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A Push for Innovation: The More the Greener?

To what extent does innovation in general technologies and innovation in environmental-related technologies affect CO_2 emissions in the European Union-15, the United States, and China in 1990-2018?

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Abstract

The threat of climate change has left countries with a dilemma of whether to chase economic growth or environmental quality. Green innovation appears to offer a bridge between these two seemingly opposing goals. This thesis explores the role of innovation in carbon dioxide emission mitigation, and the moderating effect of environmental taxation on this relationship. A Pooled OLS and Fixed-Effect estimator is employed with panel data of the European Union-15, the United States, and China over the years 1990-2018. Innovation in general technology and innovation in environment-related technology are observed, measured through R&D expenditure and patent applications. The Pooled OLS results show that a negative direct association is observed between (eco-)innovation and CO_2 emission; while the FE results show that there is a possible non-linear relationship between R&D expenditure in general technology innovation and CO_2 and no moderating effect of environmental taxation.

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1. Introduction

The dark cloud of climate change is looming over our head as news channels report failed attempts of limiting climate change and describe increasingly extreme weather conditions. Climate change results from the anthropogenic emission of greenhouse gasses that trap heat in the Earth's atmosphere, causing an accelerating rise in global temperatures. In 2021, 66% of the heating impact by human-produced greenhouse gasses could be attributed to anthropogenic carbon dioxide (CO2) emissions (National Oceanic and Atmospheric Administration, 2022). Reducing CO2 emissions would therefore be of great value in reducing the speed at which global warming, and hence climate change, is charging at us.

This seemingly simple solution, CO2 emission mitigation, proves to be a real headache for countries over the world. Climate change conferences, such as the one in Paris in December 2015, have shown the hesitance among diplomats to commit themselves to drastic changes as many countries are faced with a tradeoff: economic growth versus reducing pollution (Sivaram & Norris, 2016). Therefore, one must look for a bridge between these two apparent ends of the spectrum. One such binding element has been presented by Shivaram and Norris (2016) in their theoretical and historical analysis: eco-innovation. An example of such innovation is the investment in and development of alternative and clean energy technology (Sivaram & Norris, 2016).

In their examination of the role of innovation in combatting climate change, Sivaram and Norris (2016) argue that a drastic energy and transportation technology transformation is needed in order to offer competitive and cost-efficient long-run alternatives to the current environmentally damaging norms. However, such a change requires huge societal and financial effort from countries (Sivaram & Norris, 2016). Before making such a costly commitment, countries will need to be convinced of the effectiveness of innovation investment in lowering CO2 emissions and become aware of the different ways in which innovation can be measured and boosted. This thesis aims to explore the environmental impact of different forms of innovation through the following research question.

To what extent does innovation in general technologies and innovation in environmental-related technologies affect CO2 emissions in the European Union-15, the United States, and China in 1990-2018?

Attempting to answer this research question will contribute to guiding governments in deciding whether an innovation-led technology transformation will significantly assist in reaching pollution mitigation goals. It will also provide insight into whether focusing investment on two specific measures of innovation, research and development (R&D) expenditure and patent applications, are effective in lowering CO2 emission. This thesis will examine general technology innovation in the form of R&D expenditure and patent applications in general technology, as well as green technology innovation through the measure of patent applications in environment-related technology. If evidence is found for a negative effect of R&D expenditure on CO2 emission, a country could consider increasing public R&D budgets and subsidies (Sivaram & Norris, 2016). Policymakers can also stimulate patent applications through, for example, funding research and innovative enterprises and hosting network events to encourage collaboration between research facilities, government, and firms (Government of the Netherlands, 2022).

In addition, the research conducted in this thesis can contribute to the existing empirical literature concerning the panel study of innovation and CO2 emission mitigation. This thesis contributes to the existing literature by employing and comparing multiple methodologies and innovation measurements. As far as can be observed, this thesis is unique in that it compares input and output measurements of innovation and covers both general technology and specifically green technology innovation. Furthermore, environmental taxation, a possible moderating factor for CO2 emission and innovation, will be analyzed in this thesis. Previous literature suggests that environmental taxation may strengthen the relationship between green innovation and CO2 emission (Fan, Yitong Wang, Chen, Du, & Yuanyuan Wang, 2022; Morley, 2012; Porter & van der Linde, 1995). Morley (2012) has shown that environmental taxation can lead to reduced GHG emissions and suggests this is likely through increased development of green technology. Environmental regulation, if not too stringent, can push diffusion of eco-innovation among companies by encouraging them to explore sustainable alternatives to stay competitive, reduce their negative environmental impact, and/or imitate same-industry companies (Fan et al., 2022; Porter & van der Linde, 1995). Hence, this thesis explores the possibility that increased diffusion of eco-innovation due to the environmental regulation will strengthen the impact of eco-innovation development on pollution levels. To the best of my knowledge, no article has yet empirically explored a moderation effect of environmental taxation on the strength of relationship between green innovation and CO2 emission. This thesis will therefore contribute to filling a research gap by bringing together the study of environmental taxation and green innovation in relation to CO2 emission mitigation.

This thesis also expands on existing literature due to the timeframe of this cross-country study, which includes the most recent available data. The majority of published empirical papers from the past four years that studied the impact of (eco-)innovation on pollution across multiple countries employed data covering years up to 2012-2015. Three papers did cover more recent dates up to 2015, 2016, and 2017, but two of these papers only explored environmental innovation and CO2 emissions in China and the other performed firm-level innovation analysis instead of country-level analysis (Guo, Zhou, Ali, Shahzad, & Cui, 2021; L. Li, McMurray, X. Li, Gao, & Xue, 2021; W. Li, Elheddad, & Doytch, 2021). A recent empirical article, published in September 2022, examines the effect of environmental innovation on CO2 emission over the G-7 countries from 1990-2020 (Xie & Jamaani, 2022). This empirical paper therefore also includes more recent dates but examines a different group of countries and only explores innovation as measured through the development of environment-related technologies. Thus, it appears that this thesis is unique in its exploration of the most recent data concerning general and green innovation, measured through R&D expenditure and patent applications, on the selected country sample.

Additional value can be created by including the most recent available data on innovation and CO2 emissions when performing a cross country analysis. The newer data can contribute to the overall research question regarding innovation and CO2 emissions. A regression analysis of the 46 countries examining the changes in "information seeking behavior about climate change" between 2015-2019 showed that information seeking, indicated by the quantity of internet searches on climate change, had risen in 2019 (Sisco, Pianta, Weber, & Bosetti, 2021, p. 5). An association was also found between an increase in internet searches for climate change information and climate change protests, with the number of protests surging in 2019 (Sisco et al., 2021). Such an increase in societal demand for climate change information and political action is notable in the research on countries' efforts to reduce pollution. Furthermore, the Paris Agreement was enforced in 2016 and committed 191 countries and the European Union (EU) to reduce their own emission through setting climate goals and monitoring their progress in reducing emissions. This agreement was signed by China, the United States of America (US), and the EU-15; however, the US withdrew from the agreement in 2019 (npr, 2022; United Nations, 2022). Such an agreement and the cooperation of 192 parties signals an increasing awareness and motivation to tackle pollution. This raises the expectation that there are possibly stronger effects measured of innovation on CO2 emission when analyzing more recent data as governments and companies are increasing their environmental efforts due to rising political and social pressures.

Finally, the basis of the empirical research for this thesis is inspired by the empirical paper by Y. Fernández Fernández, M.A. Fernández López, and B. Olmedillas Blanco called *Innovation for Sustainability: The Impact of R&D Spending on CO2 Emissions* (2018). Like Fernández et al. (2018), this thesis examines the US, EU-15, and China. The EU-15 includes Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and United Kingdom (OECD, 2022a). These regions/countries were chosen due to their distinct role in global CO2 emissions with China and the US as the top two global CO2 emitters, and Germany at number six (Vanessa, 2021). Alongside their role as significant polluters, these regions/countries also express interest in lowering their harmful environmental impact and potentially employing innovation to do so. China has initiated innovation plans to both sustain economic growth as well as reduce its negative environmental impact (Gao & Yuan, 2021). For example, China has increased its renewable energy investment from 3 billion dollars in 2005 to 288.9 billion dollars in 2021 (World Bank, 2018; as described by Guo et al., 2021). The EU has introduced various legislation alongside the agreements made in the Kyoto Protocol, such as the 20-20-20 targets in 2007 that focused on GHG emission reduction and stimulating renewable energy sources. While the US government has introduced successful GHG emission reduction policy such as stronger regulation of pollution levels through the Clean Air Act, it also has at various times been unable to pass or gain support for legislation regarding environmental quality (Skjærseth, Bang, and Schruers, 2013). Nevertheless, according to an Organisation for Economic Co-operation and Development (OECD, 2008) report on US eco-innovation policies, the US R&D budget exceeded that of the EU over the years 1994-2004. In summary, the EU-15, China, and the US will be a focus because they are each prominent CO2 emitters while also exerting effort into innovation initiatives and/or legislation with the intention of lowering their environmental impact. This makes them relevant study subjects for studying the environmental impact of innovation within countries.

As mentioned previously, this thesis is expected to provide relevant insights for governmental parties and policymakers in deciding whether they should focus on environment-related innovation in combatting climate change and which form of innovation they should invest in for maximum effects. In addition to that, new insights regarding environmental regulation could inform policymakers of the potential benefits and caveats of imposing such regulation in relation to pollution mitigation and innovation diffusion. The relevance of this thesis' insights can also extent further into different branches of society. For stakeholders looking towards making socially and environmentally conscious investments, this thesis could assist in providing insight into the possible environmental impact of investing in companies that develop eco-innovation and/or promoting (eco-)innovation for its current investments (Javeed et al., 2022). Furthermore, social enterprises or firms looking towards new and environmentally conscious strategies may make use of this thesis' insights in deciding whether an innovation-led strategy could also be a sustainable strategy. If this thesis finds positive impacts of (eco-) innovation on pollution mitigation, research facilities and/or firms may consider forming clusters, collaborate, and share knowledge to enlarge the environmental impact of innovation.

The structure of the thesis is as follows. Existing literature on the main research topics will first be identified and analyzed in the theoretical framework. The theoretical framework will include theoretical and empirical articles covering the determinants of CO2 emission, the definition of (eco-) innovation, the effect of general technology innovation on CO2 emission, the effect of green technology innovation on CO2 emission, and the moderating effect of environmental taxation. The theoretical framework will build the foundation for a total of nine hypotheses. Subsequently, the data employed in the empirical analysis will be outlined and presented in a summary statistics table. This is followed by an overview of the used empirical methodology and the estimated equations corresponding to the hypotheses. The results of the empirical analysis will then be presented, including additional robustness test results. Finally, the thesis is concluded with a summary of the main findings, an analysis of the implications, a discussion of the methodology, and suggestions for future research.

2. Theoretical Framework

Before diving into the empirical analysis, the existing literature relevant to studying the relationship of (eco-)innovation and CO2 emissions are summarized in the theoretical framework. The determinants of CO2 emissions and the definition of (eco-)innovation will first be introduced. Subsequently, literature and three hypotheses on the effect of R&D expenditure for general technology on CO2 emission will be presented. This is followed by an analysis of the literature and three hypotheses for the relationship between patents in general technology and CO2 emission. Next, the effect of specifically eco-innovation, measured through patents in green technology, on CO2 emission will be explored by building two hypotheses based on previous empirical literature. The theoretical framework is concluded with an examination and hypothesis of environmental regulation as a possible moderating variable for the relationship between eco-innovation and CO2 emissions.

2.1 Determinants of Carbon Dioxide Emission

As described in the introduction, the reduction of CO2 is a vital component in mitigating the threatening global warming that the world is currently facing. Before exploring how innovation may reduce the CO2 emissions, an examination of the factors that influence the CO2 emission level is required.

In 1971, the Impact = Population*Affluence*Technology (IPAT) framework was presented by Paul Erlich and John Holdren to identify explanatory variables determining environmental impact (Bargaoui, Liouane, & Nouri, 2014). Population is self-explanatory, affluence stands for per capita economic activity and technology refers to the environmental impact per unit economic activity (Dietz & Rosa, 1997). This framework was subsequently transformed by Dietz and Rosa (1997) into a stochastic log-linear model that could be empirically tested, known as the “stochastic impacts by regression on population, affluence, and technology” (STIRPAT) model (Hashmi & Alam, 2019, p.1100). This theoretical model has become a popular staple within studies examining the determinants of CO2 emission (Wu, Jieyu Wang, Shaojian Wang, & Feng, 2021).

The STIRPAT was further developed and personalized within later studies. Hashmi and Alam (2019) presented the STIRPART model, which is the original model with the addition of environmental regulation as a determinant of environmental impact and (non-)environmental technology as a determinant for technology. They explained that the previous model was missing the impact of environmental policy instruments and failed to test specifically the effect of environment-related technology on CO2 emission. In their empirical analysis, they examined OECD countries over the years 1999-2014 using panel fixed-effects (FE), random-effects (RE), and Generalized Method of Moments (GMM) models. They found that population, gross domestic product (GDP) per capita, and non-environmental technology significantly increase CO2 emissions. Meanwhile, environment-related innovation and carbon pricing strategies significantly reduce CO2 emissions in OECD countries. However, the individual magnitude of population, GDP per capita, and traditional technology were shown to outweigh those of environmental technology and regulation (Hashmi & Alam, 2019).

Selections of determinants of CO2 emission outside of this framework have also been explored. Neves et al. (2020) studied the effect of environmental regulation, economic growth, inward foreign direct investment (FDI), (renewable) energy consumption, and policies that stimulate renewable energy use on the CO2 emission of 17 European countries over 1995-2017. Through estimates from an Autoregressive Distributed Lag model (ARDL), they found that economic growth and primary energy consumption increase CO2 emission in the long and short run. Conversely, environmental taxation, FDI, regulatory policies for renewable energy, and renewable energy and waste consumption reduce CO2 emission in the long run. Hence, the direction of impact of economic affluence and environmental regulation matches those from Hashmi and Alam (2019). The authors state that the negative impact of inward FDI on CO2 emission can be explained by successful regulatory policies that have encourage investment in green innovation, and thereby caused a positive technology spill-over effect that reduces national CO2 emission (Neves et al., 2020).

Despite naming technology as a positive outcome of regulation and FDI, Neves et al.’s (2020) analysis does not establish whether it’s a direct determinant of CO2 emission. Nevertheless, Hashmi & Alam (2019) have given evidence of a direct negative effect of green innovation. Mongo et al. (2021) also conduct research on determinants of CO2 emission, where environmental innovation is included. They state that there is a research gap as, according to them, limited studies have been done on the effect of green innovation. They used an ARDL model to study the effect of green technology patents on CO2 emission in the EU-15 countries from 1991-2014 and found a positive short-run relationship and a negative long-run relationship between the two variables. This positive short-run relationship is attributed to a phenomenon called the “rebound effect” which implies that consumer will, for example, increase consumption/use of a product when it’s made more energy efficient. The increase in consumption is then proportionally larger than the increase in energy efficiency, causing an overall increase in emitted pollution. In addition to their main study on green technology and similar to Neves et al. (2020), they find that GDP per capita increases CO2 emissions and that renewable energy consumption decreases CO_2 emission. They also find that openness to trade, measured as all imports and exports as a percentage of a country's GDP, increases CO_2 emissions.

In summary, CO_2 emission is determined by various variables and can be assessed through (variations) of a popular framework known as STIRPAT. A range of determinants have been explored in the selected articles mentioned above, of which all three identify and agree that economic growth is an important determinant of CO_2 (Hashmi & Alam, 2019; Mongo et al., 2021; Neves et al., 2020). Furthermore, other significant determinants that have been identified include primary energy consumption, renewable energy consumption, waste consumption, environmental technology, non-environmental technology, environmental regulation, FDI, trade openness, GDP per capita, and population. From these determinants, GDP per capita, population, and traditional technology are staples within the STIRPAT framework. Hashmi and Alam (2019) have further complemented this framework by also exploring environmental innovation and regulation. One of these determinants, innovation, as stated by Mongo et al. (2021), deserves more attention within empirical literature. This call is increasingly answered with various studies highlighting the valuable contribution of innovation in mitigating pollution. This determinant will be at the nucleus of this thesis, and the concept of (eco-) innovation will therefore first be described below, followed by an analysis of its relationship to CO_2 emission.

2.2 (Eco-)Innovation

One viable solution proposed to tackle climate change concerns is innovation, and more specifically, eco-innovation. The effect of general innovation and eco-innovation is at the heart of this thesis's empirical research and will therefore be defined in this section of the theoretical framework. General innovation will first be defined, followed by eco-innovation.

In his qualitative work, Fagerberg (2013) discusses various theoretical approaches and works regarding innovation, wherein he differentiates between innovation and invention. Invention is the start of an idea or concept, while innovation is defined as the process in which such an idea or concept is realized as an actual new product or process that is introduced into society. To bring such a novel product or process onto the market, a set of various skills, resources, capabilities, and knowledge capacity is often needed such as the necessary financial support or information regarding the targeted consumer market (Fagerberg, 2013). The environment-related branching of innovation is theoretically explored by Rennings (2000). Here, eco-innovation is defined as innovation that also focuses on protection of the environment and the achievement of environment-related goals (Rennings, 2000). An example of an eco-innovation is the electric car, while an example of a general non-environmental innovation would be car with an increased maximum speed which also requires a larger amount of fuel (Rennings 2000).

Existing literature has empirically and theoretically explored the role of both general innovation and eco-innovation in relation to CO_2 emission mitigation. Studies concerning R&D expenditure and patent applications for general technology will be analyzed first to explore the relationship between general innovation and CO_2 emission. The effect of environmental innovation will be examined next with summaries of studies focused on patents in environmental technology.

2.3 General R&D expenditure and CO2 Emission

In this section, empirical findings concerning general technology R&D expenditure, a proxy for general innovation, in relation to pollution will be identified as this will provide foundation to the development of this thesis' hypotheses and exploration of the research question. The following section will first identify a selection of empirical literature that explores between-country variation in relation to the R&D spending and pollution and will subsequently cover literature on within-country variation. These two forms of analysis are explored separately since they each give a different insight into the impact of increased general technology on CO_2 emission. The analysis of between-country analysis will allow for insight into whether a country with a higher level of innovation will emit more or less CO_2. The within-country analysis will shed light on whether an increase of innovation in a country over time will affect its CO_2 emission.

Fernández et al. (2018) shed light on the role of innovation in relation to pollution levels within their research on R&D spending. They state that innovation is known to stimulate economic growth and thereby also energy consumption. This effect can be linked to increased pollution; however, innovation can also lead to less energy-intensive alternatives that lower energy consumption and pollution. This presented duality makes the analysis of technological innovation, in the form of general total R&D expenditure, in relation to CO_2 emissions an interesting one. Fernández et al. (2018) employed an ordinary least squares (OLS) regression with CO_2 emission as dependent variable and R&D expenditure (lagged by two years), total final energy consumption, and a lagged variable for CO_2 emission as independent variables, for the years 1990-2013. The OLS estimation is run for each of the following three regions: the EU-15, US, and China. The authors' motivation for choosing these regions was that they all have substantial global economic power, but each manage environmental problems in different ways and with different intensities during the study's time frame. These differences in the countries' roles in tackling environmental concerns has been highlighted in the introduction of this thesis.

By running separate OLS regressions for each of the three regions, Fernández et al. (2018) place focus on the differences between the regions. They find that there is evidence that R&D spending may lower CO_2 levels in the US and EU-15, with the magnitude of the effect being the greatest for EU-15.

They suggest that this last point can be explained by the leading regulatory policy efforts in reducing CO2 emissions by the EU-15. This strict regulatory stance by the EU-15 may stimulate governments and companies to innovate more with a focus on finding greener alternatives relative to the less strongly enforced regulatory policy on emissions in the US. Fernández et al.'s (2018) results for China were inconclusive as the second model, which attempt to address autocorrelation issues, has not been able to correct the specification errors found in the parameter estimation. According to the authors, the surviving autocorrelation issue could be caused by China's recent shift in economic focus. Its economic focus was initially defined by high economic growth and harmful emission figures; however, China is now also proving itself to be a growing leader in renewable energy and innovation (IEA, 2017; as described by Fernández et al., 2018). Hence, the authors express interest in examining China again in relation to innovation and emission when newer data is available.

Petrović and Lobanov (2020) also analyze the effect of R&D expenditure on CO2 emissions in 16 OECD countries over the years 1981-2014. Their panel models are estimated using common correlated effects mean group (CCEMG) alongside augmented mean group estimators (AMG). They state that the CCEMG method can be closely compared to an augmented OLS regression. They employ two models: a short-run and a long-run time-varying coefficient panel model. Subsequently, they found that there is a negative long-run average effect of R&D expenditure on CO2 emission. However, when observing country-specific regressions, the estimates show varying negative or positive effects depending on the country. The short-run regression also shows a similar mixed results with the significant coefficients of R&D on CO2 emission being either positive or negative.

Even though Petrović and Lobanov (2020) obtained mixed results regarding the effect of R&D level on a country's CO2 emission level when observing short-run and country-specific data, they have found that in the long-run sample with all 16 countries, a negative relationship exists. This observed long-run negative relationship matches the earlier study by Fernández et al. (2018) in which a negative relationship was found for the EU-15 countries and the US. In addition, analyzing the most recent data to 2018 sets this thesis apart from the previous literature mentioned above and is relevant to the research due to the rapid global changes taking place regarding environmental action and attitudes (Sisco et al., 2021; United Nations, 2022). Therefore, it can be expected that this negative relationship is stronger when observing years up to 2018 as a positive shift towards sustainability goals is observed across countries. This brings about following first hypothesis.

H1: Countries with higher R&D expenditure on general technology will have less CO2 emissions, considering the years 1990-2018.

Research has also been conducted on the effect of an increase in R&D expenditure within a country over time on its CO2 emission. First, Alam, Apergis, Paramati, and Fang (2020) investigated the effect of R&D expenditure as a percentage of GDP on clean-energy consumption and CO2 emissions in 30 OECD countries over the years 1996-2013. Through a panel cointegration method with individual fixed country effects and accounting for common correlated effects, they observed a long-term effect that an increase in R&D expenditure reduced the CO2 emission in the OECD countries. They find that a 1% increase in R&D expenditure will lead to a .25% reduction in CO2 emission. Based on their results, the authors recommend policymakers to increase their R&D budgets as their findings indicate that the resulting green innovation and energy alternatives will reduce pollutive behavior and enhance clean energy use.

Ibrahim and Vo (2021) studied the impact of innovation on ecological footprint and CO2 emission using panel data of 27 industrially developed countries from 1991-2014. In their article, they employed an extended two-step system GMM that removes fixed effects. With an innovation proxy of gross domestic R&D spending as percentage of GDP, they find a significant and negative relationship between R&D and ecological footprint and CO2 emission. Here, ecological footprint is defined as a measure of national demand for natural reserves such as forests, cropland, and fishing areas (Global Footprint Network, 2022) This finding is explained by Ibrahim and Vo (2021) as follows: innovation within the energy sector will lead to more environmentally friendly power source alternatives and/or greener processes within this sector. Hence, due to the establishment of greener power source alternatives because of innovation, a country will be less dependent on fossil fuels and thereby decrease harmful emission levels. Nonetheless, a possibility of causality of CO2 emission levels on innovation is also addressed and confirmed. Using a panel causality method with a Wald statistic on country level, they found no causality between innovation and CO2 emission for 12 countries, a one-way causality from CO2 emission to innovation for eight countries (among which China, Germany, Italy, and the United States), one-way causality from innovation to CO2 emission in four countries, and two-way causality for three countries. Based on these results, they establish that for some industrialized countries, the CO2 emission level within a country has effect on the gross domestic R&D expenditure (Ibrahim & Vo, 2021). Therefore, the existence of a reverse causality issue in studying the relationship between CO2 emission and innovation is one that should be noted.

In addition, Ibrahim and Vo’s (2021) estimation of the effect of innovation on CO2 emission shows that the negative relationship holds to a certain threshold of innovation. A U-shape effect of innovation on CO2 emission is observed when using a squared-term for innovation, which indicates that too much innovation will increase pollution (Ibrahim & Vo, 2021). They suggest this could be due to the possibility that increased domestic R&D expenditure, which may lead to increased innovation, may be paid by government funds originating from economic activity that required substantial fossil fuel power source. Ibrahim and Vo (2021) also point out that higher available government funds for R&D could lead to increased competition among researchers to obtain these funds, which may result in blockades in innovations being shared and diffused as researchers protect their findings.

To conclude, Ibrahim and Vo (2021) provide, like Alam et al. (2020), an overall positive view of the impact of increased public domestic R&D spending on CO2 emission within countries; however, a reverse causality issue and a non-linearity in the impact of innovation in relation to environmental quality may be present. The expectation of a negative relationship between increased R&D expenditure on CO2 emission within countries brings about the second hypothesis.

H2: A country that increases its R&D expenditure on general technology over time will experience a decrease in its CO2 emission, considering the years 1990-2018.

Besides confirming a negative relationship, Ibrahim and Vo (2021) also find a possible marginal decrease in the negative effect of R&D expenditure on CO2 emission once the expenditure reaches a certain threshold. Another study published a few months prior to Ibrahim and Vo (2021) confirms a similar non-linear effect when studying the relationship through firm-level analysis instead of country-level analysis.

L. Li et al. (2021) examine the effect of R&D investment on CO2 emission reduction using data on public firms in 52 countries over the years 2002-2015. In their analysis, they use FE and GMM estimations. The level of CO2 emission associated to a firm is measured using two variables: a total CO2 equivalents emissions to the total sales ratio of a firm in a financial year and "carbon emission reduction" which measures a firm's ability to employ technology to reduce its consumption of natural resources and seek out green alternatives to these resources. Their FE model showed that R&D expenditure by firms has a significant and negative effect on their cardio emission ratio. This is observed for the full sample as well as the two sub-sample models, one with developing and one with developed countries. Additionally, they test a model that includes the squared term for R&D expenditure. Here, the FE model showed a positive significant effect of R&D and negative significant effect of squared R&D on the CO2 emission reduction for the full sample, the sample with only developed countries, and sample with only OECD countries. The other sub-samples produced insignificant coefficients. Hence, in the samples that include economically developed countries, a non-linear relationship between R&D expenditure and CO2 emission is observed. An explanation offered for this distinction between developed and developing countries samples is that firms in developing countries may own technology that still needs substantial effort and time before they are on the same level of development as the technology from firms in developed countries. In conclusion, the authors found in the total sample that an increase in R&D input decreases carbon emission of a firm; however, they have also identified an inverted U-shape effect of R&D expenditure on CO2 reduction (L. Li et al., 2021).

Even though this study observed a non-linear relationship across firms, the U-shape effect was confirmed to also exist in a country-level analysis by Ibrahim and Vo (2021) a few months later. Therefore, the expectation is that the negative impact of R&D expenditure on CO2 emission within a country will marginally decrease as the investment further increases. This leads to the third hypothesis.

H3: The negative effect of a country's R&D expenditure on general technology on its CO2 emission will experience diminishing marginal returns, considering the years 1990-2018.

2.4 Patents in General Technology and CO2 Emission

As shown by the selection of literature above, various studies have measured general technological innovation as main independent variable through general R&D expenditure. This is an interesting variable since, as mentioned before, general technology innovation has a dual role by both stimulating economic growth that could increase CO2 emissions as well as offering new sustainable innovative solutions that would decrease emissions (Fernández et al., 2018; Ibrahim & Vo, 2021). A valuable addition to this study would be to also analyze the number of patent applications as main independent variable and measure for innovation. In this section, patent applications will first be validified and explained through qualitative literature as a measure of innovation. This is then followed by an analysis of two empirical article on the effect of patents in general technology on CO2 emission and a presentation of the hypotheses.

Since innovation is a challenging concept to capture empirically (Fagerberg, 2013), multiple measures of innovation exist. Haar (2018) describes in his work the different input and output measures of innovation used in studies on company, business unit, project, employee, and country level. As this thesis will use data on country level, attention will be paid to the common indicator measures used here. Haar (2018) identified five common themes in the country innovation indices of which two are "R&D infrastructure" and innovation output (p.420). One of these indices, the Bloomberg innovation index, states that "countries whose residents earn a lot of patents (and attract patent lawsuit) tend to be those at the frontiers of science of technology" (Coy, 2022). Thus, a patent measure is another way to assess the innovativeness of a country which explains its common use as innovation measure (Fagerberg, 2013).

Measuring innovation through patent applications can also bring about challenges. In his working paper reviewing innovation studies, Fagerberg (2013) reflects on the challenges of using patent data as proxy for innovation. Some of these include that a patent is awarded to an invention and therefore do not necessarily apply for innovations. Furthermore, some industries and inventions are more likely to use patenting than others which could distort perceived innovation levels (Fagerberg, 2013). Considering that there is no perfect measure for innovation, the use of patent applications and R&D expenditure on general technology as proxies separately will give a more complete picture of a country's general technology innovation level relative to using only one measure.

Patent applications will therefore also be considered as an alternative measure for general technology innovation in this thesis. Empirical studies that analyzed the effect of general technology patents on CO2 emission will be summarized to form hypotheses. The first article by Mensah et al. (2018) is a study of the effect of higher patent applications on the CO2 emission of a country. The second and more recent article by W. Li et al. (2021) gives indication of the effect that increasing patent applications within a country over time has on its CO2 emission.

Mensah et al. (2018) studied the impact of patent applications in general technology on CO2 emission mitigation in 28 OECD countries over the years 1990-2014. In their conducted research, they transformed all variables to natural logarithms and employed a fully modified OLS regression on three models studying the effect of, among other factors, innovation on CO2 emission. The regression produced mixed results per country. The first model showed that a higher number of patent applications by OECD country residents leads to a lowering of CO2 emission by 1% in the Netherlands and Norway and an increase in CO2 emission by 2% in Denmark and Finland, significant at 10% significance level. The second model contains the same variables as the first but now adds a squared term for GDP per capita alongside a normal GDP variable. This model also produced mixed empirically significant results, with higher innovation leading to a decrease in CO2 emission for Australia, Germany, and Switzerland, while leading to an increase in CO2 emission for Denmark, Finland, Israel, and Spain. Nevertheless, the negative significant coefficients were for most countries higher in magnitude, ranging from a 1-21% decrease in emission, compared to the positive significant coefficients, ranging from a 1-9% increase in emission. Finally, the third model did not include the squared term for GDP and instead included a squared term for innovation. This model again gives mixed results with innovation leading to a decrease in CO2 emission in some countries while leading to an increase in other countries. However, the squared term of innovation reveals that, for most of the countries that produced significant coefficients, the effect measured by the original variable for innovation is counteracted by the squared-term effect, indicating a non-linear relationship. The authors conclude that they do not find a strong effect of innovation on CO2 emission. They explain that high initial costs of requesting a patent and the fact that some technologies cannot be patented causes inventors to be reluctant in sharing their technology, which may limit the diffusion and spill-over of technology that is beneficial to the mitigation of pollution.

In summary, the conducted research by Mensah et al. (2018) produced mixed results that did not provide strong evidence for an effect of general technology innovation, in the form of patents, on CO2 emission. Nevertheless, analysis on R&D expenditure did find a long-run negative relationship when examining 16 countries together and a negative relationship for separate regressions for the EU-15 countries and the U.S. (Fernández et al., 2018; Petrović & Lobanov, 2020). Since both patents and R&D expenditure are measures of innovation, and the previous study on patents produced mixed results with some countries experiencing a decrease in emission due to increased innovation, it is expected that the relationship will likely sway to being negative rather than positive. Moreover, analyzing the most recent data to 2018 differentiates this thesis from the article by Mensah et al. (2018). This change is expected to support a negative relationship due to the rapid global changes taking place in favor of environmental action and attitudes. This brings about fourth hypothesis regarding general innovation and CO2 emission.

H4: Countries with a higher number of patent applications for general technology will have less CO2 emissions, considering the years 1990-2018.

A few years after the Mensah et al. (2018) study, W. Li et al. (2021) examined the effect of general technology patents on CO2 emission per capita in China through a FE panel quantile regression estimator covering 2003-2016. They employ the natural logarithms of CO2 emission per capita and accepted patent counts. Alongside a full sample analysis, they also perform separate regressions for subsamples of more-developed provinces and less-developed provinces. In addition, they include a squared term for patent count to test for the presence of a non-linear relationship. Their full sample analysis produced a significant and positive coefficient for patents and a significant and negative coefficient for the squared-term patents. They explain this observed effect of an inverse U-shape effect of patents on CO2 emission by hypothesizing that higher levels of innovative activity will likely lead to greener or more environment-friendly patented innovation. In their subsample study of the more-developed Chinese provinces, they find that the coefficient for patent count is negative and significant, while the squared-term for patents is positive and significant. This indicates that for more-developed regions, patents will decrease pollution when at a lower patent level while they will increase pollution after passing a certain threshold of number of patents. The sample with less-developed provinces gives similar results to the full sample, with an inverse U-shape effect. The different effect found for more-developed provinces is explained, like in the article by Mongo et al. (2021), through the “rebound effect” of increased innovation. The increased efficiency in energy conservation through green technology will cause demand for energy to exceed the amount of energy conserved, thereby leading to increased pollution despite the improved green technology (W. Li et al., 2021).

W. Li et al. (2021) concludes that there is a non-linear relationship for general technology, measured in patents, on CO2 emission that takes on a U-shape for more-developed Chinese regions. Thus, an economically developed region that raises its number of patent applications will first experience a decrease in CO2 emissions, while later experiencing diminishing marginal effects and possibly a positive relationship as the level of patents further increases. The previous research on general technology, measured through R&D expenditure, reached similar conclusions. As mentioned in the previous section, the article by L. Li et al. (2021) discovered an inverted U-shape effect of general technology innovation, in the form of R&D expenditure, on CO2 reduction in their subsample of economically developed countries. In addition, Ibrahim and Vo (2021) also observe a U-shape effect of innovation on CO2 emission for 27 industrially developed countries. Based on these observations, the following hypotheses are constructed.

H5: A country that increases its number of patent applications for general technology over time will experience a decrease in its CO2 emission, considering the years 1990-2018

H6: The negative effect of a country's number of general technology patent applications on its CO2 emission will experience diminishing marginal returns, considering the years 1990-2018.

2.5 Green Technology Patents and Pollution

An interesting addition to the analysis of the effect of innovation on CO2 emission is to explore a variable that is specifically targeted towards the output of green technological innovation, with the goal to observe what happens when focusing on green innovation relative to focusing on general technology. Such a variable that is also available for empirical analysis is the number of environment-related patent applications. Therefore, in the following section, a selection of empirical studies investigating the relationship between environmental innovation, measured through green patents, and CO2 emissions will be explored. Two papers analyzing the between-country relationship will be mentioned and employed for hypothesis development, followed by various articles and a hypothesis on the within-country relationship.

Cheng, Ren, Wang, and Yan (2019) examined the effect of environmental patents on CO2 emissions per capita of Brazil, Russian Federation, India, Indonesia, China and South Africa (BRIICS) from 2000-2013. In their empirical analysis, the authors used a pooled OLS model, OLS one-way fixed-effect model, and OLS two-way fixed effect model. The latter two models produced a significant coefficient. The estimated parameters showed a positive relationship between the number of patents in environment-related technology and CO_2 emission. In the same year, another article exploring the relationship between eco-patents and CO_2 emissions was published. Different from Cheng et al. (2019), this study by Mensah, Long, Dauda, Boama, and Salman (2019) observed OECD economies and divided their research into four subsamples: OECD America, OECD Asia, OECD Europa, and OECD Oceania. However, the article does not state which exact countries it has included in the samples. Mensah et al. (2019) explored this relationship through a pooled OLS model covering the years 1990-2015. The pooled OLS estimations give a negative significant coefficient of eco-patents on CO_2 emission in the model containing all OECD countries and the subsamples with OECD America, OECD Europe, and OECD Oceania. For the sample with all OECD countries, a unit increase in eco-patents lowers CO_2 emission by 17%. Moreover, a unit increase of eco-patents lowers CO_2 emission by 15% and 16% for the OECD America and OECD Europe subsamples. The coefficient for OECD Asia was insignificant at 10% significance level. Mensah et al. (2019) explain that the overall negative effect of eco-patents on CO_2 emission in OECD countries can be a consequence of increased efforts by the OECD to employ green technology as a tool in their battle against climate change.

In summary, Cheng et al. (2019) observed that BRIICS countries with a high number of eco-patents will have higher CO_2 emission. However, Mensah et al. (2019) explored the relationship with more recent data and countries that overlap with this thesis' sample including the EU-15 and the U.S., and subsequentially found a negative relationship between eco-patents and CO_2 emission. In comparison, the research by Cheng et al. (2019) employs a sample that is different to this thesis except the inclusion of China and uses less recent data. Hence, the following hypothesis is presented.

H7: Countries with a higher number of patent applications for environment-related technology will have less CO_2 emission, considering the years 1990-2018.

Cheng et al. (2019) also employed an FE regression estimator in their analysis of eco-patents on CO_2 emissions in the BRIICS countries. The coefficients are estimated for 11 different percentiles of CO_2 emission per capita, and only the coefficient of eco-patent for the 90^{th} and 95^{th} percentile was statistically significant at 10% significance level. The estimated significant coefficients are positive, indicating a positive effect of eco-patents on emissions. Cheng et al. (2019) attribute this positive relationship to innovation diffusion challenges. Some of these challenges include lack of environmental market-based regulation to directly lower CO_2 emissions through regulatory pressure and indirectly by encouraging eco-innovation diffusion, cost barriers to applying for a patent, and barriers in knowledge and technology sharing (Cheng et al., 2019).

Other articles that have used larger and/or different country samples than that of Cheng et al. (2019) when studying the effect of an increase of eco-patents on the CO2 emission within a country have reached a different outcome. Du, Li, and Yan (2019) studied the relationship between the number of green technology patents and CO2 emission while taking into consideration how the strength of this effect is impacted by a country's income level. To do so, they transformed all the variables into natural logarithms and estimated a FE model and a panel threshold model for 71 economies over the years 1996-2012. However, contrary to the previously examined literature, they did not find significant effects of green patents on CO2 emissions for the overall sample but did find a negative effect of green patents on emissions when a country is in a high-income group. This difference between low-income economies and high-income economies is attributed to a cost-benefit analysis. According to the authors, the cost of eco-innovation outweighs the benefit for low-income economies due to lack of sufficient government funds, production, marketing, and manufacturing capacity for cost-effective realization of innovation into society. Meanwhile, high-income economies have more financial and productivity breathing room to consider environmental technology as a realistic and beneficial extension to their standards of living through environmental quality improvement (Du et al., 2019).

Hashmi and Alam (2019) also explored the impact of eco-innovation on CO2 emissions for 29 OECD countries from 1999-2014. The authors transform all variables to natural logarithms and employ FE, RE, and two-step GMM estimators. The results show that environmental innovation and regulations, measured through number of environment-related patent applications and environment-related tax revenue, significantly reduce CO2 emissions (Hashmi & Alam, 2019). Guo et al. (2021) specifically studied the impact of eco-innovation on CO2 emission levels in China, looking at Chinese provinces from 1995-2017. In their study of the short- and long-run elasticity of eco-innovation, the authors found that an increase in environmental innovation causes CO2 emissions to fall. However, it should be noted that no empirical definition of the environmental innovation variable used is given in the article.

The studies outlined above that consider samples most alike that of the thesis have found a negative relationship between eco-innovation and CO2 emission. Even though Cheng et al. (2019) found that an increase in eco-patents led to an increase in CO2 emission for the BRIICS countries, a more recent study by Guo et al. (2021) on Chinese provinces revealed a negative relationship. Since this thesis will focus on the EU-15, US, and China, it is expected that a negative relationship will hold, leading to the eighth hypothesis.

H8: A country that increases its number of patent applications for environment-related technology over time will experience a decrease in its CO2 emission, considering the years 1990-2018.

2.5 Moderating the Effect of Eco-innovation on Pollution: Environmental Regulation

Literature can also give insight into factors that could potentially strengthen the relation between green technology innovation and CO_2 emissions. One promising moderating factor is the existence and strictness of environmental regulations in a country. Examples of such regulations include taxation on GHG emission levels and energy use, agricultural controls on use of chemicals, and imposed emission standards through pollution limits (Morley, 2012; OECD, 2021; Porter & van der Linde, 1995). Cheng et al. (2019) mentioned that "environmental regulation is crucial because it is the linkage between carbon mitigation and technological innovation and can bring environmental-related patents to the market" (p.1335). This supportive role of environmental regulation in promoting diffusion of green technology and reducing CO_2 emissions is explored both qualitatively and empirically in existing literature, which will be reviewed in the following section. Furthermore, in a discussion article on moderation analysis, Memon et al. (2019) emphasize the importance of theoretically exploring why and through which path one would expect a moderation effect to take place when choosing a moderator. Therefore, this section will first refer to literature that supports the presence of a strengthening effect of environmental regulation on the hypothesized negative relationship between the main independent variable, eco-innovation, and the dependent variable, CO_2 emission. Subsequently, studies will be referenced to lay a foundation for why one may also expect a direct relationship between environmental regulation and CO_2 emission. These findings will be brought together to form the final hypothesis.

Porter and van der Linde (1995) wrote a qualitative article in which they challenge a common belief that economic and environmental quality are in a constant battle with one another. They promote a dynamic perspective in which environmental regulation can push innovative activity. Innovation is not only able to reduce the environmental damage resulting from the production processes but can also lower a company's production costs by making use of its resources more efficiently. Nevertheless, the public and private sector, although both possibly pursuing the common goal of lowering environmental costs and increasing productivity, are often misaligned in their actions when attempting to reach this goal. Regulations can be set in such a way that they hinder innovative activity, while instead of innovating, companies often respond negatively to regulations by trying to avoid or delay them. Yet, according to Porter and van der Linde (1995) this is no reason to write off regulations as a tool to stimulate innovation. They emphasize that there will always be a necessity for regulations as companies are often not fully informed, motivated, or capable of making eco-friendly changes through innovation. Nevertheless, they suggest that distinction should be made between 'good' and 'bad' regulation, in which 'good' is defined as regulation that gives companies breathing space to find their own solutions and determine their own optimal timeline (Porter & van der Linde, 1995). Based on this discussion of the interaction of innovation and environmental regulation, one can argue that environmental regulation can motivate businesses to adopt more eco-friendly technology.

Environmental regulation can thereby facilitate the diffusion of green technology alternatives into business practices and strengthen the reducing impact of innovation on CO_2 emissions by increasing the level of demand and adoption into society of eco-innovations.

The diffusion of green innovations into enterprise activities and the impact of public environmental policies on the development of diffusion has been analyzed by Fan et al. (2022). They structured an evolutionary game model which examines the intertwined effect of public environmental policy on eco-innovation of peer enterprises in China. To do so, they study three types of environmental public policy while accounting for "peer effect" among enterprises. The "peer effect" of innovation refers to the act of enterprises imitating the innovative activities and/or decisions of peer enterprises within similar industries when faced with lack of information or uncertainty (Fan et al., 2022). The three examined policies are all market-based regulations and include: green innovation incentive, environmental protection taxations, and innovation subsidy. Based on their model estimates, they conclude that public policies successfully spur diffusion of eco-innovations of same-industry enterprises. The strongest effect was found for the green innovation incentives and subsidies. Environmental taxation also positively influences green innovation diffusion under the condition that the tax is not too high since this will lead to high investment costs and hence discourage enterprises to consider green innovation (Fan et al., 2022). In summary, previous literature shines light on a possibility that environmental regulation, in the form of environmental protection taxation, can encourage the diffusion of green innovations among firms. Increased diffusion of green alternatives will likely then also positively influence environmental quality such as pollution levels.

There are studies considered here that have directly analyzed the impact of environmental regulation on pollution levels. First, Morley (2012) performed a two-step dynamic panel model for EU countries and Norway to analyze the impact of environmental taxation on GHG emissions and energy consumption within the period of 1995-2006. In doing so, environmental tax is presented as a taxation of which its environmental impact is proven (Morley, 2012). They found a negative and significant effect of two different measures of environmental taxation on GHG emission and a non-significant effect of environmental tax on energy consumption. They argue that this signifies that the reducing effect of the taxation on pollution is due to environment-friendly technology changes rather than alterations in energy consumption behavior. Furthermore, they found that the measure of environmental tax revenue as percentage of total tax revenue is empirically more significant than the measure of environmental tax revenue as percentage of total GDP (Morley, 2012).

Second, Ulucak, Danish, and Kassouri (2020) explore the relationship between environmental regulation and CO_2 emissions for Brazil, Russia, China, India and South Africa (BRICS) from 1994-2015 while controlling for per capita GDP, patents and energy-related technologies. They use a model that allows for non-linear variable analysis based on various globalization levels. For lower globalization levels, they found significant positive estimates for both environmental taxation policy and environment-related technological progress in relation to CO2 emissions. The estimate for number of environment-related patents as explanatory variable for CO2 emissions was not significant. For the higher levels of globalization, environmental taxation, environment-related technological progress, and green patent applications significantly reduce CO2 emissions. Therefore, they conclude that increased globalization improves the effectiveness of taxation and eco-innovation on CO2 emissions. They argue that this may be observed due to political and societal awareness for climate change, easier diffusion and sharing of technology, and institutional strength in globalized economies (Ulucak et al., 2020).

In conclusion, theoretical analysis gives rise to the expectation that environmental regulation, if accommodative to businesses' own solutions and timelines, will stimulate diffusion of innovation among business by promoting competitiveness and reducing environmental damage (Porter & van der Linde, 1995). In addition, game model analysis indicates that there is a possibility that environmental taxation, if not too heavily imposed, will stimulate diffusion of green innovation among same-industry firms (Fan et al., 2022). When considering the impact of regulation on pollution, Morley (2012) concluded that environmental taxation has a negative impact on GHG emissions which is likely due to increased green technology rather than reduced energy consumption. Ulucak et al.'s (2020) panel analysis of environmental taxation and eco-innovation on CO2 emissions in BRICS countries found that both significantly reduce pollution conditional on that a country has relatively high globalization level. This brings about the final hypothesis of this thesis.

H9: The negative effect of the number of patent applications for environment-related technology in a country on its CO2 emission will be strengthened by an increase in environmental taxation, considering the years 1994-2018.

3. Data

As mentioned in the introduction, the basis of the collected data and conducted research in this thesis is inspired by the article by Fernández et al. (2018). This empirical article explores the relationship between aggregate R&D expenditure and CO2 emission levels in three regions including China, U.S., and EU-15, while controlling for economic growth proxied by final energy consumption.

This thesis's dataset therefore includes CO2 emissions, gross domestic spending on R&D (as percentage of GDP), and total final energy consumption. In addition to the data collection inspired by Fernández et al. (2018), some changes have also been made in this thesis. For H4-H6, data on total patent applications in general technology will be collected since this is analyzed as main explanatory variable instead of total R&D expenditure on general technology. For the hypotheses on eco-innovation (H7-H8), data is collected on the total number of green patent applications as this will be the main independent variable instead of R&D expenditure. The final hypothesis (H9) will also involve the collection of data on environmentally related tax revenue as moderating variable. Finally, additional control variables besides total final energy consumption and a lagged dependent variable will supplement the dataset and analysis of all hypotheses. These control variables are population and trade openness. Their selection and relevance have been established by the extended version of the STIRPAT framework that is employed in the studies on CO2 emission determinants and by empirical studies that examine the significance of population and/or trade openness in relation to CO2 emission levels (Dietz & Rosa, 1997; Hashmi & Alam, 2019; Mongo et al., 2021).

The data will be collected from China, the U.S., and EU-15. Different from the research conducted by Fernández et al. (2018), this thesis will observe all countries in one full sample instead of looking at three separate regions and will cover the years 1990-2018 instead of 1990-2013 due to the availability of newer data. Most of the variable measures are available up to 2019; however, green patent data is available up to 2018 and hence it was chosen to perform the analysis on the data for 1990-2018 to ensure consistency. All variables are measured on year basis.

A full description, measurement, and data source for each variable will be provided below. The dependent variable and independent variables of interest will first be described, followed by a description of the moderating and control variables. Finally, summary statistics of all the variables will be presented.

3.1 Dependent Variable

CO2 Emission

The dependent variable (CARBON) is measured as CO2 emissions in tonnes per capita and originates from the International Energy Agency (IEA) Greenhouse Gas Emissions from Energy Highlights (International Energy Agency, 2021a). This variable estimate is inspired by Fernández et al.’s (2018) original work; however, the data used by the authors of CO2 emission from fuel combustion in million tonnes is not freely accessible. Therefore, CO2 emission per capita in tonnes will be used instead. Ibrahim and Vo (2021), and Du et al. (2019) also included a CO2 emission measure per capita as dependent variable in their regressions. The data on CO2 emission is observed for the years 1990-2018.

Additionally, a variable of CO2 emission lagged by one year will be added to the model as a control variable. This added variable is inspired by Fernández et al.’s (2018) conducted research, in which a lagged CO2 variable was used to solve an autocorrelation issue found in their Durbin Watson statistic estimations in their models for the EU-15 and China. The emission in the current year is dependent on the emission level in the previous year. Hence, serial correlation of the error terms would exist if the lagged variable for CO2 emission is not included in the model.

Figure 1 displays the mean CO2 emission per capita measured over the years 1990-2019 in China, the US, and the 2019 top five CO2 emitters per capita from the EU-15 countries (Belgium, Finland, Luxembourg, Germany, and the Netherlands). As can be seen, Luxembourg is the highest polluter per capita in 1990 and converges over the years with the US's CO2 emissions after a rapid decrease around 1994. According to the Energy Policy Review by the International Energy Agency (2020), the surprisingly high CO2 emission by Luxembourg despite its small country size can be attributed to economic and population growth. Furthermore, they emphasize the impact of non-resident commuters and fueling stops of freight trucks on the CO2 emission in Luxembourg (International Energy Agency, 2020). China emits the lowest mean level of CO2 per capita, which is notable considering its reputation as large polluter (Vanessa, 2021). Nevertheless, its vast population may explain the lower per capita measurements and its emission level has been steadily increasing from 2000 onwards.

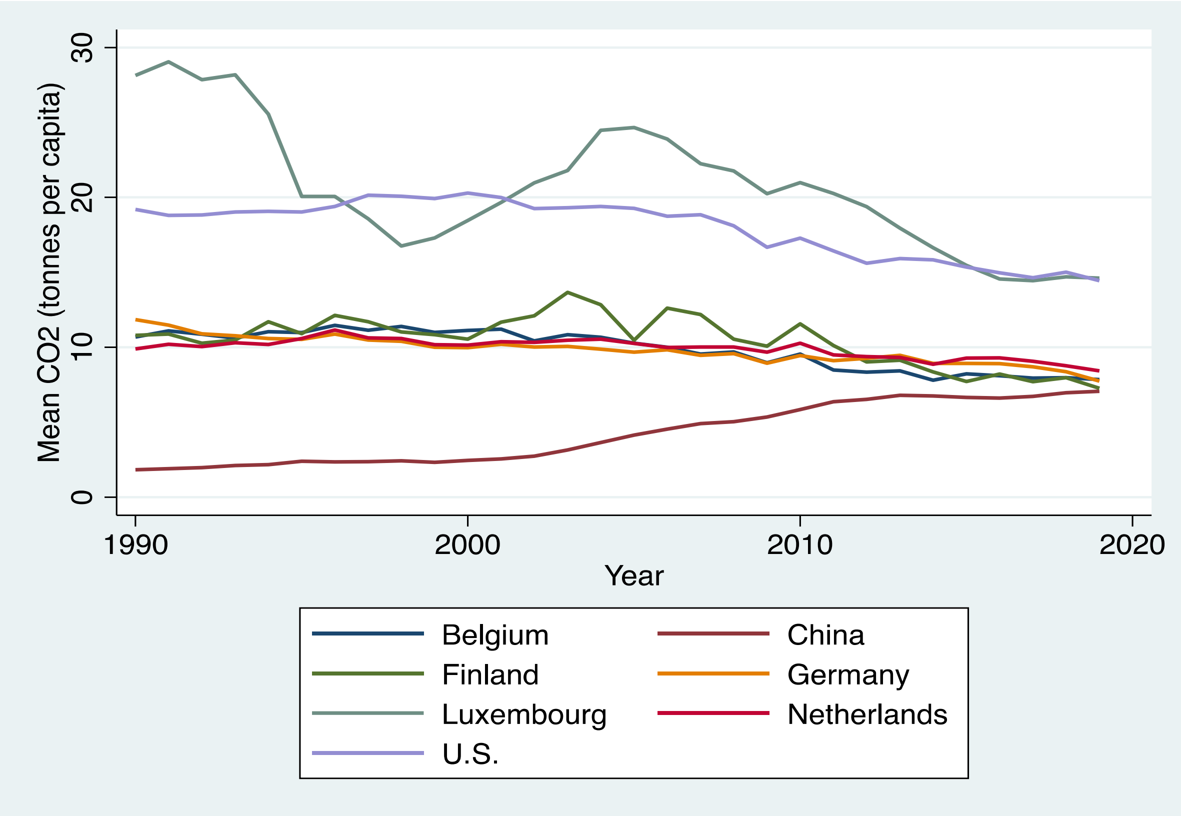

Figure 1. Mean CO2 emission per capita over the years for China, the US, and top five polluters per capita from the EU-15

3.2 Independent Variables of Interest

Domestic R&D Expenditure

Per the empirical research by Fernández et al. (2018), the independent variable of interest for H1-H3 is defined as the gross domestic spending on R&D (RD), measured in million US dollars with 2015 as base year and Purchasing Power Parities. This is collected from the OECD (2022b). Different from the data used by Fernández et al. (2018), the data used for R&D expenditure will be measured in per capita and covers the years 1990-2018.

General Technology Patents

The independent variable of interest for H4-H6 (PATENT) uses the measure of all patent application counts filed under the Patent Co-operation Treaty (PCT) in all technology areas in the inventor(s)'s country(ies) of residence from the OECD (2022c). The reference date is the priority date. The total patent counts include the following technology fields: ICT, artificial intelligence, biotechnology, nanotechnology, environment-related technologies, and health (OECD, 2022c). This thesis will measure PATENT as the total patent applications in all technology areas, except environment-related technology, per capita. This measure was collected by subtracting the total patent count in all technology fields by the patent count in environment-related technology, and subsequently dividing it by the population to get a per capita measure. The latter measure of environment-related patents will be further explained below. The data was collected for the years 1990-2018.

Green Patents

The independent variable of interest for H7 and H8 (ECOPATENT) uses the measure of the total patent application counts filed under the PCT in environment-related technologies in the inventor(s)'s country(ies) of residence from the OECD (2022c). The reference date is the priority date. The total environment-related patent count includes "climate change mitigation technologies related to buildings", "climate change mitigation technologies related to energy generation, transmission or distribution", "capture, storage, sequestration or disposal of greenhouse gases", "environmental management", "climate change mitigation technologies related to transportation", "climate change mitigation technologies in the production or processing of goods", and "climate change mitigation technologies related to wastewater treatment or waste management" (OECD, 2022c). Inspired by the measurement of environment-related inventions in the research by Cheng et al. (2019), this thesis will also measure ECOPATENT as the environment-related technology patents per capita. The data was collected for the years 1990-2018.

3.3 Moderating Variable

Environmentally Related Tax Revenue

For the final hypothesis, environmentally related tax revenue (ECOTAX) is analyzed as moderating variable. The chosen measurement used for this thesis' research is environmentally related tax revenue over all tax bases (energy, transport, pollution, and resources) as a percentage of total tax revenue. The data for this variable is obtained from OECD (2022d). The decision to measure environmentally related tax revenue as percentage of total tax revenue was based on the research by Morley (2012) in which it was concluded that environmentally related tax revenue as percentage of total tax revenue is empirically more significant than the measure of environmental tax revenue as percentage of total GDP. Measuring environment-related tax revenue relative to a country's economic size, such as total tax revenue or GDP, will also give insight into the effect of stringency and magnitude of environmental taxation. The collected observes the years 1994-2018 as data from years earlier were not available.

3.4 Control Variables

The STIRPRAT framework for CO2 emission determinants is the overarching deciding factor in the selection of control variables in the study of (eco-)innovation on CO2 emission. This framework identifies population, affluence, (eco-)technology, and environmental regulation as the major driving factors of CO2 levels in countries. The technology and regulation components have been incorporated in the heart of this study through the examination of (green) innovation as main explanatory variable and environmental regulation as moderator variable. Measures of affluence and population will therefore be included as control variables to complete the selection of factors and because studies have shown that they have a significant impact on country-level CO2 emission (Fernández et al., 2018; Hashmi & Alam, 2019; Neves et al., 2020). Affluence will be measured as final energy consumption and population through a total population measure. An addition is made by also including trade openness, which influences CO2 levels through its effects on production level, industrial structure, and flow of technology (Du et al., 2019). Thus, this group of controls cover varying aspects in society that can be considered impactful on CO2 emission. Together with the main explanatory variables and moderator variable, a complete selection of determinants of CO2 emission is given through these control variables as suggested by the STIRPRAT framework indicators with the extension of trade openness. Further detailed reasoning and specifications will be provided in the section below for each control variable.

Final Energy Consumption

For a measure of affluence, total final energy consumption was selected to serve as a proxy for economic growth. The use of this variable as proxy was inspired by the argument given by Fernández et al. (2018) that GDP and energy consumption are closely intertwined, while also both considered influential for the level of $CO2$ within a country. The authors argue that the empirical model benefits from including only one of these closely related variables as measurement of economic growth, and thereby incorporate final energy consumption in their model. Moreover, in their exploration of determinants of CO2 emission levels in OECD countries from 1980-2011 using the STIRPAT econometric model, Shafiei and Salim (2014) found a significant negative relationship between renewable energy consumption and CO2 level and a positive significant relationship between non-renewable energy consumption and CO2 level in the long run. Therefore, total final energy consumption (ENERGYCON) is added to this thesis's empirical analysis as a control variable.

The data for ENERGYCON is obtained from the "World Energy Balances Highlights" dataset by the International Energy Agency (2021b). The total final energy consumption includes the total final consumption of heat, electricity, renewables and waste, nuclear, natural gas, oil products, crude, NGL, feedstocks, coal, peat, and oil shale energy. The measure used by Fernández et al. (2018) is in millions of tonnes; however, the available International Energy Agency (2021b) dataset only observed the variable values measured in petajoules (PJ). The collected data will be measured in per capita and covers the years 1990-2018.

The decision to measure total final energy consumption and R&D expenditure per capita instead of total was inspired by other articles such as Du et al. (2019) and Cheng et al. (2019), and deviates from the data analysis by Fernández et al. (2018). The reason behind this is that per capita will also account for the population size of a country in relation to measuring whether energy consumption or technology is 'high' or 'low'. The measure of total population used to transform the variables of ENERGYCON, RD, PATENT and ECOPATENT is the same as the one employed for the control variable for population detailed below.

Total Population

For the population element of the STIRPRAT framework, a control is included for the total population of each country in the sample. In an empirical study of the STIRPAT model, Bargaoui et al. (2014) used panel data on 214 countries over the years 1980-2010. They found in their FE model that population has a positive and significant effect on CO2 emission for the sample with all countries as well as the samples differentiated based on continent. With a focus on the STIRPRAT framework, Hashmi & Alam (2018) concluded through a FE, RE, and GMM regression of OECD countries over the years 1999-2014 that total population size has a significant positive effect on CO2 emissions. From the five variables explored, population, GDP per capita, environmental patent count, non-environmental patent count, and environmental tax revenue per capita, the effect of population size was the highest in magnitude for all models (Hashmi & Alam, 2019). A prevalent positive effect of total population (POP) is therefore expected for the analysis on CO_2 emission the control variable is therefore added to this thesis' empirical analysis.

The data for total population size is obtained for each country from the World Bank and covers the period of 1990-2018. The population measure is defined as "all residents regardless of legal status or citizenship" and the estimated values are collected in the middle of the year (World Bank Group, 2022).

Trade Openness

Trade openness (TRADE) is included as a final additional control variable. This variable does not fall directly into the STIRPRAT framework that is employed as umbrella for determining the control variables; however, there is strong indication that its effects on CO_2 emission are significantly strong and fall into a category of its own. The level of international trade has been related to varying factors that can influence CO_2 emission levels within a country. First, international trade widens the market of consumers that companies can cater to, thereby potentially increasing production level and subsequently CO_2 emission. Second, the environmental effects of international trade can differ depending on the level of economic development of a country (Mongo et al., 2021).

Du et al. (2019) found that countries can experience a decrease in CO_2 emissions due to increased trade. In their FE regression of 71 countries from 1996-2012 for the analysis of green innovation and CO_2 emission, they found that trade openness (ratio of trade to GDP) has a negative significant effect on CO_2 emissions. Mongo et al. (2021) attempted to specify the effect of international trade based on the income of the country. They hypothesized that developed economies often have stricter environmental regulation which causes them to specialize in greener industries while the pollutive industries and production processes are moved to developing economies with loser regulation (Mongo et al., 2021). Yet, using an ARDL model for the EU-15 countries with panel data covering 23 years, Mongo et al. (2021) found that economic openness (sum of imports and exports as a percentage of GDP) has a significant positive effect on CO_2 emissions. This finding went against the expectation that increased trade has a positive effect on a developed country's environment.

Even though the direction of the effect differs between studies, the conclusions show that there is a significant effect of trade level on CO_2 emission. International trade also affects the flow of technology and information between countries (Mongo et al., 2021). More international trade could thereby imply that a country has access to more (green) technology which would impact both its CO_2 emission as well as its level of innovation (Mongo et al., 2021). This suggests that employing international trade as control variable could also deal with a potential omitted variable bias that would occur if it's excluded from the model. Therefore, trade openness is included as the last control variable in the form of "transactions in goods and services between residents and non-residents" as a percentage of GDP. The data for the variable is obtained from the OECD (2022e) and covers 1990-2018.

3.5 Summary Statistics

The summary statistics and the data sources of all variables are given in in Table 1. All variables are transformed to natural logarithms and the descriptive statistics of the transformed variables are displayed below. The statistics indicate that Ln(ECOTAX) contain data starting from 1994 instead of 1990. Furthermore, the panel dataset is balanced since there are the same number of time periods for each country (Wooldridge, 2012). However, observation numbers vary with Ln(ECOTAX) having less than 493 observations due to the restrained time frame, 6 missing values for China and 2 missing values for the US. Ln(RD) also has 31 less observations than the others due 12 missing values for Luxembourg and spread-out missing values among other countries. All variables have between and within standard deviation values, which indicates that they are all time-variant. Last, ECOPATENT is the only variable that contains values of zero, which will produce missing values once transformed into natural logarithms. A value of 1 was added to the count of eco-patents for all observations before the variable was transformed to a per capita variable and then transformed into a natural logarithm. This caused the previously eight dropped observations of zero to now be included in the dataset, leading to a total of 493 observations for Ln(ECOPATENT).

Table 1. Summary Statistics and Sources of Variables

Variable	Years	Number of countries	Obs.	Mean	Std. deviation	Min.	Max.	Source*
Ln(CARBON)	1990-2018	17	493	2.092	.463	.610	3.369	IEA
Ln(RD)	1990-2018	17	462	-7.416	.904	-11.384	-6.316	OECD
Ln(PATENT)	1990-2018	17	493	-10.044	1.735	-19.473	-8.064	OECD
Ln(ECOPATENT)	1990-2018	17	493	-12.202	1.721	-20.864	-9.726	OECD
Ln(ECOTAX)	1994-2018	17	417	1.901	.285	1.027	2.444	OECD
Ln(ENERGYCON)	1990-2018	17	493	-9.072	.498	-10.627	-7.905	IEA
Ln(POP)	1990-2018	17	493	16.843	1.777	12.853	21.062	WB
Ln(TRADE)	1990-2018	17	493	3.599	.628	2.201	5.286	OECD

*Abbreviations for sources elaborated on in Table 9, Appendix A

4. Methodology

4.1 Pooled OLS

A pooled OLS model will be employed for the examination of H1, H4 and H7. Fernandez et al.'s (2018) study inspired the empirical research of this method. In their methodology, they opted for a separate OLS regression with time series data for each of the three regions. For this thesis, an alternative route of employing a pooled OLS regression method on all 17 countries is chosen for the following reasons. Performing a separate regression for each region (China, the US, and EU-15) would lead to a small number of observations and pooled OLS regression is suitable for panel data across varying countries. A pooled OLS regression model will therefore be used to examine the impact of R&D expenditure, patents in general technology, patents in green technology on CO2 emissions for 17 countries over the time span of 1990-2018. Per the research by Fernández et al.

(2018), all the variables are converted to natural logarithms to allow for an elasticity interpretation of the estimated coefficients. Hence, a 1% change in one of the independent variables will results in a % change in the dependent variable as indicated by the given coefficient (Fernández et al., 2018).

Different to the OLS analysis by Fernandez et al. (2018), the estimated equation for this thesis will include year fixed effects. By adding dummy variables for each year, the estimation will control for aggregate time effects (Wooldridge, 2001). The pooled OLS models for H1, H4, and H7 are as follows:

$$\boldsymbol{H1}: Ln(CARBON)_{it} = \beta_0 + \beta_1\, Ln(RD)_{i,t-2} + \beta_2\, Ln(ENERGYCON)_{it} + \beta_3\, Ln(CARBON)_{i,t-1} + \beta_4\, Ln(POP)_{it} + \beta_5\, Ln(TRADE)_{it} + \alpha_i + \varepsilon_{it} \quad [1.1]$$

$$\boldsymbol{H4}: Ln(CARBON)_{it} = \beta_6 + \beta_7\, Ln(PATENT)_{i,t-2} + \beta_8\, Ln(ENERGYCON)_{it} + \beta_9\, Ln(CARBON)_{i,t-1} + \beta_{10}\, Ln(POP)_{it} + \beta_{11}\, Ln(TRADE)_{it} + \alpha_i + \varepsilon_{it} \quad [1.2]$$

$$\boldsymbol{H7}: Ln(CARBON)_{it} = \beta_{12} + \beta_{13}\, Ln(ECOPATENT)_{i,t-2} + \beta_{14}\, Ln(ENERGYCON)_{it} + \beta_{15}\, Ln(CARBON)_{i,t-1} + \beta_{16}\, Ln(POP)_{it} + \beta_{17}\, Ln(TRADE)_{it} + \alpha_i + \varepsilon_{it} \quad [1.3]$$

$t = the\ year = 1,2, \dots, 29$
$i = country$
$\varepsilon_{it} = idiosyncratic\ shock/error$
$\alpha_{\ i} = individual\ heterogeneity$

In line with the empirical method employed by Fernández et al. (2018), the R&D expenditure variable is lagged by two years. This is done with the assumption that it takes time for the expenditure input to materialize into actual new technology that may subsequently influence CO2 levels (Fernández et al., 2018). The variables Ln(PATENT) and Ln(ECOPATENT) will also be lagged for two years. Even though patents are considered an output measure of innovation, it is expected that it may also take time for the patents to turn into innovation that is introduced and diffused within areas of society and thereby potentially affecting CO2 emission. Due to the inclusion of a lagged explanatory variable and a lagged dependent variable, the models employed in this thesis can be described as dynamic autoregressive-distributed lag (ADL) models. This model consists of the dependent variable as a function of the dependent variable lagged by one period, explanatory variables in current and/or lagged form, and an error term (Bond, 2002).

Pooled OLS is the preferred linear estimator if the individual heterogeneity is uncorrelated with the independent variable and that the idiosyncratic shock is uncorrelated with the independent variable, and there is no serial correlation. The condition of no serial correlation is met if the error terms in two different time periods are uncorrelated, conditional on the independent variable (Wooldridge, 2012). However, it is expected that unobserved time-invariant characteristics unique to a country will be correlated to the explanatory variable of interest, (green) innovation. For example, the work culture such as presence of work hierarchy and productivity attitudes in a country generally stays fixed over longer periods of time and may be of influence on the level of innovation attained and level of CO2 emitted in a country. This would mean that the pooled OLS estimates may be biased and that use of another model is preferred (Wooldridge, 2001).

Between-variation will therefore likely be a source of correlation between the individual heterogeneity and the dependent variable since time-invariant unobserved characteristics may influence the estimated effect of the independent variables on the CO2 emission levels. It is beneficial to eliminate this form of variation (Wooldridge, 2001). As presented in the theoretical framework, several empirical papers have opted for a different approach to pooled OLS for examining cross-country panel data on pollution levels. Among those articles, Cheng et al. (2019) first estimated (pooled) OLS models and concluded that FE estimation was preferred due to its acknowledgement and elimination of the effect of individual heterogeneity.

The RE model is another alternative that uses both between and within variation, but accounts for serial correlation of the errors. Serial correlation is probable in panel data and occurs when the error terms of the same country in two different years are correlated, which leads to invalid estimated standard errors and therefore unreliable significance levels. RE only solves the issue of serial correlation, not bias issues with individual heterogeneity and/or idiosyncratic shock. If one is interested in the effect of a time-variant explanatory variable and it is likely that time-invariant unobserved variables will influence the explanatory variable's estimated effect, as is the case for this thesis' research question, the FE model is preferred (Wooldridge, 2012). To make a definite decision of which of these two models is the best fit, the Hausman test will be employed.

4.2 Hausman Test

Two possible empirical panel models that are presented as better fitting alternatives to the Pooled OLS moder are the RE and FE models. Both these models are the best-fit conditional on that the idiosyncratic shock is uncorrelated with the dependent variables. The RE model also requires the individual heterogeneity to be uncorrelated with the independent variables. As mentioned before, the latter condition is likely not met and hence it is expected that the FE model is the preferred alternative. The Hausman Test will be employed to confirm this choice.

This test compares the estimated coefficients of the time-variant variables from the FE and RE model. If the difference between the estimated coefficients is significant, it can be assumed that time-invariant unobserved variables are of importance and hence the RE estimated coefficients will likely be biased and the FE model will be a better fit as this model eliminates the time-invariant characteristics (Wooldridge, 2001). The Hausman test considers a null hypothesis that states that there is no systematic difference in the RE and FE coefficients. Rejection of the null hypothesis implies that time-invariant unobserved variables (individual heterogeneity, α_i) are of importance and that the FE model is the better choice.

4.3 Fixed Effects

The FE model applies a pooled OLS after time-demeaning all variables in the equation, and thereby eliminates the individual heterogeneity as this does not change across time (Wooldridge 2012). For each country, the equations 1.1-1.3 are each averaged over time, and the original equations 1.1-1.3 are then each subtracted from the averaged equation. Since the individual heterogeneity stays the same regardless of time, it is eliminated from the equation (Wooldridge, 2012). The transformation of the equation for H2 with R&D expenditure as main explanatory variable is shown below as example.

$$\boldsymbol{H2}: Ln(CARBON)_{it} - \overline{Ln(CARBON)_i} = \beta_{18}\left(Ln(RD)_{i,t-2} - \overline{Ln(RD)_i}\right) + \beta_{19}\left(Ln(ENERGYCON)_{it} - \overline{Ln(ENERGYCON)_i}\right) + \beta_{20}\left(Ln(CARBON)_{i,t-1} - \overline{Ln(CARBON)_i}\right) + \beta_{21}\left(Ln(POP)_{it} - \overline{Ln(POP)_i}\right) + \beta_{22}\left(Ln(TRADE)_{it} - \overline{Ln(TRADE)_i}\right) + \left(\varepsilon_{it} - \overline{\varepsilon_i}\right) \quad [2.1]$$

The final FE equations with the time-demeaned variables for H2, H3, H5, H6, and H8 are shown below. The models will include year fixed effects. Inspired by the study of W. Li et al. (2021) on a non-linear relationship between general technology, measured in patents, and CO2 emission, the equations for H3 and H6 will include a squared term of the natural logarithms of R&D expenditure (H3) and general technology patents per capita (H6).

$$\boldsymbol{H2}: Ln(CA\ddot{R}BON)_{it} = \beta_{18}\, Ln(\ddot{RD})_{i,t-2} + \beta_{19}\, Ln(ENER\ddot{G}YCON)_{it} + \beta_{20}\, Ln(CAR\ddot{B}ON)_{i,t-1} + \beta_{21}\, Ln(P\ddot{O}P)_{it} + \beta_{22}\, Ln(TR\ddot{A}DE)_{it} + \ddot{\varepsilon}_{it} \quad [2.2]$$

$$\boldsymbol{H3}: Ln(CA\ddot{R}BON)_{it} = \beta_{23}\, Ln(\ddot{RD})_{i,t-2} + \beta_{24}\, Ln(\ddot{RD})^2_{i,t-2} + \beta_{25}\, Ln(ENER\ddot{G}YCON)_{it} + \beta_{26}\, Ln(CAR\ddot{B}ON)_{i,t-1} + \beta_{27}\, Ln(P\ddot{O}P)_{it} + \beta_{30}\, Ln(TR\ddot{A}DE)_{it} + \ddot{\varepsilon}_{it} \quad [2.3]$$

$$\boldsymbol{H5}: Ln(\ddot{C}ARBON)_{it} = \beta_{31}\, Ln(PAT\ddot{E}NT)_{i,t-2} + \beta_{32}\, Ln(ENER\ddot{G}YCON)_{it} + \beta_{33}\, Ln(CAR\ddot{B}ON)_{i,t-1} + \beta_{34}\, Ln(P\ddot{O}P)_{it} + \beta_{35}\, Ln(TR\ddot{A}DE)_{it} + \ddot{\varepsilon}_{it} \quad [2.4]$$

$$\boldsymbol{H6}:\ Ln(\ddot{C}ARBON)_{it} = \beta_{36}\, Ln\big(PAT\ddot{E}NT\big)_{i,t-2} + \beta_{37}\, Ln(PAT\ddot{E}NT)^2_{i,t-2} +$$

$$\beta_{38}\, Ln(ENER\ddot{G}YCON)_{it} + \beta_{39}\, Ln(CAR\ddot{B}ON)_{i,t-1} + \beta_{40}\, Ln(P\ddot{O}P)_{it} + \beta_{41}\, Ln(TR\ddot{A}DE)_{it} + \ddot{\varepsilon}_{it} \qquad [2.5]$$

$$\boldsymbol{H8}: Ln(\ddot{C}ARBON)_{it} = \beta_{41}\, Ln\big(ECOP\ddot{A}TENT\big)_{i,t-2} +$$

$$\beta_{42}\, Ln(ENER\ddot{G}YCON)_{it} + \beta_{43}\, Ln(CAR\ddot{B}ON)_{i,t-1} + \beta_{44}\, Ln(P\ddot{O}P)_{it} + \beta_{45}\, Ln(TR\ddot{A}DE)_{it} + \ddot{\varepsilon}_{it} \qquad [2.6]$$

It should be noted that the estimates from the FE model are only unbiased if the strict exogeneity assumption holds. This implies that the idiosyncratic shock is uncorrelated with the dependent variables at any time. It is therefore of importance to question whether there an unobserved time-variant variables that could be correlated to the independent variables of interest. Furthermore, it is important to consider whether there is serial correlation among the errors over time, since the FE (and pooled OLS) estimated standard errors will be invalid if this does not hold (Wooldridge, 2001). Robust standard errors clustered on country-level will be used to account for a possible presence of the autocorrelation (Kézdi, 2003).

4.4 Moderating Variable

Inspired by Memon et al.'s (2019) article on the moderation analysis, a conceptual framework of the moderation relationship is created and shown in Figure 2. The moderation effect of environmental taxation (M) on the relationship between (green) innovation (X) and CO2 emission (Y) is shown as an interaction term, X*M. The moderator variable impacts either or both the strength and direction of the effect of green (innovation) on CO2 emission (Andersson et al., 2014; Baron & Kenny, 1986; as described by Memon et al., 2019).

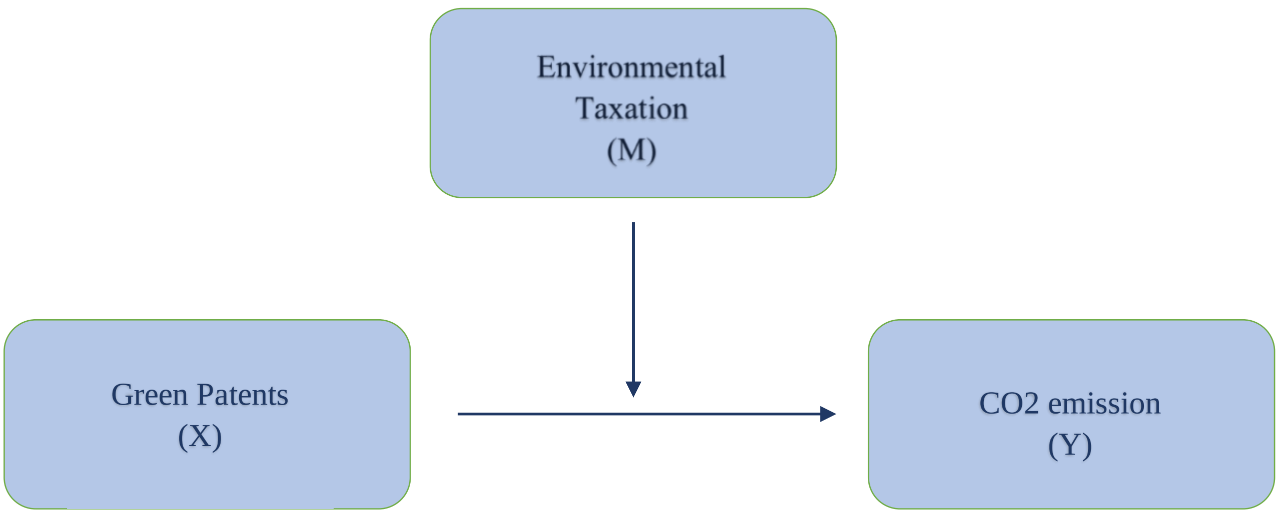

Figure 2. Conceptual Framework of Moderation Effect

Memon et al. (2019) states that moderator variables can be in the form of continuous variable, as is the case for this thesis, if it is interpreted through an interval scale (high and low level) and that one should not transform it into a categorical variable as this will bring about issues with testing for significance due to subsequential lowered statistical power (Cohen et al., 2003; Stone-Romero & Anderson, 1994; as described by Memon et al., 2019).

The moderator and the interaction term of the moderator with the main independent variable are incorporated into the FE regression equation alongside the main independent variable (green patent applications), the lagged variable for CO2 emission, and the three control variables. Whether or not environmental taxation is to be considered a moderator for the relationship between green innovation and CO2 emission is decided by whether the estimated coefficient for the interaction term, ECOTAX*ECOPATENT, is significant (Memon et al., 2019). The final FE regression equation including the moderation effect is shown below.

$$\boldsymbol{H9}: Ln(\ddot{CARBON})_{it} = \beta_{46}\, Ln\left(ECOP\ddot{A}TENT\right)_{i,t-2} + \beta_{47} Ln\left(EC\ddot{O}TAX\right)_{it} + \beta_{48}\left(Ln\left(ECOP\ddot{A}TENT\right)_{i,t-2} * Ln\left(EC\ddot{O}TAX\right)_{it}\right) + \beta_{49} Ln(ENER\ddot{G}YCON)_{it} + \beta_{50}\, Ln(CAR\ddot{B}ON)_{i,t-1} + \beta_{51}\, Ln(P\ddot{O}P)_{it} + \beta_{52}\, Ln(TR\ddot{A}DE)_{it} + \ddot{\varepsilon}_{it} \quad [3.1]$$

$t = 1,2, \ldots, 25$

Since the data for environmental taxation could be obtained only starting at 1994, the timeframe of the analysis for the third hypothesis is reduced to 1994-2018.

4.5 Multicollinearity

A multicollinearity test will be performed after running each regression. Multicollinearity occurs when two or more variables are linearly correlated at a high level, and it can lead to false signs of the coefficient estimates of the independent variables and large standard errors (Alin, 2010; Gujarati & Porter, 2010). The presence of multicollinearity is therefore of importance to the reliability of the coefficient interpretation (Alin, 2010). For each regression, pair-wise correlation is examined through a correlation coefficient matrix that corresponds to the estimated coefficients. A correlation coefficient of .8 or higher indicates a high likelihood that multicollinearity is present (Shrestha, 2020).

5. Empirical Results

5.1 Pooled OLS Regression

First, a pooled OLS regression model will be employed. As mentioned before, the results will give insight into the impact of R&D expenditure on general technology (model 1), patents for general technology (model 2), and patents for green technology (model 3) on CO_2 emissions for 17 countries over the time span of 1990-2018. This pooled OLS regression will employ clustered robust standard errors at country-level, year fixed effects, and include the following control variables: total final energy consumption, lagged CO_2 emissions, total population, and trade in goods and services. The results for H1, H4, and H7 are represented by Model 1, 2, and 3, in Table 2 below.

Table 2. Pooled OLS Regression Results for Model 1 (H1), Model 2 (H4), and Model 3 (H7)

Variables	(1)	(2)	(3)
$\text{Ln}(RD)_{i,t-2}$	-.026***		
	(.005)		
$Ln(PATENT)_{i,t-2}$		-.008***	
		(.002)	
$Ln(ECOPATENT)_{i,t-2}$			-008***
			(.002)
$\text{Ln}(ENERGYCON)_{it}$	.052***	.028*	.025*
	(.017)	(.014)	(.014)
$\text{Ln}(CARBON)_{i,t-1}$	.973***	.976***	.976***
	(.016)	(.014)	(.014)
$Ln(POP)_{it}$	.008***	.009***	.007**
	(.002)	(.002)	(.003)
$\text{Ln}(TRADE)_{it}$	.015**	.015**	.013*
	(.005)	(.006)	(.006)
Constant	.105	-.002	-.011
	(.183)	(.166)	(.161)
Year Fixed Effects	YES	YES	YES
R-squared	.990	.990	.990
Observations	428	459	459
Number of Countries	17	17	17
Years	1990-2018	1990-2018	1990-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

As can be seen in the results in Table 2, a significant negative relationship is found between (green) innovation, lagged by two years, and CO_2 emission in a country. The absolute coefficients for general technology patents and green technology patents are both .008, while the lagged R&D expenditure coefficient is relatively larger in absolute magnitude with a size of .026. Thus, a 1% increase in R&D

expenditure two years ago will lead to a .026% decrease in CO2 emitted in the current year in a country, ceteris paribus, significant at a 1% significance level. Moreover, a 1% increase in general technology patents per capita or environment-related technology patents per capita in two years ago will lead to a .008% decrease in CO2 emitted in the current year in a country, ceteris paribus, significant at a 1% significance level. Considering the magnitudes of each of these coefficients, the size of the effect of (green) technology on CO2 emission estimated in the Pooled OLS regressions is relatively small.

All control variables are significant at 10% significance level. In all three models, the lagged CO2 emission variable presents the highest magnitude with for, Model 1, a 1% increase in CO2 emission in the previous year leading to a .97% increase in C02 emission in the next year, ceteris paribus. Finally, total final energy consumption, total population, and trade in goods and services each have a positive significant relationship with CO2 emission. It should be noted that the R-squared value for all three models is very high, which could be because of the inclusion of the lagged dependent variable causing the percentage of the variation in the log of CO2 emission explained by the explanatory variables to be extremely high. A check was done to see if this is true by running the same three regressions without the lagged CO2 emission variable. Consequently, the R-squared values for the three models are lower but still relatively high without the lagged dependent variable: .712 for Model 1, .709 for Model 2, and .710 for Model 3.

Multicollinearity

Tables 10-12 in Appendix B show the pair-wise correlations for Model 1, Model 2, and Model 3 estimated by the Pooled OLS regression above. The correlation coefficients of the year dummies were estimated but excluded from the matrices displayed in the Appendix.

As can be seen in the three tables, a high likelihood of multicollinearity exists between the lagged CO2 emission and total final energy consumption with the absolute value of the correlation coefficient ranging between .879-.909. It is also possible that a multicollinearity issue exists between total population and trade in goods and services since the correlation coefficient ranges in absolute value between .728-.832. All other variables display correlation coefficients well below the threshold of .8. It is therefore expected that there may be an issue with multicollinearity within the models for lagged CO2 emission and final energy consumption, and for total population and trade.

Even though there is a higher likelihood for multicollinearity, none of the variables will not be removed from the models since it’s possible that their removal could introduce omitted variable bias (Gujarati & Porter, 2010). It is believed that these variables are strong determinants for CO2 emission and that they also could be related to the level of innovation.

5.2 Hausman Test

Due to the likely rejection of the assumption that the error term is uncorrelated with the independent variables and no autocorrelation presence of the Pooled OLS regression, a Hausman test is employed next to determine the best estimator, RE or FE, as alternative.

The Hausman statistics and p-values corresponding to each model are shown below in Table 3-5. For the three models with lagged R&D expenditure, patents in general technology, and patents in environment-related technology as main explanatory variable, the Hausman test produces a p-value less than 0.05 (see Table 3). The two models that test a non-linear relationship through including a squared-term for lagged R&D expenditure and lagged patents in general technology also produce a p-value less than 0.05 in the Hausman test (see Table 4). Last, the model that tests the moderation effect of environmental taxation on the relationship between lagged eco-patents and CO2 emission also produces a p-value less than 0.05 (see Table 5). The null hypothesis is thereby rejected for all models, meaning that unobserved individual heterogeneity influences the estimated coefficients. The FE model is therefore preferred for all models and will be employed as this controls for the time-invariant unobserved heterogeneity.

5.3 Fixed-Effects Regression

A FE regression estimator with clustered robust errors at country-level and year dummies is employed for further empirical analysis. Hypotheses 2, 3, 5, 6 and 8 will be tested using a FE model. The first three FE regression models estimated in Table 3 will analyze H2, H5, and H8 through the same equations as Table 2, but now using a FE estimator instead of the Pooled OLS estimator. Following this, H3 and H6 will be tested through a FE regression that also includes a squared-term of the main explanatory variable: lagged R&D expenditure and lagged patents per capita for general technology.

Results

Table 3 presents the results of the FE regression models and the Hausman test for H2 (Model 1), H5 (Model 2), and H8 (Model 3).

Table 3. Fixed-Effects Regression Results for Model 1 (H2), 2 (H5), and 3 (H8)

Variables	(1)	(2)	(3)
$\text{Ln}(RD)_{i,t-2}$	-.017		
	(.021)		
$Ln(PATENT)_{i,t-2}$		.014*	
		(.007)	
$Ln(ECOPATENT)_{i,t-2}$			.012
			(.007)
$\text{Ln}(ENERGYCON)_{it}$	.489***	.468***	.466***
	(.059)	(.081)	(.080)
$\text{Ln}(CARBON)_{i,t-1}$	.672***	.635***	.653***
	(.055)	(.060)	(.057)
$Ln(POP)_{it}$	-.026	.011	.021
	(.091)	(.074)	(.076)
$\text{Ln}(TRADE)_{it}$	.096***	.087**	.096***
	(.031)	(.030)	(.030)
Constant	5.044***	4.556***	4.301***
	(1.516)	(1.392)	(1.426)
Year Fixed Effects	YES	YES	YES
Hausman Statistics	135.73***	164.15***	165.77***
Observations	428	459	459
Number of Countries	17	17	17
Years	1990-2018	1990-2018	1990-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3 shows that, for Model 1 and 3, the explanatory variables for (green) innovation are not significant at 10% significance level. These insignificant coefficients are different from the Pooled OLS coefficients which produced, although relatively small in magnitude, negative and significant coefficients for R&D expenditure and green patents. Nevertheless, for Model 2, a positive significant coefficient is produced for general technology patents. A 1% increase in patents in general technology two years ago will lead to a .014% increase in CO2 emitted in the current year in a country, ceteris paribus, significant at a 10% significance level. Therefore, contrary to the Pooled OLS estimates, the FE estimate for general technology patents implies that an increase in non-green technology will lead to an increase in CO2 emission. The magnitude of the coefficient is, however, relatively small.

In all three models in Table 3, total final energy consumption, lagged CO2 emission, and trade produced positive coefficients, significant at 1% or 5% significance level. The magnitudes of the estimated coefficients for trade and total final energy consumption have increased compared to the pooled OLS estimator, while the magnitude of the coefficient for lagged CO2 emission has reduced. Contrary to the pooled OLS, the coefficient estimated by the FE regression for total population is now insignificant at 10% significance level for all three models.

Next, the FE regression results are presented in Table 4 for H3 (Model 1) and H6 (Model 2). These hypotheses are tested through equations that are like those from the previous models; however, now also including a squared-term for the explanatory variable of lagged general technology innovation (R&D expenditure and patents in general technology).

Table 4. Fixed-Effects Regression Results for Model 1 (H3) and Model 2 (H6)

Variables	(1)	(2)
$\text{Ln}(RD)_{i,t-2}$	-.263***	
	(.064)	
$\text{Ln}(\text{RD})^2_{\text{i,t}-2}$	-.014***	
	(.004)	
$Ln(PATENT)_{i,t-2}$		.003
		(.034)
$\text{Ln}(\text{PATENT})^2_{\text{i,t}-2}$		-3.922×10^{-4}
		(.001)
$\text{Ln}(ENERGYCON)_{it}$	.481***	.469***
	(.050)	(.081)
$\text{Ln}(CARBON)_{i,t-1}$	.614***	.634***
	(.056)	(.060)
$Ln(POP)_{it}$	-.071	.012
	(.078)	(.074)
$\text{Ln}(TRADE)_{it}$	.078**	.086**
	(.027)	(.031)
Constant	4.896***	4.495***
	(1.346)	(1.354)
Year Fixed Effects	YES	YES
Hausman Statistic	172.60***	125.56***
Observations	428	459
Number of Countries	17	17
Years	1990-2018	1990-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

When observing Model 1 and 2 in Table 4, a difference is observed from the FE models in Table 3. Contrary to before, the coefficient for R&D expenditure is now significant at 1% significance level while the coefficient for general technology patents is no longer significant at 10% significance level. Moreover, there is evidence of a non-linear relationship between general innovation and CO2 emission since the coefficient for the squared term for R&D expenditure is negative and significant at 1% significance level. A 1% increase in R&D expenditure two years ago leads to a .263% decrease in CO2 emission in the current year, ceteris paribus, significant at 1%. Since the squared term is also significant and negative, this indicates that the negative impact of R&D expenditure on CO2 emission within a country will marginally increase as the investment further increases. This finding goes against the expectation of H3 that a U-shape will be found with the impact of R&D expenditure marginally decreasing as the expenditure reaches higher levels. Like the regular coefficient for general technology patents, the squared term is also not significant at 10% significance level. No evidence is therefore found of a non-linear relationship between general technology patents and CO2 emission.

A test of joint significance was also performed with the null-hypothesis that coefficients for ln(RD) and its squared term are jointly equal to zero. The F-statistic produced a p-value of .003. The null-hypothesis can therefore be rejected at 5% significance level and no evidence is given that at least one of the coefficients is statistically significantly different from zero. For the test on whether ln(PATENT) and its squared term are jointly statistically significantly different from zero, a p-value of .126 was produced and the null-hypothesis therefore cannot be rejected.

Thus, partial evidence is found from this test and the FE regression that a non-linear relationship exists between general technology innovation, only in the form of R&D expenditure, and CO2 emission. Furthermore, like the results produced in Table 3, total final energy consumption, lagged CO2 emission, and trade produced positive and significant coefficients, while total population did not produce significant coefficients at 10 % significance level for both models in Table 4.

Multicollinearity

The correlation matrix corresponding to the estimated coefficients in Table 3 and Table 4 are produced next to explore the possibility of a multicollinearity issue among the independent variables. These correlation matrices can be found as Tables 13-17 in Appendix B. The correlation coefficients of the year dummies were estimated but excluded from the matrices displayed in the Appendix.

For Models 1-3 in Table 3, final energy consumption and lagged CO2 emission display high correlation as the absolute correlation coefficients ranges from .742-.822. Nevertheless, all other explanatory variables have a correlation coefficient below the threshold, with only R&D expenditure and lagged CO2 emission showing a moderately high correlation ranging in absolute value from .612-.704.

Subsequently, the correlation matrices for Model 1-2 from Table 4 are analyzed. The matrices show, as expected, a very high correlation between the general innovation variable and its squared term. Moreover, the matrices again show a high correlation coefficient for the lagged CO2 emission variable and total final energy consumption with an absolute value of .759 and .901. A possible multicollinearity issue may therefore be present in the FE analysis regarding lagged CO2 emission and final energy consumption.

5.4 Fixed-Effects Regression with Moderator Variable

Lastly, an FE regression estimator with clustered robust errors at country-level and year dummies is employed for the final analysis of the moderation effect of environmental taxation on the relationship between green innovation, measured through patents in environment-related technology, and CO2 emission. Hypothesis 9 will be tested using a FE model that includes eco-patents lagged by two years, environmental taxation, the interaction term for lagged eco-patents and environmental taxation, and the same four control variables from all the analyses (total final energy consumption, lagged CO2 emission, total population, and trade in goods and services). The results of the estimated model are displayed in Table 5.

Table 5. Fixed-Effects Regression Results for Model with Moderator Results (H9)

Variables	(1)
$Ln(ECOPATENT)_{i,t-2}$	.010
	(.020)
$\text{Ln}(ECOTAX)_{it}$	-.036
	(.111)
$Ln(ECOPATENT)_{i,t-2} \times \text{Ln}(ECOTAX)_{it}$	-.002
	(.008)
$\text{Ln}(ENERGYCON)_{it}$	.495***
	(.097)
$\text{Ln}(CARBON)_{i,t-1}$	.629***
	(.071)
$Ln(POP)_{it}$	.013
	(.090)
$\text{Ln}(TRADE)_{it}$	.122***
	(.033)
Constant	4.647**
	(1.692)
Year Fixed Effects	YES
Hausman Statistic	124.51***
Observations	385
Number of Countries	17
Years	1994-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Model 1 in Table 5, like the FE models from Table 3, shows that the explanatory variable for green innovation measured through eco-patents is not significant at 10% significance level. The coefficient for environment-related taxation is also not significant at 10% significance level, thereby giving no evidence for a direct relationship between environmental taxation and CO2 emission. There is also no evidence of a moderation relationship of environmental taxation on the effect between green innovation and CO2 emission since the interaction term and coefficient for environmental taxation is also not significant at 10% significance level. Additionally, a test of joint significance was performed with null-hypothesis that coefficients for ln(ECOPATENT), ln(ECOTAX), and the interaction term are jointly equal to zero. The F-statistic produced a p-value of .857, thus the null-hypothesis cannot be rejected at 5% significance level and no evidence is provided that at least one of the coefficients is significantly different from zero. Furthermore, like the results produced in Table 3 and 4, total final energy consumption, lagged CO2 emission, and trade produced positive and significant coefficients, while the variable for population is not significant at 10 % significance level.

Multicollinearity

The correlation matrix corresponding to the estimated coefficients in Table 5 are produced next to explore the possibility of a multicollinearity issue in this estimated model (see Table 18, Appendix B). The correlation coefficients of the year dummies were estimated but excluded from the matrix.

The matrix shows a high correlation coefficient between environmental taxation and environmental patents, with an absolute coefficient of .956. This indicates possible multicollinearity, which could lead to unreliable standard error and significance measurement in the estimation (Shrestha, 2020). To see if the significance of the variable for environmental taxation would change when this collinearity source is removed, the same FE regression was run without the variable for eco-patents and the interaction term. However, the coefficient for taxation was still not significant at 10% significance level.

As expected, the interaction term is highly correlated to the variables for environmental taxation and eco-patents. Furthermore, like the other FE regressions, total final energy and lagged CO2 emission provide a high correlation coefficient of -.913. Therefore, there could be a multicollinearity issue present in this regression.

5.5 Additional Tests

Moderation Effect of Environmental Taxation on Innovation in General Technology

The last hypothesis focuses specifically on the possible moderation effect of environmental regulation, in the form of taxation, on the diffusion and effect of green technology on CO2 emission. However, the results showed that there is no significant effect. It might therefore be interesting to see what happens when broadening the perspective to total general innovation instead of only eco-innovation. This has been done using the same FE regression as for Model 1, Table 5, now swapping eco-patents for patents in general technology (see Table 19, Appendix C). The estimations gave the similar results to those of the original regression, with the explanatory variables patents in general technology, environmental taxation, and the interaction between these two all being insignificant at 10% significance level.

All Greenhouse Gases Instead of only CO2 Emission as Dependent Variable

A robustness test is done next in which the dependent variable of CO2 emission is swapped for all GHG emissions. The greenhouse gases are defined by the sum of the following seven gases: carbon dioxide, methane, nitrous oxide, chlorofluorocarbons, hydrofluorocarbons, perfluorocarbons, sulphur hexafluoride, and nitrogen trifluoride. They are expressed in CO2 equivalents and measured in tonnes per capita. The data for this dependent variable is obtained from the OECD (2022f). One country is dropped by the statistical program from the analysis even though there is data of all 17 countries. It is expected that China is the dropped country, since there are very few data points measuring GHG emission for China. All the Pooled OLS and FE regressions done in the empirical analysis will be repeated, but now using the natural log of GHG emissions as dependent variable and the natural log of GHG emission lagged by one year as one of the control variables. The summary statistics and results can be found in Table 20-24, Appendix C.

For the Pooled OLS regressions results, lagged R&D expenditure, patents in general technology, and green patents are still negative and significantly correlated with GHG emissions at 1% significance level. They are, however, slightly smaller in magnitude compared to the model with CO2 emission. Furthermore, the coefficient for trade is no longer significant at 10% significance level for all three models. For the pooled OLS regression with green patents, the coefficient for population is also no longer significant at 10%. The multicollinearity issue in the Pooled OLS models is resolved as none of the pairwise correlations are above the threshold of .8 in these new regressions.

The FE regression for H2 and H8 with GHG emissions as dependent variable produced similar results to the FE regressions with CO2 emissions as dependent variable since R&D expenditure and green patents are not significant at 10% significance level. However, different from the original regression, the new FE regression for H5 now produced an insignificant coefficient for patents in general technology in relation to GHG emissions. The analysis of a non-linear relationship between R&D expenditure and GHG emission shows that the coefficients for the regular variable and the squared term of R&D expenditure are both not significant at 10% significance level. This indicates that there is no evidence for a relationship between R&D expenditure and GHG emission, contrary to the non-linear relationship found in the case of CO2 emission. The FE analysis of a non-linear relationship between patents in general technology patents and GHG emissions produced similar results to that with CO2 emissions as dependent variable. Finally, the moderation analysis also produced similar results to the CO2 emission models when using GHG emission as dependent variable.

The multicollinearity issue in the FE models appears to be resolved as none of the pairwise correlations, except the interaction terms with the original variables, are above the threshold of .8.

Nevertheless, the pairwise correlation coefficient for lagged GHG emission and total final energy consumption is for some models still close to the threshold.

Endogeneity: Employing the Generalized Method-of-Moments (GMM) Estimator

As addressed in the theoretical framework section concerning the relationship between general R&D expenditure and CO2 emission, reverse causality is a possible issue present within this study. Using a panel causality method with a Wald statistic on country level, Ibrahim and Vo (2021) found that for some industrialized countries, the CO2 emission level within a country has effect on the gross domestic R&D expenditure. It can also be feasible that a similar reverse causality issue is present when considering other measures of innovation such as patent applications. For instance, it may be possible that increased CO2 emission will cause a higher feeling of urgency and demand for environmental solutions, thereby also spurring an increase in the level of innovation. The presence of reverse causality would imply that the strict exogeneity assumption of the panel models used in this study does not hold, and that the model estimates may suffer from bias. One way in which this thesis has accounted for possible reverse causality is by lagging all innovation variables by two years.

Due to the inclusion of a lagged dependent variable as an explanatory variable, there is also a possible endogeneity bias present in the estimations. In the pooled OLS estimator, the lagged dependent variable is correlated with the error term's fixed effects, referred to as "dynamic panel bias". Even though the use of an FE estimator removes the fixed effects from the error term and appears to thereby fix this bias issue, the within-group transformation still causes the lagged CO2 emission variable to be correlated with the standard error for a given country (Roodman, 2009a). The presence of this correlation causes estimates of the lagged dependent variable to be biased upwards or downwards (Roodman, 2009a). Hence, a new estimator is needed to correct this endogeneity bias and the potential bias from reverse causality.

An estimator that will be employed to attempt to resolve these issues of endogeneity is the two-step system GMM estimator. This estimator estimates two equations with the same coefficients: the first transforms all variables into first differences and the second equation estimates the original variables. In both equations, the lagged dependent variable and the independent variables are internally instrumented. For the first equation, the instruments for the first-differenced variables are leveled lagged variables. For the second equation, the instruments are lagged differences. The GMM estimator therefore resolves the endogeneity by using these internal instruments and, different from the FE estimator, accounts for both unobserved time-invariant and time-variant variables that could be correlated to the independent variables of interest (Krug & Eberl, 2018). Furthermore, the system GMM estimator also accounts for autocorrelation within countries (Roodman, 2009a).

According to Krug and Eberl (2018), two main assumptions should be tested regarding the system GMM estimator: the Arellano-Bond test for serial correlation in the dependent variable and the Hansen J-Test for joint exogeneity of the instruments. The Arellano-Bond test focuses specifically on autocorrelation of the idiosyncratic shock. If serial correlation is found, this would mean that the instrument (lags of differences) is correlated to the idiosyncratic shock in the error term and therefore invalid (Roodman, 2009a). Krug and Eberl (2018) state that first-order autocorrelation is naturally assumed for the system GMM estimator, while second-order serial correlation should be tested. For the assumptions to hold, the null hypotheses of both tests need to be rejected (Krug & Eberl, 2018). Ideally, the Hansen J-Test should produce a p-value above .25, but a p-value of .10 is also acceptable (Roodman, 2009a). Moreover, the GMM estimator and Arellano-Bond test assumes that there is no autocorrelation present across countries, only within. Year dummies are therefore included in the GMM estimation to ensure this is the case.

Subsequently, the effect of (green) innovation on CO2 emission will be tested again using the two-step system GMM estimator. In this estimation, lagged CO2 emissions and lagged innovation measures are viewed as endogenous while the other explanatory variables and the year dummies are labelled as exogenous. Small-sample adjustments and Windmeijer (2005) corrections for standard errors are applied due to the relatively small country sample group of this study which could (without the correction) bias the standard errors (Roodman, 2009a).

When employing the two-system GMM model on the full dataset, Stata dropped all independent variable coefficients except one control variable. This estimation was accompanied by a warning that the number of instruments may be too large relative to the number of observations. Roodman (2009a) states that GMM only works when the number of countries is larger than the number of time periods. Additionally, a large number of time periods will also cause the number of instruments to increase substantially which creates issues with standard error estimations when the number of countries is relatively small (Roodman, 2009a). Although there is no perfect rule, Roodman (2009b) states that the number of instruments should be lower than the number of groups/countries as a relatively larger set of instruments will results in “false-positive” results due to overfitting of endogenous variables and efficiency issues. False-positive results occur if the tests mentioned above falsely indicate that there are no validity issues of endogeneity and autocorrelation, while these are affecting the results (Roodman, 2009b).

Thus, after running multiple GMM estimations with various number of years for the analysis of a relationship between (green) innovation and CO2 emission, it was decided to run the regression using the most recent five years, 2014-2018. Five years was the highest number of years that could be included without the number of instruments exceeding the number of countries for any of the models.

The five most recent years were chosen in an attempt to give the most relevant insight. Furthermore, the instrument matrix is collapsed to reduce the number of instruments by adding together sets of instruments and keeping one instrument for each lag distance (Roodman, 2009b). These adjustments allow the number of instruments to stay below the number of countries while attempting to keep as many observation values as possible. Moreover, the Arellano-Bond test for second-order serial correlation, AR(2) test, is preferred but can no longer be estimated when reducing the observations to five years. This has occurred because the observations per group have been reduced to three due to observations only being available for five years and the variable for innovation being lagged by two years.

Table 6-8 report the GMM estimation results for analyzing a linear and non-linear relationship between (green) innovation, patents and R&D expenditure, and CO2 emission as well as the moderation effect of environmental taxation on this relationship.

Table 6. GMM Estimations of Linear Relationship Between Lagged (Green) Innovation and CO2 Emission

Variables	(1)	(2)	(3)
$\text{Ln}(RD)_{i,t-2}$	.008		
	(.110)		
$Ln(PATENT)_{i,t-2}$		.012	
		(.090)	
$Ln(ECOPATENT)_{i,t-2}$			.063
			(.113)
$\text{Ln}(ENERGYCON)_{it}$	.112	.123	.037
	(.249)	(.208)	(.221)
$\text{Ln}(CARBON)_{i,t-1}$	.814*	.782	.753
	(.400)	(.452)	(.433)
$Ln(POP)_{it}$	.022	.022	.024
	(.059)	(.044)	(.042)
$\text{Ln}(TRADE)_{it}$	.049	.041	.048
	(.132)	(.086)	(.085)
Constant	.861	1.116	.922
	(1.719)	(2.218)	(2.046)
Year Fixed Effects	YES	YES	YES
Hansen test (p-value)	.089	.140	.310
Number of Instruments	13	13	13
Observations	51	51	51
Number of Countries	17	17	17
Years	2014-2018	2014-2018	2014-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7. GMM Estimations of Non-Linear Relationship Between Lagged General Technology Innovation and CO2 Emission

Variables	(1)	(2)
$\mathrm{Ln}(RD)_{i,t-2}$	.058	
	(2.292)	
$\mathrm{Ln(RD)}^2_{\mathrm{i,t-2}}$	.006	
	(.156)	
$Ln(PATENT)_{i,t-2}$		-1.040
		(1.982)
$\mathrm{Ln(PATENT)}^2_{\mathrm{i,t-2}}$		-.053
		(.100)
$\mathrm{Ln}(ENERGYCON)_{it}$	.158	.089
	(.399)	(.370)
$\mathrm{Ln}(CARBON)_{i,t-1}$	.857*	.890*
	(.441)	(.499)
$Ln(POP)_{it}$	.018	-.004
	(.069)	(.070)
$\mathrm{Ln}(TRADE)_{it}$	.031	-.013
	(.142)	(.132)
Constant	1.363	-3.947
	(10.110)	(9.923)
Year Fixed Effects	YES	YES
Hansen test (p-value)	.104	.230
Number of Instruments	16	16
Observations	51	51
Number of Countries	17	17
Years	2014-2018	2014-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8. GMM Estimations for Moderation Effect of Environmental Taxation

Variables	(1)
$Ln(ECOPATENT)_{i,t-2}$	-.077
	(.219)
$\mathrm{Ln}(ECOTAX)_{it}$	.274
	(1.294)
$Ln(ECOPATENT)_{i,t-2} \times \mathrm{Ln}(ECOTAX)_{it}$	.023
	(.118)
$\mathrm{Ln}(ENERGYCON)_{it}$	.084
	(.101)
$\mathrm{Ln}(CARBON)_{i,t-1}$	.954***
	(.061)
$Ln(POP)_{it}$	.006
	(.021)
$\mathrm{Ln}(TRADE)_{it}$	.008
	(.042)
Constant	-.179
	(2.547)
Year Fixed Effects	YES
Hansen test (p-value)	.293
Observations	17
Number of Countries	17
Years	2014-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The GMM estimations reveal that none of the independent variables are significantly correlated with CO2 emission except for lagged CO2 emission in four of the six models. Different from the FE and Pooled OLS estimations, none of the innovation variables are significant at 10% significance level. For the Hansen test, all p-values except Model 1, Table 6 are equal or above the threshold of .10 or above the more ideal threshold of .25. This indicates that for most models, the assumption of joint exogeneity of the instruments is likely met.

The difference between the GMM and FE findings could be attributed to the fact that the GMM estimations account for the endogeneity bias. However, it is hypothesized that the differences may primarily be caused by the fact that the GMM estimations include a smaller range of years and very few observations. For example, in Model 2 and 3 of Table 6, the lagged dependent variable is not significantly correlated with the current value of the dependent variable, which is highly unlikely. Hence, by using the GMM estimation, an attempt was made to shed more light on this thesis' research question as it removed the endogeneity bias. However, there are caveats to consider here as the number of observations within the research had to be drastically reduced to avoid major validity issues because of the large number of instruments.

6. Conclusion

This thesis analyzes the extent to which innovation in general technologies and innovation in environmental-related technologies affect CO2 emissions in the European Union-15, the United States, and China in 1990-2018. In the analysis, attention is paid to the effect of a country having a higher level of innovation on its CO2 emission as well as the effect of a country increasing its level of innovation over time on its CO2 emission. General technology innovation is measured through R&D expenditure and patent applications, and green innovation through patent applications in environment-related technology.

The Pooled OLS regressions indicate that green innovation and general innovation are significant and negatively related to CO2 emission. However, the estimates are likely biased due to unobserved individual heterogeneity affecting the estimated coefficients. Subsequent FE estimations show that there is only a significant linear relationship between general technology innovation, in the form of patents, and CO2 emissions. This significant effect is, against expectation, positive. This may be an indication that innovation can be associated with increased CO2 emissions. Mensah et al. (2018) also found this positive relationship for some countries in their sample and attributed this to the high costs of patenting and hesitance among inventors to share technology and work together.

When examining a possible non-linear relationship for general technology innovation, it was observed that R&D expenditure has a significant negative non-linear relationship with CO2 emission, and patent applications is not significantly correlated. This change in significance when adding a squared term of the general technology innovation measure could indicate the importance of examining a non-linear relationship for the environmental impact of innovation. The finding also suggests that contrary to what previous literature has stated, it is possible that the positive impact of innovation input on CO2 mitigation can marginally increase instead of decrease as the R&D expenditure increases (Ibrahim & Vo, 2021; L. Li et al., 2021).

In the theoretical framework, it was hypothesized that general technology innovation measured in either patents or R&D expenditure would have similar effects. However, the results in this thesis suggest that the form of innovation, input, or output, matters for its effect on CO_2 emission. This thesis shows that the impact of R&D expenditure and patent application on CO_2 emission can differ within the same study and sample group, which is a valuable contribution to previous literature that has mostly focused on one measure of innovation. Another contribution of this study is the additional test in which all the models are estimated with GHG emission instead of CO_2 emission as dependent variable. The results showed that (green) innovation does not significantly affect GHG emission. Comparing the FE estimations for CO_2 emission and GHG emission as dependent variables, the results suggest that general technology innovation may only affect specifically CO_2 emission and not all seven gasses that encompass GHG emissions. This gives insight into what form of environmental impact one can expect from increasing general technology innovation levels.

Finally, in the FE regression, no direct effect was found of green innovation on CO_2 emission and no moderation effect was found of environmental taxation within the relationship between green and general technology patents and CO_2 emission. Based on studies with similar high-income country sample groups, it was expected that green innovation would reduce CO_2 emissions (Du et al., 2019; Hashmi & Alam, 2019). The insignificant estimates in this thesis portray that the potential mitigating effect of green innovation on emissions within highly globalized countries could be less straightforward than appears at first sight. Perhaps, green innovation is not a priority in some countries within the sample and barriers mentioned by Ulucak et al. (2020) for less-globalized countries may also still apply to these more globalized countries. These barriers may include low political and/or societal awareness, lack of institutional support, and blockades in technology sharing and diffusion (Ulucak et al., 2020).

Among the possible explanations for this thesis' results, the empirical limitations should not be overlooked. First, the sample size of this study is relatively small with only 17 countries. As mentioned in the introduction, the selection of countries was inspired by the research by Fernández et al. (2018), as well as based on the view that these countries appear to actively attempt combat their pollutive behavior by employing innovation. By only including a selection of countries, it is likely that the conclusions reached may not be applicable for other countries that have comparatively less CO_2 emission and/or innovative activity. Different relationships and significance could be found when including a larger or different range of countries within the sample, which may also explain the difference in results found in this study and previous literature mentioned in the theoretical framework. Moreover, the number of observations in this study is relatively small due to the selected sample of countries and years. This could limit the scope of the study and may lead to false estimates and larger standard errors compared to studies with a greater number of observations (Hackshaw, 2008).

Another reason for the relatively low observation number in this study is the missing values in the dataset for environmental taxation and R&D expenditure. A possible solution for the removal of missing values in the analysis would be the employment of the missing-indicator method. This method transforms the missing values into a fixed constant and adds a dummy variable in the model with a value of “1” for observed values and “0” for missing values. In doing so, it allows for the inclusion of observations from all countries and years. However, according to existing empirical literature, this method has a high likelihood of creating a bias in the coefficient estimation of the original variable for both random and non-random missingness (Donders, van der Heijden, Stijnen, & Moons, 2006). In an empirical review of methods that can be employed to deal with missing values, Donders et al. (2006) discourage the use of simpler methods such as missing-indicator method. A more preferred solution to the missing values would be imputation (Donders et al., 2006), but the implementation of this method is beyond the scope of this thesis.

Another significant caution in the interpretation of the FE results is the possible dynamic panel bias that likely exists due to the inclusion of a lagged dependent variable and possible reverse causality bias between (green) innovation and CO2 emission. In response to these limitations, a GMM estimator was employed to account for these forms of bias. The GMM results showed that none of the innovation variables were significantly affecting CO2 emission. However, these results cannot be fairly compared to the FE regressions as only the latest 5 years were observed, and the results are likely influenced by this relatively small number of observations.

Based on the limitations of this study, a recommendation for future research is to expand the range of countries. Including more countries in the dataset would allow for the GMM estimation to observe a wider range of years without validity issues arising when the number of instruments becomes too large. Due to the small number of observations in the GMM analyses, one can question how much of a conclusion can be drawn based on such a low number of years observed among an already restricted number of countries. Furthermore, as mentioned before, the restricted range of countries leads to a smaller observation number for the FE estimator which could lead to false estimations and low external validity. Another recommendation would be to run the GMM estimations for the study on innovation and CO2 emission on multiple datasets with varying number of years and instruments. Goodman (2009b) recommends this as one is then also able to see whether the results are sensitive to changes regarding the number of instruments and when the number of instruments is larger than the number of countries. As the GMM estimator was included as an additional analysis within this thesis and the number of countries observed was restricted, the scope of this thesis did not allow for an in-depth dive into the sensitivity of the results regarding the number of instruments.

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Appendix A

Table 9. Data Sources

Abbreviation	Source
IEA	International Energy Agency
OECD	Organisation for Economic Co-operation and Development
TI	Transparency International
WB	World Bank

Appendix B: Correlation Matrices

Table 10. Correlation Matrix of Variables in Natural Logarithms for Model 1, Table 2

e(V)	$\text{Ln}(RD)_{i,t-2}$	$\text{Ln}(ENERGYCON)_{it}$	$\text{Ln}(CARBON)_{i,t-1}$	$Ln(POP)_{it}$	$\text{Ln}(TRADE)_{it}$
$\text{Ln}(RD)_{i,t-2}$	**1.000**				
$\text{Ln}(ENERGYCON)_{it}$	**-.595**	**1.000**			
$\text{Ln}(CARBON)_{i,t-1}$	**.263**	**-.879**	**1.000**		
$Ln(POP)_{it}$	**.419**	**-.178**	**.283**	**1.000**	
$\text{Ln}(TRADE)_{it}$	**.375**	**-.355**	**.373**	**.728**	**1.000**

Table 11. Correlation Matrix of Variables in Natural Logarithms for Model 2, Table 2

e(V)	$\text{Ln}(PATENT)$	$\text{Ln}(ENERGYCON)_{it}$	$\text{Ln}(CARBON)_{i,t-1}$	$Ln(POP)_{it}$	$\text{Ln}(TRADE)_{it}$
$\text{Ln}(PATENT)_{i,t-2}$	**1.000**				
$\text{Ln}(ENERGYCON)_{it}$	**.145**	**1.000**			
$\text{Ln}(CARBON)_{i,t-1}$	**-.477**	**-.892**	**1.000**		
$Ln(POP)_{it}$	**.021**	**.134**	**-.001**	**1.000**	
$\text{Ln}(TRADE)_{it}$	**.161**	**.733**	**-.575**	**.088**	**1.000**

Table 12. Correlation Matrix of Variables in Natural Logarithms for Model 3, Table 2

e(V)	$\text{Ln}(ECOPATE$	$\text{Ln}(ENERGYCON)_{it}$	$\text{Ln}(CARBON)_{i,t-1}$	$Ln(POP)_{it}$	$\text{Ln}(TRADE)_{it}$
$\text{Ln}(ECOPATENT)_{i,t-}$	**1.000**				
$\text{Ln}(ENERGYCON)_{it}$	**-.311**	**1.000**			
$\text{Ln}(CARBON)_{i,t-1}$	**-.036**	**-.893**	**1.000**		
$Ln(POP)_{it}$	**.247**	**.015**	**.105**	**1.000**	
$\text{Ln}(TRADE)_{it}$	**.189**	**-.133**	**.209**	**.832**	**1.000**

Table 13. Correlation Matrix of Variables in Natural Logarithms for Model 1, Table 3

e(V)	$\text{Ln}(RD)_{i,t-2}$	$\text{Ln}(ENERGYCON)_{it}$	$\text{Ln}(CARBON)_{i,t-1}$	$Ln(POP)_{it}$	$\text{Ln}(TRADE)_{it}$
$\text{Ln}(RD)_{i,t-2}$	**1.000**				
$\text{Ln}(ENERGYCON)_{it}$	**.302**	**1.000**			
$\text{Ln}(CARBON)_{i,t-1}$	**-.612**	**-.822**	**1.000**		
$Ln(POP)_{it}$	**.025**	**.349**	**-.077**	**1.000**	
$\text{Ln}(TRADE)_{it}$	**.289**	**.649**	**-.406**	**.319**	**1.000**

Table 14. Correlation Matrix of Variables in Natural Logarithms for Model 2, Table 3

e(V)	$\text{Ln}(PATENT)_{i,t-2}$	$\text{Ln}(ENERGYCON)_{it}$	$\text{Ln}(CARBON)_{i,t-1}$	$Ln(POP)_{it}$	$\text{Ln}(TRADE)_{it}$
$\text{Ln}(PATENT)_{i,t-2}$	**1.000**				
$\text{Ln}(ENERGYCON)_{it}$	**.255**	**1.000**			
$\text{Ln}(CARBON)_{i,t-1}$	**-.704**	**-.742**	**1.000**		
$Ln(POP)_{it}$	**-.144**	**-.024**	**.060**	**1.000**	
$\text{Ln}(TRADE)_{it}$	**.131**	**.250**	**.031**	**.292**	**1.000**

Table 15. Correlation Matrix of Variables in Natural Logarithms for Model 3, Table 3

e(V)	$\text{Ln}(ECOPATENT)_{it,-2}$	$\text{Ln}(ENERGYCON)_{it}$	$\text{Ln}(CARBON)_{i,t-1}$	$Ln(POP)_{it}$	$\text{Ln}(TRADE)_{it}$
$\text{Ln}(ECOPATENT)_{i,t-2}$	**1.000**				
$\text{Ln}(ENERGYCON)_{it}$	**.406**	**1.000**			
$\text{Ln}(CARBON)_{i,t-1}$	**-.665**	**-.770**	**1.000**		
$Ln(POP)_{it}$	**.010**	**.033**	**-.086**	**1.000**	
$\text{Ln}(TRADE)_{it}$	**-.312**	**.226**	**.069**	**.362**	

Table 16. Correlation Matrix of Variables in Natural Logarithms for Model 1, Table 4

e(V)	(1)	(2)	(3)	(4)	(5)	(6)
1) $\text{Ln}(RD)_{i,t-2}$	**1.000**					
2) $\text{Ln}(\text{RD})^2_{\text{i,t}-2}$	**.947**	**1.000**				
3) $\text{Ln}(ENERGYCON)_{it}$	**.311**	**.204**	**1.000**			
4) $\text{Ln}(CARBON)_{i,t-1}$	**-.142**	**.123**	**-.759**	**1.000**		
5) $Ln(POP)_{it}$	**.345**	**.410**	**.177**	**.109**	**1.000**	
6) $\text{Ln}(TRADE)_{it}$	**.393**	**.347**	**.235**	**-.121**	**.037**	**1.0000**

Table 17. Correlation Matrix of Variables in Natural Logarithms for Model 2, Table 4

e(V)	(1)	(2)	(3)	(4)	(5)	(6)
1) $\text{Ln}(PATENT)_{i,t-2}$	**1.000**					
2) $\text{Ln}(\text{PATENT})^2_{\text{i,t}-2}$	**.979**	**1.000**				
3) $\text{Ln}(ENERGYCON)_{it}$	**-.012**	**-.047**	**1.000**			
4) $\text{Ln}(CARBON)_{i,t-1}$	**-.033**	**.067**	**-.901**	**1.000**		
5) $Ln(POP)_{it}$	**.272**	**.291**	**.122**	**.019**	**1.000**	
6) $\text{Ln}(TRADE)_{it}$	**.426**	**.423**	**.673**	**-.514**	**.096**	**1.0000**

Table 18. Correlation Matrix of Variables in Natural Logarithms for Model 1, Table 5

e(V)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1) $\text{Ln}(ECOPATENT)_{i,t-2}$	**1.000**						
2) $\text{Ln}(ECOTAX)_{it}$	**-.956**	**1.000**					
3) $\text{Ln}(ECOPATENT)_{i,t-2} \times \text{Ln}(ECOTAX)_{it}$	**-.949**	**.988**	**1.000**				
4) $\text{Ln}(ENERGYCON)_{it}$	**-.025**	**.025**	**.125**	**1.000**			
5) $\text{Ln}(CARBON)_{i,t-1}$	**-.303**	**.288**	**.192**	**-.913**	**1.000**		
6) $Ln(POP)_{it}$	**-.117**	**.288**	**.280**	**.237**	**-.060**	**1.000**	
7) $\text{Ln}(TRADE)_{it}$	**-.086**	**.119**	**.214**	**.724**	**-.543**	**.321**	**1.0000**

Appendix C: Additional Tests

1. Moderation Effect of Environmental Taxation on Innovation in General Technology

Table 19. Fixed-Effects Regression Results for Model with Moderator Results (H9)

Variables	(1)
$Ln(PATENT)_{i,t-2}$	.010
	(.023)
$\text{Ln}(ECOTAX)_{it}$	.010
	(.121)
$Ln(PATENT)_{i,t-2} \times \text{Ln}(ECOTAX)_{it}$	.001
	(.010)
$\text{Ln}(ENERGYCON)_{it}$	.497***
	(.097)
$\text{Ln}(CARBON)_{i,t-1}$	.614***
	(.075)
$Ln(POP)_{it}$	.029
	(.097)
$\text{Ln}(EXPORT)_{it}$	.119***
	(.031)
Constant	4.408**
	(1.845)
Year Fixed Effects	YES
Hausman Statistic	119.060***
Observations	385
Number of Countries	17
Years	1994-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

2. *All Greenhouse Gases Instead of only CO2 Emission as Dependent Variable*

Table 20. Summary Statistics and Sources of Ln(GHG)

Variable	Years	Number of countries	Obs.	Mean	Std. deviation	Min.	Max.	Source*
Ln(GHG)	1990-2018	17	469	2.444	.386	1.194	3.543	OECD

*Abbreviations for sources elaborated on in Table 9, Appendix A

Table 21. Pooled OLS Regression Results with Alternative Dependent Variable (GHG) for Model 1 (H1), Model 2 (H4), and Model 3 (H7)

Variables	(1)	(2)	(3)
$\mathrm{Ln}(RD)_{i,t-2}$	-.020***		
	(.005)		
$Ln(PATENT)_{i,t-2}$		-.007***	
		(.002)	
$Ln(ECOPATENT)_{i,t-2}$			-.006***
			(.002)
$\mathrm{Ln}(ENERGYCON)_{it}$	.033**	.020*	.017*
	(.012)	(.010)	(.009)
$\mathrm{Ln}(GHG)_{i,t-1}$	.981***	.980***	.981***
	(.011)	(.011)	(.010)
$Ln(POP)_{it}$	.004*	.004*	.002
	(.002)	(.002)	(.002)
$\mathrm{Ln}(TRADE)_{it}$	.005	.005	.002
	(.006)	(.005)	(.005)
Constant	.096	.055	.062
	(.129)	(.127)	(.116)
Year Fixed Effects	YES	YES	YES
R-squared	.992	.991	.991
Observations	402	432	432
Number of Countries	16	16	16
Years	1990-2018	1990-2018	1990-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 22. Fixed-Effects Regression Results with Alternative Dependent Variable (GHG) for Model 1 (H2), 2 (H5), and 3 (H8)

Variables	(1)	(2)	(3)
$\text{Ln}(RD)_{i,t-2}$	-.023		
	(.014)		
$Ln(PATENT)_{i,t-2}$		8.210×10^{-6}	
		(.010)	
$Ln(ECOPATENT)_{i,t-2}$			-.001
			(.005)
$\text{Ln}(ENERGYCON)_{it}$	.360***	.377***	.377***
	(.042)	(.065)	(.064)
$\text{Ln}(GHG)_{i,t-1}$	.638***	.640***	.640***
	(.047)	(.043)	(.041)
$Ln(POP)_{it}$	-.086	-.037	-.038
	(.076)	(.068)	(.068)
$\text{Ln}(TRADE)_{it}$	.084***	.081***	.081***
	(.026)	(.026)	(.027)
Constant	5.028***	4.515***	4.516***
	(1.395)	(1.231)	(1.203)
Year Fixed Effects	YES	YES	YES
Hausman Statistics	135.72***	150.85***	154.84***
Observations	402	432	432
Number of Countries	16	16	16
Years	1990-2018	1990-2018	1990-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 23. Fixed-Effects Regression Results with Alternative Dependent Variable (GHG) for Model 1 (H3) and Model 2 (H6)

Variables	(1)	(2)
$\mathrm{Ln}(RD)_{i,t-2}$	-.014	
	(.096)	
$\mathrm{Ln}(\mathrm{RD})^2_{\mathrm{i,t-2}}$	.001	
	(.006)	
$Ln(PATENT)_{i,t-2}$		.002
		(.029)
$\mathrm{Ln}(\mathrm{PATENT})^2_{\mathrm{i,t-2}}$		6.140×10^{-5}
		(.001)
$\mathrm{Ln}(ENERGYCON)_{it}$	.359***	.377***
	(.045)	(.065)
$\mathrm{Ln}(GHG)_{i,t-1}$	.640***	.641***
	(.049)	(.044)
$Ln(POP)_{it}$	-.086	-.038
	(.079)	(.066)
$\mathrm{Ln}(TRADE)_{it}$	.084***	.081***
	(.026)	(.027)
Constant	5.042***	4.531***
	(1.317)	(1.130)
Year Fixed Effects	YES	YES
Hausman Statistic	235.72***	148.90***
Observations	402	432
Number of Countries	16	16
Years	1990-2018	1990-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 24. Fixed-Effects Regression Results with Alternative Dependent Variable (GHG) for Model with Moderator Results (H9)

Variables	(1)
$Ln(ECOPATENT)_{i,t-2}$	.024
	(.028)
$\mathrm{Ln}(ECOTAX)_{it}$	-.138
	(.135)
$Ln(ECOPATENT)_{i,t-2} \times \mathrm{Ln}(ECOTAX)_{it}$	-.010
	(.011)
$\mathrm{Ln}(ENERGYCON)_{it}$	.420***
	(.066)
$\mathrm{Ln}(GHG)_{i,t-1}$	.611***
	(.057)
$Ln(POP)_{it}$	-.023
	(.079)
$\mathrm{Ln}(TRADE)_{it}$	.121***
	(.032)
Constant	4.886***
	(1.003)
Year Fixed Effects	YES
Hausman Statistic	133.09***
Observations	366
Number of Countries	16
Years	1994-2018

Clustered robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1