\square$

Let's study the functions $f_1(T, \tau_1, \tau_2)$ and $f_2(T, \tau_1, \tau_2)$. We show that

$$\frac{\partial f_1(T, \tau_1, \tau_2)}{\partial T} = -2q_{1NN}^E \frac{\partial q_{1NN}^E}{\partial T} = \frac{4}{3} q_{1NN}^E > 0,$$

as

$$\frac{\partial q^E_{1NN}}{\partial T} = -\frac{2}{3}.$$

We also show that

$$\frac{\partial^2 f_1(T, \tau_1, \tau_2)}{\partial T^2} = \frac{4}{3}\frac{\partial q^E_{1NN}}{\partial T} < 0.$$

Thus, the function $f_1(T, \tau_1, \tau_2)$ is increasing and concave in T.

We show that

$$\frac{\partial f_2(T, \tau_1, \tau_2)}{\partial T} = -2q^E_{2NN}\frac{\partial q^E_{2NN}}{\partial T} = \frac{4}{3}q^E_{2NN} > 0,$$

as

$$\frac{\partial q^E_{2NN}}{\partial T} = -\frac{2}{3}.$$

We also show that

$$\frac{\partial^2 f_2(T, \tau_1, \tau_2)}{\partial T^2} = \frac{4}{3}\frac{\partial q^E_{2NN}}{\partial T} < 0.$$

Thus, the function $f_2(T, \tau_1, \tau_2)$ is also increasing and concave in T.

We now evaluate both functions at $T = 0$, and we show that $f_1(0, \tau_1, \tau_2) > 0 > f_2(0, \tau_1, \tau_2)$ if $\tau_1 > \tau_2$.

Proof. If $\tau_2 < \tau_1$, we show that $f_1(0, \tau_1, \tau_2) > 0$ as at $T = 0$, $q^F_{1MN} > q^E_{1NN}$. In fact $f_1(T, \tau_1, \tau_2) > 0$ is always satisfied as long as $\tau_2 < \tau_1$. We also have that $f_2(0, \tau_1, \tau_2) < 0$ as at $T = 0$, $q^F_{2NM} < q^E_{2NN}$. We show that $f_2(T, \tau_1, \tau_2) < 0$ for $T < \gamma_2(\tau_1 - \tau_2)$, and then $f_2(T, \tau_1, \tau_2) \geq 0$ for $T \geq \gamma_2(\tau_1 - \tau_2)$. Therefore, at $T = 0$, we have that $f_1(0, \tau_1, \tau_2) > 0 > f_2(0, \tau_1, \tau_2)$ if $\tau_1 > \tau_2$. A similar proof shows that $f_1(0, \tau_1, \tau_2) < 0 < f_2(0, \tau_1, \tau_2)$ if $\tau_1 < \tau_2$.

If $\tau_2 < \tau_1$, for the two functions to intersect, we need to have that $\frac{\partial f_2(T,\tau_1,\tau_2)}{\partial T} > \frac{\partial f_1(T,\tau_1,\tau_2)}{\partial T}$ or, equivalently, that $q^E_{2NN} > q^E_{1NN}$. If we assume that the markets are identical ($\alpha_1 = \alpha_2$), we have that $q^E_{2NN} > q^E_{1NN}$ if the marginal cost of firm 2

$(c_2 + \tau_2\gamma_2)$ is higher than the marginal cost of firm 1 $(c_1 + \tau_1\gamma_1)$. $\square$

We show that $f_1(T, \tau_1, \tau_2) > 0$ increases (resp., decreases) with τ_1 (resp., τ_2). Indeed,

$$\frac{\partial f_1(T, \tau_1, \tau_2)}{\partial \tau_1} = 2q_{1MN}^{F}\frac{\partial q_{1MN}^{F}}{\partial \tau_1} - 2q_{1NN}^{E}\frac{\partial q_{1NN}^{E}}{\partial \tau_1} > 0,$$

as $\frac{\partial q_{1MN}^{F}}{\partial \tau_1} > 0$ and $\frac{\partial q_{1NN}^{E}}{\partial \tau_1} < 0$.

We show that $f_2(T, \tau_1, \tau_2) > 0$ increases (resp., decreases) with τ_2 (resp., τ_1). Indeed,

$$\frac{\partial f_2(T, \tau_1, \tau_2)}{\partial \tau_2} = -2q_{2NN}^{E}\frac{\partial q_{2NN}^{E}}{\partial \tau_2} > 0,$$

as $\frac{\partial q_{2NN}^{E}}{\partial \tau_2} < 0$. Furthermore,

$$\frac{\partial f_2(T, \tau_1, \tau_2)}{\partial \tau_1} = 2q_{2NM}^{F}\frac{\partial q_{2NM}^{F}}{\partial \tau_1} - 2q_{2NN}^{E}\frac{\partial q_{2NN}^{E}}{\partial \tau_1} < 0,$$

as $\frac{\partial q_{2NN}^{E}}{\partial \tau_1} = \frac{-2\gamma_2+\gamma_1}{3} < 0$.

Lastly, firms decide to be multinational only if they have a positive profit, so that $\pi_1^{MN} \geq 0$ if $F \leq (q_{1NN}^{D})^2 + (q_{1MN}^{F})^2$, $\pi_2^{NM} \geq 0$ if $F \leq (q_{2NN}^{D})^2 + (q_{2NM}^{F})^2$, $\pi_1^{MM} \geq 0$ if $F \leq (q_{1NM}^{D})^2 + (q_{1MN}^{F})^2$ and $\pi_2^{MM} \geq 0$ if $F \leq (q_{2MN}^{D})^2 + (q_{2NM}^{F})^2$. No matter what firm 2 does, firm 1 will decide to be a multinational if $\pi_1^{MN} \geq 0$ or, equivalently, if $F \leq (q_{1NN}^{D})^2 + (q_{1MN}^{F})^2$ and $\pi_1^{MM} \geq 0$ or, equivalently, if $F \leq (q_{1NM}^{D})^2 + (q_{1MN}^{F})^2$. We rewrite the condition as $F \leq \min\{(q_{1NN}^{D})^2, (q_{1NM}^{D})^2\} + (q_{1MN}^{F})^2 \equiv f_3(T, \tau_1, \tau_2)$. We show that $f_3(T, \tau_1, \tau_2) > f_1(T, \tau_1, \tau_2)$.

No matter what firm 1 does, firm 2 will decide to be a multinational if $\pi_2^{NM} \geq 0$

or, equivalently, if $F \leq (q^D_{2NN})^2 + (q^F_{2NM})^2$ and $\pi_2^{MM} \geq 0$ or, equivalently, if $F \leq (q^D_{2MN})^2 + (q^F_{2NM})^2$. As long as $\tau_1 > \tau_2$, we have that $q^D_{2NN} > q^D_{2MN}$ and thus the only condition that needs to be satisfied is $F \leq \min\{(q^D_{2NN})^2, (q^D_{2MN})^2\} + (q^F_{2NM})^2 \equiv f_4(\tau_1, \tau_2)$, which is independent of T. We show that $f_4(\tau_1, \tau_2) > f_2(T, \tau_1, \tau_2)$.

Therefore, as long as $F < \min\{f_1(T, \tau_1, \tau_2), f_2(\tau_1, \tau_2)\}$, a multinational firm can be on the market.

A2. Optimal emission tax τ_1 with $\tau_2 = 0$

If both firms choose to be national firms (N, N), they produce in their domestic country and export in the foreign country. Therefore, country 1 chooses τ_1 that solves

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{NN} = (q^D_{1NN})^2 + (q^E_{1NN})^2 + \frac{(q^D_{1NN} + q^E_{2NN})^2}{2} - \gamma_1(1-\tau_1)(q^D_{1NN} + q^E_{1NN}) \\ \text{s.t.} & q^D_{iNN} \geq 0 \quad \text{for } i = 1, 2 \\ & q^E_{iNN} \geq 0 \\ & F - f_1(T, \tau_1, 0) \geq 0 \\ & F - f_2(T, \tau_1, 0) \geq 0 \end{cases}$$

We will check at the end that the conditions are such that all the quantities are positive. Thus, the program becomes

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{NN} = (q^D_{1NN})^2 + (q^E_{1NN})^2 + \frac{(q^D_{1NN} + q^E_{2NN})^2}{2} - \gamma_1(1-\tau_1)(q^D_{1NN} + q^E_{1NN}) \\ \text{s.t.} & F - f_1(T, \tau_1, 0) \geq 0 \\ & F - f_2(T, \tau_1, 0) \geq 0 \end{cases}$$

We write the Lagrange function as

$$L = W_1^{NN} + \lambda_1(F - f_1(T, \tau_1, 0)) + \lambda_2(F - f_2(T, \tau_1, 0)).$$

The Kuhn-Tucker conditions are

$$\frac{\partial L}{\partial \tau_1} = 0,$$
$$\frac{\partial L}{\partial \lambda_1} \geq 0,$$
$$\frac{\partial L}{\partial \lambda_2} \geq 0.$$

We consider, in turn, the case where both constraints are satisfied, the case where only one constraint binds and finally, when both constraints bind.

We first study in more details the functions $f_1(T, \tau_1, 0)$ and $f_2(T, \tau_1, 0)$. In particular, we show that if $f_1(T, \tau_1, 0) - F < 0$, then $f_2(T, \tau_1, 0) - F < 0$. To prove that, we first show that at $\tau_1 = 0$, $f_1(T, 0, 0) > f_2(T, 0, 0)$ for any T. We then show that $f_2(T, \tau_1, 0)$ is decreasing in τ_1 while $f_1(T, \tau_1, 0)$ is increasing in τ_1 for any $\tau_1 > 0$. Therefore, $f_1(T, \tau_1, 0) > f_2(T, \tau_1, 0)$ for any τ_1 and T. Recall that $\alpha_1 \geq \alpha_2$, $c_1 < c_2$, and $\gamma_1 < \gamma_2$.

Proof. At $\tau_1 = 0$, $f_1(T, 0, 0) > f_2(T, 0, 0)$ if $(\frac{\alpha - 2c_1 + c_2}{3})^2 - (\frac{\alpha - 2c_1 + c_2 - 2T}{3})^2 > (\frac{\alpha - 2c_2 + c_1}{3})^2 - (\frac{\alpha - 2c_2 + c_1 - 2T}{3})^2$, which is always satisfied as $c_1 < c_2$. Therefore, at $\tau_1 = 0$, $f_1(T, 0, 0) > f_2(T, 0, 0)$.

For $\tau_1 > 0$, we then calculate that $\frac{\partial f_2(.)}{\partial \tau_1} < 0$ and $\frac{\partial f_1(.)}{\partial \tau_1} > 0$. Therefore, $f_2(T, \tau_1, 0)$ is decreasing in τ_1 while $f_1(T, \tau_1, 0)$ is increasing in τ_1 for any $\tau_1 > 0$, and $f_1(T, \tau_1, 0) - F > f_2(T, \tau_1, 0) - F$. Thus, if $f_1(T, \tau_1, 0) - F < 0$, then $f_2(T, \tau_1, 0) - F < 0$. $\square$

Case 1: Both constraints are satisfied so that $\lambda_1 = \lambda_2 = 0$, and thus $f_1(T, \tau_1, 0) - F < 0$ and $f_2(T, \tau_1, 0) - F < 0$. We thus calculate

$$\frac{\partial L}{\partial \tau_1} = 2q^D_{1NN}\frac{\partial q^D_{1NN}}{\partial \tau_1} + 2q^E_{1NN}\frac{\partial q^E_{1NN}}{\partial \tau_1} + (q^D_{1NN} + q^E_{2NN})(\frac{\partial q^D_{1NN}}{\partial \tau_1} + \frac{\partial q^E_{2NN}}{\partial \tau_1})$$
$$+\gamma_1(q^D_{1NN} + q^E_{1NN}) - \gamma_1(1 - \tau_1)(\frac{\partial q^D_{1NN}}{\partial \tau_1} + \frac{\partial q^E_{1NN}}{\partial \tau_1}) = 0,$$

which gives

$$\tau_1^{NN} = \frac{5c_1 - c_2 + 2T - 3\alpha_1 - \alpha_2 + 12\gamma_1}{7\gamma_1}.$$

We need to insure that the conditions $f_1(T, \tau_1^{NN}, 0) - F < 0$ and $f_2(T, \tau_1^{NN}, 0) - F < 0$ are satisfied for some values of the parameters. We thus calculate that as long as $F > F_C^{NN}$ where

$$F_C^{NN} = max\{f_1(T, \tau_1^{NN}, 0), f_2(T, \tau_1^{NN}, 0)\}.$$

Therefore, there exist values of the parameters for which these conditions are satisfied. In particular, F needs to be large enough. If these conditions are not satisfied, we move to the following case.

Case 2: only one constraint is satisfied. Assume that $\lambda_1 > 0$ and $\lambda_2 = 0$, so that $F - f_1(T, \tau_1, 0) = 0$ and $F - f_2(T, \tau_1, 0) > 0$. We thus calculate τ_{1C} such that $F - f_1(T, \tau_{1C}, 0) = 0$. Two values satisfy this equality

$$\tau_{1C} = \tfrac{1}{2\gamma_1}(\alpha_2 - 2c_1 + c_2 - 2T - \sqrt{-9F + (\alpha_2)^2 + 4(c_1)^2 + (c_2)^2 - 4\alpha_2 c_2 + 2\alpha_2 c_2 - 4c_1 c_2}),$$
$$\tau_{1C}^{'} = \tfrac{1}{2\gamma_1}(\alpha_2 - 2c_1 + c_2 - 2T + \sqrt{-9F + (\alpha_2)^2 + 4(c_1)^2 + (c_2)^2 - 4\alpha_2 c_2 + 2\alpha_2 c_2 - 4c_1 c_2}).$$

Let's call F_C the value of F for which $\tau_{1C} = \tau_{1C}^{'}$. When $F > F_C$, the condition $F - f_1(T, \tau_1^{NN}, 0) > 0$ is always satisfied. However, there are other values of F for which $F - f_1(T, \tau_1^{NN}, 0) > 0$ can be satisfied for some values of τ_{1C}. Therefore, we take the smallest tax value between τ_{1C} and $\tau_{1C}^{'}$ as long as it is positive, as τ_1 cannot be too large. We verify that $F - f_2(T, \tau_{1C}, 0) > 0$ if $F > \frac{4}{9}(\tau_{1C}\gamma_2 - T)(T - \alpha_1 - c_1 + 2c_2 + (\gamma_2 - \gamma_1)\tau_{1C})$, which is satisfied for some values of the parameters.

We verify that the other cases are not possible. Indeed we cannot have that $\lambda_2 > 0$ and $\lambda_1 = 0$, so that $F - f_1(T, \tau_1, 0) > 0$ and $F - f_2(T, \tau_1, 0) = 0$, and we cannot have that $\lambda_1 > 0$ and $\lambda_2 > 0$, so that $F - f_1(T, \tau_1, 0) = 0$ and $F - f_2(T, \tau_1, 0) = 0$.

Thus, there are two possible optimal solutions: τ_1^{NN} or τ_{1C}^{NN} depending on the parameter values.

Lastly, we need to verify that the quantities are all positive at τ_1^{NN} or τ_{1C}^{NN}. They are all positive as long as $T \leq T^{NN}$ where

$$T^{NN} = \frac{2\alpha_1 + 3\alpha_2 - 8\gamma_1 - 8c_1 + 3c_2}{6}.$$

If firm 1 chooses to be a multinational firm while firm 2 decides to be a national firm (M, N), country 1 chooses τ_1 that solves

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{MN} = (q_{1MN}^D)^2 + (q_{1MN}^F)^2 + \frac{(q_{1MN}^D + q_{2MN}^E)^2}{2} - \gamma_1(1-\tau_1)q_{1MN}^D \\ \text{s.t.} & q_{iMN}^D \geq 0 \quad \text{for } i = 1, 2 \\ & q_{1MN}^F \geq 0 \\ & q_{2MN}^E \geq 0 \\ & f_1(T, \tau_1, 0) - F \geq 0 \\ & F - f_2(T, \tau_1, 0) \geq 0 \end{cases}$$

We will check at the end that the conditions are such that all the quantities are positive. Thus, the program becomes

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{MN} = (q_{1MN}^D)^2 + (q_{1MN}^F)^2 + \frac{(q_{1MN}^D + q_{2MN}^E)^2}{2} - \gamma_1(1-\tau_1)q_{1MN}^D \\ \text{s.t.} & f_1(T, \tau_1, 0) - F \geq 0 \\ & F - f_2(T, \tau_1, 0) \geq 0 \end{cases}$$

We write the Lagrange function as

$$L = W_1^{MN} + \lambda_1(f_1(T, \tau_1, 0) - F) + \lambda_2(F - f_2(T, \tau_1, 0)).$$

The Kuhn-Tucker conditions are

$$\frac{\partial L}{\partial \tau_1} = 0,$$
$$\frac{\partial L}{\partial \lambda_1} \geq 0,$$
$$\frac{\partial L}{\partial \lambda_2} \geq 0.$$

We consider, in turn, the cases where both constraints are satisfied when only one of them binds and, finally, when both constraints bind.

Case 1: Both constraints are satisfied so that $\lambda_1 = \lambda_2 = 0$, and thus $f_1(T, \tau_1, 0) - F > 0$ and $F - f_2(T, \tau_1, 0) > 0$. We thus calculate

$$\frac{\partial L}{\partial \tau_1} = 2q^D_{1MN}\frac{\partial q^D_{1MN}}{\partial \tau_1} + (q^D_{1MN} + q^E_{2MN})(\frac{\partial q^D_{1MN}}{\partial \tau_1} + \frac{\partial q^E_{2MN}}{\partial \tau_1})$$
$$+\gamma_1 q^D_{1MN} - \gamma_1(1-\tau_1)\frac{\partial q^D_{1MN}}{\partial \tau_1} = 0,$$

which gives

$$\tau_1^{MN} = \frac{c_1 - \alpha_1 + 2\gamma_1}{\gamma_1}.$$

We need to insure that the conditions $f_1(T, \tau_1^{MN}, 0) - F > 0$ and $F - f_2(T, \tau_1^{MN}, 0) > 0$ are satisfied for some values of the parameters. We thus calculate that these conditions are satisfied as long as

$$F > \tfrac{4}{9}((-\alpha_1 + c_1 + 2\gamma_1)\gamma_2 - T\gamma_1)((T - \alpha_1 - 1 - c_1 + 2c_2)\gamma_1 + (c_1 - \alpha_1 + 2\gamma_1)(\gamma_2 - \gamma_1))$$
$$F < \tfrac{4}{9}(\alpha_1 - c_1 - 2\gamma_1 - T)(T - \alpha_1 - 2\alpha_2 + \gamma_1 + 3c_1 - c_2)$$

Therefore, there exist values of the parameters for which these conditions are satisfied; in particular, F needs to be at an intermediate level or small enough. If these conditions are not satisfied, we move to the following case.

Case 2: only one constraint is satisfied. Assume that $\lambda_1 = 0$ and $\lambda_2 > 0$, so that $f_1(T, \tau_1, 0) - F > 0$ and $F - f_2(T, \tau_1, 0) = 0$. We thus calculate τ_{12C} so that

$F - f_2(T, \tau_{12C}, 0) = 0$. Two values satisfy this equality

$$\tau_{12C} = \frac{T\gamma_1 - c_1\gamma_2 + 2c_2\gamma_2 - \alpha_1\gamma_2 + \sqrt{-(9F + 4T(-c_1 + 2c_2 + T - \alpha_1))(\gamma_1 - \gamma_2)\gamma_2 + (T\gamma_1 - (c_1 - 2c_2 + \alpha_1)\gamma_2)^2}}{2(\gamma_1 - \gamma_2)\gamma_2}$$
$$\tau_{12C'} = \frac{T\gamma_1 - c_1\gamma_2 + 2c_2\gamma_2 - \alpha_1\gamma_2 - \sqrt{-(9F + 4T(-c_1 + 2c_2 + T - \alpha_1))(\gamma_1 - \gamma_2)\gamma_2 + (T\gamma_1 - (c_1 - 2c_2 + \alpha_1)\gamma_2)^2}}{2(\gamma_1 - \gamma_2)\gamma_2}$$

We take the positive value of the tax. We verify that $f_1(T, \tau_{12C}, 0) - F > 0$, and that the quantities are positives. If these conditions are not satisfied, we move to the following case.

Case 3: $\lambda_1 > 0$ and $\lambda_2 = 0$, so that $f_1(T, \tau_1, 0) - F = 0$ and $F - f_2(T, \tau_1, 0) > 0$. In that case, the solution is τ_{1C} as defined in the case (N, N).

We cannot cannot have that $\lambda_1 > 0$ and $\lambda_2 > 0$, so that $f_1(T, \tau_1, 0) - F = 0$ and $F - f_2(T, \tau_1, 0) = 0$. Thus, there are three possible optimal solutions: τ_1^{MN}, τ_{1C} or τ_{12C} depending on the parameter values.

Lastly, we need to verify that the quantities are all positive at τ_1^{MN}, τ_{1C} or τ_{12C}. They are all positive as long as $T \leq T^{MN}$ where

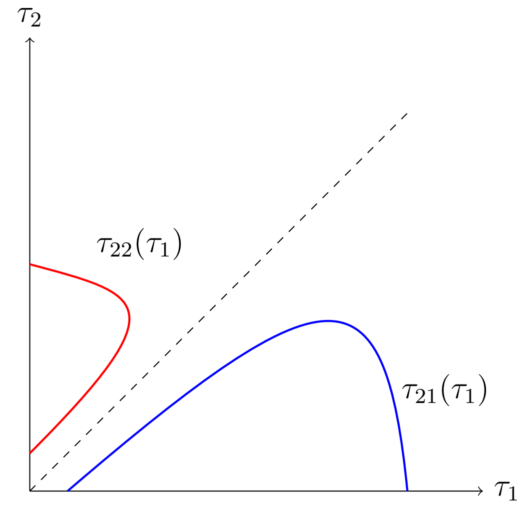
$$T^{MN} = \gamma_1 + c_1 - c_2.$$

The proofs for the other cases (N, M) and (M, M) are similar.

A3. Optimal emission taxes τ_1 and τ_2

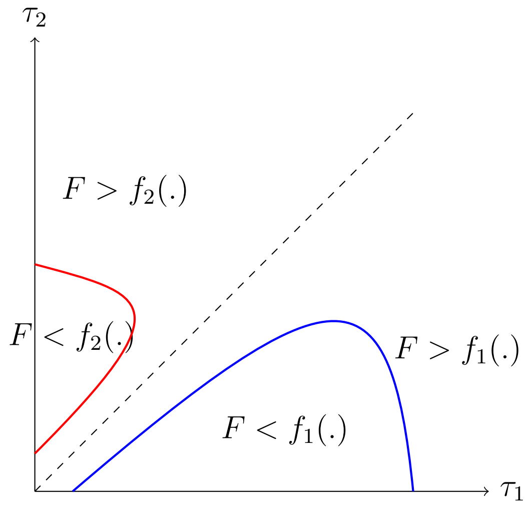
We start by determining the conditions under which $F = f_1(T, \tau_1, \tau_2)$ and $F = f_2(T, \tau_1, \tau_2)$, that we represent in a graph (τ_1, τ_2). Let's call $\tau_{21}(\tau_1)$ and $\tau_{22}(\tau_1)$ the functions that represent $F = f_1(T, \tau_1, \tau_2)$ and $F = f_2(T, \tau_1, \tau_2)$, respectively. We show that $\tau_{21}(\tau_1)$ has an oblique asymptote at $\tau_2 = \tau_1 + f(T)$, where $\tau_{21}(\tau_1)$ is below the asymptote for low values of τ_1, and above it for larger values of τ_1. We also show that $\tau_{22}(\tau_1)$ has an oblique asymptote at $\tau_2 = \tau_1 - f(T)$, where $\tau_{22}(\tau_1)$ is above the asymptote for low values of τ_1, and below it for larger values of τ_1. We only consider the lower values of τ_1 as the taxes cannot be too large. As F increases, both functions become smaller. See Figure A.1 for a representation of these functions.

Figure A.1: Constraints



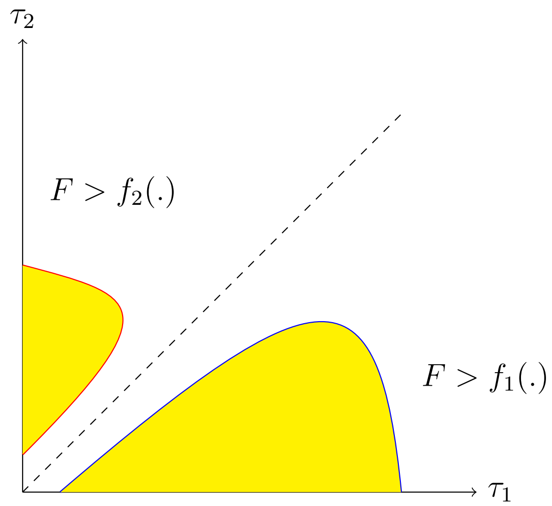
The values of τ_1 and τ_2 such as $F > f_1(T, \tau_1, \tau_2)$, $F < f_1(T, \tau_1, \tau_2)$, $F > f_2(T, \tau_1, \tau_2)$, and $F < f_2(T, \tau_1, \tau_2)$ are represented in Figure A.2.

Figure A.2: Constraints



Thus, to be in the area where $F > f_1(T, \tau_1, \tau_2)$ and $F > f_2(T, \tau_1, \tau_2)$, τ_1 and τ_2 must be in the non-yellow area in Figure A.3.

Figure A.3: Constraints



We will use these figures to understand how the constraints are satisfied. Let's now study in turn when it is optimal for both firms to be national or multinational.

If both firms choose to be national firms (N, N), they produce in their domestic country and export in the foreign country. Therefore, countries 1 and 2 choose simultaneously τ_1 and τ_2 that solve

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{NN} = (q_{1NN}^D)^2 + (q_{1NN}^E)^2 + \frac{(q_{1NN}^D + q_{2NN}^E)^2}{2} - \gamma_1(1-\tau_1)(q_{1NN}^D + q_{1NN}^E) \\ \text{s.t.} & q_{iNN}^D \geq 0 \quad \text{for } i = 1, 2 \\ & q_{iNN}^E \geq 0 \\ & F - f_1(T, \tau_1, \tau_2) \geq 0 \\ & F - f_2(T, \tau_1, \tau_2) \geq 0 \end{cases}$$

and

$$\begin{cases} \underset{\tau_2}{Max} & W_2^{NN} = (q_{2NN}^D)^2 + (q_{2NN}^E)^2 + \frac{(q_{2NN}^D + q_{1NN}^E)^2}{2} - \gamma_2(1-\tau_2)(q_{2NN}^D + q_{2NN}^E) \\ \text{s.t.} & q_{iNN}^D \geq 0 \quad \text{for } i = 1,2 \\ & q_{iNN}^E \geq 0 \\ & F - f_1(T,\tau_1,\tau_2) \geq 0 \\ & F - f_2(T,\tau_1,\tau_2) \geq 0 \end{cases}$$

We will check at the end that the conditions are such that all the quantities are positive. Thus, the programs become

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{NN} = (q_{1NN}^D)^2 + (q_{1NN}^E)^2 + \frac{(q_{1NN}^D + q_{2NN}^E)^2}{2} - \gamma_1(1-\tau_1)(q_{1NN}^D + q_{1NN}^E) \\ \text{s.t.} & F - f_1(T,\tau_1,\tau_2) \geq 0 \\ & F - f_2(T,\tau_1,\tau_2) \geq 0 \end{cases}$$

and

$$\begin{cases} \underset{\tau_2}{Max} & W_2^{NN} = (q_{2NN}^D)^2 + (q_{2NN}^E)^2 + \frac{(q_{2NN}^D + q_{1NN}^E)^2}{2} - \gamma_2(1-\tau_2)(q_{2NN}^D + q_{2NN}^E) \\ \text{s.t.} & F - f_1(T,\tau_1,\tau_2) \geq 0 \\ & F - f_2(T,\tau_1,\tau_2) \geq 0 \end{cases}$$

We write the Lagrange functions as

$$L_1 = W_1^{NN} + \lambda_1(F - f_1(T,\tau_1,\tau_2)) + \lambda_2(F - f_2(T,\tau_1,\tau_2)),$$

and

$$L_2 = W_2^{NN} + \lambda_1(F - f_1(T,\tau_1,\tau_2)) + \lambda_2(F - f_2(T,\tau_1,\tau_2)).$$

The Kuhn-Tucker conditions for the first Lagrange function are

$$\frac{\partial L_1}{\partial \tau_1} = 0,$$
$$\frac{\partial L_1}{\partial \lambda_1} \geq 0,$$
$$\frac{\partial L_1}{\partial \lambda_2} \geq 0,$$

and for the second Lagrange function

$$\frac{\partial L_2}{\partial \tau_2} = 0,$$
$$\frac{\partial L_2}{\partial \lambda_1} \geq 0,$$
$$\frac{\partial L_2}{\partial \lambda_2} \geq 0.$$

We will consider in turn the cases where both constraints are satisfied, when only one constraint binds and finally, when both constraints bind.

Case 1: Both constraints are satisfied so that $\lambda_1 = \lambda_2 = 0$, and thus $F - f_1(T, \tau_1, \tau_2) > 0$ and $F - f_2(T, \tau_1, \tau_2) > 0$, which is the case represented in Figure A.3. We thus calculate

$$\frac{\partial L_1}{\partial \tau_1} = 2q_{1NN}^D \frac{\partial q_{1NN}^D}{\partial \tau_1} + 2q_{1NN}^E \frac{\partial q_{1NN}^E}{\partial \tau_1} + (q_{1NN}^D + q_{2NN}^E)(\frac{\partial q_{1NN}^D}{\partial \tau_1} + \frac{\partial q_{2NN}^E}{\partial \tau_1})$$
$$+\gamma_1(q_{1NN}^D + q_{1NN}^E) - \gamma_1(1-\tau_1)(\frac{\partial q_{1NN}^D}{\partial \tau_1} + \frac{\partial q_{1NN}^E}{\partial \tau_1}) = 0,$$

and

$$\frac{\partial L_2}{\partial \tau_2} = 0,$$

which gives the best response of country 1 to any tax chosen by country 2

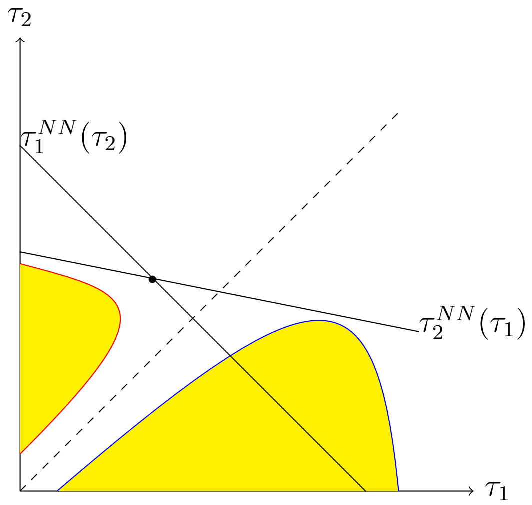
$$\tau_1^{NN}(\tau_2) = \frac{5c_1 - c_2 + 2T - 3\alpha_1 - \alpha_2 + 12\gamma_1 - \gamma_2\tau_2}{7\gamma_1}, \tag{7}$$

and the best response of country 2 to any tax level chosen by country 1

$$\tau_2^{NN}(\tau_1) = \frac{-c_1 + 5c_2 + 2T - \alpha_1 - 3\alpha_2 + 12\gamma_2 - \gamma_1\tau_1}{7\gamma_2}. \tag{8}$$

We represent these best response functions in Figure A.4, which is based on Figure A.3.

Figure A.4: Best response functions in the case (N,N) for large F



Solving for τ_1 and τ_2, we obtain

$$\tau_1^{NN} = \frac{3(3c_1 - c_2 + T) - 5\alpha_1 - \alpha_2 - 3(\gamma_2 - 7\gamma_1)}{12\gamma_1},$$

and

$$\tau_2^{NN} = \frac{3(3c_2 - c_1 + T) - \alpha_1 - 5\alpha_2 + 3(7\gamma_2 - \gamma_1)}{12\gamma_2}.$$

We verify that these optimal tax levels are positive for the parameter values. We thus need to insure that the conditions $F - f_1(T, \tau_1^{NN}, \tau_2^{NN}) > 0$ and $F - f_2(T, \tau_1^{NN}, \tau_2^{NN}) > 0$ are satisfied for some values of the parameters. We therefore calculate that as long as

$$F > F_{NN} = \max\{f_1(T, \tau_1^{NN}, \tau_2^{NN}), f_2(T, \tau_1^{NN}, \tau_2^{NN})\}.$$

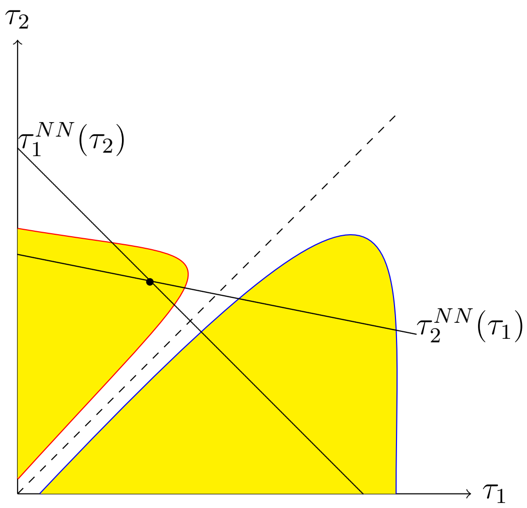
There exist values of the parameters for which these conditions are satisfied; in particular, F must be large enough. Furthermore, we need to make sure that the quantities are all positive, which is equivalent to ensuring that $q^E_{2NN} \geq 0$ evaluated at τ_1^{NN} and τ_2^{NN}. This is satisfied if $T < T_{NN}$ where

$$T_{NN} = \frac{\alpha_1 + \alpha_2 + 3c_1 - 5c_2 + 3\gamma_1 - 5\gamma_2}{3}.$$

If these conditions are not satisfied, we move to the following case.

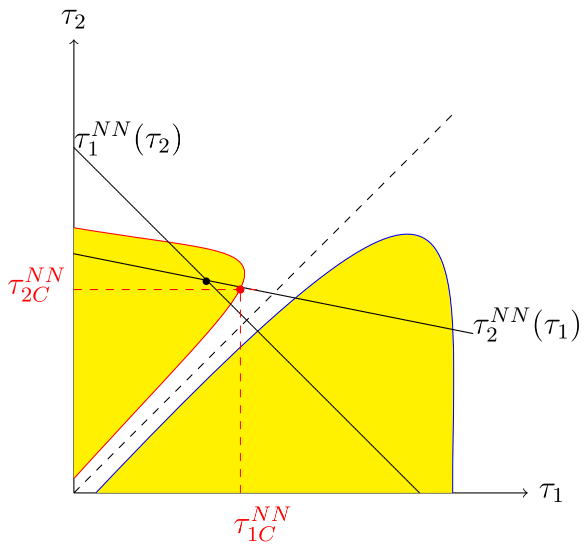
Case 2: only one constraint is satisfied. Assume that $\lambda_1 = 0$ and $\lambda_2 > 0$, so that $F - f_1(T, \tau_1, \tau_2) > 0$ and $F - f_2(T, \tau_1, \tau_2) = 0$. This case is represented in Figure A.5, where the solution $(\tau_1^{NN}, \tau_2^{NN})$ is such that $F - f_1(T, \tau_1^{NN}, \tau_2^{NN}) > 0$ and $F - f_2(T, \tau_1^{NN}, \tau_2^{NN}) < 0$.

Figure A.5: Best response functions in the case (N,N) for small F



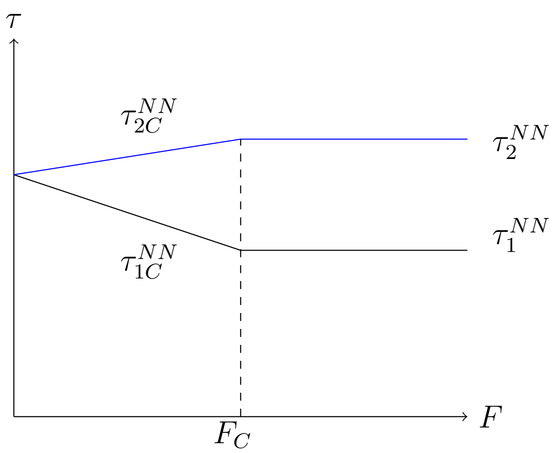
Thus, in that case, the solution $(\tau_1^{NN}, \tau_2^{NN})$ does not satisfy the second constraint, and therefore, we have a corner solution. In fact, there might be several corner solutions. First, let's consider that the solution is on the best response of country 2, $\tau_2(\tau_1)$, as defined by (8) and the constraint $\tau_{22}(\tau_1)$, as shown in Figure A.6.

Figure A.6: Constraint solution in the case (N,N) for small F



The corner solution is defined by the best response function of country 2 as expressed by (8) and the constraint $\tau_{22}(\tau_1)$. We do not obtain an easy analytical solution. Let's call τ_{1C1}^{NN} and τ_{2C1}^{NN} the solution, where C stands for constrained solution with $\tau_{1C1}^{NN} > \tau_1^{NN}$ and $\tau_{2C1}^{NN} < \tau_2^{NN}$. We represent the tax levels τ^{NN} as a function of F in Figure A.7.

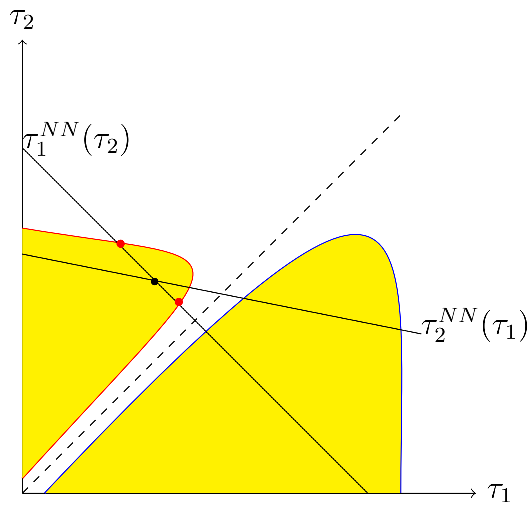
Figure A.7: Tax levels in the case (N,N) for very low values of T



We verify that these constrained tax levels are positive, that the conditions $F - f_1(T, \tau_{1C1}^{NN}, \tau_{2C1}^{NN}) > 0$ and $F - f_2(T, \tau_{C1}^{NN}, \tau_{2C1}^{NN}) = 0$ are satisfied for some values of the parameters, and the quantities are positive. F needs to be small enough. Indeed, there is a value of F such that $\tau_1^{NN} = \tau_{1C1}^{NN}$ denoted F_C. For values of $F \leq F_C$, the tax level is the constrained solution, while for $F > F_C$, the tax level is the optimal solution. The quantities are always positive if $q_{2NN}^E > 0$, which is satisfied if $F < F_{NN1}(T)$.

However, it could be that the corner solution is on the best response of country 1, $\tau_1(\tau_2)$, as defined by (7) and the constraint $\tau_{22}(\tau_1)$, as shown in Figure A.8.

Figure A.8: Tax levels in the case (N,N) for very low values of T



There are two possible solutions. Let's call them $(\tau_{1C2}^{NN}, \tau_{2C2}^{NN})$ and $(\tau_{1C3}^{NN}, \tau_{2C3}^{NN})$. When the solution is $(\tau_{1C2}^{NN}, \tau_{2C2}^{NN})$, the quantities of firm 2 are negative, so we do not consider this case. When the solution is $(\tau_{1C3}^{NN}, \tau_{2C3}^{NN})$, the quantities are positive if $F < F_{NN3}(T)$.

We verify that the other cases are not possible. Indeed we cannot have that $\lambda_1 > 0$ and $\lambda_2 = 0$, so that $F - f_1(T, \tau_1, \tau_2) = 0$ and $F - f_2(T, \tau_1, \tau_2) > 0$, and we cannot have that $\lambda_1 > 0$ and $\lambda_2 > 0$, so that $F - f_1(T, \tau_1, \tau_2) = 0$ and $F - f_2(T, \tau_1, \tau_2) = 0$ cannot be binding simultaneously. Indeed, as $\tau_1^{NN} < \tau_2^{NN}$, the optimal solution is above the 45 line, which means that the constraint $F - f_2(T, \tau_1, \tau_2^{NN}) = 0$ will bind before the constraint $F - f_1(T, \tau_1, \tau_2^{NN}) = 0$ is binding.

To summarize, the equilibrium tax levels in the case (N,N) are

$$(\tau_1^{NN*}, \tau_2^{NN*}) = \begin{cases} (\tau_1^{NN}, \tau_2^{NN}) & \text{if } F > F_{NN} \text{ and } T < T_{NN} \\ (\tau_{1C1}^{NN}, \tau_{2C1}^{NN}) & \text{if } F < min\{F_{NN}, F_{NN1}\} \\ (\tau_{1C3}^{NN}, \tau_{2C3}^{NN}) & \text{if } F < min\{F_{NN}, F_{NN3}\} \end{cases}$$

If firm 1 chooses to be a multinational while firm 2 decides to be a national firm (M, N), country 1 chooses τ_1 that solves

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{MN} = (q_{1MN}^D)^2 + (q_{1MN}^F)^2 + \frac{(q_{1MN}^D + q_{2MN}^E)^2}{2} - \gamma_1(1-\tau_1)q_{1MN}^D \\ \text{s.t.} & q_{iMN}^D \geq 0 \quad \text{for } i = 1,2 \\ & q_{1MN}^F \geq 0 \\ & q_{2MN}^E \geq 0 \\ & f_1(T, \tau_1, \tau_2) - F \geq 0 \\ & F - f_2(T, \tau_1, \tau_2) \geq 0 \end{cases}$$

and country 2 chooses τ_2 that solves

$$\begin{cases} \underset{\tau_2}{Max} & W_2^{MN} = (q_{2MN}^D)^2 + (q_{2MN}^E)^2 + \frac{(q_{2MN}^D + q_{1MN}^F)^2}{2} - \gamma_2(1-\tau_2)(q_{2MN}^D + q_{2MN}^E) - \gamma_1(1-\tau_2)q_{1MN}^F \\ \text{s.t.} & q_{iMN}^D \geq 0 \quad \text{for } i = 1,2 \\ & q_{1MN}^F \geq 0 \\ & q_{2MN}^E \geq 0 \\ & f_1(T, \tau_1, \tau_2) - F \geq 0 \\ & F - f_2(T, \tau_1, \tau_2) \geq 0 \end{cases}$$

We will check at the end that the conditions are such that all the quantities are positive. Thus, the programs become

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{MN} \\ \text{s.t.} & f_1(T, \tau_1, \tau_2) - F \geq 0 \\ & F - f_2(T, \tau_1, \tau_2) \geq 0 \end{cases}$$

and

$$\begin{cases} \underset{\tau_2}{Max} & W_2^{MN} \\ \text{s.t.} & f_1(T, \tau_1, \tau_2) - F \geq 0 \\ & F - f_2(T, \tau_1, \tau_2) \geq 0 \end{cases}$$

We write the Lagrange functions as

$$L_1 = W_1^{MN} + \lambda_1(f_1(T, \tau_1, \tau_2) - F) + \lambda_2(F - f_2(T, \tau_1, \tau_2)).$$

and

$$L_2 = W_2^{MN} + \lambda_1(f_1(T, \tau_1, \tau_2) - F) + \lambda_2(F - f_2(T, \tau_1, \tau_2)).$$

The Kuhn-Tucker conditions are

$$\frac{\partial L_1}{\partial \tau_1} = 0$$
$$\frac{\partial L_1}{\partial \lambda_1} \geq 0$$
$$\frac{\partial L_1}{\partial \lambda_2} \geq 0$$

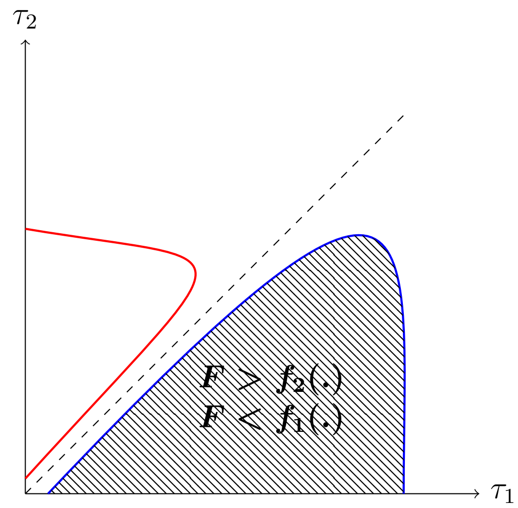
and

$$\frac{\partial L_2}{\partial \tau_2} = 0$$
$$\frac{\partial L_2}{\partial \lambda_1} \geq 0$$
$$\frac{\partial L_2}{\partial \lambda_2} \geq 0$$

We will consider cases where both constraints are satisfied, and then only one binds and finally, both constraints bind.

Case 1: Both constraints are satisfied so that $\lambda_1 = \lambda_2 = 0$, and thus $f_1(T, \tau_1, \tau_2) - F > 0$ and $F - f_2(T, \tau_1, \tau_2) > 0$. Figure A.9 illustrates the constraints. In this case, both constraints are satisfied only in the crosshatched area.

Figure A.9: Constraints in the case (M,N)



We thus calculate

$$\frac{\partial L_1}{\partial \tau_1} = 2q^D_{1MN}\frac{\partial q^D_{1MN}}{\partial \tau_1} + (q^D_{1MN} + q^E_{2MN})(\frac{\partial q^D_{1MN}}{\partial \tau_1} + \frac{\partial q^E_{2MN}}{\partial \tau_1})$$
$$+\gamma_1 q^D_{1MN} - \gamma_1(1-\tau_1)\frac{\partial q^D_{1MN}}{\partial \tau_1} = 0,$$

and

$$\frac{\partial L_2}{\partial \tau_2} = 0,$$

which gives

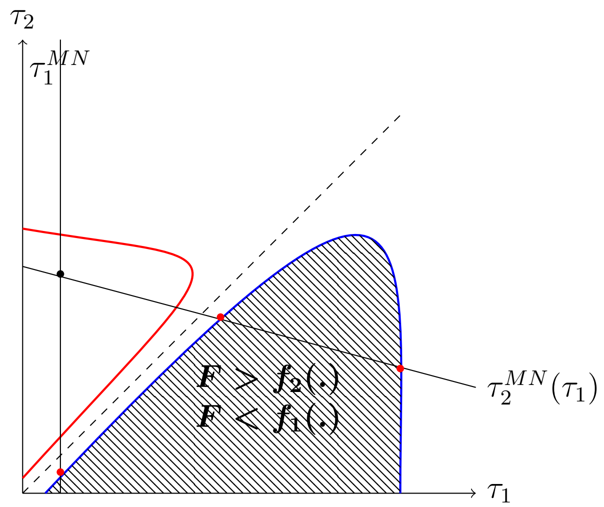
$$\tau_1^{MN} = \frac{c_1 - \alpha_1 + 2\gamma_1}{\gamma_1},$$

and

$$\tau_2^{MN}(\tau_1) = \frac{-c_1(3\gamma_1 + \gamma_2) - 3\alpha_2(\gamma_2 - \gamma_1) + \gamma_2(5c_2 + 2T - \alpha_1) + 6\gamma_2(3\gamma_2 - \gamma_1) + 6(\gamma_1 - \gamma_2)^2 - \gamma_1\gamma_2\tau_1}{9(\gamma_1)^2 - 6\gamma_1\gamma_2 + 7(\gamma_2)^2}.$$

We represent these best response functions in Figure A.10, along with the constraints.

Figure A.10: Constraints and best response functions in the case (M,N)



Per Figure A.10, we see that the optimal tax levels (intersection of the best response functions) will never satisfy the constraints. Therefore, we move to the following case.

Case 2: only one constraint is satisfied. Assume that $\lambda_1 > 0$ and $\lambda_2 = 0$, so that $f_1(T, \tau_1, \tau_2) - F = 0$ and $F - f_2(T, \tau_1, \tau_2) > 0$. There are two cases here again. Either τ_2 is solution of $F - f_1(T, \tau_1^{MN}, \tau_2) = 0$ or τ_1 is solution of $F - f_1(T, \tau_1, \tau_2^{MN}(\tau_{1C}^{MN})) = 0$. In the first case, let's denote τ_{2C1}^{MN} the value of τ_2 such that $F - f_1(T, \tau_1^{MN}, \tau_{2C}^{MN}) = 0$. Graphically, the solution will always be a corner solution as indicated by the lowest red dot in Figure A.10. Second, let's denote τ_{1C2}^{MN} the value of τ_1 such that $F - f_1(T, \tau_{1C}^{MN}, \tau_2^{MN}(\tau_1^{MN})) = 0$. Third, there is another value of τ_1, denoted τ_{1C3}^{MN} such that $F - f_1(T, \tau_{1C3}^{MN}, \tau_2^{MN}(\tau_{1C3}^{MN})) = 0$.

The other cases are not possible.

Quantities are positive only when the emission tax levels are $(\tau_1^{MN}, \tau_{2C1}^{MN})$. Thus, to summarize, the equilibrium tax levels $(\tau_1^{MN*}, \tau_2^{MN*})$ are $(\tau_1^{MN}, \tau_{2C1}^{MN})$.

If firm 1 chooses to be a national while firm 2 decides to be a multinational firm

(N,M), country 1 chooses τ_1 that solves

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{NM} \\ \text{s.t.} & q_{iNM}^D \geq 0 \quad \text{for } i=1,2 \\ & q_{1NM}^F \geq 0 \\ & q_{2NM}^E \geq 0 \\ & F - f_1(T,\tau_1,\tau_2) \geq 0 \\ & f_2(T,\tau_1,\tau_2) - F \geq 0 \end{cases}$$

and country 2 chooses τ_2 that solves

$$\begin{cases} \underset{\tau_2}{Max} & W_2^{NM} \\ \text{s.t.} & q_{iNM}^D \geq 0 \quad \text{for } i=1,2 \\ & q_{1NM}^F \geq 0 \\ & q_{2NM}^E \geq 0 \\ & F - f_1(T,\tau_1,\tau_2) \geq 0 \\ & f_2(T,\tau_1,\tau_2) - F \geq 0 \end{cases}$$

We will check at the end that the conditions are such that all the quantities are positive. Thus, the programs become

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{NM} \\ \text{s.t.} & F - f_1(T,\tau_1,\tau_2) \geq 0 \\ & f_2(T,\tau_1,\tau_2) - F \geq 0 \end{cases}$$

and

$$\begin{cases} \underset{\tau_2}{Max} & W_1^{NM} \\ \text{s.t.} & F - f_1(T,\tau_1,\tau_2) \geq 0 \\ & f_2(T,\tau_1,\tau_2) - F \geq 0 \end{cases}$$

We write the Lagrange functions as

$$L_1 = W_1^{NM} + \lambda_1(F - f_1(T, \tau_1, \tau_2)) + \lambda_2(f_2(T, \tau_1, \tau_2) - F).$$

and

$$L_2 = W_2^{NM} + \lambda_1(F - f_1(T, \tau_1, \tau_2)) + \lambda_2(f_2(T, \tau_1, \tau_2) - F).$$

The Kuhn-Tucker conditions are

$$\frac{\partial L_1}{\partial \tau_1} = 0$$
$$\frac{\partial L_1}{\partial \lambda_1} \geq 0$$
$$\frac{\partial L_1}{\partial \lambda_2} \geq 0$$

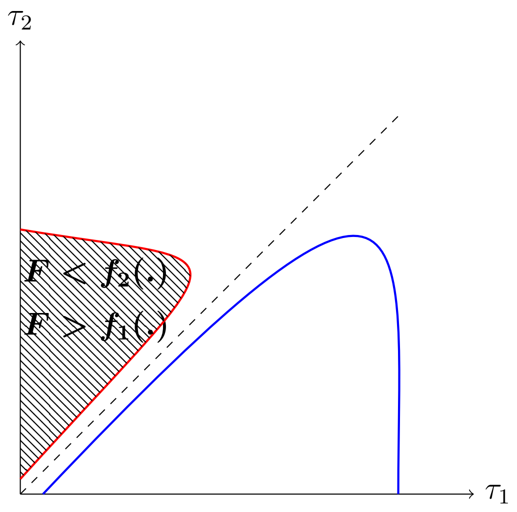
and

$$\frac{\partial L_2}{\partial \tau_2} = 0$$
$$\frac{\partial L_2}{\partial \lambda_1} \geq 0$$
$$\frac{\partial L_2}{\partial \lambda_2} \geq 0$$

We will consider in turn, cases where both constraints are satisfied, and then only one binds and finally, both constraints bind.

Case 1: Both constraints are satisfied so that $\lambda_1 = \lambda_2 = 0$, and thus $F - f_1(T, \tau_1, \tau_2) > 0$ and $f_2(T, \tau_1, \tau_2) - F > 0$. Figure A.11 illustrates the constraints. In this case, both constraints are satisfied only in the crosshatched area.

Figure A.11: Constraints in the case (N,M)



We thus calculate

$$\frac{\partial L_1}{\partial \tau_1} = 0,$$

and

$$\frac{\partial L_2}{\partial \tau_2} = 0,$$

which gives

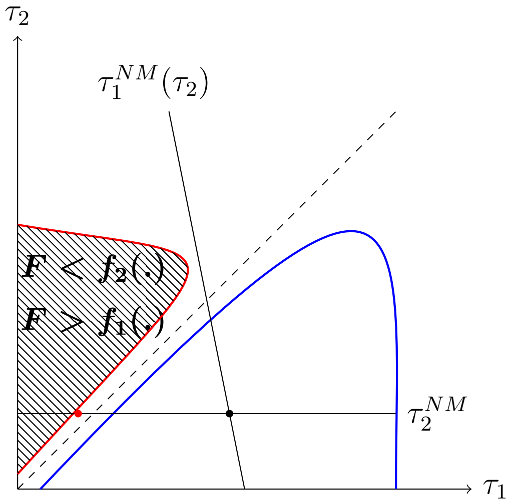
$$\tau_1^{NM}(\tau_2) = \frac{-c_2(3\gamma_2+\gamma_1)+3\alpha_1(\gamma_2-\gamma_1)+\gamma_1(5c_1+2T-\alpha_2)+6\gamma_1(\gamma_2+\gamma_1))+6(\gamma_1-\gamma_2)^2-\gamma_1\gamma_2\tau_2}{9(\gamma_2)^2-6\gamma_1\gamma_2+7(\gamma_1)^2},$$

and

$$\tau_2^{NM} = \frac{c_2-\alpha_1+2\gamma_2}{\gamma_2}.$$

We represent these best response functions in Figure A.12 and the constraints.

Figure A.12: Constraints and best response functions in the case (N,M)



We see that the optimal tax levels will never satisfy the constraints therefore we move to the following case.

Case 2: only one constraint is satisfied. Assume that $\lambda_1 = 0$ and $\lambda_2 > 0$, so that $f_1(T, \tau_1, \tau_2) - F > 0$ and $F - f_2(T, \tau_1, \tau_2) = 0$.

We thus calculate τ_{1C}^{NM} so that $F - f_2(T, \tau_{1C}^{NM}, \tau_2^{NM}) = 0$. Graphically, the solution will always be a corner solution as indicated by the red dot in Figure A.11. In fact, there are many equilibria, all the values of τ_1 and τ_2 that satisfy $F - f_2(T, \tau_1, \tau_2) = 0$ and are below τ_2^{NM}. However, we concentrate on the one that corresponds to the best response of country 2, such that the equilibrium tax levels are τ_{1C}^{NM} and τ_2^{NM}.

The other cases are not possible.

If both firms choose to be multinational firms (M, M), country 1 chooses τ_1 that solves

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{MM} \\ \text{s.t.} & q_{iMM}^D \geq 0 \quad \text{for } i = 1, 2 \\ & q_{1MM}^F \geq 0 \\ & q_{2MM}^F \geq 0 \\ & f_1(T, \tau_1, \tau_2) - F \geq 0 \\ & f_2(T, \tau_1, \tau_2) - F \geq 0 \end{cases}$$

and country 2 chooses τ_2 that solves

$$\begin{cases} \underset{\tau_2}{Max} & W_2^{MM} \\ \text{s.t.} & q_{iMM}^D \geq 0 \quad \text{for } i = 1, 2 \\ & q_{1MM}^F \geq 0 \\ & q_{2MM}^F \geq 0 \\ & F - f_1(T, \tau_1, \tau_2) \geq 0 \\ & F - f_2(T, \tau_1, \tau_2) \geq 0 \end{cases}$$

We will check at the end that the conditions are such that all the quantities are positive. Thus, the programs become

$$\begin{cases} \underset{\tau_1}{Max} & W_1^{MM} \\ \text{s.t.} & F - f_1(T, \tau_1, \tau_2) \geq 0 \\ & F - f_2(T, \tau_1, \tau_2) \geq 0 \end{cases}$$

and

$$\begin{cases} \underset{\tau_2}{Max} & W_2^{MM} \\ \text{s.t.} & F - f_1(T, \tau_1, \tau_2) \geq 0 \\ & F - f_2(T, \tau_1, \tau_2) \geq 0 \end{cases}$$

We write the Lagrange functions as

$$L_1 = W_1^{MM} + \lambda_1(F - f_1(T, \tau_1, \tau_2)) + \lambda_2(F - f_2(T, \tau_1, \tau_2)).$$

and

$$L_2 = W_2^{MM} + \lambda_1(F - f_1(T, \tau_1, \tau_2)) + \lambda_2(F - f_2(T, \tau_1, \tau_2)).$$

The Kuhn-Tucker conditions are

$$\frac{\partial L_1}{\partial \tau_1} = 0$$
$$\frac{\partial L_1}{\partial \lambda_1} \geq 0$$
$$\frac{\partial L_1}{\partial \lambda_2} \geq 0$$

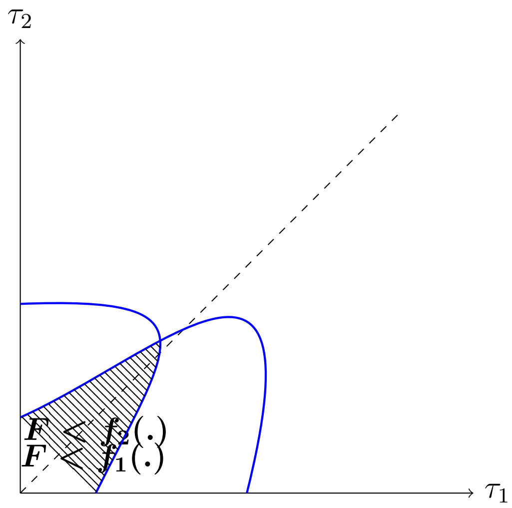
and

$$\frac{\partial L_2}{\partial \tau_2} = 0$$
$$\frac{\partial L_2}{\partial \lambda_1} \geq 0$$
$$\frac{\partial L_2}{\partial \lambda_2} \geq 0$$

We will consider in turn cases where both constraints are satisfied, and then only one binds and finally, both constraints bind.

Case 1: Both constraints are satisfied so that $\lambda_1 = \lambda_2 = 0$, and thus $F - f_1(T, \tau_1, \tau_2) > 0$ and $F - f_2(T, \tau_1, \tau_2) > 0$. Figure A.13 illustrates the constraints. In this case, if there is an intersection between the two curves, both constraints are satisfied.

Figure A.13: Constraints in the case (M,M)



We thus calculate

$$\frac{\partial L_1}{\partial \tau_1} = 0,$$

and

$$\frac{\partial L_2}{\partial \tau_2} = 0,$$

which gives

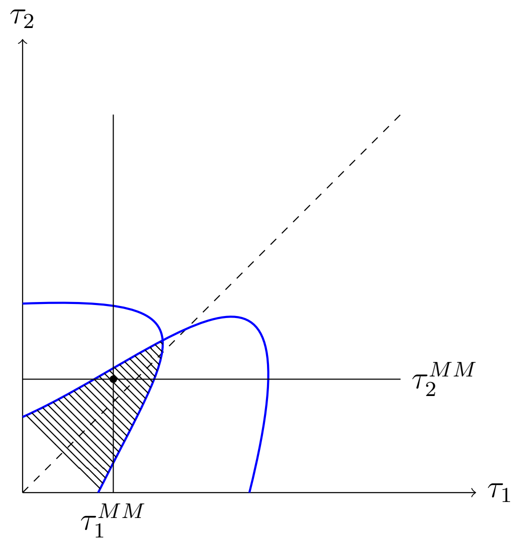
$$\tau_1^{MM} = \frac{-\gamma_1(\alpha_1 - c_1) + \gamma_2(\alpha_1 - c_2) + (\gamma_1)^2 + (\gamma_2)^2 + (\gamma_1 - \gamma_2)^2}{(\gamma_1)^2 - 2\gamma_1\gamma_2 + 3(\gamma_2)^2},$$

and

$$\tau_2^{MM} = \frac{-\gamma_2(\alpha_2 - c_2) + \gamma_1(\alpha_2 - c_1) + (\gamma_1)^2 + (\gamma_2)^2 + (\gamma_1 - \gamma_2)^2}{3(\gamma_1)^2 - 2\gamma_1\gamma_2 + (\gamma_2)^2}.$$

We represent these best response functions in Figure A.14 and the constraints.

Figure A.14: Constraints and best response functions in the case (M,M)

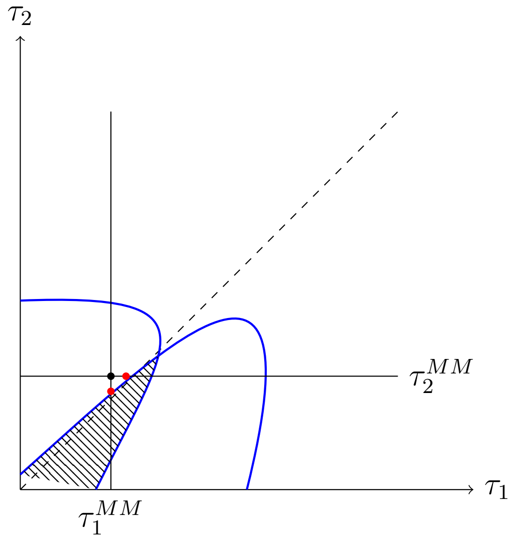


We see that the optimal tax levels satisfy the constraints for some values of the parameters.

If they do not, we move to the following case.

Case 2: only one constraint is satisfied. Assume that $\lambda_1 > 0$ and $\lambda_2 = 0$, so that $f_1(T, \tau_1, \tau_2) - F = 0$ and $F - f_2(T, \tau_1, \tau_2) > 0$. There are two cases. Either We calculate τ_{2C}^{MM} so that $F - f_1(T, \tau_1^{MM}, \tau_{2C}^{MM}) = 0$, or we calculate τ_{1C}^{MM} so that $F - f_1(T, \tau_{1C}^{MM}, \tau_2^{MM}) = 0$. Graphically, the solutions will always be corner solutions as indicated by the red dots in Figure A.15.

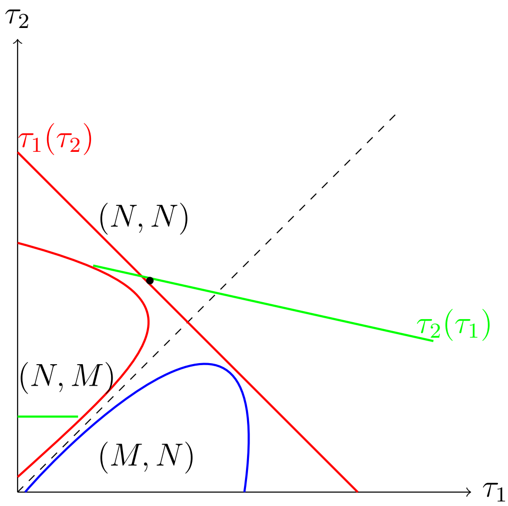
Figure A.15: Constraints and best response functions in the case (M,M)



The other cases are not possible. Thus, to summarize, the equilibrium tax levels are τ_{1C}^{MM} and τ_2^{MM} or τ_{1C}^{MN} and τ_2^{MN}.

Based on the previous analysis, we can more precisely determine each country's best response function. These best response functions are piecewise functions as, for different values of τ_1 and τ_2, we move from the area (N, N) to the area (N, M). These different areas complicate the calculation of the best response functions. For instance, when F is large and T small, we can represent the best response functions in Figure A.16.

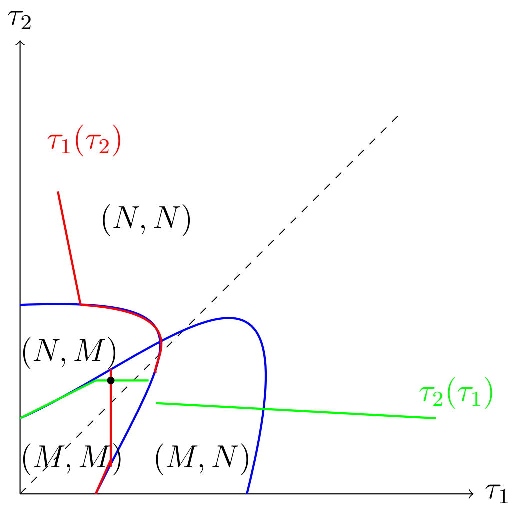
Figure A.16: Best response functions for large F and small T



In Figure A.16, the best response function of country 1 is similar to the one in Figure A.4, corresponding to the area where both firms will choose to be national. However, the best response function of country 2 is more complicated. Indeed, for lower values of τ_1, we go from area (N, N) to area (N, M) where the best response of country 2 is no longer the same. Indeed, in area (N, M), the best response of country 2 is τ_2^{NM} as presented in Figure A.12. Thus, the best response function is now discontinued. Overall, when F is large, the unique tax levels in equilibrium are τ_1^{NN} and τ_2^{NN}.

In Figure A.17, we represent the best response functions of countries 1 and 2 when F is very small and T is large.

Figure A.17: Best response functions for small F and large T



We see in Figure A.17 that for large values of τ_2, the best response function of country 1 is in the area (N, N), then it is a corner solution, and then it is in the area (M, M), before being another corner solution. It is similar for the best response function of country 2. The intersection of the two best response functions is within the area (M, M), and thus, the unique tax equilibrium is τ_1^{MM} and τ_2^{MM}.

Per Proposition 4, the equilibrium emission levels will depend on the values of F. Therefore, for large values of F, the equilibrium is (N, N), and the equilibrium taxes are τ_1^{NN} and τ_2^{NN} so that the equilibrium emission level in country 1 is $e_1^{NN} = \gamma_1[q_{1NN}^D(\tau_1^{NN}, \tau_2^{NN}) + q_{1NN}^E(\tau_1^{NN}, \tau_2^{NN})]$. As F decreases, the equilibrium is still (N, N), but it is now constrained such that the taxes are τ_{1C}^{NN} and τ_{2C}^{NN}. The emission level becomes $e_{1C}^{NN} = \gamma_1[q_{1NN}^D(\tau_{1C}^{NN}, \tau_{2c}^{NN}) + q_{1NN}^E(\tau_{1C}^{NN}, \tau_{2C}^{NN})]$. For smaller values of F, the equilibrium is (M, N), so that the emission level is $e_1^{MN} = \gamma_1 q_{1MN}^D(\tau_{1C}^{MN}, \tau_{2C}^{MN})$.

A4. Ex Post Choices of Emission Taxes

We first study the function $f_{1NN}(T)$. The first derivative gives

$$\begin{aligned}\frac{\partial f_{1NN}(T)}{\partial T} &= 2\frac{\partial q^D_{1MN}(\tau_1^{MN},\tau_2^{MN})}{\partial T} q^D_{1MN}(\tau_1^{MN},\tau_2^{MN}) - 2\frac{\partial q^D_{1NN}(\tau_1^{NN},\tau_2^{NN})}{\partial T} q^D_{1NN}(\tau_1^{NN},\tau_2^{NN}) \\ &\quad + 2\frac{\partial q^F_{1MM}(\tau_2^{MN})}{\partial T} q^F_{1MN}(\tau_2^{MN}) - 2\frac{\partial q^E_{1NN}(\tau_1^{NN},\tau_2^{NN})}{\partial T} q^E_{1NN}(\tau_1^{NN},\tau_2^{NN}),\end{aligned}$$

where

$$\begin{aligned} q^D_{1NN}(\tau_1,\tau_2) = q^D_{1MN}(\tau_1,\tau_2) &= \frac{\alpha_1 - 2(c_1+\tau_1\gamma_1)+(c_2+\tau_2\gamma_2+T)}{3}, \\ q^E_{1NN}(\tau_1,\tau_2) &= \frac{\alpha_2 - 2(c_1+\tau_1\gamma_1+T)+(c_2+\tau_2\gamma_2)}{3}, \\ q^F_{1MN}(\tau_2) &= \frac{\alpha_2 - 2(c_1+\tau_2\gamma_1)+(c_2+\tau_2\gamma_2)}{3}, \end{aligned}$$

and

$$\tau_1^{NN} = \frac{9c_1 - 3c_2 + 3T - 5\alpha_1 - \alpha_2 + 21\gamma_1 - 3\gamma_2}{12\gamma_1},$$

$$\tau_2^{NN} = \frac{-3c_1 + 9c_2 + 3T - \alpha_1 - 5\alpha_2 - 3\gamma_1 + 21\gamma_2}{12\gamma_1}.$$

$$\tau_1^{MN} = \frac{c_1 - \alpha_1 + 2\gamma_1}{\gamma_1},$$

$$\tau_2^{MN} = \frac{3\gamma_1(\alpha_2 - c_1) - \gamma_2(3\alpha_2 - 5c_2 + 2c_1 - 2T) + 2((2\gamma_2)^2 + (\gamma_1)^2) + 4\left(\gamma_2 - \gamma_1\right)^2}{7(\gamma_2)^2 - 6\gamma_1\gamma_2 + 9(\gamma_1)^2}.$$

We show that

$$\frac{\partial \tau_1^{NN}}{\partial T} = \frac{3}{12\gamma_1} > 0,$$

$$\frac{\partial \tau_2^{NN}}{\partial T} = \frac{3T}{12\gamma_1} > 0,$$

$$\frac{\partial \tau_1^{MN}}{\partial T} = 0,$$

$$\frac{\partial \tau_2^{MN}}{\partial T} = \frac{2\gamma_2}{7(\gamma_2)^2 - 6\gamma_1\gamma_2 + 9(\gamma_1)^2} > 0.$$

We show that $f_{1NN}(T)$ is a concave function of T. After plugging all the values of the equilibrium emission taxes in the quantities, we calculate that

$$\frac{\partial^2 f_{1NN}(T)}{\partial T^2} = \frac{32\gamma_1^2 - 32\gamma_1\gamma_2 - 37\gamma_2^2}{36\gamma_2^2} < 0.$$

Evaluated at $T = 0$, we show that $\frac{\partial f_{1NN}(T)}{\partial T} > 0$, so that the function $f_{1NN}(T)$ is first increasing and concave.

We proceed in a similar manner to show that the other functions, $f_{2NN}(T)$, $f_{1MM}(T)$, and $f_{2MM}(T)$ are also concave. We show that $f_{2MM}(T) < 0$ as $q^E_{2MN} > q^D_{2MM}$ and $q^F_{2MM} > q^D_{2MN}$. We also show that there are values of the parameters for which $f_{1NN}(T) > f_{2NN}(T) > f_{1MM}(T)$.

We also show that

$$\tau_1^{NM} > \tau_1^{NN} > \tau_1^{MN},$$

and

$$\tau_2^{MN} > \tau_2^{NN} > \tau_2^{NM}.$$

The equilibrium emission levels are determined by plugging the equilibrium tax levels within the emission functions. These equilibrium emission levels do not depend on F, so that we can show that $e_1^{MN} > e_1^{NN} > e_1^{NN}$. However, depending on the values of F, the emission will be either of these emission levels. Similarly, we find that $e_2^{NN} > e_2^{MN} > e_2^{NM}$.