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# BI Norwegian Business School – Master Thesis

*How does carbon emissions impact stock prices: Evidence from the UK stock market*

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## Acknowledgements

This thesis was written as a final part of our Master of Science in Finance at BI Norwegian Business School.

The main goal of our thesis is to study the relationship between carbon emissions and stock returns and contribute to the growing field of climate finance.

The process of completing this thesis has been challenging yet highly rewarding. Working with our thesis, we have gained knowledge about how carbon emissions impact asset prices using financial theory from our studies. In addition, our study has required us to use and improve our capabilities by using financial databases, Excel, and R-studio.

We express our gratitude to our thesis supervisor, Bruno Gerard, for guiding us throughout the writing process. In addition, we want to thank Karoline Palmer for her valuable insights and Tatyana Marchuk for her advice.

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## Preliminary Abstract

We investigate the relationship between stock returns and firm's carbon emissions for the cross-section of UK companies, and test whether a carbon risk premium exists. We obtain emission data, monthly stock return data, and various control variables from UK companies from 2011 to 2021. Our results suggest that stocks with high levels of unscaled emissions earn on average lower returns when controlling for various return predictors. When using emissions growth or carbon intensity, our results suggest that emissions do not impact stock returns. Our paper aims to increase understanding of the relationship between a company's carbon emissions and stock returns and contribute to the growing field of climate finance.

# Introduction

The global climate has always been in a state of flux, with weather patterns gradually changing over time. However, in the last century, the climate has changed faster than historically observed. A large body of scientific research shows that human-related activity is the driving force behind the accelerated change. If temperatures increase by 2 degrees Celsius within 2100, the economic damage to the global economy could in the same period be USD 69 trillion (Mufson, 2019). The risks and opportunities of such change have forced companies to examine their business models and evaluate their carbon footprint critically. At the same time, we have seen the emergence of climate-concerned investors and the rapid growth of sustainable investment funds.

Today, around one-third of all investing strategies of managed UK assets incorporate ESG factors into their investment selection processes (The Government of the United Kingdom, 2021). Many investors cite high returns as a top criterion for investing in ESG strategies. Some investment managers' market ESG strategies as potentially delivering higher risk-adjusted returns relative to less climate-friendly strategies (Pastor et al., 2021). The underlying idea behind many sustainable investment strategies is to capitalize on opportunities provided by climate change and reduce downside risk by moving capital away from climate-unfriendly investments. One ESG strategy fund managers use is to overweight companies with low carbon emissions and underweight companies with high carbon emissions. However, many investors believe that incorporating such ESG issues into mainstream investment processes might come at the cost of lower returns (In et al., 2017)

Investors and fund managers should understand how carbon emissions impact stock returns to position themselves optimally in the financial markets. Our thesis aims to increase the understanding of whether carbon emissions affect stock returns in the UK stock market. More specifically, our research question is: “How does carbon emissions impact stock prices: Evidence from the UK stock market”

Bolton and Kacperczyk have been instrumental in the research on returns and carbon emissions in the last years. Our study builds upon their 2021 study, where they analyze whether a carbon risk premium exists in the US for the period 2005 – 2017 (Bolton & Kacperczyk, 2021). We perform our study by conducting a pooled regression with time and industry fixed effects of UK companies' stock returns against different carbon emissions measures and using several return predictors as control variables. Our sample period is 2011 - 2021. The carbon emission measures we use are unscaled[1] emissions, year-over-year growth in emissions[2], and carbon intensity, where the latter is defined as a company's unscaled emissions to an activity measure, in our instance, revenue. We also use the measure direct emissions, which is the sum of SCOPE 1 and SCOPE 2 emissions.

Publicly listed firms headquartered in the UK have been required to report emissions data since 2013 (GOV.UK, 2019). In contrast, most other EU countries introduced mandatory reporting at a later point in time (Waard et al., 2020). The long-standing mandatory carbon reporting in the UK means that we have a large sample of actual firm disclosures, making it an ideal market to study.

We also investigate whether the relationship between returns and emissions changes before and after the Paris Climate Agreement (PCA). The PCA was signed by 195 countries and adopted in 2015 and is regarded as the most ambitious, legally binding international treaty on climate change (UN, 2020). In addition, the agreement significantly increased investor awareness of climate risks (Krueger et al., 2018). By performing regressions before and after the PCA, we can better understand the effect the PCA had on the relationship between returns and carbon emissions.

Our results suggest that a firm's returns are negatively related to unscaled carbon emissions. However, we do not find any relationship between returns and growth in emissions and returns and carbon intensity. We also find a negative relationship between returns and unscaled carbon emissions before and after the PCA. However, our results are inconclusive when regressing returns to carbon intensity and returns to growth in emissions.

[1] Unscaled emissions refer to a company’s total yearly reported emissions
[2] Hereafter referred to as growth in emissions

We add to the literature by studying the relationship between returns and carbon emissions in the UK stock market, something that, to the best of our knowledge, has not been done previously. Additionally, we have identified the usage of estimated emissions data as a problem in past research, and we avoid such problems by only using firm-disclosed climate data. Furthermore, some studies use contemporaneous emissions data instead of lagging the emissions data to account for when that data became available (Bolton & Kacperczyk, 2021). By lagging the data, we avoid potential look-ahead bias in our study. We also add to the currently limited research on the effects of the PCA on the relationship between returns and carbon emissions.

The remaining part of our thesis is structured as follows: Section two provides background information and a review of previous literature relevant to our thesis. Section three presents the data and control variables used in our study. In section four, we detail the methodology and specify the models used in our study. Section five presents the results from our regressions and includes a discussion of our findings and potential limitations of our study. Section six recommends future potential avenues of research. Finally, in section seven, we conclude our thesis.

# Background and literature review

Two currents characterize the literature on climate finance: The first current investigates how the climate is changing and the associated risks with this change. The second current studies how climate change impacts the economy and the financial performance of firms and how this again impacts asset prices (Venturini, 2022). In our paper, we focus on the latter, that is, whether climate risk impacts asset prices. Before we review the literature on the relationship between climate risk and asset returns, we discuss types of climate risks, describe how carbon emissions are measured and reported, and discuss the difference between firm-disclosed data and vendor-estimated data.

## *Climate risks*

From a financial perspective, climate risks can be divided into two categories, as seen in Figure 1: *Physical risk*, referring "to the negative impact of climate and weather-related events on company operations, society, and supply chains" (Tankov & Tantet, 2019); and *transition risk*, "referring to the changes in policies and preferences coherent with a path to a low-carbon economy and its related implication" (Curtin et al., 2019). Further, transition risks can be divided into policy risk, technology risk and preference change.

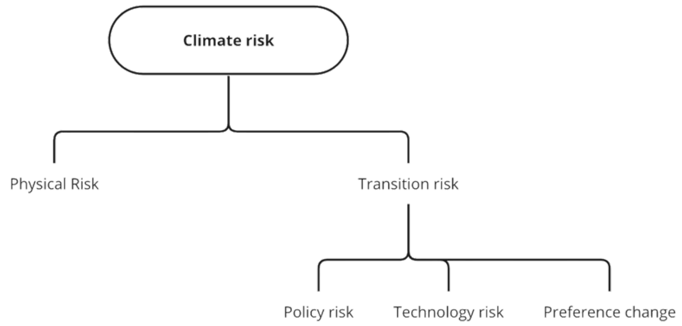


*Figure 1: Climate risk components*

The physical risks described above are negative externalities imposed upon society by companies, governments, and individuals. The higher a company's carbon emissions, the more considerable negative externalities they impose on society. These externalities impact the climate globally; hence, there is not always a direct relationship between how much a company pollutes and how much that company is impacted by the negative physical impacts of climate change.

However, there is a more direct relationship between a company's carbon emissions and transition risks. For example, an increase in carbon taxes directly impact companies with high carbon emissions. We therefore focus our discussion mostly on transition risks and how these risks impact asset prices.

***Emissions data***

The emissions data used in our study are reported based on the Greenhouse Gas Protocol – a commonly used framework by companies for estimating emissions. The protocol distinguishes between three different sources of greenhouse gas (GHG) emissions at the firm level: "SCOPE 1 emissions are direct emissions from owned or controlled sources. SCOPE 2 emissions are indirect emissions from the generation of purchased energy. SCOPE 3 emissions are all indirect emissions not included in SCOPE 2, that occur in the value chain of the reporting company" (Greenhouse Gas Protocol, 2022).

We only use firm-disclosed data in our study, and not vendor-estimated data. The distinction between firm-disclosed data and vendor-estimated data is important. This is highlighted by Aswani et al. (2021), who argues that the relationship between emissions and stock returns in Bolton and Kacperczyk's (2021) study is driven entirely by vendor-estimated data. Aswani et al. provides empirical evidence of systematic differences between firm-disclosed and vendor-estimated data. Further, they argue that vendor-estimated emissions are a function of size, sales growth, industry membership, and time. Consequently, they argue that the relationship found by Bolton and Kacperczyk between stock returns and emissions are essentially just a relationship between stock returns and operating performance. When running their regressions using vendor-estimated data and firm-disclosed data separately, they find that the carbon risk premium is significant *only* when using vendor-estimated data. We avoid the issues with vendor-estimated emission data by only including actual firm-disclosed data.

We note that the quality of reported emissions data can be questioned. It is just in the last few decades that firms started to report their carbon emissions. Hence, many companies have limited experience estimating carbon emissions, and we can expect errors in the data. Although there are issues related to emissions data, we still believe emissions data to be valuable as investors would use such data to proxy for a company's exposure to climate risk.

### *Theories on climate risks and stock returns*

According to the efficient market hypothesis, asset prices should reflect all publicly available information (Fama, 1970). Consequently, climate risks, both transition and physical, should be reflected in the cross-section of stock returns. The field of climate finance has extensively studied the relationship between returns and emissions. However, there is no consensus on the extent to which climate risks in the form of carbon emissions are reflected in stock returns.

Bolton and Kacperczyk (2021) formalize three hypotheses on how carbon emissions might impact stock returns. The first hypothesis is the *carbon risk premium hypothesis*, which states that carbon emissions present a risk to companies and that investors are compensated for bearing this risk. The second hypothesis, the *carbon alpha hypothesis*, argues that financial markets inefficiently price carbon risk and that potential abnormal returns can be generated using various low carbon strategies. The third hypothesis, the *divestment hypothesis*, argues that stocks with high emissions, or "sin stocks," are avoided by most investors and that the market pays a premium to investors for owning these stocks. In the following, we detail the theories, discuss their logic, and critique them.

*Carbon risk premium hypothesis*

The intuition behind a carbon risk premium is that carbon risk is a systematic risk factor that cannot be eliminated through diversification. For example, this would be the case if a new regulatory intervention is applied across all firms and sectors.

Carbon emissions present a risk to companies, mostly in the forms of transition risks. Semieniuk et al. (2020) divides transition risks into three different factors:

$$Transition\ risk\ =\ f\ (policy\ risk, technology\ risk, preference\ change)$$

They argue that transition risk drivers result in relative prices changing or that the market equilibrium changes in favor of low carbon goods and services, either instantly or gradually. To get a clear picture of how transition risks impact financial returns, we analyze each of the three risk drivers separately. However, it is important to note that all three risk drivers are interlinked and impact each other. Hence, separating and analyzing transition risks into three parts is done to clarify and understand how these risks might impact asset prices.

*Policy risk* is a constant risk facing companies. An example of such policies is the UK petrol tax. Adjusting for inflation, tax is around 75% higher today than the 1990 level (GOV.UK, 2022). Companies' dependent on fossil fuels are exposed to changes in fossil-fuel prices; hence, changes in petrol taxes represent a risk to many companies. We find evidence in the academic literature on how policies impact the carbon premium of companies. For example, Bolton et al. (2022) shows European companies to be sensitive to changes in carbon prices under EU Emissions Trading System (EU ETS). In the system, governments limit the total emissions an establishment can have in an area over a period. Companies can then trade the emission rights in the specified area, where the rights work as the currency in carbon markets (EU ETS, 2022). They find that premiums for large-cap companies went up from 1.01% to 2.75% between 2018 and 2019. They argue that the jump is a consequence of the 140% increase in the cost of EU Carbon Permits.

*Technology* is another risk factor relevant to carbon emissions. This risk comes from new technologies changing prices and moving the market equilibrium towards low carbon goods and services. For example, the price of solar electricity has decreased by 89% from 2010 – 2020 (Roser, 2020). Such low carbon alternatives are increasingly pressuring firms to invest in new low carbon technologies to maintain market share, reduce costs or fight off incumbents.

Lastly, *preference changes* refer to risk from changes in consumer preference and investors' preference. Consumer preference changes can represent a risk for so-called brown stocks and an opportunity for green stocks. Pastor et al. (2021) argues that shifts in preference changes can lay the ground for positive returns in green companies in the period after the change. Investors are also changing their preferences for ethical and financial reasons by moving capital away from unfriendly climate investments and towards greener investments (Venturini, 2022). For example, due to increasing shareholder pressure, large European banks reduced their financing of fossil fuel companies by 27.6% in 2021 compared to the year before (Wass, 2022). One effect of decreasing financing options for high-carbon emission companies could be a higher cost of capital. Consequently, this may result in fewer positive NPV projects available to such companies.

Changing investor preferences is tightly linked to the divestment hypothesis in Bolton and Kacperczyk's paper (2021). The argument for the hypothesis goes as follows: Investors are divided into virtuous and sin investors. The market always has to clear, meaning someone must own outstanding shares. The so-called "sin investors" end up owning the "sin stocks". The market entices the sin investors into owning sin stocks through a higher expected return. The higher expected return could be interpreted as a carbon risk premium. A critical finding from Bolton and Kacperczyk's paper (2021) is that carbon premiums are *unrelated* to a company's carbon intensity, measured as the ratio of carbon emissions to revenue. The authors argue that many investors apply exclusionary filters for investing based on companies' carbon intensity and divest from carbon-intensive companies. Because the carbon premium is not associated with carbon intensity, the authors conclude that the correlation between high returns and high emissions is not due to investors divesting, and hence they discard the divestment hypothesis.

Much of the evidence on the presence of a carbon risk premium comes from Bolton and Kacperczyk’s studies. Their 2021 study explores whether carbon emissions affect the cross-section of US stock returns. The study spans from 2005 to 2018 and includes around 3,000 listed companies. They find that when controlling for known risk factors and company characteristics, SCOPE 1, 2, and 3 of unscaled emissions all positively affect stock returns. The authors interpret the positive association as a premium investors are compensated due to their climate risk exposure. Their follow-up study extends their analysis globally and includes companies from 77 countries. They find evidence of a carbon risk premium in almost all the 77 countries covered in the study. Furthermore, they find that the carbon risk premium is present in *all* industry sectors. They argue that the result is expected as all companies with high carbon emissions are exposed to carbon transition risk (Bolton, 2020).

*Carbon alpha hypothesis*

The carbon alpha hypothesis argues that markets misprice carbon risk, and hence a positive alpha could, in theory, be achieved using various low carbon investment strategies. Consequently, the hypothesis stands in opposition to the carbon risk premium hypothesis.

Ambec and Lanoie (2008) review several empirical works showing that improvements in a firm's environmental performance tend to be associated with improvements in its economic or financial performance, owing to potential improvements in profit margins. Hoepner et al. (2016) shows that engagement on sustainability issues can benefit shareholders by reducing firms' downside risk.

However, a pertinent question is why markets might not efficiently price in climate data and carbon risk? It is only in recent years that it became common for asset managers and investors to incorporate climate data into investment decisions. In a 2010 study, 500 asset managers were asked about their approach to climate change from an investing standpoint. Only half of the respondents were quoted as saying that climate change was relevant to their investment decisions (CERES, 2010). Further, in a study by Amel-Zadeh and Serafeim (2018), questions were asked to portfolio managers about their usage of ESG data. The study found that 43.2% of the respondents cited a lack of standards in reporting of ESG information as a critical factor limiting the effective use of ESG information for investment decisions. Additionally, they revealed that managers have problems comparing ESG data across firms, that there is a lack of quantifiable data, and that data is reported too infrequently to be helpful.

Another reason as to why markets might not efficiently price in carbon risk is due to investor beliefs in climate change. Baldauf et al. (2020) examines how climate beliefs impact real estate prices and find that houses projected to be underwater in neighborhoods where people believe in climate change sell at a discount, compared to houses in neighborhoods where people do not believe in climate change. The results suggest that house prices reflect "heterogeneity in beliefs about long-run climate change risks".

Lastly, investors may not be attentive to risks associated with high carbon emissions. Mumenthaler et al. (2021) investigates the impact of short-term volatility of local temperature on climate change-related tweets from 2014 to 2017. They find that the volume of climate change tweets increases in periods of high-temperature volatility. The study highlights how readily available weather information impacts attention towards climate change on social media. Hence, if social media is a proxy for public attention, biases, and in this instance, short-term bias, can impact our attention towards climate information. This, in turn, can lead to investors failing to price long-term climate risks correctly.

Is there any evidence for the carbon alpha hypothesis? Matsamura et al. (2015) researches the link between firm value and voluntarily disclosed emissions to the Carbon Disclosure Project by listed US companies. Their results suggest a negative relationship between firm value and carbon emissions and that "for every additional thousand metric tons of carbon emissions, firm value decreases by $212,000". In et al. (2017) uses a sample of 736 US firms from 2005 to 2015. The authors create a portfolio that is long stocks with low carbon intensity and short stocks with high carbon intensity. The study finds that after 2010, an investment strategy of long carbon-efficient firms and short carbon-inefficient firms could have earned abnormal returns of 3.5–5.4% per year. Importantly, they argue that well-known risk factors do not fully explain the outperformance. Further, they argue that the alpha is due to the outperformance of carbon-efficient firms and not the underperformance of carbon-inefficient firms. Similarly, Cheema-Fox et al (2021) finds that portfolios long on firms with low carbon intensity and short on firms with high carbon intensity delivered a positive and significant alpha of around 2% annually in the US and Europe from 2009 to 2018.

However, the past outperformance seen in low carbon emission stocks might suffer from alpha decay, as described in Kuenzi et. al (2019) model for risk premia strategies that suggest there is "a pull toward commoditization for any known and profitable investment strategy". In a related study, Mclean and Pontiff (2015) study "the out-of-sample and post-publication return predictability of 97 variables shown to predict cross-sectional stock returns". They find a decay in portfolio returns post-publication. A study by Pastor et al. (2021) divides stocks as either green or brown based on MSCI ESG Ratings and finds that the green portfolios outperform the brown portfolio. They refer to the outperformance as a greenium - a premium on stocks of green companies. However, the authors caution against using this as evidence to reject a potential carbon risk premium. Instead, they interpret the outperformance as reflecting a one-time unanticipated increase in environmental concern. Further, they argue that the "outperformance caused by the strengthening of investor concerns is followed by a lower expected performance of the green factor going forward". In other words, they argue that due to transition effects, green stocks will not continue to deliver the high returns that have been seen in the past.

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## Data and sample

This section describes the data used in our study.

### *Data collection*

Our data set consists of company emissions data, stock return data, and control variables for UK companies over the period January 2011 to December 2021. We lag the control variables and the emission data for one year. Lagging these variables reduces our sample period to 2012 - 2021. We obtain most of the data from Eikon Refinitiv, while some data is manually collected from company reports to fill in missing data. We collect return data as monthly data. On the other hand, we obtain emissions and corporate financial data from balance sheets as annual data. We transform annual data into monthly data by setting the monthly data equal to that year's reported data. To illustrate, if a company had leverage of 60% in 2011, then the leverage in each of the twelve months in 2011 will have a value of 60%.

Collecting the data from Eikon Refinitiv and filtering for the UK as the country of exchange gives us a sample of 2,129 companies. We further use the filtering function so that we are only left with ordinary shares as our instrument type, leaving us with 1,830 companies. To run our regression, we need to have all data points available from control variables and stock returns for at least one time period. This constraint decreases our sample further to 447 firms, from which 92% are headquartered in the UK. To reduce the impact of outliers, some variables are winsorized at either the 2.5% level or the 0.5% level (Table 1). We winsorize the variables cross-sectionally each month. Practically, we winsorize the data by replacing values above the 98.75%, or the 99.75% percentile, with the value of the 98.75% percentile, or the 99.75% percentile. Similarly, we replace values below the 1.25%, or the 0.25% percentile, with the value of the 1.25% percentile or the 0.25% percentile.

### *Corporate carbon emissions data*

We use Eikon Refinitiv to extract SCOPE 1, 2 and 3 emissions data. Unscaled emissions data is extracted directly from Eikon Refinitiv. Direct emissions are calculated as the sum of unscaled emissions of SCOPE 1 and SCOPE 2. We use direct emissions as SCOPE 1 and SCOPE 2 emissions are mandatory to report in the UK and is the most reported emission scopes. Carbon intensity is calculated manually by taking the ratio of a firm's unscaled emissions to its revenue. We also calculate annual emission growth rates manually using the following formula:

$$\frac{Emission_t}{Emission_{t-1}} - 1$$

Since we are testing how returns react to carbon emission disclosures, we lag the emission measures by one year to account for when the data becomes available. Lagging emission variables in this way is different from what Bolton and Kacperczyk did in their 2021 paper, where they used the contemporaneous emission data in their models. Using contemporaneous emission data would assume one has the emission data for a specific year available before the year has ended, which may result in look-ahead bias in the study.

***Overview of emissions data***

Table 1 reports summary statistics of our data. SCOPE 1 and SCOPE 2 emissions have an average growth of 6.1% and -3.6%, respectively. In contrast, SCOPE 3 emissions have an average growth of 93%, while the median growth is -0.7%. The sizable observed growth in SCOPE 3 emissions indicates outliers drive our sample's high average growth.

Table 2 reports a cross-correlation table. SCOPE 1, 2, and 3 unscaled emissions are highly correlated, with correlations between 0.72 and 0.85. In other words, companies that produce large levels of SCOPE 1 unscaled emissions also tend to have large levels of SCOPE 2 and 3 unscaled emissions. There is also a positive correlation between unscaled emissions and carbon intensity, but we see a smaller coefficient for these correlations.

Table 3 reports unscaled emission, and carbon intensity averages of SCOPE 1, 2, 3 and direct emissions over time. Unscaled emission averages of SCOPE 1 are increasing up until 2013. However, after 2014 we see a decline in average SCOPE 1 unscaled emissions for companies in our sample. The decline in average unscaled emissions can stem from companies reducing their emissions. However, we contribute the decline to having more small firms in our sample. This is highlighted by the fact that in 2013 the average size of companies in our sample was 13.3 billion USD, while in 2021, this number had fallen to 9.3 billion USD. Hence, the reduction of company unscaled emissions in our sample is not necessarily indicative of those companies reducing their emissions.

Table 4 reports the number of firms disclosing their emissions each year during the period 2011 – 2020. Further, in Table 5 shows the number of unique firms in each industry from our sample. Table 6 report the carbon emissions production by industry from our sample. Unsurprisingly, we see that (i) electricity, (ii) industrial metals and mining, and (iii) oil, gas, and coal are among the industries with the highest SCOPE 1, 2, and 3 unscaled emissions. Additionally, we see that less asset-intensive industries, for example, financial services, are featured at the lower end of unscaled emissions.

***Return data***

We obtain monthly stock returns from the UK between 2012 and 2021, which we use as our dependent variable, expressed as a percentage. $RET_{i,t}$ is the monthly return of the individual company's stock *i* in month *t*. We remove return observations larger than 100% to reduce the impact of outliers.

***Control variables***

To reduce the threat of omitted variable bias, it is important to include control variables in our model (Stock & Watson, 2020). The control variables we use in our regressions are defined as follows: *LNSIZE* is the natural logarithm of the firm's market capitalization at the end of the month. We use it in a logarithmic scale so that the distribution behaves more similarly to the normal distribution. B/M is the firm's equity book value to its market capitalization at the end of the year. LEVERAGE refers to the book value of the firm's leverage, calculated as the ratio of debt to assets. ROE is the return of equity of the firm, calculated as the firm's annual net income divided by the book value of equity at the end of the year. MOM is the cumulative monthly stock return of the last 12 months, leading up to and including month *t-1*. INVEST/A is calculated as the firms' capital expenditures divided by the book value of their assets. LNPPE is the natural logarithm of the firm's property, plant, and equipment. VOLATILITY is measured as the standard deviation of the past 12 months' returns. SALESGR is the annual change in the firm's revenues and is normalized by the prior year's market capitalization. EPSGR is the annual change in earnings per share divided by the firm's prior year share price. The variables RET, LNSIZE, MOM and VOLATILITY, are given in monthly terms, while the remaining are in annual terms. Those variables in annual terms are then converted into monthly values, by assigning the year's value to every month in that year.

We winsorize B/M, LEVERAGE and INVEST at the 2.5% level, and winsorize MOM, VOLATILITY, SALESGR, and EPSGR and the 0.5% level.

## Methodology and Model Specification

This section presents the methodology used to conduct our research. We start by discussing various types of methodologies and the reasoning behind our choice of methodology. Afterwards, we present the model specifications used and the hypothesis we test in each of our models.

### *Methodology*

The scientific literature gives us three general methodologies for finding relationships between stock returns and climate variables: portfolio studies, event studies, and regression studies. With portfolio studies, researchers create mutually exclusive portfolios, rank them based on various variables, and compare the returns of the portfolios. Event studies are used to "examine the behavior of firms' stock prices around corporate events" (Khotari & Warner, 2004). Finally, regression studies "evaluate the relationship between a given variable and one or more variables" (Brooks, 2019). We decide to perform a regression study as this allow us to isolate the relationships we want to study.  Although we perform a regression study, we still believe our results can be compared to event and portfolio studies, as they also test for relationships between returns and climate variables.

The characteristics of our data indicates which methodology to apply in our regression study. We have panel data of both time series and cross-sectional dimensions. The panel is unbalanced because not all companies report all their SCOPE 1, 2, and 3 emissions throughout every year of the sample period. When having panel data, two classes of panel estimator approaches can be applied for financial research: the random and fixed-effect model. The random-effects model captures unobserved heterogeneity by assigning a different error term for each entity. However, we use the fixed effects model, which captures heterogeneity through dummy variable coefficients. In the following, we describe the logic behind two models and our rationale behind our model of choice.

#### *Random effects*

The random effects estimator is typically used when the unobserved heterogeneity is not correlated with the independent variables (Hill, 2018). The random effects model proposes different intercept terms for each entity, which are constant over time. The difference is that the intercept for each cross-sectional unit is assumed to arise from a common intercept $\alpha$, which is the same for all cross-sectional units and over time, plus a random variable that varies cross-sectionally but is constant over time $\epsilon_i$ (Hill, 2018). The random effects model is more appropriate when the sample has been randomly selected from the population (Brooks, 2019). Our sample of firms are not selected randomly, and hence we do not use this method.

*Fixed effects*

The fixed-effects estimator is a method for controlling for omitted variables. We use the fixed effects to absorb all the influences of the omitted variables (Stock & Watson, 2020). The model works by taking the disturbance term and decomposing it into an industry-specific effect $\mu_i$, and the remaining stochastic disturbance $v_{it}$. The industry-specific effects encapsulate all variables affecting our dependent variable cross-sectionally but does not vary over time. It is also possible to have time-fixed effects $\lambda_t$ , instead of industry specific effects. This model would be used when the dependent variable is thought of as changing over time but not cross-sectionally (Hill, 2018). Further, it is possible to allow for both industry and time-fixed effects in the same model (Brooks, 2019). This would be the case if some omitted variables are constant over time but vary across industries, while others are constant across industries but vary over time (Stock & Watson, 2020). In general, the fixed effects regression model limits selection bias by eliminating parts of the variation that is believed to contain confounding factors (Mummolo & Peterson, 2018).

Based on the characteristics of the two methods and our data, we use the fixed effects estimator. Industry-fixed effects aim to capture cross-sectional variation in our dependent variable. Since emissions are often clustered in certain industries, we include industry-fixed effects to account for this. The time-fixed effects encapsulate unobservable changes happening over time, but which are constant cross-sectionally. To account for the possibility of omitted variables in the cross-sectional and/or time dimension, we perform two kinds of pooled regression (i) using only time-fixed effects and (ii) using both time and industry-fixed effects.

To estimate the fixed effects model, we can use the least squares dummy variable (LSDV) method or the within transformation method. With unbalanced panel data, the within transformation for both industry and time-fixed effects is more complex than for the balanced panel. For simplicity, we use the LSDV method to capture the time and industry-fixed effects. Using the LSDV method is appropriate, given that the OLS estimates, and the sum of squared residuals are identical for both LSDV and within transformation methods (Hill, 2015). The unobserved heterogeneity is controlled by including dummy variables for each industry and month. To prevent perfect multicollinearity, we drop one of the industry dummies and one of the month dummies (Stock & Watson, 2020).

Furthermore, we cluster standard errors at firm and year levels to enhance our results' statistical robustness. We do this to reflect the possibility of firm-level emissions concentrating across firms and time. We estimate the standard errors using the Newey-West and Driscoll and Kraay covariance matrix. Using this approach guarantees that the covariance matrix estimator is consistent, independently of the cross-sectional dimension (Hoechle, 2007). This results in standard errors which are robust to general forms of cross-sectional and serial correlation.

***Model specification***

This subsection presents the regression models we use for our study. In each of the regression models, we use the methodology outlined above.

*Returns and carbon emissions*

We will now elaborate on the hypothesis we are testing, and the two models we use to test the hypothesis.

The first hypothesis (H1) we want to test is: *Does carbon emissions explain variation of stock returns for UK listed firms?*[3]

$H_0: \beta_1 = 0$ Carbon emission is **not** significantly related to the variation of stock returns for UK listed firms.

[3] We will be using the same hypothesis for all our scopes and emission measures

$H_1: \beta_1 \neq 0$ Carbon emissions is significantly related to the variation of stock returns for UK listed firms

We reject the null hypothesis if the emissions coefficient $\beta_1$ is statistically and significantly different from zero at the 95% confidence level.

*Time fixed effects*

We estimate the model for the pooled regression with time-fixed effects using the LSDV method:

$$Ret_{i,t} = \beta_0 + \beta_1 Emissions_{i,t-1} + \beta_2 Controls_{i,t-1} + \alpha_1 D_1 + \cdots + a_{T-1} D_{T-1} + u_{i,t} \ (1)$$

where our dependent variable $RET_{i,t}$ is regressed against an emission measure, the control variables, and the dummy variables accounting for the month-fixed effects. For example, $D_1$ will take the value 1 for January 2012 and 0 otherwise. We have $T-1$ dummy variables, where T refers to the total monthly periods in each regression. To prevent perfect multicollinearity, we exclude one of the time periods. We have nine different regressions, where the only variable that changes is the emission measure. The coefficient of interest in this regression is $\beta_1$. This coefficient reflects the relationship, if any, of carbon emissions to stock returns.

*Time and industry fixed effects*

The regression that includes both time and industry fixed effects is as follows:

$$Ret_{i,t} = \beta_0 + \beta_1 Emissions_{i,t-1} + \beta_2 Controls_{i,t-1} + \alpha_1 D_1 + \cdots + a_{T-1} D_{T-1} + \lambda_1 I_1 + \cdots + \lambda_{k-1} I_{k-1} + u_{i,t} \ (2)$$

Our dependent variables will be the same as in the regression with only time-fixed effects. The difference is that we add dummy variables for each of the industries. For example, $I_1$ will be 1 for Aerospace and Defense and 0 otherwise. We have $k-1$ dummy variables, where *k* refers to the total industries in each regression. Each component of the dummy variables absorbs the effects specific to the particular industry. As before, the coefficient of interest in this regression is $\beta_1$.

*Carbon emission determinants*

To better understand the drivers of emissions, we regress various firm characteristics to carbon emissions. We perform the regression on carbon emissions and firm characteristics by estimating a pooled regression with industry and time-fixed effects:

$$Emissions_{i,t} = \beta_0 + \beta_1 FirmCharacteristics_{i,t} + \alpha_1 D_1 + \cdots + a_{T-1} D_{T-1} + \lambda_1 I_1 + \cdots + \lambda_{k-1} I_{k-1} + u_{i,t} \quad (3)$$

where our dependent variable is the different emission measures. The independent variables include the firm characteristics LNSize, B/M, ROE, Leverage, Invest/A, LNPPE, SALESGr, and EPSGr, as well as the month and industry dummy variables.

*Carbon emissions before and after the Paris Climate Agreement*

Furthermore, we explore whether the relationship between emissions and stock returns is different before and after the PCA. More specifically we regress returns to four various emission measures: unscaled emissions, growth in emissions, carbon intensity and direct emissions. The underlying idea is to explore whether carbon risk has been more efficiently priced in after the PCA. The rationale behind this claim is that increased investor awareness around climate change increases the carbon risk premium. This effect would be reflected in a higher carbon risk premium, or lower carbon alpha, after the PCA. We test this by dividing our sample into two intervals: 2012-2015 and 2016-2021, and run the pooled regression with industry and time-fixed effects, using Equation 3.

The second hypothesis (H2) we want to test is: *Does carbon emissions explain variation in stock returns for UK firms before the Paris Climate Agreement?*

> $H_0: \beta_1 = 0$ Carbon emission is **not** significantly related to the variation in stock returns for UK listed firms for the period of 2012-2015.
>
> $H_1: \beta_1 \neq 0$ Carbon emission is significantly related to the variation in stock returns for UK listed firms for the period of 2012-2015.

We reject the null hypothesis if the emissions coefficient $\beta_1$ is statistically and significantly different from zero at the 95% confidence level.

The third hypothesis (H3) we want to test is: *Does carbon emissions explain variation in stock returns for UK firms after the Paris Climate Agreement?*

$H_0: \beta_1 = 0$ Carbon emission is **not** significantly related to the variation in stock returns for UK listed firms for the period of 2016-2021.

$H_1: \beta_1 \neq 0$ Carbon emission is significantly related to the variation in stock returns for UK listed firms for the period of 2016-2021.

We reject the null hypothesis if the emissions coefficient $\beta_1$ is statistically and significantly different from zero at the 95% confidence level.

*Robustness check*

To examine the robustness of our results, we observe how our coefficients of interest behave when we modify the regression specification. We perform four types of robustness checks. Two of the robustness tests are regressions where we exclude salient industries. In the first we remove the industries with the highest average unscaled emissions from our sample. In the second, we remove the industries with the highest average carbon intensity. In the next two regressions we regress returns and emissions measures to the industries we *excluded* in the two previously mentioned regressions. We perform a pooled regression with time-fixed effects and industry and time-fixed effects, following Equations (2) and (3).

In the first robustness test, where our exclusion criteria are industries with the highest unscaled average emissions, we exclude the following industries:

| SCOPE 1 | SCOPE 2 | SCOPE 3 |
|---|---|---|
| Electricity | Industrial Metals and Mining | Industrial Metals and Mining |
| Industrial Metals and Mining | Oil, Gas and Coal | Oil, Gas and Coal |
| Oil, Gas and Coal | Electricity | Gas, Water and Multi-utilities |

*Figure 2: Excluded industries with the highest unscaled average emissions*

In the second robustness test, where our exclusion criteria are industries with the highest average carbon emission intensity, we exclude the following industries:

| **SCOPE 1** | **SCOPE 2** | **SCOPE 3** |
|---|---|---|
| Electricity | Precious Metals and Mining | Industrial Metals and Mining |
| Gas, Water and Multi-utilities | Industrial Metals and Mining | Gas, Water and Multi-utilities |
| Industrial Metals and Mining | Food Producers | Oil, Gas and Coal |

*Figure 3: Excluded industries with the highest average carbon emission intensity*

## Results and Analysis

In this section, we start by presenting the various tables that include our results. Afterward, we present these results and discuss their implications. Since our study builds upon Bolton and Kacperczyk (2021) study we will throughout this section compare our results to theirs. Lastly, we put forward different limitations relating to our study.

### *Overview of tables*

Tables 7 and 8 report the regression results of SCOPE 1, 2, and 3 of unscaled emissions, growth in emissions, carbon intensity, and direct emissions on various company characteristics. These tables will be later referenced when discussing the results of our primary regressions between returns and various measures of company emissions.

Tables 9-12 report the results for SCOPE 1, 2, and 3 for unscaled emissions, growth in emissions, carbon intensity, and direct emissions to stock returns, respectively. The three regressions on the left-hand side (columns 1-3) include time-fixed effects, while the three regressions on the right-hand side (columns 4-6) include both time and industry-fixed effects.

Tables 13-16 report six separate regression results in each table. In columns 1-3, we report regression results of various emissions measures to returns before the PCA (2011 – 2015), and in columns 4-6, we report regression results of various emissions categories to returns after the PCA (2016 – 2020). These regressions include both time and industry-fixed effects.

In Tables 17 and 19, we report the regression results for the same regressions reported in Tables 9-12, but we exclude salient industries from our sample. These regressions include both time and industry-fixed effects. In Tables 18 and 20, we report the regression results for the same regressions reported in Tables 9-12, but we only include salient industries in our sample.

***Results***

In the following we report the results from our regressions in table 9-12.

*Returns and unscaled emission*

We start with the regression results of unscaled emissions and stock returns as presented in Table 9. For the regressions in columns 1-3, we find SCOPE 1 and SCOPE 3 unscaled emissions negatively affect returns. This means that we reject the null hypothesis of H1 for SCOPE 1 and 3 unscaled emissions. More specifically, we find that a one-standard-deviation increase in SCOPE 1 and SCOPE 3 unscaled emissions leads to a -3.12% and -3.76% decrease in annualized stock returns, respectively. When including both time and industry-fixed effects in our regressions, the relationship between returns and SCOPE 2 emissions become negatively related. Additionally, the coefficients presented in columns 4 and 6 for SCOPE 1, and 3 become smaller. This means that we reject the null hypothesis of H1 for the three scopes of unscaled emissions.

In contrast, Bolton and Kacperczyk (2021) study find a significant positive association between unscaled emissions and stock returns. More specifically, they find that a one-standard-deviation increase in SCOPE 1, SCOPE 2, and SCOPE 3 leads to a 1.5%, 2.8%, and 3.6% increase in annualized stock returns, respectively. Furthermore, their regressions that include both time and industry-fixed effects have larger and more significant coefficients.

Our results are strikingly different from Bolton and Kacperczyk's results. A reasonable interpretation of our regression results is that investors do not get compensated for taking on climate risk, and, by extension, our results suggest there is no carbon risk premium in the UK stock market. Furthermore, we could argue that our results are consistent with the existence of a greenium which in this instance references a premium on low carbon emission stocks. This suggests that investors could have achieved an alpha using various low carbon investment strategies over the period 2012 - 2021.

We note that unscaled emissions have a positive relationship with firm size (Table 7). In other words, there might be collinearity between unscaled emissions and firm size. Consequently, firms with high levels of unscaled emissions in our sample might just be large firms, as opposed to climate-unfriendly firms with high levels of climate risk. Since unscaled emissions are not scaled by firm size, it weakens the representativeness of unscaled emissions as a proxy for climate risk.

*Returns and growth in emission*

Next, we report results where we regressed returns to growth in emissions, as reported in Table 10. In all the regressions we fail to reject the null hypothesis H1. In other words, we find no significant relationship between returns and growth in emissions.

Again, our results stand in contrast to Bolton and Kacperczyk's results, who find significant positive relationships between growth in emissions and returns for all three scopes of emissions. A reasonable argument for Bolton and Kacperczyk's findings is that a company that grows its unscaled emissions increases its climate risk, thereby its expected stock returns.

However, our data support*s* the idea that changes in short-term emissions are related to changes in operational output. From our regressions of carbon emission determinants (Table 7), we the results suggest that SCOPE 1 and SCOPE 2 growth in emissions positively relate to sales growth. Hence, our data suggests changes in carbon emissions are related to changes in operational output, and we argue that there are challenges related to using growth in emissions as a proxy for climate risk.

*Returns and carbon intensity*

Next, we report regression results where we regress returns to carbon intensity, as reported in Table 11. In all the regressions we fail to reject the null hypothesis H1, meaning that in our sample, carbon intensity does not seem to relate to the variation of stock returns.

Our results are similar to those of Bolton and Kacperczyk (2021). They argue that this result is surprising since emission-intensive companies would be among the first to become unprofitable if carbon prices increased. We argue this could highlight a flaw in Bolton and Kacperczyk's conclusions on the presence of a carbon risk premium. Our results suggest that unscaled emissions correlate with firm size. However, we potentially mitigate correlations with firm size by using carbon intensity. To illustrate the point further, using unscaled emissions is analogous to using revenue, while carbon intensity is analogous to using a return metric such as ROE when assessing a company's financial performance. Hence, we argue that carbon intensity is potentially a better metric of climate risk than unscaled emissions. Furthermore, the lack of relationship between returns and carbon intensity suggest that no carbon-risk premium is present in the UK stock market.

*Returns and direct emissions*

Next, we report the results in Table 12, where we regress returns to direct emissions. We find that returns and direct emissions are negatively related, and that the coefficient becomes larger when we include both time and industry-fixed effects instead of just including time-fixed effects. Further, we find no relationship between returns and growth in direct emissions. Lastly, we find a significant positive relationship between returns and direct emission intensity. We note that the relationship between returns and direct emission intensity has a small coefficient and is only significant at the 5% level.

Direct emissions are the sum of SCOPE 1 and SCOPE 2 emissions. Hence, when interpreting the results where we regress returns and various measures of direct emissions, it is reasonable to compare the results to those that regress returns and SCOPE 1 and SCOPE 2 emissions separately. In Table 9, we find a significant negative relationship between returns and unscaled emissions of SCOPE 1 and SCOPE 2. Hence, our findings of a negative relationship between returns and direct emissions are expected. Furthermore, we do not find a significant relationship between returns and growth in SCOPE 1 or SCOPE 2 emissions; hence, our findings of a non-significant relationship between returns and growth in direct emissions are expected. The only surprising result is the positive relationship between returns and direct emissions intensity. The results are consistent with the idea that the market compensates investors who take on carbon risk in the form of direct emission intensity. However, we note that the economic significance of the coefficient is small.

***Paris Climate Agreement***

As mentioned previously, Table 9 reports a significant negative relationship between returns and unscaled carbon emissions. We interpret the result as consistent with the existence of a greenium for low-carbon stocks. To challenge this interpretation, we recall how Pastor et al. (2021) cautions against such a conclusion. Instead, he argues that outperformance by green stocks is most likely due to a one-time market recognition where positive risk-adjusted returns for green stocks should not be expected in the future.

We test our hypotheses H2 and H3, to examine if the relationship between emissions and returns change after the PCA. We expect the coefficients in our regression after the PCA to be higher than before the PCA due to increased transition risks and investor awareness of these risks. However, our findings are inconclusive.

The results in Table 13 report that coefficients for SCOPE 1 unscaled emissions are significant before and after the PCA but that the coefficient becomes smaller after the PCA, in line with potential alpha decay. On the other hand, the coefficient for SCOPE 2 and SCOPE 3 was not significant before the PCA but is significant and negatively related to returns after the PCA.

Table 14 reports no significant relationship between returns and growth in emissions for SCOPE 1 and SCOPE 2 before the PCA, but a significant positive relationship between returns and SCOPE 3 emissions before the PCA. In contrast, after the PCA, returns and growth in emissions for SCOPE 2 are significantly negatively related, while returns and growth in emissions for SCOPE 1 and SCOPE 3 are not significantly related after the PCA.

In Table 15, we observe that returns and SCOPE 1 emission intensity is negatively related before the PCA. However, returns and SCOPE 2 and 3 emission intensity are positively related before the PCA. In contrast, only returns and SCOPE 3 emission intensity are negatively related after the PCA, with a negative relationship.

In Table 16, we observe that only returns and direct emissions are significantly related before the PCA, with a negative relationship. In contrast, we find that direct emissions and growth in direct emissions are significantly negatively related to returns after the PCA. Additionally, we find that returns and direct emission intensity are positively related after the PCA.

As mentioned earlier, the results from the regressions are inconclusive and do not follow the pattern we were anticipating. Instead, we observe differing trends for each emission measure before and after the PCA. A possible explanation for these conflicting results could be the sample size before and after the PCA, where the sample size after the PCA is roughly three times as large as before. All else equal, a smaller sample size reduces the power of the test and reduces the likelihood of getting significant results. Our data supports this idea as we have a higher adjusted $R^2$ after the PCA compared to before the PCA.

Furthermore, as discussed in the introduction, reporting carbon emissions became mandatory in the UK in 2013. Hence, the sample before the PCA overlaps with the time when emission disclosure by publicly listed firms in the UK was voluntary. This decreases the representativeness of the emissions data in our sample. Additionally, Matsamura et al. (2015) finds that markets penalize firms that do not disclose emissions information in the form of lower firm valuations. We do not consider this effect in our study, which further reduces the representativeness of our sample before the PCA.

***Excluding salient industries***

Next, we test the robustness of our results. In these tests, we regress returns to unscaled emissions, growth in emissions, carbon intensity, and direct emissions, where the difference will be the sample used. The first robustness test (Table 17) excludes industries with the highest average unscaled emissions from our sample. The second robustness test (Table 19) excludes the industries with the highest average carbon intensity from our sample. In the third (Table 18), we include only industries with the highest average unscaled emissions in our sample. In the fourth (Table 20), we include only industries with the highest average carbon intensity in our sample. We want to test if our results become significantly different when excluding or only including the salient industries.

| Unscaled emission | | | | | |
|---|---|---|---|---|---|
| **SCOPE** | **All industries** | **Ex. HAUE** | **Inc. only HAUE** | **Ex. HACI** | **Inc. only HACI** |
| SCOPE 1 | -0.207*** | -0.215*** | 0.159 | -0.214*** | 0.031 |
| SCOPE 2 | -0.117*** | -0.123*** | -0.074 | -0.114*** | -0.199 |
| SCOPE 3 | -0.147*** | -0.136*** | -0.897*** | -0.136*** | -0.0897*** |

| Carbon intensity | | | | | |
|---|---|---|---|---|---|
| **SCOPE** | **All industries** | **Ex. HAUE** | **Inc. only HAUE** | **Ex. HACI** | **Inc. only HACI** |
| SCOPE 1 | 0.020* | 0.001 | 0.078** | 0.014 | 0.088* |
| SCOPE 2 | 0.161 | 0.066 | 0.600* | 0.179* | 0.019 |
| SCOPE 3 | -0.018 | -0.010 | -0.065*** | -0.010 | -0.065*** |

| Growth in emissions | | | | | |
|---|---|---|---|---|---|
| **SCOPE** | **All industries** | **Ex. HAUE** | **Inc. only HAUE** | **Ex. HACI** | **Inc. only HACI** |
| SCOPE 1 | -0.008 | -0.031 | 1.127* | -0.010 | -1.435 |
| SCOPE 2 | 0.272* | -0.095 | -1.929*** | -0.270 | 0.591 |
| SCOPE 3 | 0.014* | 0.013* | 0.065 | 0.013* | 0.065 |

| Direct emissions | | | | | |
|---|---|---|---|---|---|
| **Measure** | **All industries** | **Ex. HAUE** | **Inc. only HAUE** | **Ex. HACI** | **Inc. only HACI** |
| Unscaled | -0.284*** | -0.287*** | -0.396 | -0.287*** | -0.396 |
| Growth | -0.153 | -0.228 | 1.349 | -0.228 | 1.349 |
| Intensity | 0.002** | 0.002* | -0.0005 | 0.002* | -0.0005 |

*Figure 4: Results when excluding and including salient industries*[4]

Figure 4 shows that regressions that exclude salient industries have nearly identical results to the regressions that include all industries. The only different results are for direct emissions, where carbon intensity becomes insignificant when excluding industries with the highest average unscaled emissions. The results strengthen the confidence in findings from Tables 9-12 and suggest that the noise coming from industry-specific characteristics is taken into account through the industry-fixed effects in our model.

However, the regressions that include *only* the salient industries give differing results. For example, we do not get significant results between returns and unscaled emissions with *only* the industries with the highest average emissions as opposed to the regression that includes all industries. There are several different results throughout when we compare the regression results with the regressions that include all industries and those that *only* salient industries. The differences in

[4] HAUE refers to the industries with the "Highest average unscaled emissions". HACI refers to the industries with the "Highest average carbon intensity".

results could suggest that investors price carbon emissions differently for companies in industries with high average emissions. However, the number of firms in the excluded salient industries is around 700, while the total sample is about 25,000. Hence, a smaller sample could be the reason behind the differing results.

***Further discussion***

We find a negative relationship between returns and SCOPE 3 unscaled emissions. However, we question this result, and other results where we regress returns with SCOPE 3 emissions, due to our data quality. In the UK, only one of the components of SCOPE 3 unscaled emissions is mandatory to report for publicly listed companies. The emissions that are compulsory to report are "energy use and related emissions from business travel in rental cars or employee-owned vehicles where they are responsible for purchasing the fuel". Since reporting SCOPE 3 emissions are not mandatory, we have fewer firms in our sample with reported SCOPE 3 emissions. To illustrate, we have approximately 25,600 observations for unscaled emissions of SCOPE 1 and SCOPE 2, but we only have 13,956 observations for SCOPE 3 unscaled emissions.

Since we are doing a similar study to Bolton and Kacperczyk, we have naturally compared our results to theirs. However, a critical distinction from Bolton and Kacperczyk's (2021) study is that their sample includes only companies listed in the US, while our sample only includes companies in the UK. Therefore, a pertinent question is what country differences could influence our results. One hypothesis is that the stronger a country reacts to carbon emissions through carbon regulations and policies, the higher the transition risks could potentially be. In turn, this would mean that carbon risks would be more material. Hence, we expect to observe a higher carbon risk premium, or smaller carbon alpha, in countries with stricter carbon regulations as opposed to countries with weaker carbon regulations.

To compare climate regulations between the UK and the US, we use the climate change performance index (CCPI). A part of the index ranks countries from best to worst based on the quality of their climate policies. We use this part of the index as a proxy of climate regulation strictness. For 2021 the list puts the UK at 14th place, while they put the US at 28th (The Climate Change Performance Index 2021). They write that the UK has "substantial political and financial support to deliver its net-zero 2050 target and the new interim target for a net-zero power system by 2035". In contrast, they write that US policies are insufficient to deliver the emissions cuts necessary to meet net-zero targets by 2050. Additionally, the UK has been ranked above the US every year since 2011, indicating that the UK has had stricter climate regulations in place during the whole span of our sample period. Considering that the UK has stricter climate policies than the US, our results are surprising, as we would expect the strict climate measures in the UK to be reflected in a higher carbon risk premium, or a smaller carbon alpha, compared to the US.

It is also relevant to mention the potential implications of our sample period. Our sample includes company emissions, stock market data, and corporate financial data, stretching over ten years from 2012 to 2021. In contrast, Bolton and Kaczkeprcyk's sample covers thirteen years in the period 2005 - 2017. While their sample goes further back and includes periods where awareness around climate change was lower, our sample includes more recent data where awareness around climate change is higher. The differences in the sample period limit the comparability between our results. Further, emission disclosure by publicly listed firms in the UK was mandatory for most of our sample period. Conversely, in the US, it remains encouraged but not mandatory for firms to disclose GHG emissions (Downar et al., 2021). The exact implications of mandatory versus voluntary emission disclosures are unknown but may limit the comparability between our results.

### ***Limitations***

In this subsection we outline potential limitations regarding our study.

#### *Not accounting for Brexit*

After a UK-wide referendum in June of 2016, voters decided that the UK was to leave the European Union. The withdrawal was finalized on the 31st of January 2020 (EU, 2022). We have not considered the effects of Brexit in our sample selection, study design, or interpretation of our results. For example, following

Brexit, the UK replaced its participation in the EU ETS with its own UK Emissions Trading Scheme. The UK's system is smaller and less liquid than that of the EU ETS; consequently, it is estimated that UK firms pay 10% more for their emissions than firms linked to the EU ETS. This puts UK firms at a competitive disadvantage compared to their EU counterparts (Harvey, 2022). The effects of the UK's new trading scheme are one of many wide-reaching changes relating to Brexit on the UK's climate policies. Not accounting for such changes is a limitation of our study and weakens the confidence in our conclusions.

*GHG emissions*

The greenhouse gasses in SCOPE 1, 2, and 3 are carbon dioxide ($CO_2$), methane, nitrous oxide, hydrofluorocarbons, perfluorinated compound, sulfur hexafluoride, and nitrogen trifluoride (Greenhouse Gas Protocol, 2022). Each greenhouse gas impacts the environment differently, and each company emits different levels of the specific greenhouse gasses. One potential limitation of our study is that we do not distinguish between and analyze separately whether the greenhouse gasses are assessed differently by investors as potential risks. For example, methane is 25 times as potent as carbon dioxide at trapping heat in the atmosphere but disappears from the atmosphere a lot quicker than $CO_2$. On the other hand, nitrous oxide is 300 times more potent than carbon dioxide and stays in the atmosphere for over 100 years (Special report, climate change, 2007). Consequently, a company with relatively low greenhouse gas emissions but relatively high nitrous oxide emissions might be exposed to high levels of transition risk. However, our model does not capture these differences; hence, we do not fully capture all relevant emission risks that might impact asset prices.

*Sample limitation*

Another limitation could come from the way we narrowed down our sample. Eikon Refinitiv is our primary data source, and we narrowed down our sample based on data availability. However, Eikon Refinitiv often had missing data across time and different variables. This resulted in the number of firms in our sample being reduced from 1,830 to 447. Furthermore, not all 447 firms have data for each time period from 2011-2021. Missing data and sampling based on availability can cause sample selection bias. If the reason for missing data is purely random, then the estimates in our regressions will be unbiased (Stock &

Watson, 2020). However, companies in our sample might have incentives for either reporting or not reporting its emissions data. For example, companies that emit more than their peers could be incentivized to avoid reporting their emissions data. Therefore, we might lack data points from high polluting companies in our sample, increasing the likelihood of sample selection bias. If this is the reason behind missing emission data, it could result in inconsistent and biased estimators. We note that this would only be the case before 2013, when reporting carbon emissions in the UK became mandatory.

*Collinearity in the data*

Given our results from the regression of carbon emission determinants, we observed that several firm characteristics are related to carbon emission. This could give rise to collinearity in our regressions of returns to emission measures. Consequently, it is difficult to observe the individual contribution of each variable to the fit of the regression. This may result in the coefficients of one or more of these regressors being imprecisely estimated and possibly having large standard errors (Stock & Watson, 2020). The implication of having collinearity in our regressions is that significance tests may give inappropriate conclusions, and may be difficult to make inferences from the results. Hence, the interpretation of our regression results is weakened due to the possible collinearity. A possible way to address this problem is to create a ratio of the collinear variables.

*Carbon intensity limitation*

Another limitation is that there are problems related to using the carbon intensity measure. As we recall, we measure carbon intensity by dividing the unscaled emissions by the company's revenue. Although this is one of the most common ways to compute carbon intensity, there is no standard for scaling emissions data. A potential problem with using revenue to scale emissions is that an increase in revenue is not necessarily a result of increased output. Instead, it can reflect increasing prices. Hence the way we computed the carbon intensity measure might not have been the most optimal.

## Suggestions for further research

It would be interesting to research the effect of Brexit on the relationship between returns and carbon emissions. Further, one could conduct a similar study to ours on the UK market but differ between firm-disclosed data and vendor-estimated data. Another research idea would be to conduct a study that segments emissions into categories of GHG emissions and analyze how the market prices different sources of GHG emissions. Lastly, a firm's carbon emissions are a potential source of climate risk. Therefore, another research idea would be to use different measures of climate performance, and hence potential sources of climate risk, to understand better how markets price climate performance.

# Conclusion

How do carbon emissions affect stock returns? This question has gained relevance with the rising threat of climate change, and with the rapid rise of sustainable investment funds, the question is now relevant for policymakers, investors, and fund managers. Understanding this relationship is especially important as many investors believe that incorporating ESG issues into mainstream investment processes might come at the cost of lower returns.

Academic research on the relationship between returns and carbon emissions has provided conflicting results. Bolton and Kacperczyk (2021) document a positive relationship between stock returns and carbon emissions. In contrast, Matsumura et al. (2015) find a negative relationship between firm value and carbon emissions. We perform our study by conducting a pooled regression with time and industry-fixed effects of UK companies' stock returns against carbon emissions and use several return predictors as control variables.

Our results suggest a negative relationship between returns and unscaled emissions for SCOPE 1, 2, and 3, as well as for unscaled direct emissions. This effect is also present before and after the Paris Climate Agreement. In addition, our robustness tests suggest that the effect is present when excluding industries with the highest unscaled emissions from our sample and industries with the highest carbon intensity from our sample. These results potentially suggest that the market is rewarding companies with low carbon emissions. In other words, our results are consistent with the idea that investors can do well by doing good. We find a positive relationship between returns and direct emission intensity, but only significant at the 10% level and with a small coefficient. Besides the previously mentioned results, our data suggest there is no significant relationships between returns and carbon intensity and no relationship between returns and growth in emissions. The lack of relationships between returns and carbon intensity weakens our confidence in our conclusion that the market rewards companies with low carbon emissions. In addition, past performance is not indicative of future results, and we caution against interpreting our results as suggesting that low carbon companies will perform well in the future. We suspect that as climate risk becomes more material and as investor awareness of climate risks increases, the high returns observed for low carbon emissions firms will either decrease or disappear.

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# Appendix

## Table 1 – Summary statistics

In this table we report summary statistics for the variables used in our regressions. We report averages, medians, and standard deviations. Panel A reports our emissions variables. Panel B report the return and control variables. *Ret* is monthly stock returns; *LNSize* the logarithm of market capitalization; *BM* is book to market value of equity; *Leverage* is book value of leverage defined as book value of debt to assets; *MOM* is cumulative stock returns over the one-year period; *Invest/A* is CAPEX divided by book value of assets, *ROE* is return on equity, *Volatility* is monthly stock return volatility over the one-year period; *SalesGr* is the change in firm revenues divided by last month's market capitalization; *EPSGr* is the dollar change in annual earnings per share divided by the firms share price. *LNPPE* is the logarithm of property, plant and equipment.

| Statistic | Mean | Median | St. Dev. |
|---|---|---|---|
| *Panel A: Emission variables* | | | |
| Log (Carbon Emissions Scope 1 (tons CO2e)) | 9.81 | 9.76 | 3.20 |
| Log (Carbon Emissions Scope 2 (tons CO2e)) | 9.71 | 9.66 | 2.57 |
| Log (Carbon Emissions Scope 3 (tons CO2e)) | 9.72 | 9.14 | 3.94 |
| Growth Rate in Carbon Emissions Scope 1 (winsorized at 2.5%) | 0.06 | -0.01 | 0.54 |
| Growth Rate in Carbon Emissions Scope 2 (winsorized at 2.5%) | -0.03 | -0.06 | 0.34 |
| Growth Rate in Carbon Emissions Scope 3 (winsorized at 2.5%) | 0.93 | -0.01 | 5.69 |
| Carbon Intensity Scope 1 (tons CO2e/USD m.)/100 (winsorized at 2.5%) | 1.07 | 1.18 | 2.99 |
| Carbon Intensity Scope 2 (tons CO2e/USD m.)/100 (winsorized at 2.5%) | 0.44 | 0.11 | 1.13 |
| Carbon Intensity Scope 3 (tons CO2e/USD m.)/100 (winsorized at 2.5%) | 2.58 | 0.05 | 8.97 |
| Log (Direct Emissions (tons CO2e)) | 10.78 | 10.68 | 2.74 |
| Growth Rate in Direct Emissions (winsorized at 2.5%) | 0.06 | -0.01 | 0.54 |
| Direct Carbon Intensity (tons CO2e/USD m.)/100 (winsorized at 2.5%) | 2.07 | 0.27 | 22.66 |
| *Panel B: Return and control variables* | | | |
| Ret (%) | 1.10 | 0.96 | 10.89 |
| LNSize | 7.79 | 7.62 | 1.59 |
| BM (winsorized at 2.5%) | 0.56 | 0.42 | 0.51 |
| Leverage (winsorized at 2.5%) | 0.12 | 0.14 | 0.22 |
| MOM (winsorized at 0.5%) | 0.14 | 0.09 | 0.44 |
| Invest/A (winsorized at 2.5%) | 0.04 | 0.03 | 0.04 |
| ROE (winsorized at 2.5%) | 14.29 | 12.72 | 37.90 |
| Volatility (winsorized at 0.5%) | 0.09 | 0.08 | 0.06 |
| SalesGr (winsorized at 0.5%) | 0.002 | 0.007 | 0.28 |
| EPSGr (winsorized at 0.5%) | -0.0003 | 0.001 | 0.12 |
| LNPPE | 19.29 | 19.45 | 2.38 |

## Table 2 – Cross-correlations

Cross correlations table of total emissions and carbon intensities. We use our sample data from 2011 – 2020 to create the cross correlations table.

| | Scope 1 | Scope 2 | Scope 3 | Scope 1 INT | Scope 2 INT | Scope 3 INT |
|---|---|---|---|---|---|---|
| Scope 1 | 1.0000 | | | | | |
| Scope 2 | 0.7785 | 1.0000 | | | | |
| Scope 3 | 0.7203 | 0.8520 | 1.0000 | | | |
| Scope 1 INT | 0.5826 | 0.2967 | 0.1796 | 1.0000 | | |
| Scope 2 INT | 0.2289 | 0.3785 | 0.2198 | 0.3530 | 1.0000 | |
| Scope 3 INT | 0.4633 | 0.5221 | 0.6791 | 0.3557 | 0.3576 | 1.0000 |

## Table 3 – Emission averages

Averages of scope 1, 2, and 3 of unscaled emissions and carbon intensity for the time-period 2011 – 2020. Additionally, we provide the same data for direct emissions and direct emission intensity at the same time-period.

| Year | Scope 1 | Scope 2 | Scope 3 | Direct | Scope 1 INT | Scope 2 INT | Scope 3 INT | Direct INT |
|---|---|---|---|---|---|---|---|---|
| 2011 | 1 458 999 | 244 833 | 10 958 164 | 1354102 | 127 | 41 | 226 | 139 |
| 2012 | 1 776 124 | 500 299 | 21 930 054 | 2876343 | 102 | 43 | 289 | 136 |
| 2013 | 1 802 417 | 417 080 | 25 665 840 | 2244167 | 104 | 48 | 287 | 153 |
| 2014 | 1 598 740 | 372 580 | 24 796 122 | 1989902 | 116 | 50 | 308 | 162 |
| 2015 | 1 365 276 | 391 115 | 20 592 624 | 2089031 | 106 | 60 | 292 | 172 |
| 2016 | 1 332 338 | 374 506 | 17 863 002 | 2029207 | 101 | 56 | 244 | 174 |
| 2017 | 1 313 985 | 338 017 | 17 593 205 | 1973738 | 96 | 46 | 263 | 140 |
| 2018 | 1 139 536 | 263 555 | 10 807 285 | 1636678 | 99 | 44 | 307 | 156 |
| 2019 | 870 711 | 228 646 | 7 022 920 | 1300774 | 121 | 38 | 333 | 167 |
| 2020 | 585 977 | 160 281 | 4 839 529 | 771274 | 97 | 28 | 205 | 120 |

## Table 4 – Firm disclosure

The number of firms disclosing their emissions during the period 2011-2020 from the raw sample. The raw sample is before discarding firms with missing data for control variables or returns. The total number of firms extracted from Eikon was 1,830.

| Year | Scope 1 | Scope 2 | Scope 3 | Direct |
|---|---|---|---|---|
| 2011 | 153 | 145 | 114 | 145 |
| 2012 | 178 | 177 | 121 | 177 |
| 2013 | 210 | 208 | 118 | 208 |
| 2014 | 231 | 230 | 117 | 228 |
| 2015 | 257 | 259 | 136 | 256 |
| 2016 | 267 | 271 | 144 | 267 |
| 2017 | 280 | 284 | 148 | 280 |
| 2018 | 323 | 323 | 175 | 320 |
| 2019 | 408 | 418 | 253 | 408 |
| 2020 | 506 | 525 | 325 | 506 |

## Table 5 – Unique firms in each industry

This table shows the number of unique firms in each industry from our total sample using the Industry Classification Benchmark (ICB) as sector name classification.

| Industry name | Firm count | Industry Nr. |
|---|---|---|
| Aerospace and Defense | 9 | 1 |
| Alternative Energy | 1 | 2 |
| Automobiles and Parts | 2 | 3 |
| Beverages | 7 | 4 |
| Chemicals | 7 | 5 |
| Construction and Materials | 24 | 6 |
| Consumer Services | 4 | 7 |
| Electricity | 4 | 8 |
| Electronic and Electrical Equipment | 15 | 9 |
| Finance and Credit Services | 7 | 10 |
| Food Producers | 11 | 11 |
| Gas, Water and Multi-utilities | 4 | 12 |
| General Industrials | 9 | 13 |
| Health Care Providers | 4 | 14 |
| Household Goods and Home Construction | 17 | 15 |
| Industrial Engineering | 7 | 16 |
| Industrial Materials | 3 | 17 |
| Industrial Metals and Mining | 12 | 18 |
| Industrial Support Services | 45 | 19 |
| Industrial Transportation | 11 | 20 |
| Investment Banking and Brokerage Services | 31 | 21 |
| Leisure Goods | 3 | 22 |
| Media | 17 | 23 |
| Medical Equipment and Services | 4 | 24 |
| Non-life Insurance | 1 | 25 |
| Oil, Gas and Coal | 19 | 26 |
| Personal Care, Drug and Grocery Stores | 12 | 27 |
| Personal Goods | 3 | 28 |
| Pharmaceuticals and Biotechnology | 12 | 29 |
| Precious Metals and Mining | 8 | 30 |
| Real Estate Investment and Services Development | 11 | 31 |
| Real Estate Investment Trusts | 11 | 32 |
| Retailers | 27 | 33 |
| Software & Computer Services | 33 | 34 |
| Technology Hardware & Equipment | 4 | 35 |
| Telecommunications Equipment | 2 | 36 |
| Telecommunications Service Providers | 6 | 37 |
| Tobacco | 2 | 38 |
| Travel and Leisure | 35 | 39 |
| Waste and Disposal Services | 3 | 40 |
| Grand Total | 447 | 40 |

## Table 6 – Emission average by industry

This table reports the carbon emissions production by industry from our sample. Panel A reports the ten industries with the highest average unscaled emissions production for each scope and direct emissions. Panel B reports the ten industries with the lowest average unscaled emissions. Panel C reports the ten industries with the highest carbon intensity. Panel D reports the ten industries with the lowest carbon intensity.

Panel A: Highest average total emission industries

| Industry Nr. | Scope 1 | Industry Nr. | Scope 2 | Industry Nr. | Scope 3 | Industry Nr. | Direct |
|---|---|---|---|---|---|---|---|
| 8 | 11191632 | 18 | 3908541 | 18 | 230871800 | 18 | 15568411 |
| 18 | 10378676 | 26 | 1182164 | 26 | 198938569 | 8 | 11997879 |
| 26 | 6364171 | 8 | 736942 | 12 | 47467888 | 26 | 11054590 |
| 12 | 3076627 | 27 | 633752 | 27 | 20864563 | 12 | 3576320 |
| 6 | 2362244 | 12 | 517115 | 1 | 13917524 | 6 | 2674286 |
| 39 | 2006520 | 11 | 499693 | 7 | 8993002 | 39 | 2104420 |
| 13 | 1066832 | 13 | 348268 | 8 | 6088261 | 13 | 1343306 |
| 11 | 780855 | 37 | 323622 | 37 | 5353990 | 11 | 1138562 |
| 40 | 427405 | 6 | 304118 | 29 | 4572352 | 27 | 903213 |
| 27 | 386098 | 30 | 300779 | 38 | 2885279 | 37 | 897126 |

Panel B: Lowest average total emission industries

| Industry Nr. | Scope 1 | Industry Nr. | Scope 2 | Industry Nr. | Scope 3 | Industry Nr. | Direct |
|---|---|---|---|---|---|---|---|
| 36 | 154 | 22 | 2141 | 14 | 527 | 2 | 150 |
| 21 | 406 | 21 | 2479 | 35 | 597 | 21 | 2885 |
| 22 | 777 | 31 | 2689 | 25 | 1514 | 22 | 2918 |
| 28 | 985 | 25 | 3001 | 21 | 3440 | 31 | 4115 |
| 31 | 1425 | 15 | 4902 | 36 | 4041 | 36 | 5313 |
| 34 | 1775 | 36 | 5159 | 31 | 5529 | 25 | 12006 |
| 35 | 2293 | 10 | 7480 | 3 | 7714 | 35 | 13856 |
| 32 | 2526 | 17 | 7640 | 32 | 10193 | 32 | 14359 |
| 23 | 6611 | 14 | 9938 | 24 | 11727 | 10 | 14796 |
| 10 | 7317 | 7 | 11279 | 34 | 13448 | 28 | 17631 |

Panel C: Highest average carbon intensity industries

| Industry Nr. | Scope 1 | Industry Nr. | Scope 2 | Industry Nr. | Scope 3 | Industry Nr. | Direct |
|---|---|---|---|---|---|---|---|
| 8 | 873.1 | 30 | 336.27 | 18 | 2920.33 | 26 | 1525.57 |
| 12 | 467.14 | 18 | 268.48 | 12 | 2541.01 | 8 | 820.25 |
| 18 | 417.03 | 11 | 106.62 | 26 | 1110.25 | 18 | 727.98 |
| 26 | 385.09 | 12 | 97.46 | 27 | 404.59 | 30 | 683.62 |
| 40 | 315.04 | 32 | 65.85 | 8 | 391.56 | 12 | 592.46 |
| 11 | 213.29 | 13 | 62.91 | 1 | 344.66 | 6 | 421.58 |
| 6 | 211.02 | 17 | 57.58 | 16 | 300.7 | 40 | 349.25 |
| 30 | 207.57 | 26 | 57.3 | 6 | 279.81 | 11 | 316.79 |
| 39 | 196.13 | 8 | 53.69 | 37 | 259.23 | 39 | 233.52 |
| 13 | 152.19 | 5 | 49.92 | 13 | 254.53 | 13 | 213.47 |

Panel D: Lowest average carbon intensity industries

| Industry Nr. | Scope 1 | Industry Nr. | Scope 2 | Industry Nr. | Scope 3 | Industry Nr. | Direct |
|---|---|---|---|---|---|---|---|
| 36 | 0.33 | 2 | 1.16 | 14 | 0.86 | 2 | 1.63 |
| 28 | 0.43 | 15 | 2.52 | 35 | 1.23 | 28 | 8.59 |
| 2 | 0.47 | 25 | 2.84 | 2 | 1.48 | 22 | 8.79 |
| 21 | 1.49 | 10 | 4.6 | 25 | 1.73 | 25 | 10.16 |
| 23 | 1.78 | 7 | 4.79 | 21 | 2.94 | 23 | 10.19 |
| 22 | 2.39 | 22 | 6.41 | 24 | 3.1 | 21 | 10.78 |
| 24 | 3.05 | 28 | 8.15 | 10 | 6.96 | 36 | 11.31 |
| 34 | 6.51 | 23 | 8.21 | 3 | 7.5 | 10 | 12.18 |
| 25 | 7.32 | 19 | 8.66 | 20 | 7.55 | 15 | 12.54 |
| 10 | 7.58 | 14 | 9.2 | 36 | 7.89 | 24 | 17.52 |

## Table 7 – Determinants of carbon emissions

This table reports the regression results of the determinants of carbon emissions. The sample period is 2011-2020. The dependent variables are natural logarithm of total emissions and growth in emissions. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm level and year. All regressions include year-fixed effects and industry-fixed effects.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | LN Scope 1 | LN Scope 2 | LN Scope 3 | Scope 1 YoY | Scope 2 YoY | Scope 3 YoY |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LNSize | 0.161*** | 0.254*** | 0.952*** | −0.004 | 0.021*** | −0.230 |
| | (0.031) | (0.033) | (0.082) | (0.017) | (0.005) | (0.289) |
| BM | 0.410*** | 0.187* | 0.616*** | −0.044 | 0.002 | −0.950** |
| | (0.081) | (0.114) | (0.100) | (0.034) | (0.028) | (0.391) |
| ROE | 0.001 | 0.001 | −0.001 | −0.0004** | −0.0001 | −0.001 |
| | (0.001) | (0.001) | (0.002) | (0.0002) | (0.0002) | (0.001) |
| Leverage | 0.339*** | 0.891*** | −0.332* | −0.028 | −0.063** | 0.732 |
| | (0.119) | (0.147) | (0.177) | (0.043) | (0.032) | (0.657) |
| Invest_A | 0.847 | −2.939** | −0.146 | −0.071 | 0.499* | 0.638 |
| | (0.901) | (1.422) | (3.741) | (0.419) | (0.295) | (6.480) |
| LNPPE | 0.871*** | 0.675*** | 0.618*** | −0.024 | −0.024*** | 0.019 |
| | (0.034) | (0.037) | (0.051) | (0.015) | (0.007) | (0.184) |
| SalesGr | −0.069 | 0.021 | −0.218 | 0.161*** | 0.122*** | −0.783 |
| | (0.084) | (0.130) | (0.368) | (0.049) | (0.023) | (0.804) |
| EPSGr | −0.350 | −0.797* | −0.586 | −0.250 | −0.126 | −0.557 |
| | (0.220) | (0.431) | (1.370) | (0.196) | (0.116) | (0.787) |
| Constant | −8.606*** | −4.269*** | −11.359*** | 0.574*** | 0.283*** | 4.397** |
| | (0.530) | (0.422) | (0.301) | (0.188) | (0.109) | (1.798) |
| Year F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,131 | 2,148 | 1,167 | 1,849 | 1,853 | 954 |
| Adjusted $R^2$ | 0.816 | 0.784 | 0.710 | 0.032 | 0.042 | 0.010 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 8 - Determinants of carbon emissions (2)

This table reports the regression results of the determinants of carbon emissions. The sample period is 2011-2020. The dependent variables are emission intensity and direct emissions. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm level and year. All regressions include year-fixed effects and industry-fixed effects.

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | Scope 1 INT | Scope 2 INT | Scope 3 INT | LN Direct | Direct YoY | Direct INT |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LNSize | −0.152*** | −0.114*** | 0.969** | 0.182*** | 0.008 | −0.316** |
| | (0.020) | (0.027) | (0.383) | (0.021) | (0.007) | (0.123) |
| BM | −0.073 | −0.019 | 0.438 | 0.245*** | −0.033*** | 0.136 |
| | (0.202) | (0.050) | (0.808) | (0.071) | (0.009) | (0.344) |
| ROE | −0.0001 | 0.001 | −0.005* | −0.0005 | −0.0004*** | 0.010 |
| | (0.002) | (0.001) | (0.003) | (0.001) | (0.0001) | (0.008) |
| Leverage | 0.354** | 0.466*** | −3.006*** | 0.635*** | −0.033 | 0.433 |
| | (0.141) | (0.093) | (0.775) | (0.074) | (0.044) | (0.298) |
| Invest_A | 8.485*** | 2.328** | 14.867* | 0.924* | 0.210 | 39.114 |
| | (1.997) | (0.951) | (7.734) | (0.517) | (0.200) | (25.706) |
| LNPPE | 0.266*** | 0.055*** | 0.331*** | 0.798*** | −0.015*** | 0.129 |
| | (0.020) | (0.016) | (0.084) | (0.037) | (0.006) | (0.206) |
| SalesGr | −0.245 | −0.040 | −1.241** | −0.018 | 0.111*** | 0.335 |
| | (0.159) | (0.105) | (0.624) | (0.075) | (0.019) | (0.536) |
| EPSGr | −0.208 | −0.114 | −2.263 | −0.385*** | −0.135 | −0.527 |
| | (0.538) | (0.160) | (3.134) | (0.140) | (0.105) | (0.965) |
| Constant | −4.140*** | −0.039 | −11.954*** | −5.994*** | 0.290*** | −1.371 |
| | (0.364) | (0.189) | (4.179) | (0.596) | (0.078) | (2.434) |
| Year F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2,131 | 2,148 | 1,167 | 2,123 | 1,835 | 2,123 |
| Adjusted $R^2$ | 0.271 | 0.423 | 0.384 | 0.848 | 0.062 | 0.006 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 9 – Returns to unscaled emissions

This table reports the regressions results of stock returns and unscaled emissions. The sample period is 2012-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects. In columns (4) through (6), we additionally include industry-fixed effects.

| | *Dependent variable: Monthly returns* | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LNLagScope1 | −0.082*** | | | −0.207*** | | |
| | (0.026) | | | (0.024) | | |
| LNLagScope2 | | −0.045 | | | −0.117*** | |
| | | (0.069) | | | (0.034) | |
| LNLagScope3 | | | −0.122*** | | | −0.147*** |
| | | | (0.027) | | | (0.044) |
| LNSize | 0.595*** | 0.605*** | 0.630*** | 0.839*** | 0.837*** | 0.898*** |
| | (0.147) | (0.129) | (0.175) | (0.194) | (0.181) | (0.234) |
| LNPPE | −0.214*** | −0.263*** | −0.220*** | −0.308*** | −0.407*** | −0.432*** |
| | (0.049) | (0.084) | (0.063) | (0.113) | (0.128) | (0.128) |
| MOM | −0.353 | −0.323 | −0.484 | −0.673 | −0.604 | −0.803* |
| | (0.380) | (0.385) | (0.341) | (0.443) | (0.453) | (0.435) |
| Volatility | 8.817** | 8.900** | 7.592* | 9.352** | 9.333** | 8.866** |
| | (4.031) | (4.034) | (4.517) | (3.958) | (3.833) | (3.959) |
| BM | 0.905*** | 0.876*** | 1.013*** | 1.385*** | 1.351*** | 1.794*** |
| | (0.103) | (0.099) | (0.146) | (0.172) | (0.165) | (0.226) |
| Leverage | 0.096 | 0.058 | −0.164 | 0.549* | 0.637* | 0.387 |
| | (0.342) | (0.362) | (0.386) | (0.324) | (0.330) | (0.301) |
| ROE | 0.003 | 0.003 | 0.004* | 0.002 | 0.002 | 0.006*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| SalesGr | −0.602 | −0.544 | −0.817*** | −0.721* | −0.658** | −0.937*** |
| | (0.392) | (0.338) | (0.241) | (0.383) | (0.334) | (0.287) |
| EPSGr | 0.684* | 0.818 | 2.258* | 0.358 | 0.555 | 1.946* |
| | (0.369) | (0.535) | (1.290) | (0.350) | (0.552) | (1.156) |
| Invest_A | −1.604 | −1.220 | −1.981 | 0.050 | 0.878 | 2.822 |
| | (3.595) | (3.390) | (3.438) | (3.206) | (2.978) | (3.767) |
| Constant | 3.498*** | 3.767*** | 3.151*** | 4.125*** | 5.069*** | 4.673*** |
| | (0.801) | (0.707) | (0.775) | (1.251) | (1.335) | (1.303) |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 25,522 | 25,726 | 13,956 | 25,522 | 25,726 | 13,956 |
| Adjusted $R^2$ | 0.217 | 0.220 | 0.226 | 0.220 | 0.222 | 0.229 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 10 – Returns to growth in emissions

This table reports the regressions results of stock returns and growth in emissions. The sample period is 2012-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects. In columns (4) through (6), we additionally include industry-fixed effects.

| | *Dependent variable: Monthly returns* | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LagScope1YoY | −0.035 | | | −0.008 | | |
| | (0.065) | | | (0.052) | | |
| LagScope2YoY | | −0.244* | | | −0.272* | |
| | | (0.136) | | | (0.160) | |
| LagScope3YoY | | | 0.008 | | | 0.014* |
| | | | (0.006) | | | (0.008) |
| LNSize | 0.635*** | 0.652*** | 0.559*** | 0.858*** | 0.875*** | 0.847*** |
| | (0.137) | (0.130) | (0.155) | (0.187) | (0.181) | (0.195) |
| LNPPE | −0.266*** | −0.272*** | −0.289*** | −0.437*** | −0.449*** | −0.535*** |
| | (0.054) | (0.049) | (0.062) | (0.111) | (0.114) | (0.140) |
| MOM | −0.389 | −0.409 | −0.621*** | −0.667 | −0.680 | −0.925*** |
| | (0.413) | (0.411) | (0.190) | (0.502) | (0.497) | (0.286) |
| Volatility | 8.677** | 8.853** | 8.337* | 9.491** | 9.781*** | 9.873** |
| | (3.846) | (3.613) | (4.503) | (3.855) | (3.560) | (4.247) |
| BM | 0.875*** | 0.853*** | 0.897*** | 1.371*** | 1.326*** | 1.726*** |
| | (0.114) | (0.108) | (0.121) | (0.199) | (0.209) | (0.250) |
| Leverage | −0.111 | −0.075 | −0.193 | 0.306 | 0.415* | 0.360 |
| | (0.351) | (0.327) | (0.330) | (0.288) | (0.251) | (0.221) |
| ROE | 0.004 | 0.004 | 0.006** | 0.003 | 0.004 | 0.007*** |
| | (0.003) | (0.003) | (0.003) | (0.003) | (0.003) | (0.002) |
| SalesGr | −0.582** | −0.545* | −0.703*** | −0.678** | −0.647** | −0.809*** |
| | (0.283) | (0.279) | (0.218) | (0.276) | (0.273) | (0.245) |
| EPSGr | 0.929*** | 0.929*** | 0.194 | 0.772*** | 0.817*** | −0.418 |
| | (0.210) | (0.236) | (1.399) | (0.210) | (0.192) | (1.301) |
| Invest_A | −1.767 | −0.868 | −3.874 | −0.004 | 1.110 | 3.246 |
| | (3.484) | (3.167) | (2.687) | (3.426) | (3.582) | (4.679) |
| Constant | 2.679*** | 2.779*** | 3.523*** | 3.717*** | 3.936*** | 5.270*** |
| | (1.000) | (0.932) | (0.795) | (0.956) | (1.158) | (1.915) |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 22,138 | 22,186 | 11,400 | 22,138 | 22,186 | 11,400 |
| Adjusted $R^2$ | 0.216 | 0.218 | 0.206 | 0.219 | 0.220 | 0.209 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 11 – Returns to carbon intensity

This table reports the regressions results of stock returns and carbon intensity. The sample period is 2012-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects. In columns (4) through (6), we additionally include industry-fixed effects.

| | *Dependent variable: Monthly returns* | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LagScope1INT | 0.014 | | | 0.020* | | |
| | (0.017) | | | (0.012) | | |
| LagScope2INT | | 0.112 | | | 0.161 | |
| | | (0.128) | | | (0.126) | |
| LagScope3INT | | | −0.010 | | | −0.018 |
| | | | (0.008) | | | (0.014) |
| LNSize | 0.595*** | 0.608*** | 0.521*** | 0.809*** | 0.829*** | 0.774*** |
| | (0.145) | (0.147) | (0.165) | (0.193) | (0.186) | (0.221) |
| LNPPE | −0.301*** | −0.305*** | −0.298*** | −0.493*** | −0.497*** | −0.520*** |
| | (0.055) | (0.055) | (0.060) | (0.119) | (0.117) | (0.140) |
| MOM | −0.342 | −0.351 | −0.464 | −0.618 | −0.623 | −0.773* |
| | (0.374) | (0.374) | (0.324) | (0.440) | (0.427) | (0.421) |
| Volatility | 9.057** | 8.954** | 7.472* | 9.503** | 9.471** | 8.584** |
| | (3.996) | (3.698) | (4.376) | (3.960) | (3.711) | (3.820) |
| BM | 0.824*** | 0.837*** | 0.925*** | 1.304*** | 1.333*** | 1.728*** |
| | (0.107) | (0.091) | (0.139) | (0.179) | (0.165) | (0.223) |
| Leverage | −0.011 | −0.034 | −0.217 | 0.469 | 0.458 | 0.381 |
| | (0.347) | (0.341) | (0.410) | (0.332) | (0.299) | (0.317) |
| ROE | 0.003 | 0.003 | 0.004* | 0.002 | 0.002 | 0.006*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| SalesGr | −0.605 | −0.535 | −0.809*** | −0.706* | −0.654** | −0.932*** |
| | (0.376) | (0.328) | (0.226) | (0.368) | (0.328) | (0.263) |
| EPSGr | 0.657* | 0.783 | 2.127* | 0.401 | 0.666 | 1.830* |
| | (0.367) | (0.536) | (1.180) | (0.365) | (0.486) | (1.089) |
| Invest_A | −2.177 | −2.142 | −2.399 | −0.315 | 0.826 | 3.112 |
| | (3.675) | (3.568) | (3.262) | (3.268) | (3.124) | (3.660) |
| Constant | 4.402*** | 4.109*** | 4.475*** | 5.979*** | 5.570*** | 6.205*** |
| | (0.893) | (0.847) | (0.711) | (1.248) | (1.388) | (1.610) |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 25,522 | 25,726 | 13,956 | 25,522 | 25,726 | 13,956 |
| Adjusted $R^2$ | 0.217 | 0.220 | 0.225 | 0.219 | 0.222 | 0.228 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 12 – Returns to direct emissions

This table reports the regressions results of stock returns and direct emission (unscaled, YoY and intensity). The sample period is 2012-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects. In columns (4) through (6), we additionally include industry-fixed effects.

| | *Dependent variable: Monthly returns* | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LNDirect | −0.147*** | | | −0.284*** | | |
| | (0.044) | | | (0.033) | | |
| DirectYoY | | −0.089 | | | −0.153 | |
| | | (0.155) | | | (0.203) | |
| DirectINT | | | 0.001* | | | 0.002** |
| | | | (0.001) | | | (0.001) |
| LNSize | 0.612*** | 0.640*** | 0.595*** | 0.856*** | 0.860*** | 0.806*** |
| | (0.144) | (0.132) | (0.144) | (0.193) | (0.181) | (0.190) |
| LNPPE | −0.171*** | −0.265*** | −0.297*** | −0.263** | −0.441*** | −0.491*** |
| | (0.061) | (0.053) | (0.058) | (0.119) | (0.109) | (0.119) |
| MOM | −0.362 | −0.399 | −0.351 | −0.674 | −0.668 | −0.627 |
| | (0.384) | (0.384) | (0.378) | (0.449) | (0.474) | (0.446) |
| Volatility | 8.652** | 8.794** | 8.962** | 9.349** | 9.756*** | 9.487** |
| | (4.065) | (3.704) | (3.982) | (3.983) | (3.688) | (3.961) |
| BM | 0.959*** | 0.848*** | 0.861*** | 1.403*** | 1.318*** | 1.338*** |
| | (0.089) | (0.107) | (0.096) | (0.169) | (0.203) | (0.172) |
| Leverage | 0.198 | −0.076 | 0.035 | 0.745** | 0.380 | 0.561 |
| | (0.340) | (0.350) | (0.350) | (0.333) | (0.296) | (0.357) |
| ROE | 0.003 | 0.004 | 0.003 | 0.002 | 0.003 | 0.002 |
| | (0.002) | (0.003) | (0.002) | (0.002) | (0.003) | (0.002) |
| SalesGr | −0.605 | −0.569** | −0.611 | −0.727* | −0.668** | −0.727** |
| | (0.391) | (0.281) | (0.374) | (0.375) | (0.275) | (0.358) |
| EPSGr | 0.679* | 0.935*** | 0.655* | 0.384 | 0.811*** | 0.456 |
| | (0.373) | (0.257) | (0.362) | (0.377) | (0.231) | (0.371) |
| Invest_A | −0.646 | −1.262 | −1.551 | 1.098 | 0.455 | 0.707 |
| | (3.331) | (3.182) | (3.415) | (2.924) | (3.471) | (2.895) |
| Constant | 3.175*** | 2.698*** | 4.188*** | 4.063*** | 3.869*** | 5.770*** |
| | (0.700) | (0.935) | (0.945) | (1.280) | (0.970) | (1.330) |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 25,426 | 21,970 | 25,426 | 25,426 | 21,970 | 25,426 |
| Adjusted $R^2$ | 0.220 | 0.218 | 0.219 | 0.223 | 0.221 | 0.222 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 13 – Returns PCA unscaled emissions

This table reports the regressions results of stock returns and unscaled emissions before and after the Paris Climate Agreement. In columns (1) through (3) we report the regression results of the sample period 2012-2015. In columns (4) through (6) we report the regression results of the sample period 2016-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects and industry-fixed effects.

| | *Dependent variable: Monthly returns* | | | | | |
|---|---|---|---|---|---|---|
| | *Before Paris agreement* | | | *After Paris agreement* | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LNLagScope1 | −0.316*** | | | −0.195*** | | |
| | (0.045) | | | (0.024) | | |
| LNLagScope2 | | −0.041 | | | −0.126*** | |
| | | (0.040) | | | (0.034) | |
| LNLagScope3 | | | −0.001 | | | −0.214*** |
| | | | (0.018) | | | (0.027) |
| LNSize | 0.794*** | 0.691*** | 0.406* | 0.985*** | 0.994*** | 1.155*** |
| | (0.107) | (0.082) | (0.214) | (0.230) | (0.210) | (0.244) |
| LNPPE | −0.126* | −0.346*** | −0.217** | −0.414*** | −0.502*** | −0.521*** |
| | (0.074) | (0.116) | (0.095) | (0.127) | (0.139) | (0.120) |
| MOM | −0.425 | −0.396 | −1.708*** | −1.192*** | −1.095*** | −1.146** |
| | (0.266) | (0.276) | (0.097) | (0.398) | (0.400) | (0.446) |
| Volatility | 10.575 | 10.962* | 4.485 | 9.536** | 9.446** | 9.442** |
| | (6.813) | (6.273) | (12.199) | (4.357) | (4.159) | (4.338) |
| BM | 1.393*** | 1.164*** | 1.327*** | 1.550*** | 1.508*** | 1.972*** |
| | (0.252) | (0.231) | (0.373) | (0.171) | (0.173) | (0.247) |
| Leverage | −1.071*** | −0.851*** | −0.771 | 0.534 | 0.617 | 0.130 |
| | (0.257) | (0.204) | (0.709) | (0.394) | (0.404) | (0.364) |
| ROE | 0.008*** | 0.007*** | 0.010*** | 0.00003 | −0.0003 | 0.002 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| SalesGr | 0.719** | 0.596* | −0.585* | −1.032*** | −0.910*** | −1.138*** |
| | (0.363) | (0.345) | (0.299) | (0.334) | (0.296) | (0.323) |
| EPSGr | −1.040 | −0.442 | 3.004* | 0.137 | 0.325 | 2.311 |
| | (1.809) | (1.512) | (1.777) | (0.494) | (0.736) | (1.426) |
| Invest_A | −5.057*** | −4.716*** | −7.294*** | 5.186** | 5.225** | 9.191** |
| | (1.525) | (1.739) | (1.565) | (2.087) | (2.229) | (4.151) |
| Constant | 1.763 | 3.984** | 3.834*** | −5.348*** | −4.265*** | −4.454*** |
| | (1.347) | (1.633) | (0.397) | (1.305) | (1.474) | (1.474) |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,854 | 6,710 | 3,912 | 18,668 | 19,016 | 10,044 |
| Adjusted $R^2$ | 0.165 | 0.162 | 0.188 | 0.236 | 0.238 | 0.240 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 14 – Returns PCA emission growth

This table reports the regressions results of stock returns and growth in emissions before and after the Paris Climate Agreement. In columns (1) through (3) we report the regression results of the sample period 2012-2015. In columns (4) through (6) we report the regression results of the sample period 2016-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects and industry-fixed effects.

| | *Dependent variable: Monthly returns* | | | | | |
|---|---|---|---|---|---|---|
| | *Before Paris agreement* | | | *After Paris agreement* | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LagScope1YoY | −0.073 | | | −0.065 | | |
| | (0.072) | | | (0.091) | | |
| LagScope2YoY | | −0.039 | | | −0.384** | |
| | | (0.070) | | | (0.181) | |
| LagScope3YoY | | | 0.018*** | | | 0.002 |
| | | | (0.007) | | | (0.021) |
| LNSize | 0.626*** | 0.588*** | 0.662*** | 1.075*** | 1.089*** | 1.078*** |
| | (0.144) | (0.139) | (0.111) | (0.201) | (0.184) | (0.207) |
| LNPPE | −0.356*** | −0.340*** | −0.346*** | −0.547*** | −0.556*** | −0.684*** |
| | (0.120) | (0.124) | (0.054) | (0.121) | (0.120) | (0.131) |
| MOM | −0.194 | −0.217 | −1.527*** | −1.317*** | −1.270*** | −1.402*** |
| | (0.172) | (0.237) | (0.090) | (0.424) | (0.430) | (0.299) |
| Volatility | 6.647 | 9.180 | 15.123 | 10.026** | 10.386*** | 9.029** |
| | (6.597) | (5.676) | (11.296) | (4.177) | (3.885) | (4.535) |
| BM | 1.098*** | 1.035*** | 1.117*** | 1.567*** | 1.494*** | 2.069*** |
| | (0.238) | (0.224) | (0.328) | (0.193) | (0.223) | (0.233) |
| Leverage | −1.423*** | −1.184*** | −1.993*** | 0.351 | 0.474* | 0.438 |
| | (0.193) | (0.310) | (0.396) | (0.342) | (0.284) | (0.282) |
| ROE | 0.009*** | 0.009*** | 0.011*** | 0.0001 | 0.001 | 0.005* |
| | (0.001) | (0.001) | (0.002) | (0.004) | (0.003) | (0.003) |
| SalesGr | −0.006 | 0.088 | −0.309 | −0.833*** | −0.810*** | −0.989*** |
| | (0.189) | (0.161) | (0.240) | (0.278) | (0.264) | (0.248) |
| EPSGr | −0.405 | 0.160 | −0.190 | 0.697*** | 0.692*** | −0.888 |
| | (1.986) | (1.666) | (1.858) | (0.175) | (0.150) | (1.001) |
| Invest_A | −5.161*** | −5.222*** | −3.712* | 5.424** | 5.574** | 9.257 |
| | (0.836) | (0.904) | (2.050) | (2.430) | (2.824) | (6.898) |
| Constant | 4.049** | 4.008** | 3.198*** | −5.308*** | −5.222*** | −3.062 |
| | (1.807) | (1.780) | (0.491) | (1.096) | (1.369) | (2.001) |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 5,834 | 5,690 | 3,408 | 16,304 | 16,496 | 7,992 |
| Adjusted $R^2$ | 0.177 | 0.178 | 0.195 | 0.232 | 0.232 | 0.219 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 15 – Returns PCA carbon intensity

This table reports the regressions results of stock returns and carbon intensity before and after the Paris Climate Agreement. In columns (1) through (3) we report the regression results of the sample period 2012-2015. In columns (4) through (6) we report the regression results of the sample period 2016-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects and industry-fixed effects.

| | *Dependent variable: Monthly returns* | | | | | |
|---|---|---|---|---|---|---|
| | *Before Paris agreement* | | | *After Paris agreement* | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LagScope1INT | −0.065*** | | | 0.017 | | |
| | (0.021) | | | (0.021) | | |
| LagScope2INT | | 0.463*** | | | 0.083 | |
| | | (0.127) | | | (0.114) | |
| LagScope3INT | | | 0.025*** | | | −0.041*** |
| | | | (0.009) | | | (0.011) |
| LNSize | 0.698*** | 0.756*** | 0.364* | 0.961*** | 0.972*** | 0.978*** |
| | (0.109) | (0.091) | (0.218) | (0.228) | (0.219) | (0.244) |
| LNPPE | −0.370*** | −0.418*** | −0.230** | −0.590*** | −0.591*** | −0.640*** |
| | (0.091) | (0.080) | (0.101) | (0.133) | (0.128) | (0.128) |
| MOM | −0.356 | −0.455* | −1.761*** | −1.137*** | −1.099*** | −1.112** |
| | (0.256) | (0.255) | (0.091) | (0.396) | (0.393) | (0.442) |
| Volatility | 10.989 | 11.621* | 4.661 | 9.611** | 9.616** | 8.867** |
| | (6.835) | (6.299) | (12.062) | (4.348) | (4.048) | (4.090) |
| BM | 1.162*** | 1.157*** | 1.267*** | 1.496*** | 1.492*** | 1.869*** |
| | (0.223) | (0.207) | (0.357) | (0.174) | (0.170) | (0.236) |
| Leverage | −1.044*** | −0.957*** | −0.671 | 0.436 | 0.461 | 0.142 |
| | (0.288) | (0.202) | (0.703) | (0.407) | (0.363) | (0.372) |
| ROE | 0.006*** | 0.006** | 0.010*** | −0.0001 | −0.0004 | 0.002 |
| | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) | (0.002) |
| SalesGr | 0.609* | 0.706* | −0.643** | −1.008*** | −0.916*** | −1.075*** |
| | (0.338) | (0.398) | (0.307) | (0.315) | (0.280) | (0.294) |
| EPSGr | −0.491 | −0.205 | 3.084 | 0.174 | 0.414 | 2.123 |
| | (2.054) | (1.471) | (1.876) | (0.506) | (0.656) | (1.309) |
| Invest_A | −4.938*** | −4.134** | −7.625*** | 4.943** | 5.226** | 9.134** |
| | (1.467) | (1.751) | (1.238) | (2.248) | (2.365) | (4.230) |
| Constant | 4.249*** | 4.253*** | 4.282*** | −3.600*** | −3.754** | −2.435 |
| | (1.477) | (1.341) | (0.497) | (1.365) | (1.556) | (1.813) |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,854 | 6,710 | 3,912 | 18,668 | 19,016 | 10,044 |
| Adjusted $R^2$ | 0.163 | 0.163 | 0.188 | 0.235 | 0.238 | 0.239 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 16 – Returns PCA direct emissions

This table reports the regressions results of stock returns and direct emissions before and after the Paris Climate Agreement. In columns (1) through (3) we report the regression results of the sample period 2012-2015. In columns (4) through (6) we report the regression results of the sample period 2016-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects and industry-fixed effects.

| | *Dependent variable: Monthly returns* | | | | | |
|---|---|---|---|---|---|---|
| | *Before Paris agreement* | | | *After Paris agreement* | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| LNDirect | −0.354*** | | | −0.287*** | | |
| | (0.028) | | | (0.036) | | |
| DirectYoY | | 0.156 | | | −0.491*** | |
| | | (0.105) | | | (0.134) | |
| DirectINT | | | −0.007 | | | 0.001** |
| | | | (0.023) | | | (0.0005) |
| LNSize | 0.759*** | 0.590*** | 0.679*** | 1.009*** | 1.075*** | 0.960*** |
| | (0.086) | (0.136) | (0.089) | (0.223) | (0.186) | (0.222) |
| LNPPE | −0.099 | −0.337*** | −0.372*** | −0.359*** | −0.548*** | −0.590*** |
| | (0.089) | (0.125) | (0.085) | (0.135) | (0.115) | (0.131) |
| MOM | −0.423 | −0.253 | −0.388 | −1.186*** | −1.264*** | −1.135*** |
| | (0.281) | (0.253) | (0.269) | (0.395) | (0.412) | (0.395) |
| Volatility | 10.671* | 9.158 | 10.915* | 9.522** | 10.305** | 9.605** |
| | (6.106) | (5.757) | (6.213) | (4.358) | (4.065) | (4.324) |
| BM | 1.361*** | 1.048*** | 1.152*** | 1.539*** | 1.461*** | 1.494*** |
| | (0.265) | (0.225) | (0.211) | (0.178) | (0.222) | (0.177) |
| Leverage | −0.727*** | −1.139*** | −0.881*** | 0.727* | 0.422 | 0.524 |
| | (0.166) | (0.327) | (0.189) | (0.417) | (0.343) | (0.447) |
| ROE | 0.007*** | 0.009*** | 0.007*** | −0.0004 | 0.0001 | −0.0002 |
| | (0.002) | (0.001) | (0.002) | (0.002) | (0.003) | (0.002) |
| SalesGr | 0.644* | 0.058 | 0.595 | −1.026*** | −0.804*** | −1.019*** |
| | (0.344) | (0.175) | (0.365) | (0.337) | (0.271) | (0.313) |
| EPSGr | −0.934 | 0.242 | −0.370 | 0.130 | 0.637*** | 0.191 |
| | (1.417) | (1.707) | (1.508) | (0.515) | (0.133) | (0.497) |
| Invest_A | −4.509** | −5.099*** | −4.632*** | 5.457*** | 4.946* | 5.109** |
| | (1.839) | (1.095) | (1.767) | (2.003) | (2.729) | (2.013) |
| Constant | 2.180 | 3.837** | 4.261*** | −5.374*** | −5.213*** | −3.655** |
| | (1.539) | (1.835) | (1.404) | (1.355) | (1.138) | (1.483) |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 6,734 | 5,714 | 6,734 | 18,692 | 16,256 | 18,692 |
| Adjusted $R^2$ | 0.164 | 0.177 | 0.163 | 0.239 | 0.234 | 0.238 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 17 - Excluding salient industries (1)

Excluding salient industries based on the industries that have the highest average unscaled emissions. The sample period is 2012-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects. In columns (4) through (6), we additionally include industry-fixed effects. Panel A reports the results for unscaled emissions. Panel B reports the results for emission growth. Panel C reports the results for carbon intensity. Panel D reports the results for direct emissions.

Panel A: Total emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LNLagScope1 | −0.080*** | | | −0.215*** | | |
| | (0.026) | | | (0.024) | | |
| LNLagScope2 | | −0.078 | | | −0.123*** | |
| | | (0.059) | | | (0.025) | |
| LNLagScope3 | | | −0.115*** | | | −0.136*** |
| | | | (0.034) | | | (0.048) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 24,738 | 24,986 | 13,576 | 24,738 | 24,986 | 13,576 |
| Adjusted $R^2$ | 0.221 | 0.224 | 0.232 | 0.223 | 0.226 | 0.234 |

Panel B: Emission growth

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LagScope1YoY | −0.044 | | | −0.031 | | |
| | (0.070) | | | (0.059) | | |
| LagScope2YoY | | −0.034 | | | −0.095 | |
| | | (0.121) | | | (0.161) | |
| LagScope3YoY | | | 0.007 | | | 0.013* |
| | | | (0.006) | | | (0.007) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 21,426 | 21,522 | 11,064 | 21,426 | 21,522 | 11,064 |
| Adjusted $R^2$ | 0.220 | 0.222 | 0.212 | 0.222 | 0.224 | 0.215 |

Panel C: Carbon intensity

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LagScope1INT | 0.012 | | | 0.001 | | |
| | (0.022) | | | (0.019) | | |
| LagScope2INT | | 0.029 | | | 0.066 | |
| | | (0.098) | | | (0.091) | |
| LagScope3INT | | | −0.006 | | | −0.010 |
| | | | (0.010) | | | (0.016) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 24,738 | 24,986 | 13,576 | 24,738 | 24,986 | 13,576 |
| Adjusted $R^2$ | 0.221 | 0.224 | 0.231 | 0.223 | 0.226 | 0.233 |

Panel D: Direct emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LNDirect | −0.164*** | | | −0.287*** | | |
| | (0.049) | | | (0.029) | | |
| DirectYoY | | −0.118 | | | −0.228 | |
| | | (0.159) | | | (0.231) | |
| DirectINT | | | 0.002* | | | 0.002* |
| | | | (0.001) | | | (0.001) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 24,682 | 21,302 | 24,682 | 24,682 | 21,302 | 24,682 |
| Adjusted $R^2$ | 0.224 | 0.223 | 0.223 | 0.226 | 0.224 | 0.225 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 18 - Including salient industries (1)

Including *only* salient industries based on the industries that have the highest average unscaled emissions. The sample period is 2012-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects. In columns (4) through (6), we additionally include industry-fixed effects. Panel A reports the results for unscaled emissions. Panel B reports the results for emission growth. Panel C reports the results for carbon intensity. Panel D reports the results for direct emissions.

Panel A: Total emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LNLagScope1 | 0.047 | | | −0.159 | | |
| | (0.211) | | | (0.248) | | |
| LNLagScope2 | | 0.244 | | | −0.074 | |
| | | (0.294) | | | (0.224) | |
| LNLagScope3 | | | −0.640*** | | | −0.897*** |
| | | | (0.169) | | | (0.253) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 784 | 740 | 380 | 784 | 740 | 380 |
| Adjusted $R^2$ | 0.263 | 0.251 | 0.374 | 0.269 | 0.255 | 0.375 |

Panel B: Emission growth

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LagScope1YoY | 0.997 | | | 1.127* | | |
| | (0.623) | | | (0.575) | | |
| LagScope2YoY | | −1.992*** | | | −1.929*** | |
| | | (0.404) | | | (0.405) | |
| LagScope3YoY | | | 0.063 | | | 0.065 |
| | | | (0.108) | | | (0.117) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 712 | 664 | 336 | 712 | 664 | 336 |
| Adjusted $R^2$ | 0.287 | 0.268 | 0.403 | 0.291 | 0.271 | 0.402 |

Panel C: Carbon intensity

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LagScope1INT | 0.068* | | | 0.078** | | |
| | (0.037) | | | (0.035) | | |
| LagScope2INT | | 0.757** | | | 0.600* | |
| | | (0.294) | | | (0.314) | |
| LagScope3INT | | | −0.055*** | | | −0.065*** |
| | | | (0.019) | | | (0.023) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 784 | 740 | 380 | 784 | 740 | 380 |
| Adjusted $R^2$ | 0.263 | 0.261 | 0.370 | 0.269 | 0.261 | 0.368 |

Panel D: Direct emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LNDirect | 0.221 | | | −0.396 | | |
| | (0.314) | | | (0.288) | | |
| DirectYoY | | 0.755 | | | 1.349 | |
| | | (1.454) | | | (1.735) | |
| DirectINT | | | −0.001 | | | −0.0005 |
| | | | (0.001) | | | (0.001) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 744 | 668 | 744 | 744 | 668 | 744 |
| Adjusted $R^2$ | 0.225 | 0.248 | 0.224 | 0.241 | 0.259 | 0.240 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 19 - Excluding salient industries (2)

Excluding salient industries based on the industries that have the highest average carbon intensity. The sample period is 2012-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects. In columns (4) through (6), we additionally include industry-fixed effects. Panel A reports the results for unscaled emissions. Panel B reports the results for emission growth. Panel C reports the results for carbon intensity. Panel D reports the results for direct emissions.

Panel A: Total emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LNLagScope1 | −0.086*** | | | −0.214*** | | |
| | (0.027) | | | (0.028) | | |
| LNLagScope2 | | −0.044 | | | −0.114*** | |
| | | (0.070) | | | (0.033) | |
| LNLagScope3 | | | −0.115*** | | | −0.136*** |
| | | | (0.034) | | | (0.048) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 24,990 | 25,006 | 13,576 | 24,990 | 25,006 | 13,576 |
| Adjusted $R^2$ | 0.218 | 0.224 | 0.232 | 0.221 | 0.227 | 0.234 |

Panel B: Emission growth

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LagScope1YoY | −0.043 | | | −0.010 | | |
| | (0.068) | | | (0.055) | | |
| LagScope2YoY | | −0.236* | | | −0.270 | |
| | | (0.138) | | | (0.166) | |
| LagScope3YoY | | | 0.007 | | | 0.013* |
| | | | (0.006) | | | (0.007) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 21,630 | 21,558 | 11,064 | 21,630 | 21,558 | 11,064 |
| Adjusted $R^2$ | 0.217 | 0.222 | 0.212 | 0.220 | 0.224 | 0.215 |

Panel C: Carbon intensity

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LagScope1INT | 0.008 | | | 0.014 | | |
| | (0.020) | | | (0.012) | | |
| LagScope2INT | | 0.137 | | | 0.179* | |
| | | (0.101) | | | (0.097) | |
| LagScope3INT | | | −0.006 | | | −0.010 |
| | | | (0.010) | | | (0.016) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 24,990 | 25,006 | 13,576 | 24,990 | 25,006 | 13,576 |
| Adjusted $R^2$ | 0.218 | 0.225 | 0.231 | 0.220 | 0.227 | 0.233 |

Panel D: Direct emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LNDirect | −0.164*** | | | −0.287*** | | |
| | (0.049) | | | (0.029) | | |
| DirectYoY | | −0.118 | | | −0.228 | |
| | | (0.159) | | | (0.231) | |
| DirectINT | | | 0.002* | | | 0.002* |
| | | | (0.001) | | | (0.001) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 24,682 | 21,302 | 24,682 | 24,682 | 21,302 | 24,682 |
| Adjusted $R^2$ | 0.224 | 0.223 | 0.223 | 0.226 | 0.224 | 0.225 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

## Table 20 - Including salient industries (2)

Including *only* salient industries based on the industries that have the highest average carbon intensity. The sample period is 2012-2021. The dependent variable is RET. All variables are defined in Table 1. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include month-fixed effects. In columns (4) through (6), we additionally include industry-fixed effects. Panel A reports the results for unscaled emissions. Panel B reports the results for emission growth. Panel C reports the results for carbon intensity. Panel D reports the results for direct emissions.

Panel A: Total emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LNLagScope1 | 0.009 | | | 0.031 | | |
| | (0.191) | | | (0.292) | | |
| LNLagScope2 | | −0.216 | | | −0.199 | |
| | | (0.495) | | | (0.509) | |
| LNLagScope3 | | | −0.640*** | | | −0.897*** |
| | | | (0.169) | | | (0.253) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 532 | 720 | 380 | 532 | 720 | 380 |
| Adjusted $R^2$ | 0.330 | 0.205 | 0.374 | 0.327 | 0.207 | 0.375 |

Panel B: Emission growth

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LagScope1YoY | −0.949 | | | −1.435 | | |
| | (1.401) | | | (1.408) | | |
| LagScope2YoY | | 0.100 | | | 0.591 | |
| | | (1.691) | | | (1.644) | |
| LagScope3YoY | | | 0.063 | | | 0.065 |
| | | | (0.108) | | | (0.117) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 508 | 628 | 336 | 508 | 628 | 336 |
| Adjusted $R^2$ | 0.344 | 0.207 | 0.403 | 0.343 | 0.208 | 0.402 |

Panel C: Carbon intensity

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LagScope1INT | 0.076 | | | 0.088* | | |
| | (0.054) | | | (0.053) | | |
| LagScope2INT | | 0.011 | | | 0.019 | |
| | | (0.390) | | | (0.382) | |
| LagScope3INT | | | −0.055*** | | | −0.065*** |
| | | | (0.019) | | | (0.023) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 532 | 720 | 380 | 532 | 720 | 380 |
| Adjusted $R^2$ | 0.332 | 0.204 | 0.370 | 0.329 | 0.207 | 0.368 |

Panel D: Direct emissions

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LNDirect | 0.221 | | | −0.396 | | |
| | (0.314) | | | (0.288) | | |
| DirectYoY | | 0.755 | | | 1.349 | |
| | | (1.454) | | | (1.735) | |
| DirectINT | | | −0.001 | | | −0.0005 |
| | | | (0.001) | | | (0.001) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Month F.E. | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry F.E. | No | No | No | Yes | Yes | Yes |
| Observations | 744 | 668 | 744 | 744 | 668 | 744 |
| Adjusted $R^2$ | 0.225 | 0.248 | 0.224 | 0.241 | 0.259 | 0.240 |

*Note:* *p<0.1; **p<0.05; ***p<0.01