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Environmental Regulation Stringency and Green Technological Innovation in the Maritime Industry (2006-2020)

{Exploring the intricate relationship between environmental regulation stringency, green technological innovation, and maritime industry competition}

By

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Abstract: The following research paper examines the impact of varying environmental regulation stringency on the landscape of green technological innovation in the maritime industry from 2006-2020. Additionally, the paper explores the potential indirect effect of these innovations, induced by stringency levels, on industry competitiveness. The research is grounded in a theoretical framework primarily drawing from institutional theory and Porter's theory of competitive advantage. The analysis encompasses data from 22 countries across the Organization for Economic Cooperation and Development (OECD), with the additional inclusion of countries such as China, Russia, and India. This wide-ranging dataset allows for a comprehensive examination of the relationships between stringency, innovation, and competitiveness in the maritime industry. This study adopts a quantitative approach, employing random-effects logistic regressions, random effects/fixed effects panel regressions and mediation analyses. Overall, this study finds that stringency does not seem to differentiate between the types of innovation. Moreover, this study concludes that stringency has a positive, significant relationship with the total number of green innovations, and there is a mediation effect present when examining the relationship between stringency and competitiveness.

Keywords: Maritime industry, competitiveness, green technology innovation, green process innovation, green product innovation, Institutional Theory, Porter Hypothesis

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On May 19th, 2023, Ezzat N Joseph, aged 83, passed away.

Ezzat N Joseph was a quiet force, a beacon of support, a loyal soldier.

Ezzat N Joseph was an angel in his own right.

Ezzat N Joseph was a hardworking, persistent, incredibly intelligent, feeble man.

Ezzat N Joseph was a reliable man with minimal physical strength yet possessed the heart of a lion.

Ezzat N Joseph *loved* to talk about the Cuban Missile Crisis, *loved* CNN and *loved* Teta's cooking.

Ezzat N Joseph was my grandfather.

I acknowledge you, Jido. May you find peace in this life and the next.

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1.0 Introduction

Globally, shipping is the most important form of transportation, responsible for transporting 90% of goods worldwide (Lai, Lun, Wong & Cheng, 2011). The volume of sea transport continues to show an increasing trend despite temporal slowdowns due to economic crises (Makkonen & Repka, 2016). Traditionally, maritime transport was considered environmentally friendly and energy efficient; however, where other forms of transportation are showing a decreasing trend of emissions, hence improving their environmental performance, shipping is lagging (Makkonen & Repka, 2016; EEA). The share of negative environmental effects from shipping is increasing, a key reason for this being that the maritime sector is exempt from significant taxes on fossil-based fuels, which acts as a barrier to environmentally friendly change (EEA, 2018). The way it is going, it will be difficult for the industry to meet the European Union's decarbonization goals.

The public is currently concerned with environmental issues pertaining to resource depletion and pollution caused by shipping activities, which are growing rapidly due to the globalization of business activities (Lai et al., 2011; EEA, 2018). Hence why scrutiny of these sectors is increasing so rapidly. The EEA believes that a holistic approach is required if the maritime sector is going to sustainably develop long-term. Elements such as the importance of governments, supporting investment in research, product standards and subsidies for new emerging technologies as well as the sharing of viable data and information of new technologies, will all be crucial efforts that work to help the maritime industry reduce their carbon emissions long-term (EEA, 2018).

Within the maritime industry, the shipping sector and the marine engineering sector, key intermediaries in facilitating trade flows in the global supply chain, have begun responding to these environmental concerns by embracing green shipping practices (GSPs). Conceptualizing GSPs is still inconclusive. However, scholars seem to agree that it entails two key elements: (1) green technological innovations (GTIs) and (2) green business practices (Lai et al., 2011). The latter focuses on the environmental expectations of stakeholders and how this influences the operations of shipping firms. However, this paper will explore the former, GTIs. GTIs are tangible and can be conceptualized as the re-designing of ships, alterations of engines, use of alternative fuels, optimizing ship speed and mechanisms that reduce waste. They are easier to quantify compared to green business practices (Lai et al., 2011). GTIs are technologies that can reduce costs and improve productivity through effective use of energy whilst simultaneously minimizing the negative environmental impacts of shipping operations (Lai et al., 2011). The motivation to study GTI comes from the fact that it focuses on specific technological advancements that enhance competitiveness, facilitate regulatory compliance, drive cost savings, and contribute to industry formation. Alternatively, exploring green business practices would only allow for a comprehensive understanding of sustainable competitiveness in the maritime industry (Lai et al., 2011). By studying GTIs, researchers will be more likely to construct targeted recommendations and actionable insights for policymakers, industry leaders and stakeholders seeking to balance competitiveness, compliance, industry formation and environmental sustainability in the industry (Lai et al., 2011).

Environmental policies & regulations are key factors in facilitating these green technological developments in the maritime industry (Makkonen & Repka, 2016). Environmental regulations are expected to pave the way towards an environmentally friendly future by inducing a need for finding new ways of doing things. Environmental regulations are expected to boost the need for higher research and development (R&D) allocation for new, environmentally friendly technology, products, services and working methods/techniques through environmental innovations (Makkonen & Repka, 2016).

Unfortunately, the direct causal relationship between environmental regulations and environmental innovation can be easily obstructed, for example, in the instance where a firm lacks the resources needed to invest in innovation. There are still missing frameworks regarding the processes and policy guidance needed to turn environmental regulations into winning innovation-inducing strategies (Makkonen & Repka, 2016). However, environmental regulations are often viewed as potential drivers of economic growth. The famous Porter hypothesis argues that more stringent environmental policies can have a net positive effect on the competitiveness of regulated firms because such policies promote cost-cutting efficiency improvements, which directly result in reducing or completely offsetting regulatory costs, and fostering innovation and new technologies that help with international technological leadership as well as market share expansion (Porter & Van der Linde, 1995).

Environmental protection and resource conservation are at the top of the policy agenda, explaining the push from institutional forces working to shape operations in the shipping industry. These two main forces (Lai et al., 2011) include (1) regulatory bodies that enforce regulations that shipping firms must comply with and (2) international trade pressures that affect the competitive environment of shipping firms. Understanding the delicate relationship between environmental policies, green technological innovation and industry competitiveness is essential for shaping future strategies and policies hence the following research question:

How has the varying stringency of environmental regulations shaped the landscape of green technological innovation in the maritime industry from 2006-2020, and is there evidence of an indirect effect on industry competitiveness?

The reason behind following the period 2006 – 2020 is because it encompasses a timeframe marked by substantial changes in global environmental awareness, regulatory frameworks, and technological advancements. The International Maritime Organization (IMO took on a central role constructing global regulations and targets for the industry during this timeframe (IMO, 2023). They developed the Energy Efficiency Design Index (EEDI) in July 2011 (IMO, 2023) as well as the Ship Energy Efficiency Management Plan (SEEMP) in 2013 (DNV, 2023); both heavily influencing the direction of environmental policy. Moreover, the time-period witnessed remarkable maritime green technological advancements including cleaner propulsion systems, extensive use of alternative fuels, emission control technologies and energy-efficient vessel designs (IMO, 2023). Finally, the chosen period saw the introduction and modification of environmental policies targeting emissions reductions, pollution control and sustainability practices some examples being the EU's Monitoring, Reporting and Verification (MRV) regulation in 2015 (International Chamber of Shipping, 2018) as well as the US' Environmental Protection Agency's Emission Control Area designation in 2010, 2012 and 2016 (US EPA, 2016).

This research aims to provide valuable insights for policymakers, industry stakeholders, and researchers interested in fostering sustainable practices within the maritime industry and hopes to contribute to the existing body of knowledge by shedding light on the complex dynamics between environmental policies, green technological innovation, and industry competitiveness in the maritime sector. This study is one of few that empirically assesses the indirect relationship between environmental regulation stringency and maritime industry competitiveness through green technological innovation. Moreover, it encompasses a range of countries across the globe whereas existing literature is mainly China centric.

2.0 Literature and Theoretical Framework

This section will be split into four key topic areas namely: (1) What is green technological innovation, (2) environmental regulations, (3) environmental regulation stringency and green technological innovation and (4) the indirect effect of green regulation stringency on industry competitiveness. Literature as well as theory on the topic will be compiled to help build a framework that sets the tone for further quantitative analysis.

2.1 What is Green Technological Innovation?

Green technology is defined by scholars as being technology that does less to no public harm. These technologies incorporate processes and products that follow ecological principles and economic laws. Their aim is to save resources, eliminate, or reduce environmental pollution and damage and finally, get rid of negative ecological effects. Generally, GTI is separated into two categories, namely, **green product innovation** and **green process innovation** (Wang, Li, Li & Wang, 2021; Huang & Li, 2017; Lin, Chen & Huang, 2014; Xie, Huo & Zou, 2019).

Green process innovations are typically birthed as a preventative environmental management strategy. Some examples of green process innovations include clean technologies as well as end-of-pipe technologies that use pollution-control equipment to ensure compliance with environmental regulations (Xie, Hoang & Zhu, 2022). Green product innovations, however, are the most advanced form of innovation as they provide the opportunity to eradicate emission pollution at the source. Green product innovation directly relates to the manufacturing of products to ensure that they do not contribute to waste (Xie, Hoang & Zhu, 2022; Karabulut & Hatipoglu, 2020; Wang et al., 2021).

2.2 Environmental Regulations

According to scholarship surrounding environmental economics, environmental regulations consist of three elements: (1) emission limits and standards, (2) taxes and (3) certificates. There are different ways to enforce said regulations, namely, Johnstone (2005) emphasizes performance-based measures -- *specify the outcome required but leave specific means to achieving said outcomes up to the regulated entity* (Coglianese, Nash & Olmstead, 2016) and technology-based measures -- *specify exactly how to achieve the outcome* (Coglianese, Nash & Olmstead, 2016), the latter providing little incentive for innovation and the diffusion of green technologies. In short, the more freedom firms and individuals have when complying with environmental regulations, the better the outcome will be regarding overall innovation and diffusion levels; hence, why market-based instruments – *economic variables (environmental taxes, targeted subsidies, tradable permit systems etc..) that provide incentives for polluters to reduce or eliminate negative environmental externalities* – are often presented as the most effective forms of regulations (Coglianese, Nash & Olmstead, 2016). For environmental regulations to be deemed ‘successful’, total social costs need to be minimal, which occurs when the marginal costs of abatement (cost of reducing one more unit of pollution) are equal to or less than the marginal damages (harm caused by additional units of pollution) (Coglianese, Nash & Olmstead, 2016).

Environmental regulations can induce innovation through two policy types: (1)

demand-pull and (2) technology-push policies (Coglianese, Nash & Olmstead, 2016; Johnstone, 2005). Demand-pull policies are targeted at raising the payoff for successful innovations via regulatory standards and taxes on competing technologies to create greater incentives for firms to continue competing and inventing. Technology-push policies aim more at reducing the costs of producing innovations by directing R&D funding effectively and by providing tax credits.

2.3 The Role of Environmental Regulations on Green Innovation

2.3.1 Traditional View

The traditional view in economics and managerial sciences maintains that strict environmental regulations reduce environmental pollution yet simultaneously increase internal production costs; reducing the output of enterprises, hindering a firm's capacity to innovate, and decreasing national and organizational competitiveness (Liu & Xie, 2020). Guo, Xia, Zhang & Zhang (2018) give the example of the manufacturing industry in China and how high levels of regulation stringency not only restricted the efficiency of technological innovation but also reduced productivity. Environmental regulation increases environmental protection costs and hence, reduces firm profits initially. Feichtinger et al., (2003) argue that the stricter environmental regulation, the more significant the inhibitory effect will be on the benefits of industrial development. The extra cost funneled into controlling environmental pollution will affect not only enterprise innovation negatively but also a firm's competitiveness (Feichtinger et al., 2003). A study by Sinn (2008) concluded that policies that limit GHG emissions accelerate energy extraction, increasing GHG emissions in long term.

2.3.2 Institutional Theory

Over the last decade, firms have continued to incorporate environmental issues into their business plans in response to intense environmental pressure (Javeed, Teh, Ong, Lan, Muthaiyah & Latief, 2023). Environmental regulations are expected to significantly influence a firm's policy actions in accordance with the 'social game' (Javeed et al., 2023; Lee, 2020). This concept is directly related to institutional theory, which is often defined as "the rules of the game". This means that the beliefs, goals, and actions of individuals as well as of groups are strongly influenced by various institutions within their environment (Lee, 2020). Institutions can be defined as regulatory (laws and rules), cognitive (social knowledge and perception) and normative (social instruments and culture); they can be both informal and formal. Informal institutions surround behavior and politics (corruption, social instruments, and networks) whereas formal institutions are the laws, rules, and regulations of society (Lee, 2020). Institutional-based theory focuses on the dynamic interactions between institutions and organizations and considers strategic choices as the outcome, an example of this being the choice of a firm to innovate. This theory suggests that formal institutions reduce heterogenous behavior of firms and shape corporate social behavior since firms are now expected to meet certain social expectations (Lee, 2020). According to Institutional theory environmental regulations should motivate firms to engage in social practices that foster green innovation (Javeed et al., 2023) because of institutional isomorphism – *a key process in institutional theory that deals with coordinating a firm's strategy and actions with the expectations of institutions (Javeed et al., 2023)*. Firms comply because they want to enhance their reputations and environmental legitimacy. Moreover, influential stakeholders can compel firms to comply given that the government and industry associations are the source of these regulatory restrictions.

Institutional theory is often used to explain that outcomes (e.g., firm behavior) are shaped by both home and/or host country institutional environments (Lee, 2020). Almond, Edwards, Colling, Ferner, Gunnigle, Muller-Camen, Quintanilla & Waechter (2005) emphasize how the institutionalist approach puts emphasis on **country-of-origin effects** – *attitudes, behaviors, practices and norms that influence entities in the home country*; **host country effects** – *effectiveness of host countries to shape an entity's behavior so that their practices and behavior are aligned with the host country's environment* and **dominance effects** – *the extent to which institutions and individuals from the home country maintain power and control over an entity (the dominance of their voices)*. Institutional theory assumes that outcomes will differ between countries in accordance with their pre-existing, varying institutional frameworks (Lee, 2020). So, it is also expected that depending on which *effect* is prominent for a firm, outcomes may be shaped more by either the home or host country. Depending on which *effect* is most prominent, an entity's choices, decisions, and strategy should be understood.

A plethora of authors have explored the connection between environmental regulations and green innovation using institutional theory (Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Ramon-Llorens, Gracia-Meca & Pucheta-Martinez, 2019; He & Jiang, 2019; Ma & Li, 2016). These studies highlight that a firm complies because it wants to establish legitimacy within the institutional environment. Environmental regulations can help a firm improve, maintain, or safeguard their legitimacy. Nowadays, firms are being named and shamed on broadcast channels for environmental hazard issues making environmental regulations more important. Regulators implement said regulations directly to hold firms fiscally and morally accountable for their pollution; this is often resulting in a positive externality, green innovation (Javeed et al., 2023). Scholarship highlights that firms are implementing proactive environmental strategies to reduce their negative environmental externalities, obtain government backing and establish legitimacy in the face of increasingly stringent environmental policies (De Villiers, Naiker & Van Staden, 2011).

The first hypothesis of this paper is derived from institutional theory and its expectations that firms will choose to innovate in accordance with the environmental regulation stringency of their institutional environment to maintain environmental legitimacy and their reputation in the eyes of the institutional environment:

> *H_0: At the country-level, higher levels of environmental regulation stringency have no significant effect on generating green innovation in the maritime industry.*
>
> ***H1. At the country-level, higher levels of environmental regulation stringency are more effective in generating green innovation in the maritime industry.***

2.3.3 Porter's Theory of Competitive Advantage

Environmental legitimacy and upholding an admirable reputation are key drivers that encourage firms to innovate. However, Porter's theory of competitive advantage highlights others. Developing on from Hick's 1932 induced innovation hypothesis – *regulations raise the costs of pollution relative to production costs which incentivizes firms to develop new technologies, reducing emissions* – Porter & Van der Linde (1995) theorize that firms will innovate when constrained because they want to benefit from a first-mover advantage as well as innovation compensation. Within Porter's theory, three sub-hypotheses were synthesized; the **weak version** of the Porter hypothesis states that 'properly designed environmental regulation may spur innovation.'

Porter & Van der Linde (1995) highlight five main channels through which regulation is known to promote innovation. (1) regulation signals companies about potential resource inefficiencies and potential technological improvements. (2) regulation focused on accumulating information can benefit raising corporate awareness. (3) regulation reduces uncertainty of investments. (4) regulation creates pressure which motivates innovation and progress. (5) regulation levels the transitional playing field because actors are entering the endeavor at a similar time. This ensures that a company cannot opportunistically gain position by avoiding environmental investments. The idea is that environmental regulations will encourage firms to create distinctive products for the market so that they gain a reputation for themselves. Porter's theory highlights that environmental regulations encourage creativity and profitability of firms because stricter regulations force firms to find creative ways to meet the cost of compliance. Jaffe et al., (1995); Porter and Van der Linde (1995); and Barbera & McConnell (1990) all highlight that environmental regulations encourage green innovation within firms so that they thrive in cutthroat environments.

What happens when environmental regulations exist, but they are lax? Porter and Van der Linde (1995) believe that lax regulation yield light solutions that do not have significant influence over the production process, for example, secondary treatments or “end-of pipe” interventions, heavily associated with green process innovations. Stringent regulation, however, ensures that the entirety of the production process is affected and that there is a reformulation of both processes and products that generate innovations. Johnstone et al., (2010) analyzed the features that have the potential to positively affect the effectiveness of regulation policies. They found that the stringency of regulation can produce the Hicksian incentive to innovate by balancing out the compliance costs effect with the innovation compensation effect, explored more in the next section.

2.3.3.1 Applying Porter’s theory to the Maritime Industry

The emerging maritime industry continues to further its development of high and new technologies, resulting in both high-level growth and innovation. Some innovations induced by environmental regulations include energy-saving engines, more efficient propulsion, slow steaming, devices aimed at reducing dynamic drag, marine scrubber systems and the increased use of clean energy (Makkonen & Repka, 2016). Slow steaming for example has reduced emission in international containership traffic by 11%. Generally, containerships can decrease their emissions by 70% if they cut their speed in half (Makkonen & Repka, 2016). Furthermore, the increased usage of smart transportation, innovative materials, big data analytics, sensing and connectivity contribute to the new challenges and opportunities approaching the sector. Megaships are becoming increasingly larger as ship technologies continue to develop and the use of sustainable electricity is becoming more popular (Makkonen & Repka, 2016).

Ma & Li (2016) apply Porter’s theory of competitive advantage in a study associated with the maritime industry. However, instead of looking at the effect of environmental regulation stringency on overall green innovation, they separate the innovation into two types namely, green product innovation and green process innovation. Ma & Li (2016) much like Porter & Van der Linde (1995) focus on the balance between two key concepts, compliance cost and innovation compensation, to determine the effect of environmental regulation stringency on the two types of innovation. **The compliance cost effect represents the**

significant financial investments and ongoing operational expenses to meet environmental standards and **the innovation compensation effect represents the economic gains of an innovation that was produced due to environmental regulatory pressure.**

When using the maritime industry as an example these two concepts function as follows: less stringent environmental policies result in enterprises focusing more on maximizing their profits, choosing to pay environmental taxes, and/or engaging in end-of-pipe treatment; these are known as light solutions. In this case where regulations are more lax and less stringent, whatever the compliance cost is, firms will work to increase their production scale to balance out regulatory costs, likely increasing their environmental footprint. The type of innovation more likely to occur in lax regulatory environments are green process innovations; innovations that are known to be less effective as they do not address the environmental costs and wastage taking place during the manufacturing process (Ma & Li, 2016). In this situation the innovation compensation effect is expected to be lower than the compliance cost effect because green process innovations provide light solutions which are not known to give firms a competitive advantage in the market meaning that the economic costs of compliance are higher than the economic gains from the innovation. Ma & Li (2016) believe as policies become more stringent, the likelihood of a green product innovation occurring increases because balancing out the high compliance costs becomes more urgent. The innovation compensation effect of green product innovations is higher as these innovations are cutting edge and give firms a competitive advantage in the market because they address negative environmental externalities in both the manufacturing, production, and implementation process. In this situation, the innovation compensation effect will be equal to or greater than the compliance cost effect, offsetting it (Ma & Li, 2016; Porter & Van der Linde, 1995).

Porter & Van der Linde (1995), Ma & Li (2016) and Johnstone et al., (2010) all emphasize that stringent policies result in deeper more creative forms of innovations (green product innovations) whereas lax policies result in end-of-pipe treatment interventions and secondary treatments which are associated with process innovations. Moreover, using Ma & Li’s (2016) interpretation of the compliance cost effects and the innovation compensation effects when examining green product and green process innovation, hypothesis 1a and 1b are formulated.

H_0a: Higher levels of country-level environmental regulation stringency have no significant association with the likelihood of a green product innovation being produced.

H1a. Higher levels of country-level environmental regulation stringency are positively associated with the likelihood of a green product innovation being produced.

H_0b: Higher levels of country-level environmental regulation stringency have no significant association with the likelihood of a green process innovation being produced.

H1b. Higher levels of country-level environmental regulation stringency are negatively associated with the likelihood of a green process innovation being produced.

2.4 Indirect relationship between environmental regulation stringency and competitiveness

When examining the impact of environmental policies on firms, it is important to differentiate between the general 'economic effects' and the 'competitiveness effects' (Dechezleprêtre & Sato, 2018). General 'economic effects' are inherent to the policy and affect all polluting firms subject to it however, 'competitiveness effects' arise from the differences in environmental policies faced by polluting firms relative to their competitors (Dechezleprêtre & Sato, 2018). 'Competitiveness effects' result from differences and/or asymmetries in regulatory stringency applied across entities that are competing in the same market (Dechezleprêtre & Sato, 2018). When a firm suffers higher levels of stringency compared to their competitors, they often will incur greater compliance costs which affects their market competitiveness (Dechezleprêtre & Sato, 2018).

2.4.1 The Pollution Haven Hypothesis vs the Porter Hypothesis

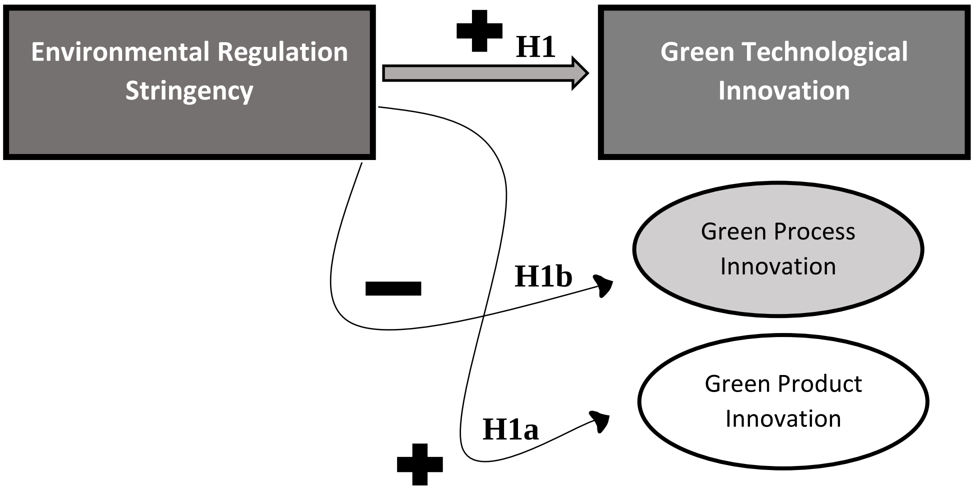
There are two key opposing theoretical views on the likely competitive effects that arise from environmental policies worldwide. The first being the Pollution Haven Hypothesis which dates to over thirty years ago (Dechezleprêtre & Sato, 2018). It states that if the only thing that differs between two firms is the environmental policy stringency they face, then firms that face stricter policies will be at a competitive disadvantage (Dechezleprêtre & Sato, 2018). This is because higher regulatory costs could crowd out productive investment in innovation or efficiency improvements, hence, slowing productive growth. Moreover, if these high regulatory costs translate directly into product prices in competitive product markets, trade distortions could occur due to prices rising in countries where environmental policy stringency is higher (Dechezleprêtre & Sato, 2018). Firms in countries with higher compliance costs will lose market share to their competitors who are able to produce pollution intensive exports more cheaply. If these regulatory differences are expected to last, then this could have effects on the establishment of new production facilities alongside foreign direct investment, with pollution-intensive sectors gravitating towards countries with lax regulatory environmental policies, creating pollution havens (Porter, 1991).

The Porter Hypothesis, embedded within Porter's theory of competitive advantage, takes a more dynamic perspective with its **strong version** by claiming that innovation triggered by environmental regulation will more than offset any additional regulatory compliance costs, leading to increased firm competitiveness through the stimulation of innovation (Fabrizi, Guarini & Meliciani, 2018). Porter and Van der Linde (1995) theorize that more stringent policies should trigger greater investment in developing new and innovative pollution-saving technologies. If these new technologies can induce input savings (e.g., energy), the compensation from innovation should be greater than or equal to the compliance cost (Ma, Li, Xu, Zhang, Wang, Wang, Liu & Tao, 2021). This offset should lower the overall production costs and boost a firm's competitiveness. The Porter hypothesis outcome is expected to occur if cleaner technologies are adopted which lead to higher productivity, input savings and innovations which long-term, offset regulatory costs and improve export performance and market share (Ma et al., 2021). Countries can generate a first-mover advantage to domestic companies by regulating sooner than other countries resulting in domestic firms moving towards international leadership in clean tech. which are increasingly in demand (Porter & Van der Linde, 1995; Wagner, 2003). Romstad (1998) highlights that it needs to be assumed that imposed regulations are efficient because if this is not the case, any empirical rejection of the hypothesis could be based on increased costs from inefficient regulations instead of a direct negative effect of regulations on firm competitiveness (Wagner, 2003). Keeping the **strong version** of the Porter Hypothesis in mind, H2 was constructed:

> *H_0: Higher levels of environmental regulation stringency do not indirectly, through green technology innovation, result in higher levels of national maritime industry competitiveness.*

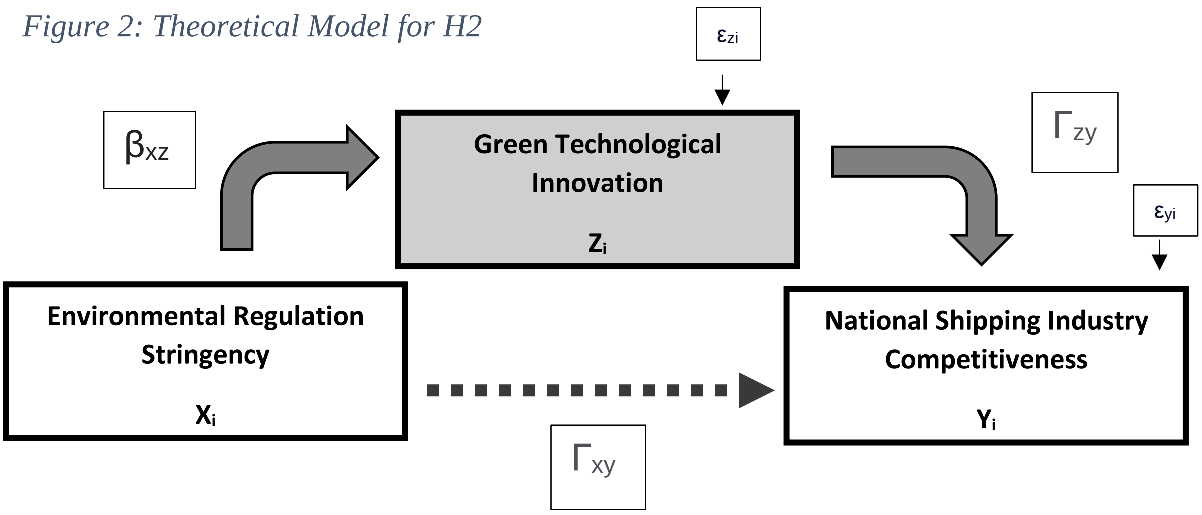
H2: Higher levels of environmental regulation stringency will indirectly, through green technology innovation, result in higher levels of national maritime industry competitiveness.

Figure 1: Theoretical Model for H1, H1a & H1b



Source: *Author's Own*

Figure 2: Theoretical Model for H2



Source: *Author's Own; Gunzler, Chen, Wu, Zhang (2013)*

3.0 Methodology

The methodology section is split into several parts. (1) data and sample; (2) conceptualization and operationalization of variables; (3,4,5) three consecutive sections addressing the different quantitative techniques that will be used to address H1, H1a, H1b and H2. The quantitative techniques that will be used include random-effects logistic regressions, fixed effects regressions, and a mediation analysis. Section 6 will delve into this study's sensitivity analysis; Section 7 will example the limitations of the study; finally, section 8 will look at external and internal validity of the chosen quantitative techniques.

3.1 Data and Sample

This study uses weakly balanced yearly panel data consisting of 543 observations from 22 different countries. Most countries are a part of the OECD apart from China, Brazil, India, and the Russian Federation. The study looks at a 14-year period (2006-2020). Of these 543 observations, 276 of them are green process innovations, 69 of them are green product innovations and 198 observations represent no innovation (years where no patents were submitted in each country). As seen in Table 1, countries with the highest number of innovations include Germany, Japan, Republic of Korea, and the United States. Countries with few innovations include Turkey, Brazil, and India. The country with the highest amount of product innovations is Japan. Japan also has the higher number of process innovations, closely followed by Germany.

Table 1: Data Overview

Country ID	Country	Green Process Innovations	Green Product Innovations	Total Number of Innovations by country
1	Australia	5	0	5
2	Brazil	2	0	2
3	Canada	7	1	8
4	China	6	5	11
5	Denmark	2	1	3
6	Finland	7	4	11
7	France	4	0	4
8	Germany	50	14	64
9	Greece	3	0	3
10	India	2	0	2
11	Italy	5	0	5
12	Japan	60	21	81
13	Netherlands	3	0	3
14	Norway	6	0	6
15	Republic of Korea	28	5	33
16	Russian Federation	2	1	3
17	Spain	5	2	7
18	Sweden	6	2	8
19	Switzerland	14	2	16
20	Turkey	1	0	1

21	United Kingdom	11	1	12
22	United States	47	10	57
	Total	**276**	**69**	**345**

3.2 Conceptualization and Operationalization of variables

3.2.1 Defining the Maritime Sector

A universal definition of the maritime sector is not agreed upon within the literature. However, after compiling the UK Ministry of Defense's (2023), the European Commission's (2023) and the International Labor Organization's (2023) definitions, the maritime industry seems to be made up of seven sub-sectors.

1. **Shipping** –revolves around the transportation of goods and people by sea. Some activities include cargo handling, ship management and shipbuilding. The shipping industry operates with complex global networks of ports, companies, and logistics providers. These actors work together to ensure efficient and cost-effective transport.
2. **Port Operations** – involves the management and operations that take place at ports and harbors, including cargo handling, container terminal operations and ship repair and maintenance.
3. **Marine tourism** – entails recreational activities like yachting and/or cruising.
4. **Offshore oil and gas exploration** – looks at the extraction, exploration and production of oil and gas offshore.
5. **Fisheries** – involves the harvesting of fish and other seafood as well as the processing and marketing of said products.
6. **Marine engineering** – involves the design, construction and maintenance of ships, offshore structures, and any other marine infrastructure.
7. **Marine environmental services** – involves any activities relating to conserving the marine environment; usually aimed at protecting wildlife but also looks at pollution control and environmental monitoring.

When referring to the maritime industry in this paper, only the shipping sector and the marine engineering sector will be considered. This is because when examining GTIs, these directly relate to shipbuilding practices as well as the design, construction, and maintenance of ships. Moreover, when examining competitiveness, this paper is most interested in seeing the results of the shipping sector and its comparative advantage within complex shipping networks.

3.2.2 Green Technological Innovation

GTI incorporates green environmental protection, non-pollution, low energy consumption, recyclability, and cleanness. Following Guo et al., (2018), this study separates GTIs into two categories, green product innovation, and green process innovation. **Green product innovation** focuses on the ‘energy saving’ elements at all stages of production (Guo et al., 2018; Karabulut & Hatipoglu, 2020). For an innovation to be classified as a green product innovation, it must fulfill at least one of the following requirements: (1) saves raw materials and energy, (2) is biodegradable, (3) reduces disposal impact, (4) is made of non-toxic materials, (5) is recyclable and/or is more durable. Innovations that address equipment renovation, upgrading and/or waste treatment are also considered green product innovations. **Green process innovations** focus on ‘emission reduction’ (Guo et al., 2018; Karabulut & Hatipoglu, 2020). Hence, any innovations that are designed to directly reduce environmental pollution, reduce emissions, utilize clean fuels and/or are considered clean technologies are included (Guo et al., 2018; Karabulut & Hatipoglu, 2020).

To operationalize the GTI variable, this study uses patent data. According to Popp (2002, 2006); Aghion, Van Reenen & Zingales (2013); Johnstone, Haščič & Kalamova (2010); Lee & Kim (2011) and Barbieri (2015), patents are good indicators of innovative efforts as they are often filed in the early stages of the innovation process. When interpreting the results from patent counts, they should be interpreted as the effect of an ‘average’ patent rather than a specific innovation. This means that patents are most useful in understanding innovation trends. All patent data in this study was extracted from the World Intellectual Property Organization’s Green outlet. This search strategy allowed for focus on all the listed green technological advancements in the maritime industry; those pertaining to the shipbuilding and marine engineering industry particularly. Some examples of patents include variations of propulsion systems, clean energy (solar, wave-powered, wind), energy-saving devices, electrical motors, fuel alternatives for vessels and drag reducing mechanisms.

The data collection process was made up of three stages. Firstly, patents were located by narrowing the search in the WIPO green database to transport, and then ‘maritime and waterways.’ All patents pertaining to the category ‘maritime/waterways’ were downloaded. All registered green technological patents in the maritime industry from 1980-2023 are listed in this database. Secondly, because this study only considers the period 2006-2020, the patent data was cleaned accordingly leaving 400/580 patents still relevant. Thirdly, all 400 patents were categorized as either a green process innovation or a green product innovation. If the patent did not fit in either category it was disregarded. All patents were listed along with the country in which they were submitted for approval (their host country in most cases). If this country was not a part of the OECD's 27 countries (plus 6 non-OECD major economies including Brazil, China, India, Indonesia, Russia, and South Africa) then it was not incorporated in this study due to insufficient data (there were very few patents submitted outside of this circle of countries). Moreover, in the data cleaning process it was important that there was available data for all indicators when it came to each patent. After cleaning the data fully, this study was left with 345 patents from 22 countries. For years between 2006-2020 where there were no innovations in a country (no patents submitted), a third category was constructed within the GTI variable, 'no innovation'. There were 198 observations from 2006-2020 where no patents were submitted bringing the total sample size to 543. The GTI variable is a categorical variable and is constructed as follows:

Table 2: Type of Green Technological Innovation Operationalized

Variable	Measurement	Source
Type of Green Technological Innovation	1= Process 2= Product 3= No Innovation	World Intellectual Property Organization Green (WIPO Green, 2022)

The patent data was also used to construct a second green innovations variable, one which is not categorical but instead is continuous. This variable looks at the total amount of innovations within a country yearly, by adding up the green product and green process innovations together. Please see Table 3 to better understand the construction of this variable.

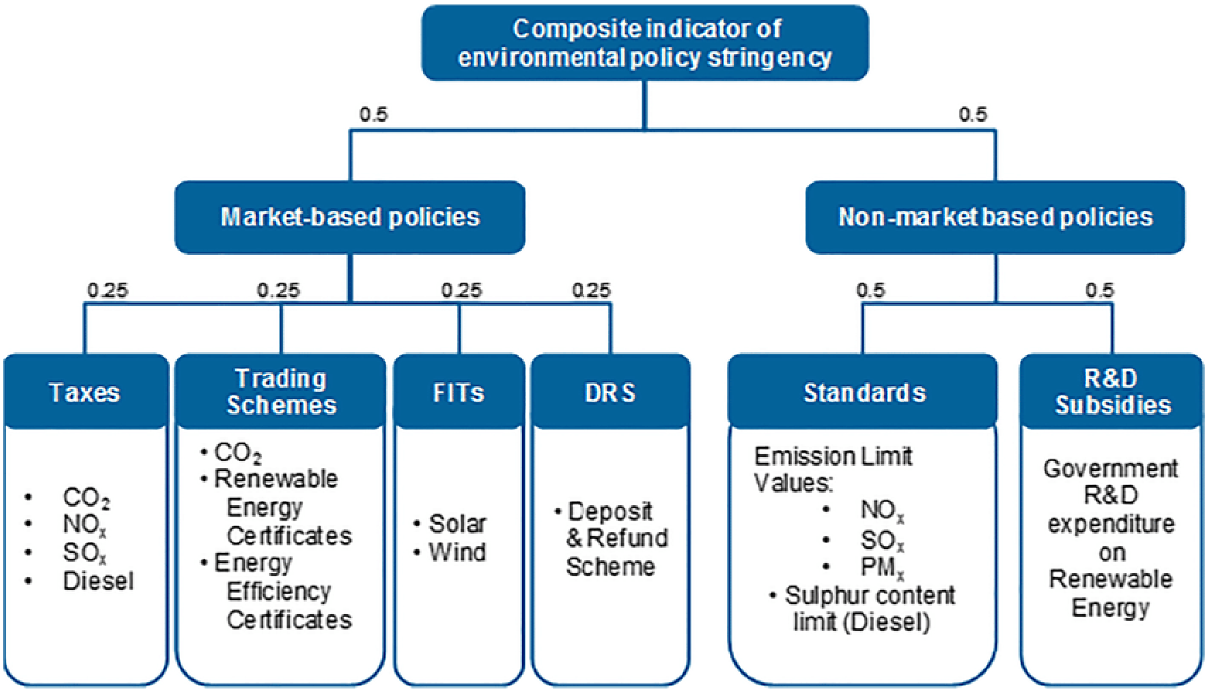
Table 3: Total Number of Green Technological Innovations Operationalized

Variable	Measurement	Source
Total Number of Green technological innovations	Sum of green **product** innovations patents in the maritime sector yearly + sum of green **process** invention patents yearly in the maritime sector	World Intellectual Property Organization Green (WIPO Green, 2022)

3.2.3 Environmental Regulation Stringency

The OECD constructed a reliable measure, environmental policy stringency index (EPSI), suitable for cross-country analyses. See Figure 3 for how the OECD constructed their EPSI. The stringency of thirteen environmental policy instruments is considered and the measure ranges from 0 (not stringent) to 6 (highly stringency). Forty countries have available data ranging from 1990-2020. Authors including Ahmed & Ahmed (2018) have already used this index to assess the impact of environmental regulation in reducing GHG emissions. Both demand-pull policies (Market-based policies) and technological push policies (R&D and subsidies) are taken into consideration (Coglianese, Nash & Olmstead, 2016).

Figure 3: Environmental Regulation Stringency Operationalized



Source: *OECD.stat (2022)*

3.2.4 Maritime Industry Competitiveness

The competitiveness of a nation when looking at seaborne trade depends on geographical factors like distance from major markets. Although this factor is not often considered, many scholars (Arvis, Vesin, Carruthers, Ducruet & De Langen, 2018; Hoffmann & Wilmsmeier, 2008; Rodriguez-Deniz, Hernandez & Tovar, 2013) highlight that transport connectivity or access to regular transport services is a key factor in determining the competitiveness of a country’s seaborne trade. Notteboom (2006) and Figueiredo de Oliveira (2010) emphasize the importance of the Liner Shipping Connectivity Index (LSCI) in facilitating trade and how having a developed, high LSCI score directly translates to competitiveness of ports and country’s maritime industry. With the evolution of containerization and the global liner shipping network, it has become more convenient for countries to both import and export. However, the extent to which countries are well connected to one another differs. For this reason, UNCTAD developed the LSCI, to capture the extent to which nations are competitive on a global scale regarding seaborne trade.

The LSCI allows for the assessment of maritime connectivity for container shipping and enables for the comparison of the maritime industry between countries over time. It is based on five components:

1. **Number of shipping companies**
2. **Number of services** – availability and frequency of container shipping services provided by different carriers.
3. **Total vessel capacity** – represents size and scale of operations.
4. **Average vessel size** – average size of container vessels deployed in a country’s shipping services. Helps indicate efficiency and economies of scale achieved in maritime operations.
5. **Number of Calling Ports** – number of ports served by container shipping services.

The LSCI was introduced in 2004 however, most countries only have data available dating back to 2006 hence, the reason this study only goes back to this period. The aim of the index is to measure and compare maritime connectivity in the container shipping industry between countries. The index is useful in evaluating maritime competitiveness relative to other countries (World Bank, 2023). The data for this variable was collected from the World Bank database (2023).

3.3 Control Variables

In addition to the core explanatory variables, other control variables both micro and macro (country) level should be considered to reduce bias in the results. Two types of control variables will be considered (1) individual-level control variables: ownership and nature of the inventor and (2) country-level development variables: GDP per capita, population size, population with tertiary education.

Beginning with country-level control variables, GDP per capita as well as population size are important to help control market development. Li, Kong & Ji (2022) highlight how these market-level characteristics can impact output and progress of different countries regarding innovation in fishery technology in China regionally and therefore, will be used in this study to control across countries. Regarding the percentage of highly educated individuals, scholars including Barbieri (2015), Li, Kong & Ji (2022) and Zhang, Kang, Li, Ballesteros-Perez & Skitmore (2020) highlight the importance of considering the impact of the geographical source of knowledge (human capital). Education provides the human capital necessary for a country's innovation system (green innovation included). The proportion of those with tertiary education in a country should help reflect the level of education.

Table 4:: Control Variables (country-level) Operationalized

Control Variables	Measurement	Source
Population Size	Based on the de facto definition of population, counts all residents regardless of legal status or citizenship (midyear estimates)	World Bank (2023)
GDP per Capita (In current US$)	GDP per capita is calculated by dividing the gross domestic product by midyear population. GDP is the sum of gross value added by all resident producers in the economy added to any product taxes and minus any subsidies not included in the value of the products.	World Bank (2023)
Population with tertiary education	This variable is split into two separate variables: **(1) population with tertiary education for those aged 25-34 years old** and **(2) population of tertiary education for those aged 55-64 years old.** Both will be measured in percentages (0-100) These variables look at the population that has completed the highest level of education. This includes both theoretical programs leading to advanced research and/or high-skill professions such as medicine as well as vocational programs leading to the labor market.	OECD (2023)

Regarding individual-level controls, the importance of property rights was highlighted by Wang & Sun (2022) and Ma et al., (2021). The nature of property rights will affect the strategic decision-making and operation management of enterprises/individuals. This can impact the heterogeneity of green innovation. This paper measures the nature of these property rights using two different variables: ownership and the nature of the inventor. Ownership looks at whether the patent data was submitted by a state-owned enterprise or a non-state entity; nature of the inventor looks at whether the patent was submitted by an individual, an enterprise or a university/research institute.

Table 5: Control Variables (individual level) Operationalized

Control Variables	Measurement	Source
Nature of ownership	Dummy variable that identifies whether the firm is a state-owned enterprise (SOE) or non-SOE. 1 for SOE and 0 for non-SOE.	(Ma et al., 2021 ; Wang & Sun, 2022)
Nature of the Inventor	A categorical variable: - 1 = universities/research institutes, - 2 = corporations/companies/enterprises - 3 = individuals.	

3.4 Quantitative Methods

3.4.1 Conditional Random-Effects Logistic Regression

When dealing with GTI as a categorical variable, there are multiple quantitative approaches that can be used. This paper uses random effects logistic regression. By estimating a random effect logistic model, one can account for both the time-invariant individual specific characteristics (ownership, nature of the inventor and country where patent was submitted) and time-varying predictors (country-level control variables, environmental policy stringency and the liner shipping connectivity index).

A Hausman test was used to determine whether the random-effects model was a better fit for the data compared to a fixed-effects model. The results showed that $p>0.05$, and so the null hypothesis – *the random effects model is the correct specification for the data, as its assumption is valid, and the individual-specific effects are uncorrelated with the regressors* – failed to be rejected making random-effects the most appropriate fit (Achsani & Kassim, 2021).This study uses the method to get a fuller picture of which independent variables differentiate between the three innovation outcomes of GTI, if any.

To run the logistic regressions, the variable 'type of green technological innovation' will be used to construct three dummy variables. (1) where 1=Process and 0=Product or No Innovation, (2) where 1=Product and 0=Process or No Innovation and (3) where 1=No Innovation and 0=Process or Product Innovation. This will allow for the investigation of the independent variables against the three innovation types separately. See equations 1,2 and 3 for further clarification. The random-effects logit regression will utilize a stepwise approach to better understand how and if coefficients or their significance levels change.

There are several assumptions that the data needs to meet to run random-effects logistic regressions. Firstly, the response variable needs to be binary (Stoltzfus, 2011). This assumption is met with the response variable being split into three dummies, each having its own regression. Secondly, observations are independent (Stoltzfus, 2011). This assumption was satisfied since after plotting the residuals of the independent variables against time a random pattern existed, indicating independence (Stoltzfus, 2011). Thirdly, logistic regression assumes that multicollinearity among explanatory variables does not exist. Logistic regression does not require normally distributed residuals, a linear relationship between the explanatory variables and the response variables or homoscedasticity (Stoltzfus, 2011).

Equation 1: Random-Effects Logistic Regression

$$\log (P (Y\_ict = 1) / P (Y\_ict = 0)) = \alpha + \beta_1 X\_ict_1 + \gamma\_c + \mu\_i + \varepsilon\_ict$$

In the following equation, log (P (Y_ict = 1) / P (Y_ict = 0)) represents the log-odds of Y_ict (the dependent variable) being 1 relative to 0 for the i (individual observation (patent)) in the c (country) at the time t. The coefficient β corresponds to the effects of the independent variable(s) – X_ict_1. The term γ_c represents the country-level fixed effects (country is the group variable. A set of dummy variables for each country will be created, with one category serving as the reference group. The dummies help capture the country-specific effects or heterogeneity that are constant over time). The term µ_i captures the random effect, individual-specific differences in the log-odds of the event occurrence within each country. This term considers unobserved heterogeneity at the individual level that is specific to each country. The term ε_ict is the errors term which captures random variation and measurement errors in the model.

3.4.2 Fixed effects & Random effects

Both fixed-effects and random effects panel regressions will be used when studying the relationship between the total number of green innovations and the relevant independent variables. These methodologies provide various benefits that help overcome some limitations of time-series and cross-sectional studies (Soltani-Sobh, Heaslip, Bosworth, Barnes & Yook, 2015). Panel data deals with heterogeneity resulting from variation of unmeasured explanatory variables that affect the behavior of states, people, countries. It also helps alleviate multicollinearity problems by creating variability through combining the variation across countries with variation overtime (Soltani-Sobh et al., 2015).

Fixed effects models aim to capture individual-specific heterogeneity or unobserved time-invariant factors (Kumar, 2023). The fixed effects model controls for individual-specific effects. Fixed effects models assume that the explanatory variables have a fixed/constant relationship with the response variable across all observations (Kumar, 2023). A random effects model considers the idea that some factors affecting the outcome may vary randomly across groups and/or individuals (Kumar, 2023). By incorporating a random effect in a model, we can better estimate the effect of the factor of interest by accounting for the random variation across individuals (Kumar, 2023).

For the original dataset, a fixed effects regression will be utilized when examining the relationship between the multiple independent variables and the total number of green innovations (Kumar, 2023) (To see how and why the random effects model is utilized, please see section 3.5). This was decided after conducting the Hausman test, $p<0.05$ as $p=0.000$, and so the null hypothesis was rejected meaning that fixed effects were more appropriate for analysis. The Hausman test is important because it improves efficiency (provides unbiased results), addressed endogeneity concerns and aids in ensuring appropriate interpretation of the estimated coefficients (Kumar, 2023).

For this fixed-effects model, fixed effects for each country in the model will be included. Essentially a set of dummy variables for each country will be created, with one category serving as the reference group. The dummies help capture the country-specific effects or heterogeneity that are constant over time (Wooldridge, 2010 pp. 270-273). The model controls for country-specific differences and estimates the within-country variation in the dependent variable (Wooldridge, 2010 pp. 270-273). This approach is important as it helps control country-specific differences, addresses time-invariant omitted variables, focuses on within-country variation, and enables valid comparative analysis across countries (Wooldridge, 2010 pp. 270-273). The following equation will be used:

Equation 2: Fixed Effects Regression

$$\mathbf{Y\_it = \beta * X\_it + \theta\_country + \varepsilon\_it}$$

Y_it represents the dependent variable (number of green innovations) for observation ID (i) at time t. X_it represents the independent variable(s) for observation ID (i) at time t. β represents the coefficients of the independent variables. θ_country is the country-specific fixed effects or heterogeneity captured by the dummy variables derived from country. ε_it is the error term or residual that captured the unexplained variation in the dependent variable.

3.4.3 Mediation Analysis

Mediation is understood as a process that intervenes between input and output (Baron & Kenny, 1986; Tikir & Lehmann, 2010). Baron and Kenny (1986) were pioneers in the founding of mediation analysis and brought forward an approach that allows for both causality and temporal ordering among three variables (intervention, mediator, and response). Standard regression analysis is not suitable because of its priori assignment of each variable as either a cause or an effect (Gunzler, Chen, Wu & Zhang, 2013). The Sobel test, Delta method and Monte Carlo simulation are used to test for the significance of a mediation. The Sobel test calculates a z-score to determine the indirect effect of the endogenous variable on the exogenous variable through the mediator variable to see significance (Nwankwo & Igweze, 2016). The Delta method uses Taylor series expansion to approximate standard error of the indirect effect which is important for internal and external validity and finally, the Monte Carlo simulation simulates the data many times to estimate distribution of the indirect effect against the null hypothesis (no mediation) (Caron, 2019). These tests are commonly used in the context of the Baron & Kenny (1986) mediation analysis approach and are retrieved from running Structural Equation Modelling (SEM) and mediation SEM (MedSEM) on STATA.

Some advantages and reasons for utilizing this mediation model are (1) allows for simultaneous estimation of multiple relationship among variables, both observed and latent in a single model; (2) incorporates measurement errors; (3) allows for easy interpretation and estimation, simplifying complicated mediation models into a single analysis (Gunzler, Chen, Wu & Zhang, 2013). The primary hypothesis of interest in a mediation analysis is whether the effect of the independent variable on the outcome can be mediated by a change in the mediating variable. In a situation with full mediation, the effect is 100% mediated by the mediator. More commonly, however, is partial mediation which is the case when the mediator only mediates part of the effect of the intervention on the outcome (Gunzler, Chen, Wu & Zhang, 2013).

Like Chien (2022), this paper utilizes SEM and MedSEM, techniques commonly used in social science research. The SEM part of the analysis is a multivariate technique that combines factor analysis and regression analysis to model complex relationships between variables. The MedSEM approach is a type of SEM that is specifically for testing mediation effects. Mediation occurs when one variable (the mediator: number of total innovations) explains the relationship between two other variables (the independent variable: environmental regulation stringency and the dependent variable: liner shipping connectivity index). This method allows researchers to test the significance of the mediation effects (partial or full mediation) as well as the strength and direction of the relationships between variables.

Equation 3: SEM model

SEM model: $Y1 = \beta 1 * M1 + \beta 2 * X1 + \xi$

Equation 4: Medsem model

Step 1: X → M: M1 = β3 * X1 + ε1

Step 2: M → Y (controlling for X) t: Y1 = β1 * M1 + β2 * X1 + ε2

Step 3: X → Y (controlling for M): X1 → M1 → Y1 = β4 * M1 + b5 * M + ε3

In these equations, Y1 represents the liner shipping connectivity index, M1 represents the total number of innovations, and X1 represents environmental regulation stringency. The coefficients (λ, β) and error terms (ε) are used to capture the relationship and measurement errors between the variable.

This paper will utilize equations 3 and 4 to understand the direct, indirect, and total effect of green regulation stringency on competitiveness through the number of green innovations in the maritime industry. SEM models include both endogenous and exogenous variables, the former acting as the dependent variable in at least one of the SEM equations (Gunzler, Chen, Wu & Zhang, 2013). The direct effect is the pathway from the exogenous to the outcome while **controlling** for the mediator (step 3) (Gunzler, Chen, Wu & Zhang, 2013). The indirect effect describes the pathway from the exogenous variable to endogenous variable **through** the mediator (step 1 and 2). Finally, the total effect is the sum of the direct and indirect effects (Gunzler, Chen, Wu & Zhang, 2013).

3.5 Robustness test (Sensitivity Analysis)

Robustness testing (sensitivity analysis) is an important aspect to ensure external validity and reliability of results on a grander scale (Camacho, 2021). The idea is to test the resilience of a system to unexpected or anomalous inputs and/or conditions that may result in the systems failing or performing poorly (Neumayer & Plümper, 2017). A common way to perform robustness testing is to insert new variables and/or alter existing variables in the quantitative analysis to see if there is any impact on the system's performance (Neumayer & Plümper, 2017).

This study will perform a particular robustness test known as a model variation test. Model variation tests change one or more model specification assumptions and replace them with an alternative assumption (Neumayer & Plümper, 2017). Examples or these alternations include changing in set of regressors, change in functional form, change in operationalization and/or change in sample (adding or subtracting cases) (Neumayer & Plümper, 2017). Most of the same quantitative techniques will be used to test H1, H1a, H1b and H2, however, the country inspected will change.

Institutional theory highlights how outcomes can alter based pre-existing institutional frameworks and well as relevant institutional pressures. The institutional approach highlights the role that home and host countries play in shaping outcomes. The original analysis examines the country in which patents were submitted, often the host country of these inventors. The sensitivity analysis will examine the home countries – *primary country of origin (where headquarters are located for firms and universities/research institutes)* -- of these inventors (Hasa, 2016). This will allow for the study to consider country-of-origin effects in contrast to host country effects (Almond, Edwards, Colling, Ferner, Gunnigle, Muller-Camen, Quintanilla & Waechter, 2005).

Despite all quantitative techniques remaining the same there is one difference. The sensitivity analysis, when testing H1 will not use a fixed-effects panel regression but instead will use a random-effects panel regression. This is because after running the Hausman test $p>0.05$ as $p=0.0575$ meaning the random-effects model was more appropriate for interpreting the results (Kumar, 2023). Like the original analysis, country will be inserted into the analysis as a group variable (Kumar, 2023). The random effects capture the unobserved heterogeneity across countries, assuming they are drawn from common distribution (Wooldridge, 2010 pp. 270-273). The random effects model in this case helps understand the average effect of the independent variables on the dependent variables, taking random effects into account. The random effects equation is as follows:

Equation 5: Random-Effects Panel Regression

$$\mathbf{Y\_it = \beta{*}X\_it + \theta\_country + \varepsilon\_it}$$

Y_it represents the total number of innovations for ID (i) at time t. X_it represents the independent variables for ID (i) at time t. β is the coefficient associated with each independent variable. θ_country is the individual-specific random effects capturing the unobserved heterogeneity across countries. The random effects allow for the estimation of the average relationship between the independent variables and the dependent variable across countries. ε_it is the error term or residual that captures unexplained variation in the dependent variable.

3.6 Limitations

The first limitation to this study is that it only spans from 2006-2020. Yes, this is a 14-year span of time which is extensive, however, patent data was available dating back to the 1980s. Unfortunately, this same data was not available for environmental regulation stringency nor for the liner shipping connectivity index which posed as a barrier to extending the time frame.

Moreover, regarding the actual measure for innovation, there are some drawbacks to using patent data like (1) not all inventions are patented, (2) the commercial value of patents differs (they do not all hold the same weight or importance), (3) they can sometimes have a weak correlation with R&D expenditure (Tang, Qiu & Zhou, 2020). Other studies incorporate other measures alongside patent data to get a more holistic understanding of innovation. This study could have used R&D investment in the industry as well as per capita R&D investment to also measure innovation efforts (Tang, Qiu & Zhou, 2020). Unfortunately, there was not any publicly available data on this for the maritime industry and so, it was not incorporated in this study.

Finally, other measures alongside the LSCI could have been used to measure the competitiveness of the maritime industry, such as financial performance indicators of firms in the industry (profitability and/or liquidity) (Ha & Seo, 2017; Xie, Hoang & Zhu, 2022). Instead, this study utilized a simplified approach when representing such a major trait (competitivenes), with the information that was available (Zhang et al., 2020). By only using the LSCI, these other measures are not considered and therefore the results could be biased.

3.7 Validity

Internal validity refers to the degrees of confidence that the causal relationship being tested is trustworthy and not influenced by other factors/variables (Hanck et al., 2021 pp.248-56). External validity refers to the extent to which results from a study can be generalized to other situations/groups/events (Hanck et al., 2021 pp.248-56). It is important to note that there is no missing data in this study hence, neither internal validity nor external validity is affected negatively (Hanck et al., 2021 p.204).

3.7.1 Internal Validity

There are two underlying conditions for internal validity to exist namely, the estimator of the causal effect, which is measuring the coefficient (s) of interest, should be unbiased and consistent; (2) statistical inference is valid (hypotheses should have ideal size and confidence intervals should have the desired coverage probability) (Hanck et al., 2021 p.198).

Some of the key threats to internal validity include selection bias; endogeneity; measurement bias; omitted variable bias; autocorrelation and heteroskedasticity (Stock & Watson, 2015 pp.316-332). Firstly, selection bias can pose a threat to internal validity if the participants in the study do not represent the population adequately. This is not an issue since a representative/population sampling technique is applied. The WIPO green provides reliable intellectual property statistics, compiled from multiple databases (WIPO, the PATENTSCOPE

Database and the European Patent Office), to better understand trends in policy business and technology worldwide (WIPO GREEN, 2023). They provide country profiles and provide information on patents, utility, models, trademark, and industrial designs. They cover incoming and outgoing filings, the share of filings in different technological fields, total patents in force and the use of international IP systems by applicants (WIPO GREEN, 2023). Approximately 6 countries (Singapore, New Zealand, U.A.E, Czech Republic, Austria, Slovakia) were not considered in the study due to missing data (for other variables) however, they made up a miniscule portion of patents from 2006-2020 and therefore their omission should not significantly impact the study.

Regarding heterogeneity and endogeneity issues, they are addressed in both the random-effects and fixed effects models. Random-effects regression allows for both time-invariant and time-varying individual-specific heterogeneity. The random effects capture the unobserved factors that may be correlated with the explanatory variables and the error term; particularly mitigating endogeneity (Stock & Watson, 2015 pp.316-332). However, the random effects model does assume that the random effects are uncorrelated with the explanatory variables; not always the case practically (Stock & Watson, 2015 pp.316-332). Fixed effects regression models account for time-invariant individual-specific heterogeneity (Stock & Watson, 2015 pp.316-332). They do this by including individual fixed effects (country dummy variable). Fixed effects regressions control for unobserved time-invariant factors that might be correlated with the independent variables of interest (Stock & Watson, 2015 pp.316-332). This helps mitigate endogeneity concerns, increasing internal validity. To address endogeneity comprehensively, extremely careful consideration needs to go into the study design, appropriate model specification, identification strategies and the use of instrumental variables and/or other advanced econometric techniques are often required. Hence, it is rare that a study completely addresses this threat to internal validity, making it a limitation of the study (Stock & Watson, 2015 pp.316-332).

Measurement errors can also pose a threat to internal validity. However, several factors have been implemented to avoid this. This study has used reliable and valid measures for relevant indicators that have been consistently utilized in published research. Moreover, the sensitivity analysis addresses measurement error by bringing forward potential problems or limitations in the system (Stock & Watson, 2015 pp.316-332). Finally, this study utilizes multiple control variables, which should help reduce the impact of the measurement error because this helps account for the effect of unmeasured variables that are correlated with the outcome variable (Stock & Watson, 2015 pp.316-332). Unfortunately, a limitation to this study is that there is not extensive use of multiple measures for variables (apart from environmental regulation intensity and the liner shipping connectivity variables which are indexes made up of multiple variables) (Stock & Watson, 2015 pp.316-332).

To somewhat address autocorrelation issues, this study tested for the ACF and the PCF however, neither the independent nor the dependent variables required lagging (Stock & Watson, 2015 pp.316-332). Moreover, clustered standard errors were applied to account for the correlation or error within groups (countries). However, once again accounting for autocorrelation issues is very complex control for holistically (Stock & Watson, 2015 pp.316-332).

3.7.2 External Validity

There seems to be two key threats to external validity when conducting quantitative analysis. (1) the differences in populations and (2) the differences in settings (de Haan, n.d.; Hanck et al., 2021 p.198). Both threats come down to the sample needing to be representative of the environment (e.g., laws, institutions) as well as the population of interest within the study (Hanck et al., 2021 p.198).

This study uses a population/representative sample when collecting data (Lohr, 2022 pp.3-4). This means that all registered available patent data from the defined population (green patent data in the maritime industry) is utilized. By using this approach, the results are expected to be representative of the entire population (Lohr, 2022 pp.3-4). This study does, however, leave out a few observations due to lack of data availability across the different independent and control variables. However, overall, this approach holds external validity because the database used includes a comprehensive and diverse range of green patents in the maritime industry, from multiple countries in many different time periods.

Moreover, to further ensure external validity a robustness test (sensitivity analysis) was conducted with the aim of increasing the generalizability of the results (Hanck et al., 2021 pp. 198-200). By conducting a robustness test, one determines the resilience of a system to unexpected inputs and conditions. The idea is to realize and identify potential limitations and/or biases of the study. By addressing the limitations, the reliability and applicability of a model improves, which positively affects external validity (Hanck et al., 2021 pp. 198-200). Finally, this study compares its findings to a plethora of existing research and utilizes popular statistical methods to ensure that the appropriate ones are used to gain relevant results and robust standard errors to help account for bias (Hanck et al., 2021 pp. 198-200).

4.0 Results

The following section is made up of the following four sections: (1) descriptive statistics, (2) three conditional-random-effects logit regressions, (3) a fixed effects panel regression and (4) a mediation analysis.

4.1 Descriptive Statistics

Table 6: All Observations

Variable	Obs	Mean	Std. Dev.	Min	Max
Percetage5664	543	33.626	15.787	10.014	99.961
Percetageeducat~2534	543	43.193	14.9	6.23	93.842
GDPperCapitainUSdo~s	543	41243.294	19872.435	802.014	102913.45
PopulationSize	543	1.772e+08	3.220e+08	4660677	1.411e+09
LinerShippingIndex1	543	66.023	27.97	8.467	162.366
ERI1	543	3.019	.868	.167	4.889

Table 7: Green Process Innovations

Variable	Obs	Mean	Std. Dev.	Min	Max
Percetage5664	276	32.323	11.045	10.183	93.569
Percetageeducat~2534	276	46.701	14.094	14.511	93.842
GDPperCapitainUSdo~s	276	45221.99	16244.208	1910.421	101524.14
PopulationSize	276	1.523e+08	2.347e+08	4709153	1.411e+09
LinerShippingIndex1	276	73.752	24.229	10.258	162.366
ERI1	276	3.175	.684	.25	4.722

Table 8: Green Product Innovations

Variable	Obs	Mean	Std. Dev.	Min	Max
Percetage5664	69	34.198	10.113	12.047	57.1
Percetageeducat~2534	69	46.529	13.492	22.5	69.852
GDPperCapitainUSdo~s	69	42128.489	13869.47	8016.431	74175.193
PopulationSize	69	2.117e+08	3.448e+08	5479531	1.403e+09
LinerShippingIndex1	69	76.768	28.158	13.271	153.377
ERI1	69	3.199	.59	1.17	4.083

Table 9: No Innovations

Variable	Obs	Mean	Std. Dev.	Min	Max
Percetage5664	198	35.244	21.793	10.014	99.961
Percetageeducat~2534	198	37.14	14.586	6.23	82.04
GDPperCapitainUSdo~s	198	35388.755	24389.753	802.014	102913.45
PopulationSize	198	1.999e+08	4.068e+08	4660677	1.396e+09
LinerShippingIndex1	198	51.505	26.895	8.467	148.656
ERI1	198	2.739	1.085	.167	4.889

Above four categories of the data have been summarized: (1) all observations, (2) observations where a green process innovation is present, (3) observations where a green product innovation is present and (4) observations where no innovation occurs. This is to help understand how country characteristics differ depending on the type of innovation produced.

When looking at Table 6 (green product, green process and no innovations combined) from 2006-2020, there are 543 observations. The average stringency statistics across the data, no matter the type of innovation, is 3.019. This is a midrange value (max 6, min 0). Moreover, the standard deviation is less than 1 indicating that the data is clustered around the mean. When examining the Liner Shipping Index variable, the average value is 66.023, an above average level of connectivity. The Max value is 162.366 and is the highest value ever recorded; held by China. Most countries, apart from China have an index score below 100. This substantial difference between China and majority of other countries in the sample explains why the standard deviation of the data is so high (27.97). As for control variables listed, they are all continuous. Percetage5664 and Percetageeducat~2534 are calculated for each country yearly, to give the percentage of tertiary educated persons in the age range 56-64 and 25-34 respectively. In the data set the mean percentage of highly educated people aged 56-64 is 33.626% and for those aged 25-34, 43.193%. Finally, there is GDP per capita in US dollars and the population size of each country. These vary rather drastically across countries hence, the large standard deviation values.

The overall observations (patent data) can be categorized into three categories namely, green process innovations, green product innovations and no innovations. Regarding ERI1 of a country, it is evident that stringency is at its highest – 3.199 – in countries producing green product innovations; country's producing green process innovations are not far behind with a value of 3.175 however, in countries and years where there are no innovations the stringency levels are drastically lower with an average value of 2.739. Regarding the liner shipping index, connectivity seems to be highest for countries producing green product innovations with a value of 76.768. Countries that produce green process innovations have an average of 73.752, making their industry competitiveness slightly lower. Finally, in situations where there are no innovations, the liner shipping index is at its lowest with a value of 51.505. Countries producing process innovations have the highest level of tertiary educated individuals aged 25-34 with 46.701%. In years where countries produce no innovation, there seem to be the highest average levels of tertiary education for those aged 56-64, with 35.244%.

Table 10: Matrix of Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) ln_GDPperCapita	1.000												
(2) ln_Percetage5664	-0.178	1.000											
(3) ln_Percetag~2534	0.619	-0.127	1.000										
(4) ln_PopulationS~e	-0.574	0.314	-0.315	1.000									
(5) LinerShippingI~1	-0.092	-0.021	0.055	0.624	1.000								
(6) ERI1	0.590	-0.166	0.478	-0.443	0.050	1.000							
(7) Process	0.264	-0.008	0.243	0.120	0.281	0.183	1.000						
(8) Product	0.067	0.058	0.093	0.100	0.147	0.079	-0.388	1.000					
(9) nopatent	-0.320	-0.032	-0.317	-0.194	-0.394	-0.244	-0.770	-0.289	1.000				
(10) nonstate_	0.333	0.015	0.322	0.115	0.288	0.252	0.743	0.222	-0.925	1.000			
(11) NatureofInven~i	0.001	-0.023	0.031	0.133	0.192	-0.007	0.064	0.124	-0.152	-0.147	1.000		
(12) NatureofInven~d	0.005	-0.004	-0.006	0.065	0.063	-0.039	0.298	0.001	-0.310	0.335	-0.082	1.000	
(13) NatureofInven~m	0.305	0.043	0.299	0.090	0.262	0.266	0.510	0.230	-0.689	0.715	-0.183	-0.373	1.000

Before delving into the correlation matrix, all continuous control variables were logged in the regression models. Variables including population size, GDP per Capita and both percentages representing tertiary education were logged. The reason for logging these variables was to improve the fit of the model, transforming the distribution of the data to fit a more normally shaped bell curve. By logging these variables, we aim to ensure the smallest error possible when making a prediction whilst refraining from overfitting the model (Stock & Watson, 2015 pp.316-332).

When running regressions and mediation analysis, it is important to analyze the correlation matrix to ensure that the homogeneity and multicollinearity assumptions are met. According to Table 10, there does not seem to be homogeneity and multicollinearity problems, as there are no major problems with highly correlated variables. A value of 0.75 (-0.75) constitutes high levels of correlation. Only two situations exist where there are highly correlated variables. Both are highlighted in Table 10. This will not be an issue when conducting the empirical analysis as variable 9 (no patent) is a dummy variable made from the original categorical variables 'type of innovation'. 'No patent,' 'process' and 'product' are all complementary dummy variables from the original categorical variable and so they will not all be run, no patent will be omitted. This means that its correlation with 'process' as well as with 'nonstate' will not be an issue.

4.2 Random-Effects Logistic Model

This section is split into three random-effects logistic regressions each of which examine the likelihood of a particular innovation occurring (green process, green product, or no innovation).

Table 11: Random-Effects Logistic Regression (Process)

Green Process Innovation	(1)	(2)
ERI1	**0.420***	-0.109
	(2.23)	(-0.43)

LSCI1	**0.0182****	0.00250
	(2.73)	(0.27)
ln_Percetageeducated2534		-0.0587
		(-0.13)
ln_Percetage5664		-0.530
		(-1.05)
ln_GDPperCapita		0.341
		(1.08)
ln_PopulationSize		-0.0316
		(-0.14)
NatureofInventor_uni		0.0145
		(0.02)
NatureofInventor_ind		0.664
		(1.63)
state_		**22.65*****
		(4.37)
nonstate_		**23.48*****
		(4.48)
_cons	**-2.843*****	-22.98
	(-4.18)	(.)
N	543	543

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results from the random-effects logistic regression for green process innovation are illustrated in Table 11. Column one runs the regression without any control variables. There were 543 observations. The dependent variable is green process innovation (1 being green process innovation and 0 being green product or no innovation). This means that if environmental policy stringency increases by one unit, the odds of there being a green process innovation increase by a factor of 0.420; significant at the 0.05 level. When examining the LinerShippingIndex1, as the variable increases by one-unit, green process innovations are expected to increase by a factor of 0.0182; significant at the 0.01 level.

Column two incorporates all the relevant control variables. Most results are insignificant, however, both state and non-state are significant at the 0.001 level. This means that for every additional unit of non-state-owned enterprises, the likelihood of a green process innovation increases by a factor of 23.48. Moreover, for every additional state-owned enterprise, green process innovations are expected to increase by a factor of 22.65.

Table 12: Random-Effects Logistic Regression (Product)

Green Product Innovation	(1)	(2)
ERI1	0.286	0.109
	(1.22)	(0.43)
LinerShippingIndex1	**0.0150***	-0.00250
	(2.21)	(-0.27)
ln_Percetageeducated2534		0.0587
		(0.13)
ln_Percetage5664		0.531
		(1.05)
ln_GDPperCapita		-0.341
		(-1.08)
ln_PopulationSize		0.0314
		(0.14)
NatureofInventor_uni		-0.0144
		(-0.02)
NatureofInventor_ind		-0.664
		(-1.63)
state_		**22.19*****
		(4.28)
nonstate_		**21.37*****
		(4.08)
_cons	**-4.242*****	-21.86
	(-4.72)	(.)
N	543	543

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 12, green product innovation is the dependent variable (1 being green product innovation and 0 being process innovation or no innovation). Column one runs the regression without any control variables. In column one, the shipping connectivity index is significant at the 0.05 level. This means that if the index increases by one unit, the odds of there being a green product innovation increase by a factor of 0.0150. These odds are like that of green process innovations.

Column two incorporates all the relevant control variables. Most results are insignificant; however once again, both state and non-state are significant at the 0.001 level. This means that for every additional unit of non-state-owned enterprises, the likelihood of a green product innovation increases by a factor of 21.37 and for every unit of state-owned enterprises, green product innovations are expected to increase by a factor of 22.19. Both types of ownership have positive effects on green product innovations, with state enterprises taking the upper hand, unlike green process innovations, which thrive more under non-state enterprises.

Table 13: Random-Effects Logistic Regression (No Innovation)

No Innovation	(1)	(2)
ERI1	**-0.551***	-0.186
	(-2.14)	(-0.62)
LinerShippingIndex1	**-0.0298****	-0.00521
	(-2.75)	(-0.40)
ln_Percetageeducated2534		-1.415
		(-1.80)
ln_Percetage5664		-0.269
		(-0.74)
ln_GDPperCapita		**-2.008*****
		(-3.62)
ln_PopulationSize		**-1.233****
		(-3.14)
_cons	**3.300*****	**49.32*****
	(3.58)	**(4.34)**
N	543	543

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 13, ‘no innovation’ is the dependent variable (1 being no innovation and 0 being process innovation or product innovation). In column one, the shipping connectivity index is significant at the 0.01 level, and the ERI value is significant at the 0.05 level. If the ERI increases by one unit, the odds of having no innovations decrease by a factor of 0.551. Moreover, if the shipping connectivity index increases by one unit, the likelihood of no innovation decreases by a factor of 0.0298. This means that higher levels of environmental stringency and connectivity results in less frequency of no innovations.

In Column two, most results are insignificant. However, control variables, GDP per capita and population size are significant at the 0.001 and 0.01 levels, respectively. This means that for every additional unit of logged GDP per capita, the likelihood of no innovation occurring decreases by a factor of 2.008. For every additional unit of logged population size, the odds of no innovation occurring are expected to decrease by a factor of 1.233. Higher levels of logged GDP per capita and population size are expected to increase the odds of green innovations occurring compared to no innovation at all.

4.3 Fixed-Effects Panel Regression

Table 14: Fixed-Effects Results

Total No. of Innovations	(1)	(2)	(3)
ERI1	**1.029***** **(5.57)**	**1.015***** **(4.69)**	**0.946***** **(4.92)**
LinerShippingIndex1	0.00265 (0.27)	-0.000370 (-0.03)	-0.000953 (-0.09)
ln_Percetageeducated2534		0.0953 (0.13)	-0.381 (-0.57)
ln_Percetage5664		0.197 (0.95)	0.0467 (0.25)
ln_GDPperCapita		**1.019*** **(2.16)**	0.655 (1.54)
ln_PopulationSize		-3.073 (-1.04)	-2.675 (-1.01)
NatureofInventor_uni			-0.225 (-0.50)
NatureofInventor_ind			**-0.361*** **(-2.06)**
state_			**1.521**** **(3.06)**
nonstate_			**2.035***** **(11.65)**
_cons	-0.560 (-0.96)	43.34 (0.83)	41.27 (0.89)
N	543	543	543

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The following fixed-effects panel regression is split into three columns: the first looking at the main independent variables, the second incorporates country-level control variables, and the third incorporates individual-level control variables as well.

In model 1, ERI is significant at the 0.001 level. For every one unit increase in policy stringency, the total number of green innovations is expected to increase by 1.029 units. In model 2, ERI remains significant at the 0.001 level and from the newly added control variables, logged GDP per capita is significant at the 0.05 level. Here, for every additional unit of ERI, the total number of green innovations is expected to increase by 1.015 units. Moreover, as the logged GDP per capita increases by one unit, the total number of green innovations is expected to increase by 1.019 units.

Finally, in model 3 ERI is still significant at the 0.001 level. For every additional unit of ERI, the total amount of innovations should increase by 0.946 units. This is in line with the predictions of institutional theory and Porter's weak hypothesis. No country-level control variables hold statistical significance however, three individual-level control variables namely, NatureofInventor_ind, state_ and nonstate_ are all significant. For inventors that are individuals, there is a negative association of 0.361 units between them and the total number of green innovations (p<0.05). Finally, both state-owned enterprises and non-state-owned enterprises are positively associated with the number of green innovations as the dependent variable is expected to increase by 1.521 (p<0.01) and 2.035 (p<0.001) units, respectively.

4.4 Mediation Analysis

Table 15: SEM results

	(1)
LinerShippingIndex1	
NoofInnovations	**4.075***** **(10.01)**
ERI1	**-2.730*** **(-2.04)**
_cons	**63.18***** **(15.84)**
NoofInnovations	
ERI1	**1.062***** **(7.95)**

_cons	-0.487
	(-1.16)
N	543

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

After conducting SEM analysis, the output suggests that both ERI and the total number of innovations have a significant direct effect on LinerShippingIndex1 at the 0.05 and 0.001 level, respectively. The direct effect of ERI on the shipping connectivity index is negative, for every additional unit of ERI, the dependent variable is expected to decrease by 2.730 units. Moreover, the total number of green innovations is positively associated with the shipping connectivity index as for every additional unit, the index is expected to increase by 4.075 units.

When looking further down Table 15, there is also a significant positive direct effect between ERI and the total number of innovations significant at the 0.001 level. For every additional unit of policy stringency, the number of innovations should increase by 1.062 units. Please see Table 16 for the mediation results.

Table 16: Significance testing of indirect effect

Estimates	Delta	Sobel	Monte Carlo*
Indirect effect	4.329	4.329	4.327
Std. Err.	0.696	0.696	0.686
z-value	6.223	6.223	6.309
p-value	0.000	0.000	0.000
Conf. Interval	2.965, 5.692	2.965, 5.692	3.051, 5.735

Baron and Kenny's approach to testing mediation
STEP 1 - NoofInnovations:ERI1 (X -> M) with B=1.062 and p=0.000
STEP 2 - LinerShippingIndex1:NoofInnovations (M -> Y) with B=4.075 and p=0.000
STEP 3 - LinerShippingIndex1:ERI1 (X -> Y) with B=-2.730 and p=0.042

RIT = (Indirect effect / Total effect)
(4.329 / 1.599) = 2.707
RID = (Indirect effect / Direct effect)
(4.329 / 2.730) = 1.586
That is, the mediated effect is about 1.6 times as
large as the direct effect of ERI1 on LinerShippingIndex1!

When examining Table 16 the Delta, Sobel, and Monte Carlo statistics (4.329, 4.329 and 4.327) are all significant at the 0.001 level. This means that the null hypothesis is rejected. The z-values are large for all three models suggesting stronger evidence against the null hypothesis. The null hypothesis refers to the assumption that there is no mediation effect. Since the null hypothesis is rejected, a significant indirect relationship between ERI and the liner shipping index does exist through the mediator, total number of green innovations.

When looking at the results from steps 1,2 and 3, a significant partial mediation between the variables can be seen as all paths are significant. In this model, the RIT (indirect effect/total effect) statistic was calculated as follows 4.329/1.599 = 2.707, meaning that approximately 271% of the effect of environmental policy stringency on the liner shipping index is mediated by total number of innovations. The RID (indirect effect/direct effect) statistics were calculated as follows: 4.329/2.730 = 1.586. This means that the mediated effect is about 1.6 times as large as the direct effect of ERI1 on LinershippingIndex1. When looking at the direction of the relationship between these variables, as ERI increases by one unit, the total number of innovations is expected to increase by 1.062 units. As innovations increase by one unit, the liner shipping connectivity index is expected to increase by 4.075 units. This shows a positive mediation. This finding is in line with Porter's strong hypothesis, which expects a positive mediation effect of green technological innovation. The direct relationship, however, is significant and negative, meaning for every extra unit of policy stringency, the shipping index is expected to decrease by 2.730.

5.0 Sensitivity Analysis (Robustness Test)

5.1 Descriptive Statistics

Table 17: Overall Descriptives

Variable	Obs	Mean	Std. Dev.	Min	Max
Percetage5664	568	33.498	16.317	10.014	99.961
Percetageeducat~2534	568	43.71	14.43	6.23	93.842
GDPperCapitainUSdo~s	568	40906.039	19493.339	802.014	102913.45
PopulationSize	568	1.675e+08	3.139e+08	4273591	1.411e+09
LinerShippingIndex2	568	63.893	28.966	7.7	162.3665
ERI2	568	2.984	.858	.167	4.89

Table 18: Green Process Innovations

Variable	Obs	Mean	Std. Dev.	Min	Max
Percetage5664	276	32.586	12.212	10.183	98.406
Percetageeducat~2534	276	47.163	13.503	14.511	93.842
GDPperCapitainUSdo~s	276	44244.582	15651.27	1910.421	101524.14
PopulationSize	276	1.607e+08	2.475e+08	4709153	1.411e+09
LinerShippingIndex2	276	72.480	25.627	9.586	162.3665
ERI2	276	3.184	.707	.25	4.89

Table 19: Green Product Innovation Descriptives

Variable	Obs	Mean	Std. Dev.	Min	Max
Percetage5664	69	34.246	10.267	12.047	57.1
Percetageeducat~2534	69	49.123	11.853	22.5	69.852
GDPperCapitainUSdo~s	69	44157.836	17553.173	8016.431	90476.759
PopulationSize	69	2.042e+08	3.482e+08	4985382	1.403e+09
LinerShippingIndex2	69	74.547	28.957	12.704	153.3767
ERI2	69	3.28	.645	1.167	4.72

Table 20: No Innovation Descriptives

Variable	Obs	Mean	Std. Dev.	Min	Max
Percetage5664	223	34.395	21.47	10.014	99.961
Percetageeducat~2534	223	37.761	14.265	6.23	82.04
GDPperCapitainUSdo~s	223	35767.868	23000.672	802.014	102913.45
PopulationSize	223	1.646e+08	3.717e+08	4273591	1.396e+09
LinerShippingIndex2	223	49.969	27.401	7.7	148.656
ERI2	223	2.645	.97	.167	4.556

Looking at the descriptive statistics for the sensitivity analysis, the overall number of observations jumped from 543 to 568 due to the addition of two new countries, namely Belgium and Portugal. The average ERI statistic across the data is 2.984, lower than the original analysis. The standard deviation is less than 1, indicating that the data is clustered around the mean. When examining the Liner Shipping Index variable, the average value is 63.893, less than the original analysis. As for the control variables listed, the mean percentage of highly educated people aged 56-64 is 33.498 and for those aged 25-34, 43.71, both like original analysis. Finally, there is GDP per capita and the population size of each count; these vary drastically across countries hence, the large standard deviation values.

For green process innovations, the mean ERI statistic is 3.184; this is comparable to the mean ERI statistic of green product innovation, which is 3.28 however, it seems that observations that read ‘no patent’ experience significantly lower levels of ERI with a mean value of 2.645. All results comparable to the original descriptives in section 4.1. Regarding the LSCI, countries with the highest average value (74.547) are those producing green product innovations. Countries producing green process innovations have an average LSCI of 72.480, making their industry competitiveness slightly lower. Observations with ‘no patents’ show significantly lower levels of LSCI (49.969). Countries producing product innovations have the highest levels of tertiary education for aged 25-34 with a value of 49.123 and observations where no patent is present have the highest mean value of those with tertiary education aged 56-64 (34.395). Once again, these results emulate the same patterns as the original analysis. The average GDP per capita is smallest in countries producing no innovation and population size is smallest in countries producing green process innovations.

Table 21: Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1) ln_GDPperCapita	1.000												
(2) ln_Percetage5664	-0.153	1.000											
(3) ln_Percetag~2534	0.648	-0.131	1.000										
(4) ln_PopulationS~e	-0.535	0.332	-0.275	1.000									
(5) LinerShippingI~2	-0.116	0.024	0.076	0.637	1.000								
(6) ERI2	0.553	-0.156	0.471	-0.351	0.077	1.000							
(7) Process	0.230	0.011	0.233	0.209	0.288	0.227	1.000						
(8) Product	0.080	0.063	0.137	0.081	0.137	0.128	-0.362	1.000					
(9) nopatent	-0.289	-0.054	-0.330	-0.268	-0.387	-0.318	-0.782	-0.299	1.000				
(10) state_	-0.051	0.080	-0.027	0.197	0.249	-0.014	0.044	0.163	-0.154	1.000			
(11) NatureofInven~i	-0.005	0.026	0.015	0.117	0.174	0.016	0.079	0.121	-0.161	0.754	1.000		
(12) NatureofInven~d	-0.027	-0.016	0.005	0.143	0.103	-0.022	0.295	0.035	-0.326	-0.077	-0.081	1.000	
(13) NatureofInven~m	0.306	0.054	0.316	0.118	0.241	0.324	0.533	0.223	-0.695	-0.088	-0.174	-0.350	1.000

Table 19 shows no major homogeneity and multicollinearity problems. For the most part there does not seem to be any major problems with highly correlated variables. There is only one situation with a value >0.75. This will not be an issue when conducting the empirical analysis as variable 9 (no patent) is a dummy variable made from the original categorical variables 'type of innovation'. 'No patent,' 'process' and 'product' are all complementary dummy variables from the original categorical variable and so they will not all be run simultaneously, no patent will be omitted. This means that its correlation with 'process' will not be an issue.

5.2 Random-Effects Logistic Model

Table 22: Random-Effects Logistic Regressions (Process)

Green Process Innovation	(1)	(2)
ERI2	**0.570****	-0.134
	(2.93)	(-0.57)
LSCI2	**0.0176****	-0.00521
	(2.66)	(-0.59)
ln_Percetageeducated2534		-0.724
		(-1.46)
ln_Percetage5664		-0.755
		(-1.64)
ln_GDPperCapita		0.308
		(0.91)
ln_PopulationSize		0.214
		(1.09)
NatureofInventor_uni		0.310
		(0.38)
NatureofInventor_ind		0.231

		(0.61)
state_		**23.07***** **(4.65)**
nonstate_		**24.37***** **(4.90)**
_cons	**-3.278***** **(-4.80)**	-23.92 (.)
N	568	568

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 20, green process innovation is the dependent variable. There seems to be similar output to the original analysis (Table 11). In column one, all values are significant at the 0.01 level. If environmental policy stringency increases by one unit, the odds of there being a green process innovation increase by a factor of 0.570. When examining LSCI2, as the variable increases by one unit, the likelihood of green process innovations occurring is expected to increase by a factor of 0.0176 compared to the reference group (green product innovation and no innovation).

Column two incorporates all the relevant control variables. Most results are insignificant, however, both state and non-state are significant at the 0.001 level much like Table 11. This means that for every additional unit of non-state-owned enterprises, the likelihood of a green process innovation increases by a factor of 24.37. Moreover, for every additional state-owned enterprise, green process innovations are expected to increase by a factor of 23.07.

Table 23: Random-Effects Logistic Regressions (Product)

Green Product Innovation	(1)	(2)
ERI2	**0.556**** **(2.61)**	0.134 (0.57)
LSCI2	**0.0150**** **(2.81)**	0.00521 (0.59)
ln_Percetageeducated2534		0.724 (1.46)
ln_Percetage5664		0.755 (1.64)

ln_GDPperCapita		-0.308 (-0.91)
ln_PopulationSize		-0.214 (-1.09)
NatureofInventor_uni		-0.310 (-0.38)
NatureofInventor_ind		-0.231 (-0.61)
state_		**22.56***** **(4.55)**
nonstate_		**21.25***** **(4.27)**
_cons	-4.864*** (-5.93)	-21.71 (.)
N	568	568

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 23 has green product innovation as the dependent variable. Unlike the in Table 12, it seems that both independent variables here are significant at the 0.01 level (Table 12 has environmental regulation stringency as insignificant). Here, If ERI2 increases by one unit, the odds of there being a green product innovation increase by a factor of 0.556. Moreover, if LSCI2 increases by one unit, the odds of a green product innovation occurring increases by 0.0150.

Column two incorporates relevant control variables. Most results are insignificant, however, once again both state and non-state are significant at 0.001. This means that for every additional unit of non-state-owned enterprises, the likelihood of a green product innovation increases by a factor of 21.25. Moreover, for every additional state-owned enterprise, green product innovations are expected to increase by a factor of 22.56. All results follow the output expressed in Table 12.

Table 24: Random-Effects Logistic Regressions (No Innovation)

No Innovation	(1)	(2)
ERI2	**-0.862***** **(-3.63)**	**-0.650**** **(-2.59)**
LSCI2	**-0.0288****	-0.00181

	(-3.24)	(-0.20)
ln_Percetageeducated2534		**-1.194***
		(-1.99)
ln_Percetage5664		-0.153
		(-0.47)
ln_GDPperCapita		**-1.755*****
		(-4.19)
ln_PopulationSize		**-1.260*****
		(-4.88)
_cons	**4.185*****	**47.06*****
	(4.98)	**(6.13)**
N	568	568

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 24, no innovation is the dependent variable. These results differ from those of Table 13. Like Table 13, here both independent variables (ERI2 and LSCI2) are significant at the 0.001 level and 0.01 level in column one. If ERI2 increases by one unit, the odds of having no innovations decrease by a factor of 0.862. Moreover, if LSCI2 increases by one unit, the likelihood of no innovation decreases by a factor of 0.0288. Higher levels of environmental stringency and connectivity results in less frequency of no innovations.

Column two incorporates all the relevant control variables (some were omitted due to omitted variable bias). Unlike Table 13, ERI2 is significant in model 2. As ERI2 increases by an additional unit, the likelihood of 'no innovation' occurring decreases by 0.650; significant at the 0.01 level. Like Table 13, both logged GDP per capita and population size are significant however, now p<0.001 in both cases. For every additional unit of population size and GDP per capita the odds of no innovation occurring decrease by factors of 1.260 and 1.755, respectively. Finally, unlike Table 13, the population with tertiary education (aged 25-34) is significant at the 0.05 level in determining the odds of no innovation occurring. For every additional unit of this variable, the odds of no innovation occurring decrease by a factor of 1.194.

5.3 Random-Effects Panel Regression

Table 25: Random-Effects Panel Regression

Total No. of Innovations	(1)	(2)	(3)
ERI2	**0.871*****	**0.862*****	**0.661*****
	(5.95)	**(5.23)**	**(4.73)**

LSCI2	0.0120 (1.83)	-0.00245 (-0.33)	-0.00535 (-0.87)
ln_Percetageeducated2534		-0.112 (-0.24)	-0.246 (-0.64)
ln_Percetage5664		0.0501 (0.29)	-0.0412 (-0.28)
ln_GDPperCapita		**1.052***** **(3.35)**	**0.638*** **(2.46)**
ln_PopulationSize		**0.966***** **(4.45)**	**0.721***** **(4.12)**
NatureofInventor_uni			0.104 (0.25)
NatureofInventor_ind			**-0.437**** **(-2.66)**
state_			**1.385**** **(2.98)**
nonstate_			**2.063***** **(13.33)**
_cons	**-1.890***** **(-3.54)**	**-28.55***** **(-4.79)**	**-19.35***** **(-3.96)**
N	568	568	568

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To begin with the similarities when compared with Table 14, across all three models, environmental regulation stringency has a significant association with the total number of green innovations at the 0.001 level. For every additional unit of ERI, the number of green innovations is expected to increase by 0.871, 0.862 and 0.661 units respectively (model 1, 2 and 3). Once again strengthening institutional theory's expectations and the weak version of Porter's hypothesis.

Moreover, regarding the control variables, like in Table 14 variables NatureofInventor_ind, state_ and nonstate_ are all significant however, they are now significant at the 0.01, 0.01 and 0.001 level, respectively. The associations are similar in size and share the same direction as in Table 14. Finally, in this model, logged GDP and population size are significant in both model 2 and 3 at the 0.001 level (GDP per capita in model 3 is significant at the 0.05 level). Both are positively associated with the total number of innovations. This implies that the larger the population size and the GDP of the host country, the greener innovation numbers will increase.

5.4 Mediation Analysis

Table 26: SEM Mediation Analysis

	(1)
LSCI2	
TotalNoofInnovations	**4.557*****
	(10.48)
ERI2	-2.116
	(-1.54)
_cons	**59.53*****
	(14.78)
TotalNoofInnovations	
ERI2	**1.038*****
	(8.32)
_cons	-0.755
	(-1.95)
N	568

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Mostly, the output of 25 emulates that of Table 15; however, a key difference to highlight is, where ERI was significant in Table 15 when looking at its relationship with LSCI, Table 24 shows that there is no longer a significant direct effect there. Instead, only the total number of green innovations is significant at the 0.001 level. As the total number of innovations increases by one unit, LSCI2 is expected to increase by 4.557.

Looking further down Table 25, there is also a significant positive direct effect between ERI2 and the total number of innovations. This direct effect is significant at the 0.001 level and for every additional unit of policy stringency, the number of innovations should increase by 1.038 units. To understand true mediation, see Table 26.

Table 27: Significance testing of indirect effect

Estimates	Delta	Sobel	Monte Carlo*
Indirect effect	4.731	4.731	4.740
Std. Err.	0.726	0.726	0.706
z-value	6.517	6.517	6.716
p-value	0.000	0.000	0.000

Conf. Interval	3.308, 6.153	3.308, 6.153	3.312, 6.052

Baron and Kenny approach to testing mediation
STEP 1 - TotalNoofInnovations:ERI2 (X -> M) with B=1.038 and p=0.000
STEP 2 - LinerShippingIndex2:TotalNoofInnovations (M -> Y) with B=4.557 and p=0.000
STEP 3 - LinerShippingIndex2:ERI2 (X -> Y) with B=-2.116 and p=0.122

RIT = (Indirect effect / Total effect)
(4.731 / 2.615) = 1.809
Meaning that about181 % of the effect of ERI2
on LinerShippingIndex2 is mediated by TotalNoofInnovations!
RID = (Indirect effect / Direct effect)
(4.731 / 2.116) = 2.236
That is, the mediated effect is about 2.2 times as
large as the direct effect of ERI2 on LinerShippingIndex2!

When examining Table 27 the Delta, Sobel, and Monte Carlo statistics (4.731, 4.731 and 4.740) are all significant at the 0.001 level. This means that the null hypothesis is rejected much like for Table 16. The z-values are large for all three models suggesting stronger evidence against the null hypothesis. The null hypothesis is rejected so, a significant indirect relationship between ERI and the LSCI does exist through the mediator, total number of green innovations.

However, unlike in the original analysis, when examining the Baron and Kenny approach, steps 1 and 2 highlight a significant relationship at the 0.001 level but step 3 is insignificant. ERI does affect the total number of innovations and the total number of innovations does affect LSCI however, the direct effect between ERI and LSCI when controlling for the mediator is not significant as p>0.05. This means that instead of partial mediation, which was the case in the original analysis, full mediation is present here. This is because the direct effect of X on Y (step 3) is not statistically significant, suggesting that it is effectively reduced to zero. Additionally, both steps 1 and 2 are significant so the relationship between X and Y is fully explained by the mediator M indicating full mediation. 181% of the effect of ERI on LSCI is mediated by the total number of innovations. Moreover, the mediated effect is about 2.2 times as large as the direct effect of ERI on LSCI. These results, despite being different from the original analysis still support Porter’s strong hypothesis which expects green innovation to act as a facilitator (mediator) between environmental regulation stringency and industry competition (Porter & Van der Linde, 1995).

6.0 Discussion

6.1 Environmental Regulation Stringency and Green Innovation Technology

Firstly, regarding the relationship between environmental regulation stringency and the total number of green innovations (***H1: At the country-level, higher levels of environmental regulation stringency are more effective in generating green innovation in the maritime industry).*** The results section highlights a significant positive relationship between the two variables and so the null hypothesis is rejected. So, as environmental regulation becomes stricter, the total number of green innovations is expected to increase. The same findings hold true for the sensitivity analysis when the home country was examined rather than the host country. How does the fit in with existing literature and theory? This paper's results reject the traditional view in economics that strict environmental regulation reduces pollution but simultaneously increases internal production costs thereby reducing the output of enterprises, hinders innovation capacity (Liu & Xie, 2020).

Regarding institutional-based theory which focuses on the dynamic interactions between institutions and organizations, added pressure from institutions to result in institutional isomorphism (firm's strategies and actions coordinating with institutional expectations). The findings of this study are in line with Aguilera-Caracuel & Ortiz-de-Mandojana, 2013; Ramon-Llorens, Gracia-Meca & Pucheta-Martinez, 2019; He & Jiang, 2019; Ma & Li, 2016 who emphasize that firms will comply with regulation because they want legitimacy and an upstanding reputation within their institutional environment. Moreover, the results are in line with Porter's weak hypothesis which highlights that properly designed environmental regulation may spur innovation. Jaffe et al., (1995); Porter and Van der Linde (1995); and Barbera & McConnell (1990) all highlight that environmental regulations encourage green innovations within firms so that they survive in competitive environments, and this study supports this expectation both for host and home countries.

6.1.1 Green Process and Product Innovation

This study also looked at green process and product innovation independently (***H1a: Higher levels of environmental regulation stringency are positively associated with the likelihood of a green product innovation being produced*** *and* ***H1b. Higher levels of environmental regulation stringency are negatively associated with the likelihood of a green process innovation being produced).*** Unfortunately, the results from the random effects logistic regressions for both home and host countries were insignificant when differentiating between the different types of green innovation, meaning that the null hypothesis for both H1a and H1b fail to be rejected, indicating no significant association between environmental regulation and green process innovation and/or green product innovation. Interestingly, for the original analysis that examines mostly host countries, environmental regulation stringency does not seem to be a significant determinant when differentiating between no innovation and an innovation (green product or process) occurring. However, for the home country analysis (sensitivity analysis), environmental regulation stringency does differentiate between the outcome of no innovation and that of green product and process innovation. The stricter environmental regulation is in the home country, the less likely no innovation will occur. How does this fit into the literature?

Literature suggests that with stricter policy comes a higher likelihood of green product innovations occurring because these are the more complex innovations that will set the firms at a more competitive advantage, giving them first-mover advantage in the market (Ma & Li, 2016; Porter & Van der Linde, 1995). Moreover, green process innovations, since they are easier to implement, are more likely to occur in a lax regulatory environment (Ma & Li, 2016; Porter & Van der Linde, 1995). This study suggests that home country environmental regulations have more of an influence on the likelihood of any innovation occurring or not, compared to host countries. Firstly, the fact that environmental regulation stringency does differentiate between no innovation and innovation in home countries strengthens Porter's weak version of his hypothesis (properly designed environmental regulations should spur innovation) as well as institutional based theory which emphasizes that the institutional environmental pressures influence induced innovation (Porter & Van der Linde, 1995; Javeed et al., 2023). However, why is there a difference in the influence of a host vs a home country? Essentially universities and research institutes, individuals as well as firms can be influenced through **host country effects** and **country-of-origin effects** as illustrated by the institutionalist approach (Almond et al., 2005). One explanation for the home country's environmental regulation stringency having significant effects on innovation and the host country not having these same effects could be **dominance effects** (Almond et al., 2005). This means that the home country has the more dominant voice when it comes to influencing environmental behavior, attitudes, and strategies and therefore is a more significant determinant when differentiating between no innovation and process and product innovation within this study (Almond et al., 2005).

6.2 Green technological Innovation as a mediator

The final relationship explored within this paper is the indirect relationship between environmental regulation stringency and maritime industry competition (***Higher levels of environmental regulation stringency will indirectly, through green technology innovation, result in higher levels of national maritime industry competitiveness).*** The results derived from the original mediation analysis show a significant partial mediation between regulation stringency and maritime industry competitiveness. This means that both an indirect and a direct relationship exists between the variables and both relationships are significant. When looking at the sensitivity analysis (home country), full mediation is present. This is because there is not a significant direct effect of regulation stringency on maritime competitiveness. However, via innovation, the indirect relationship is significant. How does this fit in with the theoretical framework?

Both Porter's theory of competitive advantage and the Pollution Haven Hypothesis suggest that innovation acts as a mediator of some sort between environmental regulation stringency and maritime competitiveness however, the direction of this relationship differs between the theories. Porter and Van der Linde (1995) suggest a positive indirect relationship whereas Pollution Haven Hypothesis emphasizes a negative one. When looking at the original results for host countries, it seems that the indirect relationship (with innovation as a mediator) is a positive one, and it is significant. This means that the higher the environmental regulation stringency, the more the number of green innovations will increase, which increases competitiveness of a country's maritime industry. This is in line with H2 and due to its significance, the null hypothesis fails to be rejected. The results confirm the strong version of Porter Hypothesis which claims that innovation triggered by environmental regulation will more than offset compliance costs, resulting in firms being more competitive in the market (Porter & Van der Linde, 1995).

However, interestingly, for the original analysis the direct relationship between regulation stringency and industry competitiveness was also significant and this relationship was negative. This finding provides support for the Pollution Haven Hypothesis that suggests that the stricter the policy is, the more likely a firm will be at a competitive disadvantage (Dechezleprêtre & Sato, 2018). Regarding the results from the sensitivity analysis, there is no significant direct effect of regulation stringency on competitiveness however, the indirect relationship does exist. Once again, this relationship is positive and significant meaning that this finding provides further support of the Porter strong hypothesis. In fact, it provides even more support for the hypothesis since the finding suggests full mediation.

Conclusion

When looking back at the findings of this paper, how do they fit in with the overarching research question: '*How has the varying stringency of environmental regulations shaped the landscape of green technological innovation in the maritime industry from 2006-2020, and is there evidence of an indirect effect on industry competitiveness?'?* Well, it does seem that the varying stringency of environmental regulations has played a significant role in shaping the landscape of green technological innovation in the maritime industry from 2006-2020 and that an indirect effect between environmental regulation stringency and industry competitiveness is evident during this period.

Institutional theory was used to build a framework in which the power of institutional environments was expected to shape outcomes (e.g., strategies, choices, behavior) within the environment. Entities were therefore expected to strive to maintain their environmental legitimacy and their reputation in accordance with the environmental policies in place. For this reason, this study expected to find a positive association with stringency levels and the total number of green innovations and that it did. Unfortunately, it seemed that stringency was not able to differentiate between the different types of innovation so, neither the compliance cost effect nor the innovation cost effect seemed relevant in whether a firm opted for green process innovations or green product innovations in both home and host countries. Porter & Van der Linde's (1995) weak version did hold true however for the home country where environmental regulation stringency was significant in differentiating between 'no innovation' occurring or some type (process of product innovation) of innovation occurring. Finally, the research uncovered a partial mediation effect of green innovation in home countries and a full mediation effect in host country when it came to the indirect relationship between environmental regulation stringency and maritime industry competitiveness; the mediator being the number of green innovations. This was in line with the expectations from the strong version of Porter's hypothesis.

This study makes several contributions to existing literature and the debate surrounding sustainable economic growth in the maritime industry. Firstly, it examples the indirect effect of environmental regulation stringency on the competitiveness of the maritime industry by considering the mediating role of innovation. This approach sheds light on the mechanisms through which environmental regulations influence industry competitiveness, highlighting the role of innovation as a pathway. Secondly, the study considers a plethora of different countries spanning over a period of 14 years. Most existing literature is China centric or focuses on different jurisdictions within the same country. This broader scope helps to capture the potential variation and complexities across different national contexts. Finally, this study explores the effects of environmental regulations on competitiveness and on green innovation for both host and home countries. This approach aligns with institutional theory, which suggests that different institutional contexts can shape outcomes of regulatory interventions and that often, the behavior of entities in an environment depends on dominance effects. By examining these institutional-level effects separately this study provides a unique contribution to literature, providing insights into the role of institutions in shaping elements of the maritime industry.

Future research could explore the specific mechanisms through which environmental regulation stringency influences green technological innovation. Understanding the different drivers and barriers that facilitate or hinder innovation regarding stringent regulations could provide further guidance for policymakers and industry stakeholders. Moreover, future studies could use more indicators for maritime industry competitiveness as well as for measuring green innovation to make the variables more holistic.

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