THE IMPACT OF CARBON EMISSIONS ON STOCK RETURNS

AN ANALYSIS OF THE CARBON RISK PREMIUM IN THE EUROPEAN STOCK MARKET

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Abstract:

We investigate the carbon emissions' effect on stock returns in European firms. The results show that firms with higher *carbon intensity*, a relative measure of carbon emission, yield a higher stock return while controlling for return-predicting factors. This suggests the existence of a carbon premium to compensate investors for additional carbon-related risk. We also note that for *total emissions* and *emissions growth* as independent variables, there are no statistically significant effects supporting the carbon risk premium hypothesis. Overall, we find weaker evidence for the existence of a carbon premium than previous, mainly American, research on the topic.

Keywords:

Stock returns, carbon emissions, carbon premium, carbon risk premium, climate change, carbon intensity, carbon growth, Europe

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1. Introduction

The aim of this paper is to contribute to the understanding of the impact of carbon emissions on stock returns in EU+28, EEA and Switzerland. Examining various financial subjects through the lens of climate change is increasingly popular within contemporary research. This growing trend of research is tied to the increasing relevance of the subject of climate change as a political topic in the wider public discourse in large parts of the world. One of the most important factors contributing to climate change and rising temperatures around the world is the increased amount of greenhouse gases in the atmosphere, where carbon dioxide accounts for the greatest portion of the emissions. (World Meteorological Organization, 2021)

High-emitting companies' negative impact on the environment leads to a number of firm-level risks. They face the risk of being subject to environmental regulations, potentially limiting the amount of carbon dioxide they are allowed to emit and introducing penal fees forcing high-emitters to pay for the damage caused by their emissions. Furthermore, companies' reputations might be negatively affected, leading to worse relationships with stakeholders and potential financial damage. Another risk is price changes in fossil fuels. Companies emitting large amounts of carbon dioxide usually have an input of fossil fuels in their operations, making them dependent and vulnerable to commodity price changes. If realised, the above-mentioned risks would have an effect on companies' cash flows and since companies are valued on discounted future cash flows, it should in turn have an effect on stock prices. This implies the possible existence of a carbon risk premium to compensate investors for the additional risk, in line with financial theory on the risk-return relationship.

Our aim with this paper is to contribute to the literature on carbon risk premiums, by examining the correlation between carbon emissions and stock returns. This paper has taken methodological inspiration mainly from two academic papers. Firstly, Bolton & Kacperczyk (2021) examine approximately 4,000 US-listed companies and control for a wide range of return-estimating factors. They find a significant positive effect of carbon emissions on stock returns. Their results suggest the existence of a carbon risk premium, through which investors obtain compensation for additional carbon-related risk. This is the most important source of inspiration for our paper. Secondly, Hsu, Li, & Tsou (2022) also study the relationship between emissions and stock returns by using a similar methodology and variables. Using data from the ASSET4 database with approximately 4.500 public companies from 1991 to 2016, they find a significant 4.42% annual excess return for a portfolio investing long in companies with high toxic emissions levels and short in companies with low levels of toxic emissions, suggesting a pollution premium.

Contrary to the previously mentioned articles and much of the related research which uses financial data and stock returns on American companies, the scope of this paper is European companies. More specifically, available data from EU+28 (including the UK), EEA and Switzerland has been used. This geographical scope is used because the European market is the only region with comparable economic size and GDP per capita to the American market. Broadening the scope beyond the American market adds value to the existing literature by examining whether the discovered connection between carbon emissions and stock returns is limited to the American market, or if it is also prevalent in Europe. That would increase the likelihood of the connection being universal and thus help advise regulatory decisions in a worldwide context and increase investors' understanding of how carbon emissions affect stock prices. Furthermore, the choice of making research centred around Europe is tied to the introduction of EU-wide environmental regulations specifically addressing greenhouse gas emissions, including the EU Emissions Trading Scheme first introduced in 2005 as well as the European Green Deal, in which the EU taxonomy for sustainable activities (2020) is a part (European Commission, n.d.).

2. Literature review

In addition to the main articles mentioned in the introduction, this paper is related to a wide range of rapidly growing literature about finance and sustainability. The previous papers touching upon the question of a possible carbon risk premium have found varying results.

Some authors find that there is a carbon risk premium prevalent in the market. For example, Chava (2014) finds that companies excluded from environmental screens have a higher implied cost of capital, as investors demand higher expected returns and lenders charge higher interest rates from these companies. Kim, An & Kim (2015) also find a positive relationship between carbon intensity and the cost of equity capital in a sample of Korean firms. This would in turn imply a carbon risk premium. Kleimeier & Viehs (2021) find that debt financing is more expensive for firms with higher carbon emissions, implying that the cost of capital increases and suggests the existence of a carbon risk premium. Moreover, Oestreich & Tsiakas (2015) examine the effect of the EU Emissions Trading Scheme on stock returns for German firms that receive carbon emitting allowances between the years 2003-2009. They demonstrate the presence of a carbon premium which the authors attribute mainly to increased cash flow from regulation.

Contrary to the results obtained by the papers mentioned in the paragraph above, the following papers find a negative relationship between carbon emissions and stock returns. Garvey, Iyer & Nash (2018) analyse carbon intensity in the stock selection process and find that firms with lower carbon intensity yield higher stock returns. In, Park & Monk (2019) create a carbon efficient-minus-inefficient portfolio and find that an investment strategy long in carbon-efficient firms and short in carbon-inefficient firms earn an abnormal return of between 3.5% and 5.4% per year. Matsumura, Prakash & Vera-Munoz (2014) find a negative relationship between reported carbon emissions and firm value. More specifically the paper finds that an increase of a thousand metric tonnes of carbon emissions would lead to a firm value decrease of $212,000. Bushnell, Chong & Mansur (2013) shows that, even after an ETS CO2 allowance price drop, which would imply a risk reduction for carbon-intensive firms and in turn an increase in stock price, stock prices fell for carbon-intensive firms. This is contrary to what the theory of a carbon risk premium would suggest since a lower level of risk should yield a lower carbon risk premium. A similar relationship is found by Jong, Couwenberg & Woerdman (2014). They find that firms with lower carbon intensity experienced stock price increases when ETS allowance prices dropped versus a sample of high carbon-intensive firms.

Other articles that discuss the relationship between carbon emissions and stock returns from other perspectives include Görgen, Jacob, Nerlinger, Riordan, Rohleder & Wilkens (2019) who create a carbon risk factor and a carbon beta for firms, making it possible for firms to evaluate the effect of carbon emissions on the equity cost of capital. Hong, Li &

Xu (2019) contribute to the discussion about the efficiency of markets in pricing climate risk, by examining stock returns for food companies in regions with drought. They find that low numbers of PDSI (a drought index) in the previous 36 months predict lower future profitability. This supports the assumption that there is an underreaction in international markets since markets with droughts yield lower returns in the future than markets without droughts. Berk & Van Binsbergen (2021) examine how investors' divestiture from firms with low ESG-scores firms affects the cost of capital. They find no meaningful effect which neither supports an ESG premium nor an ESG discount.

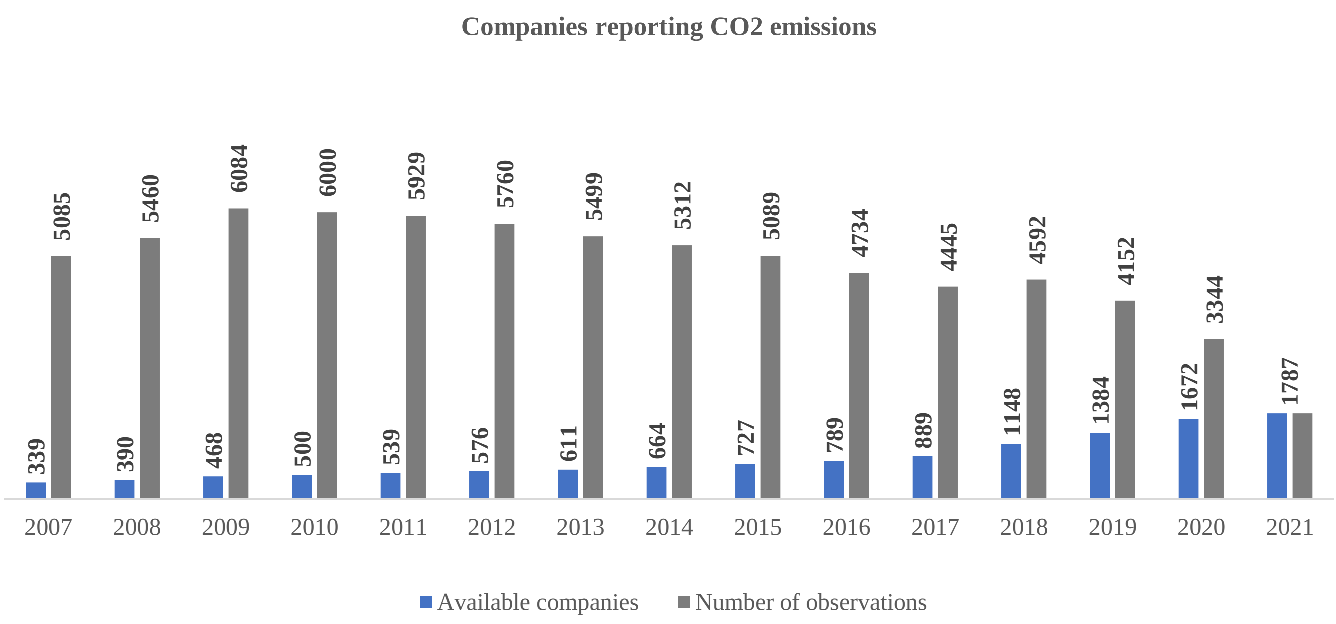
There are also papers discussing investor preferences in relation to environmental sustainability among firms and how that influences their decision-making. These include Hong & Kacperczyk (2009), who demonstrate the role of social norms regarding "sin stocks" in stock investing, i.e. stocks within industries deemed as immoral. Also on the behavioural topic, Guastella, Mazzarano, Pareglio & Xepapadeas (2022) address the reputational risk faced by companies in carbon-intensive environments and find that this risk materialises in terms of stock returns if companies' climate talk is not coherent with their actions. Furthermore, Krueger, Sautner & Starks (2020) conduct a survey showing that institutional investors believe that climate risk has a material effect on the return of their portfolios. The responding investors believe that equity valuations do not fully reflect climate risk.

3. Data and Sample

The data used in this paper consists of observations from the period between 2013 - 2021. It consists of firm-level statistics of listed firms in EU+28, EEA and Switzerland with a market capitalisation larger than 100 million Euros at the beginning of 2013 and available carbon emission data from 2013 and onwards. In Figure 1, the number of firms reporting carbon emissions in their regular operational reporting is shown. In the period 2007 to 2021, this number has been growing steadily without any interruption. We have chosen to include figures from 2013 and onwards in our analysis, which means that we use available companies from 2012 as our base year, as we use the year-over-year CO_2 growth as one of our variables. When deciding on which time period to analyse there is a trade-off between 1) available companies reporting emissions, and 2) time as a factor, i.e. between the subscripts *i*, representing firms, and *t*, representing time. By studying companies from an earlier date, the quantity of companies available is lost, but time is gained (and thus observations). We believe that using financial figures and carbon emissions during the period 2013-2021 in our analysis gives a sufficient time period, as well as enough firms reporting their carbon emissions at the outset. As illustrated by Figure 1, a longer time period, e.g. from 2009, would have resulted in a slight increase in the number of observations but a steep decrease in the number of firms, possibly resulting in a too-narrow sample. If we on the other hand would have looked at data after 2016, the total number of observations would be reduced to the detriment of the analysis.

Figure 1: Firms Reporting Carbon Emissions and Number of Observations by Year

This figure represents the number of firms that report their carbon emissions (*CO2 Equivalent)* based on the years 2007 - 2021 as well as the total number of observations. The total number of observations is calculated as the number of years remaining in the data multiplied by the number of firms reporting carbon emissions for the specific year. For example, the total number of observations for 2010 is calculated as 12 (Number of full years between 2010 and 2021) multiplied by 500 (Number of firms). Some companies have been consistently reporting their emissions while some have been reporting some years while missing others. This graph illustrates all firms reporting for a single year independent of their consistency in reporting.



The data used is sampled from two sources: Refinitiv Eikon and Yahoo Finance, and the two datasets are matched on ticker symbols. When ticker symbols differ between the data sources, the companies are instead matched on ISIN numbers. Refinitiv Eikon provides information on firm-level carbon emissions and financial fundamentals while Yahoo Finance provides information on stock returns. We use Yahoo Finance to gather stock returns data as the database can provide daily returns with adjusted close prices for splits and dividends. The stock returns are downloaded through the *yfinance* package in Python whereas Refinitiv Eikon data is downloaded through the Refinitiv application. The Refinitiv Eikon output from the geographical and market capitalisation threshold yielded a total of 4,498 companies in 2012. Out of these, only 576 companies have been reporting emission data from 2012 and onwards. After further wrangling and a manual walkthrough of the data, we find that 23 out of these 576 companies are either dually listed (e.g., main list in the US with a separate bond listing in Europe), have not been listed on an exchange for the whole sample period or have other geographical constraints (e.g. listed in Russia/Ukraine/Jersey). These 23 companies are listed in Appendix A and are not included in our sample. The remaining 553 companies serve as the database in this paper. These companies are then divided into 16 different sectors (see Table 1) and they have their domicile in 21 different countries (see Table 2).

3.1 Data on Firm-level Carbon Emissions

The data for firm-level carbon emissions is downloaded through Refinitiv Eikon. The application gathers self-reported CO2 emissions data from individual firms. We use Refinitiv Eikon's measure of *total CO2 equivalent emissions* (measured in tonnes of CO2) as the base for this paper. Eikon's variable is defined as direct scope (1) and indirect (scope 2) carbon emissions and the variable follows the greenhouse gas (GHG) protocol for all emissions and classification types. We use this rather than reported scope 1, scope 2 and scope 3 emissions (as introduced by the Green House Gas Protocol) primarily because firms have reported total emissions for a longer period of time. This broadens the number of observations in this study significantly. All the carbon data is self-reported by the firms, and although stricter non-financial audits have been implemented over time, there is a risk of selection bias in firms reporting their carbon emissions. For reputational and financial reasons, firms may adjust their carbon emissions to a greater extent than their financial figures due to the lower audit thresholds. However, carbon emission as a variable has been studied extensively in other academic papers and serves as the best option for testing our hypothesis.

Figure 2: Total Carbon Emissions by the Year

This figure represents the sum of the carbon emissions (C2) from the 553 firms that have been reporting consistently over the sample period, 2013-2021. Carbon emission is denoted in billion tonnes.

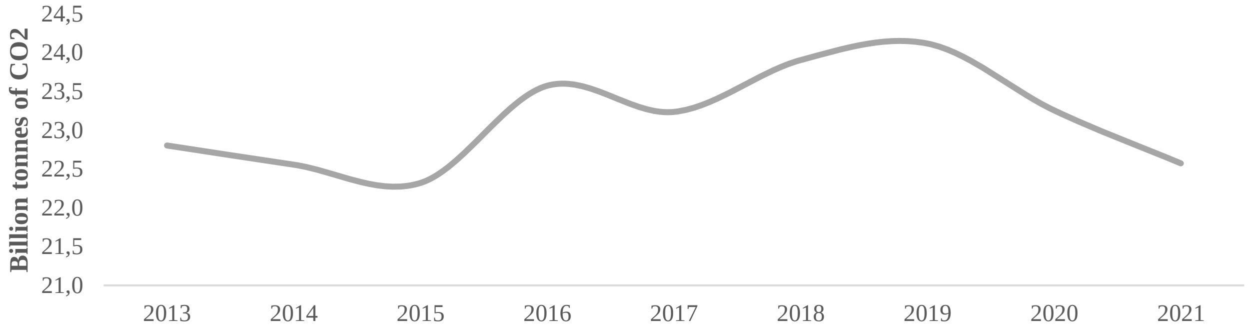


Table 1: Sector Descriptive Statistics and the Number of Firms

This table shows the distribution of firms based on their sector and descriptive statistics for each and one of them. The sector classification follows the Global Industry Classification Standard (GICS). The total figure indicates the total number of unique firms in our sample and the mean, and standard deviation refer to carbon emissions in thousand tonnes. The sample period is 2013-2021.

	Number of firms	*Mean and std. dev. of emissions*	
Sector	**N**	**Mean**	**Std. Dev.**
Utilities	35	28.347,4	47.861,4
Materials	62	18.229,5	44.979,0
Energy	31	15.501,6	28.400,1
Transportation	20	9.135,6	16.144,6
Consumer Services	11	2.716,1	4.673,4
Automobiles and Components	14	2.635,3	3.235,9
Consumer Staples	36	1.563,2	2.221,6
Capital goods	85	906,9	2.432,4
Health Care	27	660,5	1.149,5
Communication services	40	450,2	942,1
Retailing	13	292,1	601,4
Information Technology	28	246,8	417,8
Commercial and Professional services	20	232,6	312,9
Consumer Durables and Apparel	18	98,4	139,9
Financials	86	92,3	153,5
Real Estate	27	28,8	39,0
Total	**553**	-	-

Table 2: Country Descriptive Statistics and the Number of Firms

This table shows the distribution of firms based on their headquarters domicile and descriptive statistics for each country. The total figure indicates the total number of unique firms in our sample and the mean and standard deviation refer to carbon emissions in thousand tonnes. The sample period is 2013-2021.

	Number of firms	*Mean and std. dev. of emissions*	
Country	**N**	**Mean**	**Std. Dev.**
Luxembourg	5	56.824,7	112.658,7
Czech Republic	1	36.261,1	14.492,5
Poland	8	17.257,9	29.830,1
Italy	21	12.563,9	33.836,9
Germany	49	11.362,9	34.929,2
Switzerland	43	6.162,9	30.394,4
France	70	5.631,9	18.020,8
Portugal	6	5.429,2	9.679,2
Spain	30	5.417,9	12.258,7
Austria	10	4.437,8	7.129,1
Denmark	16	3.837,7	12.749,7
Hungary	3	3.705,9	5.217,4
Norway	16	3.666,1	7.722,6
Ireland; Republic of	15	3.370,6	10.719,9
United Kingdom	163	3.220,3	13.136,3
Finland	21	3.161,3	10.757,1
Belgium	11	2.609,5	5.685,5
Greece	7	1.381,0	2.163,9
Netherlands	18	1.376,9	2.029,1
Cyprus	1	1.275,1	353,4
Sweden	39	826,2	2.731,0
Total	**553**	-	-

3.2 Data on Firm-level Financial Fundamentals

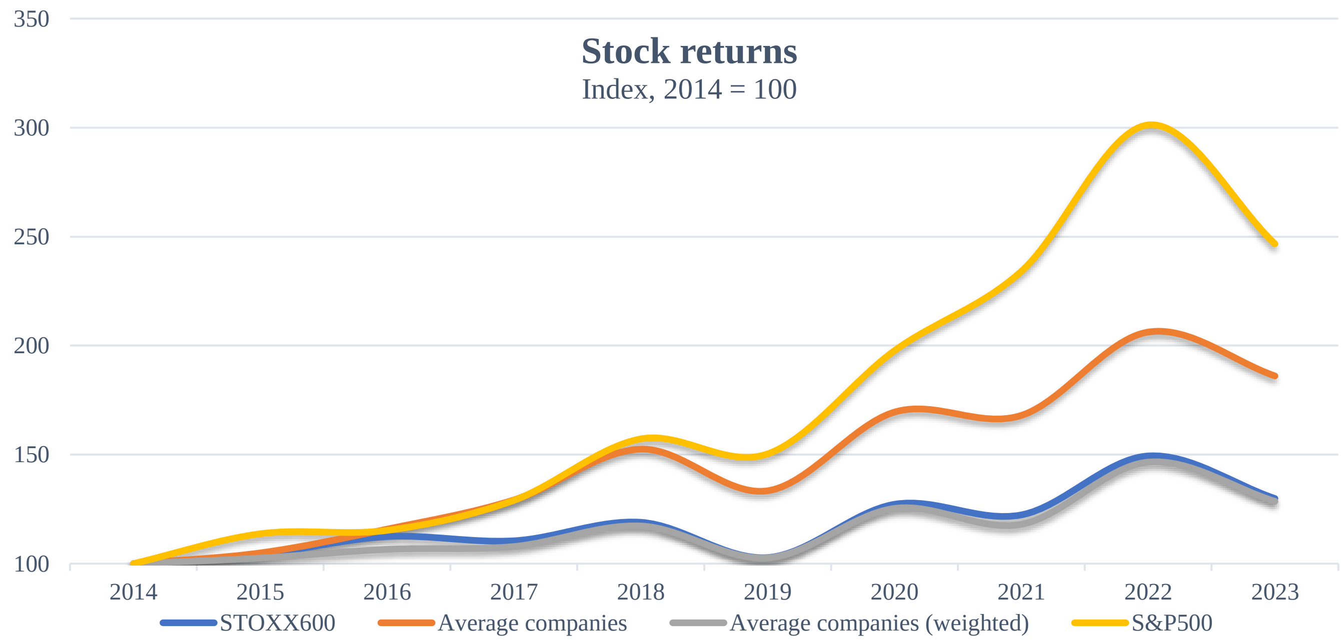
The data on firm-level financial fundamentals from 2013-2021 is downloaded through Refinitiv Eikon. All financials are denominated in the same currency (Euro). If the financials were originally reported in another currency, Eikon uses a constant currency exchange to exchange it. This might affect the robustness of the data negatively, but as the same procedure is done for all firms, we believe it is the best alternative for the research purpose.

3.3 Data on Stock Returns

The data on stock returns during the period 2014-2022 is downloaded through Yahoo Finance's Python API *yfinance*. Carbon emissions and financial data are lagged by one year compared to stock returns, which explains the different time periods compared to sections 3.1 and 3.2. The stock prices are gathered on a monthly basis and then calculated into monthly percentage returns which are then annualised in the analyses and regressions. This enables us to introduce different time lags based on months rather than years. In Figure 3, we illustrate the average returns of the 553 companies in our sample and compare them with the European index STOXX600, and S&P 500 as well as the weighted average return of the companies in our dataset.

Figure 3: Returns

vThis figure illustrates the returns for the set of 553 companies in our analysis, calculated as the average of the firms' returns on a yearly basis. The set of companies' returns is illustrated both through an average and a market-cap weighted average. We have also included STOXX600, which is a gathered index of European stocks. We have also included the S&P 500 index, which will be further discussed in our analysis.



3.4 Variables in Return Regression

The empirical analysis we conduct uses annualised monthly stock returns as its dependent variable. We name it $RETURN_{i,t}$ which is defined as the annualised return data for firm *i* in year *t*. The independent variable is carbon emissions looked at from three different levels. The first one is $LOGCO2_{i,t-1}$ (carbon emissions), which is the natural logarithm of carbon emissions for firm *i* in year *t*. The second one is $LOGCO2INTENSITY_{i,t-1}$ (carbon intensity), which is the natural logarithm of carbon emissions divided by sales. The last one is $CO2GROWTH_{i,t-1}$ (carbon growth), which is the year-over-year change in emissions. The control variables, which are also subscripted by firm *i* and year *t*, used in the analysis are $BM_{i,t-1}$ (book-to-market), defined as the book value of equity divided by market capitalisation, $ROE_{i,t-1}$ (return on equity), defined as net income divided by book value of equity, $LEVERAGE_{i,t-1}$ (leverage), defined as interest-bearing debt divided by total assets, $LOGSIZE_{i,t-1}$ (size), defined as the natural logarithm of the market capitalisation, $CAPEX_{i,t-1}$ (capital expenditure) defined as the cash flow from investing activities divided by company sales, $EPSGROWTH_{i,t-1}$ (earnings per share growth), defined as the year-over-year change in EPS, and $SALESGROWTH_{i,t-1}$ (sales growth), defined as the year-over-year change in revenue. In accordance with the method of Bolton & Kacperczyk (2021), we winsorize the following variables at a 2.5% level: $BM_{i,t-1}$, $ROE_{i,t-1}$, $LEVERAGE_{i,t-1}$, $CAPEX_{i,t-1}$, $EPSGROWTH_{i,t-1}$, and $SALESGROWTH_{i,t-1}$. By doing this, values greater than the 97.5th percentile and lower than the 2.5th percentile are changed to those of the 97.5th and 2.5th percentile. This ultimately limits the effects of outliers on the standard errors and coefficients in our study which gives more robust findings.

Differently from Bolton & Kacperczyk (2021), we use a 1-year lag effect on the independent variable and all the control variables. This is implemented because the dependent variable, stock returns, is affected by the publication of reports that are backwards-looking. For example, the result for the year 2016 was published in 2017. Consequently, the stock returns adapt to this information only when it becomes available. We note that some firms report on a quarterly or semi-annual basis and that this serves as a limitation to our regression models. However, all firms report their carbon emissions on an annual basis, and as such, we believe that the method described gives the fairest view of a firm's performance with respect to the relationship between financials, stock returns and emissions. To test this lag effect we conduct two more regressions with the same variables: one regression using a 6-month lag effect and one regression using no lag effect on the independent and control variables. This is further discussed in the section Robustness in this paper.

Table 3: Summary Statistics on Regression Variables

This table reports descriptive statistics for each variable used in our regressions. All variables are defined in the section *'3.4 Variables in Return Regression'*. The sample period is 2013-2021.

	Number of firms	*Mean, std. dev., min., and max of the logarithm of CO2 emissions*			
Variable	**N**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
CO2Growth	4743	-0.016	0.219	-0.476	0.798
LOGCO2Intensity	4424	8.447	1.939	4.29	12.193
LOGCO2	4818	12.141	2.594	2.001	19.087
LOGSIZE	4977	22.599	1.475	15.952	26.629
BM	4964	0.681	0.576	0.057	2.664
ROE	4903	0.14	0.146	-0.251	0.618
LEVERAGE	4761	0.251	0.15	0.009	0.607
Capex	4356	0.039	0.03	0	0.122
EPSGROWTH	4557	0.14	0.543	-0.718	2.381
SALESGROWTH	4564	0.039	0.161	-0.358	0.529

4. Research Design

Our method and hypothesis take inspiration from the method used by Bolton & Kacperczyk (2021). The authors develop a cross-sectional regression model using pooled OLS to study the relationship between stock returns and 1) Absolute Emissions, 2) Carbon Intensity, and 3) Carbon Growth. They control for return-predicting factors such as size, profitability, and growth while including certain fixed effects, such as time and sector.

In its essence, Bolton & Kacperczyk (2021) prove that investors want a higher expected return for the higher risk that they are taking by holding stocks with larger emissions tied to their operations. This is explained by the risk of future carbon taxes, emissions trading schemes or legal liabilities as an effect of environmental damage. The carbon risk premium could also be derived from market inefficiencies, as the carbon risk is hard to quantify in a time of rapidly changing regulatory environment and investor preferences. Regardless of the explanation of the carbon premium, by studying the relationship between stock returns and carbon emissions, investors can make more informed decisions in their own investing and adjust their internal risk profile accordingly. In light of this, the hypothesis that we test is that returns and emissions correlate positively

The relationship is tested by using the pooled OLS regression method described above, which regresses annualised stock returns on emissions. We define emissions according to the framework used in Bolton & Kacperczyk (2021). They regress emissions both on an absolute (*LOGCO2*), relative (*LOGCO2INTENSITY*) and based on the change in emissions (*CO2GROWTH)*. This is because the different emission metrics reflect risks differently. For example, absolute and relative emissions reflect a long-run risk exposure while changes in emissions reflect a short-term risk exposure, i.e. the year-over-year change in carbon risk.

$$Return_{i,t} = B_0 + B_1 * Emissions_{i,t-1} + B_2 * \ Control\ variables_{i,t-1} + u_{i,t} + e_{i,t}$$

The dependent variable is stock returns, independent variable is the different types of emissions discussed above (absolute, relative and change in emissions) and the control variables include $LOGCO2_{i,\ t-1}$, $BM_{i,\ t-1}$, $ROE_{i,\ t-1}$, $LEVERAGE_{i,\ t-1}$, $LOGSIZE_{i,\ t-1}$, $CAPEX_{i,\ t-1}$, $EPSGROWTH_{i,\ t-1}$, $SALESGROWTH_{i,\ t-1}$. All variables are firm- and time-specific. In comparison to Bolton & Kacperczyk (2021) our study researches more than one country, which increases the likelihood of country-specific effects. To control for this, we will include a country-fixed effect regression besides the sector-fixed effect used in the paper. We also cluster standard errors on company- and year-level, to mitigate the effect of heteroskedasticity. This is further discussed in the robustness section of this paper. All variables used in the regression are defined in the data section of this paper.

The coefficient of interest is B_1, and with that in mind, we form our hypothesis:

$$H_0: B_1 \leq 0$$
$$H_1: B_1 > 0$$

In this hypothesis, B_1 represents the coefficient for all the independent variables (absolute emissions, emission intensity and growth in emissions). As we expect differences in significance between these independent variables, we will investigate them on a separate basis.

5. Results

The result from the regression is reported in Table 4 columns 1 through 9. In the table, we test the three emission variables (absolute, intensity and growth) based on three different scenarios. The first scenario is with year-fixed effects. This is presented in columns 1 through 3. Our second scenario includes both year- and sector-fixed effects. This is presented in columns 4 through 6. The last scenario includes year-, sector- and country-fixed effects. This is presented in columns 7 through 9.

Sector-fixed effects are included as firms are likely to cluster according to their specific industries. This is tested by including fixed effects for sector, classified by the Global Industry Classification Standard (GICS). We also expect emissions to cluster in their specific countries. This is tested by including country fixed-effects.

To summarise, we find a significant positive effect for carbon intensity in our pooled regression model while controlling for year-fixed effects only. When controlling for sector- and country-fixed effects this effect becomes insignificant. Furthermore, we are not able to show a significant effect on absolute emissions or growth in emissions.

5.1 Regression on Carbon Emissions and Stock Returns

Our model finds a positive significant effect for carbon emission intensity (*LOGCO2INTENSITY*) when controlling for time (column 2 in Table 4). For example, a 10 per cent increase in carbon emission intensity indicates a significant 0.12 % annual return increase, when controlling for year-fixed effects. A 10 per cent increase in carbon emission intensity, while controlling for year and sector-fixed effects, yields a statistically insignificant 0.092% annual return increase (p-value of 0.15) (see column 5). A 10 per cent increase in carbon emission intensity, while controlling for year, sector and country-fixed effects, yields a statistically insignificant 0.087% annual return increase (p-value of 0.16) (see column 8). We do not find any significant effects for the other emission variables (absolute emissions and growth in emissions).

Table 4: Carbon emissions and stock returns

The sample period for the regression is 2013-2021. The dependent variable is stock returns and the independent variables are the natural logarithm of carbon emissions, carbon emission intensity and carbon emission growth. Standard errors are given in parenthesis, which are clustered at firm and year levels. In regression 1-3 we include year-fixed effects, in regression 4-6 we add sector-fixed effects and in regression 7-9 we add country-fixed effects. *** 1% significance, ** 5% significance, * 10% significance.

Dependent variable: Stock returns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LOGCO2	0.0015 (0.0025)			-0.0025 (0.0047)			-0.0023 (0.0049)		
LOGCO2INTENSITY		0.0119*** (0.0034)			0.0092 (0.0064)			0.0087 (0.0062)	
CO2GROWTH			-0.0235 (0.0226)			-0.0205 (0.0226)			-0.0209 (0.0226)
LOGSIZE	0.0157** (0.0052)	0.0164*** (0.0042)	0.0169*** (0.0042)	0.0194*** (0.0068)	0.0170*** (0.0044)	0.0170*** (0.0044)	0.0224*** (0.0067)	0.0201*** (0.0044)	0.0205*** (0.0044)
BM	-0.2038*** (0.0173)	-0.2100*** (0.0167)	-0.2032*** (0.0160)	-0.2130*** (0.0203)	-0.2221*** (0.0178)	-0.2188*** (0.0164)	-0.2203*** (0.0210)	-0.2283*** (0.0183)	-0.2253*** (0.0171)
ROE	-0.2725*** (0.0567)	-0.2545*** (0.0555)	-0.2774*** (0.0580)	-0.2607*** (0.0562)	-0.2486*** (0.0554)	-0.2616*** (0.0580)	-0.2821*** (0.0577)	-0.2707*** (0.0572)	-0.2856*** (0.0591)
LEVERAGE	-0.0839** (0.0354)	-0.1070*** (0.0349)	-0.0856** (0.0363)	-0.0948** (0.0410)	-0.1114*** (0.0400)	-0.1007** (0.0429)	-0.0839** (0.0423)	-0.1003** (0.0418)	-0.0898** (0.0445)
CAPEX	-0.1431 (0.2193)	-0.3892* (0.2245)	-0.1195 (0.2007)	-0.1178 (0.2391)	-0.2752 (0.2496)	-0.1773 (0.2218)	-0.2614 (0.2608)	-0.4015 (0.2712)	-0.3239 (0.2404)
EPSGROWTH	0.0447*** (0.0117)	0.0419*** (0.0116)	0.0435*** (0.0116)	0.0431*** (0.0118)	0.0413*** (0.0117)	0.0411*** (0.0117)	0.0409*** (0.0118)	0.0394*** (0.0118)	0.0387*** (0.0118)
SALESGROWTH	-0.0129 (0.0448)	-0.0060 (0.0446)	-0.0049 (0.0458)	-0.0258 (0.0449)	-0.0183 (0.0446)	-0.0152 (0.0461)	-0.0313 (0.0455)	-0.0244 (0.0452)	-0.0197 (0.0467)
Intercept	-0.1295 (0.1120)	-0.2137 (0.0990)	-0.1382 (0.1040)	-0.1572 (0.1320)	-0.1973 (0.1083)	-0.1251 (0.1158)	-0.1096 (0.1344)	-0.1692 (0.1141)	-0.0769 (0.1195)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E.	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	No	No	No	No	No	No	Yes	Yes	Yes
R-squared	0.2511	0.2543	0.251	0.2615	0.2624	0.2609	0.2699	0.2706	0.2695

6. Robustness

6.1 Various Biases and how we have controlled for them

There are a number of potential biases in our regressions that are addressed in line with Bolton & Kacperczyk (2021).

First, the fact that companies operate in a wide array of sectors with major differences in average carbon emissions is controlled for by using sector-fixed effects in the regressions. Furthermore, and differently from Bolton & Kacperczyk (2021) whose sample is entirely American, we use country-fixed effects to control for the effect of varying countries of origin of the companies in our sample.

Second, another important bias is related to the size of emissions data. This is controlled for by regressing the normalised variable *Carbon Intensity*, thus making the size of the total emissions relative to the company's revenue.

Third, to mitigate the effect of outliers, we winsorize a number of variables at the 2.5% level. These include $BM_{i,\ t-1}$, $ROE_{i,\ t-1}$, $LEVERAGE_{i,\ t-1}$, $CAPEX_{i,\ t-1}$, $EPSGROWTH_{i,\ t-1}$, and $SALESGROWTH_{i,\ t-1}$. This aligns with the method used by Bolton, P. and Kacperczyk, M. (2021).

Fourth, in order to address the potential issues arising with a one-year lag on the independent and control variables, all the regressions are tested with a 6-month lag and no-lag effect as well. When regressing with a 6-month lag effect, there are only minor differences in significance. However, when using a no-lag effect on the independent and control variables, all emission variables on all regressions become statistically insignificant. The results are presented in Appendix D.

Fifth, we notice that there is a strong downturn in the amount of carbon emissions from 2020 and onwards, likely related to the worldwide Covid-19 pandemic (see Figure 2). To test if this has a significant effect on our regressions, we exclude the years 2020 and 2021 in a regression found in Appendix E. We find that the magnitude of the estimate in the regression with the independent variable carbon intensity and with year-fixed effects increases by approximately 43 % when excluding the years 2020 and 2021. There are no other significant changes between the main regression and the regression in Appendix E.

6.2 Autocorrelation, Heteroskedasticity and Multicollinearity

The Gaus-Markov assumptions in ordinary least-square regressions rely on the data having no autocorrelation, the data being homoscedastic and with no multicollinearity. We test these assumptions through robustness tests performed in R.

First, we use a Durbin-Watson test to examine the data for autocorrelation. If the data would contain autocorrelation, this could lead to inefficient estimators as it would violate the assumption of independence among observations. Our Durbin-Watson tests show no signs of autocorrelation in the regressions. Consequently, we conclude that the regression models do not suffer from autocorrelation.

Second, we use a Breusch-Pagan test to examine the data for heteroskedasticity in our regression models. Heteroskedasticity refers to the different degrees of dispersion among the residuals or error terms in a regression model. When present, heteroskedasticity increases the variance of the regression estimates, but the regression model does not detect this. This would make the regression model believe the significance of an estimator to be much higher than what it actually is, corresponding to lower p-values than what would have been in a homoskedastic equivalent. The Breusch-Pagan test indicates that our model significantly suffers from heteroskedasticity (Breusch-Pagan test results reported in Appendix B). To mitigate the problems that follow a heteroskedastic regression, we cluster the standard errors on a company- and year-level. By doing this, the regression accounts for the correlation among residuals in each cluster which improves the accuracy of the statistics of the model. When clustering standard errors, the regression models become less significant than what they were before clustering the standard errors (see Appendix C). This indicates that the regression model did not account for the dispersion of residuals when standard errors were not clustered, and how clustering them helped mitigate this problem.

Third, we test for multicollinearity through the Variance Inflation Factor (VIF) in R. Multicollinearity occurs in a regression model when one predictor correlates with another predictor. In such a case, the two predictors would not give information independently of each other, resulting in problems with the interpretation of the model. The VIF-test provides us with no indication that the model would suffer from multicollinearity.

7. Discussion

In line with the financial concept of a risk-return relationship, there should be a positive relationship between increased carbon-related risk and stock returns. There are several contemporary studies providing empirical examples of this. For example, Bolton & Kacperczyk (2021) find a positive relationship between carbon emissions and stock return in a US-based setting. Other literature with similar findings includes Hsu et al. (2022), Chava (2014) and Kleimeier & Viehs (2021). However, this is not a one-sided discussion and other articles have found evidence for the opposite to be true, i.e. that low-emitting companies are rewarded with higher stock returns. These include Garvey et al. (2018) as well as In et al. (2019) among others. This shows that there is empirical evidence both of a carbon premium as well as of an 'environmental' premium. The findings in our paper weakly support the carbon premium hypothesis.

7.1 Differences in results between independent variables

Our regressions find a significant and positive effect for the carbon intensity variable when controlling for year-fixed effects. For absolute emissions and growth in emissions, we find no significant effect, or for carbon intensity when adding fixed effects for sector and country. We suggest that this is explained by the underlying difference between the variables, where carbon intensity is normalised to the firms' revenues whereas absolute emissions and growth in emissions are not. As an effect of this, carbon-intensive firms should be the most negatively affected when the potential cost of emitting CO2 increases. This can include price increases in fossil fuels as well as the introduction of Carbon Emissions Allowances among other reasons. In line with the risk-return theory and discussion above, the result shows a positive estimator. Our results are in this respect contradictory to Bolton & Kacperczyk (2021). The authors find that there is a positive and significant effect for absolute emissions and growth in emissions, while carbon intensity is not significant.

7.2 Differences in results between different fixed effects

When controlling for the three different levels of fixed effects – time, sector, and country – we find that the effect and significance of the carbon premium decrease as we increase the number of fixed effects. For example, the estimate of carbon intensity is higher when only having year-fixed effects, while becoming gradually weaker as we fix effects for sectors and then lastly for countries. The difference in estimator magnitude is quite small, for example, a 10 per cent increase in carbon intensity would indicate a 0.119 % annual return increase when controlling for year-fixed effects versus a 0.092 % annual return increase when controlling for year and sector versus a 0.087 % annual return increase when controlling for year, sector and country. The difference between the first regression, with year-fixed effects only, and the second regression, adding sector-fixed effects, indicates that the sector accounts for approximately 23% of the estimation magnitude of carbon intensity on stock returns. Adding country-fixed effects as well leads to a total reduction in the magnitude of approximately 27%, or 4 percentage points more. This indicates that the country factor affects the impact of carbon intensity on stock returns less than the sector factor does. Taken together, the result shows that a large part of the positive coefficient depends on the sector and country classification rather than carbon intensity. This can potentially be explained by the effect of investor preferences on certain sectors, especially the three highest-emitting sectors Utilities, Energy and Materials. As shown by Table 1, the mean total emissions of the lowest-emitting sector (Real Estate) is 99.9% lower than the highest-emitting sector (Utilities), illustrating a wide variation between sectors. It is worth noticing, however, that the carbon intensity coefficients for regressions with the sector- and country-fixed effects become insignificant with p-values of 0.15 and 0.16 respectively.

7.3 Differences in results when including robustness tests

As part of the robustness test, we test three alterations to our main regression. In the first two of these, we test how lagging the independent and control variables with 6 months and with no lag affects the results in comparison to our main regression with a 12-month lag for the independent and control variables. We find that these two tests decrease the explanatory power of the results by reducing the significance of the independent variables. Therefore, our 12-month lag method seems to be the most suitable option for this regression.

The third alteration to our main regression is to exclude the years 2020 and 2021 since there is a sudden downturn in total reported carbon emissions during that period (see Figure 2). Most likely, this is a result of the covid-19 pandemic and its impact on economic activity. We find that the magnitude of the coefficient of the regression with carbon intensity and with year-fixed effects increases by approximately 43%, from 0.0119 to 0.017 (see Appendix E). Since the aim of this paper is to examine the relationship between stock returns and carbon emissions over time, finding a higher magnitude on the coefficient of the independent variables when excluding a one-time event such as the covid-19 pandemic is of interest to the results. This indicates that, in normal times, the relationship between stock returns and carbon intensity is stronger than in the period examined in our main regression which includes the covid-19 years.

7.4 Differences in results versus prior research

In the regressions, it is shown that carbon intensity has a statistically significant effect on stock returns, although a small one in terms of magnitude. However, the fact that the effect is considerably smaller than the result obtained by Bolton & Kacperczyk (2021) and the fact that the other two variations of emissions (Total Emissions & Carbon Emissions Growth) yield no significant effect in any of the regressions compel us to address the question of why this is the case.

One potential explanation for the slightly weaker results could be related to the different regulatory environments of Europe and the US. The carbon risk premium hypothesis of Bolton & Kacperczyk (2021) is largely built on the idea that investors perceive an increased risk of future regulation in companies with high levels of carbon emissions, leading them to reduce exposure to these companies. This would lead to a drop in the share price, and therefore increase the expected return. In the US, no major single new law addressing environmental action was passed through Congress until 2015 (Erbach, 2015). Furthermore, the election of Donald Trump in 2016, who was very public about his intention not to address climate questions and followed up on his promises by withdrawing from the Paris Agreement, prolonged the period of lax American environmental regulation. From an investor’s perspective, the lack of regulation in place means that the risk of future regulation increases. Since most studies supporting the carbon risk premium hypothesis use an American sample, the carbon risk premium shown in these studies should to a higher degree be related to investors’ perceived risk of future environmental regulation. In the case of our regressions, however, with a different geographical scope, a different regulatory environment regarding climate questions applies. In fact, throughout the last decades, the EU has already introduced a large number of laws regulating the operations of companies in regard to their environmental footprint. These include the European Green Deal (2020), the EU taxonomy for sustainable activities (2020), as well as the EU Emissions Trading Scheme first introduced in 2005. Therefore, especially considering the ETS (2005) due to its existence throughout the entire sample period, the risk of future regulation is reduced. This is the most compelling explanation for the weaker evidence for a carbon risk premium found in our study compared to that of Bolton & Kacperczyk (2021) since it incorporates the geographical and regulatory differences of the two sample groups.

Other potential explanations for the smaller coefficients in our result could be the dispersed and heterogeneous legal, economic and cultural nature of the European sample as opposed to a relatively homogenous American sample in Bolton & Kacperczyk (2021). This is most noticeable in the stark contrast in stock market behaviour between Southern and Northern Europe. Stock market participation rates in different countries vary by many percentage points, ranging from less than 10% indirect and direct stock holding for Spain, Greece and Italy and above 60% for Sweden according to Guiso & Sodini, (2013). Furthermore, business practices and regulations in regard to reporting carbon emissions vary widely between different countries too. More concretely, Northern European countries tend to report carbon emissions to a greater extent than Southern European countries (see Table 2). This means that Northern European companies are overrepresented in the sample compared to their countries' populations and GDP.

Another factor that could play a role in the different results obtained from a European sample compared to an American one has to do with the superior American stock returns over the examined period. During the period 2013 to 2022, the Dow Jones Index yielded a compounded annual return of 10.9% whereas Euro Stoxx average return was 2.9% (see Figure 3). This should not so much have an effect on the statistical significance of the effect, but rather on the magnitude of the estimate. All else alike, smaller European average stock returns should lead to a smaller magnitude of the coefficients on the different independent variables.

7.5 Limitations

There are a number of limitations to this paper that potentially have led to biases in the data. First, the most important of these is the selection bias. The available data on carbon emissions is largely based on companies' voluntary self-reporting. Assumably, companies with low levels of carbon emissions have a greater incentive to report than companies emitting more greenhouse gases. These incentives make it likely that the available data mostly consists of companies with relatively low levels of emissions, making it flawed and biassed as a sample of European stock companies.

Second, another limitation associated with the sample of companies has to do with the sample size, i.e., the number of companies in our sample. Although our sample of 553 companies over 9 years is large enough to make statistically viable conclusions, it is significantly smaller than the sample of 4,000 American companies examined by Bolton & Kacperczyk (2021) and around 4,500 companies examined by Hsu et al. (2022). This makes the results harder to interpret and the conclusions drawn from the regressions less reliable. Third, insignificant independent variables with fixed effects reduce the possibility to draw any major conclusions. When using fixed effects for sector and year, the independent variables become statistically insignificant. Hence, the conclusions that can be made in regard to carbon emissions' impact on stock returns become noticeably weaker. For example, since the magnitude of the estimate is reduced by around a fourth, it appears as if the reduction in the estimate's magnitude is explained by investor preferences towards sectors, rather than an effect of a carbon risk premium. However, with a statistically insignificant independent variable, this cannot be stated with a high degree of certainty.

Fourth, the carbon intensity variable, which is the only significant independent variable, is not purely a measure of carbon emissions. The variable is a ratio between carbon emissions and sales. This means that carbon emissions only account for half of the variable, with the other half depending on sales. Therefore, it is more difficult to draw conclusions from carbon intensity in regard to carbon emissions' impact on stock returns.

7.6 Further research suggestions

By conducting the analysis in this paper, we have come across several interesting extensions and research questions that could be investigated further. For example, are there any differences between different time periods? It would be interesting to study whether our results would be similar if the studied time period were 10 years earlier, and if so, what the reason for that would be.

Another relevant extension could be how the carbon risk premium differs across different geographical and socioeconomic areas. For example, the countries used in this paper could be divided into more specific areas such as DACH, Nordics, Benelux, Eastern Europe etc. to provide a more comprehensive understanding of the role of the country- and region-specific factors such as business environment, GDP per capita and regulations. It would also be interesting to broaden the geographical scope beyond Europe and the US and see if it has any material impact on the results. For example, a similar study could be made on companies in emerging markets.

We have found that carbon emissions vary a lot between business sectors and that some are more prevalent than others in contributing to the higher levels of carbon dioxide in the atmosphere. Therefore, an interesting extension would investigate the more carbon-intensive sectors, and how the companies' stock returns are affected by their carbon emissions in these specific sectors.

8. Conclusion

How are carbon emissions affecting stock returns in Europe? That is the main question that this paper attempts to answer. The geographical scope of Europe provides an extension to previous research on this matter in the US. If there are similar findings from several different regions, that means more far-reaching conclusions can be drawn. Furthermore, the research question is of interest to regulators in understanding the return-related impact of financial regulation aimed at reducing carbon emissions. It is also relevant for investors to understand the underlying forces behind environmental risk and stock returns. In our results, we find a weak positive relationship between carbon intensity and stock returns, suggesting that investors of carbon-intensive companies are compensated for additional risk through a carbon premium. We also find that this relationship grows stronger when excluding the covid-19 years of 2020 and 2021, indicating that the pandemic had a negative effect on the extent to which the carbon intensity affects stock returns. At the same time, we also find that a majority of the performed tests do not yield any significant results, which is not necessarily to the detriment of the study. Rather, it provides us with the conclusion that for a majority of the independent variables, there is no significant carbon premium to compensate investors for additional assumed risk in our sample of European companies. Consequently, the overarching conclusion is that the evidence for a carbon premium is significantly weaker in our European sample, both in terms of significance and magnitude, than in previous research with American companies.

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Appendix

Appendix A): Companies excluded in our analyses

Company	Country	Reason
Capricorn Energy LLC	United Kingdom	Geographical reasons : was initially (2012) an Indian-focused asset
Gazprom PAO	Russia	Geographical reasons
Harbour Energy PLC	United Kingdom	Not listed for entire period
H Lundbeck A/S	Denmark	Not listed for entire period
International Distributions Services PLC	United Kingdom	Not listed for entire period
Inter RAO YEES PAO	Russia	Geographical reasons
Kernel Holding SA	Ukraine	Geographical reasons
Liberty Global PLC	United Kingdom	Part of a larger
NK Lukoil PAO	Russia	Geographical reasons
Novolipetsk Steel PAO	Russia	Geographical reasons
Novatek PAO	Russia	Geographical reasons
Petrofac Ltd	Jersey	Geographical reasons
Pirelli & C SpA	Italia	Not listed for entire period
RHI Magnesita NV	Austria	Not listed for entire period
NK Rosneft' PAO	Russia	Geographical reasons
Sberbank Rossii PAO	Russia	Geographical reasons
Gazprom Neft' PAO	Russia	Geographical reasons
Surgutneftegaz PAO	Russia	Geographical reasons
Seagate Technology Holdings PLC	Ireland	Geographical reasons (dual-listed)
Tatneft' PAO	Russia	Geographical reasons
Transneft' PAO	Russia	Geographical reasons
Yunipro PAO	Russia	Geographical reasons
Uralkaliy PAO	Russia	Geographical reasons

Appendix B): Results from the Breusch-Pagan test

Regression	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
BP (rounded)	83	84	77	106	109	102	139	139	135
Degrees of freedom	16	16	16	31	31	31	51	51	51
p-value	0	0	0	0	0	0	0	0	0

Appendix C): Main regression without clustered standard errors on year- and company level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LOGCO2	0.0015 (0.0024)			-0.003 (0.003)			-0.002 (0.004)		
LOGCO2INTENSITY		0.0119*** (0.003)			0.009* (0.004)			0.009* (0.004)	
CO2GROWTH			-0.024 (0.023)			-0.021 (0.023)			-0.021 (0.023)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E.	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	No	No	No	No	No	No	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix D): Main regression with a 6-month lag effect on control- and independent variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LOGCO2	0.002 (0.002)			-0.004 (0.004)			-0.004 (0.004)		
LOGCO2INTENSITY		0.009* (0.003)			0.003 (0.006)			0.003 (0.006)	
CO2GROWTH			0.005 (0.023)			0.004 (0.023)			0.006 (0.023)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E.	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Country F.E.	No	No	No	No	No	No	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix E): Main regression with no lag effect on control- and independent variables

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
LOGCO2	-0.003 (0.002)			-0.005 (0.004)			-0.004 (0.005)		
LOGCO2INTENSITY		0.005 (0.004)			0.007 (0.007)			0.008 (0.006)	
CO2GROWTH			0.002 (0.024)			0.007 (0.024)			0.010 (0.024)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E.	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	No	No	No	No	No	No	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Appendix F): Main regression excluding the covid-years (i.e., analyses between 2013 – 2019)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
LOGCO2	0.002 (0.003)			-0.004 (0.007)			-0.004 (0.007)		
LOGCO2INTENSITY		0.017*** (0.005)			0.013 (0.010)			0.0012 (0.010)	
CO2GROWTH			-0.018 (0.028)			-0.010 (0.029)			-0.011 (0.029)
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector F.E.	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Country F.E.	No	No	No	No	No	No	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes