“Brown” Risk or “Green” Opportunity?
The dynamic pricing of climate transition risk on global financial markets

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Abstract. There exists mixed evidence about the pricing of climate transition risk on financial markets. While some scholars were able to find a “brown” premium for high-risk stocks, others identified a “green” premium for stocks benefitting from the climate transition. I contribute to this debate methodologically by proposing a novel combination of a firm’s climate transition risk exposure assessment based on a granular sector/technology classification with financial factor models. Thereby, I complement approaches relying on biased/incomplete ESG data as well as CO2 data, which have been used in most previous pricing studies. Moreover, I contribute empirically by dynamically using the most recent data available (until December 2022) and by comparing the pricing of brown *and* green companies on global financial stock markets simultaneously. I find that green stocks significantly outperform both brown stocks as well as the market average when controlling for well-established risk factors. This finding is also robust when looking at specific climate sensitive sectors, namely the transportation, utility and energy sector. Interestingly, the green outperformance accelerated after the Paris Agreement, solidifying the hypothesis that green stocks profited from an unexpectedly strong increase in green preferences from both consumers and investors. It will be interesting to study whether brown stocks will start to outperform green stocks in the future which would be in line with the theoretical expectation that high-risk brown stocks yield higher expected returns. A Brown Minus Green Factor using the returns from my constructed brown/green portfolios can be used to empirically test this expectation in the future. For now, I add the tentative finding that brown portfolios carry substantially higher dividend yields in 2023, indicating higher expected returns, in line with theory.

Keywords: Climate transition risk, climate finance, climate sensitive sectors, factor models, asset pricing

1 Introduction

There is growing awareness about the relevance of financial markets for the low carbon transition of fossil fuel-based economies (e.g. Carney, 2015). Financial market can either hinder or advance the transition through various transmission channels such as available financing options, cost of capital and financial flows towards or away from “brown”/”green” economic activities. Key in evaluating whether financial markets play an enabling or a hampering role within the low carbon transition is to *ask whether and to what degree financial markets price climate risk in asset prices*. If financial markets priced climate risks strongly then financial markets play an enabling role in the envisioned low carbon transition by for example increasing (lowering) the borrowing costs of brown (green) loans. However, when financial markets are oblivious towards mounting climate risks, then financial markets will hamper the low carbon transition by delaying the relocation of investments and increasing the political as well as financial costs of the transition (Battiston et al., 2021).

Generally, there are two broad climate risk categories which might impact financial market pricing. On the one hand, physical climate risks describe risk stemming from climate change itself. The impacts of climate change will influence various stakeholders in different positive or negative ways. An example is the increase of weather extremes which will influence the insurance business significantly. On the other hand, climate transition risks, are not related to biophysical processes, but stem from the reaction to such physical climate risks, i.e. the low carbon transition to avoid the worst impacts of climate change through climate mitigation (Giglio et al., 2021).

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This paper will focus on climate transition risk and its pricing on financial markets. Generally speaking the low carbon transition can happen both in an orderly as well as in a disorderly manner. During an orderly transition, expected climate policies are put in place rapidly to then slowly increase in ambition. Market participants can form stable expectation about the future state of climate policies (Monasterolo, 2020) and no frictions such as stranded fossil assets occur (van der Ploeg & Rezai, 2020). Increasingly likely however is the second option, namely that global economies will transition towards a low carbon future in a disorderly manner. Such a scenario emerges when climate policies are enacted very late or unexpectedly and therefore must be immediately harsh. Market participants then do not have sufficient time to form a stable long-term outlook and their expectations change rapidly after the announcement of more ambitious climate policies. This creates the risk of significant losses and stranded assets for exposed investors as well as high carbon firms (Battiston et al., 2021; van der Ploeg & Rezai, 2020). Climate transition risk is higher in case of a disorderly transition as companies and investors do not plan for the low carbon future which then increases the likelihood that climate policies or technological shocks are unanticipated and surprising to market participants. In order to test for the pricing of this climate transition risk on financial markets I first differentiate the exposure to this climate transition risk or opportunity (henceforth I will use "risk", implying both upside and downside climate transition risk). In a second step the pricing of positive and negative exposure can be compared. I will focus on the climate transition risk of listed companies as they represent large global companies which are key stakeholders within the transition and good financial market pricing data is a{Zerbib, 2019 #72}vailable for these firms.

Listed companies can be positively, negatively or mostly neutrally exposed to climate transition risk. The risk exposure mainly depends on the economic activities the company is involved in as well as the technology utilized (Battiston et al., 2020). A car manufacturer can be for example negatively expose to climate transition risk, if the manufacturer focuses exclusively on diesel cars. However, a car manufacturer producing electric vehicles is positively exposed as the firm might benefit from a disorderly transition towards low carbon technologies. Standard industry classifications such as the NACE Rev.2 codes for the European Union classify all economic activities into 4-digit codes. However, to date, they do not take climate aspects into account[2]. For example, the very climate policy relevant economic activity *production of electricity* (NACE 35.11) includes both the production of electricity from renewable as well as non-renewable sources (Eurostat, 2008). Thus, NACE codes do not take technologies into account and are thus ill suited to differentiate listed firm's climate transition risk exposure. On upside/positive climate transition risk, the EU taxonomy on sustainable activities is set to fill that data gap as listed firms will have to report the percentage taxonomy alignment of their revenues, opex and capex from 2023 onwards. This metric could then be used to estimate how exposed companies are to the opportunities of a disorderly transition. However, the taxonomy only focuses on sustainable activities and thus provides no insights into the rest of the revenue and capex, i.e. whether they are exposed to negative risk or neutral from a climate relevance perspective. Partly addressing these shortcomings, Battiston et al. (2017) came up with the Climate Policy Relevant Sector (CPRS) methodology which reclassifies 4-digit NACE codes into 9 distinct sectors. The classification is based on companies GHG emissions, the relevance for climate policy and the importance of the economic activity within the energy value chain. Beyond the 9 main sectors the CPRS methodology differentiate also into granular sub-sectors which separate economic activities based on their energy technology (Bressan et al., 2022). However, in order to allow for such a reclassification, one must know very detailed company information, i.e. utilized technologies per economic activity. Such information is not (yet) disclosed by companies, thus CPRS granular requires painful company by company analysis rendering the method very time consuming until new disclosure regulations such as the EU Taxonomy or the Corporate Sustainability Reporting Directive will provide more publicly available company data.

[2] There is an update of the NACE codes expected for 2024.

For this paper I use The Refinitiv Business Classification (TRBC) in order to differentiate company's climate transition risk exposure. TRBC classifies more than 72000 companies into 13 economic sectors and 898 activities which show to the highest level of granularity what is the most relevant business activity of the company and what technology is used predominantly in the production process (TRBC, 2022). Thereby it is possible to identify firms at high-risk within a disorderly transition (e.g. diesel car manufacturers) as well as firms which might benefit from such a transition (e.g. electric vehicle manufacturers). The advantage of the TRBC approach is that large green/brown portfolios can be constructed relatively easily while still differentiating accurately between high and low climate transition risk. To the best of my knowledge this paper is first in analyzing stock returns of brown and green firms based on a granular industry classification which takes technologies into account. Next, I compare the pricing of these brown (high-risk) companies vs. the pricing of green (high opportunity) companies against one another as well as against the market. Most notably I show by using financial factor models, the different factor loadings of green and browns portfolios over time using the Fama French 3 and 5-Factor models as well as the Carhart 4-Factor model. I find a green premium compared to the market average as well as against brown stocks. This result is stable for different climate sensitive industries, different portfolio weights, differing time horizons and geographical locations. I also describe the development of this premium over time and highlight the apparent relevance of the Paris Agreement in my time series. Finally, I construct a Brown Minus Green (BMG) Factor, show its pricing properties and discuss the low correlation against other established pricing factors.

The rest of this paper is structured as follows: I first highlight previous research on pricing of climate risks on financial markets. Then I explain the methodology of first identifying high/low-risk companies and then to analyze their pricing on global financial markets over time. Subsequently, I present main results as well as interesting auxiliary findings. Finally, I debate the implication of my findings, discuss limits and provide an outlook for further research.

2 Literature Review

My research relates to a quickly expanding research field treating the relevance of climate related risks on financial markets. In what follows I briefly summarize some key qualitative research to then focus on relevant recent quantitative work on the pricing of climate transition risk both in the stock as well as on the bond market. Then I also discuss the data foundation most scholars utilize, namely ESG and/or CO2 data.

Some authors qualitatively seek to understand if/how decision makers on financial markets incorporate climate risks into their investment decisions. Christophers (2019) interviews institutional investors and finds that there is no reason to believe that the market will by itself stop investing in carbon intensive securities as long as they remain profitable. Most investors responded that they simply do not view it as their job to invest ethically. Additionally, the stated investment horizon of most investors is considerably shorter than the anticipated negative impacts from climate related risks. Krueger et al. (2020) also ask institutional investors if and how they started to incorporate climate related risk into their investment decisions. They find that institutional investors have started to incorporate climate risk as most believe that climate risks will have financial implications. Mentioned transmission channels are reputational, legal and performance related. Interesting further findings show that less than half of the respondents actually started to analyze carbon footprints and exposure to stranded assets. Most relevant for this study Krueger et al. (2020) also find that the average institutional investor believes that equity prices on financial markets do not (yet) fully reflect climate risks.

There is also quickly expanding empirical work on the pricing of climate transition risk on financial markets. Most studies employ either CO2 estimates or ESG scores in order to identify a firm's climate transition risk profile. One of the first scholars embarking on this mission is Lewandowski (2017), who focuses on firms scope 1 & 2 emissions between 2003 and 2015. He finds unconclusionary results as companies' emissions are positively related to return on sales, but exhibit a negative relation to Tobin's q. These mixed findings can be explained by the analyzed horizon, as Bolton and Kacperczyk (2021b) show that the carbon premium they were able to find only started to materialize recently. Relying on a cross-section of US stock market returns they find a significant carbon premium for both total emissions and emissions change. They provide three hypothesis which might explain the pricing of emissions on financial markets. First, the carbon premium hypothesis, in line with the efficient market hypothesis, states that rational investors want to be compensated for holding riskier assets by higher returns. As carbon intensive firms bear higher carbon transition risk, they should pay a carbon premium. Second, there could be a mispricing of climate related risks on financial markets. Thereby investors could earn extra returns by holding green stocks. Finally, the divestment hypothesis explains higher stock returns for high carbon "sin" stocks by divestment from ethically aware investors who exclude certain equity's in their investment strategies. Bolton & Kacperczyk (2021b) regard their findings as proof for the carbon premium hypothesis. The theoretical underpinning of the carbon premium hypothesis can be found in Pástor et al. (2021) who construct a theoretical model in equilibrium showing that rational investors are willing to pay higher prices for green firms, which leads to lower alphas (i.e. underperformance) compared to brown stocks which are expected to generate positive alphas (i.e. outperform). However, if customers/investors unexpectedly and significantly shift their preferences towards green products/investments, then green equities may still outperform brown ones in the medium term even though they are expected to generate lower returns.

Recent work by Bolton & Kacperczyk (2021a) reinforces their findings from the US on a global level. They are able to show a carbon premium for a panel of stocks across 77 countries from 2005 to 2018 for both carbon emission levels and growth rates. Interestingly they note that the carbon premium rises especially after the Paris Agreement. Hsu et al. (2022) find supporting evidence for industrial pollution. A high minus low portfolio in toxic emission intensity yields an outperformance of 4.42% p.a. which remains significant after controlling for risk factors in the Fama French 5-Factor model (Fama & French, 2015). Relatedly, Alessi et al. (2021) construct a synthetic weighted index of a company's environmental transparency and greenhouse gas (GHG) emissions in order to measure a firm's environmental performance. They find lower returns for greener, i.e. higher transparency and lower GHG emissions, firm`s. They explain their findings in line with Pástor et al. (2021), i.e. investors are willing to accept below average green returns as they can function as a hedge against climate related risks. However, different to Bolton and Kacperczyk (2021a, 2021b) they cannot find a carbon premium when only GHG emissions are considered.

Monasterolo and de Angelis (2020) use well known high and low carbon indices and utilize asset pricing models to test whether the market prices these indexes differently after the Paris Agreement. They find that the systematic risk (the market factor) of low carbon indices decreases significantly, while it is mildly rising for high carbon indices. Additionally, the optimal portfolio weights of low carbon indices tend to increase after the Paris Agreement. Bernardini et al. (2021) focus on European electric utilities and find different to Bolton and Kacperczyk (2021a, 2021b) a low carbon premium, i.e. firms with low GHG emission intensity ratios, produce higher risk-adjusted returns. They utilize common risk factor models and show that this premium is especially pronounced in the time period from 2012 until 2016. Pástor et al. (2022) are able to show a green outperformance both for German green bonds as well as US equity returns. They explain their results, in line with their theoretical model (Pástor et al., 2021), by the difference between realized and expected returns, i.e. they are able to show that unexpectedly strong increases in concern about climate transition risk cause high green realized returns, not high return expectations. These findings are reinforced by van der Beck (2021) who also shows a green outperformance of equities and can explain the high green returns by flows towards sustainable funds.

Other authors estimate climate transition risk of companies utilizing marked-based approaches. Most notably, Görgen et al. (2020) create a brown green score (BGS) which is constructed by combining different variables from various ESG databases, assigning a high weight to corporate carbon emissions.

For the time period from 2010 until 2017 they find that firms with higher BGS scores (i.e. browner stocks) exhibit higher expected returns. This result is in line with both Bolton and Kacperczyk (2021a, 2021b) as well as Pástor et al. (2021). However, they also find, that positive changes in the BGS score lead to negative stock returns. This implies that firms which become unexpectedly greener are rewarded with extra returns. This is in line with Pástor et al. (2021) theoretical prediction that unexpected changes towards a green economy are beneficial for green stocks but differs from Bolton and Kacperczyk (2021a, 2021b) observation that positive changes in the growth rates of carbon emissions are associated with higher returns. As a next step, Görgen et al. (2020) utilize the BGS score to create a brown minus green factor. They then run cross-sectional regression to test for a brown risk premium, which they cannot find, again diverging from the results of Bolton and Kacperczyk (2021a, 2021b). Görgen et al. (2020) conclude that financial market actors are apparently not fully incorporating climate related risk into their investment decisions. Ravina and Hentati-Kaffel (2019) create another factor aimed at capturing carbon transition risk in common factor models. They create their Green Minus Clean factor by subtracting firms participating in the EU emission trading scheme from firms which are exempted. They find a high green premium in stock returns for the time period from 2008 – 2018. Huij et al. (2021) follow a similar approach and construct a Polluting Minus Clean factor utilizing scope 1 and 2 emission data. They find that, when controlling for industry effects, firms with higher carbon beta (firms with higher emissions) tend to exhibit higher returns, all else being equal. This carbon premium is lower in times when climate change is frequently mentioned in the news, and during times of weather extremes. Similarly, Pástor et al. (2022) find that absent unexpected climate concern shocks, the highlighted green outpfermormance vanishes. This could hint at the mechanism proposed in Pástor et al. (2021), that shifts in preferences might moderate the carbon premium. Higher awareness to climate change might trigger such an unexpected reevaluation.

Several scholars developed text-based approaches to create indices supposed to measure such climate change news risk and hedge climate change exposure of firms. Most notably, Engle et al. (2020) pioneered the field by proposing two newspaper-based climate change risk indices in order to construct mimicking portfolios which are hedging against climate risks. Ardia et al. (2022) extend the proposed methodology to daily frequencies and a broader set of media outlets. They can show that on days with unexpected increases in in climate change concerns, green stocks tend to outperform brown assets. Finally, Sautner et al. (2020) utilize a machine learning approach and quarterly earning call transcripts in order to derive a proxy for companies' climate change exposure. This proxy can be used to predict green job creating, green technologies as well as some asset prices in the equity and options markets.

There is also abundant work on the relation of ESG scores and stock market performance (e.g. Demers et al., 2021; Havlinova & Kukacka, 2023; La Torre et al., 2020). Overall results are inconclusive and heavily depend on the time horizon, universe of companies, ESG data provider and ESG sub score chosen. Beyond studies focusing on the stock market there is also work on the pricing of climate related risks on the bond market. Delis et al. (2019) investigate the loan spread of corporate loans of firms with high fossil fuel reserves which are at risk of becoming stranded. They find no significant pricing of this climate transition risk before 2016 but significantly higher loan spreads for high climate risk companies after the Paris Agreement. Other scholars focus on the cost of debt for renewable energy firms. Results suggest a dynamic pricing as renewable energy firms initially pay a higher price for their debt. However, over time a cost advantage for green firms materialize compared to higher carbon firms (Kempa et al., 2021). Hyun et al. (2021) study the pricing differentials of labelled vs. unlabeled bonds and find that labelled green bonds command 24-36 basis points lower bond yields compared to unlabeled bonds.

Different to most papers presented here, my identification of companies with different degrees of climate transition risk does not rely on CO2 estimates or ESG/CSR scores. Potential shortcomings of both approaches are briefly discussed now. On the one hand, CO2 or GHG emission data comes with several data quality issues. Most notably, the data on the firm level is notoriously sparse and difficult to compare amongst companies and database providers. This is particularly true for the very relevant scope 3 value chain emissions where the disclosure is voluntary and estimates are hard to obtain and difficult to compare (Ducoulombier, 2021). Additionally, Berg et al. (2021) find that historic CO2 data on Refinitiv ESG is been rewritten or deleted retroactively on an ongoing basis, questioning the quality and validity of databank emission estimates. Bressan et al. (2022) provide a striking example of the difficulties associated with utilizing scope 3 emission data. Even though car manufacturers Stellantis and Volkswagen have similar fleet emissions in 2020, Volkswagen exhibits scope 3 GHG emission intensity 128x higher than Stellantis, simply because Stellantis uses a different methodology in calculating scope 3 emission data. Kalesnik et al. (2020) show that only roughly 50% of companies report emissions data directly. Data providers commonly estimate carbon data; however, the authors show that these estimates are roughly 2.4 times less effective than directly reported data. Beyond data quality issues a sole focus on CO2 data might be oversimplified as CO2 emissions might indicate different climate transition risk exposures across different industries. Emissions might be for example more accepted by policymakers if they are emitted by an enabling industry supporting the climate transition. Moreover, as of today a global CO2 price covering most emissions seems far out of reach and many implemented CO2 prices are still too small to matter economically (World Bank, 2023). Thus, transition risk might not only arise from high costs of CO2 emissions due to CO2 prices but can also stem from subsidies for alternative technologies, or sector specific command and control regulations. These risks are not captured when only focusing on CO2 emission data.

On the other hand, commonly used ESG scores which mix environmental, social and governance indicators, also exhibit severe data quality issues: First, they are not comparable amongst different publishers (e.g. Chatterji et al., 2016; Dimson et al., 2020; Dumrose et al., 2022; Kotsantonis & Serafeim, 2019; Yu et al., 2020). Second, they are vulnerable to greenwashing as Drempetic et al. (2020) find a significant size bias in the ESG ratings of Thomson Reuters ASSET4 ESG (later called Refinitiv ESG). Third, Berg et al. (2022) show that the huge variation in ESG scores across ESG rating agencies stems from differences in scope, weight and measurement. Most problematic, the *measurement* category is most relevant in explaining differences in ESG scores. Thus, ESG score differences rely not only on technicalities but highlight significant differences in the definition of the underlying data and on how this data is measured. They also identify a rater's bias as raters scores are correlated across assessments in different categories per firm. In other words: a high rating in one E,S,G category also prompts a higher rating in another E,S,G category. Fourth, Berg et al. (2021) show that *historic* ESG data on Refinitiv ESG is backfilled and changed by Refinitiv. While one big methodological change in 2020 was communicated by Refinitiv, Berg et al. (2021) find that Refinitiv rewrites data on an ongoing basis without communicating the changes to the public. Interestingly, Refinitiv appears to rewrite ESG data in a biased manner, that is, companies which outperformed in the last years are more likely to gain positive ESG updates. This leads to historic overperformance of high ranked ESG companies for the rewritten data. However, when using the initial data, no ex ante outperformance can be obtained.

Summing up, there is mixed evidence on the pricing of climate related risks on financial markets. Some authors find a brown carbon premium while other scholars show that green stocks outperform brown ones. Overall the results seem to be highly dependent on the respective time frame and measure for climate transition risk. I add to that literature methodologically by utilizing a different approach in identifying climate transition risk, namely the riskiness of the used technology through the TRBC business classification. By grouping companies according to the sustainability of their technologies with respect to their climate sensitive industry, I am overcoming limits from the utilization of CO2 or ESG data. Gaining a better understanding of the pricing of climate transition risk is key for all stakeholders involved in the low carbon transition. Investors gain insights into potential climate risks of their portfolio positions and may learn what value reshuffling of investments towards green assets might yield. Policymakers can better understand how credible their low carbon policy announcements are for financial market participants. Finally, climate finance scholars benefit from a sound understanding of the pricing of climate risks on financial markets. To this end I contribute empirically in different ways.

First. I analyze the factor loadings of brown and green portfolios simultaneously. To date, most studies only focused on brown or green portfolios, due to the difficulties of identifying brown/green companies at the same time with either CO2 or ESG data. Second, I use, the most current time frame until the end of 2022. Thereby my 10-year time window includes the Paris Agreement, the Covid-19 Pandemic as well as the energy price shocks following Russia's invasion of Ukraine. I exploit this current dataset also in a dynamic way as I analyze the pricing of climate transition risk on global financial markets also over time by means of rolling regressions. Third, I extend the current focus of the literature beyond the US towards global equity markets with separate analysis for 3 continental regions. Fourth, I propose the dividend channel as another means of showing that investors expect higher compensation for holding riskier brown assets compared to green portfolios as well as the market average. Finally, I use the TRBC business activity and technology classification to construct a BMG pricing factor which might significantly help explaining global cross-sections of returns as climate transition risk becomes increasingly crucial on global financial markets.

3 Methods

This section describes my data as well as my empirical strategy. First, I show how I create 8 climate sensitive portfolios through the TRBC business/technology classification. Then, I discuss some properties of these portfolios. In a second step, I highlight the financial pricing models which I employ to answer the research questions. I use the TRBC company classification in order to create different portfolios from the Thomson Reuters Eikon database. I thereby create portfolios constituted of active global brown or green companies from 3 distinct climate sensitive industries. Additionally, I create an overarching green and brown portfolio pooling all companies from different industries together. I exclude all firms with a market capitalization below 10 million USD as well as all companies with missing ISINs and download errors. After the data treatment I am left with 2235 companies.

Table 1 summarizes the portfolios. The chosen industry portfolios are all highly climate sensitive as the respective sectors transportation, utilities and energy are all either directly (scope 1-2) or indirectly (scope 3) highly CO2 intensive and are all highly relevant for the energy value chain as well as for climate politics (Battiston et al., 2020). While the sectors agriculture, energy intensive industry as well as construction are highly climate sensitive and carry high GHG emissions, TRBC does not yet offer a detailed technology differentiation which would allow to easily identify brown and green companies in these sectors. Thus, in line with (Bressan et al., 2022), I focus on few key sectors where high and low-risk technologies were easy to identify. Most notably, based on granular TRBC I was able to separate two different types of companies within the same sectors. Based on their technology, one group can be categorized as having high climate transition risk, the other group might significantly profit from the climate transition as it utilizes mostly zero or low carbon technologies. A good example to highlight the strength of the chosen categorization is the automotive sector as a subsector of the transportation sector. High risk companies are companies manufacturing predominantly vehicles with internal combustion engine (ICE) or hybrid power train such as Mercedes or Toyota whereas high climate transition opportunity companies such as Tesla or electric vehicle (EV) startups such as Li Auto exclusively use alternative powertrains. This TRBC based approach is thus able to separate companies from the same industry based on their climate transition risk profile. My portfolio construction based on the TRBC classification relates to the well-established CPRS sector classification pioneered by Battiston et al. (2017) which reclassifies climate relevant NACE codes into granular CPRS. This approach was later refined by Bressan et al. (2022) who introduced more granular CPRS2 subsectors which rank different energy technology by their climate transition risk profile similarly to my approach. However, my analysis does not start at the NACE code level but uses the TRBC. Additionally, my approach is even more granular than the CPRS approach by Bressan et al. (2022) as the TRBC is able to differentiate brown/green technologies highly accurately. For instance, I go further than pooling all road vehicles into one CPRS2 subsector by differentiating between brown ICE and green EV technologies. In order to facilitate the comparison between the TRBC and CPRS granular I included a comparison between the two classifications in table 1 wherever possible.

All in all, I create 8 distinct portfolios. Three Industry portfolios each containing two different groups of high/low climate transition risk companies in the transportation, utility and energy sectors. My two baseline portfolios combine all green and all brown firms into overarching non sector-specific portfolios. As depicted in table 1, the 8 portfolios are not exactly similar in terms of number and size of constituents as there are roughly 3.5x as many brown firms in the portfolios as green ones. This highlights the current structure of most economies where carbon intensive companies significantly outnumber green firms. This is also indicated by the mean market capitalizations of all green and brown companies across all time periods. As brown firms are mostly well-established incumbents, they carry a roughly 2x bigger market capitalization compared to green firms in the same industry. This holds for all sectoral portfolios with the notable exception of the small EV portfolio. The very high market capitalization of the Tesla stock, which crossed the 1 trillion $ threshold for parts of the time series explains this observation. Concerning the geographic dispersion of the firms in my dataset, most companies are having their headquarter in the United states (341) followed by China (294), Canada (166) and Australia (90) and India (85). While China and the US as well as India are economic superpowers, Canada and Australia are heavily focused on the extraction of natural resources, thus many companies from the fossil energy portfolio are Canadian or Australian. All in all, my portfolios cover companies from all major economies and approximately reflect economic global power structures. Interestingly, green firms are more heavily focused in Asia, as out of the 7 countries with most green firms, 6 countries are in Asia.

Table 1 | Portfolio summary. The all brown/green portfolio are aggregates of the 3 industry sub-portfolios. The market cap column indicates the mean market capitalizations at the end of 2022. The Refinitiv Business Classification (TRBC) and Climate Policy Relevant Sectors (CPRS) are granular industry classifications. The top 3 positions are based on market capitalizations. Authors' own calculation with data from the Thomson Reuters Eikon database.

Portfolio	#Firms	Market Cap	TRBC activity name	CPRS2 granular	Top 3 positions 12/2022
All Brown Firms	1732	$5.5 bn	All brown TRBC activities	All brown codes	Saudi Aramco, ExxonMobile, Chevron
ICE Manufacturers	151	$7.9 bn	Consumer Cyclicals|Automobiles and Auto Parts|Auto&Truck Manufacturers	Transportation|Road|Vehicles|Combustion	Toyota, Mercedes-Benz, BYD
Brown Utilities	307	$3.6 bn	Utilities|Natural Gas/Fossil Fuel Electric Utilities/IPP/Multiline Utilities	Electricity|Fossil|Coal/Gas/Oil/Nuclear	Abu Dhabi National Energy Company, Électricité de France, Sempra Energy
Fossil Energy	1274	$5.6 bn	Energy-Fossil Fuel|Coal/Oil & Gas/Oil & Gas Related Equipment and Services	Fuel|Nuclear & Fuel|Fossil|Coal/Gas/Oil	Saudi Aramco, ExxonMobile, Chevron
All Green Firms	503	$2.6 bn	All green TRBC activities	All green codes	Tesla, Adani Green Energy, Enphase Energy
EV Manufacturers	41	$11.5 bn	Consumer Cyclicals|Automobiles and Auto Parts| Electric (Alternative) Vehicles/ automotive batteries	Transportation|Road|Vehicles|Hydrogen/Electric	Tesla, Li Auto, Rivian
Green Utilities	214	$1.8 bn	Utilities|Renewable|IPP|Solar /Wind/Alternative/Geothermal/Hydroelectric/Biomass Utilities	Electricity|Renwable|Solar/Wind/Biomass	Adani Green Energy, China Three Gorges Renewables, EDP Renováveis
Renewable Energy	248	$1.8 bn	Renewable Energy| Renewable Fuels/ Renewable Energy Equipment & Services	/	Enphase Energy, Vestas Wind Systems, Tongwei

In order to compare the pricing of the 8 portfolios I create market capitalization (value) weighted portfolios. The portfolio weights of the value weighted portfolios are dynamically rearranged monthly. I am using total return index data as it includes dividend payments from companies. As an additional stability test, I also weight portfolios equally in order to show that my results are not only driven by some heavy weights such as Tesla. Moreover, I also form continental green/brown portfolios in order show that my results hold for all major economic regions. I use monthly return data from January 2013 until December 2022 from the Thomson Reuters Eikon database. Due to databank specific errors, which are more pronounced for small companies on EIKON, I had to adopt a dual relative/absolute winsorization approach. First, I winsorize the absolute extreme (most positive/negative) monthly return values as they would otherwise bias the relative winsorization. The relative cutoff is subsequently set at three standard deviations below/above the median. I refrain from winsorizing market capitalizations as that would bias the market capitalization of larger firms downwards. Additional to the winsorization, I also exclude zero returns, which are often reported in EIKON for missing data points. In total, 120 different time periods are utilized for the time series regressions equaling the last 10 trading years. This is the most recent data available and covers a long enough time span to infer time-specific pricing differences. Additionally, the chosen time frame covers major positive/negative climate relevant political events such as the 2015 Paris Agreement or the election of Donald Trump as the 45th President of the United States in 2016. To compare the pricing of different portfolios against each other and the market average, I use well-established factor models, i.e. the Capital Asset Pricing Model (CAPM) or multi factor models. The CAPM estimate an assets systematic risk sensitivity compared to the market (beta) through OLS time series regressions (Lintner, 1975; Sharpe, 1964). More formally one can estimate the market model through the following equation:

(3.1) $$R_{it} - RF_t = \alpha_i + \beta_i (RM_{kt} - RF_t) + \epsilon_{it}$$

R_{it} is the monthly weighted return of portfolio i, namely my portfolios 1-8. One time period t corresponds to one month in the time series. RF_t is the risk-free rate of return, approximated through the 1 Month US Treasury Bill Rate. Hence, $R_{it} - RF_t$ equals the excess return of portfolios i at time t. RM_{kt} is the return of market portfolio k at time t. Again, it follows that $RM_{kt} - RF_t$ is the excess return of market portfolio k against the risk-free rate. As a stability test I utilize different market portfolios, but as my dataset contains global companies, the Morgan Stanley Capital International (MSCI) world total return index will be the baseline market portfolio. α_i and β_i are time-invariant stationary parameters, estimated by (3.1). α_i is Jensen's alpha coefficient, the alpha coefficient is the intercept of the regression. Alpha is positive if a portfolio outperforms the market on a risk-adjusted basis and negative if a given portfolio underperforms, all other risk factors considered. The beta coefficient measures the systematic risk of portfolio i against the market. $\beta_i = 1$ implies a systematic risk of portfolio i in line with the market portfolio, and $\beta_i > 1$ a larger systematic risk than the market portfolio. Finally, ϵ_{it} is the serially uncorrelated random error term. The CAPM model explains excess returns solely through the market factor, however, there are also other more complex models developed to better explain the variation in stock market returns. The Fama French 3-Factor Model for example is estimated through the following equation:

(3.2) $$R_{it} - RF_t = \alpha_i + \beta_{1i}(RM_{kt} - RF_t) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \epsilon_{it}$$

Both the High Minus Low (HML) and the Small Minus Big (SMB) additional factors are estimated through two further beta coefficients for each respective portfolio. The HML captures potential value premia while the SMB includes the tendency of small stocks to outperform larger stocks (Fama & French, 1993). I also run the Fama French 5-Factor model:

(3.3) $$R_{it} - RF_t = \alpha_i + \beta_{1i}(RM_{kt} - RF_t) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}RMW_t + \beta_{5i}CMA_t + \epsilon_{it}$$

This model adds two more factors, namely the profitability factor Robust Minus Weak (RMW) as well as the investment factor Conservative Minus Aggressive (CMA) (Fama & French, 2015). Finally, the 4-Factor Carhart Model adds to Fama French 3-Factor Model a momentum factor (Carhart, 1997):

$$\text{(3.4)} \quad R_{it} - RF_t = \alpha_i + \beta_{1i}(RM_{kt} - RF_t) + \beta_{2i}SMB_t + \beta_{3i}HML_t + \beta_{4i}MOM_t + \epsilon_{it}$$

I am most interested in the alpha (α_i) coefficient. A significant alpha would imply that, even after accounting for all common risk factors explaining the performance of a portfolio, there remains significant outperformance of a portfolio. The existence of an alpha might thus indicate a brown risk premium, i.e. higher realized returns, that investors demand for the higher climate transition risk exposure of the brown portfolios. However, it might also indicate an outperformance of green stocks. The data on the pricing factors stems from the Kenneth French Online Data Library[3]. As I analyze global stock market portfolios heavily concentrated in developed economies, I use the Fama/French Factors for developed markets.

I will compare the pricing of the all brown, all green as well as the pricing of the sector-specific portfolios. The sector-specific portfolios can be also interpreted as industry fixed effects as I am exclusively analyzing the within variation of an industry. Table 2 provides summary statistics for the 8 portfolios as well as all the factors from the aforementioned factor models. Interestingly, green portfolios consistently exhibit higher average returns against their brown counterparts. However, they also show a higher standard deviation, which is expectable as green portfolios are on average smaller than brown portfolios. The highest average return can be found in the EV portfolio, the very high weight of Tesla and the extreme performance of this stock over the last decade explains this finding. It will be interesting to analyze by means of factor models if the outperformance of green portfolios against the market as well as the brown portfolios can be explained by common risk factors.

Table 2 | Summary statistics for the time series of monthly value weighted portfolio returns.
The Table depicts descriptive statistics for the monthly excess returns of several constructed portfolios, market indexes as well as pricing factors. Authors' own calculation with data from the Thomson Reuters Eikon database.

Variable	Obs	Mean	Std. Dev.	Min	Max
All Brown Return	120	.011	.043	-.168	.144
ICE Return	120	.012	.052	-.200	.158
Brown Utilities Return	120	.011	.035	-.160	.091
Fossil Energy Return	120	.010	.049	-.164	.152
All Green Return	120	.030	.086	-.184	.361
EV Return	120	.035	.158	-.343	.561
Green Utilities Return	120	.016	.038	-.102	.122
Renewable Energy Return	120	.034	.088	-.229	.266
MSCI World Total Return	120	.008	.042	-.133	.128
SMB Factor Return	120	-.001	.015	-.044	.032
HML Factor Return	120	-.001	.028	-.092	.120
RMW Factor Return	120	.003	.013	-.029	.046
CMA Factor Return	120	.001	.018	-.054	.081
MOM Factor Return	120	.005	.027	-.109	.067

In my baseline analysis I focus on the whole-time frame from 2013 until the end of 2022, however, it is also interesting to observe trends in the alpha and beta estimates over time. To this end, I estimate rolling regressions, which apply a specific time window over the time series dataset. I utilize a 30-month

[3] The Fama and French factors are downloaded from Kenneth French's data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

time window. The first window starts in January 2013 and stops in June 2015, the second window starts then in February 2013 and so forth. Finally, I will create a zero-cost BMG Factor, which is long the brown portfolios while being short on the green portfolios. The return of the BMG factor can be written as:

(3.5) $$R_{jt} = (R_{bt} - RF_t) - (R_{gt} - RF_t)$$

Where R_{jt} is the return of a BMG factor j. The return is calculated by subtracting the excess return above the risk-free rate of a green portfolio g from the excess return of a brown portfolio b. This approach follows the intuition of Görgen et al. (2020) and Görgen et al. (2021) albeit with two key differences. First, Görgen et al. (2021) utilize a very broad set of companies, including heavily weighted firms such as Apple which are not particularly climate relevant. I focus only on firms which are very climate sensitive. Second, I do not solely rely on (estimated) ESG and CO2 data, but use an industry/technology classification. In constructing a BMG factor, one would normally sort the constituents of the portfolios based on their brown/greenness, but as I am aiming to construct the most brown and green portfolios possible by means of the TRBC classification, I interpret the companies in my brown and green portfolios as the top/bottom climate transition risk exposed firms of a complete list of sorted global companies since they represent "pure-play" green or brown companies which earn most of their revenues in a very climate sensitive sector by either a very sustainable or very dirty technology. The construction of the BMG factor thus mimics the construction of other traditional pricing factors and I will test whether my BMG factor correlates significantly with other known factors or if an additional BMG factor might in fact increase the explanatory power of traditional pricing models. Finally, the factor can be used to test empirically whether such a BMG factor produces positive or negative alphas.

4 Results

In what follows I will present the results of the factor model regressions of my various brown and green portfolios, thereby answering the research question *whether and to what degree financial markets price climate risk in asset prices over time.*

4.1 Pricing of climate transition risk in baseline green and brown portfolios

First, I will analyze the pricing of the two big brown/green portfolios, without differentiating with respect to specific industry effects.

Table 3 | Factor model regression results. The column headers highlight which value weighted portfolio was used as dependent variable. The rows illustrate the regression results for several pricing factors and the constant. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of observations as well as the estimated R squared. Authors' own calculation.

VARIABLES	(1) All Brown	(2) All Brown	(3) All Brown	(4) All Green	(5) All Green	(6) All Green
Market	0.787***	0.812***	0.804***	1.173***	1.174***	1.135***
	(0.049)	(0.053)	(0.053)	(0.188)	(0.214)	(0.187)
SMB	0.294**	0.298**	0.205	0.812	0.812	0.361
	(0.139)	(0.139)	(0.149)	(0.561)	(0.559)	(0.604)
HML	0.634***	0.687***	0.507***	-0.848***	-0.846***	-0.763
	(0.073)	(0.086)	(0.149)	(0.219)	(0.244)	(0.514)
RMW			-0.375*			-1.282**
			(0.203)			(0.580)
CMA			0.078			-0.780
			(0.219)			(0.694)
MOM		0.107			0.003	
		(0.093)			(0.371)	
Constant	0.006***	0.005**	0.006***	0.021***	0.021***	0.026***
	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.006)
Observations	120	120	120	120	120	120
R-squared	0.744	0.747	0.752	0.441	0.441	0.479

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 depicts the regression results for the brown and green baseline portfolios. All in all, I estimate 3 different factor models for each of the portfolios. First, the Fama French 3-Factor model in columns (1) and (4) for the brown/green portfolio respectively. Second, the Carhart 4-Factor Model in columns (2) and (5) and, Third the Fama French 5-Factor model in the columns (3) and (6). The results for the alpha estimator are very constant across the different models for both the brown and the green portfolio as they do not change significantly when I add more pricing factors. All models indicate a strong outperformance of the green portfolio against the market as well as against the brown portfolio. Interestingly the brown portfolio seems to outperform the market as well on a risk-adjusted basis, albeit with significantly lower alpha estimates. The alpha estimates for both the brown (~.5%) and green (~2.3%) portfolio are highly significant in all estimated models. Annualizing the alphas for the 5-Factor Models yields an annual outperformance of ~6% for the brown and 27.6% for the green baseline portfolio. The market beta estimates are significantly higher for the green portfolio compared to the brown portfolio. The value of ~1.2 indicates that the systematic risk of the green portfolio is slightly higher than the market average. The beta value of the brown portfolios (~0.8) shows that the systematic risk of the brown portfolio is perceived to be lower than the market average of 1 across the whole time frame. These results are in line with expectations since brown firms are more established incumbents which carry higher average market capitalizations and also exhibited lower standard deviations compared to the green portfolio. Again, these results are very robust to adding additional factors.

Concerning the other factors, the Momentum as well as CMA investment factor are not significant for neither portfolio. Albeit being not significant, the signs of the coefficient indicate that green firms seem to invest more heavily than their brown counterparts. This is in line with Pástor et al. (2021) who predict based on their theoretical model that green firms should invest significantly more than brown firms. Thus, I expect to see a positive (negative) coefficient estimate for the CMA factor for the brown (green portfolio). Interestingly the RMW profitability factor is highly significant and negative for the green portfolio, indicating that green firms are rather weakly profitable compared to the market average. The HML factor shows the expected signs and is highly significant for most model specifications. It is positive for the brown portfolio indicating that brown stocks are rather value stocks, whereas it is negative for green stocks reflecting the growth stock characteristics of most green firms in the green portfolio. Finally, the SMB size factor is positive for both portfolios but higher for the green portfolio, which is again expected given that green firms are on average smaller compared to brown firms, at least in my sample. The R^2 is consistently higher for the brown portfolios indicating that common factor models are better able to explain to excess returns of brown stocks compared to green stocks. This is due to the strong outperformance of the green portfolios over the last 12 years. In other words, factor models lack explanatory power if green stocks are able to produce such large alphas.

I repeat the baseline regressions but add location information, thereby I create brown and green portfolios for three continental regions, namely Asia-Pacific, Europe and the Americas. Thereby, I can test whether the green outperformance is particularly driven by one world region. Since the momentum factor in the Carhart Model does not add significant explanatory power to the model, I will henceforth solely report the 5-Factor Fama and French Model regression results.

Table 4 | Factor model regression results in different world regions*. The column headers highlight which value weighted continental portfolio was used as dependent variable. The rows illustrate the regression results for the 5 pricing factors. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of observations as well as the estimated R squared. Authors' own calculation.*

VARIABLES	**(1) Asia Brown**	**(2) Europe Brown**	**(3) Americas Brown**	**(4) Asia Green**	**(5) Europe Green**	**(6) Americas Green**
Market	0.566***	0.849***	1.188***	0.507***	0.844***	1.740***
	(0.071)	(0.071)	(0.097)	(0.127)	(0.110)	(0.299)
SMB	0.069	-0.030	0.613**	0.611*	0.643**	0.120
	(0.210)	(0.198)	(0.272)	(0.356)	(0.309)	(1.189)
HML	0.373**	0.521***	0.985***	0.128	-0.539*	-1.562*
	(0.152)	(0.198)	(0.271)	(0.355)	(0.308)	(0.926)
RMW	-0.369	-0.347	-0.337	-0.618	-0.600	-1.951
	(0.243)	(0.270)	(0.371)	(0.485)	(0.421)	(1.208)
CMA	-0.281	0.154	0.175	-0.967*	-0.152	-0.623
	(0.257)	(0.290)	(0.399)	(0.522)	(0.453)	(1.097)
Constant	0.007***	0.006**	0.005	0.023***	0.016***	0.031***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.004)	(0.011)
Observations	120	120	120	120	120	120
R-squared	0.506	0.647	0.693	0.273	0.456	0.388

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results show that my results from table 3 are roughly stable across different world regions. As depicted in table 4, the brown outperformance is not as robust as the green outperformance as the American brown portfolio did not outperform significantly. Albeit being highly significantly positive, the green alphas show some interesting regional differences. The highest green alpha is obtained for the American regions (heavily dominated by the US). The lowest alpha is observed for the European region.

4.2 Pricing of climate transition risk in sector-specific portfolios

Next, I also report results for the three climate sensitive industries.

Table 5 | Factor model regression results for the industry portfolios. *The column headers highlight which value weighted industry portfolio was used as dependent variable. The rows illustrate the regression results for the 5 pricing factors. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of observations as well as the estimated R squared. Authors' own calculation.*

VARIABLES	(1) ICE	(2) Brown Utilities	(3) Fossil Energy	(4) EV	(5) Green Utilities	(6) Renewable Energy
Market	0.876***	0.620***	0.825***	1.932***	0.405***	0.922***
	(0.077)	(0.061)	(0.069)	(0.304)	(0.079)	(0.172)
SMB	0.166	0.097	0.257	1.324	0.393*	0.900*
	(0.215)	(0.177)	(0.193)	(0.852)	(0.220)	(0.482)
HML	0.803***	0.191	0.493**	-1.725**	0.037	-0.167
	(0.215)	(0.232)	(0.193)	(0.850)	(0.220)	(0.481)
RMW	0.185	0.445*	-0.626**	-1.802	-0.414	-1.231*
	(0.293)	(0.253)	(0.263)	(1.162)	(0.300)	(0.657)
CMA	-0.786**	0.157	0.258	-0.303	-0.221	-1.248*
	(0.316)	(0.261)	(0.283)	(1.250)	(0.323)	(0.707)
Constant	0.006**	0.005**	0.006**	0.026**	0.015***	0.032***
	(0.003)	(0.002)	(0.003)	(0.012)	(0.003)	(0.007)
Observations	120	120	120	120	120	120
R-squared	0.643	0.587	0.671	0.386	0.287	0.371

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

As depicted in table 5 the aforementioned outperformance of green stocks compared to the market average as well as against the brown portfolios is highly robust across different climate sensitive industries. The brown industry portfolios also reinforce the finding of a small brown risk premium as brown industry portfolios consistently outperform the market as measured by the positive and significant alpha estimate. However, there are interesting industry-specific differences, especially for the green portfolios. Most notably, the highest outperformance of any portfolio is measured for the renewable energy portfolio with an alpha of .032, the lowest is measured for the green utilities (.015). The outperformance of the EV portfolio is in between with an alpha of .026. The market beta estimates are also in line with expectation since the market betas are lowest for brown and green utilities. The highest beta coefficients are measured for the ICE and EV portfolios, which makes sense given the cyclical nature of these industries. Interestingly, only the EV portfolio has a market beta above 1, indicating higher than average systematic risk. The bulk of the (insignificant) factor coefficients point in the expected direction or follow the trends from the baseline estimates.

4.3 The Brown Minus Green factors

Another way of analyzing the pricing of climate transition risk for climate sensitive portfolios is to create a BMG factor which is long the respective brown portfolio and short green portfolios. I create 4 such factors, 1 baseline factor utilizing the two baseline brown/green portfolios and 3 industry-specific BMG factors. The BMG factor is then used as the dependent variable in the Fama French 5-Factor Model in order to test whether the green outperformance can be observed also when directly comparing the performance to the brown/green portfolios.

Table 6 | Brown Minus Green (BMG) factor regressions. The column headers highlight which value weighted BMG factor was utilized as dependent variable. The rows illustrate the regression results for the 5 pricing factors. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of observations as well as the estimated R squared. Authors' own calculation.

VARIABLES	(1) BMG All	(2) BMG Transport	(3) BMG Utilities	(4) BMG Energy
Market	-0.331*	-1.056***	0.214***	-0.097
	(0.188)	(0.349)	(0.075)	(0.216)
SMB	-0.156	-1.157	-0.296	-0.643
	(0.600)	(1.035)	(0.211)	(0.579)
HML	1.270**	2.528***	0.153	0.659
	(0.504)	(0.818)	(0.211)	(0.627)
RMW	0.907	1.987*	0.859***	0.605
	(0.592)	(1.037)	(0.288)	(0.742)
CMA	0.858	-0.483	0.377	1.506*
	(0.655)	(1.087)	(0.310)	(0.842)
Constant	-0.019***	-0.020*	-0.010***	-0.026***
	(0.006)	(0.012)	(0.003)	(0.008)
Observations	120	120	120	120
R-squared	0.376	0.253	0.209	0.252

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

As shown in table 6, the alpha remains significant across all BMG models. Again, the highest relative alpha can be observed in the energy industry, utilities on the other hand (again) exhibit the lowest outperformance of green stocks. Annualizing the green outperformance in the baseline BMG model leads to an annual alpha value of ~ -23%. This extreme outperformance of green stocks is higher than any other estimate in the literature. Note that the alphas are negative since I have a portfolio which is short on green stocks. Interestingly, the BMG factor return cannot be explained by most other pricing factors. Most relevant in explaining the BMG factor returns are the market factor as well as the HML factor. The HML result mimics the aforementioned finding that brown portfolios carry a heavier weight in value firms. Nevertheless, the other pricing factors (with few exceptions) do not add significant explanatory power to the models. This is also highlighted by the rather low R^2 values which indicate that the 5 pricing factors can only explain a small fraction of the variance in the BMG pricing factors. In other words: The BMG factor does not seem to correlate strongly with other known pricing factors which might indicate that a climate transition risk pricing factors might expand the explanatory power of common factor models since well-established pricing factors fall short in explaining the excess returns of companies in climate sensitive industries.

4.4 Time specific results

Most previous work on the pricing of climate risk on financial markets makes the implicit assumption that pricing remains roughly constant over time since they mostly use static regressions across the whole time frame. Given the highly dynamic nature of climate policies or technological development as well as the associated climate transition risk, this is a critical research gap to fill. I thus estimate rolling regression windows across my time frame, thereby I am able to capture time specific changes in the pricing of brown and green portfolios.

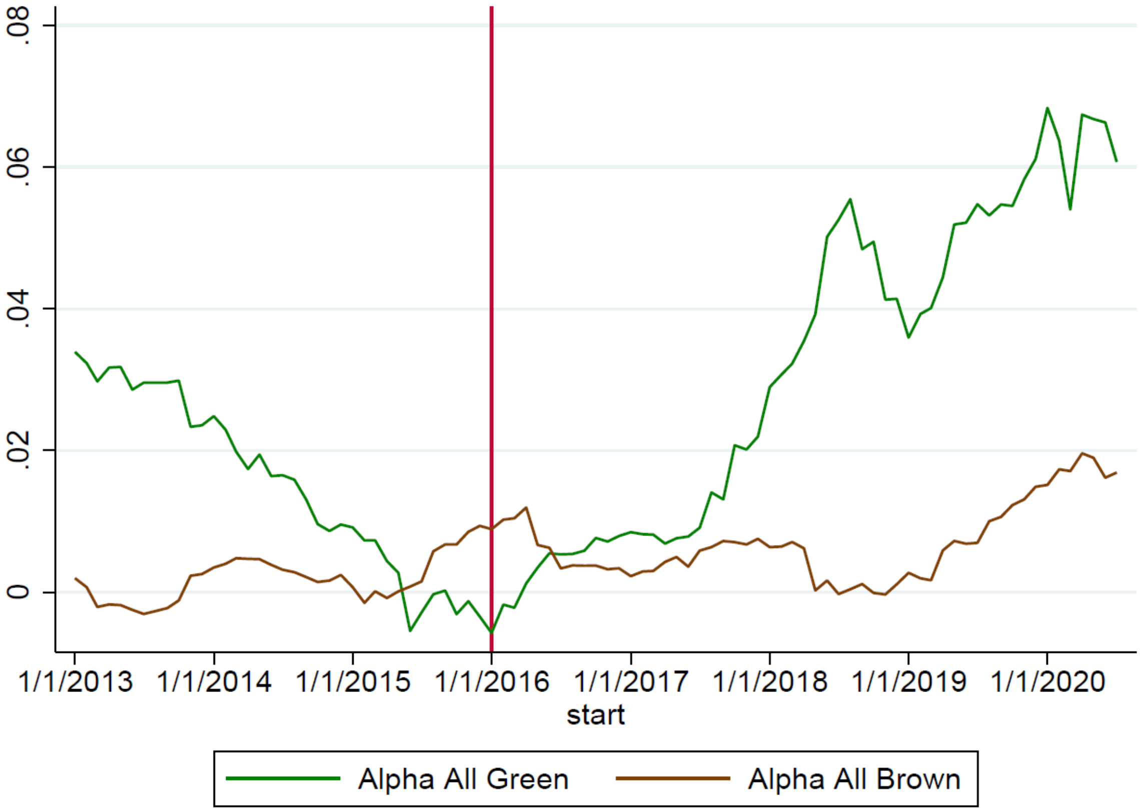

Figure 1| Alpha estimates from rolling regressions. *The graph shows the rolling alpha regression results for the baseline green and brown portfolios with a 30-month rolling regression window. The estimated model is an Fama French 5-Factor model. The x axis shows the start date of the regression window, the y axis the alpha estimates. The red vertical line indicates the first time when a full regression window incorporates the time after the Paris Agreement of 12/2015.*

Figure 1 shows the dynamic alpha estimates across time using 2.5-year regression windows. I focus on the alpha estimates as they nicely show how the market prices climate transition risk of green/brown portfolios differently across time. Most notably, the brown alpha estimates are rather constant over time, highlighting a constant risk premium of brown stocks across my dataset. One notable exception is the end of my time frame, when brown alphas are steadily rising. This is very different for my green baseline portfolio. The associated alpha estimates vary more strongly. Interestingly in the time after the Paris Agreement a clear trend emerges, while the brown alpha remains roughly flat, green stocks start a stark outperformance against the market as well as against the brown portfolio. This interesting finding might highlight the relevance of the Paris Agreement as a signaling event which strongly affected green firms, but did not impact brown companies equally strong. The aforementioned BMG factor is the difference between the brown and the green alpha over time. It follows from figure 1 that this factor was negative for most of my time series. The dynamic trends of the singular sector portfolios roughly follow the trends of the baseline portfolios, the figures can be found in the appendix (figures A1-A2). Another interesting question relates to the correlation of the brown and green portfolio over time. Based on figure 1 it seems like the performance of the two portfolios decouples to some degree after the Paris Agreement. In order to quantify this observation, I calculate the correlation coefficient of the brown and green portfolio before and after the Paris Agreement. The difference is quite strong, before the Paris agreement the correlation coefficient amounts to .69, after the Agreement the coefficient drops to .40.

The observation that the brown outperformance largely stems from the end of my time series warrants the question whether the energy price shocks in the last years might explain the brown outperformance.

I thus estimate a reduced time series until 12/2020, excluding the time with exploding prices for coal gas and oil.

Table 7 | Reduced factor regressions. *The column headers highlight which value weighted portfolio was utilized as dependent variable. The rows illustrate the regression results for the 5 pricing factors. The time window start in 01/2013 and runs until 12/2020, thus excluding the last two years of my full time series. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of observations as well as the estimated R squared. Authors' own calculation.*

VARIABLES	(1) All Brown Reduced	(2) All Green Reduced	(3) BMG All Reduced
Market	0.869***	1.139***	-0.270
	(0.056)	(0.203)	(0.205)
SMB	0.292*	0.711	-0.420
	(0.151)	(0.514)	(0.545)
HML	0.555***	-0.388	0.943*
	(0.163)	(0.477)	(0.501)
RMW	0.061	-1.069	1.130
	(0.248)	(0.806)	(0.868)
CMA	-0.194	-1.035	0.841
	(0.272)	(0.707)	(0.689)
Constant	0.002	0.024***	-0.022***
	(0.002)	(0.005)	(0.006)
Observations	96	96	96
R-squared	0.801	0.485	0.192

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results are reported in table 7 and show that indeed, brown stocks now do not show any significant alpha estimate on all common significance levels. The green outperformance on the other hand, remains highly significant and the coefficient does not change strongly compared to the full time series. This indicates that the brown outperformance can be largely explained by a one-time event, namely the strongly rising energy prices leading to record profits for brown companies.

4.5 The dividend channel

I also utilized the two baseline portfolios to investigate another interesting pricing property, namely the dividend yield for both portfolios in 2023. I downloaded expected dividend payments per company for 2023. As depicted in figure 2, the dividend payments vary quite substantially as the brown portfolio yield returns between 4% - 5% in 2023 while the green portfolios only yield roughly 1%. The findings are robust to the weighting methodology, i.e. equally or value weighted aggregation. Moreover, results are roughly similar for dividend distribution in 2022

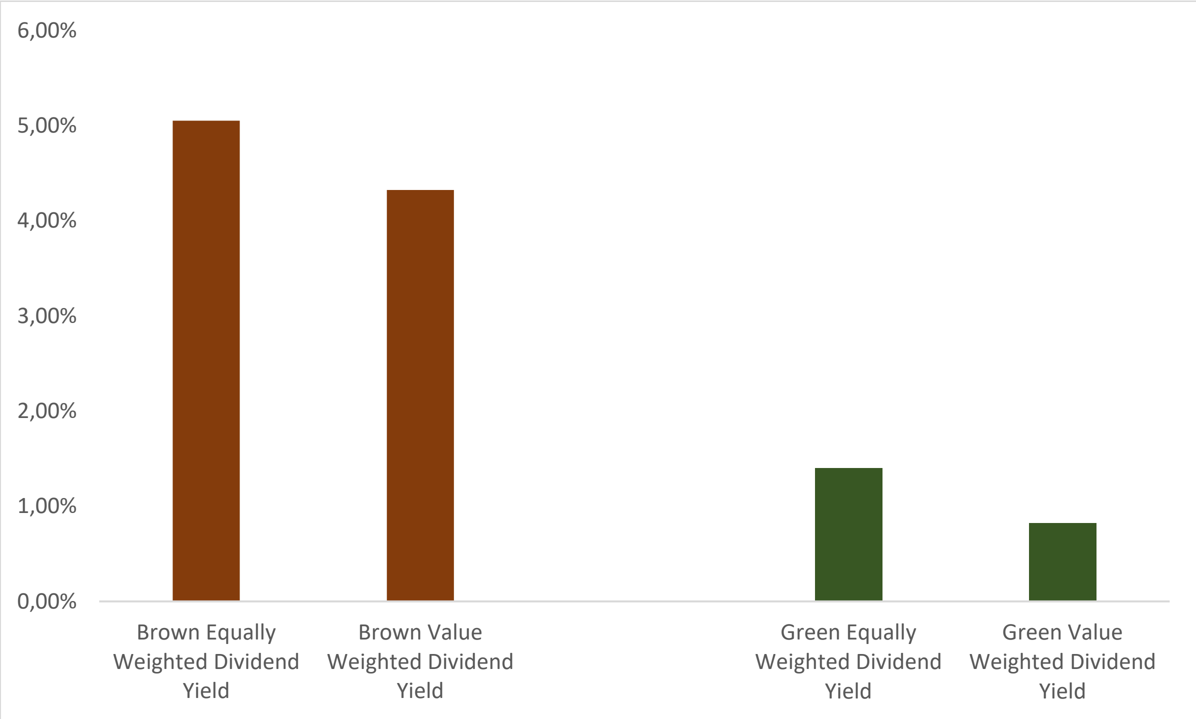

Figure 2 | Expected Dividend Yields in 2023 for both baseline portfolios. *The graphs highlights the dividend yield per portfolio for 2023 in percentages.*

4.6 Robustness tests

The aforementioned results already contain some tests for the robustness of my results. Most notably, table 3 shows that my baseline results for alpha and market beta are robust against adding more/less well-established pricing factors. Table 4 shows the robustness of the results across different world regions. Table 5 highlights the robustness across different climate sensitive industries. Additionally, I also test how my results change when including different market factors. Changing the market factor to the SP 500 or the market factor from Kenneth French's data library does not significantly affect the results for both baseline portfolios (table A1). As another robustness check, I change the weighting methodology and equally weight all constituents of the portfolios. In other words, I just consider the average return of all firms in the brown/green baseline portfolios. This reduces the weights of some mega-caps such as Tesla or Saudi Aramco but on the other hand, strongly increases the weights of very small companies. Results for the baseline green and brown portfolio remain roughly constant when changing the weighting methodology. Interestingly the market beta for the green portfolio drops substantially while the alpha for the brown portfolio loses some significance, again raising slight doubts about the robustness of the carbon alpha for the brown portfolio. However, the strong significant outperformance of the green portfolio as well as the BMG factor persists, showing the robustness of these results (table A2). Finally, I also estimate the rolling regressions with windows of 20 and 40 months. The results are very similar to the chosen 30-month window (figures A3-A4). All results of the robustness tests can be found in the Appendix. Overall, the results reinforce my aforementioned findings and I conclude that my results are stable against various robustness tests.

5 Discussion

Summing up my findings, green portfolios show significantly higher excess returns than brown portfolios as well as the market average. This is largely due to the second half of my time window, after the global Paris Agreement of late 2015, which showed the ambition of *all* countries to radically decarbonize the economy with strong implications for high/low climate transition risk companies.

Before the agreement both brown and green portfolios were highly correlated and only after the agreement the correlation significantly decreased and the green outperformance began. Brown portfolios on the other hand, did only underperform relative to the green portfolio but not to the market since they also exhibit significant positive alphas over the whole time frame. This outperformance disappears however, when I exclude the last years which brought unprecedented increases in global energy prices. My overall findings are robust across regions as well as three climate sensitive industries, i.e. the transportation, the utility and the energy sector. I chose these sectors due to their extreme climate policy sensitivity.

Concerning the market betas, I find significantly lower betas for the baseline brown portfolios. The trend over time as illustrated by the rolling regressions results (figure A5 in Appendix) highlight roughly constant market betas for the brown portfolio and rising market betas for the green baseline portfolio. This is at odds with Monasterolo and de Angelis (2020) who find that the systematic risk (market beta) of green indexes drops significantly after the Paris Agreement. Since the climate transition risks for brown firms rises over time, they expect rising systematic risk for brown firms. An important related question rarely addressed in the literature is: whether climate transition risk is of systematic nature (and thus can be found in the market beta) or idiosyncratic (i.e. firm specific). My finding would rather support the latter option since I cannot find climate transition risk being reflected in high or rising market betas, however if climate transition risk is firm/technology specific, which I would argue it is, then one can ask whether this climate transition risk is compensated for. Finance theory states that only risk which cannot be diversified away is compensated for – however green or risk neutral firms offer the possibility to diversify away from climate transition risk, hedging against the climate transition risk of brown firms (e.g. Engle et al., 2020). Thus, one could argue that the market would not compensate for the climate transition risk in brown portfolios. However, that is not what other authors (e.g. Bolton & Kacperczyk, 2021a, 2021b) find empirically and what Pástor et al. (2021) predict theoretically. Thus, the climate transition risk of brown firms seems to be compensated for. I find some limited evidence for that as I find positive alphas of brown portfolios over the whole time series. However, when excluding the last years with skyrocketing energy prices, brown portfolios performed in line with the market, questioning the robustness of the brown outperformance.

Turning to green firms, Pástor et al. (2021) postulate that investors are willing to pay a higher price for green firms since they offer two desirable properties. First, investors derive utility from holding green assets compared to brown assets as most investors have a taste for sustainable investments. Second, green assets can hedge investor portfolios against climate transition risk. These properties should (theoretically) lead to ex ante lower expected returns. In equilibrium, financial market participants are thus willing to pay higher prices for green firms, lowering their cost of capital and increasing their valuation while lowering their expected alpha. Brown firms should exhibit positives alphas in the long run as their additional risk should be compensated for. My model results show significantly positive and rising green alphas and the BMG factor strongly underperforms the market across my time period. However, the ex-ante equilibrium view of lower expected returns for green stocks is augmented by Pástor et al. (2021) with a dynamic view which nicely explains my results. Investors (consumers) can change their preferences unexpectedly towards green assets (green products/services) and thereby change the short run pricing trajectory of a BMG factor which in theory should return positive results as brown stocks carry higher expected returns. In times of such unexpected changes the BMG factor will underperform, since green assets are negatively correlated with this factor, they will outperform the market. The dynamic rolling regression results support the hypothesis that many readjustments of the BMG factor in the last years led to the strong outperformance of green stocks vs. brown stocks. While the brown alpha estimates remain roughly constant across time, the green alpha results vary strongly. More precisely, green stocks strongly outperformed after the Paris Agreement of 2016. The Paris Agreement is a perfect example of an event which might have influenced investor preferences unexpectedly towards green stocks, leading to a medium-term outperformance of green assets and causing the BMG factor to yield negative returns across my time frame. Other major events which strongly support this hypothesis are the US Inflation Reduction Act, the European Green Deal or the election of Joe Biden as President of the United States replacing climate change sceptic Donald Trump. The dynamic element thus outweighed the expected return differentials. Additionally, the expected return premium for brown assets in 2013 was almost certainly lower than today as the taste for green assets also developed strongly over my time frame. Thus, from 2013-2016 brown and green stocks likely did not even have significantly different expected returns as the awareness about climate risks on financial markets only developed in the years after, when the high valuation of green stocks was built over time through significantly positive alphas compared to brown stocks. My result thus can thus be explained by the difference between realized and expected returns. While the return expectation of brown stocks is higher, realized returns of green stocks were higher across my time frame as the expectations about climate transition risks changed dramatically. However, only because I was able to show that green stocks outperformed, this does not imply that this trend will continue indefinitely as the expected returns for a BMG factor are positive today (Pástor et al., 2022).

Pástor et al. (2022) discuss the difficulties of estimating expected equity returns as expected returns for stocks are not directly observable. They employ two approaches in order to substantiate their theoretical finding that green stocks should carry lower expected returns. First, they use ex ante data to calculate each stock implied cost of capital. Second, they use ex post data and climate concern index data. My results concerning the dividend differentials in 2023 between brown and green portfolios are further proof that expected returns are higher for brown high climate transition risk stocks as their dividend yields are substantially higher than the low yields for green stocks as well as the average yield of the MSCI world which were below 2% in the last years. The results indicate that investors expect higher payouts for holding riskier (browner) assets, in line with the findings of Pástor et al. (2022) as well as the theoretical prediction of Pástor et al. (2021).

My findings are also in line with empirical results of van der Beck (2021), who also finds a significant positive alpha for an ESG sorted portfolio from 2016 until 2021. He shows that this result can be explained by financial flows towards sustainable assets, i.e. the investor channel explained above. Van der Beck (2021) can even show that the return of the BMG portfolio without the flows would have been negative, in line with the notion of lower expected returns for green stocks. Moreover, my results are strongly in line with Pástor et al. (2022) who also find higher realized returns for green assets, but lower expected returns for green assets vs. brown assets. However, the green outperformance is significantly higher than other estimates in the literature. This could be due to my industry/technology approach which only focusses on brown/green pure play firms which are doing a majority of business in extremely climate sensitive industries utilizing high/low-risk technologies, whereas for example Görgen et al. (2020), Bolton and Kacperczyk (2021) or Pástor et al. (2022) base their results on a larger universe of companies of which many are in not particularly climate sensitive, but carry high market capitalizations such as software companies. In other words, it is harder to argue that a climate related risk factor explains the variation in Apples returns (would be categorized as "green" due to low CO2 emissions) than it is for Tesla. I would thus argue, that within industry variation due to firms technological differences in key for climate transition risk, but only in a few climate sensitive industries heavily targeted by climate policies. This is in line with the results of Sautner et al. (2020) that within industry variation is crucial when it comes to climate transition risk as their variance decomposition shows that most of the variation cannot be explained by country, industry or time fixed effects, but must stem from the firm level. I make the same argument, focusing on firms' technological differences.

Moreover, I was able to show that a BMG pricing factor constructed through "pure-play" brown and green companies in climate sensitive industries is not strongly correlated to other known pricing factors. This finding is in line with Görgen et al. (2020) who show that their BMG factor significantly improves the explanatory power of common pricing models in explaining large cross-sections of returns. Interestingly Görgen et al.'s (2020) BMG factor is only modestly correlated (coefficient estimate of .22) to my BMG factor. This again shows the significant difference in my technology-based approach compared to common approaches utilizing ESG/CO2 data to identify high/low climate transition risk assets. It will be interesting to continuously study the returns of this BMG factor in order to test whether the theoretical prediction by Pástor et al. (2021) holds in the long run. Following this prediction, one would expect the BMG factor to start returning positive monthly alphas in the coming years.

My findings are relevant for stakeholders involved on financial markets as well as climate politics. Most notably, Companies can learn that there seems to be a strong preference for green assets compared to brown ones, which unfolded over the last years after the Paris Agreement as highlighted by the outperformance of green stocks over brown stocks. Investors are willing to accept lower expected returns for green equity due to green preferences. This leads to a higher valuation for green firms, lowering their cost of capital. My TRBC based methodology might also be useful for investors to easily determine the climate transition risk exposure of their portfolios by separating firms based on their technology in different climate sensitive economic sectors. Investors who want to reduce the climate transition risk exposure of portfolios can use my BMG factor to estimate the climate risk of individual securities. If investors must hold certain sector exposures, my approach enables investors to also reduce climate transition risk exposure within sectors as I show for my three climate sensitive sectors, that both high and low-risk companies exist. Policymakers can learn that certain policy announcements seem to have a strong signaling effect for financial markets as the Paris Agreement really marked the turning point of the relative pricing of brown and green firms. My continental results show that the change in investors/consumer sentiment towards climate transition risk is highest in the Americas, which is quite logically as the US had the strongest change in climate sentiment over my time window. Starting with almost no strong climate legislation and Donald Trump as President, the US now has a democratic president which rejoined the Paris Agreement and put in place the most aggressive climate legislation in US history with the Inflation Reduction Act. In Europe on the other hand, stronger climate policies exist since a long time, explaining the smaller green alpha compared to the US.

Finally, my findings are relevant for scholars interested in the global pricing of climate risks as I contribute to the ongoing work about the pricing of climate transition risks on financial markets both methodologically and empirically. I contribute methodologically by means of a newly proposed way of determining high/low climate transition risk companies by means of sectoral/technology classifications for financial pricing exercises. This approach is opposed to the widespread use of ESG or CO2 data for financial pricing models which problems I discussed at length in the literature review. Moreover, I contribute by supporting the theoretical prediction by Pástor et al. (2021) empirically as I track changes in alpha over a recent 10-year time window by means of rolling regression windows, thereby providing insights into the dynamic pricing of climate transition risk on global financial markets as opposed to only focusing on the US. Moreover, my results clearly show the importance of analyzing both green *and* brown asset prices in parallel as I find a very high negative alpha of 23% p.a. for the BMG factor which dwarfs previous estimates well below 5% (e.g. Bernardini et al. (2021) or van der Beck (2021)). This finding is very robust across different highly climate sensitive industries, world regions and different widely utilized factor models. The estimated BMG factor can be used to augment common pricing models in order to capture the significant fraction of returns which cannot be explained by common factor models, thereby potentially increasing the explanatory power of such models. I test the correlation of this factor with other common pricing factors and find the only the HML value factor is significantly correlated with the BMG factor, highlighting the potential value this novel factor can add in common pricing models. Finally, I also use the most recent global data on monthly stocks returns, including the Covid-19 Pandemic as well as the energy price shock as a consequence of Russia's attack on Ukraine.

My approach is limited by two main issues. First, the utilization of the TRBC business activity classification is (admittedly) a rather simple approach to differentiate brown and green firms as it does not differentiate different shades of these colors. To some limited degree the industry portfolios remedy this problem as one can argue that the fossil fuel portfolio clearly carries a higher climate transition risk compared to the ICE/Brown Utility portfolio which could change their technologies more easily. Nevertheless, a superior approach would analyze different business lines and subsidiaries of a company to gain a more granular picture of a climate relevant firm (Bressan et al., 2022). Due to the very limited climate transition risk data availability, such an approach is currently very time consuming as one would need to analyze company's technology and revenue contributions separately for each business line. Future data disclosure regulation might make more granular assessment possible. A second limitation is the implicit assumption that there is no step change in the technologies of the firms over time as I only construct the portfolios once and do not reshuffle them annually since no time series of TRBC codes is available. The Chines auto manufacturer BYD illustrates this point as it changed the business model drastically in early 2022 by announcing to cease the production of ICE vehicles and solely rely on hybrid or electric power trains (Randall, 2022). Thus, going forward, I expect that BYD changes the TRBC business code to Electric (Alternative) Vehicles. Such changes will become increasingly more frequent as the climate transition continuous. However, as of the end of 2022 a complete reorganization of business technologies is still rare as most incumbent firms rather follow a long term evolutionary decarbonization schedule as opposed to radically changing technologies as highlighted by the continuously rising CO2 emissions. Additionally, a firm classified as brown today will have almost certainly been even browner 10 years ago. Thus, my approach might, at worse, underestimate (overestimate) the green (brown) outperformance when some TRBC-green firms in 2022 had a browner technology mix in previous years. Even BYD is correctly categorized as it earned the majority of revenues over my time frame with ICE vehicles and even in 2022 sold more hybrid cars with an engine than electric cars (Kane, 2023). It will thus be interesting to further study how TRBC codes for my group of companies change over time.

6 Conclusion

I utilize the TRBC business classification to categorize companies in three climate sensitive sectors into high/low-risk from a climate transition risk perspective. Thereby I complement ESG or CO2 based approaches which have been the focus of climate transition risk exposure categorizations. As a result, I create two baseline brown/green portfolios as well as 6 sectoral portfolios. Then I analyze the pricing of these portfolio against common risk factors over time. My results show that green stocks produce a highly significant double-digit annual alpha, especially in the 7 years following the Paris Agreement. This is well above all previous estimates and might be explained by my novel proposed methodology which can identify brown and green "pure-plays" in the most climate sensitive economic sectors. Opposed to most ESG funds, my portfolios do not closely mimic benchmarks which might explain the more extreme alpha estimates. This green alpha is robust across industry portfolios and might be explained by unexpected changes in investor and consumer preferences. Even though I was able to show a negative alpha for the BMG factor, this does not guarantee that green assets will continue to outperform green assets as I only analyzed realized returns. However, the return expectation today is very different from the return expectation in 2013 and rational investors today want to be compensated for the additional risk of holding brown assets, thus expecting higher returns of brown vs. green stocks. My dividend yield findings indicate that in expect return for brown portfolios *today* are indeed substantially higher compared to green portfolios.

Future research in this rapidly expanding field should take future disclosed information such as the EU Taxonomy or the CSRD into account in order to overcome self-reported and error prone data. Once such data is released annually, scholars can create yearly rebalanced portfolios in order to robustly account for dynamic changes in the business model of certain firms. My research also indicated the relevance of the Paris Agreement for the pricing of brown and green firms. It would be interesting to follow up research of Monasterolo and de Angelis (2020) by more event studies in order to substantiate the findings from my rolling regressions that positive alphas for green stocks started to materialize after the agreement. Additionally, it would be interesting to further test the theoretical prediction by Pástor et al. (2021), that green firms invest more than brown firms. My results for the CMA investment factor showed the expected signs in my baseline regressions but failed to produce significant results. Finally, it will be interesting to follow the performance of the BMG pricing factor to observe whether the realized outperformance of green stocks reverses as expected and whether the brown risk premium turns positive in the long run. Future research should definitely test the inclusion of a BMG pricing factor into asset pricing models as climate risks will increasingly play a central role on financial markets. Otherwise factor models might lack the power to explain cross-sectional returns in climate sensitive portfolios.

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8 Appendix

8.1 Value weighted baseline portfolios against other market factors

Table A1 | Value weighted portfolios against alternative market factors. *The column headers highlight which value weighted portfolio was utilized as dependent variable. The rows illustrate the regression results for the 5 pricing factors. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of observations as well as the estimated R squared. Authors' own calculation.*

VARIABLES	(1) All Brown	(2) All Brown	(3) All Green	(4) All Green
FF Market Factor	0.804***		1.136***	
	(0.054)		(0.190)	
SP 500		0.787***		1.092***
		(0.053)		(0.185)
SMB	0.082	0.318**	0.187	0.520
	(0.151)	(0.151)	(0.609)	(0.597)
HML	0.491***	0.548***	-0.787	-0.688
	(0.151)	(0.150)	(0.520)	(0.517)
RMW	-0.341*	-0.430**	-1.234**	-1.344**
	(0.205)	(0.208)	(0.586)	(0.583)
CMA	0.107	0.080	-0.737	-0.809
	(0.222)	(0.223)	(0.701)	(0.686)
Constant	0.006***	0.005**	0.026***	0.024***
	(0.002)	(0.002)	(0.006)	(0.006)
Observations	120	120	120	120
R-squared	0.747	0.743	0.477	0.466

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

8.2 Equally weighted baseline brown and green portfolios

Table A2| Equally weighted portfolios against the Fama French 5-Factor model. *The column headers highlight which equally weighted portfolio was utilized as dependent variable. The rows illustrate the regression results for the 5 pricing factors. Robust standard errors were employed for all models in which heteroskedasticity was detected. The last two rows show the number of observations as well as the estimated R squared. Authors' own calculation.*

VARIABLES	**(1)** **BMG Equally**	**(2)** **All Brown Equally**	**(3)** **All Green Equally**
Market	0.100	0.869***	0.769***
	(0.075)	(0.070)	(0.083)
SMB	0.024	0.757***	0.733***
	(0.211)	(0.206)	(0.232)
HML	0.867***	0.721***	-0.146
	(0.211)	(0.177)	(0.231)
RMW	0.448	-0.350	-0.798**
	(0.288)	(0.248)	(0.316)
CMA	0.127	-0.256	-0.382
	(0.310)	(0.240)	(0.340)
Constant	-0.006**	0.005*	0.011***
	(0.003)	(0.002)	(0.003)
Observations	120	120	120
R-squared	0.375	0.756	0.565

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

8.3 Alphas of brown and green industry portfolios

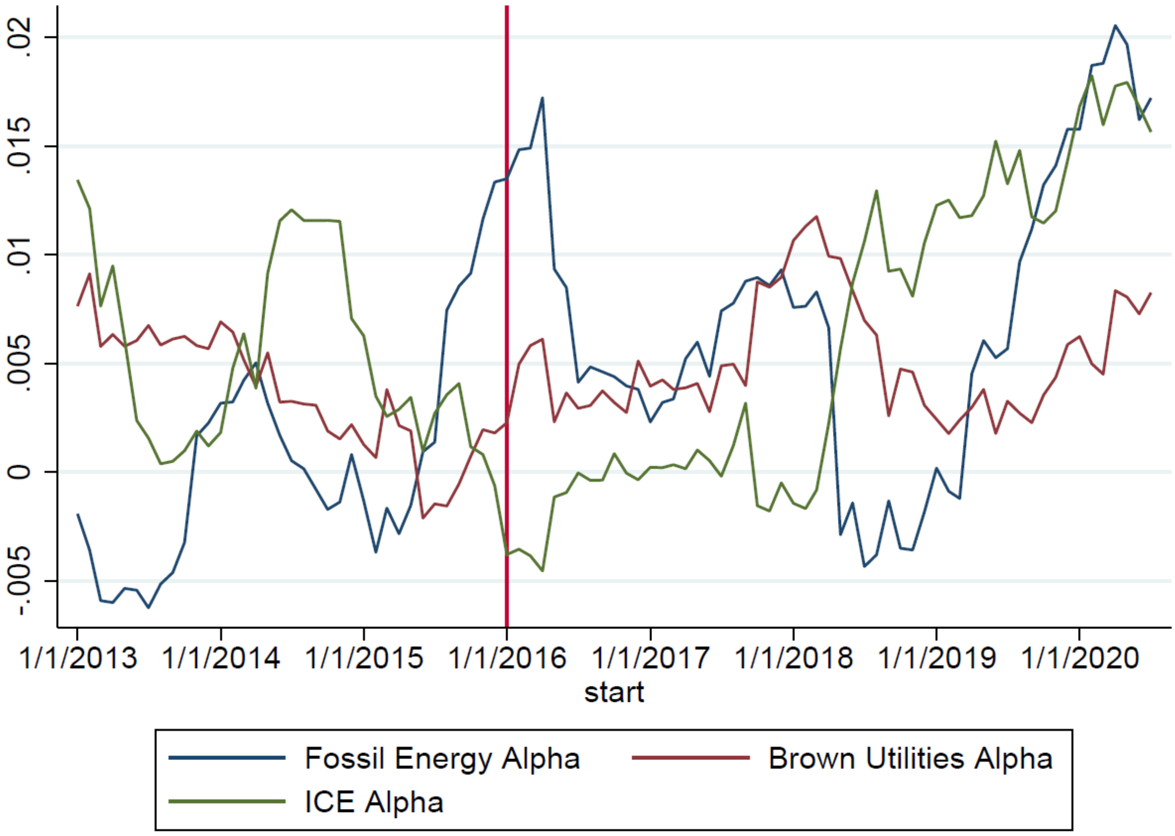

Figure A1/ Alpha estimates for the value weighted brown industry portfolios with 30-month rolling regression windows. *The x axis shows the start date of the regression windows and the y axis the alpha estimates. The red vertical line indicates the first time when a full regression window incorporates the time after the Paris Agreement of 12/2015.*

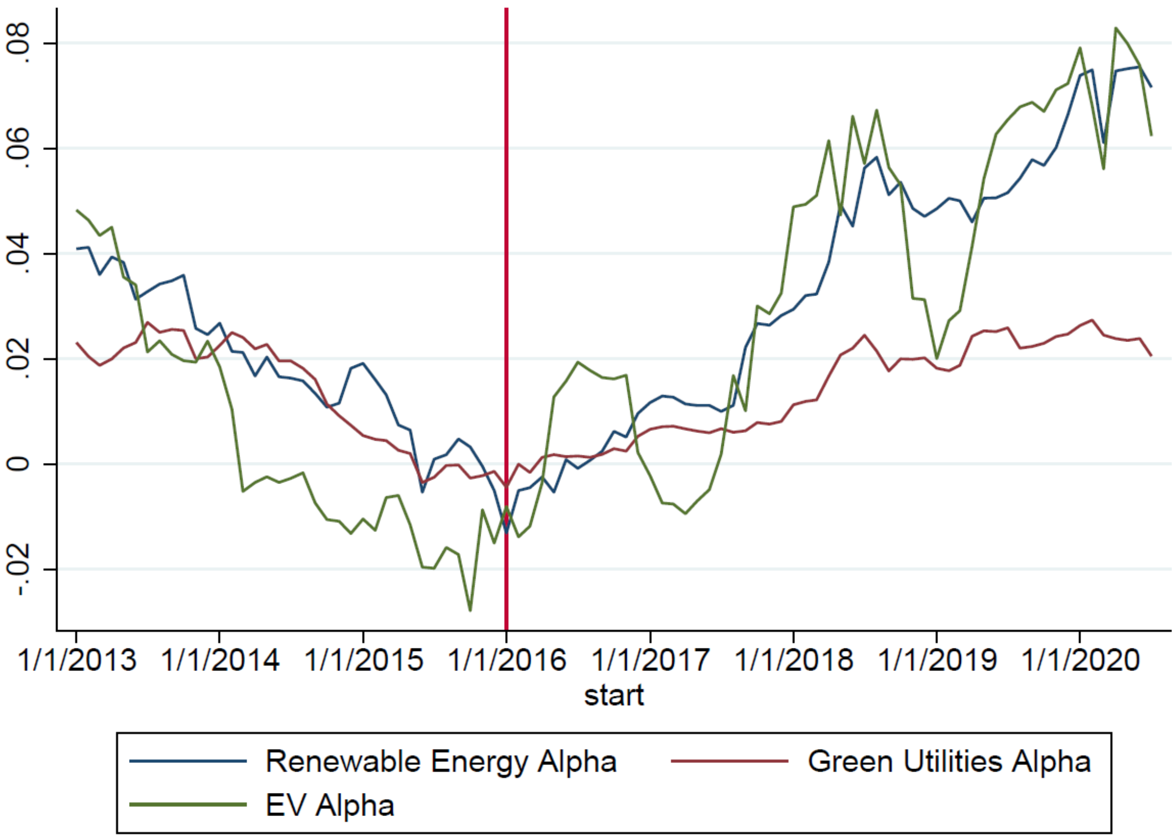

Figure A2 | Alpha estimates for the value weighted green industry portfolios with 30-month rolling regression windows. *The x axis shows the start date of the regression windows and the y axis the alpha estimates. The red vertical line indicates the first time when a full regression window incorporates the time after the Paris Agreement of 12/2015.*

8.4 Alphas of the baseline portfolio with different rolling regression windows

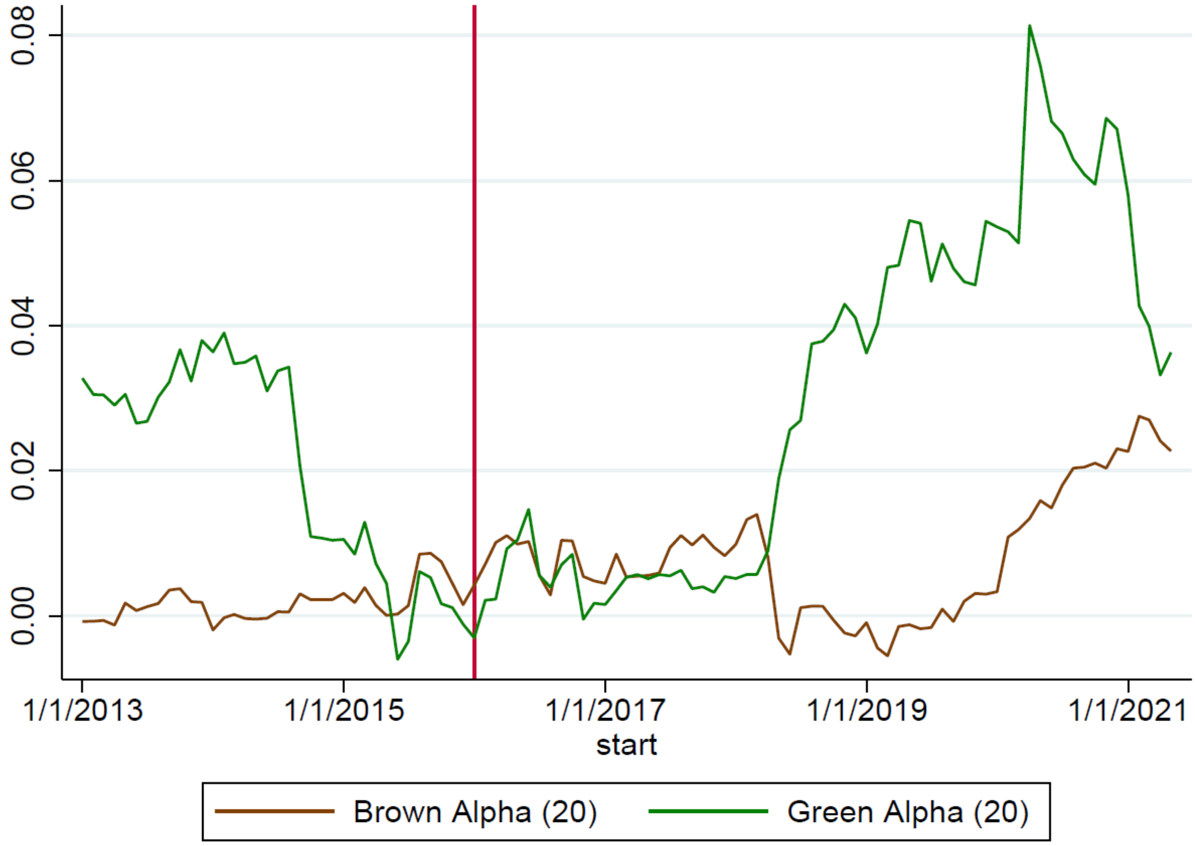

Figure A3 | Alpha estimates for the value weighted brown and green baseline portfolio with 20 month rolling regression windows. *The x axis shows the start date of the regression windows and the y axis the alpha estimates. The red vertical line indicates the first time when a full regression window incorporates the time after the Paris Agreement of 12/2015.*

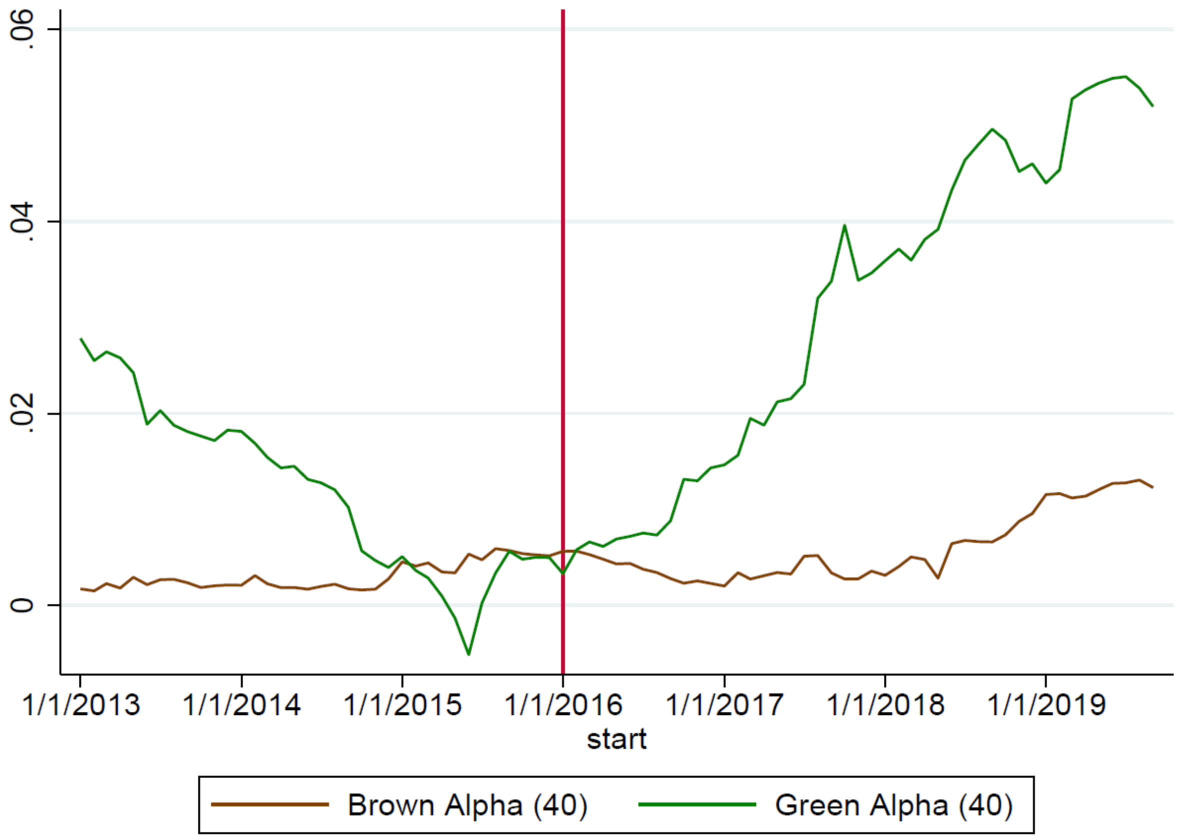

Figure A4 | Alpha estimates for the value weighted brown and green baseline portfolio with 40 month rolling regression windows. *The x axis shows the start date of the regression windows and the y axis the alpha estimates. The red vertical line indicates the first time when a full regression window incorporates the time after the Paris Agreement of 12/2015.*

8.5 Dynamic Market Betas of the baseline brown and green portfolio

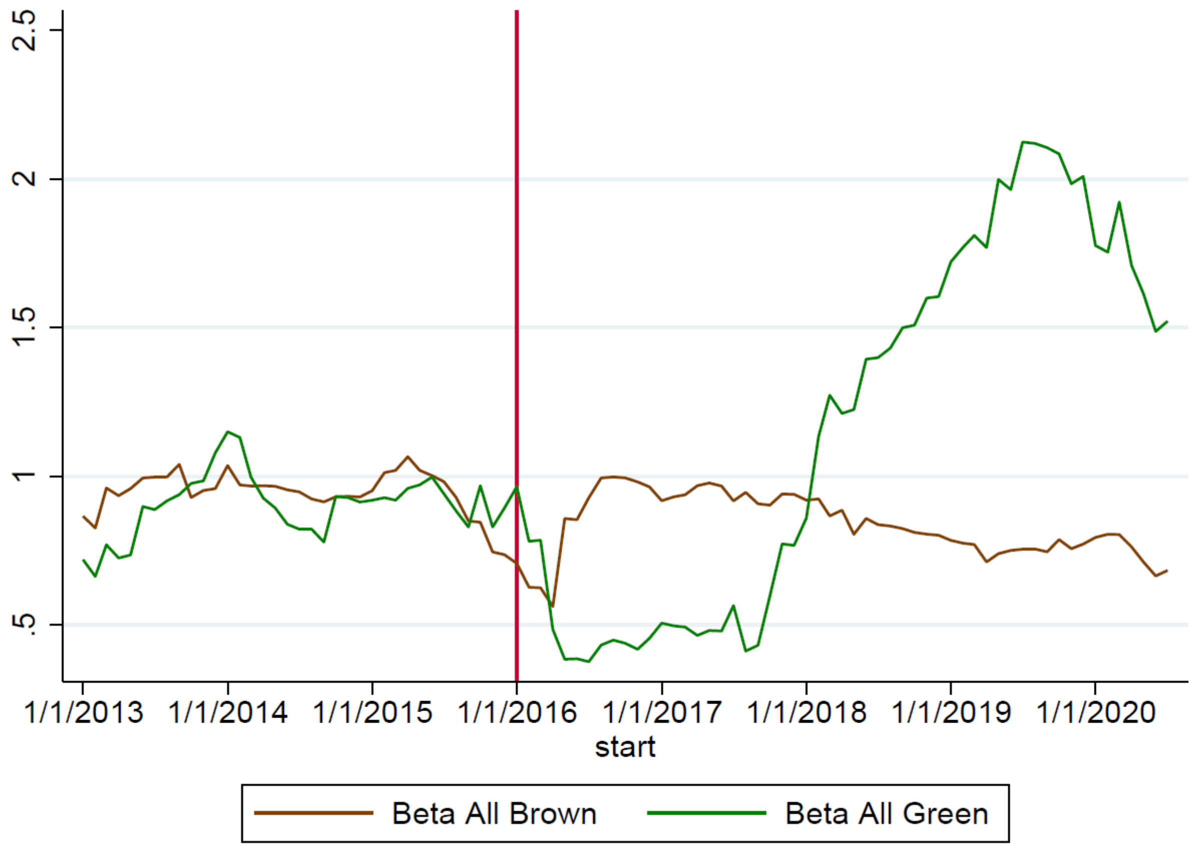

Figure A5 | Rolling regression results for the value weighted brown and green baseline portfolio betas. *The rolling regressions use 30 month rolling regression windows and the used model is the Fama French 5 market model. The x axis shows the start of the rolling window. The y axis shows the beta estimates.*

8.6 Cumulative Returns of both baseline portfolios as well as the BMG Factor

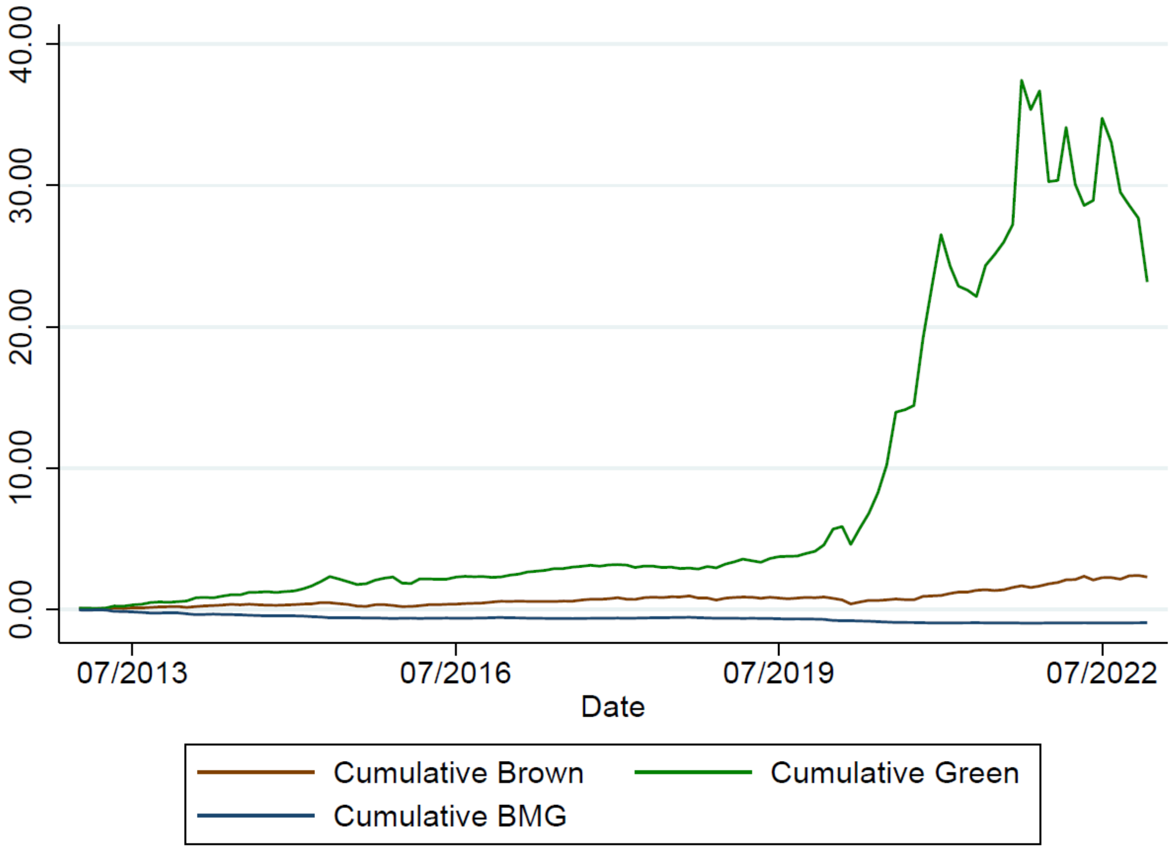

Figure A6 | Cumulative Returns of the value weighted brown and green portfolios as well as the BMG factor. *The x axis shows the time dimension while the y axis shows the cumulative total returns over time.*