RWTH Aachen University

Master's Thesis

Chair of Computational Economics

Carbon Beta:

Carbon Transition Risks in Capital Markets

Examiners

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Abstract

With the growing risk of climate change affecting the world's economy and welfare, policy makers are increasing the pressure on firms to lower their greenhouse gas emissions. Carbon policies aim to accelerate the carbon transition to a clean economy that also bears risks as well as opportunities for companies. This thesis applies an asset pricing approach to estimate the related carbon risk through a multi-factor model. We validate the relevance of carbon intensity in the cross-section of returns and use it to sort publicly listed companies into brown and green portfolios. The difference portfolio "Brown-Minus-Green" is constructed to represent carbon return premiums. The carbon risk measure, called "carbon beta", captures the price sensitivity to the carbon factor portfolio. We compute carbon betas for publicly traded companies in Europe and the United States. Investors, firms and policy makers can use carbon betas to quantify their exposure to climate risks in order to improve their decision-making.

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1 Introduction

Climate change is one of the biggest threats the modern generation is currently facing. The public is becoming aware of the associated risks and forces policy makers and in turn companies to lower greenhouse gas emissions and their carbon footprint. Countries throughout the world have sought to limit carbon emissions through international agreements. One of the most important ones was the Kyoto Protocol (UNFCCC 1997) which has led to the launch of the European Union Emissions Trading Scheme (EU ETS) in 2005 that set the basis for a market-based carbon price (Ellerman et al. 2010). The Paris Climate Agreement extended the obligations with a goal to limit global warming to below 2 or preferably 1.5 degrees Celsius (UNFCCC 2015). More recently, global parties at the Glasgow Climate Change Conference (COP 26) acknowledged that human activities already caused an increase of 1.1 degrees Celsius and that further climate actions are necessary to meet the temperature goals (UNFCCC 2021).

This increases the pressure on companies to decrease their greenhouse gas emissions and thus accelerate the move to a low-carbon economy. The transition from a high (brown) to a low (green) carbon economy can be costly and bears different risks as well as opportunities. Economists agree that a carbon price is an effective instrument to make companies accountable for their negative externalities (Fischer and Newell 2008). It can be implemented in the form of a carbon tax or an emissions trading system. Either form is designed to increase the prices and lower the demand of carbon-intensive products. Demand for many carbon-intensive products will still persist because some industries lack carbon-neutral technologies while other industries do not yet have technologies that are commercially viable. In every sector, the companies with the cleanest production, technology and product should benefit from this decarbonisation process while dirty companies' profits decline when the increased price of carbon raises their costs.

Bushnell et al. (2013) show that the carbon price impacts a company's profitability and consequently its stock's valuation. Investors need to be aware of the risks stemming from the carbon transition and make informed stock selection decisions based on carbon output. Bolton and Kacperczyk (2021) provide evidence that carbon emissions affect the cross-section of US stock returns and thus argue that institutional investors care about carbon risk by screening stocks accordingly. Carbon risks relate to all uncertainties surrounding the carbon transition, mostly stemming from political or regulatory changes.

A simple approach to lower carbon risk in a portfolio is to only select companies with low carbon output to hedge carbon risks, as suggested by Andersson et al. (2016). While this approach might be easy to implement, it is biased towards low-carbon sectors, countries or companies that simply outsource carbon-intensive processes without actually being green. This approach therefore lowers the portfolio's diversification, generally leading to higher risk and lower returns. We introduce another more sophisticated approach using capital market returns. If carbon risk is reflected in stock returns and portfolio holdings, we can use the capital market information to construct a quantitative measure of carbon risk, called "carbon beta".

To investigate carbon premiums in stock returns, we use firm level data of Refinitiv Datastream from European and US publicly listed companies that reported their total carbon emissions in the years 2009 to 2019. With data of over 1,700 firms, we first examine if the CO_2 score (standardized CO_2 output calculated as: CO_2 equivalent emissions/total revenue) has significant explanatory power in the cross-section of returns. The firms are then sorted into brown and green quintile portfolios based on their CO_2 score. Then, we construct a self-financing "Brown-Minus-Green" (BMG) portfolio that is long brown stocks (high CO_2 score portfolios) and short green stocks (low CO_2 score portfolios). Accounting for other common risk factors of Fama and French (1993) and Carhart (1997), we can compute a company's carbon beta by its exposure to the BMG portfolio. A high carbon beta means that a stock strongly moves in accordance with brown firms, a negative carbon beta on the other hand marks a stock that moves in the opposite direction of brown firms but in accordance with green firms.

We show that the CO_2 score can significantly explain the cross-section of returns and has an average negative effect in our time frame. The same effect is visible for the portfolio sorts where brown portfolios have lower mean excess returns and four factor alphas compared to the green portfolios. We report carbon beta statistics for different sectors and countries in our sample that reveal large discrepancies between as well as within them. On average, carbon betas are high for industries such as Energy and Utilities, while being low or even negative for companies in the Technology and Consumer Cyclicals sectors.

For investors, it is still possible to build diverse portfolios with low carbon risk exposure as there is a wide distribution of carbon betas even within sectors and countries. Investors can use the carbon beta to set their desired exposure to carbon transition risks, optimizing their portfolio risk. Firms can review their exposure and compare it to peers. Policy makers could use it to quantitatively measure the impact of new regulations on specific companies, sectors and countries.

This paper is structured as follows: in Section 2 we review the existing literature regarding carbon risk and its impact on capital markets. Section 3 outlines the data and research methodology. Section 4 provides statistical evidence for the introduced carbon beta by examining the effect of carbon intensity on the cross-section of returns and performances of univariat portfolio sorts. Carbon beta statistics and distributions for sectors and countries are reported. Section 5 discusses the limitations of the findings and Section 6 gives a final conclusion.

2 Literature Review

The Intergovernmental Panel on Climate Change (IPCC) undoubtedly concludes that climate change is human-induced and rapidly intensifying in their Sixth Assessment Report (IPCC 2021). Scientists agree that climate change is a threatening source of risk and uncertainty for society. Stern (2007) and the IPCC (2021) assess that climate change will affect every country and region in our climate system. Nordhaus (1991) investigates the impact of climate change on the global economy. The greenhouse effect is treated as a public good with greenhouse gas emissions as global negative externalities. The damage caused to society by the externalities describes the Social Cost of Carbon (SCC).

Computing the Social Cost of Carbon is a complicated effort as it involves various uncertainties regarding the effect of greenhouse gas emissions on the global temperature (IPCC 2013) and subsequently its effect on society and the economy (Nordhaus 1991). The temperature increase can additionally reach yet unknown climate tipping points with potentially catastrophic and irreversible impacts (Lenton 2011). Nordhaus (1992) introduces the Dynamic Integrated Climate-Economy (DICE) model to compute the SCC. He finds an optimal greenhouse gas abatement policy weighing economic costs and benefits. Multiple other integrated assessment models emerge and extend the DICE framework. Nordhaus and Yang (1996) also provide a regional version (RICE) taking into account regional differences for climate-change policies. Weitzman (2009) urges that unknown climate tipping points with high-impact catastrophes may have a large impact on SCC calculations. The Dynamic Stochastic Integrated Model of Climate and Economy (DSICE) of Lontzek et al. (2015) incorporates stochastic risks of tipping points into the DICE model and computes a much higher SCC. Daniel et al. (2016) use an asset pricing approach for the SCC, resulting in very high but declining costs over time. Because of the various uncertainties in the model calibrations, the SCC largely differs in the literature, ranging from as low as a few dollars to several hundreds of dollars per tonne of CO_2 (IPCC 2013).

Given that the social cost of carbon emissions can be very significant, scientists also focus on the best way to implement regulations to internalize the negative externalities. Nordhaus (1992) suggests to implement a carbon tax equivalent to the social cost of carbon and Goulder and Mathai (2000) analyze optimal taxation time profiles. Acemoglu et al. (2016) find an optimal policy path where early carbon taxes and research subsidies increase technological advances in clean technology, making carbon abatement cheaper in the long term. Fowlie et al. (2016) study the effects of market-based emissions regulation as an effective alternative or extension to a carbon tax. Based on different results in the literature, the likely outcome is a variety of carbon policies or even a policy mix (Sorrell and Sijm 2003).

Whatever forms of implementation regulators choose, carbon policies can have strong impacts on company profits. The transition to a low-carbon economy bears risks as well as opportunities for companies that emit greenhouse gases and should therefore be reflected in the valuations. Bolton and Kacperczyk (2021) study the effects of carbon emissions on the cross-section of returns in the US stock market. They find that stocks with higher total CO_2 emissions earn higher returns controlling for other predictors, so investors get compensated for their carbon risk exposure. Oestreich and Tsiakas (2015) also provide evidence for a positive carbon risk premium in the German stock market by investigating the effects of carbon emission allowances in the EU Emissions Trading Scheme. In contrast, Tian et al. (2016) find an inverse relationship between carbon prices and stock returns, specifically for carbon-intensive producers. Mo et al. (2012) further analyze the different phases of the EU Emissions Trading Scheme. They show a positive relationship between the EU emission allowance price in phase I but a negative relationship in phase II. Further evidence by da Silva et al. (2016) suggests that the relationship is significant but that the effect is also firm-specific.

The research suggests that there is a significant link between a firm emissions and stock returns, but the sign of the effect is not yet clear. Climate change and the carbon transition has gained more attention only in recent years and major economies are now starting to implement stricter carbon policies. Therefore, carbon risk is potentially not fully priced in equity prices yet and prices have to change first to properly compensate for their risk exposure in the future. Accordingly, this raises the question about efficient portfolio allocation for investors. Bansal et al. (2018) find that investing in socially responsible firms generates a positive alpha, in particular during good economic times. Kaiser (2020) extends the research by integrating Environmental Social Governance (ESG) scores into the investment selection process. He shows that portfolios with higher ESG scores also have higher risk adjusted return. Chava (2014) shows that investors demand higher returns from firms with bad environmental profiles. Similarly, banks charge them higher interest rates. In et al. (2017) find that being "green" can also be rewarded in the market by constructing a self-financed portfolio that is long carbon efficient stocks and short inefficient stocks. This portfolio generates a positive alpha accounting for most common risk factors.

Krueger et al. (2020) provide evidence that institutional investors care about their carbon risk and they believe that it has financial implications for their portfolios that have already started to materialize. Investors therefore require a proper scientific approach to measure carbon risk exposure. There are different attempts to construct a carbon risk measure with capital market data in the literature. Görgen et al. (2020) construct their own "Brown-Green-Score" (BGS) from 55 weighted variables related to categories of the carbon transition process: value chain, public perception and adaptability. Based on the computed BGS, companies are assigned to either brown or green portfolios. The difference portfolio "Brown-Minus-Green" (BMG) then acts as the factor mimicking portfolio of carbon risk. They compute carbon betas for equities of 43 countries and present statistics for different countries as well as sectors. With their methodology, they do not find evidence that a significant carbon risk exists in the cross-section of returns nor what effect it has. This might stem from their complex BGS scoring model with subjective weightings and benchmarks. It uses 55 variables from 4 different ESG databases that include proxy variables which are self-computed by rating agencies and often not consistent across databases (Busch et al. 2020). The true information to assign firms to brown and green categories might be lost in the process, so investors' carbon risk comprehension is not reflected correctly. In their analysis of these factors, Roncalli et al. (2020) find strong similarity between the BMG factors and factors built solely based on carbon intensity. They also wonder if carbon intensity is the only true carbon dimension reflected in their factors which is also priced in by the market.

Witkowski et al. (2021) build "dirty" (brown) and "clean" (green) portfolios based on EU emission allowances of energy-intensive electric utilities companies to examine carbon premiums in different phases of the EU ETS. They also find conflicting results with positive and significant carbon premiums before and at the beginning of the EU ETS but negative or insignificant premiums during its later phases.

We extend the current research of carbon risks in financial markets with a different approach to build brown and green portfolios that only depends on a single metric: total carbon equivalent emissions divided by total revenue (often referred to as the carbon intensity). We use data from European as well as US companies to have a sufficient amount of firms that report their carbon emissions and thus try to reduce the inherent reporting bias. In total, we analyze over 1,700 companies with 11 years of monthly return data from 2009 to 2019. The data and methodology is explained in detail in the next section.

3 Data and Methods

Our methodology modifies and extends the research of Görgen et al. (2020). Instead of a complex self-built scoring system based on different data sets to divide green and brown firms, our method uses only one variable for the classification, which is the Refinitiv CO_2 score. ESG data sets in particular suffer from gaps and wide inconsistencies because of different reporting methods and provider benchmarks (Kotsantonis and Serafeim 2019). Investors generally prefer simple approaches in their selection process so this method should better reflect the decision making regarding carbon risk screening. We limit our focus on European and US equities to further increase data quality and consistency. We also extend the analysis by reporting the significance in the cross-section of returns. The data and methods are further explained in the following subsections.

3.1 Data Description

Firm level data is collected from Refinitiv Datastream (formerly Thomson Reuters Datastream). We restrict the data collection to common stocks with a country of issuance in either the United States or Europe. These continents offer better data quality as well as reporting standards. The time frame ranges from the beginning of 2009 to the end of 2019 for a total of 11 years. We believe that awareness of carbon risk has only recently gained more attention and the carbon transition is particularly demanded by the public in the US and Europe. The time frame also excludes large non-linear effects from the financial crisis in 2007-2008 as well as the COVID-19 pandemic in 2020-2021. This amounts to a total of 19,167 companies of 32 countries.

For the return data, we use monthly returns from Thomson Reuters Total Return Index. Total returns are the stock returns adjusted for dividends, stock splits or other capital gain distributions. Ince and Porter (2006) suggest that Thomson Reuters' return data still requires additional cleaning to account for potential gaps and errors. We follow their suggestions by filtering out companies with missing return observations or implausible values.

Company financial information is collected monthly for the market value and on a yearly basis for the book (equity) value and the CO_2 score. The CO_2 score of a year t measures the total carbon equivalent emissions in year t divided by total revenue in that year t:

$$\text{CO}_2\text{ Score}_t = \frac{\text{Total Carbon Equivalent Emissions (in tonnes of CO}_2\text{e)}_t}{\text{Total Revenue (in USD)}_t} \tag{1}$$

Total Carbon Equivalent Emissions is the total CO_2 equivalent output in Scope 1 and Scope 2 as defined by the Greenhouse Gas Protocol (GHGP 2015). The GHGP (2015) defines Scope 1 emissions as all direct GHG emissions from sources that are owned by the company, e.g. a combustion-engine vehicle or a furnace from a production plant. Scope 2 mainly includes emissions from the generation of purchased electricity. For most companies, Scope 2 is the main source of CO_2 emissions and much larger than Scope 1.

Scope 3 are all indirect emissions occurring in the value chain from sources not directly owned by the company. Scope 3 is not included in the CO_2 score as it is rarely reported. Under GHGP guidelines, its reporting is optional as it can be very difficult to calculate, even though it might be substantial for the rating of a firm's environmental sustainability.

Internationally, some states require companies to report their GHG emissions (Scope 1 and 2). Most commonly, it is mandatory for carbon-intensive companies to report emissions. For example in the US, this obligation was introduced in 2009 for all facilities emitting at least 25,000 metric tons of CO_2 equivalent per year (EPA 2013). There are similar laws in other countries. The state of California even extended the requirement to all companies operating in their state under the California Global Warming Solutions Act (ARB 2006). For most international companies, GHG emission reporting is voluntary but many companies nonetheless decide to publish it to be transparent or signal their sustainability. This means that the CO_2 score data could suffer from some sort of reporting bias.

Other risk factor data and risk-free rates are retrieved from the data library of Kenneth R. French (French 2021). We use monthly factor data for US and European returns separately. The three factors of Fama and French are used to control for market risk (Mkt), size risk (SMB) and value risk (HML) (Fama and French 1993). A fourth factor to account for momentum (WML) is also used (Carhart 1997).

For the following analyses, we focus only on companies that report their carbon emissions, thus companies with a positive and non-missing CO_2 score. We further exclude companies with errors in the return data and set a minimum requirement for the market capitalization of $100 million to sort out micro and penny stocks. Similar to Fama and French (1993), we exclude firms with a negative book value and require at least 6 months of return data to be included in a portfolio. Similar to related research of carbon risks, companies that are marked as "Financials" under the Refinitiv Business Classification are also excluded, because financial firms are not directly exposed to carbon risks. The remaining data sample used in all following analyses consists of 1,709 companies of 25 countries. Table 1 provides statistical descriptions for the arithmetic mean, median and standard deviation of all the used variables.

Table 1: Data description.

Variable	Observations	Mean	Median	Std Dev
Equities	1,709			
Countries	25			
Sectors	10			
Months	132			
Total CO_2 eq. output (tonnes CO_2e in t.)	11,073	4,769	227	16,459
Revenue (USD m.)	18,686	10,251	2420	28,133
CO_2 score (tonnes CO_2e /USD m.)	11,056	436	44	1,789
Book value (USD m.)	18,085	5,275	1,402	13,871
Book-to-market ratio	17,300	0.53	0.42	3.97
Market capitalization (USD m.)	206,317	14,660	3,636	40,295
Stock return (%)	205,002	1.56	1.17	25.92

Includes all non-missing data of the filtered data sample from 2009 to 2019.

3.2 Significance in the Cross-Section

Our first analysis relates to the significance of carbon risk in the cross-section of returns. As we are using the CO_2 score to sort the stocks and build portfolios, we first have to check if the variable is a significant factor with explanatory power in the cross-section. Otherwise, the scientific basis to our approach is not given. To check the significance in the cross-section, we use the popular Fama-MacBeth approach that is widely used in asset pricing tests (Fama and MacBeth 1973). The advantage of this procedure is that it is simple to implement and adjusts the standard errors for cross-sectional correlation in the residuals (Cochrane 2009).

Every month t, we compute regressions of raw stock returns on the CO_2 score controlling for market risk, size, value and price momentum. We run 132 (T) monthly regressions from 2009 to 2019 with all stocks with valid data for a given month. The regression equation can be given as:

$$r_{nt} = \gamma_{0t} + \gamma_{1t} \ln(\mathrm{CO}_2)_{nt} + \gamma_{2t}\beta_{nt} + \gamma_{3t} \ln(Size)_{nt} + \gamma_{4t} \ln(B/M)_{nt} + \gamma_{5t} \ln(1 + Mom)_{nt} + \epsilon_{nt} \quad (2)$$

The dependent variable r_{nt} is the raw monthly return of stock n in month t. The variable that's effect we intend to examine is denoted as CO_2, which describes the CO_2 score (total carbon equivalent emissions divided by total revenue) of the firm in the prior year. We further add other popular control variables. β is the stock's market beta. $Size$ is the market capitalization lagged by one month. The book-to-market ratio (B/M) is the stock's book value of the prior year divided by its market capitalization at the end of the prior year. Price momentum (Mom) denotes the raw cumulative price return from month $t-12$ to $t-1$, we add 1 to ensure positive values for the logarithm. All independent variables are winsorized monthly at the 1% and 99% levels, as suggested by Fama and French (1992).

The result is a time-series of 132 regression coefficients. The coefficient of interest for our analysis is defined as γ_{1t}. The average effect (γ_1) of $\ln(CO_2)$ in the cross-section of returns is simply calculated as the time series average of γ_{1t}:

$$\gamma_1 = \frac{1}{T}\sum_{t=1}^{T}\gamma_{1t} \tag{3}$$

To check the significance of the effect of γ_1, we calculate t-statistics of the series. As we are dealing with a time-series, we use Newey-West adjusted t-statistics to account for autocorrelation and heteroscedasticity (Newey and West 1986). The amount of lags is set to the next integer of $T^{1/4}$, similar to current practice (Greene 2003).

3.3 Univariat Portfolio Sorts

In this analysis, we build different portfolios based on the CO_2 score of the prior year. We follow Fama and French (1993) by rebalancing the portfolios every year at the end of June, to eliminate look-ahead bias. To be included in a carbon portfolio, the company needs to have non-negative and non-missing data for carbon emissions and book value in the prior year, a current minimum of \$100 million of market capitalization and has to be listed for at least 6 months. Financial institutions are once again excluded.

At the end of June, all valid stocks are sorted in five quintile portfolios based on the CO_2 score distribution. The stocks in the low quintiles Q_1 and Q_2 thus emit fewer carbon emissions per Dollar earned in revenue so they can be considered green firms. Stocks that are put in higher quintiles Q_4 and Q_5 are considered to be carbon-intensive firms that we call brown firms. For every portfolio, we compute value-weighted mean excess returns and 4 factor alphas to examine the effect of CO_2 score sorting on stock price performance. The 4 factor alphas express the returns of the portfolio in excess of factor returns stemming from market, size, value and momentum exposure. The alpha (α_i) of portfolio i is computed as the intercept of the following time-series regression:

$$r_{it} - rf_t = \alpha_i + \beta_{1i}\, Mkt_t + \beta_{2i}\, SMB_t + \beta_{3i}\, HML_t + \beta_{4i}\, WML_t + \epsilon_{it}, \tag{4}$$

where $r_{it} - rf_t$ is the return of portfolio i minus the risk-free rate, Mkt_t is the market premium, SMB_t is the size effect, HML_t is the value premium and WML_t is the momentum premium in month t. Portfolio returns are value-weighted by the constituents' market capitalizations.

We analyze the return differences between the carbon quintile portfolios to see if sorting based on CO_2 score results in significant disparities. If we see significant and monotonic changing returns, it confirms our thesis that the CO_2 score has an effect on returns in our sample and time frame.

3.4 Carbon Beta

We continue by building a difference portfolio between brown and green portfolios. The difference portfolio is a self-financed portfolio that is equally long the brown portfolios Q_5 and Q_4 with high CO_2 scores and equally short the green portfolios Q_1 and Q_2 with low CO_2 scores. This "Brown-Minus-Green" (BMG) portfolio then mimics a carbon risk portfolio.

$$BMG = \frac{1}{2}\,(Q_5 + Q_4) - \frac{1}{2}\,(Q_1 + Q_2) \tag{5}$$

The BMG equally weights the quintile portfolios, whereas the returns of the quintile portfolios themselves are value-weighted returns.

With the carbon risk mimicking portfolio (BMG), we intend to measure a firm's carbon beta using capital market information expressed through stock returns. Focusing solely on a company's carbon emission information is often not enough to judge if it is green or brown or to measure its carbon transition risk. The data by itself cannot be interpreted directly but instead needs to be viewed in relation to similar companies in the same sector or peer-group with similar business models and revenue structures, an elaborate effort even more complicated if other companies do not report their emissions. If we assume that the market as a whole has gone through the process and efficiently divided brown and green firms as well as priced in the carbon risks, we can skip the process by only using the market information in the price returns. This also allows to compute a carbon beta for companies that do not report any emission related information.

The carbon beta β_5 of a stock n is calculated as its sensitivity to the carbon risk portfolio BMG controlling for other factor risk exposures by Fama and French (1993) and Carhart (1997). We compute the carbon beta coefficient for every stock n by running a time-series regression of the excess returns on the factor premiums of market, size, value, momentum and additionally the carbon risk portfolio:

$$r_{nt} - rf_t = \alpha_n + \beta_{1n}\, Mkt_t + \beta_{2n}\, SMB_t + \beta_{3n}\, HML_t + \beta_{4n}\, WML_t + \beta_{5n}\, BMG_t + \epsilon_{nt}, \quad (6)$$

where $r_{nt} - rf_t$ is the return of stock n minus the risk-free rate, Mkt_t is the market premium, SMB_t is the size effect, HML_t is the value premium, WML_t is the momentum premium and BMG_t is the carbon premium in month t. The time frame is 2009 to 2019.

Carbon beta measures how the stock moves, on average, when the BMG portfolio increases or decreases. A positive carbon beta implies that the stock price moves in accordance with the BMG portfolio, thus similar to brown stocks. A negative carbon beta implies that it moves in the opposite direction of the BMG and more in accordance with green firms, representing a hedge against carbon risks. A carbon beta close to 0 means no significant exposure to the BMG portfolio, representing no direct carbon transition risk.

With this method, we can compute a quantitative carbon risk measure for every stock using only publicly available market return data. We can then use our whole sample of equities to analyze carbon risk exposures in different sectors and countries. We compute carbon beta distributions of all sectors (excluding Financials) covered in the Refinitiv Business Classification. We also provide value-weighted carbon betas of the countries in our sample. We exclude sectors and countries with insufficient data.

4 Results

4.1 Significance in the Cross-Section

The first analysis concerns the significance of the CO_2 score (carbon intensity) in the cross-section of returns as laid out in Section 3.2. We examine if the CO_2 score has explanatory power for stock returns. The results of the cross-sectional Fama-MacBeth regressions for the period 2009-2019 are presented in Table 2. We run 5 different models with various control variables to check for multicollinearity and see if the effect is consistent and robust across the model specifications. The depicted values are the time-series averages of the cross-sectional regressions (see Equation 3). The parentheses below include the Newey-West adjusted t-statistics.

Table 2: Average coefficient values from cross-sectional Fama-MacBeth regressions of 132 monthly stock returns.

	(1)	(2)	(3)	(4)	(5)
$Intercept$	1.66	1.42	2.56	2.53	2.11
	(4.39)	(5.77)	(4.33)	(4.37)	(4.12)
$\ln(CO_2)$	-0.08	-0.08	-0.06	-0.06	-0.07
	(-2.20)	(-2.34)	(-1.74)	(-2.50)	(-2.32)
$Market\,Beta$		0.30	0.24	0.22	-0.06
		(0.73)	(0.62)	(0.58)	(-0.18)
$\ln(Size)$			-0.14	-0.13	-0.11
			(-2.19)	(-2.50)	(-2.51)
$\ln(B/M)$				0.01	-0.05
				(0.09)	(-0.54)
$\ln(1 + Mom)$					0.25
					(0.46)

Cross-sectional regressions computed according to Equation 2 for model (5) or fewer controls for models (1) to (4). The depicted values are the averages of the coefficients in the time-series as in Equation 3. Newey-West adjusted t-statistics are given below in parentheses. All independent variables are winsorized monthly at the 1% and 99% level.

The variable of interest in Table 2 is the logarithm of the CO_2 score defined as $\ln(CO_2)$. Model (5) shows evidence that the CO_2 score has a significant effect on the cross-section of returns with a t-statistic of -2.32, controlling for other factor premiums such as the market, size, value and momentum risk. The effect has a significant negative value of -0.07. This means that an increase in the CO_2 score of a company, on average, decreases the return of the stock. In other words, firms with higher CO_2 scores (brown firms) offer lower returns than firms with low CO_2 scores (green firms). This effect is consistent across the different model specifications (1) - (5) where we individually exclude other control variables from the regression, although the size of the effect slightly changes which hints at multicollinearity of the independent variables. Thus, the effect appears robust but it might be problematic to directly interpret individual slope coefficients.

Similar to Fama and French (1992), the size effect captured with $\ln(Size)$ is also significant across different models with a negative value of -0.11 and a t-statistic of -2.51. In contrast, the value effect of the book-to-market ratio $\ln(B/M)$ with a value of -0.05 and a t-statistic of -0.54 is not significant in our data sample during this time frame. The market beta is also insignificant with a t-statistic of -0.18, which is often the case if an intercept is included in the regression. The intercept is always highly significant with an average coefficient of 2.11 and a t-statistic of 4.12 in model (5). Finally, the momentum factor variable $\ln(1 + Mom)$ is also insignificant in this time period.

A significant coefficient of the CO_2 score provides empirical evidence that investors are actively incorporating carbon emission information in their investing process. We can assume that investors associate some sort of risks with high greenhouse gas emissions and thus adjust their valuations accordingly. If we can assume this screening behavior by market participants, carbon risks should be effectively priced in equity returns. In our data and time frame, we find a negative effect of normalized carbon emissions on the returns. This infers that carbon-intensive stocks do not offer higher returns and investors are currently not compensated for carbon risk exposure. It hints at the opposite effect that low-carbon companies earn higher returns.

This swapped risk-reward relation in our sample and time frame means that investors were not efficiently remunerated for carbon risk exposure. Attention for climate change and carbon policies has gained a lot of traction in recent years and investors potentially try to reduce their carbon exposure and have a general distaste for carbon-intensive stocks.

This results in lower or even negative returns for brown firms and similarly higher returns for green firms. In the long term, this reverse effect in recent times can lead to lower prices for brown firms that offer higher returns, compensating investors for their carbon risk exposure. As the time span is relatively short and related research also finds conflicting results, we cannot conclude the ultimate effect of carbon intensity and carbon risk on returns. However, we can conclude that a significant effect is present.

4.2 Univariat Portfolio Sorts

To further investigate the outperformance of green over brown firms, we build quintile portfolios based on the CO_2 score as explained in Section 3.3. We build five different portfolios Q_1 to Q_5, where Q_1 consists of the stocks with the lowest and Q_5 with the highest CO_2 scores. Portfolios are rebalanced yearly at the end of June. Table 3 provides the return statistics for the portfolios during our time period from 2009 to 2019. The depicted values are monthly measures given in percentage. The Sharpe Ratio introduced by Sharpe (1994) of a portfolio i is computed as:

$$\text{Sharpe Ratio}_i = \frac{\bar{D}_i}{\sigma_{Di}} , \tag{7}$$

where $\bar{D}_i$ is the mean excess return of the portfolio i over the risk free rate $(\sum_{t=1}^{T} R_{it} - Rf_t)$ and σ_{Di} is the standard deviation of the portfolio's excess returns.

Table 3: Monthly return statistics of the CO_2 score portfolio sorts.

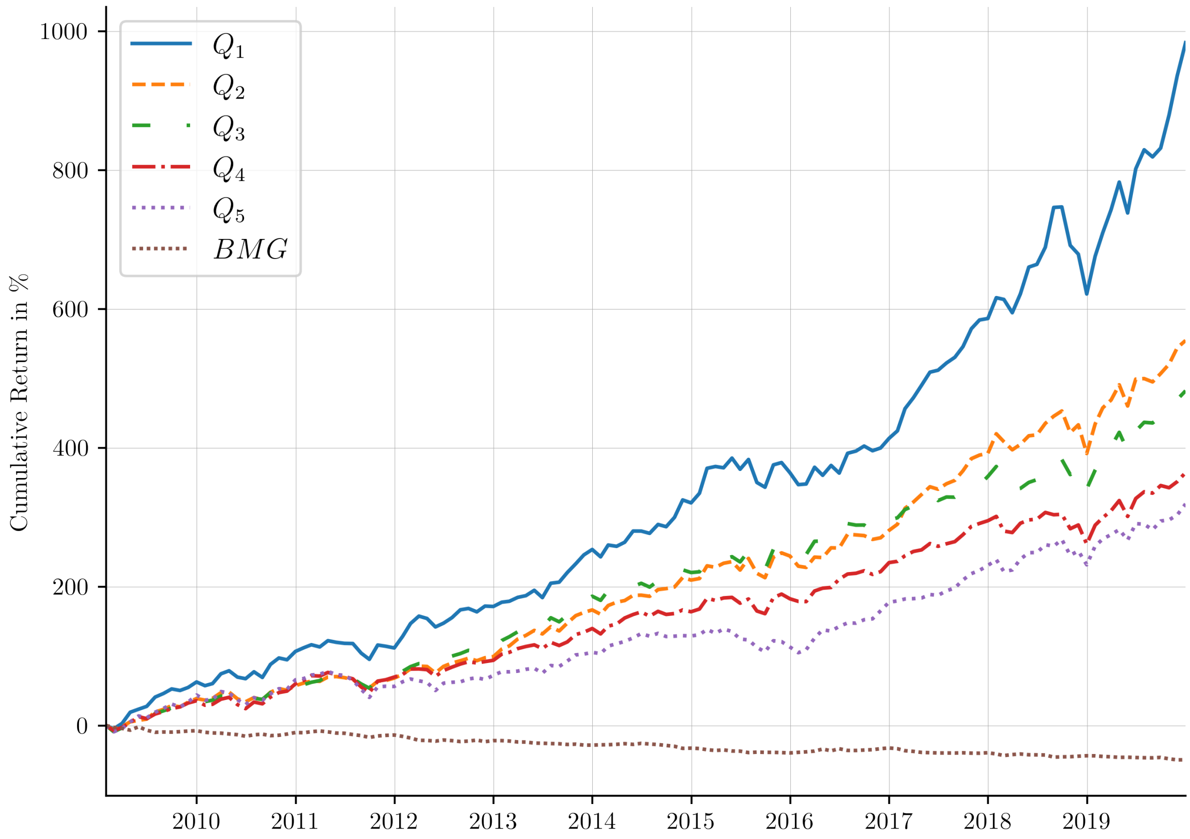
	Portfolio	Mean	Median	Std Dev	Sharpe Ratio
Green	Q_1	1.86	2.18	4.00	0.46
	Q_2	1.47	1.79	3.31	0.43
	Q_3	1.33	1.49	3.26	0.40
	Q_4	1.19	1.44	3.46	0.33
Brown	Q_5	1.13	1.10	3.91	0.28
	BMG	-0.50	-0.36	1.91	-0.28

Monthly return statistics for quintile portfolios as laid out in Section 3.3 and the BMG portfolio based on Equation 5. The values are presented in percentage (except for the Sharpe Ratio). Sharpe Ratio calculated as in Equation 7. The time period is 2009 to 2019.

The portfolio with the lowest CO_2 score Q_1 has the highest average return with a monthly mean of 1.86%. In contrast, Q_5 as the portfolio with the highest CO_2 scores has the lowest average return of 1.13%. We can see a monotonic increase in returns from portfolios Q_1 to Q_5. This trend is robust to outliers as it is also visible in the medians with a median of 2.18% for Q_1 and 1.10% for Q_5. Volatility expressed by the standard deviations are almost identical for the portfolios Q_1 with 4.00% and Q_5 with 3.91%. The Sharpe ratio is often used to measure the risk adjusted return as it takes into account the volatility of the underlying returns (see Equation 7). Looking at the Sharpe Ratios, the trend is unchanged. The green portfolio Q_1 has a Sharpe Ratio of 0.46, whereas Q_5 has a significantly lower Sharpe Ratio of 0.28. Portfolios with green firms significantly outperform the portfolios with brown firms even after adjusting for volatility risk. Consequently, the BMG portfolio as a difference portfolio of brown minus green portfolios has a negative average return of -0.5% and a Sharpe Ratio of -0.28.

We visualize the portfolio returns by showing the raw cumulative returns of the portfolios from 2009 to 2019. Figure 1 presents the results in this time period. Cumulative returns are shown in percentage.

Figure 1: Cumulative returns of the quintile portfolios and the BMG portfolio.



Over the 11 year time period, we see substantial differences between the portfolio sorts based on the CO_2 score. The green portfolios realize significant outperformance over the brown portfolios. From January 2009 to 2019, the most green portfolio Q_1 offered a cumulative return of 984%. The most carbon-intensive portfolio Q_5 merely has a cumulative return of 319%, amounting to a return difference of 665%. Figure 1 once again shows that there is a monotonic decrease in performance from Q_1 to Q_5, again confirming the negative effect of the CO_2 score on the performance. The BMG portfolio of brown-minus-green portfolios consequently has a negative cumulative return of -49%. It clearly shows return differences between the carbon portfolio sorts so investors need to consider carbon emission information in their investment process.

We continue by investigating if the outperformance of green portfolios over their brown counterparts persists if we control for risk. Table 4 provides mean excess returns as well as four factor alphas controlling for market, size, value and momentum risk. The four factor alphas are the intercepts of the time-series regression of Equation 4.

Table 4: Mean monthly excess returns and factor alphas of the quintile portfolios and the BMG portfolio.

	Portfolio	Mean Excess	4 Factor Alpha
Green	Q_1	1.82^{***}	0.64^{***}
	Q_2	1.43^{***}	0.40^{***}
	Q_3	1.29^{***}	0.31^{***}
	Q_4	1.15^{***}	0.17
Brown	Q_5	1.09^{***}	0.13
	BMG	-0.54^{***}	-0.40^{**}

Monthly return statistics for quintile portfolios as laid out in Section 3.3 and the BMG portfolio based on Equation 5. Mean excess returns are the average monthly returns in excess of the risk-free rate. 4 Factor Alphas are the intercepts of the time-series regressions based on Equation 4. Time period is 2009 to 2019. The values are presented in percentage. ** and *** represent significance at the 0.05 and 0.01 levels respectively.

All five quintile portfolios produce significantly positive average monthly returns also in excess of the risk free rate. The most green portfolio Q_1 has the highest excess returns with a monthly mean of 1.82%. The most carbon-intensive portfolio Q_5 has the lowest excess returns of the quintile portfolios of 1.09% which is still significantly positive. Controlling for risk premiums, the effect of the CO_2 score persists. Q_1 returned an average monthly alpha of 0.64% that is significant at the 1% level. Similarly, Q_2 and Q_3 also offer significant alpha returns. Again, the alpha values decrease monotonically going from Green to Brown. The brown portfolio Q_5 has a monthly alpha value of 0.13% that is no longer statistically significant. Thus, we can conclude that green portfolios produced significant alpha returns from 2009 to 2019, whereas brown portfolios did not. The BMG portfolio has a negative four factor alpha of -0.40% that is significant at the 5% level.

The results from this analysis confirm the negative effect of the CO_2 score in the cross-section of returns. We clearly see substantial differences when stocks are sorted based on the CO_2 score which again hints that carbon emissions have an effect on firm valuation. Low-carbon portfolios significantly outperform carbon-intensive portfolios even after controlling for risk factor exposure. Carbon emission information thus must have an impact on equity prices and investors actively use it in their screening process. Stock returns should reflect carbon risks and we continue to use this property to compute quantitative carbon risk measures in the next section.

4.3 Carbon Beta

In the previous section, we have seen substantial differences in the returns of carbon intensity sorted portfolios. We then build the Brown-Minus-Green (BMG) portfolio as a self-financing portfolio that is equally-weighted long the brown portfolios Q_4 and Q_5, and equally-weighted short the green portfolios Q_1 and Q_2 (see Equation 5). The returns of this BMG portfolio indicate the difference in returns between brown and green firms that stem from differences in the carbon characteristics of the firms. These differences comprise the return premiums awarded to investors for carbon transition risk exposure.

Table 5 presents the correlation table between different factor returns. The correlations of the BMG factor to other risk factors show if the carbon risk factor is in fact a novel return premium or stems from another factor risk unrelated to the carbon emissions. The BMG factor has basically no correlation with the Market factor (Mkt) or the size factor (SMB) with correlation coefficients of -0.01 and 0.01 respectively. It has a slightly negative correlation of -0.12 to the momentum factor (WML) and a small positive correlation of 0.35 to the value factor (HML) that could indicate that brown firms are more likely to be value companies and green firms tend to be growth companies. Since all correlations are relatively small, we conclude that the carbon risk factor BMG is distinct to the other factors.

Table 5: Correlation table of factor returns.

	Mkt	SMB	HML	WML	BMG
Mkt	1	0.35	0.33	-0.35	-0.01
SMB		1	0.13	-0.14	0.01
HML			1	-0.44	0.35
WML				1	-0.12
BMG					1

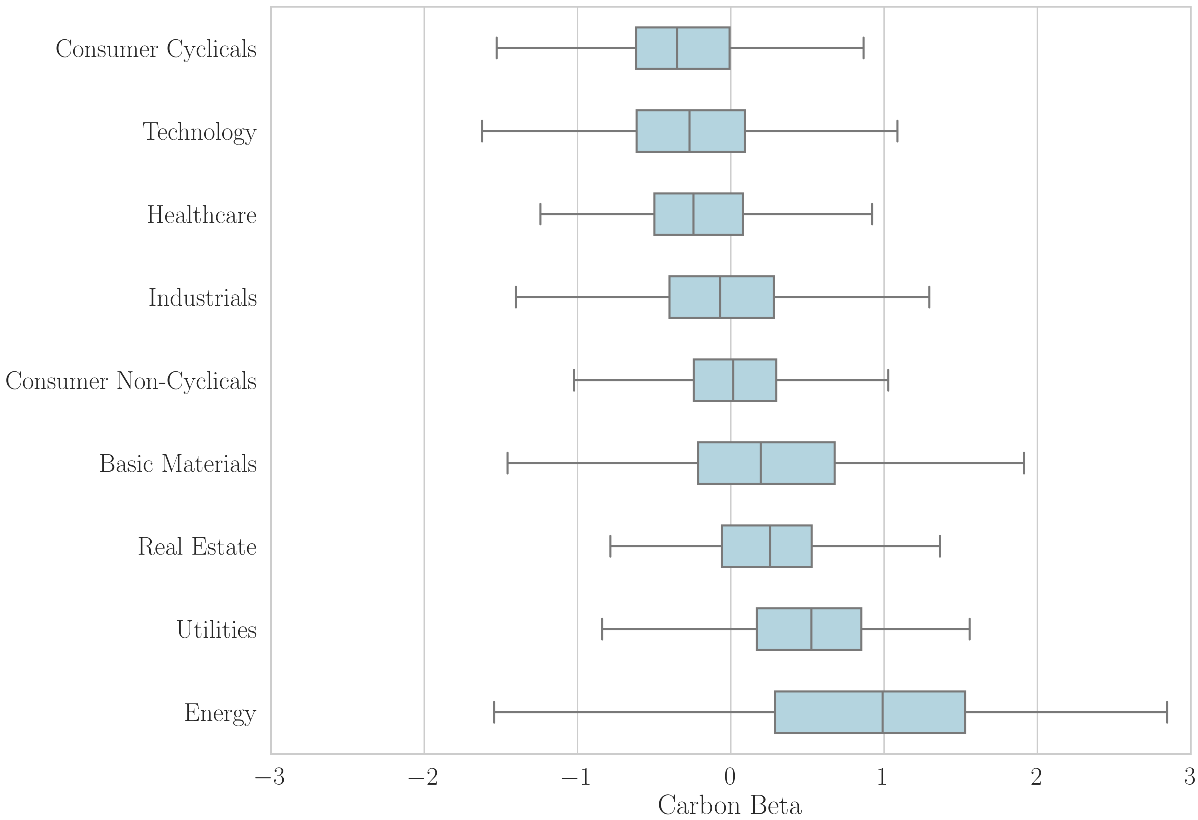
Correlation coefficients of monthly factor returns. The factor returns Mkt, SMB, HML, WML are taken from Kenneth French's website (French 2021). The BMG factor is self-computed.

Assuming the constructed BMG portfolio effectively represents carbon risks in capital market returns, we can use it to compute carbon beta statistics for all equities even if the firms do not report carbon emissions. We run a time-series regression of a stock's excess returns on multiple risk factor premiums including the BMG as in Equation 6. The carbon beta is the coefficient for the BMG returns of this multiple linear regression. It measures the relation of an equity to the BMG portfolio and thus its sensitivity to the carbon transition. It is a single quantitative measure that is easily interpreted and directly comparable between firms.

A high and positive carbon beta indicates a significant carbon risk. A negative carbon beta implies a hedge against it. For example, the oil and gas company ExxonMobil has a very high and significant estimated carbon beta coefficient of 0.90, similar to Royal Dutch Shell with 0.92. Their business is clearly strongly affected by carbon policies. In contrast, a renewable energy company such as Vestas Wind Systems that produces wind turbines should benefit from the transition to a low-carbon economy. It consequently has a significantly negative carbon beta of -1.54. Apple Inc. also established itself as a highly sustainable technology company and earns a carbon beta of -1.44. The pharmaceutical company GlaxoSmithKline has a very small and insignificant carbon beta of 0.05, meaning that its business in healthcare is not directly affected by the carbon transition in either way.

We calculate carbon betas for all stocks in our sample and break down carbon statistics on the sector and country level. Figure 2 shows box plots for carbon beta distributions of different industries. Figure 3 presents a world map of value-weighted average carbon betas for different countries. To present the current states of carbon risk, only stocks of the sample that are currently (as of October 2021) still listed are included.

Figure 2: Box plots of the carbon beta distributions for industries.



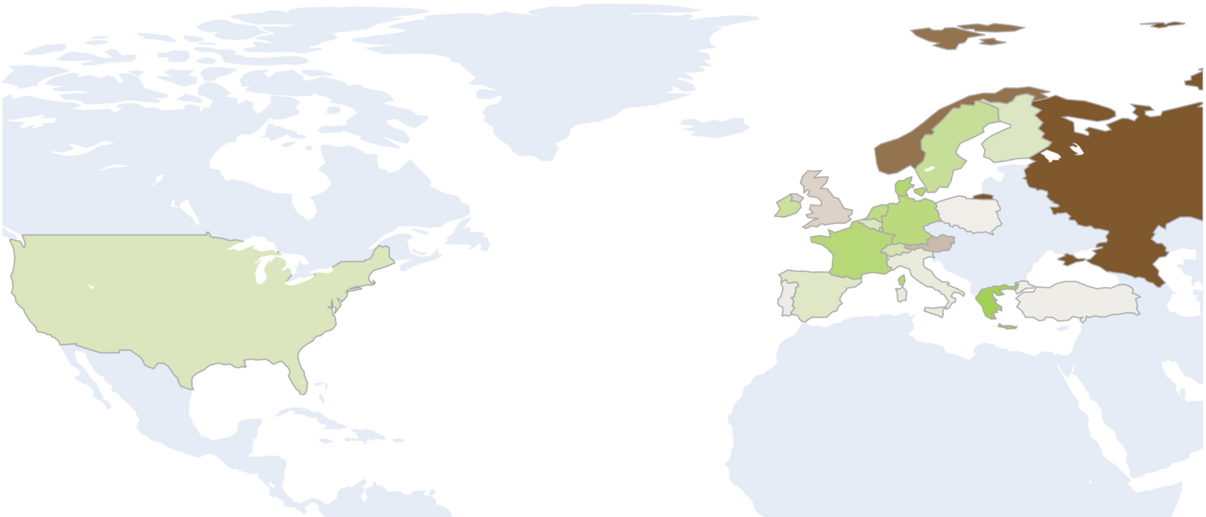
Carbon beta distributions within sectors as classified by the Refinitiv Business Classification. The boxes show the quartiles while the whiskers extend the distribution past 1.5 times the inter-quartile ranges. The bars inside of the boxes mark the medians.

In Figure 2 we can see carbon beta distributions for different industries. As one could expect, the sector at the very extreme with the highest carbon betas is the Energy sector with a median carbon beta of 0.89. The Energy sector mainly consists of oil and gas companies whose main products are very carbon-intensive and have to be phased out during the carbon transition. It is followed by Utilities with a median of 0.53 and Real Estate with a median of 0.26. These are the three sectors that bear the largest carbon risk exposure and the carbon transition is predicted to have a substantial effect on their business models. On the opposite end, the Consumer Cyclicals sector has the largest negative carbon betas with a median of -0.35. Consumer Cyclicals consists of stocks that heavily depend on the economic conditions such as furniture and luxury items. Bansal et al. (2018) also find that socially responsible stocks (also called "good" stocks") tend to outperform during good economic times similar to luxury goods. Thus, stocks of the Consumer Cyclicals industry can perform similar to our green stocks because of similarities in investors' preferences. The Technology sector also has a significant negative carbon beta of -0.28. Technology firms are known to be very innovative, forward-thinking and sustainable. These firms presents a hedge against carbon risks and can benefit from the transition to a low-carbon or even carbon-neutral economy. A sector that is distributed closely around 0 is Consumer Non-Cyclicals with a median of 0.02. This industry comprises firms that produce essential goods such as food and household products which are always in need and therefore unaffected by carbon policies.

We clearly see substantial differences of average carbon beta measures between the sectors. The effects of carbon policies, positive or negative, largely vary from sector to sector. It is notable that there is also a wide distribution within sectors. This might be important for investors that want to diversify their portfolio concentration across various sectors. Investors can screen all sectors for firms with low carbon betas. Thus, sector diversity remains possible without the need to increase carbon risk exposure.

We continue by investigating the differences of carbon risk exposures of the countries in our data sample. Figure 3 provides a world map of value-weighted carbon beta averages for all countries with sufficient data in our sample. While the data sample is relatively small for some countries, this could provide an approximate overview of the impacts of carbon policies on the countries' economies which is specifically important for policy makers.

Figure 3: Value-weighted carbon beta statistics on a country level.



Brown indicates positive average carbon beta, green indicates negative average carbon beta. Grey marks a carbon beta around 0 and light-blue indicates countries with missing data. Carbon betas per country are value-weighted by market capitalization. Countries with less than 5 stocks in the data sample are excluded.

Again, stark differences in average carbon betas are visible between the countries in our sample. The country with the highest carbon beta is Russia with a weighted mean of 0.51, most likely because of its very prominent energy sector. Norway as another dominant oil and gas exporter has the second highest carbon beta mean of 0.50, minimally less than Russia. The country with the lowest carbon beta is Greece with a mean of -0.58, although this might not be representative as the sample is very small with merely 6 equities. Greece is followed by Denmark with a carbon beta of -0.38 and then France, Germany and the Netherlands all with a rounded average of -0.32. The United States also has a negative value-weighted carbon beta of -0.13 which reverses if we consider the slightly positive unweighted mean of 0.19. This difference probably occurs because of the large US technology stocks with negative carbon betas and very high market capitalizations.

Our self-constructed carbon beta to measure carbon risk exposure for equities has in general produced plausible values for the stocks in our sample as seen by the industry and country breakdown. With the carbon risk premiums of the BMG portfolio, it is a simple and straightforward procedure to compute the carbon beta for an asset only using publicly available return data. In theory, it then contains all the market information considering the asset's carbon risk exposure. The carbon beta is a simple measure that indicates how the price moves in reaction to changes in the carbon risk portfolio. We can directly compare the values between different companies, countries, industries or portfolios. Companies can use the carbon beta to judge their vulnerability to the carbon transition. Investors can consider it to manage their investments' carbon risk exposures. Policy makers also need such tools to assess the effects of carbon policies on countries and sectors. Our asset pricing approach provides a simple method to estimate carbon betas as quantitative carbon transition risk measures. We discuss its limitations and potential improvements in the next section.

5 Discussion

Our asset pricing approach to determine carbon risk measures is dependent on the ability of the BMG portfolio to represent carbon premiums of returns. To construct the BMG portfolio, we use the CO_2 score (carbon intensity) data from Refinitiv. While we show its explanatory power in the cross-section of returns, another variable might be more appropriate to divide brown from green stocks. The CO_2 score only includes scope I and II emissions, but scope III emissions could be of much higher importance for some companies as a company can directly influence their scope I and II emissions, i.e. by outsourcing carbon-intensive production processes. There are also different data bases to retrieve firm-level greenhouse gas emissions data and we rely on a single source of Refinitiv. Different sources for the carbon intensity data should be tested because it could yield data discrepancies as ESG data often does (Kotsantonis and Serafeim 2019).

We construct the BMG portfolio by equally subtracting green quintile portfolios from brown quintile portfolios (see Equation 5). This method entails a subjective weighting function that works best for this data sample and time period based on significance tests. Instead of quintiles, one could use terciles, deciles or other limits that could have an influence on the results. Another popular construction method used by Fama and French (1993) includes the additional distinction between big and small firms based on the median market value. However, using their approach does not strongly alter the results.

Another limitation is that we only consider the stocks that report carbon emission information in Europe and the United States. Our total sample of around 1,700 stocks might not be large enough to be representative. It could also suffer from a reporting bias because some companies are obliged to report this data and others do it voluntarily. The time frame from 2009 to 2019 can also be considered too short in order to provide consistent evidence for carbon risks in stock returns. In the future, we expect that climate change will gain even more attention and more companies will report their carbon emissions, voluntarily or not. The effect of carbon risk in investments should also grow in importance and will not be limited to the western world in the future.

To compute the carbon betas, we regress the excess returns on the BMG factor and control for other risk factors. For the other risk factors, we use the data provided by Kenneth French for US and Europe (French 2021). This data generally works well for US stocks but the composite European factors can be imprecise for some stocks. Using country-specific factor data can therefore refine and improve the estimations of the carbon betas. Self-computed risk factors to fit the observed data would be a further enhancement to get more accurate coefficient estimates.

6 Conclusion

Climate change is gaining attention and the public is demanding everyone to partake in the transition to a low-carbon world. Companies are either voluntarily stepping up their efforts to lower greenhouse gas emissions or governmental carbon policies are forcing them to. Either way, this carbon transition carries a risk, positive or negative, for most firms and investors need to consider the carbon risk implications in their investment process.

We introduce an asset pricing approach to estimate the carbon risk on a firm-level using capital market information reflected in the stock price returns. The resulting estimate, called carbon beta, is a quantitative measure that indicates a company's carbon risk exposure, thus, how sensitive the company is to changes in carbon policies. We estimate the carbon beta by constructing a carbon premium portfolio "Brown-Minus-Green" (BMG). Stocks are divided into brown and green firms based on a single variable, the carbon intensity, which measure the amount of carbon equivalent emission per revenue earned.

We validate the explanatory power of the carbon intensity in the cross-section of returns using Fama-MacBeth regression. The carbon intensity has a negative and significant effect in our data sample that consists of around 1,700 stocks from 2009 to 2019. Carbon emission characteristics have a significant impact on stock returns and investors consider carbon risks in their valuations. The negative effect indicates that low-carbon firms perform better than carbon-intensive firms on average during this time period. Thus, carbon risk plays an important role but investors were not remunerated for their exposure to it. Sorting the stocks into quintile portfolios based on the carbon intensity shows a similar picture. Green portfolios significantly outperformed brown portfolios also on risk-adjusted scales.

Using the carbon premium portfolio (BMG) in a multi-factor model with other popular risk factors such as market, size, value and momentum effects, we estimate carbon beta coefficients for around 1,700 companies of the United States and Europe. We report carbon beta statistics for industries and countries. There are substantial differences in carbon risks between sectors as well as countries. Sectors with the highest carbon risks are the Energy and Utilities sector whereas the sectors with the lowest carbon betas include the Consumer Cyclicals and Technology industries. Countries with high carbon risks are Russia and Denmark. In contrast, the countries with negative carbon risks that may benefit from the carbon transition are mainly part of the European Union such as Greece, Denmark, France, Germany and the Netherlands. Within sectors and countries, there is also a wide dispersion of carbon betas. Investors thus do not have to shun certain sectors and lower their diversification to manage their portfolio's carbon risk.

Companies, investors and policy makers need simple tools to evaluate the effects and risks associated with the transition to a low-carbon economy. Companies have to consider the effects of the carbon transition on their business models. Investors need to be aware of the impacts on stocks' valuations and adjust their carbon risk exposure accordingly. Policy makers have to assess the implications of new carbon policies for sectors, countries and the general economy. While it has its limitations, our capital market based approach is an attempt to fill this need. The carbon beta is a simple measure that quantifies carbon risk and is easily interpreted and comparable. Our research is another step to accelerate and facilitate the ongoing carbon transition to tackle climate change.

A Code

The data and code that was used for the analyses is attached to this thesis on a data carrier. It includes all the relevant data as CSV files and the code as Python scripts.

The files can also be found on this following GitHub repository:
`www.github.com/Arthur-econ/carbonbeta`

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