IS THERE A CARBON EMISSION-RETURN RELATION?

EXPLORING THE EXISTENCE OF A CARBON EMISSION-RETURN RELATION IN THE SWEDISH STOCK MARKET

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Is there a Carbon Emission-Return Relation? : Exploring the Existence of a Carbon Emission-Return Relation in the Swedish Stock Market

Abstract:

We use portfolio sorting and Fama-Macbeth regressions to investigate the potential relation between carbon emissions and stock returns in the Swedish stock market, a country with stringent carbon regulations and taxes. We research the Swedish stock market between 2010-2019 and do not find evidence of such a relationship. These findings indicate that the relationship between emissions and returns in Sweden differs from that in countries with less stringent carbon regulations and taxes, such as the U.S.

Keywords:

Emission premium, emission alpha, carbon emissions, emission intensity, stock returns.

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Finance research places significant emphasis on estimating expected asset returns. In recent years, there has been a growing focus on exploring the asset pricing implications of sustainability. Researchers often employ diverse metrics to distinguish between "good" and "bad" firms in their pursuit to establish differences in returns, where ESG-based metrics are the common choice. However, these metrics suffer from inconsistent reporting frameworks, and their interpretations often involve a high degree of subjectivity. As a result, researchers are starting to turn to more tangible and quantifiable measures, such as emissions. Common among these studies, and others on related topics, is their focus on the U.S. equity market, leaving other markets less explored. Notably, the U.S. lacks strict emission regulations, including the absence of a federal carbon tax, which could increase the risk of future, more stringent emission regulations, given the market's growing emphasis on sustainability. Here, a research gap exists in studying regions with existing stringent emission regulations.

Addressing this research gap, our paper seeks to explore the presence of an emission-return relation in the Swedish stock market. Sweden is a relevant extension to current research for several reasons. The country is recognized for its strong commitment to environmental challenges and its leadership in ESG investment and ratings (Dyck, Lins, Roth, and Wagner, 2019), which implies that Sweden places a significant emphasis on environmental sustainability and responsible business practices. Furthermore, Sweden was one of the first nations to introduce a carbon tax in 1992, which remains one of the highest globally (Martinsson, Strömberg, Sajtos, and Thomann, 2022). Additionally, as a member of the EU, Sweden actively participates in the EU Emissions Trading System (EU ETS).

To study the emission-return relation, we employ a carbon equivalent emissions variable, which includes CO2, CH4, N20, HFCS, PFCS, SF6, and NF3[1], measured in tonnes, collected from Refinitiv Eikon.

We follow the procedure of Hsu, Li, and Tsou (2023) and create quintile portfolios based on different calibrations of our emission variable. In total, we conduct five different calibrations and analyze raw emissions, emissions scaled by total assets, emissions scaled by revenue, emissions scaled by market capitalization, and emissions scaled by property, plant, and equipment. Unlike Hsu et al. (2023), we include the portfolios sorted by raw emissions to ensure the robustness of our findings, as previous research by Bolton and Kacperzyk (2021) identified a significant relationship between raw emissions and stock returns. Our results indicate that the high-minus-low (H-L) portfolio strategy, which takes a long (short) position in the quintile portfolio with the highest (lowest) emissions, does not yield any statistically significant returns under any emission calibration.

We proceed with asset pricing factor tests, using the Capital Asset Pricing Model (CAPM), Fama and French (1996) three-factor model (FF3), and Carhart (1997) model (FF4), to investigate if the H-L portfolio has generated any abnormal return. We conduct tests for portfolios sorted by raw emissions, emissions scaled by total assets, and emissions scaled by revenues, given the prior research from Bolton and Kacperzyk (2021), Hsu et al. (2023), and An, Kim, and Kim (2015), who find these calibrations of emissions to have a statistically significant relationship with stock returns, respectively. However, we find no such anomalies.

Continuing our analysis, we apply Fama and Macbeth (1973) cross-sectional regressions to further explore the link between stock excess returns and emissions. We regress excess returns on different calibrations of our emissions variable, incorporating firm-level control variables associated with stock returns and different sets of fixed effects. Once again, we run these regressions by raw emissions, emissions scaled by total assets, and emissions scaled by revenues, as prior research has indicated these emission calibrations are significant

[1] Carbon dioxide (CO2), methane (CH4), nitrous oxide (N2O), hydrofluorcarbons (HFCS), perfluorinated compound (PFCS), sulfur hexafluoride (SF6), nitrogen trifluoride (NF3).

predictors of stock returns. Nevertheless, we find no robust evidence of an emission-return relationship.

Finally, to ensure that firm size has not concealed the emission-return relationship, we double-sort portfolios on emissions scaled by total assets and market capitalization. Again, we find no evidence of an emission-return relation.

We primarily consider two different explanations for the absence of evidence regarding an emission-return relationship in our study. Firstly, the lack of empirical evidence we find for an emissions premium in Sweden may be attributed to the stringent carbon tax and regulations already in place. Hsu et al. (2023) and Bolton and Kacperzyk (2021) find an emissions premium in the U.S., which they argue is compensation for the additional risk posed by high-emission firms. However, since Sweden already has stringent regulations and taxation in place, it is reasonable to assume that investors will not receive a similar premium.

Secondly, the absence of empirical support for an emissions discount may be because low-emissions stocks have not benefited from the demand-shift toward "green" (ESG-friendly) assets, as claimed by Pastor, Stambaugh, and Taylor (2022). This could be due to emissions not effectively representing a firm's overall ESG performance, given that it is only related to the environmental aspect. However, considering that climate has been an important aspect and political question in Sweden since the 1990s (Oscarsson and Homberg (2017)), it is also possible that Swedish investors and consumers began showing a preference for green assets before 2011, diminishing the impact of more recent demand-shifts.

In conclusion, we find no empirical evidence of an emission-return relationship in Sweden between 2011 and 2019. While we cannot pinpoint the exact reason for this, numerous plausible explanations arise from Sweden's distinctive position in terms of ESG and carbon regulations.

I. Literature Review

This paper builds on a recent but growing literature on asset pricing implications of environmental-related factors. Previous studies have primarily employed ESG (Environmental, Social, and Governance) variables, with a predominant focus on the U.S. Dunn, Fitzgibbons, and Pomorski (2018) find empirical support for firms with higher ESG scores having lower future risk while Hoepner, Oikonomou, Sautner, Starks, and Zhou (2019) show that engagement in ESG issues can reduce a firm's downside risk.

However, metrics based on ESG (Environmental, Social, and Governance) can be unreliable due to inconsistent reporting standards and a lack of standardized measurement methodologies across firms, industries, and regions. Additionally, subjective interpretations of ESG criteria can lead to varying assessments, making it challenging to compare and evaluate companies' sustainability practices accurately. Hence using a more tangible and reliable measure for assessing environmental performance is relevant.

Hsu et al. (2023) find an emission premium in the US stock market, which remains statistically significant after adjusting for various risk factors.[2] Further, they develop a general equilibrium asset pricing model that incorporates uncertainty related to changes in regulatory policies concerning emissions, impacting firms' cash flows. They establish that high-emission firms face greater exposure to shifts in regulatory regimes compared to low-emission firms, leading to a higher average excess return due to the additional risk undertaken. Similarly, Bolton and Kacpercyk (2021) observe a carbon emissions premium in the U.S. stock market.

[2] The suggested explanations for the emission risk premium that Hsu et al. (2023) did not find to be explanatory are: investors' emission preferences, under-reactions to emission abatement, retail investors' behavioural bias, corporate governance, political connections, technology obsolescence, financial constraints, economic and political uncertainty, adjustment costs and other potentially related systematic risks.

There are also studies showing a negative emission-return relation. In, Park, and Monk (2019) create an "Efficient-Minus-Inefficient" portfolio based on carbon emission intensity and find a positive abnormal return. An et al. (2015) discover a positive relation between carbon emission intensity and the cost of equity capital for Korean firms.

Further, Pástor, Stambaugh, and Taylor (2022) argue that in equilibrium, "green" assets should have lower expected returns because they hedge against climate risks but also because investors and consumers prefer green assets and products. However, they find that green assets have seen higher realized returns than "brown" assets between 2012-2020 in the U.S., which they argue is a consequence of investors and consumers having a taste shift toward green assets and products for this period, driving realized returns.

Our paper builds upon the existing body of research by using data from Sweden and adopting a methodological framework largely influenced by Hsu et al. (2023). This approach provides a new perspective to the predominantly U.S.-focused literature. Sweden's reputation for its environmental commitment and significant carbon emission taxes enables us to investigate whether these environmental efforts result in different emission-return relationships compared to regions like the U.S., where ESG frameworks are less comprehensive, and emissions regulations are weaker.

II. Sample and summary statistics

A. Sample Construction

We source firm-level carbon emissions and financial fundamentals from the Refinitiv Eikon database, a major provider of financial market data and infrastructure worldwide. Choosing Refinitiv Eikon as our sole data source for all data except for stock prices and risk factors helps minimize inconsistencies and enhance data accuracy. We gather data on the Fama-French factors and the risk-free rate from the Swedish House of Finance National Research Datacenter. Our focus is on companies listed on the Swedish Stock Exchange from 2010 to 2019. We limit our analysis to the year 2019 because it is the most recent year for which we have Fama-French factor data, ensuring consistency in the timeframe for all our tests. To reduce the risk of backfilling bias while maintaining a sufficiently large sample size, we do not include data before 2010. Additionally, we require that firms must have reported emissions data for at least five out of ten years to ensure a balance between data quality and the sample size. In line with the methodology of Hsu et al. (2023), we exclude financial firms from our analysis. Specifically, we exclude firms in the sectors "Financials" and "Real Estate", as defined by the Global Industry Classification Standard (GICS). This exclusion results in the removal of seven firms that otherwise meet all other criteria. Additionally, eligible firms must have a minimum market value of 300 MSEK in 2010. We use a minimum market value threshold to exclude smaller firms, which tend to exhibit higher volatility. Out of the 1019 firms from Refinitiv Eikon, our selection criteria result in a sample size of 40 firms.

B. Data on Firm-level Carbon Emissions and Firm-level Financials Fundamentals

We obtain our carbon emissions data from Refinitiv Eikon for the period 2010-2019, using their measure of CO2 Equivalent Emissions Total, measured in tonnes, to define carbon emission. This measure covers total carbon dioxide (CO2) and equivalent emissions, including CO2, methane (CH4), nitrous oxide (N2O), hydrofluorocarbons (HFCS), perfluorinated compounds (PFCS), sulfur hexafluoride (SF6), and nitrogen trifluoride (NF3). CO2 Equivalent Emissions Total follows GHG's protocol for their emission classifications by type and sums

up both direct (scope 1) and indirect (scope 2) emissions. Scope 1 emissions are direct emissions from sources owned or controlled by the company. Scope 2 emissions are indirect emissions that come from the use of electricity, heat, or steam which occur at the facility where electricity, steam, or heat is generated.

Notably, we decide to omit scope 3 emissions from our analysis. These emissions cover several activities, including contractor-owned vehicles, employee business travel, waste disposal, and outsourced activities. The decision to exclude scope 3 emissions stems from the challenges in ensuring data accuracy due to the broadness of activities covered and the absence of standardized reporting methods, which potentially compromise the reliability of the data.

We source firm-level financial fundamentals data through Refinitiv Eikon for the period 2010-2019. Our dataset includes only firms listed on the Swedish Stock Exchange, and we use SEK as currency as it is the currency all firms report in.

C. Data on Stock Returns

We obtain our stock price data from Yahoo Finance by matching it with our firm data in Refinitiv Eikon, using the ISIN code available in both systems. We collect monthly data from December 31, 2009, to December 31, 2019, focusing on the adjusted closing price on the last day of each month. The adjusted closing price, which accounts for splits, dividends, and capital gain distributions, offers a more accurate representation of a stock's current performance, considering factors that can impact its price. For our analysis, which involves computing monthly stock returns, we include the December 31, 2009, data point. This is necessary to calculate the return for January 31, 2010, as it requires the stock price from the previous month.

D. Summary Statistics

Table I reports the summary statistics of our data. Table I, Panel A shows the mean, standard deviation (Std), 5th percentile (P5), 25th percentile (P25), median, 75th percentile (P75), 95th percentile (P95), and the number of observations per variable. When selecting and defining the variables, we follow the structure of Hsu et al. (2023), with three exceptions. Firstly, we use the total CO2 emissions equivalent, which is the sum of scope 1 and scope 2 emissions, as a measure of raw emissions for firm *i*. This differs from Hsu et al. (2023), who use the cumulative sum of all toxic emissions from various chemicals across all plants owned by the firm, as recorded in the Toxic Release Inventory database as a measure for raw emissions. Secondly, we calculate the emission intensity attributed to firm *i* in year *t* by dividing emissions in year *t* by the total assets of firm *i* in year *t*, measured in million SEK (MSEK). We do not incorporate a lag in our emission intensity variable, as both the raw emissions data and financial data are published on the same date and cover the same reporting period. In contrast, Hsu et al. (2023) include a lag to account for variations in the publishing dates of their emission data compared to their financial data. Third, Hsu et al. (2023) include the Whited and Wu index to capture financial constraints, which we exclude due to a lack of reliable growth data for the Swedish markets for the specific GICS industry definitions. For the other variables, we follow the same definition as outlined in Hsu et al. (2023). The other financial variables are market capitalization (MCAP) measured in MSEK, book-to-market ratio (B/M), investment rate (I/K), return on assets (ROA), return on equity (ROE), tangibility (TANT), operating leverage (OL), and book leverage (LEV).

The average emission intensity is 12.20 tonnes, suggesting that 1 MSEK in assets is associated with 12.20 tonnes in raw emissions. The median emission intensity is 3.43 and the standard deviation is 31.37, indicating a wide difference in emission intensity among our

sample. The data for emission intensity, market capitalization, and investment rate appear to be positively skewed, implying that a few firms have notably high values in these variables. For the other variables, the skewness is less pronounced, and the data distribution is relatively balanced around the mean. A substantial difference exists between the 5th percentile market capitalization (5,392 MSEK) and the 95th percentile (243,942 MSEK), illustrating the diversity of market values within our sample.

Table I, Panel B shows a correlation matrix for all variables included in Panel A. We find that the book-to-market ratio (B/M) and tangibility (TANT) are positively correlated with emission intensity correlating 0.50 and 0.17 respectively. We also find that market capitalization (MCAP) and return-on-assets (ROA) are negatively correlated with emission intensity with a correlation of -0.19 and -0.20 respectively. The rest of the variables have a relatively low correlation with emission intensity.

Table I

Summary Statistics and Correlations of Firm-Year Data

This table presents summary statistics and a correlation matrix for our firm-year sample. Emission intensity (Emissions) is measured as the carbon equivalent emissions of scope 1 and scope 2 emissions in tonnes produced by the firm, scaled by total assets in million SEK. Market capitalization (MCAP) is the market capitalization of the firm in million SEK. The book-to-market ratio (B/M) is the book equity divided by the market capitalization. Investment rate (I/K) is capital expenditures divided by property, plant, and equipment. Return-on-assets (ROA) is operating income after depreciation scaled by total assets. Return-on-equity (ROE) is operating income after depreciation scaled by total equity. Tangibility (TANT) is property, plant, and equipment divided by total assets. Operating leverage (OL) is the summation of cost of goods sold and selling, general, and administrative expenses, scaled by total assets. Leverage (LEV) is the sum of current liabilities and long-term debt, scaled by total assets. For each variable, we report the mean, standard deviation (Std), 5th percentile (P5), 25th percentile (P25), median, 75th percentile (P75), 95th percentile (P95), and the number of observations of each variable. The sample spans from 2010-2019.

	Emissions	MCAP	B/M	I/K	ROA	ROE	TANT	OL	LEV
Panel A: Summary Statistics									
Mean	12.20	65,290.12	0.57	0.43	0.10	0.22	0.24	0.90	0.48
Std	31.37	80,391.13	0.64	1.11	0.07	0.31	0.22	0.67	0.14
P5	0.20	5,392.12	0.11	0.07	0.02	0.03	0.02	0.20	0.24
P25	0.94	18,665.47	0.26	0.16	0.06	0.15	0.09	0.56	0.41
Median	3.43	34,401.22	0.40	0.25	0.09	0.23	0.19	0.73	0.47
P75	7.86	67,029.02	0.66	0.38	0.13	0.31	0.29	1.05	0.58
P95	95.18	243,942.98	1.32	1.21	0.22	0.48	0.77	1.79	0.70
Observations	349	349	349	349	349	349	349	349	349
Panel B: Correlation									
Emissions	1.00								
MCAP	-0.19	1.00							
B/M	0.50	-0.21	1.00						
I/K	-0.08	-0.06	-0.09	1.00					
ROA	-0.20	0.25	-0.27	0.05	1.00				
ROE	-0.07	0.05	-0.07	0.04	0.29	1.00			
TANT	0.17	-0.03	0.22	-0.21	-0.04	-0.32	1.00		
OL	-0.03	-0.06	-0.17	-0.08	0.23	0.24	-0.18	1.00	
LEV	0.05	-0.12	-0.11	0.01	-0.20	-0.05	-0.31	0.18	1.00

To understand whether certain firm characteristics can predict a company's emission intensity, we conduct panel regressions as shown in Table II. We use the logarithm of a firm's emission intensity in year t+1 as the dependent variable and examine its relationship with the logarithm of emission intensity in year t, alongside other firm characteristics year t, and Industry-Year fixed effects. Firm characteristic variables include the logarithm of market capitalization (Log MCAP), the logarithm of book-to-market ratio (Log B/M), investment rate (I/K), return-on-equity (ROE), book leverage (LEV), tangibility (TANT) and operating leverage (OL). All independent variables except emission intensity are winzorized at the 1st and 99th percentile to reduce the impact of outliers and normalized to reduce scale effects. Further, emission intensity (dependent and independent variable), market capitalization, and

book-to-market ratio are logaritmized to further reduce scale effects. We first cluster standard errors at the firm level (Panel A) and then at the industry-year level (Panel B).

Our findings indicate that emission intensity has significant predictive power of future emission intensity, regardless of the chosen clustering method. This result is intuitive as a firm's emission intensity should remain relatively stable unless substantial changes are made. Furthermore, when clustering at the firm level, book leverage receives a significant estimate of -0.72. In contrast, when clustering at the industry-year level, operating leverage exhibits significant positive predictive power with an estimate of 0.36.

Table II

Firm-Level Predictive Regression for Emissions

This table reports panel regressions of the logarithm of firm-level emission intensity (Log Emissions) in year t+1 on the logarithm of emission intensity in year t and other firm characteristics in year t while including industry-year fixed effects. Firm characteristics include the logarithm of market capitalization (Log MCAP), the logarithm of book-to-market ratio (Log B/M), investment rate (I/K), return-on-equity (ROE), book leverage (LEV), tangibility (TANT) and operating leverage (OL). All independent variables, except the logarithm of emission intensity, are winsorized at the 1st and 99th percentile and normalized to zero mean. t-Statistics are based on standard errors clustered at the firm level in Panel A, and Industry-Year level in Panel B. The sample runs from January 2010 to December 2019.

Panel A: Standard Errors Clustered at the Firm Level

Variable	Estimate	[t]
Log Emissions	0.47	4.34
Log MCAP	0.05	0.30
Log BTM	0.03	0.35
I/K	-0.01	-0.18
ROE	0.02	0.54
LEV	-0.72	-2.06
TANT	-0.06	-0.60
OL	0.36	1.89

Panel B: Standard Errors Clustered at the Industry-Year Level

Variable	Estimate	[t]
Log Emissions	0.47	4.31
Log MCAP	0.05	0.28
Log BTM	0.03	0.86
I/K	-0.01	-0.16
ROE	0.02	0.49
LEV	-0.72	-1.81
TANT	-0.06	-0.62
OL	0.36	2.31

III. Univariate Portfolio Sorting: Returns, Firm Characteristics, and Fama-Macbeth Regressions

To explore the connection between emission and the cross-section of stock returns, we follow Hsu et al. (2023) and create quintile portfolios by sorting firms based on their emission scaled by four different financial variables, total assets (TA) in Panel A, property, plant, and equipment (PPE) in Panel B, revenue (REV) in Panel C, and market capitalization (MCAP) in Panel D. Further, we include portfolios sorted on raw emissions (Raw Emission) in Panel E, as Bolton and Kacperzyk (2021) found this to be a positive predictor of stock returns.

Similarly to Hsu et al. (2023), we sort the portfolios by calculating quintile breakpoints based on year *t*-1, before assigning each firm with positive emission intensity (raw emissions for Panel E) in year *t* to a quintile based on the calculated quintile breakpoints. This method is applied for all years. In their portfolio sorting, Hsu et al. (2023) create industry-specific breakpoints which they then use to form the portfolios. However, in our data sample, multiple industries in the dataset contain less than five firms. Consequently, sorting using industry-specific breakpoints is not possible and we instead create breakpoints based on the aggregate data. Portfolios are rebalanced on the first of January each year, as this is the date Refinitiv Eikon updates its database and annual rebalancing reduces the transaction costs of the investment strategy. The sample runs from 2011 to 2019. The High (Low) quintile portfolio consists of the firms with the highest (lowest) emission intensity. To examine the emission-return relation, a high-minus-low (H-L) portfolio is formed, taking a long position in the High portfolio and a short position in the Low portfolio. Postformation, we calculate the value-weighted average excess return (E[R]-Rf) for each portfolio in *annualized* terms together with the corresponding t-statistic ([t]), standard deviation (Std) and Sharpe-ratio (SR). The risk-free rate is defined as the *annualized* one-month Swedish Treasury bill rate as reported in the factor dataset from the Swedish House of Finance National Research Datacenter. Similar to Hsu et al. (2023), we calculate t-statistics based on standard errors using Newey-West correction for 12 lags.

We find that no H-L portfolio gets statistically significant excess returns, with t-statistics of 0.86, 1.21, 1.77, 1.65, and 0.05. Further, given that no definite way of calculating the appropriate number of Newey-West lags to include exist, we test the robustness of our findings using 4 Newey-West lags (see Appendix B, Table BI), consistent with the guidelines prescribed by James and Watson (2020). The results are consistent with the ones obtained initially using 12 lags. Thus, the overall conclusion from Table III is that firm-level emissions have a low predictive ability for stock returns.

Table III

Univariate Analysis of Excess Returns in Different Portfolios

This table shows the average excess returns for five different portfolios, sorted on raw emissions scaled by total assets (TA) in Panel A, property, plant, and equipment (PPE) in Panel B, revenue (REV) in Panel C, market capitalization (MCAP) in Panel D, and without scaling (Raw Emission) in panel E. In addition, a high-minus-low (H-L) portfolio is created, taking a long (short) position in the High (Low) portfolio. The sample runs from the first of January 2011 to the last of December 2019 and portfolios are rebalanced on the first of January each year *t* based on the quintile breakpoints calculated in year *t*-1. The first row in each panel shows the portfolio's *annualized* excess return (E[R]-Rf), defined as the realized return minus the risk-free rate, defined as the *annualized* one-month Swedish treasury bill. The second row shows the t-statistics ([t]), the third row shows the standard deviation (Std), and the fourth row shows the Sharpe-ratio (SR). The portfolio return is value-weighted by firms' market capitalization and t-statistics are based on standard errors using the Newey-West correction for 12 lags.

	L	2	3	4	H	H-L
Panel A: TA						
E[R]-Rf (%)	7.46	20.05	17.2	27.13	12.84	5.38
[t]	1.48	3.15	3.01	4.81	1.72	0.86
Std (%)	47.66	58.16	57.03	60.6	71.82	57.94
SR	0.16	0.34	0.30	0.45	0.18	0.09
Panel B: PPE						
E[R]-Rf (%)	10.56	21.04	15.94	25.43	24.26	13.69
[t]	1.74	3.28	2.86	3.69	2.14	1.21
Std (%)	51.91	61.16	54.14	73.8	80.46	69.79
SR	0.20	0.34	0.29	0.34	0.30	0.20
Panel C: Revenue						
E[R]-Rf (%)	10.42	15.71	20.43	19.83	23.94	13.51
[t]	2.12	3.07	3.54	2.85	3.75	1.77
Std (%)	47.34	52.5	61.41	61.85	74.81	69.54
SR	0.22	0.30	0.33	0.32	0.32	0.19
Panel D: ME						
E[R]-Rf (%)	9.99	14.5	14.86	20.28	19.17	9.18
[t]	1.68	0.24	3.04	2.58	3.32	1.65
Std (%)	49.26	63.51	51.39	69.57	74.73	59.17
SR	0.20	0.23	0.29	0.29	0.26	0.16
Panel E: Raw Emission						
E[R]-Rf (%)	16.05	14.88	18.25	13.50	16.36	0.31
[t]	3.90	1.87	3.03	2.46	2.65	0.05
Std (%)	58.27	60.25	58.56	54.03	69.59	63.54
SR	0.27	0.25	0.31	0.25	0.24	0.01

In Table IV, we present average firm characteristics across quintile portfolios sorted on emissions scaled by total assets. We find that the average emission intensity (Emissions) of the High (Low) group is 24.78 (0.85), on average generating 609,955.73 (103,074.48) tonnes of raw emissions. We also notice that firms with higher emission intensity have higher book-to-market ratios (B/M) and tangibility (TANT) than the other groups. Firms in the Low group have a higher investment rate (I/K) than the other groups. These results are in line with the correlation matrix in Table II, Panel B and are logical as Property, Plant, and Equipment is in the nominator in TANT and denominator in I/K. Small (relative) variation exists between the groups in market capitalization (MCAP), return-on-assets (ROA), and book leverage (LEV). Furthermore, we observe that raw emissions are not perfectly correlated with emission intensity, underscoring the effects of the scaling variable.

Table IV

Firm characteristics

This table reports the time-series average of the cross-sectional medians of firm characteristics for five portfolios sorted on emission scaled by total assets. Raw emissions are measured as the total emissions produced by a firm in tonnes, while emission intensity (Emissions) is measured as raw emissions year *t* in tonnes scaled by total assets year *t* in million SEK. The sample period is from 2011 to 2019. Other variables include the logarithm of market capitalization (Log MCAP), book-to-market ratio (B/M), investment rate (I/K), return-on-assets (ROA), tangibility (TANT), operating leverage (OL), and book leverage (LEV). The average number of firms in each quintile is also reported.

	Low	2	3	4	High
Raw emissions	103,074.48	48,462.07	266,548.36	250,947.81	609,955.73
Emissions	0.85	1.28	4.56	7.94	24.78
Log MCAP	4.88	4.64	4.72	4.46	4.16
B/M	0.43	0.39	0.35	0.49	0.52
I/K	0.40	0.27	0.22	0.20	0.19
ROA	0.08	0.09	0.09	0.09	0.09
TANT	0.09	0.09	0.20	0.32	0.25
OL	0.58	0.74	0.94	0.71	0.96
LEV	0.51	0.50	0.48	0.44	0.44
Number of firms	7	8	7	7	6

In Table V, we investigate the extent to which the returns of the emission intensity sorted portfolios can be explained by traditional risk factors. This table reports the results from three different asset pricing models where Panel A regresses on the Capital Asset Pricing Model (CAPM), Panel B regresses on the Fama-French three-factor model (FF3), in line with Fama and French (1996), and Panel C regresses on the Fama-French-Carhart's four factors model (FF4), following Carhart (1997). Unlike Hsu et al. (2023), due to data limitations, we do not incorporate the Fama-French five-factor model (Fama and French (2015)) nor the Hou, Xue, and Zhang (2015) q-factors. The data on the different factors is collected from the Swedish House of Finance National Research Datacenter. In the factor dataset, data for May 2019 is missing, meaning we effectively get one less data point in our sample. Results are reported in *annualized* terms. In line with Hsu et al. (2023), t-statistics are based on standard errors estimated using Newey-West correction for 12 lags.

We find that the H-L portfolio does not generate statistically significant alpha under any of the three models, having a statistically significant correlation with all risk factors except the momentum factor (MOM). Further, to make sure our results are robust, we also test portfolios sorted on emission scaled by revenue, a definition used by An et al. (2015) and Bolton and Kacperzyk (2021) (see Appendix A, Table AI) and sorting based on raw emissions, a definition used by Bolton and Kacperzyk (2021) (see appendix A, Table AII). The results from these tests are consistent with the ones presented in Table V. Additionally, we observe no significant differences in our results when using 4 Newey-West lags instead of 12 (see Appendix B, Table BII).

Table V

Asset Pricing Factors Tests

This table reports asset pricing factor tests for five quintile portfolios sorted on emission scaled by total assets. Additionally, a high-minus-low (H-L) portfolio is formed, taking a long (short) position in the High (Low) portfolio. The sample runs from the first of January 2011 to the last of December 2019 and portfolios are rebalanced at the first of January each year. We perform time-series regressions of the emission intensity sorted portfolios on the market factor (MKT) in Panel A, the Fama and French (1996) three-factor model (MKT, size-factor (SMB) and value factor (HML)) in Panel B, and Carhart (1997) model (MKT, SMB, HML and momentum factor (MOM)) in Panel C. All results are *annualized*, and t-statistics are based on standard errors estimated using the Newey-West correction for 12 lags. We collect the factor data from the Swedish House of Finance National Research Datacenter.

	Low	2	3	4	High	H-L
			Panel A: CAPM			
Alpha (%)	-2.61	7.09	4.02	15.36	-2.61	0.00
[t]	-0.93	1.42	1.86	3.49	-0.58	0.00
MKT	0.84	1.08	1.10	0.98	1.28	0.45
[t]	9.70	13.51	10.97	7.51	19.70	3.80
			Panel B: FF3			
Alpha (%)	-2,49	7.15	4.14	15.43	-2.64	-0.14
[t]	-0.92	1.50	2.08	3.48	-0.72	-0.03
MKT	0.86	1.10	1.11	0.99	1.29	0.43
[t]	12.14	13.97	13.82	7.92	21.62	4.03
SMB	-0.08	0.05	-0.25	-0.02	0.28	0.35
[t]	-0.91	0.48	-4.52	-0.22	3.81	2.73
HML	-0.35	-0.24	-0.27	-0.20	-0.05	0.30
[t]	-4.43	-1.91	-2.12	-1.34	-0.39	2.27
			Panel C: FF4			
Alpha (%)	-2.33	9.14	5.44	16.28	-2.21	0.12
[t]	-0.78	1.99	2.25	3.84	-0.49	0.02
MKT	0.86	1.08	1.10	0.98	1.29	0.43
[t]	13.38	13.92	12.89	7.76	22.69	4.12
SMB	-0.08	0.04	-0.25	-0.03	0.27	0.35
[t]	-0.92	0.41	-4.29	-0.25	3.82	2.74
HML	-0.36	-0.32	-0.33	-0.24	-0.07	0.29
[t]	-3.75	-2.32	-3.04	-1.76	-0.68	2.08
MOM	-0.01	-0.08	-0.05	-0.03	-0.02	-0.01
[t]	-0.14	-2.84	-1.61	-0.79	-0.31	-0.22

In Table VI, we use Fama-Macbeth cross-sectional regressions (Fama and MacBeth (1973)) to further research if an emission-return relationship may exist while controlling for financial variables generally related to stock return. Stock excess return is *annualized* and regressed monthly on the logarithm of emission intensity (Log Emissions) in year *t*-1 while

controlling for several variables and including industry fixed effects. Control variables include the logarithm of market capitalization (Log MCAP), the logarithm of book-to-market ratio (Log B/M), investment rate (I/K), return-on-equity (ROE), tangibility (TANT) and book leverage (LEV). Unlike Hsu et al. (2023), we do not include the Whited and Wu index as a control variable (due to data limitations). Neither do we include industry dummy variables alongside the industry fixed effects, as our firms are too scattered among the industries, consisting of 40 firms distributed across 22 industries (see Appendix C, Table CI, Panel A). To assess the risk of overfitting, we also run regressions using fixed effects based on GICS industry groups (14) and sectors (8), as firms within specific industry groups and sectors likely face similar unobserved heterogeneity. All independent variables are normalized to zero mean and unit standard deviation after winzorization at the 1st and 99th percentiles to reduce the impact of outliers. Further, emission intensity, market capitalization, and book-to-market ratio are logarithmized to reduce scale effects.

When including all control variables and industry fixed effects, we find a positive and significant relationship between emission intensity and stock excess returns. However, no other regressions demonstrate a significant emission-return relationship. Therefore, we conclude that emissions have limited predictive power for stock returns. The results remain consistent when using 4 Newey-West lags and when changing our emissions proxy variable to emissions scaled with revenues, as well as raw emissions, as shown in Appendix A, Tables AIII and AIV.

Table VI

Fama-Macbeth Regressions

This table reports Fama-MacBeth regressions of individual stocks' excess returns on emission scaled by total assets in logarithm (Log Emissions) and other firm characteristics. Cross-sectional regressions are performed each month from January year *t* to December year *t*. In each month, excess returns of individual stocks (*annualized* by multiplying with 12) are regressed on the logarithm of emission intensity (Log Emissions) in year *t*-1 while including different sets of control variables and fixed effects based on industry, industry-group, and sector. Control variables include the logarithm of market capitalization (Log MCAP), the logarithm of book-to-market ratio (Log B/M), investment rate (I/K), return on equity (ROE), tangibility (TANT), book leverage (LEV). All independent variables are winsorized at the 1st and 99th percentile to reduce the impact of outliers and then normalized to zero mean and unit standard deviation to reduce scale effects. T-statistics are based on standard errors using the Newey-West correction for 12 lags. The sample period is January 2011 to December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Log Emissions	0.07	0.09	0.04	0.09	0.01	0.02
[t]	1.49	2.16	1.23	1.93	0.20	0.45
Log MCAP	-0.04	-0.04	-0.08	-0.10	-0.06	-0.07
[t]	1.91	-2.54	-2.22	-2.67	-1.54	-1.70
Log B/M	-0.08	-0.05	-0.10	-0.12	-0.12	-0.12
[t]	-1.98	-1.32	-2.65	-2.98	-2.96	-2.90
I/K	-0.02	0.04	-0.03	-0.06	0.00	-0.01
[t]	-0.42	0.61	-0.50	-1.24	-0.14	-0.35
ROE	0.07	0.07	0.08	0.12	0.05	0.08
[t]	2.24	2.14	1.91	2.67	1.50	2.60
TANT		0.00		0.05		0.02
[t]		0.17		1.85		0.67
LEV		-0.04		0.03		-0.01
[t]		-0.98		0.92		-0.45
Industry F.E.	Yes	Yes	No	No	No	No
Industry Group F.E.	No	No	Yes	Yes	No	No
Sector F.E.	No	No	No	No	Yes	Yes

In a last attempt to discover an emission-return relationship, following the methodology of Hsu et al. (2023), we employ portfolio double sorts to assess whether firm size has concealed any emission-return relationship. In January year *t*, we assign the emission intensity-sorted firms into "Big" and "Small" groups based on their market capitalization at the time, before calculating the average value-weighted excess return for each portfolio. Portfolios are rebalanced annually in January each year. The value-weighted excess returns (E[R]-Rf) and the corresponding t-statistics ([t]), based on standard errors using Newey-West correction for 12 lags, are reported in Table VII. Although the return difference between the Big and Small portfolios is notable, we still find no empirical evidence of an emission-return relationship.

Table VII

Double Sorting on Size

This table shows the average value-weighted excess return (E[R]-Rf) for ten portfolios double sorted on emissions scaled by total assets and market capitalization. Portfolios are rebalanced at the first of January in year *t*, based on the quintile breakpoints calculated for emissions scaled by total assets in year *t*-1 and on market capitalization at the first of January year *t*. The sample runs from January 2011 to December 2019. All results are reported in annualized terms and t-statistics ([t]) are based on standard errors using the Newey-West correction for 12 lags.

	L	2	3	4	H	H-L
Big, E[R]-Rf %	6.58	20.72	17.96	28.52	15.46	8.89
[t]	1.16	3.40	3.34	4.23	2.00	1.25
Small, E[R]-Rf %	14.11	4.64	13.93	23.99	0.03	-13.79
[t]	2.51	1.76	1.67	4.07	0.03	-1.34

VI. Discussion

This paper aims to analyze whether there exists a relationship between emissions and stock returns in Sweden, as documented for other regions (Hsu et al., (2023), Bolton and Kacperzyk, (2021), and Kim et al. (2015)). We employ the methodology of Hsu et al. (2023), making necessary adjustments to account for variations in our datasets.

First, when examining the excess returns of the high-minus-low (H-L) portfolios in Table III, we find no evidence of a return difference between stocks with high and low emissions. Second, in Table V we find no statistical difference in the alpha generated by high and low emission stocks. Third, using Fama-Macbeth regressions while controlling for financial variables and different sets of fixed effects, we find no robust evidence of an emission-return relation. Fourth, we find no empirical evidence of an emission-return relationship after double sorting portfolios on emission intensity and market capitalization.

Our inability to find a significant emission-return relationship partially contradicts prior research that suggests the presence of such a positive relation (Hsu et al. (2023), Bolton and Kacperzyk (2021)). One explanation for the contrasting results may be the difference in regulatory environments between Sweden and the U.S. The U.S. has historically implemented less stringent environmental regulations. The absence of a federal carbon tax in the U.S. and the lack of significant climate change legislation passed by the U.S. Congress between 2005 and 2015 indicate limited progress in environmental regulation (Erbach, 2015). Thus, the U.S. stock markets may have anticipated and factored in a future carbon tax, which could have reduced the value of high-emission firms. However, since the tax was never put into effect, the profitability of these companies remained unaffected, and investors were consequently rewarded with higher returns for the risks they assumed.

In contrast, Sweden has been a leader in implementing carbon taxes (Martinsson et al., 2022). Therefore, Swedish high emission firms should have observed a decline in profitability, potentially leading to a lack of investor rewards comparable to the premiums observed in the U.S. by Hsu et al. (2023) and Bolton and Kacperzyk (2021).

This could imply that the risks related to carbon taxation have materialized in Sweden. However, given the difficulties in estimating the market expectations of future changes to the carbon tax, especially in Sweden which has been a historical world leader in implementing them, we cannot claim the magnitude of such materialization.

Furthermore, our results partially contradict the findings of Pastor et al. (2022), if we assume that low-emission intensity firms can be equated with “green” assets and high-emission intensity firms with “brown”. They assert that green firms, measured by ESG ratings, have witnessed higher realized returns compared to their brown counterparts between 2012-2020. This phenomenon is attributed to unexpected shifts in ESG concerns among investors and customers leading to an increased demand for green assets and products. However, our research does not find higher realized excess returns among low-emission firms. One potential reason for these contrasting findings is that our emission intensity variable may not effectively represent a firm's "greenness". This is plausible because a firm's emissions only account for one aspect of ESG. Furthermore, there is no consensus on which component of ESG has the most significant impact on stock performance (Giese, Nagy, and Lee (2021)). As a result, the suggested demand-shift proposed by Pastor et al. (2022) might have occurred in Sweden, but our use of carbon emissions as a proxy for "greenness" fails to capture it.

Another possible explanation for the conflicting results is that more of the proposed demand-shift happened in Sweden before 2010. This might be attributed to the historical significance of "climate" as one of the most crucial voter concerns in Sweden since the 1990s (Oscarsson and Homberg (2017)). Hence it is possible that Swedish investors and consumers began showing a preference for “green” assets and products before 2010, thus increasing green asset prices and decreasing the impact of more recent demand-shifts.

Our research implies that there is neither an emission premium nor an emission discount in the Swedish stock market. The results indicate that emission-based investment strategies in the Swedish stock market are unlikely to generate abnormal returns. Furthermore, it is reasonable to assume that other countries with stringent emission regulations will see a similar lack of relationship between emissions and stock returns.

Future research could benefit from analyzing and comparing the relationship between emissions and stock returns in countries with different carbon regulations. This approach can contribute to a deeper understanding of the emission-return relation and its dynamics. Additionally, it would be fruitful to investigate whether an emission risk premium has existed in Sweden during specific time periods, particularly in relation to regulatory changes, political shifts, and other significant market announcements.

A. Limitations

A primary limitation is the selection bias inherent in the carbon emission data from Refinitiv Eikon, which is voluntary and self-reported by firms. Firms with lower raw emissions may be more inclined to disclose their data, while those with higher emissions may choose nondisclosure. This tendency likely skews the available data, resulting in an underrepresentation of high-emission firms. Such a bias affects the generalizability of our findings negatively. Moreover, self-reported data are susceptible to reporting errors or intentional misrepresentations, potentially leading to inaccuracies in the reported figures.

Another limitation of our paper is the limited size of our sample. This limitation is mainly shown in two ways. Firstly, with a limited number of firms, the representation of industries in our data is not representative of the Swedish publicly traded firms. Analyzing Table CI in Appendix C, we observe differences in the industry distribution between our dataset and the firms listed on the Swedish exchange. For example, the industry “Machinery” accounts for 17,5% of our dataset, while it comprises only about 4,9% of the firms on the Swedish exchange. Nonetheless, there is a risk that our data underrepresent certain industries and overrepresent other industries, limiting the generalization of our results. Secondly, our dataset's sample size prevents us from implementing the portfolio sorting method employed by Hsu et al. (2023), which requires a minimum of 5 firms per industry. Instead, we are sorting portfolios based on

the overall data sample. Consequently, it is not possible to draw conclusions from either the univariate portfolio sorting or the asset factor pricing tests regarding whether firms with high or low emission intensity compared to industry peers exhibit a difference in returns.

Lastly, we do not include the WW-index as one of our variables in the Fama-Macbeth regressions due to the lack of reliable industry growth rate data for the Swedish markets. Hsu et al. (2023) find that the WW-index, which represents investment capacity, is statistically and economically significant when included as a control variable. This suggests that the WW-index may have had a profound impact on our model if included as a control variable. Nevertheless, we cannot precisely quantify the WW-index's impact on our results. Therefore, it is important to recognize this limitation when evaluating the reliability of our Fama-Macbeth regressions.

V. Conclusion

Is there an emission-return relation in the Swedish equity market? We address this question by first using portfolio sorts to investigate differences in realized returns and abnormal returns between firms with high and low emissions. We find no support for such a difference. To further explore the emission-return relation, we conduct Fama and MacBeth (1973) regressions, finding no robust support for emission's predictive power on stock returns. Lastly, we employ portfolios double sorted on emission intensity and size, still not finding any empirical evidence of an emission-return relation.

We suggest that the overall finding of the absence of an emission-return relation may be due to the stringent emission regulations in Sweden and because parts of the demand-shift toward green assets occurred before 2010. This differs from countries like the U.S., where less strict regulations and more recent demand-shifts contribute to the presence of an emission-return relation. Consequently, the success of an investment strategy relying on emissions is likely to depend on the specific country's regulations and demand for green assets and products.

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Appendix A. Emissions Scaling Variations

Table AI

Asset Pricing Factor Tests Sorted by Emissions Scaled by Revenues

This table reports asset pricing factor tests for five quintile portfolios sorted on emission scaled by revenues. Additionally, a high-minus-low (H-L) portfolio is formed, taking a long (short) position in the High (Low) portfolio. The sample runs from the first of January 2011 to the last of December 2019 and portfolios are rebalanced at the first of January each year. We perform time-series regressions of the emission intensity sorted portfolios on the market factor (MKT) in Panel A, the Fama and French (1996) three-factor model (MKT, size-factor (SMB) and value factor (HML)) in Panel B, and Carhart (1997) model (MKT, SMB, HML and momentum factor (MOM)) in Panel C. All results are *annualized*, and t-statistics are based on standard errors estimated using the Newey-West correction for 12 lags. We collect the factor data from the Swedish House of Finance National Research Datacenter.

	L	2	3	4	H	H-L
Panel A: CAPM						
Alpha (%)	1.39	3.94	6.65	6.54	12.54	11.16
[t]	0.44	1.65	3.04	1.73	1.48	1.11
MKT	0.75	0.98	1.15	1.11	0.95	0.20
[t]	14.51	12.95	20.72	10.33	3.18	0.67
Panel B: FF3						
Alpha (%)	1.48	4.04	6.78	6.54	12.62	11.14
[t]	0.50	1.79	3.33	1.81	1.46	1.09
MKT	0.77	0.99	1.17	1.11	0.97	0.20
[t]	14.66	16.16	24.4	10.33	3.46	0.68
SMB	-0.08	-0.18	-0.18	0.05	0.03	0.11
[t]	-1.03	-3.49	-2.45	0.49	0.20	0.69
HML	-0.28	-0.23	-0.34	-0.03	-0.29	-0.01
[t]	-3.99	-1.89	-2.98	-0.29	-1.44	-0.04
Panel C: FF4						
Alpha (%)	1.33	7.07	7.96	7.17	15.22	13.89
[t]	0.40	2.88	2.83	1.64	1.89	1.38
MKT	0.77	0.96	1.15	1.10	0.94	0.17
[t]	14.63	14.69	23.62	10.02	3.45	0.59
SMB	-0.07	-0.19	-0.19	0.04	0.02	0.09
[t]	-1.00	-4.11	-2.57	0.45	0.10	0.56
HML	-0.28	-0.36	-0.39	-0.05	-0.40	-0.12
[t]	-3.48	-3.05	-2.95	-0.49	-2.33	-0.79
MOM	0.01	-0.12	-0.05	-0.03	-0.10	0.11
[t]	0.15	-3.65	-1.02	-0.53	-1.31	-1.80

Table AII

Asset Pricing Factor Tests Sorted by Raw Emissions

This table reports asset pricing factor tests for five quintile portfolios sorted on raw emissions. Additionally, a high-minus-low (H-L) portfolio is formed, taking a long (short) position in the High (Low) portfolio. The sample runs from the first of January 2011 to the last of December 2019 and portfolios are rebalanced at the first of January each year. We perform time-series regressions of the emission intensity sorted portfolios on the market factor (MKT) in Panel A, the Fama and French (1996) three-factor model (MKT, size-factor (SMB) and value factor (HML)) in Panel B, and Carhart (1997) model (MKT, SMB, HML and momentum factor (MOM)) in Panel C. All results are *annualized*, and t-statistics are based on standard errors estimated using the Newey-West correction for 12 lags. We collect the factor data from the Swedish House of Finance National Research Datacenter.

	L	2	3	4	H	H-L
Panel A: CAPM						
Alpha (%)	6.50	2.53	5.51	2.35	0.82	-5.68
[t]	1.70	0.45	1.47	0.82	0.20	-0.99
MKT	0.79	1.03	1.06	0.93	1.29	0.50
[t]	6.42	7.46	8.95	9.41	14.95	3.26
Panel B: FF3						
Alpha (%)	6.57	2.66	5.53	2.43	0.85	-5.71
[t]	1.66	0.50	1.45	0.94	0.21	-0.93
MKT	0.82	1.05	1.06	0.94	1.29	0.48
[t]	7.47	9.02	8.47	10.87	13.37	3.06
SMB	0.13	-0.07	-0.07	-0.12	-0.15	-0.28
[t]	0.97	-0.71	-0.74	-1.49	-1.49	-1.66
HML	-0.30	-0.42	-0.04	-0.22	-0.05	0.25
[t]	-2.77	-3.57	-0.49	-1.73	-0.31	1.44
Panel C: FF4						
Alpha (%)	6.03	4.95	5.38	5.02	3.45	-2.58
[t]	1.41	1.13	1.54	1.87	0.81	-0,39
MKT	0.82	1.03	1.06	0.91	1.27	0.44
[t]	7.46	9.30	9.29	10.23	13.19	2.94
SMB	0.13	-0.08	-0.07	-0.13	-0.16	-0.29
[t]	1.00	-0.82	-0.76	-1.55	-1.62	-1.79
HML	-0.28	-0.51	-0.03	-0.33	-0.16	0.12
[t]	-2.26	-5.03	-0.34	-2.46	-1.15	0.78
MOM	0.02	-0.09	0.01	-0.10	-0.10	-0.12
[t]	0.41	-1.59	0.10	-2.09	-1.92	-1.60

Table AIII

Fama-Macbeth Regressions with Emissions Scaled by Revenues with Industry, Industry Group, and Sector Fixed Effects

This table reports Fama-MacBeth regressions of individual stocks' excess returns on emission scaled by revenues in logarithm (Log Emissions) and other firm characteristics. Cross-sectional regressions are performed each month from January year *t* to December year *t*. In each month, excess returns of individual stocks (*annualized* by multiplying with 12) are regressed on the logarithm of emission intensity (Log Emissions) in year *t*-1 while including different sets of control variables and fixed effects based on industry, industry-group, and sector. Control variables include the logarithm of market capitalization (Log MCAP), the logarithm of book-to-market ratio (Log B/M), investment rate (I/K), return on equity (ROE), tangibility (TANT), book leverage (LEV). All independent variables are winsorized at the 1st and 99th percentile to reduce the impact of outliers and then normalized to zero mean and unit standard deviation to reduce scale effects. T-statistics are based on standard errors using the Newey-West correction for 12 lags. The sample period is January 2011 to December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Log Emissions	0.04	0.07	0.04	0.08	0.01	0.02
[t]	0.84	1.46	0.92	1.63	0.22	0.51
Log MCAP	-0.04	-0.04	-0.08	-0.10	-0.06	-0.07
[t]	-1.84	-2.40	-2.22	-2.73	-1.54	-1.68
Log B/M	-0.07	-0.05	-0.10	-0.12	-0.13	-0.12
[t]	-1.76	-1.22	-2.61	-3.00	-2.97	-2.87
I/K	0.03	0.04	-0.03	-0.07	0.00	-0.01
[t]	-0.54	0.58	-0.60	-1.41	-0.19	-0.38
ROE	0.07	0.07	0.08	0.12	0.05	0.08
[t]	2.28	2.15	1.91	2.77	1.44	2.54
TANT		0.00		0.05		0.02
[t]		0.20		1.79		0.65
LEV		-0.04		0.03		-0.01
[t]		-0.93		0.99		-0.42
Industry F.E.	Yes	Yes	No	No	No	No
Industry Group F.E.	No	No	Yes	Yes	No	No
Sector F.E.	No	No	No	No	Yes	Yes

Table AIV

Fama-Macbeth Regressions with Raw Emissions and Industry, Industry Group, and Sector Fixed Effects

This table reports Fama-MacBeth regressions of individual stocks' excess returns on raw emissions in logarithm (Log Emissions) and other firm characteristics. Cross-sectional regressions are performed each month from January year *t* to December year *t*. In each month, excess returns of individual stocks (*annualized* by multiplying with 12) are regressed on the logarithm of emission intensity (Log Emissions) in year *t*-1 while including different sets of control variables and fixed effects based on industry, industry-group, and sector. Control variables include the logarithm of market capitalization (Log MCAP), the logarithm of book-to-market ratio (Log B/M), investment rate (I/K), return on equity (ROE), tangibility (TANT), book leverage (LEV). All independent variables are winsorized at the 1st and 99th percentile to reduce the impact of outliers and then normalized to zero mean and unit standard deviation to reduce scale effects. T-statistics are based on standard errors using the Newey-West correction for 12 lags. The sample period is January 2011 to December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Log Emissions	0.03	0.07	0.07	0.10	0.06	0.07
[t]	0.61	1.41	1.73	1.91	1.16	1.33
Log MCAP	-0.05	-0.05	-0.09	-0.12	-0.07	-0.07
[t]	-1.77	-2.34	-2.38	-2.81	-1.63	-1.74
Log B/M	-0.07	-0.06	-0.12	-0.13	-0.15	-0.15
[t]	-1.73	-1.39	-2.78	-3.01	-3.36	-3.15
I/K	-0.04	0.03	-0.04	-0.07	-0.01	-0.02
[t]	-0.77	0.49	-0.72	-1.42	-0.43	0.64
ROE	0.07	0.07	0.09	0.12	0.05	0.08
[t]	2.41	2.12	1.99	2.84	1.52	2.53
TANT		0.01		0.05		0.02
[t]		0.32		1.93		0.58
LEV		-0.04		0.02		-0.02
[t]		-0.98		0.72		-0.60
Industry F.E.	Yes	Yes	No	No	No	No
Industry Group F.E.	No	No	Yes	Yes	No	No
Sector F.E.	No	No	No	No	Yes	Yes

Appendix B. Newey-West Correction for 4 Lags

Table BI

Univariate Portfolio Sorting Sorted by Emissions Scaled by Total Assets with Newey-West Corrections for 4 Lags

This table reports Fama-MacBeth regressions of individual stocks' excess returns on emissions scaled by total assets in logarithm (Log Emissions) and other firm characteristics. Cross-sectional regressions are performed each month from January year *t* to December year *t*. In each month, excess returns of individual stocks (*annualized* by multiplying with 12) are regressed on the logarithm of emission intensity (Log Emissions) in year *t*-1 while including different sets of control variables and fixed effects based on industry, industry-group, and sector. Control variables include the logarithm of market capitalization (Log MCAP), the logarithm of book-to-market ratio (Log B/M), investment rate (I/K), return on equity (ROE), tangibility (TANT), book leverage (LEV). All independent variables are winsorized at the 1st and 99th percentile to reduce the impact of outliers and then normalized to zero mean and unit standard deviation to reduce scale effects. T-statistics are based on standard errors using the Newey-West correction for 4 lags. The sample period is January 2011 to December 2019.

	L	2	3	4	H	H-L
E[R]-Rf (%)	7.46	20.05	17.20	27.13	12.84	5.38
[t]	1.54	3.35	2.99	4.31	1.64	0.88
Std (%)	47.66	58.16	57.03	60.60	71.82	57.94
SR	0.16	0.35	0.30	0.45	0.18	0.09

Table BII

Asset Pricing Factor Tests Sorted by Emissions Scaled by Total Assets with Newey-West Corrections for 4 lags

This table reports asset pricing factor tests for five quintile portfolios sorted on emission scaled by total assets. Additionally, a high-minus-low (H-L) portfolio is formed, taking a long (short) position in the High (Low) portfolio. The sample runs from the first of January 2011 to the last of December 2019 and portfolios are rebalanced at the first of January each year. We perform time-series regressions of the emission intensity sorted portfolios on the market factor (MKT) in Panel A, the Fama and French (1996) three-factor model (MKT, size-factor (SMB) and value factor (HML)) in Panel B, and Carhart (1997) model (MKT, SMB, HML and momentum factor (MOM)) in Panel C. All results are *annualized*, and t-statistics are based on standard errors estimated using the Newey-West correction for 4 lags. We collect the factor data from the Swedish House of Finance National Research Datacenter.

	L	2	3	4	H	H-L
Panel A: CAPM						
Alpha (%)	-2.61	7.09	4.02	15.36	-2.61	0.00
[t]	-1.04	1.72	1.54	3.42	-0.60	0.00
MKT	0.84	1.08	1.10	0.98	1.28	0.45
[t]	11.80	13.17	12.46	6.96	15.55	3.59
Panel B: FF3						
Alpha (%)	-2.49	7.15	4.14	15.43	-2.64	-0.14
[t]	-1.05	1.76	1.78	3.40	-0.65	-0.03
MKT	0.86	1.10	1.11	0.99	1.29	0.43
[t]	13.07	13.51	15.49	7.24	16.61	3.59
SMB	-0.08	0.05	-0.25	-0.02	0.28	0.35
[t]	-0.96	0.52	-3.67	-0.16	3.00	2.57
HML	-0.35	-0.24	-0.27	-0.20	-0.05	0.30
[t]	-3.77	-1.99	-2.70	-1.40	-0.35	1.95
Panel C: FF4						
Alpha (%)	-2.33	9.14	5.44	16.28	-2.21	0.12
[t]	-0.84	2.14	2.11	3.48	-0.48	0.02
MKT	0.86	1.08	1.10	0.98	1.29	0.43
[t]	13.75	13.89	14.82	7.15	17.18	3.73
SMB	-0.08	0.04	-0.25	-0.03	0.27	0.35
[t]	-0.97	0.42	-3.81	-0.19	2.96	2.57
HML	-0.36	-0.32	-0.33	-0.24	-0.07	0.29
[t]	-3.50	-2.65	-3.56	-1.79	-0.53	1.81
MOM	-0.01	-0.08	-0.05	-0.03	-0.02	-0.01
[t]	-0.15	-2.05	-1.47	-0.72	-0.29	-0.18

Table BIII

Fama-Macbeth Regressions with Emissions Scaled by Total Assets with Newey-West Corrections for 4 lags and Industry, Industry Group, and Sector Fixed Effects

This table reports Fama-MacBeth regressions of individual stocks' excess returns on emission scaled by total assets in logarithm (Log Emissions) and other firm characteristics. Cross-sectional regressions are performed each month from January year *t* to December year *t*. In each month, excess returns of individual stocks (*annualized* by multiplying with 12) are regressed on the logarithm of emission intensity (Log Emissions) in year *t*-1 while including different sets of control variables and fixed effects based on industry, industry-group, and sector. Control variables include the logarithm of market capitalization (Log MCAP), the logarithm of book-to-market ratio (Log B/M), investment rate (I/K), return on equity (ROE), tangibility (TANT), book leverage (LEV). All independent variables are winsorized at the 1st and 99th percentile to reduce the impact of outliers and then normalized to zero mean and unit standard deviation to reduce scale effects. T-statistics are based on standard errors using the Newey-West correction for 4 lags. The sample period is January 2011 to December 2019.

	(1)	(2)	(3)	(4)	(5)	(6)
Log Emissions	0.07	0.09	0.04	0.09	0.01	0.02
[t]	1.22	1.51	0.86	1.43	0.17	0.37
Log MCAP	-0.04	-0.04	-0.08	-0.10	-0.06	-0.07
[t]	-1.72	-1.82	-2.53	-2.97	-1.71	-1.83
Log B/M	-0.08	-0.05	-0.10	-0.12	-0.12	-0.12
[t]	-1.79	-1.24	-2.37	-2.76	-2.63	-2.54
I/K	-0.02	0.04	-0.03	-0.06	0.00	-0.01
[t]	-0.31	0.48	-0.45	-1.04	-0.12	-0.33
ROE	0.07	0.07	0.08	0.12	0.05	0.08
[t]	1.90	1.71	1.94	2.56	1.53	2.41
TANT		0,00		0.05		0.02
[t]		0.13		1.85		0.52
Lev		-0.04		0.03		-0.01
[t]		-1.14		0.92		-0.49
Industry F.E.	Yes	Yes	No	No	No	No
Industry Group F.E.	No	No	Yes	Yes	No	No
Sector F.E.	No	No	No	No	Yes	Yes

Appendix C. Dataset and the Swedish Exchange

Table CI

Industry, Industry Group, and Sector Distribution of the Dataset and Firms on the Swedish Exchange

This table provides information about the industry, industry group, and sector distribution of firms in our dataset and firms on the Swedish exchange. Panel A presents the industry distribution, Panel B presents the distribution by industry groups, and Panel C presents the sector distribution. The left column currently presents the different industries, industry groups, or sectors present in the data. The right column shows the percentage distribution of firms in the industries, industry groups, and sectors in the dataset. The right column shows the percentage distribution of firms in the industries, industry groups, and sectors for firms on the Swedish exchange.

Panel A		
Industry	Distribution Sample (%)	Distribution Population (%)
Software	0.00	8.80
Health Care Equipment & Supplies	5.00	8.34
Aerospace & Defense	2.50	1.03
Food Products	0.00	1.14
Biotechnology	2.50	8.11
Oil, Gas & Consumable Fuels	0.00	1.26
Capital Markets	0.00	4.57
Electrical Equipment	0.00	2.97
Building Products	7.50	1.94
Diversified Consumer Services	0.00	0.80
Interactive Media & Services	0.00	1.60
Electronic Equipment, Instruments & Components	2.50	4.91
Hotels, Restaurants & Leisure	2.50	2.06
Pharmaceuticals	0.00	4.34
Trading Companies & Distributors	0.00	1.37
Media	0.00	1.49
Entertainment	2.50	3.43
Chemicals	2.50	2.17
Machinery	17.50	4.91
Metals & Mining	5.00	2.17
Professional Services	0.00	1.71
Health Care Technology	0.00	1.37
Life Sciences Tools & Services	0.00	1.37
Construction & Engineering	5.00	1.83
Health Care Providers & Services	0.00	1.03
Specialty Retail	7.50	3.09
IT Services	0.00	3.31

Financial Services	0.00	1.03
Beverages	0.00	0.69
Independent Power and Renewable Electricity Producers	2.50	0.46
Consumer Staples Distribution & Retail	2.50	0.11
Water Utilities	0.00	0.11
Diversified Telecommunication Services	2.50	0.91
Semiconductors & Semiconductor Equipment	0.00	0.69
Textiles, Apparel & Luxury Goods	0.00	0.57
Household Durables	7.50	1.83
Containers & Packaging	2.50	0.11
Leisure Products	0.00	0.69
Commercial Services & Supplies	7.50	2.74
Broadline Retail	0.00	0.57
Paper & Forest Products	5.00	0.57
Automobile Components	0.00	0.11
Household Products	0.00	0.46
Automobiles	0.00	0.57
Energy Equipment & Services	0.00	0.34
Transportation Infrastructure	0.00	0.23
Electric Utilities	0.00	0.11
Technology Hardware, Storage & Peripherals	0.00	0.57
Air Freight & Logistics	0.00	0.46
Personal Care Products	0.00	0.69
Communications Equipment	2.50	1.49
Ground Transportation	0.00	0.23
Marine Transportation	0.00	0.23
Consumer Finance	0.00	0.46
Industrial Conglomerates	0.00	0.91
Wireless Telecommunication Services	2.50	0.34
Tobacco	0.00	0.11
Passenger Airlines	2.50	0.11
Insurance	0.00	0.11
Distributors	0.00	0.23

Panel B

Industry Group	Distribution Sample (%)	Distribution Population (%)
Software & Services	0.00	12.28
Health Care Equipment & Services	5.00	10.89
Capital Goods	32.50	15.18
Food, Beverage & Tobacco	0.00	1.97

Pharmaceuticals, Biotechnology & Life Sciences	2.50	14.02
Energy	0.00	1.62
Financial Services	0.00	6.14
Consumer Services	2.50	2.90
Media & Entertainment	2.50	6.60
Technology Hardware & Equipment	5.00	7.07
Materials	15.00	5.10
Commercial & Professional Services	7.50	4.52
Consumer Discretionary Distribution & Retail	7.50	3.94
Utilities	2.50	0.70
Consumer Staples Distribution & Retail	2.50	0.12
Telecommunication Services	5.00	1.27
Semiconductors & Semiconductor Equipment	0.00	0.70
Transportation	2.50	3.13
Consumer Durables & Apparel	7.50	1.85

Panel C

Sector	Distribution Sample (%)	Distribution Population (%)
Information Technology	5.00	19.79
Health Care	7.50	24.60
Industrials	42.50	22.54
Consumer Staples	2.50	3.20
Energy	0.00	1.60
Financials	0.00	6.18
Consumer Discretionary	17.50	8.58
Communication Services	7.50	7.78
Materials	15.00	5.03
Utilities	2.50	0.69