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SUSTAINABLE INVESTING IN EMERGING MARKETS

CARBON RISK IN BRAZIL

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Abstract

As demand for sustainable investments continues to grow, asset managers are increasingly looking for ways to incorporate environmental, social and governance (ESG) factors into their investment strategies. However, sustainable investing in emerging markets has yet to reach its full potential. A lack of available ESG data and inconsistencies among ratings present significant challenges. With the aim of bridging the gap, this paper explores a capital market-based approach to integrate ESG aspects into portfolio management on the example of Brazil and Africa. Estimating different ESG factor betas of the stocks enables the construction of portfolios with high exposure to good ESG practices. The analysis shows that the performance of portfolios varies with the ESG factors as well as the geographic regions. None of the African portfolios with high exposure to an assessed factor outperformed the benchmark. In Brazil, the portfolio with a high exposure to factor G (governance) and ESG (MSCI ESG rating) presented a better risk-adjusted performance than the benchmark.

Keywords: ESG investing, portfolio construction, emerging markets, Brazil, Africa, climate finance, sustainable investing.

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Table of Contents

List of Figures

List of Tables

1. Introduction

Increased awareness of climate change has played a major role in raising the issue of sustainability to the top of the agenda for investors, companies, and policymakers (Kerber and Jessop 2021). Companies around the world face increasing pressure to act responsibly and the incorporation of non-financial information, including environmental, social, and governance (ESG) data has become a major trend in portfolio management. The high number of ESG funds, newly developed industry standards, and ESG indices are testimony to this growing interest among financial market participants. Among the best-known examples of this surge in sustainable investing are the United Nations Principles for Responsible Investing (PRI 2021). With more than 4,000 PRI signatories from over 60 countries, these participating financial institutions have over USD 120 trillion in assets under management in 2021 (PRI 2021). It shows that investors are adapting to a changing regulatory environment and customer base by focusing on the sustainability and longevity of investments.

While ESG investing is a global trend, around 80% of the global sustainable investing assets are from the United States or Europe (GSIA 2021). However, in 2021 emerging markets experienced a surge that increased their sustainable assets market share (Gautam et al. 2022). Even if emerging markets are considered the engine of this century's global growth, they are still facing considerable challenges ranging from poverty and pollution to corruption and diseases (Odell and Ali 2016, 96). It is precisely because of these challenges inherent in emerging markets that the integration of ESG criteria is an even greater imperative. A metastudy considering more than 2000 research papers on ESG and its impact on financial performance confirmed that ESG factors are even more relevant in emerging markets (Friede, Busch and Bassen 2015, 210). Generally, investments in emerging market equities are associated with 14.2% higher unmanaged ESG risk compared to developed market equities (Sustainalytics 2019). Nonetheless, EM investors lag in incorporating sustainability into their investment process compared to developed markets. Among the reasons thwarting investors include a lack of available ESG data and disclosure but also nascent capital markets and corporate ownership structures (Odell and Ali 2016, 96). With the aim of bridging this information gap, this thesis explores a capital market-based approach to integrate ESG aspects into portfolio management in the example of Brazil and Africa. Computing different ESG factor betas of individual stocks enables the creation of a portfolio with high exposure to good ESG practices without having to exclude companies that do not disclose sufficient non-financial information.

2. Literature Analysis

2.1. ESG in Emerging Markets

It does not come as a surprise that the economic and financial conditions across countries and regions are vastly different (Claessens and Yurtoglu 2013, 6). Emerging markets (EM) present interesting opportunities, but investors need to be aware that companies in EM operate in an environment characterized by a variety of environmental, social, and governance challenges (Odell and Ali 2016, 101). The following subchapters provide an overview of the differences between emerging and developed markets in terms of ESG aspects. This adds to understanding the complexity and the challenges of integrating ESG into the investment strategy in Africa and Brazil.

Environmental Criteria

The E in ESG stands for environmental criteria and includes greenhouse gas emissions, air and water pollution, impact on the environment, and awareness of climate change and population growth (Johnson 2020, 337). To go a bit more into detail, this includes waste management, resource scarcity, deforestation, sustainable land use, nuclear energy, and energy efficiency (Johnson 2020, 337). The environmental aspects are particularly important for frontier markets and emerging economies, as they are among the countries most exposed to the effects of climate change, resource scarcity, and severe local pollution (Odell and Ali 2016, 96). Extreme weather events caused by climate change are increasing in severity and frequency. Both regions considered in the research paper (Brazil and Africa) are among the most affected concerning flooding, typhoons, and droughts. Regarding resource scarcity, both the rising incomes and the rapidly growing population in emerging markets are intensifying the demand for resources. In

2050, the demand for food will be 60% higher than in 2016, and the global population is expected to exceed 9 billion people (Hutt 2016). Emerging Markets are among the most vulnerable to food and water stress. They have also shown a surge in demand for energy. The recent years have been marked by a shift towards sustainable energy due to external pressure from international organizations and foreign investors (Paramati, Ummalla and Apergis 2016, 40).

Social Criteria

The Social aspect of ESG covers how companies are managing their internal and external stakeholders such as employees, customers, suppliers, and communities affected by their operations (Johnson, 2020, p.337). Just to name some examples, this includes health and safety conditions for the workers, labor standards, employee relations, working conditions, human rights, supply chain standards, data security, and consumer privacy (Chauhan and Kumar 2018, 36).

Social issues in emerging markets are often a major concern for investors, who fear that inconsistent regulatory systems and weak institutions will lead to problems in the areas mentioned above. Especially consumer protection, employee exploitation, human rights abuses, and poor community relations are the areas of concern (Odell and Ali 2016, 97).

Poor working conditions, exploitative labor practices, and human rights abuses pose significant ESG risks associated with exposure to emerging markets. Investors must conduct thorough on-site inspections and due diligence checks regularly to put pressure on companies to improve these conditions. According to Hay (2020), it is better to engage with the company and relevant stakeholders than to abandon the investment altogether (Hay 2020).

Governance Criteria

The G in ESG stands for governance and concerns a firm's leadership, disclosure and audits, accounting, executive pay, board composition, gender balance, diversity, alignment of interest and ownership, cybersecurity, risk management, shareholder rights, anti-corruption, and bribery (Chauhan and Kumar 2018, 36). Corporate Governance has gained traction in recent years. This was due to the financial crises that erupted in Brazil, Russia, and Asia in 1998, triggered by poor corporate governance, which had far-reaching effects on major economies and threatened global financial stability (Claessens and Yurtoglu 2013, 2). Emerging Markets have significantly lower levels of disclosure and governance standards (Odell and Ali 2016, 97). Issues related to corporate governance are inherently different from developed markets. Reasons include restricted access to capital, low institutional ownership, and concentrated ownership structures (Claessens and Yurtoglu 2013, 3).

Both investors and local firms face vastly different challenges concerning governance in emerging markets. Odell and Ali (2016, 100) point out, that emerging markets are not necessarily suited for western-style shareholder activism due to sometimes insufficiently developed regulatory institutions. Companies in emerging markets are often owned by majority shareholders, including families and governments, making aggressive activism ineffective. The authors Odell and Ali (2016, 100) suggest that other approaches that are focused on collaboration are more suitable and successful in such environments.

2.2. ESG Data Availability and Quality

The previous paragraphs elaborated on the different realities and different challenges that firms are facing in emerging markets. Evidently, this results in differences that also translate into ESG ratings. Companies operating in emerging markets tend to lower ESG ratings in a global comparison. An additional weight on the ratings is the lack of information. Historically, the level of disclosure in emerging markets has been much lower, and this lack of transparency complicates ESG assessments (Khanna and Palepu 2000, 869). However, there have been improvements made regarding transparency due to updated listing requirements and policy changes. An increasing amount of stock exchanges in EM are joining the United Nations Sustainable Stock Exchange Initiate (SSE), which is an initiative that fosters disclosure on social and environmental issues as well as governance reporting standards. Brazil for example introduces corporate governance codes (Viegas 2007). Insufficient disclosure remains prevalent, and it negatively affects not only the ratings but also a company's valuation and cost of capital (Chauhan and Kumar 2018, 33-34).

Regarding the quality of the ratings, it should be noted that several studies have shown significant divergences between the ESG ratings of different agencies (Chatterji, Durand, Levine and Touboul 2015, 1597). An extreme example was pointed out by the Financial Times author Allen (2018), who describes that in 2016 Tesla was placed last by FTSE among automotive companies, while it ranked in the top 10 in the MSCI ratings and Sustainalytics located Tesla somewhere around the average. This shows that even if third-party ESG ratings are available for a company, an investment decision should take other sources of ESG information into account.

3. Theoretical Foundation

To understand the methodology being used to build the ESG portfolios, it is essential to understand the underlying theory of the Modern Portfolio Theory (MPT) and its evolution to factor models.

3.1. Capital Asset Pricing Model

The Capital Asset Pricing Model that originated in the 1960s is the most fundamental theory in asset management and therefore factor theory. The CAPM is based on MPT and the portfolio selection principles described by Markowitz (1952) and it explains the relationship between the expected return of an asset and market risk. It was first studied by Sharpe (1964) with the following formula:

$$R_i(t) = \alpha_i + \beta_{mkt,i} R_{mkt}(t) + \varepsilon_i(t) \tag{1}$$

$R_i(t)$ stands for the return of asset i and α_i is the alpha of the same asset. $R_{mkt}(t)$ stands for the return of the market and $\beta_{mkt,i}$ is the market beta or the systematic risk of stock i while $\varepsilon_i(t)$ stands for the idiosyncratic risk. The author Ang (2014) characterizes it as the first model that considers asset risk in comparison to other assets instead of looking at the risk in isolation. In other words, instead of taking the volatility of an asset as the risk of this investment, the risk takes into account how an asset covaries with the market, which is the market beta. The market beta is the systematic risk that cannot be diversified away (Zaher 2019, 16). As a result, the CAPM implies that an asset's expected return is a function of market risk. Although empirical studies show that the CAPM only partially explains the risk premium of an asset, the model is still relevant in asset management practice and research (Ang 2014, 195). Especially the premise, that the risk premium of an asset represents compensation for losses investors experience in “bad times” and that the risk premium is shaped by the underlying factors (Ang 2014, 197) is deeply embedded in modern factor theory.

3.2. Arbitrage Pricing Theory

In 1976, Stephen Ross published the Arbitrage Pricing Theory building upon the CAPM. It set the base for a multi-factor approach to explaining the relationship between risk and return of an asset. This already indicates that the risk premium is not only based on the market factor but can be influenced by several factors. Like the market beta, the other factors introduced by APT cannot be hedged by diversification or arbitrage. Following the argumentation of the APT, downtimes are not associated with a recession in the overall market but are determined by the individual factor itself. Also, the risk premium is factor specific. The factor-beta is the exposure of an asset to a variable (Ang 2014, 203-207). Stephen Ross (1976) named several macroeconomic factors such as inflation, exchange rate, and economic growth, but he did not define a set of specific factors. Chen, Roll and Ross (1986) identified four macroeconomic factors that influence the stock market and significantly explain the risk-return relationship of assets: economic growth, interest rates, inflation, and the yield curve. These factors affecting the asset premium have crossed the threshold from theory to practice. Nowadays, the focus shifted away from the market factor and the macroeconomic factors towards so-called style factors, which are factors within asset classes (Koedijk, Slager and Stork 2016, 195-196).

3.3. Fama and French Three-Factor Model

The best-known factors were introduced by Fama and French in 1992. They showed that the stock returns of US equities between 1963 and 1990 could be predominantly explained by two factors in addition to the market factor. On the one hand, they introduced the size factor, which shows that small-cap stocks tend to outperform stocks with large market capitalization. This effect is captured by a mimicking portfolio that is constructed by a long position in the stock portfolio with high loadings to the chosen factor and a short position for the opposite (Asgharian 2004, 2). For this reason, the size factor is referred to as small minus big (SMB). On the other hand, they added the book-to-market ratio, which is mostly called the value factor. This factor reflects that value stocks on average outperform growth stocks (Investopedia, 2022). The factor is often referred to as the high minus low factor (HML). With their three-factor model, Fama and French (1993) introduced the next significant step in factor theory. It was the first time that style factors (rather than macroeconomic factors) successfully explained U.S. stock returns (Ang 2014, 227). In the formula, the size factor is represented by the variable R_{smb} (t) while $\beta_{smb,i}$ is the size beta or the sensitivity of the asset i. R_{hml} (t) is the value factor and $\beta_{hml,i}$ is the value beta.

$$R_i (t) = \alpha_i + \beta_{mkt,i} R_{mkt} (t) + \beta_{smb,i} R_{smb} (t) + \beta_{hml,i} R_{hml} (t) + \varepsilon_i (t) \quad (2)$$

In 1997, the three-factor model was extended by Carhart (1997) with the momentum (MOM) factor which is also called the winners minus losers factor (WML). The factor captures the tendency of stocks to move in the same direction as they used to in their previous history. In the formula R_{wml} (t) is the return of the new factor while β_{wml} is the momentum sensitivity of stock i.

$$R_i (t) = \alpha_i + \beta_{mkt,i} R_{mkt} (t) + \beta_{smb,i} R_{smb} (t) + \beta_{hml,i} R_{hml} (t) + \beta_{wml,i} R_{wml} (t) + \varepsilon_i (t) \quad (3)$$

This four-factor model has led to extensive empirical evidence and retains its legitimacy in academia and practice. Since then, few theories that fundamentally alter the model have been published. Instead, science is much more concerned with the study of specific factors than with the basic determinants of factor theory (Leippold and Rueegg 2020).

4. Methodology

4.1. Beta Estimation

A major difficulty in integrating ESG into portfolio construction is the quality and consistency of ESG ratings and the lack of disclosure by the firms. This is an even bigger problem in emerging countries with less legislation setting disclosure standards. To deal with this issue, this analysis follows a market-based approach (Gören, Jacob and Nerlinger 2020). By running OLS regressions of the returns of individual firms on an ESG factor, firms with positive loadings on the factor can be distinguished from firms with negative loadings, which are considered “bad” ESG companies. Due to the data intensity associated with running the monthly regression for the returns of more than 300 stocks, the analysis was performed using python. BPI Asset Management provided their African and Brazilian Stock universe containing 270 and 56 equities respectively of publicly traded companies in this geographic area. Different ESG portfolios were constructed using three different factors as ESG proxies as described in the subsequent paragraphs.

Factor G

With ESG being an umbrella term, proxies were considered to capture different aspects of ESG. The first factor used focuses on governance and was created by the authors Pedersen, Fitzgibbons, and Pomorski (2021). The foundation of creating the factor comes from the accounting literature that states that low accruals indicate a conservative accounting approach which is adopted by better-governed companies (Kim, Park and Wier 2012, 2). In accounting, accruals are referred to as income for which the firms have not yet received the associated cash. According to research (Sloan 1996) companies tend to have noticeably large accruals prior to becoming the subject of SEC enforcement actions. The SEC (U.S. Securities and Exchange

Commission) Division of Enforcement investigates possible violations such as accounting violations, insider trading, and foreign bribery. According to Sloan (1996), firms with high accruals are also more likely to restate earnings. The companies' accruals over assets are used to classify the firm into 5 categories, ranging from high accruals (G1) to low accruals (G5). A long-short portfolio is created by calculating G5-G1. In other words, the factor G reflects the excess returns by taking the returns of companies with good governance minus the excess returns of companies with bad governance. The monthly factor G beta is estimated by running the regression below, where R_i (t) stands for the return of stock i, the alpha of the asset i is α_i. R_g (t) is the return of the G factor and $\beta_{g,i}$ is the G sensitivity or exposure of the stock i to good governance. Finally, ε_i (t) stands for the idiosyncratic risk.

$$R_i (t) = \alpha_i + \beta_{g,i} R_g (t) + \varepsilon_i (t) \tag{4}$$

Factor E

The second factor was created by the same authors as factor G and the E stands for the Environment aspect of ESG (Pedersen, Fitzgibbons, and Pomorski 2021). As a proxy, the authors used the company's carbon intensity, which is calculated by dividing a company's carbon emissions by its revenue. To be more precise, only the firm's direct emissions (scope 1) and scope 2 emissions are taken into account. Scope 2 refers to indirect emissions that result from purchasing energy. Other indirect emissions (scope 3) are difficult to measure, seldomly reported, and therefore not included. The authors (Pedersen, Fitzgibbons, and Pomorski 2019) accessed relevant data through Trucost. Similar to factor G, the authors created five categories ranging from high emissions (E1) to low CO2 emissions (E5). The factor of this long-short portfolio is the result of subtracting the excess returns of the low-emission firms from those of high-emission firms (E5-E1). The monthly factor E beta is estimated by running the following regression where R_e (t) is the return of the E factor and $\beta_{e,i}$ is the E sensitivity of the asset i.

$$R_i\,(t) = \alpha_i + \beta_{e,i}\, R_e\,(t) + \varepsilon_i\,(t) \tag{5}$$

Factor S

The third factor, also created by the same authors as factor G and E, stands for the social aspect of ESG. More specifically, this measure is a non-sin stock indicator: it gives a value of zero for sin stocks and a value of one for non-sin stocks. Higher values result in better ESG. Sin industries, as defined by Hong and Kacperczyk (2009, 16), include for example tobacco, gambling and alcohol. The factor is derived by the difference between the excess return of going long on non-sin stocks (S2) and going short on sin stocks (S1). Just like for the previous factors, the factor E beta is estimated by running the following regression where R_s (t) is the return of the S factor and $\beta_{s,i}$ is the sensitivity or exposure of the asset i to factor S.

$$R_i\,(t) = \alpha_i + \beta_{s,i}\, R_s\,(t) + \varepsilon_i\,(t) \tag{6}$$

Factor ESG

The ESG Factor tries to incorporate the above-described Factors into one. As a proxy, the authors use the widely used MSCI ESG scores that try to incorporate all aspects of ESG. Just like previously explained, they create five categories and receive the excess return by calculating ESG5 (high ratings) – ESG1 (low ratings). The same regression is run, where R_{esg} (t) is the return of the ESG factor and $\beta_{esg,i}$ is the ESG sensitivity of the stock i.

$$R_i\,(t) = \alpha_i + \beta_{esg,i}\, Resg\,(t) + \varepsilon_i\,(t) \tag{7}$$

Monthly OLS Regressions

The stocks' monthly historical stock prices were retrieved from Bloomberg reaching back until January 2010. The arithmetic returns are calculated based on the adjusted closing price. As some companies are only listed at a later point in time, not all the stocks have data starting in 2010. The following paragraphs will clarify how this is taken into account. Since the factors computed by the authors Pedersen, Fitzgibbons, and Pomorski (2019) provide data until March 2019, the monthly beta calculations start in January 2015 and end in April 2019. This allows for a burn-in period of five years (January 2010 – December 2015) and leaves four years and three months to calculate the coefficients. As previously mentioned, data for some stocks is only available at a later point in the time series. The coefficient is only computed once a stock has data available for at least twelve months. Once the stock passed this threshold, the monthly coefficients are estimated by running an OLS regression of the stocks return on the excess return of the respective factor, as described in the previous subchapter. The output of the first Python notebook is a data frame containing the months as the index, the company ticker as column heads, and their respective coefficients in the rows.

The coefficients of factor G indicate the extent to which the company has exposure to good corporate governance. To express it more intuitively, the higher the coefficient, the better the corporate governance compared to other companies. The purpose of the second python notebook is to construct different portfolios building on the computed coefficients and to calculate their monthly returns. With the overarching goal of integrating ESG into the portfolio, the coefficients are sorted from highest to lowest for each month. For the Mean Portfolio G Top, the top tercile with the highest betas is selected for each month. More precisely, the top tercile of available betas is selected. As more data becomes available over time, the number of stocks that make up the portfolio increases. The next subchapter provides an overview of the portfolios and how they are constructed. After selecting the stocks for each portfolio, they are matched with their respective returns to calculate the monthly portfolio returns. All the steps explained in the example of factor G are repeated for the other factors. The final part of the analysis is comparing the portfolios in a risk-adjusted and holistic matter by applying different metrics. This examination includes measuring cumulative returns, the Sharpe Ratio, Maximum Drawdown, the Conditional Value at Risk, Skewness, and Kurtosis.

4.2. Portfolio Construction

Mean Universe Portfolio

The Mean Universe Portfolios include all the stocks provided by BPI Asset Management for their Brazilian and African Investment Universe. They are used as a benchmark to see how the integration of ESG through exposure to a chosen factor impacts the risk-adjusted returns of a portfolio. For Brazil, a total of 56 stocks are included towards the end of the analyzed timeframe. For Africa, the universe includes a total of 272 stocks of companies from different countries, with Morocco-listed companies accounting for the largest number, followed by Kenya and South Africa. Some companies were not publicly traded in 2015, whereas others became listed companies after 2019. For example, the health care and diagnostic services company Rede D'Or Sao Luiz SA (ticker: RDOR3) had its initial public offering in December 2020 and was therefore not included in the analyzed timeframe (Laier and Mandl 2020). It is an equally weighted portfolio.

Mean Portfolio Top

The Mean Portfolio G Top is created by choosing the stocks within the BPI investment universe with high exposure to good ESG practice. As described in the methodology chapter, the returns of the individual stocks are regressed on factor G. Each month starting from January 2015, the coefficient for the individual stocks is estimated and the top tercile of stocks with the highest exposure to good governance is taken to form the portfolio. In order to estimate the coefficients, stocks that have shown returns for at least 12 months are considered and the top percentiles are selected as the result of the highest betas derived by the regressions. As the coefficients are calculated for each month, the stocks that reach the top percentile change, which means that the stock composition can change every month. As more companies have data towards the end of the period, the Brazilian portfolio starts with 15 stocks and ends with 18. The African version of the portfolio starts with 77 stocks and ends with 84. The weights are evenly distributed among the stocks in the portfolio, not considering the companies' market capitalization.

Mean Portfolio Bottom

Similarly, to the previous portfolio "Mean Portfolio G Top", this portfolio is also built considering the individual stock exposure to good governance. However, instead of picking the top percentile of betas, the bottom percentile was selected. This approach aims to compare the risk-adjusted performance of such a portfolio with the benchmark and with the portfolio ranking higher in terms of exposure to good governance. Thus, it is the portfolio that contains the stocks that perform worse in terms of governance relative to their peers.

Value Weighted Portfolio

For each month, the Value Weighted Portfolio G includes the same stocks as Mean Portfolio G Top. Therefore, it is composed of stocks with high exposure to good governance. However, instead of equally distributing the weights, bigger companies in terms of market capitalization receive a higher weight. Market capitalization is calculated by multiplying the price of a single share by the number of shares outstanding. Respective data is retrieved from Bloomberg. This is also referred to as a capitalization-weighted construction method to build a portfolio or an index. The stocks are weighted according to the relative total market capitalization. Market capitalization for Africa is retrieved in USD dollars to compute the relative market capitalization.

Industry Weighted Portfolio

Just like the previously described portfolio, the Industry Weighted Portfolio G includes the same stocks as Mean Portfolio G Top and therefore also includes stocks assumed to perform well in terms of governance. Instead of changing the weights to account for the size in terms of market capitalization, the weights were adjusted considering the different industries. In this approach, the weights of the stocks are distributed in a way that the industry receives the same weight within the portfolio as in the Portfolio Universe provided by BPI. The objective of the industry-weighted portfolio is to partially counteract part of an industry bias that might emerge by integrating the ESG layer into the portfolio. However, industries that did not pass the threshold due to the stocks not being part of the upper tercile, are not included. Only the weights of the stocks that are above the tercile threshold are adjusted. Since BPI Asset Management obtains the weighting from a bottom-up analysis, this portfolio approach is rather exploratory. However, this approach is beneficial when asset managers are aiming for a specific sector weighting.

4.3. Metrics

Sharpe Ratio

The Sharpe ratio measures the excess return per unit of risk. For the calculation, the excess return is the numerator. This is the return that exceeds the safe investment represented by the risk-free rate. Due to the low-interest environment of the analyzed timeframe, a risk-free rate of 0% is assumed. In the Sharpe Ratio formula below, the variable R_p represents the portfolio's expected return, R_f stands for the risk-free rate, and s_p is the standard deviation of the respective portfolio.

$$SR = (R_p - R_f) / s_p \tag{8}$$

Maximum Drawdown

The Maximum Drawdown measures the heaviest loss of an investment in a given period. Therefore, it is the highest possible relative loss that an investor would have suffered if he had bought at the peak and sold at the lowest price within a given period. It can be seen as an indication of the maximum potential loss (Hayes 2022). The formula is the following:

$$MDD = (\text{Trough Value} — \text{Peak Value}) / \text{Peak Value} \tag{9}$$

Skewness

Skewness is a statistical indicator that analyzes the extent to which a distribution deviates from the normal distribution. It analyzes, based on the asymmetry, to what extent a distribution deviates from the normal distribution. The normal distribution has a skewness of zero and is therefore symmetrical. Positive skew refers to a longer or "fatter" tail on the right side, whereas a negative skew refers to a left-leaning distribution. Since the standard deviation as a measure of risk assumes a normal distribution, the skewness can provide a better estimation of future return. A positively skewed investment return means that there were frequent small losses and a few large gains. The opposite is the case of a negatively skewed return, where the mean is smaller than the median, meaning that one can observe frequent small gains and a few large losses (Chen 2022).

Kurtosis

Kurtosis, just like Skewness, is another statistical measure describing the distributions of returns. Instead of comparing the extreme values of the left to the right tail, it measures the extremes on either tail. For kurtosis, the number of data points at the outer edge of a distribution is measured and compared to the rest of the distribution of the data. For a dataset with high kurtosis, the tails of the bell curve extend farther than the three standard deviations of the normal distribution. A normal distribution has a kurtosis of three, which is also referred to as a mesokurtic distribution. If Kurtosis is greater than three, it is referred to as a leptokurtic distribution and if it is less than three, it is a platykurtic distribution. A platykurtic distribution occurs when the extreme values are less extreme than in a normal distribution. For investors, this means that the returns are more stable with fewer extreme positive or negative outliers (Kenton 2022).

Conditional Value at Risk

As a risk indicator, the conditional value at risk represents an extension of the value at risk (VaR). CVaR quantifies the amount of tail risk that a portfolio has. It focuses on the extreme event, so on the residual probability that the loss in a year will exceed the specified VaR. The risk indicator is derived by calculating the weighted average of the values in the tail. The cutoff point is the Value at Risk of the respective confidence interval. VaR represents the loss in the worst case with a time horizon and a probability. In case the threshold of the worst case is crossed, CVaR indicates the expected loss (Chen 2022). The CVaR is calculated by taking the average of the values beyond the VaR.

5. Results

5.1. Factor G

Brazil Factor G

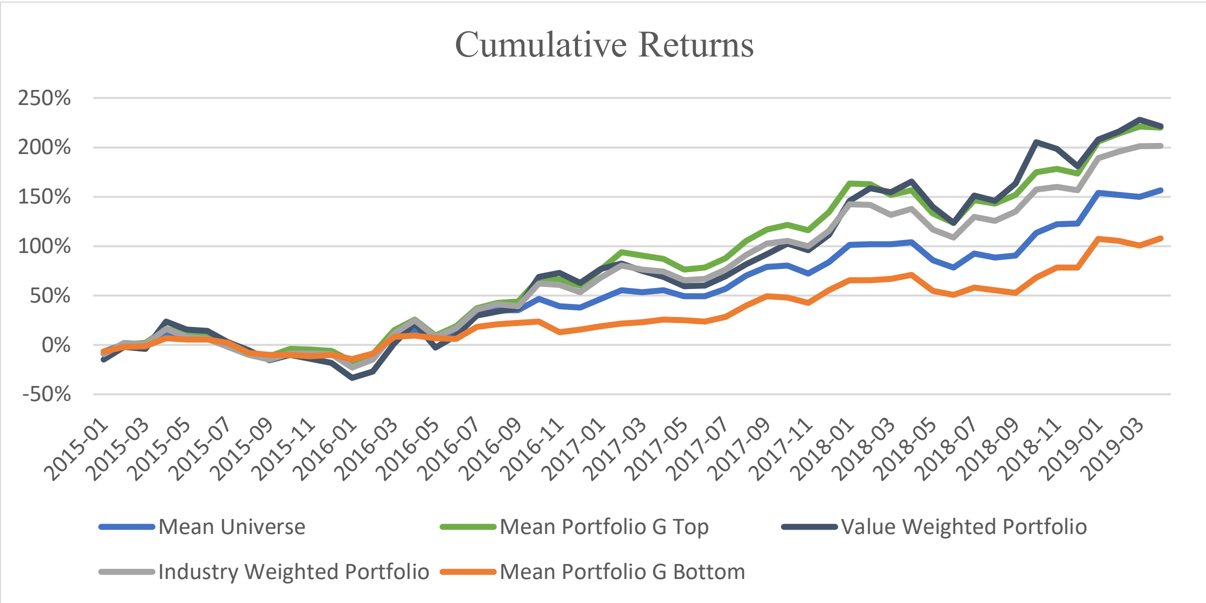

Figure 1: *Cumulative Returns - Factor G Brazil*

The cumulative returns give the impression that all three portfolios created with high exposure to factor G (good governance) outperform the benchmark (Mean Universe portfolio). Only the Mean Portfolio G Bottom, which was created with the tercile of stocks with the lowest exposure to good governance underperformed the benchmark. The following metrics indicate whether the additional returns were realized by taking on more risk.

***Table 1**: Key Performance Indicators - Factor G Brazil*

	Sharpe Ratio	Max. Drawdown	Skewness	Kurtosis	CVaR(95)
Mean Universe	1.11	-198%	0.422	0.002	-0.087
Mean Portfolio G Top	1.13	-184%	0.448	0.345	-0.097
Mean Portfolio G Bottom	0.96	-213%	0.656	1.182	-0.092
Value Weighted Portfolio	0.87	-163%	0.727	1.334	-0.121
Industry Weighted Portfolio	1.01	-192%	0.634	1.193	-0.107

Notes: This table reports key performance indicators of the benchmark portfolio (Mean Universe) and the portfolios constructed with a desired exposure to the G factor for the Brazilian universe. Portfolios 1, 2, and 3 are equally weighted, while Portfolios 4 and 5 are weighted by equity market capitalization and industry weight, respectively.

The Sharpe ratio, as a measure of return per unit of risk taken on, is highest for the Mean Portfolio G Top with 1.13 followed by the Mean Universe with 1.11. This means that the portfolio created with high exposure to good governance (Mean Portfolio G Top) outperformed the Mean Universe. The counter portfolio (Mean Portfolio G Bottom) has a lower Sharpe Ratio than the previously mentioned. When considering the portfolios with the rebalanced weights, the Value Weighted Portfolio has the lowest Sharpe Ratio and therefore the lowest risk-adjusted return for the analyzed time frame. In terms of rebalancing, the approach to rebalance with a target weight per industry leads to a better performance than the value-weighted approach.

***Table 2**: Annualized Risk and Return - Factor G Brazil*

	Mean Return	**Standard Deviation**	**Sharpe Ratio**
Mean Universe	27.07%	21.86%	1.11
Mean Portfolio G Top	35.28%	27.14%	1.13
Mean Portfolio G Bottom	20.52%	19.53%	0.96
Value Weighted Portfolio	40.42%	39.42%	0.87
Industry Weighted Portfolio	29.82%	29.57%	1.01

Notes: This table provides information on the profitability and risk of the benchmark portfolio (Mean Universe) and the portfolios built with exposure to the G factor, a proxy for governance. Portfolios are constructed with equities from the Brazilian investment universe. All values are annualized.

The volatility of the G Top portfolio (27.14%) is higher than both the Universe's (21.86%) and the G Bottom's (19.53%) annualized standard deviation. However, the average return of 35.28% exceeds the amount of additional return expected from taking on additional risk, resulting in a higher Sharpe Ratio. Nevertheless, the standard deviation shows that the high exposure to good governance did not decrease the risk. In fact, the Mean Portfolio G Bottom with the lowest exposure to good governance has the lowest standard deviation of 5.64%. The opposite can be observed when looking at the Value Weighted Portfolio, where the higher standard deviation is not compensated enough by additional returns to achieve the same Sharpe Ratio. Since larger companies, which are considered less volatile, are weighted higher in this portfolio, the increase in standard deviation is not the expected result (Investopedia, 2021). With regards to the maximum drawdown, the Value Weighted Portfolio (163%) does outperform the other portfolios. By rebalancing the weights, the portfolio experiences a drawdown of 184% (Mean Portfolio G Top**).** When comparing the Mean Universe Portfolio with the G Top and the G Bottom in terms of the maximum drawdown, the portfolio with high exposure to good governance (184%) outperforms the benchmark (198%), whereas the counterpart portfolio (213%) underperforms. Skewness and Kurtosis inform about the deviation of the return distribution from the normal distribution. All five portfolios are positively skewed, which indicates a "fatter" right tail and therefore a right-leaning distribution. Positive skewness means that returns are characterized by frequent small losses and a few large gains. This can be confirmed by looking at Table. 3, where the average of the monthly positive returns is larger in absolute terms than the average negative returns. The mean is therefore bigger than the median.

Table 3: *Average Positive and Negative Returns - Factor G Brazil*

	Mean Universe	Mean G Top	Mean G Bottom	Value Weighted	Industry Weighted
Skewness	0.422	0.448	0.656	0.727	0.634
Av. negative returns	-3.56%	-4.25%	-3.05%	-6.67%	-4.71%
Av. positive returns	6.11%	7.94%	4.95%	10.44%	8.19%

Note: The table shows to what extent the analyzed portfolios are positively skewed. The negative positive returns are bigger in absolute terms, meaning that investors experience frequent small losses and few large gains.

All five portfolios have kurtosis below three and consequently a platykurtic distribution. For investors, this signals that the extreme values are less extreme than in a normal distribution. The Conditional Value at Risk is a risk indicator that quantifies the amount of tail risk an investment portfolio has. Unlike for the other metrics, where the Mean Portfolio G Top outperformed the other equally weighted portfolios, the CVaR of the "good governance" portfolio showed a slightly higher average loss in the worst 5% of returns (-9.7%) compared to the Bottom G (9.2%) and the Mean Universe (8.7%). The rebalanced portfolios have an even higher CVaR, indicating that certain higher-weighted industries and large market-cap companies are yielding higher negative returns beyond the 5% threshold.

Africa Factor G

Looking at the graph below, one can see that after the end of 2015, the G Top portfolio outperforms the G Bottom portfolio in terms of cumulative returns. The G top portfolio presented a similar performance to that of the benchmark, especially after mid-2017. The equally weighted portfolio with low exposure to Factor G (bad Governance) resulted in the worst performance compared to the other portfolios according to the cumulative returns. The Sharpe Ratio provides further insight into the risk-return relation.

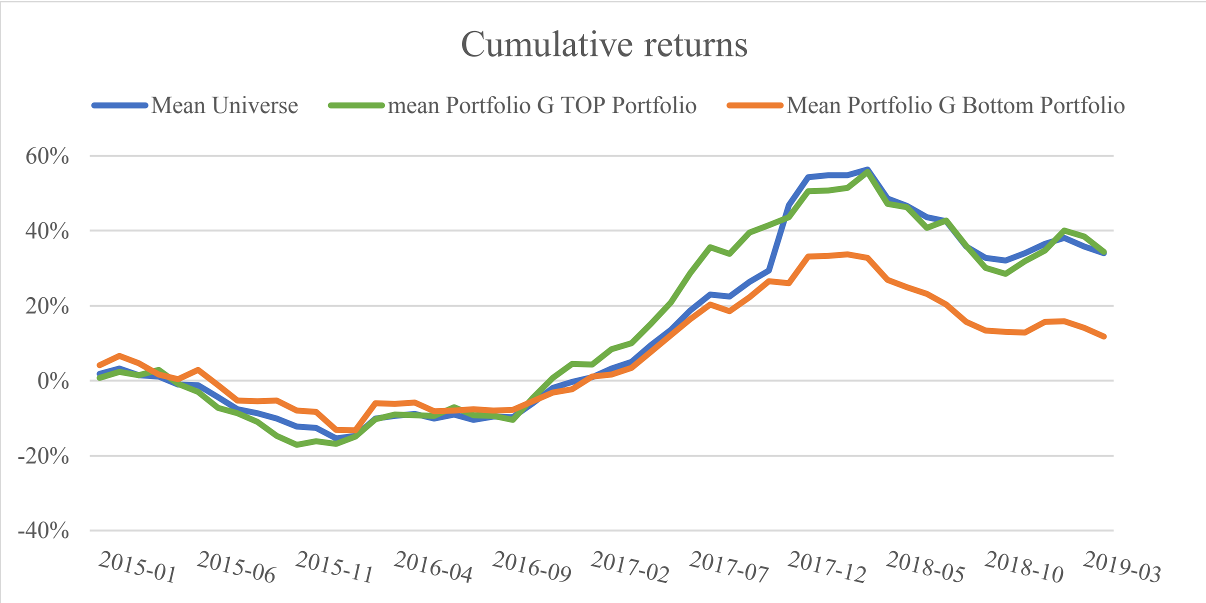

Figure 2: *Cumulative Returns - Factor G Africa*

When looking at the performance of portfolios built from an investment universe of African companies, what stands out is the superior performance of the mean universe portfolio that presents the highest Sharpe Ratio (0.69), followed by the equally weighted portfolio with high exposure to factor G (good Governance), with a Sharpe Ratio of 0.68. Rebalancing the stocks of G top with a value-weighted (0.51) or industry-weighted (0.47) approach only lowered the Sharpe Ratio. Analyzing the rebalanced portfolios, the value-weighed portfolio, based on the market capitalization of the individual stocks, performed better than the industry-weighted portfolio in terms of Sharpe Ratio and Maximum Drawdown. The industry-weighted portfolio presents the lowest Sharpe ratio of 0.47 and the biggest loss of 386% in terms of maximum drawdown.

On the other hand, it is worth noting that the CVaR (95) for the value-weighted portfolio presents the lowest value (-13.7%), indicating that large market-cap companies recorded higher negative returns beyond the 5% threshold. The other portfolios present similar CVaR (95) results, with the Mean Universe Portfolio having an average loss of 4.3% (CVaR(95)).

Table 4: *Key Performance Indicators - Factor G Africa*

	Sharpe Ratio	Max. Drawdown	Skewness	Kurtosis	CVaR(95)
Mean Universe	0.69	-287%	1.38	4.77	-0.043
Mean Portfolio G Top	0.68	-381%	0.03	-0.81	-0.049
Mean Portfolio G Bottom	0.32	-226%	0.43	0.26	-0.046
Value Weighted	0.51	-275%	0.09	1.36	-0.137
Industry Weighted	0.47	-386%	0.02	-0.76	-0.052

Notes: This table reports key performance indicators of the benchmark portfolio (Mean Universe) and the portfolios constructed with a desired exposure to the G factor for the African. Portfolios 1,2 and 3 are equally weighted, while Portfolios 4 and 5 are weighted by equity market capitalization and industry weight, respectively.

Regarding the maximum drawdown, high exposure to good governance resulted in a considerably higher drop of -381% than the mean universe (-287%). The counter portfolio G Bottom's biggest drop was 226%.

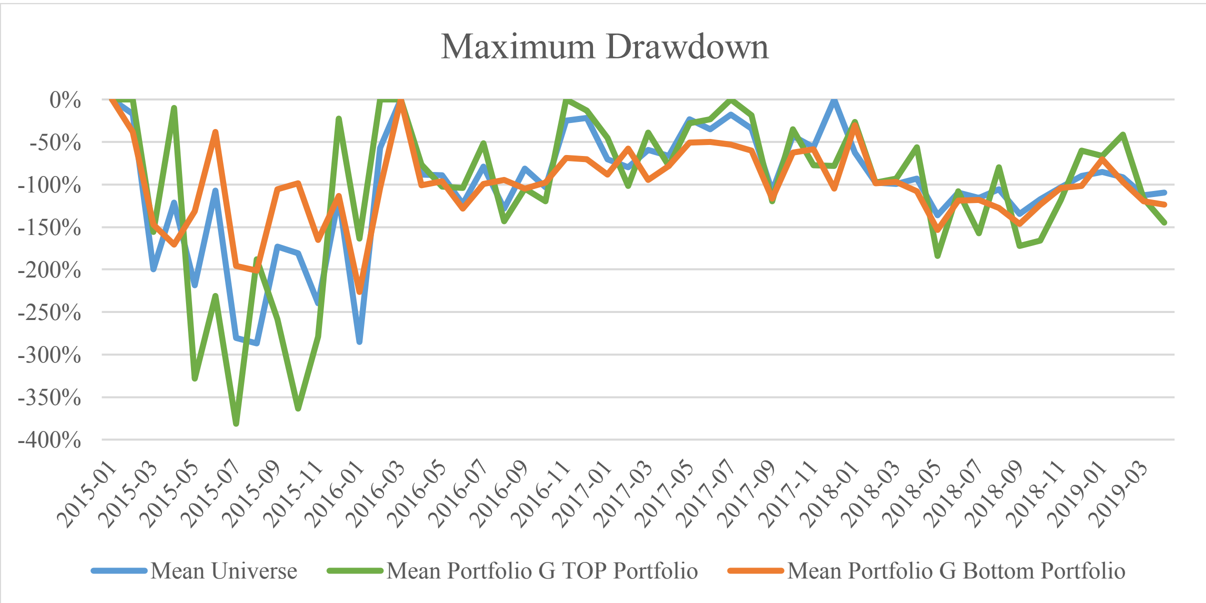

Figure 3: *Maximum Drawdown - Factor G Africa*

When analyzing the distribution of portfolio returns from the graphs above and from Table 1, one notices that all ESG-created portfolios present a symmetrical distribution as their skewness is close to zero. On the other hand, the benchmark has the highest skewness (1.38). This combined with a kurtosis of 4.77, indicates large outliers and characteristics of a leptokurtic distribution. In contrast, the other portfolios present a platykurtic distribution resulting in thinner tails compared to a normal distribution and in fewer extreme positive or negative events.

Table 5*: Annualized Risk and Return - Factor G Africa*

	Mean Return	**Standard Deviation**	**Sharpe Ratio**
Mean Universe	7.58%	10.57%	0.69
Mean Portfolio G Top	7.70%	10.91%	0.68
Mean Portfolio G Bottom	3.07%	9.42%	0.32
Value Weighted	13.95%	25.90%	0.51
Industry Weighted	5.25%	11.00%	0.47

Notes: This table provides information on the profitability and risk of the benchmark portfolio (Mean Universe) and the portfolios built with exposure to the G factor, a proxy for governance. Portfolios are constructed with equities from the African universe. All values are annualized.

As mentioned above, the Sharpe Ratio of the Mean universe (0.69) is only slightly lower than the Sharpe Ratio of the G Top portfolio (0.68). What should be noted, is that high exposure to good governance leads to an increase of risk in terms of standard deviation, whereas the G Bottom portfolio’s volatility decreases. However, the lower standard deviation comes with much lower expected returns resulting in the lowest Sharpe Ratio of 0.32.

Conclusion Factor G

In conclusion, constructing a portfolio within the Brazilian stock universe with high exposure to good governance resulted in superior risk-adjusted performance. This is supported by the fact, that the counter portfolio underperformed with a lower Sharpe Ratio than the benchmark for the annualized time frame. However, these results are not reflected within the African Universe. The African portfolio with high exposure to good governance had a very similar but slightly lower Sharpe Ratio than the Universe. For both Brazil and Africa, the G Bottom portfolios had lower risk-adjusted returns. It should also be noted, that for both geographic regions, selecting the top tercile of good governance stocks came with an increase in volatility. Whereas the opposite occurred by selecting the poor governance stocks, which resulted in a lower standard deviation.

5.2. Factor S

Brazil Factor S

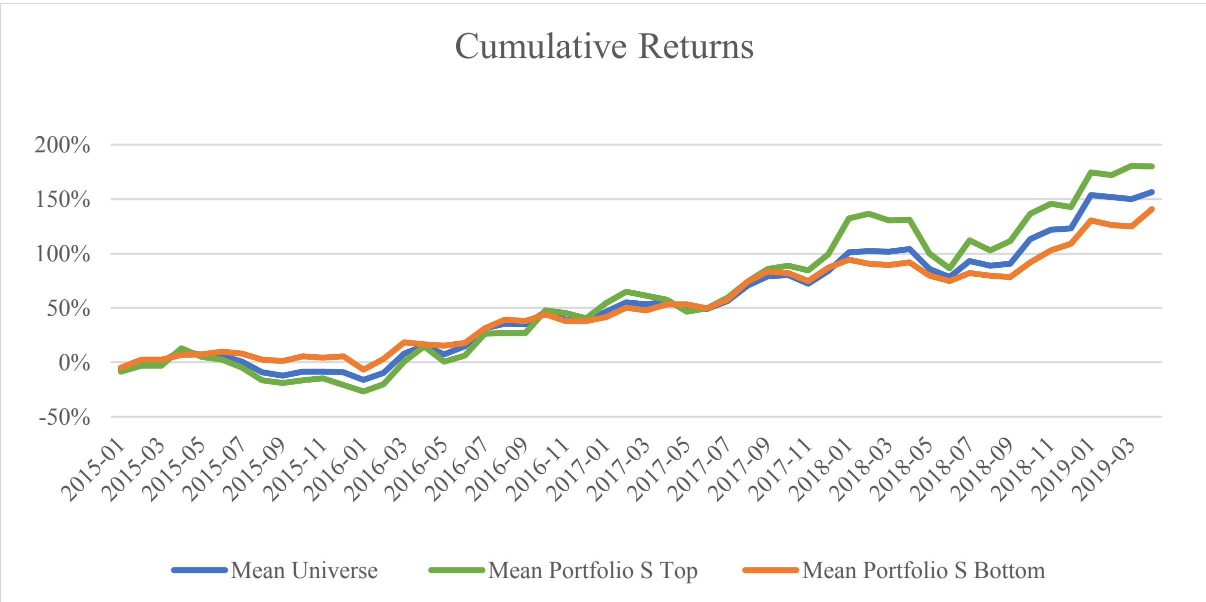

Figure 4: *Cumulative Returns - Factor S Brazil*

From the graph above, one notices that the cumulative returns of the three portfolios present a similar trend for the analyzed period. Nevertheless, from the beginning of 2018 onwards, the difference in cumulative returns becomes wider, and mean portfolio S Top outperforms both the Mean Universe and Portfolio S Bottom.

Table 6*: Key Performance Indicators - Factor S Brazil*

	Sharpe Ratio	Max. Drawdown	Skewness	Kurtosis	CVaR(95)
Mean Universe	1.11	-198%	0.42	0.00	-0.087
Mean Portfolio S Top	0.94	-175%	0.47	0.04	-0.113
Mean Portfolio S Bottom	1.25	-251%	0.21	0.29	-0.078
Value Weighted Portfolio	0.87	-156%	0.73	1.02	-0.168
Industry Weighted Portfolio	0.97	-168%	0.38	0.06	-0.114

Notes: This table reports key performance indicators of the benchmark portfolio (Mean Universe) and the portfolios constructed with a desired exposure to the S factor for the Brazilian universe. Portfolios 1,2 and 3 are equally weighted, while Portfolios 4 and 5 are weighted according to the stocks' market cap and the industry's weights respectively.

The risk-adjusted returns provide a different picture. The Bottom S portfolio presents the highest Sharpe Ratio (1.25), beating both the Mean Universe (1.11) and the Top S portfolio (0.94), which occupies the last place in terms of performance. This is consistent with previous research showing that sin stocks exhibit higher expected returns than comparable stocks (Hong and Kacperczyk 2009, 15). One reason for this is that sin-stocks are neglected by a group of norm-constrained institutions, such as pension plans (Hong and Kacperczyk 2009, 23).

Table 7: *Annualized Risk and Return - Factor S Brazil*

	Mean Return	Standard Deviation	Sharpe Ratio
Mean Universe	27.07%	21.86%	1.11
Mean Portfolio S Top	32.15%	29.91%	0.94
Mean Portfolio S Bottom	24.28%	17.60%	1.25
Value Weighted Portfolio	41.35%	40.43%	0.87
Industry Weighted Portfolio	37.51%	33.14%	0.97

Notes: This table provides information on the profitability and risk of the benchmark portfolio (Mean Universe) and the portfolios built with exposure to the S factor, a proxy for non-sin stocks. Portfolios are constructed with equities from the Brazilian investment universe. All values are annualized.

Furthermore, despite having the lowest mean return, the mean portfolio S Bottom has the lowest volatility, resulting in the highest Sharpe ratio. However, investors holding this portfolio experience the biggest loss of a -251% maximum drawdown compared to the other portfolios and a higher average (CVaR(95) = -7.8%) loss within the worst 5% of returns than the benchmark (CVaR(95) = -8.7%).

Africa Factor S

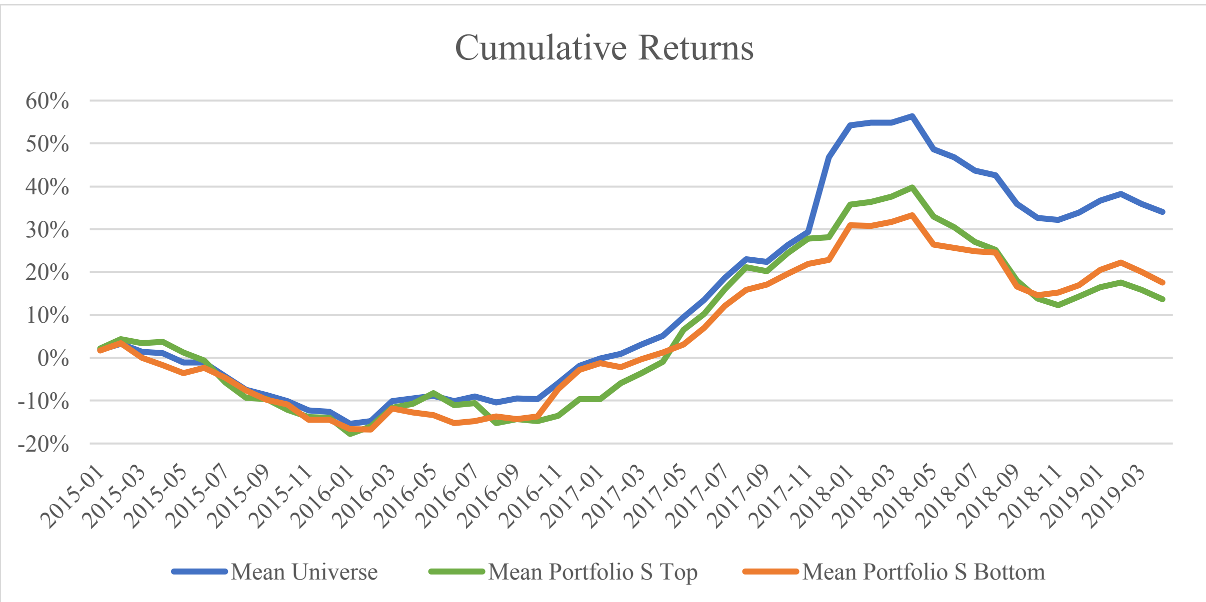

Figure 5*: Cumulative Returns - Factor S Africa*

By analyzing the cumulative returns for the African universe, one can see that the mean universe, S Top and S Bottom present similar results until the beginning of 2016 when the mean universe portfolio starts outperforming the other two. As of November 2017, the gap between the benchmark and the S Top portfolio increases significantly.

Table 8: *Key Performance Indicators - Factor S Africa*

	Sharpe Ratio	Max. Drawdown	Skewness	Kurtosis	CVaR(95)
Mean Universe	0.69	-287%	1.38	4.77	-0.043
Mean Portfolio S Top	0.33	-335%	0.05	-0.47	-0.053
Mean Portfolio S Bottom	0.43	-334%	0.28	0.54	-0.051
Value Weighted Portfolio	0.73	-207%	0.14	-0.54	-0.089
Industry Weighted Portfolio	0.41	-258%	0.11	0.04	-0.053

Notes: This table reports key performance indicators of the benchmark portfolio (Mean Universe) and the portfolios constructed with a desired exposure to the S factor for the African universe. Portfolios 1,2 and 3 are equally weighted, while Portfolios 4 and 5 are weighted according to the stocks' market cap and the industry's weights respectively.

Looking at risk-adjusted returns, the median universe emerges as the winner among the equally weighted portfolios with the highest Sharpe ratio (0.69). The ratio is more than twice as high as that of the S Top portfolio (0.33) and also higher than that of the S Bottom portfolio (0.43). Furthermore, the benchmark presents the lowest MDD (-287%), relative to the mean portfolios, and the lowest average loss within the worst 5% of returns (CVaR(95) = - 4.3%).

***Table 9**: Annualized Risk and Return - Factor S Africa*

	Mean Return (p.a.)	Standard Deviation	Sharpe Ratio
Mean Universe	7.58%	10.67%	0.69
Mean Portfolio S Top	3.56%	10.70%	0.33
Mean Portfolio S Bottom	4.27%	9.64%	0.43
Value Weighted Portfolio	14.66%	18.82%	0.73
Industry Weighted Portfolio	4.45%	10.62%	0.41

Notes: This table provides information on the profitability and risk of the benchmark portfolio (Mean Universe) and the portfolios built with exposure to the S factor, a proxy for non-sin stocks. Portfolios are constructed with equities from the African investment universe. All values are annualized

Despite presenting similar volatility, the Mean Universe and the S Top portfolio present quite different mean annualized returns, as shown in the table above: returns of the S-top portfolio are less than half those of the benchmark, which means that investors in the S-top portfolio are not rewarded for taking on additional risk like investors in the median universe. Finally, the value-weighted portfolio presents the highest volatility and the highest mean return, resulting in the highest Sharpe Ratio of all portfolios analyzed.

Conclusion Factor S

Contrarily to Factor G, where for both universes the Bottom portfolio underperformed both the benchmark and Top mean portfolio in terms of cumulative returns and Sharpe Ratio, there is a different picture for Factor S. When analyzing the Brazilian universe, one notices that the Bottom S portfolio outperforms all portfolios, showing the highest Sharpe Ratio, and the lowest volatility. This is also in line with previous research proving that sin stocks exhibit outperformance relative to various benchmarks (Hong and Kacperczyk 2009, 35). However, in the case of Africa, the mean universe presented the highest Sharpe Ratio, followed by the S Bottom portfolio, which therefore still surpassed the S Top portfolio.

The conclusions one can draw from the analysis of this factor are that stocks with low exposure to the S factor outperformed stocks with high exposure to the S factor for both universes in terms of Sharpe Ratio, and in the case of Brazil, returns also outperformed the benchmark.

5.3. Factor ESG

Brazil Factor ESG

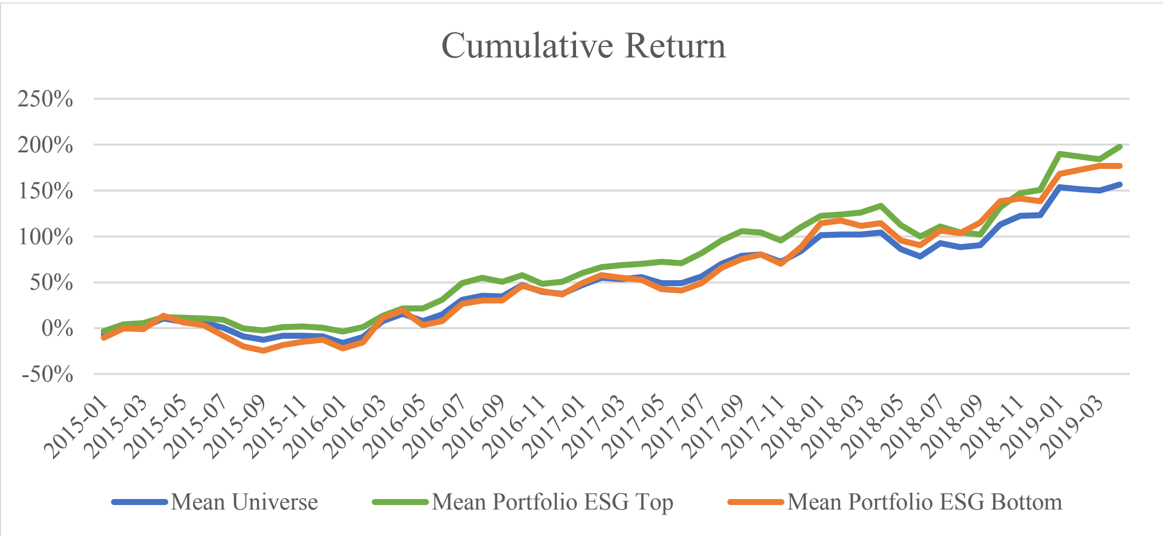

Figure 6: *Cumulative Returns - Factor ESG Brazil*

The first impression given by the graph of the cumulative returns of the Mean Universe Portfolio, the ESG Top and the ESG bottom, is that their returns seem to be correlated with a visible trend. However, the ESG Top seems to outperform the Mean Universe throughout the analyzed time. Similarly, the ESG Top portfolio yields higher returns than the ESG Bottom, apart from a few months after mid-2018.

Table 10: *Key Performance Indicators - Factor ESG Brazil*

	Sharpe Ratio	Max. Drawdown	Skewness	Kurtosis	CVaR (95)
Mean Universe	1.11	-198%	0.422	0.002	-0.087
Mean Portfolio ESG Top	1.44	-209%	0.394	0.223	-0.077
Mean Portfolio ESG Bottom	0.94	-189%	0.615	1.430	-0.123
Value Weighted Portfolio	1.03	-226%	0.652	0.170	-0.114
Industry Weighted Portfolio	1.26	-174%	0.364	1.428	-0.081

Notes: This table reports key performance indicators of the benchmark portfolio (Mean Universe) and the portfolios constructed with a desired exposure to the ESG factor for the Brazilian universe. Portfolios 1,2 and 3 are equally weighted, while Portfolios 4 and 5 are weighted by equity market capitalization and industry weight, respectively.

The risk-adjusted metrics confirm the impression given by the cumulative returns. The Top ESG portfolio has a noticeably higher Sharpe ratio (1.44) than the other created portfolios and the Mean Universe (1.11). The last place in terms of the Sharpe Ratio is occupied by the ESG Bottom portfolio, which is the portfolio containing stocks with low exposure to good ESG ratings. Taking a closer look at the values forming the Sharpe Ratio in the table below, one can see, that the risk taken on by investing in ESG Top decreases while the returns increase. For the ESG Bottom, the returns are even higher, but the standard deviation also increases from 21.86% (mean portfolio) to 29.62% leading to a lower Sharpe Ratio (0.94).

***Table 11**: Annualized Risk and Return - Factor ESG Brazil*

	Mean Return	Standard Deviation	Sharpe Ratio
Mean Universe	27.07%	21.86%	1.11
Mean Portfolio ESG Top	30.78%	18.88%	1.44
Mean Portfolio ESG Bottom	31.68%	29.62%	0.94
Value Weighted Portfolio	35.28%	29.74%	1.03
Industry Weighted Portfolio	23.19%	16.67%	1.26

Notes: This table provides information on the profitability and risk of the benchmark portfolio (Mean Universe) and the portfolios built with exposure to the ESG factor, a proxy for the MSCI ESG scores. Portfolios are constructed with equities from the Brazilian universe. All values are annualized.

Although the ESG Top portfolio reaches a higher Sharpe Ratio, investors also experience the biggest loss of a -209% maximum drawdown compared to the other equally weighted portfolios. This low point is reached in September 2015. The ESG Bottom portfolio reached the maximum drawdown in the same month but not to the same extent (MDD = -189%). Although the MDD for the ESG Bottom portfolio is lower for the analyzed period, investors experience a higher average loss within the worst 5% of returns (CVaR(95) = -12.3%).

Africa Factor ESG

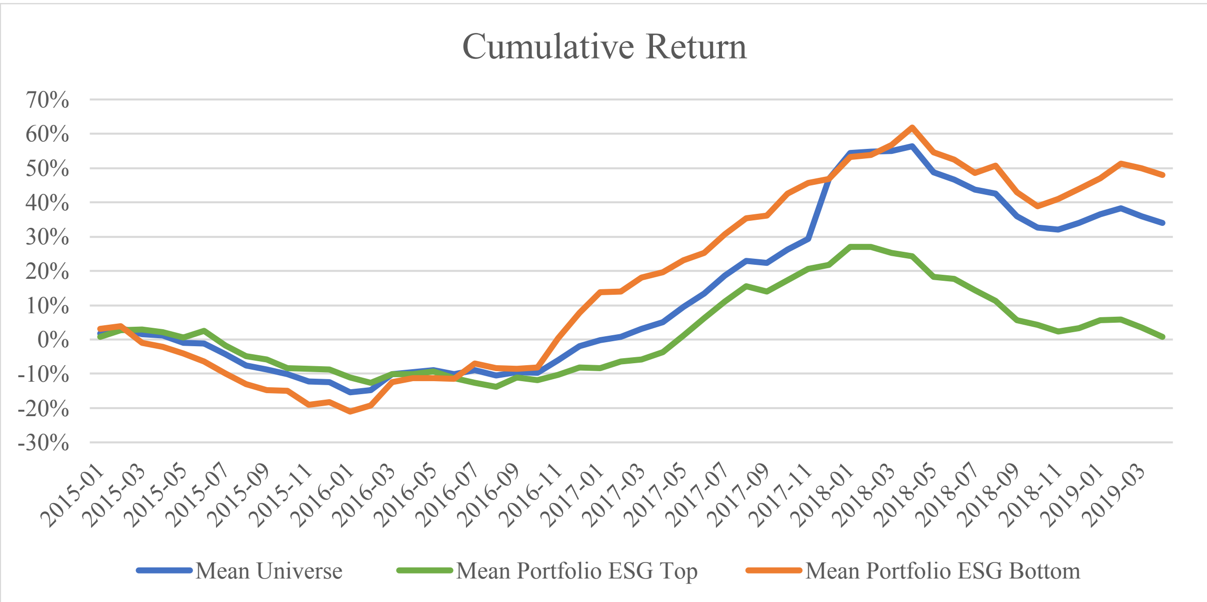

***Figure 7**: Cumulative Returns - Factor ESG Africa*

The chart illustrates that the cumulative returns of the equally weighted portfolios in Africa show larger differences than in Brazil. After September 2019, both the ESG Bottom and the Universe portfolio outperform the ESG Top portfolio until the end of the observed period.

Table 12: *Key Performance Indicators - Factor ESG Africa*

	Sharpe Ratio	**Max. Drawdown**	**Skewness**	**Kurtosis**	**CVaR (95)**
Mean Universe	0.69	-287%	1.38	4.77	-0.043
Mean Portfolio ESG Top	0.06	-310%	0.18	-0.53	-0.047
Mean Portfolio ESG Bottom	0.86	-256%	0.33	0.03	-0.049
Value Weighted Portfolio	0.69	-210%	0.50	0.02	-0.090
Industry Weighted Portfolio	0.02	-274%	0.19	-0.01	-0.054

Notes: This table reports key performance indicators of the benchmark portfolio (Mean Universe) and the portfolios constructed with a desired exposure to the ESG factor for the African universe. Portfolios 1,2 and 3 are equally weighted, while Portfolios 4 and 5 are weighted by equity market capitalization and industry weight, respectively.

This is confirmed by the risk-adjusted returns shown in the table, where the ESG Bottom has the highest Sharpe Ratio of 0.86. ESG Top, which is the portfolio with high exposure to good ESG ratings shows extremely poor performance for the analyzed time, with a Sharpe Ratio of 0.06. It also experiences the biggest loss with a maximum drawdown of -310%. By considering the size of the companies, as it is done for the Value Weighted Portfolio, the Sharpe Ratio remains at the same level as the Mean Universe (0.69) and the maximum drawdown is reduced from -287% to -274%. In terms of skewness, moving away from the Mean Universe (1.38), to an ESG Top (0.18) or bottom (0.33) portfolio, the distribution of the returns moves closer to a normal distribution. The Kurtosis shows that the Mean Universe has the only leptokurtic distribution with a kurtosis of 4.77. Therefore, the returns are less stable with more extreme positive or negative outliers. The conditional value at risk is similar to the equally weighted portfolios. In all three cases, investors can expect an average loss of below 5% (CVar(95)).

Conclusion Factor ESG

Building an ESG top portfolio based on the ESG factor led to a superior performance within Brazil (Sharpe Ratio Mean Universe = 1.11, ESG Top = 1.44) but caused a harsh drop in the Sharpe Ratio in Africa (Sharpe Ratio Mean Universe = 0.69, ESG Top = 0.06). When comparing the ESG Top and the ESG Bottom portfolio in both universes, the effect on risk-adjusted returns was diametrically opposite. In Brazil, the “good” ESG portfolio improved financial performance and the “bad” ESG led to lower returns. For Africa, the opposite can be observed.

6. Discussion

As a result of the portfolio analysis for the G, S, and ESG factors, there are similarities and differences between the Brazilian and African universes, which are elaborated on in the following passages.

First, for both investment universes, one can see that the portfolio with the low exposure to factor G underperformed the benchmark in terms of cumulative returns and risk-adjusted return. In the case of Brazil, the portfolio with high exposure to good governance outperformed the benchmark, whereas, in the case of Africa (0.68), the Sharpe ratio almost reached the level of the benchmark (0.69). For both geographic regions, the mean portfolios with high exposure to good governance presented the highest mean returns, but also the highest volatility. To conclude, high exposure to good governance could only yield superior risk-adjusted returns in Brazil, but low exposure to good governance decreased performance in both geographic areas.

In the case of the S factor, our results led to different conclusions between Africa and Brazil. Research on the financial performance of sin-stocks state that abstaining from them comes at a financial cost (Hong and Kacperczyk 2009, 35; Blitz 2017). This is reflected in the results for Brazil. Its S Bottom portfolio, with low exposure to non-sin stocks, outperforms both the benchmark and the “good” portfolio that avoids sin-stocks in terms of risk-adjusted returns. This indicates that sin-stocks in Brazil appear to yield a positive premium for the analyzed period. In contrast, considering the African universe, the S Bottom portfolio does outperform the S Top portfolio but underperforms the benchmark. As a result, in both geographic areas, the “good” portfolio containing the stocks with high exposure to the non-sin factor underperformed the sin-stock portfolio.

Finally, considering factor ESG, one can again observe diverging results between the universes. Looking at Brazil shows that the ESG Top portfolio results in superior risk-adjusted performance compared to both the ESG Bottom portfolio and the benchmark. Conversely, in the African universe, it is the ESG Bottom portfolio with a Sharpe Ratio of 0.86 that outperformed the others. It should be emphasized that the top African ESG portfolio has by far the lowest Sharpe Ratio (0.06) of all the portfolios analyzed across the two geographic regions and the different factors. For both universes, the ESG Bottom portfolios are riskier as they present higher volatility. In summary, constructing a Brazilian portfolio with high exposure to good ESG scores results in superior returns, while the extreme opposite is observed in Africa. A recent study by Pastor et al. (2022) focusing on the U.S. stock market showed that on average green stocks outperformed their brown counterparts in the last decade. However, they note that this increase in realized returns was due to an unexpected increase in environmental concerns, rather than higher expected returns. The equilibrium model constructed by Pastor et al. (2021) predicts lower expected returns for green assets because investors prefer green assets that are consistent with their values and allow them to hedge climate risk. They argue that the recent outperformance of green stocks was caused by an unexpected green shift involving two aspects. Firstly, investor demand for environmentally friendly assets increased, resulting in a direct increase in the stock price. And secondly, consumers demanded more environmentally friendly products, which increased the profits of these companies also leading to an increase in the share price. Following the reasoning of Pastor et al. (2021), a possible explanation for the outperformance of the good ESG portfolio in Brazil could be the increased demand from investors and consumers. Whereas in Africa, the reason for the poor performance of "good" ESG portfolios may be that investors are less sensitive to ESG issues such as climate shocks. The research of author Zhang (2022) confirms that emerging markets tend to have a relatively low climate-risk sensitivity compared to developed markets. As Brazil is moving closer to a developed market status compared to Africa, its sensitivity to global climate risks might be higher. In addition to lower sensitivity, the lack of trustworthy ESG information could also hinder investor demand for green stocks in Africa.

As a factor overarching trend, the risk-adjusted returns of portfolios within the Brazilian universe a considerably higher than for the African Portfolios. Another observable trend is the on average higher standard deviation among Brazilian returns compared to the African portfolio returns.

7. Conclusion and Outlook

The market-based approach used to construct ESG portfolios represents an alternative way to overcome the lack of ESG information, common in emerging markets. With this method, stocks are picked based on their level of exposure to different factors created with ESG proxies. An advantage of the approach lies in reducing the reliance on ESG ratings. As mentioned in the literature review, several issues are raised on this topic, such as the inconsistent ESG ratings given by different rating agencies.

The results show strongly diverging risk-adjusted returns between factors and regions. The authors of this paper, therefore, do not recommend building an African or Brazilian ESG portfolio based solely on exposure to the factors presented. None of the African portfolios with high exposure to an assessed factor outperformed the benchmark. In Brazil, the green portfolios based on factor G and ESG are able to outperform the benchmark in terms of the Sharpe Ratio. Nevertheless, none of the factors considered in this analysis achieved higher risk-adjusted results in both universes.

Pedersen, Fitzgibbons and Pomorsk (2021), who developed the factors used for the analysis, took returns of United States Equities to compute the factor mimicking portfolio. The construction of a region-specific factor presents an interesting opportunity to compute more accurate beta estimations by incorporating the challenges and characteristics of emerging markets. By building an in-house factor, asset managers are also able to choose proxies appropriate for the market, aligned with the investment vision, and reflecting their interpretation of ESG aspects.

As a limitation of this research, it should be noted that the portfolio analysis only extends to April 2019. This means that neither the effects of the Covid-19 crisis nor of the turmoil caused by the war in Ukraine are included in the results. This limitation is attributed to the constraints of the data available for the factors developed by Pedersen, Fitzgibbons, and Pomorski (2021). For further research, it is strongly recommended that portfolio strategies built on the created factors are backtested over a longer period, including times of crisis, to assess their resilience. To name an example, it can be expected that the portfolio with low exposure to “no-sin stocks” outperforms the “good” ESG portfolio by an even larger margin during times of war. In addition, the backtesting of portfolio returns does not take into account stocks that cease to exist. Due to this survivorship bias, portfolio returns may be overstated.

In conclusion, the market-based approach for ESG integration in emerging markets can be used as an additional source of information. However, the best results are expected when used in combination with active ownership, engagement, and fundamental analysis. Direct contact and exchange with the local management can improve understanding of the business and cultural anchoring of the firms. Combined with in-depth research and fundamental analysis, this can fuel the creation of relevant and region-specific factors that help to bridge the gap of reliable ESG data available.

Bibliography

Allen, Kate. 2018. “Lies, Damned Lies and ESG Rating Methodologies.” Financial Times. December 6, 2018. https://www.ft.com/content/2e49171b-a018-3c3b-b66b-81fd7a170ab5

Ang, Andrew. 2014. *Asset Management: A Systematic Approach to Factor Investing*. Oxford: Oxford University Press

Asgharian, Hossein. 2004. “A Comparative Analysis of Ability of Mimicking Portfolios in Representing the Background Factors.” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.493703

Blitz, David. 2017. “Research Reveals Why Sin Stocks Outperform.” Robeco. September 11, 2017. https://www.robeco.com/en/insights/2017/09/research-reveals-why-sin-stocks-outperform.html

Carhart, Mark M. 1997. “On Persistence in Mutual Fund Performance.” *The Journal of Finance* 52 (1): 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chatterji, Aaron K., Rodolphe Durand, David I. Levine, and Samuel Touboul. 2015. “Do Ratings of Firms Converge? Implications for Managers, Investors and Strategy Researchers.” *Strategic Management Journal* 37 (8): 1597–1614. https://doi.org/10.1002/smj.2407

Chauhan, Yogesh, and Surya B. Kumar. 2018. “Do Investors Value the Nonfinancial Disclosure in Emerging Markets?” *Emerging Markets Review* 37: 32–46. https://doi.org/10.1016/j.ememar.2018.05.001

Chen, James. 2022. “Conditional Value at Risk (CVAR): Definition, Uses, Formula.” Investopedia. October 5, 2022. https://www.investopedia.com/terms/c/conditional_value_at_risk.asp

Chen, James. 2022. "Skewness: Positively and Negatively Skewed Defined with Formula." Investopedia. October 29, 2022. https://www.investopedia.com/terms/s/skewness.asp

Chen, Nai-Fu, Richard Roll, and Stephen A. Ross. 1986. "Economic Forces and the Stock Market." *The Journal of Business* 59 (3): 383–403. https://doi.org/10.1086/296344

Claessens, Stijn, and B. Burcin Yurtoglu. 2013. "Corporate Governance in Emerging Markets: A Survey." *Emerging Markets Review* 15: 1–33. https://doi.org/10.1016/j.ememar.2012.03.002

Cromwell, Wendy. 2020. "Climate Change in Emerging Markets." Wellington Management. September 1, 2020. https://www.wellington.com/en-us/institutional/insights/climate-change-emerging-markets-challenges

Fama, Eugene F., and Kenneth R. French. 1992. "The Cross-Section of Expected Stock Returns." *The Journal of Finance* 47 (2): 427–65. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, Eugene F., and Kenneth R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33 (1): 3–56. https://doi.org/10.1016/0304-405x(93)90023-5

Friede, Gunnar, Timo Busch, and Alexander Bassen. 2015. "ESG and Financial Performance: Aggregated Evidence from More than 2000 Empirical Studies." *Journal of Sustainable Finance & Investment* 5 (4): 210–33. https://doi.org/10.1080/20430795.2015.1118917

Gautam, Deepali, Rohit Goel, and Fabio Natalucci. 2022. "Sustainable Finance in Emerging Markets Is Enjoying Rapid Growth, but May Bring Risks." IMF. March 1, 2022. https://www.imf.org/en/Blogs/Articles/2022/03/01/sustainable-finance-in-emerging-markets-is-enjoying-rapid-growth-but-may-bring-risks

Görgen, Maximilian, Andrea Jacob, and Martin Nerlinger. 2021. "Get Green or Die Trying? Carbon Risk Integration into Portfolio Management." *The Journal of Portfolio Management* 47 (3): 77–93. https://doi.org/10.3905/jpm.2020.1.200

Global Sustainable Investment Alliance. 2021. *Global Sustainable Investment Review 2020*. Brussels: GSIA. 2021 http://www.gsi-alliance.org/wp-content/uploads/2021/08/GSIR-20201.pdf

Hay, Jon. 2020. "ESG Investors: Be Careful with Supply Chains." Global Capital Asia. August 20, 2020. https://www.globalcapital.com/asia/article/28muavzlbw5ygj8jdaebk/sri/esg-investors-be-careful-with-supply-chains

Hayes, Adam. 2022. "Fama and French Three Factor Model Definition: Formula and Interpretation." Investopedia. September 11, 2022. https://www.investopedia.com/terms/f/famaandfrenchthreefactormodel.asp

Hayes, Adam. 2022. "Maximum Drawdown (MDD) Defined, with Formula for Calculation." Investopedia. October 10, 2022. https://www.investopedia.com/terms/m/maximum-drawdown-mdd.asp

Hong, Harrison, and Marcin Kacperczyk. 2009. "The Price of Sin: The Effects of Social Norms on Markets." *Journal of Financial Economics* 93 (1): 15–36. https://doi.org/10.1016/j.jfineco.2008.09.001

Hutt, Rosamond. 2016. "What Are the 10 Biggest Global Challenges?" World Economic Forum. January 21, 2016. https://www.weforum.org/agenda/2016/01/what-are-the-10-biggest-global-challenges/

Viegas, Leonardo. 2007."Country Report: Voluntary Corporate Governance Code in Brazil". Paris: OECD. 2007. https://www.oecd.org/corporate/ca/corporategovernanceprinciples/39741021.pdf

Johnson, Christopher. 2020. “The Measurement of Environmental, Social and Governance (ESG) and Sustainable Investment: Developing a Sustainable New World for Financial Services.” *Journal of Securities Operations & Custody* , Autumn/Fall, 12 (4): 336–56. https://www.ingentaconnect.com/content/hsp/jsoc/2020/00000012/00000004/art00004

Kenton, Will. 2022. “Kurtosis Definition, Types, and Importance.” Investopedia. December 4, 2022. https://www.investopedia.com/terms/k/kurtosis.asp

Kerber, Ross, and Simon Jessop. 2021. “Analysis - How 2021 Became the Year of ESG Investing.” Thomson Reuters. December 23, 2021. https://www.reuters.com/article/esg-yearender-analysis-idCAKBN2J20TT

Khanna, Tarun, and Krishna Palepu. 2000. “Is Group Affiliation Profitable in Emerging Markets? an Analysis of Diversified Indian Business Groups.” *The Journal of Finance* 55 (2): 867–91. https://doi.org/10.1111/0022-1082.00229

Kim, Yongtae, Myung Seok Park, and Benson Wier. 2012. “Is Earnings Quality Associated with Corporate Social Responsibility?” *The Accounting Review* 87 (3): 761–96. https://doi.org/10.2308/accr-10209

Koedijk, Kees G., Alfred M.H. Slager, and Philip A. Stork. 2016. “Investing in Systematic Factor Premiums.” *European Financial Management* 22 (2): 193–234. https://doi.org/10.1111/eufm.12081

Laier, Paula, and Carolina Mandl. 2020. “Carlyle-Backed Rede D'or Valued at $22 Billion in Brazil IPO.” Thomson Reuters. December 8, 2020. https://www.reuters.com/article/us-rededor-ipo-idUKKBN28I2N1

Leippold, Markus, and Roger Rueegg. 2020. “How Rational and Competitive Is the Market for Mutual Funds?” *Review of Finance* 24 (3): 579–613. https://doi.org/10.1093/rof/rfz011

Markowitz, Harry. 1952. “Portfolio Selection*.” *The Journal of Finance* 7 (1): 77–91. https://doi.org/10.1111/j.1540-6261.1952.tb01525.x

Odell, Jamieson, and Usman Ali. 2016. “ESG Investing in Emerging and Frontier Markets.” *Journal of Applied Corporate Finance* 28 (2): 96–101. https://ssrn.com/abstract=2808231

Paramati, Sudharshan Reddy, Mallesh Ummalla, and Nicholas Apergis. 2016. “The Effect of Foreign Direct Investment and Stock Market Growth on Clean Energy Use across a Panel of Emerging Market Economies.” *Energy Economics* 56: 29-41. https://doi.org/10.1016/j.eneco.2016.02.008

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor. 2021. “Sustainable Investing in Equilibrium.” *Journal of Financial Economics* 142 (2): 550–71. https://doi.org/10.1016/j.jfineco.2020.12.011

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor. 2022. “Dissecting Green Returns.” *Journal of Financial Economics* 146 (2): 403–24. https://doi.org/10.1016/j.jfineco.2022.07.007

Pedersen, Lasse Heje, Shaun Fitzgibbons, and Lukasz Pomorski. 2021. “Responsible Investing: The ESG-Efficient Frontier.” *Journal of Financial Economics* 142 (2): 572–97. https://doi.org/10.1016/j.jfineco.2020.11.001

Principles for Responsible Investment. 2021. *Annual Report 2021*. London: PRI. https://dwtyzx6upklss.cloudfront.net/Uploads/s/u/b/pri_annualreport_2021_15698.pdf

Ross, Sean. 2021. “What's the Difference between Small Cap Stocks and Large Cap Stocks?” Investopedia. August 27, 2021. https://www.investopedia.com/articles/markets/022316/small-cap-vs-mid-cap-vs-large-cap-stocks-2016.asp

Ross, Stephen A. 1976. “The Arbitrage Theory of Capital Asset Pricing.” *Journal of Economic Theory* 13 (3): 341–60. https://doi.org/10.1016/0022-0531(76)90046-6

Sharpe, William F. 1964. “Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk*.” *The Journal of Finance* 19 (3): 425–42. https://doi.org/10.1111/j.1540-6261.1964.tb02865.x.

Sloan, Richard G. 1996. “Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?” *The Accounting Review* 71 (3): 289–315. https://www.wm.edu/offices/auxiliary/osher/course-info/classnotes/shanesloan 1996tar1.pdf

Vezér, Martin, Aiswarya Baskaran, and Doug Morrow. 2019. Rep. *ESG Spotlight Emerging Market Equities: Key Sources of ESG Risk*. Amsterdam: Sustainalytics. https://connect.sustainalytics.com/hubfs/INV%20-%20Reports%20and%20Brochure/Thought%20Leadership/SustainalyticsESGSpotlightEmergingMarkets.pdf

Zaher, Fadi. 2019. *Index Fund Management: A Practical Guide to Smart Beta, Factor Investing, and Risk Premia*.1st ed. London: Palgrave Macmillan.

Zhang, Si Ying. 2022. “Are Investors Sensitive to Climate-Related Transition and Physical Risks? Evidence from Global Stock Markets.” *Research in International Business and Finance* 62: 101710. https://doi.org/10.1016/j.ribaf.2022.101710.

INDIVIDUAL PART

SUSTAINABLE INVESTING IN EMERGING MARKETS

CARBON RISK IN BRAZIL

Abstract

As the implications of global warming become more apparent, nations are shifting towards becoming low-carbon economies, and portfolio managers need to consider environmental aspects. Brazil has large natural resources and therefore holds the potential to be a key player in the global transition. This paper examines a capital market-based approach to construct a "green" portfolio containing Brazilian listed companies. This is achieved by computing the carbon risk beta of individual stocks using a carbon risk factor-mimicking portfolio that incorporates comprehensive carbon and transition-related information. The analysis shows that the "green", as well as the "brown" portfolio in terms of carbon risk beta, result in an inferior risk-adjusted performance.

Keywords: ESG investing, carbon risk, portfolio construction, emerging markets, economic transition, brazil, climate finance, sustainable investing.

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Table of Contents

List of Figures

List of Tables

1. Introduction

As the implications of global warming are becoming more apparent and threatening, humanity is scaling the efforts to move to sustainable energy and materials with the goal of limiting global warming to 1.5°C by 2050 (Sawaya et al. 2022). A recent McKinsey report estimates that yearly investments of over 3 trillion USD until 2030 are required to get companies to reach the carbon emission reduction targets (Sawaya et al. 2022). This would represent the largest capital relocation in human history (Sawaya et al. 2022). In 2020, the top seven emitters (China, USA, India, European Union, Russia, Indonesia, and Brazil) caused around half of the total greenhouse gas emissions (United Nations Environment Programme 2022). With Brazil being one of these seven countries, the decarbonization of Brazil's s economy is imperative. Simultaneously, Brazil holds the capabilities and natural resources which allow the country to become a driving force of global transition (Grottera et al. 2017).

The first necessary step is to change legislation around land ownership and to significantly reduce deforestation, which currently causes about half of the total emissions in Brazil (The Economist 2021). A recent McKinsey report identifies renewable energy, carbon markets, and bio-based energy and materials as the three areas where Brazil has the potential to take on a leading role (Sawaya et al. 2022). Not only is Brazil an agricultural powerhouse but it is also rich in renewable energy sources such as wind, solar, hydro, and biomass (Sawaya et al. 2022). Those natural resources present an opportunity to fuel global decarbonization. Brazil's green economy has the potential to attract significant investments.

Similar to the group contribution, this section makes use of the market-based approach to integrating ESG criteria into the composition of a portfolio. Instead of using factor E, which is a simple proxy for carbon emissions, a more integral factor, called factor C, is used to construct the portfolios. This factor results from the research of Görgen et al. (2017) who created it to quantify carbon risk. Factor C incorporates comprehensive carbon and transition-related information. This enables the construction of a sustainable portfolio which doesn't only consider a company's carbon emission but also its ability to transition to a low-carbon economy. The portfolio would then consist only of "green" stocks, referring to stocks that were emitted by companies that are considered environmentally friendly (Pastor et al. 2021). Their counterparts are brown stocks, which are harmful to the environment.

2. Methodology

The general approach used to create the portfolios follows the same logic as described in the group contribution apart from the use of a different factor and some changes in the methodology resulting from that. The following subsections describe how the factor C is formed and provide an understanding of the methodology, including existing differences from the approach in the group contribution.

2.1. Carbon Risk

The factor C receives its name as it allows to generate the carbon beta of an individual stock. It is based on the approach presented by Görgen et al. (2017) who created the factor. The data is made available by the Institute of Business Administration and Sustainable Finance (University Augsburg 2022). The authors construct a carbon risk factor-mimicking portfolio to understand carbon risk from a factor-based asset pricing model perspective. Unlike the previously described factors E, S, G, and ESG (group part) that take relatively simple proxies, such as the accounting proxy to reflect governance, the factor C considers a wide range of relevant carbon risk values.

Before going into the details, the original motivation and idea behind the factor are elaborated. There is scientific consensus that human activities are affecting global warming and that corporations contribute to the rise in global temperatures by emitting CO2 (NASA 2022). An increasing number of countries are adopting carbon pricing to reduce greenhouse gas emissions and avoid the risks associated with global warming. The price of emissions coupled with institutional divestment from the fossil fuel industry should lead to lower stock prices and a risk premium for carbon-intensive companies to compensate for the additional risk, namely carbon risk (Bolton and Kacperczyk 2021). However, the authors (Görgen et al. 2020) point out that the carbon risk arising from uncertainties in the green transition is two-sided.

Therefore, both brown stocks and green stocks are risky. On the one hand, this means that under the assumption that governments accelerate efforts to achieve the net zero target, high-carbon stocks will be riskier. On the other hand, if politicians deny global warming and support carbon-intensive business models, low-carbon stocks will be riskier. The study that built the factor finds that even if the factor can partially explain systematic variation in returns, there is no evidence of a carbon risk premium. A possible explanation might be investors' inability to adequately quantify carbon risk. The research found that brown stocks tend to have higher returns, but when they become relatively browner, returns decrease. They also show that green firms are improving faster in terms of de-carbonization than brown firms causing them to outperform the brown firms.

To study this relationship between equity prices and carbon risk, the authors (Görgen et al. 2020) constructed the factor C thereby creating a Brown-Green-Score which determines the carbon risk performance of a firm. Afterward, the mimicking portfolio representing the factor C is created by subtracting the returns of the green companies from the brown companies.

2.2. Carbon Risk Measurement

The C factor is created by measuring the carbon risk of different companies and deriving a score, which the authors (Görgen et al. 2017) named the Brown-Green-Score. The score uses four ESG databases to retrieve fundamental carbon and transition-related information: MSCI ESG Stats and the IVA ratings, the Sustainalytics ESG Ratings, the Carbon Disclosure Project Climate Change questionnaire dataset, and the Thomson Reuters ESG dataset (Görgen et al. 2017). The considered variables are categorized into three main indicators, each resulting in a subscore. Those indicators are value chain, public perception, and adaptability. The value chain indicator covers the emissions a firm emits within its supply chain and production. Public perception accounts for a company's carbon policy and how the relevant stakeholders perceive it. The final indicator (adaptability) captures a company's readiness to adapt to a low-carbon economy by assessing strategies and actions the company can take in response to a carbon tax or new regulations. It also includes plans for future emission reduction or mitigation strategies. The three subscores are calculated for over 1600 international stocks and then combined for the final BGS score to approximate their carbon risk (Görgen et al. 2017). The higher the score, the browner the company. It should be mentioned that the value chain subscore is weighted higher (70%) due to its relative importance. The other two indicators carry a 15% weight each. As a result, the authors (Görgen et al. 2017) calculate the Brow-Green-Score with the following formula:

$$BGS_{i,t} = 0.70 \text{ Value Chain}_{i,t} + 0.15 \text{ Public Perception}_{i,t} + 0.15 \text{ Adaptability}_{i,t} \quad (1)$$

2.3. Factor C - The factor-mimicking portfolio for carbon risk

With the resulting Brown-Green-Scores and the use of asset pricing theory, the understanding of the relationship between equity prices and carbon risk can be fortified. Görgen et al. (2017) create the factor C following common composition methods (Harvey and Liu, 2014). The authors (Görgen et al. 2017) refer to the factor as the Brown-minus-Green factor. However, for the sake of simplicity and consistency, it is called the C factor in the course of this thesis. It is a factor-mimicking portfolio for carbon risk and the construction is similar to the approach used for the renowned size factor by Fama and French (1995) or for factor G explained in detail in the methodology of the group part. Each year, the analyzed firms are allocated into six portfolios according to their BGS (High = H, Low = L) and their size (Small = S, Big = B), measured in market capitalization. The upper tercile and the median are used as breaking points. The factor C equation uses the value-weighted monthly returns as follows:

$$BMG_t = 0.5\,(SH_t + BH_t) - 0.5\,(SL_t + BL_t) \quad (2)$$

Figure 1 illustrates the cumulative returns of the brown-, the green- and the factor C portfolio (BMG). From 2010 to 2012, the factor C returns are slightly positive which means that brown stocks were outperforming green stocks. The reverse is observable from 2013 until the beginning of 2016 when the factor C (BMG) drops by around 20%. The drop is followed by an increase in 2017. For the sample period, green firms performed on average better than brown firms. The authors reason that after 2013 the global economy moved faster than expected toward a low-carbon economy, which boosted green stocks and caused them to outperform brown stocks (Görgen et al. 2017).

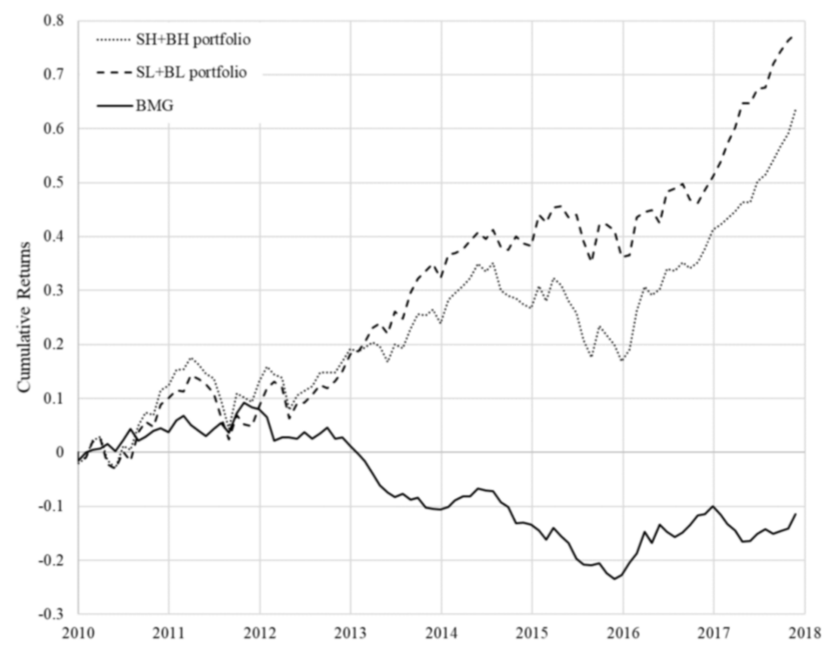

***Figure 1**: Cumulative returns of the BMG factor (C- factor). Source: Görgen et al. (2017)*

2.4. Carbon Beta Estimation

After clarifying the background and content of the C factor, the beta estimation follows the same logic as described in detail in the methodology part of the group paper. Therefore, the returns of the 56 stocks in the Brazilian Universe provided by BPI Asset Management are regressed on the factor C to receive the monthly carbon risk beta. The formula for the regression is the following:

$$R_i (t) = \alpha_i + \beta_{c,i} R_c (t) + \varepsilon_i (t) \tag{3}$$

$R_i (t)$ stands for the return of stock i, the alpha of the asset i is α_i. $R_c (t)$ is the return of the C factor and $\beta_{c,i}$ is the exposure of the stock to carbon risk. Finally, $\varepsilon_i (t)$ stands for the idiosyncratic risk. This market-based approach allows estimating the exposure to carbon risk for companies that do not have respective data available. The unavailability of carbon data is an underlying problem in emerging markets. How insightful the beta is, depends on market participants' ability to incorporate carbon risk information into the stock prices. Resulting from the methodology used in the factor creation, some adjustments must be made in the stock selection process to construct the portfolios. For the Mean Portfolio Top, which is the equally weighted portfolio with high exposure to the respective ESG practice, the tercile with the highest betas was chosen for factors described in the group contribution. For example, the factor G mimicking portfolio (group part) is computed by subtracting the returns of "bad governance" companies from "good governance" companies (G5-G1). Therefore, the highest coefficients for factor G represent the companies with good governance relative to their peers in the investment universe. Since factor C is created by taking the excess returns of brown companies minus green companies, the approach is reversed. The tercile with the lowest coefficients represents the companies included in the green portfolio (Mean Portfolio C Top). Consequently, the Mean Portfolio C Bottom is created by selecting the tercile of stocks with the highest betas (brown stocks). These are the stocks with high carbon risk resulting from the exposure to a high BGS score. As previously elaborated, the higher the score, the browner the company. The Mean Universe portfolio serves as a benchmark portfolio and includes all stocks in the Brazilian BPI investment universe. All three portfolios are equally weighted. By rebalancing the weights of the Mean Portfolio C Top according to market capitalization and the target weight of the industry, the Value-Weighted C Portfolio and the Industry-Weighted C Portfolio are constructed. Therefore, they both include the same tercile of (green) stocks with the lowest exposure to a high Brown-Green-Score. The portfolios' performance is analyzed using the same metrics described in the group contribution: Sharpe Ratio, maximum drawdown, cumulative returns, skewness, kurtosis, and conditional value at risk.

3. Results

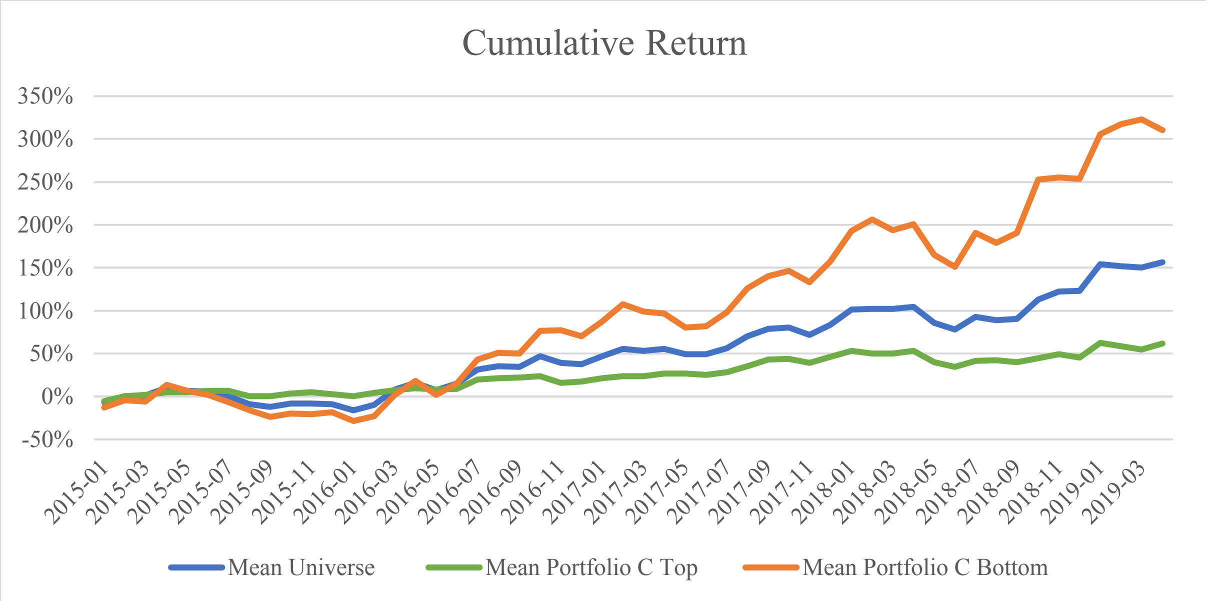

***Figure 2**: Equally weighted cumulative returns Brazil (C factor)*

The cumulative returns show that within the analyzed time frame, the brown portfolio (Mean Portfolio C Bottom) outperformed both other equally weighted portfolios. The Mean portfolio C top, which was constructed with the green stocks, has the lowest cumulative returns. As shown in Figure 3, including the rebalanced portfolios, a different allocation of weights did not increase the cumulative returns.

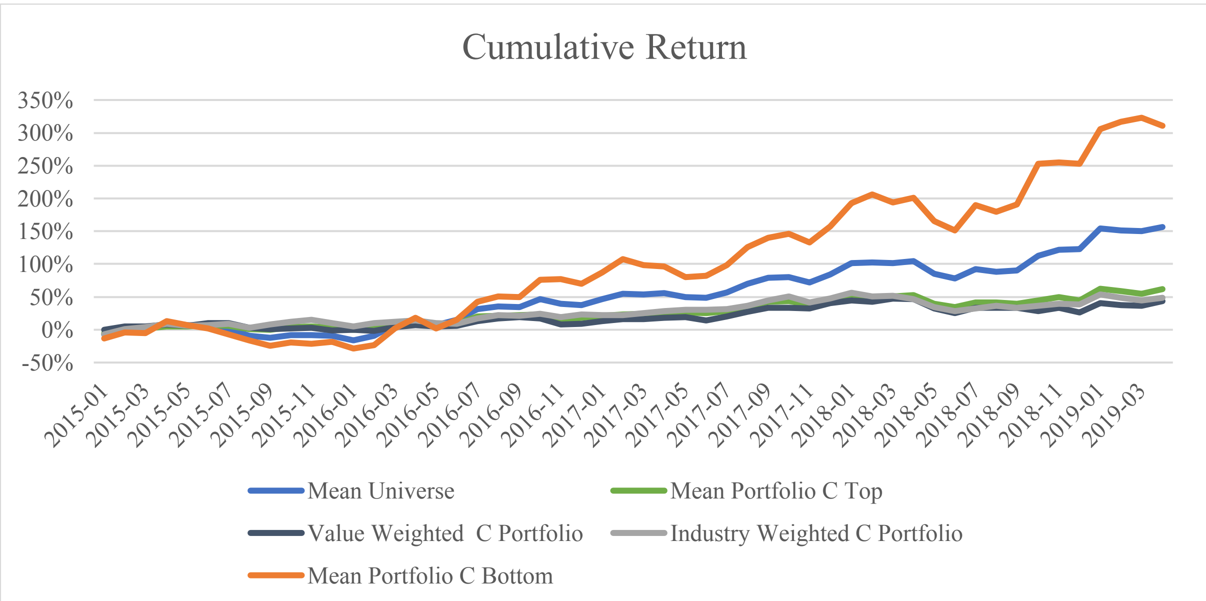

***Figure 3**: Cumulative returns Brazil (C factor)*

Therefore, none of the portfolios constructed with the green stocks were able to achieve returns in line with the universe portfolio. The risk-adjusted return metrics provide more insight into whether the higher returns were achieved by taking more risk. With a Sharpe Ratio of 1.11, the Mean Universe has the highest risk-adjusted return, followed by the “brown” portfolio. This result suggests that investing in the “brown” portfolio during this analyzed period exposes the investor to unrewarded risk. Choosing the top tercile green stocks resulted in a decrease in standard deviation (3.84%) compared to the Universe (6.32%) whereas the “brown” stocks portfolio experiences an increase (10.38%) and therefore a higher level of risk. Both rebalancing approaches cause the returns to decrease while the risk increases, resulting in the lowest Sharpe Ratios (Value Weighted Portfolio: 0,68, Industry Weighted Portfolio: 0,71).

Table 1: Annualized Risk and Return

	Mean Return	**Standard Deviation**	**Sharpe Ratio**
Mean Universe	27.07%	6.31%	1.11
Mean Portfolio C Top	12.67%	3.84%	0.90
Mean Portfolio C Bottom	46.86%	10.38%	1.09
Value Weighted Portfolio	9.72%	3.98%	0.68
Industry Weighted Portfolio	10.19%	4.15%	0.71

Notes: This table provides information on the profitability and risk of the benchmark portfolio (Mean Universe) and the portfolios built with exposure to the C factor, a proxy for carbon risk. Portfolios are constructed with equities from the Brazilian BPI universe. All values are annualized.

The rebalanced portfolios are also the only portfolios that are negatively skewed (Value Weighted Portfolio: -0.115, Industry Weighted Portfolio: -0.085). Investors would experience frequent small gains and a few large losses. The opposite can be observed for the other portfolios, which have a slight positive skew. With a skewness of 0.157, the returns of the Mean Portfolio C Top are closest to the normal distribution. The same applies to the kurtosis: all portfolios have a platykurtic distribution due to the kurtosis being less than three. For investors, this signals that the extreme values are less extreme than for normally distributed returns.

Table 2: Key Performance Indicator

	Sharpe Ratio	Max. Drawdown	Skewness	Kurtosis	CVaR(95)
Mean Universe	1.11	-198%	0.422	0.002	-0.087
Mean Portfolio C Top	0.90	-191%	0.157	0.948	-0.068
Mean Portfolio C Bottom	1.09	-164%	0.535	0.059	-0.134
Value Weighted C Portfolio	0.68	-237%	-0.115	0.509	-0.078
Industry Weighted C Portfolio	0.71	-199%	-0.085	-0.094	-0.072

Notes: This table reports key performance indicators of the benchmark portfolio (Mean Universe) and the portfolios constructed with a desired exposure to the carbon risk factor for the Brazilian universe. Portfolios 1,2 and 3 are equally weighted, while Portfolios 4 and 5 are weighted according to the stocks' market cap and the industry's weights respectively.

Not only does the brown portfolio (Mean Portfolio C Bottom) outperform the green portfolio (Mean Portfolio C Top) in terms of cumulative returns and Sharpe Ratio, but it also shows a lower and therefore better maximum drawdown (brown: -164% vs. green: -191%). However, both outperform the Mean Universe which experienced a drop of -198%. The maximum drawdown chart also illustrates the correlation of the portfolios as they experience lows at similar points in time.

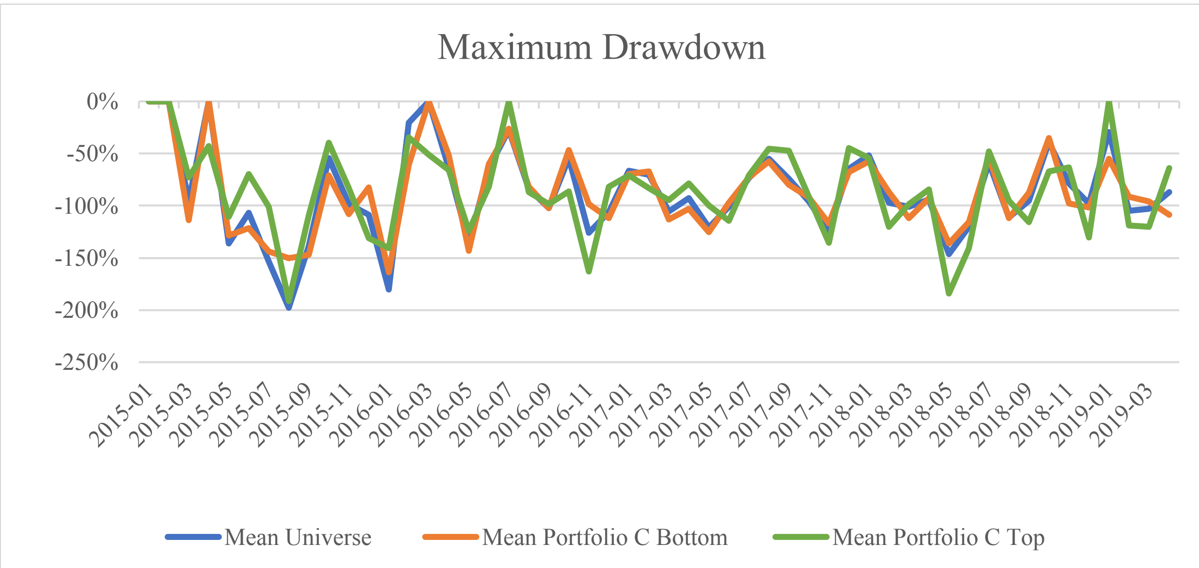

Figure 4*: Maximum Drawdown Brazil (C factor)*

The mean universe and the "brown" portfolio have the biggest losses (maximum drawdown) only one month apart in August and September 2015 respectively.

Table 3: Maximum Drawdown and Date

	Mean Universe	Mean C Top	Mean C Bottom	Value Weighted	Industry Weighted
Max. Drawdown	-198%	-191%	-164%	-237%	-199%
Date	2015-08	2015-09	2016-02	2018-06	2018-06

Notes: This table shows on what date the portfolios constructed with desired exposure to the carbon risk factor reached their maximum observed loss from a peak to a trough.

Part of the reason behind the drop in the Brazilian stock market in the summer of 2015 was the downgrade of Brazil's S&P credit rating from BBB-minus to BB-plus, which is considered the highest so-called "junk" rating (Brandimarte 2015). A warning of a possible downgrade came two months prior on the grounds that mounting political problems were disrupting economic policy. More concisely, the government under President Dilma Rousseff failed to present a 2016 budget that included the policy corrections promised after her reelection in 2015 (Brandimarte 2015). In addition, the political and investment climate deteriorated in the wake of the Petrobras corruption scandal involving high-ranking officials (Jones 2017).

As investors' perceived risk rose, the cost of borrowing for the government and Brazilian companies increased, weighing on already troubled financial markets. In the first 3 months of 2015, Brazil's GDP shrank by 3.2% due to a steep decline in investment and lower family consumption (Economic Commission for Latin America and the Caribbean 2022). The chart shows that during this economic decline, as in other downturns, the brown portfolio did not drop as far as the green portfolio. This suggests that the green portfolio was less resilient to economic turbulence during the period under review. The only metric in which the green portfolio could outperform the others is in terms of average losses in the worst 5% of the returns. Its CVaR for the 95% confidence level is -6.8%, while the brown portfolio has a CVaR of -13.4% and the mean universe has a CVaR of -8.7%.

4. Discussion

The analysis shows that selecting the green stocks from the Brazilian investment universe provided by BPI Asset Management results in an inferior risk-adjusted performance for the analyzed period. None of the portfolios created can match or exceed the Sharpe Ratio of the Mean Universe portfolio. This occurs despite the global trend of green assets outperforming the market over the past decade (Pastor et al. 2021).

Although the green stocks on average outperformed the brown stocks in the factor C portfolio (Figure 1), this is not the case for the created portfolios in Brazil. The Mean Portfolio C Bottom, which contains the brown stocks, achieved a higher risk-adjusted return than the Mean Portfolio C Top, which represents the green portfolio. This is in line with the equilibrium model created by Pastor et al. (2021) which states that green stocks are expected to yield lower returns due to investors' preference for sustainable stocks and the possibility of hedging climate-related risks. Pastor et al. (2021) claim that green stocks can outperform brown stocks only when an unexpected increase in demand from the consumer and investor side causes stock prices to rise. The observed results suggest that for the analyzed time frame the effect of lower expected returns for green stocks overcomes the effect of unexpected changes toward a greener Brazilian economy.

Although the brown portfolio outperformed the green portfolio, neither surpasses the risk-adjusted performance of the benchmark. Following the reasoning of the authors Görgen et al. (2020), who created factor C with the dual nature of carbon risk, the results show that the additional carbon risk taken is not sufficiently remunerated on either side by the financial market. They name investors’ inability to adequately quantify carbon risk as a possible explanation.

As a limitation, it should be mentioned that the factor C was created based on a global stock data sample that does not take into account the specific conditions of emerging markets. Since the results are sensitive to the measure used, a factor C tailored to the characteristics of the Brazilian market has the potential to provide a better estimate of the carbon risk beta.

5. Conclusion

Brazil is in a unique position to step up as a leading player in the global transition to a net-zero economy. Factor C developed by Görgen et al. (2020) is a factor-mimicking portfolio for carbon risk which allows to generate the carbon risk beta for stocks even if no corresponding information is available. With the aim of constructing a green portfolio, the stocks with the lowest exposure to a high (brown) BGS score are chosen. The result is a green portfolio based on a monthly rolling coefficient for factor C that captures information on carbon emissions and green transition (Mean Portfolio C Top).

Given the results of this thesis, it is not recommended to build a green portfolio solely based on the introduced factor as the resulting portfolios underperform the benchmark in terms of risk-adjusted returns. Nevertheless, looking at carbon risk through the lens of a market-based approach gives investors a better understanding of a stock's carbon risk. It is especially valuable when the respective information is neither disclosed by the companies nor available from third-party data providers. Quantifying carbon risk allows asset managers to create portfolios with the desired level of exposure to that factor. ESG aspects can thus be integrated, but also beliefs about whether Brazil is capable of realizing its potential to become a major player in the transition to a low-carbon economy. The carbon risk beta is best used to complement information gained from an in-depth analysis and the direct exchange with the local companies. As mentioned in the group contribution and the previous discussion, the knowledge gained through engagement and fundamental analysis can be further used to create a region-specific version of the carbon risk factor. This would allow for a more precise estimation of carbon risk exposure of Brazilian stocks, enabling portfolio managers to account for and manage the risk arising from the uncertain transition process towards a net-zero economy.

Bibliography

Bolton, Patrick, and Marcin Kacperczyk. 2021. "Do Investors Care about Carbon Risk?" *Journal of Financial Economics* 142 (2): 517–49. https://doi.org/10.1016/j.jfineco.2021.05.008.

Brandimarte, Walter. 2015. "Brazil Downgraded to Junk Rating by S&P, Deepening Woes." *Thomson Reuters*. September 10, 2015. https://www.reuters.com/article/us-brazil-ratings-s-p-idUSKCN0RA06120150910.

Economic Commission for Latin America and the Caribbean. 2022. "*Preliminary Overview of the Economies of Latin America and the Caribbean 2015*." CEPAL. October 14,

Fama, Eugene F., and Kenneth R. French. 1995. "Size and Book-to-Market Factors in Earnings and Returns." *The Journal of Finance* 50 (1): 131–55. https://doi.org/10.1111/j.1540-6261.1995.tb05169.x.

Görgen, Maximilian, Martin Nerlinger, Marco Wilkens, Andrea Jacob, Ryan Riordan, and Martin Rohleder. 2017. "Carbon Risk." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2930897.

Görgen, Maximilian, Andrea Jacob, and Martin Nerlinger. 2020. "Get Green or Die Trying? Carbon Risk Integration into Portfolio Management." *The Journal of Portfolio Management* 47 (3): 77–93. https://doi.org/10.3905/jpm.2020.1.200.

Grottera, Carolina, Emilio La Rovere, and William Wills. 2017. "Low Carbon Infrastructure Priorities in the Brazilian Context." Centro Clima. July 2017. https://www.oecd.org/env/cc/g20-climate/.

Harvey, Campbell R., and Yan Liu. 2014. “How Many Factors?” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2528780.

Jones, Alexander. 2017. “What's behind Brazil's Massive Stock-Market Rally?” *International Banker*. March 21, 2017. https://internationalbanker.com/brokerage/whats-behind-brazils-massive-stock-market-rally/.

NASA. 2022. “Scientific Consensus: Earth's Climate Is Warming.” August 5, 2022. https://climate.nasa.gov/scientific-consensus/.

Pástor, Ľuboš, Robert F. Stambaugh, and Lucian A. Taylor. 2021. “Sustainable Investing in Equilibrium.” *Journal of Financial Economics* 142 (2): 550–71. https://doi.org/10.1016/j.jfineco.2020.12.011.

Sawaya, Alexandre, Nelson Ferreira, Reinaldo Fiorini, Roberto Fantoni, and Wieland Gurlit. 2022. “The Green Hidden Gem – Brazil's Opportunity to Become a Sustainability Powerhouse: Brazil.” McKinsey & Company. November 9, 2022. https://www.mckinsey.com/br/en/our-insights/all-insights/the-green-hidden-gem-brazils-opportunity-to-become-a-sustainability-powerhouse.

The Economist. 2021. “Brazil Wants More from COP26 than It Is Willing to Give.” November 6, 2021. https://www.economist.com/the-americas/2021/11/06/brazil-wants-more-from-cop26-than-it-is-willing-to-give.

United Nations Environment Programme. 2022. *Emissions Gap Report 2022*. October 12, 2022. https://www.unep.org/resources/emissions-gap-report-2022.

Universität Augsburg. Accessed December 11, 2022. https://www.uni-augsburg.de/de/fakultaet/wiwi/prof/bwl/wilkens/sustainable-finance/downloads/.