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## - Effects of Emissions on Financial Performance in Global Energy Companies, Considering Firm-, Sector- and Country Characteristics -

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## Preface

This thesis represents the culmination of our journey as master's students in Business with a major in Finance at Handelshøyskolen BI in Oslo. Throughout our two-year program, we have been exposed to various topics that have piqued our interest, but it is within the realm of this thesis that we have truly delved into a subject that captivated us - the intersection of finance and Environmental, Social, and Governance (ESG) factors within the energy industry.

Undertaking this thesis has not been without challenges and difficulties. However, with perseverance and dedication, we have managed to overcome these obstacles and reach an outcome that fills us with genuine pride. Along the way, we have learned invaluable lessons within teamwork, planning, and, most importantly, the significance of ESG considerations in the energy sector.

We would like to express our gratitude to the individuals who have contributed to the completion of this assignment. We extend our thanks to our first supervisor, Professor Loreta Rapushi, who provided us with valuable guidance and advice at the beginning of our thesis journey. Although she had to take maternity leave during the process, her initial insights were instrumental in shaping the early stages of our work. We are immensely grateful to our second supervisor, Professor Nataliya Gerasimova, who stepped in and provided continuous guidance and support throughout the majority of our thesis. Her expertise and mentorship have been invaluable in navigating the challenges we encountered over the past year.

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## Abstract

This thesis investigates the relationship between environmental performance measured by emissions and financial performance in the energy industry, focusing on the link between scope 1 and 2 emissions and financial indicators such as return on equity (ROE) and Return on Assets (ROA).

Previous research explores the connection between environmental and financial performance, based on studies from the 1970s to 2017. The relationship appears mixed, with some studies finding a positive, negative, or no correlation between the two. Some research indicates that good environmental performance may lead to a market premium, while others suggest the opposite. The link between environmental and financial performance is complex, and more research is needed to fully grasp it.

Our research employs a panel data analysis using a dataset of 80 energy companies sourced from Bloomberg, with annual data from 2014 to 2021. The data encompasses variables such as scope 1 and scope 2 emissions, return on equity, return on assets, market capitalization, debt-to-equity ratio, energy sector, and industry segments. To test the hypothesis that financial and environmental performance are positively linked, our research employs various research methodologies, including pooled ordinary least squares (POLS), fixed effects (FE), and first differences (FD) models. Multicollinearity and autocorrelation are examined, and potential omitted variable and selection biases are addressed.

The findings in our study provides new insights between the effects of environmental performance, particularly between emissions and financial performance in the global energy industry with additional country and sector specific findings. Our results show no link between greenhouse gas emissions (GHG) and ROE or ROA. We find firm size and if the company originates from a high- or low-income country to be the most important factors.

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# 1. Introduction

## 1.1 Introduction

The phenomenon of climate change and global warming has been widely recognized since its discovery. In 1938, Guy Callendar connected carbon dioxide increases in the atmosphere with global warming (Callendar G. , 1938). Similarly, the utilization of solar and wind energy is not a novel concept. However, what is novel is the current stage of transition from traditional hydrocarbon energy sources to renewable energy sources. Renewable energy and its related technologies are now widely acknowledged as credible sources of power and a viable alternative to natural gas and oil.

As a result of growing environmental awareness and a commitment to sustainable development, the world has embraced the United Nations' Sustainability Development Goals (SDGs). Among the 17 goals, SDG 13 – Climate action is based on the Paris Agreement, to limit global warming to 1.5 Celsius above pre-industrial levels. Greenhouse gas emissions will need to peak by the latest 2025, and then be reduced by 43% by 2030, before achieving zero-net emissions by 2050 (Sachs, Lafortune, Fuller, & Woelm, 2022). This shift has put pressure on energy companies to invest in green energy, with varying degrees of commitment. Some companies are merely paying lip service to the cause by using language such as "transition" and "low carbon" in their reports, while others are making substantial investments in renewable energy and turning into integrated energy companies.

Some investors are motivated by the desire for profits, and while environmental concerns are a factor, they are not the sole driving force. Others also focus on environmental aspects for various reasons. The attention given to climate change is often cyclical and subject to fluctuations, with investors in general being focused on profits over environmental concerns. There is a possibility that oil and gas companies may be ignored by investors if they are viewed as environmentally harmful, but as public focus wanes, investors may begin to realize the potential profits that these companies offer. This thesis aims to explore the effect the emissions in energy companies have on their financial performance considering these developments.

Energy companies have four ways of implementing renewable energy solutions. The first one is to use renewable energy for efficiency gain, like enhanced oil recovery (EOR). A second way is to leverage in-house expertise from decades in the oil business to produce renewable energy, like building hydropower, offshore wind, and producing biofuels. The third way is to operate as venture capital, investing in promising technologies and solutions. The final way is to build a fully integrated energy business, with end-to-end solutions in power production, grid, storage, sale, and analysis. No matter what a company chooses, the goal is to reduce emissions and still operate a profitable company.

Low- and high-income countries have different starting points in the energy transition, with implications for prosperity and quality of life. High-income countries have the financial means to invest in renewable energy, contributing to environmental sustainability while maintaining a high standard of living. In contrast, low-income countries face challenges in balancing their energy needs with limited resources, potentially affecting their path to prosperity and the well-being of their populations. Bridging the energy transition gap is crucial to ensure that all countries can achieve sustainable development and enhance the quality of human life.

## 1.2 Research contribution

In this study, our focus is exclusively on the environmental aspect of the Environmental, Social, and Governance (ESG) criteria and more specifically its relation to emissions. This is different from previous studies which have investigated the combined ESG score or other various subcategories of ESG. Previous studies have focused on the relationship between ESG and the economic or financial performance of companies in specific countries regions, or continents, whereas we will examine how ESG subcategories affect companies within a particular industry in the whole world. We have also created a dummy variable which is country specific and sector specific, whereas we can compare countries and sectors within the same industry.

The recent heightened focus on environmental and social issues from the SDGs, as well as the mentioned goal set forth by the Paris Agreement, make it increasingly



important for energy companies to align their focus with these goals to create value. This shift in focus has also led to a change in investors' perceptions, with more and more investors adopting sustainable responsible investing (SRI) strategies.

Climate Action 100+ is an investor-led initiative aimed at reducing emissions from the world's largest greenhouse gas emitters, further illustrating this trend. The initiative has more than 700 investors and 166 companies responsible for over \$68 trillion in assets committed to improving climate change governance, emissions reduction, and financial disclosure related to climate change. These initiatives could help accelerate the transition towards green energy within the industry (Climate Action 100+, 2023). In addition, the Government Pension Fund of Norway, managed by NBIM gets restrictions from the Ethics Council and the Norwegian Ministry of Finance regarding investments. Overall, the expert group recommends that Norges Bank's SRI strategy aims to reach a long-term goal of net zero emissions from their investments (Olsen & Tangen, 2021).

Our research contributes to the understanding of the relationship between emissions, financial performance, and whether there are differences among the countries within the global energy industry. The results of our study will be of interest to practitioners such as investors and managers of listed energy companies, due to the understanding of the economic implications of environmental sustainability within the energy industry. This research can provide insights into the costs and benefits associated with emissions reduction efforts and shed light on the financial motivations and incentives for energy companies to adopt environmentally friendly practices, or not. Our findings could support investors in making informed investment decisions and give guidance to managers on the energy industry on how to balance their environmental responsibilities with their financial objectives. Furthermore, our research can contribute to the development of policy recommendations and regulatory frameworks aimed at incentivizing emissions reduction in the energy sector.

## 2. Theory and Literature Review

### 2.1 Literature Review

#### 2.1.1 Previous research: Emissions and financial performance

This literature review summarizes several studies on the relationship between environmental performance and financial performance of companies. Early studies by Nutt & Fogler (1975), Rockness et al. (1986), and Spicer (1978) find no significant correlation between environmental and financial performance. Their studies are criticized due to low sample size and infrequent observations. However, later studies find a positive link between the reduction in emissions and financial performance. For example, Hart & Ahuja (1996) find a positive link between emission reduction and financial performance for a sample of 127 companies from S&P 500, while Russo & Fouts (1997) find that the effect of environmental performance on financial profitability depends on industry context and industry growth. Ernhart & Lizal (2007) examines Czech companies during the transition period to the EU and found that higher environmental performance has positive effects on financial performance by strongly reducing costs and a weak reduction of revenues.

Busch (2011) distinguished between outcome-based and process-based corporate environmental performance and found that outcome-based measurements of emissions had a significant effect on financial performance, but only for Tobins q, implying that good environmental performance can generate a market premium. On the other hand, the effect was the opposite for the process-based measure, carbon management was negatively related to Tobins q. Nishitani et al. (2011) found that a reduction in emissions leads to increased economic performance through an increase in demand and productivity, but the increase in productivity was conditional on the implementation approach of the firm. Cantore et al. (2016) found that energy efficiency tends to have a positive effect on firms' profitability for a sample of 29 developing countries.

Matsumura et al. (2014) find that higher emissions hurt financial performance of companies that disclose emissions for companies in the S&P500 between 2006 and 2008. Lee et al. (2015) find that carbon emissions decrease firm value, while EcoR&D have a positive impact on firm value, but with varying significance

through the years. The market penalizes negative environmental performance more than it rewards positive performance.

Capece (2017) explore the effect of environmental management on firm performance for a sample of 237 Italian firms and find a positive connection, even for small and medium-sized companies. Lewandowski (2017) find that improving carbon performance further leads to better financial performance for companies with superior carbon performance, while Cucchiella (2017) find that EMS adoption could lead to profits through an increase in demand and productivity, but with a delay from the start of initiatives to the realization of economic performance. These studies suggest that the relationship between environmental and financial performance is complex and context-dependent, and that good environmental performance can generate a market premium in some cases.

Our research contributes to the literature by including the variables of country and sector in further exploring the relationship between emissions and financial performance. We examine the relationships between the variables and explore what causes them.

#### [2.1.2 Previous research: GDP per Capita and renewable energy usage](#)

Simionescu et al. (2019) conduct a study on the relationship between GDP per capita and the share of renewable energy sources (RES) in electricity generation in European Union (EU) countries. They find a positive, but minimal impact of GDP per capita on the share of RES in electricity, with Luxembourg being an outlier. However, no causality is established between the two variables. The study suggests the need for further research to obtain more reliable results and develop specific policy recommendations.

Sadorsky (2009) investigate the potential of emerging economies to increase their usage of renewable energy due to economic growth and energy demand. The study find that higher real per capita income has a positive and significant impact on per capita renewable energy consumption in emerging economies. It also reveals that renewable energy consumption is more responsive to price changes than electricity demand. Sadorsky (2009) emphasize the importance of these findings for designing effective energy policies in emerging economies.

Armeanu et al. (2017) examine the relationship between renewable energy and sustainable economic growth in the EU. They find that renewable energy has a positive influence on GDP per capita, with biomass energy having the highest impact. The study confirms an unidirectional causal relationship where sustainable economic growth leads to increased production of renewable energies. Armeanu et al. (2017) recommend intensifying cooperation mechanisms among EU countries to achieve renewable energy targets and enhance energy infrastructure.

Ntanos et al. (2018) investigate the relationship between renewable energy consumption and economic growth in 25 European countries. The study reveals a correlation between GDP per capita and renewable energy consumption in the long run. Countries with higher GDP showed a stronger correlation. The authors identified clusters of countries based on their GDP and renewable energy consumption levels, emphasizing the need for increased efforts to promote renewable energy adoption. They propose creating an investment-friendly environment, providing financial incentives, and addressing barriers to further develop renewable energy sources. The study also suggests avenues for future research, including comparative analyses and the inclusion of carbon emissions reduction as a parameter.

Our research contributes to earlier studies by examining the financial return and sector of energy companies. Earlier research finds that there is a difference in renewable energy consumption between high and low GDP per capita countries. We aim to examine why this is the case.

## 2.2 Theory

### 2.2.1 Resource Management

In the energy sector, effective resource management plays a crucial role in ensuring the sustainable operation of energy companies. We highlight the significance of resource management and its impact on various aspects of energy companies' performance.

Efficient utilization of resources, including energy sources, materials, and human capital, has several benefits for energy companies. One key benefit is improved operational efficiency. By optimizing resource allocation and reducing waste, energy companies can enhance their overall productivity and operational effectiveness. For example, implementing energy-efficient technologies and practices can lead to reduced energy consumption and lower operating costs, ultimately improving the bottom line (Wang et al., 2022).

Cost reduction is another important aspect of effective resource management. By carefully managing resources, energy companies can minimize expenses associated with procurement, transportation, and storage. For instance, implementing inventory management systems can help optimize stock levels and reduce excess inventory, resulting in cost savings. Efficient resource utilization can also reduce maintenance and repair costs, as well as mitigate the risks of equipment downtime or failures (Bowers & Ruediger, 2017).

Enhanced environmental performance is a critical aspect of effective resource management in the energy sector. By minimizing resource consumption and implementing sustainable practices, energy companies can reduce their environmental footprint and contribute to climate change mitigation. For example, optimizing energy usage, promoting renewable energy adoption, and implementing emissions reduction strategies can help reduce greenhouse gas emissions and promote a cleaner and greener energy sector (Modi & Mishra, 2011).

The positive impact of effective resource management on financial performance is supported by various studies and demonstrated in industry examples. As 3M did in their Pollution Prevention Pays program (3p's) (United States Environmental Protection Agency, 2022).

Several industry examples illustrate the benefits of effective resource management. For instance, a renewable energy company that invests in advanced monitoring systems and predictive maintenance can optimize the performance of wind turbines and maximize energy production. This not only improves operational efficiency but also enhances the company's financial performance by increasing revenue generation (Wang et al., 2022).

Another example is an oil and gas company that implements a comprehensive waste management program, including recycling and reuse initiatives. By minimizing waste generation and disposal costs, the company can achieve significant cost savings while demonstrating its commitment to environmental responsibility (Bowers & Ruediger, 2017).

### 3. Hypothesis and Research Methodology

#### 3.1 Hypothesis

Financial performance (ROE or ROA) and GHG emissions is negatively correlated. We expect Solar to be the least profitable sector. We expect higher financial return in low-income countries, compared to high-income countries.

By better resource management, technology, and efficient processes, it is possible to increase financial performance and decrease GHG emissions.

Energy companies in low-income countries can be more profitable than high-income countries because of differences in regulation between the groups. High income countries invest more in renewable energy, which is less profitable.

#### 3.2 Research Methodology, Models and Reliability

We utilize regression analysis to explore the interactions between the variables. Various model specifications are employed in our research, including Pooled OLS (POLS), Fixed Effects (FE), and First Differences (FD). We then test with reliability analysis, examination of multicollinearity and autocorrelation, and consideration of omitted variable and selection bias. These methodologies allow us to investigate and address different aspects of the data and model specification, ensuring a comprehensive and rigorous analysis<sup>1</sup>. We use a five-percentile level to determine significance.

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<sup>1</sup> The regressions in this thesis are computed using the linearmodels Python project in a Jupyter Notebook (Sheppard, linearmodels 5.0, 2023). See Appendix for Jupyter Notebook.

### 3.2.1 Pooled OLS

We use robust standard errors that allow heteroskedasticity and cluster correlation because OLS standard errors are otherwise incorrect (Wooldridge, 2012). OLS standard errors can be biased when residuals are correlated across observations, leading to over or underestimation of coefficient variability (Petersen, 2009). Therefore, we also fit FE and RE models to our data. The fitted POLS model is used as a benchmark for the other models.

*Equation 1: Pooled OLS Model*

$$Y_{it} = \beta_1 + \beta_2 GHG_{it} + \beta_3 MCAP_{it} + \beta_4 DE_{it} + \beta_5 Sector_{it} + \beta_6 Country_{it} + u_{it}$$

Where  $i = 1, 2, \dots, 80$  and  $t = 2014, 2015, \dots, 2021$

### 3.2.2 Fixed Effects

We utilize a Fixed Effects (FE) OLS regression model in our analysis. The FE regression is run in three variants. One controlling for time-invariant effects, one with entity-invariant effects, and one where we control for both dimensions. The models are used to reduce bias.

We use fixed effects estimators to address selection bias in our analysis. Fixed effects models are commonly used in panel data analysis to control for time-invariant confounding factors and estimate the effect of independent variables using within-unit variation (Mummlo & Peterson, 2018). Standard errors clustered by firm are unbiased and produce correct confidence intervals when a firm effect exists, regardless of its permanence (Petersen, 2009). When controlling for both time- and entity-dimensions, the FE model requires a sufficient number of clusters in each dimension to ensure unbiased results (Petersen, 2009). In the FE models with entity-fixed effects, all sector and country data are fully absorbed, we therefore specify the model without sector and country data.

*Equation 2: Fixed Effects Model*

$$y_{it} - \hat{\theta}_i \bar{y}_i = (1 - \hat{\theta}_i) \alpha_i + (x_{it} - \hat{\theta}_i x_i) \text{LogGHG} + (x_{it} - \hat{\theta}_i x_i) \text{LogMCAP} \\ + (x_{it} - \hat{\theta}_i x_i) \text{DE} + (x_{it} - \hat{\theta}_i x_i) \text{Sector} + (x_{it} - \hat{\theta}_i x_i) \text{Country} \\ + (\epsilon_{it} - \hat{\theta}_i \bar{\epsilon}_i)$$

Where  $i = 1, 2, \dots, 80$  and  $t = 2014, 2015, \dots, 2021$

### 3.2.3 First Differences

The FD model is useful for eliminating time-constant unobserved effects. The model has a strict assumption that the regressors are exogenous, failure of the assumption subjects the model to serious biases. The model also struggles when measurement error is present, resulting in substantial bias. Including more time periods does not necessarily reduce the inconsistency of the estimator (Wooldridge, 2012).

*Equation 3: First Differences Model*

$$\Delta Y_{it} = \beta_1 \Delta \text{LogGHG}_{it} + \beta_2 \Delta \text{LogMCAP}_{it} + \beta_3 \Delta \text{DE}_{it} + u_{it}$$

Where  $i = 1, 2, \dots, 80$  and  $t = 2014, 2015, \dots, 2021$

### 3.2.4 Multicollinearity and Autocorrelation

Multicollinearity, which refers to the degree of linear relationship among independent variables in a multiple regression model, is a crucial concern in our econometric model (Gujarti, 2009; Kennedy, 2008). When high correlations exceeding 0.8 exist among the independent variables, severe multicollinearity problems arise, undermining the statistical significance of individual variables (Gujarati, 2009). Failure to address multicollinearity can lead to biased coefficient estimates and misleading interpretations of variable importance (Gujarati, 2009; Kennedy, 2008). To detect and mitigate multicollinearity, we have employed a correlation matrix and considered variable selection techniques (Gujarati, 2009; Kennedy, 2008).

Autocorrelation, also known as serial correlation, occurs when the error term in a time series exhibits correlation from one period to the next (Verbeek, 2017; Johnston & DiNardo, 1997). Autocorrelation can introduce significant issues in regression analysis, including biased coefficient estimates, underestimated standard errors, and spurious significance levels (Verbeek, 2017). To address autocorrelation, we have utilized various techniques such as the Wooldridge test, which corrects for autocorrelation and heteroskedasticity (Wooldridge, 2012; Johnston & DiNardo, 1997). By accounting for autocorrelation, we can ensure the



validity and reliability of regression results, particularly in time series analysis (Wooldridge, 2012; Johnston & DiNardo, 1997).

### 3.2.5 Omitted Variable and Selection Bias

Omitted Variable Bias is a critical concern in our regression analysis, occurring when essential control variables are not included in the model specification. The omission of relevant variables introduces bias into the results, potentially inflating the estimated effects of the included variables. This bias arises due to the failure to account for confounding factors that influence both the outcome variable and the included variables (Brooks, 2014; Wooldridge, 2012). The estimated coefficients may not accurately represent the true relationships between the variables of interest.

In the context of our research, it is important to acknowledge the potential presence of omitted variable bias. By excluding variables, we risk distorting the estimated effects and drawing misleading conclusions. These omitted variables could hold significant explanatory power and, if not accounted for, may lead to overestimation or underestimation of the true relationships of interest (Brooks, 2014; Wooldridge, 2012). In our research, we have chosen to exclude companies with a market cap less than \$ 1bn, which we could have included as for instance a dummy variable. However, there were only three companies excluded of that reason and we believe the influence from excluding the companies is low. In addition, we have included sector, which may have changed during our sample period. A significant portion of the companies in our dataset have developed to operate within several sectors (Integrated Oil and Gas Companies) under the timeframe. We have chosen to investigate the sector from the newest data to research whether there are differences or not between the current sectors.

Selection Bias is another issue that can arise in our regression analysis, particularly when the OLS estimator is affected by endogenous sample selection. This bias occurs when the entities included in the data sample are not representative of the entire population to which they belong. Such biased sampling can arise from non-random selection processes or missing data that result in an incomplete representation of the population (Wooldridge, 2012). Ignoring selection bias can lead to misleading conclusions and biased estimates of the model parameters.

In our research, selection bias may be a concern due to data limitations. Despite initially collecting data from all listed energy companies worldwide, we encountered missing data for several companies in the initial sample, especially related to GHG emissions. These companies had to be excluded from the analysis, potentially resulting in a non-representative sample, and compromising the generalizability of our findings (Cameron & Trivedi, 2013; Stock & Watson, 2015). We acknowledge this limitation and recognize that the conclusions drawn from the final sample of the 80 included companies may not be applicable to the entire population of listed energy companies, but only for our sample of 80 companies.

### 3.2.6 Survival Bias

We acknowledge the potential presence of survival bias in our dataset, as all the companies included in our research have been operational and listed during the period of 2014-2021. This means that our sample represents a selected group of companies that have managed to sustain their operations and remain in the industry. We believe that this is a result of our data represents serious actors in the energy industry who have resources to report on GHG emissions earlier than less serious actors that suffers more of default risk. The companies in our dataset stand out from the rest of the industry by demonstrating a willingness to disclose their emissions data, showcasing a commitment to transparency and environmental responsibility. We recognize that the absence of companies that have defaulted or exited the industry introduces a survival bias to our analysis. By excluding companies that have faced financial difficulties or operational challenges leading to defaults or closures, our dataset may not capture the full range of experiences and outcomes within the industry. This limitation should be considered when interpreting our findings, as they may not be generalizable to all energy companies but rather reflect the performance and practices of those that have been able to sustain their operations and remain in the market.

## 4. Data

### 4.1 Data Description

The data is sourced from Bloomberg. In our dataset, we have annual data from 2014 to 2021 on 80 energy companies. The variables in the dataset are GHG Scope 1 and Scope 2 emissions, return on assets, return on equity, market capitalization, debt to

equity ratio, country and in which segment they operate in. The 80 companies in our dataset give us 5064 observations with our mentioned variables.

## 4.2 Data Processing and Cleaning

We fill in missing data with data from annual reports. 10 companies are removed because of insufficient data. We utilize winsorization to adjust for outliers in the data, defining observation below the 2 percentile and above the 98 percentiles as outliers.

## 4.3 Variable Description

In this section, we discuss the variables selected for our analysis. We initially describe the dependent variables, which are the financial performance indicators. Then, we provide a description of the independent variable, GHG emissions. Further, we examine the firm characteristics that we aim to incorporate and point to notable observations in the Sector and Country variables.

### 4.3.1 Financial Performance

The variables used to measure financial performance in the analysis are ROA and ROE. These are the dependent variables in the regressions.

*Equation 4: Return on Equity*

$$ROE = \frac{\text{Net Income}}{\text{Average Shareholder Equity}}$$

*Equation 5: Return on Assets*

$$ROA = \frac{\text{Net Income Before Preferred Dividends} + ((\text{Interest Expense on Debt} - \text{Interest capitalized}) \cdot (1 - \text{Tax Rate}))}{\text{Average Total Assets}}$$

### 4.3.2 Environmental Performance

Scope 1 emissions are the direct greenhouse gas (GHG) emissions that result from sources under the control or ownership of an organization. Examples include emissions from fuel combustion in boilers, furnaces, and vehicles. Scope 2 emissions are the indirect GHG emissions associated with an organization's energy consumption. These emissions occur at the facility where the energy is generated, but they are accounted for in the organization's GHG inventory because they stem from the organization's energy use. Scope 2 emissions are linked to the purchase of electricity, steam, heat, or cooling (United States Environmental Protection

Agency, 2023). We use the natural logarithm of GHG, since the GHG variable is strongly skewed to the right (Keene, 1995). We define LogGHG as in Equation 6 below.

*Equation 6: LogGHG*

$$\text{LogGHG} = \ln(\text{Scope 1} + \text{Scope 2})$$

#### 4.3.3 Firm Characteristics

We use DE as a measure of risk. According to the capital asset pricing model (CAPM), higher risk is accompanied by higher return. DE represents the extent to which a company relies on debt financing. It can amplify returns on investment but also introduces financial risk. The preferred level of leverage varies based on industry, growth prospects, and risk tolerance. It affects a company's cost of capital, credit rating, and access to financing. Effective management of leverage involves assessing cash flow capabilities, considering interest rate fluctuations, and maintaining a sustainable capital structure. Striking the right balance is essential for long-term financial stability.

We use MCAP as a measure of firm size. Firm size is a risk factor identified by Fama & French (1993). When analyzing the relationship between financial performance and emissions, economies of scale can play a significant role. Larger companies may have higher total emissions, but they may also have a more efficient emission profile due to cost advantages from increased production or market power. This means that larger companies could have lower emissions per unit compared to smaller companies. To adjust some for economies of scale in our regression analysis, we exclude three companies in our dataset with a market capitalization of less than 1 billion. We use the natural logarithm of MCAP, since the MCAP variable is strongly skewed to the right (Keene, 1995).

*Equation 7: LogMCAP*

$$\text{LogMCAP} = \ln(\text{MCAP})$$

#### 4.3.4 Sector

The firms are divided into six sectors. The number of companies in each sector is shown in Figure 1 below.

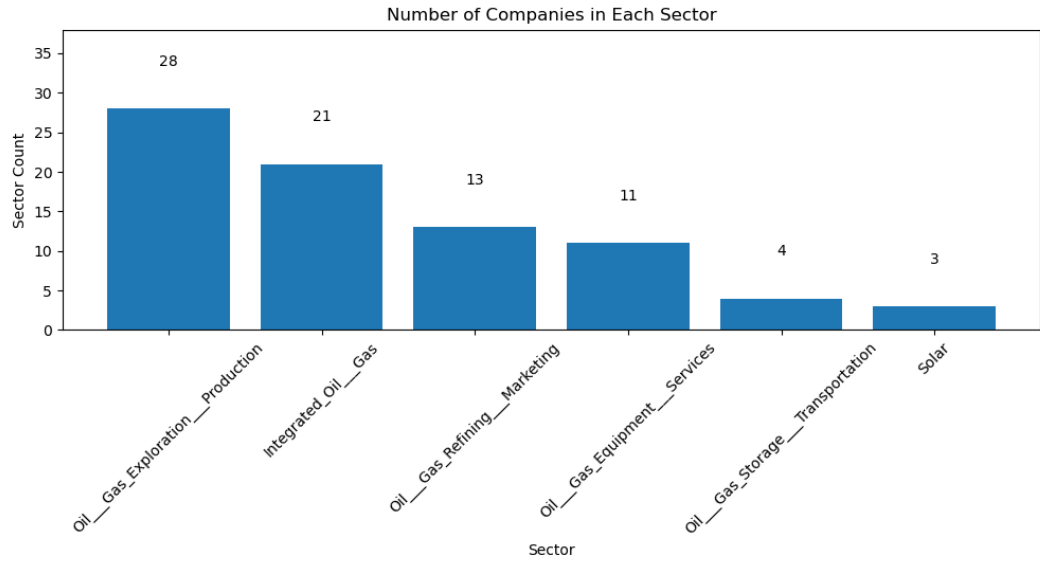


Figure 1: Number of Companies from Each Sector

#### 4.3.5 Country

We examine companies from 25 countries. The countries are unevenly distributed. The majority of the companies in our dataset, over 50 percent, are concentrated in the top four countries. The biggest countries are western countries, Canada, the United States, and the United Kingdom. Including this variable in the analysis controls for country-specific effects, such as regulatory frameworks, political stability, access to capital markets, and cultural aspects.

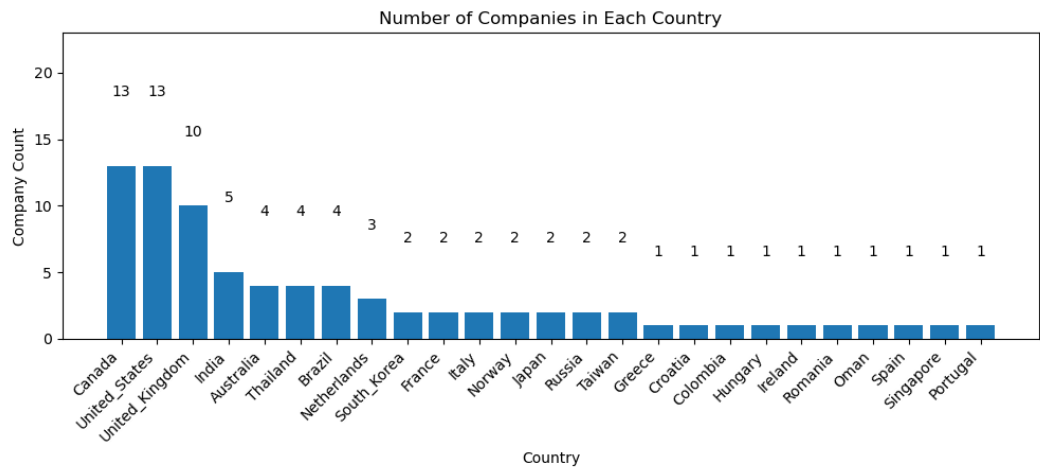


Figure 2: Number of Companies from Each Country

Due to the small sample size within each country, we divide the countries into high and low GDP per capita. The dataset contains four firms from Brazil, three from

the Netherlands, and one single firm from Oman. Based on the available data, we believe that insufficient evidence exists to draw meaningful inferences regarding the country variable. More data on each specific country is needed. We divide the countries into high and low GDP per capita to better examine the effect of the economic development of countries on financial return of the companies. We divide the 24 countries into two equally sized groups. This results in 56 companies in the high group and 24 companies in the low group. The list of countries and which group they are placed in is available in the Appendix.

## 4.4 Descriptive Statistics

### 4.4.1 Time Dependent Central Tendencies

All graphs contain a linear regression to show trend and the overall mean value for all years as a reference.

#### 4.4.1.1 Financial Performance

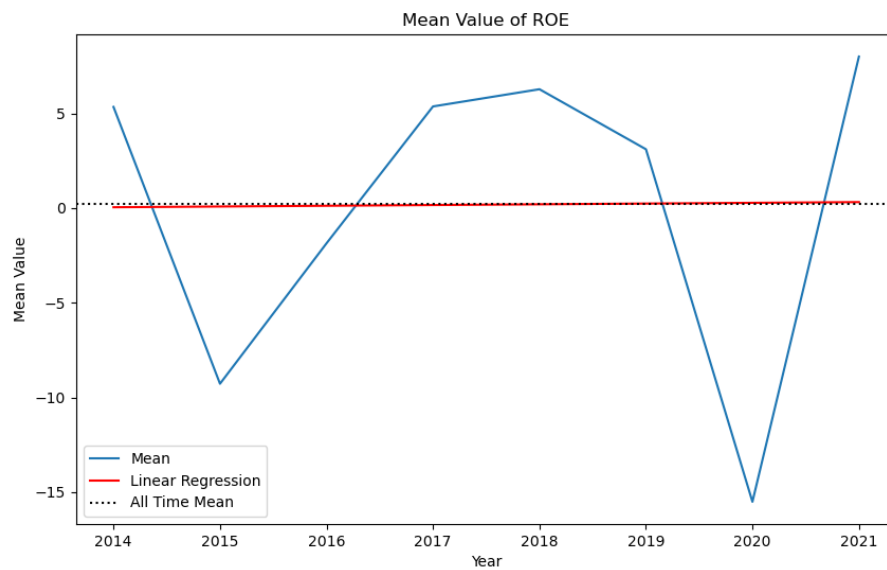


Figure 3: Mean Value of ROE

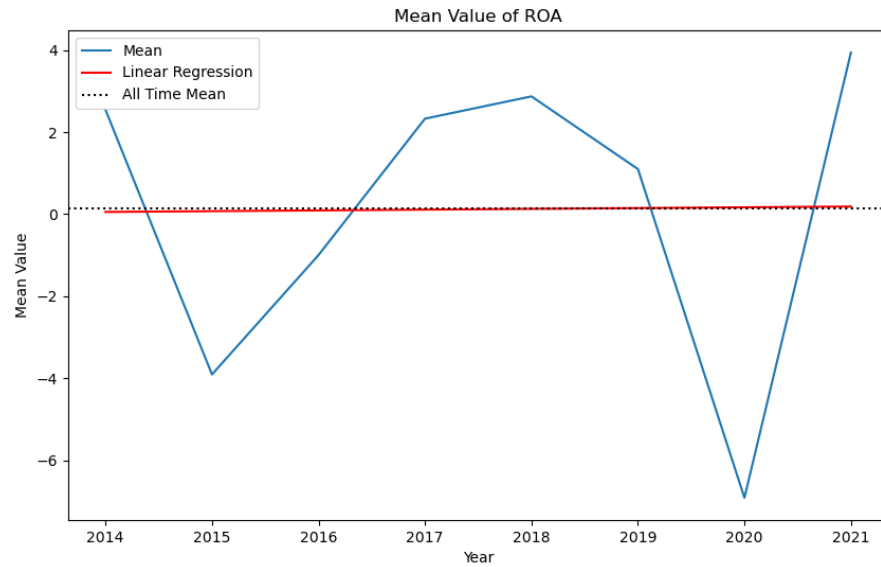


Figure 4: Mean Value of ROA

Both measures of financial performance show great volatility from 2014 to 2021. The variances in crude oil prices are highly correlated with ROE and ROA. We can see that the energy companies were highly affected by first the oil collapse and then the Covid-19 pandemic and lockdown.

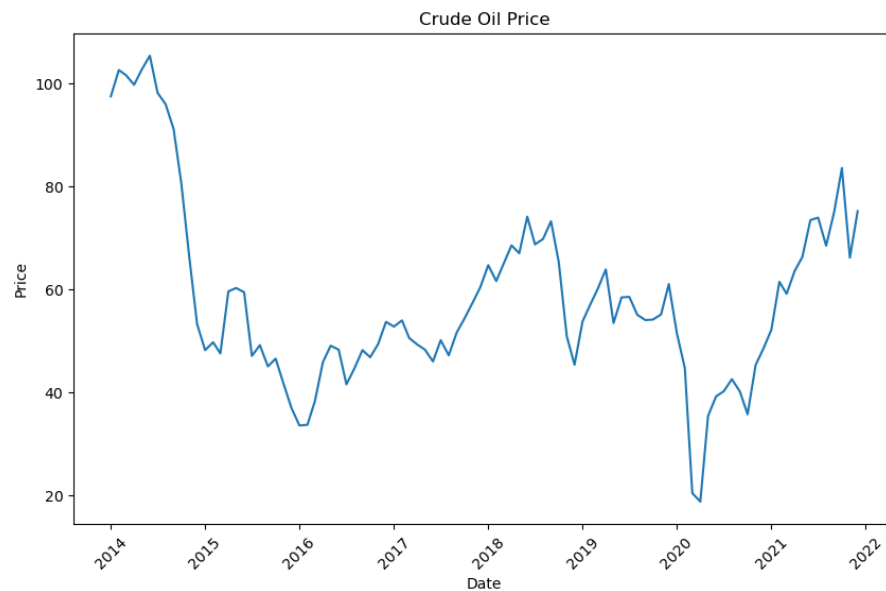


Figure 5: Crude Oil Futures Prices. Data from investing.com

#### 4.4.1.2 Environmental Performance

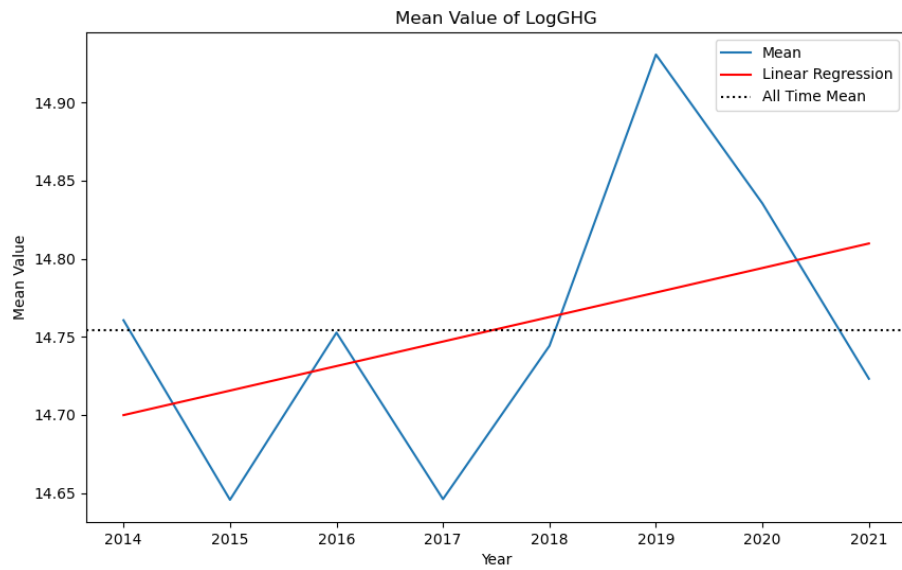


Figure 6: Mean Value of GHG

The mean values of GHG emissions from 2014 to 2021 show a general upward trend with some fluctuations. There was a slight increase in 2015, followed by a decrease in 2016. Emissions then rose in 2017 and remained stable in 2018. A significant increase occurred in 2019, followed by a slight decrease in 2020. The highest value was recorded in 2021. From the lowest point in 2016 to the highest point in 2021, the mean value of GHG emissions rose by 35%.

#### 4.4.1.3 Firm Characteristics

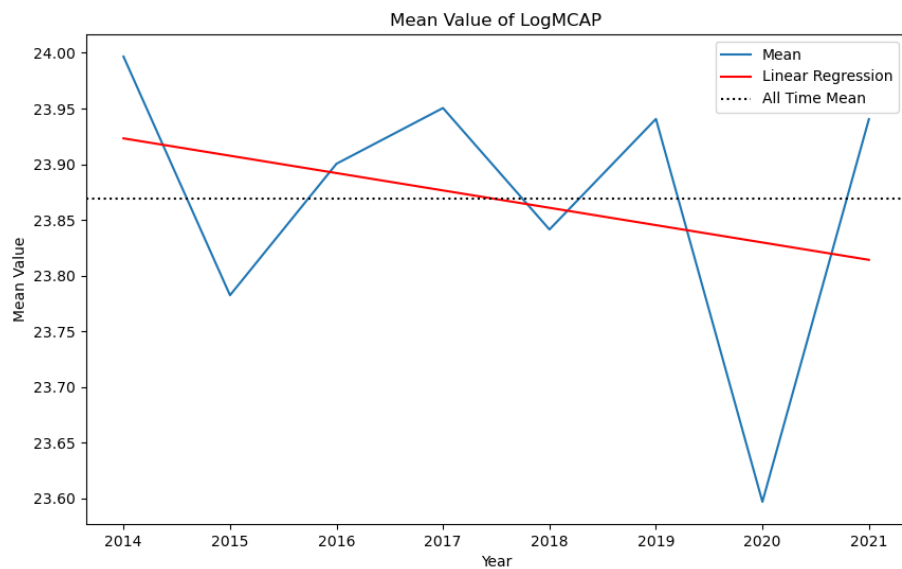


Figure 7: Mean Value of LogMCAP



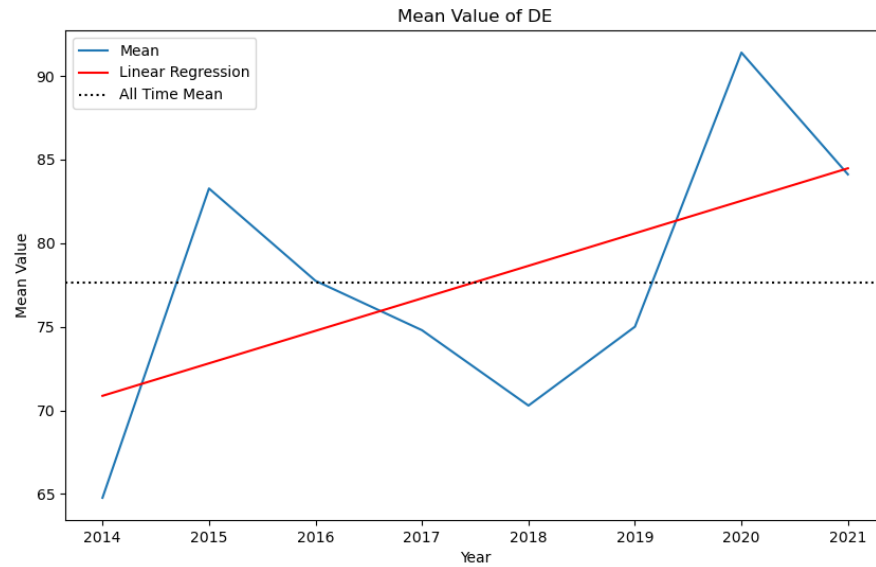


Figure 8: Mean Value of DE

The mean values of MCAP from 2014 to 2021 exhibit a fluctuating pattern with some notable increases and decreases. In 2015, there was a significant surge in MCAP, followed by a decrease in 2016. The values then showed a gradual increase from 2017 to 2020, with a step up in 2021.

The mean value of DE moves in a pattern opposite of financial performance and LogMCAP. The amount of leverage coincides with the crude oil price and the financial performance. When the value of equity shrinks, DE increases as equity is in the denominator of the DE equation.

#### 4.3.2 Descriptive Statistics

Table 1: Descriptive Statistics

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
<b>ROE</b>	633	0.2	24.6	-98.0	-5.2	6.4	13.0	40.8
<b>ROA</b>	633	0.1	9.5	-35.8	-2.5	2.5	5.4	15.2
<b>DE</b>	633	77.7	65.2	3.4	32.3	61.3	102.0	327.0
<b>LogMCAP</b>	633	23.9	2.8	18.9	21.9	23.5	25.6	30.2
<b>LogGHG</b>	633	14.8	2.2	10.0	13.3	15.4	16.4	18.2

Table 2: Skew and Kurtosis before Processing

Before	ROE	ROA	DE	MCAP	GHG	LogMCAP	LogGHG
<b>Skew</b>	7.5	-1.9	23.8	9.2	3.0	0.5	-0.8
<b>Kurtosis</b>	116.8	9.0	589.5	91.0	10.2	0.0	0.8

Table 3: Skew and Kurtosis after Processing

After	ROE	ROA	DE	MCAP	GHG	LogMCAP	LogGHG
<b>Skew</b>	2.0	-1.8	1.7	4.3	2.3	0.5	-0.5
<b>Kurtosis</b>	5.6	4.1	3.5	18.4	-1.0	-0.4	-0.5

#### 4.4.3 Correlations

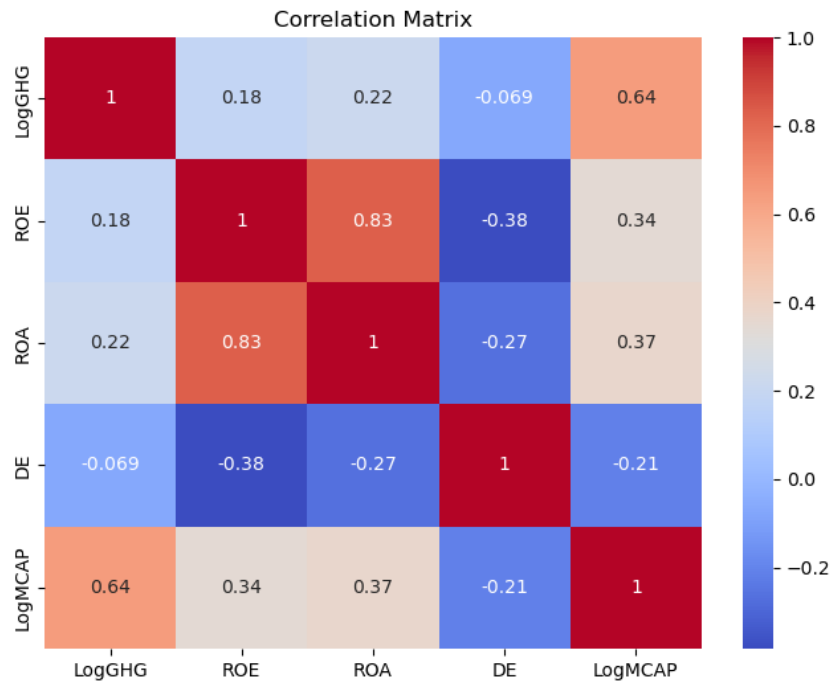


Figure 9: Correlation Matrix

There is a positive correlation between LogGHG and ROE. Similarly, there is a positive correlation between LogGHG and ROA. This positive relationship suggests that companies with higher GHG emissions tend to have higher ROE or ROA. This is in line with our hypothesis.

There is a positive correlation between LogMCAP and LogGHG emissions. This suggests that companies with larger market capitalization tend to have higher GHG

emissions, which is expected. The correlation between LogGHG and DE is close to zero.

There is a negative correlation of -0.38 between DE and ROE. This indicates a moderate negative relationship, suggesting that companies with higher leverage tend to have lower returns on equity. This is in line with Pedersen & Frazzini (2014). There is also a negative correlation of -0.27 between leverage and ROA. The correlation coefficient between LogMCAP and ROE is positive. Likewise, is the correlation between LogMCAP and ROA. This indicates a returns-to-scale effect.

The correlation coefficient between DE and LogMCAP is negative at -0.21.

#### 4.4.4 Sector

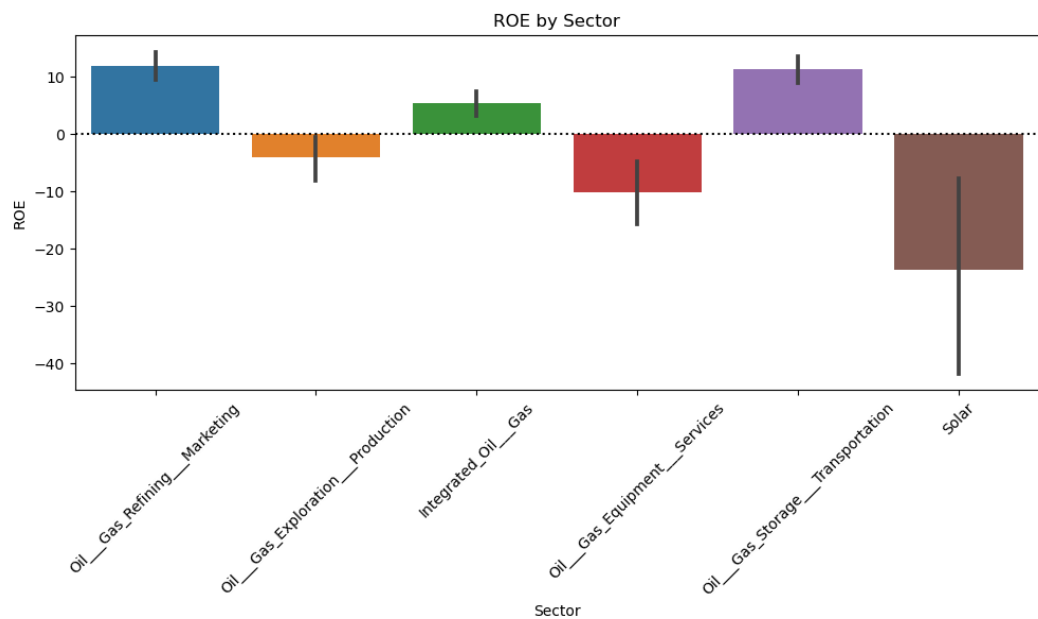


Figure 10: ROE by Sector

The 2014 oil crisis, characterized by a significant decline in oil prices, had a profound effect on the profitability of oil-related sectors. Oil and Gas Exploration and Production as well as Oil and Gas Equipment and Services sectors likely faced challenges due to lower oil prices, and cost pressures. The sectors Oil & Gas Refining & Marketing, Integrated Oil & Gas and Oil & Gas Storage & Transportation made on average positive returns on equity in the period. They also made positive returns on assets. Integrated oil and gas companies, which have

operations spanning upstream and downstream, may have benefited from diversification and the ability to optimize their operations across the value chain. Solar was the worst performing sector. High capital expenditure and low profit margins results in a low financial rate of return in photovoltaics manufacturing (Powell et al. 2015). Charts for the variables not shown here are in the Appendix.

#### 4.4.5 Country and GDP per Capita

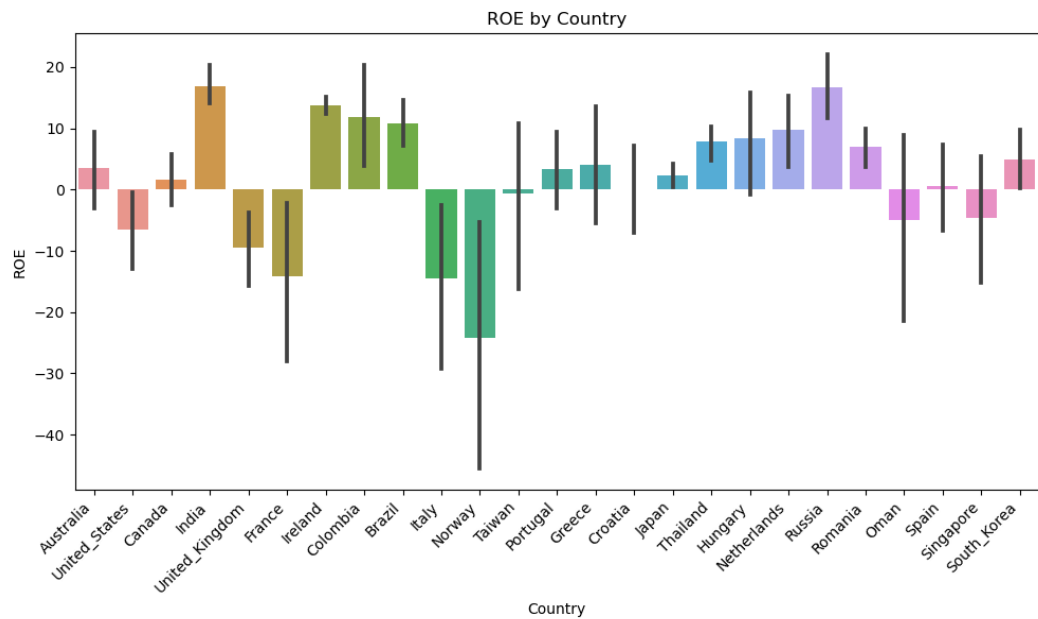


Figure 11: ROE by Country

We find it interesting that the countries that perform best over the period are India, Ireland, Colombia, Brazil, Thailand, Hungary, Netherlands and Russia. Countries that perform poorly are western countries, US, UK, France, Italy and Norway. We suspect a part of this can be explained by the unbalanced panel data. The explanation that Western countries prioritize investment in renewable energy while lower GDP per capita countries focus on oil and gas production is compelling. This is supported by research on renewable energy consumption and GDP per capita (Simionescu et al. (2019), Sadorsky (2009), Armenanu et al. (2017) and Ntanos et al. (2018)).

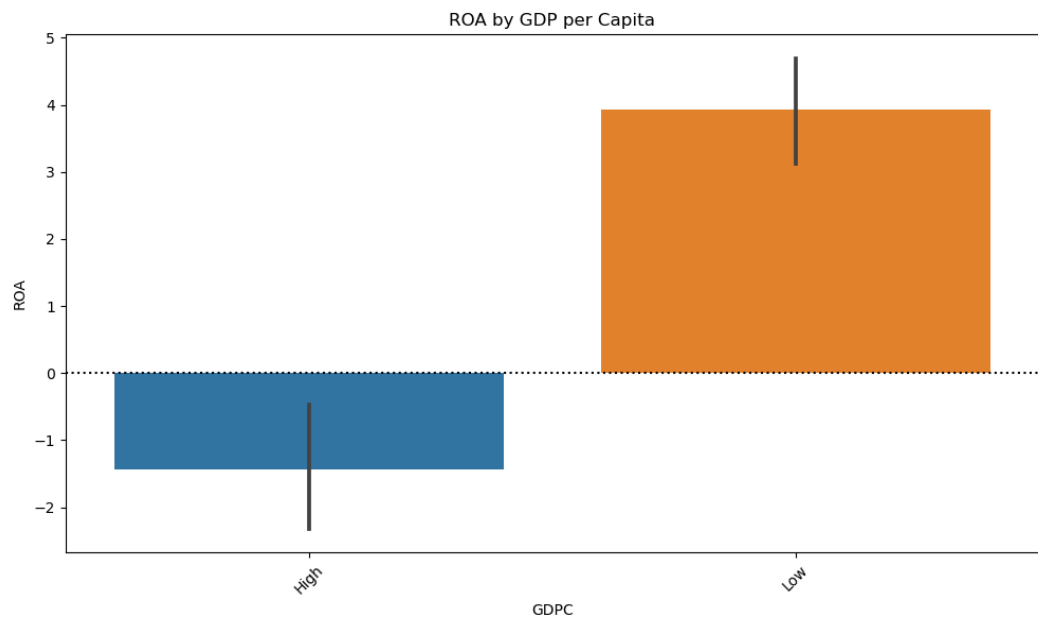


Figure 12: ROA by high and low GDP per Capita

Examining the average ROA of high and low GDPC countries, we find a notable difference. The average ROA for high income countries is -1.43, compared to 3.92 for countries with low income. We find similar results for ROE. LogGHG is 1.77 times higher for low-income countries. LogMCAP is 11 times higher for low-income countries. There are no notable differences in DE between high and low GDPC countries. Figures for the variables not shown here are available in the Appendix.

## 4.5 Sources of error

### 4.5.1 Noise in the correlation between ROE/ROA and GHG

Firms can vary a lot in GHG emissions without variations in profitability. An example is Genel Energy's abandonment of exploration wells in Africa and the exploration well at Miran in the Kurdistan Region of Iraq in 2015. The abandonment resulted in GHG emissions in 2015 of 1605tCO<sub>2</sub>, compared to 36284tCO<sub>2</sub> in 2014 (Genel Energy, 2015). Abandoning projects that have sizable emissions and no monetary return results in lower reported GHG emissions. ROE on the other hand can stay unchanged. ROA can in this scenario grow, as unproductive assets are sold. This creates noise.

#### 4.5.2 Error in Variables

The presence of measurement errors in the variables undermines the validity of statistical inferences drawn from the regression analysis. If the errors are non-random or systematic, they bias the coefficient estimates and lead to incorrect conclusions about the relationships between variables. Here we mention what measurement errors might be present in our analysis.

##### 4.5.2.1 ROE

Different companies may adopt different accounting methods, leading to inconsistencies in reported earnings, equity calculations and thereby ROE. Comparisons across companies or countries can be misleading if accounting practices vary significantly. We include a country variable in the regressions, but since the panel data is unbalanced, it might not capture the systematic differences.

##### 4.5.2.2 ROA

The accurate valuation of assets can be challenging, especially for complex or intangible assets. Inaccurate asset valuation can distort the calculation of ROA and affect comparisons between companies. Different depreciation methods can lead to variations in asset values over time, impacting the ROA calculation. Inconsistent or inaccurate depreciation estimates can introduce measurement errors when analyzing profitability and asset utilization. Comparisons across companies or countries can be misleading if asset calculations vary significantly and be a source of measurement error.

##### 4.5.2.3 GHG

Gathering comprehensive data on emissions sources within a company's operations can be complex. Incomplete or inaccurate data collection can lead to underestimations or overestimations of GHG emissions, compromising the accuracy of environmental impact assessments. Converting activity data (e.g., energy consumption) into GHG emissions requires accurate conversion factors. Inappropriate or outdated conversion factors can introduce measurement errors when estimating emissions. The GHG emissions is a best estimate and may lead to some error when comparing companies and countries.

#### 4.5.2.4 DE

Complex financial instruments, such as hybrid securities or derivative contracts, can have complex features that make their measurement and classification challenging. Determining the appropriate debt or equity treatment for these instruments may involve subjective judgments, increasing the risk of measurement errors. The possibility of off-balance sheet debt and financing introduces uncertainty in the real debt level of the firms.

#### 4.5.2.5 MCAP

Market cap is influenced by stock prices, which can fluctuate significantly due to market conditions and investor sentiment. It is common knowledge that market prices sometimes emotes irrational exuberance and other times crashes far below the value of the firm's assets. The analysis can be impacted if the effect of the stock market does not uniformly affect all firms or if it is not adequately captured by the country or sector variable.

#### 4.5.2.6 Country

With only a few companies in certain countries, the dummy variable may not capture the full range of country-specific characteristics or variations in the business environment. As a result, the effectiveness of the dummy variable in distinguishing between countries may be limited. The limited sample size for some countries may lead to less precise coefficient estimates and wider confidence intervals, making it more challenging to detect significant effects or draw robust conclusions. If the companies within a country are not representative of the broader business landscape or if certain countries are over- or under-represented, it may introduce biases in the analysis and compromise the generalizability of the findings. With limited data for some countries, the estimated coefficients may be influenced by a small number of observations and may not provide a comprehensive understanding of the true effects of those countries on the dependent variable.

#### 4.5.2.7 Instrumental Variable

Instrumental variables (IV) are used in regression analysis to address endogeneity, which occurs when the independent variable of interest may be correlated with the error term, which can lead to biased and inconsistent estimates. We tried fitting

several IV's but found no valid results. We tried using EU Emission Trading System (EU ETS) credits, new electric vehicle sales, created a proxy for emissions taxes globally and by country. None of the applied methods were significant, and thereby discarded.

#### 4.5.2.8 Oil Crises 2014

The oil crises of 2014 had a significant impact on energy companies and their investments in the following years. These crises were triggered by a combination of factors, including oversupply in the global oil market, geopolitical tensions, and slowing economic growth in key oil-consuming countries. The sharp decline in oil prices during the period led to financial strain and uncertainty in the energy industry. Energy companies, especially those heavily reliant on oil revenues, faced challenges in maintaining profitability and sustaining their investment activities (Stocker, Baffes, Vorisek, & Wheeler, 2018). The plummeting oil prices resulted in reduced cash flows and profitability for energy companies related to both their equity and assets, since assets are reliant on the oil prices. Particularly those engaged in exploration and production activities were affected. This financial strain forced energy companies to reassess their investment plans and make difficult decisions regarding capital expenditure (Stocker, Baffes, Vorisek, & Wheeler, 2018).

The oil crises in 2014 and the subsequent years can introduce potential errors in our regression analyses due to the impact on the dataset. When the dataset is heavily influenced by a specific event or period, such as the oil crises, it can lead to biases and distortions in the regression results. An example of an issue is the presence of outlier observations. The extreme fluctuations in oil prices during the timeframe can create outliers in the data, which may disproportionately affect the estimated relationships in the regression analysis. These outliers can distort the coefficients and statistical significance of the variables under investigation, potentially leading to inaccurate conclusions.



## 5. Results

### 5.1 Tests

#### 5.1.1 Durbin-Watson – Autocorrelation

The Durbin-Watson-Test will have an output between 0 – 4. The mean, 2, would indicate that there is no autocorrelation identified, 0 – 2 means positive autocorrelation (the nearer to zero the higher the correlation), and 2 – 4 means negative autocorrelation (the nearer to four the higher the correlation). If there is autocorrelation a FE-model will be more suitable. There is no significant autocorrelation present in the residuals of the models. Results in Table 4 below.

*Table 4: Durbin-Watson Test Results*

Durbin-Watson Results	ROE	ROA
<b>Country</b>	2	1.76
<b>GDPC</b>	1.89	1.73

## 5.2 Regression Results

Model Comparison				
	Model 0	Model 1	Model 2	Model 3
Dep. Variable	ROE	ROE	ROE	ROE
Estimator	PooledOLS	PanelOLS	PanelOLS	PanelOLS
No. Observations	633	633	633	633
Cov. Est.	Unadjusted	Unadjusted	Unadjusted	Unadjusted
R-squared	0.3847	0.3960	0.2972	0.2648
R-Squared (Within)	0.2515	0.2407	0.2972	0.2919
R-Squared (Between)	0.6825	0.7038	-4.7325	-2.1614
R-Squared (Overall)	0.3847	0.3833	-1.2171	-0.4463
F-statistic	11.725	12.152	77.538	64.909
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000
const	-111.52 (-5.1115)	-93.084 (-4.4866)	-281.85 (-6.1131)	-200.42 (-4.3855)
LogGHG	-0.4464 (-0.5547)	-0.0305 (-0.0399)	-0.7106 (-0.7410)	-0.5125 (-0.5599)
LogMCAP	5.1751 (4.7887)	4.1716 (4.0472)	12.923 (6.7914)	9.3739 (4.9414)
DE	-0.1491 (-9.9903)	-0.1441 (-10.156)	-0.2050 (-11.205)	-0.2003 (-11.404)
Sector.Oil__Gas_Equipment__Services	6.6954 (1.5902)	5.2328 (1.3144)		
Sector.Oil__Gas_Exploration__Production	6.4693 (1.7923)	4.5322 (1.3263)		
Sector.Oil__Gas_Refining__Marketing	18.985 (4.4604)	17.697 (4.3998)		
Sector.Oil__Gas_Storage__Transportation	10.637 (2.2030)	10.056 (2.2046)		
Sector.Solar	2.9689 (0.4421)	0.1170 (0.0184)		
Country.Brazil	15.996 (2.9384)	15.003 (3.0739)		
Country.Canada	6.1525 (1.4492)	5.3856 (1.3434)		
Country.Colombia	-12.817 (-1.2458)	-8.0354 (-0.8247)		
Country.Croatia	7.2939 (0.8411)	4.9340 (0.6023)		
Country.France	-1.8661 (-0.2814)	-3.3082 (-0.5283)		
Country.Greece	14.869 (1.7172)	12.018 (1.4686)		
Country.Hungary	-12.395 (-1.3688)	-9.3715 (-1.0945)		
Country.India	-8.7598 (-1.2842)	-5.2847 (-0.8178)		
Country.Ireland	11.017 (1.2563)	10.971 (1.3248)		
Country.Italy	-5.2020 (-0.7864)	-6.5959 (-1.0557)		
Country.Japan	-21.685 (-2.7481)	-16.979 (-2.2696)		
Country.Netherlands	26.531 (4.4381)	24.735 (4.3792)		
Country.Norway	-6.0666 (-0.8709)	-7.2833 (-1.1071)		
Country.Oman	30.874 (3.3912)	27.164 (3.1554)		
Country.Portugal	13.505 (1.5093)	11.503 (1.4332)		
Country.Romania	3.6635 (0.4381)	2.4963 (0.3162)		
Country.Russia	-4.0745 (-0.5271)	-0.8602 (-0.1176)		
Country.Singapore	12.704 (1.4845)	11.887 (1.4711)		
Country.South_Korea	-39.862 (-4.1874)	-33.991 (-3.7653)		
Country.Spain	5.8301 (0.6940)	3.9448 (0.4972)		
Country.Taiwan	-19.620 (-2.5490)	-17.419 (-2.3949)		
Country.Thailand	-11.593 (-1.9653)	-9.2559 (-1.6588)		
Country.United_Kingdom	2.6461 (0.5725)	1.6591 (0.3801)		
Country.United_States	-6.1606 (-1.4600)	-6.1046 (-1.5326)		
Effects		Time	Entity	Entity Time

T-stats reported in parentheses

Figure 13: Regression Results, ROE

Model Comparison				
	Model 0	Model 1	Model 2	Model 3
Dep. Variable	ROA	ROA	ROA	ROA
Estimator	PooledOLS	PanelOLS	PanelOLS	PanelOLS
No. Observations	633	633	633	633
Cov. Est.	Unadjusted	Unadjusted	Unadjusted	Unadjusted
R-squared	0.3091	0.3216	0.2260	0.1688
R-Squared (Within)	0.1600	0.1468	0.2260	0.2180
R-Squared (Between)	0.6337	0.6571	-11.349	-6.3871
R-Squared (Overall)	0.3091	0.3069	-3.3534	-1.8236
F-statistic	8.3876	8.7855	53.542	36.769
P-value (F-stat)	0.0000	0.0000	0.0000	0.0000
const	-60.723 (-6.8104)	-52.257 (-6.2919)	-177.90 (-9.5943)	-140.61 (-7.8127)
LogGHG	-0.5495 (-1.6709)	-0.3591 (-1.1735)	-0.2062 (-0.5347)	-0.1057 (-0.2933)
LogMCAP	2.9516 (6.6832)	2.4912 (6.0373)	7.6947 (10.055)	6.0599 (8.1116)
DE	-0.0299 (-4.9033)	-0.0273 (-4.8008)	-0.0333 (-4.5305)	-0.0302 (-4.3652)
Sector.Oil__Gas_Equipment__Services	4.3459 (2.5258)	3.6564 (2.2943)		
Sector.Oil__Gas_Exploration__Production	3.2044 (2.1724)	2.3038 (1.6841)		
Sector.Oil__Gas_Refining__Marketing	7.5431 (4.3366)	6.9423 (4.3115)		
Sector.Oil__Gas_Storage__Transportation	2.9286 (1.4842)	2.6235 (1.4367)		
Sector.Solar	3.4030 (1.2401)	2.0715 (0.8149)		
Country.Brazil	3.9915 (1.7942)	3.8723 (1.8815)		
Country.Canada	1.7818 (1.0270)	1.4220 (0.8860)		
Country.Colombia	-12.331 (-2.9332)	-10.165 (-2.6062)		
Country.Croatia	4.2429 (1.1973)	3.1531 (0.9615)		
Country.France	-1.4065 (-0.5191)	-2.0932 (-0.8349)		
Country.Greece	4.2795 (1.2094)	2.9348 (0.8959)		
Country.Hungary	-8.8184 (-2.3831)	-7.4421 (-2.1712)		
Country.India	-9.9254 (-3.5605)	-8.3582 (-3.2309)		
Country.Ireland	0.5394 (0.1505)	0.4942 (0.1491)		
Country.Italy	-2.2522 (-0.8331)	-2.9125 (-1.1645)		
Country.Japan	-11.998 (-3.7207)	-9.8350 (-3.2839)		
Country.Netherlands	4.1963 (1.7177)	3.3567 (1.4845)		
Country.Norway	-3.2539 (-1.1430)	-3.8376 (-1.4571)		
Country.Oman	11.531 (3.0994)	9.7951 (2.8423)		
Country.Portugal	4.7130 (1.3573)	3.7722 (1.1741)		
Country.Romania	4.2837 (1.2535)	3.7485 (1.1860)		
Country.Russia	-5.6236 (-1.7801)	-4.1669 (-1.4228)		
Country.Singapore	0.8233 (0.2354)	0.4218 (0.1304)		
Country.South_Korea	-22.884 (-5.8825)	-20.203 (-5.5903)		
Country.Spain	2.1425 (0.6240)	1.2610 (0.3970)		
Country.Taiwan	-8.8507 (-2.8130)	-7.8672 (-2.7019)		
Country.Thailand	-7.5836 (-3.1460)	-6.5226 (-2.9200)		
Country.United_Kingdom	-1.3962 (-0.7392)	-1.8654 (-1.0674)		
Country.United_States	-3.7391 (-2.1685)	-3.7233 (-2.3350)		
Effects		Time	Entity	Entity Time

T-stats reported in parentheses

Figure 14: Regression Results, ROA

Model Comparison		
	Model 0	Model 1
Dep. Variable	ROE	ROE
Estimator	PooledOLS	PanelOLS
No. Observations	633	633
Cov. Est.	Unadjusted	Unadjusted
R-squared	0.3042	0.3153
R-Squared (Within)	0.2173	0.2095
R-Squared (Between)	0.5081	0.5237
R-Squared (Overall)	0.3042	0.3035
F-statistic	30.259	31.521
P-value (F-stat)	0.0000	0.0000
const	-19.883 (-1.7826)	-17.448 (-1.6545)
LogGHG	0.2097 (0.3535)	0.2827 (0.5034)
LogMCAP	1.0259 (2.1786)	0.8674 (1.9459)
DE	-0.1518 (-10.852)	-0.1436 (-10.781)
Sector.Oil__Gas_Equipment__Services	1.4014 (0.3833)	0.5443 (0.1574)
Sector.Oil__Gas_Exploration__Production	-0.6472 (-0.2388)	-1.0718 (-0.4184)
Sector.Oil__Gas_Refining__Marketing	9.9364 (3.5807)	9.9125 (3.7788)
Sector.Oil__Gas_Storage__Transportation	21.103 (4.8007)	19.995 (4.8088)
Sector.Solar	-18.439 (-3.5241)	-19.491 (-3.9405)
GDPC.Low	8.1739 (3.7686)	8.1594 (3.9806)
Effects		Time

T-stats reported in parentheses

Figure 15: Regression Results, ROE & GDPC

Model Comparison		
	Model 0	Model 1
Dep. Variable	ROA	ROA
Estimator	PooledOLS	PanelOLS
No. Observations	633	633
Cov. Est.	Unadjusted	Unadjusted
R-squared	0.2340	0.2488
R-Squared (Within)	0.1019	0.0958
R-Squared (Between)	0.5281	0.5384
R-Squared (Overall)	0.2340	0.2328
F-statistic	21.140	22.671
P-value (F-stat)	0.0000	0.0000
const	-17.134 (-3.7965)	-16.037 (-3.8438)
LogGHG	0.2069 (0.8621)	0.2430 (1.0938)
LogMCAP	0.6474 (3.3976)	0.5734 (3.2514)
DE	-0.0393 (-6.9384)	-0.0353 (-6.6909)
Sector.Oil__Gas_Equipment__Services	1.5740 (1.0640)	1.1686 (0.8541)
Sector.Oil__Gas_Exploration__Production	-9.394e-05 (-8.568e-05)	-0.1980 (-0.1953)
Sector.Oil__Gas_Refining__Marketing	2.7852 (2.4805)	2.7700 (2.6690)
Sector.Oil__Gas_Storage__Transportation	6.7839 (3.8140)	6.2414 (3.7940)
Sector.Solar	-4.6227 (-2.1836)	-5.1305 (-2.6216)
GDPC.Low	3.3811 (3.8527)	3.3671 (4.1519)
Effects		Time

T-stats reported in parentheses

Figure 16: Regression Results, ROE and GDPC

Model Comparison		
	Model 0	Model 1
Dep. Variable	ROA	ROE
Estimator	FirstDifferenceOLS	FirstDifferenceOLS
No. Observations	550	550
Cov. Est.	Unadjusted	Unadjusted
R-squared	0.2776	0.3422
R-Squared (Within)	0.1861	0.2354
R-Squared (Between)	-2359.3	-1455.4
R-Squared (Overall)	-735.06	-441.11
F-statistic	70.075	94.868
P-value (F-stat)	0.0000	0.0000
LogGHG	-0.0807 (-0.2224)	-0.0879 (-0.0945)
LogMCAP	10.936 (11.332)	22.451 (9.0790)
DE	-0.0463 (-4.7286)	-0.2602 (-10.364)

T-stats reported in parentheses

Figure 17: First Differences Regression Results, ROE and ROA

We perform 14 regressions, seven for each dependent variable. The independent variables are GHG, DE, MCAP, Sector and Country or GDPC. Here we present the results and statistical significance of each variable. We then discuss the explanatory power of the regressions. As mentioned in the methodology section, we utilize a five-percentile level of significance. The FE models mentioned in connection with Sector or GDPC control for time-invariant effects.

### 5.2.1 Environmental performance

The variable LogGHG does not exhibit statistical significance in any of the regressions at the predetermined significance level of 5 percent. Nonetheless, it is noteworthy that LogGHG demonstrates statistical significance at a 10 percent level specifically in the POLS regression when assessing its impact on ROA. In this case, the coefficient for LogGHG is observed to be negative at -0.5495.

### 5.2.2 Firm Characteristics

The variable LogMCAP consistently demonstrates statistical significance across all regressions, with one exception. In the regression including ROE and GDPC, LogMCAP is significant at 5.21 percent. The beta coefficients associated with LogMCAP are positive for both ROA and ROE. Notably, the beta values for LogMCAP in the FE models that incorporate entity effects, ranging from 6 to 13, are larger compared to the POLS models, ranging from 2.5 to 5.2. Furthermore, the

beta value of LogMCAP is also greater for ROE compared to ROA. The influence of LogMCAP on financial return is significantly lower in the regressions including GDPC. Here, the coefficients for regressions on ROE are 1.0259 (POLS) and 0.8674 (FE). Similarly for ROA, 0.6474 (POLS) and 0.5734 (FE).

DE is negatively correlated with both ROE and ROA in all regressions, with statistical significance. However, the effect is small. For ROE, the beta value of DE is between -0.046 and -0.2. Similarly, for ROA the beta value for DE lies between -0.027 and -0.046. The effect of DE in the regressions including GDPC as independent variable is also mildly negative, close to zero, and significant.

### 5.2.3 Sector

The sector of Oil & Gas Refining & Marketing exhibits statistically significant results across all regressions, demonstrating a positive correlation with both ROE and ROA. Conversely, the Solar sector does not show statistical significance in any of the regressions. The significance of the remaining sectors varies.

In terms of ROE, both the POLS and the FE regression models exhibit comparable results concerning statistical significance and beta coefficients for the sector variable. They find Oil & Gas Refining & Marketing significant, with coefficients of 18.985 (POLS) and 17.697 (FE). Oil & Gas Storage and Transportation is also found to be significant, with coefficients 10.637 (POLS) and 10.056 (FE). The remaining variables are not found statistically significant.

For ROA, Oil & Gas Equipment & Services is found statistically significant in both the POLS and the FE models. The coefficients are 4.3459 (POLS) and 3.6564 (FE). Oil & Gas Exploration and Production is statistically significant in the POLS regression with a beta coefficient of 3.2044, but not the FE regression. Finally, Oil & Gas Refining & Marketing is statistically significant for both POLS and FE models, with beta coefficients 7.5431 (POLS) and 6.9423 (FE).

### 5.2.4 Country and GDP per Capita

In terms of countries, the POLS model and the FE model agree on the effects on ROE, with one exception. The models find positive effects from Brazil (15.99 POLS, 15.803 FE), Netherlands (26.531 POLS, 24.735 FE), and Oman (30.874

POLS, 27.164 FE). They find negative effects from Japan (-21.685 POLS, -16.979 FE), South Korea (-39.862 POLS, -33.991 FE), and Taiwan (-19.62 POLS, -17.419 FE). Only the POLS model finds Thailand (-11.593) statistically significant.

The models with ROA as the dependent variable agree on Japan (-11.998 POLS, -9.835FE), Oman (11.531 POLS, 9.7951 FE), South Korea (-22.884 POLS, -20.203 FE), and Taiwan (-8.8507 POLS, -7.8672 FE). POLS and FE models also find Thailand (-7.5836 POLS, -6.5226 FE) significant. Here, Oman is the only country with positive beta coefficient. Colombia (-12.331 POLS, -10.165 FE), Hungary (-8.8184 POLS, -7.4421 FE), India (-9.9254 POLS, -8.3582 FE), and the United States (-3.7391 POLS, -3.7233 FE) are statistically significant, and all with negative beta coefficients.

GDPC is significant in all regressions where the variable is included. For ROE, the beta coefficient is 8.1739 (POLS) and 8.1594 (FE). The beta coefficients for the models with ROA as the dependent variable are lower, at 3.3811 (POLS) and 3.3671 (FE).

#### 5.2.5 R-Squared and F-statistic

R-squared is between 0.17 and 0.4. This suggests that the independent variables in the regressions can explain between 17% and 40% of the variance in the dependent variable. The resulting F-statistics lie between 8.4 and 77.5. The pooled effect of the independent variables on ROE and ROA is significantly different from zero in all models.

## 6. Discussion

In our research we find no causal relationship between financial returns and greenhouse gas (GHG) emissions. This coincides with the studies by Fogler & Nutt (1975), Rockness et al. (1986), and Spicer (1978). Depending on the model specification, we find market capitalization and high or low GDP per capita to be better indicators of financial return.

Our results indicate that it is possible to reduce carbon emissions without impacting financial return. Following the theory of Ernhart & Lizal (2007), our results can be explained by the cost of reducing emissions offsetting the positive effects of

reducing costs. This results in zero net change in financial return. This resonates with the notion that environmental stewardship and financial success are not mutually exclusive. However, investing in any project occupies time and resources. This leads profit-seeking firms to invest in other positive net present value projects.

We find market capitalization to be an important factor in determining financial return. This has multiple explanations. Larger companies often possess greater resources, knowledge, and experience compared to smaller counterparts. This enables them to implement efficient strategies, leverage economies of scale, and access a wider range of markets and opportunities. These advantages can lead to improved profitability and, consequently, a higher ROE. Larger companies tend to have more robust research and development capabilities, allowing them to invest in innovation and stay ahead of the competition. Innovations can lead to the development of new products or services, enhanced operational efficiencies, or disruptive business models. The size of a company provides it with bargaining power and influence over its suppliers and customers. Larger companies can negotiate favorable terms, bulk discounts, or exclusive agreements, resulting in lower input costs and increased revenues. Larger companies may benefit from economies of scale, which arise from spreading fixed costs over a larger production or customer base. As a result, their average costs per unit decrease, leading to higher profit margins. These are all possible explanations, but the results can also be interpreted as an instance of omitted variable bias. When including high or low GDP per capita in the model, market capitalization loses its explanatory power, the beta coefficient drops substantially. The market capitalization of firms in low GDP per capita countries is 11 times bigger than in high GDP per capita countries. This leads the market capitalization variable to incorrectly capture information in the financial return variable that is attributable to high or low GDP per capita.

We find GDP per capita to be a significant indicator of financial return. Our results show that companies from low GDP per capita countries have higher ROE and ROA. On average, ROA in the group of high GDP per capita countries is -1.43, compared to 3.92 for the low group. We find companies from low GDP per capita countries emit 1.77 times more greenhouse gases. In this instance, GDP per capita connects both financial return and greenhouse gas emissions. This indicates a difference in firm investment and behavior between the groups. We know that high



GDP per capita companies invest more in renewable energy sources, which today is not a profitable endeavor (Simionescu et al. (2019), Sadorsky (2009), Armenanu et al. (2017) and Ntanos et al. (2018) and Powell et al. (2015)). Our results show that the Solar sector contributes negatively to financial return, though the significance of this result suffers from a small sample size in the sector. This points to the investment in renewable energy and projects with lower greenhouse gas emissions as the source of lower profitability in high GDP per capita countries.

The increase in productivity is conditional on the implementation approach of the firm (Nishitani et al., 2011). Our findings indicate that firms can effectively lower emissions without compromising their financial returns, suggesting that firms operating in high GDP per capita countries are adopting inefficient investment strategies in renewable energy. This leads us to two ways of implementing emission reducing solutions. The first one is to invest for a gain in efficiency. The second way is any of the following: leverage in-house expertise from decades in the oil business to produce renewable energy, operate as venture capital, or build a fully integrated renewable energy business. Our research leads us to believe high income countries are following the second investment philosophy, leading to financial loss. We find three possible explanations.

First, it is due to the regulatory environment. Regulatory frameworks and policies differ between high and low GDP per capita countries. Stricter regulation in high GDP per capita countries set boundaries for what investments they can make and demand more investment in renewable energy. This includes the adherence to emission trading schemes, guiding the investment decisions of the companies. The regulatory powers in lower GDP per capita countries have a lower budget and a population that strives for a higher standard of life. Different objective functions between the groups leads to serious ethical issues that must be discussed as part of the energy transition. Energy is life. Low-income countries want to produce as much energy as possible, to grow and prosper. Substituting the current energy sources with less efficient renewable energy is not aligned with this goal. This points to the widely different points of departure for high- and low-income countries on the road to sustainability. High GDP per capita countries can afford to make the high cost, necessary investments in renewable energy sources, and must work adamantly to help lower income countries through the transitions of energy sources

and quality of life. We currently see the growth of Malthusian environmentalism, the thought of demanding stagnant or declining prosperity to save the globe. We find it ethically challenging to deny groups of people a better standard of living. For example, the growing middle class in India will demand more energy when moving out of poverty. The share of the Indian middle class is set to grow from 31% in 2021 to 63% by 2047 (People Research on India's Consumer Economy, 2021). We face the challenge of a growing need for energy, combined with climate considerations. The prosperity of people must be a consideration and element in the plan to reach the climate goals. The balancing act between the future and current prosperity of the population became evident in the 2022-2023 energy crises. High income countries deviated from their climate goals; Germany turned to burning coal at the first sign of discomfort (Pladson, 2022). The crises led to a newfound global focus on energy security. The sudden shortage of energy trumped sustainability goals, exemplified by Pakistan's retreat to coal (Peshimam, 2023).

Second, it is possible that investments in emission reduction activities lead to superior financial performance with a delay (Cucchiella, 2017). Investing in renewable energy is costly but can provide future returns with advancements in technology, lowering costs. Securing technology and patents is a hedge against future regulations and changes. Therefore, even though the GHG emission variable did not show statistical significance in the regressions, it is worth considering the long-term benefits and potential future returns associated with emission reduction activities. Using energy as a unit of currency, energy return on energy investment (EROI) shows viability for renewable energies in the future. Today, the EROI of oil is approximately 30 and for wind and solar approximately 10. The EROI of oil liquids is expected to decrease to 6.7 in 2050 (Delannoy, Longaretti, Murphy, & Prados, 2021). This makes renewable energy worthwhile in terms of EROI in the future, making it sensible to invest in technology today. Our results show different willingness to accommodate the risk of future regulations and different beliefs about the future of energy between the groups.

Third, Lee et al. (2015) point to market demand and investor preferences as an explanation. Differences in renewable energy investment in high- or low-income countries can be due to a difference in investor preference when investing in the groups. Foreign direct investors prefer large cap companies when investing in India

(Chhimwal, Bapat, & Sarthak, 2020). This shows that investors prefer security, they have lower risk tolerance when investing abroad. Risk is directly connected with information (Hicks, 2023). There is more corruption and less adherence to Rule of Law in lower GDP per capita countries (Bhagat & Michael, 2020), which mean investors have lower certainty of the correctness of the information they receive. Foreign investors have lower access to information leading them to prefer financially stable, large capitalization companies, when investing in lower income countries. Less sophisticated forms of greenwashing may be declining due to increased stakeholder vigilance (Bowen & Aragon-Correa, 2014). Firms in high-income countries invest in projects that are visible to investors as a form of greenwashing. These projects are not good financially, but they are chosen because of their visibility. That means high-income firms invest in renewable energy instead to making investments in efficiency and better resource management. As the amount of sustainable and green funds grow, it is important to invest in visible projects to be considered for inclusion.

The sharp decline in oil prices during the crises put significant financial strain on the energy companies, forcing them to adopt cost-cutting measures and prioritize financial resilience, over new growth, and investments. This transformation may have profound implications for our research as it influenced the financial performance and decision-making of oil companies during this period. Another concern is the potential endogeneity issue, as the decline in oil prices may be influenced by multiple factors such as supply and demand dynamics and macroeconomic conditions. The transformation from a profitable operation to survival mode affected the relationship between emissions and financial performance. Since companies focused on immediate financial survival, the investment in emission reduction initiatives may have been deprioritized, leading to potential variations in the relationship between emissions and financial performance during the period with low oil prices. Therefore, it is important to consider this transformation and its impact on our research.

## 7. Conclusion

Sustainability is of ever-increasing importance to investors, understandably investors also want their investments to be financially profitable. We consider 80 energy companies during the period 2014-2021 and find no significant relation between financial return (ROE and ROA) and the amount of Scope 1 and Scope 2 emissions reported by the companies. This suggests it is possible to reduce carbon emissions without impacting financial performance. We divide between two methods of implementing emission reducing initiatives. The first is investing in increased productivity and efficiency. We explain the possibility to reduce greenhouse gas emission without affecting financial returns as zero NPV projects in resource management. The second approach includes all other types of initiatives.

High- and low-income (GDP per capita) countries have considerable different prospects for successfully reaching the globally accepted climate goals. Low-income countries have fewer financial resources and an additional challenge of a growing middle class. We find that companies from low-income countries have significantly better financial performance, higher greenhouse gas emissions and higher market capitalizations. The differences between the groups are explained by different objective functions in regulation, different willingness to carry risk and different beliefs about the future among the firms, and risk-aversion in foreign investors. The visibility of projects drives firms to invest in projects with negative profitability.

We address the ethical issues policymakers face and the need to find a balance between climate goals and the current and future prosperity of populations. Policy should support lower-income countries in their energy transitions, foster sustainable development, and develop resilient energy systems to ensure both environmental sustainability and energy security.

## 8. Future Research

Future research in the field can explore several avenues to expand and enhance the understanding of the relationship between emissions and financial performance in energy companies. It can delve deeper into examining the distribution of emissions and financial returns across different countries. By analyzing the variations in emissions intensity and financial performance metrics among countries, valuable insights can be gained regarding the effectiveness of different regulatory frameworks, policy incentives, and market conditions in shaping the emissions-financial performance nexus.

Including nuclear energy in the analysis can provide a more comprehensive perspective on the relationship between emissions and financial performance. Nuclear power is a significant source of low-carbon energy and understanding its impact on financial performance can contribute to the ongoing debate on the role of different energy sources in sustainable development. By incorporating nuclear energy data into the analysis, future research can explore its potential as a mitigating factor for emissions and its implications for financial returns in the energy sector.

Expanding the dataset to include more companies from various sectors and countries is another avenue for future research. As reporting and transparency around emissions and financial performance continue to improve, access to a larger and more diverse dataset becomes possible, especially if combining Bloomberg and Thomson Reuters Eikon Data. By encompassing a broader range of companies and countries, future research can achieve a more robust and representative analysis, capturing the nuances of emissions and financial performance across different industries and geographical contexts.

The recent energy crises that occurred between 2021 and 2023 had a significant impact on energy companies. These crises were characterized by a combination of factors such as supply chain disruptions, geopolitical tensions, and a surge in energy demand. The consequences of the crises were far-reaching, affecting various aspects of energy companies' operations, financial performance, and sustainability practices, and therefore it holds implications for future research.

The development of a significant instrument variable can address the endogeneity challenges faced in our research. By identifying a variable that is correlated with emissions but unrelated to financial performance, future research can discard the endogeneity bias, and establish a more robust causal relationship between emissions and financial outcomes.

## Bibliography

- Abu-Mostafa, Y. S., Magdon-Ismael, M., & Lin, H.-T. (2012). *Learning From Data*. ALMbook.com.
- Armeanu, D. S., Vintila, G., & Gherghina, S. C. (2017). Does Renewable Energy Drive Sustainable Economic Growth? Multivariate Panel Data Evidence for EU-28 Countries. *Energies*.
- Bhagat, S., & Michael, W. (2020). Economic Growth, Income Inequality, and the Rule of Law.
- Bowen, F., & Aragon-Correa, J. (2014). Greenwashing in Corporate Environmentalism Research and Practice: The Importance of What We Say and Do. *Sage Journals*.
- Bowers, B., & Ruediger, K. R. (2017). Key metrics for evaluating energy management in the US manufacturing sector. *Energy Efficiency*, 443-460.
- Brooks, C. (2014). *Introductory econometrics for finance (3rd ed)*. Cambridge University Press.
- Busch, T. (2011). How Hot Is Your Bottom Line? Linking Carbon and Financial Performance. *Business and Society*, 233-265.
- Callendar, G. (1938). The artificial production of carbon dioxide and its influence on temperature.
- Callendar, G. S. (April 1938). *The artificial production of carbon dioxide and its influence on temperature*. Quarterly Journal of the Royal Meteorological Society Volume 64, Issue 275 p. 223-240.
- Cameron, A. C., & Trivedi, P. K. (2013). *Regression analysis of count data (2nd ed.)*. Cambridge University Press.
- Cantore, N., Cali, M., & Willem te Velde, D. (2016). Does energy efficiency improve technological change and economic growth in developing countries? *Energy Policy*, 279-285.
- Capece, G., Pillo, F., Levialdi, N., & Miliacca, M. (2017). Examining the effect of managing GHG emissions on business performance. *Business Strategy and the Environment*, 1041-1060.
- Chhimwal, B., Bapat, V., & Sarthak, G. (2020). Investors' preferences and the factors affecting investment in the Indian stock market: an industry view. *Managerial Finance*, 723-744.
- Climate Action 100+. (2023, January 25). *Climate Action 100+*. Retrieved from climateaction100.org: <https://www.climateaction100.org/about/>
- Cucchiella, F., Gastaldi, M., & Miliacca, M. (2017). The management of greenhouse gas emissions and its effects on firm performance. *Journal of Cleaner Production*, 1387-1400.
- Delannoy, L., Longaretti, P.-Y., Murphy, D. J., & Prados, E. (2021). Peak oil and the low-carbon energy transition: A net-energy perspective. *Applied Energy*.

- Earnhart, D., & Lizal, L. (2007). Effect of pollution control on corporate financial performance in a transition economy. *Environmental Policy and Governance*, 247-266.
- Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 3-56.
- Genel Energy. (2015). *Genel Energy 2015 Annual Report*. Retrieved from genelenergy.com: <https://genelenergy.com/wp-content/uploads/2020/07/genel-energy-2015-annual-report-final.pdf>
- Gujarti, D. N. (2009). *Basic econometrics (5th ed)*. McGraw-Hill.
- Hart, S., & Ahuja, G. (1996). DOES IT PAY TO BE GREEN? AN EMPIRICAL EXAMINATION OF THE RELATIONSHIP BETWEEN EMISSION REDUCTION AND FIRM PERFORMANCE. *Business Strategy and the Environment*.
- Hicks, A. (2023). Risky (information) business: An informational risk research agenda. *Journal of Documentation*.
- Johnston, J., & DiNardo, J. (1997). *Econometric methods (4th ed.)*. McGraw-Hill.
- Keene, O. N. (1995). The Log Transformation is Special. *Statistics in Medicine*, 811-819.
- Kennedy, P. (2008). *A guide to econometrics (6th ed.)*. Blackwell Publishing.
- Lee, K.-H., Min, B., & Yook, K.-H. (2015). The impacts of carbon (CO<sub>2</sub>) emissions and environmental research and development (R&D) investment on firm performance. *International Journal of Production Economics*, 1-11.
- Lewandowski, S. (2017). Corporate Carbon and Financial Performance: The Role of Emission Reductions. *Business Strategy and the Environment*, 1196-1211.
- Matsumura, E. M., Prakash, R., & Vera-Munzo, S. C. (2014). Firm-Value Effects of Carbon Emissions and Carbon Disclosures. *The Accounting Review*, 695-724.
- Modi, S. B., & Mishra, S. (2011). What drives financial performance—resource efficiency or resource slack? *Journal of Operations Management*.
- Mummolo, J., & Peterson, E. (2018). Improving the Interpretation of Fixed Effects. *Political Science Research and Methods*, 829-835.
- Nishitani, K., Kaneko, S., Fujii, H., & Komatsu, S. (2011). Effects of the reduction of pollution emissions on the economic performance of firms: an empirical analysis focusing on demand and productivity. *Journal of Cleaner Production*, 1956-1964.
- Ntanos, S., Skordoulis, M., Kyriakopoulos, G., Arabatzis, G., Chalikias, M., Galatsidas, S., . . . Katsarou, A. (2018). Renewable Energy and Economic Growth: Evidence. *Sustainability*.
- Nutt, F., & Fogler, R. H. (1975). A Note on Social Responsibility and Stock Valuation. *The Academy of Management Journal*, 155-160.
- Olsen, Ø., & Tangen, N. (2021). *Work on climate risk in the Government Pension Fund Global*. Oslo: Norges Bank.
- Pedersen, L. H., & Frazzini, A. (2014). Betting Against Beta. *Journal of Financial Economics*, 1-25.
- People Research on India's Consumer Economy. (2021). *Household level view of India's Consumer Economy & India's Citizen Environment*. ice360.
- Peshimam, G. N. (2023, 2 14). *Exclusive: Pakistan plans to quadruple domestic coal-fired power, move away from gas*. Retrieved from reuters.com: <https://www.reuters.com/business/energy/pakistan-plans-quadruple-domestic-coal-fired-power-move-away-gas-2023-02-13/>

- Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches. *The Review of Financial Studies*, 435-480.
- Pladson, K. (2022, 12 29). *Lützerath: How Germany's energy crisis reignited coal*. Retrieved from dw.com: <https://www.dw.com/en/1%C3%BCtzerath-how-germanys-energy-crisis-reignited-coal/a-64203214>
- Powell, D. M., Fu, R., Horowitz, K., Basore, P. A., Woodhouse, M., & Buonassisi, T. (2015). The capital intensity of photovoltaics manufacturing: barrier to scale and opportunity for innovation. *Energy Environ. Sci.*, 3395-3408.
- Rice, J. A. (2007). *Mathematical Statistics and Data Analysis*. Cengage Learning.
- Rockness, J., Schlachter, P., & Howard, R. O. (1986). Hazardous waste disposal, corporate disclosure, and financial performance in the chemical industry. *Advances in Public Interest Accounting*, 167-191.
- Russo, M., & Fouts, P. (1997). A Resource-Based Perspective on Corporate Environmental Performance and Profitability. *The Academy of Management Journal*, 534-559.
- Sachs, J., Lafortune, G., Fuller, C., & Woelm, F. (2022). From Crisis to Sustainable Development: the SDGs as Roadmap to 2030 and Beyond.
- Sadorsky, P. (2009). Renewable energy consumption and income in emerging economies. *Energy Policy*, 4021-4028.
- Sheppard, K. (2023, May 24). *linearmodels 5.0*. Retrieved from pypi.org: <https://pypi.org/project/linearmodels/5.0/>
- Sheppard, K. (2023, May 24). *linearmodels.panel.model.PanelOLS*. Retrieved from linearmodels 5.0: [https://bashtage.github.io/linearmodels/panel/panel/linearmodels.panel.model.PanelOLS.html#linearmodels.panel.model.PanelOLS.\\_\\_init\\_\\_.check\\_rank](https://bashtage.github.io/linearmodels/panel/panel/linearmodels.panel.model.PanelOLS.html#linearmodels.panel.model.PanelOLS.__init__.check_rank)
- Simionescu, M., Bilan, Y., Krajčůňková, E., Streimikiene, D., & Gedek, S. (2019). Renewable Energy in the Electricity Sector and GDP. *Energies*.
- Soytas, M. A., Denizel, M., & Usar, D. D. (2019). Addressing endogeneity in the causal relationship between sustainability and financial performance. *International Journal of Production Economics*, 56-71.
- Spicer, B. H. (1978). Investors, Corporate Social Performance and Information Disclosure: An Empirical Study. *The Accounting Review*, 94-111.
- Stock, J. H., & Watson, M. W. (2015). *Introduction to econometrics (2nd ed)*. Pearson.
- Stocker, M., Baffes, J., Vorisek, D., & Wheeler, C. M. (2018). The 2014-16 Oil Price Collapse in Retrospect: Sources and Implications. *Policy Research Working Papers*.
- United States Environmental Protection Agency. (2022, September 29). *3M - Lean Six Sigma and Sustainability*. Retrieved from EPA: <https://www.epa.gov/sustainability/3m-lean-six-sigma-and-sustainability>
- United States Environmental Protection Agency. (2023, June 4). *Scope 1 and Scope 2 Inventory Guidance*. Retrieved from www.epa.gov: <https://www.epa.gov/climateleadership/scope-1-and-scope-2-inventory-guidance>
- Verbeek, M. (2017). *A guide to modern econometrics (5th ed.)*. Wiley.
- Wang, Y., Zhang, S., & Xu, S. (2022). Impact of Efficient Resource Management Practices on Sustainable Performance: Moderating Role of Innovative Culture-Evidence From Oil and Gas Firms. *Frontiers Psychology*.
- Wooldridge, J. M. (2012). *Introductory Econometrics: A Modern Approach (5th Edition)*. Cengage Learning.



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## Appendix

### Appendix 1: Companies, Country and Sector.

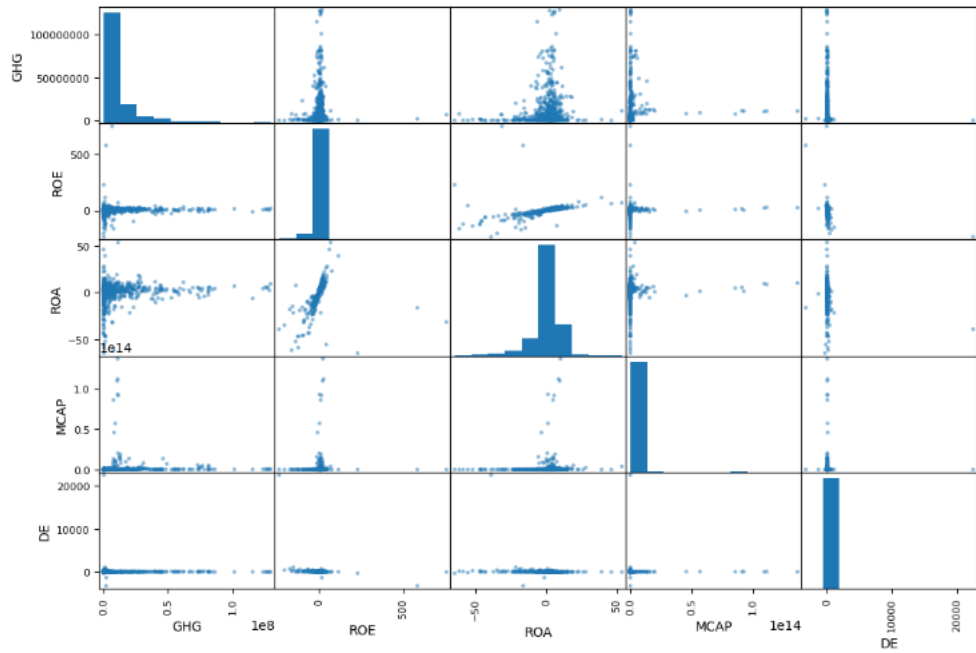
Name	Country	GICS SubInd Name
<b>AMPOL LTD</b>	Australia	Oil & Gas Refining & Marketing
<b>APA CORP</b>	United States	Oil & Gas Exploration & Production
<b>ARC RESOURCES LTD</b>	Canada	Oil & Gas Exploration & Production
<b>BAYTEX ENERGY CORP</b>	Canada	Oil & Gas Exploration & Production
<b>BEACH ENERGY LTD</b>	Australia	Oil & Gas Exploration & Production
<b>BHARAT PETROLEUM CORP LTD</b>	India	Oil & Gas Refining & Marketing
<b>BP PLC</b>	United Kingdom	Integrated Oil & Gas
<b>CANADIAN NATURAL RESOURCES</b>	Canada	Oil & Gas Exploration & Production
<b>CAPRICORN ENERGY PLC</b>	United Kingdom	Oil & Gas Exploration & Production
<b>CENOVUS ENERGY INC</b>	Canada	Integrated Oil & Gas
<b>CGG SA</b>	France	Oil & Gas Equipment & Services
<b>CNX RESOURCES CORP</b>	United States	Oil & Gas Exploration & Production
<b>CONOCOPHILLIPS</b>	United States	Oil & Gas Exploration & Production
<b>DCC PLC</b>	Ireland	Oil & Gas Refining & Marketing
<b>DENBURY INC</b>	United States	Oil & Gas Exploration & Production
<b>DEVON ENERGY CORP</b>	United States	Oil & Gas Exploration & Production
<b>ECOPETROL SA</b>	Colombia	Integrated Oil & Gas
<b>ENAUTA PARTICIPACOES SA</b>	Brazil	Oil & Gas Exploration & Production
<b>ENBRIDGE INC</b>	Canada	Oil & Gas Storage & Transportation
<b>ENERPLUS CORP</b>	Canada	Oil & Gas Exploration & Production
<b>ENI SPA</b>	Italy	Integrated Oil & Gas
<b>EQUINOR ASA</b>	Norway	Integrated Oil & Gas
<b>ESKEN LTD</b>	United Kingdom	Oil & Gas Equipment & Services
<b>EXXON MOBIL CORP</b>	United States	Integrated Oil & Gas
<b>FIRST SOLAR INC</b>	United States	Solar
<b>FORMOSA PETROCHEMICAL CORP</b>	Taiwan	Oil & Gas Refining & Marketing
<b>GALP ENERGIA SGPS SA</b>	Portugal	Integrated Oil & Gas
<b>GENEL ENERGY PLC</b>	United Kingdom	Oil & Gas Exploration & Production
<b>HALLIBURTON CO</b>	United States	Oil & Gas Equipment & Services
<b>HARBOUR ENERGY PLC</b>	United Kingdom	Oil & Gas Exploration & Production
<b>HELLENIQ ENERGY HOLDINGS SA</b>	Greece	Oil & Gas Refining & Marketing
<b>HESS CORP</b>	United States	Oil & Gas Exploration & Production
<b>HINDUSTAN PETROLEUM CORP</b>	India	Oil & Gas Refining & Marketing
<b>HUNTING PLC</b>	United Kingdom	Oil & Gas Equipment & Services
<b>IMPERIAL OIL LTD</b>	Canada	Integrated Oil & Gas
<b>INA INDUSTRIJA NAFTE DD</b>	Croatia	Integrated Oil & Gas
<b>INDIAN OIL CORP LTD</b>	India	Oil & Gas Refining & Marketing
<b>INPEX CORP</b>	Japan	Oil & Gas Exploration & Production
<b>IRPC PCL</b>	Thailand	Oil & Gas Refining & Marketing
<b>JAPAN PETROLEUM EXPLORATION</b>	Japan	Oil & Gas Exploration & Production

<b>JOHN WOOD GROUP PLC</b>	United Kingdom	Oil & Gas Equipment & Services
<b>MARATHON OIL CORP</b>	United States	Oil & Gas Exploration & Production
<b>MARATHON PETROLEUM CORP</b>	United States	Oil & Gas Refining & Marketing
<b>MOL HUNGARIAN OIL AND GAS PL</b>	Hungary	Integrated Oil & Gas
<b>MOTECH INDUSTRIES INC</b>	Taiwan	Solar
<b>NOSTRUM OIL &amp; GAS PLC</b>	Netherlands	Oil & Gas Exploration & Production
<b>NOVATEK PJSC</b>	Russia	Integrated Oil & Gas
<b>NUVISTA ENERGY LTD</b>	Canada	Oil & Gas Exploration & Production
<b>OCCIDENTAL PETROLEUM CORP</b>	United States	Integrated Oil & Gas
<b>OIL &amp; NATURAL GAS CORP LTD</b>	India	Integrated Oil & Gas
<b>OMV PETROM SA</b>	Romania	Integrated Oil & Gas
<b>PETROBRAS - PETROLEO BRAS-PR</b>	Brazil	Integrated Oil & Gas
<b>PETROFAC LTD</b>	United Kingdom	Oil & Gas Equipment & Services
<b>PEYTO EXPLORATION &amp; DEV CORP</b>	Canada	Oil & Gas Exploration & Production
<b>PTT EXPLOR &amp; PROD PUBLIC CO</b>	Thailand	Oil & Gas Exploration & Production
<b>PTT PCL</b>	Thailand	Integrated Oil & Gas
<b>REC SILICON ASA</b>	Norway	Solar
<b>RELIANCE INDUSTRIES LTD</b>	India	Oil & Gas Refining & Marketing
<b>RENAISSANCE SERVICES SAOG</b>	Oman	Oil & Gas Equipment & Services
<b>REPSOL SA</b>	Spain	Integrated Oil & Gas
<b>ROSNEFT OIL CO PJSC</b>	Russia	Integrated Oil & Gas
<b>SAIPEM SPA</b>	Italy	Oil & Gas Equipment & Services
<b>SANTOS LTD</b>	Australia	Oil & Gas Exploration & Production
<b>SAO MARTINHO SA</b>	Brazil	Oil & Gas Exploration & Production
<b>SBM OFFSHORE NV</b>	Netherlands	Oil & Gas Equipment & Services
<b>SCHLUMBERGER LTD</b>	United States	Oil & Gas Equipment & Services
<b>SEMBCORP MARINE LTD</b>	Singapore	Oil & Gas Equipment & Services
<b>SHELL PLC</b>	United Kingdom	Integrated Oil & Gas
<b>SK INNOVATION CO LTD</b>	South Korea	Oil & Gas Refining & Marketing
<b>S-OIL CORP</b>	South Korea	Oil & Gas Refining & Marketing
<b>SUNCOR ENERGY INC</b>	Canada	Integrated Oil & Gas
<b>TC ENERGY CORP</b>	Canada	Oil & Gas Storage & Transportation
<b>THAI OIL PCL</b>	Thailand	Oil & Gas Refining & Marketing
<b>TOTALENERGIES SE</b>	France	Integrated Oil & Gas
<b>TOURMALINE OIL CORP</b>	Canada	Oil & Gas Exploration & Production
<b>TULLOW OIL PLC</b>	United Kingdom	Oil & Gas Exploration & Production
<b>ULTRAPAR PARTICIPACOES SA</b>	Brazil	Oil & Gas Storage & Transportation
<b>VERMILION ENERGY INC</b>	Canada	Oil & Gas Exploration & Production
<b>VOPAK</b>	Netherlands	Oil & Gas Storage & Transportation
<b>WOODSIDE ENERGY GROUP LTD</b>	Australia	Oil & Gas Exploration & Production

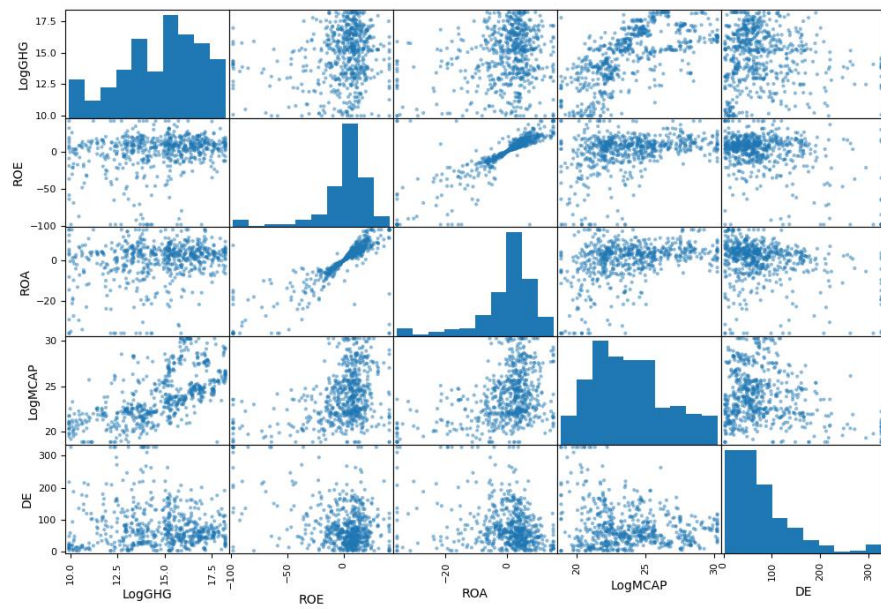
Appendix 2: High – and Low GDPC Countries

Country	Division	GDP per Capita
Republic of Ireland	High	77629.99
Norway	High	75419.63
United States	High	65280.68
Singapore	High	65233.28
Netherlands	High	52447.83
Canada	High	46940.6
United Kingdom	High	42300.27
France	High	40493.93
Japan	High	40259.11
South Korea	High	39238.74
Italy	High	33189.57
Spain	High	29613.67
Portugal	Low	23145.04
Taiwan	Low	20307.12
Greece	Low	19582.54
Hungary	Low	16475.74
Croatia	Low	14853.24
Oman	Low	14617.41
Romania	Low	12919.53
Russia	Low	11774.16
Brazil	Low	8655.265
Thailand	Low	7808.193
Colombia	Low	6432.388
India	Low	1910.836

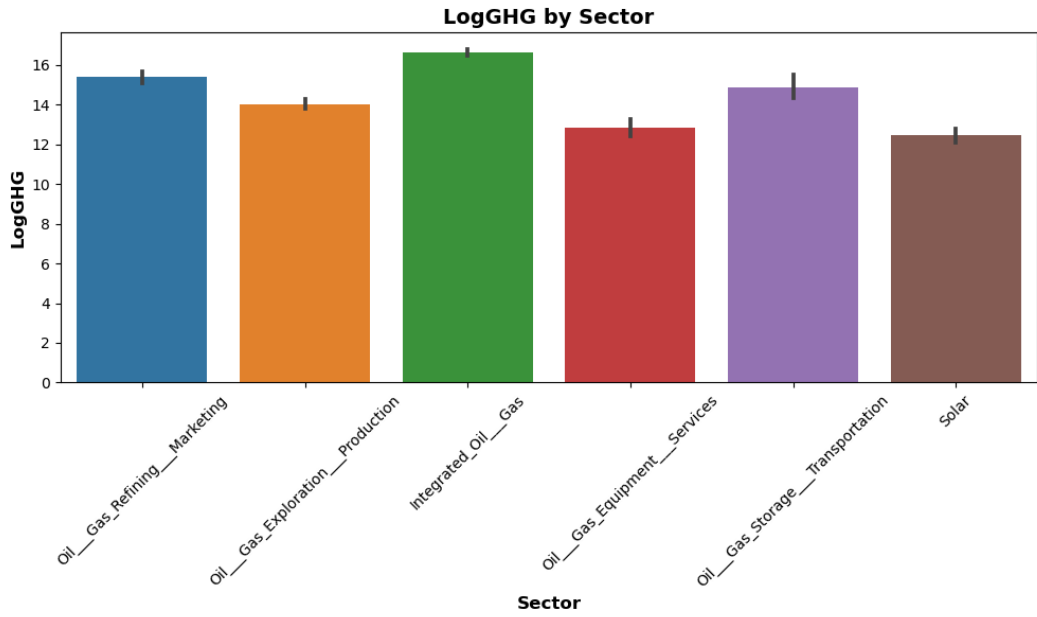
### Appendix 3: Data Before Processing



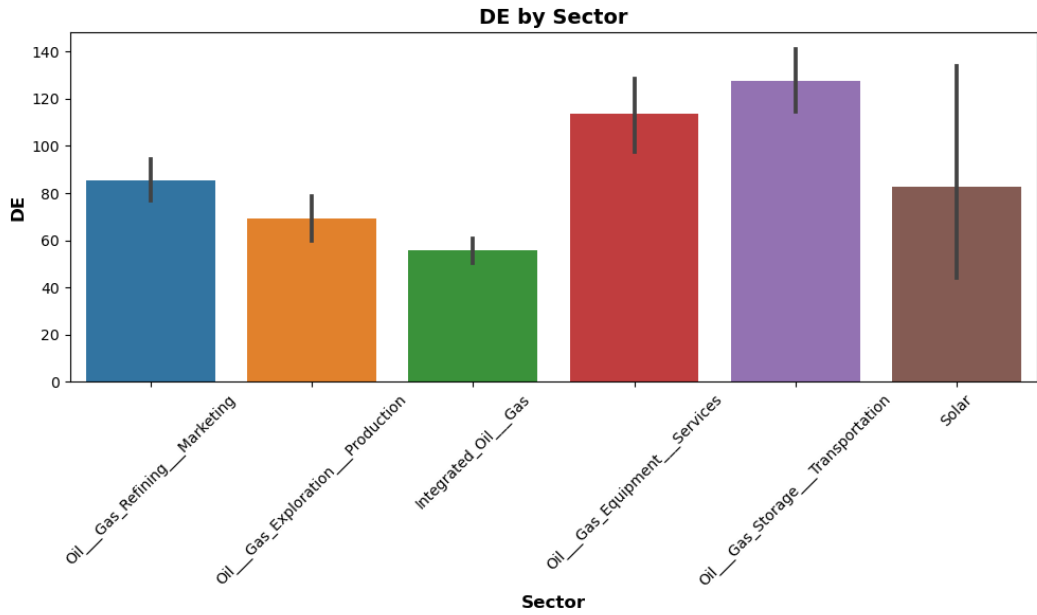
### Appendix 4: Data After Processing



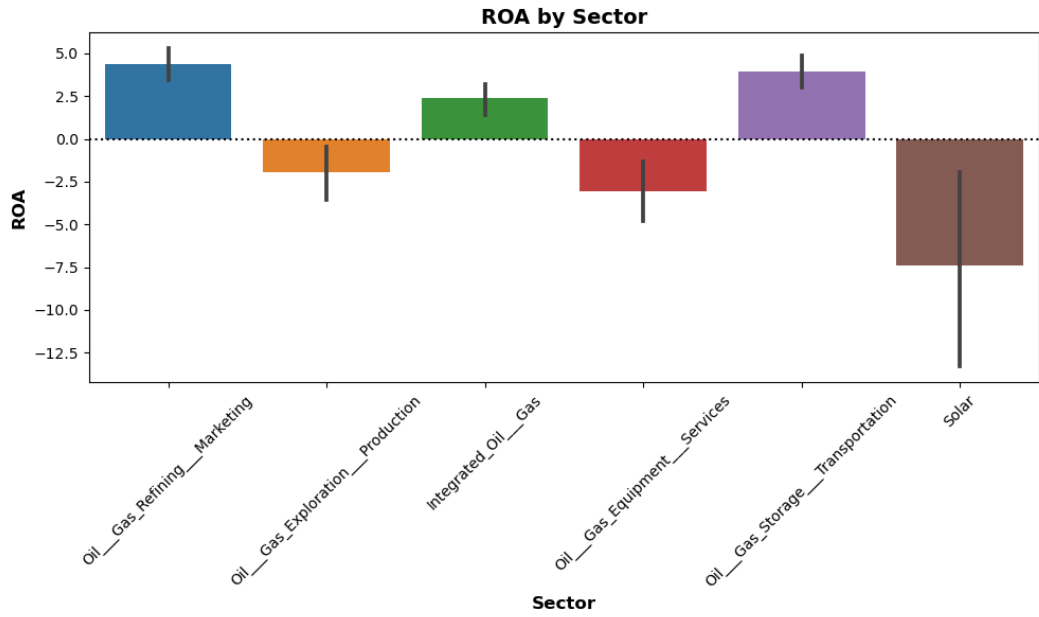
### Appendix 5: GHG by Sector



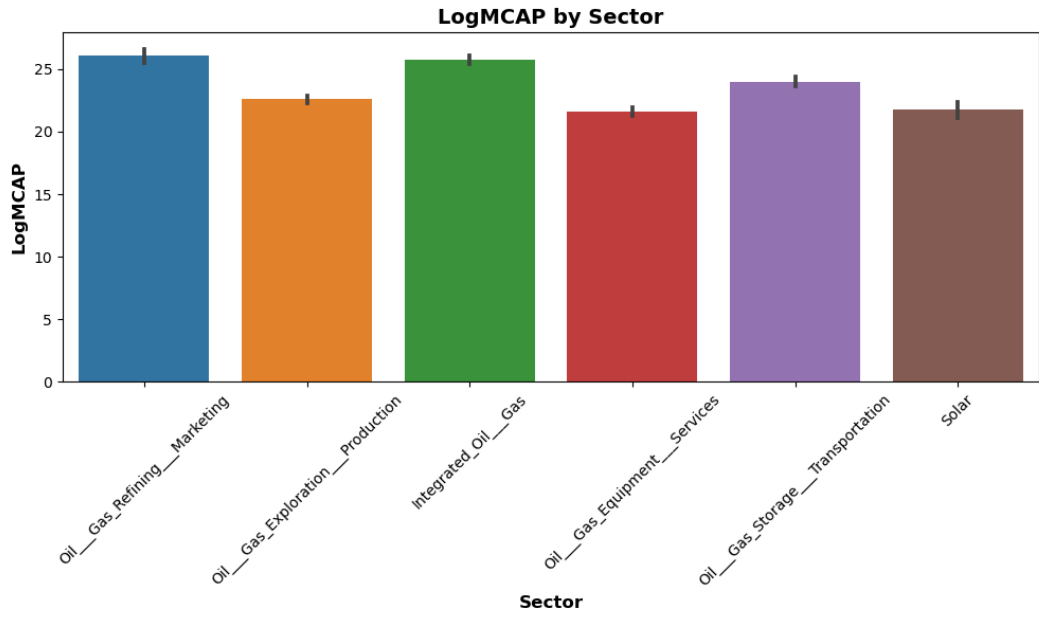
### Appendix 6: DE by Sector



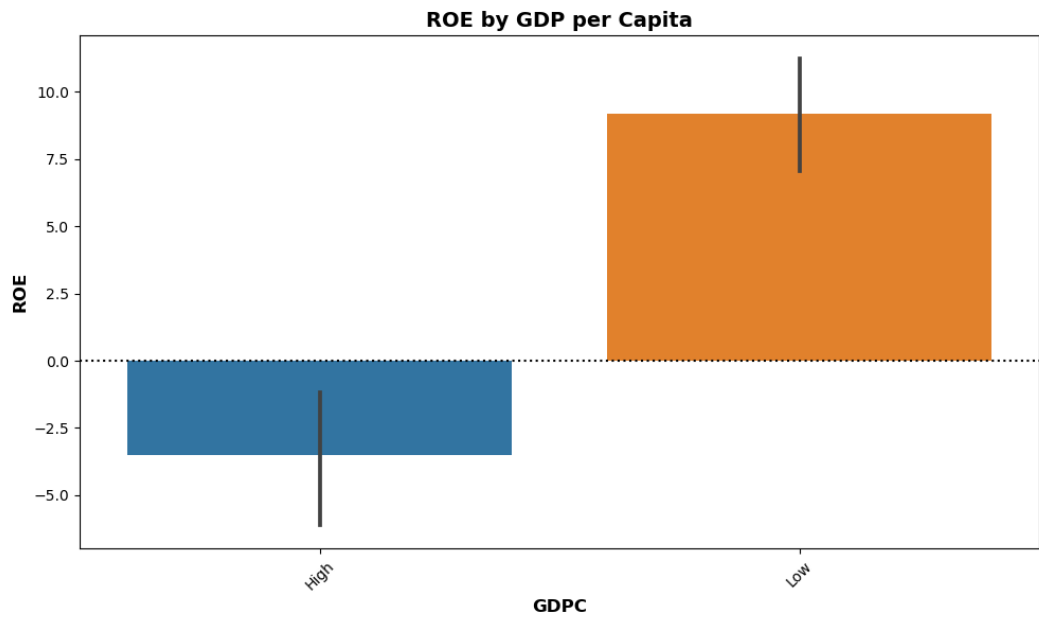
### Appendix 7: ROA by Sector



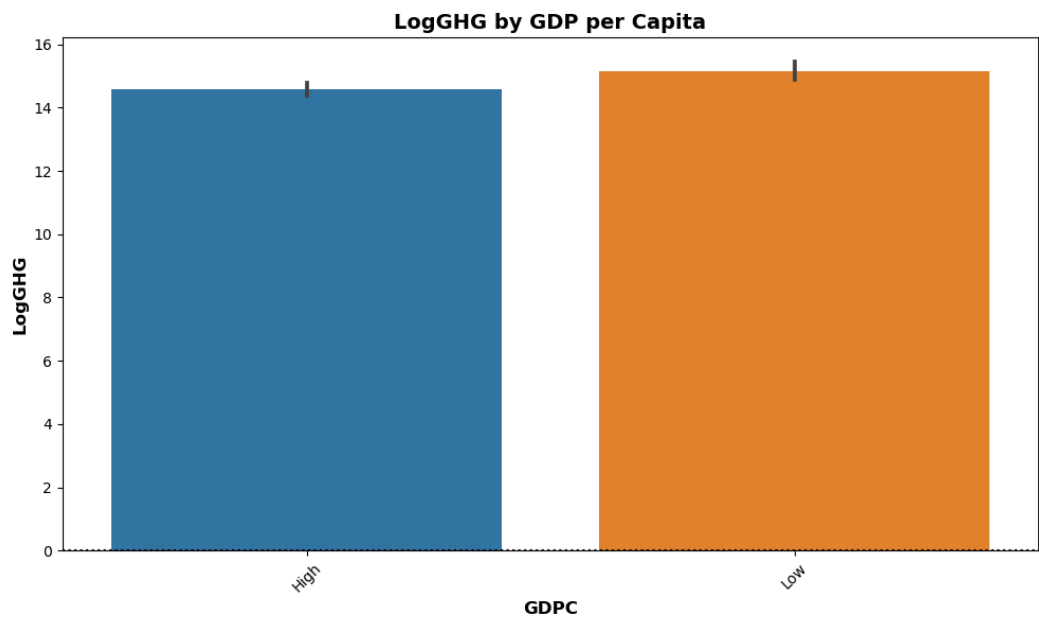
### Appendix 8: MCAP by Sector



### Appendix 9: ROE by GDPC

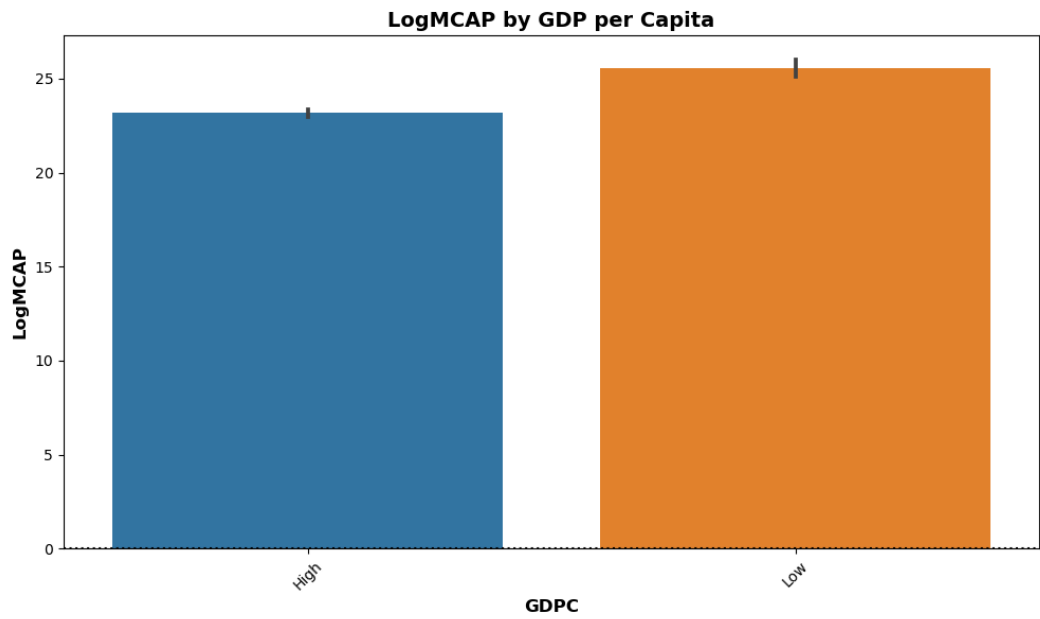


### Appendix 10: GHG by GDPC

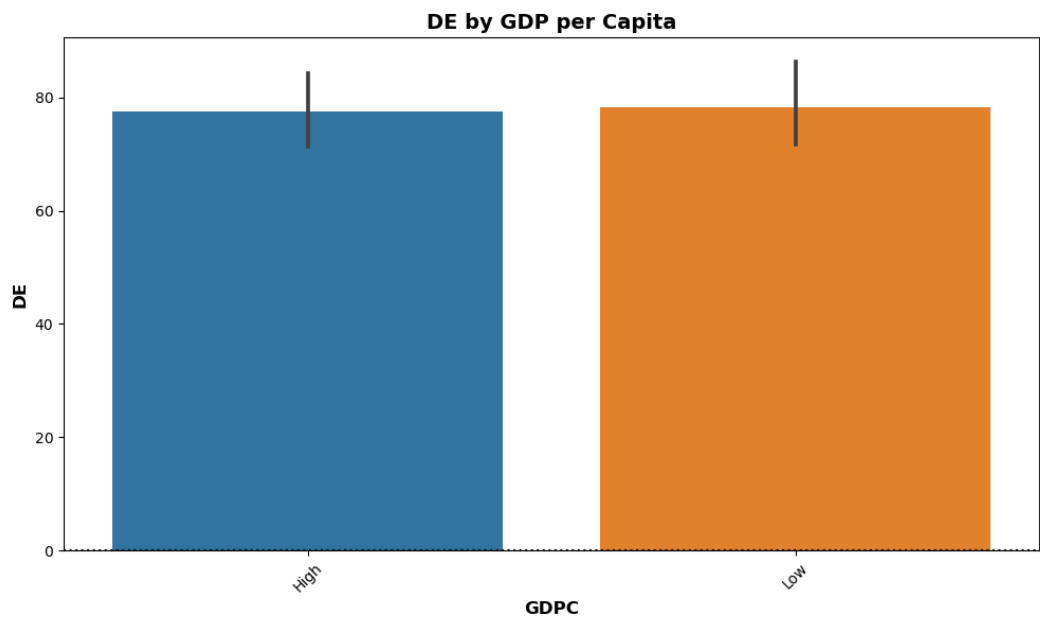




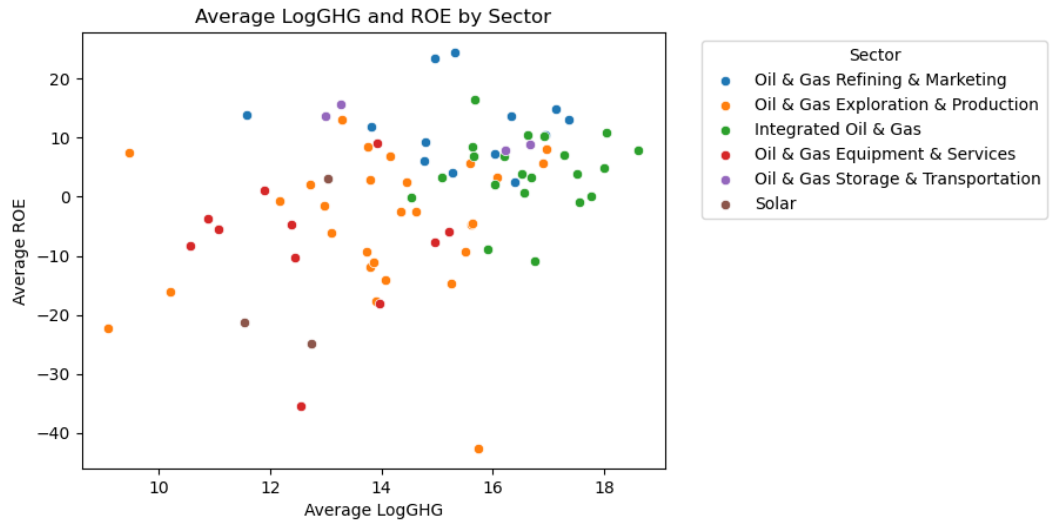
### Appendix 11: MCAP by GDPC



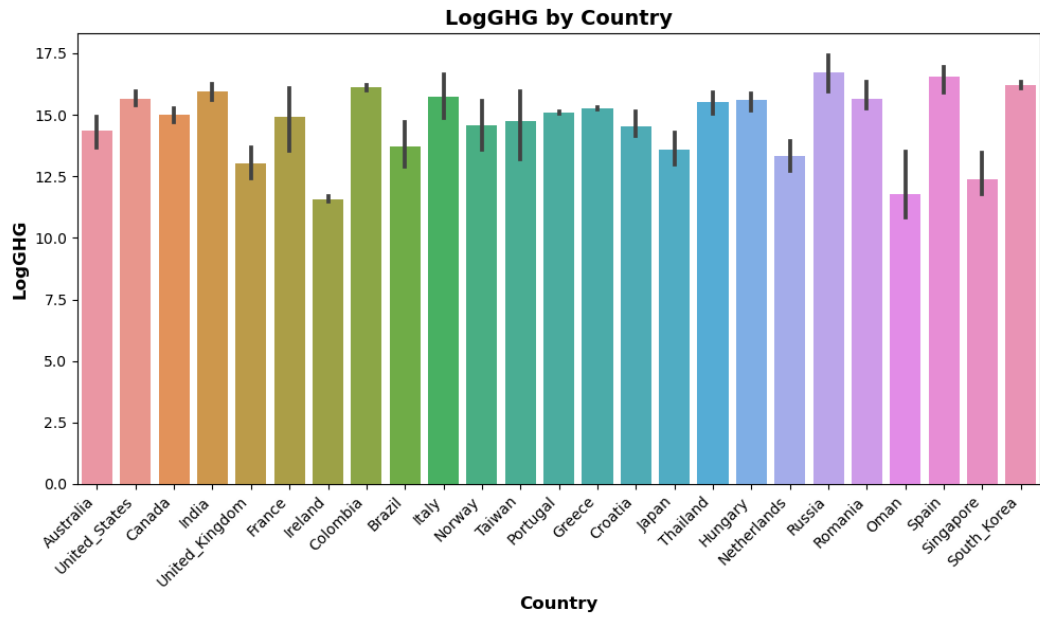
### Appendix 12: DE by GDPC



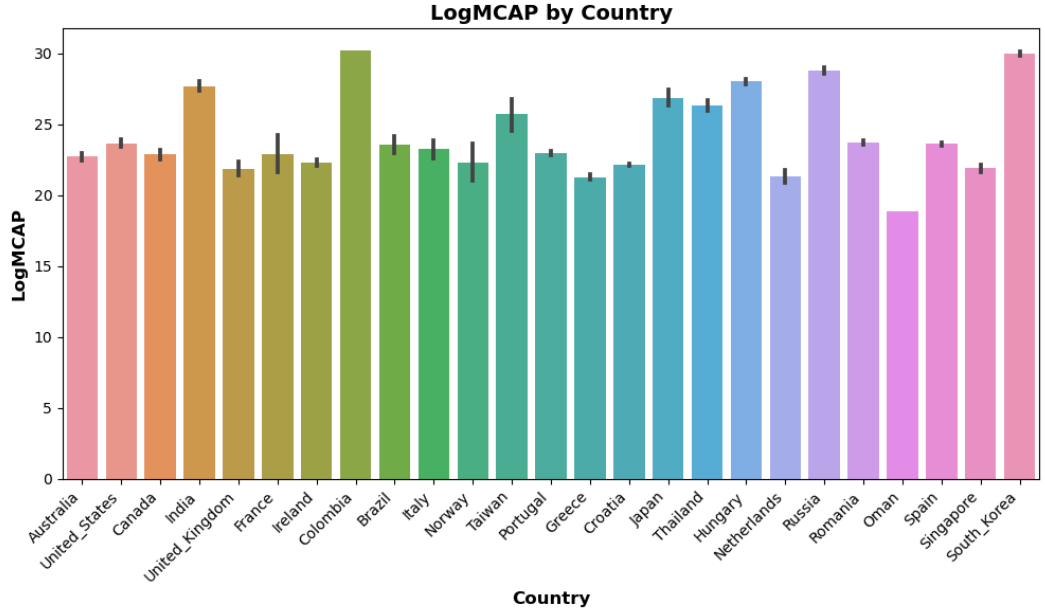
### Appendix 13: Average GHG & ROE by Sector



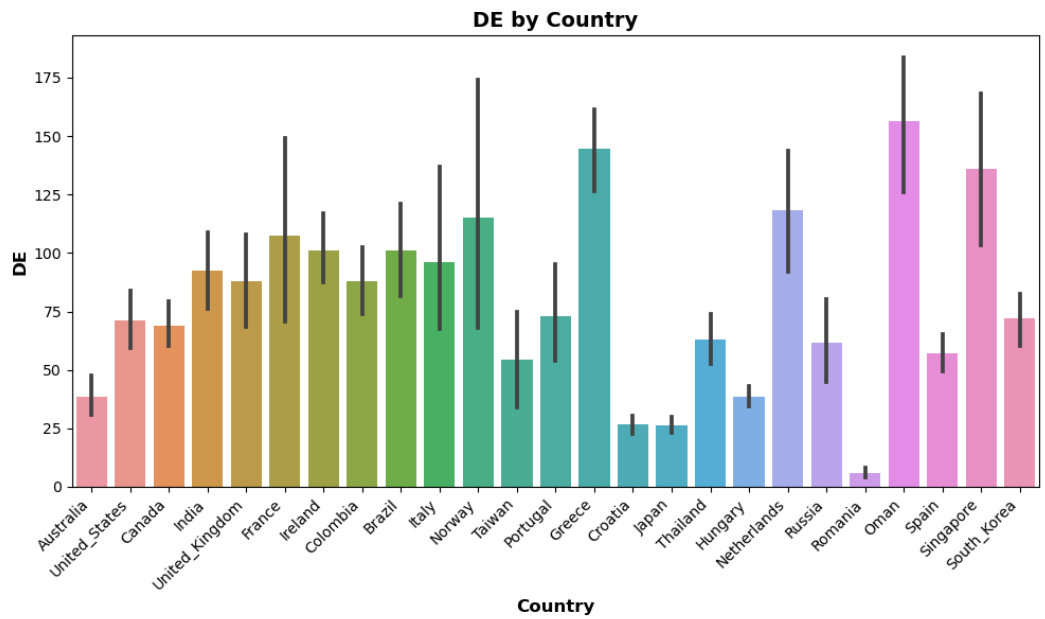
### Appendix 14: GHG by Country



Appendix 15: MCAP by Country



Appendix 16: DE by Country



## Appendix 17: POLS Resression Results, ROA, LogGHG, LogMCAP, DE, Sector and Country

PooledOLS Estimation Summary						
=====						
Dep. Variable:	ROA	R-squared:	0.3091			
Estimator:	PooledOLS	R-squared (Between):	0.6337			
No. Observations:	633	R-squared (Within):	0.1600			
Date:	Fri, Jun 16 2023	R-squared (Overall):	0.3091			
Time:	14:30:20	Log-likelihood	-2206.0			
Cov. Estimator:	Unadjusted	F-statistic:	8.3876			
Entities:	80	P-value	0.0000			
Avg Obs:	7.9125	Distribution:	F(32,600)			
Min Obs:	5.0000					
Max Obs:	8.0000	F-statistic (robust):	8.3876			
		P-value	0.0000			
Time periods:	8	Distribution:	F(32,600)			
Avg Obs:	79.125					
Min Obs:	78.000					
Max Obs:	80.000					
Parameter Estimates						
=====						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
-----						
const	-60.723	8.9162	-6.8104	0.0000	-78.234	-43.212
LogGHG	-0.5495	0.3289	-1.6709	0.0953	-1.1953	0.0964
LogMCAP	2.9516	0.4416	6.6832	0.0000	2.0842	3.8189
DE	-0.0299	0.0061	-4.9033	0.0000	-0.0419	-0.0179
Sector.Oil_Gas_Equipment_Services	4.3459	1.7206	2.5258	0.0118	0.9668	7.7250
Sector.Oil_Gas_Exploration_Production	3.2044	1.4751	2.1724	0.0302	0.3075	6.1013
Sector.Oil_Gas_Refining_Marketing	7.5431	1.7394	4.3366	0.0000	4.1270	10.959
Sector.Oil_Gas_Storage_Transportation	2.9286	1.9732	1.4842	0.1383	-0.9466	6.8037
Sector.Solar	3.4030	2.7442	1.2401	0.2154	-1.9865	8.7925
Country.Brazil	3.9915	2.2247	1.7942	0.0733	-0.3777	8.3606
Country.Canada	1.7818	1.7349	1.0270	0.3048	-1.6254	5.1891
Country.Colombia	-12.331	4.2041	-2.9332	0.0035	-20.588	-4.0748
Country.Croatia	4.2429	3.5437	1.1973	0.2317	-2.7167	11.202
Country.France	-1.4065	2.7095	-0.5191	0.6039	-6.7278	3.9149
Country.Greece	4.2795	3.5385	1.2094	0.2270	-2.6697	11.229
Country.Hungary	-8.8184	3.7004	-2.3831	0.0175	-16.086	-1.5512
Country.India	-9.9254	2.7876	-3.5605	0.0004	-15.400	-4.4507
Country.Ireland	0.5394	3.5838	0.1505	0.8804	-6.4989	7.5777
Country.Italy	-2.2522	2.7033	-0.8331	0.4051	-7.5613	3.0570
Country.Japan	-11.998	3.2247	-3.7207	0.0002	-18.331	-5.6651
Country.Netherlands	4.1963	2.4429	1.7177	0.0864	-0.6015	8.9941
Country.Norway	-3.2539	2.8468	-1.1430	0.2535	-8.8448	2.3370
Country.Oman	11.531	3.7204	3.0994	0.0020	4.2244	18.838
Country.Portugal	4.7130	3.4724	1.3573	0.1752	-2.1066	11.533
Country.Romania	4.2837	3.4174	1.2535	0.2105	-2.4277	10.995
Country.Russia	-5.6236	3.1591	-1.7801	0.0756	-11.828	0.5807
Country.Singapore	0.8233	3.4973	0.2354	0.8140	-6.0451	7.6917
Country.South_Korea	-22.884	3.8902	-5.8825	0.0000	-30.524	-15.244
Country.Spain	2.1425	3.4332	0.6240	0.5328	-4.6001	8.8850
Country.Taiwan	-8.8507	3.1455	-2.8138	0.0051	-15.028	-2.6732
Country.Thailand	-7.5836	2.4105	-3.1460	0.0017	-12.318	-2.8495
Country.United_Kingdom	-1.3962	1.8887	-0.7392	0.4600	-5.1054	2.3130
Country.United_States	-3.7391	1.7243	-2.1685	0.0305	-7.1256	-0.3527
=====						

## Appendix 18: POLS Resression Results, ROE, LogGHG, LogMCAP, DE, Sector and Country

PooledOLS Estimation Summary						
Dep. Variable:	ROE	R-squared:	0.3847			
Estimator:	PooledOLS	R-squared (Between):	0.6825			
No. Observations:	633	R-squared (within):	0.2515			
Date:	Fri, Jun 16 2023	R-squared (Overall):	0.3847			
Time:	14:29:25	Log-likelihood	-2772.5			
Cov. Estimator:	Unadjusted					
		F-statistic:	11.725			
Entities:	80	P-value	0.0000			
Avg Obs:	7.9125	Distribution:	F(32,600)			
Min Obs:	5.0000					
Max Obs:	8.0000	F-statistic (robust):	11.725			
		P-value	0.0000			
Time periods:	8	Distribution:	F(32,600)			
Avg Obs:	79.125					
Min Obs:	78.000					
Max Obs:	80.000					
Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	-111.52	21.818	-5.1115	0.0000	-154.37	-68.674
LogGHG	-0.4464	0.8047	-0.5547	0.5793	-2.0269	1.1340
LogMCAP	5.1751	1.0807	4.7887	0.0000	3.0527	7.2976
DE	-0.1491	0.0149	-9.9903	0.0000	-0.1784	-0.1198
Sector.Oil_Gas_Equipment_Services	6.6954	4.2103	1.5902	0.1123	-1.5733	14.964
Sector.Oil_Gas_Exploration_Production	6.4693	3.6095	1.7923	0.0736	-0.6195	13.558
Sector.Oil_Gas_Refining_Marketing	18.985	4.2564	4.4604	0.0000	10.626	27.345
Sector.Oil_Gas_Storage_Transportation	10.637	4.8284	2.2030	0.0280	1.1543	20.120
Sector.Solar	2.9689	6.7153	0.4421	0.6586	-10.219	16.157
Country.Brazil	15.996	5.4439	2.9384	0.0034	5.3050	26.688
Country.Canada	6.1525	4.2454	1.4492	0.1478	-2.1852	14.490
Country.Colombia	-12.817	10.288	-1.2458	0.2133	-33.021	7.3877
Country.Croatia	7.2939	8.6715	0.8411	0.4006	-9.7364	24.324
Country.France	-1.8661	6.6303	-0.2814	0.7785	-14.888	11.155
Country.Greece	14.869	8.6587	1.7172	0.0865	-2.1365	31.874
Country.Hungary	-12.395	9.0550	-1.3688	0.1716	-30.178	5.3885
Country.India	-8.7598	6.8214	-1.2842	0.1996	-22.157	4.6369
Country.Ireland	11.017	8.7697	1.2563	0.2095	-6.2055	28.240
Country.Italy	-5.2020	6.6152	-0.7864	0.4320	-18.194	7.7897
Country.Japan	-21.685	7.8910	-2.7481	0.0062	-37.182	-6.1876
Country.Netherlands	26.531	5.9780	4.4381	0.0000	14.791	38.271
Country.Norway	-6.0666	6.9662	-0.8709	0.3842	-19.748	7.6146
Country.Oman	30.874	9.1039	3.3912	0.0007	12.994	48.753
Country.Portugal	13.505	8.4972	1.5893	0.1125	-3.1830	30.193
Country.Romania	3.6635	8.3624	0.4381	0.6615	-12.760	20.087
Country.Russia	-4.0745	7.7305	-0.5271	0.5983	-19.257	11.108
Country.Singapore	12.704	8.5579	1.4845	0.1382	-4.1027	29.512
Country.South_Korea	-39.862	9.5194	-4.1874	0.0000	-58.557	-21.167
Country.Spain	5.8301	8.4012	0.6940	0.4880	-10.669	22.329
Country.Taiwan	-19.620	7.6971	-2.5490	0.0111	-34.737	-4.5034
Country.Thailand	-11.593	5.8987	-1.9653	0.0498	-23.177	-0.0082
Country.United_Kingdom	2.6461	4.6216	0.5725	0.5672	-6.4304	11.723
Country.United_States	-6.1606	4.2195	-1.4600	0.1448	-14.447	2.1261

Appendix 19: FE time-effects Regression Results, ROA, LogGHG, LogMCAP, DE, Sector and Country

PanelOLS Estimation Summary						
Dep. Variable:	ROA	R-squared:	0.3216			
Estimator:	PanelOLS	R-squared (Between):	0.6571			
No. Observations:	633	R-squared (Within):	0.1468			
Date:	Fri, Jun 16 2023	R-squared (Overall):	0.3069			
Time:	14:31:56	Log-likelihood	-2152.8			
Cov. Estimator:	Unadjusted	F-statistic:	8.7855			
		P-value	0.0000			
Entities:	80	Distribution:	F(32,593)			
Avg Obs:	7.9125					
Min Obs:	5.0000	F-statistic (robust):	8.7855			
Max Obs:	8.0000	P-value	0.0000			
Time periods:	8	Distribution:	F(32,593)			
Avg Obs:	79.125					
Min Obs:	78.000					
Max Obs:	80.000					

Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	-52.257	8.3055	-6.2919	0.0000	-68.569	-35.945
LogGHG	-0.3591	0.3060	-1.1735	0.2411	-0.9602	0.2419
LogMCAP	2.4912	0.4126	6.0373	0.0000	1.6808	3.3016
DE	-0.0273	0.0057	-4.8008	0.0000	-0.0384	-0.0161
Sector.Oil__Gas_Equipment__Services	3.6564	1.5937	2.2943	0.0221	0.5264	6.7864
Sector.Oil__Gas_Exploration__Production	2.3038	1.3680	1.6841	0.0927	-0.3829	4.9905
Sector.Oil__Gas_Refining__Marketing	6.9423	1.6102	4.3115	0.0000	3.7799	10.105
Sector.Oil__Gas_Storage__Transportation	2.6235	1.8260	1.4367	0.1513	-0.9627	6.2096
Sector.Solar	2.0715	2.5422	0.8149	0.4155	-2.9213	7.0643
Country.Brazil	3.8723	2.0580	1.8815	0.0604	-0.1697	7.9142
Country.Canada	1.4220	1.6049	0.8860	0.3760	-1.7300	4.5740
Country.Colombia	-10.165	3.9003	-2.6062	0.0094	-17.825	-2.5049
Country.Croatia	3.1531	3.2793	0.9615	0.3367	-3.2874	9.5937
Country.France	-2.0932	2.5070	-0.8349	0.4041	-7.0168	2.8304
Country.Greece	2.9348	3.2760	0.8959	0.3707	-3.4992	9.3688
Country.Hungary	-7.4421	3.4276	-2.1712	0.0303	-14.174	-0.7104
Country.India	-8.3582	2.5870	-3.2309	0.0013	-13.439	-3.2775
Country.Ireland	0.4942	3.3152	0.1491	0.8815	-6.0168	7.0052
Country.Italy	-2.9125	2.5011	-1.1645	0.2447	-7.8246	1.9996
Country.Japan	-9.8350	2.9949	-3.2839	0.0011	-15.717	-3.9531
Country.Netherlands	3.3567	2.2612	1.4845	0.1382	-1.0842	7.7976
Country.Norway	-3.8376	2.6337	-1.4571	0.1456	-9.0100	1.3349
Country.Oman	9.7951	3.4462	2.8423	0.0046	3.0269	16.563
Country.Portugal	3.7722	3.2129	1.1741	0.2408	-2.5380	10.082
Country.Romania	3.7485	3.1608	1.1860	0.2361	-2.4591	9.9561
Country.Russia	-4.1669	2.9288	-1.4228	0.1553	-9.9189	1.5851
Country.Singapore	0.4218	3.2347	0.1304	0.8963	-5.9311	6.7748
Country.South_Korea	-20.203	3.6139	-5.5903	0.0000	-27.300	-13.105
Country.Spain	1.2610	3.1764	0.3970	0.6915	-4.9774	7.4994
Country.Taiwan	-7.8672	2.9118	-2.7019	0.0071	-13.586	-2.1486
Country.Thailand	-6.5226	2.2338	-2.9200	0.0036	-10.910	-2.1355
Country.United_Kingdom	-1.8654	1.7476	-1.0674	0.2862	-5.2975	1.5668
Country.United_States	-3.7233	1.5946	-2.3350	0.0199	-6.8551	-0.5916

F-test for Poolability: 15.523  
P-value: 0.0000  
Distribution: F(7,593)

Included effects: Time

Appendix 20: FE time-effects Regression Results, ROE, LogGHG, LogMCAP, DE, Sector and Country

PanelOLS Estimation Summary						
Dep. Variable:	ROE	R-squared:	0.3960			
Estimator:	PanelOLS	R-squared (Between):	0.7038			
No. Observations:	633	R-squared (Within):	0.2407			
Date:	Fri, Jun 16 2023	R-squared (Overall):	0.3833			
Time:	14:32:40	Log-likelihood	-2732.3			
Cov. Estimator:	Unadjusted	F-statistic:	12.152			
Entities:	80	P-value	0.0000			
Avg Obs:	7.9125	Distribution:	F(32,593)			
Min Obs:	5.0000	F-statistic (robust):	12.152			
Max Obs:	8.0000	P-value	0.0000			
Time periods:	8	Distribution:	F(32,593)			
Avg Obs:	79.125					
Min Obs:	78.000					
Max Obs:	80.000					
Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	-93.084	20.747	-4.4866	0.0000	-133.83	-52.338
LogGHG	-0.0305	0.7645	-0.0399	0.9682	-1.5320	1.4709
LogMCAP	4.1716	1.0308	4.0472	0.0001	2.1473	6.1960
DE	-0.1441	0.0142	-10.156	0.0000	-0.1720	-0.1162
Sector.Oil__Gas_Equipment__Services	5.2328	3.9810	1.3144	0.1892	-2.5859	13.051
Sector.Oil__Gas_Exploration__Production	4.5322	3.4172	1.3263	0.1853	-2.1792	11.244
Sector.Oil__Gas_Refining__Marketing	17.697	4.0222	4.3998	0.0000	9.7975	25.597
Sector.Oil__Gas_Storage__Transportation	10.056	4.5613	2.2046	0.0279	1.0974	19.014
Sector.Solar	0.1170	6.3504	0.0184	0.9853	-12.355	12.589
Country.Brazil	15.803	5.1410	3.0739	0.0022	5.7062	25.900
Country.Canada	5.3856	4.0090	1.3434	0.1797	-2.4879	13.259
Country.Colombia	-8.0354	9.7430	-0.8247	0.4099	-27.170	11.100
Country.Croatia	4.9340	8.1918	0.6023	0.5472	-11.154	21.022
Country.France	-3.3082	6.2624	-0.5283	0.5975	-15.607	8.9909
Country.Greece	12.018	8.1834	1.4686	0.1425	-4.0542	28.090
Country.Hungary	-9.3715	8.5622	-1.0945	0.2742	-26.187	7.4444
Country.India	-5.2847	6.4622	-0.8178	0.4138	-17.976	7.4068
Country.Ireland	10.971	8.2814	1.3248	0.1858	-5.2934	27.235
Country.Italy	-6.5959	6.2477	-1.0557	0.2915	-18.866	5.6744
Country.Japan	-16.979	7.4812	-2.2696	0.0236	-31.672	-2.2862
Country.Netherlands	24.735	5.6484	4.3792	0.0000	13.642	35.829
Country.Norway	-7.2833	6.5789	-1.1071	0.2687	-20.204	5.6374
Country.Oman	27.164	8.6086	3.1554	0.0017	10.256	44.071
Country.Portugal	11.503	8.0259	1.4332	0.1523	-4.2596	27.266
Country.Romania	2.4963	7.8955	0.3162	0.7520	-13.010	18.003
Country.Russia	-0.8602	7.3160	-0.1176	0.9064	-15.229	13.508
Country.Singapore	11.887	8.0803	1.4711	0.1418	-3.9823	27.757
Country.South_Korea	-33.991	9.0274	-3.7653	0.0002	-51.721	-16.262
Country.Spain	3.9448	7.9347	0.4972	0.6193	-11.639	19.528
Country.Taiwan	-17.419	7.2736	-2.3949	0.0169	-31.704	-3.1342
Country.Thailand	-9.2559	5.5800	-1.6588	0.0977	-20.215	1.7031
Country.United_Kingdom	1.6591	4.3654	0.3801	0.7040	-6.9143	10.233
Country.United_States	-6.1046	3.9833	-1.5326	0.1259	-13.928	1.7184
F-test for Poolability: 11.475						
P-value: 0.0000						
Distribution: F(7,593)						
Included effects: Time						

Appendix 21: FE entity-effects Regression Results, ROA, LogGHG, LogMCAP and DE.

```

=====
PanelOLS Estimation Summary
=====
Dep. Variable:          ROA      R-squared:              0.2260
Estimator:             PanelOLS  R-squared (between):    -11.349
No. Observations:     633      R-squared (within):     0.2260
Date:                 Fri, Jun 16 2023  R-squared (Overall):    -3.3534
Time:                 14:33:04      Log-likelihood          -2123.9
Cov. Estimator:       Unadjusted

Entities:              80      F-statistic:            53.542
Avg Obs:              7.9125    P-value                 0.0000
Min Obs:              5.0000    Distribution:            F(3,550)
Max Obs:              8.0000    F-statistic (robust):   53.542
Time periods:         8      P-value                 0.0000
Avg Obs:              79.125    Distribution:            F(3,550)
Min Obs:              78.000
Max Obs:              80.000

```

```

=====
Parameter Estimates
=====
Parameter  Std. Err.  T-stat  P-value  Lower CI  Upper CI
-----
const      -177.90    18.543  -9.5943  0.0000    -214.32  -141.48
LogGHG     -0.2062    0.3856  -0.5347  0.5931    -0.9637  0.5513
LogMCAP     7.6947    0.7653  10.055   0.0000     6.1915  9.1979
DE         -0.0333    0.0074  -4.5305  0.0000    -0.0478 -0.0189
=====

```

F-test for Poolability: 3.7990  
P-value: 0.0000  
Distribution: F(79,550)

Included effects: Entity

Appendix 22: FE entity-effects Regression Results, ROE, LogGHG, LogMCAP and DE.



```

=====
PanelOLS Estimation Summary
=====
Dep. Variable:          ROE      R-squared:              0.2972
Estimator:             PanelOLS  R-squared (Between):    -4.7325
No. Observations:      633      R-squared (within):     0.2972
Date:                  Fri, Jun 16 2023  R-squared (Overall):    -1.2171
Time:                  14:33:27      Log-likelihood           -2700.5
Cov. Estimator:        Unadjusted

Entities:              80      F-statistic:            77.538
Avg Obs:               7.9125  P-value                 0.0000
Min Obs:               5.0000  Distribution:            F(3,550)
Max Obs:               8.0000  F-statistic (robust):   77.538
Time periods:          8      P-value                 0.0000
Avg Obs:               79.125  Distribution:            F(3,550)
Min Obs:               78.000
Max Obs:               80.000

```

```

=====
Parameter Estimates
=====
Parameter  Std. Err.  T-stat  P-value  Lower CI  Upper CI
-----
const      -281.85   46.106  -6.1131  0.0000   -372.42  -191.28
LogGHG     -0.7106   0.9589  -0.7410  0.4590   -2.5941  1.1730
LogMCAP     12.923   1.9029   6.7914  0.0000    9.1854  16.661
DE         -0.2050   0.0183  -11.205  0.0000   -0.2409  -0.1691
=====

```

F-test for Poolability: 4.1350  
P-value: 0.0000  
Distribution: F(79,550)

Included effects: Entity

### Appendix 23: FE time- and entity-effects Regression Results, ROA, LogGHG, LogMCAP and DE.

```

=====
PanelOLS Estimation Summary
=====
Dep. Variable:          ROE      R-squared:              0.2640
Estimator:             PanelOLS  R-squared (Between):    -2.1614
No. Observations:      633      R-squared (within):     0.2919
Date:                  Fri, Jun 16 2023  R-squared (Overall):    -0.4463
Time:                  14:34:16      Log-likelihood           -2664.1
Cov. Estimator:        Unadjusted

Entities:              80      F-statistic:            64.909
Avg Obs:               7.9125  P-value                 0.0000
Min Obs:               5.0000  Distribution:            F(3,543)
Max Obs:               8.0000  F-statistic (robust):   64.909
Time periods:          8      P-value                 0.0000
Avg Obs:               79.125  Distribution:            F(3,543)
Min Obs:               78.000
Max Obs:               80.000

```

```

=====
Parameter Estimates
=====
Parameter  Std. Err.  T-stat  P-value  Lower CI  Upper CI
-----
const      -200.42   45.701  -4.3855  0.0000   -290.20  -110.65
LogGHG     -0.5125   0.9154  -0.5599  0.5758   -2.3105  1.2856
LogMCAP     9.3739   1.8970   4.9414  0.0000    5.6475  13.100
DE         -0.2003   0.0176  -11.404  0.0000   -0.2348  -0.1658
=====

```

F-test for Poolability: 4.9776  
P-value: 0.0000  
Distribution: F(86,543)

Included effects: Entity, Time

### Appendix 24: FE time- and entity-effects Regression Results, ROE, LogGHG, LogMCAP and DE.

```

=====
PanelOLS Estimation Summary
=====
Dep. Variable:          ROA      R-squared:              0.1688
Estimator:             PanelOLS  R-squared (Between):    -6.3871
No. Observations:     633      R-squared (Within):     0.2180
Date:                 Fri, Jun 16 2023  R-squared (Overall):    -1.8236
Time:                 14:33:52      Log-likelihood           -2074.2
Cov. Estimator:       Unadjusted

Entities:              80      F-statistic:            36.769
Avg Obs:              7.9125    P-value                  0.0000
Min Obs:              5.0000    Distribution:             F(3,543)
Max Obs:              8.0000    F-statistic (robust):    36.769
Time periods:         8      P-value                  0.0000
Avg Obs:              79.125    Distribution:             F(3,543)
Min Obs:              78.000
Max Obs:              80.000

```

```

=====
Parameter Estimates
=====
Parameter  Std. Err.   T-stat   P-value   Lower CI   Upper CI
-----
const      -140.61    17.997   -7.8127   0.0000    -175.96   -105.25
LogGHG     -0.1057    0.3605   -0.2933   0.7694    -0.8138   0.6024
LogMCAP     6.0599    0.7471   8.1116    0.0000    4.5924    7.5273
DE         -0.0302    0.0069   -4.3652   0.0000    -0.0438   -0.0166
=====

```

F-test for Poolability: 5.1059  
P-value: 0.0000  
Distribution: F(86,543)

Included effects: Entity, Time

## Appendix 25: FD Regression Results, ROA, LogGHG, LogMCAP and DE.

```

=====
FirstDifferenceOLS Estimation Summary
=====
Dep. Variable:          ROA      R-squared:              0.2776
Estimator:             FirstDifferenceOLS  R-squared (Between):    -2359.3
No. Observations:     550      R-squared (Within):     0.1861
Date:                 Fri, Jun 16 2023  R-squared (Overall):    -735.06
Time:                 14:31:30      Log-likelihood           -2035.8
Cov. Estimator:       Unadjusted

Entities:              80      F-statistic:            70.075
Avg Obs:              7.9125    P-value                  0.0000
Min Obs:              5.0000    Distribution:             F(3,547)
Max Obs:              8.0000    F-statistic (robust):    70.075
Time periods:         8      P-value                  0.0000
Avg Obs:              79.125    Distribution:             F(3,547)
Min Obs:              78.000
Max Obs:              80.000

```

```

=====
Parameter Estimates
=====
Parameter  Std. Err.   T-stat   P-value   Lower CI   Upper CI
-----
LogGHG     -0.0807    0.3628   -0.2224   0.8241    -0.7934   0.6320
LogMCAP     10.936    0.9650   11.332    0.0000    9.0402    12.831
DE         -0.0463    0.0098   -4.7286   0.0000    -0.0656   -0.0271
=====

```

## Appendix 26: FD Regression Results, ROA, LogGHG, LogMCAP and DE.

FirstDifferenceOLS Estimation Summary			
Dep. Variable:	ROE	R-squared:	0.3422
Estimator:	FirstDifferenceOLS	R-squared (Between):	-1455.4
No. Observations:	550	R-squared (Within):	0.2354
Date:	Fri, Jun 16 2023	R-squared (Overall):	-441.11
Time:	14:30:53	Log-likelihood	-2553.4
Cov. Estimator:	Unadjusted		
		F-statistic:	94.868
Entities:	80	P-value	0.0000
Avg Obs:	7.9125	Distribution:	F(3,547)
Min Obs:	5.0000		
Max Obs:	8.0000	F-statistic (robust):	94.868
		P-value	0.0000
Time periods:	8	Distribution:	F(3,547)
Avg Obs:	79.125		
Min Obs:	78.000		
Max Obs:	80.000		

Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
LogGHG	-0.0879	0.9297	-0.0945	0.9247	-1.9142	1.7384
LogMCAP	22.451	2.4729	9.0790	0.0000	17.594	27.308
DE	-0.2602	0.0251	-10.364	0.0000	-0.3095	-0.2109

## Appendix 27: POLS Regression Results, ROA, LogGHG, LogMCAP, DE, Sector and GDPC

PooledOLS Estimation Summary						
Dep. Variable:	ROA	R-squared:	0.2340			
Estimator:	PooledOLS	R-squared (Between):	0.5281			
No. Observations:	633	R-squared (Within):	0.1019			
Date:	Sat, Jul 01 2023	R-squared (Overall):	0.2340			
Time:	17:50:56	Log-likelihood	-2238.7			
Cov. Estimator:	Unadjusted					
		F-statistic:	21.140			
Entities:	80	P-value	0.0000			
Avg Obs:	7.9125	Distribution:	F(9,623)			
Min Obs:	5.0000					
Max Obs:	8.0000	F-statistic (robust):	21.140			
		P-value	0.0000			
Time periods:	8	Distribution:	F(9,623)			
Avg Obs:	79.125					
Min Obs:	78.000					
Max Obs:	80.000					

Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	-17.134	4.5131	-3.7965	0.0002	-25.997	-8.2714
LogGHG	0.2069	0.2400	0.8621	0.3890	-0.2644	0.6783
LogMCAP	0.6474	0.1905	3.3976	0.0007	0.2732	1.0216
DE	-0.0393	0.0057	-6.9384	0.0000	-0.0504	-0.0282
Sector.Oil & Gas Equipment & Services	1.5740	1.4793	1.0640	0.2877	-1.3310	4.4789
Sector.Oil & Gas Exploration & Production	-9.394e-05	1.0965	-8.568e-05	0.9999	-2.1533	2.1532
Sector.Oil & Gas Refining & Marketing	2.7852	1.1228	2.4805	0.0134	0.5802	4.9901
Sector.Oil & Gas Storage & Transportation	6.7839	1.7787	3.8140	0.0002	3.2909	10.277
Sector.Solar	-4.6227	2.1170	-2.1836	0.0294	-8.7800	-0.4653
GDPC.Low	3.3811	0.8776	3.8527	0.0001	1.6577	5.1045

## Appendix 28: POLS Regression Results, ROE, LogGHG, LogMCAP, DE, Sector and GDPC

PooledOLS Estimation Summary

```

=====
Dep. Variable:          ROE      R-squared:              0.3042
Estimator:             PooledOLS R-squared (Between):    0.5081
No. Observations:     633      R-squared (Within):     0.2173
Date:                 Sat, Jul 01 2023 R-squared (Overall):    0.3042
Time:                 17:51:52  Log-likelihood          -2811.5
Cov. Estimator:       Unadjusted

Entities:              80      F-statistic:           30.259
Avg Obs:              7.9125  P-value                0.0000
Min Obs:              5.0000  Distribution:          F(9,623)
Max Obs:              8.0000  F-statistic (robust):  30.259
Time periods:         8      P-value                0.0000
Avg Obs:              79.125  Distribution:          F(9,623)
Min Obs:              78.000
Max Obs:              80.000
    
```

Parameter Estimates

```

=====
Parameter      Std. Err.    T-stat    P-value    Lower CI    Upper CI
-----
const          -19.883     11.154   -1.7826   0.0751     -41.787    2.0205
LogGHG         0.2097     0.5932   0.3535   0.7238     -0.9553    1.3746
LogMCAP        1.0259     0.4709   2.1786   0.0297     0.1012     1.9507
DE             -0.1518    0.0140  -10.852   0.0000     -0.1793    -0.1243
Sector.Oil & Gas Equipment & Services  1.4014     3.6559   0.3833   0.7016     -5.7780    8.5808
Sector.Oil & Gas Exploration & Production -0.6472    2.7099  -0.2388   0.8113     -5.9688    4.6744
Sector.Oil & Gas Refining & Marketing  9.9364     2.7749   3.5807   0.0004     4.4870    15.386
Sector.Oil & Gas Storage & Transportation 21.103     4.3959   4.8007   0.0000     12.471    29.736
Sector.Solar   -18.439     5.2321  -3.5241   0.0005     -28.713    -8.1639
GDPC.Low       8.1739     2.1689   3.7686   0.0002     3.9146    12.433
    
```

## Appendix 29: FE fixed-time Regression Results, ROA, LogGHG, LogMCAP, DE, Sector and GDPC

PanelOLS Estimation Summary

```

=====
Dep. Variable:          ROA      R-squared:              0.2488
Estimator:             PanelOLS R-squared (Between):    0.5384
No. Observations:     633      R-squared (Within):     0.0958
Date:                 Sat, Jul 01 2023 R-squared (Overall):    0.2328
Time:                 17:53:53  Log-likelihood          -2185.1
Cov. Estimator:       Unadjusted

Entities:              80      F-statistic:           22.671
Avg Obs:              7.9125  P-value                0.0000
Min Obs:              5.0000  Distribution:          F(9,616)
Max Obs:              8.0000  F-statistic (robust):  22.671
Time periods:         8      P-value                0.0000
Avg Obs:              79.125  Distribution:          F(9,616)
Min Obs:              78.000
Max Obs:              80.000
    
```

Parameter Estimates

```

=====
Parameter      Std. Err.    T-stat    P-value    Lower CI    Upper CI
-----
const          -16.037     4.1722   -3.8438   0.0001     -24.230    -7.8435
LogGHG         0.2430     0.2222   1.0938   0.2745     -0.1933    0.6794
LogMCAP        0.5734     0.1764   3.2514   0.0012     0.2271     0.9198
DE             -0.0353    0.0053  -6.6909   0.0000     -0.0456    -0.0249
Sector.Oil & Gas Equipment & Services  1.1686     1.3682   0.8541   0.3934     -1.5183    3.8555
Sector.Oil & Gas Exploration & Production -0.1980    1.0135  -0.1953   0.8452     -2.1883    1.7923
Sector.Oil & Gas Refining & Marketing  2.7700     1.0378   2.6690   0.0078     0.7319    4.8082
Sector.Oil & Gas Storage & Transportation 6.2414     1.6451   3.7940   0.0002     3.0108    9.4720
Sector.Solar   -5.1305     1.9570  -2.6216   0.0090     -8.9736    -1.2873
GDPC.Low       3.3671     0.8110   4.1519   0.0000     1.7745    4.9597
    
```

F-test for Poolability: 16.258  
P-value: 0.0000  
Distribution: F(7,616)

Included effects: Time

Appendix 30: FE fixed-time Regression Results, ROE, LogGHG, LogMCAP, DE, Sector and GDPC

PanelOLS Estimation Summary						
Dep. Variable:	ROE	R-squared:	0.3153			
Estimator:	PanelOLS	R-squared (Between):	0.5237			
No. Observations:	633	R-squared (Within):	0.2095			
Date:	Sat, Jul 01 2023	R-squared (Overall):	0.3035			
Time:	17:53:10	Log-likelihood	-2772.0			
Cov. Estimator:	Unadjusted					
		F-statistic:	31.521			
Entities:	80	P-value	0.0000			
Avg Obs:	7.9125	Distribution:	F(9,616)			
Min Obs:	5.0000					
Max Obs:	8.0000	F-statistic (robust):	31.521			
		P-value	0.0000			
Time periods:	8	Distribution:	F(9,616)			
Avg Obs:	79.125					
Min Obs:	78.000					
Max Obs:	80.000					
Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	-17.448	10.545	-1.6545	0.0985	-38.157	3.2617
LogGHG	0.2827	0.5616	0.5034	0.6149	-0.8202	1.3856
LogMCAP	0.8674	0.4458	1.9459	0.0521	-0.0080	1.7428
DE	-0.1436	0.0133	-10.781	0.0000	-0.1698	-0.1174
Sector.Oil & Gas Equipment & Services	0.5443	3.4582	0.1574	0.8750	-6.2469	7.3355
Sector.Oil & Gas Exploration & Production	-1.0718	2.5616	-0.4184	0.6758	-6.1024	3.9588
Sector.Oil & Gas Refining & Marketing	9.9125	2.6232	3.7788	0.0002	4.7610	15.064
Sector.Oil & Gas Storage & Transportation	19.995	4.1579	4.8088	0.0000	11.829	28.160
Sector.Solar	-19.491	4.9463	-3.9405	0.0001	-29.205	-9.7775
GDPC.Low	8.1594	2.0498	3.9806	0.0001	4.1340	12.185
F-test for Poolability: 11.681						
P-value: 0.0000						
Distribution: F(7,616)						
Included effects: Time						