THE IMPACT OF INNOVATION ON CORPORATE EMISSION

A Thesis

Submitted to the Master's Study Program of Sustainable Finance at the Faculty of Economics and Business in partial fulfillment of the requirements for the degree of

Master of Finance in Sustainable Finance (M.Fin.)

by:

Azizah

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ABSTRACT

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The emergence of climate-related risk enforce companies across global to minimize their environmental impact, particularly on GHG emissions. As innovation expected as supportive tools in assisting the company toward cleaner business operation, this study investigates the impact of innovation on emission reduction, Innovation is captured through four independent variables: Environmental R&D Expenditure; Disclosure on Pollution, Resource, and Water R&D; and Disclosure on Green Capital Expenditure. To control for other potential influences on emissions, Commitment Consistency, Total Waste and Market Capitalization are included as control variables. Since the mandatory of disclosing innovation-related information remains uncommon, even in the global scale, this study utilize panel data from 358 companies across various industries between 2018 and 2024, sourced from Refinitiv Eikon. The analysis estimate 3 types of total emissions, including Scope 1, Scope 1&2, and Scope 1, 2, and 3 as the dependent variables. To highlight the difference impact of innovation, the author also conduct separated examination by dividing the sample companies into two category, namely high polluting industries and non-high polluting industries. The results under the fixed effect model reveal a nuanced and evolving influence. Green capital expenditure consistently reduces Scope 1 (direct) and Scope 1 & 2 (direct and energy-related indirect) emissions, particularly for "All Industry" and "High Polluting" groups. Conversely, environmental R&D initially correlates with increased Scope 1 emissions, suggesting complexities in its immediate impact, but loses significance for Scope 1 & 2. Consistent commitment significantly lowers Scope 1 and Scope 1 & 2 emissions for "Non-high Polluting" companies. However, the analyzed variables largely fail to explain total Scope 1, 2, and 3 (value chain) emissions. Only market capitalization shows a significant positive correlation with total emissions across "All Industry" companies, indicating larger companies may have higher overall emissions due to extensive value chains. These results emphasize that while direct green investments and strategic commitments effectively manage operational and energy-related emissions, addressing comprehensive value chain emissions requires more intricate strategies and a broader set of policies, including optimized innovation, climate commitment, waste management, and proportional regulation.

Keywords: *Innovation, R&D, Emissions, Climate Change*

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Finally, and most profoundly, I dedicate this work to my beloved family. To my wonderful husband, Apif, thank you for your endless love, unwavering support, and boundless patience. And to my precious little daughter, Hanaya, who arrived and graced our lives right in the midst of this thesis journey, you are my greatest inspiration. Your tiny presence and pure joy became my most powerful motivation, reminding me daily of the important future we are working to build. Their belief in me has been my greatest strength.

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ABBREVIATIONS DIRECTORY

BOD	:	Biological Oxygen Demand
CCS	:	Carbon Capture And Storage
CEM	:	Common Effect Model
CH_4	:	Methane
CO_2	:	Carbon Dioxide
COD	:	Chemical Oxygen Demand
COP	:	Conference Of The Parties
DDT	:	Dichloro-Diphenyl-Trichloroethane
EIO-LCA	:	Economic Input-Output Life Cycle Assessment
Eq	:	Equilibrium
ESG	:	Environment Social Governance
EU	:	European Union
FEM	:	Fixed Effect Model
F-gases	:	Fluorinated Gases
FSB	:	Financial Stability Board
GHG	:	Green-House Gas
GICS	:	Global Industry Classification Standard
Gt	:	Giga Tonnes
Hg	:	Mercury
JRC	:	Joint Research Centre
LCA	:	Life Cycle Assessment
N_2O	:	Nitrous Oxide
NAICS	:	North American Industry Classification System
NEV	:	New Energy Vehicles
NO_x	:	Nitrogen Oxides
OECD	:	Economic Co-Operation And Development
PPP	:	Public-Private Partnerships
R&D	:	Research And Development
REM	:	Random Effect Model
SBTs	:	Science-Based Emission-Reduction Targets
SFDR	:	Sustainable Finance Disclosure Regulation
SIC	:	Standard Industry Classification
SO_2	:	Sulfur Dioxide
TCFD	:	Task Force on Climate-Related Financial Disclosures
UN	:	United Nations
UNFCCC	:	Convention On Climate Change
VOC	:	Volatile Organic Compounds
WBCSD	:	World Business Council For Sustainable Development
WRI	:	World Resources Institute

CHAPTER I
INTRODUCTION

1.1. Background

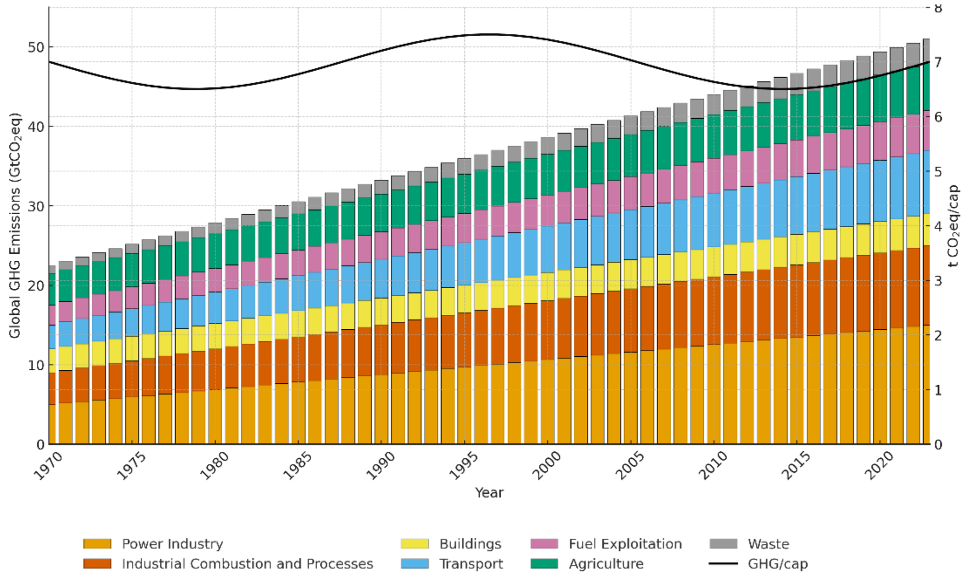
The rise of greenhouse gas (GHG) emission occurs along with the growth of businesses worldwide as the scaled-up business often lead to increased energy consumption, transportation, and resource extraction. This phenomenon has continued over the years globally. In the long term, the global increase in GHG emissions concentrations has led to the erosion of the atmosphere, increasing the earth's average temperature, and ends with the big phenomenon called climate change. Climate change refers to statistically significant variations in the mean state or variability of climate that persist over long periods of time, typically decades or more (Mercogliano et al., 2020).

The impacts of climate change are wide-ranging and include sea-level rise, changes in precipitation patterns, and increased frequency of extreme weather events (Dharmawan, 2021). These changes have significant implications for ecosystems, human health, and socio-economic systems. The Intergovernmental Panel on Climate Change (IPCC) states that there are approximately 3.3 to 3.6 billion people are highly vulnerable to climate change. Increasing weather and climate extreme events lead to acute food and water insecurity, increase in mortality, and driving displacement through destruction of homes and infrastructure.

From a physical science perspective, limiting the impact of climate change to a specific level requires strong reductions on the cumulative CO_2 emissions along with in other GHG emissions. Eventually, the world need to reach "net zero" emissions, meaning there is a balance between the amount of emissions released to the atmosphere with the amount of emission removed from the atmosphere. The climate scenario from IPCC 2023 discover that every 1000 $GtCO_2$ emissions will warm the planet by about 0.45°C. In the scenario of carbon budget, currently the world already emitted about 80% of the 1.5°C scenario. This carbon budget will be totally used in 2030 if the world keep emitting constantly as in 2019, meanwhile to stay in 1.5°C, the world should cut the emissions drastically by 50%; or 67% under the scenario 2°C.

Amidst the increasing trend of GHG emissions, there are several business sectors that are highlighted as the top global emitters as statistic released by the Joint Research Centre (JRC) of the European Commission in figure 1.1. The statistics illustrate that global GHG emissions constantly increase since 1970, meanwhile the slight decrease that occurred in 2020 is expected to be due to the Covid-19 pandemic which caused strict restrictions on human activities globally. However, the increase in GHG emission in 2023 reached 1.9% compared to 2022. Meanwhile, in the 5 decades since 1970, GHG emissions have increased relatively by 120% from 24 Gt CO_2eq to 53 Gt CO_2eq. Based on the business category, this data highlights 6 sectors that contribute significantly to the increase in GHG emission, namely: power industry, industrial combustion and processes, buildings, transportation, fuel exploitation, agriculture, and waste. Among these six sectors, the transportation sector is notable as the sector that experiences the highest increase in GHG emissions by 2023, at 3.7%.

Figure 1.1 Global GHG Emissions 1970 - 2023



Source: Joint Research Centre, 2024

Such polluting business sectors that contribute significantly to GHG emissions may face more challenges as they are in the spotlight amid the intense climate change issue. Currently, reducing emissions from business activities could be very complicated for several reasons. In general, the use of non-renewable energy for business operation is the biggest dilemma. The use of non-renewable energy will produce more pollutants, especially if the company is unable to apply the efficiency for energy consumption. Meanwhile, to shift the source of the energy from non-renewable to the renewable energy requires big cost, one of the reasons is the limited technology and financing which makes renewable energy still expensive. On the other hand, the companies also deal with the economic pressure that they have to maintain competitiveness in the market (Gaude-Fugarolas, 2019; Pandey & Nandan, 2022).

Generally, the businesses worldwide also face challenges in terms of policy and regulation as most country authorities try to cut their emission. As the implications, environmental regulations often lead to higher operational costs due to the need for pollution control technologies and compliance measures. In the case of highly regulated industrial sectors, the dynamics of regulatory changes can lead to excessive operational costs (Y. Li et al., 2024). This condition potentially lead to the occurrence of other risks such as disinvestment. Thus, companies will be even more difficult to manage the strategic plans (B. Zhang et al., 2015).

The various barriers that arise due to climate change spur companies to pay attention to sustainability practice for several critical reasons, which can be categorized into economic, regulatory, reputational, and ethical considerations. According to Mukherjee et al. (2016) addressing environmental damage can lead to cost savings and improved efficiency for company's operation. For instance, green initiatives can reduce waste and energy consumption, leading to lower operational cost. Conversely, Williamson (2007) state that ignoring environmental responsibilities can lead to significant financial liabilities and penalties. Meanwhile, from the perspective of reputational benefits, Ray (2019) demonstrated that a commitment to environmental sustainability can build trust that will lead to the loyalty of stakeholders, including investors, regulators, and the community. Lastly, from the perspective of business ethic, mitigating environmental impact is a moral responsibility of every company.

In response to the risks posed by climate change, every company has to reduce emissions. This action is a priority that applies across the board in any business sector since emissions is the main driver of climate change (Hisne et al., 2022). Some literature states several components of strategic planning that are significant in addressing the risk associated with the impact of climate change, one of which is innovation which can bring technologies and processes that can achieve rapid, large-scale emission reductions across all sectors (Alic & Sarewitz, 2016; Matos et al., 2022).

There is indication that companies which integrate innovation into their strategic planning often see better performance outcomes as innovation could navigate the company remains adaptable. Furthermore, innovation could create competitive advantages that lead to an increase in market share by guiding the company to delve more into the market needs, so that the new product could be more effective in meeting the market demand (Pelser, 2014). Beside that, innovation tend to improve the decission making through structured approach to identifying and leveraging new opportunities and challanges so that the company will be better prepared to stay ahead of competitors (Al-Kahtani et al., 2024).

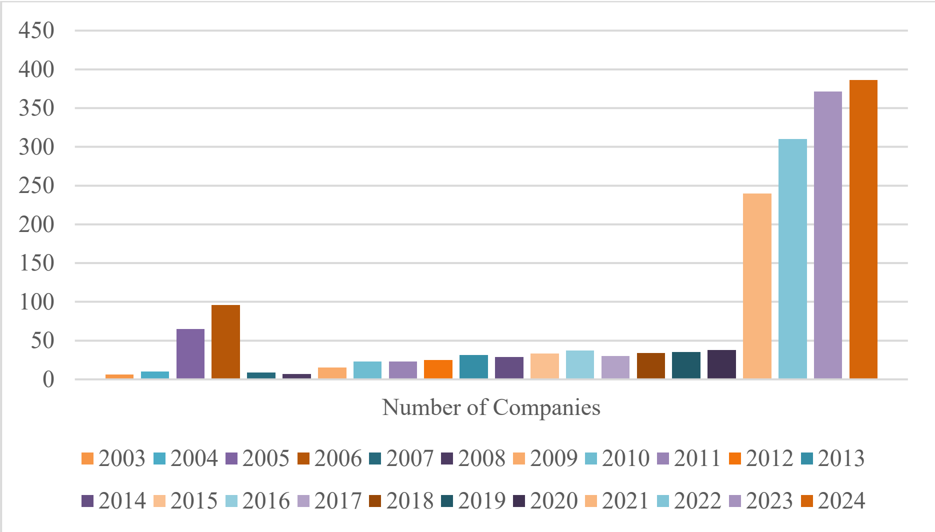
Considering the contribution of innovation in maintaining the adaptability of the company, there is an expectation that it can help companies reduce emissions as well. In general, the implementation of innovations may vary. Research by Liu et al. (2025) discuss about innovation from the perspective of technology. It discovers that technological innovation could promote efficiency in resource allocation and production process. To achieve this goal, Dabuo et al. (2023) demonstrate that developing technology should be supported with the investment in research and development (R&D) in order to optimize the impact of the technology changes in reducing emission. Furthermore, research by Xiao et al. (2024) highlight that a set of innovative policies could encourage the sustainability practice.

Nevertheless, the implementation of innovations comes with challenges. First, spending investment for innovation is less attractive for the companies due to the huge externalities that lead to inadequate returns. Furthermore, the incentives for innovative activities, particularly in environmental issue are diluted by imitation (Nordhaus, 2024). Second, financing constraints are a significant barrier to environmental innovation. Tax incentives can promote it, but somehow it has limited impact unless combined with other stimuli (C. Wang et al., 2022). Third, the misalignment between innovation and the grand strategic planning of company might end up with wasted resources. Additionally, ensuring that innovation does not negatively impact productivity also complicated (Lan & Zhou, 2024; Wehde, 2018).

Amid those big obstacles, the support for companies to adopt environmental innovation is still very limited. There are only few countries are encouraging the corporate environmantal innovation intensively, including China and Europe. In case of China, the local government provides subsidies in order to promote the environmental innovation, particularly in the middle and western regions. This subsidy successfully reflected through the increasing number of green patents as found by Y. Zhao et al. (2022). Beside subsidies, other environmental-related regulation are issued as the supporting tools for green business ecosystem, such as such as the New Energy Pilot City Policy (NEPCP) and environmental protection taxes (Y. Wang, Liao, et al., 2025; Y. Zhou & Su, 2025). On the other hand, Europe has a good ecosystem to motivate companies to innovate. The sets of country-level eco-innovation policies have created an encouraging environment for companies to adopt environmentally friendly practices, helping them achieve CO_2 targets and mitigate the climate change. This condition could happen due to the effective combination of public incentives and private incentives in promoting the environmental innovation (Stojčić, 2021).

Figure 1.2 shows the number of companies across global which publish their environmental innovation, particularly in environmental R&D expenditure.

Figure 1.2 Companies' R&D Expenditure Reports



Source: Refinitiv Eikon 2003 – 2024 (processed by Author)

The figure illustrates a notably low number of companies engaged in environmental R&D between 2003 and 2020, followed by a sharp increase from 2021 to 2024. The significant rise in recent years can be attributed to the stricter regulatory and policy changes. In case of China, the Environmental Protection Law has been shown to promote environmental R&D. Similarly, the ratification of the Paris Agreement in 2016 led to stricter penalties and increased support for environmental protection, boosting environmental innovation. In addition, the output of Conference of Parties (COP) 27 have pushed companies to innovate to meet environmental targets, such as carbon neutrality by 2060. This changes and the stabilization of policies post-2021 may have reduced the policy uncertainty, encouraging more companies to invest in environmental innovation. Lastly, the increased media attention on environmental issues has driven companies to invest more in environmental R&D to maintain a positive public image and comply with societal expectations (Amin et al., 2025; W. Su et al., 2022; Y. Wang, Ni, et al., 2025).

However, the percentage of companies that publish their environmental innovation activities is still relatively small, with the highest number in 2024 being only 386 companies, equivalent to 0.75% of the total global listed companies in the Refinitiv Eikon. Nonetheless, this study remains interesting to be explored and can be considered relevant in reflecting the global condition for several reasons. First, this study consists only of companies that meet strict data availability and completeness criteria, particularly on innovation and emissions. This ensures that the analysis of this study is based on reliable, comparable, and robust data. Second, the eligible companies likely represent industries both the major emitters (e.g., energy, mining, transportation, etc.) and the non-major emitters, indicating that this study aim illustrate "where the innovation matters most". In addition, the large, multinationals, or globally operating companies included in this research enrich the analysis as those companies has significant influence in mirroring broader market trends and strengthening the ability of this research in generalizing the findings. Third, as the portion of global companies publicly disclose environmental innovation and emissions data is small, it means that this study includes the most transparent and influential companies, which can set benchmarks or shape industry standards globally.

Another urgency that makes this research important to be conducted is because involving innovation and emissions as the main focus of this research aligns with the global climate agenda by drawing on the frameworks provided by the IPCC. This institution emphasizes the urgent need for systemic transformation, including rapid emissions reductions in order to limit global warming to 1.5°C. In this context, the corporate innovation is notable as a critical driver in advancing low-carbon technologies and operational efficiencies. By examining the relationship between innovation and emissions, this study contributes empirical evidence to support one of the key mitigation strategies highlighted by the IPCC.

In addition, the involvement of disclosures data in the innovation proxies makes this study also align with the Task Force on Climate-related Financial Disclosures (TCFD) framework, which encourages companies to disclose their climate-related risks, strategies, and performance through standardized metrics and targets. The focus on emissions and innovation corresponds directly with the TCFD's emphasis on aligning corporate strategy with climate goals. Furthermore, this study helps fill an existing gap between global climate frameworks and company-level action by providing real-world insights into how innovation strategies influence emissions outcomes.

Besides innovation, the commitment of a company in adopting climate policy often associated with the emissions due to the regulatory and policy influence. Companies that integrate climate change issues into their governance structures tend to show a higher commitment to climate action. This integration helps address climate risks and opportunities more effectively (Albitar et al., 2023). Additionally, the demand of stakeholders in enhancing transparency and accountability regarding their climate actions encourages companies to adopt more stringent climate policies and commit to reducing their emissions. It is further emphasized by the correlation between corporate climate commitments and actual emission reductions. Therefore, companies that are more transparent about their climate actions tend to have better performance in reducing GHG emissions (Trapero et al., 2023; Xhindole & Tarquinio, 2024).

The waste generated from the business activities also linked with the level of emissions both directly and indirectly. Direct emissions occur from on-site activities such as fuel combustion, while indirect emissions arise from external processes like waste treatment (Hashim et al., 2015). In general, waste is categorized into 3 types, namely: municipal solid waste, industrial waste, and hazardous waste (Bacinschi et al., 2010). The used materials and production process can determine the amount of those waste. In practice, improper waste management may produce more waste which leads to more emissions. In this connection, large-scale companies may generate more waste simply due to higher production volumes, but they may also have more resources to implement waste reduction strategies. To some extent, companies may invest in advanced waste reduction technologies if the disposal costs are too high (Gull et al., 2022; Shahab et al., 2022). On the other hand, financially constrained companies might struggle to invest in waste reduction technologies, leading to higher waste generation. This particularly happens in companies with lower profitability and cash flow, which may result in reduced investment in waste management (Atawnah et al., 2024).

Related to the explanation in the previous paragraph, it is clear that financial-related resources have an important role in emission reduction efforts. In this context, market capitalization is also one of the factors discussed in some literature as a contributing factor in the amount of waste. Alongside better access to finance, companies with higher market capitalization often have more comprehensive strategies in addressing the emissions problems. This could happen as a result of the well-established management systems and processes. These systems include robust governance oversight and comprehensive reporting mechanisms, which are crucial for tracking and reducing emissions (Sullivan, 2010). Furthermore, effective engagement with supply chain partners is another critical factor. Companies with big market capitalization have power to influence their suppliers to adopt greener practices, which significantly impacts Scope 3 (Mahapatra et al., 2021).

1.2. Problem Identification

Based on the background above, the author identifies the following problems:

a) The buildup of GHG emissions is notable as the main driver of climate change that brings risks in various aspects of business.

b) The climate change risks push the businesses to face the economic pressure which has domino effect for the business sustainability.
c) Along with the transition phase in business worldwide, the intense market competition and global pressure inevitably required companies to initiate innovation as the response to address the climate change risks.
d) Considering the urgency of innovation that collides with the challenges described in background, it is interesting to further explore the connection between innovation and emission reduction.

1.3. Research Objective

This study aims to examine the impact of innovation in reducing emissions from business activities. In defining the innovation as the independent variable of this research, the author sets 3 proxies, namely the total of Environmental R&D Expenditure; Disclosure on Pollution, Resource, and Water R&D; and Disclosure on Green Capital Expenditure. Meanwhile in defining the total emission as the dependent variable, the author refers to the 3 types of emissions data, namely: Total Emission Scope 1; Total Emission Scope 1 & 2; and Total Emission Scope 1,2, and 3. These variables are taken from the ESG matrix compiled by Refinitiv Eikon. In addition, the author also utilize 3 control variables, namely: Commitment Consistency, Total Waste, and Market Capitalization.

1.4. Hypothesis

Considering the challenges in reducing emissions, there is a question mark whether there is any different impact between innovations adoption in high polluting industries and non-high polluting industries in light of their different business characteristics, where the high polluting industries "seems" to be more disadvantaged because their business core is categorized as non-environmentally friendly. Therefore, the hypotheses in this study are as follows:

a. H1: Environmental R&D Expenditure has significant impact on total emission.
b. H2: Disclosure on Pollution, Resource, and Water R&D has significant impact on total emission.
c. H3: Disclosure on Green Capital Expenditure has significant impact on total emission.

1.5. Research Questions

The author determines some key questions in order to navigate the research fulfill the research objectives. The questions are as follows:

a. How does innovation impact on total emission?
b. How does the control variable commitment consistency, total waste and market capitalization influences emission?
c. Is there any difference in high polluting and non-high polluting industries?

1.6. Research Significance

Based on the author's tracing, most previous studies define innovation as limited to R&D carried out by companies in reducing their emissions. On the other hand, company initiatives in reducing emissions are not only limited to R&D. Therefore, this study includes the other two variables that are expected to explain in more detail the components of innovation that affect emission. Beside Environmental R&D Expenditure, the innovation in this study also represented through Disclosure on Pollution, Resource, and Water R&D, and Disclosure on Green Capital Expenditure. In addition, the dependent variables in this study involve 3 types of emissions data from Scope 1; Scope 1 & 2; and Scope 1, 2, 3. The estimation from these data expected to enrich the analysis by highlighting the different result from each data, providing more comprehensive discussion regarding the emissions. Furthermore, the analysis also divides the research subjects into two categories, namely high polluting category companies and non-high polluting category companies. This classification aims to provide a comprehensive picture that compares the conditions between companies engaged in the high polluting and non-high polluting sectors.

1.7. Thesis Outline

Chapter I: Introduction

This section provides the background of this study, followed by sub-chapters that aim to define more clearly the direction of this research, namely: problem identification, research objective, research originality, hypothesis, research questions, research significance, and thesis outline.

Chapter II: Literature Review

This chapter encompasses the explanation on theoritical framework and previous studies which is the exploring the relevant theories and findings. This section also inform about the research framework as the big capture about this study.

Chapter III: Methodology

This chapter aims to provide understanding about the overview of the research procedures. It contains the research design, definition of each operational variables, collectiong data method, and data analysis method.

Chapter IV: Result and Discussion

This section shows the data processing results and its interpretation. In addition, the comprehensive explanation related to the findings and the previous studies also become the part of this chapter.

Chapter V: Conclusion

This chapter is the last part of this research which contains conclusion of the research findings and recommendation based on the previous chapter.

CHAPTER II
LITERATURE REVIEW

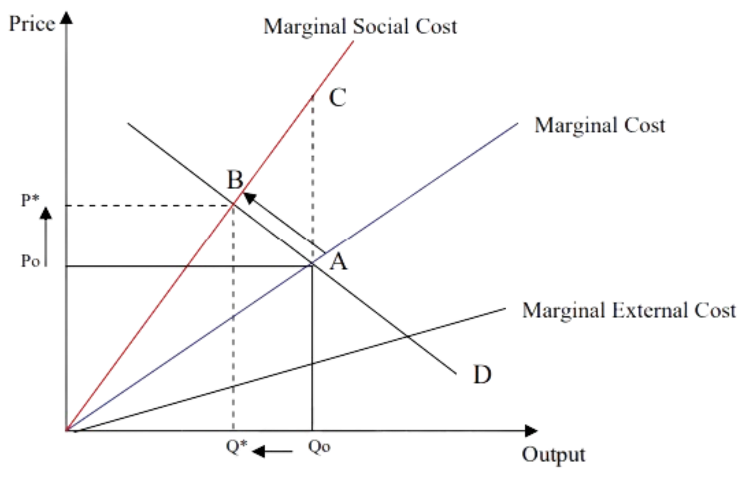
2.1. Theoretical Framework

In this section, the author intends to explain the relevant theoretical basis in order to facilitate understanding of the research flow in this study. The discussion in this section covers the theory of externalities since this research focuses on the discussion of GHG emissions generated by the business sector. Then the author provides an explanation about climate-related risks and sustainable finance as an introduction to illustrate how the global concern for the environment ultimately leads to the creation of a new business model. Furthermore, to understand deeper about the research variables that are the core of the discussion, the author includes an explanation of GHG emissions and innovation.

2.1.1. Externality

The climate change issue is fundamentally related to externalities phenomenon. Buchanan and Stubblebine (1962) define externalities as costs or benefits perceived by third parties that are not reflected in the market prices (Batabyal, 2023). In the context of climate change issue, GHG emissions are the example of negative externalities which is commonly not accounted in the cost of production or consumption (Z. Yang, 2020).

Figure 2.1 Marginal Social Cost



Source : Pindyck dan Rubinfeld (2005)

Figure 2.1 demonstrates the externalities phenomenon. The displacement of points from point A to point B results from negative externalities. The condition at point A is where the economic agent determines the price of their product by the Marginal Cost or the price that is considered to provide maximum profit. Behind it, there are costs that the company should bear due to the environmental impact caused by the existence of the company on society, which is reflected by the Marginal Social Cost line, which is at point C. However, the production level of a company will seem maximum when it has to include social costs in its production, namely when the Marginal Social Cost line is on the Demand line; so that the optimum point will be at point B. As the consequences, the price will increase from the previous Po to P *, and the production quantity will eventually decrease from Qo to Q * (Pindyck & Rubinfeld, 2005).

Furthermore, Heller and Starrett (1976) specify that negative externalities occur when the private sector refuses to provide proper incentives to create competitive markets. In other words, the existance of externalities indicates a market failure. The private sector's reluctance to pay incentives for the negative externalities might be because the incentives are too high meanwhile their ability to generate profit is not enough to cover their natural resource use and pollution costs Smeets et al., (2021).

The climate change appears as the greatest market failure. This failure occurs because the social cost of GHG emissions are borne by the society instead of the emitters. Therefore, the impact of climate change not only reflected as the environmental degredation but also lead to societal welfare reduction. This social impact encompasses damage on human health, agricultural productivity, and infrastructure (Bachman, 2019; Halkos, 2015).

Addressing climate change requires internalizing the external costs of emissions. This can be achieved through various policy instruments at each different scales, starting from the issuance of policies by the government which will later be ratified by each company. These policy aim to reflect the true social cost of emissions in market prices, thereby providing a catalyst for reducing greenhouse gas emissions (Halkos, 2015; Perrings, 2021). In connection with this issue, the effort in internalizing the externalities have been introduced by Arthur Cecil Pigou (1920) through pigouvian intervention logic. This approach aim to restore market efficiency by ensuring that the social costs of consumption or production are reflected in market prices through pigouvian taxes. These are taxes imposed on activities that generate negative externalities, such as pollution. The tax is set equal to the marginal external damage, encouraging producers and consumers to reduce their harmful activities to socially optimal levels (Caldari & Masini, 2011; Kang, 2023).

2.1.2. Climate-related Risk

Climate change poses a growing diverse threat not only to the environment but also to global financial and economic systems. In the context of corporations, the implications extend beyond mere environmental concern, manifesting as a trifecta of interconnected climate-related risks: physical, transitional, and liability.

Physical risks represent the most direct and tangible impacts of the climate change. This risk consists of two main types; acute physical risk and chronic physical risk. The acute physical risks are basicly extreme short-term events, such as hurricanes, floods, and heatwaves. This risk can directly damage physical assets, disrupt supply chains, and incapacitate operations. Meanwhile the chronic physical risks are the long term changes such as sea level rise, prolonged droughts, and gradual temperature increases. These subtle yet profound changes can lead to decreased agricultural yields, water scarcity, increased cooling costs, and the degradation of critical infrastructure. For companies, this translates into potential asset impairment, operational downtime, increased insurance premiums, and the erosion of market value. (Di Febo & Angelini, 2025; Macoskey, 2022).

Complementing physical risks are the equally potent transitional risks, which arise from the global economy's inevitable shift towards a low-carbon economy. Transitional risks can affect various sectors and industries, influencing their operations, profitability, and overall viability. This transition is driven by changes in policy, technology, and market dynamics aimed at addressing climate change. The new policy aimed at reducing carbon emissions can lead to increased operational costs for companies as they adapt to comply with new environmental standards. Meanwhile the technology changes may place the companies on reputational issues if the company fail to adapt to these changes, in worse scenario, the company can be driven out of the market by more compliant competitors. In addition, companies exposed to high transitional risks may struggle to maintain creditworthiness, as the costs associated with compliance can impact their financial health.

Finally, lurking beneath the surface of both physical and transitional risks are liability risks, which represent the potential for legal claims and litigation related to climate change impacts. In case of companies failing to mitigate climate risks, companies may face lawsuits from affected parties of the business operations that exacerbate the impacts of climate change (O’Donnell, 2020). Various types of climate litigation have emerged, including government framework cases aimed at increasing mitigation efforts, greenwashing cases, and securities/shareholder actions against directors. These cases help to clarify rights and responsibilities, manage uncertainties, and influence societal decisions about climate change (Brook et al., 2023)

In responding those risks, businesses are increasingly devoting more resources to enterprise risk management (ERM) to navigate the escalating risk environment. This includes continuous risk identification and the adoption of tailored risk governance strategies. Moreover, fostering collaboration and shared responsibility are becoming initiatives to bring together businesses, governments, and other parties to mitigate common risks In case of companies in high polluting industries, they tent to leverage dynamic capabilities to integrate, build, and reconfigure competencies to address rapidly changing markets and manage strategic risks effectively (Beasley et al., 2023; Brende, 2019; Shuen et al., 2014).

2.1.3. Sustainable Finance

The world began realizing the sustainability after Rachel Carson wrote an ecological book entitled "Silent Spring" in 1962. The book made the world realize that using DDT (Dichlorodiphenyltrichloroethane) to eradicate pests has broader impacts, such as threatening other animal populations and endangering human health. The ideas in this book led to the formation of the Environmental Protection Agency (EPA) in 1970, which issued a domestic ban on the use of Dichloro-Diphenyl-Trichloroethane (DDT) in 1972 (Sen, 2020; Tuazon et al., 2013).

Recognizing that economic development were increasing the frequency of serious environmental problems, the United Nations (UN) held a summit in Stockholm, Sweden, in 1972. This summit produces 26 principles and 106 recommendations aimed at guiding nations in environmental conservation and sustainable development (Mallikamarl & Karnchanawat, 2006). The principles and momentum generated by the Stockholm Conference influenced later significant environmental conferences, such as the 1992 Rio Earth Summit. The Rio Summit led to the adoption of the United Nations Framework Convention on Climate Change (UNFCCC), which established the framework for international climate change negotiations and the annual Conference of the Parties (COP) meeting (Baratti, 2023; Doelle, 2023).

Among the of COPs that have been held, there are some COPs with significant key contributions. The COP-3 marked the global action in tackling climate change by adopting the Kyoto Protocol which established legally binding obligations for developed countries to reduce greenhouse gas emissions. This agreement highlighted the need for financial mechanisms to support emissions reductions, paving the way for carbon markets and climate finance initiatives. Then the COP-21 which resulted the Paris Agreement. It explicitly calls for making financial flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development under Article 2(1)(c) (Iozzelli & Slingenberg, 2024). This directive has been a driving force behind the integration of environmental, social, and governance (ESG) considerations into financial systems globally. In addition, this conference also highlighted the importance of private finance in achieving low-carbon investments, stressing the need for ending fossil fuel subsidies and implementing higher carbon prices to attract capital for green investments to keep global temperature increases below 2°C (Peake & Ekins, 2017).

Besides the United Nations, The European Union also play vital role in implementing the sustainable finance policies. The EU launched the European Green Deal that aims to achieve climate neutrality by 2050. It includes initiatives covering climate, environment, energy, transport, industry, agriculture, and sustainable finance. The Green Deal also involves significant green investments, mobilizing public funds and aligning state aid policies with sustainability goals (Ottomano et al., 2025). The EU strongly supports the ambition of the Paris Agreement and has been a leader in integrating green finance into its economic strategies since the enactment of disclosure obligations called Sustainable Finance Disclosure Regulation (SFDR) and the EU Taxonomy for green investments to provide detailed criteria for sustainable investments and enhance transparency (Bengo et al., 2022; Cochran et al., 2024).

In relation to emissions reporting, one of the standards widely adopted is the framework developed by the Task Force on Climate-related Financial Disclosures (TCFD) established by the Financial Stability Board (FSB). The TCFD promotes transparency and accountability of sustainability disclosure by recommending that companies have to disclose climate-related risks and opportunities in their mainstream financial filings. This integration includes the impact of climate change on financial performance and the valuation of production assets (Scholten et al., 2020).

The transition from voluntary to mandatory disclosure regimes has been observed to increase the pressure on companies to enhance their sustainability reporting since the market demand requires comprehensive information on the company's position amid climate change risks (Bolognesi et al., 2025). Moreover, the requirement for disclosures on climate change-related risk encourages the development and adoption of sustainable finance instruments, such as green bonds, green loans, sustainability bonds, blue bonds, carbon credits, and impact investment funds. These instruments are designed to finance projects that mitigate climate risks and promote sustainability (Shaydurova et al., 2018).

Each instrument has the same function of financing climate change mitigation projects. However, there are slight differences, especially in the character of the projects financed and the financing scheme. Green bonds are debt instruments with fixed-income securities for environmental projects. Meanwhile green loans are loans for financing environmental intitiatives with more flexible terms (Niyazbekova et al., 2024; Suljić

Nikolaj et al., 2023). The blue bonds also similar to green bonds but it specifically aimed at financing marine and ocean-based projects (Singhania et al., 2024). Then, the sustainability bonds refers to are debt instruments for financing projects with environmental and social impact (Aracil & Sancak, 2023). In addition, carbon credits are tradable certificates representing the right to emit a certain amount of carbon dioxide. It is used in carbon markets to incentivize reductions in greenhouse gas emissions. Companies can buy and sell these credits to meet regulatory requirements or voluntary commitments to reduce their carbon footprint. Lastly, the impact investment which refers to funds pool capital to invest in projects that generate social and environmental benefits alongside financial returns (Federico & Adamo, 2024).

2.1.4. Greenhouse Gas (GHG) Emissions

Greenhouse gases (GHG) refer to gaseous constituents of the atmosphere, both natural and anthropogenic, that absorb and emit radiation at specific wavelengths in the terrestrial spectrum. This radiation is reflected back by the atmosphere to the Earth's surface. This phenomenon is known as the greenhouse effect (Meyer-Ohlendorf, 2019). GHGs prevent heat from escaping into space, contributing to the warming of the Earth's surface and lower atmosphere. These gases include water vapor, carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and fluorinated gases (F-gases), which absorb solar radiation reflected from the ground and re-emit some radiation (Ulku & Ulku, 2022; X. Zhao et al., 2019).

Each GHG comes from different primary sources. The CO_2 emissions known as combustion emissions which comes from stationary sources such as burning fossil fuels for electricity, and mobile sources such as transportation (Lal, 2019). Then, the CH_4 and N_2O emissions mostly comes from agriculture activities such as the digestive processes of livestock, the decomposition of animal waste, the flooded rice fields, and the application of synthetic and organic fertilizers. Meanwhile the F-gasses commonly generated through industrial processes, refrigeration, and air conditioning systems (Quiroz-Castañeda et al., 2013).

The establishment of Kyoto Protocol encourage the stage for more structured and comprehensive approaches to GHG emissions accounting. In 2001 the World Resources Institute (WRI) and the World Business Council for Sustainable Development (WBCSD) launched the GHG Protocol as specific measurement standard that apply globally. In this standardized measurement, the concept of categorizing GHG emissions divided into 3 categories. Scopes 1, 2, and 3. This categorization provide a standardized framework for measuring and managing the carbon footprints across different sectors and organizations by categorizing emissions based on their sources and the level of control the organization has over them. Each category represents emissions based on their source, what activity the emissions come from. Scope 1 refers to direct emissions which comes from owned or controlled sources, such as fuel combustion in company-owned vehicles or facilities. Scope 2 refers to indirect emissions from the generation of purchased electricity, steam, heating, and cooling consumed by the reporting company. Scope 3 refers to all other indirect emissions that occur in the value chain of the reporting company, including both upstream and downstream emissions (Rodríguez-Jiménez et al., 2023; Rosing, 2024).

In the context of the calculation method, emissions scope 1 typically involves direct measurement or estimation based on fuel consumption data and emission factors such as emissions from on-site energy use and transportation of raw materials. Meanwhile, emissions scope 2 calculate the amount of energy purchased and the emission factors provided by energy suppliers or national averages, such as emissions from electricity consumption in administrative offices. Furthermore, the estimation of emissions scope 3 is much more complex since this scope covers all other indirect emissions along the value chain. It often requiring life cycle assessment (LCA) or economic input-output life cycle assessment (EIO-LCA) models to estimate emissions from various activities such as purchased goods and services, waste disposal, and employee commuting (Duarte et al., 2025; Roston, 2021).

Considering the estimation methods, the significant challenges in measuring emissions remain. The estimation of scope 1, scope 2, and scope 3 emissions requires accurate data meanwhile ensuring the precise measurement of emissions from various sources can be complicated, especially for scope 3. As scope 3 covers all carbon footprint in value chain, gathering data from numerous stakeholders across the supply chain is often the biggest challenge. Many stakeholders may not share their emission data, leading to gaps and inaccuracies. In addition, it is also important to ensure that emissions are not counted multiple times across different scopes (De Kergret, 2023; Huang et al., 2009).

Despite the challenges associated with measuring and reporting emissions, the categorization of GHG emissions into Scope 1, 2, and 3 is still widely used. However, this framework remains a critical framework for comprehensive GHG accounting which is crucial for effective carbon management and reduction strategies (Rosing, 2024). Moreover, this framework has been the part of regulatory requirements for many countries in mandating the business sector to disclose their emission comprehensively (Luin et al., 2025). The detail measurement of scope 1, scope 2, and scope 3 also meet the stakeholder needs in accessing the information related to the climate change risk for better decission making (Nguyen et al., 2023). At this point, ongoing technological advancements and regulatory developments are expected to address some of the existing challenges, making this framework even more robust and essential for achieving global climate goals (Luin et al., 2025; Y. Wang et al., 2024).

2.1.5. Innovation

In the context of sustainability practice, innovation refers to a strategic approach where businesses integrate environmental, social, and economic considerations to addresses global challenges and enhances business competitiveness and long-term viability (Bocken et al., 2014). There are some types of innovation, namely: product innovation, process innovation (improving manufacturing processes or business operational), business model innovation, and service innovation (Akbarov, 2023; Lichtenthaler, 2016; Linåker et al., 2015).

Achieving the goals of innovation requires technological advancements as an important tool for the climate neutrality. On the other hand, developing low-carbon technologies might be costly and need significant amount of research and development (R&D) expenditures. This condition occurs due to the complexity of the R&D which explores the unknown territories with high level of uncertainty and risks of failure. Moreover, the impactful R&D needs compatible research infrastructure and quaified human resources. The research infrastructures provide the necessary tools and environments for conducting advanced research, meanwhile quaified human resources is essential for developing new ideas. However, the impact of R&D often takes years to materialize. This delay creates difficulties in measuring the immediate benefits of R&D investments (Gumbi, 2010). Therefore, companies need to manage their R&D portfolios to balance high-risk, high-reward projects.

Different sectors respond differently to environmental regulations (C. Li, 2019). In this case of companies in high polluting sectors often invest more in R&D to develop innovative solutions for emissions reduction. This is driven by both regulatory pressures and the potential for improved financial performance through enhanced sustainability (Haque & Ntim, 2022; Vaitiekuniene et al., 2024). The effort in reducing emissions might be executed to avoid strict regulations, while others may innovate to reduce costs associated with pollution abatement (Milani, 2017).

Company innovation in the form of R&D particularly effective in large-scale companies and regions with advanced financial development. Since the R&D needs a large amount of cost, the financial resources enable them to overcome financing constraints and invest heavily in R&D (Fu et al., 2025; Perez-Alaniz et al., 2023). Other advantages that large companies have in spending budget on R&D are the technological and knowledge spillovers. Large-scale companies often engage in collaborative R&D activities and benefit from knowledge spillovers due to their extensive networks and partnerships with universities, research institutes, and other companies (Malecki, 2011). This condition has implications on access to information. Thus, they can leverage their reputation to secure funding more easily, reducing the impact of information asymmetry (Dong & Yu, 2023). Lastly, the most powerful advantage is the ability of large companies to influence policy by utilizing their resources (Perez-Alaniz et al., 2023). Those resources include the capital expenditure, organizational resources, political influence and market power. Considering those advantages it is reasonable that R&D in large companies will be more impactful.

Besides R&D, other supporting component of innovation include organizational culture which encompasses leadership and management. The intrinsic motivations related to sustainability inherent in company management will lead to the creation of environmental responsibility culture. This effective leadership and management practices will be able to ensure that the decision-making processes consider social and environmental impacts (Castro & González-Masip, 2020; Sposato & Dittmar, 2025). As the implication, it will be easier for the company to adopt the supportive policies that are consistent with the local government regulation or the global agreement. At this point, the sustainability-oriented management not only addresses environmental concerns but also enhances organizational image, employee satisfaction, and overall sustainability performance (Susanto et al., 2017).

The adoption of consistent policy on climate change-related risk leads to financial benefits. Aligning with local and international legal frameworks can utilize companies to avoid regulatory and judicial risks associated with non-compliance with climate-related regulations. As the implication, companies may also benefit from favorable treatment by financial markets (Genovese, 2021; Hösli & Weber, 2021). Furthermore, companies can gain a competitive edge, in terms of lower adjustment costs compared to their competitors. This condition can lead to increased market share and financial performance (Kennard, 2020).

2.2. Corporate Strategy in Reducing Emission

Corporate strategies to reduce emissions encompass a variety of approaches and initiatives aimed at mitigating climate change. Resource efficiency often conducted for addressing the direct emissions. It is implemented through minimizing material input and optimizing production yields (Worrell et al., 2016). Furthermore, redesigning industrial processes to be less energy-intensive, reduce chemical usage, or capture fugitive emissions becomes crucial to reduce the waste (Hassim et al., 2012). For industries, particularly high-polluting ones, reducing total waste can directly lower Scope 1 emissions associated with waste treatment or inefficient processes (Rahnama Mobarakeh & Kienberger, 2025).

Furthermore, the energy efficiency is a fundamental strategy in reducing emissions by improving energy efficiency across all operations, from manufacturing facilities to office buildings. This includes upgrading to more energy-efficient machinery, optimizing heating, ventilation, and air conditioning (HVAC) systems, implementing smart building technologies, and improving insulation (P. Liu et al., 2024; Y. Su & Xu, 2025). This directly reduces energy consumption and, consequently, Scope 1 (from on-site fuel combustion) and Scope 2 (from purchased electricity) emissions (Cagno & Trianni, 2010).

In the specific context of addressing the Scope 3, some efforts include the establishment of programs for product take-back and recycling to reduce emissions associated with waste disposal. The influence of a company's overall scale and market capitalization becomes particularly relevant, as larger companies often have more extensive and complex supply chains that contribute significantly (Y. Li et al., 2025).

Additionally, stratetgic planning on emission reduction include the climate risk integration by incorporating climate-related risks and opportunities into core business strategy, financial planning, and risk management frameworks. The target setting contributes through committing to ambitious emission reduction targets, such as Science Based Targets (SBTs), which provide a clear roadmap for decarbonization aligned with climate science. To optimize the output, companies conduct (Al-Mohannadi et al., 2019; Eleftheriadis & Anagnostopoulou, 2017; Georgiou et al., 2024).

2.3. Current Practice of Corporate Innovation

Innovation is increasingly recognized as a critical approach for businesses to address climate change concerns while enhancing their market performance and sustainability. Most of companies across the world are triggered by regulatory mechanisms and market pressures. These factors play a significant role in pushing businesses towards innovation in the era of global transition.

In connection with the regulation and policy, each country has their own mechanisms that applied to businesses which operate in its territory. The national policies encompass various types such as environmental-related regulations and financial incentives. The financial incentives might be in form of government R&D subsidies on innovation in order to alleviate the financing constraints. This type of financial incentives often be practiced in China as observed by J. Li & Wang, (2024); Shi & Zhou (2024); and Zhu & Tan (2022). In addition, the supportive policies in promoting green finance also bring significant impact to provide funding for green projects. This type of incentives has become common practice in many countries.

The regulation framework of a country might be influenced by several global regulations. The author found that European Union (EU) and Organization for Economic Co-operation and Development (OECD) have a big contribution in promoting innovation. Although both groups of countries impose policies that apply to member countries only, the globalization of markets and the integration of global value chains necessitate innovation policies that go beyond national scales. Thus, the regulations also affect the non-European and the non-OECD countries as well. This statement is supported by Manca et al. (2011) who state that the EU's internal market regulations significantly impact innovation adoption by fostering cooperation among businesses. These regulations enhance cooperation, which in turn positively influences innovation adoption rates.. In addition, the implemention of strong patent protection policies by OECD countries can also be credited for its impact in encouraging innovation in business practice. Bergek & Berggren (2014) argue that these policies play crucial role in stimulating business R&D spending, where robust enforcement of patent rights significantly boosts business R&D investments.

2.3.1. Innovation in High polluting Industries

As the global spotlight, the current practices of innovation in high polluting industries are multifaceted, focusing on green technology, regulatory compliance, and efficiency improvements. The green technology is required to supress the amount of emissions produced by high polluting industries. Some of key technologies currently implemented encompass Carbon Capture and Storage (CCS), renewable energy integration, circular economy and waste management.

CCS refers to a technology to capture carbon dioxide (CO_2) emissions from large point sources like power plants and storing it underground in geological formations such as depleted oil fields and saline aquifers. The United States is a leader in this technology. Since their energy system heavily dependent on coal, this technology aims to overcome the emissions issue on their energy industry. There are numerous projects and significant government support, including plans to sponsor half of the 20 commercial-scale demonstrations pledged by the G8 nations (Stephens, 2013).

The integration of renewable energy also adopted by industrial operations to reduce reliance on fossil fuels. Hybrid systems are often economically viable, reducing electricity costs and providing stable energy supplies. This system might be more convenient to implement than radically switching the whole energy sources. China, United States, and India are the leading countries in developing this system for power generation, particularly in microgrids (Santos et al., 2022).

The implementation of well-developed circular economy and waste management reflected by some developed countries, such as Germany, Netherlands, Sweden, Japan, and China. Germany is a leader in circular economy implementation, with robust policies and practices that support sustainable development and waste management across various business sectors, including manufacturing, agriculture, and textiles. The supporting tools in realizing circular economy in this country include innovative technologies, green employee behaviors, and corporate social responsibility initiatives. Furthermore, Netherlands and Sweden have advanced practices of circular economy due to their policies in emphasizing ecological programs and investment in innovative recycle technologies. Likewise Japan which has adopted circular economy principles extensively, particularly in the manufacturing sector. In case of China, there are also several policies supporting circular economy including the Circular Economy Promotion Law and Extended Producer Responsibility to reduce waste and promoting sustainable resource use across various industries (Marti & Puertas, 2021; Ogunmakinde, 2019).

2.3.2. Innovation in Non-high polluting Industries

Although the intensity in producing emissions is less massive comparing to high polluting industries, the non-high polluting industries still have to engage with innovation in order to tackle climate change-related risks because after all, reducing emissions has several benefits for the company, including cost reduction and long-term sustainability. The current practice of non-high polluting industries in implementing innovation mostly focused on green manufacturing practices, technology integration, and green financing.

In case of tire manufacturing industry, the adoption of green manufacturing practices is prioritized in order to contribute to sustainable development goals. According to Hariadi et al. (2023) the key factors influencing these practices include top management commitment, pollution prevention practices, and product stewardship practices, which significantly affect green product service innovation and sustainable product-service system performance. Moreover, Shao et al. (2024) argue that machinery manufacturing industry mostly emphasizes on corporate governance to monitor the execution of green business initiatives to enhance corporate reputation and operational efficiency.

The technology integration of non-high polluting industries often related to big data analytics for facilitating accurate, efficient, and data-driven decision-making. The adoption of this technology is vital to enhanch the effectiveness of innovation adoption as has been the case of automobile industry in India. The factors such as knowledge management, climate for innovation, learning agility, and internal corporate communication has been found to affect innovation adoption (Alarabiat et al., 2025; Gouda & Tiwari, 2022).

Specific to the financial industry, the key elements in fostering environmental innovation is the green financing products. The allocation of financial resources through green finance optimizes the funding for green innovation projects, promoting their widespread application and industrial development. Moreover, green finance stimulates continuous research and development (R&D) investment, which is crucial for sustainable green innovation. Some evidence of green finance contributions channeled by financial companies, one of which is in China. According to Liu et al. (2025) green finance plays significant role in promoting the new energy vehicles (NEVs) sector.

2.4. Previous Research

2.4.1. Innovation on Total Emission

Research conducted by Mo (2022) examined the relationship between innovation and emissions by utilizing data from 558 Korean companies along 2015 – 2018. This study defines innovation activities into number of patents and the expenditures on R&D investment, while emissions refer to total carbon emissions. Based on the estimation using panel data analysis, the result suggest that innovation have a significant negative relationship with carbon emissions across various manufacturing industries. Yet, the impact of these innovation activities varies by industry. This finding is in line with the research conducted by Wang et al. (2021) who investigates 589 listed Japanese companies along 2006 – 2014. This study involved R&D expenditure to respresent innovation. In addition, carbon emission data adopted from the the Green House Gas Emissions Accounting, Reporting, and Disclosure System. The result from panel data analysis discovers the positive correlation between research and development expenditure and carbon emission reductions.

Contradictary findings found in the study conducted by Erdoğan et al. (2020). After examining the sectoral basis data accross 14 countries from 1991 to 2017, they discovered that innovation does not always have a significant impact on emission reduction due to the sector-specific effects. This condition was demonstrated by the construction sector. The innovation in this industry can paradoxically increase emissions, while in others, like the industrial sector can reduce emissions. Beside that, findings from Czerny & Letmathe (2024) suggest that innovation need a time lag to manifest. Therefore, observing the immadiate impact of innovation somehow will be challanging. Moreover, study by Garrone & Grilli (2010) adds that the effectiveness of innovation in reducing emissions is heavily influenced by the design and implementation of the relevant policies.

2.4.2. Commitment Consistency on Total Emission

Dahlmann et al. (2019) distinguish the intention of a company in adopting climate commitment into two; symbolic and substantive. The symbolic commitment attempts to manage external stakeholder perceptions via "greenwashing" , meanwhile the substantive commitments reflected through longer time frame and ambitious emissions reduction effort. The finding suggests that companies with substantive commitment tend to achieve significant reductions in emissions. This indicates that the consistency and ambition of climate commitments are crucial for actual emission reductions. Additionally, Sharaf-Addin & Al-Dhubaibi (2025) highlight that the consistency principle in sustainability practices is essential for credibility of emission reduction claims and facilitate progress towards climate goals.

Contradictary, some literature state that climate commitments contribute nothing to emissions reduction due to several reasons. Arendt (2024) mentioned that many corporate carbon neutrality pledges lack integrity as they rely heavily on carbon offsets rather than actual emission reductions. Only a small percentage of companies aim to reduce emissions to a residual level and compensate with removals, which questions the effectiveness of these pledges. Despite increased corporate participation in climate action, Trapero et al. (2023) identified that there is a significant and positive relationship between the number of companies involved and greenhouse gas emissions, indicating that corporate commitments have marginal contributions to actual emission reductions. Additionally, Trouwloon et al. (2023) emphasized that corporate climate claims are often lead to greenwashing due to the unregulated scheme. This undermines genuine climate mitigation efforts and creates skepticism about the effectiveness of corporate commitments.

2.4.3. Waste on Total Emission

A study by Paleologos et al. (2025) demonstrate the relationship between waste and emission reduction. According to their analysis, a proper waste management could reduce the amount of waste which will lead to emission reduction. This statement is supported by

Lee et al. (2016) who analyze the causality of the waste generation and GHG emissions from waste sector. They argue that total waste generation and recycling rates have a direct impact on GHG emissions reduction. Other research which indicates the significant impact of waste on emission also represented by Gu (2021) highlights that the effective waste strategies is closely related to the reduction of GHG emissions. Related to this finding, Dieste et al. (2019) support that integrating slender production principles, which focus on waste reduction, coupled with green production practices can improve emission reductions.

On the other hand, waste may sometimes not have a significant impact on emission due to some conditions. Zandieh et al. (2024) found that significant improvements in waste management would not even give any changes on emissions of particular sectors due to small portion of GHG emission. This research demonstrate the waste sector in the United Kingdom which only take 3.7% from the aggregate emissions, meanwhile the dominant emissions comes from landfills which take 70% of the total emissions. Furthermore, Zhang et al. (2016) illustrate the dual effect between waste and economic growth on emission. Industrial waste reuse has a direct negative effect on carbon emissions but can indirectly increase emissions through economic growth. This dual effect might distort the impact of waste on emission reduction. Moreover, L. Wang et al. (2022) argue that corporations often more pragmatic by prioritizing emission reduction strategies with more substantial impact, such as digital transformation and green.

2.4.4. Market Capitalization on Emission Reduction

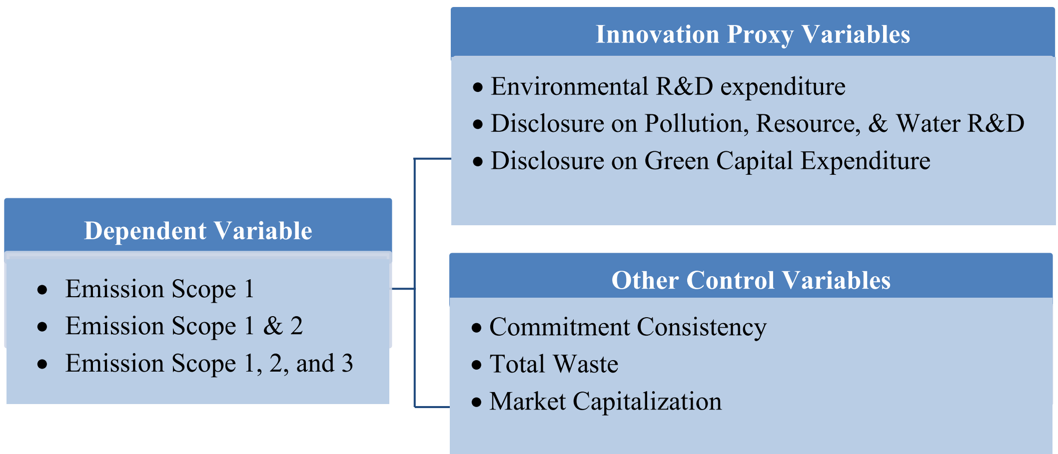
Study by Bendig et al. (2023) investigates companies with Science-Based Emission-Reduction Targets (SBTs) which encompass more than a third of the global market capitalization. The analysis covers the period 2015 – 2020 resulting that large companies are more ambitious in committing to stringent emission reduction goals. This finding is in line with the research by Mahapatra et al. (2021) who examine the top 500 non-financial global companies as the representation of the biggest market capitalization. It reveals that these companies are actively engaging in both internal and external initiatives to reduce their carbon footprints. However, the effectiveness of these initiatives varies, and significant reductions in emissions are not always observed. Furthermore, analysis from Zhou et al. (2023) implies that the market mechanism which are currently available, such as carbon emission trading systems are particularly effective for larger companies with significant market capitalization, as they can better leverage these mechanisms to optimize resource allocation and reduce emissions.

Although most of literatures conclude that market capitalization has positive relationship with the emission reduction, there are some literature which reveals that larger market capitalization does not necessarily lead to better emission reductions. According to Colangelo (2024) companies in particular high polluting industries may have inherent challenges in reducing emissions due to the nature of their operations. Even big companies in these sectors may struggle to implement effective emission reduction strategies, regardless of their market capitalization. The study of Janicka et al. (2020) explain further that big market capitalizations may prioritize short-term financial performance over long-term sustainability goals. This focus can lead to decisions that favor immediate profits rather than investments in emission reduction technologies or practices. Dramatically, research conducted by Badhwar et al. (2024) explain that Some big companies may engage in "greenwashing," where they promote themselves as environmentally friendly without making substantial changes to their operations. Thus, minimal actual impact on emission reduction might be happen.

2.5. Research Framework

By considering the theoretical framework and previous research, the authors determine the research framework as shown in Figure 2.2.

Figure 2.2 Research Framework



Source: Author’s compilation

CHAPTER III
METHODOLOGY

3.1. Research Approach

This study use a quantitative approach in order to analyze the relationship between innovation and emission. Quantitative methods involve the systematic investigation of phenomena through the collection and analysis of numerical data. This approach aims to measure relationships between variables, and confirm or disconfirm hypotheses using statistical techniques (Helmold, 2019; Seeram et al., 2022). Quantitative method has advantage in term of precise measurement of variables. The advanced quantitative techniques increase the statistical power of studies, allowing for more robust and reliable results (Brown & Lassoie, 2010). Moreover, quantitative methods often involve large sample sizes and random sampling, which enhance the generalizability of findings to broader populations (Little et al., 2024; Slater & Hasson, 2024).

3.2. Data and Data Collection Method

This research employs secondary data. According to Näher et al. (2023) secondary data refers to information was collected by someone other that comes from various sources such as surveys, administrative records, electronic health records, and more. This study covers the period 2018 – 2024. The author's reason for determining this time span is based on data availability, where if the author draws a longer period than 2018, the missing data (especially on the dependent variable data) will be more and more so that the data needs are difficult to fulfill. Furthermore, the author found that the reason why the publication of data related to scope 1 emissions by companies began massively in 2018 is because of several reasons. According to Stachelscheid & Dutzi (2025) the growing demand from investors, regulatory bodies, and other stakeholders for more transparent and consistent corporate greenhouse gas (GHG) emissions data, particularly Scope 1 & 2 emissions are getting more intense and driven companies to enhance their disclosure practices to meet these expectations.

The operational variables in this research are entirely obtained from Refinitiv Eikon. The author considers this platform as the data source due to the comprehensive data coverage as needed to fulfill the research objectives. Moreover, Strekalina et al. (2023) argue that Refinitiv Eikon is best for financial research due to the reliable and accurate data. In order to support the analysis, the author also collect data from various publications from reputable journals and official websites of any organizations related to climate change mitigation.

The business sector nomenclature in this study refers to the Global Industry Classification Standard (GICS). GICS organizes companies into a hierarchical structure with multiple levels of granularity. It provides detailed classification, starts from broad sectors and narrows down to specific industries. GICS is effective in grouping companies with similar operating characteristics, which enhances the homogeneity of stock groupings (Chan et al., 2007; Hrazdil et al., 2014). The author's reason for choosing this standard is because of the reliability. Some literatures state that GICS is more reliable industry groupings comparing to other grouping standards, such as North American Industry Classification System (NAICS), Standard Industry Classification (SIC), and Fama-French classification (Chung et al., 2017; Hrazdil et al., 2014; Hrazdil & Scott, 2013).

This research uses all data from Refinitiv Eikon, a platform covers data of approximately 67,300 companies across global. In the process of searching for companies based on the research variables, the author found 5,050 companies from 241 countries across 76 industries. However, there are only 358 companies disclosed their emission and other environmental-related activities along 2018 – 2024 which represents 7.09% of the entire companies in Refinitiv Eikon.

The further analysis in this research involves industry categorization which is divided into two groups, namely high polluting and non-high polluting industries. The author identified that 526 companies are categorized as high polluting companies, this amount represents 65,31% of the entire dataset. To facilitate the explanation related to the author's consideration in sorting high polluting industries, the author categorizes these industries based on their characteristics as follows:

a) Fossil Fuel & Energy Production

This category consists of (1) Oil, Gas & Consumable Fuels, (2) Energy Equipment & Services, (3) Electric Utilities, (4) Gas Utilities, (5) Water Utilities. In general, this category stated as high polluting industries due to their major impact on water and soil contamination, air pollution which mostly comes from the resource extraction process. The oil and gas industry is a significant source of various pollutants, including volatile organic compounds (VOCs), sulfur dioxide (SO_2), nitrogen oxides (NO_x), methane, and particulate matter, meanwhile Energy Equipment & Services produces various pollutants from the energy-intensive processes. In addition, Electric Utilities (fossil fuel-based) are major sources of sulfur dioxide (SO_2), nitrogen oxides (NO_x), mercury (Hg), and carbon dioxide (CO_2). Gas Utilities is the major pollutants of Methane and CO_2 from the production, processing, transportation, and storage. Lastly, the Water Utilities which are energy-intensive, primarily due to the processes involved in water treatment and distribution (Cera & Finarelli, 2024; DiSano, 2010; Fetisov et al., 2023; Haruna et al., 2023).

b) Heavy Transportation & Logistics

This category consists of (6) Aerospace & Defense, (7) Air Freight & Logistics, (8) Marine Transportation, (9) Ground Transportation, (10) Passenger Airlines, (11) Transportation Infrastructure. In general, these industries categorized as high polluting industries due to high fuel consumption and causing noise and air pollution, CO_2 and NO_x emissions, noise pollution, environmental impact of infrastructure. Beside the emissions, the manufacturing and operating of Aerospace products are energy-intensive processes. In addition, the Air Freight & Logistics becomes a major emitters due to the reliance on fossil fuels. Marine transportation is responsible for oil spills, and ballast water discharge. Ground Transportation also causes noise pollution and vibrations, which affecting urban environments. Beside the GHG emissions, environmental impact of Passenger Airlines comes from the land use which leads to biodiversity loss. Lastly, the Transportation Infrastructure contributes on emissions through biodiversity loss from the building project and the high energy use from the building and maintaining processes (Daley, 2016; Ellram, 2021; Galieriková & Sosedová, 2016; Miah et al., 2017; Randone et al., 2019; J. Zhang et al., 2021).

c) Materials & Industrial Manufacturing

This category consists of (12) Construction Materials, (13) Building Products, (14) Metals & Mining, (15) Chemicals, (16) Paper & Forest Products, (17) Industrial Conglomerates, (18) Electrical Equipment (19) Electronic Equipment. Generally, these industries belong to high-pollutants due to energy-intensive production, toxic emissions, mining impacts, high material and energy use. The construction and building industry are the major emitters due to the production of materials which are energy-intensive and generate significant GHG emissions. Beside that, construction activities consume vast amounts of natural resources and energy. Then, Metals & Mining considers to produce heavy metal pollution and contamination on air and water. Likewise with chemicals industry which also contaminate air, water, and soil by producing a wide range of pollutants, including volatile organic compounds, heavy metals, and hazardous waste. Paper & Forest Products belongs to high polluting industry as the production process involve numerous chemicals. Beside that, this industry is notable in deforestation issue. Industrial conglomerates encompass various sectors, each contributing to pollution through emissions, waste generation, and resource consumption. Lastly, Electrical and Electronic Equipment involves the use of numerous chemicals which contains hazardous substances (Abed et al., 2022; Boudh & Singh, 2017; Duodu et al., 2022; Fuentes et al., 2013; Mutz, 2015; Tu, 2023; Yu et al., 2024).

d) Consumer Goods

This category consists of (20) Household Products, (21) Household Durables, (22) Personal Care Products, (23) Beverages, (24) Food Products, (25) Tobacco, (26) Textiles, Apparel & Luxury Goods. The same characteristics that make these industries classified as high polluting industries are because of the waste generation, packaging pollution, chemical use, water and energy consumption. The household and personal care products contain harmful chemicals and contribute to microplastic pollution, particularly from products with microbeads. Similarly, household durables which contains hazardous substances. The beverages industry is a major consumer of water and generates significant amounts of wastewater, which can be heavily polluted with organic content, particularly from packaging, which poses a significant environmental challenge. Meanwhile the Food Products known as high-pollutant due to the production process such as slaughterhouses and potato processing plants, generate wastewater with high levels of biological oxygen demand (BOD) and chemical oxygen demand (COD). In addition related to the carbon footprint, the food waste becomes the top issue as emissions contributors. Tobacco industry involves the use of pesticides and fertilizers, which can lead to soil and water contamination. It might also linked to the deforestation since the tree planting requires a large area of land. Lastly, Textiles, Apparel & Luxury Goods is a major polluter, discharging dyes, chemicals, and microfibers into water bodies. Same as food products, the textile products also deal with the issue of waste which bring significant impact on environment (Alhumoud, 2009; Anderson et al., 2016; Barooah et al., 2023; Brinkmann, 2023; Ledesma-Carrión et al., 2020; Popescu et al., 2024; Valta et al., 2015).

e) Construction & Engineering

This category consists of (27) Construction & Engineering; and (28) Trading Companies & Distributors which are contributors on material waste, dust and particulate pollution, land use change, habitat disruption. Specifically, the construction industry consumes a significant amount of natural resources, including materials, water, and energy that lead to a large volume of waste. Furrthermore, Trading Companies & Distributors are also categorized as high polluting industries due to the supply chain emissions that engage in extensive transportation and logistics operations (Ab Rahman et al., 2011; Doniak, 2025; Lai et al., 2015).

f) Service Industries with High Operational Emissions

This category consists of (29) Hotels, Restaurants & Leisure; and (30) Communications Equipment which have issue on high operational emissions, energy and water use, e-waste, food and packaging waste. The hospitality industry, including hotels and restaurants, consumes substantial quantities of energy, water, and non-durable products, leading to significant environmental impacts. Moreover, it also enerate large amounts of waste, including food waste, which poses ethical, environmental, and financial challenges. Meanwhile Communications Equipment deals with the issue of electronic waste from the electronic devices. This waste contains hazardous materials that can pollute air, water, and soil, posing serious environmental and health risks (Edoun et al., 2019; Juvan et al., 2023; Kumar et al., 2025).

3.3. Definition of Operational Variables

The emission reduction as dependent variable refers to data of each company emissions on Scope 1; Scope 1,2; and Scope 1,2,3. The innovation consists of three variables, namely: Environmental R&D Expenditure; Disclosure on Pollution, Resource, and Water R&D; and Disclosure on Green Capital Expenditure. The consideration in choosing the variable of emissions intensity and the R&D expenditure are influenced by the previous research conducted by Mo (2022) and J. Wang et al. (2021). To the best of the author's knowledge that there is no research includes disclosure variables, particularly on Resource, and Water R&D and Green Capital Expenditure. Therefore, the author selects these variables as additional variables in representing innovation since these variables also included as the innovation matrix in the Refinitiv Eikon.

Furthermore, to reduce the risk of spurious findings, the author account for another potential influencing factors which is included in control variables, namely: Commitment Consistency, Total Waste, and Market Capitalization. The author also provide dummy variable for further analysis. This dummy variable includes the grouping of business sectors into 2 groups, namely the high polluting sector group and the non-high polluting sector group. The more details about each variable are described in table 3.1.

Table 3.1 Operational Variables

Variable		Proxy	Abbreviated by	Measurement Unit	Definition
Dependent	Total Emission	Total emissions Scope 1	totscope1	Tons	Natural log of the amount of direct emissions from owned or controlled sources.
		Total emissions Scope 1, 2	totscope12		Natural log of the sum of direct emissions from owned or controlled sources and indirect emissions from the generation of purchased electricity, steam, etc.
		Total emissions Scope 1, 2, 3	totscope123		Natural log of sum of direct emissions from owned or controlled sources and indirect emissions from the generation of purchased electricity, and all other indirect emissions in the value chain
Independent	Innovation Proxies	Environmental R&D Expenditure	envrd	USD	Natural log of the total amount of environmental R&D costs for development of products and services focusing on improving the environmental impact reduction and innovation.
		Disclosure on Pollution, Resource, and Water R&D	pollutionrd	1 = if the company disclose the pollution, resource, and water R&D	Disclosure on investment in research and development on reducing or avoiding the impacts of pollution, waste or resource use.

				0 = if the company does not disclose the pollution, resource, and water R&D	
		Disclosure on Green capital expenditure	greencapex	1 = if the company disclose the amount of green capital expenditure 0 = if the company does not disclose the amount of green capital expenditure.	Disclosure on share or amount of green capital expenditure deployed to climate-related opportunities.
	Control Variables	Commitment Consistency	commitcons	1 = if the company has relevant policy or commitment 0 = if the company has no relevant policy or commitment	Commitment statement to ensure consistency between its climate change policy and the positions taken by the trade associations of which it is a member.
		Total Waste	totwaste	Tons	Natural log of total amount of waste per year.
		Market capitalization	marketcap	USD	Natural log of the sum of market value for all relevant issue level share types.
Dummy	High polluting industry	High polluting industry	highpolluting	1 = the company is categorized as high polluting companies 0 = the company is not categorized as high polluting companies	The significance of company's operations in producing GHG emissions based on the industry grouping as attached in Appendix 1.

Source: Author's compilation

3.4. Data Analysis

In connection to answering the research question, this study utilizes the panel data regression. as the data consists of time-series and cross-section data. By combining cross-sectional and time-series data, panel data can address the heterogeneity of the dependent variable, which is crucial for accurate statistical analysis In addition, panel data has advantage in providing researchers to control for individual-specific variables that are not observable or measurable, thus reducing bias in the estimation of model parameters (Akay & Yüksel, 2018; Homburg et al., 2021). The procedure of panel data regression consists of 4 steps, namely: classical assumption tets, model estimation, and model specification test, robustness test. Additionally, the equation 3.1 shows the general equation in panel data analysis:

$$Y_{it} = \alpha + \alpha_1 X_{1it} + \alpha_2 X_{2it} + ... + \alpha_n Xn_{it} + \varepsilon_{it} \quad (3.1)$$

Where;

Y	: Dependent variable
α	: Constanta
X_1 X_2 X_n	: Variable coefficient
i	: Individual i-th
t	: Time t-th
ε	: error term

Therefore, this research adopts the model below as the general equation

$$Totscope_{it} = \alpha + \alpha_1 envrd_{it} + \alpha_2 pollutionrd_{it} + \alpha_3\ greencapex_{it} + \alpha_4\ commitcons_{it} + \alpha_5 totwaste_{it} + \alpha_6 marketcap_{it} + \varepsilon_{it} \quad (3.2)$$

Where;

Totscope	: Total emissions
α	: Constanta
i	: Company i-th
t	: Year t-th
ε	: Error term
Envrd	: Environmental R&D Expenditure
Pollutionrd	: Pollution, Resource, and Water R&D Disclosure
Greencapex	: Green capital Expenditure Disclosure
Commitcons	: Commitment Consistency

Totwaste : Total waste

Marketcap : Market Capitalization

3.4.1. Estimation Model

This study uses panel data regression estimation. According to Labra & Torrecillas (2018) there are three approaches commonly used in conducting panel data regression, namely the Common Effect Model (CEM), Fixed Effect Model (FEM) and Random Effect Model (REM). It should be noted that the author applies lag 1 to all explanatory variables (independent variables) in order to mitigate the endogeneity concerns in the econometric models. According to Fingleton & Le Gallo (2010) endogeneity arise when explanatory variables are correlated with the error term, leading to biased and inconsistent parameter estimates. To address this issue, researchers often use lagged independent variables. Wooldridge (2017) argues that lagged variables can reduce endogeneity bias, assuming that past values of the variables are less likely to be correlated with current errors. Gujarati & Porter (2013) add that lagged variables can serve as instruments because they are predetermined and, under certain conditions, not correlated with the current error term. Therefore, this approach can be utilized for addressing endogeneity, especially in time series and panel data contexts.

3.4.1.1. Common Effect Model (CEM)

The simplest of the panel data modes is the Common Effect mode, which combines time series and cross-section data without considering time or individual differences. In this model, it is assumed that the behavior of company data is uniform across time series. This method usually used to estimate the panel data models where the goal is to estimate the average effect of certain variables on all companies (De Vos & Stauskas, 2024).

The equation 3.3 represents the Common Effect Model of this research

$$totscope_{it} = \alpha + \alpha_1(\ln)envrd_{it-1} + \alpha_2 pollutionrd_{it-1} + \alpha_3\ greencapex_{it-1} + \alpha_4\ commitcons_{it-1} + \alpha_5(\ln)totwaste_{it-1} + \alpha_6(\ln)marketcap_{it-1} + \varepsilon_{it} \qquad (3.3)$$

Where;

totscope : Total emissions

α : Constanta

i	: Company i-th
t	: Year t-th
ε	: Error term
envrd	: Environmental R&D Expenditure
pollutionrd	: Pollution, Resource, and Water R&D Disclosure
greencapex	: Green capital Expenditure Disclosure
commitcons	: Commitment Consistency
totwaste	: Total waste
marketcap	: Market Capitalization

3.4.1.2. Fixed Effect Model (FEM)

The Fixed Effect model assumes that differences between individuals can be explained through differences in their intercept, which captures the unique characteristics of the unit which is not changing over time, meaning that the effect of the independent variables on the dependent variable is consistent for all units in the panel data. (Danilevicz et al., 2024). Although the intercepts vary, the model's slope is considered uniform across units. The mode is also denoted by involving dummy variables for each unit in the panel through Least Square Dummy Variable (LSDV) technique, which allows researchers to estimate a fixed effect while taking into account specific differences between units in the panel data (Peković, 2017).

$$Totscope_{it} = \alpha_i + \alpha_1(\ln)envrd_{it-1} + \alpha_2 pollutionrd_{it-1} + \alpha_3\ greencapex_{it-1} + \alpha_4\ commitcons_{it-1} + \alpha_5(\ln)totwaste_{it-1} + \alpha_6(\ln)marketcap_{it-1} + \varepsilon_{it} \quad (3.4)$$

Where;

totscope	: Total emissions
α	: Constanta
i	: Company i-th
t	: Year t-th
ε	: Error term
envrd	: Environmental R&D Expenditure
pollutionrd	: Pollution, Resource, and Water R&D Disclosure
greencapex	: Green capital Expenditure Disclosure
commitcons	: Commitment Consistency

totwaste	: Total waste
marketcap	: Market Capitalization

3.4.1.3. Random Effect Model (REM)

The random effect model designed to capture variability between groups by allowing the intercept to vary randomly across these groups. This model includes both fixed effects and random effects, with the random effects capturing the unobserved heterogeneity between groups. In this model, intercept differences are accommodated by the error component of each company. This model is also known as the Error Component Model (ECM) or the Generalized Least Square (GLS) technique, which allows for adjusting random variation in panel data (Schäfer, 2021). The random effect model of this research is represented by the equation 3.5 as follows.

$$Totscope_{it} = \alpha_i + \alpha_1 (ln)envrd_{it-1} + \alpha_2 pollutionrd_{it-1} + \alpha_3\, greencapex_{it-1} + \alpha_4 commitcons_{it-1} + \alpha_5 (ln)totwaste_{it-1} + \alpha_6 (ln)marketcap_{it-1} + u + \varepsilon_{it} \ldots\ldots \quad (3.4)$$

Where;

totscope	: Total emissions
α	: Constanta
i	: Company i-th
t	: Year t-th
ε	: Error term
envrd	: Environmental R&D Expenditure
pollutionrd	: Pollution, Resource, and Water R&D Disclosure
greencapex	: Green capital Expenditure Disclosure
commitcons	: Commitment Consistency
totwaste	: Total waste
marketcap	: Market Capitalization

3.4.2. Model Specification Test

Several stages of testing need to be carried out to determine the best mode of analysis of panel data reintegration. The test consists of three stages: the Chow Test, the Hausman Test, and the Lagrange Multiplier (LM) Test. The following is a review of each mode specification test.

3.4.2.1. Chow Test

The Chow test is used to determine the most appropriate mode between the Fixed Effect Model and the Common Effect Model by detecting structural changes in time series data (Takeda et al., 2010). This test compares a fixed effect model, which considers variation between individual units, with a common effect mode, which ignores variation between units. By testing whether the intercept differences between units are significant, the Chow test helps to select the most appropriate mode to analyze the panel data more accurately (Saha, 2017).

The hypothesis in this test is as follows:

H1 : Fixed Effect Model

H0 : Common Effect Model

The significance level (α) is a threshold used to determine whether the null hypothesis can be rejected. A common choice for α is 0.05, meaning there is a 5% risk of concluding that there is a structural break when there is none. If the probability value is less than α = 5% (0.05), then H0 is accepted, and the best mode is CEM. On the other hand, if the probability value is less than the significance level of α = 5% (0.05), then H1 is accepted, so the best mode is FEM (Kumbhare & Alavinia, 2019).

3.4.2.2. Hausman Test

The Hausman test is used to choose between the Fixed Effect Model or the Random Effect Model in the panel data analysis by testing for the presence of endogeneity in the regressors. This test assesses whether there is a significant difference between the estimates obtained from the two modes. Suppose the test results show that the difference is substantial. The Fixed Effect Model is recommended because it is more reliable in handling unobserved variables that may affect the results. On the other hand, if the difference is insignificant, the Random Effect Model can be chosen because it is more efficient in data processing.

The hypothesis in this test is as follows:

H1 : Fixed Effect Model

H0 : Random Effect Model

If the random cross-validation probability value is less than α = 5% (0.05), then H0 is accepted, and the best mode is the Random Effect Model. On the other hand, if the random cross-validation probability value is less than the significance level α = 5% (0.05), H1 is accepted, so the best mode is the Fixed Effect Model. The next step is to confirm whether the Random Effect Model is the best to estimate the model to be known using the Lagrange Multiplier Test (Amini et al., 2012; Baltagi, 2015).

3.4.2.3. Lagrange Multiplier Test

The Lagrange Multiplier test is used to test for the presence of random individual effects in panel data models. This is essential to decide whether the REM is appropriate over the CEM. This test assesses whether the variability between individual units is significant enough to warrant using the Random Effect Model compared to the more straightforward Common Effect Model. The Random Effect Model is more suitable if the test results show a significant random effect. Conversely, the Common Effect Model may be more appropriate if no significant differences are identified (Breitung et al., 2016).

The hypothesis for this test is as follows:

H1 : Random Effect Model

H0 : Common Effect Model

If it is found that the result in the Breiusch-Pagan Cross-Seiction probability is less than α = 5% (0.05), then H0 is accepted, and the best mode to use is the Common Effect Model. On the other hand, if the probability is less than α = 5% (0.05), H1 is accepted, or the best mode for estimation is the Random Effect Model.

3.4.3. Classical Assumption Test

In some literature, the classical assumption tests on panel data analysis vary. However, the authors identified that most of the literature conducts 2 essential classic assumption tests before running the regression, these tests include Heteroscedasticity Test and Multicollinearity Test as mentioned in (Basheer et al., 2022; Hidayat et al., 2023, 2024). These classical assumption tests in panel data analysis are essential for ensuring the validity and reliability of the regression models. First, the heteroscedasticity test is required to ensure that the regression coefficients are unbiased and efficient. Second, the multicollinearity test aims to check whether independent variables are highly correlated in order to prevent inflated variance of coefficient estimates and model instability. Third, the autocorrelation test ensures efficient estimates and valid statistical tests by detecting the residuals that might be correlated across time.

CHAPTER IV
RESULT AND DISCUSSION

4.1. Result

4.1.1. Descriptive Statistics

Table 4.1 shows the descriptive statistic for the three estimation, which are the aggregate estimation of all industry, the estimation of high polluting industries, and the estimation of non-high polluting industries.

Table 4.1 Descriptive Statistic

Variable	All Industry					High Polluting Industries					Non-high Polluting Industries				
	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max	Obs	Mean	SD	Min	Max
totscope1	1,536	12.520	2.880	-1.204	18.696	1,080	13.291	2.718	5.434	18.969	518	11.005	2.576	-1.204	18.606
totscope12	1,536	13.507	2.285	2.174	18.960	1,080	14.065	2.168	6.192	18.960	518	12.411	2.107	2.174	18.674
totscope123	1,536	15.861	1.959	3.085	21.904	1,080	16.101	1.930	10.009	21.904	518	15.390	1.931	3.085	19.730
envrd	1,536	15.960	2.950	-4.237	27.542	1,080	15.756	2.875	-4.237	22.004	518	16.359	3.055	6.976	27.542
totwaste	1,536	11.181	2.516	0.706	19.231	1,080	11.562	2.461	0.706	19.231	518	10.433	2.458	1.386	16.720
marketcap	1,536	22.505	1.443	17.455	30.698	1,080	22.585	1.468	17.560	30.698	518	22.349	1.380	17.455	25.513

Source: Refinitiv Eikon (processed data by author)

Dependent Variables

Referring to table 4.1, the aggregate estimation result show that the mean scores for totscope1, totscope12, and totscope123 from 2018–2024 are 12.520; 13.507; and 15.861, respectively. These figures approximate the actual average emissions: 273,790 tons for direct operational emissions (totscope1), 734,934 tons for direct and indirect energy emissions (totscope12), and 7,035,766 tons for total emissions including the supply chain (totscope123).

In the estimation of high polluting industry, the mean scores shows numbers with a considerable difference. The scores for totscope1, totscope12, and totscope123 are 13.291, 14.065, and 16.101, respectively. These represent approximately 588,134 tons of direct emissions (totscope1); 1,287,759 tons of direct and indirect emissions from energy usage (totscope12); and 9,853,591 tons of direct and indirect emissions that include the supply chain.

In contrast, the mean of non-high polluting industries emissions are 11.005; 12.411; and 15.390, respectively which indicate the actual direct emissions of 59,982 tons (totscope1); 246,172 tons of direct and indirect emissions (totscope12); and 4,847,836 tons of emission that also count the supply chain.

The minimum score of totscope1, totscope12, and totscope123 are -1.204; 2.174; and 3.085, respectively. These results corresponds to approximately 0.299 tons of direct emissions (scope1), 8.792 tons of direct and indirect emissions, and 21.862 tons of direct and indirect emissions that include the supply chain. These numbers entirely comes from Aker Carbon Capture ASA which moves in non-high polluting industry, particularly on Commercial Services & Supplies. The minimum score indicates that the company has the lowest emission compared to other companies.

On the other side, the estimation of high polluting industries shows the minimum score at 5.434 and 6.192 (attributed to thyssenkrupp nucera AG & Co KgaA from Metals and Mining industry) and 10.009 (attributed to Triple i Logistics PCL from Air Freight & Logistics industry). This results indicate that these companies have the lowest emissions level among the companies in the group of high polluting industries.

Conversely, the maximum score for totscope1, totscope12, and totscope123 reached 18.696 (attributed to ArcelorMittal SA) and 18.960 and 21.904 (attributed to China Petroleum & Chemical Corp.). As both entities operate within inherently high-polluting industries (Metals & Mining, and Oil, Gas & Consumable Fuels, respectively), these elevated scores directly indicate that these companies generated the highest levels of emissions over the course of the study. Additionally, the minimum score on the estimation of non-high polluting industries shows 18.606; 18.674; and 19.730, repectively, which attributed to RWE AG, company moves in Independent Power and Renewable Electricity Producers industry.

Independent Variables

The mean score of envrd on the aggregate estimation is 15.960 which is equivalent with 7,777,181, meaning that on average, companies spend USD7,777,181 on environmental R&D annually. In addition, the average score for high polluting and non-high polluting industries are 16.101 and 16.360, respectively, which are equal with 9,853,591 and 12,720,109. This indicates that on the average, high polluting companies spend USD9,853,591 for Environmental R&D, meanwhile the average of non-high polluting industries in spending Environmental R&D is USD12,720,109.

The minimum score envrd -4.237 which represents the actual value 0.145, indicating the lowest spending of Environmental R&D approximately USD0.145 from Oil India Ltd, moves in high polluting industries particularly on Oil and Gas industry. On the side of non-high polluting industries, the minimum score is 6.976 which is equivalent with the actual value 1,070. It indicates that among non-high polluting companies, the lowest spending on Environmental R&D is USD1,070 attributed to Turkiye Halk Bankasi AS from Bank industry.

The maximum score of envrd is 27.542 which is equivalent with the actual value 914,879,763,389. This number belongs to Renault SA from non-high polluting industry of Automobile, meaning that along the period 2018 – 2024, this company reach the highest spending approximately USD914,879,763,389 for environmental R&D. Meanwhile from the side of high polluting industry, the maximum score 22.004 equivalent with 3,600,000,000. This indicates that the highest spending on Environmental R&D among high polluting companies is USD3,600,000,000 attributed to Enel Americas SA as the Electric Utilities company.

The control variable of totwaste shows mean score 11.181 on the aggregate estimation, it is equal to the actual value approximately 72,203, meaning that on the average during 2018 – 2024, the companies produce 72,203 tons of waste. Conversely, the average waste produced by the high polluting companies indicated through the mean score 11.562 which represents the actual value 105,197 tons of waste. In addition, the average waste produced from non-high polluting industries is relatively smaller 10.433 which is equal to actual value 33,818 tons of waste.

In addition, the minimum score of total waste 0.706 represent the actual value 2.025 tons of waste by Heranba Industries Ltd as the company moves in high polluting industry, particularly in Chemicals industry. Meanwhile, from the category of non-high polluting industry shows the minimum score 1.386, equivalent with 4 tons of waste produced by AK Sigorta AS from Insurance industry.

The maximum score of total waste 19.231 equals to the actual value 224,968,100 tons of waste, which belongs to high polluting industry, particularly in Metals & Mining company namely En+ Group MKPAO. Furthermore, the maximum score from the non-high polluting group is 16.720 equivalent with 18,255,930 tons of emissions from Fomento de Construcciones y Contratas SA in Commercial Services & Supplies industry.

The last control variable is marketcap that shows the mean 22.505 that represent the actual value of 6,083,490,149, meaning that the average of global market capitalization along the period 2018 – 2024 approximately USD6,083,490,149. In the group of high polluting industries, the mean of marketcap is 22.585 that equals to actual value 5,867,534,187. Indicating that on the average, the market capitalization of high polluting companies is USD5,867,534,187. Meanwhile, the mean of non-high polluting companies is 22.349 that equals to 4,746,755,217, indicating that the average market capitalization of non-high polluting industries is USD4,746,755,217.

The minimum score shows 17.455 equals to actual value 38,085,651 belongs to Solarworld AG as the non-high polluting companies in Semiconductors & Semiconductor Equipment industry. This result indicates that this company has the lowest market cap USD38,085,651. From the side of high polluting industry, the minimum score is 17.560 equals to actual value 42,278,573 from Saipem SpA that moves in Energy Equipment & Services industry. Meaning that this company has the lowest market capitalization approximately USD42,278,573.

4.1.2. Frequency Counts and Percentages of Dummy Variables

Table 4.2 Tabulation Dummy Variables

Variables		All Industry			High Polluting			Non-high Polluting		
		Freq.	**Percent**	**Cum.**	**Freq.**	**Percent**	**Cum.**	**Freq.**	**Percent**	**Cum.**
pollutionrd	0	29,971	98.59	98.59	12,053	97.41	97.41	17,918	99.40	99.40
	1	430	1.41	100.00	321	2.59	100.00	109	0.60	100.00
Total		30,401	100.00		12,374	100.00		18,027	100.00	
greencapex	0	60,396	96.10	96.10	23,819	94.95	94.95	36,577	96.87	96.87
	1	2,448	3.90	100.00	1,268	5.05	100.00	1,180	3.13	100.00
Total		62,844	100.00		25,087	100.00		37,757	100.00	
commitcons	0	34,164	96.16	96.16	13,715	94.63	94.63	20,449	97.20	97.20
	1	1,366	3.84	100.00	778	5.37	100.00	588	2.80	100.00
Total		35,530	100.00		14,493	100.00		21,037	100.00	

Source: Refinitiv Eikon (processed data by author)

Table 4.2 presents a detailed tabulation of three dummy variables—pollutionrd, greencapex, and commitcons—providing insights into corporate environmental engagement. The findings consistently indicate that overall environmental engagement among companies remains notably low, with a marginally elevated level of participation observed within high-polluting industries.

For the pollutionrd variable, which measures engagement in R&D on Pollution, Resource and Water, only 1.41% of all companies reported such activity. A disaggregation by industry type reveals a notable disparity: 2.59% of high-polluting companies engage in pollution-related R&D, in contrast to a mere 0.60% of non-high-polluting companies. This pattern suggests that entities within environmentally sensitive sectors may experience augmented pressure or possess stronger incentives to allocate resources towards innovations aimed at pollution mitigation.

Similarly, the greencapex variable, indicative of investments in disclosure on green capital expenditures, shows that only 3.90% of all companies reported such spending. Consistent with the trend observed for pollutionrd, this proportion is higher among high-polluting industries (5.05%) than among non-high-polluting ones (3.13%). This implies a relatively more robust environmental capital investment response emanating from sectors with significant polluting activities.

Finally, the commitcons variable, which reflects companies' commitments consistency on climate change, indicates that 3.84% of all companies report such data. Among high-polluting companies, 5.37% have commitments consistency, a higher figure compared to 2.80% of their non-high-polluting counterparts.

Collectively, these findings underscore that while high-polluting industries exhibit a comparatively higher degree of environmental responsiveness across all three indicators, the absolute levels of engagement remain notably constrained. This highlights a persistent gap in corporate environmental action and transparency, even within industries characterized by a more substantial environmental footprint.

4.1.3. Model Specification Tests

The model specification tests encompass Chow, Hausman. The detailed output of those tests attached in Appendix 4 and Appendix 5, meanwhile table 4.4 shows the result summary of the model specifications for the scheme 1 which is belong to the estimation for all industries.

Table 4.3 Result Summary of Model Specification Test

Test	Scope 1	Scope 1 & 2	Scope 1, 2, and 3
Prob > F (Chow Test)	0.000	0.000	0.000
Prob > Chi square (Hausman)	0.000	0.000	0.000

Source: Refinitiv Eikon (processed by Author)

The Chow Test compares between the Common Effect Model and Fixed Effect Model. Based on the result, Prob F value= 0.000, it indicates that the best model for the entire models is Fixed Effect Model as the Prob (p-value) < 0.05. Next, the author examine the Hausman Test in order to compare beteween Fixed Effect Model and Random Effect Model. The result of Prob Chi Square 0.000 suggest that the best model is Fixed Effect model as the Prob (p-value) < 0.05. Since both tests show that the best model is the Fixed Effect Model, the authors do not continue the Lagrange Multiplier Test which compares the Common Effect Model and Random Effect model as these two models have been eliminated in the Chow and Hausman tests.

4.1.4. Classical Assumption Test

The result of the classical assumption test is attached in the Appendix 6 and Appendix 7. Based on the result of multicollinearity test, the Variance Inflation Factor (VIF) mean score is 1.16. These results indicate that the models have no multicollinearity as the Mean VIF < 10. In addition, the heteroscedasticity test shows the same result in the model of Scope 1, Scope 1 & 2, and Scope 1, 2, and 3. The value of prob > chi square are 0.0000, meaning that the three models have heteroscedasticity.

Based on the classical assumption result that the entire models did not pass the heteroscedasticity tests. Therefore, the author will use the robust standard error in the estimation in order to addresses this issue.

4.1.5. Estimation Result Scope 1

Table 4.4 Estimation Result of Scope 1

Variables	**All Industry**		**High Polluting**		**Non-high Polluting**	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
envrd	0.046**	0.015	0051**	0.022	0.061*	0.034
pollutionrd	0.182	0.146	0.079	0.111	0.542	0.459
greencapex	-0.162**	0.071	-0.210**	0.101	0.141	0.109
commitcons	-0.058	0.068	0.043	0.847	-0.322**	0.110
totwaste	0.051	0.094	0.194*	0.099	-0.127	0.165
marketcap	0.000	0.094	-0.019	0.084	-0.021	0.168
_constant	11.035**	2.113	10.487**	2.110	11.646**	3.821
R-squared	0.219		0.301		0.314	
Prob>F	0.000		0.005		0.036	

Obs	843	559	284
Groups	358	234	124

Notes: Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$
Source: Refinitiv Eikon (processed data by author)

Table 4.4 shows the estimation results from fixed effect model. The results reveal distinct patterns of influence on Scope 1 emissions across different industry classifications; All Industry, High Polluting, and Non-high Polluting sectors. The models, while statistically significant overall (evidenced by Prob > F values), demonstrate moderate explanatory power, with R-squared values 0.219, 0.301, and 0.314, respectively. It suggests that the model represent the relationship of total emission scope 1 with the explanatory variables approiximately 21.9%, 30.1%, and 31.4%, meanwhile a substantial portion of the variation in direct emissions remains attributable to unobserved factors.

A consistently counter-intuitive finding across all industry groups is the statistically significant positive association between environmental R&D expenditure (envrd) and Scope 1 emissions. This unexpected positive relationship, where increased spending on environmental R&D corresponds to higher emissions, warrants further investigation, potentially indicating that companies undertaking such R&D are initially those with greater existing emission challenges, or that the benefits of this R&D are realized with a time lag (Álvarez-Herránz et al., 2017; Gonenc & Poleska, 2023).

Conversely, the disclosure on green capital expenditure (greencapex) is significantly and negatively associated with Scope 1 emissions for both "All Industry" and, more prominently, for "High Polluting" companies. This suggests that concrete investments in environmentally friendly infrastructure and technologies are effective in reducing direct emissions, particularly in sectors with higher inherent environmental impact.

The observed lack of a statistically significant impact from disclosure on pollution, resource, and water R&D (pollutionrd) on Scope 1 emissions can be attributed to several factors inherent in the nature of this variable and the complexities of environmental impact. Furthermore, the broad scope of "pollution, resource, and water R&D" may encompass initiatives focused on areas such as water efficiency, non-GHG air pollution, or waste management, which do not necessarily translate directly or immediately into reductions in Scope 1 (direct greenhouse gas) emissions. Even if some of this R&D targets Scope 1, its scale or the maturity of the technology might not yet be sufficient to generate a measurable impact. Additionally, companies' disclosure practices could be influenced by external pressures or reputational motives, meaning that disclosure does not always equate to substantive, emission-reducing innovation. Finally, the time lag between R&D investment and its tangible environmental outcomes might extend beyond the timeframe captured by the current panel data, preventing the detection of a significant effect in the short term.

Notably, the impact of climate commitment consistency (commitcons) emerges as significant only for "Non-high Polluting" companies, where a greater consistency in climate commitments is associated with lower Scope 1 emissions. This distinct finding suggests that for industries with comparatively smaller environmental footprints, formal and consistent climate strategies translate more directly into tangible emission reductions. Furthermore, within high-polluting industries, an increase in total waste (totwaste) is significantly linked to higher Scope 1 emissions, intuitively reflecting the interconnectedness between waste generation and the intensity of industrial processes that produce direct emissions. Market capitalization (marketccap), however, does not appear to be a significant predictor of Scope 1 emissions in any of the examined industry categories.

The differential impacts observed across industry groups underscore the importance of segmented analyses, revealing that the drivers influencing direct emissions are not uniform, necessitating tailored strategies for emission reduction efforts.

4.1.6. Estimation Result Scope 1 & 2

Table 4.5 Estimation Result of Scope 1 & 2

Variables	**All Industry**		**High Polluting**		**Non-high Polluting**	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
Envrd	0.013	0.013	0.019	0.014	0.016	0.024
pollutionrd	0.053	0.100	-0.050	0.080	0.373	0.301
greencapex	-0.121**	0.048	-0.123*	0.064	-0.046	0.092
commitcons	0.014	0.078	0.080	0.107	-0.145*	0.080
totwaste	0.046	0.080	0.127	0.080	-0.055	0.144
marketcap	0.078	0.065	0.075	0.058	0.061	0.121
_constant	10.910**	1.535	10.474**	1.245	11.288**	3.026
R-squared	0.439		0.413		0.040	
Prob>F	0.053		0.009		0.200	
Obs	843		559		284	
Groups	358		234		124	

Notes: Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$

Source: Refinitiv Eikon (processed data by author)

The table 4.5 shows the expanded analysis, encompassing both Scope 1 (direct) and Scope 2 (indirect from purchased energy) emissions as the dependent variable. It reveals a more nuanced and dynamically different picture compared to the previous model focusing solely on Scope 1. A striking initial observation is the substantial increase in the model's explanatory power for "All Industry" and "High Polluting" groups, with R-squared values rising significantly to 0.439 and 0.413 respectively, indicating that the models have ability to ecplain the relationship between total emission Scope 1 & 2 with the explanatory variables. This suggests that the chosen environmental and company-specific variables, particularly greencapex, are considerably better at explaining the broader spectrum of combined direct and energy-related emissions.

A pivotal shift in findings pertains to environmental R&D expenditure (envrd). While a perplexing positive association with Scope 1 emissions was observed in the prior analysis, this variable loses all statistical significance when Scope 2 emissions are integrated. This change suggests that the previously detected link may have been specific to direct operational emissions or possibly an artifact of unobserved company characteristics, and its influence dissipates when the broader category of energy-related emissions is included.

In contrast, disclosure on green capital expenditure (greencapex) emerges as a consistently robust and statistically significant negative predictor across "All Industry" and "High Polluting" groups. Its sustained negative coefficient (e.g., -0.121 for All Industry, -0.123 for High Polluting) strongly indicates that concrete investments aimed at green infrastructure or energy efficiency effectively reduce a company's overall carbon footprint, especially within high-polluting sectors where the potential for such reductions is often greater.

Furthermore, the influence of total waste (totwaste), which previously showed a significant positive link to Scope 1 emissions in high-polluting industries, diminishes to non-significance in the combined Scope 1 & 2 model. This implies that while waste generation is linked to direct operational emissions, its connection to broader energy consumption patterns, and thus Scope 2 emissions, is less pronounced.

Conversely, climate commitment consistency (commitcons) maintains its unique and statistically significant negative relationship exclusively for "Non-high Polluting" companies. This sustained finding underscores that for companies with inherently lower direct and indirect footprints, a coherent and consistent strategic approach to climate commitments plays a tangible role in reducing their overall emissions, possibly through energy sourcing decisions or supply chain efficiencies. Interestingly, the model's explanatory power for "Non-high Polluting" companies actually diminishes when Scope 2 is included, suggesting that factors influencing their combined emissions might lie outside the scope of the current independent variables, perhaps due to lower absolute emission levels or different emission drivers not captured in this model.

The other control variables, neither total waste (totwaste) nor market capitalization (marketcap) demonstrated a statistically significant correlation with combined emissions across any of the industry groups (All Industry, High Polluting, or Non-high Polluting). This indicates that, within the context of this model and controlling for other variables, the amount of total waste generated by a firm does not reliably predict its combined direct and energy-related emissions. Similarly, a company's market valuation does not appear to be a significant factor influencing its Scope 1 & 2 emissions. This suggests that the drivers of overall emissions are more closely tied to direct environmental investments like green capital expenditure and, for non-high polluting companies, consistent climate commitments, rather than the volume of waste produced or the company's financial market standing.

Overall, this dynamic shift in results highlights that the mechanisms driving direct emissions are distinct from those influencing the broader emission profile that includes indirect energy consumption, emphasizing the necessity of tailoring analytical approaches to the specific scope of emissions under investigation.

4.1.7. Estimation Result Scope 1, 2, and 3

Table 4.6 Estimation Result of Scope 1, 2 and 3

Variables	**All Industry**		**High Polluting**		**Non-high Polluting**	
	Coefficient	SE	Coefficient	SE	Coefficient	SE
envrd	-.000	0.016	0.005	0.015	-0.005	0.033
pollutionrd	0.002	0.076	-0.052	0.070	0.195	0.205
greencapex	0.063	0.063	0.033	0.080	0.144	0.117
commitcons	-0.015	0.074	-0.021	0.087	-0.016	0.157
totwaste	-0.147	0.143	-0.016	0.056	-0.305	0.284
marketcap	0.174*	0.098	0.150	0.066	0.170	0.176
_constant	13.533**	1.33	12.783**	1.431	14.807	2.400
R-squared	0.046		0.286		0.344	
Prob>F	0.596		0.398		0.660	
Obs	843		559		284	

Groups	358	234	124

Notes: Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$
Source: Refinitiv Eikon (processed data by author)

Table 4.6 shows the third set estimation result which involve Scope 1. 2, and 3 as the dependent variable. This result representing the most comprehensive measure of a company's GHG emissions, encompassing direct emissions, indirect emissions from purchased energy, and all other indirect emissions across the entire value chain. The overall findings for this model are critically important: for all three industry classifications ("All Industry," "High Polluting," and "Non-high Polluting"), the model's explanatory power is notably low (R-squared values ranging from a mere 0.046 to 0.344). More significantly, the overall models themselves are not statistically significant (indicated by high Prob > F values of 0.596 for "All Industry," 0.398 for "High Polluting," and 0.660 for "Non-high Polluting"). This fundamental lack of overall significance implies that the set of independent variables included in this analysis (environmental R&D expenditure, pollution R&D disclosure, green capital expenditure disclosure, climate commitment consistency, total waste, and market capitalization) does not, as a group, reliably explain the variations in a company's total Scope 1, 2, and 3 emissions.

Delving into individual variables within this context, most independent variables, including the innovation variables (encompass environmental R&D expenditure (envrd), pollution R&D disclosure (pollutionrd), green capital expenditure disclosure (greencapex)) and control variables (encompass climate commitment consistency (commitcons), and total waste (totwaste)), do not exhibit a statistically significant impact on total Scope 1, 2, and 3 emissions across any of the industry groups. This is a crucial finding, as it suggests that factors which might influence direct emissions or emissions related to energy consumption do not necessarily scale up or directly translate to a measurable effect on the vastly more complex and often diffuse Scope 3 emissions that constitute a large part of the total (Bonelli & Coqueret, 2024; Buchenau et al., 2025).

The only exception to this widespread non-significance is market capitalization (marketcap), which shows a statistically significant positive coefficient for the "All Industry" group. This indicates that for companies across all sectors, a larger market capitalization is associated with higher total Scope 1, 2, and 3 emissions. This correlation is plausible given that companies with higher market caps are often larger, more diversified, and possess more extensive and intricate global value chains, inherently leading to a greater volume of difficult-to-track and influence Scope 3 emissions.

Overall, the results underscore the immense challenge in accurately modeling and influencing a company's complete carbon footprint, particularly its far-reaching indirect value chain emissions, with the standard set of environmental and firm-specific variables typically examined.

4.1.8. Model Equation of Scope 1

Based on the estimation result on table 4.4, the model equation for each group are as follows:

a) All Industries

$$totscope1 = 11.035 + 0.046envrd + 0.182pollutionrd - 0.162greencapex - 0.058commitcons + 0.051totwaste - 0.000marketcap + \varepsilon_{it} \quad (4.1)$$

Equation 4.1 is the estimated baseline Scope 1 emission level for companies in the "All Industry" group. The intercept of 11.035 suggests a baseline Scope 1 emission level when all other variables are zero, the emissions level remains 11.035 tons. Notably, a USD1 increase in environmental R&D expenditure (envrd) is associated with a statistically significant 0.046 tons increase in estimated Scope 1 emissions, a counter-intuitive finding that warrants further investigation into its underlying causes. Conversely, companies disclosing green capital expenditure (greencapex) are estimated to have significantly lower Scope 1 emissions by 0.162 tons, highlighting the direct benefits of such investments. Other variables like pollutionrd, commitcons, totwaste, and marketcap do not exhibit statistically significant relationships, implying their direct linear impact on Scope 1 emissions for the entire industry is not reliably discernible.

b) High polluting Industries

$$totscope1 = 10.487 + 0.051envrd + 0.079pollutionrd - 0.210greencapex + 0.043commitcons + 0.194totwaste - 0.019marketcap + \varepsilon_{it} \quad (4.2)$$

Shifting to the High Polluting Industry model, the baseline emission is 10.487 tons. In this model, environmental R&D expenditure (envrd) again shows a statistically significant positive association, with a 0.051 tons increase in Scope 1 emissions for every USD1 increase in envrd, suggesting similar complexities as in the aggregate model but potentially intensified by the sector's inherent challenges. The effectiveness of disclosure on green capital expenditure (greencapex) is even more pronounced in this sector, with a significant 0.210 tons reduction in Scope 1 emissions associated with its disclosure, underscoring its critical role in decarbonizing heavy industries. Furthermore, total waste (totwaste) emerges as a statistically significant positive predictor, with a 0.194 tons increase in Scope 1 emissions for every 1 ton increase in waste, directly linking operational inefficiency to higher direct carbon output in this sector. Other variables, including pollutionrd, commitcons, and marketcap, do not show significant effects.

c) Non- high polluting Industries

$$totscope1 = 11.646 + 0.0611envrd + 0.542pollutionrd + 0.141greencapex - 0.322commitcons - 0.127totwaste - 0.021marketcap + \varepsilon_{it} \quad (4.3)$$

Finally, in the Non-high Polluting Industry model, the baseline emission is 11.646 tons. Environmental R&D expenditure (envrd) continues to show a statistically significant positive association, with a 0.0611 tons increase in Scope 1 emissions per unit increase in envrd, albeit with weaker significance than in other groups. Critically, climate commitment consistency (commitcons) stands out as a strong and statistically significant negative predictor, indicating that company with commitment consistency has lower emissions 0.322 tons in Scope 1 emissions. This highlights the importance of strategic and consistent climate governance for companies with lower inherent environmental impacts.

Interestingly, for this group, greencapex and totwaste do not show statistically significant relationships with Scope 1 emissions, suggesting that their direct impact on emissions is less pronounced compared to high-polluting sectors, perhaps because these companies already operate with relatively lower direct emissions where such investments might yield diminishing marginal returns on Scope 1, or due to the waste generation is less directly linked to their primary emission sources. Across all models, the statistical insignificance of pollutionrd and marketcap consistently implies that their direct linear influence on Scope 1 emissions is not reliably established.

4.1.9. Model Equation of Scope 1 & 2

a) All Industries

$$totscope12 = 10.910 + 0.013envrd + 0.053pollutionrd - 0.121greencapex + 0.014commitcons + 0.046totwaste + 0.078marketcap + \varepsilon_{it} \quad (4.4)$$

For all industries combined, the model estimates a baseline emission of 10.910 tons for combined Scope 1 & 2 emissions when all independent variables are at zero, a baseline that is statistically significant. Regarding environmental R&D expenditure (envrd), the relationship is not statistically significant, suggesting that broad environmental R&D spending does not reliably influence combined direct and energy-related emissions across the board. Similarly, disclosure on pollution, resource, and water R&D (pollutionrd) with a coefficient of 0.053, climate commitment consistency (commitcons) with 0.014, total waste (totwaste) with 0.046, and market capitalization (marketcap) with 0.078, all show no statistically significant impact on combined Scope 1 & 2 emissions.

In stark contrast, green capital expenditure (greencapex) stands out with a statistically significant negative coefficient of -0.121. This means that companies disclosing green capital expenditure are estimated to have 0.121 tons lower combined Scope 1 & 2 emissions than those that do not, demonstrating a clear and reliable beneficial effect of such investments on a company's total direct and energy-related carbon footprint.

b) High Polluting Industries

$$\text{totscope12} = 10.474 + 0.019\text{envrd} - 0.050\text{pollutionrd} - 0.123\text{greencapex} + 0.080\text{commitcons} + 0.127\text{totwaste} - 0.075\text{marketcap} + \varepsilon_{it} \ldots \quad (4.5)$$

Within the high-polluting industry, the estimated baseline for combined Scope 1 & 2 emissions is 10.474 tons, a statistically significant constant. Examining the independent variables, environmental R&D expenditure (envrd) with a coefficient of 0.019, disclosure on pollution, resource, and water R&D (pollutionrd) with -0.050, climate commitment consistency (commitcons) with 0.080, total waste (totwaste) with 0.127, and market capitalization (marketcap) with -0.075, all exhibit no statistically significant relationship with combined Scope 1 & 2 emissions. This is a notable change from the Scope 1-only model where envrd and totwaste were significant for this group, suggesting their direct operational links diminish when energy-related emissions are included.

However, green capital expenditure (greencapex) maintains its statistically significant negative impact, with a coefficient of -0.123. This indicates that for high-polluting companies, the disclosure of green capital expenditure is associated with an estimated 0.123 tons lower combined Scope 1 & 2 emissions, reinforcing its robust role in reducing overall direct and energy-related emissions in this carbon-intensive sector.

c) Non-high Polluting Industries

$$\text{totscope12} = 11.288 + 0.046\text{envrd} + 0.373\text{pollutionrd} - 0.046\text{greencapex} - 0.145\text{commitcons} - 0.055\text{totwaste} + 0.061\text{marketcap} + \varepsilon_{it} \ldots \quad (4.6)$$

For the non-high polluting industry, the model estimates a baseline of 11.288 tons for combined Scope 1 & 2 emissions, a statistically significant constant. In this specific context, the impact of most environmental and firm characteristics does not reach statistical significance. Environmental R&D expenditure (envrd) with a coefficient of 0.046, disclosure on pollution, resource, and water R&D (pollutionrd) with 0.373, green capital expenditure (greencapex) with -0.046, total waste (totwaste) with -0.055, and market capitalization (marketcap) with 0.061, all show no statistically significant relationship with combined Scope 1 & 2 emissions. This implies that for companies with lower inherent emission profiles, these factors do not reliably predict changes in their total direct and energy-related emissions.

The sole significant predictor in this model is climate commitment consistency (commitcons), which has a statistically significant negative coefficient of -0.145. This means that companies with climate commitment consistency estimated have 0.145 tons lower in combined Scope 1 & 2 emissions for non-high polluting companies, suggesting that for these companies, strategic alignment and consistent adherence to climate goals are effective drivers of overall emission reduction.

4.1.10. Model Equation of Scope 1, 2, and 3

a) All Industries

$$totscope123 = 13.533 - 0.000envrd + 0.002pollutionrd + 0.063greencapex - 0.015commitcons - 0.147totwaste + 0.174marketcap + \varepsilon_{it} \quad (4.7)$$

. For all industries combined, this model, which attempts to explain total Scope 1, 2, and 3 emissions, is largely ineffective, as most of its variables lack statistical significance. The baseline total emission level is estimated at 13.533 tons. However, the coefficients for environmental R&D expenditure (envrd), disclosure on pollution R&D (pollutionrd), green capital expenditure (greencapex), climate commitment consistency (commitcons), and total waste (totwaste) are all not statistically significant. This suggests that for the average firm, these internal environmental management and governance strategies do not reliably predict changes in their overall, value-chain-inclusive emissions. The one notable exception is market capitalization (marketcap), which has a statistically significant positive coefficient of 0.174. This indicates that a firm's total emissions, particularly the expansive Scope 3 component, are primarily associated with its overall economic scale and complexity rather than its specific internal environmental actions. In essence, while companies may manage their direct emissions, their total carbon footprint is a function of their size and the breadth of their value chain

b) High Polluting Industries

$$totscope123 = 10.474 - 0.019envrd - 0.050pollutionrd + 0.123greencapex - 0.080commitcons - 0.127totwaste + 0.075marketcap + \varepsilon_{it} \quad (4.8)$$

. In the high-polluting industry, the model for total Scope 1, 2, and 3 emissions is also not statistically significant. The baseline for total emissions is estimated at 10.474 units. However, none of the independent variables in the model—including environmental R&D (envrd), pollution R&D (pollutionrd), green capital expenditure (greencapex), climate commitment consistency (commitcons), total waste (totwaste), and market capitalization (marketcap)—show a statistically significant relationship with total emissions. This is a crucial finding, as it demonstrates that the very strategies that were effective in reducing Scope 1 and Scope 1 & 2 emissions for these companies (e.g., greencapex) do not have a discernible impact when the entire value chain is considered. This underscores the vast and difficult-to-influence nature of Scope 3 emissions in high-polluting sectors, which are not reliably explained by a firm's internal environmental management or financial metrics.

c) Non-high Polluting Industries

$$totscope123 = 11.288 - 0.046envrd + 0.373pollutionrd + 0.046greencapex - 0.145commitcons - 0.055totwaste + 0.061marketcap + \varepsilon_{it} \quad (4.9)$$

. For the non-high polluting industry, the model for total Scope 1, 2, and 3 emissions is similarly not statistically significant. The baseline for total emissions is 11.288 units. Critically, none of the coefficients for the independent variables—including envrd, pollutionrd, greencapex, commitcons, totwaste, and marketcap—demonstrate a statistically significant relationship. This highlights a key limitation: even for companies with lower inherent emission profiles, the strategies that were effective in managing their direct and energy-related emissions (e.g., commitcons) do not reliably extend to their broader value chain emissions. The non-significance of all variables in this model reinforces the conclusion that the drivers of a company's total carbon footprint are complex and likely reside in factors outside of a firm's direct control or traditional environmental and financial metrics.

4.2. Discussion

4.2.1. The Impact of Environmental R&D Expenditure on Emission

Statistical testing on the fixed effect model shows that on the estimation Scope 1, envrd consistently significant across All Industry, High Polluting, and Non-high Polluting groups possitively. This implies a counter-intuitive association where higher environmental R&D spending is linked to increased direct emissions. Meanwhile on the estimation of Scope 1 & 2; and estimation of Scope 1, 2, and 3, this variable is not significant for any industry group. Its previously observed link to direct emissions disappears when energy-related indirect emissions are included.

Interestingly, this study discover contradictary finding on positive relationship between environmental R&D expenditure on emissions. It is possible that increased environmental R&D expenditure can lead to higher emissions under certain circumstances. This phenomenon can be attributed to several factors. First, the rebound effect of new technologies can result in increased overall consumption and emissions. This rebound effect can be illustrated through several mechanism. For instance, if an energy-efficient factory can produce 30% more goods using the same amount of energy, it may ramp up production due to higher profitability, offsetting the emission reductions from the efficiency. Additionally, if the companies only adopt partial technology, the older and dirtier methods are still in use. Therefore, the net emissions can remain high or even rise. This explanation is in line with the study from Kinyar & Bothongo (2025) who also found that environmental R&D expenditure increased environmental degradation due to such rebound effects.

Looking more detail at the model, it reveals that the impact of environmental R&D expenditure in the non-high polluting industries is higher compared to the high polluting industries. This counter-intuitive positive relationship, can be explained by several factors. First is due to lower baseline emissions factor. Non-high polluting industries inherently have lower Scope 1 emissions to begin with. When they engage in environmental R&D, any associated emissions (e.g., from running a new lab, prototyping, or small-scale testing) could represent a proportionally larger increase relative to their existing, smaller emission footprint. In high-polluting industries, the same amount of R&D-related emissions might be dwarfed by their much larger operational emissions, making the coefficient appear smaller. Second non-high polluting tend to take actio earlier in their journey of integrating environmental R&D into their core operations for direct emission reduction. The initial phases of R&D often involve significant resource consumption before efficiency gains or emission reductions are realized. High-polluting industries, having faced more pressure for longer, might have more mature envrd processes where some initial inefficiencies have already been addressed.

The different result occurs due to several key factors. First, Scope 1 emissions are direct emissions from owned or controlled sources, such as company facilities and vehicles. These emissions are more directly influenced by internal R&D efforts aimed at improving processes, technologies, and efficiencies within the company's immediate control. This argument is reinforced by Roston (2021) who stated that although companies can influence Scope 2 emissions through energy efficiency and renewable energy investments, the impact of R&D is less direct compared to Scope 1. Moreover, the complexity of scope 3 measurement potentially lead to double counting, internal and external boundary problems, financial engineering offsets, and off-balance sheet exposures confound the usefulness of Scope 3. On the other hand, Mahieux et al. (2025) expand that the measurement of Scope 1 emissions is highly reliable, making it easier to track the direct impact of R&D investments on reducing these emissions.

4.2.2. The Impact of Disclosure on Pollution, Resource, Water R&D on Emission

Although disclosure on Pollution, Resource, Water R&D indicates the company's concern on environmental issue, the findings from this research does not fit with this assumption. Based on the estimation results, disclosure on Pollution, Resource, Water R&D has no significant correlation on emission, either in the Scope 1, Scope 1 & 2, or Scope 1, 2, and 3 – while the R&D expenditure variable itself has a significant impact on emission Scope 1. In this condition, the author identifies a gap between the actual efforts (which is represented by the environmental R&D expenditure variable) and the company's claims (which is represented by the Disclosure on Pollution, Resource, Water R&D variable). Although the two variables are not exactly the same, they still have the same characteristics in terms of objectives, that is the orientation towards reducing emissions. This gap can be explained by several factors, one of which is greenwashing. According to Ferrón-Vílchez et al. (2021) greenwashing refers to the practice of companies misleading stakeholders about their environmental efforts, often to appear more environmentally responsible than they are in reality.

In connection to the greenwashing issue, this argument is supported by the finding from Bîzoi & Bîzoi (2025) who suggest that greenwashing is most likely to occur when the companies have to meet consumer expectations and regulatory pressures can drive as a shortcut to appearing compliant and responsible. This explanation implies that disclosures related to R&D investments tend to be used as a corporate instrument in meeting regulatory demands instead of reducing actual emissions.

Moreover, disclosure on pollution, resource, and water R&D may not directly translate into immediate emission reductions due to the outcomes of R&D are uncertain and may take time to materialize into effective emission reduction technologies. This time lag also discussed in a research conducted by Feng & Peng, (2019) who argue that the process of technological innovation and its integration into practical applications can be lengthy, therefore information contained in the disclosure may be less comprehensive in describing the contribution to emissions reductions.

4.2.3. The Impact of Disclosure on Green Capital Expenditure on Emission

Based on the estimation result, the disclosure on green capital expenditure has significant impact on emission Scope 1 and Scope 1&2, consistently on group of All Industry and High Polluting Industry. Meanwhile it remains insignificant in all non-high polluting estimations. This condition might occur due to the lack of immediate regulatory pressure faced by non-high polluting companies. This reduced pressure means that the incentives to reduce emissions through green capex are weaker, compared to high polluting companies as found by Jin et al. (2021) and Lou & Zhu (2025).

Yet, it become insignificant when the Scope 3 involved in the estimation. This changes can be attributed to the complexity and standardization of Scope 3. Scope 3, which include all other indirect emissions that occur in a company's value chain, are more challenging to measure and standardize. The lack of adequate data and standardized guidelines makes it difficult for companies to accurately report and manage these emissions. This explanation further supported by Panjwani et al. (2023) who argue that there are substantial discrepancies in Scope 3 disclosures across different regions, sectors, and time periods, which undermines the reliability of the data. This inconsistency makes it harder for companies to effectively manage and reduce their Scope 3 emissions through green capital expenditures.

Moreover, the significant correlation between disclosure on green capital expenditure with the total emissions, particularly in Scope 1 and Scope 1&2 might indicate that there is a positive impetus from green capital expenditure towards emission reduction as it is directly linked to decarbonization efforts and resource efficiency. Green capital expenditure reflects a real commitment to sustainability, as these capital expenditures are long-term and represent a structural change in the company's operations. Therefore, the disclosure on this matter might bring impact on emissions reduction through particular mechanism. Yun & Hu (2025) argue that disclosure of green capital expenditures increases transparency, which enhances market governance mechanisms. This transparency allows investors and stakeholders to better assess a company's commitment to environmental sustainability, leading to increased pressure on companies to reduce emissions. Moreover, Ren & Du (2024) explain that green finance plays a crucial role in supporting companies' green transformation. By disclosing green capital expenditures, companies can attract green finance, which is often tied to specific environmental performance metrics, thereby ensuring that the funds are used effectively for emission reduction.

4.2.4. The Impact of Commitment Consistency on Emission Reduction

Interestingly, commitment consistency has negatively significant influence on emission for non-high polluting industries only, particularly in the estimation of Scope 1 and Scope 1&2. The significant correlation between commitment consistency can be attributed to the condition, where the non-high polluting industries are more responsive to environmental issues and able to adapt their environmental strategies more easily due to less stringent operational constraints, especially compared to high polluting industries, therefore the consistent implementation on policy related to environmental issue is easier to achieve. This statement is in line with Wang et al. (2020) who argue that the non-manufacturing that also reflects the non-high polluting industries – are more agile in change their environmental strategies in order to address the stakeholder pressure.

Furthermore, the non-high polluting industries often have more specific and effective policies targeting, leading to significant emission reductions. Research by Aziz et al. (2024) demonstrate this statement through the carbon taxes and clean energy incentives that might bring benefit for the non-high polluting industries. This economic incentives encourage companies to remain consistent in implementing the environment-related policies.

In addition, the effectiveness of Commitment Consistency in reducing emissions might occur due to the resource allocation. Non-high polluting industries can benefit from resource reallocation from high-polluting to low-polluting companies, which helps in reducing overall emissions. This explanation is supported by the finding from Bu & Ren (2023) that the resources transfer from high polluting industries to non-high polluting industries are facilitated by industrial policies which promote cleaner technologies and practices.

The insignificant correlation can be explained by connecting the complexity of implementing the “consistency” itself. The author argue that consistency, especially in adopting climate-change policies requires tight monitoring and good governance which makes the impact measurement becomes more complex. Corrupt leadership might distort the ideal goal of a policy, thus the impact of the policy cannot be measured. This statement is in line with Rawhouser et al. (2018) who found that effective stakeholder engagement is the key factor for the success of climate change policies. Furthermore, (Sandink et al., 2016) mentioned that engaging stakeholders in the development and implementation of policies can enhance their legitimacy and ensure that the outputs are used in decision-making processes.

Although the policy initiative is issued by an association that houses businesses of the same group, the design of uniform policies framework might not be equally effective across all companies, it potentially leads to inconsistent outcomes in emission reductions. This opinion is in line with Coria & Kyriakopoulou (2018) who explained the sufficient environmental policies of each company might be different. They demonstrated the emission standards may favor small companies, while emission taxes and performance standards impact larger companies' profits and optimal scale.

To some extent, the commitment consistency of a company is also influeced by the trust factor. Distrust among companies regarding the regulator's intentions might occur due to the policies that are not dynamically consistent. This inconsistency can affect companies' willingness to declare accurate emissions reduction targets. This perspective is confirmed by Dowling et al. (2018) who described that dynamic inconsistency in regulatory and policy approaches can erode trust and lead to compliance strategies that are more about avoiding penalties than improving quality.

4.2.5. The Impact of Waste on Emission Reduction

This study discovers that waste positively gives significant impact on emission. However, this variable only found significant influencing emission reduction on high polluting industry, particularly in Scope 1. This finding can be further explored by linking the high baseline of emissions. The high polluting industry inherently produce large amounts of emissions due to their energy-intensive processes and the nature of their production activities. Therefore, any waste management initiatives can clearly impact to the substantial absolute reductions in emissions, compared to the non-high polluting companies. This argument is supported by Sun et al. (2017) who found that waste reduction in the iron and steel industry is positively impact on reducing emissions.

Moreover, in specific case of high polluting industry, the concern on waste management might be more intense due to the regulatory pressure. The author found an indication that waste capture effort such as recycling gives significant potential in reducing emissions. This statement is based on the finding by Paleologos et al. (2025) who found that aggressive recycling and composting programs have led to a 38% reduction in methane emissions from waste in the European Union.

Highly polluting industries are more commonly referred to as high-regulated industries in the context of environmental issue. Therefore regulation pressure in emission reduction instantly linked with the the waste management since regulatory frameworks are often more stringent for high polluting industries. This statement has been proved by Dwyer (2007) who suggested that European regulations and landfill taxes pressure industries to reduce and recycle waste, leading to lower emissions.

4.2.6. The Impact of Market Capitalization on Emission Reduction

The finding of this research implies that market capitalization of a company has significant impact on group of all industry, particularly in the estimation of Scope 1, 2, and 3. Yet, the results of estimation on Scope 1 and Scope 1&2 show that market capitalization has no significant impact on emissions reduction, points to its relationship primarily with the broader, more indirect, and complex aspects of a company's carbon footprint.

Market capitalization is a strong indicator of a company's overall size, influence, and global reach. Companies with very high market caps are often large, multinational corporations with extensive operations, diverse product lines, and complex, far-reaching supply chains. Additionally, Scope 3 emissions are inherently tied to the value chain. These include emissions from purchased goods and services, upstream transportation, waste generated in operations, employee commuting, business travel, downstream distribution, use of sold products, end-of-life treatment of sold products, and investments. The sheer scale and complexity of a large company's value chain mean that its Scope 3 emissions will likely be vast and multifaceted, even if its direct (Scope 1) or energy-related (Scope 2) emissions are relatively managed or small compared to a heavy industrial company. This argument is supported with the findings from Downie & Stubbs (2013) and Mahapatra et al. (2021).

The explanation behind this finding can comes from the side of the role of the green investor. Although environmental concerns continue to grow among investors, however, the current condition is still in the transition stage towards a green business ecosystem. Therefore, it is possible that the behaviour of investors has not fully shifted to prioritize the environmental performance of companies, after all, economic profit remains a significant orientation for many investors.

On the other side, the insignificant correlation on Scope 1 and Scope 1&2 might be attributed to the Scope 1 & 2 are more directly managed. Therefore, it may not scale proportionally with market cap as Scope 3 emissions do. This limited view can distort the understanding of a company's environmental impact and its correlation with market capitalization. This statement is supported by Gurvich & Creamer (2021) and Stachelscheid & Dutzi (2025).

Moreover, even though some investors may already be “the true green investors” which has strong commitment in investing on environmental-friendly company only, they might be still limited by their current wealth share and practices. This explanation is in line with the finding of De Angelis et al. (2023) suggests that market cap may not be the primary factor driving emission reductions due to the increased uncertainty about future climate risks implies on green investors' pressure on company cost of capital.

CHAPTER V
CONCLUSION

5.1. Conclusion

This research examine the impact of innovation on emission reduction among various industries across the globe from 2018 to 2024 through panel data analysis. The innovation consists of three variables, namely: environmental R&D expenditure; disclosure on pollution, resource, and water R&D; and disclosure on green capital expenditure;– while the emission reduction reflected from the data of three types of total emission, include Scope 1; Scope 1 & 2; and Scope 1, 2, and 3. Additionally, commitment consistency, total waste and market capitalization are included as control variables. For further analysis, the author also conduct estimation based on the industry category by dividing the sample company into high polluting and non-high polluting.

On testing the model specification, it was found that the best model for the entire estimation is the fixed effect model. The result reveals vary. One of three innovation proxies found not statistically not significant on the entire estimations. Additionally, the environmental R&D expenditure found significant in influencing emissions in all estimation Scope 1. The disclosure on green capital expenditure found significant in the estimation Scope 1 and Scope 1 & 2, particularly in the group of all industry and high polluting industry. Furthermore, each control variables has significant influence in the different estimations. The commitment consistency uniquely found significant only in non-high polluting industries, particularly in the estimation of Scope 1 and Scope 1 & 2. Total waste found significant in Scope 1, particularly in high polluting industry. Lastly, the market capitalization found significant for high polluting industries in Scope 1, 2, and 3 estimation.

5.2. Recommendation

Based on the regression results, the consistent and statistically significant positive correlation between environmental R&D expenditure (envrd) and Scope 1 emissions across all industry classifications (All Industry, High Polluting, and Non-high Polluting) is a notable finding. This suggests that companies investing more in environmental R&D paradoxically tend to have higher direct emissions. Therefore, it is recommended for companies to rethink broad environmental r&d investments for immediate emission cuts. Companies should critically evaluate the direct, short-term emission reduction returns from broad environmental R&D expenditure. Companies should focus R&D efforts on specific, proven technologies with clear pathways to emission reduction, and recognize that benefits may accrue over a longer timeframe. Chen et al. (2021) argue that there are different types of green R&D activities have varied impacts on emissions. The research reveals that utility-type R&D activities show significant positive effects on reducing SO2 emissions, indicating the importance of targeted R&D investments.

At some extent, policymakers should scrutinize public funding and mandates for general environmental R&D, especially if the goal is immediate emission reduction. Instead, policies should aim to direct R&D towards specific, proven technologies that yield verifiable emission reductions, possibly incorporating performance-based incentives or focusing on areas with long-term transformative potential, while acknowledging potential time lags for benefits. It is crucial to ensure that the R&D addresses the most pressing environmental issues. In line with this statement, finding from Mastrángelo et al. (2024) indicate that misalignment can lead to ineffective use of resources and missed opportunities for impactful research.

Moreover, the significance of green capital expenditure disclosure encourages companies to prioritize green capital expenditure for tangible emission reductions. Companies should strategically invest in green capital expenditure, such as energy-efficient machinery, renewable energy infrastructure, and process upgrades. This is especially critical for high-polluting companies, where these investments show a strong and consistent statistically significant negative correlation with Scope 1 and Scope 1 & 2 emissions. This suggests that tangible asset-based investments directly translate into reduced direct and energy-related emissions, offering a clear path to decarbonization. This statement is supported by De Angelis et al. (2023) who found that green investing can raise the cost of capital for carbon-intensive companies, incentivizing them to reduce emissions to attract investment.

From the side of policymakers, it is crucial to create robust financial incentives, such as enhanced tax credits, grants, and favorable loan programs, specifically for green capital expenditure. These incentives should be particularly amplified for high-polluting industries, where the emission reduction potential from such investments is most pronounced as recommended by Niyazbekova et al.(2024), Rana et al., (2021), and H. Wang et al. (2024).

As the non-high polluting industries have climate commitment consistency that found significant influencing emissions, the companies in this group need to emphasize and consistently adhere to strong climate commitments. This includes integrating climate goals into core business strategy and governance.

In optimizing the output of commitment consistency on emission reduction, the policymakers should emphasize "soft" policy instruments that encourage and reward robust climate commitment consistency, transparent reporting, and strong corporate environmental governance. This can include recognition programs, voluntary reporting standards, and regulatory frameworks that encourage the integration of climate goals into business strategy. This kind of integration may benefit the companies. Gardener et al. (2011) suggest that integrating climate goals helps businesses anticipate and mitigate these risks, ensuring long-term sustainability and resilience.

The influence of waste in high polluting companies should be addressed. Companies in high-polluting industries should focus on waste reduction and resource efficiency initiatives within their operations. The analysis indicates a statistically significant positive link between total waste and Scope 1 emissions for this group. Reducing waste can thus offer a dual benefit of environmental improvement and direct GHG emission reduction. Gribincea (2024) further describe that good waste management often linked to cost savings through efficient use of resources. Thus, industries can lower their expenditure on raw materials and energy, which are substantial components of manufacturing costs.

In addition, the policymakers should develop targeted policies for high-polluting industries that specifically address total waste reduction and resource efficiency. This could include waste taxes, subsidies for recycling and reuse infrastructure, or regulatory mandates for process optimization to minimize waste and associated direct emissions. The typical regulation in reducing waste was observed by Salemdeeb et al. (2022). It reveals that policies focusing on waste prevention rather than just waste management can yield greater environmental benefits. Preventing waste at the source reduces the overall environmental footprint more effectively than managing waste after it is created. Moreover, Ajayi et al. (2015) explain that implementing regulatory mandates for process optimization can ensure that industries adhere to best practices for waste reduction and resource efficiency.

In case of large companies, it is essential to recognize the total Scope 1, 2, and 3 emissions which are highly influenced by their overall scale and the complexity of their value chain, largely unexplained by typical environmental management variables. Therefore, the companies should invest in advanced Scope 3 measurement as this scope has complex measurement. X. Yang et al. (2025) argue that advanced measurement tools and methodologies, such as environmentally extended input-output models and blockchain technology, can enhance the accuracy and transparency of Scope 3 emissions data.

On the other hand, policymakers must acknowledge the significant challenge in directly influencing Scope 1, 2, and 3 emissions with traditional policy levers, as these models were largely non-significant for this broadest scope. New frameworks are needed that can address the complexity of supply chain emissions, potentially involving industry-wide collaborations, enhanced data transparency requirements across value chains, and incentivizing product lifecycle assessments. Consideration should be given to how the sheer scale of companies correlates with overall emissions, necessitating approaches that consider systemic impacts. This consideration is based on the findings from van Lieshout et al. (2011) who argue that different actors often deploy conflicting scale frames, leading to mismatches that can stagnate decision-making processes. By recognizing and addressing these mismatches, policymakers can facilitate smoother and more effective policy implementation.

5.3. Research Limitation

This research explores the impact of innovation on emission reduction through examination of four variables which are Environmental R&D Expenditure, Disclosure on Pollution, Resource, and Water R&D, Disclosure on Green Capital Expenditure, and Commitment Consistency during the period 2018 -2024. The model in this study also includes another variables out of innovation which are the amount of total waste and market capitalization. To distinguish the impact of innovation on emission reduction in high polluting industries and non-high polluting industries, the examination by using dummy variable was also conducted.

After all, the examination of this study in investigating the impact of innovation still has room of improvement to enhance point of view and the comprehensiveness. A primary boundary of this research lies in the number of the sample is relatively small due to the number of companies publishing innovation-related information is still low. Therefore, the exploration on this topic remains interesting in the future as the quality of the data will be better and more comprehensive. Furthermore, the issue of measurement error might occur due to the subjectivity of some self-reported indicators, leads to disproportionate data. Beside that, there is potential endogeneity issue. Applying approach to overcome endogeneity might result more robust resut in future study.

In addition, specific set of independent variables chosen for analysis could be the limitation of this study. The models relied on envrd, pollutionrd, greencapex, commitcons, totwaste, and marketcap to explain variations in emissions. While these variables are significant in the corporate sustainability discourse, they do not encompass the exhaustive range of factors that could influence a company's carbon footprint. Other potential determinants, such as specific regulatory frameworks, technological maturity within an industry, the age of capital stock, macroeconomic conditions, or detailed firm-level operational characteristics beyond those measured, were not included. Consequently, the findings are limited to the explanatory power offered by these selected variables, and the influence of unobserved or unquantified factors remains outside the model's scope.

Beside the boundaries aspect above, this study also have other limitations. First, the process of categorizing the industries may play a major role in modeling the relationship of innovation to emission reduction. Although the industry categorization in this study has a scientific basis, literature exploration conducted by other researchers may lead to different categorizations. Second, the measurement of emissions based on GHG protocols might be not applicable for those companies operating in some countries that apply other measurement standard for GHG emissions.

Since this sudy is limited in exploring the innovation impact, further exploration to explain how and why innovation influence the emission reduction in high polluting industries is still necessary. This exploration can be deepened by asking whether the effect of R&D on emissions is moderated by other factors beyond the variables observed in this study. Hence, the findings on this research topic can provide a more robust view for both industry and policy authorities in understanding how innovation works to reduce corporate emissions.

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APPENDIX

Appendix 1: List of Industries

High Polluting Industries

1) Aerospace & Defense
2) Air Freight & Logistics
3) Beverages
4) Building Products
5) Chemicals
6) Communications Equipment
7) Construction & Engineering
8) Construction Materials
9) Electric Utilities
10) Electrical Equipment
11) Electronic Equipment, Instruments & Components
12) Energy Equipment & Services
13) Food Products
14) Gas Utilities
15) Ground Transportation
16) Hotels, Restaurants & Leisure
17) Household Durables
18) Household Products
19) Industrial Conglomerates
20) Marine Transportation
21) Metals & Mining
22) Oil, Gas & Consumable Fuels
23) Paper & Forest Products
24) Passenger Airlines
25) Personal Care Products
26) Textiles, Apparel & Luxury Goods
27) Tobacco
28) Trading Companies & Distributors
29) Transportation Infrastructure
30) Water Utilities

Non-high Polluting Industries

1) Automobile Components
2) Automobiles
3) Banks
4) Biotechnology
5) Broadline Retail
6) Capital Markets
7) Commercial Services & Supplies
8) Consumer Finance
9) Consumer Staples Distribution & Retail
10) Containers & Packaging
11) Distributors
12) Diversified Consumer Services
13) Diversified REITs
14) Diversified Telecommunication Services
15) Entertainment
16) Financial Services
17) Health Care Equipment & Supplies
18) Health Care Providers & Services
19) Health Care REITs
20) Health Care Technology
21) Hotel & Resort REITs
22) Independent Power and Renewable Electricity Producers
23) Industrial REITs
24) Insurance
25) Interactive Media & Services
26) IT Services
27) Leisure Products
28) Life Sciences Tools & Services
29) Machinery
30) Media
31) Mortgage Real Estate Investment Trusts (REITs)
32) Multi-Utilities
33) Office REITs
34) Pharmaceuticals

35) Professional Services
36) Real Estate Management & Development
37) Residential REITs
38) Retail REITs
39) Semiconductors & Semiconductor Equipment
40) Software
41) Specialized REITs
42) Specialty Retail
43) Technology Hardware, Storage & Peripherals
44) Wireless Telecommunication Services

Appendix 2: Stata Output - Descriptive Analysis

1) All industries

Variable	Obs	Mean	Std. dev.	Min	Max
l_totscope1	1,536	12.52002	2.88025	-1.203973	18.69604
l_totscope12	1,536	13.50699	2.285239	2.173849	18.96021
l_totsco~123	1,536	15.86078	1.958912	3.084627	21.90446
l_envrd	1,536	15.9595	2.950135	-4.236712	27.54206
l_totwaste	1,536	11.18124	2.516152	.7055697	19.23147
l_marketcap	1,536	22.50547	1.442787	17.45535	30.69785

2) High polluting Industries

Variable	Obs	Mean	Std. dev.	Min	Max
l_totscope1	1,018	13.29086	2.717569	5.433722	18.69604
l_totscope12	1,018	14.06463	2.168321	6.192362	18.96021
l_totsco~123	1,018	16.10059	1.930052	10.0085	21.90446
l_envrd	1,018	15.7562	2.875463	-4.236712	22.0042
l_totwaste	1,018	11.56159	2.460906	.7055697	19.23147
l_marketcap	1,018	22.5849	1.468089	17.55979	30.69785

3) Non-high polluting Industries

Variable	Obs	Mean	Std. dev.	Min	Max
l_totscope1	518	11.00514	2.575647	-1.203973	18.60633
l_totscope12	518	12.41108	2.107381	2.173849	18.64702
l_totsco~123	518	15.3895	1.931259	3.084627	19.73095
l_envrd	518	16.35903	3.055246	6.97559	27.54206
l_totwaste	518	10.43374	2.457531	1.386294	16.72
l_marketcap	518	22.34936	1.379835	17.45535	25.51278

Appendix 3: Frequency Counts and Percentages of Dummy Variables

1) All industries

pollutionrd	Freq.	Percent	Cum.
0	29,971	98.59	98.59
1	430	1.41	100.00
Total	30,401	100.00	

greencapex	Freq.	Percent	Cum.
0	60,396	96.10	96.10
1	2,448	3.90	100.00
Total	62,844	100.00	

commitcons	Freq.	Percent	Cum.
0	34,164	96.16	96.16
1	1,366	3.84	100.00
Total	35,530	100.00	

2) High polluting Industries

pollutionrd	Freq.	Percent	Cum.
0	12,053	97.41	97.41
1	321	2.59	100.00
Total	12,374	100.00	

greencapex	Freq.	Percent	Cum.
0	23,819	94.95	94.95
1	1,268	5.05	100.00
Total	25,087	100.00	

commitcons	Freq.	Percent	Cum.
0	13,715	94.63	94.63
1	778	5.37	100.00
Total	14,493	100.00	

3) Non-high polluting Industries

pollutionrd	Freq.	Percent	Cum.
0	17,918	99.40	99.40
1	109	0.60	100.00
Total	18,027	100.00	

greencapex	Freq.	Percent	Cum.
0	36,577	96.87	96.87
1	1,180	3.13	100.00
Total	37,757	100.00	

commitcons	Freq.	Percent	Cum.
0	20,449	97.20	97.20
1	588	2.80	100.00
Total	21,037	100.00	

Appendix 4: Stata Output - Chow Test

1) Scope1

```
Fixed-effects (within) regression               Number of obs     =        843
Group variable: ID                              Number of groups  =        358

R-squared:                                      Obs per group:
     Within  = 0.0412                                         min =          1
     Between = 0.2090                                         avg =        2.4
     Overall = 0.2190                                         max =          7

                                                F(6,479)          =       3.43
corr(u_i, Xb) = 0.3985                          Prob > F          =     0.0025
```

l_totscope1	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
l_envrd	.045851	.0208748	2.20	0.029	.0048335	.0868685
pollutionrd	.1820283	.081682	2.23	0.026	.0215289	.3425276
greencapex	-.1624805	.0540324	-3.01	0.003	-.2686503	-.0563107
commitcons	-.0581633	.0629752	-0.92	0.356	-.1819051	.0655785
l_totwaste	.0509327	.0402216	1.27	0.206	-.0280998	.1299653
l_marketcap	.000134	.0489882	0.00	0.998	-.0961243	.0963922
_cons	11.03543	1.278687	8.63	0.000	8.522904	13.54796
sigma_u	2.9217102					
sigma_e	.35247296					
rho	.98565494	(fraction of variance due to u_i)				

F test that all u_i=0: F(357, 479) = 83.61 Prob > F = 0.0000

2) Scope 1 & 2

```
Fixed-effects (within) regression               Number of obs     =        843
Group variable: ID                              Number of groups  =        358

R-squared:                                      Obs per group:
     Within  = 0.0256                                         min =          1
     Between = 0.4541                                         avg =        2.4
     Overall = 0.4394                                         max =          7

                                                F(6,479)          =       2.10
corr(u_i, Xb) = 0.6062                          Prob > F          =     0.0525
```

l_totscope12	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
l_envrd	.0132713	.0171104	0.78	0.438	-.0203494	.046892
pollutionrd	.0528802	.0669521	0.79	0.430	-.0786759	.1844363
greencapex	-.1209023	.0442886	-2.73	0.007	-.2079262	-.0338784
commitcons	.0143389	.0516187	0.28	0.781	-.0870883	.115766
l_totwaste	.0455812	.0329683	1.38	0.167	-.0191992	.1103617
l_marketcap	.0779689	.040154	1.94	0.053	-.0009309	.1568687
_cons	10.91017	1.048098	10.41	0.000	8.850727	12.9696
sigma_u	2.2837693					
sigma_e	.28891061					
rho	.98424831	(fraction of variance due to u_i)				

F test that all u_i=0: F(357, 479) = 69.74 Prob > F = 0.0000

3) Scope 1, 2, and 3

```
Fixed-effects (within) regression               Number of obs     =        843
Group variable: ID                              Number of groups  =        358

R-squared:                                      Obs per group:
     Within  = 0.0449                                         min =          1
     Between = 0.0642                                         avg =        2.4
     Overall = 0.0465                                         max =          7

                                                F(6,479)          =       3.75
corr(u_i, Xb) = -0.3748                         Prob > F          =     0.0012
```

l_totsco~123	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
l_envrd	-.000171	.0233929	-0.01	0.994	-.0461365	.0457945
pollutionrd	.0021438	.0915355	0.02	0.981	-.1777169	.1820045
greencapex	.0628078	.0605504	1.04	0.300	-.0561694	.1817851
commitcons	-.0153033	.070572	-0.22	0.828	-.1539723	.1233657
l_totwaste	-.1469922	.0450736	-3.26	0.001	-.2355587	-.0584258
l_marketcap	.173764	.0548977	3.17	0.002	.065894	.2816341
_cons	13.53344	1.432938	9.44	0.000	10.71782	16.34906
sigma_u	2.2078599					
sigma_e	.39499243					
rho	.9689864	(fraction of variance due to u_i)				

F test that all u_i=0: F(357, 479) = 28.22 Prob > F = 0.0000

Appendix 5: Stata Output - Hausman Test

1) Scope 1

	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
l_envrd	.045851	.0483143	-.0024633	.0113314
pollutionrd	.1820283	.1731095	.0089188	.0247111
greencapex	-.1624805	-.2106479	.0481674	.0126227
commitcons	-.0581633	.0146462	-.0728095	.0133162
l_totwaste	.0509327	.3676294	-.3166967	.0304391
l_marketcap	.000134	.169722	-.1695881	.0293703

```
                  b = Consistent under H0 and Ha; obtained from xtreg.
       B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            = 141.88
Prob > chi2 = 0.0000
```

2) Scope 1 & 2

	(b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
l_envrd	.0132713	.0287719	-.0155006	.0098671
pollutionrd	.0528802	.0573989	-.0045186	.0219561
greencapex	-.1209023	-.1596706	.0387683	.0111582
commitcons	.0143389	.0663418	-.0520029	.0118405
l_totwaste	.0455812	.3288049	-.2832237	.0260288
l_marketcap	.0779689	.2354344	-.1574655	.0254671

```
                  b = Consistent under H0 and Ha; obtained from xtreg.
       B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            = 143.87
Prob > chi2 = 0.0000
```

3) Scope 1, 2, and 3

	Coefficients (b) fixed	(B) random	(b-B) Difference	sqrt(diag(V_b-V_B)) Std. err.
l_envrd	-.000171	.085979	-.08615	.017191
pollutionrd	.0021438	.0517154	-.0495716	.0434001
greencapex	.0628078	-.0091012	.0719091	.0217937
commitcons	-.0153033	.0551303	-.0704336	.0237157
l_totwaste	-.1469922	.234852	-.3818442	.0408756
l_marketcap	.173764	.3968261	-.2230621	.0431945

```
                          b = Consistent under H0 and Ha; obtained from xtreg.
           B = Inconsistent under Ha, efficient under H0; obtained from xtreg.

Test of H0: Difference in coefficients not systematic

    chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
            = 112.35
Prob > chi2 = 0.0000
```

Appendix 6: Stata Output – Varians Inflation Factor (Multicollinearity Test)

Variable	VIF	1/VIF
l_marketcap	1.33	0.754512
l_totwaste	1.29	0.774740
l_envrd	1.25	0.802105
pollutionrd	1.05	0.954812
commitcons	1.04	0.964039
greencapex	1.01	0.991968
Mean VIF	1.16	

Appendix 7: Stata Output - Heteroscedasticity Test

1) Scope 1

```
Breusch–Pagan/Cook–Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of l_totscope1

H0: Constant variance

    chi2(1) =  25.53
Prob > chi2 = 0.0000
```

2) Scope 1 & 2

```
Breusch–Pagan/Cook–Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of l_totscope12

H0: Constant variance

    chi2(1) =  16.38
Prob > chi2 = 0.0001
```

3) Scope 1, 2, and 3

```
Breusch–Pagan/Cook–Weisberg test for heteroskedasticity
Assumption: Normal error terms
Variable: Fitted values of l_totscope123

H0: Constant variance

    chi2(1) =  33.23
Prob > chi2 = 0.0000
```

Appendix 8: Stata Output –Estimation Results

1) Scope 1 – All Industries

```
Fixed-effects (within) regression               Number of obs     =        843
Group variable: ID                              Number of groups  =        358

R-squared:                                      Obs per group:
     Within  = 0.0412                                         min =          1
     Between = 0.2090                                         avg =        2.4
     Overall = 0.2190                                         max =          7

                                                F(6,357)          =       4.48
corr(u_i, Xb) = 0.3985                          Prob > F          =     0.0002

                                  (Std. err. adjusted for 358 clusters in ID)
------------------------------------------------------------------------------
             |               Robust
 l_totscope1 | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     l_envrd |    .045851   .0147137     3.12   0.002     .0169146    .0747874
 pollutionrd |   .1820283   .1455361     1.25   0.212    -.1041875     .468244
  greencapex |  -.1624805   .0717264    -2.27   0.024    -.3035398   -.0214212
  commitcons |  -.0581633   .0680748    -0.85   0.393    -.1920413    .0757147
  l_totwaste |   .0509327   .0942748     0.54   0.589     -.134471    .2363365
 l_marketcap |    .000134   .0938364     0.00   0.999    -.1844076    .1846756
       _cons |   11.03543   2.113697     5.22   0.000     6.878571     15.1923
-------------+----------------------------------------------------------------
     sigma_u |  2.9217102
     sigma_e |  .35247296
         rho |  .98565494   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

2) Scope 1 – High Polluting Industries

```
Fixed-effects (within) regression               Number of obs     =        559
Group variable: ID                              Number of groups  =        234

R-squared:                                      Obs per group:
     Within  = 0.0841                                         min =          1
     Between = 0.3220                                         avg =        2.4
     Overall = 0.3010                                         max =          7

                                                F(6,233)          =       3.23
corr(u_i, Xb) = 0.3861                          Prob > F          =     0.0046

                                 (Std. err. adjusted for 234 clusters in ID)
```

l_totscope1	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
l_envrd	.0510595	.0215215	2.37	0.018	.0086579	.0934611
pollutionrd	.0794744	.1106797	0.72	0.473	-.1385865	.2975353
greencapex	-.2097905	.1011881	-2.07	0.039	-.409151	-.01043
commitcons	.0428025	.0847295	0.51	0.614	-.1241313	.2097364
l_totwaste	.1935197	.0990553	1.95	0.052	-.0016388	.3886782
l_marketcap	-.0187137	.084079	-0.22	0.824	-.1843659	.1469386
_cons	10.48676	2.110164	4.97	0.000	6.329323	14.6442
sigma_u	2.5661507					
sigma_e	.31646462					
rho	.98501935	(fraction of variance due to u_i)				

3) Scope 1 – Non-high Industries

```
Fixed-effects (within) regression               Number of obs     =        284
Group variable: ID                              Number of groups  =        124

R-squared:                                      Obs per group:
     Within  = 0.1089                                         min =          1
     Between = 0.3409                                         avg =        2.3
     Overall = 0.3140                                         max =          7

                                                F(6,123)          =       2.34
corr(u_i, Xb) = -0.6467                         Prob > F          =     0.0360

                                 (Std. err. adjusted for 124 clusters in ID)
```

l_totscope1	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
l_envrd	.0611159	.0338726	1.80	0.074	-.0059329	.1281646
pollutionrd	.5452065	.4592337	1.19	0.237	-.3638186	1.454231
greencapex	.0141156	.1089507	0.13	0.897	-.2015456	.2297767
commitcons	-.3221117	.1099338	-2.93	0.004	-.5397189	-.1045046
l_totwaste	-.1270723	.1645488	-0.77	0.441	-.4527866	.1986419
l_marketcap	-.0207692	.1680697	-0.12	0.902	-.3534528	.3119145
_cons	11.64605	3.821076	3.05	0.003	4.082459	19.20963
sigma_u	3.0421371					
sigma_e	.39661248					
rho	.98328696	(fraction of variance due to u_i)				

4) Scope 1 & 2 - All Industries

```
Fixed-effects (within) regression               Number of obs     =        843
Group variable: ID                              Number of groups  =        358

R-squared:                                      Obs per group:
     Within  = 0.0256                                         min =          1
     Between = 0.4541                                         avg =        2.4
     Overall = 0.4394                                         max =          7

                                                F(6,357)          =       2.10
corr(u_i, Xb) = 0.6062                          Prob > F          =     0.0530

                                   (Std. err. adjusted for 358 clusters in ID)
```

l_totscope12	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
l_envrd	.0132713	.0127803	1.04	0.300	-.0118627	.0384054
pollutionrd	.0528802	.1000801	0.53	0.598	-.1439405	.2497009
greencapex	-.1209023	.0481976	-2.51	0.013	-.2156891	-.0261155
commitcons	.0143389	.0780966	0.18	0.854	-.1392483	.167926
l_totwaste	.0455812	.0800413	0.57	0.569	-.1118304	.2029929
l_marketcap	.0779689	.0654866	1.19	0.235	-.050819	.2067568
_cons	10.91017	1.534772	7.11	0.000	7.891835	13.9285
sigma_u	2.2837693					
sigma_e	.28891061					
rho	.98424831	(fraction of variance due to u_i)				

5) Scope 1 & 2 – High polluting Industries

```
Fixed-effects (within) regression               Number of obs     =        559
Group variable: ID                              Number of groups  =        234

R-squared:                                      Obs per group:
     Within  = 0.0493                                         min =          1
     Between = 0.4433                                         avg =        2.4
     Overall = 0.4132                                         max =          7

                                                F(6,233)          =       2.90
corr(u_i, Xb) = 0.5189                          Prob > F          =     0.0095

                                   (Std. err. adjusted for 234 clusters in ID)
```

l_totscope12	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
l_envrd	.0189065	.0146906	1.29	0.199	-.010037	.04785
pollutionrd	-.050185	.0802167	-0.63	0.532	-.2082278	.1078578
greencapex	-.123161	.0635648	-1.94	0.054	-.2483963	.0020743
commitcons	.0800938	.1065411	0.75	0.453	-.1298132	.2900008
l_totwaste	.1268277	.0796462	1.59	0.113	-.0300911	.2837464
l_marketcap	.074728	.0577362	1.29	0.197	-.0390238	.1884798
_cons	10.47423	1.245279	8.41	0.000	8.020782	12.92768
sigma_u	2.0724167					
sigma_e	.28009099					
rho	.98206164	(fraction of variance due to u_i)				

6) Scope 1 & 2 – Non-high polluting Industries

```
Fixed-effects (within) regression               Number of obs     =        284
Group variable: ID                              Number of groups  =        124

R-squared:                                      Obs per group:
     Within  = 0.0808                                         min =          1
     Between = 0.0579                                         avg =        2.3
     Overall = 0.0403                                         max =          7

                                                F(6,123)          =       1.45
corr(u_i, Xb) = -0.2836                         Prob > F          =     0.2003

                                 (Std. err. adjusted for 124 clusters in ID)
```

l_totscope12	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
l_envrd	.01602	.0239466	0.67	0.505	-.0313807	.0634208
pollutionrd	.3726045	.3011549	1.24	0.218	-.2235132	.9687223
greencapex	-.0469745	.0922102	-0.51	0.611	-.2294989	.1355499
commitcons	-.1453142	.0799059	-1.82	0.071	-.303483	.0128546
l_totwaste	-.0558557	.1444956	-0.39	0.700	-.3418758	.2301644
l_marketcap	.0609552	.1213223	0.50	0.616	-.1791949	.3011052
_cons	11.28758	3.02585	3.73	0.000	5.298098	17.27707
sigma_u	2.3597551					
sigma_e	.29628115					
rho	.98448037	(fraction of variance due to u_i)				

7) Scope 1, 2 and 3 – All Industry

```
Fixed-effects (within) regression               Number of obs     =        843
Group variable: ID                              Number of groups  =        358

R-squared:                                      Obs per group:
     Within  = 0.0449                                         min =          1
     Between = 0.0642                                         avg =        2.4
     Overall = 0.0465                                         max =          7

                                                F(6,357)          =       0.77
corr(u_i, Xb) = -0.3748                         Prob > F          =     0.5956

                                 (Std. err. adjusted for 358 clusters in ID)
```

l_totsco~123	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
l_envrd	-.000171	.0158785	-0.01	0.991	-.0313982	.0310563
pollutionrd	.0021438	.0762604	0.03	0.978	-.1478324	.1521199
greencapex	.0628078	.0634156	0.99	0.323	-.0619073	.187523
commitcons	-.0153033	.0740681	-0.21	0.836	-.1609679	.1303613
l_totwaste	-.1469922	.1426068	-1.03	0.303	-.4274473	.1334628
l_marketcap	.173764	.0976083	1.78	0.076	-.0181955	.3657236
_cons	13.53344	1.333006	10.15	0.000	10.91191	16.15498
sigma_u	2.2078599					
sigma_e	.39499243					
rho	.9689864	(fraction of variance due to u_i)				

8) Scope 1, 2 and 3 – High Polluting Industry

```
Fixed-effects (within) regression               Number of obs     =        559
Group variable: ID                              Number of groups  =        234

R-squared:                                      Obs per group:
     Within  = 0.0239                                         min =          1
     Between = 0.2494                                         avg =        2.4
     Overall = 0.2861                                         max =          7

                                                F(6,233)          =       1.04
corr(u_i, Xb) = 0.4508                          Prob > F          =     0.3980

                                 (Std. err. adjusted for 234 clusters in ID)
------------------------------------------------------------------------------
             |               Robust
l_totsco~123 | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     l_envrd |    .005099   .0150257     0.34   0.735    -.0245045    .0347025
 pollutionrd |  -.0520417   .0704599    -0.74   0.461    -.1908616    .0867782
 greencapex  |   .0334582    .080469     0.42   0.678    -.1250817    .1919981
 commitcons  |  -.0213977   .0871073    -0.25   0.806    -.1930162    .1502208
  l_totwaste |  -.0165668   .0564836    -0.29   0.770    -.1278506     .094717
 l_marketcap |   .1496911   .0655487     2.28   0.023     .0205472     .278835
       _cons |   12.78317   1.430725     8.93   0.000     9.964359    15.60198
-------------+----------------------------------------------------------------
     sigma_u |  1.9291012
     sigma_e |  .30859828
         rho |  .97504813   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

9) Scope 1, 2 and 3 – Non-high Polluting Industry

```
Fixed-effects (within) regression               Number of obs     =        284
Group variable: ID                              Number of groups  =        124

R-squared:                                      Obs per group:
     Within  = 0.0970                                         min =          1
     Between = 0.3399                                         avg =        2.3
     Overall = 0.3443                                         max =          7

                                                F(6,123)          =       0.69
corr(u_i, Xb) = -0.7594                         Prob > F          =     0.6606

                                 (Std. err. adjusted for 124 clusters in ID)
------------------------------------------------------------------------------
             |               Robust
l_totsco~123 | Coefficient  std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
     l_envrd |  -.0053257   .0325554    -0.16   0.870    -.0697672    .0591158
 pollutionrd |    .195227   .2047318     0.95   0.342    -.2100271     .600481
 greencapex  |   .1443392   .1165817     1.24   0.218    -.0864272    .3751055
 commitcons  |    -.01608   .1569664    -0.10   0.919    -.3267854    .2946254
  l_totwaste |  -.3045755   .2845464    -1.07   0.287    -.8678176    .2586667
 l_marketcap |   .1697426   .1755184     0.97   0.335    -.1776853    .5171705
       _cons |   14.80724   2.400006     6.17   0.000     10.05657    19.55791
-------------+----------------------------------------------------------------
     sigma_u |   2.607267
     sigma_e |  .52563829
         rho |  .96094285   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```