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THE ESG FACTOR

IMPACT OF ESG CRITERIA ADOPTION ON STOCK RETURNS AND VOLATILITY

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This work is dedicated to myself, since I proved to be more resilient than I thought I could be in such tough times. I sincerely had no idea that I could carry out this entire work only using Python and LaTeX, without touching MS Word and Excel for the very first time. To my mother Dina, who gave me support and love.

I am thankful to all taxpayers from São Paulo, who invested in me and my colleagues. Although I do not know each of them personally, I am grateful for all the benefits I got and I can assure them I gave my very best.

To the University of São Paulo, which offered me the opportunity to become a better citizen, professional and human being. This place makes me proud of my country every single day. Whenever I cross the campus gates I remember the professors, researchers, students and staff members, who create an inspiring atmosphere and work so hard, sometimes during very difficult conditions. I have no words to express how respectful I am to this community.

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To Elise and Ewerton, who helped me to cross this road in a healthier manner.

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To this University, every professor, researcher, staff member and student, for a life changing experience.

“Se você não se preocupa com a justiça social, com quem paga a conta,
você não é um economista sério, você é um tecnocrata.”

Maria da Conceição Tavares, 1995

Resumo

Este artigo analisou retornos de ativos financeiros socialmente e ambientalmente responsáveis e comprometidos com a qualidade de governança corporativa, os quais são identificados como ESG. Esses ativos foram representados em grupo por ETFs, que são carteiras de investimentos contendo ações de empresas do segmento em estudo. Os retornos mensais desses ETFs foram comparados com os retornos mensais de índices de referência em quatro cenários: (1) curto prazo no Brasil e (2) longo, (3) médio e (4) curto prazo nos Estados Unidos. O primeiro cenário utiliza o IBOVESPA como índice de referência, enquanto os demais cenários utilizam o índice S&P500. Esses cenários foram divididos de acordo com a disponibilidade de dados. Nos três cenários dos Estados Unidos, não encontramos um padrão de risco expressivamente menor ou maior em ativos ESG em comparação com o índice S&P500, nem um prêmio em seus retornos. Por outro lado, no cenário do Brasil, encontramos um padrão de volatilidade e retorno esperado expressivamente menor que o IBOVESPA, implicando em menor risco sistemático ao investidor.

Palavras-Chave: ESG, Mercado Financeiro, Renda Variável, Investimentos Sustentáveis

Códigos JEL: C12, G12, G15, Q56

Abstract

This article analyzed returns from socially and environmentally responsible financial assets, which are committed to governance quality, identified as ESG (Environment, Social, Governance). These assets are collectively represented by ETFs (exchange tradable funds), which are investment portfolios containing company shares in the segment under study. We compared these ETFs monthly returns to benchmark monthly returns in four scenarios: (1) Short-Term in Brazil and (2) Long, (3) Medium and (4) Short-Term in the United States. The first scenario uses the IBOVESPA index, while the other scenarios use the S&P500 as benchmark. We divided these scenarios according to data availability. In the three US scenarios, we did not find neither a relevant lower or higher risk pattern in ESG assets compared to the S&P500 index, nor a premium on their returns. On the other hand, in the Brazilian scenario, we found an expressive lower pattern of volatility and expected return compared to the IBOVESPA index, implying a lower systematic risk for investors.

Keywords: ESG, Stock Market, Variable Income, Sustainable Investments

JEL Codes: C12, G12, G15, Q56

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1 Introduction

Recently the ESG criteria has been spread through the stock market. This acronym stands for Environment, Social and Governance concerns. The number of ESG concerned investors is progressively growing so that the demand for “green” and social responsible alternatives in investment is also increasing. Probably some or all ESG values might be compulsory for all companies listed in the stock market in a few decades. However, just some companies are taking them into account now. Comparing ESG stocks to a benchmark will allow us to identify the impact of “ESG factor” stocks’ return and volatility.

The aim of this article is to check if ESG values lead to better returns and/or provide a lower risk, measured by asset volatility. If any finding in that way is proved it could draw strong reasons for carefully watching environmental and social impact. Therefore, this perception could be a milestone in the path of conciliating the Principles of Responsible Investing at the contemporary capitalism core. If the results show no evidence that ESG assets are neither better nor worse, at least they would be a desirable conclusion in favor of “The ESG Factor”. Since the refusal of ESG values will not grant larger returns nor lower risks, there will not be reasons to avoid them.

ESG stocks’ performance have been more deeply studied during the last two decades since 2000, especially after 2006 when the United Nations launched the Principles for Responsible Investment. There is a major mentality shift in investing from 1970 to the present time. Until late in the twentieth century, the mainstream leading literature for portfolio selection was represented by the Markowitz Theory (Portfolio Selection, 1952), which considers risk adjustment according to expected return to volatility ratio (Sharpe Ratio Definition), correlation among stocks and specific weightings to find the optimal choice along the efficient frontier. This theory neglected both social and environmental impacts, as well as investor preferences towards sustainable stocks, as this kind of information was poorly covered at that time and in fact the only matter was profit maximization.

To start the Environmental, Social and Governance (ESG) discussion, the interpretation presented by Milton Friedman (1970) summarizes the predominant market perception at least until the nineteen nineties, which exempts companies from

being socially and environmentally responsible. According to Friedman (1970, p. 2), responsibilities like

“providing employment, eliminating discrimination, avoiding pollution [... are] preaching pure and unadulterated socialism [...] undermining the basis of a free society these past decades.”

Obviously, he writes with the Cold War political tension born in mind. He openly criticizes price controls to tackle inflation and private actions to fight poverty or reduce pollution, such as hiring very low qualified people and conscious pro-environmental expenses because these measures would harm the companies' profit. When he mentions social responsibility, he considers that companies do not and should not have this natural criterion, since business owners, to whom corporate executives must obey, “want to make as much money as possible”, provided it is within the “law and ethical custom” (1970, p. 2). This last expression is vague. Are companies responsible for their own pollution emission or for their indirect effect in deepening poverty or worsening the environment? According to this economic approach, no. Expending towards social responsibility would take money either from stockholders and/or customers, or it would end up lowering employee wages. This is his key argument to give up on social responsibility within corporate boundaries. It denies the public benefit from air pollution control or lower criminality and poverty rates with lower unemployment. To Friedman, this kind of corporate expenditure would function as a taxation, and this should be reserved for the government, since it is a public objective. He regards the ESG values as conflict of interest (1970, p. 4) if taken by a corporate executive, who would put the company competitiveness and profitability at risk. The indirect benefits taken by a positive public opinion about the company when it takes better social and environmental practices are not considered. In a competitive market system, he admits that socially responsible employers and producers would be at a disadvantage competing with less scrupulous peers, willing to pollute more and/or exploit workers in poor working conditions, unless there are legal constraints.

The following contemporary literature showcases quite a different approach. Jagannathan et al. (2017) found that investors and money managers can take advantage of the ESG factor, since sustainable stocks are less prone to sudden

shifts provoked by stricter regulations concerning social and environmental issues. According to these authors (2017, p. 4), "Investors may reduce portfolio risks by considering how these regulatory risks are reflected in their investment decisions."

Their major finding is that asset prices can be mostly influenced by sudden regulations, but also by customer preferences. They (JAGANNATHAN, RAVIKUMAR, & SAMMON, 2017, p. 5) also point out the increase in managed assets which follow ESG criteria from 13.3 trillion US dollars in 2012 to \$ 22.9 trillion US dollars in 2016, which stands for more than 52 percent of the total managed assets in Europe and more than 21 percent in the United States. This may confirm a trend of a growing ESG stock market and sustainable investment concern as well as the relevance in studying the differences between the ESG market and the non-ESG market.

Another contemporary approach begins with Eugene Fama & Kenneth French (2007). They conclude that stock picking is not driven exclusively by future payoffs but also by investor preferences as they may regard stocks as consumption goods. Concerning ESG, they wrote (FAMA & FRENCH, 2007, p. 675):

" 'Socially responsible investing' (for example, refusing to hold the stocks of tobacco companies or gun manufacturers) is an extreme form of tastes for the assets as consumption goods that are unrelated to returns."

They put this sort of concern at the same level of misinformation (FAMA & FRENCH, 2007, p. 675):

"Market equilibrium in a world where some investors have tastes for assets as consumption goods is generally like equilibrium in a world where some investors trade based on misinformed beliefs."

In this sense, ESG concern would stand more for noisy stock behavior rather than a premium. The authors do not foster the idea that social responsibility would aggregate useful information for enhancing the stock picking process. Considering ESG values merely as a personal taste, which is considered exogenous to economic logic, the effect would be like misinformation about the monetary expected returns.

Another model which analyzes "green assets" versus "brown assets" (respectively,

ESG assets and non-ESG assets) through returns is presented by Pastor, Stambaugh & Taylor (2019, p. 6). According to their model and following Fama & French (2007) interpretation, ESG investors derive utility beyond stock performance itself, because they enjoy holding sustainable assets, which they take as a non-pecuniary benefit, such as environment preservation and social responsibility. However, they assume that companies adopt ESG values voluntarily because they lead to higher market values, despite lower expected returns. Thus, being socially responsible would bring not only external benefits to society but also better market values to the companies themselves.

The following research conducted by Cao, Titman, Zhan & Zhang (2020) found that ESG investors have a less active profile in responding to price shifts compared to non-ESG investors. Social Responsible (SR) institutional investors have a longer investment horizon compared to non-SR investors. Since the latter focus exclusively on stock performance, they are more prone to buy and sell in higher frequency than the ESG peers, considerably less sensitive to price shocks (2020, p. 24). As these have preferences according to non-financial traits, they lead to higher stock prices than the prices obtained through fundamental valuation, reducing the efficiency of quantitative signals.

The literature brought above takes at least three different approaches on why Environmental, Social and Governance (ESG) aspects should be considered. None of them proposed a model including public externalities which also benefit employees, customers and stockholders, such as better air quality due to pollution control, despite its corporate costs. However, the three approaches presented are relevant and pragmatic in supporting why ESG should be a standard concern for the whole market, either preventing future regulation shifts, assuming that ESG stocks are less risky or inducing their respective companies to achieve larger market values. The present article intends to find empirically how “The ESG Factor” might (or not) help stockholders pay off.

2 Methodology

Exchange Tradable Funds are used in this work instead of company stocks to rule out particularities of firm behavior. Using ETFs, a smoother performance is expected and we could obtain the actual relevance of social and environmental sustainability traits. In this sense, all selected ETFs excluded companies involved in nuclear energy, genetic modification, tobacco, controversial weapons in general, civilian firearms, thermal coal and oil sands as well as companies with low MSCI ESG scores, which assess their sustainability.

The data used are extracted from Yahoo Finance with Python coding and manipulation tools. The coding will be preserved in this document at the appendix to keep data extraction and analysis reproducible without interruptions. We have downloaded all data concerning the ESG and benchmark ETFs as daily prices in local currency and then transformed them into daily and monthly returns. All daily and monthly returns available will be calculated for each selected ETF. We tried to catch the largest time horizon available with the datasets. Different time horizon analysis might be necessary to statistically confirm the results. We have screened the stock markets in Brazil and the United States to find the ESG assets for this study. While in Brazil there is only one ESG ETF available with an acceptable time length, in the United States there are at least eight good ESG ETF alternatives with different time lengths. Research based only on Brazilian stock market data may not be sufficient due to the Short-Term dataset, so the US market data are used to provide more reliable conclusions as their time horizons are larger.

The core idea is to analyze and compare ESG ETFs with their benchmarks, respectively for both the US and Brazilian markets. This analysis will present descriptive statistics and graphics for each ETF. The comparison between ESG ETF and benchmark ETF will be tested with inference statistics to check if the ESG ETFs monthly return distributions differ from the market reference, have normal distribution and are strongly correlated with the benchmark. Additionally, we will use simple linear regressions, using Ordinary Least Squares (OLS) method. We will take ESG ETFs as dependent variables and the benchmark ETF as the independent variable, as follows:

$$ESG_{return} = \alpha + \beta * Benchmark_{return} + u$$

$$ESG_{return} = \beta * Benchmark_{return} + u$$

We want to find out whether ESG ETFs offer a premium (alpha > 0) or penalty (alpha < 0) independently from the benchmark influence (ASSAF NETO, p. 321). Moreover, we want to discover if and how ESG ETFs are dependent to their respective benchmarks. We also want to find if the ESG ETFs have less volatile and less risky response to the benchmark returns (beta < 1).

In Brazil we have selected the following ESG ETF, available at B3 (São Paulo Stock Market):

- BTG Pactual ESG FI S&P/B3 Brazil ESG (ESGB11.SA)

This one will be compared to and tested against the Brazilian benchmark ETF:

- Ishares Ibovespa Fundo de Índice (BOVA11.SA)

For this test we expect low statistical relevance since the Brazilian ETF is just a few months old. These two datasets are extracted in local currency, without loss for statistical purposes.

In the US, the selected ETFs are available at NYSE:

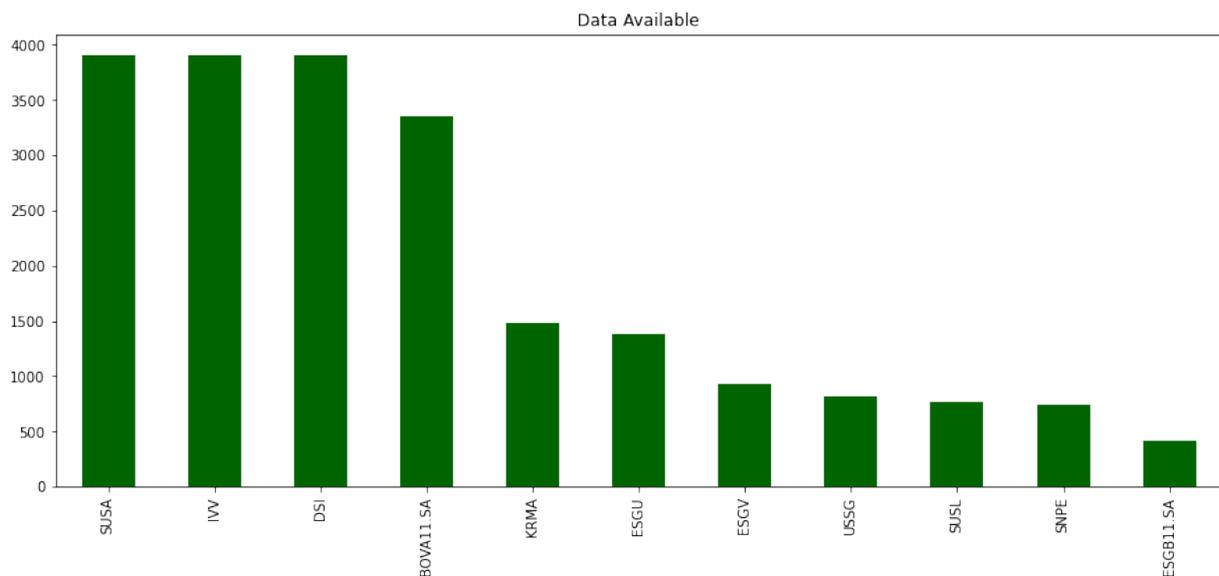
- iShares MSCI KLD 400 Social ETF (DSI)
- iShares MSCI USA ESG Select ETF (SUSA)
- iShares ESG Aware MSCI USA ETF (ESGU)
- iShares ESG MSCI USA Leaders ETF (SUSL)
- Global X Conscious Companies ETF (KRMA)
- Vanguard ESG US Stock ETF (ESGV)
- Xtrackers S&P500 ESG ETF (SNPE)
- Xtrackers MSCI USA ESG Leaders Equity ETF (USSG)

These assets will be compared to and tested against the S&P500 ETF:

- iShares Core S&P500 ETF (IVV)

3 Data

Initially there are two groups: one with two Brazilian ETFs (BOVA11.SA and ESGB11.SA) and another with nine US ETFs (IVV, DSI, SUSA, KRMA, ESGU, ESGV, USSG, SUSL and SNPE) measured in local currency. The amount of available data for all of them are depicted by the following plot:



The Brazilian group yields the following simple scenario to study:

- Short-Term Brazil: BOVA11 and ESGB11 (2020-2022)

The USA group can be split into three cumulative sets according to their time horizon and derived count for prices, daily and monthly returns. These three groups are assigned as follows:

- Long-Term USA: IVV, DSI and SUSA (2007-2022)
- Medium-Term USA: IVV, DSI, SUSA, ESGU and KRMA (2017-2022)
- Short-Term USA: IVV, DSI, SUSA, ESGU, KRMA, ESGV, SNPE, SUSL and USSG (2019-2022)

This division yields the following Daily Returns Matrix for each group:

- Short-Term Brazil: 409 Daily Return rows \times 2 ETF columns
- Long-Term USA: 3900 Daily Return rows \times 3 ETF columns
- Medium-Term USA: 1380 Daily Return rows \times 5 ETF columns
- Short-Term USA: 736 Daily Return rows \times 9 ETF columns

As a result, we have the following Monthly Returns Matrix for each group:

- Short-Term Brazil: 20 Monthly Return rows \times 2 ETF columns
- Long-Term USA: 186 Monthly Return rows \times 3 ETF columns
- Medium-Term USA: 66 Monthly Return rows \times 5 ETF columns
- Short-Term USA: 35 Monthly Return rows \times 9 ETF columns

Consequently, from these databases we have four scenarios to study. We provide the analysis, testing and linear regression for the following scenarios in the next sections:

Scenario 1 - Short-Term (2020-2022) - Brazil

Scenario 2 - Long-Term (2007-2022) - USA

Scenario 3 - Medium-Term (2017-2022) - USA

Scenario 4 - Short-Term (2019-2022) - USA

We will use the Monthly Returns samples as the standard along this article, but the Daily Returns samples will be statistically needed sometimes. All conclusions will be summarized and discussed right after, in the *Conclusion* section.

4 Scenario 1 - Short-Term (2020-2022) - Brazil

4.1 Descriptive Statistics

Monthly Returns

The scenario designed for Brazilian Stock Market has two ETFs: BOVA11 representing local market index and ESGB11 representing the ESG alternative ETF. We extracted 409 daily prices in local currency. This yields 20 monthly returns described in the following table:

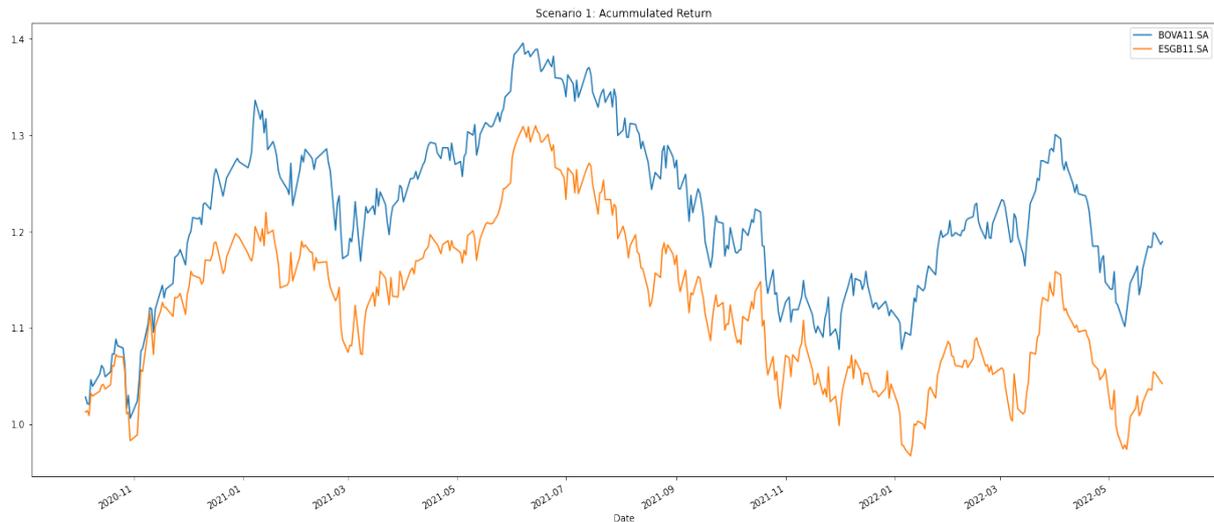
Table 1 - Summary Statistics

	BOVA11	ESGB11
count	20	20
mean	1.06	0.36
std	6.30	5.68
min	-10.55	-7.92
25%	-3.64	-4.12
50%	0.73	-0.74
75%	6.03	4.61
max	15.82	13.34

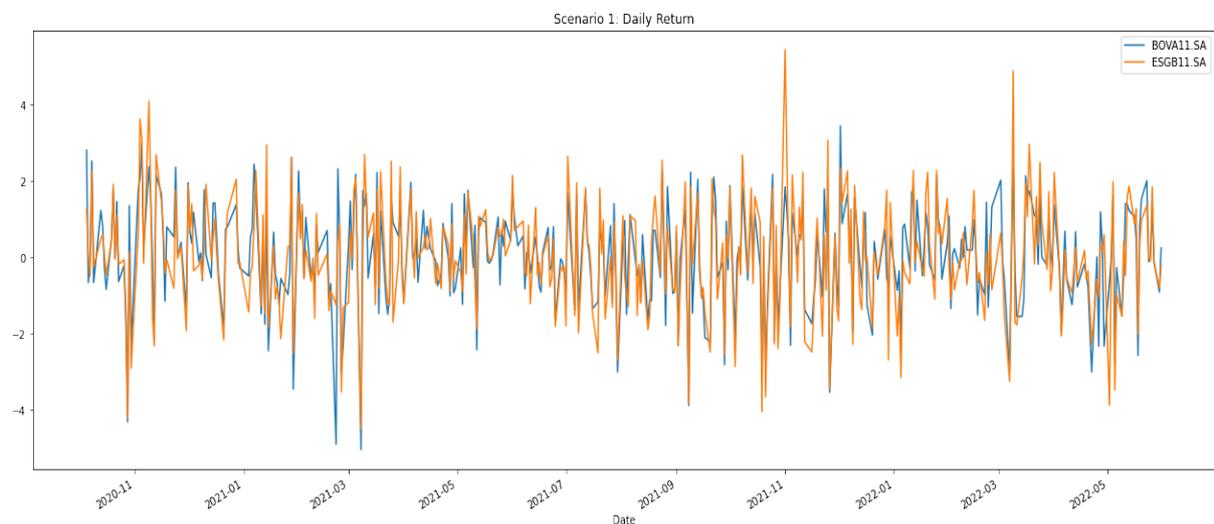
Objectively, the dataset summary shows a sign that the average return for the ESG ETF is lower compared to the local market index. However, the ESG ETF seems to have a lower standard deviation, which is a good starting point to support our thesis and may confirm the authors' findings that ESG assets are better and safer alternatives. In the following sections we will test if these findings are consistent.

Accumulated Return

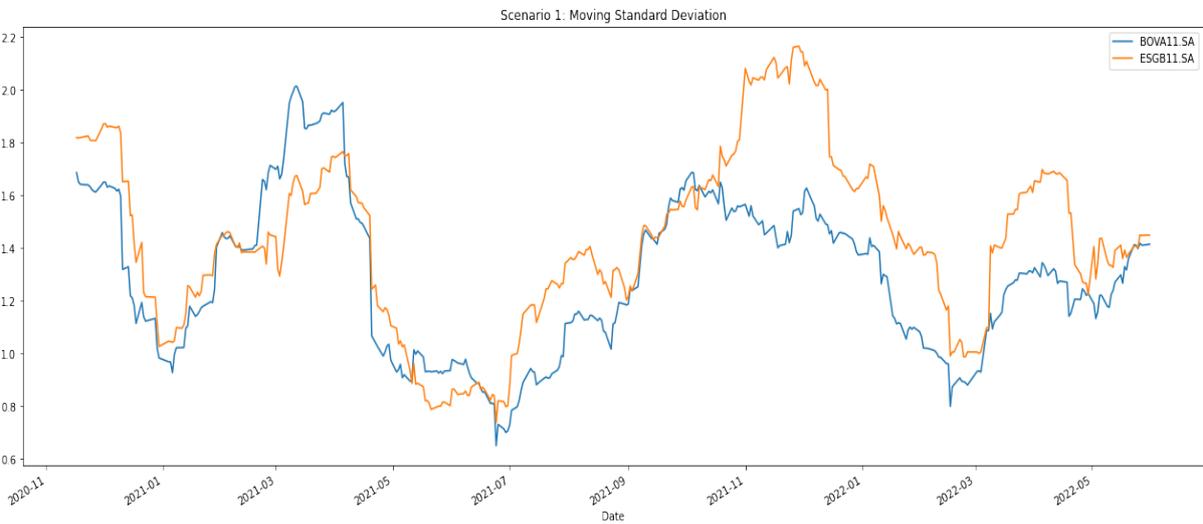
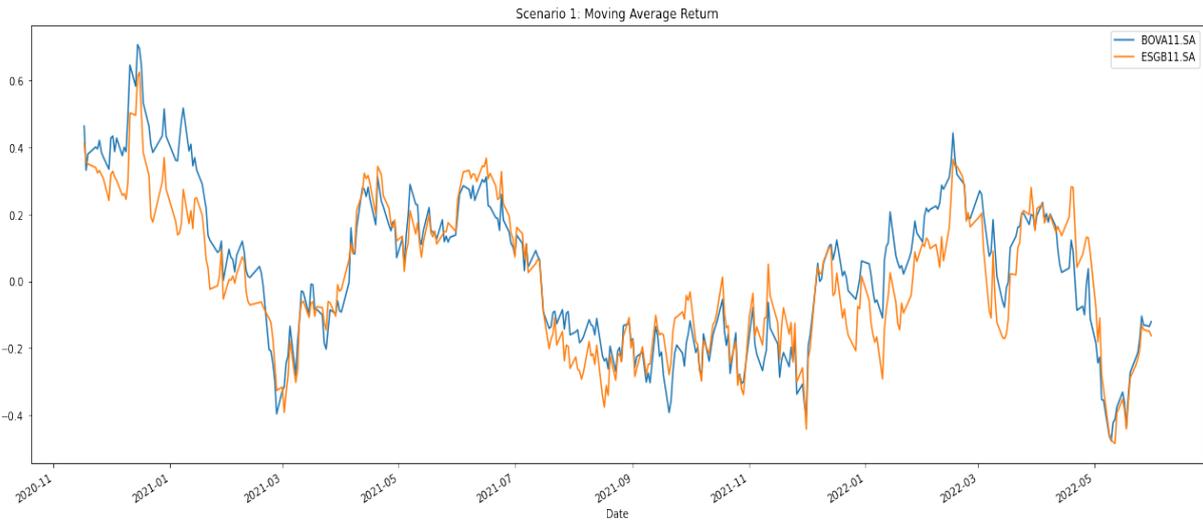
Since 2020, the two selected ETFs yielded the following accumulated returns considering local currency prices:



Differently from the US assets, these ETFs are inserted in an Emerging Market and for this reason present higher volatility than usual for Developed Markets. Also, the Short-Term dataset might not be enough to draw statistically consistent results; rather, it may suggest if the results found for the Brazilian context are also held in the United States. The Accumulated Return plot shows that the Brazilian ESG ETF (ESGB11) performed poorer compared to the benchmark (BOVA11). At first sight, we infer qualitatively that the main thesis - green assets perform better and/or are less risky - is wrong.



As we plot the Daily Returns time series for the Brazilian Market, it's easy to verify a quite unstable pattern and higher standard deviations compared to the US peers. Let us see the Moving Average and Moving Standard Deviation for the Brazilian assets:



One can observe a close correlation between them. The Brazilian ESG ETF had a poorer performance during this period, which may suggest that the restrictions applied to ESG stocks can reflect negatively on their returns and deny what the authors claimed in favor of ESG. The Moving Average Return pair is closely intertwined while the Moving Standard Deviation seems to be wider for ESGB11. These assumptions will be tested in the following sections.

4.2 Exploratory Data Analysis

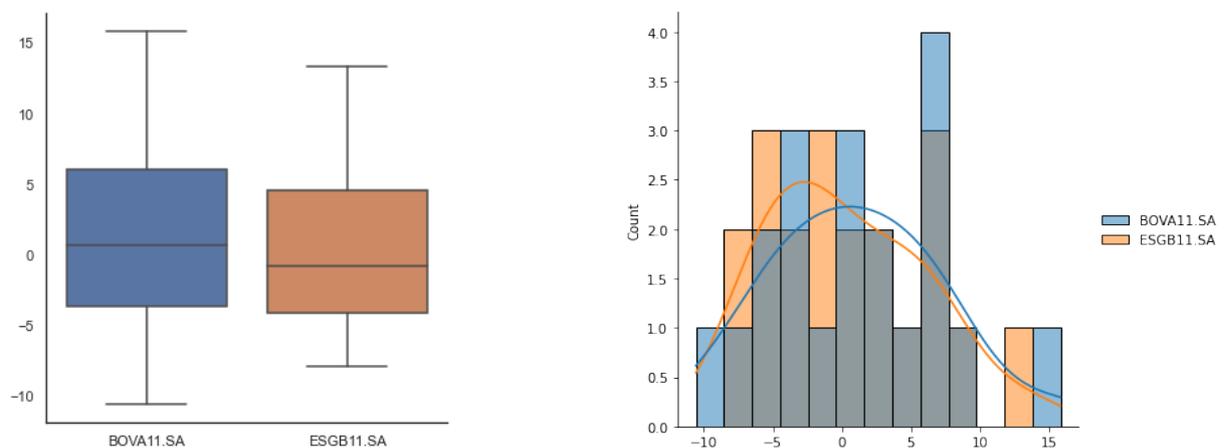
With a simple correlation test we can check if ESGB11 and BOVA11 are correlated and dependent:

Pearson Correlation Test

$R = 0.945$, $p\text{-value} = 0.000$

Dependent (reject H_0) at 0.05

The test yields a high correlation between the two assets. Actually, one can presume that ESGB11 depends on the local market index closely, as we will see. Let us see with boxplots and overlaid histograms how the Monthly Returns for these two are distributed:



The graphics above show great similarity between ESGB11 and BOVA11 monthly returns. Visually ESGB11 has a lower average return, whilst it holds a lower standard deviation compared to BOVA11. However, tests are needed to confirm if these descriptive statistics are significantly different and normally distributed.

4.3 Statistical Inference

Normality Test

Since we have just a small sample, with $n=20$, we have small power when testing for normality. Even using the Shapiro-Wilk Test, which is one of the most powerful normality tests, we should use the daily returns to extract a more reliable result.

BOVA11

Shapiro-Wilk Test
W Stat. = 0.982, p-value = 0.000
Not Normal (reject H_0) at 0.05

ESGB11

Shapiro-Wilk Test
W Stat. = 0.992, p-value = 0.030
Not Normal (reject H_0) at 0.05

According to the Shapiro-Wilk Test result for daily returns we conclude that both ESGB11 and BOVA11 are not normally distributed. When we tested for normality with monthly returns, we failed to reject the Null Hypothesis, but this result has very low probability to be true since we have just 20 monthly returns.

Hypothesis Test

We already know that BOVA11 and ESGB11 are not normally distributed, strongly correlated and probably not independent. To check if the means and standard deviations for monthly returns are consistently different, we apply the Paired Student's T-Test for both distributions, despite the normality condition is not fully met.

Paired T-Test
Mean Difference: 0.699
SD Difference: 0.603
T Statistic = 1.509, p-value = 0.148
Same distribution (fail to reject H_0) at 0.05

According to the test the monthly distributions for BOVA11 and ESGB11 are statistically equal, so we cannot assume that mean return and standard deviation differ. There was an even larger p-value when we tested the daily returns, which strongly fails to reject the Null Hypothesis. Concluding the Brazilian scenario, in the Short-Term the selected ETFs are strongly correlated and dependent, the monthly returns distributions are not gaussian and are not statistically different.

4.4 Simple Linear Regression Models

We will design the following models to test how ESGB11 returns are explained by BOVA11 returns.

$$ESGB11_{return} = \alpha + \beta * BOVA11_{return} + u$$

$$ESGB11_{return} = \beta * BOVA11_{return} + u$$

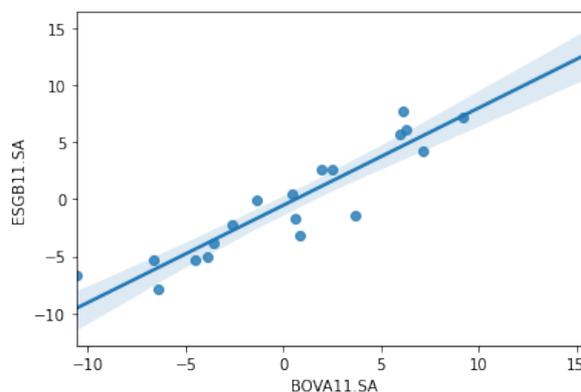
Using the monthly and daily returns we got the following results:

Table 2 - OLS Regressions

	ESGB11(a)	ESGB11(b)
const	-0.54 (0.43)	
BOVA11	0.85*** (0.07)	0.84*** (0.07)
R2	0.89	0.88
R2.Adj.	0.89	0.88
No. obs.	20	20
AIC	84.4	84.1
BIC	86.4	85.0

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01



Using Monthly Returns

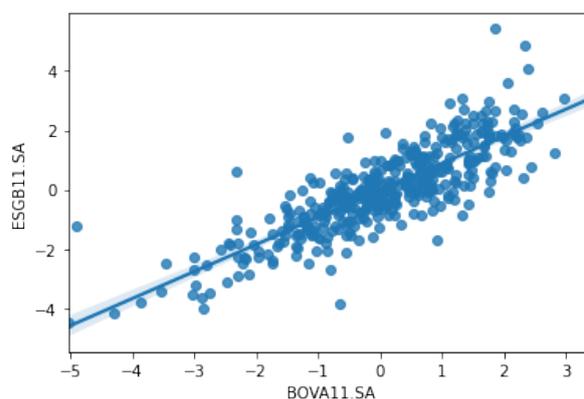
By the linear regression results we can conclude that the BOVA11 monthly returns can explain more than 87% of the ESGB11 monthly returns. Although the alpha is negative (-0.54), it is not statistically significant, so it may be ignored without relevant statistical loss. The second model - without intercept - does not consider intercept and the slope we obtain is almost the same: 0.84, with 88% goodness of fit. This means that the predicted monthly return for ESGB11 is just 85% of the BOVA11. This result confirms the idea that taking ESG investments is less risky than just following the benchmark, at least in the Brazilian stock market.

Table 3 - OLS Regressions

	ESGB11(a)	ESGB11(b)
const	-0.03 (0.04)	
BOVA11	0.91*** (0.03)	0.91*** (0.03)
R2	0.70	0.70
R2.Adj.	0.70	0.70
No. obs.	408	408
AIC	981.1	979.6
BIC	989.2	983.6

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01



Using Daily Returns

The daily returns dataset is larger and can confirm if the results obtained from the monthly returns dataset: the alpha is negligible and the slope 0.91 is near 0.85 but still below 1, which means that ESGB11 is supposed to react mildly to the benchmark volatility. The model for predicted daily returns can explain less information (70%) than the monthly return models (88%).

Model Selected

To conclude, the model using the monthly returns sample without intercept has the lowest Akaike and Bayesian Criteria and can explain 88% the returns. Thus, we can ignore the models obtained from daily returns and with intercept and consider the following model to predict ESGB11 monthly returns:

$$\widehat{ESGB11}_{mreturn} = 0.84 * BOVA11_{mreturn}$$

5 Scenario 2 - Long-Term (2007-2022) - USA

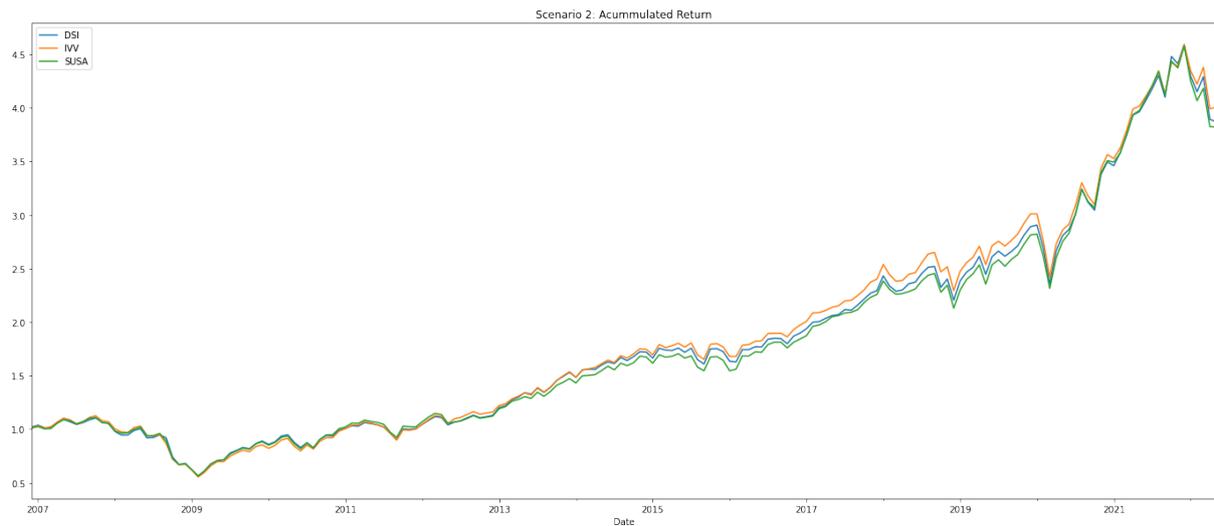
5.1 Descriptive Statistics

Monthly Returns One can attribute bad statistical results for the first scenario to the Emerging Market or the Short-Term dataset. Now we will see a totally different scenario: the USA market in the Long-Term. In this section, we will be comparing two pioneer ESG ETFs (DSI and SUSU) with the benchmark S&P500, represented here by the ETF IVV. We have extracted 186 monthly returns in percentage according to Table 4. DSI and SUSU returns have a larger standard deviation and slightly lower mean compared to IVV. They also present deeper minimum returns compared to the benchmark.

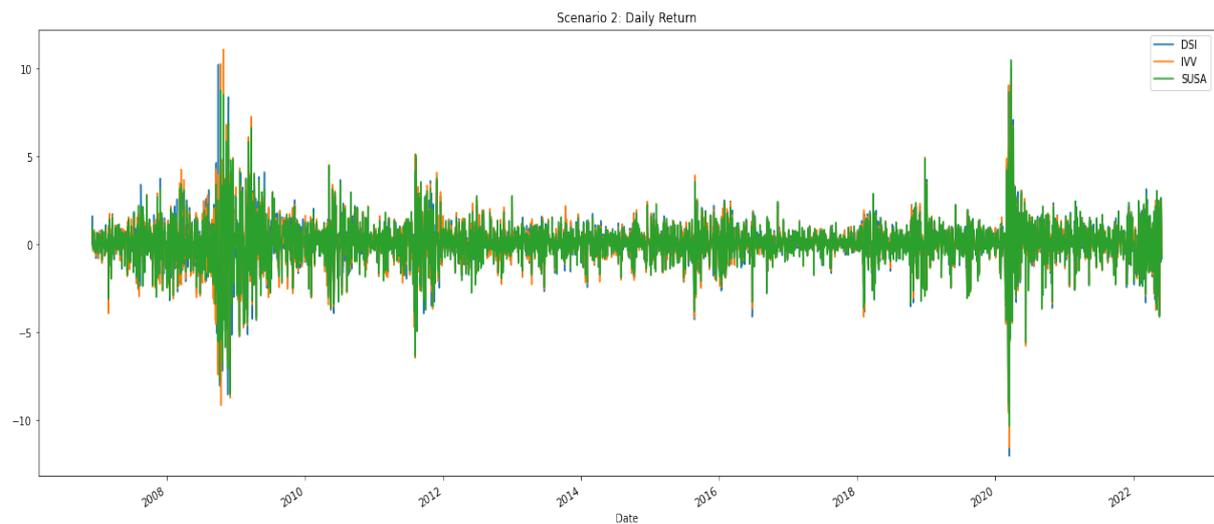
Table 4 - Summary Statistics

	DSI	IVV	SUSA
count	186	186	186
mean	0.83	0.85	0.83
std	4.52	4.44	4.50
min	-19.45	-16.63	-18.29
25%	-1.38	-1.58	-1.40
50%	1.56	1.40	1.21
75%	3.36	3.63	3.33
max	12.96	12.68	12.23

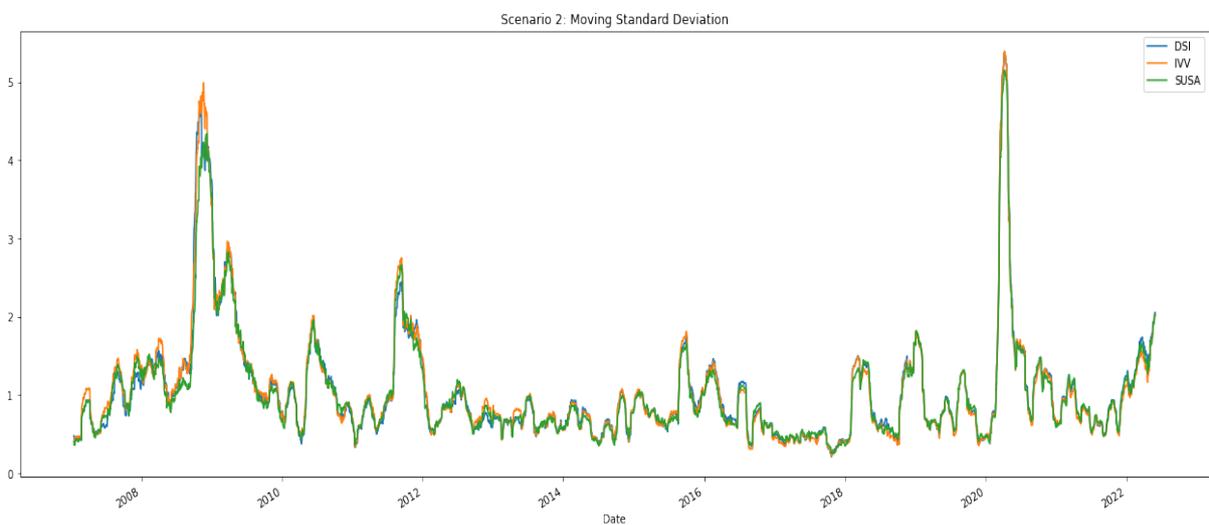
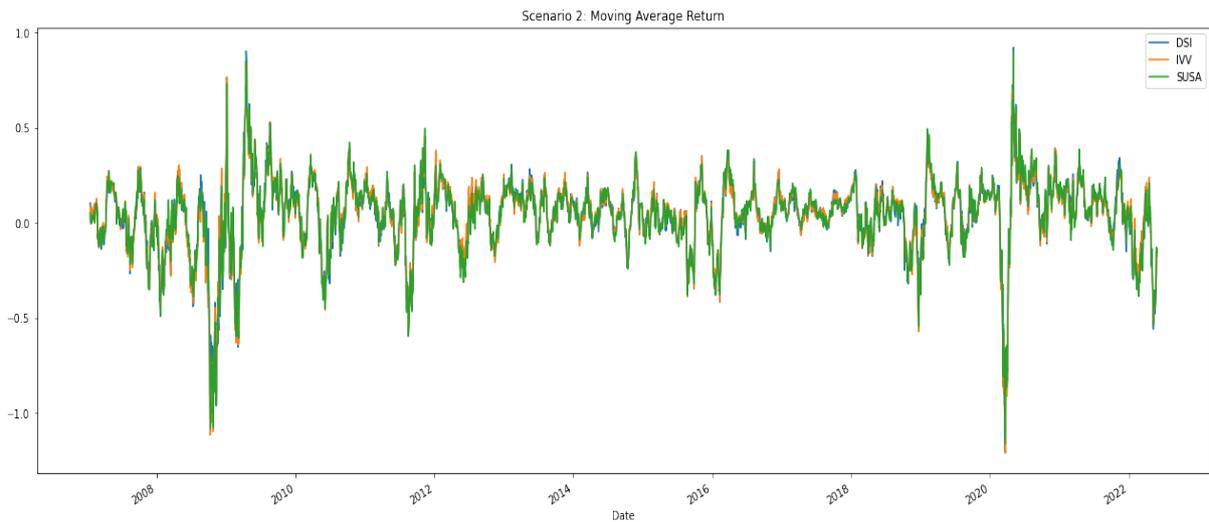
Accumulated Return Since 2007, these three ETFs have had the following accumulated returns:



This is a key plot to be sure that the two ESG ETFs (DSI and SUSA) closely follow the IVV ETF, which accounts for the S&P500 index. Only slight differences can be seen and are probably not statistically significant. So far, we have seen no clear pattern that ESG ETFs differ from S&P500. Let us then check the Daily Return series:



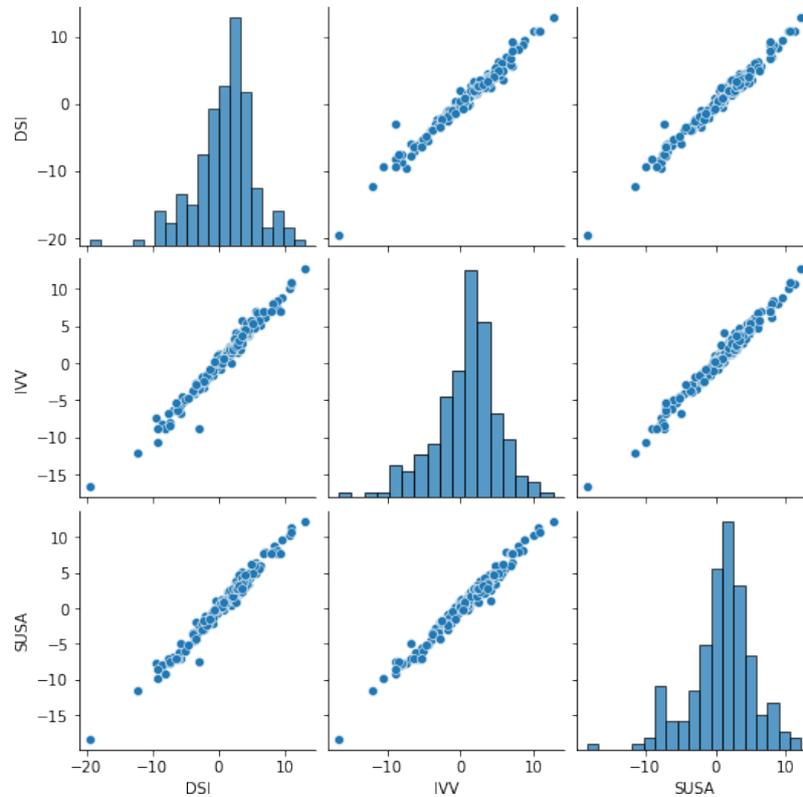
All daily return sets seem to coincide quite closely. Let us check the moving average and moving standard deviation time series:



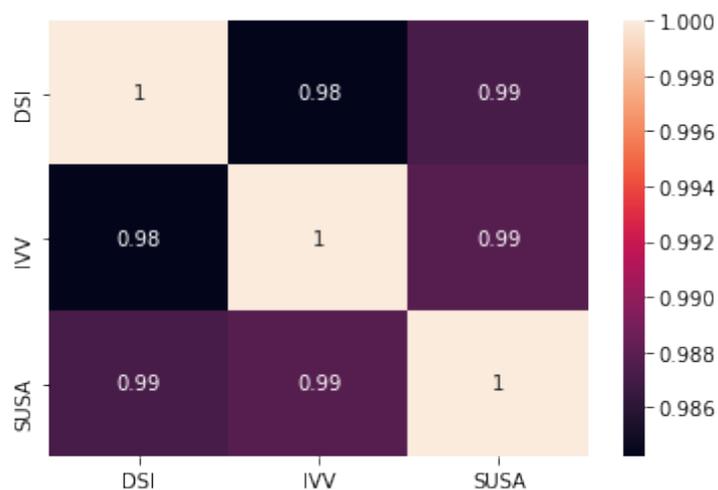
Even concerning the standard deviation evolutions the difference between them seems to be negligible: DSI and SUSA follow IVV quite closely. We still perceive moving averages and moving standard deviations intimately correlated. It is possible to identify through these two plots odd spikes corresponding to the 2008 crisis and the COVID-19 pandemic outbreak in the Americas since March 2020. More recently in 2022 there, is a clear standard deviation growth accompanied by lower returns regarding the Russia-Ukraine conflict impact onto the stock market.

5.2 Exploratory Data Analysis

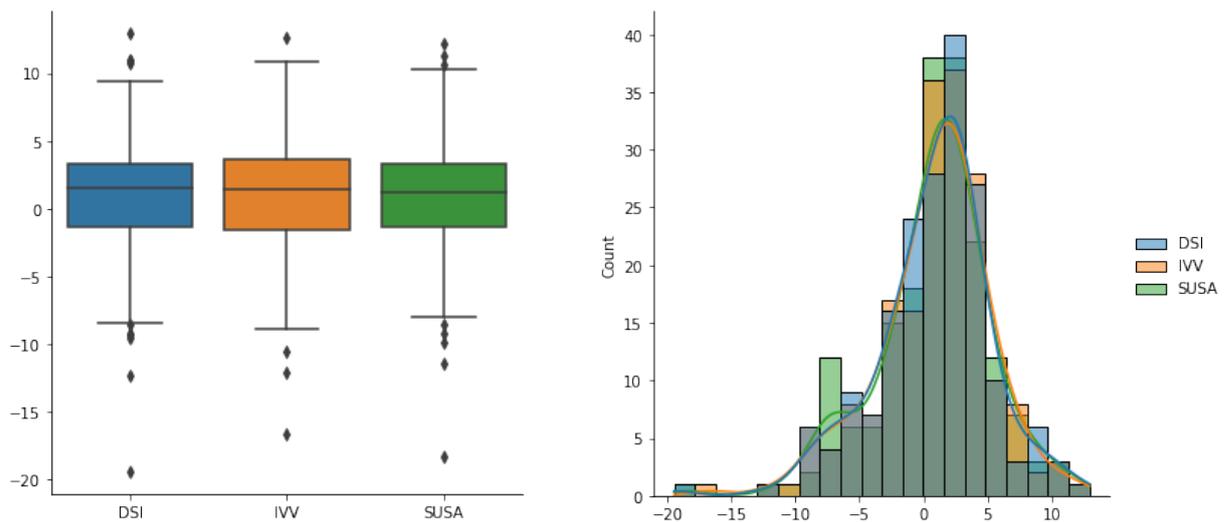
A quick glance at the correlation plots and histograms shows how LT Monthly Returns are distributed and correlated to each other.



Firstly, we observe an apparent strong correlation in all ETF pairs. Secondly, all histograms seem to approach a normal distribution at first sight. To check our first impression, we have the following Correlation Matrix, showing the correlations among all three ETFs:



The minimum correlation between the three datasets for MT Monthly Returns is 0.986, which can be considered extremely high. This perception holds, since the two ESG ETFs composition are derived from S&P500 index subsets. To visually check our second impression, concerning normality, the boxplots and collapsed histograms for Monthly Returns are presented as follows:



These three boxplots depict a strong similarity among the ETFs: practically the same mean and standard deviation. Seen from the side, all distributions have practically the same histogram. The accumulated distributions signed by the lines describe almost equal sets of information to the reference ETF (IVV). Further testing is needed to find out whether or not these Monthly Returns are normally distributed.

5.3 Statistical Inference

We will test the three distributions for normality and check if they are unequal as the histograms and boxplots suggested.

Normality Test

IVV

Shapiro-Wilk Test

W Stat. = 0.968, p-value = 0.000

Not Normal (reject H0) at 0.05

DSI

Shapiro-Wilk Test

W Stat. = 0.959, p-value = 0.000

Not Normal (reject H0) at 0.05

SUSA

Shapiro-Wilk Test

W Stat. = 0.964, p-value = 0.000

Not Normal (reject H0) at 0.05

The monthly distributions for DSI, SUSA and IVV in the Long-Term are not normal, according to the Shapiro-Wilk Test, with 1% significance, strongly rejecting the Null Hypothesis of normality. We applied the same test to the daily return samples and we still obtained strong rejection to normality.

Hypothesis Test

To check if DSI and SUSA have a different distribution compared to IVV, we apply the Paired T-Student Test to each ESG ETF:

DSI and IVV

Paired T-Test

Mean Difference: 0.014

SD Difference: -0.084

T Statistic = 0.247, p-value = 0.805

Same distribution (fail to reject H0) at 0.05

SUSA and IVV

Paired T-Test

Mean Difference: 0.022

SD Difference: -0.061

T Statistic = 0.435, p-value = 0.664

Same distribution (fail to reject H0) at 0.05

By those tests, we got that DSI and SUSA do not differ from IVV in terms of monthly returns. Besides that, we saw that in the Long-Term, the selected ETFs are strongly correlated and dependent, with R's above 0.986 and that they are not normally distributed. We applied the same test for daily returns and we got the same results, failing to reject the Null Hypothesis.

5.4 Simple Linear Regression Models

We begin the simple linear regressions with and without intercept according to the following models to explore how ESG ETFs respond to IVV stimulus, on a monthly return basis:

$$ESG_{return} = \alpha + \beta * IVV_{return} + u$$

$$ESG_{return} = \beta * IVV_{return} + u$$

Table 5 - OLS Regressions

	DSI(a)	DSI(b)	SUSA(a)	SUSA (b)
const		-0.02 (0.06)		-0.02 (0.05)
IVV	1.00*** (0.01)	1.00*** (0.01)	1.00*** (0.01)	1.00*** (0.01)
R-squared	0.97	0.97	0.98	0.98
R-squared Adj.	0.97	0.97	0.98	0.98
No. observations	186	186	186	186
AIC	447.8	445.9	398.5	396.7
BIC	454.3	449.1	405.0	399.9

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01

We checked if the same models applied for the daily return samples return lower Akaike and Bayesian Criteria, just as we did for scenario 1, but they did not. We keep the monthly returns models and select those without intercept, since they return lower Akaike and Bayesian Information Criteria:

$$\widehat{DSI}_{mreturn} = IVV_{mreturn}$$

$$\widehat{SUSA}_{mreturn} = IVV_{mreturn}$$

By these linear regressions results we conclude that not only are the intercepts close to zero but also statistically irrelevant, so they can be ignored considering the alternative models without constant, with no goodness of fit loss. That means that there is no risk premium in purchasing the ESG assets (ASSAF NETO, p. 321). The slope for the selected models is statistically significant at 1%: they are all equal 1. This means that the two ESG ETFs studied in the Long-Term - DSI and SUSA - respond with 97% and

98% goodness of fit respectively and that they have no different standard deviation compared to the IVV returns nor a risk premium. In other words, they are just equal to the benchmark, neither better nor worse. We found no evidence in favor or against ESG returns with this dataset, except the fact that there is no disadvantage in investing in ESG, according to these samples.

6 Scenario 3 - Medium-Term (2017-2022) - USA

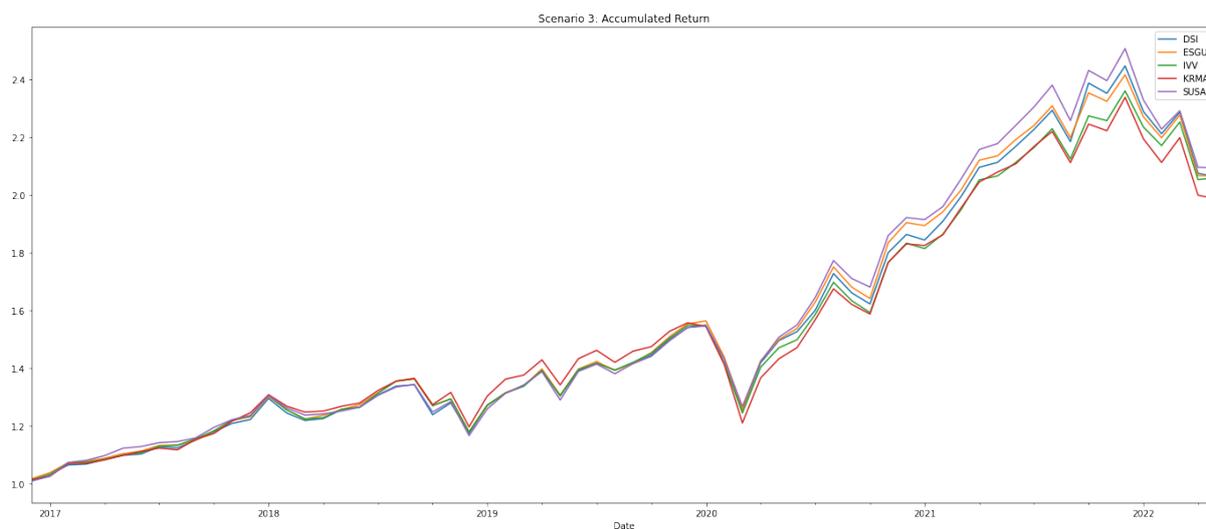
6.1 Descriptive Statistics

Monthly Returns From Yahoo Finance we got 66 monthly returns for the five ETFs selected for the third scenario: IVV, DSI, ESGU, KRMA and SUSA. The MT Monthly Returns matrix has the following descriptive statistics:

Table 6 - Summary Statistics

	DSI	ESGU	IVV	KRMA	SUSA
count.	66	66	66	66.	66
mean	1.21	1.21	1.20	1.16	1.23
std	4.63	4.60	4.52	4.69	4.58
min	-12.38	-12.55	-12.13	-14.34	-11.42
25%	-0.57	-0.04	0.03	-0.61	0.01
50%	2.04	1.80	1.92	1.58	1.80
75%	3.42	3.39	3.72	3.65	3.33
max	12.96	13.29	12.68	12.87	12.23

Accumulated Return Since 2017, the five selected ETFs yielded the following accumulated returns:



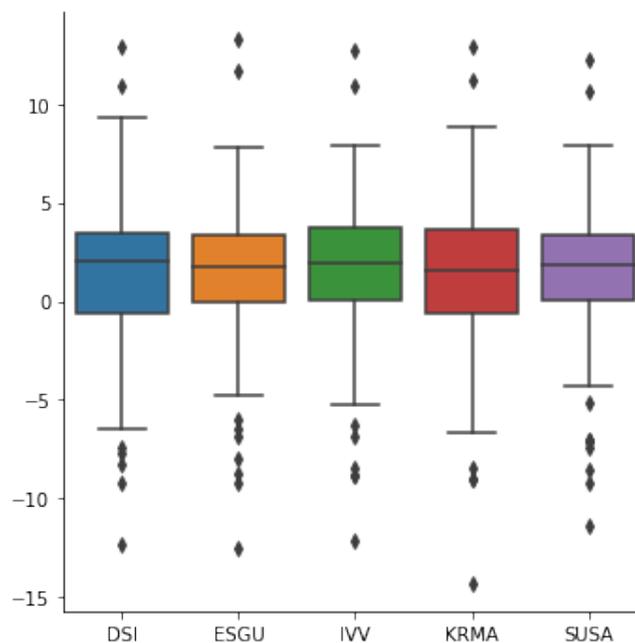
The four ESG ETFs (DSI, SUSA, KRMA and ESGU) closely follow the IVV ETF. That happened in the previous scenario with two ESG ETFs in the Long-Term. IVV is in the middle of the other four ETFs, meaning that ESG ETFs do not seem to behave differently from the S&P500 index.

6.2 Exploratory Data Analysis

The following heatmap can show how the MT Monthly Returns are correlated:



The minimum correlation between the five datasets for MT Monthly Returns is 0.984. Again, we observe strong correlations, emulating what we have found for the Long-Term scenario. Concerning normality, we have the following boxplots:



The strong similarity among the ETFs still holds. The ETFs have almost the same mean and slight differences in standard deviations. Again, we have practically equal sets of information. However, we still cannot conclude for normality. To check this, we will use statistical inference in the following subsection.

6.3 Statistical Inference

For statistical inference purposes, the monthly returns samples ($n = 66$) may be too small, so the power of tests might be inaccurate. Whenever needed, we will apply each test to daily returns samples ($n = 1380$) and compare these results to monthly returns.

Normality Test

We applied the Shapiro-Wilk Test to monthly return samples:

IVV

Shapiro-Wilk Test
W Stat. = 0.950, p-value = 0.010
Not Normal (reject H_0) at 0.05

KRMA

Shapiro-Wilk Test
W Stat. = 0.949, p-value = 0.008
Not Normal (reject H_0) at 0.05

DSI

Shapiro-Wilk Test
W Stat. = 0.952, p-value = 0.013
Not Normal (reject H_0) at 0.05

ESGU

Shapiro-Wilk Test
W Stat. = 0.943, p-value = 0.004
Not Normal (reject H_0) at 0.05

SUSA

Shapiro-Wilk Test
W Stat. = 0.951, p-value = 0.011
Not Normal (reject H_0) at 0.05

According to the Shapiro-Wilk Test results, we conclude that ESGU Monthly Returns are not normally distributed with a 5% significance level. We tested all samples with the Jarque-Bera Test as well and we got different results for DSI and SUSA monthly returns. We checked whether this divergence is solved by testing the daily returns samples ($n = 1380$) with Shapiro-Wilk Test and we concluded that the daily returns are not normally distributed. Therefore, one can assume that monthly returns are not gaussian either, since monthly returns are just simplified samples of daily return samples.

Hypothesis Tests

Now we need to confirm if all distributions are equivalent or not. To check that, the appropriate tool is the Analysis of Variation Test (ANOVA). Let us call back its conditions:

1. Independence: within dataset and between different datasets
2. Near normality
3. Equal standard deviation

We already know that these time series are not independent among them at all. All correlations are extremely high, with Pearson R's all above 0.98 for Monthly Returns. We also know that the Monthly Returns samples are not normally distributed. Even knowing that not all conditions are fully met, the ANOVA Test shows the following result for the five MT Monthly Returns samples at once:

```
Analysis of Variance Test ANOVA
F Statistic = 0.005, p-value = 0.995
Same distribution (fail to reject H0) at 0.05
```

The ANOVA Test shows that all distribution means do not differ from each other and one can assume that the samples have the same distribution. As we should not rely on ANOVA Test because the criteria are not fully met, since all distributions are strongly dependent and not gaussian, Non-Parametric Tests are required to check if the distributions can be considered as equal. For that reason, we apply the Friedman Test to all five samples simultaneously:

```
Friedman Test
Friedman Chi-square = 0.273, p-value = 0.873
Same distribution (fail to reject H0) at 0.05
```

Friedman Test p-value is quite high and far for the 5% significance level, failing to reject the Null Hypothesis. This means it shows that the five distributions do not differ from each other, so they can be considered as equal. To sum up, in the Medium-Term the selected ETFs are strongly correlated and dependent, the monthly returns distributions are not gaussian and are not statistically different.

6.4 Simple Linear Regression Models

Considering DSI, SUSA, KRMA and ESGU as the ESG ETFs, we kept the models used for the Long-Term scenario:

$$ESG_{return} = \alpha + \beta * IVV_{return} + u$$

$$ESG_{return} = \beta * IVV_{return} + u$$

In the Medium-Term for the US stock market, the linear regressions for ESG ETF against S&P500 mainly provide no relevant intercepts (alphas). They are close to zero and with no statistical significance, which means that there is no predicted premium or penalty for choosing these ESG assets. Moreover, the model with intercept offered larger Akaike and Bayesian Criteria, which are not wanted. Then we will just present the results for alphas and betas for the second model (without intercept), on the table below:

Table 7 - OLS Regressions

	DSI (b)	SUSA (b)	KRMA (b)	ESGU (b)
IVV	1.02*** (0.01)	1.01*** (0.02)	1.02*** (0.02)	1.02*** (0.01)
R-squared	0.99	0.98	0.98	0.99
R-squared Adj.	0.99	0.98	0.98	0.99
No. observations	66	66	66	66
AIC	111.7	136.4	145.8	62.8
BIC	113.9	138.6	148.0	65.0

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01

The results for the Medium-Term begin to show something different from the Long-Term findings. All ESG ETFs in the Medium-Term presented statistically significant slopes (betas) at 1% greater than 1, regardless if the model considers intercept or not. This is an important result, because if the slopes are larger than 1 as shown, the predicted ESG ETF returns are 1% to 2% more volatile and risky than the benchmark returns. All regressions show an extremely high R-squared (0.98 or superior), meaning that the models can accurately predict the monthly returns for ESG ETFs. However, coding with daily return samples renders lower Information Criteria

for the DSI and SUSA models:

Table 8 - OLS Regressions

	DSI(b)	SUSA(b)	KRMA(b)	ESGU(b)
IVV	1.01*** (0.00)	0.98*** (0.00)	0.95*** (0.01)	0.98*** (0.01)
R-squared	0.98	0.97	0.86	0.94
R-squared Adj.	0.98	0.97	0.86	0.94
No. observations	1379	1379	1379	1379
AIC	-1228.3	-492.1	1856.5	589.4
BIC	-1223.1	-486.9	1861.8	594.6

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01

These two models have respectively slopes equal to 1.01 and 0.98, which are statistically significant at 1%. While the slope for the DSI model with daily returns is still greater than 1, the slope for the SUSA model with daily returns is below 1. In practice, the slopes obtained with daily and monthly returns are significant but still very close to 1. So, the results obtained once more are not conclusive in favor or against ESG. While the best models for DSI and SUSA use daily returns, they have different responses to the benchmark:

$$\widehat{DSI}_{dreturn} = 1.01 * IVV_{dreturn}$$

$$\widehat{SUSA}_{dreturn} = 0.98 * IVV_{dreturn}$$

DSI reacts 1% deeper than IVV, while SUSA reacts 2% shallower to the benchmark. In other words, according to this model, SUSA reacts mildly to sudden shifts in S&P500, whereas DSI reacts a bit harsher. However, both closely follow the index. On the other hand, the best models for KRMA and ESGU use monthly returns, and have slopes larger than 1, meaning a 2% surplus on volatility:

$$\widehat{KRMA}_{mreturn} = 1.02 * IVV_{mreturn}$$

$$\widehat{ESGU}_{mreturn} = 1.02 * IVV_{mreturn}$$

We can partially infer that these results suggest a tiny riskier profile assigned to ESG ETFs, although that is not conclusive.

7 Scenario 4 - Short-Term (2019-2022) - USA

7.1 Descriptive Statistics

Monthly Returns

The Short-Term scenario is fertile to support one of the other three previous scenarios. Recalling the previous results, the Brazilian scenario (1) showed that the ESG ETF has predicted returns below the benchmark, whereas the Long-Term scenario (2) in the US tells us that ESG ETFs are equal to the reference index and the Medium-Term scenario (3) in the US provided evidence that the predicted returns for ESG ETFs are larger than the S&P500 index. In all scenarios we got strong correlations and high goodness of fit for the linear regressions. Now we will see what the Short-Term scenario in the US holds. Here we have almost half time length compared to the third scenario, but we have also double amount of ESG ETFs. They consist of eight ESG ETFs, comprising the five ones in the previous dataset plus four new ESG ETFs. The monthly returns in the Short-Term are described as follows:

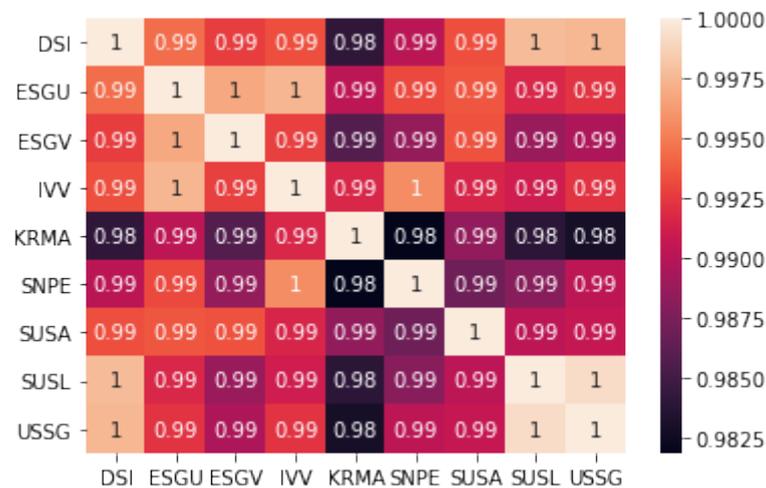
Table 9 - Summary Statistics

	DSI	ESGU	ESGV	IVV	KRMA	SNPE	SUSA	SUSL	USSG
count	35	35	35	35	35	35	35	35	35
mean	1.25	1.23	1.21	1.23	1.06	1.37	1.29	1.26	1.25
std	5.39	5.38	5.48	5.21	5.49	5.26	5.25	5.33	5.29
min	-12.38	-12.55	-12.46	-12.13	-14.34	-10.77	-11.42	-12.71	-12.31
25%	-1.63	-1.71	-1.42	-1.34	-1.54	-1.18	-1.60	-1.55	-1.36
50%	2.06	2.52	2.34	2.16	1.94	2.23	2.53	1.93	1.80
75%	3.88	3.85	3.98	4.17	4.32	3.99	4.19	3.97	3.95
max	12.96	13.29	13.34	12.68	12.87	12.95	12.23	12.56	12.38

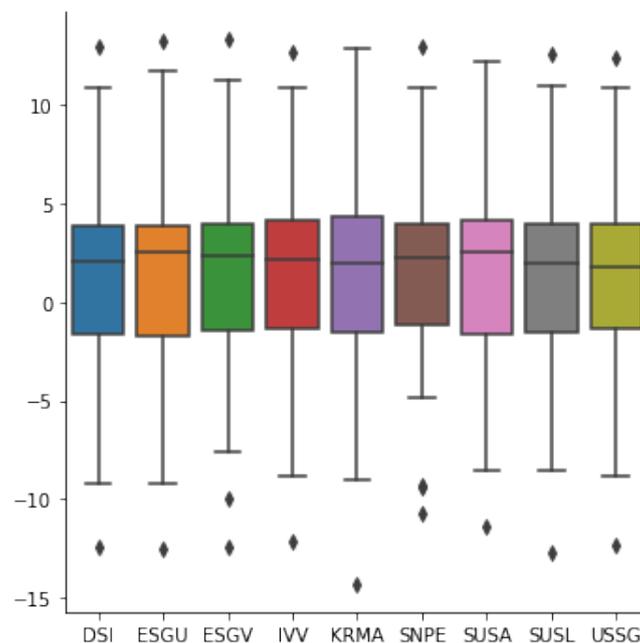
In this section we will skip the accumulated return and daily return time series. They do not differ significantly from what we saw in the previous two sections.

7.2 Exploratory Data Analysis

As we see through the following heatmap, the ESG ETFs keep an extremely high correlation with IVV and among them. Nothing new here: they follow the benchmark closely.



Once more, we visually check the ESG ETFs and IVV. Compared to the previous sections, nothing clearly changed, but maybe we can find more information supporting some of the previous scenarios.



So far, no clear difference between these ETFs: they present almost the same mean and standard deviation. We proceed with the normality and hypothesis tests.

7.3 Statistical Inference

Similarly to the first scenario, the monthly returns samples ($n = 35$) may be too small for statistical inference purposes, so the power of tests might be compromised. Whenever needed, we will apply each test to daily returns samples ($n = 736$) and compare the results to monthly returns.

Normality Test

Since we have just a small sample, we have small power when testing for normality. Thus, we should use the daily returns samples to extract a more reliable result instead of monthly returns samples. We tested for both situations - monthly and daily returns - and got different results. We will consider the larger samples test results as follows:

IVV

Shapiro-Wilk Test
W Stat. = 0.843, p-value = 0.000
Not Normal (reject H_0) at 0.05

To spare the reader's time and patience, we present other two tests respectively with maximum and minimum W Statistics using daily return samples. Both strongly reject the Null Hypothesis for normality. The other tests can be checked in the appendix.

USSG

Shapiro-Wilk Test
W Stat. = 0.846, p-value = 0.000
Not Normal (reject H_0) at 0.05

SNPE

Shapiro-Wilk Test
W Stat. = 0.878, p-value = 0.000
Not Normal (reject H_0) at 0.05

We conclude that all samples, either daily or monthly returns, are not normally distributed.

Hypothesis Tests

We know that the returns in the Short-Term are not normally distributed, but they are not independent. Still, we will test two subsets of four ESG ETFs with IVV with ANOVA:

IVV, DSI, SUSA, KRMA and ESGU - the benchmark and the veteran ESG ETFs

Analysis of Variance Test ANOVA

F Statistic = 0.017, p-value = 0.983

Same distribution (fail to reject H0) at 0.05

IVV, SNPE, SUSL, USSG and ESGV - the benchmark and the new ESG ETFs

Analysis of Variance Test ANOVA

F Statistic = 0.001, p-value = 0.999

Same distribution (fail to reject H0) at 0.05

The test concludes that the Short-Term dataset is composed of equal return distributions. As we do not follow all ANOVA conditions, we check again with the Friedman Test:

IVV, DSI, SUSA, KRMA and ESGU - the benchmark and the veteran ESG ETFs

Friedman Test

Friedman Chi-square = 0.914, p-value = 0.633

Same distribution (fail to reject H0) at 0.05

IVV, SNPE, SUSL, USSG and ESGV - the benchmark and the new ESG ETFs

Friedman Test

Friedman Chi-square = 1.086, p-value = 0.581

Same distribution (fail to reject H0) at 0.05

We fail again to reject the Null Hypothesis, meaning that all ETFs have similar distributions. We tested each ESG ETF together with the benchmark using Paired T-Student Test, with monthly and daily returns samples. The results are unanimous failing to reject the Null Hypothesis. To conclude, in the Short-Term, the selected ETFs are strongly correlated and dependent, whereas the monthly returns distributions are not gaussian and are not statistically different.

7.4 Simple Linear Regression Models

We keep the same regression models and apply for each ESG ETF. We begin with the model with an intercept:

$$ESG_{return} = \alpha + \beta * IVV_{return} + u$$

Table 10 - OLS Regressions

	DSI	SUSA	KRMA	ESGU	ESGV	SNPE	SUSL	USSG
const	-0.01 (0.11)	0.06 (0.12)	-0.22* (0.12)	-0.03 (0.07)	-0.07 (0.12)	0.13 (0.09)	0.02 (0.12)	0.02 (0.12)
IVV	1.03 *** (0.02)	1.00 *** (0.02)	1.04 *** (0.02)	1.03 *** (0.01)	1.04 *** (0.02)	1.01 *** (0.02)	1.01 *** (0.02)	1.01 *** (0.02)
R2.	0.99	0.98	0.98	0.99	0.99	0.99	0.98	0.98
R2.Adj.	0.99	0.98	0.98	0.99	0.99	0.99	0.98	0.98
No. obs.	35	35	35	35	35	35	35	35
AIC	69.2	75.3	78.1	35.2	73.0	51.9	78.1	73.2
BIC	72.3	78.4	81.2	38.3	76.1	55.0	81.3	76.3

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01

In the Short-Term the linear regressions for ESG ETF against S&P500 mainly present no relevant intercepts (alphas), which means that there is no expected premium for choosing these ESG assets. The only exception is KRMA, which yields a -0.22 alpha with 10% significance. From the eight regressions, four alphas are negative and four are positive, but they can be ignored. On the other hand, all ESG ETFs presented statistically significant slopes (betas), where seven are positive and one is neutral. If the slopes are larger than 1 as shown, the predicted ESG ETF returns are from 1% to 4% more volatile than the benchmark returns. This would be against the evidence found in the first scenario, for Brazil in the Short-Term. Let us see if these results hold for the model without intercept:

$$ESG_{return} = \beta * IVV_{return} + u$$

Table 11 - OLS Regressions

	DSI	SUSA	KRMA	ESGU	ESGV	SNPE	SUSL	USSG
IVV	1.03 *** (0.02)	1.00 *** (0.02)	1.04 *** (0.02)	1.03 *** (0.01)	1.04 *** (0.02)	1.01 *** (0.02)	1.01 *** (0.02)	1.01 *** (0.02)
R2.	0.99	0.98	0.98	1.00	0.99	0.99	0.98	0.99
R2.Adj.	0.99	0.98	0.98	1.00	0.99	0.99	0.98	0.98
No. obs.	35	35	35	35	35	35	35	35
AIC	67.2	73.6	79.2	33.4	71.4	52.3	76.2	71.2
BIC	68.8	75.1	80.7	34.9	72.9	53.9	77.7	72.8

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01

Putting away the model with intercept, we get the exact same results for the slopes with no information loss, according to the Bayesian Criteria. The slopes are all statistically significant and show that ESG ETFs react from 0% to 4% wider than S&P500 monthly returns. Therefore, ESG ETFs are supposedly riskier than the benchmark. The models predict with 98% to 99% goodness of fit, showing that ESG ETFs respond closely to the index market. This would be a shy indication against investing in ESG. However, using the daily returns instead of monthly returns we have the following results for the models without an intercept:

Table 12 - OLS Regressions

	DSI	SUSA	KRMA	ESGU	ESGV	SNPE	SUSL	USSG
IVV	1.01 *** (0.00)	0.98 *** (0.01)	0.97 *** (0.01)	1.00 *** (0.00)	1.01 *** (0.00)	0.95 *** (0.01)	0.92 *** (0.01)	1.00 *** (0.01)
R2.	0.99	0.98	0.88	0.99	0.98	0.97	0.92	0.98
R2.Adj.	0.99	0.98	0.88	0.99	0.98	0.97	0.92	0.98
No. obs.	735	735	735	735	735	735	735	735
AIC	-466.6	-220.4	1213.2	-1026.6	-303.5	108.6	812.6	-240.8
BIC	-462.0	-215.8	1217.8	-1022.0	-298.9	113.2	817.2	-236.2

Standard errors in parentheses.

* p<.1, ** p<.05, ***p<.01

Again, we found extremely high goodness of fit (R's > 0.92) and slopes around 1,

but between 0.92 and 1.01. Some models present much lower Information Criteria, whereas others present the opposite compared to the models using monthly returns.

Using Daily Returns

$$\widehat{DSI}_{dreturn} = 1.01 * IVV_{dreturn}$$

$$\widehat{SUSA}_{dreturn} = 0.98 * IVV_{dreturn}$$

$$\widehat{ESGU}_{dreturn} = IVV_{dreturn}$$

$$\widehat{ESGV}_{dreturn} = 1.01 * IVV_{dreturn}$$

$$\widehat{USSG}_{dreturn} = IVV_{dreturn}$$

Using Monthly Returns

$$\widehat{KRMA}_{mreturn} = 1.04 * IVV_{mreturn}$$

$$\widehat{SNPE}_{mreturn} = 1.01 * IVV_{mreturn}$$

$$\widehat{SUSL}_{mreturn} = 1.01 * IVV_{mreturn}$$

While the regressions with monthly returns suggest beta > 1 (wider response to benchmark stimulus), the regressions using daily returns suggest that beta equals 1, meaning that ESG ETFs have equivalent risk compared to S&P500. In both cases the slope - meaning the sensibility to the benchmark - is close to 1 anyway. Still, we have no clear and conclusive indication for the whole ESG category, but maybe for one or another ETF.

8 Conclusion

For all the four scenarios (Long, Medium and Short-Term in the United States and Short-Term in Brazil), the selected ESG ETFs available are strongly correlated to each respective benchmark, namely S&P500 and IBOVESPA. In Brazil, the ESG ETF has a correlation of 0.945, while in the US the minimum correlation found in all time length scenarios is 0.98.

Concerning normality, we used the Shapiro-Wilk Test, which is one of the most powerful tests available. We kept in mind that the monthly return samples should be tested carefully, since too small samples might lead to inaccurate results. We tested all monthly return samples and checked if the results still hold for daily return samples. While in the Long and Medium-Term scenarios in the US all monthly returns samples are not normally distributed, we needed to use the daily returns series to confirm that in the Short-Term in Brazil and the US returns are likewise not normally distributed. Thus, for the Short-Term monthly returns samples (scenarios 1 and 4; $n = 20$ and $n = 35$, respectively) we wrongly rejected the Null Hypothesis of normality using the Shapiro-Wilk Test. The checking procedure allowed us to assume that all ETFs returns in all scenarios are not normally distributed.

In order to check if the ESG ETFs monthly returns have different distributions in comparison with the benchmarks, we used the Paired T-Student Test for the first and second scenarios; and the Analysis of Variance (ANOVA) Test - despite the samples non-normality - and the Friedman Test (non-parametric) for the third and fourth scenarios. Then we checked each pair of ESG ETF and benchmark ETF in all scenarios. The results were unanimous in all scenarios for all ETFs failing to reject the Null Hypothesis of equal distributions. In all three US scenarios the p-values were all above 0.50, far from rejecting the Null Hypothesis. Although the plots in the Brazilian scenario suggested that the ESG ETF returns sample is different from the benchmark sample, the p-value in the Paired T-Student Test was 0.148, still not allowing the assumption that the returns differ. Again, all results were checked and confirmed using the daily returns samples in all the four scenarios. According to the inferential statistics, we found no relevant evidence that the sampled ESG ETFs have a different pattern of returns and standard deviation from the market index in all time

horizons and in both countries studied.

Then we proceeded by applying simple linear regressions to check how the ESG ETFs react to the benchmark ETFs returns in all four scenarios. In all the scenarios we obtained irrelevant alphas close to zero. Thus we continued with models without intercept with some marginal gain in information criteria and found that the slope in the Brazilian scenario is clearly below 1 while in the Long-Term scenario in the US the predicted monthly returns for ESG ETFs are exactly equal to the benchmark returns.

To sum up, we discovered that the ESG ETFs are strongly correlated to the benchmark, chiefly in the United States. Therefore, the simple linear regressions presented have all large goodness of fit, with high R-squared. While in Brazil we can undoubtedly affirm that the selected ESG ETF has a lower risk pattern, we cannot conclude this for the selected US ESG ETFs, which respond quite closely to the S&P500 returns. We also found that there is no risk premium associated with ESG at all, regarding to the four scenarios.

Although these findings cannot conclusively support the authors quoted in favor of ESG assets, they can be positively regarded, since there was no relevant loss in considering "The ESG Factor". This is an important remark since one can imagine that social and environmental constraints might compromise stock returns or offer a larger risk, which is not true.

Still, we do not intend to close this debate. Not all ESG ETFs are included here, but the most relevant ones until 2022 midterm. We also consider that different interpretations can be inferred depending on the country stock market studied or even that results might vary depending on the time length, shifts in ESG regulations and stock picking. We hope that this study can call attention to a more sustainable approach in investing and foster interest in social and environmental investment. Furthermore, we think that this article may open a debate: if and how ESG should be incorporated in our society.

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10 Appendix

10.1 Python Coding for Data Extraction

General Data

```
[55]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import yfinance as yf
import statsmodels.api as sm
import texttable as tt
```

```
[3]: # Selected ETFs
tickers = "IVV DSI SUSA ESGU KRMA ESGV SNPE SUSL USSG BOVA11.SA ESGB11.
↳SA"
# ETF Prices
price = yf.download(tickers, start="2006-12-01", end="2022-06-01")["Adj_
↳Close"]
```

Short-Term Data Brazil

```
[8]: # STB Selected ETFs
stbtickers = "BOVA11.SA ESGB11.SA"
# STB ETF Prices
stbprice = yf.download(stbtickers, start="2020-10-02",
↳end="2022-06-01")["Adj Close"]
# STB ETF Daily Returns
stbdrets = stbprice.pct_change().dropna()
# STB ETF Monthly Returns
stbmrets = stbdrets.resample('M').agg(lambda x: (x + 1).prod() - 1)
# STB Accumulated Daily Return
stbadr = (stbdrets+1).cumprod()
# STB Accumulated Monthly Return
stbamr = (stbmrets+1).cumprod()
# STB ETF Monthly Returns %
stbmrets = stbmrets*100
# STB ETF Daily Returns %
stbdrets = stbdrets*100
```

Long-Term Data US

```
[9]: # LT Selected ETFs
lttickers = "IVV DSI SUSA"
# LT ETF Prices
```

```

ltprice = yf.download(lttickers, start="2006-12-01",
    ↪end="2022-06-01")["Adj Close"]
# LT ETF Daily Returns
ltdrets = ltprice.pct_change().dropna()
# LT ETF Monthly Returns
ltmrets = ltdrets.resample('M').agg(lambda x: (x + 1).prod() - 1)
# LT Accumulated Return
ltadr = (ltdrets+1).cumprod()
# LT Accumulated Monthly Return
ltamr = (ltmrets+1).cumprod()
# LT ETF Monthly Returns %
ltmrets = ltmrets*100
# LT ETF Daily Returns %
ltdrets = ltdrets*100

```

Medium-Term Data US

```

[10]: # MT Selected ETFs
mttickers = "IVV DSI SUSA ESGU KRMA"
# MT ETF Prices
mtprice = yf.download(mttickers, start="2016-12-06",
    ↪end="2022-06-01")["Adj Close"]
# MT ETF Daily Returns
mtdrets = mtprice.pct_change().dropna()
# MT ETF Monthly Returns
mtmrets = mtdrets.resample('M').agg(lambda x: (x + 1).prod() - 1)
# MT Accumulated Daily Return
mtadr = (mtdrets+1).cumprod()
# MT Accumulated Monthly Return
mtamr = (mtmrets+1).cumprod()
# MT ETF Monthly Returns %
mtmrets = mtmrets*100
# MT ETF Daily Returns %
mtdrets = mtdrets*100

```

Short-Term Data US

```

[11]: # ST Selected ETFs
sttickers = "IVV DSI SUSA ESGU KRMA ESGV SNPE SUSL USSG"
# ST ETF Prices
stprice = yf.download(sttickers, start="2019-06-30",
    ↪end="2022-06-01")["Adj Close"]
# ST ETF Daily Returns
stdrets = stprice.pct_change().dropna()
# ST ETF Monthly Returns
stmrets = stdrets.resample('M').agg(lambda x: (x + 1).prod() - 1)
# ST Accumulated Daily Return

```

```
stadr = (stdrets+1).cumprod()  
# ST Accumulated Monthly Return  
stamr = (stmrets+1).cumprod()  
# ST ETF Monthly Returns %  
stmrets = stmrets*100  
# ST ETF Daily Returns %  
stdrets = stdrets*100
```

10.2 Complementary Normality Tests - Scenario 4

DSI

Shapiro-Wilk Test
W Stat. = 0.857, p-value = 0.000
Not Normal (reject H0) at 0.05

SUSA

Shapiro-Wilk Test
W Stat. = 0.867, p-value = 0.000
Not Normal (reject H0) at 0.05

KRMA

Shapiro-Wilk Test
W Stat. = 0.855, p-value = 0.000
Not Normal (reject H0) at 0.05

ESGU

Shapiro-Wilk Test
W Stat. = 0.848, p-value = 0.000
Not Normal (reject H0) at 0.05

ESGV

Shapiro-Wilk Test
W Stat. = 0.872, p-value = 0.000
Not Normal (reject H0) at 0.05

SUSL

Shapiro-Wilk Test
W Stat. = 0.868, p-value = 0.000
Not Normal (reject H0) at 0.05