Onni Järvinen

Assessing Transition Risk in Equity Portfolios: Measurement and Strategic Management

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Author: Onni Järvinen
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ABSTRACT: Tämän tutkielman tarkoituksena on tarkastella ilmastonmuutokseen liittyvien siirtymäriskien vaikutusta osakeportfolioihin sekä strategioita, joilla sijoittajat voivat hallita ja mahdollisesti hyödyntää riskejä, jotka syntyvät siirtymästä kohti vähähiilistä taloutta. Siirtymäriskit johtuvat lainsäädännön muutoksista, teknologisista innovaatioista ja muuttuvista kuluttajamieltymyksistä, jotka kaikki vaikuttavat yritysten taloudelliseen suorituskykyyn ja sitä kautta myös sijoittajien osakeportfolioihin. Valtioiden siirtyessä kohti hiilineutraaliutta sijoittajat kohtaavat sekä haasteita että mahdollisuuksia mukauttaessaan strategioitaan näiden riskien hallitsemiseksi tehokkaasti.

Taloudellisten vaikutusten arvioinnin lisäksi tässä tutkielmassa tarkastellaan viimeaikaisia kvantitatiivisia menetelmiä yrityksen siirtymäriskialtistuksen mittaamiseen. Erityisesti keskitytään Brown-Minus-Green (BMG) -arvoon sekä siitä johdettuun markkinalähtöiseen hiilibetaan, jotka mahdollistavat siirtymäriskin systemaattisen arvioinnin, sekä yksittäisten sijoituskohteiden, että koko osakeportfolion tasolla. Näitä riskimittareita sovelletaan yhdessä vakiintuneiden rahoitusteorioiden, kuten modernin portfolioteorian sekä Fama-Frenchin multifaktorimallien kanssa.

Vaikka tietoisuus ilmastonmuutokseen liittyvistä taloudellisista riskeistä on kasvanut, siirtymäriskin tarkka mittaaminen sekä sen integrointi salkunhoitoon on edelleen puutteellista. Tämä tutkimus edistää aihealuetta osoittamalla, kuinka multifaktorimallien käyttö parantaa siirtymäriskien matemaattista arviointia ja mahdollistaa tehokkaiden salkunhoitostrategioiden kehittämisen.

KEYWORDS: Transition risk, Multifactor models, Portfolio management, Brown-minus-green factor, Carbon beta, Climate policy uncertainty index

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1 Introduction

A joint effort to combat climate change began in 1997 when multiple countries signed the Kyoto Protocol (Barberà-Mariné et al., 2023). However, the protocol was concise and originally affected only 36 developed countries. The first significant legally binding agreement was the 2015 Paris Agreement (Barberà-Mariné et al., 2023). The Paris Agreement was adopted by 196 countries and the aim was to limit global warming to under 2°C above pre-industrial levels. The 2nd article of the agreement states the following*:" Making finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development."* (UNFCCC, 2015, p. 5). This statement establishes clear objectives, emphasizing the shift towards a low-carbon economy, thus presenting significant challenges for high-emission industries and companies.

According to the Intergovernmental Panel on Climate Change (IPCC), in addition to the Paris Agreement, global net carbon emissions must reach net zero by the year 2050 to limit global warming to 1.5°C (Semieniuk et al., 2021). The authors say that many countries have already adopted carbon neutrality laws before or by the year 2050. According to them, decarbonizing the global economy on a tight schedule is not an insignificant task. The transition process will require large-scale structural changes, particularly impacting high-carbon-emission sectors. At the centre of this transition lies the transition risk—the financial and economic risks related to the shift towards a low-carbon economy.

Transition risk threatens companies across economic sectors, making it crucial for investors to understand and manage these risks in their portfolios. According to Reboredo and Ugolini (2022), transition risks are more pervasive than physical risks making companies' internal decisions crucial. Companies operating in highly polluting industries face direct exposure to transition risk due to regulatory and policy changes. In addition, firms with poor adaptation strategies struggle, since failure to transition effectively can result in significant financial losses and competitive disadvantages. Therefore, understanding the financial risks and opportunities posed by climate-related transition risks is crucial for investors in equity markets. Notably, equities are the asset class most vulnerable to transition risk, suffering losses over twice as severe as those of the next most affected class (Crisóstomo, 2022).

1.1 Purpose of the study

This thesis examines the complex issue of climate transition risk in equity portfolios. As awareness of climate change grows and global efforts to mitigate its effects intensify, investors must adapt their strategies to navigate the financial implications of the transition to a low-carbon economy. Successfully managing these risks requires reliable methodologies to accurately assess stock's exposure to transition risk.

H_1: Transition risks are part of previously unknown risks that explain stock returns.

H_2: Investors incorporating transition risk in portfolio management achieve higher risk-adjusted returns than those who do not.

These hypotheses rest on the premise that transition risk affects all companies to some degree and should therefore contribute to the explanatory power of return models. Furthermore, companies categorized as "brown" (i.e., those with high exposure to transition risk) are particularly vulnerable to an accelerated transition process, which should impact their financial performance.

1.2 Structure of the study

This thesis is structured as follows, after the introduction and hypotheses, chapter two examines transition risk, its main components, and their effects on companies. Chapter three provides the theoretical background of portfolio management, tracing its development from the beginning to modern multifactor models. Chapter four examines the methods for measuring transition risk and explains how these measures are constructed using established financial theory frameworks discussed in chapter three. Chapter five analyses the performance differences between green and brown stocks and portfolios, while also examining effective portfolio management strategies to mitigate risks and capitalize on opportunities arising from the transition to a low-carbon economy. Finally, Chapter six summarizes the main findings and presents suggestions for future research.

2 Transition risk

Climate change produces a variety of risks, which can be broadly categorized into two classes: Physical risks and transition risks. Physical risks are tangible and easily observable, and according to Venturini (2022), they are often linked to extreme weather events, which are becoming more frequent due to climate change.

However, this thesis focuses exclusively on transition risks, which are the risks that arise from moving on to a low-carbon economy (Semieniuk et al., 2021). Transition risk is usually divided into three main risk drivers (Semieniuk et al., 2021; Reboredo & Ugolini, 2022; Crisóstomo, 2022; Bua et al., 2022). These drivers are presented by Venturini (2022) as follows:

$$Transition\ risk = f(policy\ risk, technology\ risk, preference\ change) \qquad (1)$$

2.1 Policy risk

Policy risk refers to the political and legal regulations that are implemented to combat climate change (Reboredo & Ugolini, 2022). In response to growing concerns regarding climate change, there is significant public pressure to strengthen climate policies (Yousaf et al., 2022). Climate change mitigation policies can be implemented either through market-based or non-market-based methods (Venturini, 2022).

Market-based mitigation is known as carbon pricing, which can be done either by carbon tax or cap-and-trade schemes (Semieniuk et al., 2021; Venturini, 2022). According to-Semieniuk et al. (2021) only about 20% of global greenhouse gas (GHG) emissions are priced, and less than 5% of these meet the levels set in the Paris Agreement. The authors go on to say that this significant gap between current GHG emission pricing and the target levels agreed upon in 2015, indicates that effective implementation of climate change mitigation policies could substantially increase operating costs for highly polluting companies, ultimately leading to higher prices for consumers. Additionally, as these prices rise, consumers are likely to adapt by reducing their reliance on these commodities or services. The International Monetary Fund (Parry, 2019) estimated that to reach the objectives set in the Paris Agreement, the global carbon tax could rise to $75 a ton of CO_2 in by 2030.

Non-market-based methods consist of environmental regulation, green subsidies, and voluntary commitments by companies and governments (Venturini, 2022). Environmental regulations refer to new legislation that influences companies' operating fields. This could be done by limiting the sale of certain environmentally harmful products. A notable example of a regulatory ban is the European Union's policy, prohibiting the sale of automobiles that emit any amount of CO_2 by the year 2035 (Regulation (EU) 2019/631).

Green subsidies are government support plans for green transition (Semieniuk et al., 2021). According to the authors plans such as Europe's Green New Deal, which directs funds to help accelerate the transition process. Moreover, this support from governments makes low-carbon products more accessible to the public as the prices of these goods decrease. Government-driven support through voluntary or mandatory commitments modifies the market environment and gives advantages to companies with low-level exposure to transitional risk and vice versa.

2.2 Technology risk

Technology risk emerges from new cost-saving technological advancements and innovations (Semieniuk et al., 2021). According to the authors, the creation of these innovations is often incentivized by climate policy and new regulations, Venturini (2022) also points out that the two risk categories are therefore closely linked with one another. A notable example of this connectedness is the previously mentioned Green New Deal. Innovations together with significant policy incentives, help lower the prices of green technologies possibly causing them to be widely adopted, and thus becoming the new standard (Semieniuk., 2021). When low-carbon technologies become widely adopted, older, more expensive, and polluting technologies risk becoming stranded assets, those being investments that lose value or become obsolete due to the market's shift (Birindelli et al., 2023). According to Venturini (2022), technological shift can be a significant driver towards a low-carbon economy since approximately 80% of the world's energy consumption is still fossil-fuelled. Companies may also be pushed to accelerate the adoption of new technologies (Venturini, 2022). The author goes on to say that along with the aforementioned policy incentives, companies may also be pressured by shareholders or the ongoing market environment, not adopting cheap low-carbon technologies could lead to the loss of competitive advantages once held by a company.

2.3 Preference change

Preference change is the shift in consumption patterns of environmentally conscious customers towards more sustainable alternatives (Reboredo & Ugolini, 2022). Preferences can be a market driver (Semieniuk et al., 2021). According to the authors, through the market-based nature of preference change produced risks, consumer behaviour can also be a driver of policy changes and through that interconnectedness, it assists in accelerating technological innovations as well. Thus, as shown through these links, all three risk drivers—preference change, policy risk, and technology risk—are interconnected (Semieniuk et al., 2021). An increase in one of these factors can trigger an acceleration in the others, meaning each driver can influence and amplify the impact of the others.

3 Portfolio management

3.1 Modern Portfolio Theory

Modern Portfolio Theory (MPT), introduced by Harry Markowitz in 1952, provided the first coherent framework for investors to approach portfolio construction and risk management. MPT emphasizes the importance of diversification, meaning that investors should be considering multiple assets simultaneously to minimize portfolio variance. However, Markowitz (1952) points out that diversification must be done in a way that makes mathematical sense. To effectively spread risk across assets, investors should select assets with low covariance. According to Markowitz (1952), this is typically achieved by choosing assets from different economic sectors, as they generally have lower covariances compared to assets within the same sector. While effective diversification reduces risk, it cannot eliminate it, since the total risk is two-fold. It consists of systematic risk (market-wide risk) and idiosyncratic risk (asset-specific risk). Diversification can reduce idiosyncratic risk but leaves the portfolio exposed to systematic risk, which cannot be diversified away.

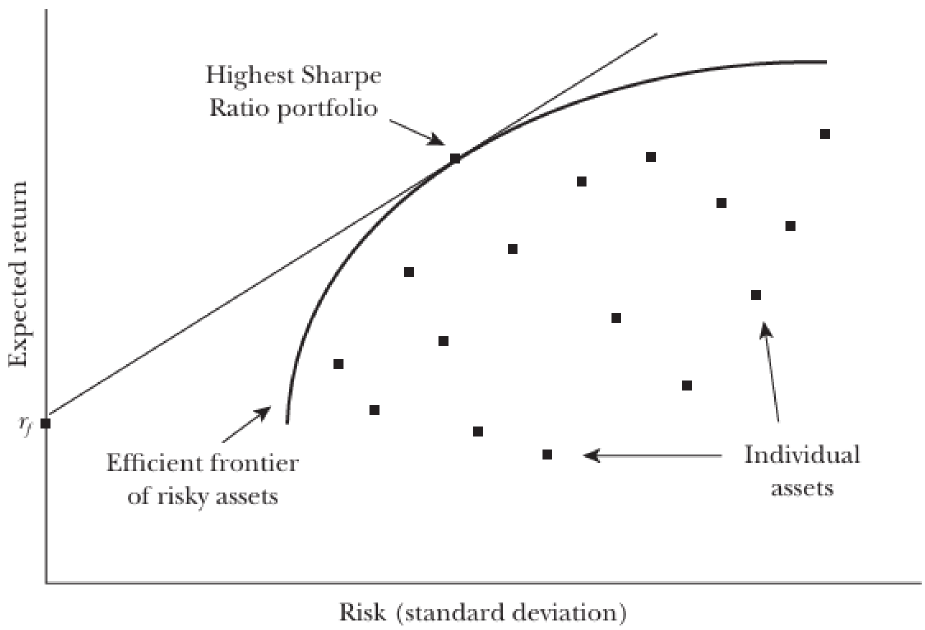

Figure 1. Efficient Frontier with Many Risky Assets (Perold, 2004).

MPT's main concept is the efficient frontier (See Figure 1). The efficient frontier graphically presents optimal portfolios that offer the best risk-return trade-offs. The effectiveness of these optimized portfolios is measured by the Sharpe ratio, which Perold (2004) has graphically demonstrated in Figure 1. According to Markowitz (1952), investors should construct portfolios that position them on the efficient frontier.

3.2 Capital asset pricing model

The Capital Asset Pricing Model (CAPM) was the first structured framework designed to assess the relationship between risk and return on investment (Perold, 2004). Developed over multiple years during the 1960s, Perold (2004) credits the development of the CAPM to William Sharpe, Jack Treynor, John Lintner, and Jan Mossin. CAPM builds on the foundations laid out by Markowitz (1952), by moving into asset-level risk calculations. While Markowitz (1952) managed to prove the effectiveness of diversification on the portfolio level, he did not study the risk-return relationship of individual assets.

CAPM focuses solely on systematic risk to measure asset-level risk. According to Perold (2004), the use of systematic risk is derived from the results of Markowitz (1952), since diversifiable risk should not be seen as an asset-level risk factor. To quantify the risk-return relationship, CAPM uses beta (β) to measure an asset's sensitivity to the market risk. A market portfolio has a beta of 1, while each asset's beta is calculated using the following formula:

$$\beta_i = \frac{Cov(R_i, R_m)}{Var(R_m)} \tag{2}$$

Where $Cov(R_i,R_m)$ is the covariance between an asset and the market, $Var(R_m)$ is the market portfolio's variance and beta illustrates the systematic risk embedded in the asset. Assets with a beta value of over one, are perceived as riskier than the market and vice versa. CAPM is based on the expectation that riskier assets should compensate for the increased risk by offering higher expected returns. The formula for CAPM is presented below:

$$(E)r_i = r_f + \beta_i\big(E(r_m) - r_f\big) \tag{3}$$

Where $E(r_i)$represents the expected return, r_f is the risk-free rate, which is often represented by a government treasury bond yield, β_i is the asset's beta, and $E(r_m)$is the expected return of a market portfolio.

CAPM is still widely used, and it can offer valuable insight into asset pricing, however according to Fama and French (2003) the model suffers from multiple significant drawbacks that lead to its empirical performance being poor. Firstly, CAPM relies on unrealistic market assumptions (Fama & French, 2003). Additionally, on the asset level, CAPM assumes that every investor has access to the same market portfolio (Perold, 2004; Fama & French, 2003). Perold (2004) challenges this assumption, noting that factors like taxes lead to diverse investor behaviours, making a single, universal market portfolio impractical. Fama and French (2003) further argue that the exact composition of the market portfolio is unknown, complicating the calculation of consistent betas across all assets.

3.3 Multifactor modelling

Multifactor models extend single-factor asset pricing models like the CAPM. The assumption for multifactorial approaches is that there is more than just a single risk premium (i.e. beta in CAPM) (Roncalli et al., 2020). Following the introduction of CAPM, researchers identified additional risk factors that significantly improve the explanatory power of asset pricing models beyond what systematic risk alone can capture (Fama & French, 2003). In addition, multifactor models have become the standard approach for analysing transition risk effects on stock returns.

3.3.1 Fama-French three-factor model

Eugene Fama and Kenneth French introduced the Fama-French three-factor model in 1992 as an extension of the CAPM. According to Fama and French (1992), the model extends the CAPM by adding two additional factors that drive returns.

New factors, which try to measure previously unknown risks, are derived from historical data. In their (1992) study, Fama and French found that stocks with high book-to-market ratios (value stocks) generally outperform those with low book-to-market ratios (growth stocks). In addition, they found that small-cap stocks tend to outperform large-cap stocks. In line with their findings, Fama and French (1992) created two new factors that drive returns: Small Minus Big (SMB) and High Minus Low (HML).

The construction of these factors is detailed in Kenneth French's database (French, n.d.). The SMB factor is derived from six portfolios and is calculated as the difference between the average returns of three small-cap portfolios and three large-cap portfolios. The HML factor is based on four portfolios, representing the difference between the returns of two value portfolios and two growth portfolios. In addition, all the portfolios are self-financed by going long on small and value stocks and short on big and growth stocks. The formulas for both factors are presented below:

$$SMB = \frac{1}{3}(Small\ Value + Small\ Neutral + Small\ Growth) - \frac{1}{3}(Big\ Value + Big\ Neutral + Big\ Growth) \tag{4}$$

$$HML = \frac{1}{2}(Small\ Value + Big\ Value) - \frac{1}{2}(Small\ Growth + Big\ Growth) \tag{5}$$

The Fama-French three-factor model expands the Capital asset pricing model by adding the SMB and HML factors to the CAPM, thus the formula for expected portfolio return becomes:

$$r_p - r_f = \alpha + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \varepsilon \quad (6)$$

Where $r_p - r_f$ is the portfolio return excess of the risk-free rate, α is the portfolio's return not explained by the three factors, market risk (CAPM) ($\beta_1(r_m-r_f)$) measures the portfolio's exposure to market risk, and SMB and HML factors capture the portfolio's exposure to size and value effects. The impact of SMB and HML factors is measured by coefficients β_2 and β_3 which represent the portfolio's sensitivities towards these factors. These coefficients can be either positive or negative, depending on whether the portfolio is leaning toward small-cap or large-cap stocks (SMB) and value or growth stocks (HML). Finally, ε is the error term.

3.3.2 Carhart four-factor model

Fama and French's (1992) methodology, which measures risk by forming self-financing portfolios from historical performance data, is widely known and accepted. The authors' groundbreaking work resulted in the creation of additional factors that continued to increase the empirical performance of multifactor models.

Jegadeesh and Titman's study (1993) examined abnormal returns of stocks that had been doing well during the past 3- to 12-months. The authors concluded that trading strategies that focused on buying stocks that had been doing well in the past year known as winners and selling stocks that had been doing poorly in the same timeline known as losers, realized significant abnormal returns. However, the authors also found that the returns from the winner's portfolio significantly decreased when examined for a longer period, eventually, reversing the returns, where the original winners underperform relative to the original losers. Due to the observed return reversal, this anomaly is highly dependent on time.

Mark Carhart introduced the momentum factor in 1997. The momentum factor explains the anomaly observed by Jegadeesh and Titman in 1993 (Carhart, 1997). Carhart constructed the factor by taking the weighted average monthly returns of the top 30% and bottom 30% of stocks lagged by one month. The most recent month is excluded from return calculations to avoid short-term reversal effects, which could distort the momentum signal and obscure the true persistence of past returns (Carhart, 1997). In line with SMB and HML factors, the momentum factor is a self-financing investment by going long on the top 30% of stocks and short on the bottom 30%. The construction of the momentum factor is presented below:

$$MOM_t = AVG_{rW} - AVG_{rL} \tag{7}$$

The Carhart four-factor model is done by including the momentum factor into the Fama-French three-factor model. Here the momentum factor is written as winners minus losers (WML), thus the formula becomes:

$$r_p - r_f = \alpha + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \beta_4(WML) + \varepsilon \tag{8}$$

According to Carhart (1997), the four-factor model explains most of the relative returns he observed. Furthermore, the majority of returns were explained by the SMB and WML factors, demonstrating the importance of the momentum factor in explaining returns.

3.3.3 Fama-French five-factor model

In 2015, Fama and French expanded their original three-factor model due to growing evidence that it could not fully explain the variation in average returns when factoring in profitability and investment (Fama & French, 2015). To increase the model's effectiveness Fama and French (2015) introduced two additional factors: Robust minus weak (RMW) and conservative minus aggressive (CMA). RWM measures profitability, distinguishing firms with high profitability (robust) from those with low profitability (weak). CMA measures investment, differentiating firms with conservative investment strategies from those with aggressive strategies (Fama & French, 2015). The construction of these factors is as follows (Fama & French, 2015; French, n.d.):

$$RMW = \frac{1}{2}(Small\ Robust + Big\ Robust) - \frac{1}{2}(Small\ Weak + Big\ Weak) \quad (9)$$

$$CMA = \frac{1}{2}(Small\ Conservative + Big\ Conservative) - \frac{1}{2}(Small\ Aggressive - Big\ Aggressive) \quad (10)$$

With the addition of the RMW and CMA factors the Fama-French five-factor model can be written as:

$$r_p - r_f = \alpha + \beta_1(r_m - r_f) + \beta_2(SMB) + \beta_3(HML) + \beta_4(\mathrm{RMW}) + \beta_5(\mathrm{CMA}) + \varepsilon \quad (11)$$

An important distinction between Fama and French's five-factor model and Carhart's four-factor model is that Fama and French do not include the established momentum factor in their five-factor model. In addition, when testing the model Fama and French (2015) discovered that the model made the HML factor nearly obsolete. The authors go on to say that this is due to the high correlation between the HML and the other factors in the model. Especially the correlation between CMA and HML was substantial and statistically significant. However, even with significant overlapping between factors, the five-model improved the explainability of cross-section stock returns significantly compared to the original three-factor model.

4 Measuring transition risk

4.1 Multifactorial measuring

Climate change is a twofold risk factor since it carries both transition risks and physical risks. Separating the two risk categories seems easy; however, accurately measuring them is challenging (Barberà-Mariné et al., 2023). This thesis uses one of the most established methods for quantitatively measuring transition risk, which is built upon the groundwork of Fama and French (1992) and Carhart (1997).

4.1.1 Brown-Green-Score

The Brown-Green Score (BGS), developed by Görgen et al. (2019), measures an asset's overall exposure to climate transition risk. To construct the BGS, the authors utilized 55 different variables related to transition risk, sourcing data from four major ESG databases, eventually resulting in a total sample size of 1,637 companies globally. According to the authors, the chosen variables prioritise the environmental aspect of ESG and specifically target the niche of transition risk, thereby excluding any variables related to physical risk. The BGS captures transition risk factors from three distinct perspectives, each weighted according to its relative importance in determining overall transition risk exposure. Venturini (2022) later simplified the BGS into the following formula:

$$BGS_{i,t} = 0{,}70\ Value\ Chain_{i,t} + 0{,}15\ Adaptability_{i,t} + 0{,}15\ Public\ Perception_{i,t} \tag{12}$$

According to Görgen et al. (2019), each of the 55 variables is assigned a value of either zero or one, based on whether the asset is above or below the median value. An average is then calculated from the original 55 variables for each of the three main BGS drivers shown in Eq. 12. Therefore, the BGS fluctuates between zero and one, where zero resembles a green asset with low risk and one resembles a brown asset with significant exposure to transition risk. Venturini (2022) classified the BGS variables as proxies for the three transition risk drivers, value chain for policy risk, adaptability for technology risk, and public perception for consumer preferences. Thus, according to both Venturini (2022) and Görgen et al. (2019), policy risk poses the greatest threat to investors. This may be because investors perceive policy risk as more immediate compared to other transition risks. As Venturini (2022) highlights, many investors view policy risk as a threat that has already begun to materialize.

Görgen et al. (2019) tested the robustness of the BGS and found that its results remained economically consistent on a global scale. However, since their analysis was based on a sample size of only 1,637 companies, there is a notable possibility of sample bias in the data. Additionally, climate policies vary significantly across regions, affecting an asset’s value chain exposure in different ways. These regional disparities could justify adjusting the weightings of transition risk components to reflect evolving climate policy environments. Nonetheless, there is currently no conclusive evidence supporting the need for alternative weight allocations.

4.1.2 Brown-Minus-Green Factor

The Brown-Minus-Green (BMG) factor, introduced by Görgen et al. (2019), measures an asset's sensitivity to transition risk using a factor-based approach. A similar factor, Pollutive-Minus-Clean (PMC), was later developed by Huij et al. (2023). However, the PMC factor relies solely on greenhouse gas emissions to differentiate between green and brown companies, making it a rather one-dimensional measure. In contrast, the BMG factor is derived from the annual brown-green-score (BGS) (Görgen et al., 2019), described in the previous chapter, which provides a more comprehensive measure of transition risk. Unlike PMC, the BGS captures a broader range of transition risk dimensions, offering a more complete dataset across all economic sectors. The construction of both the BMG and PMC factors follow the Fama & French (1993, 2015) methodology, ensuring a robust execution.

To build the BMG factor, assets are classified into four portfolios based on their annual market capitalization. In line with the factors proposed by Fama & French (1993, 2015) and Carhart (1997), the BMG portfolios are self-financing. Görgen et al. (2019) achieve zero-cost portfolios by going long on brown and short on green assets. Thus, the construction formula for the BMG becomes:

$$BMG_t = \frac{1}{2}(Small\ High\ BGS + Big\ High\ BGS) - \frac{1}{2}(Small\ Low\ BGS + Big\ Low\ BGS) \quad (13)$$

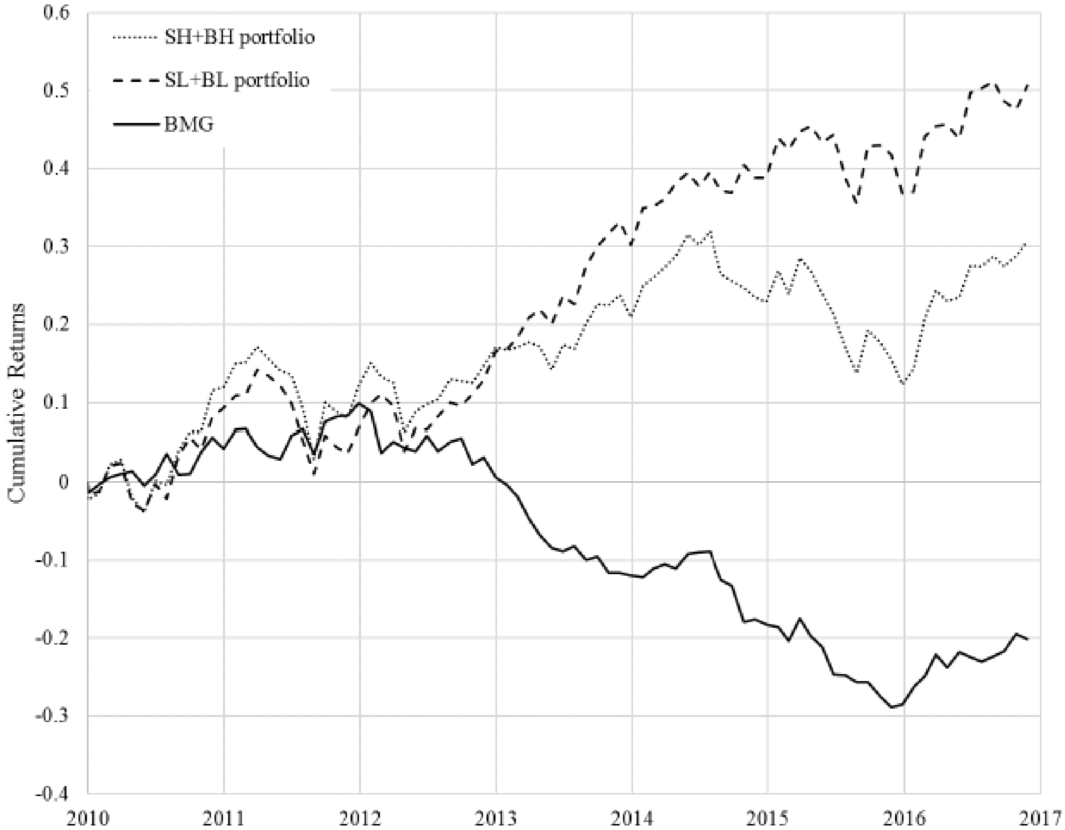

Figure 2. Cumulative returns of BMG and the long and short portfolios. (Görgen et al., 2019).

Görgen et al. (2019) studied the movement of the zero-cost BMG factor from 2010 to 2017 (See Figure 2). Since the authors went long on brown stocks and short on green stocks a negative BMG score means that green stocks outperformed brown stocks during that observation period. Figure 2 shows that in the beginning (2010) the BMG was marginally positive which means that brown firms overperformed green firms. However, from the start of 2013, the factor fell to nearly -30% cumulatively meaning that green firms outperformed brown firms significantly during that period. Finally, in 2016 the BMG slightly increased to -20%, nevertheless, green firms outperformed brown firms on average during the observation period.

4.1.3 Carbon beta

Carbon beta is a market-based measure of an asset’s exposure to transition risk (Huij et al., 2023; Görgen et al., 2019). According to the authors due to its market-based nature, carbon beta captures market-wide expectations about an asset’s exposure to transition risk, reflecting on how investors anticipate and price these risks.

Carbon beta is constructed by running time-series regressions to explain stocks’ excess returns (Görgen et al., 2019). The regressions are done by expanding the Carhart four-factor model (1997) to include the transition risk factor, which in the following formula is the BMG (Görgen et al., 2019; Huij et al., 2023).

$$er_{i,t} = \alpha_i + \beta_i^{mkt} er_{M,t} + \beta_i^{smb} SMB_t + \beta_i^{hml} HML_t + \beta_i^{wml} WML_t + \beta_i^{BMG} BMG_t + \varepsilon_{i,t} \tag{14}$$

Carbon beta is described in Eq. (9) as β_i^{BMG} and it describes an asset’s sensitivity to the BMG factor. Carbon beta can take either positive or negative values, where positive values represent brown assets and vice versa (Görgen et al., 2019). Carbon beta's distinctive feature is its applicability across all asset classes, enabling transition risk measurement even where traditional climate metrics are unavailable (Huij et al., 2023). Görgen et al. (2019) successfully calculated carbon betas for over 39,000 companies worldwide, expanding from the original BGS sample of 1,637 companies, thus demonstrating the method's effectiveness.

Görgen et al. (2019) ran a regression test where they compared the BMG to other commonly used risk factors, which were described in chapter three, and found no significant correlations, thus demonstrating its unique explanatory power in relation to stock performance. Additionally, the authors found that the inclusion of the BMG factor enhanced the explanatory rates of traditional factor models, further supporting its utility in capturing transition risk and its effect on stock returns. Furthermore, these results were later tested by (Roncalli et al., 2020), who ran a Fischer test on three different significance levels, confirming the original results. The findings of Görgen et al. (2019) and Roncalli et al. (2020) are in line with H_1, confirming the hypothesis that transition risk has been a previously unknown risk factor that can explain stock returns.

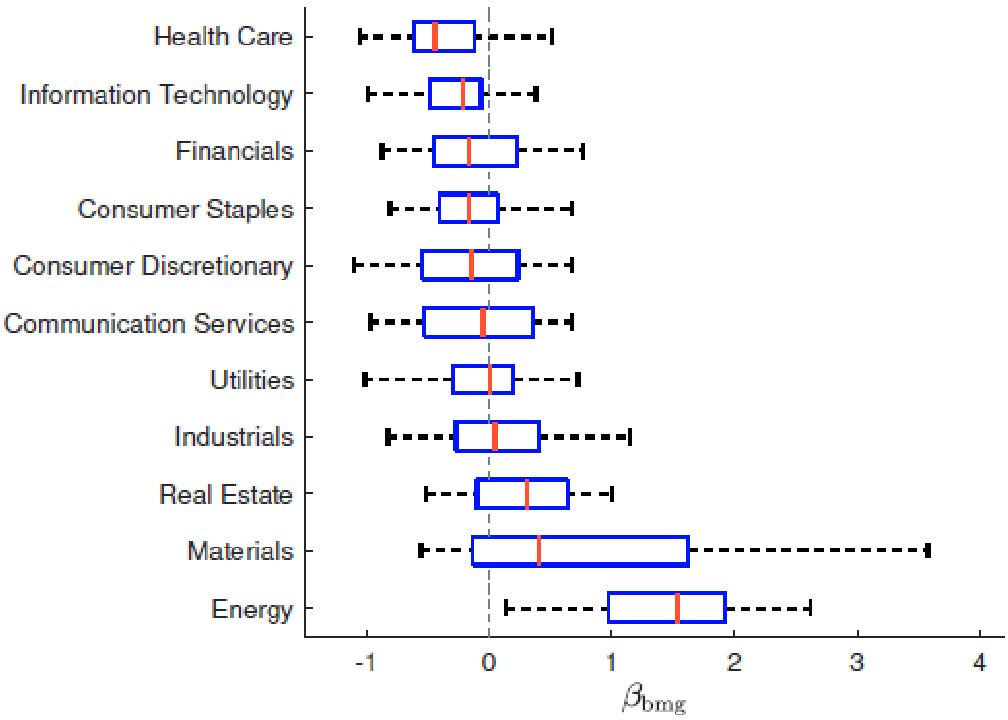

Figure 3. Box plots of the carbon sensitivities (Roncalli et al., 2020).

Figure 3. presents carbon beta estimation results divided into different economic sectors (Roncalli et al., 2020). The authors constructed the graph to show the median, quartiles, and the top and bottom 5% carbon betas across eleven sectors. As expected, the sectors with the highest GHG emissions, those being energy and materials, also display the

highest carbon betas and thus are the most vulnerable to transition risks. High carbon beta sectors are likely to encounter the problem of assets becoming stranded (Görgen et al., 2019), implying that because of the shift to a low-carbon economy, their assets become obsolete, and they cannot capitalize on their previous value. Andersson et al. (2018) approximated that to reach the objectives of the Paris Agreement, half of the known remaining oil and natural gas reserves can never be used. According to Carattini et al. (2023) asset stranding leads to the partial or complete loss of their value. Furthermore, according to Andersson et al. (2018), many investors are unaware of the likelihood of their assets becoming stranded.

In addition to sectoral fluctuations, Görgen et al. (2019) identified significant regional differences in carbon betas, noting that Europe and Japan were the only regions with negative carbon betas. These findings align with Barberà-Mariné et al. (2023), Reboredo and Ugolini (2022), and Birindelli et al. (2023), who highlight the regions' strict climate policies. However, Roncalli et al. (2020) argue that even ambitious climate targets have limited short-term impact on carbon betas, often due to the non-binding nature of climate-related agreements. This suggests that alternative factors may also contribute to low carbon betas alongside strict policies.

4.2 Climate policy uncertainty index

Thus far all measurements have been single asset or portfolio level measurements of transition risk exposure. As it has been shown previously by Görgen et al. (2019) and Venturini (2022) policy risk is the most significant of the risk drivers. To be able to measure the overall macro-environment surrounding climate policy, Gavriilidis (2021) developed the climate policy uncertainty (CPU) index. The CPU index was constructed following a methodology first proposed by Engle et al. (2020), who created the Climate change news (CCN) index. Engle et al. (2020) constructed the CCN index by calculating the correlation between climate change-related words used in The Wall Street Journal and a fixed climate change vocabulary, which they obtained from different government and research publications.

CCN index relied on the assumption that when climate change is big on the news, the news is negative or pessimistic in tone (Engle et al. 2020). Moreover, the authors included all possible news related to climate change, thus including physical risks such as natural disasters and extreme temperatures that do not directly relate to transition risk. Gavriilidis (2021) constructed the CPU index from eight newspapers, thus obtaining greater overall coverage and reducing plausible sample bias within the data used by Engle et al. (2020). Furthermore, Gavriilidis (2021) limited the CPU index to only consider news that could introduce policy uncertainty, thus cutting out physical risks. To ensure that both the CCN and CPU indexes succeed in measuring their intended targets, Gavriilidis (2021) calculated the correlation between the two and found the correlation to be only 0,41. Low correlation helped to further enhance the robustness of the CPU methodology, thus creating confidence in its ability to effectively measure macro-level movements within the biggest transition risk driver.

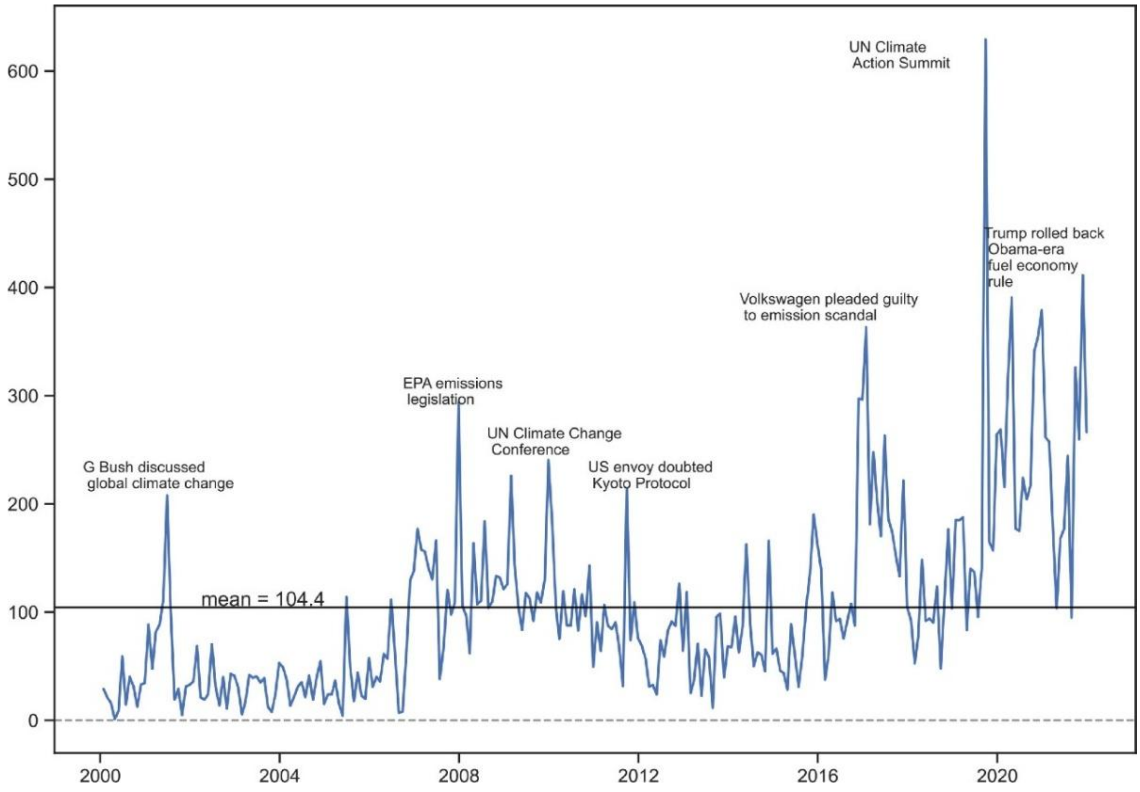

Figure 4. Climate policy uncertainty (CPU) index (Treepongkaruna et al., 2023).

Figure 4. visually details the movement of the CPU index during the last twenty years. There were multiple times when the index spiked notably high. Gavriilidis (2021) developed the index to account for all uncertainties, whether positive or negative, as even news seen as favourable for climate change mitigation can negatively affect certain (brown) stocks, and vice versa.

However, even with a proven and strong empirical record of the CPU, it is important to note the one significant shortcoming of the index, which is its regional bias. Since the index is constructed solely from US-based newspapers its applicability globally still requires more empirical evidence.

5 Transition risk in portfolio management

In the previous chapter, Görgen et al. (2019), Roncalli et al. (2020), and Huij et al. (2023), provided evidence confirming H_1, revealing that transition risk is a previously unaccounted-for factor that can, at times, significantly impact stock returns. To determine whether investors can benefit from integrating transition risk into their portfolios and management strategies, it is essential to evaluate risk-adjusted returns. According to MPT (Markowitz, 1952), higher risk-adjusted returns indicate superior portfolio performance.

5.1 Return disparity: Green & brown stocks

Portfolio's risk-adjusted performance is calculated using the Sharpe ratio, which was briefly discussed in chapter 3.1. The portfolios that lie on the MPT's efficient frontier achieve better Sharpe ratios (See Figure 1). Sharpe ratio is calculated as follows:

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{15}$$

Where R_p is the portfolio return, R_f is the risk-free rate, and σ_p is the portfolio's standard deviation, also known as portfolio volatility. As shown by Eq. 15, the Sharpe ratio can increase even if returns decrease, if volatility decreases simultaneously.

Barberà-Mariné et al. (2023) found a negative correlation between carbon intensity and stock returns, indicating that firms with high carbon footprints tend to underperform compared to those with lower emissions. Their findings align with those of Reboredo and Ugolini (2022), who discovered that stocks with low transition risk exposure yielded higher returns than those with high exposure. However, they also identified a significant disparity between returns in the US and Europe. While the overall performance patterns were similar, the green stock overperformance was notably stronger in Europe.

According to the authors, this is due to US stocks being insensitive to transition risk, except in the most extreme cases. The authors suggest that the disparity between these sensitivities could be due to investor behaviour, where in Europe, investors are much more likely to price transition risk in their decision-making compared to the US.

Dutta et al. (2023) incorporated the climate policy uncertainty index, described in chapter 4.2, and studied its effect on the energy sector. As previously shown by Görgen et al. (2019) and Roncalli et al. (2020), the energy sector has the highest carbon beta, making it the most volatile when transition risk intensifies. According to Dutta et al. (2023), an increase in CPU leads to higher returns and lower volatility for green energy companies, thus enhancing their Sharpe ratios. Their results support the notion studied by Yousaf et al. (2022), that investors seek safer assets (i.e. safe havens) when uncertainty rises. These findings reinforce the arguments made by Venturini (2022) and Görgen et al. (2019) regarding the role of policy risk as the most significant transition risk driver.

The performance of green stocks is also linked to the prominence of climate change in news and public discourse. Monasterolo and De Angelis (2020) found that risk-adjusted returns of green assets surged following the Paris Agreement in 2015. Their findings are supported by Bua et al. (2022), who examined the same concepts while limiting their study to Europe. Bua et al. (2022) also discovered that brown stocks outperformed green stocks before 2015, however, the relationship turned after the Paris Agreement. The authors found exceptionally high returns from green stocks, a result that other studies have generally reported as moderate and have been unable to confirm the abnormally high results. As shown previously, during the last decade, green stocks have consistently outperformed brown stocks on a risk-adjusted basis. These findings support H_2, by providing evidence that abnormal returns are easier to achieve by allocating funds into green stocks.

In contrast to the previous findings, Bolton and Kacperczyk (2021) find no significant relation between carbon intensity and stock returns at any point in time, even after the

Paris Agreement. However, they acknowledge the difficulty of accurately measuring return correlations due to the inherent noisiness of these returns. Furthermore, they conclude that their methodology of known risk factors and variables such as industry could explain these contrary findings. Despite this opposing evidence, the majority of studies consistently report higher returns and notably lower volatility for green stocks.

5.2 Efficient management strategies

Investors have ranked climate change as the fifth most important risk (Venturini, 2022). Due to the growing impact of transition risk, effective management strategies are needed to retain the portfolio efficiency while simultaneously reducing the exposure to transition risk. As previously mentioned, equity is the worst asset class in relation to transition risk, so how can equity portfolios be managed effectively?

According to Crisóstomo (2022), surprisingly the best green equities are also one of the most resilient towards transition risk. However, Andersson et al. (2018) caution against constructing purely green portfolios, arguing that such strategies often lack sectoral diversification and, as a result, are unlikely to achieve risk-adjusted returns on the efficient frontier.

Roncalli et al. (2020) proposed three management strategies that rely on the solid integration of transition risk. The strategies they present are factor investing, the minimum variance strategy, and the enhanced index portfolio. The authors based these strategies on the assumption that investors are often interested solely in long portfolios.

The factor investing strategy can be effectively implemented using a best-in-class categorization approach (Görgen et al., 2019). By integrating the Fama-French three-factor model with the BMG factor, Görgen et al. (2019) identified optimal risk sensitivities that significantly reduced portfolio volatility, with only a slight decline in average returns. Importantly, the reduction in volatility outweighed the modest decrease in returns, resulting in an overall improvement in the portfolio's risk-adjusted performance. However, even with these results Roncalli et al. (2020) argue that the BMG factor is too specific to be seen as a new risk factor, even though it has been proven to enhance the explainability of the factor models. According to the authors, BMG could better be utilized in defining the minimum variance strategy. Thus Roncalli et al. (2020) endorse the use of the minimum variance strategy and the enhanced portfolio strategy to capture transition risk-related returns.

The minimum variance strategy is derived from Markowitz’s (1952) MPT and the CAPM. According to the authors, the objective is to minimize unwanted risk. According to Roncalli et al. (2020), decreasing the carbon beta (the portfolio’s sensitivity to the Brown-Minus-Green (BMG) factor) is crucial for mitigating carbon risk. This is achieved by shifting allocation toward greener stocks to eliminate all possible extra volatility.

The enhanced portfolio index strategy is built to manage a known index but to modify (lower) its exposure to transition risk. Roncalli et al. (2020) point out that the optimization of the portfolio could be challenging in the short term. They note that if investors shift assets into low BMG stocks and the BMG factor performs positively in the short term, the portfolio could significantly underperform the benchmark index. Therefore, Andersson et al. (2018) suggest this strategy to be executed by passive and long-term investors to minimize the effect of the aforementioned short-term shock, as well as save money in transaction costs. The authors found that correctly executing the strategy produced significantly lower volatility, without compromising returns. The findings are in line with Görgen et al. (2019) multifactor results.

All the effective strategies discussed in this chapter enhance risk-adjusted returns, thus supporting the asset-level findings in chapter 5.1 and confirming H_2: Investors who incorporate transition risk into equity portfolio management strategies achieve better risk-adjusted returns.

6 Conclusions

This thesis explored the complexities of measuring transition risks and their implications for equity portfolio management. This research focused on evaluating established financial models alongside emerging climate risk metrics. The hypotheses were drawn from established theoretical frameworks and answered through the findings of recent studies.

The findings of this study confirm that transition risk has become a significant risk factor, that has been previously unexplored risk influencing stock returns. The integration of the BMG factor and carbon beta into multifactor models, such as the Fama-French and Carhart frameworks, enhances the explanatory power of these models, providing investors with deeper insights into their risk exposure. Additionally, as expected, differences in policies and overall knowledge of climate change differ regionally and so do the risk factor sensitivities. The CPU index assists in understanding the macro-environment that relates to the three transition risk drivers of policy risk, technology risk, and preference change.

With investors having access to these new risk metrics, they can more effectively adapt to transition risks. When studying stock returns, it was observed that in general green stocks tend to outperform brown stocks. This disparity grows significantly during times of uncertainty as measured by the CPU index. For investors, the dominant portfolio management strategy ended up being long-term investing with a portfolio that is tilted towards green stocks (i.e. portfolio displays negative carbon beta) to minimize transaction costs and benefit from the overall lower volatility that is empirically proven to be connected to green stocks. With these proven results, investors should consider integrating transition risk into their management strategies. As demonstrated in Chapter 5.2, there are multiple effective approaches to incorporating transition risk, allowing investors with diverse goals and portfolio construction strategies to benefit.

Future research should focus on developing the transition risk measures outlined in this thesis. Their usability could be increased by studying different economic regions, where regulatory environments, cultural factors, and economic structures do not stay the same. Solid empirical evidence could lead to the refinement of these methodologies and thus improve on their accuracy and explainability.

Additionally, climate finance and the understanding of the risk related to climate change is still a relatively new field of study. A comprehensive exploration of the long-term performance of green and brown assets and portfolios would help to mitigate any impact of economic cycles and other unwanted anomalies that could disrupt the overall findings. Moreover, as the deadlines for the decarbonization of the economy are closing in, both regionally and globally it would be interesting to see whether green assets get more of a boost compared to brown assets. Finally, incorporating more qualitative measurement factors, for example EU's CSRD reporting standard would help the overall robustness of these studies.

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