The term structure of carbon emissions *

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First version: February 24, 2022
This version: July 11, 2022

Abstract

I construct a measure of cash flow duration at the firm level and link it to carbon emissions of the same firm. Firms with higher carbon emissions generate their cash flows in the near term, reflecting that long-term cash flows are relatively more exposed to transitional climate risks. This relationship leads to high correlations of emission and duration premiums. Until 2008, risk-adjusted returns increase with emissions and decrease with duration. Thereafter, high emission and low duration stocks underperform. Return differences are driven by emissions instead of duration. Overall, these patterns are consistent with a change in investors' climate concerns after 2008. This change sheds light on divergent findings in the literature on the effect of emissions on stock performance and, together with the relationship between duration and carbon emissions, explains much of the recent underperformance of value stocks.

Keywords: Duration, carbon emissions, climate change, cross-section of stock returns
JEL classification: G10, G12, G18, Q50

*I am grateful for helpful comments from Claus Munk, Jan Starmans (discussant), Michael Weber, David Lando, Marcus Opp, Jesper Rangvid, and Lasse Heje Pedersen, as well as seminar, workshop, and conference participants at Stockholm School of Economics, Copenhagen Business School, and the World Finance Conference. All mistakes are mine.

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1 Introduction

With increasing awareness of the greenhouse effect, that is the rise in global temperature from the emission of greenhouse gases (GhG), calls for coordinated actions to mitigate the warming emerge. A major milestone is the so-called Paris agreement adopted in 2015 by 195 states including all major economies.[1] The agreement is legally binding and involves the reduction of GhG emissions to net-zero by 2050 to limit global warming to well below 2°Celsius (**UNFCCC**). Also participants in the financial markets become increasingly aware of climate risks. Institutional investors form coalitions to engage with firms and monitor the reduction of emissions[2] and financial regulators consider "climate-related financial risk disclosure" and an overall "responsibility to ensure the resiliency of the financial system to climate-related risks".[3]

Potential measures to reduce aggregate emissions to net-zero can involve far-ranging consequences for a large share of the cross section of firms. Examples include policies such as mandatory disclosure of and taxes on carbon emissions, technological advancements or regulations, but also reputation risks as well as changing investor or consumer preferences. Hence, the transition towards a net-zero emission economy may expose firms' future cash flows to risks that are often summarized as transitional climate risks (**Giglio2020**).

This paper establishes a relationship between transition risks and the time to maturity of cash flows on the firm level: Today, the emission of carbon is cheap and subject to only little regulation.[4] To match the increasing marginal cost of carbon reduction[5] and to reach the target of a net-zero emission economy, however, incentives to reduce emissions have to become stronger over time. A potential tax on emissions is therefore proposed to increase with time (**Nordhaus1993**; **Marron2014**). As a consequence,

[1] In 2020, the USA withdrew from the agreement and rejoined in 2021. As of January 2022, 194 states and the European Union have signed the agreement representing 97% of global GhG emissions (**WorldResourcesInsitute2022**).

[2] Examples are climateaction100+ or the UN-convened Net-Zero Asset Owner Alliance with combined $65 and $10 trillion assets under management.

[3] Quotes by Secretary of the US Treasury Janet L. Yellen at the Institute of International Finance and COP26 in Glasgow, Scotland.

[4] Firm-level carbon emission disclosure is still voluntary in most countries, including the US, and the global average price to emit one ton of carbon is $3 and covers about 20% of global emissions (**Black2021**).

[5] Intuitively, avoiding the release of an additional ton of carbon requires extra effort and, therefore, becomes increasingly costly over time.

cash flows generated in the more distant future are relatively more exposed to transition risks than cash flows produced in the near term.

I proxy for transition risk using carbon emission data on the firm level (hence, I use carbon risk as a synonymous term). I then construct a measure of cash flow duration for the same firm where the term duration, in analogy to the fixed-income literature, refers to the value weighted time to maturity of future equity cash flows.

Using portfolio sorts and regression analysis, I find a negative relationship between the duration of firms' cash flows and three measures of carbon emissions. I consider the total level of carbon emissions (TCE), the intensity of carbon emissions (ICE) as the total emissions normalized by sales, and the footprint of carbon emissions (FCE) as the total emissions divided by firms' market capitalization. Low duration firms exhibit 14 times more TCE and FCE and 3 times more ICE than long duration firms. The cash flow duration of a firm is up to 5 years shorter if it is among the 10% highest carbon emitters than if it belonged to the 10% of firms emitting the least.

These findings are consistent with the interpretation that firms generate a larger share of cash flows in the near term if they are more exposed to transition risks. Conversely, firms that produce a large share of their cash flows in the distant future, and are therefore more long-term focused, act more sustainably and emit less carbon. While the relationship between duration and carbon emissions is significantly negative already at the beginning of my sample, this effect becomes stronger over time. On the investor level, a shorter cash flow duration for firms with high carbon emissions implies that investors already incorporate transitions risks by adjusting the present value of future cash flows downwards. This horizon effect that becomes stronger over time is in line with recent findings of **Krueger2020** who, in a survey among institutional investors, find that in particular long-term investors are increasingly aware of potential climate risks.

So far, the duration literature and the literature on the impact of transitional climate risk on financial markets have been considered only in separation. The relationship between cash flow duration and carbon emissions, therefore, provides a novel channel to connect and extend the literature of two active and fast growing research areas.

Motivated by this new relation, I sort stocks into quintile portfolios either based on duration or one of three measures of carbon emissions. First, I find the term premium (long duration quintile minus short duration quintile) and carbon premium (high emission quintile minus low emission quintile) to be highly correlated. Second, until 2008 average returns, Sharpe ratios, and CAPM alphas increase with carbon emissions and decrease with years of cash flow duration. Short duration firms outperform long duration firms by 0.5% per month while high emission stocks outperform low emission stocks by 1.1% (TCE) to 1.6% (ICE) per month. This pattern reverses post 2008. Monthly abnormal CAPM returns increase with duration and are 0.7% higher for long duration stocks than for short duration stocks. The premium on carbon emission is now negative, ranging from -1.0% (TCE) to -1.2% (ICE). Common equity risk factors cannot explain these patterns. Over the full sample (2003-2020), the effects are much smaller and mostly insignificant.

Previous research on duration and the cross section of stock returns find that short duration firms produce higher average returns, Sharpe ratios, and CAPM alphas than long duration firms (**Dechow2004**; **Weber2018**). Studies utilizing environmental data to proxy for the effect of climate risks on stocks returns are inconclusive. **Bolton2021** and **Hsu2021** consider carbon emissions and chemical pollution, respectively, and find that investors demand a premium for the exposure to these risks. Others, however, find an outperformance of environmentally friendly stocks (**In2019**; **Pastor2021**).

This paper provides an explanation for the diverging findings in previous literature on the effect of corporate emissions on stock returns. Until 2008, high emission stocks pay a premium, while thereafter, low emission stocks pay higher returns. The magnitude of abnormal returns is much larger - in both directions - than in previous studies, suggesting that their results may be diluted by the respective opposite effect.

The reversal in emission premium is in line with **Pastor2020** who show in an equilibrium model that low emission stocks have lower expected returns. However, they also show that shocks to preferences for clean stocks and products can lead to temporary higher realized returns of these firms. Taking advantage of a relatively long sample period, this paper is the first to document such a change in realized returns post 2008, around the time of the 15th Climate Change Conference where both the climate change news index of **Engle2020** and **Ardia2020** peak. With the outperformance of green stocks, many studies associate an increase in realized returns for environmentally friendly firms (**In2019**; **VanderBeck2021**; **Pastor2021**). However, I find returns of low emission stocks are not different after 2008. Instead, it is the long-leg, that is the relative underperformance of high emission stocks, that drives the change in emission premium.

Several recent studies suggest that duration explains various common equity risk factors and thereby drives large parts of cross-sectional returns (**Chen2018**; **Gormsen2021b**; **Goncalves2021**). Given that short duration firms exhibit high emissions, it could be that changes in the duration premium lead to the observed patterns on emission-ranked stocks. However, in a similar argument, **Pastor2021** derive a green factor capturing shocks to investors' concerns about climate change that explains the large abnormal returns of green stocks and, with the market factor, parts of the cross section of returns. To disentangle the duration and emission effects, I double-sort stocks into portfolios based on duration and one of the carbon emission measures. I find that most of the return variation comes from carbon emissions instead of duration, both before and after 2008.

After controlling for carbon emissions, I find the duration effect to be small and insignificant. In addition, I construct a measure of unexpected shifts in investors' climate concerns similar to that of **Ardia2020** and **Pastor2021**. I find that shocks to climate concerns not only explain the underperformance of high emission stocks but also the lower returns of short duration stocks. Hence, with the higher carbon risk exposure of short duration firms, I provide an explanation for the (recent) return difference between short and long duration firms in addition to short-sale constraints (**Weber2018**), horizon dependent optimism bias (**Cassella2021**), risk-pricing (**Lazarus2018**), and firms' capital structure decisions (**Belo2015a**).

Finally, **Pastor2021** argue that their green factor is correlated with the HML-factor of **Fama1993** and as a consequence, investors' increased environmental concerns led to the underperformance of the value factor. The relationship between climate risk and the timing of cash flows established in this paper, and the fact that emissions appear to drive the term premium, support this claim and provide an intuitive argument for the correlation of the carbon premium and the value factor. I find that both cash flow duration and carbon emissions help to explain the recent underperformance of value stocks.

The remainder of this paper is structured as follows. I discuss related literature immediately below. In Section 2, I introduce data and measures of carbon emissions and cash flow duration. Section 3 establishes the relationship between cash flow duration and carbon emissions and its time-variation. Motivated by this relation, Section 4 studies characteristics of portfolios sorted on duration and emission metrics and dissects their effects.

Section 5 concludes.

This paper builds on recent literature studying the effect of transitional climate risks on financial markets. The studies most closely related to mine also use carbon emission data to proxy for transition risk to explore its effect on stock returns. **In2019** find that in the latter part of their sample (2010-2015) stocks with low carbon emissions per dollars of revenue pay abnormal returns of 3% to 5% per year. They do not find a significant effect in their full sample (2006-2015), however. **Bolton2021**, on the other hand, find that investors demand an annual premium of 2% to 4% for stocks with high levels and growth in carbon emissions. The authors attribute the premium to institutional investors' exclusionary screening efforts of certain industries in order to mitigate transitional climate risks. Considering stocks ranked on chemical emissions, **Hsu2021** find that high emission firms pay a premium of similar size and relate it to environmental policy uncertainty. **VanderBeck2021** shows that environmental, social, and governance (ESG) fund flows lead to large demand-induced realized returns that do not imply high expected returns. Similarly, **Pastor2021** empirically show that firms scoring higher in environmental metrics outperform by more than 5% per year and relate this to unexpected shocks to environmental concerns.

In a preceding paper, **Pastor2020** show in an equilibrium model that low emission stocks have lower expected returns. Changes in investors' and consumers' preferences for clean stocks and products, however, can lead to price pressure for these stocks and thus, temporary larger realized returns. In an alternative model, also **Pedersen2021** shows that stocks scoring high on ESG metrics can lead to high returns depending on investors who only consider financial metrics.

Further studies explore the reflection of transition risks for other assets such as equity options (**Ilhan2021**), and fixed income (**Cao2021**; **Flammer2021**; **GreenBonds2018**). **Engle2020** consider the hedging of climate change news based on textual analysis. A comprehensive literature summary on the impact of climate change on financial markets is provided in **Giglio2020**.

This paper also relates to the literature on cash flow duration of equity. **VanBinsbergen2012** and **VanBinsbergen2017** find that claims on aggregate near-term cash flows have higher returns and Sharpe ratios but lower market betas than the market portfolio. Using firm-level dividend futures, **Gormsen2021a** studies the time variation of the equity term structure and finds that it is downward sloping in normal times but upward sloping in bad times. Given that firms produce cash flows at different maturities, **Dechow2004** derive a measure of firm level cash flow duration on the basis of accounting data and find that on average high duration firms have lower returns than short duration firms and duration is correlated with the value factor. The authors explain this pattern by relating duration to the value premium. **Lettau2007** offer a theoretical explanation for their findings. Empirically, **Weber2018** finds the duration premium increases with investor sentiment and is explained by short-sale constraints. **VanBinsbergen2017** provide an overview of newer models reconciling the empirical patterns on cash flow duration. Finally, **Giglio2021** estimate an affine state space model to price claims on finite-maturity dividends that allows to derive a term structure of equity without the need of traded dividend strips.

2 Data

I retrieve data from Standard and Poor's Compustat North America Universe. I follow standard conventions and exclude financial ($6000 <= SIC < 7000$) and utility firms ($4900 <= SIC < 5000$). The book value of equity (BV) is defined as the total value of common stock, treasury stock, additional paid-in capital and retained earnings. The market value of equity is measured as the total number of common shares outstanding multiplied by the closing price. I use income before extraordinary items as measure for earnings (E). Sales and sales growth rates in fiscal year t are defined as the annual net sales in year t and corresponding discrete growth rate across period $t-1$, respectively. All measures are as of the respective firm's fiscal year end.

I gather firm-level carbon emission data for years 2002 until 2019 from Thomson Reuter's Refinitiv and match it to existing fundamental data on a firm/year basis. Details on CO2 emission data and the matching procedure to Compustat fundamentals are provided in Section 2.1.

I exclude observations with missing financial balance sheet or carbon emission data. In addition, I delete observations with zero sales or non-positive book values of equity. To reduce the impact of extreme outliers, all variables are winsorized at the 1% and 99% levels.

Data on stock returns stem from the monthly tape of the Center for Research on Security Prices (CRSP). I restrict my sample to common stocks trading on NYSE, Amex, Nasdaq, or ARCA stock exchanges. In addition, I consider implications of biased CRSP stock returns as a result of a delisting of the stock. I account for a potential delisting bias in accordance with findings in **Shumway1997**. Therefore, if delisting returns are missing and if a firm is removed for cause ($400 <= DelistCode < 592$), I assume a return of -30% over the month following the delisting of the stock. The market return is the monthly value weighted return on all NYSE, Amex, Nasdaq, and ARCA common stocks. The risk free rate is the one-month treasury bill rate. I get data on equity risk factors including size, value, momentum, profitability, and investment style from the U.S. Reasearch Returns Data Library on Kenneth French's website.

2.1 Carbon emissions

Several major data providers have specialized on gathering non-financial firm information such as CO2 emission data. Among others, firm-level carbon emission data of MSCI ESG Research, Trucost or Thomson Reuter's Refinitiv are frequently used in related studies (**In2019**; **Bolton2021**; **Flammer2021**). I prefer CO2 data from Refinitiv that follow the Greenhouse Gas Protocol setting the standards for measuring corporate emissions. Hence, their database includes reported CO2 emission equivalents by firm and year.[6] In addition, Refinitiv fills data gaps and estimates CO2 emissions if reports are not available at the firm level. In this case, estimates of CO2 emissions account for previous reported carbon emissions, firm-level energy consumption and emission levels of peers.[7] Following the Greenhouse Gas Protocol, the sources of carbon emissions are distinguished in three scopes. My measure of total carbon emissions includes direct emissions from firm or firm-controlled resources (Scope 1) and indirect emissions (Scope 2) that stem from consumption of purchased power. As it is difficult to measure, I do not include other indirect emissions (Scope 3) arising along the value chain such as emissions from purchased raw materials.

There are concerns about the disagreement between providers on non-financial firm data, particularly in studies on environmental, social and governance (ESG) data. **Berg2019** find an average correlation between ESG ratings of only 0.54. However, this seems less of a concern for corporate carbon emissions. **Busch2020** study the correlation of reports and estimates of CO2

[6] Besides carbon dioxide (CO2), this measure includes other climate risk relevant greenhouse gases such as methane(CH4) or nitrous oxide(N2O). For details, see the website of the Greenhouse Gas Protocol: https://ghgprotocol.org.

[7] Detailed information on estimation procedure can be found here: https://www.refinitiv.com/content/dam/marketing/en_us/documents/fact-sheets/esg-carbon-data-estimate-models-fact-sheet.pdf

emissions among different data providers between 2005 and 2016. According to their findings, the correlation between Refinitiv CO2 data and those of other providers is on average 0.97 for Scope 1 reports, 0.93 for Scope 2 reports and 0.82 for Scope 1+2 estimates.

I match Refinitiv carbon emission data to Compustat data on CUSIP identifier and fiscal year. For some firms, Refinitiv does not provide CUSIP codes. In this cases, I use ISINs as primary identifier. If Compustat observations have the same CUSIP or ISIN codes and a sub-sample of these miss CUSIP and ISIN identifiers in the Refinitiv universe, I match these observations, provided they have the same Refinitiv PermID.[8]

To proxy for firms' carbon risk, **In2019** use the total level of carbon emissions divided by net revenue and **Bolton2021** additionally study the level and change of carbon emissions. Apart from that, the literature provides little guidance on which metric best measures transition risks. Therefore, I also rely on carbon emission metrics recommended by the Task Force on Climate-Related Financial Disclosures (TCFD) established by the G20 countries. Similar to previous literature and in line with the three metrics proposed by **TCFD2017**,[9] I use the total level of carbon emissions (TCE), intensity of carbon emissions (ICE), and the footprint of carbon emissions (FCE) which are defined as:

$$TCE_{i,t} = Scope1_{i,t} + Scope2_{i,t} \tag{1}$$

$$ICE_{i,t} = \frac{Scope1_{i,t} + Scope2_{i,t}}{Sales_{i,t}} \tag{2}$$

$$FCE_{i,t} = \frac{Scope1_{i,t} + Scope2_{i,t}}{P_{i,t}} \tag{3}$$

Hence, $TCE_{i,t}$ of firm i in year t is the sum of Scope 1 and Scope2 emission estimates in tonnes of CO2 equivalents. $ICE_{i,t}$ and $FCE_{i,t}$ are the total carbon emission normalized by net sales and the market value of the same firm and year, respectively.

[8] For 253 firms or 3% of the total number of firms in my sample, I cannot find corresponing Refinitiv identifiers. I remove these firms in my sample.

[9] These metrics are for voluntary and partially mandatory disclosure for investors including banks, asset managers and asset owners in the G20 countries. Thus, investors may arguably consider these metrics in the selection of their investments.

2.2 Cash flow duration

With the growth of literature on the term structure of equity, various methods to empirically disentangle short-term assets from long-term assets have emerged. One possibility is to study dividend strips of different maturities on the aggregated market (**VanBinsbergen2012**) or on individual firms (**Gormsen2021b**).

Another option is to directly calculate a measure for the timing of cash flows similar to the Macaulay duration known from the fixed-income literature. The Macaulay duration $D_{i,t}$ of firm i in year t is defined as a weighted average time to reception s of the respective cash flow where the share of future discounted cash flow to the market price serve as corresponding weights:

$$D_{i,t} = \frac{\sum_{s=1}^{T} s * CF_{i,t+s}/(1+r)^s}{P_{i,t}} \tag{4}$$

with cash flows $CF_{i,t+s}$ at time $t+s$, the end-of-year t observed market price $P_{i,t}$ and expected return on equity r.

Similar to bonds, the duration for equity can be interpreted as the sensitivity of future cash flows to changes in their discount rates. However, while the size and number of cash payments for bonds are typically pre-determined, stock cash flows are uncertain in size and have potentially infinite maturity. I address these issues in a 3-step procedure similar to **Dechow2004**; **Weber2018**.

First, I split (4) into a finite forecasting period of length T and an infinite terminal period starting at time $T + 1$. This partitioning is common in the corporate finance literature as it allows for a detailed projection of cash flows up until T while accounting for cash flow maturities of infinite length.

Second, I project firm-level net free cash flow (the difference between cash flow from operations and cash flow in investing activities) for the finite forecasting period. Based on clean surplus accounting assumption, i.e. the book value of equity only increases with earnings and issuance of new shares and decreases with dividend payments and share buybacks, I can express $CF_{i,t+s}$ as:

$$
\begin{aligned}
CF_{i,t+s} &= E_{i,t+s} - (BV_{i,t+s} - BV_{i,t+s-1}) \\
&= BV_{i,t+s-1}\left(\frac{E_{i,t+s}}{BV_{i,t+s-1}} - \frac{BV_{i,t+s} - BV_{i,t+s-1}}{BV_{i,t+s-1}}\right) \\
&= BV_{i,t+s-1}(ROE_{i,t+s} - g_{i,t+s})
\end{aligned}
\tag{5}
$$

where $E_{i,t+s}$ and $BV_{i,t+s-1}$ denote earnings and lagged realization of book value of equity, respectively. It follows from (5) that $CF_{i,t+s}$ can be projected forward by finding predictors for the return on book equity $ROE = E_{i,t+s}/BV_{i,t+s-1}$ and the growth rate of book equity $g = \Delta BV_{i,t+s}/BV_{i,t+s-1}$. **Nissim2001** study the forecasting properties of ROE and g. In line with their findings, I assume ROE follows a mean-reverting process towards the average cost of capital.[10] **Nissim2001** also report that g is better predicted by past growth in sales than past growth in book values of equity and its convergence towards the mean is faster than for ROE. As in **Dechow2004**, I let g mean revert to the average growth of the economy where the speed of mean reversion is equal to that of past average sales growth. Hence, I model ROE and g as an autoregressive process where coefficients are estimated from a pooled regression of the annual Compustat North America Universe.

Third, I assume the infinite cash flow stream in the terminal period follows a level perpetuity.[11] The implied terminal value of infinite discounted cash flows is then the difference of the observed stock price $P_{i,t}$ and the total of the present value of cash flows derived in the forecast period according to (5).

$$
\sum_{s=T+1}^{\infty} \frac{CF_{i,t+s}}{(1+r)^s} = P_{i,t} - \sum_{s=1}^{T} \frac{CF_{i,t+s}}{(1+r)^s} \tag{6}
$$

Assuming a flat, firm-wide discount rate r allows me to solve for the present value of perpetual cash flows implicit in the stock price. **Weber2018** discusses the assumptions of a discount rate that is constant across time and firms. He shows that a firm specific or time-varying discount rate does not

[10] Also **Freeman1982** and **Fama2000** find mean reversion of ROE

[11] The assumption of constant cash-flows throughout the terminal period is not standard in the equity valuation literature. A constant terminal growth rate, however, would not change the relative cross-sectional rank of the duration measure as long as T is sufficiently large to allow for firm and industry specific growth. (See **Dechow2004** and **Weber2018** for details.)

affect the cross-sectional ranking of duration. Moreover, his main result indicate lower returns for high duration stocks. This would increase cross-sectional differences but again, not change the duration ranking.[12]

The final market implied measure of cash flow duration is then the sum of the cash flow duration in the finite forecast period derived according to (4) and the value-to-price weighted duration of the level perpetuity. With the value of the perpetuity determined in (6) and recognizing that the duration of a level annuity starting at the end of T is $T + (1+r)/r$, the duration of cash flows is given by:

$$D_{i,t} = \frac{\sum_{s=1}^{T} s * CF_{i,t+s}/(1+r)^s}{P_{i,t}} + \left(T + \frac{1+r}{r}\right) \frac{P_{i,t} - \sum_{s=1}^{T} CF_{i,t+s}/(1+r)^s}{P_{i,t}} \tag{7}$$

I use a finite forecasting horizon T of 15 years. Coefficients of first-order autoregressions for ROE and g are 0.41 and 0.24, respectively. I assume long-run means of the cost of equity and nominal growth rate to be 0.12 and 0.06, respectively. The discount rate r is 0.12. All parameters are reasonably in line with values in **Dechow2004** and **Weber2018**.[13]

2.3 Descriptive statistics

My sample of annual fundamental and CO2 emission data starts from January 2002, when Refinitv began to provide carbon emission data for firms in the S&P500 and Nasdaq 100 indexes, and ends at the end of December in calendar year 2019. Table 1 reports summary statistics for variables that either are used to construct the measure of cash flow duration or are part of subsequent regressions relating cash flow duration and carbon emissions. Panel A includes all firm/year observations for which I can calculate a duration measure. The average duration of cash flows is close to 20 years. Duration exhibits substantial cross-sectional dispersion as indicated by a standard deviation of 5 years. ROE appears to be left-skewed while $SalesGrowth$ is

[12] In the following chapter, I am relating $Dur_{i,t}$ to carbon emissions of the same firm and year. **Pastor2020** shows environmentally friendly firms have lower expected returns. Hence, if anything, assuming a constant discount rate across firms constitutes an upper bound for the negative relation between duration and emission.

[13] **Weber2018** studies the sensitivity of cash flows duration to changes in parameter values.

skewed to the right.

Panel B includes observations of Panel A for which I find corresponding firm-identifiers and available carbon emission data in the Refinitiv database. I end up with about one-third of the initial Compustat firm/year observations. This sample is at the center of my analysis. It includes on average firms with larger *Size* and lower *B/M* values than the duration-only sample. This is not surprising, as larger firms are more likely to report carbon emission data. As in the duration-only sample, *ROE* is left-skewed in my final sample but exhibits higher median and average values. The fact that firms who disclose their carbon emissions are larger in size and more profitable has been noted earlier (**Matsumura2014**; **Bolton2021**). The measure of equity duration, however, is very similar to that of Panel A, with average and standard deviation close to 20 and 5 years, respectively. Overall, with the exception of firm size and *ROE*, the addition of carbon emission data does not seem to add substantial selection bias.

TCE appears to be substantially skewed to the right. The average firm in my sample emits about 3 million tonnes of carbon equivalents while emissions of the median firm is one order of magnitude lower. With an average standard deviation of 16 million emitted tonnes of CO2, the cross-sectional heterogeneity is large. Similarly, with an *ICE* of 900 tonnes of carbon emissions per dollar of net sales, the average firm exhibits a level of carbon intensity that is 30-times larger than that of the median firm. To mitigate the effect of skewness, I log-transform all substantially skewed variables. These variables include *TCE*, *ICE*, *Size* and, *Sales*.

Table 6 in the Appendix reports the time variation of the number of observations and the median values of variables across the sample. As one may expect, the number of firms disclosing emission data increases with the awareness of climate related risks. Thus, the number of observations in my sample quadruples from around 500 to more than 2000 firms per year. Apart from a slight drop in 2008 and 2009, median cash flow duration appears stable over time. Annual median *TCE*, on the other hand, fall substantially. While the median firm in my sample emits 360 thousand tonnes of CO2 in 2002, the same firm in 2019 emits only 4 thousand tonnes. Median *ROE* and *Sales* values are relatively constant, except the last 4 years where both decrease. *Sales Growth* is less stable and even becomes negative in 2008, potentially due to the financial crisis.

Contemporary cross-correlations of the same variables are reported in Table 7 in the Appendix. *Duration* decreases with return-on-equity and increases

Table 1: Summary statistics. This table reports summary statistics (number of observations, mean, median, and standard deviation) for all the variables used to construct implied cash flow duration or included in the regressions that relate cash flow duration to carbon emission. All variables are winsorized at the 1% level. Panel A includes firm/year observations for which I have data to measure cash flow duration. *Duration* is my measure of cash flow duration, *log(Size)* and *log(Sales)* are the natural logarithm of total market capitalization and net sales, respectively. Both denoted in $million. *B/M* is the book value of equity divided by the total market capitalization. *ROE* is the earnings of the current fiscal year divided by the lagged book value of equity. *Sales growth* is the annual growth rate in sales. Panel B includes all observations of Panel A to which I can match carbon emission data. *TCE* denotes the estimated total CO2 emission equivalent in million tonnes and *log(TCE)* is its natural logarithm. Similarly, *log(ICE)* and *log(FCE)* are the natural logarithm of the intensity and footprint of carbon emission equivalents as defined in Equations (2) and (3).

Variables	Obs	Median	Mean	SD
Panel A: Duration sample (2002 - 2020)				
Duration	59,011	20.31	19.28	5.36
log(Size)	59,011	6.34	6.34	2.20
log(Sales)	59,011	6.11	6.01	2.42
B/M	59,011	0.48	0.66	0.65
ROE	59,011	0.07	-0.01	0.41
Sales Growth	59,011	0.07	0.14	0.49
Panel B: Emission sample (2002 - 2020)				
Duration	18,847	20.64	19.68	4.37
TCE (in Mio. t)	18,847	0.15	2.76	16.23
log(TCE)	18,847	11.92	11.89	2.54
log(ICE)	18,847	3.63	3.96	1.60
log(FCE)	18847	3.42	3.51	2.03
log(Size)	18,847	8.40	8.38	1.57
log(Sales)	18,847	8.02	7.93	1.96
B/M	18,847	0.38	0.50	0.47
ROE	18,847	0.12	0.09	0.34
Sales Growth	18,847	0.07	0.12	0.39

with growth in sales. This is consistent with predictions from Equation (5) as ROE adds more and $Sales\ Growth$ less weight on the maturity of near-term cash flows. With -0.75, duration is also strongly negatively correlated with B/M. This supports the frequent interchangeable use of both terms. However, I will show later that my duration measure contains information beyond book-to-market. Overall, the correlations between variables used to calculate cash flow duration are very similar to those reported in **Dechow2004** and **Weber2018**. $log(TCE)$ shows a high positive correlation coefficient with both $log(Size)$ and $log(Sales)$. Again, this is not unexpected since corporate carbon emissions increase with economic activity (**Nordhaus1977**). Perhaps less evident is the negative correlation of $Duration$ with $log(TCE)$, $log(ICE)$ and $log(FCE)$ that I will study in subsequent section.

3 Linking Duration and Carbon Emissions

In order to reach the target of a net-zero emission economy, policies must be introduced that encourage the reduction of carbon emissions. One intriguing tool to efficiently internalize the externalities of climate change is the introduction of a price on carbon emissions. The Nobel laureate **Nordhaus1993** is the first to discuss the introduction of carbon tax in a dynamic integrated climate-economy (DICE) model. He derives an optimal policy that minimizes climate damage and costs of GhG reductions and proposes a steady increase of the carbon price, in line with most other recommendations on carbon tax policy (**Marron2014**). In addition, **Marron2014** list three arguments for an increase of the carbon price over time. First, the social cost of carbon increases with the amount of GhG in the atmosphere. Second, a credible and transparent path of carbon prices reduces future costs by encouraging technological innovation. Lastly, a relative low introductory price avoids abrupt price shocks and allows for higher political acceptance.

All else equal, an increase in the price on carbon emissions leads to a decline in future cash flows. This is true, as long as the marginal cost of abating carbon emissions is increasing. If firms operate in a cost optimum, this is intuitive, as it requires extra effort to avoid an additional ton of emissions. Hence, firms future cash flows are affected either from increases in low-emission investments or larger prices on their remaining emissions. As a result, firms with high levels of carbon emissions might face a larger decline in future cash flows than firms with relatively low emissions. Conversely, given that the emission of a ton of carbon becomes more costly over time, firms that generate a larger share of their cash flows in the distant future are more exposed to transition risks than firms that produce most of their cash flows in the near term. Investors aware of these risks may therefore pay lower prices for affected long-term cash flows leading to a decrease in duration. Alternatively, firms whose cash flows are generated in the distant future may be more long-term focused and thereby act more sustainably.

One concern might be that a carbon tax would be simply passed forward to consumers. Indeed, it is often assumed that, like other taxes, such a tax on carbon emission would be carried by consumers in the long-run (**Marron2014**). However, as long as there is sufficient variation in the intensity of carbon emissions across sectors, there must be a more price attractive alternative for consumers. Thus, even if firms pass on a potential carbon tax, product prices of carbon intensive firms become less competitive and cash flows decrease via the demand channel.[14]

While a carbon tax is a tangible and widely discussed example of risk to future cash flows, other transition risks may affect firm cash flows equally negative. Technological disruptions, tighter environmental regulation, reputation loss or shifts in consumer demand may predominately affect firms that are perceived as "climate damaging". In a survey on climate risk perception of institutional investors, **Krueger2020** find that half of the participants believe transition risks have already financial implications on their portfolio firms. They further find that the most frequent use to manage these risks is to analyze firm-level carbon emissions. Hence, if investors have considered climate risks already by the time of answering the survey, the perceived implications should be reflected in the stock market. Moreover, if firms' carbon emissions proxy for the exposure to transition risk, variation in emissions may give important insights on how this risk is perceived by market participants.

If transition risk is priced, I hypothesize, this should translate into a shorter duration of cash flows for firms that are more exposed to the same risk. For this reason, I sort firms into portfolios either sorted on their cash flow duration or their carbon emission exposure. In particular, each calendar year t, I rank firms into deciles according to the realization of the sorting variable in the fiscal year ending in the same year.

[14] In my sample, the average annual coefficient of variation of the intensity of carbon emissions ICE for the most granular 4-digit SIC level is 0.96. Thus, on average the dispersion appears sufficiently large to provide low-emission, price-attractive alternatives across industries.

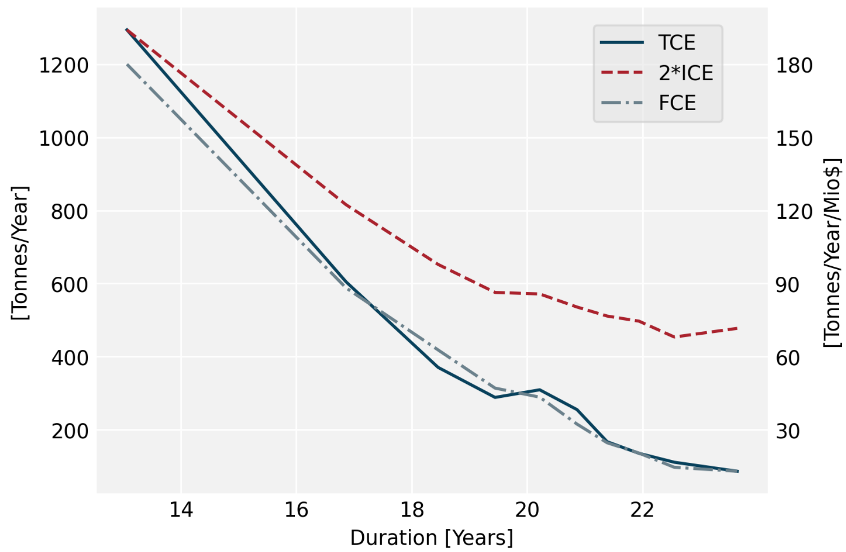


Figure 1: Median total carbon emissions TCE, intensity of carbon emissions ICE, and carbon emission footprint FCE per median duration of portfolio deciles ranked on annual cash flow duration. TCE (blue solid line) is plotted against the left vertical axis while two times ICE and FCE (red dashed and grey dot-dashed lines) are plotted on the right-hand axis. Portfolios are rebalanced every calendar year t based on the realization of the sorting variable of the fiscal year ending in the same year.

In Figure 1, I plot time-series average median carbon emissions on the median duration of ten portfolios sorted on duration. TCE, ICE, and FCE decline almost monotonically with cash flow duration. The difference in emission measures between high and low duration firms is remarkable. The median firm in the lowest duration decile exhibits a cash flow duration of 13 years and emits 1.3 million tonnes of CO2. Emissions per million dollars of revenue and market capitalization are about 100 and 180 tonnes, respectively. With a cash flow duration of 24 years, on the other hand, the median firm in the highest duration portfolio only has 7% of TCE and FCE of the short duration firm and about one third of its ICE. One interpretation of this pattern could be that more long-term oriented firms, who generate a large amount of their cash flows in the more distant future act more environmentally friendly in anticipation of the transition towards a zero-emission economy.

In Figure 4 in the Appendix, I also plot the time-series average median cash flow duration as a function of the ten decile portfolios that are sorted on TCE, ICE, and FCE. With the exception of the 4th and 7th decile of the ICE-ranked portfolios, cash flow duration is monotonically decreasing with all three emission variables. Relative to the median firm in the lowest TCE-decile, the duration of cash flows reduces by more than 4 years or 18.3% for the median firm in the highest TCE-decile. Similarly, the median cash flow duration is up to 2 and 5 years years shorter depending on their rank of ICE and FCE exposure, respectively.

The negative relation of carbon emissions and cash flow duration could be an artefact that is driven by few industries. Indeed, it appears that high cash flow duration firms with low carbon emissions often belong to similar industries. This is analogous to firms with relatively low cash flow duration and high CO2 emissions. The largest change in value-weighted industry share in the long duration portfolio compared to that in the short duration portfolio include firms that operate in the service and retail trade industry. Firms in the transportation and mining industry exhibit most often low cash flow duration. On the other hand, mining, transportation, and manufacturing firms are most frequently included in high TCE, ICE, and FCE portfolios, while firms in the service and retail trade industry are the most carbon emission friendly. Relative value weighted industry share differences of duration and TCE, ICE, and FCE sorted firms can be retrieved from Figure 5 in the Appendix.

Next, I study the relation between cash flow duration and carbon emissions more formally. While with ICE and FCE, I implicitly control for potential sales and size effects, a regression setup allows me to do this explicitly. Using pooled OLS, I regress my measure of cash flow duration on the level of carbon emissions and add additional controls:

$$Dur_{it} = \lambda_t + \alpha_j + \beta_1 log(TCE)_{it} + \beta_2 Controls_{it} + \epsilon_{it} \tag{8}$$

where λ_t and α_j capture time-fixed and industry-fixed effects for year t and industry j, respectively. $log(TCE)_{it}$ is the log-transformed level of carbon emissions of firm $i \in j$ and $Controls_{it}$ is a vector of additional control variables.

Table 2 reports the regression results. To mitigate the concern of time variation in variables, mainly prevalent in $log(TCE)$, I include year-fixed effects in all specifications. I further add industry-fixed effects for specifications reported in columns (2) and (3)[15]. In addition to $log(Size)$ and $log(Sales)$, I also control for B/M in columns (3) and (4). Standard errors are clustered at the firm and year levels to account for the potential constellation of firm-level CO2 emissions across firm and time.

Table 2: Cash flow duration and carbon emissions. Linear regression coefficients of the dependent *Duration* on $log(TCE)$ and control variables. T-statistics are in parenthesis. I control for variations in $log(Size)$ and $log(Sales)$, and additionally B/M in columns (3) and (4). I include year-fixed effects and, in columns (2) and (3), industry fixed effects. Standard errors are clustered at the firm and year levels. The sample period is from 2002-2020. Variables are defined in Table 1. Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	Duration			
Variables	(1)	(2)	(3)	(4)
Log(TCE)	-0.59***	-0.43***	-0.10***	-0.11**
	(-8.93)	(-5.92)	(-2.79)	(-2.51)
Controls:				
Log(Size)	1.53***	1.87***	-0.07	-0.02
	(14.61)	(17.22)	(-1.32)	(-0.31)
log(Sales)	-1.08***	-1.54***	-0.53***	-0.51***
	(-12.02)	(-10.71)	(-8.16)	(-5.07)
B/M			-6.86***	-6.69***
			(-55.55)	(-52.26)
Year F.E.	yes	yes	yes	yes
Industry F.E.	no	yes	no	yes
No. Obs	18,847	18,847	18,847	18,847
R-squared	0.27	0.40	0.64	0.68
R-Squared (Within)	0.15	0.18	0.54	0.54

The coefficients on $log(TCE)$ are all negative and significant at conventional significance levels. The coefficient of -0.59 in column (1) indicates that the average firm has to reduce about 81% of its CO2 emissions to gain an additional year of cash flow duration. This may sound effortful, however, such a reduction reduction moves the median firm in the highest emission decile portfolio only into the second highest decile.[16] Controlling for industry-fixed effects substantially improves the explanatory power of the regression model. In column (2), the coefficient increases to -0.43 as part of the relation is ab-

[15]I specify the industry-fixed effect at the most granular 4-digit SIC level. Results of alternative specifications are similar.

[16]Relative to neighboring higher emission deciles in the TCE sorted portfolios, the average carbon emission reduction is 54%.

sorbed by industry-fixed effects. Overall, $log(TCE)$ coefficients in columns (1) and (2) indicate an increase in median cash flow duration, from the highest to the lowest TCE-sorted decile, of 4.6 and 3.3 years, respectively.[17]

The addition of B/M in columns (3) and (4) shows that my measure of cash flow duration carries information beyond book-to-market. Both coefficients are still negative and significant, although much smaller in size. Controlling for industries has little effect on the relationship between carbon emissions and cash flow duration. Moreover, the $log(Size)$ effect disappears after the inclusion of B/M into the regression model.

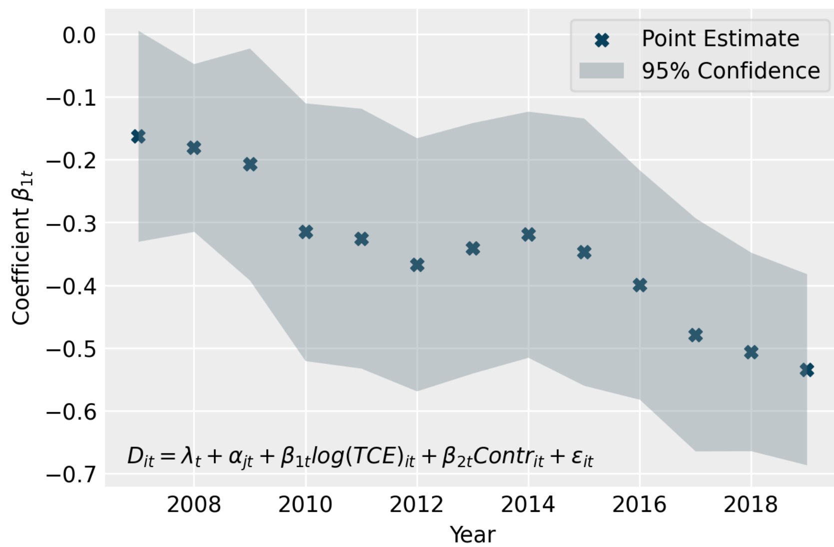


Figure 2: Point estimate (blue stars) and 95% confidence (shaded area) of the coefficient of $log(TCE)$ in a 5-year rolling-window regression. Specification as in column (2) in Table 2.

Since climate risk is a relatively recent phenomenon, I am also interested in the time-variation of the relationship between cash-flow duration and carbon emissions. Therefore, I use a 5-year rolling window regression of the same specification as in column (2) in Table 2. Figure 2 plots point estimates and 95% confidence intervals of the $log(TCE)$ coefficient across time. In line with investors' increased awareness of transition risks due to climate change, the

[17] I calculate the increase in cash flow duration as: $log(medianTCE_{d1}/medianTCE_{d10}) * \beta_1$ where $medianTCE_{d1}$ is the median of TCE in the first TCE-sorted decile and β_1 is the coefficient on $log(TCE)$.

duration of cash flows becomes increasingly shorter for the same level of CO2 emissions. In 2007, the coefficient of -0.16 is significantly negative only at the 5% level, indicating a median increase of only 1.0 year across the range of TCE-sorted decile portfolio. In contrast, the same coefficient decreased to -0.54 until the end of fiscal year 2019. The larger negative association between $log(TCE)$ and duration and greater dispersion of median emissions between portfolio ranks in 2019, leads to a difference of more than 5.1 years across TCE-sorted deciles.

4 Duration and Emission Sorted Portfolios

In Section 3, I have shown that a relationship between firm-level cash flow duration and carbon emissions of the same firm exists. All else equal, the duration of a firm's cash flows becomes shorter with higher CO2 levels, CO2 intensity, and CO2 levels per firm size. So far, return premiums of both carbon emissions and cash flow duration have only been studied separately. Using portfolios sorted on cash flow duration, **Weber2018** shows that average returns and CAPM alphas decrease with duration. **In2019** finds positive abnormal returns for a portfolio that is long low carbon intensive stocks and short stocks with high CO2 intensity, however, only significant for the latter part of their sample. In a similar sample with a 2 years longer period, **Bolton2021** find no such effect associated with carbon intensity. In contrast, their results show a significant return premium for firms with high levels of CO2 emissions. One major challenge of studies on firm-level carbon emissions is that these data have been available only from the early 2000s and thus, the sample size is naturally relatively small. As data provider typically release emission data on a rolling basis within a given year, **In2019** base their return analysis on emissions reports from the previous year. **Bolton2021**, in contrast, use carbon emission data in one year to explain monthly stock returns over the same year and thereby gain an additional year of observations. My data allows me to both study returns based on previous years' carbon emissions and financial statement reports to avoid a potential look-ahead bias and analyze a longer time series.

4.1 Return Premiums

At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. This means the sample period of returns reduces to July 2003 until December 2020. Unless otherwise stated, the sorting variables include Dur, TCE, ICE, and FCE. Portfolios are rebalanced annually and within each portfolio, I weight individual stocks equally.[18]

For each univariate portfolio sort, I define an HML portfolio that holds a long position in the highest quintile portfolio and a short position in the lowest quintile portfolio. Figure 3 plots annual returns of the four HML portfolios sorted on Dur, TCE, ICE, and FCE across time.

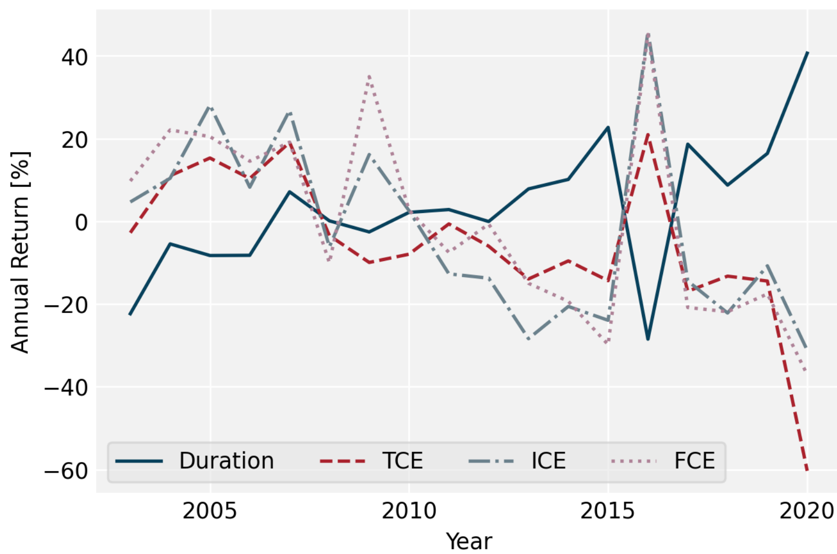


Figure 3: Annual returns in percent of high-minus-low quintile portfolios across time. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t - 1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. Returns are equally weighted and include delisting returns. The sample period is from June 2003 until December 2020.

It appears, there is a large co-variation of all HML portfolios over time. Since TCE, ICE, and FCE all are designed to proxy for carbon risk, their high correlation is not surprising. Table 8 in the Appendix reports correlation coefficients of monthly returns between all HML portfolios. Panel A shows that the correlation of monthly returns among HML carbon emission portfolios is between 75% and 88% over the full sample. The large negative correlation between the Dur sorted HML portfolio and carbon risk mimicking portfolios is surprising. Even though I have shown that on average

[18]Results of value-weighted portfolios are similar to those of equally weighted returns.

high duration firms exhibit low CO2 emissions and vice versa, the effect on corresponding HML portfolios appears large and relatively stable over time, in particular from 2008. Over the full sample the correlation coefficient between Dur and TCE, ICE, FCE monthly HML portfolio returns is -68%, -62% and -81%, respectively. Panel B and C of Table 8 report the same coefficients on return correlations for sub sample periods of July 2003 until June 2008 and July 2008 until December 2020. In the early part of my sample, correlations of duration and emission sorted portfolios are negative, but substantially smaller in magnitude. However, for the more recent sub-sample, these time-series are highly negatively correlated. The larger correlation between duration premium and emission premium over time seems in line with the increasing negative relationship between cash flow duration and carbon emissions found earlier and more generally, an increased awareness of transitions risks among investors.

Figure 3 also helps to shed light on the (partially inconclusive) findings in previous literature. In line with **Weber2018**, low duration duration stocks exhibit higher average returns than high duration stocks up until 2008. Also until 2008, firms with high CO2 levels, carbon intensity and carbon footprint paid higher average returns than their low emission counterparts. This is similar as found in **Bolton2021**. However, the pattern changes after 2008. Now firms with low carbon risk pay on average larger returns than firms that are more exposed to the same risk. This is similar to the green outperformance hypothesis of **In2019** and **Pastor2021**. At the same time, the term premium appears to reverse. Post 2008, average returns appear higher for long than for short duration stocks. One notable exception is during early 2016, when the Paris Climate Accords have been signed. At this time, both low duration and high emission stocks paid larger average returns than their high duration and low emission counterparts.

Table 3 reports mean returns across quintile and HML portfolios univariately sorted on Dur and the three carbon risk proxies TCE, ICE, FCE. Panel A includes average returns over the full sample. It seems returns are increasing with the years of cash flow duration and decreasing with the exposure to carbon risk. However, none of the HML portfolios are significantly different from zero. This seems to be an artefact of a structural change after 2008. Panel B reports mean returns across quintiles from July 2003 until June 2008. In the first years of my sample, returns *decrease* with duration and *increase* with all three measures of carbon emissions. Long duration firms earn with an annual mean return of 11.9% significantly less than short duration firms (17.8%). At the same time, HML portfolios of TCE, ICE,

FCE are all positive and significant. With 10.8%, 17.1%, and 16.8%, respectively, the annual return difference between high and low carbon risk portfolios is large. From 2008, however, this pattern reverses. In Panel C which includes observations from June 2008 until December 2020, mean returns monotonically increase with duration while they monotonically *decrease* with exposure to carbon risk. Again, with the exception of FCE, return differences are significant and substantial in size.

To test whether differences in risk in terms of volatility drive the returns, I derive Sharpe ratios for each portfolio. Table 9 in the Appendix presents annualized Sharpe ratios across quintile portfolios sorted on Dur and the three measures for carbon risk. I use the 1-month treasury bill rate as proxy for the risk free rate. The resulting picture is very similar to that of average returns. Panel A suggests that, in the full sample, Sharpe ratios are increasing with cash flow duration and decreasing with exposure to carbon emissions. However, the differences across portfolio quintiles are modest and Sharpe ratios of the HML portfolios are small in magnitude. In contrast, Panel B shows that before 2008, Sharpe ratios are decreasing with duration and increasing with emissions, diluting the effect of the full sample. Sharpe ratios of the HML portfolios are now large. Post 2008, this effect again reverses as shown in Panel C. The HML portfolios exhibit Sharpe ratios that are large in magnitude but with opposite signs than before 2008.

Next, I test whether these patterns can be explained by traditional equity risk factors. Therefore, I regress monthly portfolio level excess returns on various portfolios mimicking these risk factors:

$$r_{i,t} - r_{f,t} = \alpha_i + \sum_k \beta_{i,k} F_{i,k,t} \epsilon_{it}, \tag{9}$$

where $r_{i,t}$ is the monthly return of portfolio i at time t, $r_{f,t}$ is the monthly 1-month treasury bill rate, α_i quantifies the pricing error according to the asset pricing model, $F_{i,k,t}$ is the factor-mimicking portfolio and $\beta_{i,k}$ is the loading on corresponding risk factor k.

I first consider the Capital Asset Pricing Model (CAPM) (**Lintner1965**; **Sharpe1964**). Table 4 reports estimates of α_i for the quintile and HML portfolios sorted on Dur, TCE, ICE, and FCE. Over the full sample (Panel A), all portfolios appear correctly priced by the CAPM. Even though pricing errors increase in duration and decrease with all measures of carbon emissions, they are small in size and insignificant. However, it seems again that the results over the full sample are diluted by two opposing effects

Table 3: Time series average annual return of in quintiles sorted portfolios in percent. In parenthesis, I report t-statistics based on **Newey1987** corrected standard errors. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. HML is the high-minus-low quintile portfolio. Returns are equally weighted and include delisting returns. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	Low	2	3	4	High	HML
Panel A: Jul2003 - Dec2020						
Dur	13.16**	13.60**	15.00***	14.38***	16.62***	3.45
	(2.12)	(2.50)	(3.09)	(2.95)	(3.08)	(0.98)
TCE	17.87***	15.73***	13.99**	12.84**	12.50**	-5.37
	(3.31)	(3.04)	(2.42)	(2.46)	(2.27)	(-1.47)
ICE	16.18***	14.66***	13.87***	14.30***	13.90*	-2.28
	(3.27)	(2.87)	(2.97)	(2.67)	(1.92)	(-0.57)
FCE	15.69***	14.89***	13.97***	13.38**	15.10**	-0.59
	(3.34)	(3.26)	(2.88)	(2.30)	(2.06)	(-0.19)
Panel B: Jul2003 - Jun2008						
Dur	17.78***	13.97***	14.33***	12.00***	11.86**	-5.92*
	(3.28)	(2.99)	(3.40)	(2.65)	(2.48)	(-1.65)
TCE	10.65*	12.44**	10.89**	14.52***	21.45***	10.79**
	(1.75)	(2.31)	(2.42)	(3.97)	(5.02)	(2.50)
ICE	10.17*	9.67*	9.77**	13.09***	27.25***	17.08***
	(1.91)	(1.69)	(2.11)	(3.48)	(5.51)	(3.69)
FCE	8.67*	9.51**	11.49**	15.01***	25.48***	16.81***
	(1.66)	(2.03)	(2.46)	(3.43)	(5.09)	(4.22)
Panel C: Jul2008 - Dec2020						
Dur	9.82	12.30*	14.05**	14.17**	17.38**	7.56*
	(1.26)	(1.73)	(2.21)	(2.24)	(2.42)	(1.74)
TCE	19.60***	15.80**	14.19*	10.94	7.49	-12.11***
	(2.87)	(2.42)	(1.86)	(1.60)	(1.05)	(-3.13)
ICE	17.42***	15.58**	14.48**	13.56*	7.16	-10.25**
	(2.81)	(2.43)	(2.44)	(1.91)	(0.68)	(-2.32)
FCE	17.51***	15.94***	13.87**	11.49	9.37	-8.14
	(2.96)	(2.76)	(2.23)	(1.50)	(0.93)	(-1.62)

before and after 2008.[19] Panel B reports alphas of the early sample period. Until June 2008, monthly pricing errors of low duration stocks are large and significant and decrease with years duration. The HML duration portfolio exhibits significant abnormal returns of -0.5% per month. Abnormal returns of the low emission portfolios, on the other hand, are all insignificant, but increase with the level, intensity, and footprint of carbon emissions. The high emission portfolios exhibit large and highly significant positive alphas, leading to sizable emission premiums ranging from 1.1% (TCE) to 1.6% (ICE) per month. Post 2008, this pattern again reverses. Panel C shows that CAPM alphas now increase with duration and decrease with ranks of the carbon emission portfolios. With 0.7%, the monthly pricing error on the HML duration portfolio is now significantly positive and large. Also the premium on emission sorted portfolios switched sign and are now all negative and large in absolute terms, ranging from -1.0% (TCE) to -1.2% (ICE) per month.

Interestingly, alphas of low emission quintiles are not substantially different to the alphas observed before 2008. It is the alphas on large emission stocks, however, that switched sign for all three measures of carbon emissions. Compared to the pre-2008 sample, abnormal returns for high emission stocks have not only switched signs but decreased by more than 2% per month. Thus, instead of an out-performance of environmentally friendly stocks along the line of **In2019**; **Pastor2020**; **Pastor2021**; **VanderBeck2021**, it is the relative under-performance of high emissions stocks driving the change in HML carbon portfolios after 2008. Also for duration sorted portfolios, most of the change between sub-samples comes from low duration stocks. This is not very surprising, however, as on average low duration stocks are also stocks with high carbon emissions.

Next, I explore whether other well-known risk factors can explain the differences in returns. I consider the **Fama1993** 3-factor model ($FF3$), the the Fama-French 3-factor model augmented with the **Carhart1997** momentum factor ($FF4$), and the **Fama2015** 5-factor model ($FF5$). Tables 10, 11, 12 in the Appendix report monthly $FF3$, $FF4$, and $FF5$ pricing errors, respectively. Again, all tables show results of the full sample (Panel A) and of the two sub-samples (Panel B and C) where I split the time series at June 2008.

None of the thee factor models can explain the observed return patterns.

[19] Whether the break-point is December 2007, June 2008, or January 2009 does not substantially affect the results.

Table 4: Monthly CAPM pricing errors of in quintiles sorted portfolios in percent. OLS t-statistics are in parenthesis. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. HML is the high-minus-low quintile portfolio. Returns are equally weighted and include delisting returns. The market excess returns are retrieved from Kenneth French's website. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	Low	2	3	4	High	HML
Panel A: Jul2003 - Dec2020						
Dur	-0.25	-0.13	0.06	0.02	0.11	0.36
	(-1.14)	(-0.88)	(0.52)	(0.20)	(0.68)	(1.62)
TCE	0.19	0.08	-0.13	-0.15	-0.19	-0.38
	(1.14)	(0.59)	(-0.89)	(-1.10)	(-0.94)	(-1.59)
ICE	0.13	0.01	-0.01	-0.06	-0.27	-0.41
	(1.11)	(0.06)	(-0.07)	(-0.45)	(-0.89)	(-1.35)
FCE	0.15	0.10	-0.01	-0.20	-0.23	-0.38
	(1.02)	(1.03)	(-0.09)	(-1.15)	(-0.83)	(-1.25)
Panel B: Jul2003 - Jun2008						
Dur	0.79***	0.51***	0.56***	0.34**	0.33	-0.45*
	(3.63)	(2.87)	(3.30)	(2.10)	(1.62)	(-1.67)
TCE	0.11	0.33**	0.24	0.64***	1.22***	1.11***
	(0.40)	(2.07)	(1.41)	(5.59)	(3.67)	(2.72)
ICE	0.11	0.03	0.16	0.50***	1.70***	1.59***
	(0.57)	(0.17)	(1.11)	(4.33)	(3.61)	(3.35)
FCE	-0.02	0.11	0.31**	0.64***	1.50***	1.52***
	(-0.08)	(0.98)	(2.06)	(3.37)	(3.75)	(3.38)
Panel C: Jul2008 - Dec2020						
Dur	-0.67**	-0.39**	-0.15	-0.11	0.02	0.69**
	(-2.29)	(-2.01)	(-1.03)	(-0.88)	(0.08)	(2.39)
TCE	0.22	-0.03	-0.27	-0.47**	-0.76***	-0.98***
	(1.04)	(-0.15)	(-1.44)	(-2.56)	(-3.34)	(-3.55)
ICE	0.14	-0.01	-0.07	-0.28	-1.08***	-1.22***
	(0.93)	(-0.08)	(-0.50)	(-1.50)	(-2.93)	(-3.43)
FCE	0.20	0.09	-0.14	-0.53**	-0.93***	-1.14***
	(1.15)	(0.73)	(-0.94)	(-2.39)	(-2.77)	(-3.14)

Over the full sample, abnormal portfolio returns appear largely absent as most alphas are insignificant. However, when I split the sample, the opposing effects persist. With the exception of pre-2008 TCE in the $FF5$-model, all HML emission portfolios remain significant and switch sign after 2008. The magnitude of the emission premium is still big, with HML emission alphas largely above 1% before 2008 and close to -1% after 2008. The difference between duration sorted portfolios becomes substantially smaller, as the effect is largely absorbed by the value factor. Only the $FF5$ HML duration portfolio remains significant. Nonetheless, low duration stocks still exhibit significant mispricing across all factor models, with monthly abnormal returns of about 0.6% before and -0.5% after 2008.

Overall, results of the early sample until 2008 are consistent with the study of **Bolton2021** and the hypothesis that abnormal returns for high emission stocks compensates investors for transitional climate risk. In addition, average returns, Sharpe ratios and factor alphas decrease with cash flow duration similiar to **VanBinsbergen2012**; **VanBinsbergen2017**; **Weber2018**. However, this changes from 2008. Average returns, Sharpe ratios and factor alphas decrease with measures of carbon risk and increase with years of cash flow duration.

4.2 Disentangling Return Premiums

Given that the duration of firm-level cash flows and carbon emissions are related and the correlation between portfolios sorted on duration and measures of carbon risk is large, either duration, carbon emissions or a common factor of both may be driving the returns. Indeed, **Goncalves2021**; **Gormsen2021b**; **Chen2018** argue that the duration premium subsumes major equity risk factors and thereby cash flow duration is a main driver of cross-sectional returns. In addition, **Gormsen2021a** studies the time variation of the equity term structure and finds that it is downward sloping in good times but upward sloping in bad times. Hence long duration firms may have outperformed in the aftermath of the financial crisis in 2008 because their long-term cash flows yielded relatively higher returns. As, on average, short duration firms exhibit high carbon emissions and vice versa, the change in duration premium might be an explanation for the underperformance of high carbon emission stocks after 2008.

An alternative explanation could be that unexpected changes in investors' preferences for carbon emissions of their stock holdings lead to demand-induced price pressure on these stocks and subsequent higher realized returns. In an equilibrium model, **Pastor2020** show that green assets have lower expected returns than their brown counterpart, but unexpected shocks to investors' tastes for green stocks can temporarily result in higher realized returns for these stocks.[20]

4.2.1 Neutralizing Duration and Emission Effects

Next, I disentangle the duration and carbon emission effects on returns and test to which extent it is carbon emissions or cash flow duration that affect the return variation of the univariately sorted portfolios. Therefore, I double-sort stocks into portfolios based on both Dur and one of the carbon emission variables TCE, ICE, FCE. This approach allows me to study the variation effect across one sorting variable while keeping the characteristics of the second variable constant.

As duration and carbon emission variables are negatively related, I expect fewer firms in the high (low) emission and high (low) duration portfolios. To reduce idiosyncratic risk in the double sorted portfolios, I intersect firms at tertile (instead of quintile) breakpoints and form 3x3 portfolios.[21] Thus, the (1,1) portfolio includes firms of the lowest duration tertile that are also firms in the lowest tertile of carbon emissions. Likewise, the (1,3) portfolio comprises firm in the lowest duration tertile that are also in the upper emission tertile.

As with the univariate portfolio sorts, the bivariately sorted portfolios are rebalanced at the end of June every calender year t based on the realization of the two sorting variables in the fiscal year that ends in $t-1$. HML is the portfolio that goes long the highest tertile portfolio and short the lowest tertile portfolio for each sorting variable. As the HML portfolios comprise the return premiums of one sorting variable while controlling for the other, I expect the returns of HML duration portfolios to be significant if the return

[20] In a follow up study, **Pastor2021** empirically show that green stocks are outperforming brown stocks. They also show that this outperformance disappears when they control for unanticipated changes in climate related news. In a similar study on ESG funds, **VanderBeck2021** shows that the reallocation of funds from the market portfolio towards a portfolio capturing ESG preferences can increase the price of ESG stocks by a factor of 2.5. However, both empirical studies do not capture the change in sign of realized returns that might be caused by changes in investors' preferences as their samples start in late 2012 and 2010, respectively.

[21] The time-series average number of firms in the $(1_{Dur}, 1_{TCE})$ and $(3_{Dur}, 3_{TCE})$ portfolios is 67 and 61, respectively, while the $(1_{Dur}, 3_{TCE})$ and $(3_{Dur}, 1_{TCE})$ portfolios include 162 and 170 firms.

pattern of the univariate portfolio sorts is driven by duration. Similarly, if emissions are the source of return variation potentially as a result of a shift in investor preferences, the HML emission portfolio returns may be significantly different from zero. A third possibility could be that a third common factor affects both carbon emission and duration portfolios, then both HML portfolios may exhibit similar patterns.

As there are opposing effects across the full sample that may dilute the results, I again split the time-series into two subsamples. The first column in Table 5 shows monthly CAPM alphas of double sorted portfolios from July 2003 until June 2008 and the second column shows the same for the period from July 2008 until 2020.[22]

Even though most emission-neutral duration premiums appear to be negative during the early sample period, none of the HML duration portfolios shows significant CAPM alphas. In contrast, HML emission returns are all positive and highly significant. With one exception, duration-neutral abnormal returns increase with emissions across all tertile portfolios and measures of carbon risk. For ICE and FCE sorted portfolios the differences in CAPM alphas is above 1% per month, while TCE sorted HML alphas are substantially smaller. This is interesting, as even before 2008, when carbon risks have arguably been less prominent, carbon emissions have been a greater source of return variation. Thus, the annual duration-neutral emission premium, that is the average monthly pricing error of the HML emission portfolios across duration sorts, is 0.71% (TCE), 1.18% (ICE), and 1.21% (FCE) before 2008. At the same time, the duration effect, calculated as the mean of average HML duration returns over emission sorts across sorting variables, is only -0.13%.

Also in the more recent period (see second column in Table 5), the CAPM alphas on HML duration portfolios are small and largely insignificant. On the other hand, duration-neutral carbon risk premiums appear to be large and significantly negative across all HML emission portfolios. On average and neutral of the duration effect, low emission stocks pay 0.65% (TCE), 0.80% (ICE), and 0.86% (FCE) higher abnormal returns than low emission stocks after 2008. With 0.32%, the average post-2008 duration effect is much smaller. Hence, similar to the period before 2008, returns seem to be driven by carbon emissions rather than duration.

[22]Over the full sample, untabulated results reveal small and insignificant CAPM alphas across all portfolios.

Table 5: Monthly CAPM pricing errors of 3x3 double sorted portfolios in percent. In parenthesis, I report t-statistics based on **Newey1987** corrected standard errors. At the end of June in each calendar year t, I sort stocks into 3x3 tertile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are bivariately sorted on both Dur and one of TCE (Panel A), ICE (Panel B), or FCE (Panel C). HML is the corresponding high-minus-low tertile portfolio. Returns are equally weighted and include delisting returns. The first column includes the early sample (July 2003 - June 2008), and the second columns includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

Sample Period: Jul2003 - Jun2008

Dur	Low	Mid	High	HML
Panel A: TCE, Dur				
TCE				
Low	0.75***	0.26	0.39*	-0.36
	(3.72)	(1.35)	(1.82)	(-1.38)
Mid	0.58**	0.58***	0.68***	0.10
	(2.01)	(4.70)	(4.26)	(0.28)
High	1.28***	1.25***	1.02***	-0.26
	(8.52)	(5.79)	(3.39)	(-1.05)
HML	0.53**	0.99***	0.64**	
	(2.47)	(4.14)	(2.18)	
Panel B: ICE, Dur				
ICE				
Low	0.50**	0.30*	0.09	-0.41
	(2.36)	(1.95)	(0.38)	(-1.15)
Mid	0.56***	0.38**	0.52***	-0.05
	(3.25)	(2.54)	(2.93)	(-0.21)
High	1.66***	1.43***	1.36***	-0.29
	(6.23)	(5.91)	(4.18)	(-0.94)
HML	1.15***	1.14***	1.27***	
	(3.37)	(4.49)	(3.77)	
Panel C: FCE, Dur				
FCE				
Low	0.34	0.20	0.25	-0.09
	(1.63)	(1.18)	(1.19)	(-0.32)
Mid	0.56***	0.53***	0.61***	0.05
	(3.12)	(3.37)	(5.38)	(0.23)
High	1.45***	1.41***	1.57***	0.13
	(6.32)	(5.44)	(3.69)	(0.33)
HML	1.11***	1.22***	1.32***	
	(4.60)	(4.40)	(3.42)	

Sample Period: Jul2008 - Dec2020

Dur	Low	Mid	High	HML
Panel A: TCE, Dur				
TCE				
Low	-0.14	0.25	0.18	0.32
	(-0.49)	(1.59)	(0.73)	(1.18)
Mid	-0.47	-0.10	-0.03	0.43*
	(-1.60)	(-0.50)	(-0.18)	(1.89)
High	-0.83***	-0.39**	-0.45**	0.38
	(-2.93)	(-2.21)	(-2.10)	(1.54)
HML	-0.69***	-0.64***	-0.62**	
	(-2.90)	(-4.20)	(-2.23)	
Panel B: ICE, Dur				
ICE				
Low	-0.10	0.13	0.22	0.32
	(-0.43)	(0.95)	(1.17)	(1.24)
Mid	-0.23	0.09	0.10	0.33
	(-1.13)	(0.60)	(0.56)	(1.60)
High	-1.10***	-0.52**	-0.53*	0.57**
	(-3.04)	(-1.98)	(-1.79)	(2.40)
HML	-1.00***	-0.65***	-0.75***	
	(-3.46)	(-3.21)	(-3.06)	
Panel C: FCE, Dur				
FCE				
Low	-0.14	0.20	0.24	0.39*
	(-0.91)	(1.50)	(1.21)	(1.80)
Mid	-0.21	-0.01	-0.00	0.20
	(-1.01)	(-0.05)	(-0.03)	(1.07)
High	-0.88**	-0.47*	-0.95***	-0.07
	(-2.55)	(-1.79)	(-2.67)	(-0.37)
HML	-0.74**	-0.66***	-1.19***	
	(-2.46)	(-2.90)	(-3.39)	

Most of the observed return pattern in the univariate portfolio sorts appear to be driven by carbon emissions rather than cash flow duration. This is evidence against previous findings of duration-driven returns and the hypothesis that a flip in the term premium post 2008 is the source of large returns on low emission stocks. On the other hand, the change in the sign of the carbon emission premium is in line with the hypothesis of a change in investors' preferences for carbon emissions of their stock holdings. After 2008, demand-induced price pressure seems to lead to larger realized returns of emission friendly stocks. As high emission stocks are on average low duration stocks and vice versa, changes in climate concerns may also affect the equity term premium.

4.2.2 Climate Concerns as Performance Driver

As **Ardia2020** and **Pastor2020**; **Pastor2021** argue, unexpected changes to investors´ or customers´ climate concerns may push prices of green stocks upwards relative to brown stocks and thereby lead to temporary higher realized returns.

Next, I study whether unanticipated shocks to the perception of climate change drive the high realized returns of low emission and short duration stocks in the period after 2008. **Ardia2020** create an index of media climate change concerns (MCCC) based on textual analysis of news coverage in major US media outlets. A similar index is provided by **Engle2020**, however, I prefer the index of **Ardia2020** to measure climate change perception as it is based on 12 media outlets, as opposed to one in **Engle2020** and entails more recent data.

I use the MCCC to construct a measure of shocks to the perception of climate change risks. In particular, $MCCC_t$ in month t denotes the aggregate index of the updated 2022 version of **Ardia2020**.[23] Similar to **Pastor2021**, I assume the presence of climate news to decay slowly over time and model unexpected climate news ζ as the residual between realized news and a weighted moving average of past climate shocks:

$$\zeta_t = MCCC_t - (1-\lambda)\sum_{\tau=1}^{T} MCCC_{t-\tau}\lambda^{\tau-1} - \lambda^T MCCC_{t-1-T} \qquad (10)$$

where $\lambda \in (0,1)$ captures the persistence of news in investors' climate risk perceptions. I use a rolling window of $T = 36$ months and set $\lambda = 0.95$ such

[23] Data is available at https://sentometrics-research.com/download/mccc/.

that the most recent year of climate news receives a total weight of 50%.[24]

To measure the effect of unexpected climate news on stock returns in the more recent sample period (July 2008 - June 2018), I regress emission and duration sorted portfolios on my proxy of unanticipated shocks to climate concerns ζ.[25]

Table 14 in the Appendix reports the regression results for long-minus-short duration and the three brown-minus-green portfolios as well as their respective long-short legs. In accordance with results in **Pastor2021**, none of the portfolios loads on contemporaneous climate news shocks. Instead, I also included climate shocks lagged by one month. With past month's shocks, each of the three high emission portfolios as well as the short duration portfolio exhibit significant negative coefficients. T-statistics of high emission portfolios range from -1.9 (TCE) to -2.3 (FCE) and are about a factor of two larger than their low emission counterparts. The same is true for the short duration portfolio (t-statistics of -2.4) relative to the long duration portfolio (t-statistics of -1.1). Hence, with the exception of TCE-sorts, the lagged climate concern shocks load significantly negative on HML emission portfolios and significantly positive on the HML duration portfolio.

It appears, unexpected shocks to climate concerns, albeit with a one month lag, explain about 10% of the high emission portfolios' variance sorted on ICE or FCE. With 6%, the TCE-sorted portfolio's R^2 is substantially smaller.[26] Hence, unlike in **Ardia2020** but similar to **Pastor2021**, changes in climate concerns negatively affect stock returns of high emission firms but do not increase those of low carbon firms. Even more interesting, also duration sorted portfolios respond to shifts in climate concerns. With 10%, shocks to climate news explain a substantial part of the short duration portfolio's variance.

Next, I construct counterfactual portfolios for which I eliminate the effect of climate concern shocks. I compute climate-shock neutral returns as the realized returns of the original portfolios in excess of the product of their estimated coefficients from Table 14 and their respective time series of re-

[24] All results are similar for similar values of λ and T which are in turn similar in **Pastor2021** and **Ardia2020**.

[25] As I use a 3-year window to estimate ζ and the MMMC index is only available from 2003, I cannot compare results to the earlier sample period.

[26] With 17% and a similar measure of shocks to climate concerns, **Pastor2021** find a larger portion of a green factor can be explained. However, they use a different sample period and proxy for greenness. **Ardia2020** do not report such a measure.

gressors derived in Equation (10). This allows me to study how stocks would have performed in absence of unexpected changes in climate news.

In Table 15 in the Appendix, I report monthly CAPM pricing errors for counterfactual portfolio returns where climate news shocks are set to zero. For comparison, I additionally add realized CAPM alphas for the same portfolios. As the climate news index is only available until June 2018, I also shorten the time series of realized returns. Therefore, the CAPM alphas of realized returns differ slightly from returns reported in Table 4, Panel C.

Controlling for changes in climate concerns, the underperformance of high emission stocks post 2008 vanishes. This is similar to results in**Pastor2021** and **Ardia2020**. However, the same is also true for short duration stocks. The realized CAPM alpha for low duration stocks is significantly negative at -74bps and increases with duration to -18bps, indistinguishable from zero. After controlling for climate shocks, the effect on low duration stocks decreases by half and all duration portfolios become insignificant. Also for high emission stocks the magnitude of CAPM alphas shrink approximately to half.

Curiously, alphas of low emission and high duration stocks increase slightly when climate concern shocks are set to zero. This comes mechanically from an insignificant but negative (positive) loading of low emission (long duration) stocks on the climate news shocks. However, the effect is small, such that large and significant realized CAPM alphas on both HML emission and HML duration portfolios become substantially smaller and insignificant when correcting for changes climate concerns.

Hence, it appears that not only large parts of the higher returns of low emission stocks, relative to high emission stocks, are driven by unanticipated shocks to climate concerns. They also explain a substantial amount of the relative underperformance of short duration firms post 2008.

4.3 Duration and Emissions as Risk Factors

Motivated by the explanatory properties of duration and environmental concerns found in previous literature, I create alternative 2-factor models in the spirit of **Pastor2021**. The first factor is the excess return on the market portfolio and the respective second factor is one of the equally weighted HML quintile portfolios sorted either on duration or one of the emission measures TCE, ICE, FCE.

The market factor augmented with the duration premium cannot explain the return differences on emission sorted portfolios. Table 16 in the Appendix reports monthly alphas of the 2-factor model on the univariate portfolio sorts. While, relative to the CAPM, the magnitude of pricing errors somewhat decreased, all HML duration sorted portfolio returns are still large, significant and switch sign after 2008.

With the emission sorted factors, in addition to the market factor, however, most of the return differences become insignificant. Tables 17, 18, and 19 in the Appendix report alphas corresponding to the factor models that extend the CAPM with a TCE, ICE, and FCE factor, respectively. The emission factors appear to explain in particular the more recent returns (Panels C) well. While before 2008 (Panels B), some of the abnormal returns for high emission and low duration firms remain, pricing errors are largely absent after 2008. Among the emission factors, ICE performs best in explaining the differences in emission and duration sorted portfolio returns.

I am also interested if the 2-factor models can explain known equity risk factors. **Pastor2021** report that the CAPM augmented with their green-minus-brown factor explains the value (SMB) and momentum (UMD) factors. Table 20 in the Appendix presents intercepts of the CAPM and 2-factor models for the portfolios mimicking the size (SMB), value (SMB), profitability (RMW), investments (CMA), and momentum (UMD) risk factors. It appears both duration and emission factors can explain the recent underperformance of the value factor. While the CAPM pricing error is close to -0.4% over the full sample (Panel A) and -0.6% over the recent sample period from June 2008 (Panel C), the intercept becomes insignificant by adding either the HML duration portfolio or one of the HML emission portfolios as a second factor. In the early subsample (Panel B), the three emission factors help the explain investment and momentum factors, where FCE and ICE perform best, respectively. However, this is not true for the more recent subsample (Panel C). Besides value, Dur does not help to explain any other risk factor.

5 Conclusion

I construct a measure of cash flow duration at the firm level based on financial statement data and market prices. With traded dividend strips, **VanBinsbergen2012**; **VanBinsbergen2017**; **Gormsen2021b** use a more clean measure of cash flow duration. My approach, however, allows me to study cash flows in a larger cross-section, a longer time-series, and, with more than 30 years of duration, a larger set of maturities. In addition, I can link my measure of cash flow duration on the firm level to carbon emission data of the same firm.

I find that high duration firms emit less CO2. In line with investors' increased awareness of climate transition risk, this relation becomes stronger over time and holds for the level, intensity, and footprint of carbon emissions. As a result, duration and emission premiums exhibit large and negative correlation.

I also find evidence for changes in investors' taste for carbon emissions in their stock holdings after 2008. Until 2008, risk-adjusted returns increase with carbon risk and decrease with cash flow duration. This is consistent with a positive risk premium on carbon emissions that proxies for transition risk (**Bolton2021**) and with high emission firms being located at the short end of a downward sloping term structure of equity (**VanBinsbergen2012**; **VanBinsbergen2017**; **Weber2018**). After 2008, this pattern reverses. High emission and low duration stocks underperform. The negative premium on carbon emissions is in line with an outperformance of 'green' stocks (**In2019**) and demand driven returns (**Pastor2021**; **VanderBeck2021**).

Differences in returns are small and largely insignificant for the full sample, but high and mostly significant if I split the time-series at the point of perceived change in preference. This structural change might explain and help to interpret divergent results of previous literature on the carbon premium of equity. My study is the first to empirically acknowledge and measure this structural break which further studies may find helpful to consider.

I further explore the nature of the large correlation between the equity term premium and the carbon risk premium. Rather than duration, I find carbon emissions to be the predominant source of return variation. This is inconsistent with previous literature (**Gormsen2021b**) and suggests the change in preference for low carbon stocks may help to explain the recent underperformance of value firms.

6 Robustness

- Rank correlations/regressions value weighted returns include utility different sic levels include industry fixed effects in ff3 regressions check results for large sample of duration

With the inclusion of more firms in the sample (likely included firms are increasingly smaller), the size effect would lead to higher returns over time. Control for SMB in FF3 regression.

Correlation of full sample 1964-2004 is 99 percent across all 10 portfolios (with exception of portfolio 1 (98 percent))

Appendix

Table 6: Summary statistics.This table reports the number of observations and cross-sectional median values of all variables per year from 2002 until 2019. Variables are defined in Table 1.

Year	Obs	Duration	TCE	log(TCE)	log(ICE)	log(FCE)	log(Size)	log(Sales)	B/M	ROE	Sales Growth
2002	402	20.41	0.36	12.79	3.98	3.88	8.70	8.55	0.41	0.13	0.05
2003	411	20.89	0.32	12.69	3.79	3.62	8.95	8.68	0.33	0.15	0.11
2004	574	20.91	0.37	12.82	3.95	3.77	8.84	8.51	0.34	0.17	0.13
2005	654	20.97	0.38	12.86	3.92	3.74	9.06	8.63	0.32	0.18	0.10
2006	643	20.87	0.37	12.82	3.75	3.63	9.18	8.74	0.32	0.18	0.12
2007	634	20.75	0.38	12.85	3.75	3.62	9.16	8.77	0.33	0.18	0.10
2008	783	19.00	0.30	12.62	3.80	4.21	8.32	8.54	0.58	0.14	0.08
2009	869	19.88	0.24	12.37	3.83	3.81	8.49	8.26	0.43	0.12	-0.06
2010	907	20.47	0.23	12.36	3.80	3.58	8.70	8.31	0.40	0.15	0.12
2011	909	20.02	0.23	12.33	3.69	3.69	8.56	8.37	0.43	0.15	0.11
2012	908	20.06	0.23	12.33	3.68	3.64	8.72	8.40	0.42	0.14	0.04
2013	914	20.70	0.24	12.37	3.67	3.46	8.95	8.45	0.36	0.14	0.03
2014	913	20.98	0.24	12.40	3.69	3.41	9.03	8.48	0.34	0.13	0.04
2015	1291	20.91	0.14	11.84	3.62	3.37	8.33	8.01	0.35	0.11	0.01
2016	1721	21.03	0.07	11.19	3.51	3.15	7.91	7.51	0.35	0.10	0.03
2017	1988	21.14	0.05	10.82	3.43	2.97	7.75	7.28	0.35	0.10	0.08
2018	2085	20.50	0.04	10.70	3.36	3.05	7.53	7.29	0.42	0.09	0.09
2019	2241	20.84	0.04	10.52	3.26	2.89	7.56	7.15	0.39	0.07	0.04

Table 7: Summary statistics. Cross-sectional Pearson correlation coefficients between variables. The sample period is from 2002 until 2019. All variables are defined in Table 1

	Duration	TCE	log(TCE)	log(ICE)	log(FCE)	log(Size)	log(Sales)	B/M	ROE	Sales Growth
Duration	1.00	-0.26	-0.36	-0.21	-0.45	0.00	-0.30	-0.75	-0.14	0.24
TCE		1.00	0.36	0.27	0.30	0.19	0.25	0.09	0.03	-0.01
log(TCE)			1.00	0.63	0.78	0.60	0.78	0.16	0.31	-0.16
log(ICE)				1.00	0.79	-0.00	0.00	0.23	-0.03	-0.04
log(FCE)					1.00	-0.03	0.37	0.44	0.09	-0.16
log(Size)						1.00	0.78	-0.32	0.39	-0.05
log(Sales)							1.00	0.01	0.43	-0.17
B/M								1.00	-0.17	-0.10
ROE									1.00	-0.10
Sales Growth										1.00

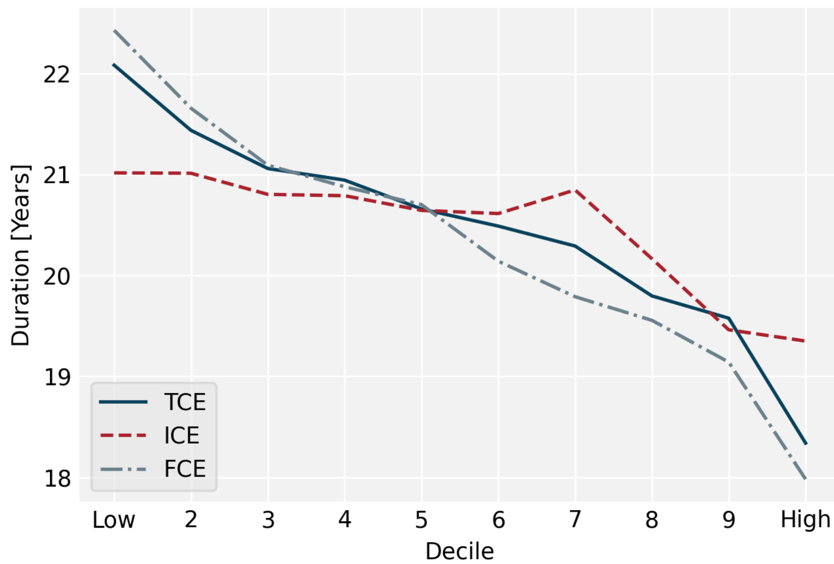
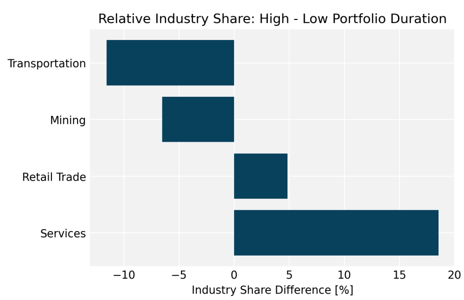
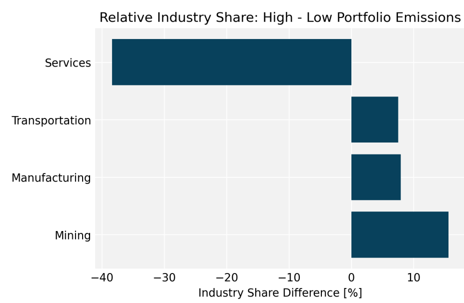


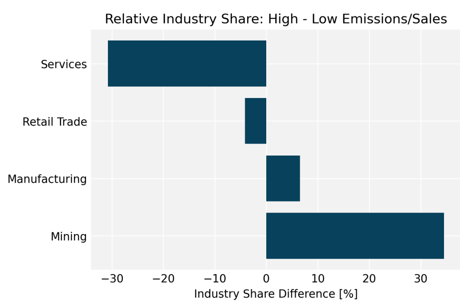
Figure 4: Time-series average median duration of decile portfolios sorted either on TCE (blue line), ICE (red dashed line), and FCE (grey dash-dot line). Portfolios are rebalanced every year t based on the realization of the sorting variable of the fiscal year ending in the same year.



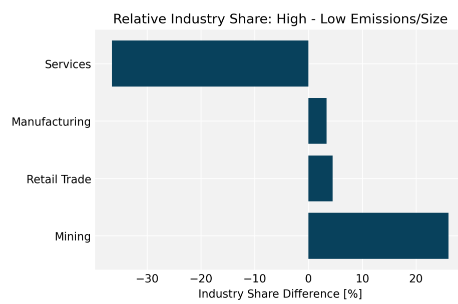
(a)



(b)



(c)



(d)

Figure 5: Value weighted share of industry in the highest quintile minus that in the lowest quintile Sorting variables are Duration (a), TCE (b), ICE (c), and FCE (d). Industries are classified at the 1-digit SIC division level.

Table 8: Pearson correlation coefficients of monthly returns of high-minus-low (HML) quintile portfolios. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. Returns are equally weighted and include delisting returns. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020).

	Dur_{HML}	TCE_{HML}	ICE_{HML}	FCE_{HML}
Panel A: Jul2003 - Dec2020				
Dur_{HML}	1.00	-0.68	-0.62	-0.81
TCE_{HML}		1.00	0.75	0.81
ICE_{HML}			1.00	0.88
FCE_{HML}				1.00
Panel B: Jul2003 - Jun2008				
Dur_{HML}	1.00	-0.47	-0.27	-0.54
TCE_{HML}		1.00	0.81	0.90
ICE_{HML}			1.00	0.88
FCE_{HML}				1.00
Panel C: Jul2008 - Dec2020				
Dur_{HML}	1.00	-0.74	-0.68	-0.86
TCE_{HML}		1.00	0.72	0.78
ICE_{HML}			1.00	0.88
FCE_{HML}				1.00

Table 9: Annualized Sharpe ratios of in quintiles sorted portfolios. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. HML is the high-minus-low quintile portfolio. Returns are equally weighted and include delisting returns. I use the one-month treasury bill rate as measure of the risk free rate. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020).

	Low	2	3	4	High	HML
Panel A: Jul2003 - Dec2020						
Dur	0.51	0.60	0.73	0.73	0.77	0.31
TCE	0.81	0.75	0.62	0.58	0.53	-0.45
ICE	0.79	0.70	0.68	0.65	0.48	-0.15
FCE	0.78	0.79	0.69	0.56	0.52	-0.04
Panel B: Jul2003 - Jun2008						
Dur	1.18	0.93	0.99	0.80	0.73	-0.83
TCE	0.52	0.81	0.71	1.22	1.39	0.94
ICE	0.57	0.50	0.65	1.06	1.49	1.35
FCE	0.43	0.61	0.80	1.09	1.45	1.41
Panel C: Jul2008 - Dec2020						
Dur	0.35	0.50	0.64	0.68	0.75	0.61
TCE	0.85	0.70	0.59	0.46	0.30	-1.05
ICE	0.82	0.73	0.67	0.57	0.23	-0.66
TCE/Size	0.84	0.80	0.64	0.45	0.30	-0.49

Table 10: Monthly **Fama1993** 3-factor model ($FF3$) pricing errors in percent. OLS t-statistics are in parenthesis. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. HML is the high-minus-low quintile portfolio. Returns are equally weighted and include delisting returns. The market excess returns as well as size, and value factors are retrieved from Kenneth French´s website. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	Low	2	3	4	High	HML
Panel A: Jul2003 - Dec2020						
Dur	-0.08	-0.03	0.12	0.00	0.01	0.09
	(-0.39)	(-0.21)	(1.22)	(0.00)	(0.11)	(0.51)
TCE	0.12	0.13	-0.06	-0.06	-0.09	-0.21
	(0.94)	(1.25)	(-0.49)	(-0.49)	(-0.48)	(-1.00)
ICE	0.12	0.03	0.03	-0.00	-0.15	-0.27
	(1.22)	(0.31)	(0.30)	(-0.01)	(-0.51)	(-0.92)
FCE	0.04	0.09	0.05	-0.08	-0.06	-0.10
	(0.36)	(1.09)	(0.50)	(-0.54)	(-0.23)	(-0.37)
Panel B: Jul2003 - Jun2008						
Dur	0.67***	0.45***	0.54***	0.38**	0.37**	-0.30
	(3.63)	(2.89)	(3.34)	(2.57)	(2.19)	(-1.37)
TCE	0.13	0.28**	0.19	0.62***	1.18***	1.05**
	(0.57)	(2.00)	(1.31)	(5.43)	(3.55)	(2.58)
ICE	0.08	-0.01	0.15	0.52***	1.63***	1.55***
	(0.47)	(-0.03)	(1.06)	(4.43)	(3.55)	(3.21)
FCE	0.03	0.13	0.26*	0.59***	1.41***	1.38***
	(0.15)	(1.10)	(1.95)	(3.38)	(3.66)	(3.13)
Panel C: Jul2008 - Dec2020						
Dur	-0.39	-0.21	-0.04	-0.14	-0.14	0.26
	(-1.51)	(-1.33)	(-0.36)	(-1.22)	(-0.88)	(1.10)
TCE	0.12	0.06	-0.17	-0.32*	-0.62***	-0.74***
	(0.76)	(0.48)	(-0.99)	(-1.94)	(-2.78)	(-3.08)
ICE	0.13	0.03	-0.01	-0.18	-0.90**	-1.03***
	(1.02)	(0.32)	(-0.05)	(-1.05)	(-2.50)	(-2.89)
FCE	0.05	0.09	-0.04	-0.34*	-0.67**	-0.72**
	(0.34)	(0.84)	(-0.37)	(-1.77)	(-2.13)	(-2.19)

Table 11: Monthly pricing errors of the Fama-French 3-factor model augmented with the **Carhart1997** momentum factor ($FF4$) in percent. OLS t-statistics are in parenthesis. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. HML is the high-minus-low quintile portfolio. Returns are equally weighted and include delisting returns. The market excess returns as well as size, value, and momentum factors are retrieved from Kenneth French´s website. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	Low	2	3	4	High	HML
Panel A: Jul2003 - Dec2020						
Dur	-0.02	0.01	0.14	0.02	0.04	0.07
	(-0.13)	(0.11)	(1.60)	(0.23)	(0.37)	(0.39)
TCE	0.14	0.16*	-0.02	-0.02	-0.07	-0.21
	(1.11)	(1.84)	(-0.17)	(-0.17)	(-0.36)	(-0.97)
ICE	0.15	0.05	0.06	0.05	-0.11	-0.26
	(1.57)	(0.60)	(0.73)	(0.41)	(-0.38)	(-0.87)
FCE	0.06	0.11	0.08	-0.03	-0.01	-0.07
	(0.57)	(1.42)	(0.96)	(-0.24)	(-0.06)	(-0.28)
Panel B: Jul2003 - Jun2008						
Dur	0.58***	0.46***	0.51***	0.33**	0.31*	-0.26
	(3.06)	(2.79)	(2.99)	(2.18)	(1.79)	(-1.15)
TCE	0.08	0.39***	0.22	0.59***	0.91***	0.83*
	(0.33)	(2.86)	(1.48)	(4.90)	(2.79)	(2.00)
ICE	0.15	0.02	0.25*	0.53***	1.21***	1.06**
	(0.82)	(0.11)	(1.81)	(4.35)	(2.75)	(2.34)
FCE	0.02	0.13	0.36***	0.60***	1.08***	1.06**
	(0.10)	(1.06)	(2.73)	(3.30)	(2.89)	(2.42)
Panel C: Jul2008 - Dec2020						
Dur	-0.45*	-0.25*	-0.07	-0.16	-0.17	0.28
	(-1.95)	(-1.87)	(-0.68)	(-1.57)	(-1.19)	(1.24)
TCE	0.10	0.04	-0.20	-0.36***	-0.66***	-0.76***
	(0.67)	(0.31)	(-1.49)	(-2.75)	(-3.20)	(-3.20)
ICE	0.10	0.01	-0.03	-0.22	-0.96***	-1.06***
	(0.93)	(0.15)	(-0.29)	(-1.61)	(-2.87)	(-3.08)
FCE	0.03	0.07	-0.07	-0.38**	-0.73**	-0.75**
	(0.22)	(0.74)	(-0.69)	(-2.43)	(-2.59)	(-2.41)

Table 12: Monthly **Fama2015** 5-factor model ($FF5$) pricing errors in percent. OLS t-statistics are in parenthesis. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. HML is the high-minus-low quintile portfolio. Returns are equally weighted and include delisting returns. The market excess returns as well as size, value, investment, and profitability factors are retrieved from Kenneth French´s website. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	Low	2	3	4	High	HML
Panel A: Jul2003 - Dec2020						
Dur	-0.19	-0.11	0.07	0.02	0.08	0.27
	(-0.95)	(-0.90)	(0.70)	(0.22)	(0.70)	(1.61)
TCE	0.24*	0.11	-0.12	-0.15	-0.21	-0.44**
	(1.90)	(1.08)	(-0.95)	(-1.15)	(-1.08)	(-2.18)
ICE	0.15	0.07	-0.01	-0.05	-0.29	-0.44
	(1.49)	(0.71)	(-0.10)	(-0.35)	(-0.97)	(-1.48)
FCE	0.19*	0.08	0.01	-0.20	-0.20	-0.38
	(1.83)	(0.92)	(0.08)	(-1.32)	(-0.77)	(-1.47)
Panel B: Jul2003 - Jun2008						
Dur	0.59***	0.37**	0.41**	0.47***	0.45**	-0.14
	(3.01)	(2.23)	(2.44)	(3.09)	(2.50)	(-0.62)
TCE	0.39*	0.30**	0.16	0.56***	0.88***	0.49
	(1.77)	(2.08)	(1.02)	(4.59)	(2.77)	(1.38)
ICE	0.16	0.14	0.24*	0.53***	1.21***	1.04**
	(0.87)	(0.84)	(1.67)	(4.17)	(2.75)	(2.32)
FCE	0.30	0.13	0.31**	0.48**	1.07***	0.77**
	(1.64)	(1.06)	(2.30)	(2.62)	(2.90)	(2.05)
Panel C: Jul2008 - Dec2020						
Dur	-0.50*	-0.29*	-0.07	-0.11	-0.04	0.46**
	(-1.90)	(-1.82)	(-0.57)	(-0.95)	(-0.29)	(2.08)
TCE	0.22	0.06	-0.19	-0.38**	-0.71***	-0.92***
	(1.40)	(0.46)	(-1.16)	(-2.31)	(-3.13)	(-3.98)
ICE	0.16	0.06	-0.04	-0.20	-1.00***	-1.16***
	(1.32)	(0.56)	(-0.33)	(-1.16)	(-2.72)	(-3.24)
FCE	0.19	0.09	-0.08	-0.42**	-0.78**	-0.97***
	(1.56)	(0.82)	(-0.64)	(-2.20)	(-2.47)	(-3.10)

Table 13: Time series average annual return of 3x3 double sorted portfolios in percent. In parenthesis, I report t-statistics based on **Newey1987** corrected standard errors. At the end of June in each calendar year t, I sort stocks into 3x3 tertile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are bivariately sorted on both Dur and one of TCE (Panel A), ICE (Panel B), or FCE (Panel C). HML is the corresponding high-minus-low tertile portfolio. Returns are equally weighted and include delisting returns. The first column includes the early sample (July 2003 - June 2008), and the second columns includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

Sample Period: Jul2003 - Jun2008

Dur	Low	Mid	High	HML
Panel A: TCE, Dur				
TCE				
Low	15.56**	9.44	10.45**	-5.11
	(2.31)	(1.64)	(1.97)	(-1.48)
Mid	12.95**	11.91***	12.13***	-0.82
	(2.12)	(2.71)	(3.17)	(-0.00)
High	19.83***	18.38***	15.91***	-3.92
	(4.48)	(5.13)	(3.65)	(-1.15)
HML	4.27	8.94**	5.46	
	(1.31)	(2.29)	(1.31)	
Panel B: ICE, Dur				
ICE				
Low	11.99**	9.76*	7.42	-4.57
	(1.97)	(1.74)	(1.38)	(-0.96)
Mid	12.43**	9.57**	10.75**	-1.68
	(2.29)	(2.20)	(2.36)	(-0.47)
High	24.53***	20.76***	19.85***	-4.68
	(4.85)	(5.33)	(4.33)	(-1.15)
HML	12.54***	11.00***	12.42**	
	(3.40)	(3.02)	(2.54)	
Panel C: FCE, Dur				
FCE				
Low	9.79*	8.60	8.46*	-1.33
	(1.88)	(1.59)	(1.75)	(-0.35)
Mid	11.96**	11.09**	11.62***	-0.34
	(2.22)	(2.52)	(2.77)	(-0.04)
High	22.47***	20.75***	22.83***	0.36
	(4.22)	(4.94)	(4.42)	(0.24)
HML	12.68***	12.15***	14.36***	
	(4.48)	(3.37)	(3.28)	

Sample Period: Jul2008 - Dec2020

Dur	Low	Mid	High	HML
Panel A: TCE, Dur				
TCE				
Low	15.91**	17.76***	18.21***	2.30
	(1.96)	(2.96)	(2.70)	(0.78)
Mid	13.06	14.78**	15.30**	2.24
	(1.53)	(2.17)	(2.19)	(0.36)
High	6.21	10.51	10.90	4.69
	(0.91)	(1.63)	(1.41)	(1.24)
HML	-9.70***	-7.25***	-7.31**	
	(-2.81)	(-3.69)	(-2.21)	
Panel B: ICE, Dur				
ICE				
Low	14.36**	15.85***	18.00***	3.63
	(2.21)	(2.73)	(2.73)	(0.93)
Mid	13.28*	15.68***	16.65***	3.37
	(1.90)	(2.59)	(2.66)	(1.03)
High	6.17	11.06	11.37	5.20
	(0.64)	(1.39)	(1.35)	(1.42)
HML	-8.19**	-4.80*	-6.63**	
	(-2.10)	(-1.80)	(-2.38)	
Panel C: FCE, Dur				
FCE				
Low	11.85**	16.27***	17.88***	6.03**
	(2.26)	(2.85)	(2.90)	(2.07)
Mid	12.29**	14.50**	15.97**	3.68
	(2.02)	(2.42)	(2.29)	(1.07)
High	9.30	12.04	8.34	-0.97
	(0.94)	(1.53)	(0.80)	(-0.84)
HML	-2.54	-4.22	-9.55**	
	(-0.66)	(-1.30)	(-2.16)	

Table 14: Regression coefficients of duration and emission sorted portfolios on contemporaneous and lagged climate concern measures ζ. In parenthesis, I report t-statistics based on **Newey1987** corrected standard errors. ζ is measured as in Equation (10). At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. High and Low are the respective 5th and 1st quintiles, and HML their difference. Portfolios are sorted either on Dur, TCE, ICE, or FCE as reported in Panels A, B, C, and D, respectively. Returns are equally weighted and include delisting returns. The sample period is from July 2008 until June 2018. Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

Panel A: Duration

Dur	Low	High	HML
ζ_t	-0.00	-0.01	-0.00
	(-0.18)	(-0.30)	(-0.13)
ζ_{t-1}	-0.06**	-0.02	0.04**
	(-2.37)	(-1.11)	(2.06)
R^2(%)	10.0	2.6	9.7

Panel B: CO2 Totals

TCE	Low	High	HML
ζ_t	-0.00	-0.00	-0.00
	(-0.04)	(-0.25)	(-0.32)
ζ_{t-1}	-0.02	-0.04*	-0.02
	(-1.14)	(-1.90)	(-1.59)
R^2(%)	1.9	6.1	4.5

Panel C: CO2 Intensity

ICE	Low	High	HML
ζ_t	-0.00	-0.01	-0.00
	(-0.30)	(-0.40)	(-0.29)
ζ_{t-1}	-0.02	-0.07**	-0.04*
	(-1.23)	(-2.15)	(-1.84)
R^2(%)	2.8	9.3	8.6

Panel D:CO2 Footprint

FCE	Low	High	HML
ζ_t	-0.00	-0.00	-0.00
	(-0.06)	(-0.21)	(-0.22)
ζ_{t-1}	-0.02	-0.07**	-0.05**
	(-0.83)	(-2.30)	(-2.36)
R^2(%)	1.2	10.2	12.8

Table 15: Monthly CAPM pricing errors of realized and for climate shocks corrected quintile portfolios. In parenthesis, I report t-statistics based on **Newey1987** corrected standard errors. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE and reported in Panels A, B, C, and D, respectively. HML is the high-minus-low quintile portfolio. Returns are equally weighted and include delisting returns. The market excess returns are retrieved from Kenneth French's website. The sample period is from July 2008 until June 2018. Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	Low	2	3	4	High	HML
Panel A: Duration						
Realized	-0.74**	-0.37*	-0.20	-0.21	-0.18	0.56*
	(-2.32)	(-1.89)	(-1.42)	(-1.21)	(-0.86)	(1.85)
No shock	-0.37	-0.11	-0.02	-0.07	-0.01	0.36
	(-1.04)	(-0.45)	(-0.11)	(-0.35)	(-0.02)	(1.20)
Panel B: TCE						
Realized	-0.09	-0.20	-0.21	-0.51**	-0.68***	-0.59**
	(-0.37)	(-1.14)	(-1.17)	(-2.55)	(-2.63)	(-2.05)
No shock	0.06	0.00	0.01	-0.24	-0.41	-0.47
	(0.23)	(0.00)	(0.06)	(-1.03)	(-1.27)	(-1.54)
Panel C: ICE						
Realized	-0.03	-0.12	-0.21*	-0.31*	-1.02**	-0.99**
	(-0.18)	(-0.83)	(-1.70)	(-1.65)	(-2.13)	(-2.23)
No shock	0.14	0.02	-0.05	-0.09	-0.58	-0.73
	(0.80)	(0.09)	(-0.33)	(-0.40)	(-1.09)	(-1.55)
Panel D: FCE						
Realized	0.02	-0.01	-0.24*	-0.58**	-0.88**	-0.91**
	(0.12)	(-0.09)	(-1.75)	(-2.19)	(-2.20)	(-2.26)
No shock	0.14	0.13	-0.07	-0.31	-0.45	-0.59
	(0.64)	(0.75)	(-0.39)	(-1.18)	(-0.99)	(-1.41)

Table 16: Monthly market and duration factor alphas of in quintiles sorted portfolios in percent. OLS t-statistics are in parenthesis. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. HML is the high-minus-low quintile portfolio. Returns are equally weighted and include delisting returns. The duration factor is the equally weighted HML duration portfolio. The market excess returns are retrieved from Kenneth French´s website. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	Low	2	3	4	High	HML
Panel A: Jul2003 - Dec2020						
Dur	0.06	0.04	0.17*	0.07	0.06	0.00**
	(0.47)	(0.38)	(1.83)	(0.71)	(0.47)	(2.22)
TCE	0.17	0.17	0.00	0.03	0.04	-0.13
	(1.04)	(1.44)	(0.04)	(0.29)	(0.24)	(-0.74)
ICE	0.17	0.06	0.08	0.06	0.04	-0.14
	(1.47)	(0.49)	(0.73)	(0.50)	(0.15)	(-0.57)
FCE	0.09	0.14	0.09	-0.00	0.10	0.01
	(0.72)	(1.55)	(0.92)	(-0.01)	(0.50)	(0.04)
Panel B: Jul2003 - Jun2008						
Dur	0.43***	0.32*	0.41**	0.27*	0.43***	0.00***
	(2.85)	(1.97)	(2.51)	(1.72)	(2.85)	(5.50)
TCE	0.14	0.20	0.11	0.48***	0.92***	0.78**
	(0.59)	(1.21)	(0.63)	(4.68)	(3.04)	(2.12)
ICE	-0.00	-0.05	0.09	0.44***	1.34***	1.34***
	(-0.00)	(-0.22)	(0.57)	(3.49)	(3.03)	(2.82)
FCE	0.03	0.06	0.21	0.44**	1.12***	1.09***
	(0.13)	(0.50)	(1.29)	(2.47)	(3.11)	(2.78)
Panel C: Jul2008 - Dec2020						
Dur	-0.02	-0.01	0.11	0.00	-0.02	0.00
	(-0.10)	(-0.06)	(0.91)	(0.04)	(-0.10)	(1.02)
TCE	0.21	0.20	0.03	-0.07	-0.30*	-0.51***
	(1.03)	(1.23)	(0.17)	(-0.58)	(-1.88)	(-2.68)
ICE	0.24	0.12	0.13	0.00	-0.43	-0.67**
	(1.63)	(0.85)	(0.95)	(0.03)	(-1.56)	(-2.46)
FCE	0.13	0.21*	0.10	-0.11	-0.25	-0.38**
	(0.84)	(1.73)	(0.76)	(-0.66)	(-1.11)	(-2.10)

Table 17: Monthly market and TCE factor alphas of in quintiles sorted portfolios in percent. OLS t-statistics are in parenthesis. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. HML is the high-minus-low quintile portfolio. Returns are equally weighted and include delisting returns. The TCE-factor is the equally weighted HML TCE portfolio. The market excess returns are retrieved from Kenneth French´s website. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	Low	2	3	4	High	HML
Panel A: Jul2003 - Dec2020						
Dur	-0.05	-0.02	0.15	0.04	0.06	0.11
	(-0.27)	(-0.12)	(1.51)	(0.48)	(0.42)	(0.67)
TCE	0.07	0.10	-0.05	-0.01	0.07	0.00***
	(0.57)	(0.83)	(-0.37)	(-0.12)	(0.57)	(11.98)
ICE	0.10	-0.02	0.02	0.02	0.06	-0.04
	(0.97)	(-0.18)	(0.15)	(0.15)	(0.26)	(-0.22)
FCE	0.04	0.10	0.03	-0.06	0.08	0.04
	(0.36)	(1.14)	(0.33)	(-0.37)	(0.38)	(0.27)
Panel B: Jul2003 - Jun2008						
Dur	0.44**	0.32*	0.32*	0.37**	0.37*	-0.07
	(2.22)	(1.86)	(1.93)	(2.34)	(1.82)	(-0.29)
TCE	0.41**	0.34**	0.20	0.44***	0.41**	0.00
	(2.05)	(2.07)	(1.12)	(4.13)	(2.05)	(1.08)
ICE	0.22	0.20	0.22	0.45***	0.69**	0.47
	(1.20)	(1.10)	(1.48)	(3.50)	(2.04)	(1.67)
FCE	0.26	0.15	0.38**	0.42**	0.60**	0.34**
	(1.44)	(1.36)	(2.44)	(2.24)	(2.19)	(2.00)
Panel C: Jul2008 - Dec2020						
Dur	-0.12	-0.09	0.06	-0.06	-0.20	-0.08
	(-0.47)	(-0.49)	(0.44)	(-0.55)	(-1.17)	(-0.38)
TCE	-0.14	0.02	-0.05	-0.11	-0.14	-0.00***
	(-0.86)	(0.12)	(-0.30)	(-0.67)	(-0.86)	(-11.58)
ICE	0.03	-0.08	-0.03	-0.08	-0.27	-0.29
	(0.19)	(-0.58)	(-0.20)	(-0.44)	(-0.89)	(-1.17)
FCE	-0.12	0.06	-0.01	-0.16	-0.18	-0.06
	(-0.94)	(0.56)	(-0.09)	(-0.82)	(-0.65)	(-0.28)

Table 18: Monthly market and ICE factor alphas of in quintiles sorted portfolios in percent. OLS t-statistics are in parenthesis. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. HML is the high-minus-low quintile portfolio. Returns are equally weighted and include delisting returns. The ICE-factor is the equally weighted HML ICE portfolio. The market excess returns are retrieved from Kenneth French´s website. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	Low	2	3	4	High	HML
Panel A: Jul2003 - Dec2020						
Dur	-0.01	0.01	0.18*	0.09	0.17	0.18
	(-0.05)	(0.12)	(1.92)	(0.95)	(1.13)	(0.98)
TCE	0.22	0.14	-0.01	0.01	0.08	-0.14
	(1.30)	(1.15)	(-0.05)	(0.06)	(0.89)	(-0.88)
ICE	0.14	0.04	0.04	0.06	0.14	-0.00*
	(1.28)	(0.37)	(0.41)	(0.44)	(1.28)	(-1.89)
FCE	0.15	0.13	0.06	-0.03	0.13	-0.02
	(1.07)	(1.49)	(0.57)	(-0.19)	(0.97)	(-0.11)
Panel B: Jul2003 - Jun2008						
Dur	0.36*	0.21	0.22	0.27	0.16	-0.20
	(1.85)	(1.27)	(1.38)	(1.55)	(0.76)	(-0.70)
TCE	0.18	0.36**	0.11	0.41***	0.18	-0.00
	(0.65)	(2.12)	(0.58)	(3.82)	(1.18)	(-0.00)
ICE	0.21	0.09	0.22	0.47***	0.21	-0.00
	(1.10)	(0.43)	(1.43)	(3.55)	(1.10)	(-1.31)
FCE	0.07	0.17	0.38**	0.34*	0.28	0.21
	(0.30)	(1.43)	(2.34)	(1.79)	(1.39)	(0.85)
Panel C: Jul2008 - Dec2020						
Dur	0.11	0.04	0.17	0.07	0.15	0.04
	(0.53)	(0.26)	(1.39)	(0.59)	(0.77)	(0.17)
TCE	0.27	0.17	0.11	0.02	-0.03	-0.30
	(1.25)	(1.00)	(0.66)	(0.12)	(-0.23)	(-1.53)
ICE	0.15	0.08	0.07	0.08	0.15	-0.00**
	(1.02)	(0.60)	(0.48)	(0.51)	(1.02)	(-2.30)
FCE	0.18	0.19	0.08	-0.02	0.12	-0.06
	(1.03)	(1.54)	(0.57)	(-0.09)	(0.66)	(-0.33)

Table 19: Monthly market and FCE factor alphas of in quintiles sorted portfolios in percent. OLS t-statistics are in parenthesis. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are univariately sorted either on Dur, TCE, ICE, or FCE. HML is the high-minus-low quintile portfolio. Returns are equally weighted and include delisting returns. The FCE-factor is the equally weighted HML FCE portfolio. The market excess returns are retrieved from Kenneth French´s website. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	Low	2	3	4	High	HML
Panel A: Jul2003 - Dec2020						
Dur	0.00	0.03	0.18**	0.08	0.13	0.13
	(0.02)	(0.26)	(2.01)	(0.87)	(0.91)	(1.00)
TCE	0.19	0.16	0.00	0.01	0.06	-0.13
	(1.18)	(1.33)	(0.01)	(0.12)	(0.61)	(-1.08)
ICE	0.17	0.05	0.06	0.06	0.08	-0.09
	(1.44)	(0.42)	(0.55)	(0.53)	(0.49)	(-0.61)
FCE	0.11	0.14	0.08	-0.02	0.11	0.00
	(0.91)	(1.59)	(0.77)	(-0.12)	(0.91)	(0.29)
Panel B: Jul2003 - Jun2008						
Dur	0.26	0.20	0.22	0.36**	0.30	0.04
	(1.47)	(1.22)	(1.36)	(2.15)	(1.40)	(0.16)
TCE	0.35	0.29	0.11	0.38***	0.20	-0.15
	(1.43)	(1.64)	(0.62)	(3.68)	(1.16)	(-0.95)
ICE	0.15	0.16	0.23	0.46***	0.32	0.17
	(0.73)	(0.76)	(1.49)	(3.44)	(1.18)	(0.68)
FCE	0.27	0.15	0.34**	0.32*	0.27	-0.00***
	(1.32)	(1.22)	(2.04)	(1.70)	(1.32)	(-3.00)
Panel C: Jul2008 - Dec2020						
Dur	0.14	0.10	0.18	0.06	0.04	-0.10
	(0.74)	(0.71)	(1.59)	(0.48)	(0.22)	(-0.64)
TCE	0.20	0.23	0.14	0.03	-0.08	-0.28*
	(0.93)	(1.41)	(0.91)	(0.26)	(-0.70)	(-1.74)
ICE	0.22	0.11	0.12	0.11	-0.05	-0.27
	(1.47)	(0.81)	(0.84)	(0.71)	(-0.25)	(-1.44)
FCE	0.08	0.22*	0.13	0.02	0.08	-0.00*
	(0.47)	(1.77)	(1.05)	(0.15)	(0.47)	(-1.81)

Table 20: Monthly CAPM and 2-factor alphas of common factor mimicking portfolios. OLS t-statistics are in parenthesis. At the end of June in each calendar year t, I sort stocks into five quintile portfolios based on the realization of the sorting variable of the fiscal year ending in $t-1$. Portfolios are sorted either on Dur, TCE, ICE, or FCE. The respective second factor is the corresponding high-minus-low (HML) quintile portfolio. Returns are equally weighted and include delisting returns. The market excess returns and size (SMB), value (SMB), profitability (RMW), investments (CMA), and momentum (UMD) factors are retrieved from Kenneth French´s website. Panel A includes the full sample (July 2003 - December 2020), Panel B includes the early sample (July 2003 - June 2008), and Panel C includes the late sample (July 2008 - December 2020). Significance at the 10%, 5% and 1% level are indicated by (*), (**) and (***), respectively.

	SMB	HML	RMW	CMA	UMD
Panel A: Jul2003 - Dec2020					
CAPM	-0.07	-0.35*	0.31***	-0.01	0.39
	(-0.46)	(-1.93)	(2.81)	(-0.13)	(1.35)
Market+Dur	-0.05	-0.17	0.35***	0.06	0.22
	(-0.31)	(-1.15)	(3.22)	(0.65)	(0.81)
Market+TCE	-0.13	-0.24	0.38***	0.01	0.32
	(-0.84)	(-1.41)	(3.79)	(0.13)	(1.10)
Market+ICE	-0.06	-0.30	0.34***	-0.00	0.34
	(-0.40)	(-1.65)	(3.15)	(-0.01)	(1.17)
Market+FCE	-0.05	-0.24	0.35***	0.02	0.29
	(-0.32)	(-1.49)	(3.31)	(0.22)	(1.03)
Panel B: Jul2003 - Jun2008					
CAPM	0.05	0.22	0.52***	-0.08	0.76*
	(0.21)	(0.99)	(2.80)	(-0.47)	(1.82)
Market+Dur	0.08	-0.00	0.44**	-0.11	0.87**
	(0.32)	(-0.01)	(2.37)	(-0.65)	(2.03)
Market+TCE	0.15	0.10	0.23	0.09	0.63
	(0.55)	(0.45)	(1.41)	(0.56)	(1.40)
Market+ICE	-0.02	0.18	0.27	0.13	0.17
	(-0.07)	(0.75)	(1.44)	(0.77)	(0.42)
Market+FCE	-0.01	0.01	0.19	0.11	0.44
	(-0.04)	(0.04)	(1.12)	(0.61)	(0.99)
Panel C: Jul2008 - Dec2020					
CAPM	-0.13	-0.56**	0.24*	0.01	0.19
	(-0.67)	(-2.37)	(1.85)	(0.06)	(0.53)
Market+Dur	-0.08	-0.22	0.30**	0.16	-0.16
	(-0.39)	(-1.13)	(2.29)	(1.51)	(-0.48)
Market+TCE	-0.32	-0.25	0.39***	0.17	-0.12
	(-1.63)	(-1.08)	(3.01)	(1.41)	(-0.32)
Market+ICE	-0.12	-0.39	0.29**	0.12	-0.17
	(-0.58)	(-1.62)	(2.11)	(0.91)	(-0.46)
Market+FCE	-0.06	-0.21	0.32**	0.19*	-0.27
	(-0.31)	(-0.97)	(2.38)	(1.70)	(-0.80)