CARBON INTENSITY AND FIRM FINANCIAL PERFORMANCE: EVIDENCE FROM NORDIC FIRMS

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ABSTRACT

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Carbon intensity and firm financial performance: evidence from Nordic firms

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Keywords: carbon intensity, firm performance, renewable energy, energy intensity

This Master's thesis explores two research questions: 1) *Does reducing carbon intensity impact the financial performance of a firm?* 2) *What factors influence firm level carbon emissions?* This thesis aims to provide evidence to fill the evidence gap around Nordic firms and to add to the wider discussion around the relationship between financial performance and environmental performance.

The analysis starts by looking at the relationship between carbon intensity and accounting based measures of financial performance. The following analysis explores how three factors: R&D, energy intensity and the use of renewable energy influence carbon intensity. The analysis uses data for Nordic firms from four countries: Denmark, Finland, Sweden and Norway and the dataset covers years 2015-2023.

The panel data regression results show that increasing carbon intensity has a statistically significant negative impact on financial performance when the sample is split in 2020 to account for COVID-19 impacts. The results also show that this relationship is sensitive to changes in model specifications and to the choice of financial performance measure. The analysis of factors influencing carbon intensity shows that there is no statistically significant relationship between R&D and carbon intensity or between energy intensity and carbon intensity. The results show that there is a statistically significant negative relationship between renewable energy and carbon intensity indicating that increasing the use of renewable energy can be an effective way to reduce carbon intensity.

TIIVISTELMÄ

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Riikka Korhonen

Hiili-intensiteetti ja yritysten taloudellinen kannattavuus: näyttöä Pohjoismaisista yrityksistä

Kauppatieteiden pro gradu -tutkielma

2025

80 sivua, 0 kuvaa, 25 taulukkoa ja 5 liitettä

Tarkastajat: Apulaisprofessori Mahinda Mailagaha Kumbure, Professori Eero Pätäri

Avainsanat: hiili-intensiteetti, yritysten kannattavuus, uusiutuva energia, energiatehokkuus

Tämä pro gradu -tutkielma tarkastelee kahta tutkimuskysymystä: 1) Vaikuttaako hiili-intensiteetin vähentäminen yrityksen kannattavuuteen? 2) Mitkä tekijät vaikuttavat yritystason hiilidioksidipäästöihin? Tutkielman tavoitteena on tuottaa uutta tietoa pohjoismaisia yrityksiä koskevaan tutkimukseen sekä täydentää laajempaa keskustelua taloudellisen ja ympäristövastuun välisestä suhteesta.

Analyysi käynnistyy tarkastelemalla hiili-intensiteetin vaikutusta taloutta mittaaviin tunnuslukuihin. Seuraavaksi analyysissä tarkastellaan kolmen tekijän: T&K-toiminnan, energiatehokkuuden ja uusiutuvan energian käytön vaikutusta hiili-intensiteettiin. Analyysissä käytetään dataa yrityksistä neljästä pohjoismaasta: Tanskasta, Suomesta, Ruotsista ja Norjasta, ja aineisto kattaa vuodet 2015–2023.

Panelidata-regressioanalyysi osoittaa, että hiili-intensiteetin kasvu vaikuttaa tilastollisesti merkitsevästi negatiivisesti taloutta mittaaviin tunnuslukuihin, kun otetaan huomioon COVID-19-pandemian vaikutukset jakamalla aineisto vuoden 2020 kohdalta kahtia. Tulokset osoittavat myös, että tämä suhde on herkkä mallin ja taloutta mittaavien tunnuslukujen muutoksiin. Hiili-intensiteettiin vaikuttavien tekijöiden analyysi osoittaa että, T&K-toiminnan ja hiili-intensiteetin välillä sekä energiatehokkuuden ja hiili-intensiteetin välillä ole tilastollisesti merkitsevää yhteyttä. Tulokset osoittavat, että uusiutuvan energian käytöllä on tilastollisesti merkitsevä negatiivinen vaikutus hiili-intensiteettiin, mikä viittaa siihen, että uusiutuvan energian käytön lisääminen voi olla tehokas tapa vähentää hiili-intensiteettiä.

SYMBOLS AND ABBREVIATIONS

Abbreviations

AI	Artificial Intelligence
CSR	Corporate Social Responsibility
EU	European Union
GHG	Green House Gass
GRI	Global Reporting Initiative
OECD	Organisation for Economic Co-operation and Development
pp	Percentage point
SMEs	Small and Medium Enterprises
UN	United Nations

Symbols

β	Time-variant regression coefficient
γ	Time-invariant regression coefficient
ν	Composite error term

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Abstract

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1 Introduction

The neoclassical economic theory suggests that the main purpose of a firm is to maximise its profits (Garbo et al., 2020). However, in the real-world firms need to navigate different operational and ethical challenges while looking to maximise their profits. One of the large operational and ethical challenges of the 21st century is sustainability. Globally, there is a growing concern around greenhouse gas (GHG) emissions and their impact on the environment. To combat the threat of raising emission levels, 196 countries have adopted an international treaty known as the 2015 Paris Agreement. The Paris Agreement aims to cut GHG emissions by 43% by 2030 (United Nations n.d). To hit this target, governments need to work with firms to reduce emissions. However, requirements to reduce emissions might be seen as a burden by firms due to potential negative impacts on profitability. For this reason, the two main research questions this thesis aims to answer are: 1) *Does reducing carbon intensity impact the financial performance of a firm?* 2) *What factors influence firm level carbon emissions?*

The latest Emission Gap Report from the United Nations Environment Programme (2024) shows that some progress has been made towards the Paris Agreement targets. According to the report, in 2015 when the Paris Agreement was signed the GHG emissions were estimated to grow 16% by 20230. However, the latest data shows that the GHG emissions are estimated to grow 3% by 2030. Despite this progress, the report states that the annual global GHG emissions growth was 1.2% in 2022 reaching a new record level of 57.4 gigatons of CO_2 equivalent, indicating that more work is still needed to reach the Paris Agreement target (United Nations Environment Programme, 2024). The environmental concerns are also reflected in the new EU Directive 2022/2464 which states that from 2024 onwards, large firms operating within EU need to publicly disclose information on sustainability.

As a result of these targets and regulations, firms operating across the world face pressures to cut their emissions to comply with these emission targets while continuing to deliver value to their shareholders. The new EU directive also means that large firms need to make emission data available. This allows investors and other stakeholders to evaluate the financial and sustainability performance of firms, which may also act as an incentive for firms to improve their green credentials.

Many firms already include sustainability as one of their core values and produce sustainability reports as part of their annual reports however, many firms are still in the infancy of their sustainability journey. One way firms could reduce their emissions would be to scale back their operations however, this would also reduce their output, which most likely would not be viewed favourably by their shareholders. Instead, to maintain economic performance firms could look to reduce their emission intensity.

Emission intensity measures the ratio between carbon emissions and firm's revenue (Le and Nguyen-Phung, 2024). A simple example of how to reduce emission intensity would be to source energy from renewable sources. This way a firm could reduce their emissions without needing to scale back their operations.

Previous research on the relationship between firm performance and emission intensity has identified that emission reductions can improve financial performance (Le and Nguyen-Phung, 2024; Trinks et al., 2020; Oestreich and Tsiakas, 2024) and that firm size (Cole et al., 2013) and choice of factors of production (Subrahmanya, 2006) are one the driving factors for emissions. The literature review has identified that the relationship between emissions and financial performance has been extensively researched using data from China but not many papers have focused on the firm level data from the Nordic countries.

This thesis contributes to the existing literature by using firm level data from four Nordic countries: Denmark, Finland, Norway and Sweden. The dataset covers years 2015-2023 and firms have been selected from the big stock market indices of each country: OMX Copenhagen 25, OMX Helsinki 25, OBX Index and OMX Stockholm 30. As highlighted by the two research questions, the objective of this thesis is to analyse the relationship between carbon intensity and firm financial performance, and to gain further insight into the factors impacting the carbon intensity of a Nordic firm. Financial performance in this thesis is measured using three accounting based estimates: gross profit, return on equity, return on assets and Tobin's Q. This thesis has some limitations in terms of wider application of the results. This thesis only uses data for large, listed companies and therefore, the results presented might not be applicable to smaller companies. Furthermore, the results presented this thesis cover the Covid-19 pandemic period which may influence the results presented. The second chapter of this thesis reviews the previous research in the field. The third chapter discusses data collection and analytical methods. The fourth chapter presents the results from the data analysis and the final chapter concludes the outcomes of the research.

2 Literature Review

This chapter covers literature review on previous research. The first section outlines the current state of GHG emission in the four Nordic countries: Denmark, Finland, Sweden and Norway. The second section discusses macroeconomic evidence on the factors driving decoupling of emissions and economic growth. The third section reviews the relationship between sustainability reporting and firm performance. The fourth section covers previous research done on the relationship between emissions and firm level performance and the final section covers research done on the impact of technology on emissions.

2.1 Nordic GHG emission levels

Greenhouse gas (GHG) is an umbrella term used for a group of gases in the atmosphere. The four main gasses are carbon dioxide, methane, nitrous oxide and fluorinated gasses. Carbon dioxide is released to the atmosphere through burning fossil fuels, biological matter and through chemical reactions, and it makes up the majority of GHG gasses. Methane emissions are generated from the transportation and production of coal, natural gas and oil. Methane is also emitted as part of agricultural processes. Nitrous oxide is emitted as part of agricultural and industrial processes whereas fluorinated gasses are synthetic, and they are emitted from household and industrial processes (U.S Environmental Agency 2024).

In 2021, the top three GHG emitters in terms of gigatons of CO_2 equivalent were China, USA and India whereas the top sectors were energy supply, industry and agriculture (United Nations Environment Programme, 2024). Out of the four Nordic countries, Finland has had the highest levels of GHG emissions (when measured in millions metric tons of CO_2 equivalent) from 1990 to 2014 after which Norway has taken over as the number one emitter. Norway’s GHG emissions increased until 1999 after which they have remained relatively stable, whereas Finland has had a steady downward trend since 2010. Both Sweden and Denmark have had a downward trend from 1996 onwards. In 2022, Denmark had the lowest level of GHG emissions out of the four countries (Appendix 1).

Denmark, Finland, Sweden and Norway have all signed the Paris Agreement (United Nations 2016) which means that they are commited to the emission reduction targets set out in the agreement. Denmark, Sweden and Finland also belong to the EU and therefore, they are obligated to follow EU environmental regulations. Norway is part of the European Economic Area and therefore, cooperates closely with the EU.

The GHG emissions vary by sector and across countires. The industry sector within the EU accounted for 20% of the GHG emissions in 2022. The GHG emissions in this sector have fallen 35% when 2021 levels are compared with 1990 levels (European Environment Agency, 2023). The GHG emissions levels in this sector are strongly correlated with the production volumes which saw fall during the 2008 financial crises and during the 2020 covid-19 pandemic. Improvements in energy efficiency and the use of biomass and waste energy have been one of the driving factors for emission reductions (European Environment Agency, 2023). In Norway, industry sector is the second largest emitter and it accounted for 18% of emissions in 2022 (International Energy Agency, 2022).

Out of Denmark, Finland and Sweden, Finland has seen the largest reduction in GHG emission in industry sector between 2005 and 2022, followed by Sweden and Denmark (European Environment Agency, 2023). To reduce emissions, the EU has set out to be climate neutral by 2050. To achieve this, country level intermediate emission and renewable energy targets have been set out for 2030. Norway has also set a target to reduce GHG emissions by 55% compared with 1990 levels by 2030 (European Environment Agency, 2023).

2.2 Macroeconomic evidence on emission reductions and economic growth

The Paris Agreement and EU emission targets imply that emissions need to come down over the next 10 years. However, at the same time governments around the world look to generate economic growth to improve living standards. There is a strong positive correlation between GDP per capita and emissions per capita suggesting that higher income countries also have higher emissions (Ritchie, 2021). To achieve the emission reduction targets and economic growth, countries need to decouple emissions and economic growth.

2.2.1 Decoupling in the Nordic countries

There is evidence to suggest that Denmark, Finland, Norway and Sweden have all managed to decouple economic growth and emissions growth. Between 2012 and 2022, GDP per capita has grown 17.1% in Denmark, 6.6% in Finland, 7.8% in Norway and 12.5% in Sweden while CO_2 emissions per capita have reduced -32.4%, -30.9%, -15.1% and -27.2% respectively (Ritchie, 2021). One potential reason for the fall in emissions is changes in energy consumption. Between 2012 and 2022, primary energy consumption has decreased in all four Nordic countries: -4% in Denmark, -6% in Finland, -5% in Norway and -4% in Sweden (Ritchie et al., 2020). Another potential reason for the fall in emissions per capita is transition to low-carbon energy sources. Between 2012 and 2022 the share of primary energy consumption from low-carbon sources has increased 19.2pp in Denmark, 12.6pp in Finland, 0.4pp in Norway and 4.8pp in Sweden (Energy Institute 2024).

Alola and Adebayo (2023) analysed the factors influencing GHG emissions in the Nordic region and found that raw materials are efficiently used in the Nordic region and therefore improvements in raw material productivity have reduced GHG emissions. The results also indicate that increases in export intensity reduces GHG emissions. Furthermore, their results suggest that shifts in environment-related technologies decrease GHG emissions.

2.2.2 Factors influencing emissions at country level

Factors influencing the relationship between emissions and economic growth have been a topic of interest for previous research. Wang and Su (2020) used panel data for 192 countries to examine the decoupling relationship between emissions and economic growth. They found that for EU countries, GDP per capita and energy intensity were main factors influencing carbon emissions. Population size and carbon intensity were also found to have an impact on carbon emissions. Papież et al. (2021) and Bianco et al. (2024) also found that energy intensity, carbon intensity and energy structure are driving factors for emission reductions within EU countries. Naqvi (2021) conducted a panel data analysis using data for EU countries and found that there were considerable variations in decoupling trends across and within EU regions. Results showed that emissions reductions were greater before the

2008 financial crisis and that post-financial crisis, some EU regions even showed coupling of emission and economic growth.

These results are not unique to the EU countries. Chen et al. (2022) used data for the 10 largest emitters (China, US, India, Russia, Japan, Germany, Iran, South Korea, Indonesia and Saudi Arabia) to explore the decoupling of emissions and economic growth. Results from their research also suggest that economic and population growth increase emissions while energy intensity and carbon intensity slow the growth of CO_2 emissions. Similarly, Wang et al. (2021) used data for 25 countries along the Belt and Road Initiative and evidence from their research indicates that increasing the use of renewable energy inhibits the growth of CO_2 emissions. However, they did not find the impact of carbon efficiency to be statistically significant.

Aslani et al. (2013) studied the use of renewable energy in the Nordic countries and found that Nordic countries have been successful in their policies to promote the use of renewable energy. Wu et al. (2024) studied the impact of the use of renewable energy on GHG emissions in the Nordic countries and found that increasing the use of renewable energy reduced GHG emissions. Jin and Han (2021) also conducted decoupling analysis of carbon emissions using data from Chinese manufacturing industry. Their results suggest that investment carbon intensity, carbon productivity, investment efficiency, and energy intensity are restraining factors to emission growth. However, they also found that energy consumption and energy structure present inconsistent effects.

There are different policy instruments that governments can use to reduce emissions. Naqvi (2021) analysed the impact of environmental policies and concluded that emissions do respond to policies however, there is variation in the magnitude and speed of response based on income levels. High income regions saw smaller emission reductions than the lower income regions. The positive impact of EU policy on emissions reductions is also present in studies by Papież et al. (2021) and Bianco et al. (2024). Ko and Lee (2022) examined the impact of emission trading scheme and carbon tax using data from EU. Their results suggest that emission trading does impact decoupling whereas carbon tax is found to have no impact. The authors do note that their research design might be the reason why carbon tax was not found to have an impact.

The evidence on the impact of carbon tax is inconclusive as the results appear to vary by country, and for some countries such as Sweden, researchers have found differing results. Brännlund et al. (2014) used data from Swedish manufacturing sector to analyse the impact of climate policy on emissions. Carbon tax was introduced in Sweden in 1991 and between 1991-2004, the manufacturing output increased by 35% while the emissions fell by 10%. These results suggest that carbon tax can be an effective way to reduce carbon emissions and that fossil fuel prices also have an impact on the emission reductions. Martinsson et al. (2024) used data from Sweden to estimate an emission-to-pricing elasticity. The estimation results indicate that there is a statistically significant inverse relationship between CO_2 emissions and the marginal cost of emitting CO_2 which would imply that carbon tax in Sweden reduces emissions.

Lin and Li (2011) found that carbon tax had a statistically significant negative impact on CO_2 emissions in Finland however, the impact was not statistically significant for Denmark, Sweden and Norway. Lin and Li (2011) propose that carbon tax exemptions for energy intensive sectors such as manufacturing in Denmark, Sweden and Norway might be one of the reasons for the carbon tax impact not being statistically significant. These results for Norway conflict with the results from an older paper by Bruvoll et al. (2004). Their results imply that carbon tax in Norway had a modest impact on CO_2 emission reductions while improvements in energy intensity and changes in energy mix were estimated to be the driving factors.

2.3 Review of sustainability reporting and firm performance

At the firm level, the relationship between economic performance and emission can be assed using data from traditional financial statements and from sustainability reports. There are various frameworks for sustainability reporting, but the Global Reporting Initiative (GRI) is one of the most used frameworks (KPMG International, 2022). The GRI framework requires firms to report data on their impact on economy, environment and society (Global Reporting Initiative n.d).

Investors today are increasingly interest in sustainability matters. According to a report by Morgan Stanley Institute for Sustainable Investing (2024) 77% of global investors are interested in sustainable investing and 57% state that their interest has increased over the last two years. The findings from the report also suggest that 82% of global investors think that firms should address environmental issues and that 19% of the respondents think that firm's reporting on sustainability practices, carbon footprint and commitments to reduce GHG gasses over time are a top priority when new investments are considered.

In terms of level of reporting, the number of large companies reporting on sustainability has increased over the last 10 years. In 2002, 64% of N100 companies produced sustainability reports and by 2022, this figure increased to 79% (KPMG International, 2022). In 2022, 94% of the Finnish N100 firms reported on sustainability while the figure was 98% for Swedish firms and 91% for Norwegian firms (KPMG International, 2022).

There have also been changes to the regulations around sustainability reporting in the EU. From 2024 onwards, large companies, listed SMEs and non-EU companies generating over 150 million Euros within EU must report on sustainability (European Commission n.d). The previous research on the impact of mandatory sustainability reporting suggests that mandatory reporting of emissions data does impact firm behaviour. Bauckloh et al. (2023) studied data on US firms and found that those firms that were affected by the Greenhouse Gas Reporting Program improved their carbon intensity more than firms not impacted by the regulation.

Previous research has additionally identified that disclosure of emission data impacts firm valuation. Matsumura et al. (2014) studied data for S&P500 firms and found that those firms who disclosed carbon emissions had a $2.3 billion higher median value than comparable firms that did not disclose carbon emissions. Bolton and Kacperczyk (2021) suggest that this negative relationship could be due to investors evaluating the impact of carbon emissions on the firm performance through pricing in carbon risk

Previous literature on the impact of sustainability reporting on firm performance suggests that sustainability reporting can have a positive impact on firm performance. Prashar (2023) conducted a meta-analysis of the relationship between sustainability reporting and firm performance using data from 60 reported studies. The results suggest that quality and level of sustainability reporting does influence accounting based measures of firm performance and that there is firm level heterogeneity in the relationship. The results point out that sustainability reporting is particularly effective for large and matured firms that have institutional investors in their boards.

Similarly, Kofi and Mallikarjunappa (2022) used data from Indian stock market to examine the impact of Corporate Social Responsibility (CSR) expenditure on firm performance and found a statistically significant positive relationship between CSR expenditure and return on assets and Tobin's Q. Studies by Rashid (2018) and Singhania et al. (2024) also found that CSR reporting positively influences return on assets and Tobin's Q.

The previous research on CSR reporting and firm performance suggest that CSR reporting could influence firm performance through enhancing firm reputation. Miller et al. (2020) analysed data on 7317 banks and found that gaining a positive CSR reputation resulted in 4.04% increase in profits, whereas Liu and Lu (2021) found that firm reputation partly mediates the impact CSR activities have on firm performance and risk. CSR was found to have a positive impact on firm performance and that CSR can be a mitigating factor to firm risk.

CSR reporting can also have a negative impact on firm performance. Walker and Wan (2012) analysed data on Canadian firms operating in polluting industries and found that symbolic green actions and green-washing (discrepancy between substantive and symbolic actions) had a negative impact on firm financial performance. Ruiz-Blanco et al. (2022) explored data on firm from S&P 500 and found there to be less green-washing when firms published sustainability information in a sustainability report rather than as part of their annual report. Additionally, the results suggest that green-washing was less prominent in industries that are environmentally sensitive and in companies that followed the GRI reporting guidelines.

2.4 Microeconomic evidence on firm performance and emissions

Emissions associated with the operations of a firm come from various sources. The GRI guidelines state that firms should report their emission levels using the GHG Protocol Corporate Standards. The GHG Protocol Corporate Standards includes two definitions of emissions: direct and indirect. Direct emissions come from sources that are owned or controlled by the firm whereas indirect emissions are produced as part of the firm's operations but occur at sources that are not owned or controlled by the firm. The GHG protocol breaks GHG emissions into three scopes. Scope 1 includes direct GHG emissions from sources that a firm owns or controls. Scope 2 includes electricity indirect GHG emissions: GHG emissions generated from the purchased electricity. Scope 3 is an optional category that includes all other indirect emissions (World Resource Institute & World Business Council 2004).

2.4.1 Emission intensity and firm performance

Like the macroeconomic research, the relationship between emissions and economic performance have been researched at the firm level. Le and Nguyen-Phung (2024) explored data from African nations and found that increasing GHG emission intensity has a negative impact on the return on assets and on return on equity, especially in high-emission sectors. They also found that those firms that reduced their GHG emissions following the Paris Agreement experienced improved financial performance. Trinks et al. (2020) used a panel dataset of 1572 firms to explore firms' carbon emission levels relative to their comparable best-in practice peers. Their results indicate that 0.1 higher carbon efficiency is associated with 1.0% higher profitability. The analysis also suggests that carbon efficiency of a firm is related to its resource efficiency.

These results are also supported by findings by Oestreich and Tsiakas (2024). They used data from S&P 500 firms to analyse the impact of carbon intensity on firm profitability which they defined as a ratio between gross profits (revenues minus the cost of goods sold) to total assets. The results indicate that firms that have high carbon intensity have low profitability. The robustness of this result was also tested using alternative accounting based profitability measure return to assts and the results were consistent. The paper also analysed the industry effect and concluded that the relationship between firm profitability and carbon intensity is not driven by the industry effect. Similarly, Makridou et al. (2019) used data from EU and found that reduction in CO_2 emissions can positively influence firm's profits.

Previous research has also identified that environmental actions might not always improve financial performance. Trumpp and Guenther (2017) conducted research to examine whether the relationship between corporate financial performance (CFP) and corporate environmental performance (CEP) displayed a U-shaped association. The CEP variable was defined as GHG emissions over sales. The results suggest that for manufacturing firms, the relationship between CEP and CFP is U-shaped and therefore, CEP can have a negative impact on profitability. The authors suggest that the evidence from their research points to the conclusion that "it pays to be green after exceeding a minimum level of CEP".

Brouwers et al. (2018) also noted that reducing carbon emissions doesn't always pay off. They used data for listed firms from European Union to study the relationship between carbon emissions and financial performance in the context of the European Union Emission Trading System (EU ETS). Their results indicate that those firms that are able to pass on the cost of polluting to their customers display a weaker relationship between emissions and financial performance. This is because the negative impact carbon emissions have on the financial performance are mitigated through passing these costs to the customers. Following this, they suggest that those firms that are not able to pass on the cost associated with polluting benefit from improving their carbon efficiency.

In terms of firm value, results from previous research also indicate that carbon emissions can negatively influence the market value of a firm. Perdichizzi et al. (2024) used data on European firms and found that increases in CO_2 intensity were associated with reduced market valuation and that the results were driven by Scope 1 emissions. Radu and Maram (2021) suggest that investors use data on GHG emissions to evaluate the future environmental liabilities of a firm. They studied Canadian firms and found that increases in emissions are associated with reduction in firm value. The results suggest that the magnitude of this impact is greater for low-polluting firms as each additional tonne of GHG emission was associated with $548 drop in firm value, whereas the associated drop for high-polluting firms was $35. Matsumura et al. (2014) used data on S&P500 firms and observed that every additional thousand metric tons of carbon emissions was associated with $212,000 decrease in the value of a firm.

Similarly, Choi and Luo (2021) analysed the impact of voluntary disclosure of carbon emissions information on firm value and found that carbon emissions were negatively associated with firm value. Furthermore, the results suggest that there is country level variation as firms operating in countries that have carbon trading schemes and strict environmental regulations saw a more prominent negative association.

In addition to the negative impact on firm valuation, previous research has identified that there is a relationship between carbon emissions and firm risk. Trinks et al. (2020) found that 0.1 increase in carbon efficiency is associated with 0.6% lower systematic risk whereas Kabir et al. (2021) found that carbon emissions intensity increases the risk of default, and this effect is more evident in industries with higher carbon-intensity. Similarly, Ding et al. (2023) found that firms with higher carbon emissions were more likely to end up in financial distress and that this effect was more pronounced for firms with lower operational capacities and for firms with weaker credit financing abilities.

There is also evidence to suggest that carbon emissions can have a negative impact to cost of debt financing. Caragnano et al. (2020) analysed data for EuroStoxx 600 firms and identified that reducing carbon emissions had a positive impact on cost of debt financing in both high and low emitting industries. Based on this evidence, they suggest that financial markets account for the firms current carbon risk profile while making lending decisions. Similarly, Palea and Drogo (2020) used data from the Eurozone and found that risk premium increases with carbon emissions. They also found that the introduction of Paris Agreement was a turning point after which lender became more environmentally aware as they started to charge less-polluting industries a higher spread for their emissions.

2.4.2 Energy intensity and green investment and firm performance

The amount of carbon emissions firms produce is dependent on several factors energy intensity being one of them. By reducing the energy intensity firms can reduce carbon emission intensity (Tao et al., 2024). Previous literature has established a relationship between energy intensity and firm performance. Fan et al. (2017) used panel data for Chinese manufacturing firms to analyse the relationship between financial performance and energy intensity. Their model used six different accounting based measured of financial performance and the results from the study suggest that reducing energy intensity does have a statistically significant positive impact financial performance. Choi et al. (2017) used panel data from several countries to analyse relative energy intensity and firm growth. The results suggest that improvements in relative energy intensity do have a positive relationship with profit growth however, country level differences exist. Subrahmanya (2006) uses data for Indian small manufacturing firms to analyse energy intensity, improving energy efficiency has a positive impact on financial performance.

Makridou et al. (2019, 257) suggest that “Since energy efficiency improvement tends to positively influence a firm's profitability, switching to green technologies become a more feasible investment option even when large adoption costs are imposed. Energy efficiency can reduce costs and fight potential risks including fluctuations in energy prices and energy shortages”. Siedschlag and Yan (2023) used data for Irish industry sector to analyse the relationship between green investment and firm performance. The green investment in their study was defined as capital expenditure on plant and equipment aimed at pollution control and cleaner production technologies. The results suggest that in the medium term, green investment has a positive impact on firm performance. However, the impact varies across firms. For example, the results suggest that larger firms and firms operating in low tech industries benefit more from the green investment. Additionally, green investment did not significantly improve energy efficiency.

Previous research is not unanimous in terms of the benefits of green investment as there is evidence to suggest that not all types of green innovation improve firm profitability. Ghisetti and Rennings (2014) used data from Germany to analyse the relationship between green innovation and profitability. They split the green innovation into two types: innovation aimed at reducing negative externalities such as air pollution and innovation aimed at efficiency improvements and cost savings. The results from their study indicate that innovation aimed at improving energy and resource efficiency does positively influence firm profitability and that innovation aimed at reducing negative externality negatively impacts profitability. The authors suggest that this is due to innovation accruing costs but externality reducing innovation does not contribute to cost reductions or enhancing competitive advantage and therefore costs outweigh the benefits. Khalid et al. (2023) found that overall, there is a positive relationship between green investment and profitability however, this relationship was not statistically significant for environmentally sensitive sectors such as manufacturing or energy.

2.4.3 Factors influencing emission and energy intensity

As the previous literature covered in the previous section shows, firms can influence their economic performance through reducing the energy and emission intensity of their operations. Previous research shows that firm size influences emission and energy intensity. Sahu and Mehta (2018) studied the determinants of emission intensity using data from India’s manufacturing sector. Their results suggest that there is a quadratic relationship between energy and emission intensity and firm size. Small and large firms are more emission and energy intensive than medium sized firms. Cole et al. (2013) analysed data from Japan and found that medium and large firms have lower emissions intensities than small firms. Yagi and Managi (2018) also analysed data from Japan and found that firm size measured as equity had statistically significant impact on emissions.

Similar to the macroeconomic evidence, firm level research has identified that energy intensity also influences firm level emissions (Yagi and Managi, 2018). Furthermore, previous research has identified that the choice of energy source also matters. Cao and Karplus (2014) used a panel dataset of 800 Chinese firms to study emission and energy intensity in the context of Chinese industrial firms. Intensity in their study is defined as physical quantity of energy/emissions divided by economic output in value terms. They found that reduction of coal use in energy production reduced emission intensity. Sahu and Mehta (2018) also found that primary energy source impacts energy intensity, and that coal as primary energy source had a negative impact on energy efficiency. However, firms that use natural gas were found to be energy and emission efficient.

Previous research has also identified that the firm's choice of factors of production: labour and capital influences emissions levels and energy intensity. Both Subrahmanya (2006) and Sahu and Mehta (2018) found that more capital intensive firms are also more energy intensive. Likewise, Cole et al. (2013) found that CO_2 emissions per unit of output increase as the capital to labour ratio increases. In addition, there is evidence to suggest that the financial planning of a firm influences emission levels. Alam et al. (2022) found that firms with higher cash reserves had smaller emission levels and that this effect was more evident for firms with low leverage.

There is also evidence to suggest that the way firms operate impact their emission intensity. Richter and Schiersch (2017) studied data from Germany and found that firms that export their goods have better CO_2 productivity which is the inverse of emission intensity. Lin and He (2023) explored data from China and their results also suggest that emissions are lower for firms with high export intensity however, this is due to lower energy intensity rather than more advanced technologies. Dardati and Saygili (2021) argue that the relationship between exports and emission intensity depends on the choice of output measure. They used data from Chile and found that when total sales were used to calculate emission intensity, export status did have a negative relationship with emission intensity whereas no relationship was found when value added was used as an output measure. The authors suggest that the total sales based measure is downward biased due to intermediate input emissions not being attributed to the exporting firm.

Previous research has identified that innovation is another important factor that reduces emissions. Data from European companies suggest that sustainability initiatives such as efficient use of resources, environmental innovations and emission reduction initiatives lower the GHG emission intensity, and this effect is particularly notable for firms operating in high-pollution industries (Haque and Ntim, 2022). Furthermore, there is also evidence to suggest that firms that spend on R&D are more energy and emission efficient (Sahu and Mehta, 2018; Cole et al., 2013).

There is also evidence to suggest that structural changes at the industry level can drive changes in firm level emissions. Deng et al. (2024) analysed data from China and found that servitization of manufacturing firms reduced emission intensity and that the impact was more prominent in high-polluting industries, whereas Barrows and Olliver (2018) used data on Indian companies and found that increases in sector level competition and trade liberalisation can reduce emission intensity.

Similar to the macroeconomic research, firm level research has also identified that carbon pricing policies influence emission levels. Li et al. (2024) explored the impact of emission trading and carbon tax on carbon emissions using data for listed companies in China and found that these policies can help to reduce firm level carbon emissions. Their results indicate that these policies can encourage firms to optimise their energy structure, improve levels of green innovation and help accelerate industry structure optimisation.

Similarly, Le and Azhgaliyeva (2023) analysed data for Japan, Korea and China and found that carbon pricing policies did reduce firm level GHG emissions, and that this relationship was notable for heavy-polluting industries such as energy and utilities. Ahmadi et al. (2022) explored data on Canadian manufacturing firms and found that carbon tax reduced plant level emissions and that this changed was driven by plant being more energy efficient.

2.5 The role of technology in reducing emissions and energy use

Previous research on emissions has also explored the role of technology as a factor for reducing emissions and improving energy efficiency. Pons et al. (2013) studied the relationship between cleaner production technologies and firm performance. The results from their study suggest that energy saving technologies have no clear relationship with financial performance however, the implementation of environmental management systems has a positive impact on energy and material efficiency.

The ISO14001 standard is an internationally recognised standard for environmental management systems, and it helps the adopting firm to minimize their environmental footprint (International Organization for Standardization n.d). Arocena et al. (2021) used data from 46 different countries to analyse the impact of ISO14001 adaptation and found that it contributed to the reducing carbon emission intensity and increasing firm profitability. Sam and Song (2022) used data from Korea and found that implementation of ISO14001 was associated with 34% reduction on GHG emissions. Ferron et al. (2012) used data from Brazil, and they also found ISO14001 adaption to have a positive impact on firm profitability.

Majumdar and Kar (2017) analysed the relationship between technology diffusion and emission intensity using data for Indian manufacturing and agriculture industries and found that technology adoption reduced emission intensity. Similarly, Zhao et al. (2023) used data from China and found that the level of technological innovations has an inhibiting effect on the carbon emission intensity and that regional economic development level influences the magnitude of this impact.

Regional differences were also found by Wang et al. (2012) who explored the relationship between energy technology patens and CO_2 emissions. They found that patens for carbon-free energy technologies reduced emissions in parts of China but not in all the regions. The authors suggest that regional differences in energy infrastructure, insufficient R&D and long wait time for patents to be granted might be influencing the regional differences. Milindi and Inglesi-Lotz (2022) also used data on environment-related patents as a proxy for the adaptation of green technology and found that environment-related patents only reduce CO_2 emissions in high-income countries.

According to data from the emerging and developing economies, increasing the level of technology adaptation might not always lead to emission reductions. Kassouri and Alola (2023) suggest that the relationship between technology adaptation and emissions might display a U-shaped pattern where initially technology adaptation helps to reduce emissions but after a certain point the relationship reverses.

The role of artificial intelligence (AI) has also been explored in the previous literature. Chen and Jin (2023) analysed Chinese manufacturing firms to investigate the relationship between corporate AI and carbon emissions. Their research found that corporate AI can help to reduce carbon emissions and that the levels of green technology, management and product innovation strengthen the slowing effect that AI development has on carbon emissions. The authors suggest that the reason for this might be that the use of AI can help firms to reduce their resource consumption and to improve their energy efficiency. Zhong et al. (2024) studied data from 66 countries to explore the impact of AI on carbon emissions and found that there is variation across countries and that greatest impact is seen in high income and high emission countries.

3 Data Collection and Theoretical Framework

The first part of this section discusses how the data for the analysis was collected and the theoretical framework used to analyse the data. The second part of this section describes the dependent and explanatory variables used in the analysis.

3.1 Data Collection

The analysis presented in this thesis utilises data from two sources. The financial data is sourced from Orbis Bureau van Dijk database and data for the variables related to emissions and energy usage are sourced from the sustainability reports that firms publish each year on their websites. Full list of firms and links to their sustainability reports can be found in Appendix 2.

The analysis in this thesis utilises data from Denmark, Finland, Norway and Sweden. The analysis focuses on large firms due to financial and sustainability data being publicly available. Iceland has been omitted from the sample due to not having a sufficient number of large internation companies. Firms for this analysis have been selected from the big stock market indices for each country: OMX Copenhagen 25, OMX Helsinki 25, OBX Index and OMX Stockholm 30. The total number of firms included in the four stock market indices is 105. Out of the 105 firms, 7 firms operating in oil and gas production or in utilities industry have been excluded due to their operations having very different energy requirements and emission profiles. This approach draws from the methodology adapted by Cao and Karplus (2014).

Nordea bank is listed in 3 stock indices: Denmark, Finland and Sweden, but sustainability information is not sufficiently broken down by country and therefore, Nordea is excluded from the sample. Similarly, Telia is listed in Finland and in Sweden and therefore, it is excluded from the sample. In addition, both Maersk and Atlas Copco have A and B shares listed in the stock exchanges however, only one entry per firm is included in the analysis. Furthermore, 34 firms have been excluded from the sample due to not publishing scope 1 and 2 emission data back to 2019 at least or due to not providing information in English. After these exclusions, 57 firms remain in the sample.

Firms listed in the Swedish and Finnish stock market indices make up the largest portions of the sample while firms listed in the Norwegian index makes up the smallest portion. The data collection exercise indicated that many of the firms listed in the Norwegian stock market index operate in the maritime industry, and many of them started to publish sustainability information from 2021 onwards. This is reflected in the lower number on Norwegian firms in the sample.

Table 1: summary of the sample

Country	No. of Firms	% of the sample
Denmark	12	21.1 %
Finland	16	28.1 %
Norway	9	15.8%
Sweden	20	35.1 %
Total	57	-

The dataset covers annual data for the years 2015-2023. The dataset has missing values for the emission and energy related variables for years 2015-2018 due to not all firms publishing this data from 2015 onwards. Review of sustainability reporting as part of the data collection showed that several firms started to publish a more comprehensive set of sustainability data from 2019 onwards. This most likely reflects the Directive 2014/95/EU which came into force in 2018. The Directive 2014/95/EU requires firms to disclose non-financial information such as sustainability data (European Parliament, 2021).

To maintain consistency across the time series and where possible, the emission data in this analysis only includes scope 1 and scope 2 emissions as several firms do not include scope 3 emissions in their emissions data for years 2015-2019. Despite the best efforts to create a consistent time series, it is possible that some inconsistencies remain, as number of companies have updated their sustainability reporting methods and revised some but not all of their data during the time period covered in this analysis. The data collection exercise shows that scope 2 emissions appear to be impacted by these changes. In addition, many firms publish market-based and location-based versions of scope 2 emissions. The data collection for this analysis uses market-based scope 2 emission data due to this being available for most years and most firms.

3.2 Theoretical Framework

To explore the first research question: *Does reducing carbon intensity impact the financial performance of a firm?,* the first part of the analysis in this thesis examines the relationship between carbon emissions and firm performance and it draws from two different theoretical models: the neoclassical economic theory of a firm that looks to maximise its profits and from the stakeholder theory.

The neoclassical economic theory suggests that in the long-run, a firm will be able to determine a desired level of output and to choose the optimal level of input to minimise cost of production for that level of output (Garbo et al., 2020). Following the neoclassical economic theory, this thesis hypothesises that emissions are produced as part of the operations of a firm, and to minimise the cost of production, the firm will look to efficiently use its resources. Thus, if a firm can efficiently utilise its resources and therefore reduce emissions, it should also see improvements to its financial performance. This argument is consistent with findings by Trinks et al. (2020) who suggest that carbon efficient production that largely stems from resource efficiency can have operational benefits and that on average, more carbon efficient firms are also more profitable.

The stakeholder theory based model for value creation for sustainability by Freudenreich et al. (2020) proposes that stakeholder relationships are a core aspect of business models, and in the sustainability context, stakeholders play an important role in the joint value creation process that aims to achieve a joint purpose. Based on this theory, this thesis hypothesises that firms may wish to cut emissions to improve their green credentials and thus add value to their stakeholders which would lead to improved financial performance. Evidence from the previous literature on sustainability reporting suggests that gaining a positive CSR reputation can result in improved financial performance (Miller et al., 2020; Liu and Lu, 2021).

Both of these theories may be true when firms implement emission reduction initiatives. This thesis does not distinguish which of the two theories cause firms to cut emissions due to data limitations, rather it uses them to support the development of first hypothesis:

Hypothesis 1: reducing carbon intensity improves the accounting based measures of financial performance of a Nordic firm.

Financial performance in the context of hypothesis 1 means accounting based measures of financial performance. This thesis uses return on equity, return on assets, gross profit and Tobin's Q as measures of financial performance.

To answer the second research question: *What factors influence firm level carbon emissions?* this thesis looks at three specific factors: innovation, use of renewable energy and energy intensity. There are different ways to measure innovation. Some studies have used patents (Milindi and Inglesi-Lotz, 2022; Wang et al., 2012) and some have used R&D expenditure (Alam et al., 2022; Cole et al., 2013; Li et al., 2024). Innovation is one of the driving factors for economic growth as technological advancement can help economies to increase their long-run steady state income (Sloman et al., 2014). For this reason, governments across the world are setting targets for R&D spending as a share of GDP. For example, the Finnish government aims to increase R&D expenditure to 4% of GDP by 2030 (State Treasury Republic of Finland 2022).

In addition to the economic benefits, previous research has shown that R&D expenditure is an influential factor in reducing carbon intensity (Alam et al., 2022; Cole et al., 2013; Li et al., 2024). Therefore, if carbon intensity is calculated as carbon emissions/sales, this thesis hypothesises that the firm level R&D expenditure improves business processes and/or products/services to be more energy and resource efficient which would reduce the numerator and additionally increase the denominator through improved financial performance. Together these two changes would reduce the carbon intensity.

MacGregor Pelikánová (2019, 2) proposes that "spending money on innovation can, but not necessarily, lead to innovations" which suggests that R&D expenditure as a measure of innovation might be biased. However, due to data availability, this thesis follows the approach by Alam et al. (2022), Cole et al. (2013) and Li et al. (2024) and uses R&D expenditure. Thus, the second hypothesis to be tested in this thesis is:

Hypothesis 2: R&D reduces carbon intensity of Nordic firms.

There is macroeconomic evidence to suggest that the use of renewable energy can reduce carbon emissions (Wang et al., 2021) and at the firm level, the firm's choice of electricity source is one of the contributing factors to their scope 2 emissions (World Resource Institute and World Business Council 2004). The role of renewable energy at the firm level has not been extensively studied in the context of carbon intensity of Nordic firms and therefore, the analysis presented in this thesis aims to add to this evidence gap.

Renewable energy sources such as wind and hydro power are available in the Nordic countries (Aslani et al., 2013) and therefore, firms operating in these countries have the ability to choose renewable energy sources. The analysis in this thesis looks to explore weather increasing the share of renewable energy has a statistically significant impact on reducing the carbon intensity, and therefore the third hypothesis is:

Hypothesis 3: Increasing the use of renewable energy reduces carbon intensity of Nordic firms.

Energy is needed in most parts of the operations of a firm: offices need lighting, gas might be used to heat the offices, and machinery requires electricity to operate. Therefore, energy usage forms a part of the firm's operating costs. Recent events such as the war in Ukraine have showed that global shocks can influence energy prices and firm financial performance, and that the magnitude of these effects increase with the firm's energy consumption and carbon intensity (Ferriani and Gazzani, 2023). Therefore, reducing energy intensity could act as a way to reduce the impact of external shocks on operating costs.

In terms of energy intensity, macroeconomic evidence suggests that reducing energy intensity can reduce carbon emissions (Wang et al., 2020; Papież et al., 2021; Bianco et al., 2024). At the firm level, Tao et al. (2024) also found that by reducing energy intensity, firms can reduce carbon emission intensity. For this reason, the analysis in this thesis looks to add to the evidence base by determining whether reducing energy intensity also reduces carbon intensity of Nordic firms.

This thesis hypothesises that if a profit maximising firms changes their processes to be more energy efficient to reduce costs, they should also see a fall in their carbon intensity. The fourth hypothesis to be explored in this thesis is:

Hypothesis 4: Decreasing energy intensity reduces carbon intensity of Nordic firms.

3.2.1 Analytical framework to test hypothesis 1

Table 2 summarises analytical methods and variables used in the previous literature that analysed the relationship between emissions and financial performance. The summary shows that different panel data regression models have been widely used (Brouwers et al., 2018; Le and Nguyen-Phung, 2024; Perdichizzi et al., 2024; Trinks et al., 2020) and therefore, the validity of hypothesis 1 is analysed using a panel data regression approach.

In terms of measures for the dependent variable, Table 2 shows that previous studies have used a selection of financial variables such as ROE, Tobin's Q and ROA to measure financial performance (Brouwers et al., 2018; Le and Nguyen-Phung, 2024; Trinks et al., 2020). Therefore, financial performance is measured using accounting based measures in this thesis.

Previous studies have also included control variables to measure firm characteristic such as assets, leverage, and cash holdings (Le and Nguyen-Phung, 2024; Trumpp and Guenther, 2017). The impact of emissions has been measured using carbon intensity (Le and Nguyen-Phung, 2024; Oestreich and Tsiakas, 2024; Trumpp and Guenther, 2017). Following this, the research presented in this thesis uses carbon intensity and variables measuring firm characteristics to analyse hypothesis 1.

Table 2: Summary of previous research on financial performance and emissions

Paper	Topic	Dependent variable	Explanatory variables	Analytical method	R^2 of the model
Brouwers et al. (2018)	Carbon cost pass through and the link between emissions and FP	Tobin's Q, ROA, ROE	Instrumented: carbon intensity (emissions/sales) Instruments: lagged carbon intensity, yearly % change in emissions-to-cap, environmental stringency, Control: Size (ln(total assets), % change in sales, debt-to-equity, capital intensity (capital expenditure/total assets)	Two-stage instrumental variable regression (GMM)	-

Choi and Luo (2021)	Market value and GHG emissions	Market value of equity	Emissions, book value of equity, income before extraordinary items, stringency of environmental regulations, corporate governance score, public enforcement index, enforceability of contract, disclosure requirement index, anti-self-dealing index	Heckman model	-
Le and Nguyen-Phung (2024)	Impact of environmental performance on financial performance	ROA, ROE	GHG intensity, size (ln(total assets), leverage (liabilities/total assets), firm age (ln(age)), revenue growth	Fixed-effects regression model	0.294 (ROA) 0.191 (ROE)
Makridou et al. (2019)	Financial performance of firms participating in the EU ETS	EBIT to total assets	Current ratio, solvency ratio, size (ln(assets)), no. of employees/total assets, GDP % growth, no. of main electricity retailers, annual growth rate of future prices, energy efficiency policies score, emission allocation factor, verified emissions/sales	Multilevel cross-classified model	-
Oestreich and Tsiakas (2024)	Carbon emission and firm profitability	Gross profits/total assets	Emission intensity (emissions/revenue), size (market value of equity), value (book-to-market value/market value of equity), book leverage (total assets/book equity), market leverage (total assets/market equity), cash, earnings volatility	Fama-MacBeth regression	-
Perdichizzi et al. (2024)	Carbon emissions and firm value	Market-to-book value	Inverse book value, earnings (net income/book value of equity), emissions, leverage (debt/assets), dummy to indicate if net income was positive, intangibles, board size, board independence,	Fixed-effects regression model	0.798

			governance score, formal institutions, informal institutions		
Trinks et al. (2020)	Carbon emissions and financial performance	ROA, Tobin's Q	Carbon efficiency, Resource efficiency, capital, labour, Energy, good output, bad output, size (ln(total assets), leverage (debt/assets), book-to-market ratio	Fixed-effects regression model	0.122 (ROA) 0.291 (Tobin's Q)
Trumpp and Guenther (2017)	U-shaped relationship between CEP and CFP	Annual change in stock price, ROA	Carbon efficiency (GHG/sales), R&D (R&D expenses over sales), capital intensity, leverage (debt/assets), growth (% change in assets), cash flow, size (ln(assets), legal origin	One-way clustered OLS	0.34 (stock price) 0.42 (ROA)

The analysis for hypothesis 1 presented in this thesis aims to build on the previous research by filling the research gap around firms operating in the Nordic countries. The research presented in this thesis also aims to contribute to the wider discussion around environmental issues and financial performance by determining whether COVID-19 pandemic influenced the relationship between financial performance and carbon intensity.

This thesis tests two different panel data regression models to estimate the relationship between carbon intensity and financial performance. Equation (1) presents the first model tested in this thesis. The regression model is based on the model used by Le and Nguyen-Phung (2024). This model has been chosen based on the data availability from financial statements and from Orbis database.

Model 1

$$FP_{it} = \alpha + \beta_1 Assets_{it} + \beta_2 CI_{it} + \beta 5_3 Lev_{it} + \beta_4 Growth_{it} + \beta_5 Age_{it} + \nu_{it} \qquad (1)$$

Equation (2) presents model 2 which is based on the specification used by Trumpp and Guenther (2017). However, capital intensity is excluded as data for this is not available for the selected firms from Orbis database. Furthermore, Trumpp and Guenther (2017) also included lagged values of carbon intensity in their model but those are excluded from the model used in this thesis. This model has been chosen based on the data availability from financial statements and from Orbis database.

Model 2

$$FP_{it} = \alpha + \beta_1 CI_{it} + \beta_2 RD_{it} + \beta_3 Assets_{it} + \beta_4 lev_{it} + \beta_5 Growth_{it} + \gamma_1 Country_i + \beta_6 CashFlow_{it} + \nu_{it} \quad (2)$$

In both models γ represents the time-invariant coefficients and β represents the time-varying coefficients. Subscript *i* refers to firm *i* and subscript *t* refers to time period *t*. The component ν_{it} is the composite error term: $\nu_{it} = u_i + \epsilon_{it}$ where u_i measures the unobserved time-invariant factors and ϵ_{it} measures idiosyncratic error. Detailed description of the variables is presented in section 3.3.

3.2.2 Analytical framework to test hypothesis 2, 3 & 4

Hypotheses 2, 3 and 4 explore factors influencing emission intensity and therefore, the validity of these hypotheses are tested using a separate regression model. Table 3 below summarises previous research on the factors driving firm level carbon emissions. Table 3 shows that many of the papers have used carbon emission intensity as the dependent variable (Barrows and Olliver, 2018; Cao and Karplus, 2014; Cole et al., 2013) and firm characteristics such as size, sales growth and profitability have been used as control variables (Alam et al., 2022; Haque and Ntim, 2022). Fixed-effects regression model has been used as the estimation method in several studies (Alam et al., 2022; Barrows and Olliver, 2018; Cao and Karplus, 2014; Dardati and Saygili, 2021).

Table 3: summary of previous research on factors influencing firm level carbon emissions

Paper	Topic	Dependent variable	Explanatory variables	Analytical method	R^2 of the model
Ahmadi et al. (2022)	Impact of carbon tax on emissions	Emissions (tons)	Energy expenditure, output, salary workers, production workers, age, total expenses	Difference -in- difference	0.90-0.95

Alam et al. (2022)	Cash holdings and firm level emissions	Carbon emissions, direct carbon emissions, indirect carbon emissions	Cash holdings, firm size, sales growth, capital expenditure, leverage, R&D intensity, profitability, institutional ownership, board independence, board size, CEO duality	Fixed-effects regression	0.042-0.090
Barrows and Olliver (2018)	Product mix and carbon emissions	Emission intensity	Number of products, industry, sales value	Fixed-effects regression model	0.102-0.523 depending on the industry
Cao and Karplus (2014)	Firm level determinants of emission intensity	Primary energy intensity, electricity intensity, carbon intensity	Electricity price, coal price, labour price, industry dummy, year dummy	Fixed-effects regression model and pooled OLS	Ranges between 0.3940 and 0.6123
Cole et al. (2013)	Factors influencing firm carbon emissions	Carbon intensity	Capital-labour ratio, wage rate, firm size, R&D expenditure, advertising expenditure, exported output, % of foreign owned equity, outsourcing from abroad, industry dummy, regional manufacturing/total output, regional population density, regional per capita income, number of officials working on pollution control, age distribution of a region	Spatial error model	0.21-0.23 depending on model specification
Dardati and Saygili (2021)	Firm exports status and emissions	Emissions/sales	Outsourcing, size, capital intensity, skill intensity,	OLS and fixed-effects	Ranges between 0.003 and

		Emissions/value added	dummies for plant, year, region, industry	regression models	0.081 depending on model specification
Deng et al. (2024)	Manufacturing servitization and emission intensity	Emission intensity	Level of servitization, firm age, size, (ln(no. of employees), ownership dummy, GDP per capita, industrial structure, regional variable to control for emission policy	Fixed-effects regression model	Range between 0.661 and 0.659
Haque and Ntim (2022)	Corporate sustainability initiatives and carbon emissions	Emission intensity	Corporate sustainability initiatives, emission reduction initiatives, environmental innovations, efficient use of resources, board size, board independence, CEO-chair independence, CSR committee, firm size (ln(total assets), ROA, leverage, firm value, market-to-book value, sales growth, tangible assets, cash holdings, no. of employees	Three-way fixed-effects regression model	Ranges between 0.168 and 0.496
Le and Azhgaliyeva (2023)	Carbon pricing and firm GHG emissions	GHG emissions and GHG intensity	Carbon pricing dummy, carbon price rate, country level carbon intensity, firm size(ln(assets)), leverage, firm age, profitability	Fixed-effects and instrumental variable regression	Ranges between 0.015-0.281
Lin and He (2023)	Export intensity and emissions	Emissions, emission intensity, output value, emission technology, labour productivity	Export intensity, capital intensity, financial constraints, profit, dummy variables for ownership type	Fixed-effects regression model and probit model	Ranges between 0.04 and 0.28

Li et al. (2024)	Carbon emission trading, carbon tax and carbon emissions	Emission intensity	Carbon tax, carbon policy, green innovation, energy structure, industrial structure, government subsidies, R&D expenditure, ownership dummy, profitability, book-to-market ratio, growth rate, ROE, equity concentration, foreign capital, GDP per capita	Fixed-effects regression model	Ranges between 0.385 and 0.8766
Richter and Schiersch (2017)	Carbon emissions and export orientation	CO_2 productivity	Export orientation, industry, number of employees, capital stock, materials, carbon emissions	Two-stage instrumental variable regression (GMM) and OLS	-
Sahu and Mehta (2018)	Determinants of energy and emission intensities	Energy/sales Emissions/ sales	Capital intensity (capital stock/net sales), Labour intensity (compensation to employees/sales), raw material intensity, R&D intensity (R&D expenses/sales), repair and maintenance intensity (R&M expenses/sales), firm age, firm age squared, firm size (ln(sales)), size squared, export and technology intensity, dummies for environmental pollution, ownership, coal and natural gas	Fixed-effects regression model	0.27
Yagi and Managi (2018)	Decomposition of GHG emissions	Carbon emissions	Energy consumption, sales, assets, equity, cost of goods sold	Index decomposition analysis	-

The research to test the validity of hypotheses 2,3 and 4 in this thesis aims to explore how firms can reduce their emission intensity to contribute to the wider discussion around tangible actions firms can take to reduce their impact on the environment. Furthermore, the research presented in this thesis aims to provide more evidence in the context of Nordic firms to fill an evidence gap.

Equation (3) outlines model 3 for the panel data regression used to estimate the impact of energy intensity, R&D and renewable energy have on firm level carbon intensity. The variable for R&D and control variables for the model have been selected based on model specification used by Alam et al. (2022). To test hypothesis 3, an additional variable for renewable energy has been added to the mode based on findings by Wang et al. (2021) and Wu et al. (2024). Furthermore, to test hypothesis 4 a variable for energy intensity is added based on work by and Tao et al. (2024).

Due to lack of data availability, variables for capital expenditure, CEO duality and institutional ownership are not included in model 3 despite being included in the model by Alam et al. (2022). Furthermore, variables 'BI' and 'BS' that measure board size and independence are time-invariant due to data availability in the Orbis database.

Model 3

$$CI_{it} = \alpha + \beta_1 CashHoldings_{it} + \beta_2 Assets_{it} + \beta_3 Growth_{it} + \beta_4 Lev_{it} + \beta_5 RD_{it} + \beta_6 ROA_{it} + \gamma_1 BI_{it} + \gamma_2 BS_{it} + \beta_7 RE_{it} + \beta_8 EI_{it} + \nu_{it} \quad (3)$$

Where γ represents the time-invariant coefficients β represents the time-varying coefficients. Subscript *i* refers to firm *i* and subscript *t* refers to time period *t*. The component ν_{it} is the composite error term: $\nu_{it} = u_i + \epsilon_{it}$ where u_i measures the unobserved time-invariant factors and ϵ_{it} measures idiosyncratic error. Detailed description of the variables is presented in section 3.3.

3.3 Variable Description

The dependent variable in models 1 and 2 is financial performance which is measured using four different accounting based measures. The dependent variable in model 3 is carbon intensity. All models use a selection of explanatory variables which are listed in Table 5.

3.3.1 Dependent variables

Financial performance in this thesis means improving accounting based financial performance metrics and therefore, the dependent variable ‘financial performance’ of a firm *i* at time *t* in models 1 and 2 is measured using four different accounting based measures as shown in Table 4 below. These four measures have been chosen as they measure financial performance from different points of view and therefore, they allow a richer analysis of the relationship between carbon intensity and financial performance.

Literature review points that ROA (return on assets), ROE (return on equity) have been widely used in the previous literature (Fan et al., 2017; Brouwers et al., 2018; Le and Nguyen-Phung, 2024) as measures of financial performance. The ROA ratio relates the income generated to those assets that were invested to generate the earnings. To improve ROA, a firm needs to increase its profit margin and/or utilise its assets more efficiently (Lewis, 2012). On the other hand, the ROE ratio provides information on the income of stockholders. The important difference between the two is that ROE ratio accounts for the firm debt while ROA doesn’t (Lewis, 2012).

The study by Oestreich and Tsiakas (2024) followed approach by Novy-Marx (2013) and used the ratio gross profit/total assets as a financial performance measure. They suggest that gross profit is the cleanest measure because it is not influenced by expenses such as human capital development that are aimed at enhancing future profitability.

Studies by Brouwers et al. (2018) and Trinks et al. (2020) used Tobin’s Q as a measure of financial performance. Tobin’s Q can be seen as reflecting the long-term performance of a firm as it includes forward-looking valuations from the stock market (Trinks et al., 2020).

Table 4: Description of dependent variable in models 1 and 2

Variable	Description
GP	Gross profit measured as gross profit/total assets.
ROA	Return on assets, measured as net profit/total assets.
ROE	Return on equity, measured as after-tax profit/stockholder’s equity.
Tobin’s Q	Measured as market capitalisation / total assets

The dependent variable for model 3 is carbon intensity (CI) of a firm *i* at time *t.* This variable is calculated as total emissions over sales following the methodology by Sahu and Mehta (2018).

$$CI_{it} = \frac{Total\ emissions_{it}}{Sales_{it}} \tag{4}$$

3.3.2 Explanatory variables

The explanatory variables used in the analysis are described in Table 5 below. Variable of interest in models 1 and 2 is ‘CI’, while variables ‘RD’, ‘RE’ and ‘EI’ are the variables of interest in model 3. In addition, the analysis controls for firm specific characteristics.

Similar to studies by Le and Nguyen-Phung (2024), Alam et al. (2022), Oestreich, Perdichizzi et al. (2024) and Tsiakas (2024) variable ‘Lev’ measuring leverage is included in the models to control for the effect of firm’s debt level has on its financial performance and carbon emissions. Leverage measures the risk associated with high levels of debt and therefore, it can negatively impact financial performance of a firm (Trumpp and Guenther, 2017).

The variable ‘CashFlow’ that measures the cash flow of a firm is included in the model 2 based on work by Trumpp and Guenther (2017) who suggest that large cash flows might influence financial performance. The variable ‘CashHoldings’ is included in the model 3 based on work by Alam et al. (2022) who suggest that firms that are cash-rich allocate more investments to carbon reduction, and they also tend to have higher renewable energy usage.

Variable ‘Growth’ which measures the annual growth of sales is included in both models following work by Alam et al. (2022), Brouwers et al. (2018) and Haque and Ntim (2022). In terms of carbon emissions, Alam et al. (2022) suggest that firms with high sales growth have higher levels of carbon emissions while Trumpp and Guenther (2017) propose that growth opportunities can also positively influence financial performance through generating additional sales.

Variable ‘Assets’ is included in the models to control for variance in the dependent variables that is related to firm size. In terms of carbon emissions, larger firms may naturally produce more emissions than smaller firms (Le and Nguyen-Phung, 2024). However, larger firms can also be less carbon intensive reflecting economies of scale (Cole et al., 2013). Brouwers et al. (2018) suggest that larger firms might be better able to implement carbon reduction activities due to their stronger economic position allowing them to invest in such activities. From financial performance point of view, Makridou et al. (2019) propose that size can have a negative or a positive impact depending on the type of firm.

Variable ‘Age’ is included in the model to control for variation attributable to the age of a firm. In relation to financial performance, Nguyen-Phung (2024) used ‘Age’ variable to control for firm experience whereas in the context of carbon emissions, Deng et al. (2024) suggest that older firms have more experience with pollution control and have a greater capacity to reduce emissions.

Variables ‘BS’ and ‘BI’ are used in the model by Alam et al. (2022) to control for the impact of corporate policies on environmental issues.

Table 5: Description of explanatory variables

Variable	Model	Description
CI	Model 1 & 2	Carbon intensity, measures as total emissions/sales
Assets	Model 1, 2 & 3	Measured as natural logarithm of total assets (mil Eur.)
RD	Model 1 & 3	Research and Development, measured as R&D expenses/sales
Lev	Model 1, 2 & 3	Leverage, measures as debt/total assets
Growth	Model 1, 2 & 3	Growth rate, measured as annual % change in sales
Country	Model 2	A categorical variable indicating country
CashFlow	Model 2	Cash flow/total sales (mil Eur.)
CashHoldings	Model 3	Cash holdings/total assets (mil Eur.)
RE	Model 3	Renewable energy, measured as % share of total energy used
EI	Model 3	Energy intensity measured as total energy usage/sales
BS	Model 3	Board size, measured as number of board members
BI	Model 3	Board independence, measured using the Bureau van Dijk independence indicator
Age	Model 1	Firm age, measured as current year – year of incorporation +1

4 Data Analysis

This section starts by covering the descriptive statistics and an analysis of within and between variation. The following analysis focuses on pairwise correlation analysis and the final section discusses findings from the regression analysis.

4.1 Descriptive statistics

Table 6 below shows the summary statistics for the variables used in the analysis. The ’Assets’ variable shows that there are considerable size differences between the firms. The smallest firm in the sample has just over 4 million Euros worth of assets when the largest firm has over 500 billion in assets. Similarly, some firms in the sample are very young and some are over 100 years old. In addition, the ‘ROE’ and ‘ROA’ profitability ratios show that firms in the sample take both negative and positive values. Despite the large range of values these variables take, no firms have been classified as outliers and removed from the sample. This is because the firms in the sample operate in different industries and are of different age which are likely factors to explain the range of values seen for variables ‘Assets’, ‘ROE’ and ‘ROA’.

The variable ‘CI’ measuring carbon intensity also shows that some firms have a very low carbon intensity, and some have very high intensity. Similarly, the variable ‘RD’ shows that some firm spend very little on RD compared to others, but on average RD spending is greater than zero.

The variable ‘RE’ shows that some firms in the sample do not use renewable energy and that some firms use mainly renewable energy. On average, 35% of energy comes from renewable sources. The ‘RE’ variable has several missing values due to many firms not publishing this data. When the whole dataset is observed, 57.9% of the observations is missing data. The data collection exercise showed that firms started to publish more extensive set of sustainability data post-2019. Therefore, when the dataset is restricted to start in 2019, the variable ‘RE’ has 42.8 % missing data.

The variable 'EI' shows that the average energy intensity in the sample is 2.73 GWh per unit of sales however, the largest energy intensity is over 40 times larger. Similar to 'RE', 'EI' has 33.7% missing values when the whole time period is observed. The missingness falls down to 21.4% post-2019.

Table 6: Descriptive statistics

Variable	**Obs.**	**Type**	**Mean**	**Std. dev.**	**Min**	**Max**	**Skewness**	**Kurtosis**
GP	424	Numerical	0.42	0.30	0.03	2.03	2.44	10.53
ROE	504	Numerical	20.91	28.45	-129.73	241.57	2.37	20.03
ROA	504	Numerical	6.92	9.66	-36.47	51.73	1.10	8.76
TobinQ	525	Numerical	1.48	184	0.021	14.72	3.37	17.32
CI	403	Numerical	2.14	10.62	0.00	90.60	5.99	40.05
Assets	505	Numerical	29077.03	80797.78	4.10	552815.50	4.49	23.70
RD	450	Numerical	3.85	7.49	0.00	76.65	4.74	34.49
Lev	505	Numerical	44.93	18.77	0.00	98.28	0.08	4.02
Growth	457	Numerical	0.17	0.93	-0.69	15.34	12.42	180.85
Country	513	Categorical	2.65	1.16	1.00	4.00	-0.10	1.52
CashFlow	447	Numerical	0.21	0.55	-3.3	5.68	5.17	54.38
CashHoldings	446	Numerical	0.09	0.1	0.00	0.95	4.27	30.95
RE	216	Numerical	0.35	0.33	0.00	1.00	0.73	2.23
EI	340	Numerical	2.73	14.25	0.00	131.69	6.87	52.11
BI	570	Categorical	2.19	1.43	1	5	0.84	2.19
BS	570	Numerical	26.25	10.57	5	64	1.06	5.01
Age	513	Numerical	69.89	42.92	0	177	0.12	1.90

4.2 Within and between variation

The use of panel data for firm level analysis enables researchers to analyse variation across time (within variation) and across firms (between variation). The two panel data estimation methods explored in this thesis are random-effects and fixed-effects models. The fixed-effects and random effects models assume that the ϵ_{it} error term is independent of time variant and time invariant explanatory variables. The random-effects model assumes the u_i error term to be a set of random variables with a specified probability distribution, whereas in fixed-effects models the u_i error term represents fixed parameters that can be removed through transforming the model (Allison, 2009). The u_i error term allows for heterogeneity in the model and to avoid biases, fixed-effect model removes it by de-meaning the regression equation (Bell et al., 2019) as shown by equation (5).

$$y_{it} - \overline{y}_i = \alpha + \beta x_{it} + \gamma z_i + u_i + \epsilon_{it} - (\alpha + \beta \overline{x}_i + \gamma z_i + u_i + \bar{\epsilon}_{it})$$
$$\Rightarrow \ddot{y}_{it} = \beta \ddot{x}_{it} + \ddot{\epsilon}_{it} \qquad (5)$$

Therefore, one of the important differences between these two estimation methods is that fixed-effects models only use within variation whereas random-effects models utilise both within and between variation. The benefit of fixed-effects models only using within variation is that the estimates do not suffer from heterogeneity bias (Bell and Jones, 2015). However, this means that the fixed effects models do not use all the available information. Therefore, if the heterogeneity bias is not present, random-effects models are often preferred as they account for both within and between variation (Bell and Jones, 2015).

One of the challenges with the fixed-effects models is that if a variable has no within variation, it cannot be estimated using fixed-effects approach due to the de-meaning transformation (Bell and Jones, 2015). However, random-effects models are able to estimate time-invariant variables. Furthermore, if a variable has very low level of within variation, fixed-effects models may fail to show relationship between variables (Bell and Jones, 2015). Therefore, fixed-effects models often give only a partial picture of the relationship between dependent and explanatory variables (Bell et al., 2019).

To provide further information on the four variables of interest, Table 7 presents the within and between variations. For all four explanatory variables the between variation is greater than the within variation. This indicates that the firms in the sample vary more between themselves than across time. However, the between variation is present for all four variables indicating that there is variation across time. Based on the work by Bell and Jones (2015) results presented in Table 7 suggest that fixed-effects models may fail to provide a comprehensive picture of the relationship between the dependent and explanatory variables analysed in this thesis due to not being able to account for the between variation. Thus, if the heterogeneity bias is not present, random-effects models would allow for a richer analysis of the relationship between explanatory and dependent variables.

Table 7: between and within variation of explanatory variables of interest

Variable	Variation	Std. dev.	Min	Max
CI	Overall	10.62	0.00	90.60
	Between	9.28	0.00	61.58
	Within	3.89	-41.84	31.16
RE	Overall	0.33	0.00	1.00
	Between	0.31	0.00	1.00
	Within	0.11	-0.26	0.74
EI	Overall	14.25	0.00	131.69
	Between	12.17	0.00	82.78
	Within	5.22	-52.97	51.67
RD	Overall	7.49	0.00	76.65
	Between	6.97	0.00	40.24
	Within	2.90	-22.74	40.27

The research by Bell and Jones (2015) highlighted the importance of understanding the level of within and between variation. Therefore, to further explore how much the variables listed in Table 7 change over time, new categorical variables with four categories are created. The thresholds for the categories are chosen based on the distribution of values in years 2015 and 2022. The categorical variables are then used in the calculation of transition probability matrixes as described in equation (6).

$$P = \begin{pmatrix} p_{11} & \cdots & p_{14} \\ \vdots & \ddots & \vdots \\ p_{41} & \cdots & p_{44} \end{pmatrix} \tag{6}$$

Transition probabilities have been used in previous economic literature to explore various topics such as credit risk (Jones, 2005; Xing et al., 2012). Jones (2005) used transition probabilities to estimate how likely it was for commercial banks to change from one credit rating to another given their current rating and to assess if the credit rating variable was time invariant.

Therefore, the transition probability analysis of variables presented in Table 7 explores how likely it is that the firms in the sample move from one category to another at period *t+1* given their state at period t. If the likelihood to move to a different state is low, then there is an indication that the issue related to fixed-effects models highlighted by Bell and Jones (2015) might be present. Furthermore, the transition probabilities give a deeper insight into the within variation presented in Table 7 through indicating whether Nordic firms are more likely to move to a higher or lower category.

Equation (7) is another way to describe the meaning of a transition probability. It shows that the transition probability of a firm x_i represents the probability to be at stage *v2* at period *t+1* in condition to state *v1* at period *t*. Tables 8-11 present these transition probabilities so that period *v1* stage is represented as rows and *v2* stage is represented as columns.

$$P(x_{i,t+1} = v2 \mid x_{i,t} = v1) \tag{7}$$

Table 8 shows the transition probabilities for a categorical version of variable 'CI'. The diagonal line shows that carbon intensity is quite stable over time, meaning that firms in the sample do not change their carbon intensity to a great extent. However, the probabilities to reduce carbon intensity are greater than increasing carbon intensity indicating that firms in the sample are implementing carbon reducing initiatives to an extent. For example, if a firm is in the 2nd carbon intensity category at period *t*, there is a 2.3% probability that it has increased its carbon intensity and moved to the 3rd category at period *t+1* whereas, the probability for it to reduce carbon intensity and to move category 1 at period *t+1* is 21.8%. The least time variant category is the 1st category.

Table 8: Transition probabilities of variable 'CI'

	To category				**Total**
From category	**1**	**2**	**3**	**4**	
1 CI<0.01	96.74	3.36	0	0	100
2 CI>=0.01 & CI<0.025	21.84	75.86	2.30	0	100
3 CI>=0.025 & CI<0.1	1.30	14.29	83.12	1.30	100
4 CI>=0.1	0	1.05	6.32	92.63	100
Total	31.05	23.08	20.51	25.36	100

Table 9 shows the transition probabilities for a categorical version variable 'RE'. The diagonal line shows that the variable is fairly time-invariant. However, the probabilities to increase the use of renewable energy are greater than reducing the use of renewable energy.

If a firm was in the 2nd category at time *t,* then there is a 15.6% probability that it had increased its use of renewable energy to be in category 3 at period *t+1*. Nevertheless, it is also important to note that some firms reduce their share of renewable energy. If at period *t* a firm was in the 2nd category, there is a 4.4% probability that it reduced the share of renewable energy and moved into category 1 at period *t+1*.

Table 9: Transition probabilities of variable 'RE'

From category	**To category**				**Total**
	1	**2**	**3**	**4**	
1 RE<10%	84.21	14.04	1.75	0	100
2 RE 10%-29.9%	4.44	77.78	15.56	2.22	100
3 RE 30%-59.9%	0	2.5	85.0	12.5	100
4 RE >=60%	0	0	2.63	97.37	100
Total	27.78	24.44	23.89	23.89	100

Table 10 shows the time variability of a categorical version of variable ‘EI’. The diagonal line shows that the variable is quite stable over time. The least time variant category is category 3. If a firm was in category 3 at a time *t*, there is 3.6% probability that it has increased its energy intensity and moved to category 4 at period *t+1*. Whereas the probability that the firm reduced its energy intensity and moved to category 2 at period *t+1* is 20%.

Table 10: Transition probabilities for variable 'EI'

From category	**To category**				**Total**
	1	**2**	**3**	**4**	
1 EI<0.05	91.8	3.28	4.92	0	100
2 EI>=0.05 & EI<0.10	12.86	82.86	4.29	0	100
3 EI>=0.10 & EI<0.2	3.64	20.00	72.73	3.64	100
4 EI>=0.2	0	0	6.48	93.52	100
Total	22.79	24.15	18.03	35.03	100

Table 11 below shows the time variability of variable ’RD’. The diagonal line shows that the variable is stable across time. The 3rd category is the least time variant category. If a firm was in the 3rd category at time *t*, then the probability that it increased its R&D spending and moved up to the 4th category at time *t+1* is 8.1%. Whereas the probability that it dropped down to 2nd category at time *t+1* is 3%.

Table 11 shows the time variability of ‘RD’.

From category	To category				Total
	1	2	3	4	
1 RD<0.18	94.85	4.12	0	1.03	100
2 RD>=0.18 & RD<1.59	2.91	90.29	5.83	0.97	100
3 RD>=1.59 & RD<3.59	1.01	3.03	87.88	8.08	100
4 RD>=3.59	2.02	2.02	6.06	89.9	100
Total	24.62	25.63	24.87	24.87	100

In summary, the analysis of transition probabilities shows that firms in the sample are more likely to improve the sustainability aspect of their operations than worsen them. That is, firms are more likely to reduce their carbon and energy intensities and to increase their use of renewable energy. However, the transition probabilities show that variables covered in Table 7 do not change hugely across time. This suggests that challenges with fixed-effects estimation might be present as highlighted by Bell and Jones (2015).

4.3 Correlation analysis

Table 12 below shows the pairwise correlations between dependent and explanatory variables. The carbon intensity variable ’CI’ is negatively correlated with three dependent variables: ROE, ROA and Tobin’s Q but it has a small positive correlation with the gross profit dependent variable. Variables ‘RD’ and ‘RE’ have a negative correlation with ‘CI’ suggesting that R&D spending and the use of renewable have an inverse relationship. Variable ‘EI’ has a positive correlation with carbon intensity indicating that as energy intensity increase carbon intensity is expected to increase as well.

Overall, the pairwise correlation between explanatory variables are moderate ranging between -0.52 and +0.53 suggesting that the regression models 1-3 should not suffer from multicollinearity.

Table 11: Correlation statistics

	GP	ROE	ROA	Tobinq	CI	Assets	RD	Lev	Growth	CashF	CashH	EI	RE	Age	BI	BS	Country
GP	1.00																
ROE	0.43	1.00															
ROA	0.37	0.82	1.00														
Tobinq	0.33	0.56	0.53	1.00													
CI	0.01	-0.06	-0.01	-0.01	1.00												
Assets	-0.17	-0.07	-0.15	-0.21	-0.12	1.00											
RD	-0.11	-0.05	-0.03	0.12	-0.08	0.12	1.00										
Lev	-0.20	-0.10	0.16	0.19	0.21	-0.52	0.16	1.00									
Growth	-0.04	0.03	-0.01	-0.05	-0.02	-0.05	-0.02	-0.10	1.00								
CashF	-0.07	0.30	0.36	-0.01	0.00	0.18	-0.07	0.16	0.39	1.00							
CashH	0.04	-0.03	-0.04	0.04	0.21	-0.01	0.53	0.14	-0.02	-0.09	1.00						
EI	0.21	-0.10	-0.13	-0.09	0.40	-0.11	-0.09	0.02	0.03	0.02	0.13	1.00					
RE	0.39	0.40	0.34	0.20	-0.06	-0.02	0.21	-0.15	-0.04	0.07	0.08	-0.30	1.00				
Age	-0.17	-0.07	-0.12	-0.15	-0.05	0.31	0.01	0.00	-0.13	-0.02	-0.06	0.17	-0.05	1.00			
BI	0.36	0.16	0.12	0.26	-0.16	0.12	0.15	-0.11	0.01	-0.05	0.06	-0.13	0.20	-0.07	1.00		
BS	-0.24	-0.22	-0.22	-0.23	0.00	0.15	0.13	0.11	-0.10	-0.07	0.08	0.05	-0.12	0.44	-0.22	1.00	
Country	-0.32	0.00	-0.03	-0.29	-0.14	0.02	-0.07	0.07	0.09	0.13	-0.13	-0.19	-0.19	0.04	-0.42	0.08	1.00

4.4 Variable transformations

Table 6 shows that several variables do not appear to be normally distributed as they are skewed, and kurtosis is greater than 3. Variables ‘GP, ‘CI’, ’ROE’, ‘ROA’, ‘Assets’, ‘CashFlow’, ‘CashHoldings’, TobinQ’ ‘Growth’, ‘EI’ and ‘RD’ are transformed by taking natural logarithm. Taking the natural logarithm can improve the distribution of variables to be closer to normal distribution (Lütkepohl and Xu, 2012). Histograms for the transformed variables can be found in Appendix 3. Table 13 below shows the pairwise correlations between transformed variables as denoted by “ln” prefix and the rest of the variables. The pairwise correlations between the explanatory variables are again moderate suggesting that the variable transformations do not introduce multicollinearity into regression models 1-3.

Table 12: Correlation of transformed variables

	lnGP	lnROE	lnROA	lnTobinQ	lnCI	lnAssets	lnRD	Lev	lnGrowth	lnCashF	lnCashH	lnEI	RE	Age	BI	BS	Country
lnGP	1.00																
lnROE	0.33	1.00															
lnROA	0.23	0.78	1.00														
lnTobinQ	0.34	0.33	0.58	1.00													
lnCI	0.11	0.21	0.13	0.12	1.00												
lnAssets	0.32	0.16	0.40	0.55	0.30	1.00											
lnRD	0.07	0.11	0.09	0.27	0.25	0.04	1.00										
Lev	0.26	0.11	0.44	0.45	0.01	0.31	0.04	1.00									
lnGrowth	0.18	0.13	0.08	0.21	0.08	0.08	0.11	0.03	1.00								
lnCashF	0.06	0.38	0.54	0.09	0.10	0.05	0.08	0.28	0.03	1.00							
lnCashH	0.10	0.03	0.02	0.00	0.21	0.10	0.43	0.00	0.05	0.13	1.00						
lnEI	0.15	0.16	0.05	0.22	0.50	0.35	0.28	0.13	0.05	0.00	0.07	1.00					
RE	0.39	0.32	0.30	0.04	0.44	0.16	0.18	0.15	0.04	0.29	0.13	0.32	1.00				
Age	0.17	0.12	0.18	0.25	0.01	0.38	0.10	0.00	0.02	0.05	0.02	0.22	0.05	1.00			
BI	0.30	0.06	0.03	0.09	0.11	0.03	0.17	0.11	0.11	0.08	0.01	0.24	0.20	0.07	1.00		
BS	0.18	0.21	0.17	0.15	0.11	0.40	0.03	0.11	0.05	0.13	0.18	0.11	0.12	0.44	-0.22	1.00	
Country	0.34	0.02	0.03	0.23	0.17	0.22	0.07	0.07	0.09	0.16	0.17	0.05	0.19	0.04	-0.42	0.08	1.00

4.5 Regression results for the relationship between financial performance and carbon intensity

To estimate models 1 and 2 presented in equations (1) and (2), pooled OLS is first run as the baseline model. Fixed-effects and random-effects models are then run and Hausman test, F-test $all\, u_i = 0$ for fixed-effects and Breusch-Pagan Lagrange multiplier test are used to determine the most suitable estimation model.

The Hausman test is a specification test to check if the fixed-effects and random-effects coefficient estimates are different. For random-effects estimators to be consistent and unbiased, the conditional mean of u_i should be independent from the x_{it}'s. By design, the fixed-effects model is not impacted by this assumption as it treats the u_i as a fixed unknown constant. If this assumption does hold for random-effects model, then the difference between random-effects and fixed-effects coefficients should be 0 or close to 0 (Hausman, 1978).

If the difference is not 0 or close to 0, then the Hausman test indicates that random-effects coefficients are biased while fixed-effects estimates are not (Hausman, 1978) and therefore, fixed-effects would be the preferred estimation method.

If the results from the Hausman test indicate that random-effects model are unbiased, then next step is to use the Breusch-Pagan Lagrange multiplier test (Breusch and Pagan, 1980) to test for random effects $H_0: \sigma^2{}_u = 0$. That is, to test whether there is heterogeneity between the firms. If the null hypothesis is rejected, random-effects is then chosen as the estimation method.

The four different dependent variables measuring accounting based financial performance are included in their original form following the methodology by Le and Nguyen-Phung (2024) and Trumpp and Guenther (2017) and in their log transformed form as described in section 4.4. The analysis presented in the following section refers to these different versions of the dependent variable as model specifications 1-8. The model specifications 1-8 are separately estimated for models 1 and 2.

All the hypothesis testing done in the analysis section uses 5% confidence level.

4.5.1 Baseline pooled OLS estimates

Table 14 presents the regression coefficients for the baseline pooled OLS model 1 as represented by equation (1) and standard errors in parentheses. The estimated regression coefficient for carbon intensity is not statistically significant for specifications 1 and 2 that use gross profit as an estimate of financial performance. In the other specifications the estimated regression coefficient for carbon intensity has a negative sign and it is statistically significant at least at 5% level. These baseline results suggest that increasing carbon intensity has a negative impact on the firm financial performance when ROE, ROA and Tobin's Q are used as measures of financial performance. Thus, suggesting that there is evidence to support hypothesis 1.

The estimated regression coefficient for the control variable 'lnAssets' which represents the size of a firm is statistically significant in all specifications. In specifications 3-8 the R-squared ranges between 0.07 and 0.19 suggesting that the model 1 explain less than 20% of the variation in the dependent variable.

Table 13: Baseline regression results for model 1

Spec. Variables	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
lnAssets	-0.150***	-0.0723***	-0.0499	-4.978***	-0.0863**	-1.097***	-0.262***	-0.544***
	(0.0287)	(0.0139)	(0.0344)	(1.264)	(0.0405)	(0.374)	(0.0422)	(0.103)
lnCI	0.0218	-0.0114	-0.0455**	-2.508***	-0.0528**	-0.650***	-0.0828***	-0.196***
	(0.0156)	(0.00755)	(0.0205)	(0.737)	(0.0241)	(0.218)	(0.0229)	(0.0558)
Lev	-0.0101***	-0.00322***	-0.0119***	-0.455***	0.0111***	0.0470	0.00884**	0.0140*
	(0.00227)	(0.00110)	(0.00307)	(0.112)	(0.00362)	(0.0331)	(0.00349)	(0.00849)
lnGrowth	-0.0885***	-0.0296**	-0.0926**	-2.630**	-0.0686	-1.071***	-0.0876**	-0.111
	(0.0269)	(0.0131)	(0.0357)	(1.295)	(0.0419)	(0.383)	(0.0404)	(0.0985)
Age	-0.00106	-0.000516	-0.00156	0.0243	-0.00166	-0.00896	-0.00222*	-0.00209
	(0.000911)	(0.000442)	(0.00116)	(0.0425)	(0.00139)	(0.0126)	(0.00133)	(0.00324)
Constant	0.667***	1.118***	3.744***	71.88***	1.925***	11.26***	1.653***	5.020***
	(0.252)	(0.122)	(0.312)	(11.14)	(0.366)	(3.292)	(0.386)	(0.941)
Obs.	272	272	273	293	272	293	273	273
R-squared	0.238	0.171	0.119	0.133	0.071	0.079	0.191	0.128

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 15 presents the baseline pooled OLS regression coefficients and standard errors for the model 2. The results for the model 2 differ from the result for model 1. The estimated regression coefficient for carbon intensity is statistically significant at 5% level only in specification 1 which uses gross profit as a measure of financial performance. However, the estimated regression coefficient for variable 'lnCI' in specification 1 has a positive sign indicating that increasing carbon intensity would improve financial performance which contradicts the findings by Trumpp and Guenther (2017).

The R-squared values for all model 2 specification are higher than model 1 R-squared values. This likely reflects model 2 having a greater number of explanatory variables than model 1. Model 2 includes a categorical variable for country which is statistically significant at 1% level in specification 2. Furthermore, the estimated regression coefficients for 'lnR&D' and for 'lnCashFlow' are statistically at 1% level in both specifications 1 and 2. These baseline results suggest that the relationship between carbon intensity and firm financial performance is sensitive to changes in the explanatory and dependent variables.

Table 14: Baseline pooled OLS regression results for model 2

Spec. Variables	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
lnCI	0.0342**	-0.0103*	0.0349	-0.341	0.0285	-0.129	0.0118	-0.0258
	(0.0147)	(0.00564)	(0.0221)	(0.508)	(0.0252)	(0.182)	(0.0249)	(0.0640)
lnRD	0.111***	0.0392***	0.0489	2.517***	0.0209	1.007***	0.176***	0.321***
	(0.0267)	(0.0103)	(0.0401)	(0.904)	(0.0468)	(0.324)	(0.0444)	(0.114)
lnAssets	-0.179***	-0.0512***	-0.103**	-0.181	-0.146***	-0.319	-0.336***	-0.626***
	(0.0284)	(0.0109)	(0.0423)	(0.984)	(0.0484)	(0.353)	(0.0492)	(0.126)
Lev	-0.0130***	-0.00201**	-0.0271***	-0.424***	-0.00591	0.0301	-0.00372	-0.00754
	(0.00220)	(0.000848)	(0.00360)	(0.0762)	(0.00411)	(0.0273)	(0.00378)	(0.00970)
lnGrowth	-0.0903***	-0.0386***	-0.0453	-1.213	-0.0357	-0.589**	-0.0792*	-0.176*
	(0.0239)	(0.00921)	(0.0349)	(0.829)	(0.0395)	(0.297)	(0.0406)	(0.104)
Country								
DNK	0.272***	0.109***	0.0763	10.03***	0.129	1.907*	0.709***	2.629***
	(0.0825)	(0.0317)	(0.123)	(2.850)	(0.143)	(1.021)	(0.139)	(0.358)
NOR	0.415***	0.107***	0.0939	-0.270	0.106	-1.030	0.165	0.362
	(0.0823)	(0.0317)	(0.118)	(2.826)	(0.135)	(1.013)	(0.138)	(0.355)
SWE	-0.105	-0.0836**	0.156	-2.043	0.173	-1.714	-0.00521	0.239
	(0.0877)	(0.0338)	(0.127)	(3.015)	(0.144)	(1.081)	(0.151)	(0.389)
lnCashFlow	0.121***	0.0475***	0.673***	10.97***	0.784***	4.714***	0.275***	0.662***
	(0.0415)	(0.0160)	(0.0771)	(1.332)	(0.0899)	(0.478)	(0.0652)	(0.167)
Constant	1.034***	0.832***	6.372***	59.95***	4.873***	16.60***	3.438***	7.625***
	(0.325)	(0.125)	(0.543)	(11.12)	(0.625)	(3.986)	(0.559)	(1.435)
Obs.	219	219	217	223	215	223	221	221
R-squared	0.477	0.405	0.338	0.374	0.358	0.434	0.448	0.435

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.5.2 Fixed-effects and random-effects estimates

Next, fixed-effects and random-effects models are estimated for model 1. The most suitable estimation method is chosen using Hausman test which tests the hypothesis that the difference in random-effects and fixed-effects coefficients is not systematic (Hausman, 1978). The results from the Hausman test for model 1 specifications are shown in Table 16.

The Hausman test suggests that fixed-effects would be the preferred for model 1 specifications 1-5. To further tests this, the F-test for all $u_i = 0$ is conducted, and the null hypothesis is rejected for all five specifications. Therefore, fixed-effects are non-zero which indicates that fixed-effects model should be preferred over pooled OLS model in all five cases.

The Hausman test null hypothesis is not rejected for specification 6-8 indicating that random-effect model is the preferred specification. Next, the Breusch-Pagan Lagrange multiplier test is conducted to test the null hypothesis of no random effects. The results from this test indicate that the null hypothesis is rejected for model 1 specifications 6-8. Therefore, random-effects is preferred over pooled OLS.

Table 15: Preferred estimation method for model 1 based on Hausman test

Model	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
FE	X	X	X	X	X			
RE						X	X	X

Hypothesis testing uses 5% confidence level

Table 17 below reports the regression coefficients and standard errors for model 1 specifications based on the preferred estimation method reported in Table 16. Out of the eight specifications, the estimated regression coefficient for carbon intensity statistically significant at least at 5% level in four specifications.

Similar to findings by Le and Nguyen-Phung (2024), the estimated sign for the regression coefficient for variable ‘lnCI’ is negative in all four specifications. The results in Table 17 differ from the baseline pooled OLS estimates in Table 14 as both specifications that use gross profit as a measure of financial performance find carbon intensity to have a statistically significant relationship. Additionally, carbon intensity was statistically significant at 1%

level in specification 6 that uses ROA as a measure of financial performance in Table 14 but not in Table 17. One reason for this could be that fixed-effects models utilise the time dimension in the data and therefore, makes more efficient use of the data. Furthermore, specifications 6-8 are estimated using random-effects model and therefore, the results account for both within and between variation which could further explain the difference between Tables 14 and 17.

Specification 1 regression coefficient for 'lnCI' estimates that 1% increase in carbon intensity would result in 0.1% fall in gross profit per unit of asset while holding other variables constant. When specification 4 is used, 1% increase in carbon intensity is estimated to result in 0.06 fall in ROE which is close to the fall of 0.04 estimated by Le and Nguyen-Phung (2024). In terms of Tobin's Q, specification 7 estimates that 1% increase in carbon intensity would result in 0.08% fall in Tobin's Q, while holding other variables constant.

In terms of estimated model R-squared, the largest R-squared values 0.474 and 0.44.6 are reported when gross profit is used a measure of financial performance. These estimates indicate that model 1 explains over 40% of the variation in gross profit. The smallest R-squared values are reported when ROA is used as a measure of financial performance as model 1 specification 6 explains less than 10% in the variation of ROA. The R-squared values for model 1 differ from the results by Le and Nguyen-Phung (2024) who report R-squared of 0.294 when ROA is used and 0.191 when ROE is used.

The fixed-and random-effects regression results for model 1 specifications 1, 2, 4 and 7 suggest that increasing carbon intensity reduces financial performance and that this relationship is significant at 5% level. Therefore, findings from model 1 support the hypothesis 1 at 5% significance level.

However, the results from model 1 also suggest that the relationship between carbon intensity and financial performance is sensitive to the measure of financial performance.

Table 16: Panel data regression results for model 1 specifications

Spec.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	**lnGP**	**GP**	**lnROE**	**ROE**	**lnROA**	**ROA**	**lnTobinQ**	**TobinQ**
lnAssets	-0.534***	-0.193***	-0.470***	-19.22***	-0.639***	-1.757***	-0.216***	-0.603***
	(0.0404)	(0.0160)	(0.124)	(3.643)	(0.155)	(0.621)	(0.0644)	(0.163)
lnCI	-0.0984***	-0.0258**	-0.150	-6.324**	-0.0953	-0.576	-0.0753**	-0.171*
	(0.0322)	(0.0128)	(0.0958)	(2.929)	(0.124)	(0.393)	(0.0360)	(0.0885)
Lev	0.0105***	0.00325***	-0.0215***	-0.410**	0.00670	0.130***	0.0101***	0.0234**
	(0.00196)	(0.000775)	(0.00575)	(0.174)	(0.00745)	(0.0425)	(0.00334)	(0.00954)
lnGrowth	0.0108	-0.00152	-0.0367	-1.699*	-0.00785	-0.643**	-0.0193	-0.0174
	(0.0111)	(0.00438)	(0.0327)	(0.990)	(0.0417)	(0.289)	(0.0193)	(0.0590)
Age	0.0288***	0.00959***	0.0547***	1.362**	0.0683***	-0.000	-0.000867	-0.000190
	(0.00654)	(0.00259)	(0.0188)	(0.592)	(0.0241)	(0.0254)	(0.00277)	(0.00602)
Constant	0.741*	1.175***	3.811***	89.65**	2.227	13.76***	1.183**	5.091***
	(0.395)	(0.156)	(1.093)	(35.60)	(1.390)	(5.088)	(0.556)	(1.430)
Obs.	272	272	273	293	272	293	273	273
R-squared	0.474	0.446	0.139	0.145	0.081	0.054[a]	0.1765[a]	0.118[a]
Number of Firm_id	49	49	52	52	52	52	49	49

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[a] overall R-squared

Next, fixed-effects and random-effects models are estimated for model 2 specifications and Hausman tests is used to choose the preferred estimation method. The results from the Hausman test for model 2 specifications are shown in Table 18. The results indicate that the Hausman test null hypothesis is rejected for specifications 6 and 7.

The Hausman test suggests that fixed-effects would be the preferred for model 2 specifications 1-5 and 8. To further tests this, the F-test for all $u_i = 0$ is conducted, and the null hypothesis is rejected for these specifications. Therefore, fixed-effects are non-zero which indicates that fixed-effects model should be preferred over pooled OLS model in all six cases. The Hausman test null hypothesis is not rejected for specification 6 and 7 indicating that random-effects model is the preferred estimation method. Next the Breusch-Pagan Lagrange multiplier test is conducted to test the null hypothesis of no random effects. The results from indicate that the null hypothesis is rejected for model 2 specifications 6 and 7. Therefore, random-effects is preferred over pooled OLS.

Table 17: Preferred estimation method for model 2 based on Hausman test

Model	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
FE	X	X	X	X	X			X
RE						X	X	

Hypothesis testing uses 5% confidence level

Table 19 reports the estimated regression coefficients and standard errors for model 2 specifications based on the preferred estimation method reported in Table 18. Similar to model 1, model 2 results suggest that the significance of the relationship between carbon intensity and firm financial performance varies based on the measure of financial performance.

The estimated regression coefficient for carbon intensity is statistically significant at either 5% or 1% level in model 2 specifications 1-5 but not statistically significant in specifications 6-8. Trumpp and Guenther (2017) used ROA as a measure of firm financial performance and their results suggest that carbon emissions have a statistically significant negative impact on ROA. However, this relationship only holds for the natural logarithm of ROA in model 2 specification 5.

When results from Table 19 are compared with the baseline pooled OLS results reported in Table 15, it can be seen that the sign for variable 'lnCI' is negative in Table 19 for all specifications suggesting that increasing carbon intensity has a negative impact on the financial performance. The regression coefficient for 'lnCI' in specification 1 estimates that 1% increase in carbon intensity would result in 0.08% fall in gross profit per unit of asset while holding other variables constant. This estimate is close to the model 1 specification 1 estimate. When specification 4 is used, the model 2 regression coefficient for 'lnCI' estimates that 1% increase in carbon intensity would result in 0.03 fall in ROE holding other variables constant. This estimate is considerable smaller than model 1 specification 4 estimate in Table 17 indicating that the relationship between ROE and carbon intensity is sensitive to changes in the control variables.

Model 2 includes three additional variables when compared with model 1: 'R&D', 'CashFlow' and 'Country'. The estimated regression coefficient for 'lnR&D' is statistically significant at 5% level in specifications 3, 5 and 7, whereas estimated regression coefficient for 'lnCashFlow' is significant at least at the 5% level in specifications 1-7. Variable

'Country' is time-invariant and therefore, it is only estimated in random-effects models. The results show that when compared with the base case Finland, only Norway seems to be significant at 10% level indicating that 'Country' is not a significant explanatory variable.

In terms of R-squared, specification 5 has the highest R-squared of 0.498 indicating that the model explains 49.8% of the variation in ROA which is aligns with Trumpp and Guenther (2017) who report R-squared of 0.42 when ROA is used. The lowest R-squared of 0.103 is for specification 8 indicating that model 2 explains 10.3% of the variation in Tobin's Q.

Table 18: Panel data regression results for model 2 specifications

Spec. Variables	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
lnCI	-0.0771***	-0.0319**	-0.197***	-3.349**	-0.208**	-0.260	-0.0371	-0.305
	(0.0291)	(0.0133)	(0.0717)	(1.413)	(0.0896)	(0.316)	(0.0391)	(0.212)
lnRD	-0.0121	-0.00462	-0.248**	0.228	-0.271**	0.328	0.126**	0.0181
	(0.0385)	(0.0176)	(0.102)	(1.832)	(0.127)	(0.500)	(0.0598)	(0.275)
lnAssets	-0.348***	-0.182***	-0.520***	-7.758***	-0.493***	-1.683***	-0.291***	-1.229***
	(0.0477)	(0.0218)	(0.119)	(2.312)	(0.146)	(0.574)	(0.0711)	(0.346)
Lev	0.00472**	0.00254**	-0.0202***	-0.237**	0.0109*	0.114***	0.00175	0.0277*
	(0.00215)	(0.000983)	(0.00527)	(0.105)	(0.00653)	(0.0337)	(0.00388)	(0.0157)
lnGrowth	0.00600	0.00119	0.0413	0.688	0.0387	-0.0350	-0.0117	0.0308
	(0.0105)	(0.00479)	(0.0258)	(0.508)	(0.0318)	(0.195)	(0.0209)	(0.0761)
lnCashF	0.0468**	0.0207**	1.045***	6.205***	1.478***	3.594***	0.0961***	0.169
	(0.0187)	(0.00855)	(0.0974)	(0.904)	(0.124)	(0.344)	(0.0370)	(0.135)
Country								
DNK						0.392	0.596*	
						(2.367)	(0.324)	
NOR						-1.966	0.0612	
						(2.259)	(0.309)	
SWE						-0.692	-0.108	
						(2.192)	(0.306)	
Constant	1.527***	1.762***	9.941***	103.7***	7.907***	23.85***	2.456***	10.53***
	(0.410)	(0.187)	(1.066)	(19.87)	(1.311)	(5.506)	(0.679)	(2.982)
Obs.	219	219	217	223	215	223	221	221
R-squared	0.294	0.361	0.446	0.244	0.498	0.334[a]	0.407[a]	0.103
Number of Firm_id	40	40	41	41	41	41	40	40

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[a] overall R-squared

4.5.3 Robustness checks

Next, robustness checks are performed by using a different specification for the error term. The heteroskedasticity robust standard errors assume the independence of errors (White, 1980). The clustered standard errors modify this assumption by assuming that errors are independent between clusters (Liang and Zeger, 1987) but the errors for units belonging to the same cluster may be correlated (Cameron et al., 2011). The clustered standard errors are heteroskedasticity and autocorrelation robust (Arellano, 1987). Therefore, to account for heteroskedasticity and autocorrelation, models 1 and 2 are estimated using clustered standard errors which are calculated using the cross-sectional identifier variable 'Firm_id'.

The regression coefficients and clustered standard errors for model 1 specifications are presented in Table 20. The regression result show that clustered standard errors are larger than the standard errors reported in Table 17. Therefore, the estimated regression coefficient for carbon intensity is only statistically significant in specifications 1 and 8 and only at the 10% significance level. These results suggest that results presented in Table 17 suffer from autocorrelation and/or heteroskedasticity. Additionally, results in Table 20 suggest that model 1 does not provide sufficient support at 5% confidence level to hypothesis 1.

Table 19: Model 1 regression results with clustered standard errors

Spec. Variables	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
lnAssets	-0.534***	-0.193***	-0.470**	-19.22**	-0.639**	-1.757	-0.216**	-0.603*
	(0.0589)	(0.0333)	(0.197)	(7.418)	(0.252)	(1.190)	(0.105)	(0.364)
lnCI	-0.0984*	-0.0258	-0.150	-6.324	-0.0953	-0.576	-0.0753	-0.171*
	(0.0586)	(0.0199)	(0.158)	(4.664)	(0.206)	(0.531)	(0.0482)	(0.0986)
Lev	0.0105**	0.00325**	-0.0215**	-0.410	0.00670	0.130*	0.0101**	0.0234
	(0.00517)	(0.00145)	(0.00905)	(0.327)	(0.00951)	(0.0707)	(0.00500)	(0.0223)
lnGrowth	0.0108	-0.00152	-0.0367	-1.699	-0.00785	-0.643	-0.0193	-0.0174
	(0.0171)	(0.00337)	(0.0305)	(1.565)	(0.0462)	(0.402)	(0.0185)	(0.0387)
Age	0.0288***	0.00959***	0.0547*	1.362*	0.0683*	-0.000	-0.000867	-0.000190
	(0.0102)	(0.00346)	(0.0285)	(0.689)	(0.0358)	(0.0174)	(0.00244)	(0.00419)
Constant	0.741	1.175***	3.811*	89.65**	2.227	13.76	1.183	5.091**
	(0.585)	(0.232)	(2.174)	(42.19)	(2.312)	(10.63)	(0.975)	(2.570)
Obs.	272	272	273	293	272	293	273	273
R-squared	0.474	0.446	0.139	0.145	0.081	0.054[a]	0.177[a]	0.118[a]
Number of Firm_id	49	49	52	52	52	52	49	49

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[a] overall R-squared

Table 21 presents the estimated regression coefficients and clustered standard errors for model 2 specifications. The clustered standard errors are calculated using the cross-sectional identifier variable ‘Firm_id’. The estimated clustered standard errors in Table 21 are larger than the standard errors presented in Table 19. As a result, the estimated regression coefficient for carbon intensity is statistically significant in specifications 3 and 5 only at 10% level suggesting that model 2 specifications presented in Table 19 suffer from heteroskedasticity and/or autocorrelation. Therefore, results in Table 21 do not provide sufficient evidence at 5% significance level to support hypothesis 1.

Again, these results from models 1 and 2 suggest that the relationship between firm financial performance and carbon intensity is sensitive to changes in the measure of financial performance and to changes in the model specification.

Table 20: Model 2 regression results with clustered standard errors

Spec. Variables	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
lnCI	-0.0771	-0.0319	-0.197*	-3.349	-0.208*	-0.260	-0.0371	-0.305
	(0.0551)	(0.0238)	(0.112)	(2.476)	(0.122)	(0.305)	(0.0436)	(0.261)
lnRD	-0.0121	-0.00462	-0.248	0.228	-0.271	0.328	0.126**	0.0181
	(0.0410)	(0.0189)	(0.158)	(2.955)	(0.194)	(0.610)	(0.0532)	(0.331)
lnAssets	-0.348***	-0.182**	-0.520***	-7.758*	-0.493**	-1.683	-0.291***	-1.229
	(0.102)	(0.0688)	(0.171)	(4.204)	(0.212)	(1.124)	(0.101)	(0.798)
Lev	0.00472	0.00254	-0.0202***	-0.237*	0.0109	0.114	0.00175	0.0277
	(0.00306)	(0.00188)	(0.00657)	(0.127)	(0.00766)	(0.0751)	(0.00541)	(0.0427)
lnGrowth	0.00600	0.00119	0.0413**	0.688*	0.0387	-0.0350	-0.0117	0.0308
	(0.00847)	(0.00350)	(0.0197)	(0.387)	(0.0243)	(0.191)	(0.0249)	(0.0523)
lnCashF	0.0468	0.0207	1.045***	6.205***	1.478***	3.594***	0.0961*	0.169
	(0.0425)	(0.0129)	(0.198)	(2.177)	(0.335)	(0.806)	(0.0516)	(0.120)
Country								
DNK						0.392	0.596*	
						(3.570)	(0.351)	
NOR						-1.966	0.0612	
						(1.330)	(0.203)	
SWE						-0.692	-0.108	
						(1.813)	(0.356)	
Constant	1.527*	1.762***	9.941***	103.7***	7.907***	23.85**	2.456***	10.53*
	(0.781)	(0.526)	(1.591)	(32.42)	(2.151)	(9.795)	(0.952)	(5.365)
Obs.	219	219	217	223	215	223	221	221
R-squared	0.294	0.361	0.446	0.244	0.498	0.333[a]	0.407[a]	0.103
Number of Firm_id	40	40	41	41	41	41	40	40

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[a] overall R-squared

As the dataset covers years 2015-2023, it is likely that the data is impacted by COVID-19 pandemic. To examine the impact of COVID-19 pandemic, a ‘Covid’ dummy that takes value 1 for years 2020 and 2021 and otherwise 0 is created. After which the models 1 and 2 are estimated with fixed-effects and random-effects estimation methods and Husman test, Breusch-Pagan Lagrangian multiplier test and F-test for fixed effects are used to determine if the preferred estimation methods presented in Tables 16 and 18 still hold for models 1 and 2 specifications.

The regression results for model 1 specifications with ‘Covid’ dummy and clustered standard errors indicate that the estimated coefficient for ‘Covid’ dummy is negative and statistically significant at 1% level in specification 1 and positive and statistically significant at 1% level in specifications 7 and 8. Model 2 results suggest that the estimated sign of the coefficient for the ‘Covid’ dummy is positive and significant at 1% level in specifications 7 and 8. Therefore, there is some evidence to suggest that COVID-19 pandemic influenced firm financial performance. However, the significance and sign of the COVID-19 pandemic is sensitive to the measure of financial performance and model specification. Full regression results can be found in Tables 3 and 4 in Appendix 5.

Next, to further explore the impact of COVID-19 pandemic, models 1 and 2 are estimated separately for the pre-COVID (“Pre”) period of 2015-2019 and for the COVID-19 impacted (“Post”) period 2020-2023. After which Hauman test, Breusch-Pagan Lagrangian multiplier test and F-test for fixed effects are used to check the correct estimation method. The results can be seen in Table 22.

Table 21: Preferred estimation methods for Model 2 pre- and post-COVID regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model	**lnGP**	**GP**	**lnROE**	**ROE**	**lnROA**	**ROA**	**lnTobinQ**	**TobinQ**
FE	Pre, Post	Pre, Post	Pre	Pre, Post	Post	Pre, Post	Post	Post
RE			Post		Pre		Pre	Pre

5% confidence level is used for testing

The regression results for model 1 that are calculated using clustered standard errors suggest that regression coefficient for variable ‘lnCI’ is only statistically significant at 10% level in specification 6 during the pre-COVID period, and not statistically significant for any specification during the COVID impacted period. Full results can be found in Appendix 4 in Tables 3 and 4.

The regression coefficients for model 2 specifications with clustered standard errors in parentheses in Table 23 indicate that during the pre-COVID period, the estimated regression coefficient for variable ‘lnCI’ is negative and statistically significant at the 5% level in specifications 4 and 6. When ROE is used as a measure of firm financial performance, the results from this model suggest that increasing carbon intensity by 1% is estimated to result in 0.09 fall in ROE.

The R-squared of this model indicates that the model explains 20% of the variation in ROE. Similarly, when ROA is used as the measure for financial performance the model estimates that a 1% increase in carbon intensity is estimates to result in 0.04 fall in ROA. The R-squared of this model indicates that the model explains 36.7% of the variation in ROA.

Overall, these results suggest that during the pre-pandemic period, carbon intensity did have a statistically significant negative impact at 5% confidence level on financial performance when ROE and ROA are used as measure of financial performance. Therefore, there is pre-pandemic evidence to support hypothesis 1.

Table 22: Model 2 pre-Pandemic regression with clustered standard errors

Spec. Variables	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
lnCI	-0.154*	-0.0843*	-0.233*	-9.306**	-0.0450	-3.937**	0.0149	-0.119
	(0.0791)	(0.0420)	(0.128)	(3.588)	(0.0728)	(1.620)	(0.0392)	(0.119)
lnRD	-0.0277	-0.0114	-0.123	2.241	-0.204	1.007	0.105*	0.0647
	(0.0368)	(0.0182)	(0.109)	(2.813)	(0.164)	(0.788)	(0.0609)	(0.189)
lnAssets	-0.499**	-0.322**	-0.480	-7.050	-0.317	-2.070	-0.293***	-0.297*
	(0.215)	(0.150)	(0.450)	(6.586)	(0.284)	(2.383)	(0.106)	(0.167)
Lev	0.00119	-0.000329	-0.0129	-0.133	0.00418	0.178*	0.00577	0.0174
	(0.00491)	(0.00253)	(0.00897)	(0.254)	(0.00918)	(0.0999)	(0.00484)	(0.0145)
lnGrowth	0.00682	0.00232	0.0407*	0.174	0.0371	-0.218	0.00205	0.0269
	(0.00926)	(0.00398)	(0.0235)	(0.480)	(0.0410)	(0.216)	(0.0287)	(0.0463)
lnCashF	0.0318	0.0216	0.881**	3.986*	1.018***	2.039**	0.0362	0.111
	(0.0589)	(0.0221)	(0.357)	(2.182)	(0.350)	(0.793)	(0.0326)	(0.0908)
Country								
DNK					0.463		0.811**	2.718**
					(0.466)		(0.367)	(1.289)
NOR					0.210		-0.104	-0.419
					(0.437)		(0.253)	(0.402)
SWE					0.384		-0.0762	-0.457
					(0.666)		(0.370)	(0.426)
Constant	2.675	2.900**	8.721**	64.53	6.028**	6.603	2.383***	3.093**
	(1.819)	(1.248)	(4.212)	(58.42)	(2.782)	(21.63)	(0.869)	(1.371)
Obs.	112	112	111	114	111	114	113	113
R-squared	0.286	0.432	0.495	0.200	0.378[a]	0.367	0.519[a]	0.5[a]
Number of Firm_id	37	37	38	38	38	38	38	38

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[a] overall R-squared

Table 24 shows the model 2 regression coefficients and clustered standard errors in parentheses for COVID-19 impacted period. The regression coefficient for carbon intensity is negative and statistically significant at 5% level in specifications 1 and 2 that use gross profit as a measure of financial performance. Table 23 showed that variable 'lnCI' is statistically significant only at 10% level in model 2 specifications 1 and 2 during the pre-COVID-19 period. This suggests that the negative relationship between carbon intensity and gross profit it more statistically significant for the COVID-19 impacted period. The full sample results presented in Table 21 showed that the regression coefficient for 'lnCI' was not statistically significant at 5% level in specifications 1 and 2. Therefore, the split sample regression results differ from the full sample results.

Furthermore, the R-squared values in Table 24 for model 2 specifications 1 and 2 indicate that they explain 43.6% and 56.3% of the variation in gross profit. These R-squared values for model 2 specifications 1 and 2 are higher than the ones reported in Table 23 for the pre-

COVID period indicating that model 2 better explains the variation in gross profit during the COVID-19 impacted period.

On the other hand, the regression coefficient for ‘lnCI’ does not have a statistically significant impact on ROE during the COVID-19 impacted period, but this relationship does hold for the pre-COVID-19 period. This indicates that the COVID-19 pandemic did impact the relationship between carbon intensity and ROE. The full sample regression results for model 2 specifications in Table 21 showed that carbon intensity did not have a statistically significant relationship with ROE. Therefore, the split sample regression results differ from the full sample results.

The regression results in Table 24 suggest that when gross profit is used as a measure of firm financial performance, there is evidence to support hypothesis 1 for the COVID-19 impacted period at the 5% significance level. The combined results from Tables 23 and 24 for model 2 suggest that COVID-19 pandemic may have impacted the relationship between carbon intensity and firm financial performance as the results vary based on the time period considered and based on the measure of financial performance.

Table 23: Model 2 COVID-19 impacted period regression with clustered standard errors

Spec. Variables	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
lnCI	-0.194**	-0.0567**	0.0285	-4.133	-0.193*	-0.545	-0.116	-0.771
	(0.0796)	(0.0275)	(0.0447)	(3.350)	(0.111)	(1.487)	(0.0783)	(0.506)
lnRD	-0.0120	-0.00874	0.00799	2.384	-0.220	0.421	0.292	0.501
	(0.199)	(0.0679)	(0.0849)	(7.092)	(0.462)	(2.577)	(0.202)	(0.959)
lnAssets	-0.492**	-0.252**	-0.0268	-12.05	-0.355	-5.736	-1.205***	-5.990***
	(0.189)	(0.103)	(0.103)	(11.34)	(0.369)	(4.578)	(0.222)	(1.874)
Lev	0.00826**	0.00448**	-0.0248***	-0.146	0.0164	0.244**	-0.00452	0.0436
	(0.00400)	(0.00180)	(0.00680)	(0.152)	(0.0115)	(0.0948)	(0.00627)	(0.0505)
lnGrowth	0.0146	0.00409	-0.0168	0.622	0.0275	0.232	0.0468	0.363***
	(0.0169)	(0.00686)	(0.0403)	(0.987)	(0.0382)	(0.368)	(0.0325)	(0.131)
lnCashF	0.0668	0.0221*	0.555**	8.378***	1.560***	4.716***	0.172*	0.461
	(0.0565)	(0.0121)	(0.227)	(2.322)	(0.404)	(1.083)	(0.0930)	(0.388)
Country								
DNK			-0.0720					
			(0.345)					
NOR			0.127					
			(0.198)					
SWE			0.269					
			(0.206)					
Constant	2.206	2.205**	5.419***	136.4	6.606	54.58	10.78***	50.90***
	(1.654)	(0.849)	(1.328)	(98.35)	(4.044)	(38.40)	(2.135)	(16.32)
Obs.	107	107	106	109	104	109	108	108
R-squared	0.436	0.563	0.355[a]	0.228	0.547	0.575	0.403	0.509
Number of Firm_id	37	37	38	38	38	38	37	37

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[a] overall R-squared

4.6 Regression results for the factors influencing carbon intensity

To further explore the carbon intensity variable, model 3 is estimated to allow for closer analysis of the impact of R&D, use of renewable energy and energy intensity have on carbon intensity. As the data collection exercise indicated that data for renewable energy becomes more readily available from 2019 onwards, the analysis presented in this section limits the sample to years 2019-2023. The regression coefficients and standard errors in parentheses are presented in Table 25.

Pooled OLS model is first estimated as a baseline regression model (1). Next, fixed-effects and random-effects models are estimated and Hausman test is used to determine that fixed-effects is preferred over random effects, after which the F-test for fixed-effects is used to determine that fixed-effects is preferred over pooled OLS. Therefore, the preferred estimation method is fixed-effects (2). To account for issues with heteroskedasticity and autocorrelation, clustered standard errors are calculated using the cross-sectional identifier variable ‘Firm_id’ (3).

The results show that 22 firms are included in the estimates reflecting the amount of missingness in the variable ‘RE’. The regression coefficient for variable ‘RD’ is statistically significant in the baseline pooled OLS model. However, there is no evidence at the 5% significance level to suggest that R&D spending reduces carbon intensity when model 3 is estimated using the preferred fixed-effects method. Therefore, model 3 suggest that there is no support for hypothesis 2. These results contradict with the findings by Sahu and Mehta (2018) and Cole et al. (2013).

The regression coefficient for variable ‘RE’ is statistically significant at 1% level in all three models suggesting that there is strong evidence to suggest that increasing the use of renewable energy reduces carbon intensity. Therefore, model 3 suggest that there is evidence to support hypothesis 3. These results align with findings by Wang et al. (2021) and Wu et al. (2024).

The regression coefficient for variable ‘EI’ is not statistically significant in any of the specifications suggesting that there is no evidence to suggest that reducing energy intensity reduces carbon intensity. Therefore, model 3 suggest that there is no evidence to support hypothesis 4. These results contradict with findings by Tao et al. (2024) and Yagi and Managi (2018).

The R-Squared values for all three specifications of model 3 suggest that model 3 explains around 60% of the variation in carbon intensity.

Table 24: Regression results for model 3

Spec.	(1)	(2)	(3)
Variabled	**lnCI**	**lnCI**	**lnCI**
lnCashH	0.177	-0.0913	-0.0913
	(0.191)	(0.0823)	(0.0676)
lnAssets	0.120	-0.471**	-0.471
	(0.302)	(0.207)	(0.352)
lnGrowth	-0.290***	0.0261	0.0261
	(0.105)	(0.0383)	(0.0321)
Lev	0.0394**	0.00312	0.00312
	(0.0154)	(0.00670)	(0.00757)
lnRD	-0.444***	0.185	0.185
	(0.166)	(0.211)	(0.175)
lnROA	0.155	-0.0124	-0.0124
	(0.167)	(0.0490)	(0.0408)
BI			
A+	-0.691		
	(0.677)		
B+	-1.235		
	(0.913)		
C+	-1.495*		
	(0.752)		
D	-0.497		
	(0.705)		
BS	0.0307		
	(0.0205)		
RE	-2.996***	-2.176***	-2.176***
	(0.572)	(0.415)	(0.491)
lnEI	-0.0712	0.0362	0.0362
	(0.119)	(0.112)	(0.157)
Constant	-6.090**	0.712	0.712
	(2.469)	(1.903)	(2.925)
Obs.	77	77	77
R-squared	0.614	0.607[b]	0.607[b]
Number of Firm_id		22	22

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[b] Within R-squared

5 Conclusions

This thesis started by analysing the relationship between carbon intensity and firm financial performance to answer the first research question: *Does reducing carbon intensity impact the financial performance of a firm?* The financial performance was measured using four accounting based measures: ROE, ROA, gross profit and Tobin's Q. The analysis used data for Nordic firms from four countries: Denmark, Finland, Sweden and Norway to test the validity of hypothesis 1: *reducing carbon intensity improves the accounting based measures of financial performance of a Nordic firm.* The analysis was conducted using two models: model 1 drew from research by Le and Nguyen-Phung (2024) and model 2 drew from research by Trumpp and Guenther (2017). Furthermore, the models were first estimated using the whole sample and then separately for the pre-and post-COVID-19 periods to analyse if COVID-19 pandemic impacted the relationship between financial performance and carbon intensity.

The results from the whole sample regression analysis using models 1 and 2 and clustered standard errors show that the regression coefficient for carbon intensity has a statistically significant negative impact on firm financial performance only at 10% significance level. Therefore, the results from the whole sample analysis suggest that there is no sufficient evidence to support hypothesis 1 at the 5% significance level. These results conflict with findings by Le and Nguyen-Phung (2024), Oestreich and Tsiakas (2024) and Makridou et al. (2019). Furthermore, the results from the whole sample regressions for models 1 and 2 suggest that the relationship between carbon intensity and firm financial performance is sensitive to the changes is model specification and to the choice of financial performance measure.

The split sample regression results for pre-COVID and COVID impacted periods with clustered standard errors show that the relationship between carbon intensity and firm financial performance varies based on the choice of financial performance measure and based on the time period. The regression results for the pre-COVID period show that the estimated regression coefficient for carbon intensity is negative and statistically significant at the 5% level when ROE and ROA are used as measures of financial performance. The regression results for the COVID impacted period show that the regression coefficient for carbon intensity is negative and statistically significant at 5% level when gross profit is used as the measure of financial performance. Therefore, the split sample regression analysis results suggest that there is evidence to support hypothesis 1 at 5% significance level. However, the relationship between financial performance and carbon intensity is sensitive to the choice of financial performance measure.

Next, to explore the second research question: *What factors influence firm level carbon emissions?*, the analysis focused on three potential factors influencing carbon intensity: R&D, use of renewable energy and energy intensity. The impact of these factors was tested using model 3 which draws from work by Alam et al. (2022). The panel data regression results found no evidence to support hypothesis 2: *R&D reduces carbon intensity of Nordic firms.* This conflicts with findings by Sahu and Mehta (2018) and Cole et al. (2013) who found R&D to have a mitigating impact carbon intensity.

Model 3 estimates show that increasing the use of renewable energy reduces carbon intensity and that this relationship is statistically significant at 1% level. Therefore, there is evidence to support hypothesis 3*: Increasing the use of renewable energy reduces carbon intensity of Nordic firms.* These results align with findings from macroeconomic research by Wang et al. (2021) and Wu et al. (2024) who found that increasing the use of renewable energy reduced GHG emissions.

Results from model 3 did not find evidence to support hypothesis 4: *Decreasing energy intensity reduces carbon intensity of Nordic firms.* These results contradict with findings from macroeconomic research by Papież et al. (2021) and Bianco et al. (2024) and the results also contradict with findings from firm level research by Tao et al. (2024) and Yagi and Managi (2018).

The research presented in this thesis has some limitations. First, the data used in this analysis only considers large companies from the Nordic countries and therefore, the results might not be applicable to small companies and companies operating in different countries. Second, the carbon emissions data did not include scope 3 emissions due to data availability issues and therefore, results from model 3 may not hold if scope 3 emissions are included. Third, most of the specifications were estimated using fixed-effects methodology. Bell and Jones (2015) note that fixed-effects models only use within variation and therefore, do not capture all the information available. Therefore, the fixed-effects based results presented in this thesis might not give the full picture of the relationship between dependent and explanatory variables.

The impact of this thesis is to add to the evidence gap around the relationship between carbon intensity and the financial performance of Nordic firms. The results from this thesis imply that Nordic firms could improve their accounting based measures of financial performance through reducing their emission intensity. Therefore, the results indicate that the emission reductions needed to fulfil the Paris Agreement do not need to come in the expense of financial performance. This should serve as an encouraging reminder that environmental performance and financial performance are not mutually exclusive.

Furthermore, the results from this thesis suggest that increasing the use of renewable energy is an effective way to reduce carbon intensity and for this reason, policy makers should encourage investment in making renewable energy accessible and reasonably priced. More widely, reducing carbon intensity and moving towards renewable energy sources reduce the negative externalities associated with emissions and therefore, benefit the society as a whole. Future research in the context of Nordic firms could add further variables to account for the factors of production following the work by Subrahmanya (2006) and Sahu and Mehta (2018). In the policy context future research could analyse the impact of carbon tax and trading schemes following work by Papież et al. (2021), Bianco et al. (2024), Brouwers et al. (2018) and Lin et al. (2011). Furthermore, as more data becomes available, the impact of new EU regulations on sustainability reporting could be analysed to see if results by Bauckloh et al. (2023) also hold for Nordic firms.

The literature review also identified that green investment could improve the financial performance of a firm (Siedschlag and Yan, 2023; Khalid et al., 2023) and therefore, future research could explore the role of green investment in the context of Nordic firms. In addition, future research could analyse the role of technological advancements have on carbon emissions in the Nordics as previous research by Majumdar and Kar (2017) and Zhao et al. (2023) found that technology adaptation and technological innovation can reduce emission intensity. Finally, future research could look to explore alternative estimation methods to overcome challenges proposed by fixed-effects models. Bell and Jones (2015) propose that the use of flexible random-effects models would enable heterogeneity to be modelled. They suggest that the use of Mundlak's formulation could be used for this purpose.

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Appendix 1. Nordic GHG emissions

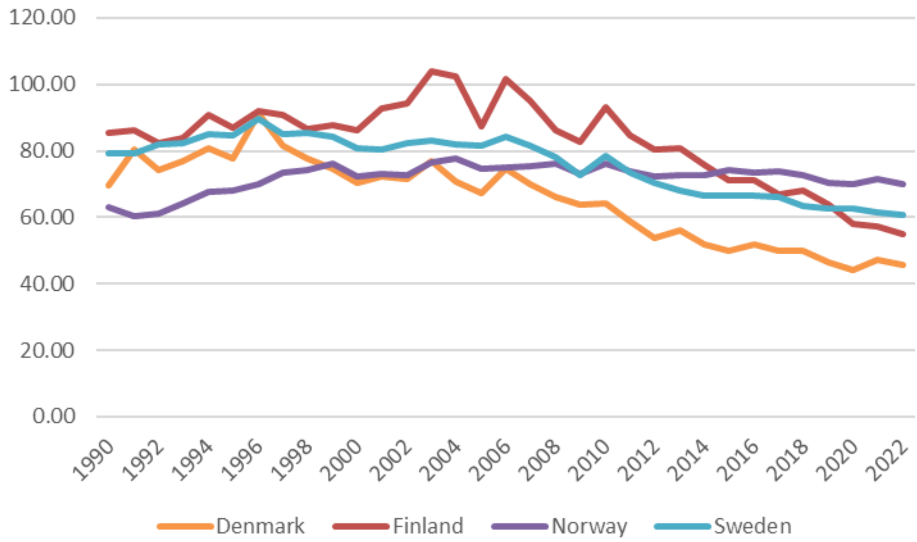

Figure 1: GHG emissions by country 1990-2022

Source: Statista 2023. Greenhouse gas emissions in the Nordic countries from 1990 to 2023 (in million metric tons of CO_2 equivalent). Cited: 12 Oct 2024. Available at: https://www.statista.com/statistics/1427113/greenhouse-gas-emissions-nordic-countries/

Appendix 2. Firms in the sample

Table1: List of firms in the sample

Company	Country	Link
A.P. Møller-Mærsk	DEN	https://www.maersk.com/sustainability/reports-and-resources
Ambu	DEN	https://www.ambu.com/corporate-info/investors/reports/reports-in-english
Bavarian Nordic	DEN	https://www.bavarian-nordic.com/investor/financials.aspx
Carlsberg Group	DEN	https://www.carlsberggroup.com/investor-relations/investor-home/reports-downloads/
Coloplast	DEN	https://investor.coloplast.com/investor-relations/reports-presentations2/annual-reports/
Danske Bank	DEN	https://danskebank.com/investor-relations/reports
Demant	DEN	https://www.demant.com/investor-relations/reports
DSV	DEN	https://investor.dsv.com/reports-presentations
ISS	DEN	https://www.issworld.com/en/investor/investor-relations/financial-reports-and-presentations
NKT	DEN	https://investors.nkt.com/financial-information/quarterly-results
Novo Nordisk	DEN	https://www.novonordisk.com/sustainable-business/esg-portal/integrated-reporting.html
Rockwool International	DEN	https://www.rockwool.com/group/about-us/investors/financial-reports/?selectedCat=financial%20reports
Kongsberg Gruppen	NOR	https://www.kongsberg.com/investor-relations/reports-and-presentations/other-presentations/
Mowi	NOR	https://mowi.com/investors/reports/
Norsk Hydro	NOR	https://www.hydro.com/en/global/investors/reports-and-presentations/annual-reports/
Orkla	NOR	https://investors.orkla.com/English/financial-reports/annual-reports/default.aspx
SalMar	NOR	https://www.salmar.no/en/investor/annual-reports/
Subsea 7	NOR	https://www.subsea7.com/en/investors/results-reports-and-presentations.html
Tomra Systems	NOR	https://www.tomra.com/investor-relations

Wallenius Wilhelmsen	NOR	https://www.walleniuswilhelmsen.com/who-we-are/investors
Yara International	NOR	https://www.yara.com/investor-relations/reports-presentations/
Cargotec	FIN	https://www.hiabgroup.com/en/investor-relations/reports-presentations/
Elisa	FIN	https://elisa.com/corporate/investors/results-centre/previous-annual-reports/
Huhtamäki	FIN	https://www.huhtamaki.com/en/investors/reports-and-releases/reports-and-presentations/
Kesko	FIN	https://www.kesko.fi/en/investor/financial-information-and-publications/Annual-reports/
Kojamo	FIN	https://kojamo.fi/en/investors/releases-and-publications/financial-reports/
Kone	FIN	https://www.kone.com/en/investors/reports-and-presentations/?year=2024
Metso	FIN	https://www.metso.com/corporate/investors/reports-and-presentations/
Nokia	FIN	https://www.nokia.com/about-us/sustainability/sustainability-downloads/
Nokian Tyres	FIN	https://company.nokiantyres.com/investors/reports-and-presentations/
Orion Corporation	FIN	https://www.orionpharma.com/investors/reports-and-presentations/annual-reports/
Outokumpu	FIN	https://www.outokumpu.com/en/investors/materials
Sampo	FIN	https://www.sampo.com/investors/annual-reporting/
Stora Enso	FIN	https://www.storaenso.com/en/investors/reports-and-presentations
TietoEVRY	FIN	https://www.tietoevry.com/en/investor-relations/financial-reports/
Valmet	FIN	https://www.valmet.com/investors/reports-and-presentations/
Wärtsilä	FIN	https://www.wartsila.com/sustainability/reporting/sustainability-reports
ABB Ltd	SWE	https://global.abb/group/en/sustainability/reports
Assa Abloy	SWE	https://www.assaabloy.com/group/en/sustainability/sustainability-reports
AstraZeneca	SWE	https://www.astrazeneca.com/sustainability/resources.html
Atlas Copco	SWE	https://esg.atlascorporation.com/library/

Boliden	SWE	https://investors.boliden.com/en/investor-relations/reports-and-presentations/financial-reports
Ericsson	SWE	https://www.ericsson.com/en/investors/esg-resource-hub/reporting-and-data
Essity	SWE	https://www.essity.com/investors/financial-reports/annual-reports/
Getinge	SWE	https://www.getinge.com/int/company/investors/reports-presentations/?cat2407958=21834#block-2407958
Handelsbanken	SWE	https://www.handelsbanken.com/en/investor-relations/reports-and-presentations
Investor	SWE	https://www.investorab.com/investors-media/reports-presentations
Kinnevik	SWE	https://www.kinnevik.com/investor-relations/reports-and-presentations/
Nibe Industrier	SWE	https://www.nibe.com/investors/pm-news-reports/news-reports-2024
Samhällsbyggnadsbolaget i Norden	SWE	https://corporate.sbbnorden.se/en/sustainability-reports/
Sandvik	SWE	https://www.home.sandvik/en/investors/reports-presentations/annual-reports/
SEB	SWE	https://sebgroup.com/our-offering/reports-and-publications/annual-and-sustainability-reports
Sinch	SWE	https://investors.sinch.com/reports-and-presentations
SKF	SWE	https://investors.skf.com/en/annual-report
Swedbank	SWE	https://www.swedbank.com/investor-relations/reports-and-presentations/annual-reports.html
Tele2	SWE	https://www.tele2.com/investors/reports-and-presentations/?type=AR&year=
Volvo	SWE	https://investors.volvocars.com/en/results-and-reports/results-centre

Appendix 3. Variable transformations

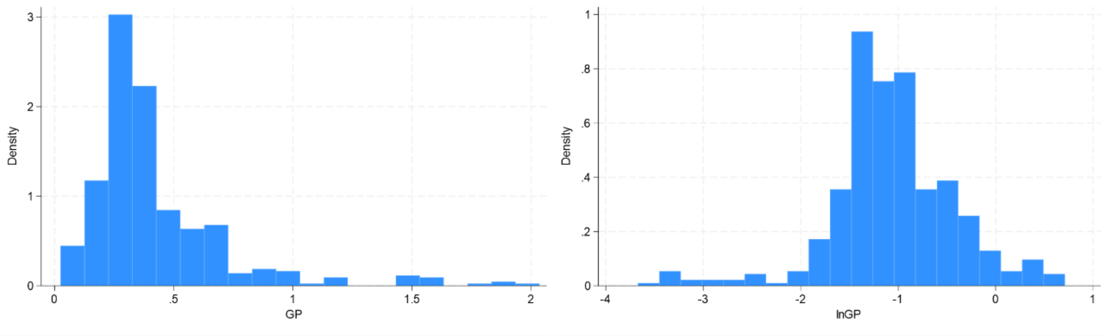

Figure 2: variable 'GP' transformation

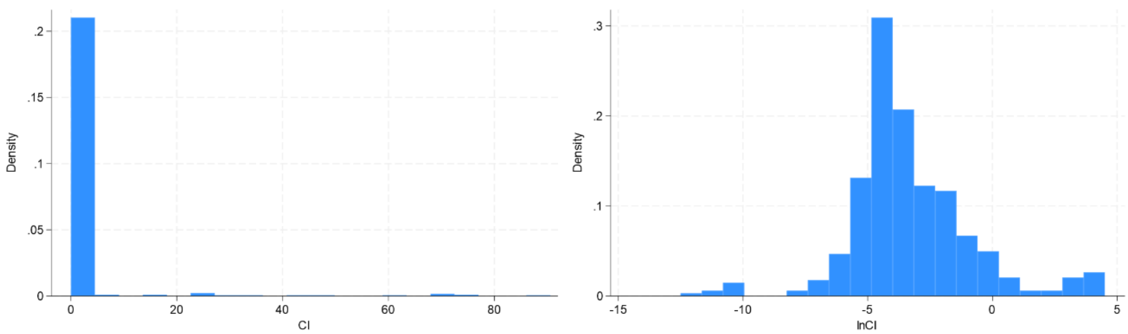

Figure 3: Variable 'CI' transformation

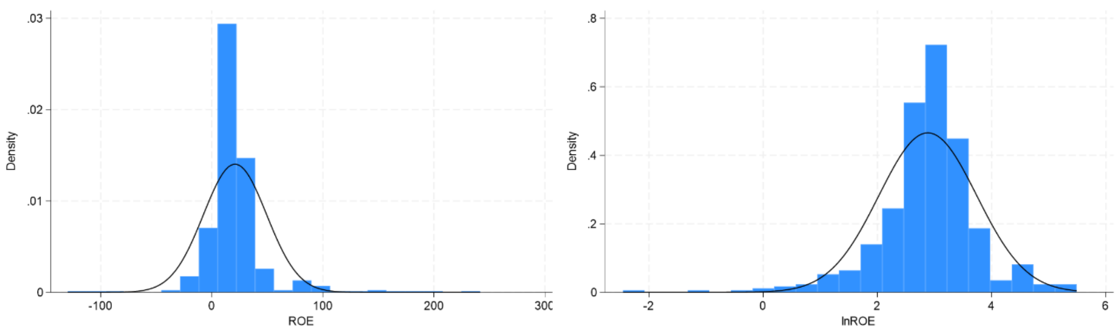

Figure 4: Variable 'ROE' transformation

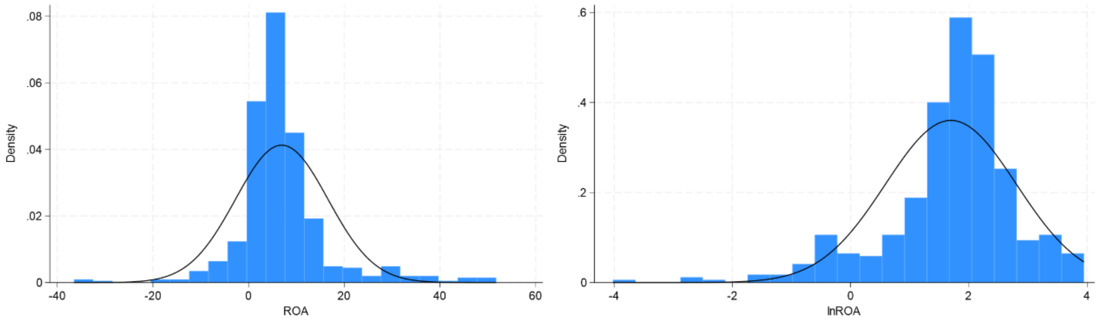

Figure 5: Variable 'ROA' transformation

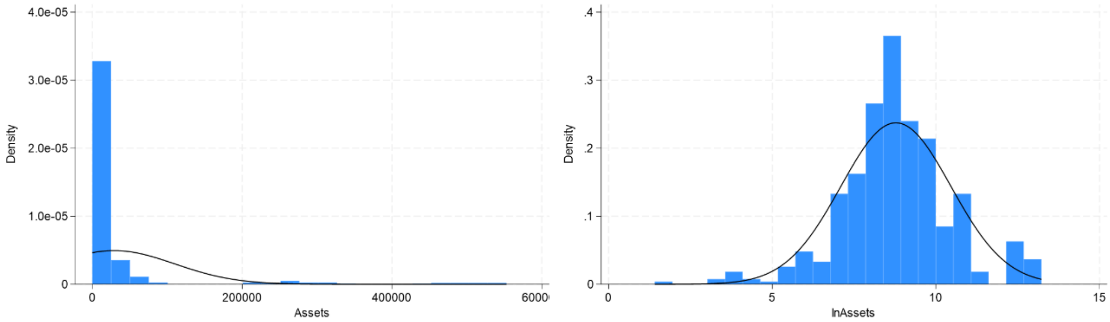

Figure 6: Variable 'Assets' transformation

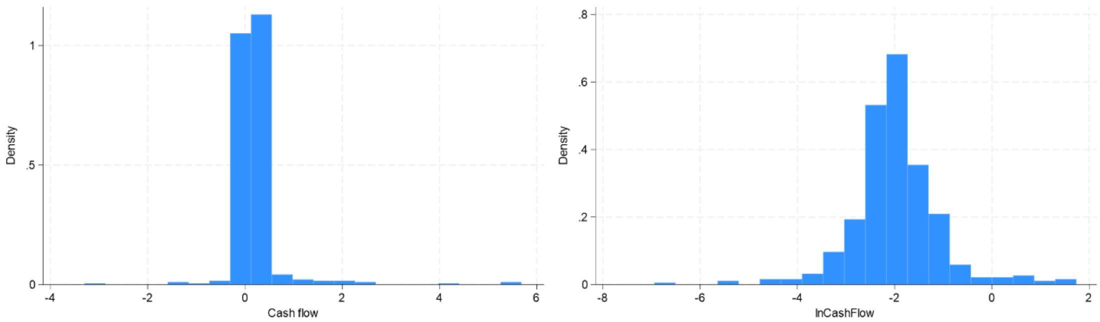

Figure 7: Variable 'Cash flow' transformation

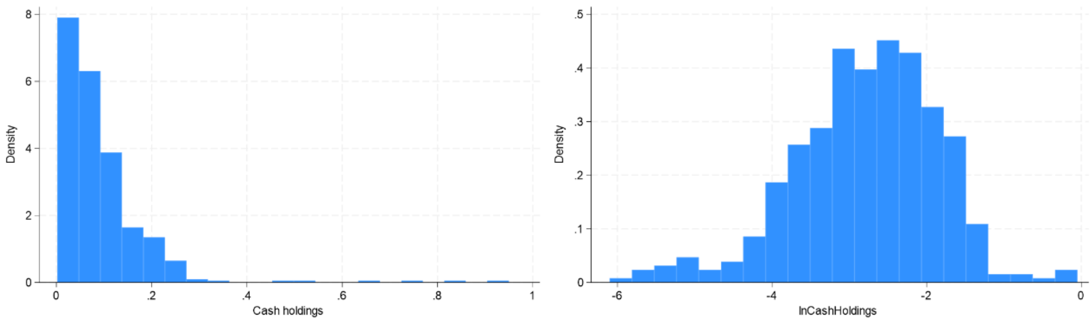

Figure 8: Variable 'Cash holdings' transformation

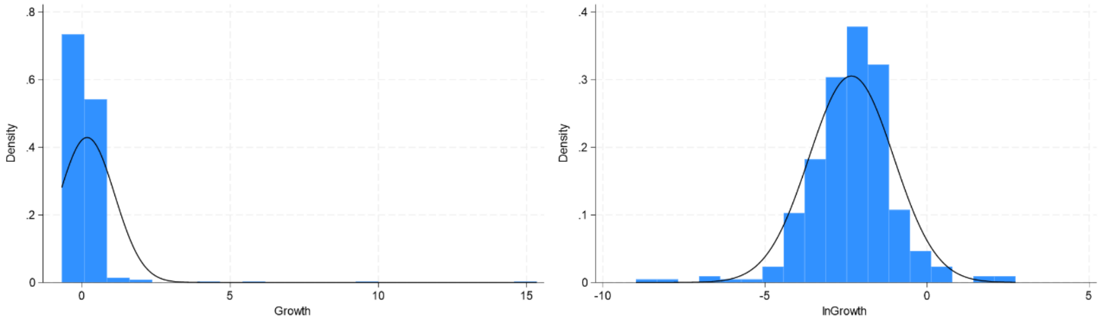

Figure 9: Variable 'Growth' transformation

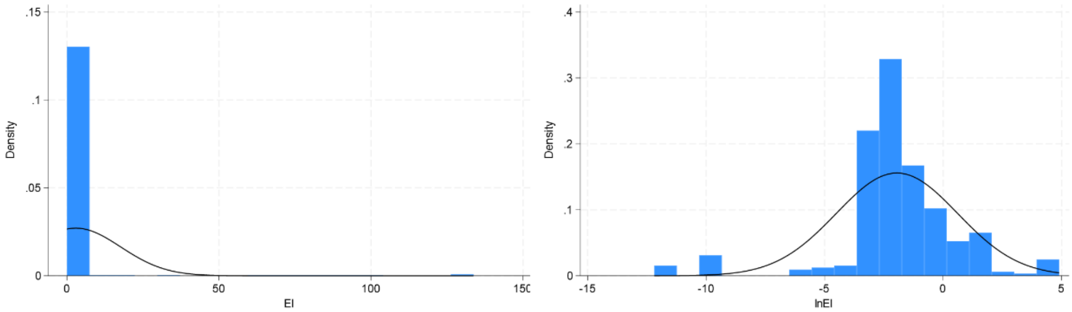

Figure 10: Variable 'EI' transformation

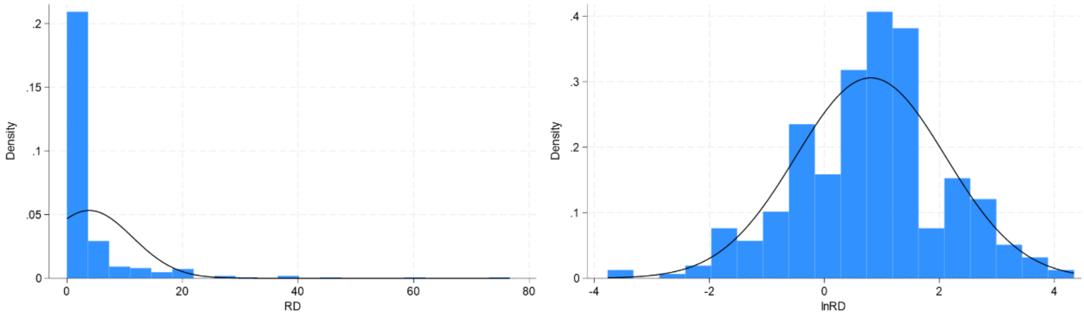

Figure 11: Variable 'RD' transformation

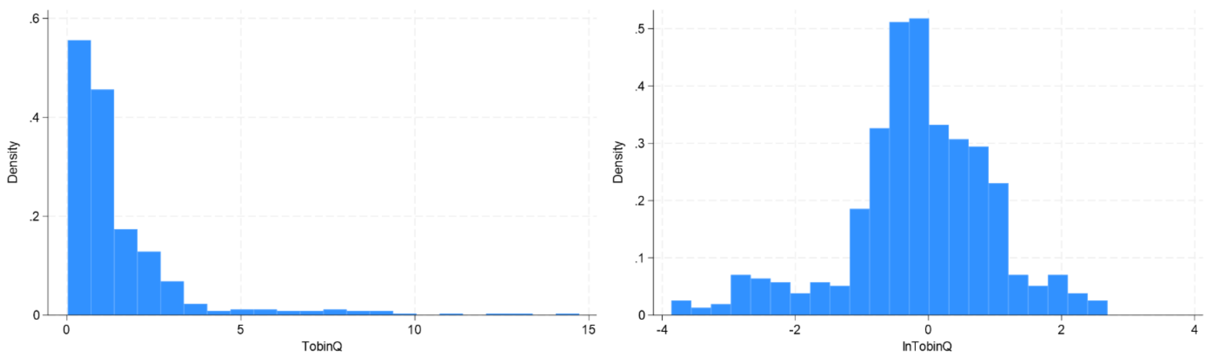

Figure 12: Variable 'TobinQ' transformation

Appendix 4. Summary of previous research on energy intensity, green investment and financial performance

Table 2: Summary of previous research on energy intensity, green investment and financial performance

Paper	Topic	Dependent variable	Explanatory variables	Analytical method	R^2 of the model
Choi et al. (2017)	Energy intensity and firm growth	Firm profits and capital accumulation	Total assets, squared total assets, cash holdings, tangibility, relative energy efficiency, interaction terms between relative energy efficiency and GDP per capita, resources per capital	Fixed-effects regression	0.01 and 0.02 depending on model specification
Fan et al. (2017)	Energy efficiency and financial performance	ROE, ROA, ROI, ROIC, ROS, Tobin's Q	Size, growth, energy intensity, interaction between energy intensity and growth	Random effects regression	Varies between 0.4179 and 0.6826 depending on the dependent variable
Ghisetti & Rennings (2014)	Environmental innovations and profitability	ROS	Environmental innovation, size, regional, market concentration, R&D, patent stock, market share, market regulation	Interval regression model	Varies between 0.055 and 0.067 depending on model specification
Khalid et al. (2023)	Green investment and profitability	ROA	Green investment, green policy, regional, industry, corporate governance, environmental	Dummy variable regression (LSDV)	Varies between 0.2919 and 0.3386 depending on the

			performance, age, leverage, fixed assets		model specification
Siedschlag & Yan (2023)	Green investment and firm performance	Firm performance	Green investment, GVA per employees, export intensity, fuel consumption per employee, GVA, employees, labour cost, dummies for importer and exporter, supply chain dummy, Irish ownership dummy	One-to-two nearest matching	-
Subrahmanya (2006)	Energy intensity and economic performance	Value added	Energy intensity, energy productivity, total variable cost, capital intensity, labour productivity, capital productivity	OLS	Varies between 0.88 and 0.98 depending on model specification
Tao et al. (2024)	Energy intensity and carbon emissions	Energy intensity	Energy consumption intensity, R&D, urbanization rate, GDP per capita, labour clustering, capital clustering	Dynamic panel threshold regression and panel vector autoregressive model	-

Appendix 5. Additional regression results

Table 3: Model 1 specifications including Covid dummy and clustered standard errors

Specification Variables	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
lnAssets	-0.527***	-0.191***	-0.468**	-19.20**	-0.642**	-1.822	-0.257**	-0.691*
	(0.0568)	(0.0338)	(0.197)	(7.374)	(0.260)	(1.201)	(0.111)	(0.396)
lnCI	-0.0854	-0.0228	-0.147	-6.286	-0.109	-0.589	-0.0850*	-0.189*
	(0.0592)	(0.0206)	(0.161)	(4.462)	(0.206)	(0.528)	(0.0469)	(0.100)
Lev	0.0108**	0.00333**	-0.0214**	-0.409	0.00613	0.127*	0.00923*	0.0221
	(0.00519)	(0.00146)	(0.00913)	(0.335)	(0.00954)	(0.0713)	(0.00504)	(0.0221)
lnGrowth	0.00977	-0.00175	-0.0374	-1.702	-0.00565	-0.641	-0.0125	-0.00329
	(0.0169)	(0.00341)	(0.0307)	(1.597)	(0.0459)	(0.410)	(0.0152)	(0.0320)
Age	0.0324***	0.0104***	0.0564*	1.374*	0.0607*	-0.000880	-0.00149	-0.000622
	(0.0108)	(0.00363)	(0.0293)	(0.755)	(0.0351)	(0.0177)	(0.00266)	(0.00461)
Covid	-0.0665***	-0.0152*	-0.0294	-0.221	0.126	1.049	0.298***	0.690***
	(0.0237)	(0.00848)	(0.0777)	(3.131)	(0.0772)	(0.906)	(0.0496)	(0.241)
Constant	0.483	1.116***	3.695	88.80*	2.701	14.21	1.529	5.741**
	(0.598)	(0.238)	(2.261)	(47.49)	(2.407)	(10.80)	(1.033)	(2.834)
Obs.	272	272	273	293	272	293	273	273
R-squared	0.487	0.451	0.139	0.145	0.087	0.058[a]	0.183[a]	0.133[a]
Number of Firm_id	49	49	52	52	52	52	49	49

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[a] overall R-squared

Table 4: Model 2 specifications including Covid dummy and clustered standard errors

Spec. Variables	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
lnCI	-0.0750	-0.0322	-0.191	-3.387	-0.209*	-0.258	-0.123	-0.394
	(0.0554)	(0.0240)	(0.114)	(2.477)	(0.123)	(0.302)	(0.0794)	(0.258)
lnRD	-0.00903	-0.00509	-0.235	0.159	-0.274	0.325	0.0534	-0.136
	(0.0408)	(0.0192)	(0.153)	(2.954)	(0.198)	(0.602)	(0.0782)	(0.365)
lnAssets	-0.343***	-0.183**	-0.506***	-7.853*	-0.496**	-1.674	-0.394***	-1.446*
	(0.105)	(0.0702)	(0.176)	(4.257)	(0.214)	(1.136)	(0.141)	(0.812)
Lev	0.00472	0.00254	-0.0204***	-0.237*	0.0109	0.113	0.00163	0.0280
	(0.00310)	(0.00188)	(0.00644)	(0.126)	(0.00769)	(0.0748)	(0.00586)	(0.0403)
lnGrowth	0.00538	0.00128	0.0395*	0.701*	0.0392	-0.0340	-0.000191	0.0602
	(0.00889)	(0.00361)	(0.0204)	(0.374)	(0.0249)	(0.184)	(0.0218)	(0.0472)
lnCashF	0.0484	0.0204	1.064***	6.175***	1.474***	3.588***	0.0601	0.101
	(0.0435)	(0.0129)	(0.203)	(2.194)	(0.335)	(0.826)	(0.0388)	(0.0990)
Covid	-0.0198	0.00303	-0.0688	0.373	0.0165	0.104	0.274***	0.858**
	(0.0230)	(0.00986)	(0.0829)	(1.153)	(0.0669)	(0.513)	(0.0562)	(0.324)
Country								
DNK						0.394		
						(3.560)		
NOR						-1.970		
						(1.336)		
SWE						-0.694		
						(1.804)		
Constant	1.498*	1.767***	9.885***	104.3***	7.920***	23.79**	3.170**	11.91**
	(0.798)	(0.534)	(1.615)	(32.64)	(2.162)	(9.719)	(1.218)	(5.553)
Obs.	219	219	217	223	215	223	221	221
R-squared	0.297	0.361	0.450	0.244	0.498	0.334[a]	0.243	0.212
Number of Firm_id	40	40	41	41	41	41	40	40

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[a] overall R-squared

Table 5: Model 1 results for pre-COVID period

Spec. Variables	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
lnAssets	-0.710***	-0.323***	-0.822***	-45.13***	-0.520	-2.201**	-0.282**	-0.381**
	(0.120)	(0.0660)	(0.256)	(14.43)	(0.350)	(1.081)	(0.135)	(0.173)
lnCI	-0.112	-0.0548	-0.231	-6.813	-0.268	-1.113*	-0.0697	-0.236
	(0.0903)	(0.0422)	(0.209)	(7.087)	(0.243)	(0.641)	(0.0493)	(0.146)
Lev	0.0143**	0.00116	-0.0289**	-0.884	0.000199	0.0797	0.0111***	0.0208**
	(0.00608)	(0.000766)	(0.0109)	(0.538)	(0.0103)	(0.0632)	(0.00351)	(0.00836)
lnGrowth	0.0116	0.00308	0.0118	0.214	0.00175	-0.378	-0.00299	0.0286
	(0.0153)	(0.00541)	(0.0324)	(1.117)	(0.0446)	(0.325)	(0.0269)	(0.0378)
Age	0.0269*	0.0135**	0.0828**	3.014**	0.0637	-0.0115	0.000922	0.000585
	(0.0153)	(0.00508)	(0.0347)	(1.305)	(0.0399)	(0.0213)	(0.00340)	(0.00371)
Constant	2.116**	2.021***	5.229***	221.0***	1.329	19.13*	1.640	3.160**
	(0.892)	(0.465)	(1.917)	(75.61)	(2.336)	(9.921)	(1.132)	(1.246)
Obs.	133	133	134	141	134	141	129	129
R-squared	0.572	0.601	0.365	0.416	0.096			
Number of Firm_id	44	44	47	47	47	47	44	44

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[a] overall R-squared

Table 6: Model 1 results for post-COVID period

Spec. Variables	(1) **lnGP**	(2) **GP**	(3) **lnROE**	(4) **ROE**	(5) **lnROA**	(6) **ROA**	(7) **lnTobinQ**	(8) **TobinQ**
lnAssets	-0.698***	-0.215**	-0.203	-4.024	-0.348	-0.875	-0.366**	-0.672
	(0.101)	(0.0909)	(0.215)	(10.48)	(0.271)	(1.631)	(0.146)	(0.413)
lnCI	-0.130**	-0.0270	-0.00331	-8.552	0.216	-0.528	-0.0413	-0.156
	(0.0554)	(0.0225)	(0.139)	(7.361)	(0.224)	(0.589)	(0.0379)	(0.0963)
Lev	0.00587	0.00381	-0.0130	0.351	0.0175	0.154*	0.00896	0.0324
	(0.00542)	(0.00241)	(0.00974)	(0.338)	(0.0108)	(0.0846)	(0.00670)	(0.0278)
lnGrowth	0.0236	-0.00105	-0.0715	-3.360	0.0374	-1.007	0.00421	-0.0320
	(0.0329)	(0.00599)	(0.0527)	(3.322)	(0.100)	(0.836)	(0.0283)	(0.0924)
Age	0.0811***	0.0211**	0.103	1.359	0.0463	-0.00212	-0.00150	-0.00258
	(0.0147)	(0.0102)	(0.0645)	(2.897)	(0.0552)	(0.0161)	(0.00294)	(0.00456)
Constant	-1.358	0.529	-1.822	-90.31	1.958	4.785	2.821**	5.540*
	(1.202)	(0.620)	(4.536)	(164.5)	(4.590)	(15.51)	(1.365)	(2.953)
Obs.	139	139	139	152	138	152	144	144
R-squared	0.480	0.488	0.060	0.113	0.101			
Number of Firm_id	48	48	52	52	52	52	49	49

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
[a] overall R-squared