Norwegian School of Economics
Bergen, Fall 2020

# Climate Change: The Transition Risk

*An empirical analysis of the inclusion of a Green-Minus-Brown factor in common factor models*

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Master thesis, Economics and business administration

NORWEGIAN SCHOOL OF ECONOMICS

# Acknowledgements

This thesis is written as a final part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics (NHH). Our aim with this thesis is to contribute to the field of climate finance, as we believe businesses and financial markets play a key role in the transition to a low-carbon economy.

Writing this thesis has indeed been a challenge, yet fulfilling and rewarding. We started the process as two students finding our common interest in sustainability and the greening of the financial system. Throughout the process, we have learned about financial theories and empirical methods and we have gained a deeper understanding on the interesting and relevant research field of climate finance.

We would like to thank our supervisor Aksel Mjøs for his support in the process of finalizing our thesis. In addition, we would like to thank Lars Erik Mangset and Rune Røkke for their inspiring passion and for interesting discussions. Finally, we want to give our gratitude to friends and family who have supported us in the process of finishing our thesis.

Bergen, December 2020

# Abstract

The transition towards a greener economy is highly uncertain. This thesis explores the impact of transition risk on equity prices. More specifically, we first study whether differences in return between companies with high climate-related performance (Green companies) and low climate-related performance (Brown companies) can be explained by common risk factors included in the CAPM, Fama French three-factor and Carhart four-factor model. Subsequently, we extend these models with a Green-Minus-Brown (GMB) factor, and analyze whether the factor possesses unique return-affecting properties that will have a statistically significant impact on the explanatory power of common factor models. The analysis is conducted on stocks included in the iShares MSCI World ETF in the period from January 2014 to December 2019.

We find that differences in return between a Green and Brown portfolio cannot be explained by common risk factors. Yet, there are no significant differences in abnormal returns. Moreover, our results indicate that common factor models extended with the GMB factor explain variations in risk-adjusted return better than the original models.

Our findings suggest that a transition towards a low-carbon economy will be profitable for Green companies, whilst Brown companies will suffer from losses. However, both Green and Brown companies are exposed to high transition risk because of the uncertainty of the transition pathway.

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# 1. Introduction

The urgency and scale of the climate challenge is clear. The United Nation's Intergovernmental Panel of Climate Change (IPCC) estimates that human activity has so far caused approximately 1.0 °C of global warming above the pre-industrial levels (IPCC, 2018). Global warming will likely increase the occurrence of climate- and weather-related events, for instance floods, drought and storms. Climate change is thereby posing a global threat to the future viability of our societies and planet, often referred to as climate risk. Happening at large-scale and with long-term consequences without historical precedent, climate risk is the most significant and misunderstood risk that organizations face today (TCFD, 2017).

To avoid the catastrophic consequences of climate change, scientists agree on the need to decarbonize the economy, preferably through strong regulatory policies (IPCC, 2018). This transition to a global low-carbon economy will undoubtedly have significant consequences on the global economy. The economic shift needed to combat climate change therefore pose a transition risk (Carney, 2015; TCFD, 2017).

The awareness of transition risks is increasing among financial market participants. Carney (2015) expressed concern about the stability of the financial system as a result of the transition towards a green economy. As a result, he initiated the Task Force on Climate-related Disclosure (TCFD), which urges for disclosure on climate-related governance, strategy, risks and management of climate risk. Their publication was a wake-up call for the financial sector (NCE, 2018).

As investors become more aware of climate risk, there is an increasing demand for corporate disclosures that display firms' exposure to transition risk. Carbon intensity is currently the most common measure of transition risk (TCFD, 2017). However, credit rating agencies now provide hundreds of metrics on measures such as companies' climate-related strategies, operational exposures and policies providing a more holistic view on transition risk (Mathiesen, 2018).

Our thesis contributes to the growing literature on the connection between climate risk and financial performance. Closest to our approach is the market-based studies of Görgen et al. (2020). They find that so-called carbon risk explains systematic variation in return well by including a Brown-Minus-Green factor in the CAPM, Fama French three-factor, Carhart four-factor and Fama French five-factor models. However, they do not find a carbon premium. The findings on the topic are contradicting. Chava (2014) finds that investors demand significantly higher expected returns for investing in companies with higher environmental concerns compared to companies with lower environmental concerns. Trinks et al. (2018) find that investors demand a premium for investing in companies with higher carbon intensity. They find a significant impact of carbon intensity on cost of equity, and argue that the effect is explained by systematic risk factors. On the contrary, Bolton and Kacperczyk (2020) find a carbon premium that cannot be explained by common risk factors.

Including climate risk in valuation processes requires investors to have a long-term mindset and to reconsider their risk management strategies. We are curious to what extent climate risk is priced in markets today. With our thesis, we want to bridge the gap between financial asset pricing and the transition towards a low-carbon economy.

We study the relationship between transition risk and equity prices. Our analysis is based on stocks included in the iShares MSCI World ETF in the period from January 2014 to December 2019. Using the methodology of Görgen et al. (2020), we first construct a Green Score based on scores from the Refinitiv Eikon to create a measure of climate-related performance. We use the Green Score to divide companies into annually rebalanced portfolios. The result of the process is a Green-Minus-Brown (GMB) portfolio measuring differences in return between Green and Brown companies. The GMB factor is regressed with risk factors included in the CAPM, Fama French three-factor model and the Carhart four-factor model, referred to as common factor models, to analyze whether the risk factors can explain differences in return between the Green and Brown portfolio. Subsequently, we extend the common factor models with the GMB factor to analyze whether it enhances the explanatory power of the models, furthermore testing our hypothesis through F-tests and GRS climate-related performance.

We find that differences in return between the Green and Brown portfolio cannot significantly be explained by the risk factors included in common factor models. However, we do not find significant differences in abnormal return between the Green and Brown portfolio. When the GMB factor is included in the common factor models it provides significant coefficients at a 1% level for Most Brown and Most Green companies. Our results indicate that the factor explains variations in risk-adjusted return of such companies well. The results from our F-test are also significant, indicating that the inclusion of the GMB factor enhances the explanatory power of the model. However, the results from the GRS tests indicate that the original models are better fit in explaining risk-adjusted return in our sample.

Our thesis contributes to the current flow of literature on the transition risks of financial markets to the low-carbon economy. Firstly, it adds understanding of the impact of climate-related performance on companies' financial risk and asset prices through a market-based approach. Secondly, it contributes to the asset pricing theories by including a mimicking portfolio based on companies' climate-related performance. Thirdly, it adds to the empirical literature as it combines studying transition risk at both portfolio level and company level using panel regression techniques.

The thesis is structured as follows: Chapter 2 outlines the background and literature relevant to answering our research question. Chapter 3 presents the data sources and the variables retrieved and constructed. Chapter 4 elaborates on the methodologies used in our analysis, whilst Chapter 5 analyze the results. Lastly, Chapter 6 offers discussions and Chapter 7 adds the concluding remarks of the thesis.

# 2. Background and literature review

## 2.1 Climate change

Climate change is the defining issue of our time and we are at a defining moment (UNFCCC, 2020). Recent anthrophogenic emissions of greenhouse gases (GHG) are the highest in history, and the atmospheric concentrations of carbon dioxide, methans and nitrous oxide are unprecedented in at least the last 800,000 years (IPCC, 2014). Without further actions, the future holds severe consequences such as rising sea levels, shifting weather patterns, extinction of species and higher risks of drought and floods. We need to urgently reduce emissions and prepare for the consequences of climate change.

As the global population has grown and experienced increased standards of living, the climate has changed relative to the pre-industrial period. There are multiple evidences that suggest a clear relationship between human activities and climate change (IPCC, 2018). Industrialization, large-scale agriculture and deforestation have led to an increase in the cumulative level of GHGs emissions, causing a warmer global climate since the mid-20th century.

In the past few years, public concern about climate change has increased dramatically. In 2015 the Paris Agreement was announced at the UNFCCC COP21 conference in Paris. For the first time most UN countries consented to combat climate change together, agreeing on the need to limit global temperature increase below 2 °C above pre-industrial levels (UNFCCC, 2015). The agreement entails substantial investments in low-carbon and energy-efficient production technologies and consumption activities, and divestment from carbon-intensive activities and fossil fuels production (NCE, 2018).

## 2.2 Climate change awareness in the financial markets

As a response to the challenges of climate change, there has been an emerge in the field of sustainable finance. Climate finance is a relatively new concept that has become increasingly important due to the growing awareness of climate change. UNFCCC (2020) states that climate finance refers to "local, national or transnational financing — drawn from public, private and alternative sources of financing — that seeks to support mitigation and adaptation actions that will address climate change".

As climate finance has gained momentum, the concept of socially responsible investing (SRI) has expanded significantly (ter Horst et al., 2007; Nilsson, 2008). Døskeland and Pedersen (2016) defines SRI as "investments that are designed to yield the highest possible risk-adjusted financial return while also taking into account social, ethical and environmental concerns", thereby integrating both financial and non-financial objectives. The idea of implementing ethical concerns when making investment decisions has existed for over a century, primarily through the exclusion of sin stocks such as tobacco, alcohol and pornography (Hong and Kostovetsky, 2012). However, over the last decades, SRI has evolved to adopt both environmental, social and governance issues, often referred to as ESG investing.

According to traditional financial theory, SRI and ESG investing are inefficient as it constraints diversification and reduces investment opportunities (Fama, 1970; Markowitz, 1952; Sharpe, 1964). The SRI objective has thereby often been seen as achieving ethical goals rather than maximizing financial return.

However, with a growing awareness of the consequences of climate change, we see a shift towards considering climate change as a risk rather than solely a responsibility. Warmer climate, raising sea levels, polluted air and water poses a long-term financial risk as it will threaten the stability of the financial system (Carney, 2015). As Chief executive of BlackRock, Laurence D. Fink stated "climate change has become a defining factor in companies' long-term prospects" (Fink, 2020). The evidence on climate risk as a financial risk is compelling investors to reassess core assumptions about modern finance, recognizing that climate-related risk is indeed material to all companies.

## 2.3 Climate-related financial risk

The growing awareness among companies and investors is partly a result of actions by central banks and international institutions. The former Governor of the Bank of England, Mark

Carney, stated that climate change is the tragedy of the horizon (Carney, 2015). He was one of the initiators of the Task force on Climate-related Financial Disclosures (TCFD), a task force set to help identify the information needed by investors, lenders and insurance underwriters to assess and price climate-related risks and opportunities. In their report, they part the risk factors of climate change into 2 categories: physical and transition risk (TCFD, 2017).

### 2.3.1 Physical risk

Physical risks are the costs related to the physical impact of climate change (TCFD, 2017). According to the Intergovernmental Panel on Climate Change IPCC (2018), human activities have lead to an increase in the intensity and frequency of climate and weather extremes since the pre-industrial times. Physical risk can be acute or chronic. Acute physical risks are event-driven, such as an increase in the incidents of extreme weather, whilst chronic physical risk refer to longer-term shifts in climate patterns that may lead to a warmer climate or rising sea levels (TCFD, 2017).

### 2.3.2 Transition risk

In order to reach the goals set in the Paris Agreement, GHG emissions must be reduced drastically (IPCC, 2018). Transition risk refers to the risks associated with the transition to a low-carbon economy. These risks can be parted into 4 subcategories: legal and policy risk, technology risk, market risk and reputation risk (TCFD, 2017).

The transition to a low-carbon economy creates both opportunities and challenges for companies. The introduction of policies and regulations aiming to reduce emissions, such as carbon-pricing mechanisms, will likely involve losses for high-emitting firms and create shifts in demand for low-emitting energy sources. In addition, regulations could accelerate the emergence of climate-friendly technology.

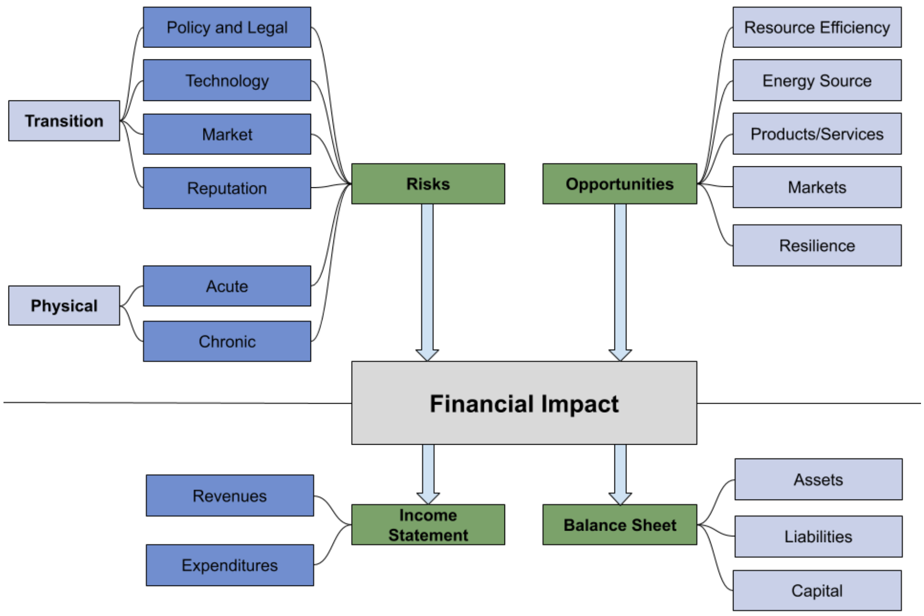


**Figure 2.1:** Climate risk and opportunities, adopted from (TCFD, 2017)

Figure 2.1 shows the different climate risks and opportunities identified by TCFD (2017). All the above risks could materially affect the financial positions of companies either through their income statement or balance sheets. Further, it could affect the valuation of a firm as it is dependent on its expected future cash flows and its discount rate. Climate-related costs may decrease the cash-flows of a company, increase the risk of default, and reduce the liquidation value of the assets of a firm (TCFD, 2017).

### 2.3.3 Transition Pathway

The transition risk highly depends on the timing, speed and focus of the policies introduced to ensure emission-reduction (Batten et al., 2016). It is uncertain which sectors and businesses the mechanisms will impact and when the mechanisms will be introduced. Therefore, scenario analysis has gained popularity as a tool to stress-test financial assets using different policy scenarios. In the following section will discuss the different transition pathways by looking at different macro-scenarios presented by the Network for Greening the Financial System (NGFS).

TCFD (2017) deem scenario analysis as a necessary assessment tool when measuring the potential financial impacts of climate-related risk and opportunities. In the aim for becoming carbon neutral by 2050, NGFS has developed a framework to provide a common reference for analysing climate risks to the economy and financial system (NGFS, 2020). To begin with, NGFS defined three potential scenarios based on whether climate targets are met or not. The scenario "Orderly" involves least risk. In this scenario, the economy will undergo an orderly approach to meet the emission goals, thereby implementing early, ambitious actions to a net zero $CO_2$ economy. On the other hand, the alternative scenario "Disorderly" will involve more transition risk as it means that action will be late, disruptive, sudden and unanticipated. The "Hot house world" scenario involves limited action which will lead to significant global warming and consequently strongly increased exposure to physical risks. Later, NGSF added a fourth scenario "Too little, too late", which involves both high transition risks and physical risks. The scenarios are presented in Figure 2.2.

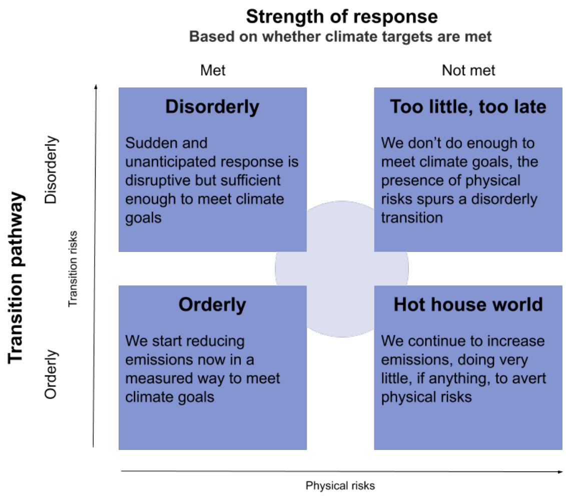


**Figure 2.2:** NGFS Climate Scenarios Framework

In an Orderly scenario, a significant amount of capital is invested to meet the objectives of the Paris Agreement. By proposing orderly policies, the cumulative global GDP impact from transition risk is relatively small, from $-2\%$ in 2030 to $-4\%$ in 2100. In contrast, the Disorderly scenario, where policies are introduced at a later time will lead to less impact on the global GDP in a 10-year perspective. However, the impact will increase significantly in 2050 and 2100 to respectively a 6% and 10% reduction in cumulative global GDP. There are limited losses from transition risk in a Hot-house-world scenario (NGFS, 2020).

The scenarios emphasizes the uncertainty of the transition pathway. Certainly, the scenarios will affect firms differently dependent on the nature of the firm. In our study we want to quantify the market's assessment of the transition pathway, and discuss how it will impact portfolios and companies financially.

#### 2.3.4 Climate-related disclosure

As investors become aware of climate risk, there is an increasing demand for corporate disclosures that display firms' exposure to transition risk. TCFD (2017) is the leading framework on disclosing climate-related financial risk. They recommend to measure exposure to transition risk by total GHG emissions and relative GHG emissions. These are often measured through three different scopes: Scope 1, Scope 2 and Scope 3. Scope 1 measures direct GHG emissions. Scope 2 includes a company's indirect emissions generated from the company's purchase of energy. The last scope, Scope 3, counts for all other emissions that occur in the value chain, from both suppliers and consumers (Ranganathan et al., 2004).

Today, there are several companies that provide carbon footprint measures such as Trucost, CDP, Sustainalytics, Refinitiv and MSCI ESG Research. However, without standardized and regulated reporting frameworks there will be inconsistencies in ESG ratings. This can pose a significant challenge that can decrease the efficiency of ESG investing strategies (OECD, 2020).

## 2.4 Literature review

The management of the transition to a low-carbon economy will affect all market participants. This has also led to an increased interest in the research field of climate risk. In the following section we will present relevant literature and outline empirical evidence before developing our hypotheses.

### 2.4.1 Efficient Market Hypothesis

An investment will only yield higher risk-adjusted returns than required if financial markets do not price risk accurately. Investors facing investment decisions involving climate risk therefore ask themselves whether climate risk is priced into financial assets. The Efficient Market Hypothesis states that stock prices efficiently represent the value of a discounted future cash flow. In other words, all relevant information is incorporated into the prices of financial assets (Fama, 1970). This implies that it is theoretically impossible to buy undervalued stocks at a bargain or sell overpriced stocks with a margin.

Stiglitz and Grossman (1980) argue that gathering information is a costly activity, and that information seekers therefore require a return on their activity. As a result, stock prices cannot reflect all information available, and markets cannot be efficient. In their model, a rational investor collects information until the expected marginal value of new information equals the cost of collecting it. As a consequence perfect informationally efficient markets are impossible, as there would be no incentive to gather information if there was no reward.

### 2.4.2 Climate-related performance in investments and valuation

In practice, stock prices are affected both by direct regulations related to the transition towards a low-emitting economy and investors' expectations about a future pricing path and preferences for green. Investors may have different objectives when looking at the climate-related performance of their investments. Roughly, their goals can be parted into i) reducing the climate impact of assets under management, ii) contribute to the transition towards a low-carbon economy and iii) reducing exposure to climate-related risks (Natixis, 2016).

The first two strategies involve that investors' main objective is to reduce its negative externalities or increase their positive externalities. This implies that investors are willing to reduce the expected return of an investment if the asset's climate-related performance is better (Trinks et al., 2018). These approaches contradict the Efficient Market Hypothesis, which states that market participants only maximize mean return and minimize variance.

The latter strategy is a neutral method viewing assets' greenness from a traditional financial risk perspective. Investors thereby use traditional valuation approaches when deciding whether to invest or not. One of the most commonly used valuation approaches is the Discounted Cash-flow (DCF) (Pinto et al., 2019). According to the approach, climate risk considerations can affect the valuation of a firm through two channels: the cash flow-channel and the cost of capital-channel. In a traditional DCF model, the two channels are exposed to different types of risks. According to the Capital Asset Pricing Model (CAPM), the total risk of an individual asset can be divided into two components: Systematic and idiosyncratic risk (Sharpe, 1964). The systematic risk of an asset measures how the asset covaries with the economy, whilst the idiosyncratic risk is asset-specific. In a traditional DCF model, systematic risk, which cannot be diversified away, will influence firm's cost of capital, whilst idiosyncratic risk affects the firms' cash flows and can be hedged (Albuquerque et al., 2020).

If high-carbon assets are screened by a sufficiently large share of the market, this would make investors require additional returns for holding those assets (Trinks et al., 2018). Yet, these kinds of preferences would likely not be explained by systematic risk, as this would require the entire market to screen the same stocks. In the same way, the climate-related performance of an asset could be explained by systematic risk if regulations aiming to limit carbon emissions applied or was expected to apply uniformly to all sectors, industries and companies (Bolton and Kacperczyk, 2020). However, if different regulations are introduced for different regions, sectors and industries at different times, the return would likely not be explained by systematic risk (Pastor et al., 2020).

Andersson et al. (2016) argue that there is a mispricing in the market of risks related to carbon-emissions, making it possible to hedge against climate risk in the long run. However, preferences for low-carbon stocks will lead to a short-term increase in prices as investors are willing to pay more for these kinds of stocks relative to high-carbon stocks (Pastor et al., 2020).

### 2.4.3 Empirical evidence on the climate-related and financial performance

Over the past decades, a large body of literature has provided important insights into how climate-related performance impact both the cash-flow-channel and the cost of capital-channel. However, very few research papers make the distinction between what is caused by which channel in their studies. As mentioned above, climate risk can affect the cash flow-channel through changes in profitability and changes in firm-specific downside risk. Through the cost of capital-channel, climate risk can be priced by adjusting the discounted rates for climate risk (Albuquerque et al., 2020; Pastor et al., 2020). In the following section we will look at climate-related and financial performance, while exploring how equity valuation accounts for climate risk through evidence from regression studies, event studies and portfolio studies. [1]

**Evidence from regression studies**

Regression studies can be used to study the relationship between two variables (Wooldridge, 2016). Several regression studies estimate the relationship between firm value and climate-related performance. Matsumura et al. (2014) examine the effect of carbon emissions on firm value. They find that for every additional thousand metric tons of carbon emissions, firm value decreases by USD 212,000. Furthermore, they investigate the firm-value effects of managers' decisions to disclose carbon emissions, finding that the median value of firms that disclose their carbon emissions is about USD 2.3 billion higher compared to non-disclosing firms.

An increasing number of studies have provided evidence that climate-related performance is related to profitability and decreased downside risk, thereby how climate-related performance and risk affects the cash flow-channel. Eccles et al. (2014) study the impact of corporate sustainability on organizational processes and performance. They find that companies that have adopted sustainability policies significantly outperform their counterparts in both stock market and accounting performance in the long term. Furthermore, Friede et al. (2015) provide aggregated evidence from more than 2,000 empirical studies, showing that a large majority of the studies report positive findings from ESG on corporate financial performance. In terms of idiosyncratic risk, Dunn et al. (2017) discuss the risk and return implications of incorporating ESG considerations in an investment strategy. They find robust results saying that the stocks with worst ESG exposure have total and stock-specific volatility that is up to 10-15% higher

[1] Climate-related performance is not distinguished from ESG performance, as these are highly correlated.

and betas up to 3% higher than stocks with the best ESG exposures. Furthermore, Ilhan et al. (2020) find strong evidence that firms with higher carbon emissions exhibit more tail risk and more variance risk than firms with lower emissions. Relatedly, Hoepner et al. (2018) observe that ESG engagement reduces firms' exposure to downside risk.

When studying the cost of capital-channel, systematic risk is the primary consideration. The most common way to forecast an asset's cost of capital, is through the CAPM (Pinto et al., 2019). In efficient markets, CAPM should lead to correctly pricing of assets. Today, an increasing number of studies find that better climate-related performance is associated with a reduction in cost of capital. Sharfman et al. (2008) find this in their study of 267 U.S. firms. Correspondingly, Chava (2014) finds that investors demand significantly higher expected returns on stocks with high environmental concerns, such as hazardous chemicals, substantial emissions and climate change concerns, using implied cost of capital derived from analysts' earnings estimates. Furthermore, these companies are also found to be charged with a significantly higher interest rate on bank loans. Moreover, Trinks et al. (2018) test to what extent investors demand a premium to compensate for transition risks by looking at firms' cost of equity. They base their analysis on data from 1,897 companies spanning 50 countries in the years 2008-2016 using both CAPM, Fama French three-factor model and Carhart four-factor model, often referred to as common factor models. Their findings suggest a distinct and robust positive impact of carbon intensity on cost of equity using carbon emissions per unit of output as proxy for carbon intensity. Furthermore, Trinks et al. (2018) find that their results are primarily explained by systematic risk factors, which in turn entails that high-emitting assets are significantly more sensitive to macroeconomic fluctuations than low-emitting firms.

The lack of historical data and uncertainties about climate risk may suggest that transition risk is not correctly priced in financial markets today. In the CAPM, a mispricing is evident as an significant alpha or abnormal returns, which is different from the expected returns based on the risk factors in the model (Jensen, 1969). Liesen (2015) studies whether financial markets in Europe during 2005-2009 are efficient with regards to information about the climate. She finds that they are not, and thereby rejects the Efficient Market Hypothesis. Furthermore, several studies try to find a mispricing of climate risk in the market. Bolton and Kacperczyk (2020) hypothesizes that financial markets are pricing carbon risk inefficiently, implying that the risk is underpriced. They discuss the idea that investors have a habit of ignoring information about global warming, thereby overlooking the physical and transition risks in their future cash-flow projections. In their cross-sectional study, Bolton and Kacperczyk (2020) find a carbon premium that cannot be explained by known risk factors or through a negative screening effect. In other words, the level of carbon emissions contains independent information about return.

**Evidence from event studies**

Event studies can show whether and how financial markets react to climate-related events such as new regulations, publications, legal changes or news from the media, as they measure the impact of a specific event on the value of a firm (MacKinlay, 1997). If markets are efficient, firms' valuation, and thereby stock prices, will be affected by a post-event adjustment dependent on the severity of the event.

Chapple et al. (2013) and Ramiah et al. (2013) both study the effect of forthcoming the Emission Trading Scheme (ETS) on the Australian market. Chapple et al. (2013) look at how 5 ETS events in the time-period 2006-2009 affect the market evaluation of a firm. Each announcement increases the likelihood of an enforcement of environmental policies, for instance the authors looks at the Government's release of Green Paper which reports the design of the ETS. They find a statistically significant evidence that the capital market is pricing the the announcements, implying that markets penalize more carbon intensive assets because of new information about the transition towards a greener economy. Ramiah et al. (2013) expand both time period and number of events as they analyze 19 events in the period of 2005-2011. In addition to the ETS announcements, they look at international announcements such as the Kyoto Protocol and the release of emission targets in the US and China. Their aim is to estimate the change in systematic risk that results from the events and assess whether the announcements are value constructive or destructive for equity investors. However, their results are not significant.

Griffin et al. (2015) document the markets' reaction to one of the most cited articles in environmental science studies. The article stated that there is only a fraction of the world's existing petroleum reserves could be emitted if global warming were not to exceed 2 °C above pre-industrial levels by 2050. The study finds that stock prices of the 63 largest U.S. oil and gas companies dropped between 1.5 percent to 2 percent in the three days after the publication controlling for oil price changes, market changes and other relevant news releases the surrounding days.

More recently, Mukanjari and Sterner (2018) analyzed how the signing of the Paris Agreement and the election of the president of the U.S. in 2016 affected the stock market value of firms in the energy sector. They found a moderate effect of both events. Later, Monasterolo and de Angelis (2020) tested if the financial markets priced the Paris Agreement by decreasing the systematic risk and increasing the portfolio weights of low-carbon indices as a result of the announcement. Their results suggest that low-carbon assets were generally perceived as riskier than the market before the Paris Agreement. After the announcement of the Paris Agreement, however, the risk-return profile of low-carbon assets decrease significantly. Additionally, they find that after the Paris Agreement the correlation among low-emitting firms and carbon-intensive indices drops, thereby that the betas of low-emitting indices decreases, while the stock market's reaction to carbon-intensive indices is more mild. Furthermore, Monasterolo and de Angelis (2020) find that the weight of the low-carbon indices within an optimal portfolio increases after the Paris Agreement. Their evidence suggest that investors assess low-emitting assets as more attractive post the announcement of the Paris Agreement, however, they do not seem to penalize more carbon-intensive assets yet.

**Evidence from portfolio studies**

Most relevant to our approach are studies on the effect of transition risk on the financial performance of portfolios. According to asset pricing theory, a portfolio's exposure to different types of systematic risk can be measured through factor models (Fama and French, 1993; Carhart, 1997).

One of the earliest contributors on the topic were White (1996). He examined the performance of "green", "oatmeal" and "brown" equity portfolios in the time-period 1989-1992. The study demonstrated that the green portfolios had a significantly positive alpha using CAPM, suggesting climate-related risk is firm specific, thereby idiosyncratic risk.

However, most of the differences in return can be explained by idiosyncratic risk. Derwall et al. (2005) extend their findings by using multi-factor models. They compose two portfolios that differ in eco-efficiency characteristics, thereby differing in historical liabilities, operating risk, sustainable and eco-efficient risk, managerial risk and environmentally-related strategic profit opportunities. Subsequently, Derwall et al. (2005) construct one high-ranked portfolio represented by stocks with high eco-efficient characteristics and one low-ranked portfolio represented by less eco-efficient stocks by ranking U.S. companies in the time-period 1997-2003. They find that high-ranked portfolios provide substantially higher returns than low-ranked portfolios.

Oestreich and Tsiakas (2015) use CAPM, Fama and French three-factor model and Carhart four-factor model to study the effect of the European Union's Emission Trading Scheme on German stock returns. By constructing a "dirty", "medium" and "clean" portfolio, they test whether the "dirty-minus-clean" portfolio have abnormal excess returns, thereby a carbon premium. The authors find that firms that received free carbon emissions during the first two phases of the scheme on average significantly outperformed firms that did not. Their findings suggest that there exists a large and statistically significant "carbon premium" in stock returns which can be explained by higher cash flows due to the free allocation, thereby an abnormal return of a portfolio of "clean" firms. In addition, Oestreich and Tsiakas (2015) find that a carbon risk factor based on returns from a dirty-minus-clean portfolio can explain a large amount of the cross-sectional variation in expected stock return.

Closest to our approach is the study of Görgen et al. (2020). Their working paper is a result of a two-year research project aiming to quantify existing risks and opportunities that occur from the transition towards a low-carbon economy (Wilkens et al., 2019). In the paper Görgen et al. (2020) analyze whether a Brown-Minus-Green portfolio can increase the explanation of variations in stock returns. They first construct a Brown-Green-Score (BGS) as a metric for carbon risk based on ESG data from 2010-2017. Based on the BGS they construct a mimicking portfolio that is long in stocks of companies that have low climate-related performance and short in stocks of companies that are high climate-related performance. This results in a Brown-minus-Green (BMG) factor which they use to expand the factor models CAPM, Fama French three-factor model and Carhart four-factor model. In contrast to most other approaches to manage carbon risk, this method creates a market-based measure of carbon risk, which can be used to identify carbon risk of a specific market. By regressing the BMG factor with the mentioned risk factors in time-series, the authors estimate so-called carbon betas that can be interpreted as carbon-related systematic risk. Görgen et al. (2020) do not find a priced carbon risk premium which suggest that investor may not require compensation for bearing carbon risk. To better understand the missing carbon premium, they show that the variance of the BMG factor is dominated by cash-flow news rather discount-rate news, furthermore that the cash-flow beta is higher than the discount rate beta.

## 2.5 Hypotheses

The purpose of this thesis is to bridge the gap between financial asset pricing and the transition towards a low-carbon economy. We do this by providing empirical research aiming to quantify how investors assess the existing risks of financial assets with regards to climate change. Our hypotheses are formed in line with the findings in recent literature: that investors will require a risk-premium for investing in companies with worse climate-related performance as these are more exposed in a transition towards a low-carbon economy.

The findings in our literature review suggest that transition risk can impact both systematic and idiosyncratic risk in assets. In our study we will look at the systematic risk of assets as the idiosyncratic is difficult to measure, and furthermore because it can be diversified away. Like TCFD (2017), Battiston et al. (2017), Fink (2020) and Carney (2015), we believe that climate-related performance will impact systematic risk due to the economy-wide effects of transitioning from a high-carbon economy. Because regions, sectors and industries are interdependent in terms of resources with low climate-related performance, such as fossil fuels, the ability to fully diversify away from transition risk seems unlikely. However, as is outlined in our literature review, several studies find that the differences in return between green and brown companies cannot be explained by systematic risk factors in common factor models. In line with these findings, we form our first hypothesis:

**Hypothesis 1 (H1):** *Differences in return between a portfolio of Green and Brown companies cannot significantly be explained by common risk factors.*

Our first hypothesis is a novel contribution to the understanding of transition risk. To answer the hypothesis, we base our analysis on a portfolio study with similarities to the one of Görgen et al. (2020), Derwall et al. (2005) and Oestreich and Tsiakas (2015) by employing a Green-Minus-Brown portfolio. A finding that common factor models cannot significantly explain differences in return creates room for a discussion on the existence of a missing systematic risk factor in common factor models. We therefore form our second hypothesis:

**Hypothesis 2 (H2):** *A Green-Minus-Brown factor will have a statistically significant impact on the explanatory power of common factor models.*

By extending common factor models with a GMB factor we are able to extract coefficients which we refer to as "Transition Betas". These coefficients determine how the value of an asset is likely to change in relation to the market as a whole if expectations about the transition process of the economy change: an asset's transition risk. Our thesis will contribute with interpretations and discussion of transition risk across Green and Brown companies. In addition to answering our research questions, we also investigate differences in transition risk of Green and Brown companies before and after the publication of the report Recommendations of the Task Force on Climate-related Financial Disclosures in June 2017. Furthermore, we discuss the implications for investors and companies.

# 3. Data

We use data from Refinitiv Eikon, Refinitiv Datastream and Kenneth R. French's data library to answer our research questions. In this chapter we will provide descriptions of the data sources used to retrieve relevant data, the sample used to answer our analyses, screening processes and construction of variables. Lastly, we will justify our data choices and comment on our concerns about the dataset.

## 3.1 Data retrieved from Refinitiv

Refinitiv is an industry leading analytic data source with data on equities, fundamentals, bonds, commodities, mutual funds and investment trusts, futures and options, fund indices, interest and exchange rates and ESG from 175 countries (Refinitiv, 2020a). From Refinitiv Eikon, we retrieve data on climate-related performance and firm characteristics and from Refinitiv Datastream we retrieve monthly financial prices.

### 3.1.1 Financial data on companies

We are interested in how companies' returns are affected by their exposure to transition risk. For companies, we retrieve company names, monthly stock prices from the end of the month, total revenue, country, market capitalization and sector categorization from the period January 2014-December 2019. This provides us with the time-series data needed in our analyses.

### 3.1.2 Data on climate-related performance

In addition to financial data, we are interested in data that can be used to measure transition risk. Refinitiv Eikon offers one of the most comprehensive ESG databases covering over 80% of global market cap, across more than 450 different ESG metrics. Their data go back to 2002, and are designed to measure a company's relative ESG performance, commitment and effectiveness across 10 main ESG themes (Refinitiv, 2020b).

In order to categorize companies as "green" and "brown" we need to create a metric for "greenness". By combining several scores on carbon emissions and carbon mitigation performance extracted from Refinitiv Eikon, we create a Green Score aiming to capture the climate-related performance of companies. We choose variables according to the recommendations of TCFD (2017), as they provide the most widespread and accepted framework for disclosing climate-related financial performance and risk. Furthermore, our chosen variables are all used in Görgen et al. (2020). The used metrics are explained in Table 3.1.

**Table 3.1:** Explanation of variables used to construct the Green Score

| Variable name | Abbreviation | Explanation |
|---|---|---|
| Carbon Intensity Score | TRS | Score based on total $CO_2$ and $CO_2$ equivalent emissions in tonnes divided by net sales or revenue in USD dollars. |
| Emission Score | ES | Score based on the company's commitment and effectiveness towards reducing environmental emission in the production and operational processes. |
| Policy Score | PES | Score based on whether the company has a policy to improve emission reduction or not. |
| Targets Score | TES | Score based on whether the company has set targets or objectives to be achieved on emission reduction. |
| Environmental Supply Chain Management Score | ESCS | Score based on whether a company use environmental criteria (ISO 14000, energy consumption, etc.) in the selection process of its suppliers or sourcing partners. |
| Climate Change Commercial Risks Opportunities | CRU | Score based on whether the company is aware that climate change can represent commercial risks and/or opportunities. |

The most common method to measure climate-related performance is through GHG emissions and GHG intensity. Hence, we retrieve the variable Total $CO_2$ Equivalents Emission to Revenues USD Score (hereafter $TRS$) which exhibit the total Scope 1 and 2 $CO_2$ equivalents emission in tonnes divided by net revenue in US dollars. $TRS$ is calculated by using a percentile-formula, where companies are ranked based on their relative performance compared to their industry group in the Refinitiv universe (Refinitiv, 2020b). Refintiv scale the score from 0 to 100, where higher score means lower relative carbon intensity. This provides a size-adjusted metric for each company's carbon impact.

In addition to a company's emission state, we wish to account for factors that could affect a company's transition risk in the long run. Therefore, we add the variables Emission Score ($ES$), Policy Emission Score ($PES$), Targets Emissions Score ($TES$), Environmental Supply Chain Management Score ($ESCS$) and Climate Change Commercial Risks Opportunities ($CRO$). Table 3.2 provides the summary statistics of the variables. The statistics are based on the scores in the sample period 2014-2019.

**Table 3.2:** Summary Statistics, data on climate-related performance

| Statistic | N | Mean | St. Dev. | Min | Median | Max |
|---|---|---|---|---|---|---|
| TRS | 4,150 | 53.5 | 25.9 | 0.7 | 54.0 | 99.7 |
| ES | 5,677 | 59.7 | 32.2 | 0.0 | 68.6 | 99.8 |
| PES | 5,677 | 55.5 | 30.0 | 0.0 | 67.9 | 96.7 |
| TES | 5,595 | 48.1 | 41.2 | 0.0 | 75.0 | 95.7 |
| ESCS | 5,575 | 54.0 | 34.9 | 0.0 | 71.5 | 93.1 |
| CRO | 5,730 | 60 | 50 | 0 | 100 | 100 |
| BGS | 4,102 | 56.6 | 20.9 | 5.7 | 57.1 | 96.3 |

All variables are calculated on a yearly basis, and measure companies' relative performance on the specific attributes relative to their industry group (Refinitiv, 2020b). As with the $TRS$ score, Refinitiv scale each variable using a percentile calculation formula for each measure. Hence, all the variables are scaled in hundreds where higher score means better climate-related performance. Our method is different from Görgen et al. (2020) as they transform continuous and discrete variables into dummies based on the median value. We see it as more appropriate to use scaled values to additionally capture the distances from the median. The $CRO$ variable was the only variable that was originally a dummy in our sample. After the data treatment, the score does therefore have the value 0 or 100 in our data set.

## 3.2 Data on company risk factors

The Kenneth R. French data library provides constructed risk factors for developed markets (French, 2020). These will be used in our analysis.

We use both single-factor and multiple-factor asset pricing models to answer our research question. We retrieve the value-weighted market portfolio return, the risk-free rate, and factors from Fama French three-factor and Carhart four-factor, thereby the equally-weighted HML, SMB and WML portfolio returns.

## 3.3 Sample selection

We answer our research question by running analyses on companies included in the iShares MSCI World ETF during the period of 2014 to 2019. The iShares MSCI World ETF follows the MSCI World index closely, and consists of less than 2,000 stocks, capturing large and mid-cap representation across 23 developed countries in Asia, Europe, the U.S. and Oceania (Blackrock, 2020). They aim to provide exhaustive coverage of relevant investment opportunities while prioritizing index liquidity, investability and replicability (MSCI, 2020). We see the index as suitable for our analysis as it is a close representation of the market.

We aim for diversity in our sample, however, an important criteria for our sample was comparable expectations on the transition towards a green economy. IPCC (2014) stated that developed countries will need to reduce their emissions more than other countries in order to reach the Paris Agreement. Furthermore, all regions in our sample have introduced climate-related policies aiming to reduce emissions (OECD, 2019). We believe our sample represents stocks that are reasonably equally exposed to expectations towards the transition to a low-carbon economy.

The materiality of data quality has restricted our time-period. We only collect companies' financial and environmental data from January 2014-December 2019, due to the fact that there is a substantial amount of missing observations in the environmental data in the years before 2014. Furthermore, we remove companies from the financial sector. Based on these screening operations, our main analysis are based on 955 companies across 10 sectors in 4 regions, as shown in Figure 3.1 and Figure 3.2.

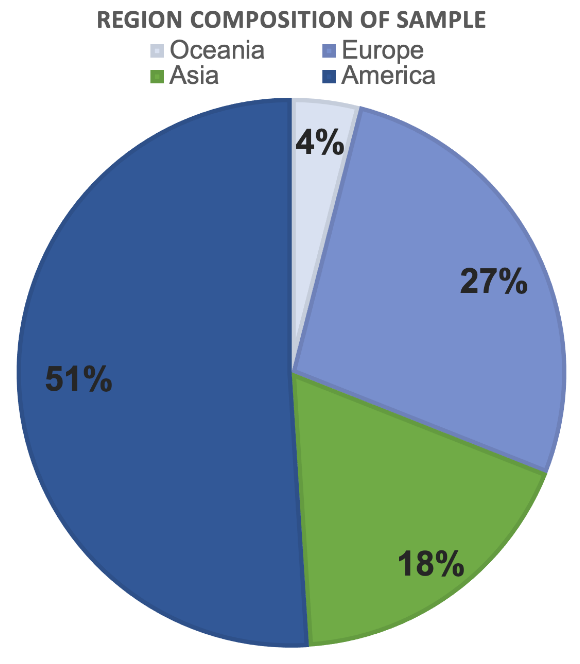


**Figure 3.1:** Region composition of sample

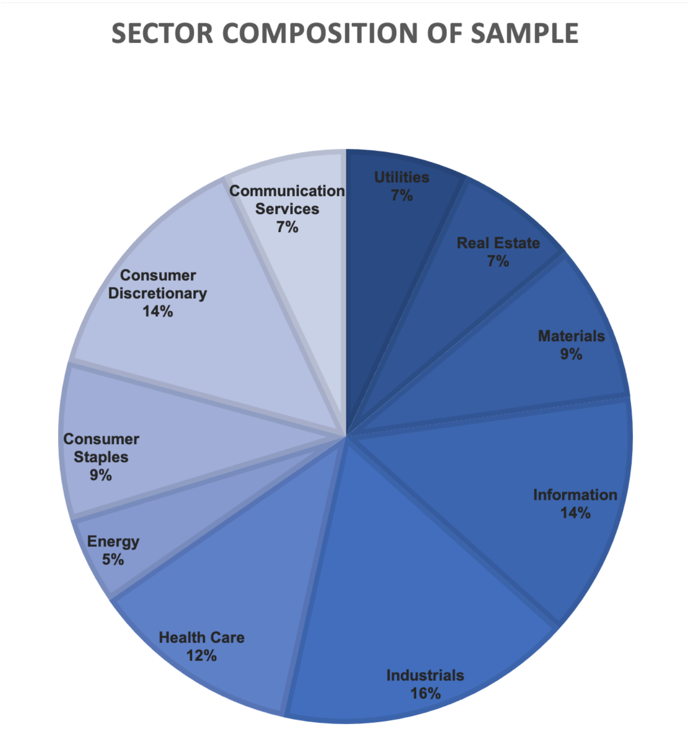


**Figure 3.2:** Sector composition of sample

## 3.4 Constructing variables

In order to answer our research questions, we had to construct and merge variables in our datasets. We first construct a measure of climate-related performance based on the mentioned variables in section 3.1.2. We also present how we calculate monthly return for both individual stocks and portfolios that will be used in our analysis.

### 3.4.1 Green Score

Most studies use carbon intensity as a proxy for a company's climate-related performance (Matsumura et al., 2014; Trinks et al., 2018; Ilhan et al., 2020; Bolton and Kacperczyk, 2020). In our study we search to expand the measure providing a more holistic view of a company's greenness. In order to do so, we need to find an appropriate method to gauge the climate-related performance of a firm - their Green Score ($GS$), by using the variables mentioned in section 3.1.2.

The $TRS_{i,t}$ calculates the carbon intensity of a firm and is an expression for their relative emission performance. Since the total emissions of a company is the most used metric to assess its exposure to transition risk, we consider this score most important when gauging a company's climate-related performance. The carbon intensity score is therefore weighted 0.8 in the calculation of our Green Score.

However, a company's current emissions will not tell the whole story of a company's climate-related performance. We therefore include scores on policies, targets, supply chain and awareness, all included in the score constructed in CARIMA research project (Wilkens et al., 2019). Although these measures are important when explaining a company's greenness, the lack of standards and regulations for reporting is a concern. Companies are not obliged by law to disclose information on climate-related financial risk, and as a result, there are many different practices and standards in the market often resulting in the practice of "greenwashing" (Delmas and Burbano, 2011). Furthermore, recent empirical findings suggest that larger companies have advantages compared to smaller firms in terms of ESG score (Drempetic et al., 2020). Due to these concerns, we put less weight on these scores than the $TRS_{i,t}$. Since our score is, unlike the one of Görgen et al. (2020), based on variables from one single data source, it is more vulnerable to the mentioned concerns. Our weights on the scores are therefore less than the ones of Görgen et al. (2020). We put a weight of 0.05 on all scores except $PES_{i,t}$ and $TES_{i,t}$ which each have a weighting of 0.025 as we see from our sample that companies with targets for their climate-related performance almost always have internal policies as well. Our weighting of carbon intensity is consequently higher than the CARIMA project which use a weighting of 0.7 (Wilkens et al., 2019). For robustness, we provide results from scores based on different weightings in Chapter 5 under Robustness. The yearly Green Score of a company used in our main analysis is calculated as follows:

$$GS_{i,t} = 0.8 \times TRS_{i,t} + 0.05 \times ES_{i,t} + 0.05 \times \frac{PES_{i,t} + TES_{i,t}}{2} + 0.05 \times CRO_{i,t} + 0.05 \times ESCS_{i,t}$$

Before constructing the Green Score, we remove companies in the finance sector, as these differ considerably from other sectors in their exposure to transition risk. For example, an investment bank has almost no direct emissions on their own, but they finance companies that are more or less exposed to transition risk. Therefore, these companies are indirectly affected through their portfolio. This kind of transition risk exposure will not be reflected in our Green Score, and we therefore find it better to exclude these companies from our sample.

Furthermore, we ensure sufficient data quality by excluding companies that are missing observations on one or more of the mentioned metrics used to calculate the Green Score as this will reduce the quality of our analysis (Wooldridge, 2016). Because the scores provided by Refinitiv are updated annually, we get inconsistencies in the number of observations each year as displayed in Table 3.3. However, this is unproblematic for our analysis, as the constructed portfolios used is rebalanced each year[1].

[1]For a more detailed explanation of the construction method of the portfolios used in our analysis, see Chapter 4.

As our objective is to create a precise and accurate Green Score, we aim to keep as many observations as possible. However, our concern was that the companies missing Green Score in some years might have some similar properties and that the inclusion of those might skew our Green Score in the years the companies are included. Nevertheless, as showed in Table 3.3, this does not seem to be the case as mean, standard deviation, minimum, median and maximum values does not appear to differ significantly.

**Table 3.3:** Descriptive Statistics of Green Score

| Year | N | Mean | St. Dev. | Min | Median | Max |
|---|---|---|---|---|---|---|
| 2014 | 631 | 56.24 | 20.86 | 11.538 | 57.395 | 95.929 |
| 2015 | 639 | 55.71 | 21.28 | 5.716 | 56.305 | 96.038 |
| 2016 | 672 | 56.15 | 21.28 | 6.252 | 56.506 | 96.130 |
| 2017 | 707 | 55.98 | 21.07 | 9.234 | 55.899 | 96.095 |
| 2018 | 731 | 57.14 | 20.49 | 10.209 | 57.900 | 96.309 |
| 2019 | 722 | 57.97 | 20.38 | 13.705 | 58.615 | 95.706 |

### 3.4.2 Calculating return

In addition to the Green Score, we need to calculate returns of stocks and portfolios. The prices provided by Refinitiv are adjusted for dividends and corporate actions (Refinitiv, 2020a). We calculate simple returns for all stocks by dividing the price of a stock in the end of the current month by the price in the end of the prior month subtracted by 1:

$$r_t = \frac{P_t}{P_{t-1}} - 1$$

*Where,* $r_t$ = *Return in month t*

$P_t$ = *Stock price in month t*

When constructing portfolios, the choice of weighting scheme has the power to influence the interference we make of our results. In our analysis, we wish to weight all companies the same. Therefore, we conduct our primary analysis on equally-weighted portfolios, because value-weighting implies putting more weight on information regarding returns of large-cap stocks (Plyakha et al., 2012). In addition, to ensure robustness of our interpretations, we will include results from value-weighted portfolios.[2] We calculate equally-weighted returns by assigning equal weights to each stock:

$$R_t = \sum_{n=1}^{N} \times \frac{r_{i,t}}{Nfirms_t}$$

*Where,*

$R_t$ = *Return on portfolio in month t*

$r_{i,t}$ = *Return on stock in month t*

*N firms*$_t$ = *Number of stocks in the portfolio in month t*

[2]Results from value-weighted portfolios can be found in Chapter 5 under Robustness.

For the calculation of the value-weighted returns in our robustness analysis, we assign weights to each stock based on their market capitalization. The returns of value-weighted portfolios are calculated as follows:

$$R_t = \frac{\sum_{n=1}^{N}(w_{i,t} \times r_{i,t})}{\sum_{n=1}^{N}(w_{i,t})}$$

*Where,*
$w_{i,t}$ = *Market value of stock i divided by the total market value of the portfolio in month t*

## 3.5 Discussion of data choices and concerns

Before we present the methodology of the thesis, we find it worth elaborating on the reasoning for our decisions and discuss some of our concerns about the data sets used to answer our research questions.

**The Green Score**
We wish to provide a measure of climate-related performance that stretches beyond solely including companies' emissions or carbon intensity. We therefore construct a new measure, the Green Score, which accounts for additional measures that provide extended information about a company's climate-related performance (TCFD, 2017; Görgen et al., 2020). We base our weightings on the ones used in the CARIMA project Wilkens et al. (2019), however we put more weight on carbon intensity (0.8 instead of 0.7) due to concerns about the limited number of variables used. Still, the score is based on what can be argued to be coarse assumptions which can potentially impact our results. We are aware of the risk of this choice in our analysis, and therefore provide robustness through analyzing our results with different weightings in our robustness tests. We find that our weighting does not appear to differ from a weighting based solely on carbon intensity.

In contrast to Görgen et al. (2020), we use a modest number of variables to determine a company's climate-related performance. It can be argued that this reduces the efficiency of the score in measuring transition risk, and that including more metrics would provide a more nuanced and accurate measure. However, we assessed the risk of double counting problems to be more serious. We have attempted to use variables that measure mutually exclusive aspects of transition risk. In addition, we believe our approach is more realistic for market participants to adopt.

Another concern about the construction of the Green Score is that the metrics on companies' greenness is solely based on publicly reported data. Due to the lack of regulations and standards on climate-related reporting, these metrics are less reliable than other financial data. Like with all research on climate-related risks and performance, this might reduce the quality of our results.

**Concerns about the sample**

As seen from both Figure 3.1 and 3.2, our data set contains a skewed sample of both regions and sectors. Furthermore, our analysis is based on a rather short time-period. The fact that our sample is skewed in both regions and sectors can lead to biased conclusions from our analysis (Saunders et al., 2009). A concern is that region and/or sector exposure have larger impact on the performance of our portfolios than the climate-related performance.

Even though it might be beneficial to have a bigger dataset when studying highly uncertain issues like climate risk (Wooldridge, 2016), we believe that there are several advantages of having a more restricted universe. Firstly, we find that data on companies' climate-related performance is more accessible for larger companies than SMBs. Secondly, the stocks included in the MSCI World Index are publicly traded with high-liquidity (MSCI, 2020). This makes it easier to calculate more resolute Transition Betas in our main analysis. Lastly, we also believe that the pricing of climate risk has increased with climate awareness, and it is therefore likely that it is most apparent in observations from recent years.

# 4. Methodology

This chapter describes the methods used to answer our research questions. In order to test our hypotheses, we first construct a Green-Minus-Brown portfolio which reflects the differences in return between companies with high Green Score (Green) and low Green Score (Brown). Secondly, we use the CAPM, Fama French three-factor model and Carhart four-factor model, referred to as common factor models, to explore the relationship between transition risk and systematic risk. We do this by regressing the relationship between the GMB factor and the risk factors included in the factor models, before testing the inclusion of the GMB factor as a dependent variable in a portfolio study. Lastly, we present our model testing methods.

## 4.1 Constructing the GMB factor

We create a portfolio that mimics a factor related to transition risk: A Green-Minus-Brown (GMB) factor. The return time-series of the GMB factor contains information about the pace of the transition process that market participants expect in a condensed form (Görgen et al., 2020). The construction follows the methodology of Fama and French (1993) by using a long-short zero investment strategy.

Fama and French (1993) extended the CAPM with a Small-Minus-Big factor by splitting portfolios according to size and book-to-market value. Following their methodology, we split the stocks according to their Green Score and size. First, we divide all stocks according to their median market capitalization into two independent portfolios: Small and Big. Furthermore, we split the stocks into three portfolios based on their Green Score: Green, Neutral and Brown. As a result, the stocks are split into six portfolios, based on Green Score and size, shown in Table 4.1.

**Table 4.1:** Portfolios used to construct GMB factor

| | Green | Neutral | Brown |
|---|---|---|---|
| Small | SG | SN | SB |
| Big | BG | BN | BB |

The GMB factor is a hypothetical portfolio that is invested long in Green and short in Brown, in line with our belief that Green companies outperform Brown companies. By using the historical equally-weighted average monthly returns of the four portfolios SG, BG, SB and BB we can calculate the monthly return of the GMB factor. This measure reflects the differences in return between the Green portfolio and Brown portfolio adjusted for size. The GMB factor is calculated as follows:

$$GMB_t = 0.5 \times (SG_t + BG_t) - 0.5 \times (SB_t + BB_t)$$

## 4.2 Model specification

The aim of our analyses is to explain the relationship between stock returns and transition risk. Factor models are broadly recognized in academia and in a wide range of financial practices (Cochrane, 2005). We will use the CAPM, Fama French three-factor and Carhart four-factor model as we aim to measure systematic risk. Our hypotheses are based on a belief that the combat of the climate crisis will affect the entire economy, and thereby that part of the risk should be priced as systematic risk in the market. We will first test our initial hypothesis by using the GMB factor as a dependent variable in models with the risk factors of CAPM, Fama French and Carhart. To test our second hypothesis we will include the GMB factor as an independent variable in the same models and conduct test if the factor can significantly enhance the explanatory power of the models.

The CAPM is often recognized as the foundation for factor models. The model states that the expected returns of an asset is ultimately a result of systematic risk and that investors should not be compensated for exposure to idiosyncratic risk (Sharpe, 1964). Later, Fama and French (1993) recognized the need for supplementary factors of priced risk to explain why some firms yield higher returns than others. They extended the model by introducing two additional factors accounting for size and firm value. However, the Fama French three-factor model does not account for the momentum of stocks. Carhart (1997) argues that buying top performing funds and selling bottom performing funds will increase excess return, and that this increase cannot be explained by other risk factors. Therefore, they extended the three-factor model from Fama and French (1993) by adding a performance attribution factor, a momentum factor.

### 4.2.1 Differences in return between green and brown companies

To analyze our first hypothesis, whether there are differences in return between Green and Brown companies that cannot be explained by common risk factors, we apply the risk factors of CAPM, Fama French three-factor model and Carhart four-factor model to see if they can explain the constructed GMB factor. This methodology is based on Fama and French (2014), however not conducted by Görgen et al. (2020), thereby being a novel contribution to the research on transition risk.

As a starting point, we employ the risk factor of the CAPM. We test our GMB factor with the market risk factor by regressing the following:

$$GMB_t = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \epsilon_{it}$$

*Where,*

$R_{it}$ = *Return on asset i in month t*

$R_{ft}$ = *Risk-free rate at month t*

$\alpha_i$ = *Abnormal return*

$\beta_i$ = *Asset i's market risk exposure*

$R_{mt}$ = *Market return in month t*

$\epsilon_{it}$ = *Error term in month t*

However, CAPM is based on strict and simplified assumptions about the market, and thereby has a narrow view on expected return. Fama and French (1993) expand the CAPM by introducing two additional factors: SML and HML. The size factor, Small-Minus-Big, mimics a portfolio that is long in small cap and short in big cap stocks. Furthermore, the value factor, High-Minus-Low mimics a portfolio that is long in high book-to-market stocks, also known as value stocks, and short in low book-to-market stocks, referred to as growth stocks. As a result, it accounts for the effect of value stocks outperforming growth stocks. We use their risk factors to construct the following model:

$$GMB_t = \alpha_i + \beta_{0i}(R_{mt} - R_{ft}) + \beta_{1i}SMB_t + \beta_{2i}HML_t + \epsilon_{it}$$

*Where,*

$SMB_t =$ *Difference in return between a Small (market cap) portfolio and a Big portfolio in month t*

$HML_t =$ *Difference in return between a High (book-to-market) and Low in month t*

As mentioned above, the Fama French three-factor model does not account for the momentum of stocks. Carhart (1997) argues that buying top performing funds and selling bottom performing funds will increase excess return, and that this increase cannot be explained by the mentioned risk factors. Therefore, they extend the three-factor model from Fama and French (1993) by adding a performance attribution factor, a momentum factor. Hence, we add the factor to our model:

$$GMB_t = \alpha_i + \beta_{0i}(R_{mt} - R_{ft}) + \beta_{1i}SMB_t + \beta_{2i}HML_t + \beta_{3i}WML_t + \epsilon_{it}$$

*Where,*

$\mathrm{WML}_t =$ *Difference in return between a portfolio of past 12-months winners and a portfolio of and a portfolio of past 12-months losers in month t*

An important distinction between the original factor models and our specification is that we put a difference-term on the left hand side. This changes the interpretations of the R-squared and coefficients from the model. Insignificant coefficients mean that there are no differences in the exposure to the risk factor between the Green and Brown portfolio. In other words, the risk factors cannot significantly explain the differences in return between the Green and Brown portfolio.

In addition to the coefficients of the risk factors, we will interpret the coefficient of the intercept. Originally, alpha, or abnormal return, captures the average return of the portfolio above or below the return predicted by the factor model (Jensen, 1969). If a portfolio is fairly priced, the alpha will be zero, however, if the alpha is negative (positive) a stock is earning below (above) the expected return, or the return is explained by other factors not included in the model. In our model, the interpretation is different; if there are significant differences in returns that the model cannot explain, the intercept should be significant.

### 4.2.2 Determining Transition Beta

If the GMB factor is not significantly associated with the common risk factors, it is interesting to investigate whether an inclusion of the factor will have a statistically significant impact on the explanatory power of common factor models. In this subsection we present the methods used to answer our second hypothesis.

### 4.2.3 Green Score-sorted quintile portfolio analysis

In order to test our second hypothesis, we create test portfolios based on the companies' Green Score. This method was first introduced by Blume (1970), who argued that constructing portfolios based on firm-specific characteristics enhances the efficiency of the factor loading as it removes some of the errors-in-variables problem of the coefficients compared to regression on single stocks. Thus, the estimation errors will cancel each other out when using portfolios, assuming that an investor's assessment of the $\alpha_i$ and $\beta_i$ is unbiased and the errors in the assessment is independent (Blume, 1970).

We construct portfolios based on Green Score to assess the factor loadings and how they affect firms' monthly excess return. In line with the method of Görgen et al. (2020), we sort firms into annually rebalanced quintiles where quintile 1 and 5 consist of firms with 20% lowest and

20% highest Green Score referred to as Most Brown and Most Green Portfolio. Quintile 2 and 4 consist of firms with respectively 20% second lowest and highest Green Score, hereafter Brown and Green Portfolio. The third quintile is referred to as the Neutral Portfolio including firms with Green Score not in the upper 40% nor lower 40%. [1]

After sorting firms from our sample into quintiles, we run time-series regressions on respectively the CAPM, Fama French three-factor, and Carhart four-factor model, and extend the models with the GMB factor:

$$R_{it} - R_{ft} = \alpha_i + \beta_0 i(R_{mt} - R_{ft}) + \beta_{GMBi} GMB_t + \epsilon_{it} \tag{1}$$

$$R_{it} - R_{ft} = \alpha_i + \beta_{0i}(R_{mt} - R_{ft}) + \beta_{1i} SMB_t + \beta_{2i} HML_t + \beta_{GMBi} GMB_t + \epsilon_{it} \tag{2}$$

$$R_{it} - R_{ft} = \alpha_i + \beta_{0i}(R_{mt} - R_{ft}) + \beta_{1i} SMB_t + \beta_{2i} HML_t + \beta_{3i} WML_t + \beta_{GMBi} GMB_t + \epsilon_{it} \tag{3}$$

The $\beta_{GMBi}$, hereafter Transition Beta, reflects the capital market's assessment of the transition risk of the respective financial asset or portfolio. In other words, it is the aggregated perception about transition risk of all market participants. The Transition Beta estimates the impact of changes in investors' expectations of a firm's value or stock prices. The higher the absolute Transtition Beta value, the greater the impact on the stock price. Unexpected changes that affect all firms to the same extent is not captured by individual Transition Betas, as it is in relation to the overall market risk. Transition Beta thereby determines how the value of the stock is likely to change in relation to the market as a whole if expectations about the transition process of the economy change.

If the Transition Beta is greater than zero, it can be expected that the value of the asset will fall compared to the market if the transition towards a greener economy accelerates unexpectedly. If the Transition Beta is less than zero, the value of the asset will rise compared to an average asset in expectation if the transition process of the economy towards a green economy decelerates unexpectedly.

[1] Calculation of portfolio return can be found in Chapter 3

To test our second hypothesis, whether the GMB factor explains the variations of risk-adjusted stock returns significantly better than the original models, we compare the adjusted $R^2$. The $R^2$ measures the goodness-of-fit. A value close to 1 indicates that the variables explains much of the variation in the sample (Wooldridge, 2016). However, we should be careful about putting too much weigth on $R^2$, especially since we use a time-series regression, as it can lead to nonsensical models (Wooldridge, 2016). As Ordinary Least Square estimates (OLS) minimize the sum of squared residuals (SSR), an increase in variables will increase the SSR, leading to an increased $R^2$. Therefore, we are interested in whether the increase in SSR is relatively large enough to accept our hypothesis. This is done by conducting a F-test on nested models with the null hypothesis that all coefficients under consideration are zero. The F-statistic is defined by

$$F = \frac{SSR_r - SSR_{ur}/q}{SSR_{ur}/(n-k-1)}$$

$$\begin{aligned}
&\textit{Where,} \\
SSR_r &= \textit{Sum of squared residuals from the restricted model} \\
SSR_{ru} &= \textit{Sum of squared residuals from the unrestricted model} \\
q &= \textit{Numerator degrees of freedom} \\
n-k-1 &= \textit{Denominator degrees of freedom}
\end{aligned}$$

We can reject the null hypothesis in favor of the alternative hypothesis if the critical value, c, is less than the F-statistic (Wooldridge, 2016). The common asset pricing models is the restricted model while the extended model with GMB is the unrestriced model.

To further test our hypothesis, we test whether adding a GMB factor explains variation in risk-adjusted returns better than common asset pricing models we apply a Gibbons, Ross and Shanken (GRS) test statistic (Gibbons et al., 1989). The test is a finite-sample F distribution given by (Cochrane, 2005):

$$\frac{T-N-1}{N} \times \left[1 + (\frac{E_t(f)}{\hat{\sigma}(f)})^2\right]^{-1} \hat{\alpha}' \hat{\sum} \hat{\alpha} \sim F_{N,T-N-1}$$

*Where,*

$T =$ *Number of months*

$N =$ *Number of test portfolios*

$E_t(f) =$ *Sample mean*

$\hat{\sigma}(f) =$ *Sample variance*

$\hat{\alpha} =$ *A vector containing all the N estimated alphas*

$\hat{\Sigma} =$ *Estimated residual covariance matrix*

The null hypothesis of the GRS test states that all the alphas from the test portfolios are zero:

$H_0$: $\alpha_i = 0$, $\forall$ i.

A model that fits better has less pricing errors, thus a small GRS-statistic indicates that the model explains variations in excess return well. Thereby, we cannot reject the null hypothesis.

### 4.2.4 Firm regression analysis

To strengthen our findings on the second hypothesis we also conduct time-series regression on individual stocks from our sample, thereby investigating whether the GMB factor is able to enhance the explanatory power of variations in risk-adjusted returns. We regress the risk-adjusted return of stocks from the 925 stocks in our sample using the mentioned asset pricing models.

We first calculate the mean difference in adjusted $R^2$ from our regressions. Using these results, we conduct F-tests on nested models to find the proportion of regressions that significantly increases the goodness-of-fit. A high proportion indicates that the GMB factor increases the goodness-of-fit for a large amount of the stocks in our sample. Lastly, we calculate the mean difference in root mean square error to assess how wrong the regression model is on average (Wooldridge, 2016).

To ensure robustness of our results on the coefficients, we conduct a two-sided t-test at a 10%, 5% and 1% level to test the null-hypothesis that the true slope of the coefficients are significantly different from 0 (Wooldridge, 2016). We calculate the proportion of regressions that are significant for each coefficient in the Carhart four-factor model.

### 4.2.5 Event study on the publication of the TCFD report

As an additional contribution we study differences in Transition Betas following the publication of the Recommendations of the Task Force on Climate-related Financial Disclosures by TCFD, often seen as the "break-through" of transition risk awareness (TCFD, 2017; NCE, 2018). We hypothesize that an increased awareness about transition risk will decrease the transition risk of Green companies and increase the risk of Brown companies. We follow the approach of Bolton and Kacperczyk (2020) by estimating the Carhart extended model on two sub-periods: January 2014 to June 2017, and July 2017 to December 2019, and use Transition Betas as a proxy for transition risk.

## 4.3 Model testing

In order to verify our results, we conduct model testing. Since our model is based on the OLS regression method, our data has to follow the five Gauss-Markow assumptions. Furthermore, we will test for stationarity as we use time-series data. All tests are included in the chapter Appendix.

### 4.3.1 Gauss-Markow assumptions

Ordinary least squares is the simplest form of statistical regression analysis. However, the validity and accuracy of the results relies on the five Gauss-Markow conditions are met: i) Linear in parameters, ii) zero conditional mean, iii) no perfect collinearity, iv) homoscedasticity and v) no autocorrelation (Wooldridge, 2016). If these conditions are not met, the regression results can be subject to significant bias which implies that the estimated coefficients will provide misleading information.

One of the most common problems when using time-series data is autocorrelation, which suggests that condition v) is not met. Autocorrelation means that the error terms between time periods correlate, making the standard deviation biased (Wooldridge, 2016). We test for autocorrelation by applying a Breusch-Godfrey test.

Another problem that can lead to biased results from OLS regressions is multicollinaerity. The phenomenon occurs when an independent variable can be linearly predicted by another independent variable, and it makes it impossible to tell the true effect of the collinear variables on the dependent variable (Wooldridge, 2016). We check for multicollinaerity by examining a correlation matrix that includes all our independent variables.

Furthermore, we are concerned that the model is exposed to heteroscedasticity which can reduce the efficiency of the model (Wooldridge, 2016). We use a Breusch-Pagan test to detect heteroscedasticity in our models. The test regress the squared residuals on all independent variables and rejects the null hypothesis of homoscedasticity if the p-value is under a certain critical level. We find that our initial model is proned to heteroscedasticity. This means that our model estimates are no longer the best, thereby that there are other models which will provide estimates with lower variance. Furthermore, the standard errors may be misleading and incorrect. We attempt to correct for the standard error-problem by using robust standard errors for the relevant models. [2]

Our greatest concern is however endogeneity issues. In an unbiased model, the expected value of the error term is zero for any independent variable, $E(\epsilon \mid x) = 0$. However, with endogeneity issues, the coefficient will be affected in a positive or negative way, creating serious bias in our results. This issue often arise when we omit a variable that should have been included in explaining the dependent variable (Wooldridge, 2016).

[2] The results from the model testing can be found under Model Testing in Appendix.

### 4.3.2 Stationarity

In addition to the Gauss-Markow assumptions, an essential condition for unbiased models is that the variables must be stationary (Wooldridge, 2016). Non-stationary variables should not be used in linear regressions as they can indicate invalid significant relationships. To assess our models' stationarity we conduct an augmented Dickey-Fuller test for unit root, applying the optimal lag constructed by Ng and Perron (1995).

# 5. Results

In this chapter, we will present the results of our analysis. First, we study whether differences between the Green and Brown portfolios can be explained by the risk factors included in CAPM, Fama French three-factor model and the Carhart four-factor model. Second, we explore whether the GMB factor will have a statistically significant impact on the explanatory power when included in the asset pricing models. In order to provide insights into our results, we will first present descriptive statistics. Thereafter, we will display and comment on the regression results for both our research questions. Subsequently, we will elaborate on the estimates of Transition Betas for different time periods. Lastly, we will present the robustness tests conducted to analyze the strength of our results.

## 5.1 Descriptive analysis

We want to explore the differences in return between Green and Brown companies, the GMB portfolio. Table 5.1 displays the descriptive statistics of the constructed Green, Brown and GMB portfolios.

**Table 5.1:** Descriptive statistics on the return from the Green, Brown and GMB portfolio

| Statistic | N | Mean | St. Dev. | Min | Median | Max |
|---|---|---|---|---|---|---|
| Green | 72 | 0.008 | 0.033 | −0.073 | 0.010 | 0.092 |
| Brown | 72 | 0.007 | 0.034 | −0.083 | 0.012 | 0.094 |
| GMB | 72 | 0.001 | 0.008 | −0.022 | 0.002 | 0.015 |

The descriptives indicate that the constructed Green portfolio performs slightly better than the Brown portfolio in the sample period, with a GMB of 0.1% and median of 0.2%. Furthermore, the standard deviation of the Brown portfolio is slightly higher indicating higher volatility. However, the difference between the portfolios appears rather small. Additionally, the GMB factor varies from the minimum value of −2.2% to maximum value of 1.5%.

We also present the monthly return of the GMB portfolio graphically through Figure 5.1. The graph suggests the existence of a difference in return between the constructed Green and Brown Portfolio for the sample period January 2014-December 2019. In line with our expectations, the differences vary across the time-period, however, there are no apparent trends in the differences in monthly return. It also appears that the time-series is stationary. [1]

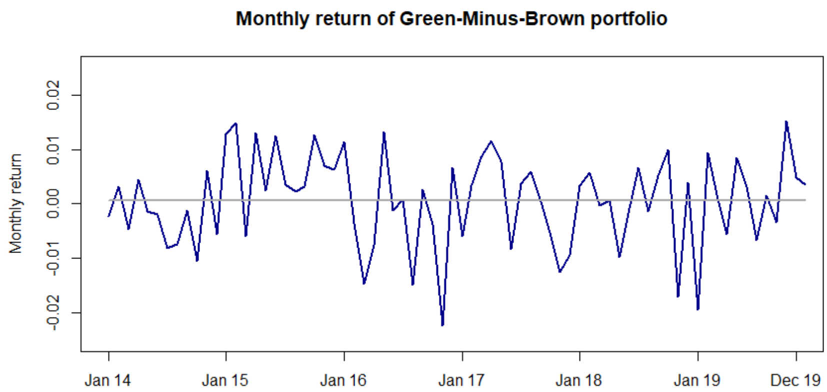


**Figure 5.1:** Monthly return from the GMB portfolio from January 2014-December 2019

[1] We formally test our model for non-stationarity through an Augmented Dickey-Fuller test

In addition to regular monthly returns, we wish to explore the cumulative returns of the portfolios. Cumulative returns express the total percentage increase in the return of the stocks from the basis year 2014. Figure 5.2 shows the computed cumulative returns of companies in the Green, Brown and GMB portfolios for each month in our sample period.

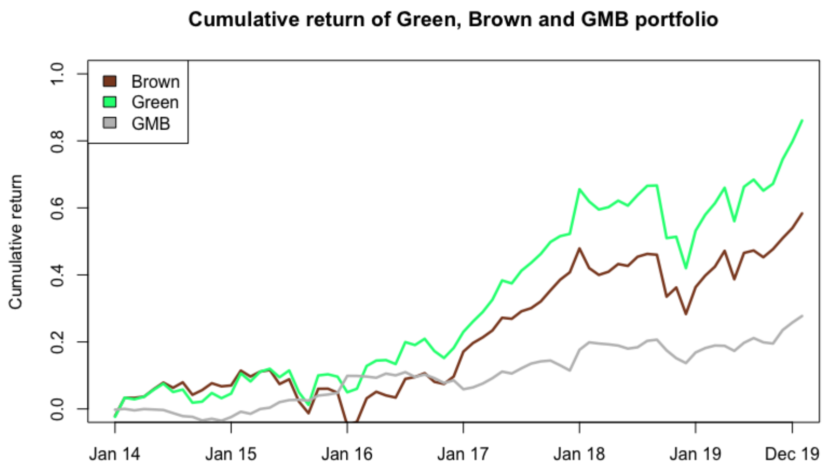


**Figure 5.2:** Cumulative returns from the Green, Brown and GMB portfolio from 2014-2019

From Figure 5.2 we see a difference in performance between Green and Brown companies during the sample period. The cumulative returns of the GMB portfolio is trending upwards, meaning that the difference in return between Green and Brown companies is increasing over time, thereby that Green companies perform increasingly better on average than Brown firms relative to the basis year.

Before testing our hypotheses, we want to ensure that the factor has unique features that does not correlate with the other risk factors. Therefore, we investigate the correlation matrix of the monthly factor returns in the sample period. In line with the findings of Görgen et al. (2020), Table 5.2 indicates that the correlation between the GMB factor and the other common risk factors are relatively low. The correlations are not significant for the market factor and size factor. However, the value factor and momentum factor are significant at 10% and 5% level respectively. The matrix indicates a low correlation between the GMB factor and the other risk factors.

**Table 5.2:** Correlation matrix

| | Mkt.RF | SMB | HML | WML | GMB |
|---|---|---|---|---|---|
| Mkt.RF | 1 | -0.031 | -0.006 | -0.363*** | -0.137 |
| SMB | -0.031 | 1 | 0.098 | 0.004*** | -0.157 |
| HML | -0.006 | 0.098 | 1 | -0.628*** | -0.199* |
| WML | -0.363*** | 0.004*** | -0.628*** | 1 | 0.259** |
| GMB | -0.137 | -0.157 | -0.199* | 0.259** | 1 |

*Note:* *p<0.1;**p<0.05; ***p<0.01

## 5.2 Differences between the Green and Brown portfolio regressed with common risk factors

From the descriptive analysis it appears that there exists differences between Green and Brown companies, and furthermore that the GMB factor provides unique features that does not correlate with the other risk factors. In this section we will provide the results from MM estimation method used to account for heteroscedasticity and OLS regressions on GMB and the common risk factors, aiming to answer our first hypothesis.

Table 5.3 reports the regression results. As displayed in the table, the goodness-of-fit of the models are low, indicating that there are variables missing to explain variation in the GMB factor. Additionally, none of the factors can significantly explain the differences in return between the Green and Brown portfolio.

It is worth noticing that the alpha is close to zero and insignificant for all the models on 10%, 5 %, and 1% level, implying that there are no evidence of significant differences in return that the models cannot explain (Fama and French, 2014). Despite this finding, the alphas of the regressions are positive. A positive alpha suggests that the Green portfolio provides a higher return than the Brown portfolio that the market cannot explain (Jensen, 1969).

**Table 5.3:** Results from CAPM, Fama French 3-factor and Carhart models with GMB factor as dependent variable

| | *Dependent variable:* | | |
|---|---|---|---|
| | GMB | | |
| | *MM-type linear* | *OLS* | *MM-type linear* |
| | (CAPM) | (Fama French) | (Carhart) |
| Mkt.RF | −0.032 | −0.037 | −0.022 |
| | (0.035) | (0.030) | (0.031) |
| SMB | | −0.089 | −0.098 |
| | | (0.073) | (0.060) |
| HML | | −0.084 | −0.031 |
| | | (0.053) | (0.075) |
| WML | | | 0.001 |
| | | | (0.001) |
| Constant | 0.001 | 0.0004 | 0.0003 |
| | (0.001) | (0.001) | (0.001) |
| Observations | 72 | 72 | 72 |
| $R^2$ | 0.015 | 0.079 | 0.089 |
| Adjusted $R^2$ | 0.001 | 0.039 | 0.035 |
| *Note:* | *p<0.1; **p<0.05; ***p<0.01 | | |

The table reports the results from CAPM, Fama-French 3-factor model and Carhart four-factor model. CAPM and Carhart four-factor model is estimated using a MM-type linear model and Fama French three-factor model using OLS. The dependent variable is the return of a Green-Minus-Brown portfolio that is long in green and short in brown. The variable Mkt.RF is the value-weighted market return less the risk-free rate. The SMB factor picks up the portfolios' exposure to small cap stocks. The HML factor captures the portfolios' exposure to high book-to-market value firms. The WML factor shows the rate of recent price movements in the portfolios. All coefficients captures the difference in exposure between the Green and the Brown portfolio to the respective risk factor. Finally, the intercept captures the difference in abnormal return of the portfolios. We estimated the model with monthly data from January 2014-December 2019.

We question the lack of a significant abnormal return, as we initially believed differences between the Green and Brown portfolio would lead to significant abnormal returns, in line with the results of Derwall et al. (2005) and Oestreich and Tsiakas (2015). However, we find a small, positive, yet, insignificant alpha and a low correlation between the GMB factor and the other common risk factors. Furthermore, we find that the Green and Brown portfolios do not significantly differ in exposure to the other risk factors. In order to better understand the relation between transition risk and return, we include the GMB factor as an independent variable in the common factor models, thereby testing our second hypothesis.

## 5.3 Including the GMB factor in common factor models

To answer our second research question, we first present the regression results on the Green Score-sorted quintile portfolios. The interpretation of the GMB factor will lay the foundation for the discussions in Chapter 6.

### 5.3.1 Results from quintile regressions

We test whether extending common factor models with the GMB factor will have a statistically significant impact on the explanatory power of the model. As mentioned in Chapter 4, we divide the sample into quintiles based on their Green Score, referred to as Most Brown, Brown, Neutral, Green and Most Green. Table 5.4, 5.5 and 5.6 report the results from the common factor models with and without inclusion of the GMB factor.

**Table 5.4:** Results from CAPM and extended CAPM model

| | *Dependent variable: $R_{it} - R_{ft}$* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Most Brown | | Brown | | Neutral | | Green | | Most Green | |
| | (CAPM) | (Extended CAPM) | (CAPM) | (Extended CAPM) | (CAPM) | (Extended CAPM) | (CAPM) | (Extended CAPM) | (CAPM) | (Extended CAPM) |
| Mkt.RF | 1.004*** | 0.991*** | 0.993*** | 0.981*** | 1.003*** | 1.006*** | 0.908*** | 0.923*** | 1.038*** | 1.060*** |
| | (0.030) | (0.029) | (0.035) | (0.034) | (0.032) | (0.033) | (0.037) | (0.035) | (0.035) | (0.029) |
| GMB | | −0.367*** | | −0.335** | | 0.097 | | 0.411*** | | 0.615*** |
| | | (0.110) | | (0.130) | | (0.126) | | (0.136) | | (0.113) |
| Constant | 0.001 | 0.001 | −0.0005 | −0.0002 | −0.001 | −0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 |
| $R^2$ | 0.940 | 0.948 | 0.920 | 0.927 | 0.932 | 0.933 | 0.896 | 0.908 | 0.928 | 0.950 |
| Adjusted $R^2$ | 0.939 | 0.947 | 0.919 | 0.925 | 0.931 | 0.931 | 0.894 | 0.905 | 0.927 | 0.948 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the results from CAPM and CAPM extended with the GMB factor on the 5 different equally-weighted portfolios spanning from Most Brown to Most Green constructed based on Green Score. The dependent variables represents the risk-adjusted returns of the respective portfolios. The variable Mkt.RF is the value-weighted market return less the risk-free rate. The intercept captures the abnormal return of the portfolios. We estimated the model with monthly data from 2014-2019.

**Table 5.5:** Results from Fama French three-factor model and extended Fama French model

| | *Dependent variable:* $R_{it} - R_{ft}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Most Brown | | Brown | | Neutral | | Green | | Most Green | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| | (FF) | (Extended FF) | (FF) | (Extended FF) | (FF) | (Extended FF) | (FF) | (Extended FF) | (FF) | (Extended FF) |
| Mkt.RF | 1.005*** | 0.990*** | 0.993*** | 0.981*** | 1.003*** | 1.008*** | 0.907*** | 0.921*** | 1.038*** | 1.060*** |
| | (0.030) | (0.029) | (0.035) | (0.034) | (0.033) | (0.033) | (0.037) | (0.036) | (0.035) | (0.030) |
| SMB | 0.057 | 0.021 | −0.032 | −0.060 | 0.022 | 0.033 | −0.091 | −0.058 | −0.043 | 0.011 |
| | (0.073) | (0.068) | (0.084) | (0.082) | (0.079) | (0.079) | (0.089) | (0.086) | (0.083) | (0.072) |
| HML | −0.045 | −0.078 | 0.096 | 0.069 | 0.035 | 0.045 | −0.075 | −0.043 | −0.076 | −0.026 |
| | (0.053) | (0.050) | (0.060) | (0.060) | (0.057) | (0.058) | (0.064) | (0.063) | (0.060) | (0.052) |
| GMB | | −0.396*** | | −0.319** | | 0.126 | | 0.376*** | | 0.606*** |
| | | (0.113) | | (0.135) | | (0.131) | | (0.142) | | (0.118) |
| Constant | 0.001 | 0.001 | −0.0002 | −0.0001 | −0.0005 | −0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 |
| $R^2$ | 0.941 | 0.950 | 0.923 | 0.929 | 0.933 | 0.934 | 0.899 | 0.909 | 0.930 | 0.950 |
| Adjusted $R^2$ | 0.939 | 0.947 | 0.920 | 0.925 | 0.930 | 0.930 | 0.895 | 0.904 | 0.927 | 0.947 |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

This table reports the results from a Fama French three-factor model and a Fama French extended with the GMB factor on the 5 different equally-weighted portfolios spanning from Most Brown to Most Green constructed based on Green Score. The dependent variables represent the risk-adjusted returns of the respective portfolios. The variable Mkt.RF is the value-weighted market return less the risk-free rate. The SMB factor picks up the portfolios' exposure to small cap stocks. The HML factor captures the portfolios' exposure to high book-to-market value firms. Finally, the intercept captures the abnormal return of the portfolios. We estimated the model with monthly data from 2014-2019.

**Table 5.6:** Results from Carhart four-factor model and extended Carhart model

| | *Dependent variable:* $R_{it} - R_{ft}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Most Brown | | Brown | | Neutral | | Green | | Most Green | |
| | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) |
| Mkt.RF | 0.993*** | 0.986*** | 0.954*** | 0.948*** | 0.999*** | 1.002*** | 0.908*** | 0.916*** | 1.027*** | 1.038*** |
| | (0.035) | (0.032) | (0.038) | (0.038) | (0.037) | (0.037) | (0.042) | (0.040) | (0.039) | (0.033) |
| SMB | 0.061 | 0.023 | −0.018 | −0.045 | 0.023 | 0.036 | −0.092 | −0.055 | −0.040 | 0.021 |
| | (0.074) | (0.069) | (0.082) | (0.081) | (0.079) | (0.080) | (0.090) | (0.087) | (0.084) | (0.071) |
| HML | −0.079 | −0.090 | −0.023 | −0.030 | 0.023 | 0.027 | −0.070 | −0.059 | −0.109 | −0.092 |
| | (0.072) | (0.067) | (0.080) | (0.078) | (0.078) | (0.078) | (0.088) | (0.084) | (0.082) | (0.069) |
| WML | −0.0004 | −0.0001 | −0.001** | −0.001* | −0.0001 | −0.0002 | 0.0001 | −0.0002 | −0.0004 | −0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| GMB | | −0.392*** | | −0.284** | | 0.133 | | 0.382** | | 0.630*** |
| | | (0.115) | | (0.134) | | (0.133) | | (0.144) | | (0.118) |
| Constant | 0.001 | 0.001 | 0.0001 | 0.0002 | −0.0004 | −0.0005 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 |
| $R^2$ | 0.942 | 0.950 | 0.928 | 0.933 | 0.933 | 0.934 | 0.899 | 0.909 | 0.931 | 0.951 |
| Adjusted $R^2$ | 0.938 | 0.947 | 0.924 | 0.928 | 0.929 | 0.929 | 0.893 | 0.902 | 0.926 | 0.948 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the results from Carhart four-factor model and Carhart extended with the GMB factor on the 5 different equally-weighted portfolios spanning from Most Brown to Most Green constructed based on Green Score. The dependent variables represent the risk-adjusted returns of the respective portfolios. The variable Mkt.RF is the value-weighted market return less the risk-free rate. The SMB factor picks up the portfolios' exposure to small cap stocks. The HML factor captures the portfolios' exposure to high book-to-market value firms. The WML factor shows the rate of recent price movements in the portfolios. Finally, the intercept captures the abnormal return of the portfolios. We estimated the model with monthly data from 2014-2019.

The market beta is close to 1 in all factor models and across portfolios. This finding suggests that the companies that are included in the different portfolios make up sub-samples that are fluctuating relatively close to the market average. However, there seems to be a tendency for firms in the Most Green portfolio to have a significant market beta above 1, meaning that they appear to have higher volatility compared to rest of the market stocks.

The explanatory power of the CAPM is over 80 % for all portfolios. Thereby, the model explains the variation in risk-adjusted return well. When we extend the model with a GMB factor, we observe an increase in the adjusted explanatory power of the model. These results are also found in the Fama French three-factor model and Carhart four-factor model. Similar to the results of CAPM, we observe that the explanatory power of the models increase for all portfolios when the GMB factor is included. The strongest effect of including the GMB factor is on the Most Green portfolio, where the explanatory power increase with over 2 percentage points for all models.

In addition to increasing the explanatory power of the model, adding the GMB factor provides significant coefficients in all the models on a 10%, 5% and 1% level for all portfolios except the Neutral portfolio. In all models, the Most Brown portfolio has a negative Transition Beta at about $-0.4$. The interpretation of this result is that a 1 unit increase in GMB factor, meaning that green companies outperforms brown companies by 1 unit, relates to a decrease in risk-adjusted return at $-0.4$ unit for the Most Brown companies. For the Most Green portfolio, a 1 unit increase in the GMB factor will provide a positive increase in risk-adjusted return at about 0.6 units. The result indicates that transitioning to a greener economy will on average positively affect the Most Green companies while the Most Brown portfolio will suffer from losses. On the other side, if the there is an unexpected change towards a browner economy the Most Green companies will suffer more from losses than the Most Brown companies.

Adding the GMB factor also affects the other factors included in the model. In all three models, we see a similar trend. An inclusion of the GMB factor reduces the coefficients of the Mkt.RF, SMB and HML in the Most Brown and Brown portfolios. For the Neutral, Green and Most Green portfolios the trend is opposite: the inclusion results in an increase in the coefficients. However, the changes in the coefficients are rather small, and few of the factors change signs. Moreover, non of the factors turn significant after the inclusion.

### 5.3.2 F-test on nested models

We aim to test if the inclusion of the GMB factor will have a statistically significant impact on the explanatory power of the model. To test our hypothesis further, we conduct a one-sided F-test on nested models. The results are displayed in Table 5.7. For the Most Green, Green and Most Brown portfolios the F-test on nested models is significant at 1% level providing strong evidence against the null hypothesis that Transition Beta is zero, indicating that the GMB factor enhances the explanatory power of the asset pricing models. Additionally, the Brown portfolio provides statistical evidence that the Transition Beta is not equal to zero at a 5% level. For the Neutral portfolio the null hypothesis cannot be rejected and, as expected, the Transition Beta is insignificant. This is in line with the results of Görgen et al. (2020).

**Table 5.7:** F-test on nested models

| | | F-Statistic | |
|---|---|---|---|
| Quintiles | CAPM | Fama French | Carhart |
| Most Brown | 10.997*** | 12.329*** | 11.678*** |
| Brown | 6.481** | 5.604** | 4.519** |
| Neutral | 0.586 | 0.932 | 0.997 |
| Green | 8.977*** | 7.054*** | 7.032*** |
| Most Green | 29.213*** | 26.342*** | 28.301*** |

The the table displays the one-sided F-test on nested models for all quintiles were $H_0$: $\beta_i^{BMG} = 0$. The columns presents the F-statistic on the CAPM, Fama French three-factor and Carhart four-factor model and the respective extended model with GMB factor. *, **, *** denote significance level 10%, 5%, and 1% respectively.

### 5.3.3 GRS tests

The alphas are low in all models, suggesting that there is little abnormal return. We further investigate the intercept by conducting a GRS test on all models. The results in Table 5.8 show that all the models have relatively low GRS-statistic. Consequently, we reject the null hypothesis that all intercepts from the quintile regressions jointly equals zero. The GRS-statistic decrease in value from CAPM, Fama French three-factor model to Carhart four-factor model. However, adding the GMB factor increases the GRS-statistic of the models. This result indicates that the models extended with GMB factor capture slightly less variation in risk-adjusted returns than the common factor models. The result contradicts the other findings, thereby suggesting a rejection of our hypothesis that including the factor will increase the explanatory power of the model.

**Table 5.8:** GRS tests

| Model | GRS | P-value |
|---|---|---|
| CAPM | 1.170 | 0.333 |
| CAPM + GMB | 1.335 | 0.261 |
| Fama-French | 0.753 | 0.587 |
| Fama-French + GMB | 0.985 | 0.434 |
| Carhart | 0.654 | 0.659 |
| Carhart + GMB | 0.888 | 0.659 |

In summary, we find similar results as Görgen et al. (2020); the GMB factor is most significant for the Most Green and Most Brown portfolio. The significance levels decrease the more neutral the portfolios gets. The increase in adjusted $R^2$ and the significant F-tests indicate that the GMB factor will enhance the explanatory power of common factor models. On the contrary, the results from the GRS tests impair our findings. Our results are therefore contradictory, thus, we will devote the next section to get more familiar with the features of the GMB factor at firm-level to better understand whether the GMB factor can provide unique properties in explaining transition risk.

### 5.3.4 Company level regressions

To better understand the differences in transition risk, we run the regressions on single stocks in the sample. In other words, we estimate an individual Transition Beta for each company which can be used to enrich our analyses.

First, we compare the asset pricing models with the extended models to see how the GMB factor changes the explanatory power of the models. From Table 5.9 we see that the average difference in adjusted $R^2$ is approximately 1% for all the models compared with their extended models, suggesting that the extended models is a slightly better fit. The increase is significant for 17.08% of all firms with CAPM, and 18.05% and 18.16% for respectively Fama French three-factor model and Carhart four-factor model.

Moreover, the increase in adjusted $R^2$ from CAPM to extended model is significant for 28.76% of the regressions compared to 26.92% of the comparison of CAPM and Carhart four-factor model. The increase suggests that adding GMB factor to the Carhart four-factor model enhanced the explanatory power more than solely adding the other risk factors.

Finally, a negative average difference in Root Mean Square Errors (RMSE) implies that the extended models have lower RMSE suggesting a better fit of the extended models (Wooldridge, 2016). From Table 5.9 we see that this is the case from comparing the average difference in RMSE of the Carhart - CAPM and Carhart + GMB - CAPM.

**Table 5.9:** Comparison of common factor models and extended versions

| Regression Models Compared | Mean difference Adjusted $R^2$ (%) | F-test - Proportion Significant at 5% level (%) | Mean difference RMSE |
|---|---|---|---|
| CAPM+GMB - CAPM | 1.05 | 17.08 | -0.09 |
| Fama French+GMB - Fama French | 1.07 | 18.05 | -0.27 |
| Carhart+GMB - Carhart | 1.04 | 18.16 | -0.09 |
| Carhart - CAPM | 3.16 | 26.92 | -0.34 |
| Carhart+GMB - CAPM | 4.21 | 28.76 | -0.43 |

The table displays a comparison of CAPM, Fama French three-factor and Carhart four-factor model and their extended model regressions on individual firms. Secondly, a comparison of Carhart and CAPM and Carhart extended and CAPM. The table shows the average differences in adjusted $R^2$, proportion of regressions that are statistically significant at a 5% level based on one-sided F-tests for nested models and average differences of Root Mean Square Errors.

Table 5.10 displays the results of the two-tailed t-test on the coefficient of the extended Carhart four-factor model. The results from the analysis above indicate that the Carhart four-factor model is the best fit. We will therefore only present the coefficients of the Carhart four-factor model in the following. As expected the Mean Beta of the market coefficient is 0.916, close to 1. The coefficient of the GMB factor has an average beta of 0.073, implying that on average the companies in our sample benefit from a transition to a low-carbon economy.

**Table 5.10:** Significance t-tests of factor coefficients for the extended Carhart model

| Factor | Mean Beta | Proportion significant at 10% level (%) | Proportion significant at 5% level (%) | Proportion significant at 1% level (%) |
|---|---|---|---|---|
| $\alpha$ | 0.004 | 10.81 | 5.73 | 0.76 |
| GMB | 0.073 | 26.60 | 18.16 | 6.27 |
| Mkt.RF | 0.916 | 88.23 | 84.87 | 74.81 |
| SMB | -0.230 | 21.19 | 12.87 | 4.97 |
| HML | -0.181 | 23.35 | 16.22 | 6.27 |
| WML | -0.197 | 10.70 | 5.19 | 0.97 |

The table presents the results of coefficients from the extended Carhart model regressions on 925 individual firms from our sample in the period 2014-2019. The first column displays the average coefficient of the common factor betas. The other columns provide the proportion (%) of statistically significant beta coefficients from a two-sided t-test at 10%, 5% and 1% level.

The market beta is significant for 74.8% of the companies in our sample at a 1% level. Furthermore, the Transition Beta is significant for 26.6% of the companies at a 10% level. However, the proportion of companies with significant t-tests decreases to 18.2% and 6.3% at a 5% and 1% level respectively. Moreover, the results provide evidence that the Transition Beta has a larger proportion of companies with significant coefficients than the SMB, HML and WML coefficients for all significance levels. In compliance with (Görgen et al., 2020), the GMB factor performs well compared to common risk factors in explaining variations in risk-adjusted return for the companies in our sample.

At this point, we find it important to emphasize the difference between a market-based and a fundamental approach in measuring transition risk. Figure 5.3 presents the relationship between Green Score and Transition Beta. The linear correlation is on average 0.126 suggesting a low relationship. The difference is due to the fact that the market-based approach reacts to the transition risk of the changes in stock prices caused by market participants. Hence, if there is a difference between the market's awareness of transition risk and value of the greenness, differences may occur. The same can be said about the other common risk factors such as size or value.

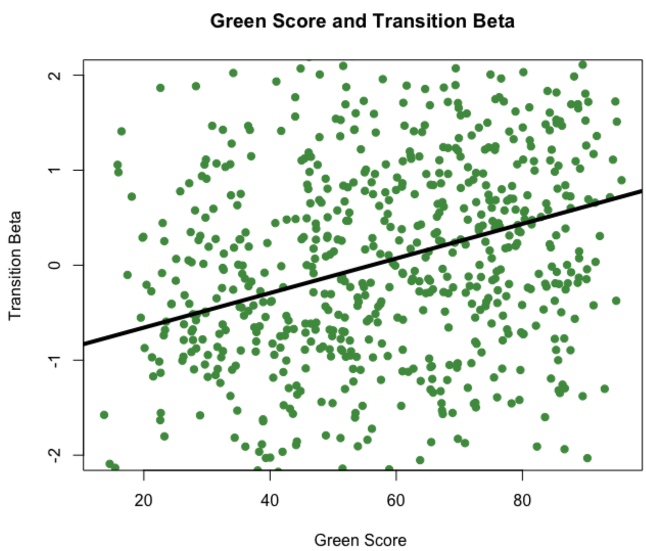


**Figure 5.3:** Green Score and Transition Beta

## 5.4 Additional findings on the Transition Betas

In addition to answering our research questions, we provide novel insights to the differences in Transition Betas before and after the "break-through" of transition risk awareness which is often said to be with the publication of their final report Recommendations of the Task Force on Climate-related Financial Disclosures in 2017 (NCE, 2018).

### 5.4.1 Transition Beta before and after June 2017

We test our hypothesis that an increased awareness about transition risk will decrease the transition risk of Green companies and increase the risk of Brown companies by conducting a regression on the two sub-periods. The results are presented for the period before June 2017 in Table 5.11 and after in Table 5.12.

**Table 5.11:** Results from Carhart and extended Carhart from January 2014 to June 2017

| | *Dependent variable: $R_{it} - R_{ft}$* | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Most Brown | | Brown | | Neutral | | Green | | Most Green | |
| | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) |
| Mkt.RF | 1.001*** | 1.005*** | 0.992*** | 0.994*** | 0.995*** | 0.994*** | 0.945*** | 0.941*** | 1.072*** | 1.067*** |
| | (0.057) | (0.055) | (0.060) | (0.060) | (0.054) | (0.054) | (0.064) | (0.061) | (0.065) | (0.058) |
| SMB | 0.066 | 0.029 | −0.010 | −0.031 | 0.023 | 0.027 | −0.153 | −0.111 | −0.006 | 0.054 |
| | (0.103) | (0.100) | (0.108) | (0.110) | (0.097) | (0.099) | (0.115) | (0.111) | (0.116) | (0.106) |
| HML | −0.103 | −0.164 | −0.082 | −0.117 | −0.199* | −0.192* | −0.285** | −0.216* | −0.207 | −0.109 |
| | (0.115) | (0.113) | (0.120) | (0.124) | (0.107) | (0.112) | (0.128) | (0.126) | (0.129) | (0.119) |
| WML | −0.016 | −0.006 | −0.143 | −0.138 | −0.093 | −0.095 | −0.034 | −0.045 | −0.056 | −0.073 |
| | (0.092) | (0.088) | (0.097) | (0.097) | (0.086) | (0.088) | (0.103) | (0.098) | (0.104) | (0.093) |
| GMB | | −0.383** | | −0.220 | | 0.044 | | 0.440** | | 0.616*** |
| | | (0.181) | | (0.198) | | (0.179) | | (0.201) | | (0.190) |
| Constant | 0.001 | 0.001 | 0.0001 | 0.0003 | 0.0002 | 0.0001 | 0.002 | 0.002 | 0.002 | 0.001 |
| | (0.002) | (0.001) | (0.002) | (0.002) | (0.001) | (0.001) | (0.002) | (0.002) | (0.002) | (0.002) |
| Observations | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 | 42 |
| $R^2$ | 0.917 | 0.927 | 0.916 | 0.918 | 0.930 | 0.930 | 0.894 | 0.907 | 0.912 | 0.932 |
| Adjusted $R^2$ | 0.908 | 0.916 | 0.906 | 0.907 | 0.922 | 0.920 | 0.883 | 0.894 | 0.902 | 0.922 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

The table reports the results from the Carhart four-factor model and Carhart extended with the GMB factor of the period January 2014-June 2017 on the Green Score - sorted portfolios with equally-weighted returns spanning from Most Brown to Most Green. The dependent variables represent the excess returns of the respective portfolios. The variable Mkt.RF is the value-weighted market return less the risk-free rate. The SMB factor picks up the portfolios' exposure to small cap stocks. The HML factor captures the portfolios' exposure to high book-to-market value firms. The WML factor shows the rate of recent price movements in the portfolios.

**Table 5.12:** Results from Carhart and extended Carhart from July 2017 to December 2019

| | *Dependent variable:* $R_{it} - R_{ft}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Most Brown | | Brown | | Neutral | | Green | | Most Green | |
| | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) | (Carhart) | (Extended Carhart) |
| Mkt.RF | 0.988*** | 0.960*** | 0.918*** | 0.888*** | 1.001*** | 0.998*** | 0.870*** | 0.863*** | 0.987*** | 1.013*** |
| | (0.040) | (0.029) | (0.049) | (0.040) | (0.045) | (0.047) | (0.037) | (0.038) | (0.042) | (0.034) |
| SMB | 0.031 | 0.003 | 0.004 | −0.026 | 0.104 | 0.101 | 0.105 | 0.098 | −0.084 | −0.058 |
| | (0.113) | (0.082) | (0.140) | (0.113) | (0.128) | (0.130) | (0.106) | (0.107) | (0.119) | (0.095) |
| HML | −0.059 | 0.017 | 0.051 | 0.133 | 0.281*** | 0.292** | 0.186** | 0.205** | −0.007 | −0.078 |
| | (0.088) | (0.066) | (0.109) | (0.090) | (0.100) | (0.104) | (0.083) | (0.086) | (0.092) | (0.076) |
| WML | −0.072 | −0.006 | −0.132 | −0.061 | 0.062 | 0.071 | 0.040 | 0.056 | −0.019 | −0.080 |
| | (0.069) | (0.052) | (0.085) | (0.071) | (0.078) | (0.082) | (0.065) | (0.068) | (0.072) | (0.060) |
| GMB | | −0.615*** | | −0.668*** | | −0.084 | | −0.148 | | 0.577*** |
| | | (0.128) | | (0.176) | | (0.202) | | (0.166) | | (0.147) |
| Constant | −0.0001 | 0.0002 | 0.0005 | 0.001 | 0.0002 | 0.0002 | 0.001 | 0.001 | 0.001 | 0.0004 |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 | 30 |
| $R^2$ | 0.970 | 0.985 | 0.949 | 0.968 | 0.960 | 0.961 | 0.964 | 0.965 | 0.966 | 0.979 |
| Adjusted $R^2$ | 0.965 | 0.981 | 0.941 | 0.962 | 0.954 | 0.952 | 0.958 | 0.958 | 0.960 | 0.975 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the results from Carhart four-factor model and Carhart extended with the GMB factor of the period July 2017-December 2019 on the Green Score sorted portfolios with equally-weighted returns spanning from Most Brown to Most Green. The dependent variables represent the excess returns of the respective portfolios. The variable Mkt.RF is the value-weighted market return less the risk-free rate. The SMB factor picks up the portfolios' exposure to small cap stocks. The HML factor captures the portfolios' exposure to high book-to-market value firms. The WML factor shows the rate of recent price movements in the portfolios.

The change in Transition Betas from the first sub-period to the second indicates that sudden changes in expectations will affect Most Brown and Brown portfolio more in the latter sub-period than in the first. Table 5.6 shows that the Transition Betas are insignificant for the Brown portfolio in the first sub-period, albeit becoming increasingly significant at a 1% level in the second sub-period. The Most Brown portfolio also reduces its value and increases the significance level from 5% to 1%. To conclude, the effect on firms represented in the Brown portfolio is larger in the second than in the first sub-period.

The opposite is found for the Most Green and Green portfolios. In the first sub-period the Most Green portfolio has an estimated Transition Beta of 0.61 and Green portfolio of 0.44 at a 1% and 5% significance level respectively. In the second sub-period the estimated Transition Betas for the Most Green portfolio reduces slightly to 0.58, however, still being significant at a 1% level. In contrast, the significance level of the Green portfolio drops, indicating that an unexpected change will not affect the Green portfolio in the second sub-period.

Similarly to the regressions on the whole sample period the Neutral portfolios stay insignificant and close to zero for both sub-periods. It is worth mentioning that the time-series regressions are based on few observations and that companies represented in the portfolios may have changed due to the yearly rebalancing of the portfolios.

## 5.5 Robustness

In order to test the robustness of the findings from our main regressions, we test our model under different assumptions. First, we perform OLS regressions on different Green Scores. Second, we provide results from a value-weighted GMB portfolio and test portfolios instead of the original equally-weighted. We base our robustness tests on the Carhart four-factor model as it is the best fitted model. It is also worth noting that we perform model testing as described in section 4.3 on all robustness models to ensure validity of the results. The findings from the model testing indicate that all models are in line with the Gauss-Markow assumptions and that the models are stationary. [2]

[2] All tables from this section are included in Robustness Results in Appendix.

### 5.5.1 Varieties of Green Score

As mentioned in Chapter 3.4, our Green Score is constructed using several scores provided by Refinitiv (2020b). The constructed Green Score is mainly based on the most used metric to measure transition risk, carbon intensity. However, it is interesting to see whether our results remain the same using different scoring schemes.

**Even Green Score**

We first conduct our analysis on a more evenly weighted Green Score, putting more weight on policy, target, supply chain and awareness scores. More specifically, our Even Green Score is calculated as follows:

$$GS_{i,t} = 0.5 \times TRS_{i,t} + 0.125 \times ES_{i,t} + 0.125 \times \frac{PES_{i,t} + TES_{i,t}}{2} + 0.125 \times CRO_{i,t}) + 0.125 \times ESCS_{i,t}$$

As seen in Table A.1, changing the weightings to a more evenly weighted Green Score turns the SMB factor significant on a 5% level for our first regression of differences in return between a Green and Brown portfolio. The result implies that the Green and Brown portfolio differ in exposure to the SMB risk factor. This result is in line with recent empirical findings. Drempetic et al. (2020) find a positive correlation between company size and ESG score and discuss the advantages of larger companies with more resources when disclosing their climate-related efforts. As stated in Chapter 3, such findings make it questionable to base the Green Score on such metrics.

As for the results on our second hypothesis, displayed in the extended Carhart model shown in Table A.2, we do not see any new variables turning significant at a 5% level or lower. Both the Mkt.RF and the GMB factor follow the same trend as in our original results, and the explanatory power of the model increases when adding the GMB factor to the model.

**Emission Green Score**

On the other hand, it is interesting to investigate the results with a Green Score solely decided by a company's carbon intensity. In Emission Green Score, we calculate the Green Score based entirely on the Total $CO_2$ Equivalents Emission to Revenues USD Score from (Refinitiv, 2020b). The Emission Green Score is closer to our original score, as we weighed this measure with 0.8 out of 1 in our main regressions.

$$GS_{i,t} = TRS_{i,t}$$

As seen in Table A.3, the HML factor turns significant for the Fama French three-factor model at a 5% level when basing the GMB factor on the Emission Green Score. Thereby, the risk exposure differs between the Green and Brown portfolio and HML. We also observe that the explanatory power of the model increases when employing the factors used in Fama French three-factor and Carhart four-factor model.

The results from the second hypothesis show that the HML factor turns significant at a 5% level for the Most Green portfolio suggesting that the low carbon intensity portfolio was somewhat value-stock oriented. We also notice that the WML factor turns significant at a 5% level for the Brown portfolio, however, the significance level is reduced to 10% after adding the GMB factor. It is worth mentioning that the results do not change notably, as there is still an increase in adjusted $R^2$ and no significant differences in trends from the original regressions.

### 5.5.2 Value-weighted portfolios

In addition to testing our Green Score, we want to consider whether the value-weighting approach affects our results. Tables A.5 and A.6 present the results when using value-weighted returns in the GMB portfolio and Green Score-sorted quintiles.

Table A.5 shows that the results from our first hypothesis hardly change when using value-weighted returns. On the second hypothesis, we note that the adjusted $R^2$ decreases for all of the portfolios when performing value-weighting. However, Table A.6 shows that the explanatory power of the models still increase when adding the GMB factor, indicating the same results as with equally-weighting. An interesting observation is that the estimated alphas for the Green and Brown portfolios turn significant with a positive loading using value-weighting. The results show that the Most Green and Most Brown portfolio have earned a significant average factor-adjusted return of 0.5 % and 0.4 % respectively. The finding indicates that investors demand a premium for holding both Most Green stocks and Most Brown stocks regardless of adding the GMB factor or not.

The SMB coefficients have a 1% significant level for all quintiles. Furthermore, the estimated Transition Betas are still significant at a 1% level for the Most Green and Most Brown portfolios. However, the coefficients increase from 0.630 to 0.898 for the Most Green and decrease from $-0.392$ to $-0.739$ for the Most Brown portfolio. The change indicates that the GMB factor is more influenced by companies with large capitalization than companies with small capitalization. The GMB coefficient of the Brown portfolio also decreases, yet stays significant at 5% level. On the contrary, the significance level of the Green portfolio drops and there is a reduction in the estimated coefficient from 0.382 to 0.093. The Neutral portfolio turned significant at 10% level with an estimated coefficient of 0.164. Further, estimated coefficient of the SMB and HML factors turn more significant using value-weighting.

To summarize, the alternative methods provide some differences from the original results. For our first hypothesis we get a significant SMB factor with an evenly weighted Green Score for both the Fama French three-factor model and the Carhart four-factor model, and a significant HML factor from the Fama French three-factor model on the Emission Green Score. This result imply that some of the differences in return can be explained by common risk factors under different assumptions, thereby questioning the robustness of our findings on the first hypothesis.

On the second hypothesis, the weightings in the Green Score do not make any significant differences in the results. However, for the value-weighted portfolio, the $R^2$ drop and the alpha turns significant, indicating that some of the variation in risk-adjusted return cannot be explained by the model. The $R^2$ is however still high, most of the time above 0.8. In addition, the findings suggest that the value and size of companies are better at explaining differences in risk-adjusted return from value-weighted portfolios than for equally-weighted portfolios.

However, adding the GMB factor to the model change the coefficients of the factors to a limited extent. In addition, the GMB factor appears to have the same trend for all portfolios and weightings of return. The $R^2$ still increases when adding the GMB factor and we therefore find the results of our second hypothesis rather robust.

# 6. Discussion

In this chapter, we discuss the results of our analysis in light of the theory and empirical studies presented in Chapter 2. Additionally, we will discuss practical implications of the estimated Transition Betas for investors and companies. Lastly, we address some of the limitations of our thesis.

## 6.1 Discussions of results

We will first discuss the results from our initial hypothesis, which states that there exists differences in return between the Green and Brown portfolios that common risk factors cannot explain. Secondly, we discuss the findings from expanding common factor models with the GMB factor, elaborating on whether our results indicate an inclusion of a new factor. Additionally, we will discuss how Transition Betas have developed over time.

### 6.1.1 Discussion of differences in returns

Our descriptive analysis implies that the GMB factor possesses unique return-estimating features and the regression results show a slightly positive alpha suggesting evidence for an underlying financial risk. However, due to the absence of a significant alpha, there is no evidence of a transition risk premium. Our results indicate that investors do not require significant additional returns for holding stocks that have a low Green Score compared to those with high Green Score. This finding contrasts previous studies. Derwall et al. (2005) find abnormal returns at a 10% significance level between high and low eco-efficient-ranked portfolios on US-companies in the period of July 1995-December 2003. Our findings also contradict the results of Oestreich and Tsiakas (2015), who find significant abnormal returns from their Dirty-minus-Clean portfolio regressed using CAPM and CAPM with additional controls.

A plausible explanation is that investors are not fully aware of the financial risks of a potential transition to a low-carbon economy, thereby not pricing the risk in their investment decisions. This is in line with the concerns of TCFD (2017), Carney (2015), and Fink (2020).

### 6.1.2 Discussion of extended models

The results from the regressions on Green Score-sorted quintile portfolios and regressions on individual risk-adjusted stock return, show that the GMB factor enhances the explanatory power of common factor models. The GMB factor has a greater average coefficient and explains more of the variations in excess return compared to the other common factors used in our analysis. However, it can be argued that the proportions are relatively low, thereby that the models should not be extended with the GMB factor.

Still, our findings are consistent with Görgen et al. (2020). They found that the adjusted $R^2$ increased with 0.90% in firm level regressions of the Carhart four-factor model to the extended model. Our results show a 1.04% increase when performing the same regression. Furthermore, we observe that the results of Görgen et al. (2020) was significant at a 5% level for 14.34% of the firms compared to our results that had a proportion of 18.16% significant increases of the sample. When comparing the results of our studies we observe rather small differences, which indeed provides robustness to our findings as the study of Görgen et al. (2020) is based on 25,000 stocks.

Our results show that transition risk explains variation in excess returns well compared to common risk factors. However, the GRS test and the absence of a significant alpha could imply that transition risk should not be considered as a systematic risk factor as there is no evidence for mispricing in the market (Fama and French, 2014).

As emphasized in section 2.4 the academic literature on whether climate risk should be seen as a systematic risk factor is not clear. We believe this is a result of market participants having different understanding and accounting for climate-related issues in their decision making. The complexity and uncertainty regarding the transition to a low-carbon economy makes an optimal pricing of transition risk unlikely. Customers may shift their demands for greener products, technologies that promotes low-carbon production processes might suddenly improve and authorities may introduce new policies aiming to reduce emissions (Pastor et al., 2020). These shifts will all affect the cash flow-channel. Furthermore, the market may change preferences towards green assets either due to considering financial risk or from a moral perspective, which can affect the cost of capital channel.

Arguably, transition risk can be considered to be both systematic and idiosyncratic due to the expected economy-wide effects of the transition and the sector and company specific effects of new technologies and policies hitting specific parts of the economy.

**Discussion of Transition Betas**

We use the methodology of Görgen et al. (2020) to measure Transition Beta, which is a market-based approach. As a result, the estimated Transition Betas correspond to the transition risk of the stock priced by the market participants and not a direct climate-related performance effect on risk-adjusted returns. As mentioned before, this implies that Transition Beta can be interpreted as the aggregated assessment of transition risk by all market participants in the market (Görgen et al., 2020). As our analysis is based on historical fluctuations in stock prices, the results display the real-time status of investors' expectations on the transition to a low-carbon economy. The low average correlation between the two measures displayed in Figure 5.3 demonstrate that the market's assessment of transition risk and the climate-related performance of stocks diverge.

Another interesting finding from our results is that we see a common trend for the Transition Betas; firms represented in both the Most Green and Most Brown portfolios have the highest absolute Transition Betas. However, the Most Green portfolio have the highest transition risk in all models. The absolute value decreases for the Brown and Green portfolio and diminishes for the Neutral. This finding suggests that transition risk is high both for the Most Green and Most Brown companies. Our findings from the value-weighted analysis also indicate that investors demand a higher risk premium the Greener or Browner the portfolio is. The same is true for equally-weighted analysis, however, the alphas are not significant.

Our results on the absolute value of Transition Beta makes sense when studied over time. When analyzing Transition Betas before and after the publication of the TCFD report, we find from section 5.4.1 that the Transition Beta decreased in value for the Brown portfolios, implying that transition risk increases for Brown companies after the publication. On the contrary, the Green portfolio's Transition Beta decreases after the publication, indicating a reduction in transition risk for green companies. Our result suggests that the Brown portfolio is more sensitive to an unexpected change post the publication. The opposite is true for the Green portfolios.

On the basis of our findings it is still not clear if the GMB factor is of relevance for asset pricing models. However, the method of Görgen et al. (2020) can be useful for all market participants in their assessment of transition risk of assets. In the following section we will discuss the practical implication of the Transition Beta.

## 6.2 Practical implications

### 6.2.1 Implications for investors

An increasing number of portfolio managers seek to hedge against climate risk when constructing portfolios (Andersson et al., 2016). One of the most common approaches to hedge transition risk is by divesting from stocks with high carbon-emissions (Pastor et al., 2020). However, this practice involves the risk of the investor underperforming her benchmark for as long as climate mitigation policies are delayed and market expectations about the introduction of regulations and policies are low. In this context, an investor can use Transition Betas to obtain insight to the market's perception on industries and stocks and better quantify risks and opportunities.

However, it is worth noting that some of the risk might not be hedgeable. The average correlation between the GMB factor and market factor indicates the direction of which the transition process will affect the market. The constant correlation from Table 5.2 of $-0.137$ suggests that an acceleration of the transition to a low-carbon economy will lead to a decrease in the overall market value. This finding implies that climate risk can be seen as a systematic risk. That being said, the correlation is not significant.

For investors willing to take on more risk, Transition Betas can be used when speculating on the transition process that is unexpected by the market (Pastor et al., 2020). For instance, if an investor speculate in more restrictive emission policies than the market expect, she can construct a portfolio that has relatively high Transition Betas. The opposite is also true; if an investor believes in less jurisdictions on carbon emissions, she should steer the exposure to a negative Transition Beta.

### 6.2.2 Implications for companies

Quantifying transition risks and opportunities can also be valuable when managing companies. As mentioned earlier, the company's Transition Beta reflects the market's assessment of the transition risk of the company. As a result, it can give management an indication on how the valuation of the company will be affected by changes in expectations about the transition towards a greener economy.

The global transition pathway is still highly uncertain. Some companies will likely survive the transition, whilst others will not, as their competitive position is eroded. The Transition Beta can be used to quantify the risk of losses, but also the opportunities of profits for companies. By being aware of their exposure to transition risk, decision makers in the company are better suited to manage it. An important tool in managing the uncertainty of transition risk is scenario analysis (NGFS, 2020). By assessing uncertainty about upcoming policies, technologies, and preferences through projections of different outcomes, while using the Transition Betas, companies can forecast their potential losses and profits from different transition pathways (Schoenmaker and Schramade, 2017).

If the transition pathway develops according to the goals of the Paris Agreement, our results show that greener companies will earn higher risk-adjusted returns, while brown companies will suffer from losses. In the belief of an orderly or disorderly transition to a low-carbon economy, referred to as climate-change mitigation scenarios, the best way a company can decrease its exposure to transition risk is by becoming greener, thus improving their climate-related performance.

In such a scenario, a first step towards decreasing exposure to transition risk is to assess the company's material sustainability issues (Schoenmaker and Schramade, 2017). By undertaking internal research and engaging in stakeholder dialogues, companies can understand their most important climate-related issues and furthermore, align their strategy and business model towards accounting for these. Moreover, increasing the understanding of the consequences of different transition pathways can allow companies to make better decisions for the long run (Schoenmaker and Schramade, 2017). The result of these activities might involve rethinking the way the business create, deliver and capture value (Jørgensen et al., 2018).

## 6.3 Limitations of our analysis

Throughout the analysis we have aimed to explore the relationship between stock prices and climate-related performance, furthermore, measuring companies' and portfolios' exposure to transition risk. However, quantifying transition risk is indeed a challenge. In this section we will elaborate on some of the limitations of our analysis. We note that we have discussed our data choices and concerns in section 3.5.

We perform portfolio analyses based on Fama and French (1993) on a monthly level. As mentioned in chapter 3.5 our time period is from January 2014-December 2019, thus considering 72 months. One of our concerns is that the sample is small which can imply additional statistical error, thereby decrease the validity of our findings (Wooldridge, 2016). However, our findings are in line with Görgen et al. (2020), which increases the robustness of our results.

Another concern about our findings is that our sample is based on a skewed selection of both regions and sectors. Therefore, we are concerned that region and/or sector exposure have larger impact on the performance of our portfolios than climate-related performance does. However, our regression studies show that risk-adjusted return from the sample can significantly be explained by the Mkt.RF, the return in the market, and we believe that the negative effect from this concern is limited. Consequently, we assess it as unnecessary to account for differences across sectors like for instance Derwall et al. (2005), as there are also disadvantages of adding more variables to our somewhat small sample (Wooldridge, 2016).

We investigate whether adding an additional factor to common factor models have a statistically significant impact on the explanatory power of the models, using techniques from Fama and French (2014). However, these methods are exposed to criticism. Cochrane (2011) discuss the limitations of evaluating fitness of asset pricing factors that are regressed with test portfolios formed on the same characteristics as the factors, implying high correlation between the explained variable and explanatory variables. He argues that the method leads to artificially small pricing errors and high $R^2$ (Cochrane, 2011). We considered the methods of Fama and French (2014) as the best fitted alternative for our analysis, however, we agree that this could be a limitation.

Lastly, we find it worth mentioning that using historic data is a limitation when quantifying transition risk because of the uncertainty of the development of the transition pathway, and the rapid changes in the market's assessment of transition risk.

# 7. Conclusion

The purpose of this thesis has been to study the relationship between climate-related performance and equity prices. Based on the methods of Görgen et al. (2020), we constructed a Green Score measuring climate-related performance. We used the Green Score and companies' market capitalization to construct a mimicking portfolio using a zero investment strategy long in Green and short in Brown companies. In line with Fama and French (1993), we also constructed test portfolios by dividing our sample into quintiles based on their Green Score.

First, we examined whether differences in return between Green and Brown companies cannot significantly be explained by the risk factors included in the CAPM, Fama French three-factor and Carhart four-factor model, referred to as common risk factors. Our results suggest that the differences in return between the Green and Brown portfolio cannot be explained by common risk factors. However, we do not find any significant differences in abnormal return between Green and Brown companies.

Thereafter, we included the GMB factor as an explanatory variable in the mentioned factor models. We found that the GMB factor provides significant coefficients at a 1% level for Most Brown and Most Green companies and that the factor explains variations in risk-adjusted return of such companies well. The results from our F-test are also significant, indicating that the inclusion of the GMB factor enhances the explanatory power of the model. However, the results from the GRS test indicate that the original models are better fit in explaining excess return in our sample.

The results related to our second hypothesis are contradicting and create room for discussions. On the basis of our findings, it is still not clear if the GMB factor is of relevance for asset pricing models. We believe further exploration of the factor is needed to make a formal conclusion. Still, the method of Görgen et al. (2020) can be useful for all market participants when assessing the transition risks of assets.

Traditional financial theories and models does not account for the climate change dimension of risk. In our study, we challenge standard asset pricing models' view on systematic risk, by pointing out that the factors cannot fully explain the systematic risk of a transition to the low-carbon economy. By including a GMB factor, we provide valuable insights on how unexpected changes towards a low-carbon economy will affect companies with high climate-related performance and low climate-related performance differently. The GMB factor can be an important tool for both investors and managers to measure and manage transition risk.

Transition risk is still a field of great uncertainty and unexplored dimensions. To further investigate the relation between differences in equity prices and transition risk, we encourage future research on transition risk in samples of SMBs and in different scenarios, conducted on specific regions, sectors, industries or even companies to better understand the interesting dimensions of transition risk.

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# A. Appendix

## A.1 Robustness regressions

#### A.1.0.1 Even Green Score

**Table A.1:** Robustness of CAPM, Fama French three-factor and Carhart four-factor models with Even Green Score

| | *Dependent variable:* | | |
|---|---|---|---|
| | GMB | | |
| | (CAPM) | (Fama French) | (Carhart) |
| Mkt.RF | −0.026 | −0.029 | 0.00004 |
| | (0.036) | (0.035) | (0.039) |
| SMB | | −0.188** | −0.198** |
| | | (0.084) | (0.083) |
| HML | | 0.002 | 0.088 |
| | | (0.060) | (0.081) |
| WML | | | 0.001 |
| | | | (0.001) |
| Constant | −0.001 | −0.001 | −0.001 |
| | (0.001) | (0.001) | (0.001) |
| Observations | 72 | 72 | 72 |
| $R^2$ | 0.008 | 0.077 | 0.109 |
| Adjusted $R^2$ | −0.006 | 0.036 | 0.056 |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

The table reports the results of the robustness test from CAPM, Fama French three-factor model and Carhart four-factor model regression on a Green-Minus-Brown portfolio based on evenly estimated Green Score. The estimation of the Even Green Score is found in chapter 5.5.1. The carbon intensity score has 50% weighing while the other variables have a total weight of 50%. We estimated the model with monthly data from 2014-2019.

**Table A.2:** Robustness result from Carhart four-factor model and extended Carhart with Even Green Score

| | *Dependent variable:* $R_{it} - R_{ft}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Most Brown | | Brown | | Neutral | | Green | | Most Green | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Mkt.RF | 1.017*** | 1.017*** | 0.944*** | 0.944*** | 0.962*** | 0.962*** | 0.963*** | 0.963*** | 0.986*** | 0.986*** |
| | (0.039) | (0.035) | (0.038) | (0.038) | (0.037) | (0.036) | (0.037) | (0.034) | (0.042) | (0.033) |
| SMB | 0.150* | 0.061 | 0.075 | 0.048 | −0.023 | 0.025 | −0.155* | −0.080 | −0.105 | 0.031 |
| | (0.083) | (0.078) | (0.080) | (0.083) | (0.078) | (0.079) | (0.079) | (0.076) | (0.090) | (0.072) |
| HML | −0.090 | −0.051 | −0.104 | −0.092 | −0.029 | −0.050 | −0.080 | −0.114 | 0.035 | −0.026 |
| | (0.081) | (0.074) | (0.079) | (0.079) | (0.076) | (0.075) | (0.077) | (0.072) | (0.088) | (0.069) |
| WML | −0.001 | −0.0003 | −0.001* | −0.001* | −0.0004 | −0.001 | −0.0001 | −0.0005 | 0.0001 | −0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| GMB | | −0.449*** | | −0.135 | | 0.238** | | 0.381*** | | 0.690*** |
| | | (0.110) | | (0.118) | | (0.111) | | (0.107) | | (0.102) |
| Constant | 0.001 | 0.001 | 0.0003 | 0.0002 | −0.0002 | 0.00004 | −0.0003 | 0.0001 | 0.001 | 0.002** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 |
| $R^2$ | 0.931 | 0.945 | 0.928 | 0.930 | 0.932 | 0.936 | 0.930 | 0.941 | 0.913 | 0.948 |
| Adjusted $R^2$ | 0.927 | 0.941 | 0.924 | 0.924 | 0.928 | 0.931 | 0.925 | 0.937 | 0.908 | 0.945 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

The table reports the robustness test of Carhart four-factor and the extended model with GMB factor based on evenly estimated Green Score. The estimation of the Even Green Score is found in chapter 5.5.1. The carbon intensity score has 50% weighing while the other variables have a total weight of 50%. We estimated the model with monthly data from 2014-2019.

### A.1.1 Emission Green Score

**Table A.3:** Robustness of CAPM, Fama French three-factor and Carhart four-factor models with Emission Green Score

| | *Dependent variable:* | | |
|---|---|---|---|
| | GMB | | |
| | (CAPM) | (Fama French) | (Carhart) |
| Mkt.RF | −0.027 | −0.028 | −0.007 |
| | (0.030) | (0.029) | (0.032) |
| SMB | | −0.027 | −0.035 |
| | | (0.069) | (0.069) |
| HML | | −0.120** | −0.058 |
| | | (0.050) | (0.068) |
| WML | | | 0.001 |
| | | | (0.001) |
| Constant | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) |
| Observations | 72 | 72 | 72 |
| $R^2$ | 0.012 | 0.094 | 0.117 |
| Adjusted $R^2$ | −0.002 | 0.054 | 0.065 |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

The table reports the results of the robustness test from CAPM, Fama French three-factor model and Carhart four-factor model regression on a Green-Minus-Brown portfolio based solely on carbon intensity score. We estimated the model with monthly data from 2014-2019.

**Table A.4:** Robustness result from Carhart four-factor model and extended Carhart with Emission Green Score

| | textitDependent variable: $R_{it} - R_{ft}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Most Brown | | Brown | | Neutral | | Green | | Most Green | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Mkt.RF | 0.964*** | 0.961*** | 0.999*** | 0.998*** | 0.990*** | 0.990*** | 0.915*** | 0.917*** | 1.017*** | 1.022*** |
| | (0.035) | (0.031) | (0.035) | (0.035) | (0.038) | (0.038) | (0.039) | (0.038) | (0.040) | (0.035) |
| SMB | −0.027 | −0.044 | 0.048 | 0.041 | −0.008 | −0.007 | −0.112 | −0.099 | 0.041 | 0.064 |
| | (0.074) | (0.066) | (0.074) | (0.074) | (0.080) | (0.081) | (0.083) | (0.080) | (0.086) | (0.074) |
| HML | −0.083 | −0.112* | −0.051 | −0.061 | 0.037 | 0.040 | −0.017 | 0.004 | −0.186** | −0.148** |
| | (0.072) | (0.065) | (0.073) | (0.073) | (0.079) | (0.079) | (0.082) | (0.079) | (0.084) | (0.073) |
| WML | −0.0004 | −0.00002 | −0.001** | −0.001* | −0.001 | −0.001 | 0.001 | 0.0003 | −0.001 | −0.001* |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| GMB | | −0.493*** | | −0.184 | | 0.043 | | 0.364** | | 0.650*** |
| | | (0.116) | | (0.131) | | (0.143) | | (0.142) | | (0.131) |
| Constant | 0.0002 | 0.001 | 0.0002 | 0.0004 | −0.0004 | −0.0005 | 0.001 | 0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Observations | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 |
| $R^2$ | 0.938 | 0.952 | 0.944 | 0.946 | 0.932 | 0.933 | 0.911 | 0.919 | 0.927 | 0.947 |
| Adjusted $R^2$ | 0.935 | 0.948 | 0.941 | 0.942 | 0.928 | 0.927 | 0.905 | 0.913 | 0.922 | 0.943 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

The table reports the robustness test of Carhart four-factor model and the extended model with GMB factor based on solely Green Emission Score. The carbon intensity score has 100% weighing thus excluding the other variables. We estimated the model with monthly data from 2014-2019.

### A.1.2 Regression on value-weighted portfolios

**Table A.5:** Results from CAPM, Fama French three-factor and Carhart four-factor models with value-weighted GMB return

| | *Dependent variable:* | | |
|---|---|---|---|
| | GMB | | |
| | (CAPM) | (Fama French) | (Carhart) |
| Mkt.RF | −0.020 | −0.021 | −0.018 |
| | (0.044) | (0.044) | (0.051) |
| SMB | | −0.061 | −0.062 |
| | | (0.106) | (0.108) |
| HML | | −0.018 | −0.011 |
| | | (0.077) | (0.106) |
| WML | | | 0.0001 |
| | | | (0.001) |
| Constant | 0.0002 | 0.00005 | 0.00003 |
| | (0.001) | (0.001) | (0.001) |
| Observations | 72 | 72 | 72 |
| $R^2$ | 0.003 | 0.009 | 0.009 |
| Adjusted $R^2$ | −0.011 | −0.035 | −0.050 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | | |

The table reports the robustness test from CAPM, Fama-French 3-factor model and Carhart four-factor model regression on value-weighted return of a Green-Minus-Brown portfolio. We estimated the model with monthly data from 2014-2019.

**Table A.6:** Results from Carhart four-factor model with value-weighted portfolio returns

| | *Dependent variable:* $R_{it} - R_{ft}$ | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Most Brown | | Brown | | Neutral | | Green | | Most Green | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
| Mkt.RF | 0.934*** | 0.921*** | 1.057*** | 1.050*** | 0.910*** | 0.913*** | 0.893*** | 0.895*** | 1.109*** | 1.126*** |
| | (0.075) | (0.066) | (0.052) | (0.049) | (0.038) | (0.037) | (0.039) | (0.039) | (0.071) | (0.055) |
| SMB | −0.394** | −0.440*** | −0.232** | −0.257** | −0.258*** | −0.248*** | −0.321*** | −0.316*** | −0.380** | −0.324*** |
| | (0.160) | (0.140) | (0.111) | (0.104) | (0.080) | (0.079) | (0.082) | (0.082) | (0.150) | (0.116) |
| HML | −0.351** | −0.359** | −0.093 | −0.097 | 0.035 | 0.037 | −0.139* | −0.138* | −0.362** | −0.352*** |
| | (0.157) | (0.137) | (0.109) | (0.102) | (0.079) | (0.077) | (0.081) | (0.081) | (0.147) | (0.114) |
| WML | 0.001 | 0.001 | 0.0001 | 0.0002 | 0.001 | 0.0005 | 0.001 | 0.001 | −0.001 | −0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| GMB | | −0.739*** | | −0.396*** | | 0.164* | | 0.093 | | 0.898*** |
| | | (0.159) | | (0.118) | | (0.090) | | (0.093) | | (0.131) |
| Constant | 0.004** | 0.004** | 0.003* | 0.003* | 0.001 | 0.001 | 0.003** | 0.003** | 0.005** | 0.005*** |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Observations | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 | 72 |
| $R^2$ | 0.759 | 0.818 | 0.888 | 0.904 | 0.917 | 0.921 | 0.911 | 0.912 | 0.838 | 0.905 |
| Adjusted $R^2$ | 0.744 | 0.804 | 0.881 | 0.897 | 0.912 | 0.915 | 0.906 | 0.906 | 0.828 | 0.898 |

*Note:* *p<0.1; **p<0.05; ***p<0.01

This table reports the robustness test for Carhart four-factor model and the model expanded with the constructed value-weighted GMB portfolio return. The dependent variables represents the value-weighted excess returns of the Green Score-sorted portfolios spanning from Most Brown to Most Green. The variable Mkt.RF is the value-weighted market return less the risk-free rate. The SMB factor picks up the portfolios' exposure to small cap stocks. The HML factor captures the portfolios' exposure to high book-to-market value firms. The WML factor shows the rate of recent price movements in the portfolios. We estimated the model with monthly data from 2014-2019.

## A.2 Model testing

**Table A.7:** Results of Augmented Dickey-Fuller test

| Variables | t-value | P-value |
|---|---|---|
| $R_{1t} - R_{ft}$ | -9.745 | 0.000 |
| $R_{2t} - R_{ft}$ | -10.057 | 0.000 |
| $R_{3t} - R_{ft}$ | -9.441 | 0.000 |
| $R_{4t} - R_{ft}$ | -9.941 | 0.000 |
| $R_{5t} - R_{ft}$ | -9.455 | 0.000 |
| GMB | -5.133 | 0.000 |
| Mkt.RF | -9.770 | 0.000 |
| SMB | -5.485 | 0.000 |
| HML | -7.980 | 0.000 |
| WML | -9.366 | 0.000 |

The table shows the results from Augmented Dickey-Fuller tests for stationarity. The test is conducted on all variables. The null-hypothesis is non-stationarity, thereby a low p-value indicates that we can reject the null-hypothesis. The results shows that the variables are stationary.

**Table A.8:** Results from Breusch-Pagan test

| Model | BP | P-value |
|---|---|---|
| GMB˜CAPM | 6.415 | 0.011 |
| GMB˜Fama-French | 6.967 | 0.073 |
| GMB˜Carhart | 12.533 | 0.014 |
| Q1 CAPM | 0.883 | 0.347 |
| Q1 CAPM + GMB | 1.039 | 0.595 |
| Q2 CAPM | 0.180 | 0.671 |
| Q2 CAPM + GMB | 0.313 | 0.855 |
| Q3 CAPM | 0.540 | 0.462 |
| Q3 CAPM + GMB | 0.820 | 0.664 |
| Q4 CAPM | 0.155 | 0.694 |
| Q4 CAPM + GMB | 4.378 | 0.112 |
| Q5 CAPM | 0.459 | 0.498 |
| Q5 CAPM + GMB | 2.714 | 0.257 |
| Q1 Fama-French | 4.009 | 0.261 |
| Q1 Fama-French + GMB | 3.554 | 0.470 |
| Q2 Fama-French | 2.223 | 0.528 |
| Q2 Fama-French + GMB | 0.619 | 0.961 |
| Q3 Fama-French | 2.324 | 0.508 |
| Q3 Fama-French + GMB | 2.839 | 0.585 |
| Q4 Fama-French | 2.214 | 0.529 |
| Q4 Fama-French + GMB | 4.069 | 0.397 |
| Q5 Fama-French | 0.753 | 0.861 |
| Q5 Fama-French + GMB | 5.171 | 0.270 |
| Q1 Carhart | 3.843 | 0.428 |
| Q1 Carhart + GMB | 3.363 | 0.644 |
| Q2 Carhart | 5.564 | 0.234 |
| Q2 Carhart + GMB | 2.347 | 0.799 |
| Q3 Carhart | 2.645 | 0.619 |
| Q3 Carhart + GMB | 3.176 | 0.673 |
| Q4 Carhart | 3.648 | 0.456 |
| Q4 Carhart + GMB | 5.280 | 0.383 |
| Q5 Carhart | 0.717 | 0.949 |
| Q5 Carhart + GMB | 5.060 | 0.409 |

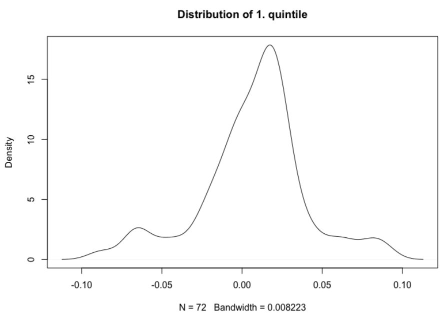
The table shows our results from the Breusch-Pagan test for heteroscedasticity. The null-hypothesis is that there is homoscedasticity in the constructed portfolios. A low p-value indicate that we have a problem with heteroscedasticity. As we can see from the first part of the model, both GMB CAPM and GMB Carhart have P-values below the 5% significance level, which means we cannot reject the null-hypothesis. In order to correct for the problem of heteroscedasticity we run regressions with robust standard errors in our proned regression models. However, the results from the models do not differ from our original regression models.

**Table A.9:** Results from Breusch-Godfrey

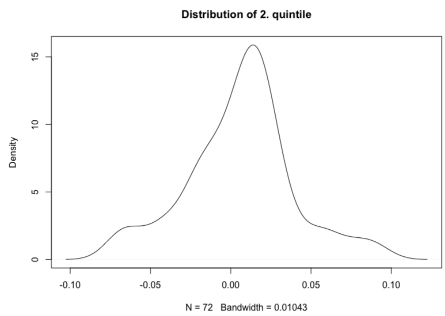
| Model | BG | P-value |
|---|---|---|
| GMB˜CAPM | 0.002 | 0.968 |
| GMB˜Fama-French | 0.007 | 0.935 |
| GMB˜Carhart | 0.032 | 0.859 |
| CAPM - model | | |
| Q1 CAPM | 0.938 | 0.333 |
| Q1 CAPM + GMB | 0.440 | 0.507 |
| Q2 CAPM | 0.932 | 0.334 |
| Q2 CAPM + GMB | 0.438 | 0.508 |
| Q3 CAPM | 0.070 | 0.791 |
| Q3 CAPM + GMB | 0.010 | 0.919 |
| Q4 CAPM | 0.035 | 0.852 |
| Q4 CAPM + GMB | 0.049 | 0.824 |
| Q5 CAPM | 0.037 | 0.848 |
| Q5 CAPM + GMB | 0.730 | 0.393 |
| Q1 Fama-French | 0.971 | 0.324 |
| Q1 Fama-French + GMB | 0.275 | 0.600 |
| Q2 Fama-French | 0.615 | 0.433 |
| Q2 Fama-French + GMB | 0.510 | 0.475 |
| Q3 Fama-French | 0.149 | 0.700 |
| Q3 Fama-French + GMB | 0.058 | 0.809 |
| Q4 Fama-French | 0.006 | 0.937 |
| Q4 Fama-French + GMB | 0.151 | 0.698 |
| Q5 Fama-French | 0.093 | 0.760 |
| Q5 Fama-French + GMB | 0.791 | 0.374 |
| Q1 Carhart | 0.680 | 0.410 |
| Q1 Carhart + GMB | 0.223 | 0.637 |
| Q2 Carhart | 0.052 | 0.819 |
| Q2 Carhart + GMB | 0.061 | 0.806 |
| Q3 Carhart | 0.192 | 0.662 |
| Q3 Carhart + GMB | 0.101 | 0.750 |
| Q4 Carhart | 0.012 | 0.914 |
| Q4 Carhart + GMB | 0.089 | 0.766 |
| Q5 Carhart | 0.044 | 0.834 |
| Q5 Carhart + GMB | 0.321 | 0.571 |

The table shows our results from the Breusch-Godfrey test for autocorrelation in error-terms. The null-hypothesis is that there is no autocorrelation in the model. A large BG-value and low p-value indicate that we have a problem with autocorrelation. As evident in the table, autocorrelation does not seem to be a problem in any of our models.

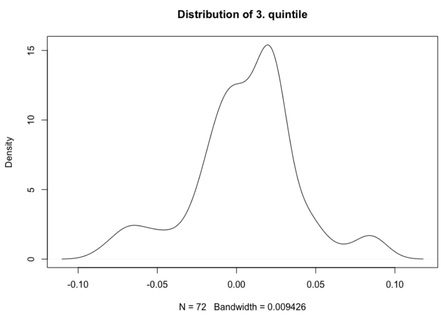
**Figure A.1:** Distributions of portfolios



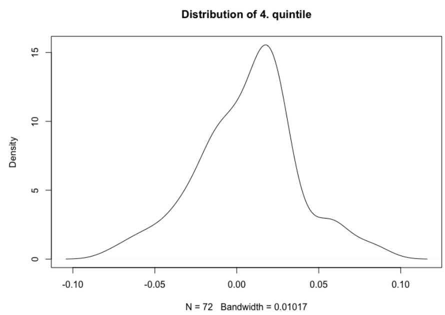

**(a)** Distribution 1st quintile



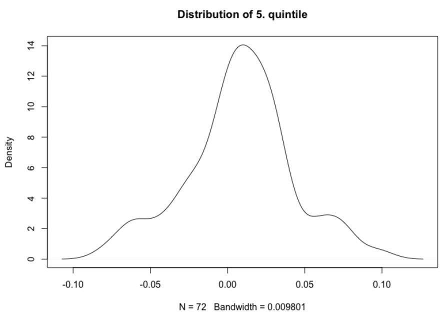

**(b)** Distribution 2nd quintile



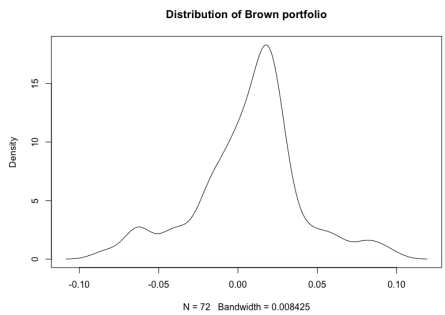

**(c)** Distribution 3rd quintile



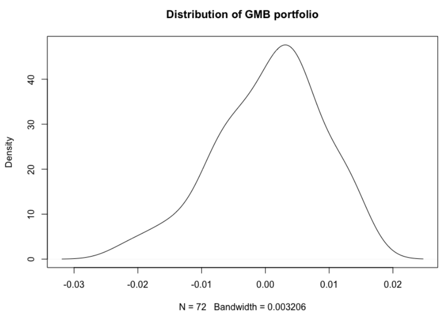

**(d)** Distribution 4th quintile



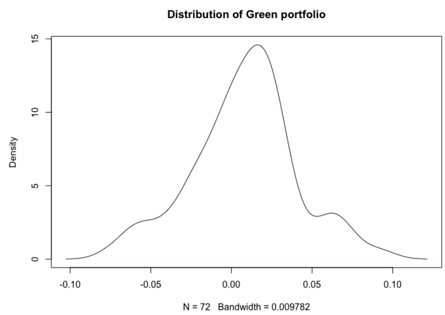

**(e)** Distribution 5th quintile




**(f)** Distribution Brown portfolio




**(g)** Distribution GMB portfolio




**(h)** Distribution Green portfolio