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V. List of Abbreviations

CAPM	-	Capital Asset Pricing Model
CON	-	Conventional
CSR	-	Corporate Social Responsibility
ESG	-	Environmental Social Governance
ETF	-	Exchange Traded Fund
S&P 500	-	Standard & Poor's 500
SRI	-	Socially Responsible Investing

1. Introduction

Over the past years, when choosing an investment method, it got more popular to look at more than just performance measures. Now more than ever, investors also take non-monetary metrics like environmental, social, and corporate governance (ESG) principles and the generated stakeholder value of companies into account. As methods such as ESG investing and socially responsible investing (SRI) are still a growing topic of research, there are multiple different terms used to describe similar concepts such as sustainable investing, socially responsible investing, thematic investing, and responsible investing.

As for most retail investors realizing profits is of great interest, it can be useful to look at the performance of those responsible investment methods. In general, there is no common opinion on whether sustainable funds are doing better than non-sustainable ones and researchers find contradicting results. All in all, there is still a rising number of studies showing that companies with higher ESG scores outperform those with weaker values in the long term. According to these studies, there are multiple reasons for that. First of all, sustainable businesses can profit from their image and at the same time, differentiate themselves from competitors. This can lead to higher loyalty from both customers and investors who share the same non-financially driven values. Furthermore, this loyalty lets them enjoy a higher profitability and lower sensitivity to risk and economic downturns. In accordance with literature, another reason for the outperformance is that sustainable businesses tend to have high-quality management. Again, a well-run business can lead to higher productivity, performance, increased sales and higher profits (Silvola and Landau, 2021). However, it is unclear if this is also the case during a period of crisis such as the one, we were experiencing due to Covid-19.

In the beginning of 2020, this global health crisis forced the world to go into lockdown which impacted not only everyone's daily life but also had a significant impact on global economics. As a result, also the financial market experienced dramatic movements, both in advanced as well as emerging markets. On March 12th, 2020, BBC News reported that in the United States the S&P 500 experienced its steepest daily fall (-9.5%) since 1987 due to the corona virus. Similar reactions were also visible on European markets. In France and Germany, for instance, indexes plunged more than 12% (BBC News, 2020). In Japan the downfall due to the Covid outbreak was even steeper as the stock market dropped more than 20% in comparison to its highest point (Bloomberg, 2020).

Additionally, several different researchers have found an existing relation and impact of the corona crisis on financial markets (see, e.g., Zaremba et al., 2020; Corbet et al., 2020; Ashraf, 2020; Sharif et al., 2020; Goodell, 2020). Due to the high level of uncertainty caused by the

pandemic, financial market risks have increased significantly. Research has also shown substantial increases in volatility due to the outbreak (Albulescu, 2021, Zhang et al., 2020).

This paper aims to bring these two topics together by trying to find out if investors did profit from investing more ethically, especially in times of crisis as we experienced because of the corona pandemic. This is concluded with the following research question:

> *To what extent did retail investors who invest in sustainable ETFs had a better performance during and after the Covid-19 crash than those who invested in traditional ETFs?*

To answer this question, the core of our empirical analysis is the Fama-French five-factor model. The factors of the model address and neutralise local market developments, making it possible for us to compare the strategies not only within a region but also cross regional.

	Developed World	**Europe**	**USA**	**Japan**
Conventional	iShares MSCI World ETF	iShares Core MSCI Europe ETF	iShares MSCI USA UCITS ETF USD (Acc)	iShares MSCI Japan ETF
ESG-Screened	iShares MSCI World ESG Screened UCITS ETF USD Acc	iShares MSCI Europe ESG Screened UCITS ETF EUR Acc	iShares MSCI USA ESG Screened UCITS ETF USD Acc	iShares MSCI Japan ESG Screened UCITS ETF USD Acc
SRI	iShares MSCI World SRI UCITS ETF EUR (Acc)	iShares MSCI Europe SRI UCITS ETF EUR (Acc)	iShares MSCI USA SRI UCITS ETF USD (Acc)	iShares MSCI Japan SRI UCITS ETF USD Acc

Table 1: ETFs used in the analysis

The basis of our research are different Exchange Traded Funds (ETFs) by Blackrock. Comparing conventional (later abbreviated as “CON”), ESG-screened and SRI ETFs within developed countries, Europe, the USA and Japan (Table 1) give a profound data base to draw our conclusions on.

	USA and Europe	**Japan**
Lead-up	19th Oct 2018 – 19th Feb 2020	19th Oct 2018 – 10th Feb 2020
Covid-19 crash	20th Feb 2020 – 22nd Mar 2020	11th Feb 2020 – 16th Mar 2020
Recovery	23rd Mar 2020 – 31st Aug 2021	17th Mar 2020 – 31st Aug 2021

Table 2: Definition of the observation periods. The observation period starts on the inception date of the “youngest” of those ETFs (19th October 2018) and ends on August 31st, which at the time of writing marks the end point of the available Fama-French Data. The observation period was split up into a pre-corona phase, the corona crash, and post corona recovery. Since the Covid-19 crash happened a bit earlier in Japan, we adapted the respective timeframe

The data was split into three periods (Table 2) to be able to investigate and compare specific market developments. The “Covid-19 crash” period was altered for Japan to maintain comparability between the regions, since the Japanese stock market was affected earlier from the Covid crash.

With our work we contribute to the existing literature in multiple ways. First of all, we offer new insights of the resilience of SRI and ESG investments during a period of crisis. Furthermore,

our study adds details on the performance of those sustainable investment methods. Lastly, we provide the analysis of the performance of those investment methods not only before and during the Covid-19 pandemic but also focus on the period afterwards.

The structure of this paper is as followed. In section two we shed light on the background of ESG-investing as well as SRI to getter a better understanding of the history and approach to the topic. Section three focuses on the methodology of the empirical analysis which will then be presented and discussed in section four. After that, we will compare our findings with the already existing literature. In the final section six concluding remarks and topics for future research are identified.

2. Background of Sustainable Investing

2.1. History & Background

Responsible investing methods such as ESG and SRI are not necessarily a new trend but go back way longer. The first form of cutting out inadequate behavior was already seen in the 18th century where the Religious Society of Friends - an English Christianity movement - did not allow their members to invest in slavery and war (Schueth, 2003).

However, in the US the root of the modern form of socially responsible investment can be found in the 1960s where first changes in the values of civil society could be seen. At this time, world-wide social issues like women's equality, the Vietnam War or civil rights got more important in economic activities. This was made visible in the financial world when investors in the US first started screening their investments based on different environmental, social and political criteria. From there on investment funds emerged that excluded stocks from several companies and simultaneously, consisted of stocks of companies that tried protecting the environment as well as human rights (Nakajima et al., 2021).

From the 1990s on, responsible investing approaches have grown and evolved. As a result of it becoming increasingly popular, more and more investment companies started to launch various investment products based on environmentally conscious, socially responsible and ethical criteria (Entine, 2003).

When reaching the mid 1990s nearly 60 SRI mutual funds were existing, which summed up to about 640 billion USD of SRI assets under management. In the early 2000s, different incidents such as climate change, corporate scandals and humanitarian crises shaped the term of responsible investment even further and continued to broaden the spectrum (Caplan et al., 2013).

Nowadays, responsible investing spans a broad variety of different products and according to a recent report of the U.S. Forum for Sustainable and Responsible Investment, represents a third of the total US assets under professional management. In the U.S., assets managed under sustainable and responsible investing principles were estimated to have grown from 12.0 trillion USD to 17.1 trillion USD between 2018 and 2020, which resembles an increase of 42%. Furthermore, 1.98 trillion USD were controlled by 149 institutional investors and 56 investment managers that filed or co-filed resolutions on ESG issues (US SIF, 2020).

2.2. Retail Investors' Motivation for Sustainable Investing

Even though studies have shown that sustainable investors do not need to sacrifice returns in order to promote their good values, researchers also found that there is a small group of ethical investors that are willing to put values over returns. Still, for a majority of sustainable investors the aspect of doing good and contributing to a better world is the primary driver of considering ESG aspects in their investment decisions (Silvola and Landau, 2021).

2.3. Difference between ESG and SRI

With the growing demand for sustainable investing, comes an increasing number of different strategies to do so. In general, we can consider three different types of responsible investing: SRI, ESG-investing and impact investing. Despite of there being distinct differences between the terms, in practice they are often used interchangeably by both clients as well as professionals. While both, SRI and ESG investing are forms of sustainable investing, one of the differences lies in their approaches. SRI is known for attempting to avoid or restrict investing in specific stocks, companies or industries based on defined ethical guidelines, which is referred to as negative screening. In comparison, ESG investing is based on integrating environmental, social and governance factors into fundamental investment analysis in order to turn those into material for investment performance (Caplan et al., 2013).

However, ESG scores are not easy to interpret. For one, there is no common reporting standard and companies provide very different qualities of ESG data. Secondly, due to the high number of rating providers using different rating approaches, there is no official and consistent ESG score rating method. This is why it can happen that that one company scores really high on the scale from one provider, while only getting a low ranking from another one (Silvola and Landau, 2021).

2.4. iShares Screening Criteria

The indices used in this paper are ESG Screened ETFs from iShares by BlackRock. The rules behind their iShares MSCI ESG screenings are the exclusion of companies dealing in different specific fields such as controversial weapons, nuclear weapons and all companies violating the UN Global Compact principles. Moreover, companies that derive a certain percentage of revenue from thermal coal, civilian firearms, tobacco or oil sands are excluded from the indices as well (iShares, 2021).

The difference to their SRI screened ESG ETFs is that those indices target the top 25% companies in each sector according to their MSCI ESG rating and therefore use a so-called “best-in-class" selection approach. As a result, the criteria are stricter compared to the ESG screened ETFs (MSCI, 2021).

3. Methodology

For the analysis of this paper, we make use of several performance measures. The measures of which we thought are feasible, are stated in the following section.

3.1. General Performance Measures

Sharpe ratio

The Sharpe ratio, which was originally called “reward-to-variability”, was developed by W.F. Sharpe and is defined as:

$$S = \frac{(R_p - R_f)}{\sigma_p}$$

Equation 1: Sharpe Ratio Formula

R_p = Return of portfolio

R_f = Risk-Free rate

σ_p = Standard deviation of portfolio’s excess return

The Sharpe ratio is calculated by dividing the return that exceeds the risk-free rate by the standard deviation. A high value indicates a good risk-adjusted development and the other way round. The aim is to measure the expected return per unit of risk for a zero-investment strategy. Thus the difference between the returns of two investment assets represents the results of such a strategy (Sharpe, 1994).

The strengths of the Sharpe ratio are the simplicity of its formular, the ability to easily interpret the value and the fact that it relies on the investment's own numbers. Even though the Sharpe ratio is a meaningful measure of the portfolio performance when it comes to a measure of risk with the standard deviation it can result in misleading conclusions when the return distributions are skewed though (Mistry and Shah, 2013).

Information ratio

The Information ratio is a measure which pursues to summarize the mean-variance properties of an active portfolio in a single number.

$$IR = \frac{R_p - R_i}{\sigma_p}$$

Equation 2: Information Ratio Formula

R_p = Annualized Return of an investment or portfolio

R_i = Annualized Return of an index

σ_p =Standard Deviation of Excess Returns

The calculation of this measure is based on the standard statistical formulas for the mean and the standard deviation. It is defined as the average excess return per unit of per unit of its volatility. A positive Information ratio implies that the manager has achieved a higher return than the benchmark index. Generally, the higher the better. Negative values would indicate the contrary (Israelsen, 2005).

The strength of the information ratio lies in the fact, that it is a powerful tool to assess the skills of an active manager. Although we don't assess the skills of an active manager in this paper but look at a fixed index, we implement the information ratio anyway as our portfolios distinguish themselves from one another. It is a great measure of the mean-variance characteristics of an active portfolio. What should be kept in mind, though, is that it is based on historical data. This means that a high information ratio in the past does not guarantee a high one in the future and the other way round. Moreover, the information ratio can be manipulated. So being cautious with interpreting the information ratio is of high importance (Goodwin, 1998).

Tracking error

Vardharaj et al. (2004) defines the tracking error as an assessment of the portfolio's risk. To do so, it is measuring the dispersion of a portfolio's returns relative to the returns of the manager's benchmark (Vardharaj et al., 2004). The quality of an ETF is the better, the lower the tracking error is. In practice the value of the tracking error for ETFs which is seeked is below 1%.

The economic perspective would define this performance measure as a degree of differentiation of an index fund's portfolio performance from the return of underlying index.

$$TE = \sqrt{\frac{\sum_{i=1}^{n}(R_p - R_\beta)^2}{N-1}}$$

Equation 3: Tracking Error Formula

R_p = Return of portfolio

R_b = Return of benchmark

N = Number of return periods

It is calculated by using the annualized standard deviation of the difference in the portfolio and the benchmark returns (Dorocáková, 2017).

The tracking error makes it possible to validate the performance of a portfolio and the ability of the ETF issuer.

A weakness of this measure is that it can provide an incomplete and misleading picture. The issue is that the analysis of the tracking error still remains a misunderstood and complicated process for investors (Financial Times, 2020).

Beta and Alpha

Beta measures the sensitivity of the investment to market movements in regard to volatility or systematic risk. The calculation of beta is carried out with the regression line of the market model. The regression equation thereby measures the relationship between the stock return and the market return. The gradient of the regression line is the Beta of the stock.

$$\beta = \frac{Covariance\ (r_a, r_b)}{Var(r_b)}$$

Equation 4: Beta Formula

A Beta bigger than one indicates that the stock returns move in the same direction as the market, but stronger. A Beta below one indicates that the asset is inverse to the movement of

the market. Is the Beta exactly one then the asset represents the market directly (Mondello, 2017).

Alpha determines the return of an investment compared to the underlying benchmark index, which makes Alpha a measure of excess return.

$$\alpha = R_p - (R_f + (R_m - R_f)\beta)$$

Equation 5: Alpha Formula

Rp = Return of portfolio

Rf = Risk-free rate

R_m = Market return

Positive Alpha show that the investment was undervalued and offers an attractive return. A negative alpha on the other hand characterizes an overvalued investment, so it is underperforming compared to the market average (Mondello, 2017).

Both measures are standard calculations that use historical data, which makes them easy to calculate.

3.2. Fama-French Five Factor Model

3.2.1 General Model and Difference to CAPM/ Three Factor Model

The model was created by Eugene Fama and Kenneth French and is aiming to explain the risk and return of an investment. It is an asset-pricing model which expands on the capital asset pricing model (CAPM). CAPM is a single factor model that explains stock returns as a function of market return. Unlike CAPM the Fama-French three-factor model is based on stock return and takes three risk factors into account: market, size and value or book to market-based factor (Blanco, 2012). Studies have shown that the CAPM is not able to explain certain return patterns. For this reason, the three-factor model was developed which performs well in the description of cross section of stock returns. The motivation of two more factors, the introduction of the five-factor model, originated from the valuation theory by recent empirical findings which concern the strong effects of profitability and investment on asset returns (Chiah et al., 2016).

3.2.2 Factors of Model

$$R_{it} - R_{Ft} = a_i + b_i(R_{Mt} - R_{Ft}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{it}$$

Equation 6: Fama-French five-factor model

The five factors of the model are defined by Fama and French (2015) as follows:

- *SMB (small minus big) is the return on a portfolio of small stocks minus the return on portfolio of big stocks.*
- *HML (high minus low) is the difference between the returns on diversified portfolios of high and low book to market stocks.*
- *RMW (robust minus weak) stands for the difference between the returns on portfolios of stocks with robust and weak operating profitability.*
- *CMA (conservative minus aggressive) defines the difference between the returns on portfolios of the stocks of low and high investment firms, which Fama and French named conservative and aggressive (Fama and French, 2015).*

The superiority of the five-factor model lies in the fact that it is able to explain more asset pricing anomalies than other competing asset pricing models (Chiah et al., 2016). Fama and French (2015) find that the five-factor model outperforms the three-factor model when it comes to the explanation of the cross section of stock returns. To be specific, fewer pricing errors occur with the five-factor model when explaining asset pricing anomalies (Fama and French, 2015).

4. Sustainable and Non-Sustainable ETF-Performance in Times of Covid-19

In this analysis we investigate whether retail investors who invest in sustainable ETFs have had a better performance before, during, and after the Covid-19 crisis than those who invested in conventional (CON) ETFs. To minimize possibly disruptive factors, we decided to focus on ETFs from one single provider. With Blackrock we chose the largest provider of ETFs. In 2018 they obtained a market share of almost 37% worldwide (Statista, n.d.). Their product portfolio among others includes ETFs on the MSCI World Index, which represents large- and mid-cap firms of 23 developed countries. With a total of over 96% of the holdings, the index focuses on the US (68.5 %), Europe (21.4 %) and Japan (6,5 %). Therefore, those regions form the core of our analysis. For each region and type of ETF (CON, ESG, SRI) we chose one fund representing the respective financial market performance of companies.

We begin the analysis by looking at the world-wide market and the reactions of private investors to the Covid-19 crash. Later, we evaluate inter-regional differences of the ETF types in USA, Europe, and Japan. To compare cross region differences, we will conclude by applying the Fama-French five-factor model.

4.1. Data

The data for the funds (Table 1) is obtained through Refinitiv Eikon as well as the official iShares website. Information about individual companies' portfolio weight and the performance was also retrieved through Refinitiv Eikon. Values for the Fama-French five-factor regression were gathered from the official website of Kenneth French.

The Data was prepared via a python script (Appendix 1). If an ETF was to pay out dividends during the observation period, it is treated like a direct reinvestment.

4.2. Analysis

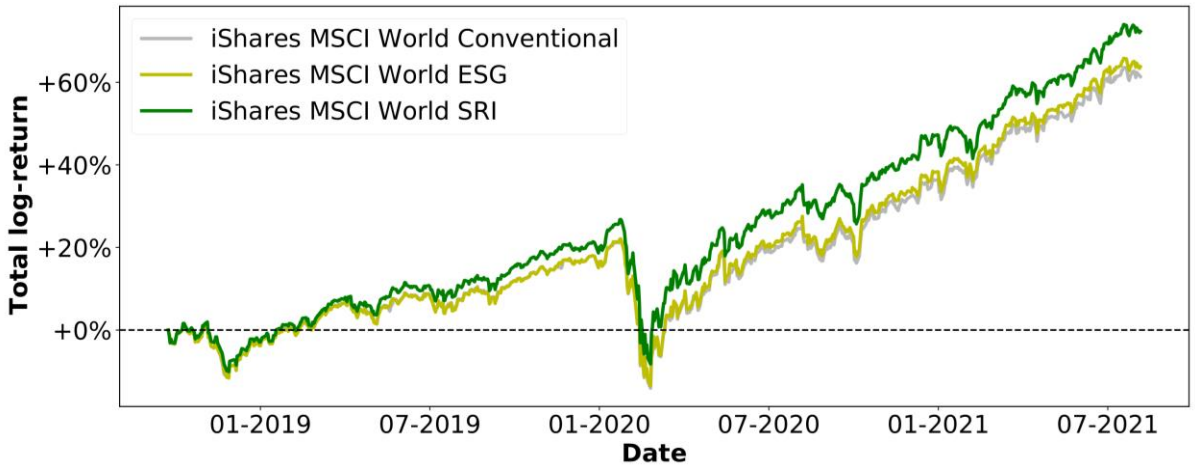


Figure 1: Accumulated log-returns of the iShares MSCI World (CON, ESG Screened, and SRI) ETFs during the observation period (19/10/2018 to 31/08/2021)

To provide a general overview of the world stock market's reaction towards the Covid-19 pandemic, we plotted the log-return data on the chosen iShares MSCI World funds of the type CON, ESG, and SRI. When looking at Figure 1 we can see a steady rise of the net asset values (NAV) of the ETFs shares in the initial phase. Here the SRI fund seems to slightly outperform the others. When the pandemic hit, all three funds lost about 20-30% in value. This, while it seems a lot, is significantly lower compared to other crashes like the dot-com-bubble or the world financial crisis. In those cases, investors of the same index could have lost about 50%. Interesting to see is the short time needed for the Index's to recover and surpass previous all-time highs. During the recovery phase one can see that the SRI ETF

offered the highest returns. Later in the analysis we look at if SRI ETFs outperformed the others throughout all time periods in Europe, the USA, and Japan.

When considering the whole observation period, the ESG Screened ETF only seems to have a slightly higher performance than the CON ETF. This we trace back to the 85-90% identical portfolio holdings of the two indices. That becomes especially obvious when looking at the top ten holdings of each respective fund.

	iShares MSCI World ETF	iShares MSCI World ESG Screened UCITS ETF USD Acc	iShares MSCI World SRI UCITS ETF EUR (Acc)	Performance over the observation period (in %)
Apple Inc	4.18	4.39		177
Microsoft Corp	3.57	3.75	4.46	178
Amazon.com Inc	2.59	2.73		97
Tesla Inc	1.5	1.04	4.35	1,315
Alphabet Inc Class A	1.43	1.51		162
Alphabet Inc Class C	1.4	1.47		174
Meta Platforms Inc	0.99	1.57		146
NVIDIA Corp	0.92	0.97	4.03	291
JP Morgan Chase & Co	0.79	0.84		48
UnitedHealth Group Inc	0.74			57
Johnson & Johnson		0.79		25
Home Depot Inc			2.52	81
ASML Holding NV			2.5	350
Walt Disney Co			2.38	52
Roche Holding AG			2.04	50
Cisco Systems Inc			1.8	30
Coca-Cola Co			1.67	22
PepsiCo Inc			1.56	42
SUM	**18.11**	**19.06**	**27.31**	

Table 3: Analysis of the top ten biggest shares of the respective ETFs (in %) and their performance over the observation period. The portfolio share is as of 31/08/2021

Table 3 confirms the proximity of the portfolio holdings between the ESG and CON ETF, since nine out of the ten shares are identical with a maximum weight deviation of only 0,6%. In contrast to that, the comparison from those two to the MSCI World SRI provides three significant insights:

(1) The portfolio holdings differ tremendously, as seven out of the top ten holdings are different for the SRI fund.
(2) The three companies that every fund has in common turned out to be amongst the top performers of this list. The SRI fund profited most by this development, as they held a higher percentage.

(3) The weight of the top ten holdings is the lowest in the CON ETF (18%), followed by the ESG (19%) and the SRI (27%) variant. Therefore, the SRI fund relies significantly more on the performance of those few companies.

Most important for the positive development of the SRI fund was the performance of ASML (+178 %), NVIDIA (+291 %) and Tesla (+1,315 %). We note that although the SRI fund performed better, it has a higher cluster risk as to the top 10 holdings more weight is allocated. This not only is the case for this iShares MSCI World SRI fund, but also for the SRI USA, Europe, and Japan in respect to their counterparts.

4.3. People's Reaction to the Crash Concerning their Investments

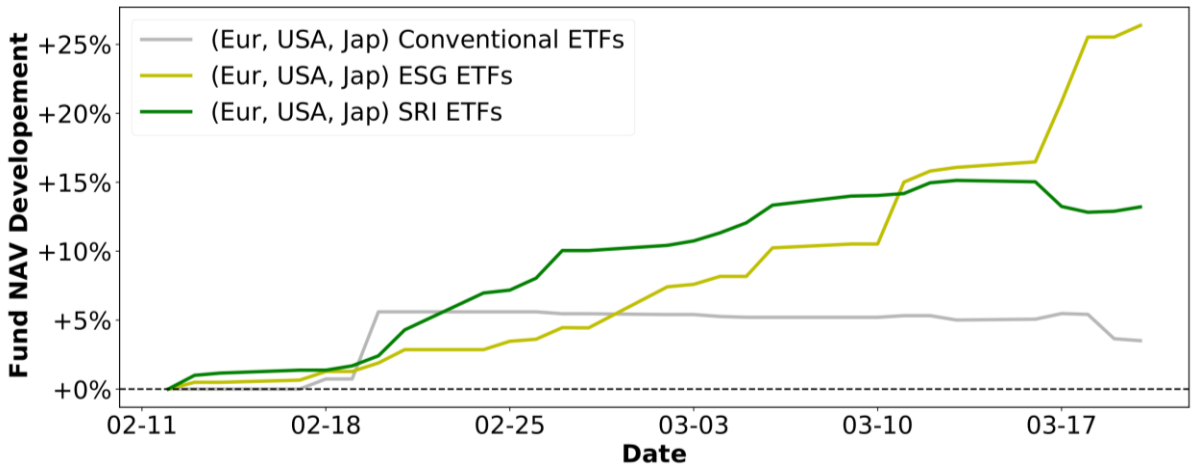


Figure 2: Development of the fund's outstanding share volume during the Covid-19 crash. This represents the cumulative growth of the CON, ESG, and SRI ETFs across the regions in the time period from 11/02/2020 to 23/03/2020

After having established the general developments, we now switch the focus to the three chosen regions: Europe, USA, and Japan. The possibility of a lower return is a premium many investors of more ethical financial products are willing to pay in order to invest responsibly. (Berry and Yeung, 2012). Therefore, for some investors being ethical exceeds the aspiration or need for a higher return. Consequently, it is our assumption that the outstanding share volumes of the more sustainable ETFs during the period of crisis, are more stable/ positive. Figure 2 shows that the CON ETFs remains stable, while both even experience an increase in outstanding shares. Investors of CON ETFs seemingly didn't majorly react to the crash indicating an unbroken trust. The demand for ESG and SRI ETFs rose significantly indicating not only an unbroken, but even increased trust in those strategies. This supports our assumption.

4.4. Performance Data

Having set the groundwork, we now conduct the performance comparison of the fund types in the observed regions. For this, we calculated the simple returns of the respective ETFs during the time periods which were defined in Table 2 For a better overview we also included the total value for the complete observation period.

	CON			ESG			SRI		
	Eur	USA	Jap	Eur	USA	Jap	Eur	USA	Jap
complete	33	74	21	45	78	30	63	86	32
before	12	26	1	17	27	5	24	31	7
during	-32	-30	-24	-30	-29	-24	-28	-29	-22
after	74	96	57	77	99	62	83	98	59

lower (worse) (relative to other values) higher (better)

Table 4: Performance Data (returns) of the ETFs in % over the observation period. The color scale is set up per period and orders the values from lowest (red) to highest (green). The boundaries of the individual periods "before", "during", and "after" can be derived from Table 2, whereas "complete" combines those three periods

The first observation we can obtain from Table 4 is that on a regional level the European stock market was hit hardest by the crisis, closely followed by the US, which only performed slightly worse regarding the SRI ETF. Before and after the crisis the US market performed best compared to the other countries. Table 4Table 4 furthermore offers the insight that the Japanese ETFs across all fund types performed worst before and after the crash by about 7%. This might be a result of the well-known phenomenon of the "lost decades" in Japan.[1] The slow recovery and development of the economy is thought to still exist (Bloomberg.com, n.d.), expanding the "lost decades". This can explain the worse performance before and after the crash but does not offer an insight concerning the comparably high values during the crisis, where Japan outperformed the USA as well as Europe. This could be due to Japan not being hit as hard by the Covid-19 pandemic during the crash-period (World Health Organization, 2021).

[1] Those describe the inability of the Japanese economy and stock market to recover from the asset bubble burst in 1990 during the following two decades (Aoki, 2013).

	Eur			USA			Jap		
	CON	ESG	SRI	CON	ESG	SRI	CON	ESG	SRI
complete	33	45	63	74	78	86	21	30	32
before	12	17	24	26	27	31	1	5	7
during	-32	-30	-28	-30	-29	-29	-24	-24	-22
after	74	77	83	96	99	98	57	62	59

lower (worse) (relative to other values) higher (better)

Table 5: Performance Data in % from Table 4 but ordered differently. Here we ordered it to compare the returns within a region in a certain period. Therefore, we can evaluate performance differences of each ETF type within a region. The color scale shows the best to worst performing ETF of one region during one period. The boundaries of the individual periods "before", "during", and "after" can be derived from Table 2, whereas "complete" combines those three periods

While in Table 4Table 4 we can already see that the SRI ETFs tend to obtain higher return values, we reordered the performance values in Table 5 to get better insight about the ESG and SRI ETF performance in the individual regions. For six out of the nine time periods we can see that SRI ETFs offered their investors a higher return. Two deviations from this can be seen in the USA and Japan during the recovery period, where the ESG funds outperformed SRI and CON funds. The last exception is that during the Covid-19 crisis in Japan the ESG funds performed worst. This may be a first indicator towards a positive relationship between sustainability and portfolio return.

4.5. Sharpe Ratio

To complete the investigation of the simple returns, we now add an important metric which accounts for the risk taken to achieve the returns. For this reason, we now look at the Sharpe Ratio. To compute those values, we used the identical return values from Table 4 and Table 5, deducted the risk-free rate of the respective region and divided this by the standard deviation of this excess return.

	CON			ESG			SRI		
	Eur	USA	Jap	Eur	USA	Jap	Eur	USA	Jap
complete	0.57	0.69	0.38	0.59	0.73	0.44	0.82	0.80	0.47
before	0.69	1.00	0.22	0.75	1.02	0.30	1.09	1.21	0.38
during	-7.88	-4.92	-10.22	-7.52	-4.86	-10.73	-7.38	-4.71	-10.89
after	2.01	2.19	1.58	1.95	2.22	1.61	2.12	2.24	1.59

lower (worse) (relative to other values) higher (better)

Table 6: Sharpe Ratios of the ETFs over the observation period. The color scale is set up per period and orders the values from lowest (red) to highest (green). The boundaries of the individual periods "before", "during", and "after" can be derived from Table 2 whereas "complete" combines those three periods

In Table 6 we can see that the USA had best risk-reward ratio throughout all periods, followed by Europe and then Japan. Interesting to see is, that although Japan offered the highest return during the Covid-19 crash (Table 4), they offer the lowest Sharpe Ratios. Since the risk-free rate didn't deviate significantly between the regions, we can derive that the Japanese stock

market was significantly more volatile during the crash. Moreover, we can see that throughout eight of the nine periods the US offered the highest Sharpe Ratio, supposedly making it the best investment when accounting for the standard deviation (retrospective risk). In Table 6 we can already see a slight tendency towards sustainable oriented ETFs having higher values.

	Eur			USA			Jap		
	CON	ESG	SRI	CON	ESG	SRI	CON	ESG	SRI
complete	0.57	0.59	0.82	0.69	0.73	0.80	0.38	0.44	0.47
before	0.69	0.75	1.09	1.00	1.02	1.21	0.22	0.30	0.38
during	-7.88	-7.52	-7.38	-4.92	-4.86	-4.71	-10.22	-10.73	-10.89
after	2.01	1.95	2.12	2.19	2.22	2.24	1.58	1.61	1.59

lower (worse) (relative to other values) higher (better)

Table 7: Sharpe Ratio from Table 6 but ordered differently. Here we ordered it to compare the returns within a region in a certain period. Therefore, we can evaluate the risk adjusted performance of different ETF types within regions. The color scale shows the best to worst performing ETF of one region during one period. The boundaries of the individual periods "before", "during", and "after" can be derived from Table 2 whereas "complete" combines those three periods.

This observation is confirmed when reordering the values of Table 6 to get an easier to interpret overview (Table 7) concerning the CON vs. ESG. vs. SRI investigation. In Europe and USA, we can see that SRI always had the best risk-return ratio, followed by ESG funds. Only in the recovery period the CON ETF in Europe performed better than its ESG equivalent. Japan on the other hand shows inconsistent results. While the SRI fund had the highest Sharpe ratios before the crash, the CON fund was best during the crisis, and the ESG fund had the best ratio during the recovery period. But we note that the outperformance of the SRI fund before the crisis was clearly more significant than the underperformance in the other two periods, where the Sharpe Ratio of all funds were relatively equal.

4.6. Information Ratio and Tracking Error

	Information Ratio	Tracking Error
Europe CON	0.0065	0.0046
Europe ESG	0.0095	0.0040
Europe SRI	0.0088	0.0040
USA CON	0.0043	0.0026
USA ESG	0.0077	0.0026
USA SRI	0.0051	0.0026
Japan CON	-0.0067	0.0045
Japan ESG	-0.0042	0.0021
Japan SRI	-0.0041	0.0021

Table 8: Information ratio and Tracking Error of the individual funds for the observation period

Before performing the regression, we analyse two metrics concerning the funds' ability to perform in the market (Information Ratio) and how closely they follow their benchmark index

(Tracking Error). While differences in the Information Ratio are not major, we derive, that sustainable funds have the highest Information Ratio (by a small margin), which is in line with the observation that SRI funds tend to have a more advantageous risk-volatility-ratio from Table 7. The Tracking error of all funds is pretty low, therefore replicating the respective index well.

4.7. Fama-French Five-Factor Model

Having gathered evidence that sustainable funds (ESG and SRI) perform better during the total observation period and also most smaller timeframes, we now take a look which region performed best before, during and after the Covid-19 crash.

To make the data comparable cross regions we have to account for the general regional developments during the periods. We conduct regressions in accordance with the Fama-French five-factor model. We decided to calculate the regressions on a weekly basis for the time periods “complete”, “before”, and “after”. Since for this procedure we don’t have enough values for the crash period, we performed those regressions on a daily basis.

Unfortunately, in our regression results (Appendix 2) we were not able to obtain significant p-values for our Fama-French alphas, making concrete values insignificant. Nevertheless, the models themselves all are significant, as the F-Statistics are low (maximum value: 5.38e-12) and additionally the R^2-values are high (lowest value: 0.867; mean: 0.956, average: 0.95). Therefore, we analyse the differences in the alpha (outperformance) of a fund type across the regions (Japan, USA, Europe) with 95% confidence intervals.

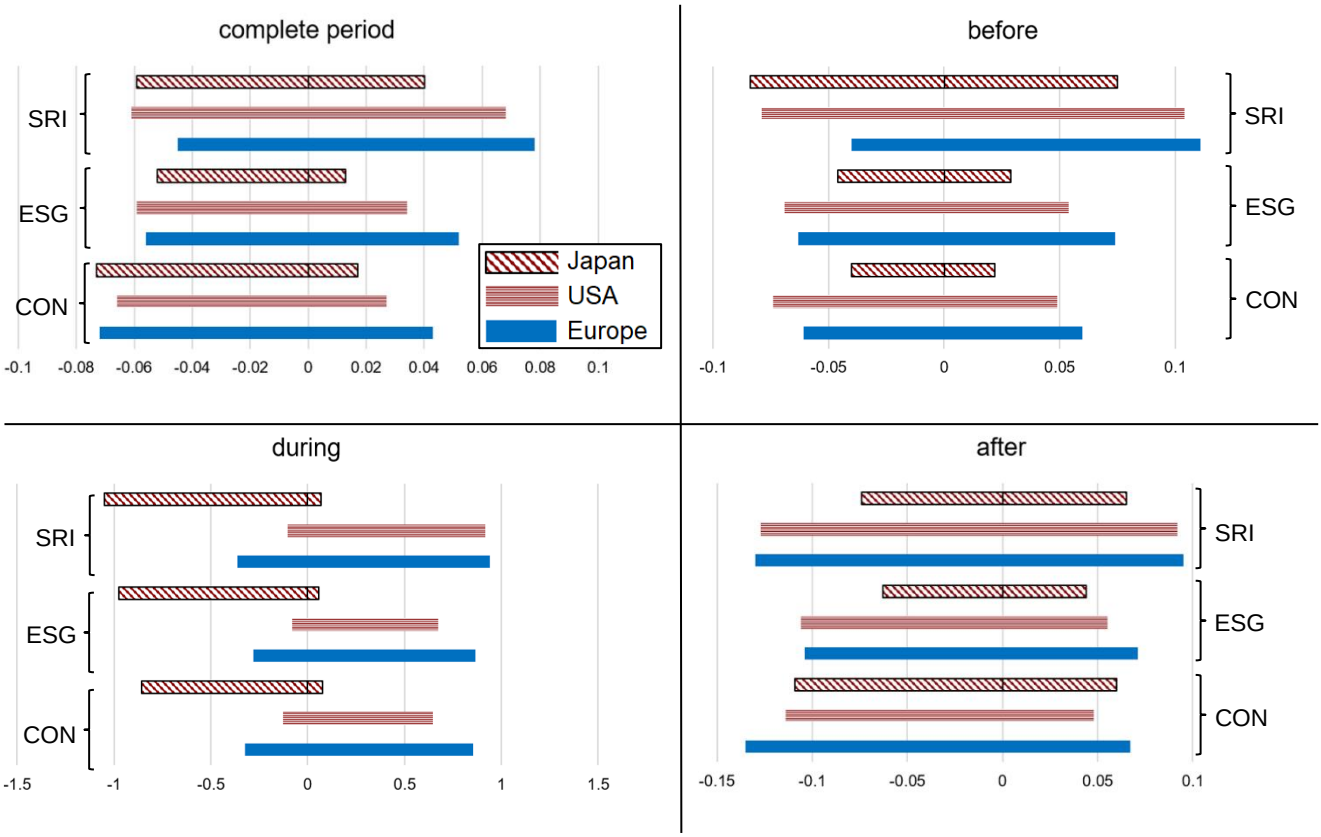


Figure 3: Display of the 95% confidence interval of the Fama-French α. To calculate the α for the complete period, as well as "before" and "after" we used the weekly Fama-French Regression. As the Covid-19 crash only lasted one month this would not have been possible and we had to adapt the regression to daily values. The low count of data points and short timeframe result in the wide interval. In the individual plots of the figure, we ordered as follows: The three funds on top are the SRI funds of Japan, USA, Europe (in that order) being followed below by the three ESG funds (countries in the same order) and finally there are the three CON funds on the bottom (countries in the same order)

When looking at the complete period in Figure 3 (upper left graph) we can see the tendency of SRI funds outperforming their counterparts across all regions throughout the observation period, which is in line with our previous findings. The graph also offers the insight that across all regions the European funds seem to have a higher market outperformance than the USA and Japan funds. This observation is also true for the "before"-period (upper right graph). During the Covid-19 crash we observe wide confidence intervals (lower left graph), which makes a stand-alone analysis harder. Therefore, we only shortly touch upon that topic by solely comparing it to previously obtained data.

We can see a somewhat identical outperformance rate in the USA and Europe, with Europe having a wider interval. We cannot derive any major outperformance of a fund type, which is in line with our observations of Table 5, where the differences of the total return during the crash are minor as well.

Surprising is the majorly negative interval of the Japanese funds. We are unable to explain such a one-sided interval. While it is not necessarily out of line with the observation of outperformance in Table 5, the extreme negative values seems unlikely.

In the recovery period (lower right graph) we have usual sized intervals. We can see a pretty similar outperformance rate throughout the fund types and regions, with the only difference of Europe having the widest interval and Japan the most precise.

From this analysis we derive that throughout the complete observation period, and especially before the crash, the European ETFs most likely outperformed their respective market in a more significant manner than the USA and Japan ETSs did.

5. Limitations

Like with every analysis one must respect the limitations, of which we identified seven main ones:

(1) The ETFs in use are not necessarily representative for their fund type's development.
(2) While concentrating on one provider reduces noise in the analysis, we cannot capture different approaches to SRI and ESG.
(3) Retrospective risk measures like volatility are easy to analyse and to understand but can be misleading and do not ipso facto represent future risk.
(4) Equivalently to past risk not being a predictor for future risk, past performance is not a predictor for future risk.
(5) By choosing passive mutual funds for the analysis, we miss out on the opportunity to investigate the fund managers individual reactions towards the Covid-19 crash and if their asset selection, which mostly is significantly smaller than in an MSCI Index, performed better or worse compared to the other fund types.
(6) Due to the short timeframe the Fama French model didn't yield concrete results.
(7) Still, it is unclear in how far the outperformance of more sustainable companies on the stock market is due to hype and investor concentration.

Having all those limitations in mind we must critically reflect the informative value and validity of or analysis. Latterly, we can only provide limited insights, but the results we find are with the underlying assumptions indeed relevant.

6. Comparison with Existing Literature

During the last years, sustainable investing became more and more attractive, therefore it has also become a matter of interest in finance research. There have been several studies investigating the performance differences between sustainable and conventional investment portfolios in times of stable markets as well as in times of crisis. The widely supported position is that sustainable (ESG, SRI, CSR) funds outperform conventional ones (Omura et al., 2020).

Kempf and Osthoff (2007) for example investigate the effect of different SRI criteria on screened stock portfolios. They conclude that SRI ratings offer valuable information for investment decisions. A strategy based on this information can offer high abnormal returns. Furthermore, Auer (2014) with his results gathered on European stock market data supports the view that socially reasonable investments do not imply a sacrifice in performance but much more offer investors to outperform a conventional portfolio. Nevertheless, contradictive evidence is reported by Nofsinger and Varma (2013) which suggests that conventional funds outperform SRI funds by 0.67-0.95% in non-crisis times.

Naturally, it became of interest whether this outperformance continues or becomes even greater in times of unstable markets. Some studies have looked at data concerning the financial crisis 2007/08 to analyze this question. The results are once more mixed. On the one hand, Lins et. al. (2017) conclude that during the financial crisis the stocks of firms with a higher CSR score outperformed the ones with none or a lower CRS rating by four to seven percentage points. This suggests that in times of a negative shock the trust built up with firm's social investments pays off. On the other hand, Morales et al. (2019) report the opposite (Omura et al., 2020).

The resent Covid-19 Pandemic and the economic crisis as well as shock to the financial markets that was triggered by it, represents a great opportunity to further investigate the stability and performance of reasonable investing. Due to its novelty and the fact that other than the financial crisis the Covid-19 crash could not the anticipated the data truly represents the result of an unexpected shock to the financial markets. Therefore, it offers the chance to measure unbiased performance differences. Many researchers have taken this opportunity already. Yet, first study results are anew inconclusive regarding the over- or underperformance of reasonable investment portfolios. Some find that ESG stock prices performed better than the ones of portfolios without a focus on sustainability. Albuquerque et al. (2020) for example conclude that firms with higher ES scores perform much better than the ones with lower rankings. Supporting evidence is also provided by Broadstock et al. (2020). They find that higher ranked ESG portfolios generally outperform the lower scored ones indicating that ESG portfolios in general outperform conventional ETFs. There results contradict with the findings presented in this paper. Reasons for this could be in the case of the research conducted by Albuquerque et al. (2020) that they left the governance (G) factor out of their analysis and performed their comparison on the firm instead the ETF level as we did. However, the data applied in the analysis by Broadstock et al. (2020) only includes the Chinese market which is left out of our analysis and therefore is not directly comparable.

Engelhardt et al. (2021) report mixed results on their analysis of ESG rating and associated stock performance during the Covid-19 crisis from European firms. On the one hand they find that firms with a higher ESG rating can be associated with higher abnormal returns and lower stock volatility, but on the other hand the coefficients indicating this conclusion are not statistically significant.

Nevertheless, other research concluded similar findings to ours. Supporting our results that ESG EFTs did not manage to significantly outperform conventional ETFs, Pavlova and Boyrie (2020) find no difference in the performance between ESG and non-ESG ETFs during the Covid-19 crash. Demers et al (2021) also report the variable ESG as insignificant in explaining firm's returns during the crash and therefore conclude that an ESG portfolio did not preserve stocks during the Covid-19 crash. Our finding, that SRI portfolios outperform ESG ones is in line with the results reported by Pástor and Vorsatz (2020). They also conclude a better performance by firms with higher SRI ratings.

Omura et al. (2020) support our results almost entirely. Their research compares the performance of SRI, ESG and conventional ETFs as well. They conclude that SRI ETFs outperform ESG as well as conventional ETFs whose performance is by a large extend on the same level. Nevertheless, the analysis they perform with a view on a pre Covid and during Covid period whereas our analysis extends the conclusions with insights on an after crash and recovery period.

Moreover, some research investigates the Covid-19 crash's effects on the investor's demand for reasonable funds. Our results suggest that the Covid-19 crash triggered a higher growth rate in the demand of reasonable ETFs than in conventional funds. This view is supported by Rubbaniy et al (2021). Their analysis finds positive co-movement between ESG stock returns and their health fear index during the times of Covid. They conclude from this finding, that ESG stocks own a safe-haven[2] characteristic for investors which leads to a higher demand in times of crisis and uncertainty. (Rubbaniy et al, 2021)

In contrast, the results presented by Döttling and Kim (2021) deduce that the investor's demand in ESG funds significantly dropped under the pressure of the Covid-19 crash. They observe a significantly higher likelihood of a net capital outflow from sustainable funds compared to conventional funds during the crisis (Döttling and Kim, 2021).

[2] "Safe-haven" describes an investment with the expectation to hold or increase value in times of market turbulence (Kopyl and Lee, 2016).

7. Concluding Remarks

Our findings suggest that SRI is indeed better and ESG investing no worse performing then conventional investment portfolios in times of market turbulences and the recovery period afterwards. As a retail investor, these findings implicate, that reasonable investment is indeed profitable. Even though it is prone to be associated with high cluster risks in the composition of the portfolio. The risk is rather dependent on the firm's strategy and performance than on the market fluctuations. Nevertheless, the existing literature is not conclusive about the question if reasonable invested portfolios outperform conventional ones in times of crisis as well as stable markets. The aim of our analysis is to contribute to the research on that question. With our limited resources we can only partly add new insights. Our design distinguishes from previous research since we use a longer period of data and are therefore able to further analyze a post Covid-19 recover phase as well. Furthermore, with the selection the European, US-American, and Japanese markets, we focus on transcontinental differences in the performance. Other research mostly solely investigates the developments in one market.

As long, as research concludes with contradictive results, there remain interesting questions to be investigated in the future. For the most, the actual long-term effects of the Covid-19 crash are yet to be observed and analyzed. Moreover, most of the research including our work focuses on developed country's markets. There is a lot of potential for interesting insights in the developing world as well.

8. Appendix

Appendix 1 Python code to process data (without Output)

FIN11

November 24, 2021

1 Imports

```
[ ]: import numpy as np
import pandas as pd
import pandas_datareader.data as web
import matplotlib.pyplot as plt
import statsmodels.api as sm
from datetime import datetime
from scipy import stats
from pandas_datareader import DataReader
from functools import reduce
from matplotlib.dates import DateFormatter
import matplotlib.dates as mdates
```

2 Import and preparation Fama French Faktoren

```
[ ]: FamaFrench_Dev = pd.read_csv(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading and Market␣
↪Microstructure\TermPaper\FF_Developed_5_Factors_Daily.csv')
FamaFrench_Eur = pd.read_csv(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading and Market␣
↪Microstructure\TermPaper\FF_Europe_5_Factors_Daily.csv')
FamaFrench_Jap = pd.read_csv(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading and Market␣
↪Microstructure\TermPaper\FF_Japan_5_Factors_Daily.csv')
FamaFrench_USA = pd.read_csv(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading and Market␣
↪Microstructure\TermPaper\FF_Research_Data_5_Factors_2x3_daily.csv')

FamaFrench_Dev.rename(columns={'Unnamed: 0':'Date'}, inplace=True)
FamaFrench_Eur.rename(columns={'Unnamed: 0':'Date'}, inplace=True)
FamaFrench_Jap.rename(columns={'Unnamed: 0':'Date'}, inplace=True)
FamaFrench_USA.rename(columns={'Unnamed: 0':'Date'}, inplace=True)
```

```
[ ]: #Fama Frnch data is in % --> divide by 100 to match the scale from the ETF returns
FamaFrench_Dev[["Mkt-RF", "SMB", "HML", "RMW", "CMA", "RF"]] = FamaFrench_Dev[["Mkt-RF", "SMB", "HML",␣
↪"RMW", "CMA", "RF"]]/100
FamaFrench_Eur[["Mkt-RF", "SMB", "HML", "RMW", "CMA", "RF"]] = FamaFrench_Eur[["Mkt-RF", "SMB", "HML",␣
↪"RMW", "CMA", "RF"]]/100
FamaFrench_Jap[["Mkt-RF", "SMB", "HML", "RMW", "CMA", "RF"]] = FamaFrench_Jap[["Mkt-RF", "SMB", "HML",␣
↪"RMW", "CMA", "RF"]]/100
FamaFrench_USA[["Mkt-RF", "SMB", "HML", "RMW", "CMA", "RF"]] = FamaFrench_USA[["Mkt-RF", "SMB", "HML",␣
↪"RMW", "CMA", "RF"]]/100
```

```
[ ]: #FamaFrench prepare date format
def FamaFrench_daily (FamaFrench):
    FamaFrench['Date'] = FamaFrench[['Date']].applymap(str).applymap(lambda s: "{}/{}/{}".format(s[4:6],s[6:
↪], s[0:4]))
    FamaFrench["Date"] = pd.to_datetime(FamaFrench["Date"])
    FamaFrench = FamaFrench.set_index('Date')
    FamaFrenchDaily = FamaFrench.resample("D").sum()
    return FamaFrenchDaily
```

```
[ ]: #FamaFrench apply date function
FamaFrench_Dev_d = FamaFrench_daily(FamaFrench_Dev.copy())
FamaFrench_Eur_d = FamaFrench_daily(FamaFrench_Eur.copy())
FamaFrench_Jap_d = FamaFrench_daily(FamaFrench_Jap.copy())
FamaFrench_USA_d = FamaFrench_daily(FamaFrench_USA.copy())
```


3 Import and preparation of ETFs

```
[ ]: #Format and prepare ETF data from Refinitiv Eikon
def Aufbereitung(df, FamaFrench):
    df = df.drop(['e','e.1', 'e.2','Offer'], axis=1, errors='ignore')
    #Change pf nan values in column "Dividendens" to "0"
    df["Dividends"] = df["Dividends"].fillna(0)
#Da das Datumsformat innerhalb einer Excel zufällig zwischen YYYY-MM-DD und DD-Mon-YYYY wechselt ist die␣
↪Formatierung des Datums etwas komplizierter
    #Sofern ein Bid-Preis angegeben ist, jedoch kein Wert für das NAV, so wird der Bid-Wert in die NAV␣
↪Spalte übertragen. Bid-Preis und NAV sind Definitionsgemäß identisch
    if 'Bid' in df.columns:
        df["NAV"] = df["NAV"].replace(['--'], int(0))
        df["Bid"] = df["Bid"].replace(['--'], int(0))
        df["NAV"] = df[["NAV", "Bid"]].max(axis=1)
    df = df.drop(['Bid'], axis=1, errors='ignore')

    #Aufteilung der Datumsbestandteile in jeweils eigene Spalten
    df["Date"] = df["Date"].astype(str)
    df["Date"]= df["Date"].str.split(" ", n = 1, expand = True)
    df[['S1', 'S2', "S3"]] = df['Date'].str.split('-', 2, expand=True)

    #Umkodierung der Monate zu Zahlenformat, falls es nicht bereits so ist (z.B. wird aus Jan -> 01; Sollte␣
↪bereits ein Monat in Form von Zahlen vorhanden sein, bleibt dies bestehen)
    df['S2'] = np.where(df['S2']=="Jan", '01', df["S2"] )
    df['S2'] = np.where(df['S2']=="Feb", '02', df["S2"] )
    df['S2'] = np.where(df['S2']=="Mar", '03', df["S2"] )
    df['S2'] = np.where(df['S2']=="Apr", '04', df["S2"] )
    df['S2'] = np.where(df['S2']=="May", '05', df["S2"] )
    df['S2'] = np.where(df['S2']=="Jun", '06', df["S2"] )
    df['S2'] = np.where(df['S2']=="Jul", '07', df["S2"] )
    df['S2'] = np.where(df['S2']=="Aug", '08', df["S2"] )
    df['S2'] = np.where(df['S2']=="Sep", '09', df["S2"] )
    df['S2'] = np.where(df['S2']=="Oct", '10', df["S2"] )
    df['S2'] = np.where(df['S2']=="Nov", '11', df["S2"] )
    df['S2'] = np.where(df['S2']=="Dec", '12', df["S2"] )

    #Zwischenzeitliche Anpassung des Datentyps der YYYY, MM und DD Spalte zu float values
    df["S1"] = df["S1"].astype(str).astype(float)
    df["S2"] = df["S2"].astype(str).astype(float)
    df["S3"] = df["S3"].astype(str).astype(float)

    #Da aufgrund der durch Refinitiv Eikon bereitgestellten Daten das Jahr im Datum in einigen Fällen vorne␣
↪(YYYY-MM-DD) und in einigen Fällen hinten steht (DD-Mon-YYYY) importiere ich jeweils den höheren Wert in␣
↪die extra dafür erstellte Spalte "Year" und den geringeren der beiden Werte aus Spalten "1" und "3" in␣
↪die dafür neu erstellte Spalte "Day"
    #Dies Funktioniert, da die Werte der Jahre stets größer sind als die der Tage
    df["Year"] = df[["S1", "S3"]].max(axis=1)
    df["Day"] = df[["S1", "S3"]].min(axis=1)
    df["Month"] = df["S2"]

    #Rückformatierung zu strings
    df["Year"] = df["Year"].astype(int).astype(str)
    df["Month"] = df["Month"].astype(int).astype(str)
    df["Day"] = df["Day"].astype(int).astype(str)

    #Löschen der alten Datumsspalte
    df = df.drop(['S1','S2','S3'], axis=1, errors='ignore')

    #Zusammensetzen des Datums aus den drei Spalten
    df["Date"] = pd.to_datetime(df[['Year', 'Month', 'Day']]).astype(str)

    #Anpassung der Formatierung an FamaFrench mittels entfernung der Bindelstriche im Datum
    df['Date'] = df['Date'].str.replace('-','')
    df["Date"] = df["Date"].astype(str).astype(int)

    #Entfernen der Hilfsspalten "Year", "Day", "Month"
```

4 Splitting the DFs into the time-frames

[ ]:
```
ETF_Dev_before = ETF_Dev.copy()[(ETF_Dev.index > '2018-10-18') & (ETF_Dev.index <= '2020-02-19')]
ETF_Dev_during = ETF_Dev.copy()[(ETF_Dev.index > '2020-02-19') & (ETF_Dev.index <= '2020-03-23')]
ETF_Dev_after =  ETF_Dev.copy()[(ETF_Dev.index > '2020-03-23') & (ETF_Dev.index <= '2021-08-31')]

ETF_Eur_before = ETF_Eur.copy()[(ETF_Eur.index > '2018-10-18') & (ETF_Eur.index <= '2020-02-19')]
ETF_Eur_during = ETF_Eur.copy()[(ETF_Eur.index > '2020-02-19') & (ETF_Eur.index <= '2020-03-23')]
ETF_Eur_after =  ETF_Eur.copy()[(ETF_Eur.index > '2020-03-23') & (ETF_Eur.index <= '2021-08-31')]

ETF_USA_before = ETF_USA.copy()[(ETF_USA.index > '2018-10-18') & (ETF_USA.index <= '2020-02-19')]
ETF_USA_during = ETF_USA.copy()[(ETF_USA.index > '2020-02-19') & (ETF_USA.index <= '2020-03-23')]
ETF_USA_after =  ETF_USA.copy()[(ETF_USA.index > '2020-03-23') & (ETF_USA.index <= '2021-08-31')]

ETF_Jap_before = ETF_Jap.copy()[(ETF_Jap.index > '2018-10-18') & (ETF_Jap.index <= '2020-02-10')]
ETF_Jap_during = ETF_Jap.copy()[(ETF_Jap.index > '2020-02-10') & (ETF_Jap.index <= '2020-03-16')]
ETF_Jap_after =  ETF_Jap.copy()[(ETF_Jap.index > '2020-03-16') & (ETF_Jap.index <= '2021-08-31')]


ESG_ETF_Dev_before = ESG_ETF_Dev.copy()[(ESG_ETF_Dev.index > '2018-10-18') & (ESG_ETF_Dev.index <=␣
↪'2020-02-19')]
ESG_ETF_Dev_during = ESG_ETF_Dev.copy()[(ESG_ETF_Dev.index > '2020-02-19') & (ESG_ETF_Dev.index <=␣
↪'2020-03-23')]
ESG_ETF_Dev_after =  ESG_ETF_Dev.copy()[(ESG_ETF_Dev.index > '2020-03-23') & (ESG_ETF_Dev.index <=␣
↪'2021-08-31')]

ESG_ETF_Eur_before = ESG_ETF_Eur.copy()[(ESG_ETF_Eur.index > '2018-10-18') & (ESG_ETF_Eur.index <=␣
↪'2020-02-19')]
ESG_ETF_Eur_during = ESG_ETF_Eur.copy()[(ESG_ETF_Eur.index > '2020-02-19') & (ESG_ETF_Eur.index <=␣
↪'2020-03-23')]
ESG_ETF_Eur_after =  ESG_ETF_Eur.copy()[(ESG_ETF_Eur.index > '2020-03-23') & (ESG_ETF_Eur.index <=␣
↪'2021-08-31')]

ESG_ETF_USA_before = ESG_ETF_USA.copy()[(ESG_ETF_USA.index > '2018-10-18') & (ESG_ETF_USA.index <=␣
↪'2020-02-19')]
ESG_ETF_USA_during = ESG_ETF_USA.copy()[(ESG_ETF_USA.index > '2020-02-19') & (ESG_ETF_USA.index <=␣
↪'2020-03-23')]
ESG_ETF_USA_after =  ESG_ETF_USA.copy()[(ESG_ETF_USA.index > '2020-03-23') & (ESG_ETF_USA.index <=␣
↪'2021-08-31')]

ESG_ETF_Jap_before = ESG_ETF_Jap.copy()[(ESG_ETF_Jap.index > '2018-10-18') & (ESG_ETF_Jap.index <=␣
↪'2020-02-10')]
ESG_ETF_Jap_during = ESG_ETF_Jap.copy()[(ESG_ETF_Jap.index > '2020-02-10') & (ESG_ETF_Jap.index <=␣
↪'2020-03-16')]
ESG_ETF_Jap_after =  ESG_ETF_Jap.copy()[(ESG_ETF_Jap.index > '2020-03-16') & (ESG_ETF_Jap.index <=␣
↪'2021-08-31')]


SRI_ETF_Dev_before = SRI_ETF_Dev.copy()[(SRI_ETF_Dev.index > '2018-10-18') & (SRI_ETF_Dev.index <=␣
↪'2020-02-19')]
SRI_ETF_Dev_during = SRI_ETF_Dev.copy()[(SRI_ETF_Dev.index > '2020-02-19') & (SRI_ETF_Dev.index <=␣
↪'2020-03-23')]
SRI_ETF_Dev_after =  SRI_ETF_Dev.copy()[(SRI_ETF_Dev.index > '2020-03-23') & (SRI_ETF_Dev.index <=␣
↪'2021-08-31')]

SRI_ETF_Eur_before = SRI_ETF_Eur.copy()[(SRI_ETF_Eur.index > '2018-10-18') & (SRI_ETF_Eur.index <=␣
↪'2020-02-19')]
SRI_ETF_Eur_during = SRI_ETF_Eur.copy()[(SRI_ETF_Eur.index > '2020-02-19') & (SRI_ETF_Eur.index <=␣
↪'2020-03-23')]
SRI_ETF_Eur_after =  SRI_ETF_Eur.copy()[(SRI_ETF_Eur.index > '2020-03-23') & (SRI_ETF_Eur.index <=␣
↪'2021-08-31')]

SRI_ETF_USA_before = SRI_ETF_USA.copy()[(SRI_ETF_USA.index > '2018-10-18') & (SRI_ETF_USA.index <=␣
↪'2020-02-19')]
```



```
    df = df.drop('Year', 1)
    df = df.drop('Day', 1)
    df = df.drop('Month', 1)

#Anpassung des Datenzeitraums auf den Beobachtungszeitraum.
    indexNames = df[df['Date'] <= 20181019].index
    df.drop(indexNames , inplace=True)
    indexNames = df[df['Date'] >= 20220831].index
    # Delete these row indexes from dataFrame
    df.drop(indexNames , inplace=True)

#Formatieren der Datumsspalte von den Integer Werten in das Datetime Format und Verschieben der Spalte in␣
↪den Index der Dataframes
    df['Date'] = df[['Date']].applymap(str).applymap(lambda s: "{}/{}/{}".format(s[4:6],s[6:], s[0:4]))
    df["Date"] = pd.to_datetime(df["Date"])
    df = df.set_index('Date')

# Zusammenbringen der Fondsdaten mit den FamaFrench-Faktoren (Auf das Datum gematcht)
    df = pd.merge(df,FamaFrench , on = ['Date'])

#Annahme: Schüttet ein Fonds Geld aus, so wird dieses vom Investor direkt in neue Fonds-Anteile investiert
    if "Dividends" in df.columns:
        df["DividendPercentageOfNAV"] = df["Dividends"]/df["NAV"]
        df["DividendReinvest"] = df["DividendPercentageOfNAV"].cumsum()+1
        df["RealNAV"] = df["DividendReinvest"]* df["NAV"]
        del df['DividendReinvest']
        del df["DividendPercentageOfNAV"]

#Berechnen der prozentualen Realrendite bis zu Tag X
    df["RealReturnFromStart"] = df["RealNAV"]/df["RealNAV"].iloc[0]
    df["LogReturnRealNAVDaily"] = np.log(df['RealNAV']/df['RealNAV'].shift())

#Abhängigen Faktor für Fama French Modell berechnen
    df["FundMinusRiskFree"]= df["LogReturnRealNAVDaily"]-df["RF"]

    return df
```

[ ]:
```
ETF_Dev = Aufbereitung(pd.ExcelFile("iShares MSCI World ETF.xls").parse(), FamaFrench_Dev_d)
ETF_Eur = Aufbereitung(pd.ExcelFile("iShares Core MSCI Europe ETF.xls").parse(), FamaFrench_Eur_d)
ETF_Jap = Aufbereitung(pd.ExcelFile("iShares MSCI Japan ETF.xls").parse(), FamaFrench_Jap_d)
ETF_USA = Aufbereitung(pd.ExcelFile("iShares MSCI USA UCITS ETF USD (Acc).xls").parse(), FamaFrench_USA_d)

ESG_ETF_Dev = Aufbereitung(pd.ExcelFile("iShares MSCI World ESG Screened UCITS ETF USD Acc.xls").parse(),␣
↪FamaFrench_Dev_d)
ESG_ETF_Eur = Aufbereitung(pd.ExcelFile("iShares MSCI Europe ESG Screened UCITS ETF EUR Acc.xls").parse(),␣
↪FamaFrench_Eur_d)
ESG_ETF_Jap = Aufbereitung(pd.ExcelFile("iShares MSCI Japan ESG Screened UCITS ETF USD Acc.xls").parse(),␣
↪FamaFrench_Jap_d)
ESG_ETF_USA = Aufbereitung(pd.ExcelFile("iShares MSCI USA ESG Screened UCITS ETF USD Acc.xls").parse(),␣
↪FamaFrench_USA_d)

SRI_ETF_Dev = Aufbereitung(pd.ExcelFile("iShares MSCI World SRI UCITS ETF EUR (Acc).xls").parse(),␣
↪FamaFrench_Dev_d)
SRI_ETF_Eur = Aufbereitung(pd.ExcelFile("iShares MSCI Europe SRI UCITS ETF EUR (Acc).xls").parse(),␣
↪FamaFrench_Eur_d)
SRI_ETF_Jap = Aufbereitung(pd.ExcelFile("iShares MSCI Japan SRI UCITS ETF USD Acc.xls").parse(),␣
↪FamaFrench_Jap_d)
SRI_ETF_USA = Aufbereitung(pd.ExcelFile("iShares MSCI USA SRI UCITS ETF USD (Acc).xls").parse(),␣
↪FamaFrench_USA_d)
```

```
SRI_ETF_USA_during = SRI_ETF_USA.copy()[(SRI_ETF_USA.index > '2020-02-19') & (SRI_ETF_USA.index <=␣
↪'2020-03-23')]
SRI_ETF_USA_after =  SRI_ETF_USA.copy()[(SRI_ETF_USA.index > '2020-03-23') & (SRI_ETF_USA.index <=␣
↪'2021-08-31')]

SRI_ETF_Jap_before = SRI_ETF_Jap.copy()[(SRI_ETF_Jap.index > '2018-10-18') & (SRI_ETF_Jap.index <=␣
↪'2020-02-10')]
SRI_ETF_Jap_during = SRI_ETF_Jap.copy()[(SRI_ETF_Jap.index > '2020-02-10') & (SRI_ETF_Jap.index <=␣
↪'2020-03-16')]
SRI_ETF_Jap_after =  SRI_ETF_Jap.copy()[(SRI_ETF_Jap.index > '2020-03-16') & (SRI_ETF_Jap.index <=␣
↪'2021-08-31')]
```

5 Calculation Fama French 5-Factor model

```
#Berechnung des Fama French Modells. Davor Reduzierung der Daten auf Monatliche Returns
def FamaFrenchReg_d(df):
    df = df.copy()
    df = df.resample("D").sum()
    A = df["FundMinusRiskFree"]
    B = df[["Mkt-RF", "SMB", "HML", "RMW", "CMA"]]
    B_sm = sm.add_constant(B)
    model = sm.OLS(A,B_sm)
    results = model.fit()
    results.summary()
   #Ergebnis in Dataframe zum weiterverarbeiten
    pvals = results.pvalues
    coeff = results.params
    conf_lower = results.conf_int()[0]
    conf_higher = results.conf_int()[1]

    x = results.rsquared_adj
    results_df = pd.DataFrame({"coeff":coeff, "pvals":pvals, "conf_lower":conf_lower, "conf_higher":
↪conf_higher})
    return results.summary()

#Berechnung des Fama French Modells. Davor Reduzierung der Daten auf Monatliche Returns
def FamaFrenchReg_w(df):
    df = df.copy()
    df = df.resample("W").sum()
    A = df["FundMinusRiskFree"]
    B = df[["Mkt-RF", "SMB", "HML", "RMW", "CMA"]]
    B_sm = sm.add_constant(B)
    model = sm.OLS(A,B_sm)
    results = model.fit()
    results.summary()
   #Ergebnis in Dataframe zum weiterverarbeiten
    pvals = results.pvalues
    coeff = results.params
    conf_lower = results.conf_int()[0]
    conf_higher = results.conf_int()[1]

    x = results.rsquared_adj
    results_df = pd.DataFrame({"coeff":coeff, "pvals":pvals, "conf_lower":conf_lower, "conf_higher":
↪conf_higher})
    return results.summary()
```

```
FamaFrenchReg_w(ETF_Dev.copy()*52)
```

```
FamaFrenchReg_w(ETF_Eur.copy()*52)
```

```
FamaFrenchReg_w(ETF_USA.copy()*52)
```

```
FamaFrenchReg_w(ETF_Jap.copy()*52)
```



```
FamaFrenchReg_w(ESG_ETF_Dev.copy()*52)
```

```
FamaFrenchReg_w(ESG_ETF_Eur.copy()*52)
```

```
FamaFrenchReg_w(ESG_ETF_USA.copy()*52)
```

```
FamaFrenchReg_w(ESG_ETF_Jap.copy()*52)
```

```
FamaFrenchReg_w(SRI_ETF_Dev.copy()*52)
```

```
FamaFrenchReg_w(SRI_ETF_Eur.copy()*52)
```

```
FamaFrenchReg_w(SRI_ETF_USA.copy()*52)
```

```
FamaFrenchReg_w(SRI_ETF_Jap.copy()*52)
```

```
# now FF individual periods
```

```
FamaFrenchReg_w(ETF_Dev_before.copy()*52)
```

```
FamaFrenchReg_d(ETF_Dev_during.copy()*252)
```

```
FamaFrenchReg_w(ETF_Dev_after.copy()*52)
```

```
FamaFrenchReg_w(ETF_Eur_before.copy()*52)
```

```
FamaFrenchReg_d(ETF_Eur_during.copy()*252)
```

```
FamaFrenchReg_w(ETF_Eur_after.copy()*52)
```

```
FamaFrenchReg_w(ETF_USA_before.copy()*52)
```

```
FamaFrenchReg_d(ETF_USA_during.copy()*252)
```

```
FamaFrenchReg_w(ETF_USA_after.copy()*52)
```

```
FamaFrenchReg_w(ETF_Jap_before.copy()*52)
```

```
FamaFrenchReg_d(ETF_Jap_during.copy()*252)
```

```
FamaFrenchReg_w(ETF_Jap_after.copy()*52)
```

```
FamaFrenchReg_w(ESG_ETF_Dev_before.copy()*52)
```

```
FamaFrenchReg_d(ESG_ETF_Dev_during.copy()*252)
```

```
FamaFrenchReg_w(ESG_ETF_Dev_after.copy()*52)
```

```
FamaFrenchReg_w(ESG_ETF_Eur_before.copy()*52)
```

```
FamaFrenchReg_d(ESG_ETF_Eur_during.copy()*252)
```

```
FamaFrenchReg_w(ESG_ETF_Eur_after.copy()*52)
```

```
FamaFrenchReg_w(ESG_ETF_USA_before.copy()*52)
```

```
FamaFrenchReg_d(ESG_ETF_USA_during.copy()*252)
```

```
FamaFrenchReg_w(ESG_ETF_USA_after.copy()*52)
```

```
FamaFrenchReg_w(ESG_ETF_Jap_before.copy()*52)
```

```
[ ]: getVals(SRI_ETF_Eur)
```

```
[ ]: getVals(SRI_ETF_USA)
```

```
[ ]: getVals_Jap(SRI_ETF_Jap)
```

7 Sharpe Ratio

```
[ ]: ## logreturn -riskfree / std
def sharpeR(df):
    zähler = df["LogReturnRealNAVDaily"].mean() - df["RF"].mean()
    sharpeR = zähler/np.std(df["LogReturnRealNAVDaily"])
    sharpeR = sharpeR*252**.5
    return sharpeR
```

```
[ ]: print("All", sharpeR(ETF_Dev),"before", sharpeR(ETF_Dev_before),"during", sharpeR(ETF_Dev_during),"after",␣
↪sharpeR(ETF_Dev_after))
```

```
[ ]: print("All", sharpeR(ETF_Eur),"before", sharpeR(ETF_Eur_before),"during", sharpeR(ETF_Eur_during),"after",␣
↪sharpeR(ETF_Eur_after))
```

```
[ ]: print("All", sharpeR(ETF_USA),"before", sharpeR(ETF_USA_before),"during", sharpeR(ETF_USA_during),"after",␣
↪sharpeR(ETF_USA_after))
```

```
[ ]: print("All", sharpeR(ETF_Jap),"before", sharpeR(ETF_Jap_before),"during", sharpeR(ETF_Jap_during),"after",␣
↪sharpeR(ETF_Jap_after))
```

```
[ ]: print("All", sharpeR(ESG_ETF_Dev),"before", sharpeR(ESG_ETF_Dev_before),"during",␣
↪sharpeR(ESG_ETF_Dev_during),"after", sharpeR(ESG_ETF_Dev_after))
```

```
[ ]: print("All", sharpeR(ESG_ETF_Eur),"before", sharpeR(ESG_ETF_Eur_before),"during",␣
↪sharpeR(ESG_ETF_Eur_during),"after", sharpeR(ESG_ETF_Eur_after))
```

```
[ ]: print("All", sharpeR(ESG_ETF_USA),"before", sharpeR(ESG_ETF_USA_before),"during",␣
↪sharpeR(ESG_ETF_USA_during),"after", sharpeR(ESG_ETF_USA_after))
```

```
[ ]: print("All", sharpeR(ESG_ETF_Jap),"before", sharpeR(ESG_ETF_Jap_before),"during",␣
↪sharpeR(ESG_ETF_Jap_during),"after", sharpeR(ESG_ETF_Jap_after))
```

```
[ ]: print("All", sharpeR(SRI_ETF_Dev),"before", sharpeR(SRI_ETF_Dev_before),"during",␣
↪sharpeR(SRI_ETF_Dev_during),"after", sharpeR(SRI_ETF_Dev_after))
```

```
[ ]: print("All", sharpeR(SRI_ETF_Eur),"before", sharpeR(SRI_ETF_Eur_before),"during",␣
↪sharpeR(SRI_ETF_Eur_during),"after", sharpeR(SRI_ETF_Eur_after))
```

```
[ ]: print("All", sharpeR(SRI_ETF_USA),"before", sharpeR(SRI_ETF_USA_before),"during",␣
↪sharpeR(SRI_ETF_USA_during),"after", sharpeR(SRI_ETF_USA_after))
```

```
[ ]: print("All", sharpeR(SRI_ETF_Jap),"before", sharpeR(SRI_ETF_Jap_before),"during",␣
↪sharpeR(SRI_ETF_Jap_during),"after", sharpeR(SRI_ETF_Jap_after))
```

8 NAV Development

```
[ ]: #Funktionen zum Formatieren und Aufbereiten Funds from Refinitiv Eikon
def AufbereitungNAV(df):
    #Aufteilung der Datumsbestandteile in jeweils eigene Spalten
    df["Date"] = df["per"].copy().astype(str)
    #df["Date"]= df["Date"].str.split(".", n = 2, expand = True)
    df[['S1', 'S2', "S3"]] = df['Date'].str.split('.', 2, expand=True)
    df = df.drop(['per'], axis=1, errors='ignore')
```



```
[ ]: FamaFrenchReg_d(ESG_ETF_Jap_during.copy()*252)
```

```
[ ]: FamaFrenchReg_w(ESG_ETF_Jap_after.copy()*52)
```

```
[ ]: FamaFrenchReg_w(SRI_ETF_Dev_before.copy()*52)
```

```
[ ]: FamaFrenchReg_d(SRI_ETF_Dev_during.copy()*252)
```

```
[ ]: FamaFrenchReg_w(SRI_ETF_Dev_after.copy()*52)
```

```
[ ]: FamaFrenchReg_w(SRI_ETF_Eur_before.copy()*52)
```

```
[ ]: FamaFrenchReg_d(SRI_ETF_Eur_during.copy()*252)
```

```
[ ]: FamaFrenchReg_w(SRI_ETF_Eur_after.copy()*52)
```

```
[ ]: FamaFrenchReg_w(SRI_ETF_USA_before.copy()*52)
```

```
[ ]: FamaFrenchReg_d(SRI_ETF_USA_during.copy()*252)
```

```
[ ]: FamaFrenchReg_w(SRI_ETF_USA_after.copy()*52)
```

```
[ ]: FamaFrenchReg_w(SRI_ETF_Jap_before.copy()*52)
```

```
[ ]: FamaFrenchReg_d(SRI_ETF_Jap_during.copy()*252)
```

```
[ ]: FamaFrenchReg_w(SRI_ETF_Jap_after.copy()*52)
```

6 Get NAV at period start and end

```
[ ]: def getVals(df):
    A =  df[(df.index == '2018-10-22')]["NAV"]
    B =  df[(df.index == '2020-02-19')]["NAV"]
    D =  df[(df.index == '2020-03-23')]["NAV"]
    F =  df[(df.index == '2021-08-31')]["NAV"]
    print("A:", A, "B:", B, "D:", D, "F:", F)

def getVals_Jap(df):
    A =  df[(df.index == '2018-10-22')]["NAV"]
    B =  df[(df.index == '2020-02-11')]["NAV"]
    D =  df[(df.index == '2020-03-16')]["NAV"]
    F =  df[(df.index == '2021-08-31')]["NAV"]
    print("A:", A, "B:", B, "D:", D, "F:", F)
```

```
[ ]: getVals(ETF_Dev)
```

```
[ ]: getVals(ETF_Eur)
```

```
[ ]: getVals(ETF_USA)
```

```
[ ]: getVals_Jap(ETF_Jap)
```

```
[ ]: getVals(ESG_ETF_Dev)
```

```
[ ]: getVals(ESG_ETF_Eur)
```

```
[ ]: getVals(ESG_ETF_USA)
```

```
[ ]: getVals_Jap(ESG_ETF_Jap)
```

```
[ ]: getVals(SRI_ETF_Dev)
```

```
    df = df.fillna(method='ffill')

    #string to float
    df["Umlaufende Anteile"] = pd.to_numeric(df["Umlaufende Anteile"], downcast="float")
    return df
```

[ ]:
```
info_ETF_Dev     = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-Core-MSCI-World-UCITS-ETF_fund.xlsx',␣
↪sheet_name='Historisch'))
info_ETF_Eur     = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-Core-MSCI-Europe-UCITS-ETF-EUR-Acc_fund.xlsx',␣
↪sheet_name='Historisch'))
info_ETF_USA     = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-MSCI-USA-UCITS-ETF-USD-Acc_fund.xlsx',␣
↪sheet_name='Historisch'))
info_ETF_Jap     = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-MSCI-Japan-UCITS-ETF-USD-Acc_fund.xlsx',␣
↪sheet_name='Historisch'))


info_ESG_ETF_Dev = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-MSCI-World-ESG-Screened-UCITS-ETF-USD-Acc_fund.xlsx',␣
↪sheet_name='Historisch'))
info_ESG_ETF_Eur = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-MSCI-Europe-ESG-Screened-UCITS-ETF-EUR-Acc_fund.xlsx',␣
↪sheet_name='Historisch'))
info_ESG_ETF_USA = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-MSCI-USA-ESG-Screened-UCITS-ETF-USD-Acc_fund.xlsx',␣
↪sheet_name='Historisch'))
info_ESG_ETF_Jap = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-MSCI-Japan-ESG-Screened-UCITS-ETF-USD-Acc_fund.xlsx',␣
↪sheet_name='Historisch'))


info_SRI_ETF_Dev = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-MSCI-World-SRI-UCITS-ETF-EUR-Acc_fund.xlsx',␣
↪sheet_name='Historisch'))
info_SRI_ETF_Eur = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-MSCI-Europe-SRI-UCITS-ETF-EUR-Acc_fund.xlsx',␣
↪sheet_name='Historisch'))
info_SRI_ETF_USA = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-MSCI-USA-SRI-UCITS-ETF-USD-Acc_fund.xlsx',␣
↪sheet_name='Historisch'))
info_SRI_ETF_Jap = AufbereitungNAV(pd.read_excel(r'C:\Users\andre\Kurse Auslandssemester\FIN11 - Trading␣
↪and Market Microstructure\TermPaper\NAV_iShares-MSCI-Japan-SRI-UCITS-ETF_fund.xlsx',␣
↪sheet_name='Historisch'))


NAV_ETF_Dev = timeframe(info_ETF_Dev.copy(), 20200211,20200323)
NAV_ETF_Eur = timeframe(info_ETF_Eur.copy(), 20200211,20200323)
NAV_ETF_USA = timeframe(info_ETF_USA.copy(), 20200211,20200323)
NAV_ETF_Jap = timeframe(info_ETF_Jap.copy(), 20200211,20200323)

NAV_ESG_ETF_Dev = timeframe(info_ESG_ETF_Dev.copy(), 20200211,20200323)
NAV_ESG_ETF_Eur = timeframe(info_ESG_ETF_Eur.copy(), 20200211,20200323)
NAV_ESG_ETF_USA = timeframe(info_ESG_ETF_USA.copy(), 20200211,20200323)
NAV_ESG_ETF_Jap = timeframe(info_ESG_ETF_Jap.copy(), 20200211,20200323)

NAV_SRI_ETF_Dev = timeframe(info_SRI_ETF_Dev.copy(), 20200211,20200323)
NAV_SRI_ETF_Eur = timeframe(info_SRI_ETF_Eur.copy(), 20200211,20200323)
NAV_SRI_ETF_USA = timeframe(info_SRI_ETF_USA.copy(), 20200211,20200323)
NAV_SRI_ETF_Jap = timeframe(info_SRI_ETF_Jap.copy(), 2020021,20200323)
```

[ ]:
```
NAV_ETF_Dev["ETF_Dev_Umlaufende_Anteile"] = NAV_ETF_Dev["Umlaufende Anteile"]
NAV_ETF_Eur["ETF_Eur_Umlaufende_Anteile"] = NAV_ETF_Eur["Umlaufende Anteile"]
NAV_ETF_USA["ETF_USA_Umlaufende_Anteile"] = NAV_ETF_USA["Umlaufende Anteile"]
```



```
    #Umkodierung der Monate zu Zahlenformat, falls es nicht bereits so ist (z.B. wird aus Jan -> 01; Sollte␣
↪bereits ein Monat in Form von Zahlen vorhanden sein, bleibt dies bestehen)
    df['S2'] = np.where(df['S2']=="Jan", '01', df["S2"] )
    df['S2'] = np.where(df['S2']=="Feb", '02', df["S2"] )
    df['S2'] = np.where(df['S2']=="Mär", '03', df["S2"] )
    df['S2'] = np.where(df['S2']=="Apr", '04', df["S2"] )
    df['S2'] = np.where(df['S2']=="Mai", '05', df["S2"] )
    df['S2'] = np.where(df['S2']=="Jun", '06', df["S2"] )
    df['S2'] = np.where(df['S2']=="Jul", '07', df["S2"] )
    df['S2'] = np.where(df['S2']=="Aug", '08', df["S2"] )
    df['S2'] = np.where(df['S2']=="Sep", '09', df["S2"] )
    df['S2'] = np.where(df['S2']=="Okt", '10', df["S2"] )
    df['S2'] = np.where(df['S2']=="Nov", '11', df["S2"] )
    df['S2'] = np.where(df['S2']=="Dez", '12', df["S2"] )

    #Zwischenzeitliche Anpassung des Datentyps der YYYY, MM und DD Spalte zu float values
    df["S1"] = df["S1"].astype(str).astype(float)
    df["S2"] = df["S2"].astype(str).astype(float)
    df["S3"] = df["S3"].astype(str).astype(float)

    #Da aufgrund der durch Refinitiv Eikon bereitgestellten Daten das Jahr im Datum in einigen Fällen vorne␣
↪(YYYY-MM-DD) und in einigen Fällen hinten steht (DD-Mon-YYYY) importiere ich jeweils den höheren Wert in␣
↪die extra dafür erstellte Spalte "Year" und den geringeren der beiden Werte aus Spalten "1" und "3" in␣
↪die dafür neu erstellte Spalte "Day"
    #Dies Funktioniert, da die Werte der Jahre stets größer sind als die der Tage
    df["Year"] = df[["S1", "S3"]].max(axis=1)
    df["Day"] = df[["S1", "S3"]].min(axis=1)
    df["Month"] = df["S2"]

    #Rückformatierung zu strings
    df["Year"] = df["Year"].astype(int).astype(str)
    df["Month"] = df["Month"].astype(int).astype(str)
    df["Day"] = df["Day"].astype(int).astype(str)

    #Löschen der alten Datumsspalte
    df = df.drop(['S1','S2','S3'], axis=1, errors='ignore')

    #Zusammensetzen des Datums aus den drei Spalten
    df["Date"] = pd.to_datetime(df[['Year', 'Month', 'Day']]).astype(str)

    #Anpassung der Formatierung an FamaFrench mittels entfernung der Bindelstriche im Datum
    df['Date'] = df['Date'].str.replace('-','')
    df["Date"] = df["Date"].astype(str).astype(int)

    #Entfernen der Hilfsspalten "Year", "Day", "Month"
    df = df.drop('Year', 1)
    df = df.drop('Day', 1)
    df = df.drop('Month', 1)
    return df

def timeframe(df,startdate, enddate):
    #Anpassung des Datenzeitraums auf den Beobachtungszeitraum.
    indexNames = df[df['Date'] <= startdate].index
    df.drop(indexNames , inplace=True)
    indexNames = df[df['Date'] >= enddate].index
    # Delete these row indexes from dataFrame
    df.drop(indexNames , inplace=True)

    #Formatieren der Datumsspalte von den Integer Werten in das Datetime Format und Verschieben der Spalte␣
↪in den Index der Dataframes
    df['Date'] = df[['Date']].applymap(str).applymap(lambda s: "{}/{}/{}".format(s[4:6],s[6:], s[0:4]))
    df["Date"] = pd.to_datetime(df["Date"])
    df = df.set_index('Date')

    #fill values with "--" with value from cell above
    df = df.iloc[::-1]
    df = df.replace('--', np.nan)
```

```
ax.spines['bottom'].set_color('k')
ax.spines['top'].set_color('k')
ax.spines['right'].set_color('k')
ax.spines['left'].set_color('k')

fig.tight_layout()
plt.savefig("NAV_Development_EU_USA_JAP.pdf")
```

9 Information Ratio

[ ]:
```
BenP_ETF_Dev = timeframe(info_ETF_Dev.copy() , 20181019,20210900)
BenP_ETF_Eur = timeframe(info_ETF_Eur.copy() , 20181019,20210900)
BenP_ETF_USA = timeframe(info_ETF_USA.copy() , 20181019,20210900)
BenP_ETF_Jap = timeframe(info_ETF_Jap.copy() , 20181019,20210900)
BenP_ESG_ETF_Dev = timeframe(info_ESG_ETF_Dev.copy() , 20181019,20210900)
BenP_ESG_ETF_Eur = timeframe(info_ESG_ETF_Eur.copy() , 20181019,20210900)
BenP_ESG_ETF_USA = timeframe(info_ESG_ETF_USA.copy() , 20181019,20210900)
BenP_ESG_ETF_Jap = timeframe(info_ESG_ETF_Jap.copy() , 20181019,20210900)
BenP_SRI_ETF_Dev = timeframe(info_SRI_ETF_Dev.copy() , 20181019,20210900)
BenP_SRI_ETF_Eur = timeframe(info_SRI_ETF_Eur.copy() , 20181019,20210900)
BenP_SRI_ETF_USA = timeframe(info_SRI_ETF_USA.copy() , 20181019,20210900)
BenP_SRI_ETF_Jap = timeframe(info_SRI_ETF_Jap.copy() , 20181019,20210900)
```

[ ]:
```
#logreturns of benchmark

BenP_ETF_Dev["Benchmark Ertragserie"] =  np.log(BenP_ETF_Dev['Benchmark Ertragserie']/
 ↪BenP_ETF_Dev['Benchmark Ertragserie'].shift())
BenP_ETF_Eur["Benchmark Ertragserie"] =  np.log(BenP_ETF_Eur['Benchmark Ertragserie']/
 ↪BenP_ETF_Eur['Benchmark Ertragserie'].shift())
BenP_ETF_USA["Benchmark Ertragserie"] =  np.log(BenP_ETF_USA['Benchmark Ertragserie']/
 ↪BenP_ETF_USA['Benchmark Ertragserie'].shift())
BenP_ETF_Jap["Benchmark Ertragserie"] =  np.log(BenP_ETF_Jap['Benchmark Ertragserie']/
 ↪BenP_ETF_Jap['Benchmark Ertragserie'].shift())
BenP_ESG_ETF_Dev["Benchmark Ertragserie"] =  np.log(BenP_ESG_ETF_Dev['Benchmark Ertragserie']/
 ↪BenP_ESG_ETF_Dev['Benchmark Ertragserie'].shift())
BenP_ESG_ETF_Eur["Benchmark Ertragserie"] =  np.log(BenP_ESG_ETF_Eur['Benchmark Ertragserie']/
 ↪BenP_ESG_ETF_Eur['Benchmark Ertragserie'].shift())
BenP_ESG_ETF_USA["Benchmark Ertragserie"] =  np.log(BenP_ESG_ETF_USA['Benchmark Ertragserie']/
 ↪BenP_ESG_ETF_USA['Benchmark Ertragserie'].shift())
BenP_ESG_ETF_Jap["Benchmark Ertragserie"] =  np.log(BenP_ESG_ETF_Jap['Benchmark Ertragserie']/
 ↪BenP_ESG_ETF_Jap['Benchmark Ertragserie'].shift())
BenP_SRI_ETF_Dev["Benchmark Ertragserie"] =  np.log(BenP_SRI_ETF_Dev['Benchmark Ertragserie']/
 ↪BenP_SRI_ETF_Dev['Benchmark Ertragserie'].shift())
BenP_SRI_ETF_Eur["Benchmark Ertragserie"] =  np.log(BenP_SRI_ETF_Eur['Benchmark Ertragserie']/
 ↪BenP_SRI_ETF_Eur['Benchmark Ertragserie'].shift())
BenP_SRI_ETF_USA["Benchmark Ertragserie"] =  np.log(BenP_SRI_ETF_USA['Benchmark Ertragserie']/
 ↪BenP_SRI_ETF_USA['Benchmark Ertragserie'].shift())
BenP_SRI_ETF_Jap["Benchmark Ertragserie"] =  np.log(BenP_SRI_ETF_Jap['Benchmark Ertragserie']/
 ↪BenP_SRI_ETF_Jap['Benchmark Ertragserie'].shift())
```

[ ]:
```
#formula for Information ratio and implicitly also Tracking error (=vol)
def IR(ETF_ret, benchmark_logret, tradingYear):
    retDiff = ETF_ret-benchmark_logret
    vol = retDiff.std()##np.sqrt(tradingYear)
    IR = retDiff.mean() / vol
    print("IR ",IR)
    print("Tracking ", vol)
    return IR
```

[ ]:
```
IR_ETF_Eur = IR(ETF_Eur["LogReturnRealNAVDaily"], BenP_ETF_Eur["Benchmark Ertragserie"],252)
IR_ETF_USA = IR(ETF_USA["LogReturnRealNAVDaily"], BenP_ETF_USA["Benchmark Ertragserie"],252)
IR_ETF_Jap = IR(ETF_Jap["LogReturnRealNAVDaily"], BenP_ETF_Jap["Benchmark Ertragserie"],252)
IR_ESG_ETF_Eur = IR(ESG_ETF_Eur["LogReturnRealNAVDaily"], BenP_ESG_ETF_Eur["Benchmark Ertragserie"],252)
IR_ESG_ETF_USA = IR(ESG_ETF_USA["LogReturnRealNAVDaily"], BenP_ESG_ETF_USA["Benchmark Ertragserie"],252)
```



```
NAV_ETF_Jap["ETF_Jap_Umlaufende_Anteile"] = NAV_ETF_Jap["Umlaufende Anteile"]
NAV_ESG_ETF_Dev["ESG_ETF_Dev_Umlaufende_Anteile"] = NAV_ESG_ETF_Dev["Umlaufende Anteile"]
NAV_ESG_ETF_Eur["ESG_ETF_Eur_Umlaufende_Anteile"] = NAV_ESG_ETF_Eur["Umlaufende Anteile"]
NAV_ESG_ETF_USA["ESG_ETF_USA_Umlaufende_Anteile"] = NAV_ESG_ETF_USA["Umlaufende Anteile"]
NAV_ESG_ETF_Jap["ESG_ETF_Jap_Umlaufende_Anteile"] = NAV_ESG_ETF_Jap["Umlaufende Anteile"]
NAV_SRI_ETF_Dev["SRI_ETF_Dev_Umlaufende_Anteile"] = NAV_SRI_ETF_Dev["Umlaufende Anteile"]
NAV_SRI_ETF_Eur["SRI_ETF_Eur_Umlaufende_Anteile"] = NAV_SRI_ETF_Eur["Umlaufende Anteile"]
NAV_SRI_ETF_USA["SRI_ETF_USA_Umlaufende_Anteile"] = NAV_SRI_ETF_USA["Umlaufende Anteile"]
NAV_SRI_ETF_Jap["SRI_ETF_Jap_Umlaufende_Anteile"] = NAV_SRI_ETF_Jap["Umlaufende Anteile"]
```

[ ]:
```
###hier mergen und dann grafik
ETFs_combined_COM = pd.DataFrame()
ETFs_combined_ESG = pd.DataFrame()
ETFs_combined_SRI = pd.DataFrame()
#ETFs_combined_COM["ETF_Dev_Umlaufende_Anteile"] = NAV_ETF_Dev["ETF_Dev_Umlaufende_Anteile"]
ETFs_combined_COM["ETF_Eur_Umlaufende_Anteile"] = NAV_ETF_Eur["ETF_Eur_Umlaufende_Anteile"]
ETFs_combined_COM["ETF_USA_Umlaufende_Anteile"] = NAV_ETF_USA["ETF_USA_Umlaufende_Anteile"]
ETFs_combined_COM["ETF_Jap_Umlaufende_Anteile"] = NAV_ETF_Jap["ETF_Jap_Umlaufende_Anteile"]
#ETFs_combined_ESG["ESG_ETF_Dev_Umlaufende_Anteile"] = NAV_ESG_ETF_Dev["ESG_ETF_Dev_Umlaufende_Anteile"]
ETFs_combined_ESG["ESG_ETF_Eur_Umlaufende_Anteile"] = NAV_ESG_ETF_Eur["ESG_ETF_Eur_Umlaufende_Anteile"]
ETFs_combined_ESG["ESG_ETF_USA_Umlaufende_Anteile"] = NAV_ESG_ETF_USA["ESG_ETF_USA_Umlaufende_Anteile"]
ETFs_combined_ESG["ESG_ETF_Jap_Umlaufende_Anteile"] = NAV_ESG_ETF_Jap["ESG_ETF_Jap_Umlaufende_Anteile"]
#ETFs_combined_SRI["SRI_ETF_Dev_Umlaufende_Anteile"] = NAV_SRI_ETF_Dev["SRI_ETF_Dev_Umlaufende_Anteile"]
ETFs_combined_SRI["SRI_ETF_Eur_Umlaufende_Anteile"] = NAV_SRI_ETF_Eur["SRI_ETF_Eur_Umlaufende_Anteile"]
ETFs_combined_SRI["SRI_ETF_USA_Umlaufende_Anteile"] = NAV_SRI_ETF_USA["SRI_ETF_USA_Umlaufende_Anteile"]
ETFs_combined_SRI["SRI_ETF_Jap_Umlaufende_Anteile"] = NAV_SRI_ETF_Jap["SRI_ETF_Jap_Umlaufende_Anteile"]
```

[ ]:
```
ETFs_combined_COM['pct'] = ETFs_combined_COM.mean(axis=1).pct_change()
ETFs_combined_ESG['pct'] = ETFs_combined_ESG.mean(axis=1).pct_change()
ETFs_combined_SRI['pct'] = ETFs_combined_SRI.mean(axis=1).pct_change()
```

[ ]:
```
ETFs_combined_COM['pct'][0] = 1
ETFs_combined_ESG['pct'][0] = 1
ETFs_combined_SRI['pct'][0] = 1

ETFs_combined_COM['fromBeg'] = ETFs_combined_COM['pct'].cumsum()
ETFs_combined_ESG['fromBeg'] = ETFs_combined_ESG['pct'].cumsum()
ETFs_combined_SRI['fromBeg'] = ETFs_combined_SRI['pct'].cumsum()
```

[ ]:
```
plt.clf()
plt.style.use('default')
plt.style.use('ggplot')
fig, ax = plt.subplots(figsize=(15, 6))

ax.plot(ETFs_combined_COM["fromBeg"], label="(Eur, USA, Jap) Conventional ETFs", color␣
 ↪="darkgrey",linewidth=3)
ax.plot(ETFs_combined_ESG["fromBeg"], label="(Eur, USA, Jap) ESG ETFs", color ="y",linewidth=3)
ax.plot(ETFs_combined_SRI["fromBeg"], label="(Eur, USA, Jap) SRI ETFs", color ="g", linewidth=3)
ax.set_xlabel('Date', fontsize=22, weight = 'bold')
ax.set_ylabel('Fund NAV Developement', fontsize=22, weight = 'bold')
ax.legend(facecolor='white', fontsize=22)
ax.axhline(y=1, color='k', linestyle='--')
ax.set_facecolor('white')
ax.xaxis.label.set_color('k')
ax.yaxis.label.set_color('k')
ax.tick_params(axis='x', colors='black')
ax.tick_params(axis='y', colors='black')
plt.xticks(fontsize=22)
plt.yticks(fontsize=22)

# Define the date format
date_form = DateFormatter("%m-%d")
ax.xaxis.set_major_formatter(date_form)
ax.xaxis.set_major_locator(mdates.WeekdayLocator(interval=1))
```

```
IR_ESG_ETF_Jap = IR(ESG_ETF_Jap["LogReturnRealNAVDaily"], BenP_ESG_ETF_Jap["Benchmark Ertragserie"],252)
IR_SRI_ETF_Eur = IR(SRI_ETF_Eur["LogReturnRealNAVDaily"], BenP_SRI_ETF_Eur["Benchmark Ertragserie"],252)
IR_SRI_ETF_USA = IR(SRI_ETF_USA["LogReturnRealNAVDaily"], BenP_SRI_ETF_USA["Benchmark Ertragserie"],252)
IR_SRI_ETF_Jap = IR(SRI_ETF_Jap["LogReturnRealNAVDaily"], BenP_SRI_ETF_Jap["Benchmark Ertragserie"],252)
```

10 Intro graph with mean of common, ESG, SRI over whole period

[ ]:
```
plt.clf()
plt.style.use('default')
plt.style.use('ggplot')
fig, ax = plt.subplots(figsize=(15, 6))

ax.plot(ETF_Dev["RealReturnFromStart"], label="iShares MSCI World Conventional", color␣
↪="darkgrey",linewidth=3)
ax.plot(ESG_ETF_Dev["RealReturnFromStart"], label="iShares MSCI World ESG", color ="y",linewidth=3)
ax.plot(SRI_ETF_Dev["RealReturnFromStart"], label="iShares MSCI World SRI", color ="g", linewidth=3)

ax.set_xlabel('Date', fontsize=22, weight = 'bold')
ax.set_ylabel('Total log-return', fontsize=22, weight = 'bold')
ax.legend(facecolor='white', fontsize=22)
ax.set_facecolor('white')
ax.xaxis.label.set_color('k')
ax.yaxis.label.set_color('k')
ax.tick_params(axis='x', colors='black')
ax.tick_params(axis='y', colors='black')
plt.xticks(fontsize=22)
plt.yticks(fontsize=22)
ax.spines['bottom'].set_color('k')
ax.spines['top'].set_color('k')
ax.spines['right'].set_color('k')
ax.spines['left'].set_color('k')

date_form = DateFormatter("%m-20%y")
ax.xaxis.set_major_formatter(date_form)
ax.xaxis.set_major_locator(mdates.WeekdayLocator(interval=26))

fig.tight_layout()
plt.savefig("percentageDevelopmentETFWorld.pdf")
```

[ ]:
```
ETF_Dev["RealReturnFromStart"][-1]
```

[ ]:
```
ESG_ETF_Dev["RealReturnFromStart"][-1]
```

[ ]:
```
SRI_ETF_Dev["RealReturnFromStart"][-1]
```

Appendix 2 Condensed result of the Fama-French regression models. The columns "Standard error", "t-value", "P>|t|", "[0.025", and "0.975]" describe the variable "const". "const" indicates the out- or underperformance of the ETF in respect to the market. "[0.025", and "0.975]" marks the confidence interval which we used in our analysis.

Nr	Fund type	Fund	Period	R^2	R^2 adj	const	Standard error	t-value	P>|t|	[0.025	0.975]
1	Conventional	Europa	Combined	0.956	0.956	-0.0144	0.029	-0.492	0.624	-0.072	0.043
2	ESG	Europa	Combined	0.959	0.958	-0.0022	0.027	-0.08	0.937	-0.056	0.052
3	SRI	Europa	Combined	0.945	0.943	0.0168	0.031	0.542	0.589	-0.045	0.078
4	Conventional	USA	Combined	0.963	0.962	-0.0199	0.024	-0.843	0.401	-0.066	0.027
5	ESG	USA	Combined	0.963	0.962	-0.0124	0.024	-0.523	0.602	-0.059	0.034
6	SRI	USA	Combined	0.929	0.927	0.0036	0.033	0.111	0.912	-0.061	0.068
7	Conventional	Japan	Combined	0.968	0.967	-0.0281	0.023	-1.243	0.216	-0.073	0.017
8	ESG	Japan	Combined	0.983	0.982	-0.0195	0.016	-1.199	0.232	-0.052	0.013
9	SRI	Japan	Combined	0.958	0.957	-0.0099	0.025	-0.396	0.692	-0.059	0.04
10	Conventiona	Europa	before	0.925	0.919	-4.77E-05	0.03	-0.002	0.999	-0.061	0.06
11	ESG	Europa	before	0.902	0.894	0.0055	0.034	0.16	0.873	-0.063	0.074
12	SRI	Europa	before	0.867	0.856	0.0353	0.038	0.934	0.354	-0.04	0.111
13	Conventiona	USA	before	0.948	0.944	-0.0128	0.031	-0.416	0.679	-0.074	0.049
14	ESG	USA	before	0.95	0.946	-0.0078	0.031	-0.255	0.8	-0.069	0.054
15	SRI	USA	before	0.89	0.881	0.0126	0.046	0.275	0.785	-0.079	0.104
16	Conventiona	Japan	before	0.979	0.977	-0.0089	0.015	-0.583	0.562	-0.04	0.022
17	ESG	Japan	before	0.967	0.964	-0.0082	0.019	-0.437	0.664	-0.046	0.029
18	SRI	Japan	before	0.881	0.872	-0.0046	0.04	-0.116	0.908	-0.084	0.075
19	Conventiona	Europa	during	0.971	0.966	0.2649	0.288	0.921	0.365	-0.325	0.855
20	ESG	Europa	during	0.972	0.967	0.2942	0.28	1.051	0.303	-0.28	0.868
21	SRI	Europa	during	0.959	0.951	0.2889	0.318	0.907	0.372	-0.364	0.942
22	Conventiona	USA	during	0.993	0.992	0.2594	0.188	1.381	0.179	-0.126	0.645
23	ESG	USA	during	0.993	0.992	0.2951	0.184	1.604	0.12	-0.082	0.673
24	SRI	USA	during	0.988	0.986	0.4056	0.249	1.63	0.115	-0.105	0.916
25	Conventiona	Japan	during	0.924	0.911	-0.3903	0.228	-1.708	0.098	-0.858	0.077
26	ESG	Japan	during	0.9	0.883	-0.4604	0.253	-1.822	0.079	-0.977	0.057
27	SRI	Japan	during	0.87	0.848	-0.4899	0.274	-1.785	0.085	-1.051	0.071
28	Conventiona	Europa	after	0.945	0.941	-0.0339	0.051	-0.669	0.505	-0.135	0.067
29	ESG	Europa	after	0.958	0.955	-0.0164	0.044	-0.376	0.708	-0.104	0.071
30	SRI	Europa	after	0.926	0.921	-0.0176	0.057	-0.311	0.757	-0.13	0.095
31	Conventiona	USA	after	0.95	0.946	-0.0331	0.041	-0.814	0.419	-0.114	0.048
32	ESG	USA	after	0.951	0.947	-0.0255	0.04	-0.634	0.528	-0.106	0.055
33	SRI	USA	after	0.91	0.904	-0.0177	0.055	-0.323	0.748	-0.127	0.092
34	Conventiona	Japan	after	0.952	0.948	-0.0245	0.042	-0.579	0.564	-0.109	0.06
35	ESG	Japan	after	0.979	0.978	-0.0095	0.027	-0.354	0.725	-0.063	0.044
36	SRI	Japan	after	0.964	0.962	-0.0043	0.035	-0.124	0.901	-0.074	0.065

9. References

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