DO SOCIALLY RESPONSIBLE HEDGE FUNDS PERFORM BETTER THAN THEIR CONVENTIONAL PEERS?
–
AN EMPIRICAL ANALYSIS

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Summary

List of Figures

List of Tables

List of abbreviations

AUM	assets under management
bp	basispoints
BofA	Bank of America
conv.	conventional
CO_2	carbon dioxide
CSFB	Credit Suisse First Boston
CTA	commodity trading advisor
E	environmental
e.g.	for example
EPBR	equal percent bias reduction
ESG	Environmental Social Governance
ESGC	Environmental Social Governance Controversy
ETF	exchange traded fund
EU	European Union
FAANG	Facebook Amazon Apple Netflix Google
FMB	Fama MacBeth
FTSE	Financial Times Stock Exchange
G	governance
GDP	gross domestic product
GLS	generalized least squares
GP	General Partner
GPIF	government pension investment fund
HF	hedge fund
HFI	hedge fund index
HFR	Hedge Fund Research
HWM	high water mark
ISG	Investor Stewardship Group
LP	Limited Partner
MSCI	Morgan Stanley Capital International
OLS	ordinary least squares
P/E	price earnings ratio
PRI	Principles for Responsible Investment

PSM	Propensity Score Matching
QQ	quantile-quantile
ROE	return on equity
S	social
SAS	Statistical Analysis System
SD	standard deviation
SDG	sustainable development goals
SRI	Socially responsible investment
S&P	Standard & Poor’s
UK	United Kingdom
USA	United States of America
US	United States
VC	Venture Capital

1 Introduction and Summary

Over the past decade and especially in recent years, there has been a surge in ESG investment strategies. The increased cash inflow from investors, as well as the heightened interest in ESG research, has forced all stakeholders to make sustainability an essential part of their daily business. The plans set up by the European Union is carbon neutrality by end of 2050 (EU, 2021). SRI gained popularity in recent years, especially in the mutual funds industry. Also, a good way of signaling their commitment towards SRI is to endorse the PRI launched by the United Nations. The PRI signatories AUM have ballooned from $6,5 trillion in 2006 to $103,4 trillion by end of March 2020, distributed among 3038 signatories. The trend is clearly going in one direction. By only looking on the first three months of 2020, the AUM has increased 20% from $86,3 trillion (PRI, 2020).

The hedge fund industry stands for $3,31 trillion by end of the third quarter 2020; first quarter of net asset inflows with $13 billion since first quarter of 2018 (HFR, 2020). Reasons are manifold, through the pandemic volatility over the uncertainty about the upcoming U.S. elections and the vaccine progress. The latest AUM numbers I got is from the fourth quarter of 2020 with $3,82 trillion (Barclayhedge, 2021). This in turn means a rapid quarterly increase of 15,4%, or 61,6% annually. Basically, all but one strategy is gaining, indeed a few are the main drivers of the sharp increase, namely equity long-only (+42,1%) and emerging markets (19,6%) hedge funds.

Sustainable investing is mainly driven by institutional investors with more than $30 trillion of AUM in 2018, which is around 75% of the whole investment universe (GSIR, 2018). But hedge funds are by far with 14% the lowest percentage implementing SRI strategies among institutional investors (Morgan Stanley, 2020, p.7). Do hedge funds implement SRI strategies and have potential of alpha generation through ESG factors? Institutional investors are with 85% the biggest drivers of demand for ESG oriented hedge funds (KPMG, 2020). According to the KPMG study hedge fund managers target three goals with ESG investing, namely alpha returns, beta returns and risk management, whereas the first and third are much more pronounced for them. But for sure they are more complex than mutual funds, hence lower transparency levels, less disclosure and more steep strategies increase the probability that the actual ESG implementation will be obscured.

The Financial Times (2017) mentioned at the beginning of its article how investments in renewable technologies can pay off, using Mr. Buffets stake in Chinese automaker BYD as an example. This shows just one example, but it is a small part of a larger trend. Not only retail investors, but also institutional investors believe that doing good to the planet and the people result in higher financial benefits. However, there are some geographical differences. In emerging markets, the trend is especially pronounced. This has to do with the fact that such investing is diverse but an "outperformance of ESG strategies is beyond doubt" (Financial Times, 2017). Climate change and the fulfillment of the SDG's excessive influence emerging markets (PRI, 2020). The trend is poised to continue in particular in the context of the ongoing COVID-19 pandemic.

ESG investing has gained popularity in the past years, partly as an increasing number of institutional investors focused not only on the financial impact, but also on the ethical behind their investment decisions. The awareness of climate change is displayed by several big players investment policy, namely the world largest sovereign wealth fund. The $1 trillion Norwegian sovereign wealth fund wants to get rid of all oil and gas companies (Marketwatch, 2019). The world's largest pension fund GPIF of Japan manages $1,5 trillion and the largest pension fund in Europe, the Dutch pension fund ABP holds $565 billion, both are also practicing sustainable investing following the SDG's (AAM, 2021; ABP, 2021).

The fact that sustainability aspects now have a significant influence on what happens on the stock market is impressively reflected in the Bank of America analyses from the USA. For the Earth Day 2021 the analysts of BofA revealed that sustainable companies are valued higher. The S&P 500 companies show that companies with low greenhouse gas emissions are valued more than 15% higher than those with above average CO_2 emissions. For companies that do not publish data on their emissions, the discount is even greater. A breakdown of the companies by water consumption shows a similar pattern. Moreover, in the industrial, energy and utilities sectors which together account for 70% of the S&P 500 direct and indirect emissions; companies that have set themselves the goal of climate neutrality are valued at on average P/E of 32, while the other companies are valued at only 20 (Marketwatch, 2021). I see this development as a structural change in the market that even ESG- skeptical investors should not ignore. The markets attention to sustainability could be further enhanced by the online climate summit that took place on 22 of April 2021. Support for stronger emissions policies has been growing since 2015 and 354 out of 500 companies in the S&P500 already have emission policies in place (Refinitiv, 2019).

The well-known Wall Street Journal (2016) has asked in 2016 if socially responsible investing makes financial sense? And even if these investments cannot provide higher financial returns, investors can feel satisfied by making ethical sound decisions.
For sure, financial markets cannot tackle alone the negative externalities in the area of global warming. But markets handle the future and future-proofed business will reduce negative externalities and hence produce positive spin-over effects for the whole society. So, dealing with climate change is not only about mitigating negative externalities, but also adapting incentives for green investments and pricing the risk (see literature section Pastor et al., 2020).

The world's biggest asset manager BlackRock defines in a simple definition sustainable investing as "Combining traditional investing with environmental, social and governance-related insights to improve long term outcomes for our clients" (BlackRock, 2020, p.2). Companies with strong ESG profiles have potential to outperform those with poor profiles. This has been shown in various studies I introduce in my Literature review section. Hence it should be obvious to look if hedge funds pursuing SRI strategies outperforming their conventional peers in normal market periods, but also in crisis periods.

Research from J.P. Morgan (2016) show that companies in the top bracket of ESG scores carry less risk and can deliver better long-term performance. Moreover, the ESG mutual fund landscape with the largest number of funds (290) and AUM ($100 billion, which is 94% of total) is dominated by countries like the US, Norway France, Sweden, Canada, Ireland, UK and Luxembourg. 83% of ESG mutual funds have a global, only US or only Europe mandate. The US SIF (2020) trends report found with data by end of 2019 that investors are considering ESG factors across 17$ trillion USD of professionally US-domiciled managed assets, which is 42% higher than the year before. Like Morningstar (2020) they found that sustainable equity funds outperformed their peers not only in the first but also in the second quarter of 2020.

Hedge funds can invest without any constraints in a big scope of markets to generate absolute returns, thus it is unclear if ESG should take place in that sector or is it even contradictory when restricting the investment set. But there should be a clear tendency for hedge funds investing socially responsible, because 29% of hedge fund investors have an ESG policy and 20% want to implement one in 2019 (Preqin, 2019). But only 20% of all hedge fund manager have an ESG policy and 15% plan to implement one in 2019. The hedge fund market is challenging, and this way will be easier to attract new investors. Moreover, the private equity industry is one step forward, where 53% of all managers have an ESG policy and 15% expect to have one in 2019. According to Preqin (2019) ESG investing is expected to be the key driver of some growth within the next years. In the private equity industry LP's and GP's still say that considering ESG factors when making investments lead to more sustainable return by reducing risk. Surprisingly the hedge fund industry is the only one with the biggest discrepancy among investors and fund managers. When asked if ESG factors will become more important in the next five years, only 37% of hedge fund managers say yes, but 65% of investors (see figure 1). It is likely that those hedge funds have more investor inflow money. Therefore, SRI is no longer a nice-to have for hedge fund managers, it's a must have. There are different approaches for SRI investing. SRI integration, negative screening, shareholder engagement, impact investing, positive screening and thematic investing. Only 15% of the asked hedge funds manager have a mature ESG-implementation, but 35% are having a PRI signatory (KPMG, 2020, p.6)

I will not focus during my master thesis on evaluating the reliability of ESG scores for hedge fund companies as well as the individual approach they execute, like shareholder engagement, impact investing, restriction screening, thematic investing and ESG integration. Moreover, I will not cover the ESG scores calculation methodology used by Thomson Reuters or from other data vendors. The focus is also not on explaining various hedge fund strategies.

In this master-thesis the words environmental, social and governance (ESG), sustainable and responsible investment (SRI), or socially responsible investment/investing (SRI) are used as acronyms interchangeable. Even among experts is much debate about the difference of these two words. SRI is generally more qualitative and takes a top-down approach which excludes criteria and is long-term, whereas ESG include all criteria but weighs factors positively and negatively to get scores both qualitative and quantitative. Besides, there is no comparable hedge fund data available, like it is for mutual funds, where funds can be distinguished between conventional, SRI and green. The same interchangeable usage is given for the words non-SRI hedge funds and conventional hedge funds.

Further agency problems with apparently false usage of the words ESG or SRI will not be covered in this master-thesis. However, greenwashing is an important problem and must be tackled with a consistent taxonomy, on the EU and global level. The SEC focused on the criteria managers use for their classification if an investment can be considered as SRI or ESG, or rather nothing. No common accepted definitions and methodologies can be conducive for more confusion and errors in SRI practices (Wall Street Journal, 2019). Expressed in numbers, 92% of sustainable AUM increase ($1,16 trillion) between December 2016 and November 2019 account for fund re-brandings. It is still unknown what ESG-integration means for the particular manager. One clear way is conducting disclosures where the SRI strategies are described and implemented, in a way like the traditional financial reports.

What are hedge funds?

Hedge funds use investment strategies that are “alternative” and so to speak not fulfill regulatory limitations to pursue their goals, like capital protection and generation of positive return and low volatility with low market correlation. The major difference to mutual funds is no tracking error against a benchmark. Hence hedge funds seek absolute returns even when market indices are plummeting. That’s why mutual funds cannot protect their portfolio unless they sell or stay more liquid. Hedge fund managers have a bigger investment universe and the direction of financial markets don’t play any big role. Eurekahedge estimates that the number of hedge funds went from approximately 2.000 in the year 2000 to 10.000 in the year 2020.
Assets managed by hedge funds went from an estimated $1.800 billion in January 2010 to $2.136 billion by end of November 2020 (Eurekahedge, 2020).
The time horizon plays an important role for all type of hedge fund managers. For example, a manager invests 10 million in a stake of a company and gets 15 million when selling. This investment turns out to be great if closing occurs in year 1 or 2 with an annual return of 50% or 22,5% respectively. However, if the manager sells after 5 years, he only gets an annual return of 8,4%.

The long/short strategy is by end of September 2020 with 25,4% the most popular strategy among all other strategies (Eurekahedge, 2020, p.20). Interestingly this characteristic was much stronger in beginning of past decade (46,7% in September 2007 and 44,7% in September 2011). It all starts in 1949, when the father of hedge funds, Alfred Winslow Jones created the first hedge fund with $100.000 starting capital, which was a long/short strategy (Medium, 2018).
Most hedge funds I collected pursuing a long/short strategy. Because of the interesting findings in the empirical results section, as well as the introduced new sample in the robustness section I will short summarize this strategy. Basically, the manager takes a long position on stocks he thinks the market underprices and short sells overpriced ones. In practice this can mean selling one automobile stock, while buying another. For example, short $10 million of Daimler and long $10 million of Tesla. If the whole sector goes down, the manager profits on Daimler and

loses on Tesla. If the opposite happens and the overall market goes up, he will earn from Tesla and loose on Daimler. In both cases the gains and losses should approximately offset each other. However, the intention of the manager was that he thought Tesla is doing better than Daimler in the near future. If he is right, he will profit regardless of any market or industry sentiment. Another good reason for short selling is the reduced market exposure of a portfolio when hedging against the systematic risk. Generally, the net market exposure is positive (net long bias) to take advantage of bull markets or a net short bias with a negative market exposure. If dollar amounts of long and short positions are the same, it is a market-neutral strategy. The portfolio is not managed against a benchmark, rather in absolute terms. The mandate of a long/short hedge fund can be distinguished into geography (e.g. Europe, world, US), sector (e.g. technology, mining) and many more.

What can be dangerous with such strategies has shown beginning of this year. In January retail investors have pre-decided on the "Reddit" platform in the "WallStreetBets" forum buying the company GameStop which had forced hedge funds unwinding their bets on the fall of GameStop's share price. This rally caused a short squeeze for the hedge fund Melvin Capital and a 53% loss in January. In general, they used this forum to target companies that were heavily shorted by hedge funds. Moreover, it was a demonstration of power and an attack on big institutional investors. After trading restrictions by various brokers, the publicity for the hedge fund industry wasn't the best (CNBC, 2021).

This master-thesis consists of eight sections. Followed by this introduction, a sweeping literature overview will be carried out on sustainable investing breaking down on different parties. After that research questions will be proposed, followed by the data generation process. The following methodologies section describes the statistical approaches which are used to answer my research questions in the empirical analyses and discussion section. The robustness section will further discuss my results. The conclusion closes my master thesis with the main findings and with an outlook for further research. All tables and figures are provided in the appendix.

2 Literature overview

In this section several past literatures will be introduced. First, I start with mutual funds studies that investigated performance differences between green or SRI and conventional mutual funds, followed by theoretical studies on sustainable investing. Third, I will go one step closer to hedge funds, by looking on recent studies on institutional investors from leading investment banks, an asset manager and a global consulting firm. Finally, literature about hedge funds and how SRI strategies affect their overall performance is to my best knowledge really rare. I will summarize the main findings of three published papers, some of these statistical approaches will be also used in my master thesis. I created on every part a table with the main findings to give a fast overview, except for mutual fund studies (table 1-3).

2.1 Mutual fund studies

The use of multi-factor models (3-Factor Fama/French, 4-Factor Carhart or modifications of these models) is a standard tool in past and recent studies, which is often used with a matched pair approach of selecting the sample data (Mallin et al., 1995). I will describe my selection process in the next section. These models are really powerful, because it has shown that SRI performance is in particular affected by the small firm effect (Bauer et al., 2005, p.1756, Gregory and Whittaker, 2007, p.1328). Also, the use of different timespan for the implementation of crisis and non-crisis periods are common practice. For example, the U.S. SRI mutual funds are performing better in periods of distress, while performing worse in normal periods (Nofsinger and Varma, 2014, p.186). This isn’t true for European SRI mutual funds explained by Muñoz et al. (2014, pp.565-566) and by Silva and Cortez (2016, p.564).

Many studies have shown that socially responsible investing affect the return, because the screening process is a constraint for any wealth-maximizing investor (Rudd, 1981, Grossmann and Sharpe, 1986 and Diltz, 1995). Early academic SRI research studies show no statistically significant difference between conventional investing and SRI. Hamilton et al. (1993, pp.63-64) found no evidence for different returns between socially and non-socially responsible mutual funds in an early time period of 1981 to 1990. Bauer et al. (2005, p.1761), Renneboog et al. (2008, p. 321) and Derwall et al. (2011, pp.2145-2146) confirmed the results by Hamilton et al. (1993) and showed that investors of SRI mutual funds are willing to pay a premium to pursue social goals and thus turn away from the rational goal of maximizing wealth. SRI mutual funds underperformed the market, but not significantly different from conventional funds.

Also, Kurtz and DiBartolomeo (2011) found no significant difference between the whole period and its two subperiods 1992-1999 and 1999-2010 and conclude no advantage for investors. Lean et al. (2015, p.264) got different results in the persistence of performance in North America and Europe, where they found SRI funds outperform the market benchmark, even stronger in North America. Four different SRI indexes outperformed the S&P500 index as Statman (2006) showed during the stock market boom in the late 1990, but no persistence a few years later. The alphas are not statistically significant.

Bollen (2007) finds that the volatility of SRI fund flows is statistically smaller than towards conventional funds in the timespan 1992-2002, while Bialkowski and Starks (2015) confirmed this result and find an interesting difference from 2003 to 2011. The volatility is much smaller and no longer statistically significant. Interestingly, the timing and peaks of the investments into SRI mutual funds is increasing after ecological disasters like the accident of Fukushima nuclear power plant in 2011 and the Deepwater Horizon oil spill in 2010. Moreover Bollen (2007) identified a different transaction turnover between investors holding SRI mutual funds compared to conventional ones. The cashflow is significantly less in and out SRI mutual funds during 1980-2002. Social responsible investors have a larger response to positive returns, but a smaller response to negative returns compared to conventional fund investors. This shows that there must exist some extra utility in excess of financial returns.

The oldest SRI benchmark is tested by Minor (2007) on the Vanguard500 index. The Domini Social Equity fund underperforms by 0,61% per year. Utz and Wimmer (2014, p.79) find no significant differences between SRI and conventional funds on average. They used a dataset with ESG scores and ranked SRI and conventional funds in different quintiles according to their ESG scores. Interestingly the conventional funds are roughly equally distributed over the quintiles. In addition, they showed that the worst firm is similar unethical in both type of funds. Hence, they criticize the label “SRI”.

Bello (2005, p.45-47) matches 42 SRI funds with 84 conventional funds based on size of net assets from 1994 to 2001. The mean monthly return is for both groups not different which is tested by the Wilcoxon z-score, only the standard deviation is slightly higher for SRI funds and highly significant. For the other fund characteristics like net assets and bond holding no statistical significance is given. Both fund groups underperformed the DSI400 and S&P500.

Moreover, the investment performance and the portfolio diversification haven't any significant correlation between conventional and SRI mutual funds.

With an unique dataset of 976 conventional, 259 black and 175 green mutual funds over the 1991-2014 investment period, Ibikunle and Steffen (2015) find that green mutual funds significantly underperform against conventional funds in the full time period, but no risk-adjusted return could be discerned during the most recent time window. Notable is the outperformance of green funds against black funds during the 2012-2014 horizon. They report a significant exposure for green funds towards small cap and growth stocks and for black funds to value stocks. Climent and Soriano (2011) found in the 1987-2009 period a lower performance for green funds with a higher risk. During the financial crisis period 2007-2009 the performance for green funds gets even worse. Ito et al. (2013) applied a mean-variance model and explained a significant outperformance of green funds against conventional funds in the U.S. and Europe.

In a recent study from Morningstar (2020), they found that in the first quarter of 2020 51 out of 57 sustainable funds outperformed their closest conventional counterparts. They ranked first quarter returns of 206 sustainable equity open-ended funds and ETF's against their conventional peers in the US. More sustainable funds ranked in the best quartile with 44% and top halves with 70%. Hence, sustainable funds are overrepresented in the top quartiles and top halves of their peer groups. This means financial returns are closely related to the ranking in the group itself. MSCI (2020) reports similar findings for their indices, where 15 out of 17 sustainable indices outperformed their conventional peers. This was proven through different regions in developed markets and in emerging markets.

2.2 Recent studies on sustainable investing

Pastor et al. (2020) contribute to the literature with an equilibrium model that analyzes both real and financial effects of SRI. The equilibrium model implies the three-fund separation. Green firms generate positive externalities whereas brown firms generate negative ones. The agents have different ESG preferences, but in general get utility from green firms and disutility from brown firms. They show that the agents are willing to pay more for green firms, which lowers the cost-of capital of each firm. Hence green assets have negative alphas, whereas brown assets have positive alphas. However, agents with stronger preferences for ESG are more towards green assets and imply lower expected returns, without being more unhappy.

In the three-fund separation each agent holds the market-portfolio, the risk-free asset and the ESG portfolio which is basically going long a portfolio of green assets and shorting brown assets. Agents who are more into ESG, so to speak have higher than average ESG preferences go long, whereas agents with weaker preferences go short the ESG portfolio. Agents who are holding the market portfolio have average ESG preferences. They conclude that agents care about the social impact of the firms but also about financial wealth. However, they sacrifice some expected return for their higher utility generated by green investing. They also show that the greener the asset, the lower the CAPM alpha, the opposite holds for brown assets. Simply because SRI investing pushes green asset prices up (COC lower) and brown asset prices down (COC higher) the agents taste for green holdings cause more investments by green firms and less by brown ones. Moreover, their model show that agents taste changes a firms social impact by increasing their greenness, because market values are positively correlated to greenness. This is a positive effect, but also real investments shift toward green firms.

Interestingly they show that green assets still can outperform brown ones even with lower expected returns. The ESG risk factor can overcome the negative alpha of green stocks, because investors dislike climate worsening (e.g. government regulation penalize brown firms). Thus, brown assets are riskier because of the larger exposure to climate risk but also because of the agents distaste for brown assets. They concluded that green companies only outperform brown companies in good times, they behave like luxury goods. Financial concern matter less and the economy does well, an investor would have low risk aversion and the green tilt is higher. Therefore, they conclude that green stocks outperform in some periods. Greener firms invest more when risk-aversion is low and investments have a strong effect on stock prices. This finding strengthens the distinction for different subperiods and crisis periods in my research questions introduced in the next chapter. To conclude, the theoretical model by Pastor et al. (2020) implies that the return of green stocks against brown ones are a function of unexpected climate change concerns. To be more specific, if there is an unexpected increase in climate change concerns, green stocks outperform.

Ardia et al. (2020) empirically tests the predictions of the Pastor et al. (2020) paper that green firms tend to outperform brown ones when concerns about climate change increase. They use data from 2010 to 2018 and S&P 500 companies. They constructed an index which captures and tracks the U.S. newspapers concerns about climate change. Articles are classified into a concern score and are aggregated on a daily basis. The greenness of a firm is quantified by the ASSET4 dataset of greenhouse gas emissions scaled by firm revenue. They grouped firms below the 25% percentile into green firms and above 75% percentile into brown ones. Interestingly they confirm the Pastor et al. (2020) results and find that when climate change increases green firm stock prices increase and brown firm stocks decrease.

Does ESG help or hurt performance asks Pedersen et al. (2020) and developed a framework that have potential costs and benefits of ESG investing. Each stocks ESG score includes information about the firms fundamentals and about investor preferences. The framework shows how the adoption of ESG affects equilibrium asset prices and portfolio choice. Their ESG-efficient frontier shows the highest achievable Sharpe ratio of every ESG level. The benefit of ESG information can be quantified if the Sharpe ratio increases relative to the frontier of no ESG information, whereas the costs if the Sharpe ratio drops with better ESG characteristics. They claim that their model is the first one, that shape the ways investor use ESG information. Only with ESG preferences an investment set can be found. This is important because ESG is often discussed as a possible alpha signal. Expected returns can be positive, negative or neutral and depend on the market and the different investor types.

They considered three types of investors, type U, A and M standing for ESG-unaware, ESG aware and ESG motivated respectively. This is an expansion compared to Pastor et al. (2020) who only considered type A and M. Every investor has the optimization problem between risk, return and ESG; they reduced the decision problem into a trade-off between Sharpe ratio and ESG. The optimization problem resulted for each level of ESG the highest Sharpe ratio, which lies on the efficient frontier. For example, if there are more type U investors in an economy and high ESG means high future profits, then high expected returns for high ESG scores. Contrary to that if there are more type A or M investors, they will bid up the prices lowering the expected returns.

They tested the predictions of this theoretical framework with different ESG proxies, E, S, G respectively alone and ESG combined. They have estimated different efficient frontiers. Proxies for E, S and ESG have a stronger investor demand and higher valuations for such stocks. The G proxy offered strong performance, as a reason they claim a good governance implies more stable future fundamentals but attracting less investors.

This model has shown how asset owners, portfolio and hedge fund manager incorporate ESG considerations to their investment decisions within a framework of costs and benefits analysis. The ESG efficient frontier (tradeoff ESG score and Sharpe Ratio) is derived from a four-fund separation. Stocks with higher ESG scores can have higher or lower expected returns, which is up to the wealth of the motivated investor.

Barber et al. (2020) find out that venture capital funds that take financial return into account, but also social impact earn lower returns than traditional funds. They justify that investors derive nonpecuniary utility by investing into these funds. Their sample consist of 159 impact funds, vintage years between 1995 to 2014. The economic conjecture is that impact funds must earn below average returns, because they have a smaller investment opportunity set that hurts performance. Or they argue that markets fail to fully price sectors impact funds invest in (e.g. natural resources). Their approach was to regress each funds IRR on an impact dummy variable which is 1 for an impact fund. Moreover, six control variables for impact funds are added. These six variables are the different categories of impact funds (e.g. environmental impact, poverty alleviation). Even after controlling for these different variables, financial returns are on average 4,7% lower than for traditional VC funds.

2.3 Corporate studies on SRI and Institutional investors

One key takeaway from the J.P. Morgan (2016, p.38) study is that ESG enhance your portfolio by reducing volatility, increasing Sharpe Ratios and limiting drawdowns. They show that different investment strategies, like low volatility, quality or high dividend yield enhance returns and Sharpe ratios by adding an ESG component to the portfolio. In addition, they compared ESG high and low scores towards ESG momentum, because for an investor it is often unclear whether the absolute ESG score or the change is a better guide for future companies performance (see discussion in Robustness section on 13F data). For that, they grouped 100 companies from the MSCI All country world index, which is a combination of emerging and developed markets into four quadrants, namely high and rising, high and falling, low and rising and low and falling. After 12 months they found that high and rising and high and falling have higher returns with lower volatility and higher Sharpe Ratios. Also, the maximum drawdown is smaller. The higher rated ESG portfolios outperforming the lower rated ones, not only global but also across most regions (Europe, US, Japan to name a few). Besides P/E ratios and ROE were higher for high ESG portfolios, but for ROE only in recent years, while historically quite similar but the difference hasn't been significant. The volatility for high ESG portfolio has been lower than for low ESG portfolios. Moreover, the Environmental factor is strongest in USA and Japan, the governance factor is strongest in Europe (J.P. Morgan, 2016, p.21). Furthermore, risk-adjusted returns for ESG indices are higher than for regional MSCI benchmarks, for example the MSCI Japan earned 0,8% whereas the Japan ESG 1,0% yearly in the 2007 to 2016 period. Interestingly the biggest absolute positive difference of 3,2% was found in the Emerging markets for EM ESG against MSCI EM, a market where many SRI hedge funds in my Eurekahedge sample invest in (J.P. Morgan, 2016, p.9).

BlackRock (2020) name further reasons for the outperformance of SRI. It is more than just the underperformance of traditional energy stocks, instead it ranges from job satisfaction of employees and persistence of customer relation till the effectiveness of the board of directors. Especially during the 2020 market turbulences and the economic uncertainty, ESG has indicated the characteristics of resilience. Investors increasingly preferring SRI over traditional assets. Global sustainable mutual funds and ETF's brought $40,5 billion in new assets, a 41% increase regarding 2019. They reported over the last 6 years an outperformance of sustainable indices and 88% of sustainable funds outperformed in the first 4 months of 2020. Hence BlackRock (2020) claims that no return tradeoff across different market environments is required. They tested with 15 hypothetical portfolios the main reasons for the persistence in sustainable funds. Each portfolio consists of a sustainable factor (in total 15 different factors), for example water management, board effectiveness, clean technology, workers rights and eleven more factors. The approach is going long the respective sustainability factor with positive scores and going short with negative scores and taking the MSCI world as the benchmark. The sustainability scores were collected end of December 2019. The results show that the combined sustainability portfolio generate a 4-month excess return of 1,5% (4,6% annualized) with 11 positive factors and only 4 negative. Interestingly the fact that governance-related factors which mattered most during the beginning of the corona pandemic are highest (factor board effectiveness is 2,4%).

Morgan Stanley (2020) made a survey among 110 institutional asset owners by end of 2019. They answered the question what the most important factors for the adoption of sustainable investing are and got the answers with the highest importance are constituent demand and financial return. In summary they find that 95% of asset owners are integrating or considering integrating ESG factors in all parts of their portfolios. Interestingly the ESG integration is the most common approach for sustainable investing. ESG considerations are widely used across the whole value chain during the investment process and their survey show strong momentum for sustainable investing. The asset owners seek for better tools and data for measuring the sustainability, where nearly a half say that social and environmental returns have the same priority than financial returns and 29% say that the lack of quality in data is the main barrier for sustainable investing. So far, the hedge funds class is the asset class with the smallest SRI adoption of 14% among the institutional investors (e.g. Private Equity has 54%).

KPMG (2020) mentioned also the debate about shorting and SRI. Should ESG have a place in long/short hedge funds? In general, it can be said that sustainability is a long-term game, but short selling promotes a short-term mindset. On the one hand, it requires holding non-sustainable stocks, when betting against a tobacco-stock for example. On the other hand, it increases the COC of non-sustainable stocks. Hence it should not be a problem if a hedge fund manager profits from the disappearing of a non-sustainable industry.

The Achilles heel is indeed the lack of a robust template with explanations, definitions and data on how companies score on sustainable factors. Over 150 data vendors exist worldwide, all end up with different scores for the same company and in general bigger companies get a rating rather than smaller one (KPMG, 2020, p. 48). Some constraints slow down the adoption of ESG, the lack of good ESG data and the inexistence of ESG expertise as 135 institutional investors confirmed. First constraint is about inconsistent company disclosures or unreliable ratings. But this constraint is seen as an advantage by hedge fund managers who try to find market inefficiencies to obtain alpha. On the contrary they should do the difficult work and identify which signals are strong enough with the availability of data. This inexistence of ESG expertise can be reduced by hiring ESG specialists and build ESG teams by upskilling (KPMG, 2020, p. 28). Moreover, the G word, now not standing for Governance, but for Greenwashing. A strong due diligence is essential in order to isolate the leaders from the pretenders.

2.4 SRI hedge fund studies

There are not many studies in the field of ESG/SRI and hedge funds. One study is directly comparing in two samples according to my pre-described mutual fund studies if hedge funds implementing SRI strategies perform better (Filbeck et al., 2016). The two other studies look on the holdings of companies inside each hedge fund by ranking according their ESG scores and PRI signatories. Liang et al. (2020) compared hedge funds that greenwash by constructing different portfolios of PRI signatories with low and high ESG scores, respectively and non-signatories with low and high ESG scores. Brandon et al. (2020) constructed an own sustainable measure and showed that 13F institutions are positively correlated.

The central study I found over hedge fund performance and SRI strategies is from Filbeck et al. (2016). They identified two main strategies for SRI hedge funds, namely fund of funds and long/short equity. The starting point is set on year 2005. After deducting for all other hedge funds strategies, their overall sample consist of 36 SRI hedge funds and 3607 conventional hedge funds, all denominated in the U.S. dollar. For their later Fama and MacBeth (FMB) (1973) regressions, they collected also hedge funds typical variables, in addition to the monthly return, fund size, fund age and a dummy variable which is 1 if the hedge fund is implementing a SRI strategy and also management fee, performance fee and a dummy variable for HWM and leverage. They compared the means of both groups in a simple t-test, but found no statistical differences in the monthly returns, therefore they started with the two-step FMB procedure. Three variables are included in their first equation, namely fund age, fund size and the dummy for SRI. The monthly cross-sectional regressions were constructed for the full sample, but also for fund of funds and for long/short hedge funds as a comparison. Like in the t-test before, fund size and age are statistically significant for the full sample. Also, for the two sub-categories, despite the fund age coefficient in the fund of funds column. Interestingly, they haven't found any statistical significance for the SRI dummy for the full sample but found one for the funds of funds at the 5 percent level. Therefore, they fail to reject their null hypothesis for the full sample and long/short equity strategy that SRI-strategies yield superior returns. But they can reject the null hypothesis for the funds of funds category. The coefficient of the dummy is 0,245 which stands for a 24,5 bp monthly outperformance or 2,94% annually. This is a first evidence of a better performance in their SRI hedge funds sample. Because of the low explanatory power, indicating by the low R^2 they extend their equation by some more variables, namely incentive fee, leverage, management fee and HWM. The results are similar and with only a small higher explanatory power. Additional significant results are found for the new introduced variables. Leverage and incentive fee both on the 1% level for the full sample period. The HWM is only significant for the long/short equity hedge funds and leverage dummy variable on the 5% level. Again, they fail to reject null hypothesis for the full sample and long/short category but reject the null hypothesis for the fund of funds sample with 24 bp or 2,88% annually outperformance.

As a last statistical approach Filbeck et al. (2016) introduces the propensity score matching (PSM) method. They decided for the nearest neighbor matching technique with k =1,2 and 3 nearest neighbors. The basic hedge fund characteristics of the first equation (fund size and age), were now matched with the nearest neighbor matching procedure. SRI-hedge funds are still on average younger and smaller after matching. Other variables have similar means and standard deviations. The coefficients on the SRI dummy variable show, that all three coefficients from the nearest neighbors are positive (k=1,2,3>0). Hence SRI HF have higher returns, but they still couldn’t reject their null hypothesis, because of no significance.

What have changed now if they include the rest variables is interesting. In general, both fund groups become more similar, obviously the matching worked well. Strikingly the mean monthly return is now higher for SRI hedge funds with 0,443% against 0,382% (Filbeck et al., 2016, p.418), before it was less with 0,238%. Finally, when looking on the nearest neighbors matching dummy coefficients for SRI they find positive and significant coefficients. All three k’s are positive but are declining in value and significance level with every neighbor higher. SRI hedge funds achieve abnormal returns of 12bp to 22 bp, or 1,5% to 2,67% annually. Because a very big crisis is included in their 2005-2015 period, they want to look how the results are changing, by making two subperiods. A pre-crisis, the financial crisis and a post-crisis period are constructed with following results: In both periods without including the financial crisis strong positive results, even higher for the pre-crisis period than of the full sample period are seen. This means that the SRI hedge funds outperformed by 34 bp and 24 bp matched with 1-neighbour during the pre-crisis and post-crisis period respectively.

Liang et al. (2020) found that a significant number of hedge funds that support the United Nations PRI are doing this for greenwashing purposes. They are able to identify 307 hedge fund management companies who are matched with the PRI signatories by name and headquarter country. They classified their hedge funds into 12 different investment strategies.

To model the risk of hedge funds, the 7-factor Fung and Hsieh (2004) model is used. They used scores from the Asset4 database by Thomson Reuters and the MSCI ESG score from Sustainalytics in order to construct raw scores, by subtracting the number of concerns by the number of strengths. For several qualitative strengths issue areas, like corporate governance, human rights, environment, community, diversity, employee relations raw scores are calculated. Concern business areas are alcohol, gambling, firearms, military, nuclear power and tobacco. The raw score is the sum of all strengths and concern areas. Because the ratings and hence the strengths and concerns will differ over time, they adjusted their scores by the maximum number of strengths and concerns in a given issue area. To calculate the ESG exposure, the 13F data is required. They used a database from Thomson Reuters, called 13F long-only holding. I will use a similar approach with 13F data from Eurekahedge in my Robustness section. Interestingly is the fact, that they are facing the same issue than me. Not every hedge fund stock holding data is reported, therefore they had to reduce from 11387 to 3281 hedge funds. Because 13F data is only available for hedge fund firms, there must be an adjustment for the number of hedge funds. This is best done value weighted. As a first comparison of their distribution of data, as expected the average ESG score for signatories is higher than for non-signatories. Another interesting finding is the persistence in ESG ratings in both directions from the median. Firms below the median stay with 81,6%, above with 81,4% chance the following year in the same rating (Liang et al., 2020, p.14).

They sorted now the abnormal returns of hedge funds with PRI signatories and firm ESG scores. In a first step we have two double-sorted portfolios of PRI signatory and non-PRI signatories. Second step is extending these 2 portfolios to 6 portfolios (each with ESG score low, middle, high). Only looking on the raw returns, without adjusting for risk factors, they show a higher return for the non-signatories over the full sample period 2006-2019. This is a first sign for greenwashing. As a first drawback of their calculation is that 13F data doesn’t contain short positions (see Robustness section), hence including only hedge funds that have a long-only strategy is less biased.

As a further test on the validity of scores, they decompose ESG into two components, namely E&S and a G factor and do the double sorting test again with no big differences than before.
PRI hedge funds charge lower fees, both management and performance are statistically significant, have shorter notice periods, raise more capital for investment and are older. All

variables are statistically significant. In contrary for low and high ESG signatories, only management fee and age have significant meaning (Liang et al., p 39).

In general, over then whole time-period non signatories management companies and their total number of hedge funds are decreasing from a high level of 2783 (4971) to 1429 (2235) by end of April 2019. In contrast, PRI signatories management companies are increasing, as well as their number of hedge funds, from 16 (90) to 174 (489).

In order to see how big, the greenwashing effect in terms of percent is, Liang et al. (2020) use the 7 risk factors by Fung and Hsieh (2004). They identified a significant underperformance of hedge funds with PRI signatories with a spread of -2,45% on the 0,01 level, without adjusting -1,44% on the 0,05 level. These findings are also relevant for smaller hedge funds with a still significant spread of -2,24% on the 0,01 level. In this second panel, they selected only hedge funds with greater than 20 million USD. Last but not least, by looking on the hedge fund management companies itself, companies that are in favor of PRI underperform significantly on the 0,01 level with -2,97% (value-weighted hedge fund returns).

They comment their findings of an underperformance and connection with PRI with the big exposure and limited access to socially responsible companies. Pastor et al. (2020) has shown one reason, that too many investors for green assets will decrease returns and lead to negative alphas. Another reason is driven by greenwashing. To look on these hypotheses, they double group again, but now match one portfolio of PRI signatories with low ESG against non-signatories with low ESG. Another portfolio with PRI signatories with high ESG against non-signatories with high ESG and finally the last portfolio PRI signatories with low ESG against PRI signatories with high ESG. The finding confirms the hypotheses of Pastor et al. (2020) that the underperformance of signatory hedge funds is not pushed by more exposure to socially responsible firms. The spread between PRI signatory with low ESG and non-signatories with high ESG is highly significant -7,72%.
All these results show that signatory hedge funds underperform non-signatory ones. With several tests addressing greenwashing, Liang et al. (2020) included ESG scores and justified their overall hypotheses that funds that greenwash, underperform both genuinely green and nongreen funds.

In the same year, the working paper of Brandon et al. (2020) draw my attention. Similar than the paper before, they use 13F data to measure a "sustainability footprint" of each hedge fund company. They had access to different ESG score data providers.

They made several explanations, one is that investors remain invested in ESG stocks for longer periods of time, justifying by their portfolio turnover. This will lead to higher price pressure. To isolate this price pressure into specific and passing demand shocks they use natural disaster data. The idea behind is to see how price pressure is affected by a natural disaster close to a hedge funds headquarter. This goes certainly into the area of psychology, but research by Demski et al. (2017) displayed that sustainable behavior for individuals increased with the occurrence of extreme weather events. And this is also true for institutional ones. Interestingly they calculate contrary to the Liang et al. (2020) study a combined score using the two ESG score data providers MSCI and Thomson Reuters. Again, the ESG parts are broken apart, but now into E and S.

Because a simple average of the two scores doesn't make any sense, a fair method is the standardization of both scores with mean equal to 0 and standard deviation equal to 1. After standardization a combined score can be calculated with a simple average. Combining two data providers and hence the expertise of two research teams makes these scores more robust compared to the Liang et al. (2020) study. But as a drawback the sample size will suffer because using this approach will need company scores available from both data providers. If the intersection is too low, this approach must be questioned. The overall sustainability score is calculated by the sum of half times the Environmental and Social score.

To measure the effect of natural disasters they use the overall footprint, because natural disasters effect both components and cannot be cut only into E or S. A natural disaster is defined with a total damage above 1 billion USD and less than 30 days occurrence. Most disasters are hurricane strikes, followed by floodings or blizzards. Brendon et al. (2020) use the SHELDUS database and the FIPS code which includes a list of all affected counties hit by the natural disaster. Then the ZIP codes of the hedge funds headquarters are matched with data from the SEC. In a first step, they showed that sustainability footprints increase significantly when natural disasters occur close to the hedge fund headquarter. In a second step, they showed that risk-adjusted performance is positive and highly significant over the last quarters (t, t+1, t+2) with 3,47%, 3,37% and 2,50%.

The rated companies between both rating agencies differ strongly with the CRSP-Compustat sample. Therefore, this combing score is better for a broad picture over all companies available. It can be said that stocks which are covered by Thomson Reuters and MSCI are larger in terms of market capitalization, assets, sales and number of employees, but are lower in terms of cash holdings, lower book-to market, higher gross profitability and lower stock volatility.

As a second step, like in the Liang et al. (2020) study, they combine 13F filing data through the Thomson Reuters s34 database with the before calculated sustainability scores. Again, they see a big problem in changing sustainability ratings over time at the company level, but also that both rating agencies could have changed their criteria to assess sustainability scores between 2005-2015. To eliminate this problem, normalized ranks between 0 and 1 are calculated. Thus, the overall sustainable footprint of hedge funds depends on the rank of the company's sustainability scores and the size of each stock holding on the total holding. All company's holdings go therefore equally weighted into the overall score, which make this weighting more precise.

Panel regressions are used to identify performance between sustainable footprints. They found a positive and significant overperformance of the sustainability footprint combined portfolios, but also a negative sign between portfolio risk and sustainability. When regressing separately for E and S, the relation is now much stronger for the environmental and less pronounced for the social footprint (Brandon et al., 2020, p. 43). The direction of the social footprint is negative for mean portfolio return and total risk, meaning that a better social footprint implies lower return with lower risk. Most interesting finding is the highly significant positive 0,6% alpha of the environmental footprint. By looking on more recent years, a post2010 dummy regression is run with an even higher alpha of 1,80%. But the social footprint is now also higher with an alpha of 1,90%, consequently the overall sustainability score is higher than before with 1,81%, against 0,43%.

To conclude, this paper revealed that 13F companies with better sustainable footprints outperform, while these positive effects are more concentrated in recent time periods and in the environmental factor.

3 Research questions

While some papers have documented that investors receive a higher return for stocks or mutual funds with good ESG scores than for assets with poor ESG characteristics. Also a few papers which I mentioned before (table 3) have considered hedge funds pursuing ESG strategies or not. I test the following null hypothesis:

H_0 = SRI does not yield in superior returns for hedge funds (1)

$$H_0 = \mu_{SRI\text{-}RF} - \mu_{CONV\text{-}RF} = 0$$

H_1 = SRI does yield in superior hedge funds returns (2)

The primary objective of this master thesis is to examine if significant differences in financial performance between SRI and non-SRI hedge funds exist. This will be analyzed with an unique selected, recent dataset of hedge funds.

Building on Hypothesis 1 I suppose that given institutional investment managers increasingly adopt SRI principles in their investment decisions, returns are stronger in a more recent subperiod (Brandon et al., 2020). This confirms that AUM of PRI signatories have soared from \$6,5 trillion to \$86,3 trillion from 2006 to 2019 (PRI, 2020). Moreover, SRI investing has observed unprecedented growth in recent years, increasing from \$569 billion in 2010 to \$12 trillion beginning of 2018. In the following two years the AUM using SRI strategies have grown once more by 42 percent to astonishing \$17,1 trillion (US SIF, 2010; 2018; 2020). I thus suppose:

H_{1a}: superior returns are stronger in more recent years (3)

Past literature on mutual funds or general SRI investing find evidence for differences between different market periods (Filbeck et al., 2016 among others). Furthermore, Black Rock (2020) indicated a much higher demand by investors for sustainable assets during the 2020 corona crisis. Hence, I will look in detail on the last year 2020, heavily affected by this pandemic. I thus suppose:

H_{2a}: superior returns are stronger in terms of economic downturn. (4)

4 Data

The data for my following study is obtained through Eurekahedge database. From this database I collect monthly returns from different hedge fund classes. I exclude no category but identified most HF-SRI hedge funds can be assigned into 2 main categories, long-only and long/short strategies respectively. The difficulty in my screening process lies into the fact that Eurekahedge haven’t provided a search button for SRI or sustainable funds. Therefore, it wasn’t possible to get an excel file with returns on selected hedge funds, this was done by hand. Closed funds were excluded, this means only active reporting funds till end of December 2020 were considered. The whole sample period is from January 2010 to December 2020.

4.1 Socially responsible hedge fund sample

In order to find hedge funds implementing SRI-strategies I used the keyword search in the Advanced Search tool. I searched for words like ESG, sustainable, ethical, sustainability, impact, development goals, best practice, green, social and environmental. For example, the word “sustainable” and “ESG” gave an output of 307 and 55 funds respectively, where a lot of funds are listed more than one time. I deleted these different share classes of funds. Mostly because they are traded in different markets and they are listed in different currencies, indicating by Class A, B, C, D and so on. Moreover, they could have later inception dates and different management fees, but it is still the same one hedge fund. This can be seen by the same management team and by looking on the fund size which is for all classes the same. As an example, the C-QUADRAT Absolute Return ESG Fund trades in “Class (R) T” and “Class (R) VTIA”. Or Sycomore L/S Opportunities fund in “Class A, I, ID and R”. Also funds which are listed only for some months or haven’t return data available were excluded from my sample. However, because of these constraints my sample of SRI-HF is quite small for a 11-year period. Furthermore, I haven’t set a currency filter to find more funds, because not all are listed in dollar. I also looked on the fund description if the fund really implementing SRI strategies. For example, if the fund description indicated the fund manager is “only” pursuing a sustainable growth in assets and returns, my keyword “sustainable” is misleading, and the purpose is indeed different (table 4). For that reason, I have to look into all fund descriptions before putting the fund into my sample. Finally, my full sample consist of 50 HF-SRI. The fund strategies are allocated into 24 long-only absolute return, 15 long/short equities and 11 others (table 5).

4.2 Conventional hedge fund sample

The amount of funds in the Eurekahedge database was much larger for non-SRI hedge funds, I now only included funds denominated in US dollars. The SRI hedge fund sample consists of a lot of Bottom-up funds, I decided to match them with the same category. Bottom-up is a long-only strategy, thus I searched for "long-only" as a keyword in the Advanced Search tab at Eurekahedge. I have to do this, because I couldn't select after Bottom-up directly in the Basic Search. There were only 11 subcategories as a main investment strategy search possible. These are: Arbitrage, CTA/managed Futures, Distressed debt, Event Driven, Fixed income, Long-Only Absolute Return, Long/Short Equities, Macro, Multi-Strategy, Others and Relative Value. This search gave me an output of 357 funds, where many are Bottom-up, but also a big part were Long/Short Equites, Dual-Approach and Fixed-Income. Another way was to search after Long-Only Absolute Return and an inception date equal or before January 2010. This gave an output of 519 funds, where many are listed in a bunch of times and haven't return data provided. This was the better search, because I had also Diversified Debt and Dual-Approach funds in my HF-SRI sample. So, I went through this list and selected 48 funds, trying to get the biggest amount in the emerging markets, followed by Europe and Global. Finally, I select for the Others category the main investment strategy to arbitrage, CTA/Managed Futures, Macro and Multi Strategy. These are the categories I have also for the HF-SRI sample. After selecting for at least 11 years and dollar nominated, I got 750 funds. I chose 22 for my sample. The same process was done for the long/short equities with 30 funds. The total list of hedge fund names with their strategy is shown in the excel file, which is also available upon request.

Moreover, in addition to collecting monthly returns on hedge funds, I also collected some control variables that are typically used in the literature, namely size and fund age. I made a dummy variable whether the fund is investing into SRI or not. Moreover, I collected typical hedge fund variables like management and performance fee and some other dummy variables like penalty, leverage, dividend policy, lock-up and HWM.

Short explanation on my collected hedge funds variables (Eurekahedge, 2021)

The ESG dummy variable of 1 indicates that a hedge fund is pursuing SRI strategies. This decision was taken by me after reading the "manager profile" and "strategy" text like above described. The ESG Framework made by Eurekahedge was used as a double check. A 1 indicates that the fund has a dedicated ESG framework which integrates ESG factors into the investment analysis and decision-making process. However, all funds I identified as ESG, have a disclosure made by Eurekahedge. A few had no disclosure therefore it was also a good way to find some more SRI hedge funds. But most hedge funds I identified as SRI, had a disclosure of an ESG framework. A high water-mark (HWM) is like a peak value that insures the investor for too fast paid managers performance fees. If hedge funds went "underwater" managers were forbidden to collect performance fees. Only after getting the hedge fund value back above this HWM, the manager gets the performance-based compensation paid out. However, it's really difficult to recover a loss (e.g. HF return objective is 20%, on year t you suffer a loss of 20%, on year t+1 you have to generate in order to compensate the past year loss a return of 80%).

The performance fee is the percentage that the manager takes from the returns of the fund, the most common fee structure I could identify is a 2/20, which means 2% management fee and 20% performance fee. The infamous 20% performance structure goes back to Alfred Jones (Medium, 2018). If a hedge fund has a hurdle rate, then the performance fee is paid above that hurdle. A fund manager wrote in his fund profile: 15% of any absolute outperformance over MSCI World benchmark with a HWM. But the hurdle rate wasn't a variable I collected for my further analysis. The management fee variable was collected and is the annual fee payable to the hedge fund company, which is fixed in percentage of total assets, regardless of the managers performance. However, the rewarding system is asymmetric in the hedge fund industry, meaning that managers receive an amount of the gains but don't take part in the losses.

Lock-up and penalty is closely related. During the lock-up period, an investor is not allowed to sell or redeem shares, if he does, a penalty is due for early redemption. This is often common practise for hedge funds pursuing illiquid strategies, where the manager needs some time to exit its investments without driving prices in unfavourable directions. Thus, Long/Short hedge funds have no, or shorter lock-up periods compared to event-driven hedge funds. Moreover, often the existence of one variable excludes the other variable, meaning if no lock-up period is set, then a penalty is set and the other way round. Therefore, it's really seldom that a hedge fund manager wants to have both penalty and lock-up at the same time. The variable leverage is used to increase the total net assets and the return on investment by a given debt multiple (e.g. Up to 2x). A dividend policy of 1 means, that dividends are reinvested. Hedge funds are not the best way to get paid dividends, because they can increase their overall profitability by reinvesting dividends, hence this variable is assumed to be rather low. Finally, the variable fund age in years and total assets (AUM) in million dollars are collected.

Matching approach

In the literature are two fundamentally different methods when comparing selected funds. The matched pairs approach and the no matching before running the cross-sectional regression. If I would use the matched approach, I would select funds for example according to their age and size with at least two corresponding from the opposite group in the sample. This should reduce the small cap bias, because smaller funds are typically investing in small companies with higher return potential, have a faster growth and can often outperform larger funds (Fama and French, 2010, p.1920). SRI hedge funds are on average smaller than non-SRI hedge funds, which is also the case in my sample. Researchers who are against this approach justify their opinion, that large parts of monthly return data are lost through a matching procedure and can reinforce the survivorship bias (Ibikunle and Steffen, 2017, p.343; Gregory et al., 2007).

In this master thesis a partially matched pair approach is used because the market of HF-SRI funds is still very young. In the matching procedure, a ratio of 1:2 is used, which means that there are two non-SRI HF for each SRI-HF. This is similar to some mutual funds studies, where conventional and ethical funds were selected (Renneboog et al., 2008; p.317, Climent and Soriano, 2010, p.278). Furthermore, the funds were matched according to their strategy. This means that every category is twice in the other sample (see table 5). Matching according to the asset size and age wasn't possible, as well as the country they invest.

Another often used approach in literature is equally or value weighted. An equally weighted sample gives relatively more weight to the performance of smaller funds, whereas value-weighted (by AUM) give relatively more weight to the performance of larger hedge funds. By looking on my hedge fund summary statistics in table 6 and my full data in excel[1], it can be seen that I have some strong outliers. For example, the smallest SRI hedge fund has $3 million AUM, whereas the biggest $7.550 million AUM. This huge difference in AUM would neglect the performance of small hedge funds when calculating value-weighted portfolios. Thus, I calculated equally weighted portfolios, like also done in the study of Capocci and Hübner (2004, p.74).

But the strong focus on emerging markets for my SRI-HF sample is roughly maintained through matching. My sample consist of 50 HF-SRI which is only a little bit higher than the 36 SRI hedge funds Filbeck et al. (2016) identified in their older time period from 2005-2015.

[1] Available upon request

This is surprising, because it is assumed that the trend for sustainable investing is far stronger increasing in recent years (US SIF, 2020). It can be partially explained with the usage of a different database and by selecting only hedge funds with inception dates of at least 11 years. So, the intersection between Filbeck et al. (2016) and my timeline is 2010-2015, whereas beginning of 2005 should be found less SRI hedge funds than in 2010. But on the other hand, these authors had access to the Thomson Reuters Lipper database. Moreover Agarval et al. (2020, p.40) show in a Venn diagram of all hedge fund databases combined, that only some funds are overlapping, but others are only existing in one database. Therefore, I had only access to around 20% of total hedge funds. In addition, SRI is not too big in HF, explaining the total finding of 50 SRI-HF. Besides they argue that it is important to merge all four big databases for a comprehensive overview together (Agarval et al., 2020, p.9).

4.3 Data Biases

As Agarval et al. (2020, p.40) in a Venn diagram described and I only had access to the Eurekahedge database; my sample cannot represent the whole hedge fund universe. Fung and Hsieh (2004, p.66) also speak of sampling differences inside hedge fund databases. Moreover, indexes or subindex returns will be different among databases. For example, for equity market-neutral hedge funds indices, HFR have reported -1,57%, but CSFB[2]/Tremont reported 2,13% for the same month. Thus, a matching of all databases make return data much plausible and realistic. But either way, according to Fung and Hsieh (2004, p.66) hedge fund data is sensitive to selection bias, survivorship bias and instant history bias.

Selection bias

Different to my before mentioned mutual funds studies, hedge funds are not mandatory to make public disclosure of their performance, as well as buy and sell activities with some constraints (see Robustness section 13F data). In addition, no hedge fund organization like the Investment Company Institute (ICI) for mutual funds exists. Hedge fund data is collected with the agreement of the hedge fund manager by data vendors who sell the data to investors. Therefore, it will be always unsure how representative the sample actually is. The reason is, hedge funds don’t need to disclose their information, because they cannot make public marketing and advertisement anyway. They can be recommended through word of mouth or through the membership inside data vendors.

[2] former Credit Suisse investment banking division

Survivorship bias

It is much noticed in academic literature and there are two definition of performance calculations used in past studies. First, surviving funds minus dissolved funds (Ackermann et al., 1999) and living funds minus all funds performance (Liang, 2000). My database reports hedge funds which are active, but also obsolete funds are reported. Obsolete hedge funds are dead hedge funds that have been liquidated. Only funds which are in the Eurekahedge database as active can move after the business wound down into obsolete fund database. Other terms often used for obsolete are dead or closed, where the latter rather have the meaning that it is only closed for investors to new investments. As pointed out by Fung and Hsieh (2004, p.66) most databases provide fund information and return only on active funds. However, Eurekahedge provided also information on obsolete funds. But for the above reasons, I had to exclude obsolete funds in my sample. There are many reasons for closing a fund, but typically if a fund stops reporting and/or closing afterwards, this is rather a sign of worse performance compared to surviving funds (Fung and Hsieh, 2004, p.66). This phenomenon is reported much stronger in 1994 to 2000 compared to 1984-1993 (Capocci and Hübner, 2004, p.63). They claim that poor hedge fund performance can be the main driver for closing a fund. They plot 801 dissolved hedge fund returns in a diagram and show a declining mean return over the last 24 months of 3,5% (Capocci and Hübner, 2004, p.65). I found only a few obsolete SRI hedge funds, but with no past return available, hence I couldn't calculate survivorship bias. For my non-SRI hedge fund sample, I have only selected active funds, without considering for dead funds. For a fair comparison I have to look on all funds at the Eurekahedge database, but exporting all fund returns in an excel file wasn't possible.

Instant-history bias

Any hedge funds who enter into databases will provide the past performance history before the entering date. This creates instant history bias, because only hedge funds will enter with good performance to attract new investors (Fung and Hsieh, 2004, p.66). If the performance is bad, they simply have the opportunity to close the hedge fund. Therefore, the average return in a database will be upward biased. The portfolio where the first 12 monthly returns has been dropped earns on average 8,9%, whereas the observable portfolio earns 10,3%. Fung and Hsieh (2000, p.298) have estimated this 1,4% bias with a 12-month (median was 343 days) incubation period in the 1994-1998 period. My full sample period consists of 11 years. I haven't calculated this bias following the methodology of Capocci and Hübner (2004, p.66) by deleting the first 12, 24, 36, 60 months of each fund return.

Fund of Funds

Another approach for reducing some of the above-mentioned biases is to use fund of funds returns. The selection bias is eliminated, because a fund that doesn't report to the database is inside the fund of fund return reported. The second bias is eliminated through reporting historical returns, where funds that are finishing are still part in historical returns of the fund of fund. The instant-history bias is eliminated when fund of funds investing into another hedge fund, because the starting date is the investment time. Interestingly, Fung and Hsieh (2000, p.301) estimated the fund of funds instant-history bias with 0,7%, which is the half of individual hedge funds. My sample consists of no fund of funds, to my best knowledge Eurekahedge do not provide such a category. Filbeck et al. (2016) included a funds of funds category and compared against long/short hedge funds using the Lipper Hedge fund database.

5 Methodologies

In order to estimate and compare the performance of SRI HF and non-SRI HF in a first step, two common models are used as a performance measure to run several time-series regressions. Moreover, a difference portfolio regression is estimated by deducting non-SRI HF from the monthly returns of SRI-HF. In addition, the well-known Fung and Hsieh (2004) 7 and 8-factor model is applied. Moreover, I will construct an own multi-factor model which is based on the Fung and Hsieh (2004) 8-factor model and the Capocci and Hübner (2004) multi-factor model. Finally, FMB regressions and the more sophisticated PSM technique is used; respective R-and Stata- packages with commands are displayed in quotation marks.

5.1 The capital asset pricing model (CAPM)

I start my analysis with the Capital Asset Pricing Model (CAPM), which is an improvement of the Markovitz Portfolio Selection by Sharpe (1963; 1964), Lintner (1965) and Jensen (1968). It is a one-factor model that describes the excess return in equilibrium of a portfolio of risky assets and the market portfolio. Its equation is estimated as follows:

$$r_{ht}-r_{ft} = \alpha_i + \beta_i (r_{mt} - r_{ft}) + \varepsilon_{it}. \qquad (5)$$

where r_{ht}-r_{ft} is the excess return made up by the difference of r_{ht} = return of the portfolio of hedge fund h in month t and r_{ft} is the monthly return on the one-month T-Bill from Ibbotson in month t. r_{mt} is the return of the market benchmark in month t. The intercept α_i is the Jensen alpha and reports the ability of the hedge fund manager to generate on average abnormal returns in excess of the market benchmark. The coefficient β_i measures the systematic risk of the hedge fund portfolio in the CAPM and shows an indication of the market sensitivity of the portfolio. ε_{it} denotes the error term (Jensen, 1968, pp.391-394).

5.2 The Fama/French 3-factor model

However, the CAPM was empirically tested and criticized in many papers at a later date. Banz (1981, p.17) added a size factor and showed that the explanation of the expected returns of an asset increase. This effect was afterwards attempted to explain by the fact that illiquidity of small firms underestimates the beta factors of the CAPM and hence leads to an overestimation of the abnormal returns (Roll, 1981). Another study on the performance of U.S. stocks by Rosenberg et al. (1985, pp.11-12) noticed a significant relationship between the value factor (e.g. price-earnings ratio, book-to market ratio) and the mean return of U.S. stocks. From this point of multidimensionality of asset risk, Fama and French (1993) extended the CAPM by the size and the value factor into the so-called 3-factor model. The equation of the 3-factor model is estimated as follows:

$$r_{ht}\text{-}r_{ft} = \alpha_i + \beta_i (r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + \varepsilon_{it} \qquad (6)$$

where the new factors SMB_t and HML_t mimic the risk in return related on the size and on the book-to-market value of the funds in month t (Fama and French, 1993, p.9). Hence, the coefficient s_i measures the influence of small/growth companies on the portfolio return. The reason behind is, that smaller companies can act differently, often said to have higher returns than large companies and therefore greater growth potential (Fama and French, 1992, pp.450-451). In other words, it's the return of an investment portfolio, that invests into small companies and sells big companies short (Steiner and Ammann, 2008).
At last, h_i is an indicator for the value premium of large companies.

5.3 The Carhart 4-factor model

Few years later, the measuring of portfolio performance was extended by one additional factor. The one-year momentum of the funds in month t brings greater details into the multi factor model and is measured by going long and short on high- and low-return stocks, respectively (Carhart, 1997, p.61). All data is retrieved from the Kenneth R. French data library[3].
The equation of the 4-factor model is estimated as follows:

$$r_{ht}\text{-}r_{ft} = \alpha_i + \beta_i (r_{mt} - r_{ft}) + s_i SMB_t + h_i HML_t + m_i MOM_t + \varepsilon_{it} \qquad (7)$$

where the factor MOM_t measures the effect of buying and selling stocks that were past winner and losers in the last 12 months at month t.

Fama and French (1998) considered an international version of the model with 12 major countries and several emerging markets for an international factor which should best explain the book to market value (HML). According to him the factor couldn't explain value premium

[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

in international returns, I will not include it in my model. For all models a different portfolio is estimated by the difference of SRI and non-SRI HF ($(r_{mtSRI} - r_{ft}) - (r_{mconv.} - r_{ft})$). With different portfolios, risk and return can better examined between both investment approaches (Bauer et al., 2005, p.1759). If here a difference exists, it can be accounted for implementing SRI strategies or not.

5.4 The Fung/ Hsieh 8-factor model

In 2004 Fung and Hsieh (2004) developed a model with 7 different factors which can explain up to 80 percent of monthly hedge funds returns. The factors consist of two equity orientated risk factors, two bond-orientated risk factors and three trend-following risk factors. Later, because of the huge increase of hedge funds investing into emerging markets, an eight-risk factor for emerging markets were added. The equation of the 8-factor model is estimated as follows:

$$\begin{aligned} r_{ht}-r_{ft} = \quad & \alpha_i + \beta_{i1}(r_{mt} - r_{ft}) + \beta_{i2}SizeSpr_t + \beta_{i3}DGS10_t + \\ & \beta_{i4}CredSpr_t + \beta_{i5}PTFSBD_t + \beta_{i6}PTFSFX_t + \\ & \beta_{i7}PTFSCOM_t + \beta_{i8}Emerging_t + \varepsilon_{it} \qquad (8) \end{aligned}$$

where the two equity orientated risk factors are the market benchmark r_{mt} which is originally the Standard & Poor 500 (S&P) index monthly total return and the $SizeSpr_t$ is the difference between the Russel2000 and the S&P. These two factors are downloaded from Thomson Reuters. One bond-orientated risk factor is $DGS10_t$ which is the monthly change of the 10-year treasury constant maturity yield, which I have downloaded over the Federal Reserve Bank of St. Louis website[4]. The second bond risk factor is the credit spread factor $CredSpr_t$ which is the difference of the monthly change in the Moody's Baa yield and the former bond risk factor. I downloaded this data also over the Federal Reserve Bank of St. Louis website[5]. The three trend-following risk factors are $PTFSBD_t$, $PTFSFX_t$ and $PTFSCOM_t$ which mimic bonds, currencies and commodities with lookback straddle options respectively. All three factors are retrieved from David A. Hsieh's Data Library website[6]. Finally, an eight factor $Emerging_t$ is added to include the steady increase of investing institutional money besides the traditional markets. The

4 https://fred.stlouisfed.org/series/DGS10
5 https://fred.stlouisfed.org/series/DBAA
6 https://faculty.fuqua.duke.edu/~dah7/HFRFData.htm

index MSCI Emerging market index is used for this factor and downloaded over Thomson Reuters.

All these eight risk factors are found in different hedge fund strategies. For example, the first two risk factors are found in long/short hedge funds. The fixed income risk factors 3 and 4 in the above model are major risk factors for only a small amount of hedge funds, mostly fixed-income hedge funds. The risk factors 5 to 7 are portfolios of lookback straddles, which are major risk factors for managed future hedge funds. All 7 risk factors can explain 57% and 37% of hedge fund returns in TASS and HFR database respectively (Fung and Hsieh, 2004, p.71).

5.5 Own multi-factor model

In addition, I will combine both models to determine the components of hedge funds returns that are strong connected with superior risk-adjusted performance. I estimate time-series regressions on SRI-HF and non-SRI HF monthly returns in month t on 10 different factors.
I enlarge the Fung and Hsieh (2004) eight factor model by the Fama and French (1993) book-to market factor (HML) and the Carhart (1997) momentum factor (MOM).
For the market factor I use several different proxies, regression results are shown with the MSCI World index. The equation of this multi-factor model is estimated as follows:

$$\begin{aligned} r_{ht}\text{-}r_{ft} = \quad \alpha_i + \quad & \beta_{i1}\,(r_{mt} - r_{ft}) + \beta_{i2}HML_t + \beta_{i3}MOM_t + \beta_{i4}SizeSpr_t + \\ & \beta_{i5}DGS10_t + \beta_{i6}CredSpr_t + \beta_{i7}PTFSBD_t + \\ & \beta_{i8}PTFSFX_t + \beta_{i9}PTFSCOM_t + \beta_{i10}Emerging_t + \varepsilon_{it} \end{aligned} \tag{9}$$

Choice of the right benchmark

As mentioned in past studies, it is a challenge to identify a robust benchmark. Agarwal (2001, p.12) has used a global hedge fund index. Capocci and Hübner (2004, p.62) propose the value-weighted NYSE Amex Composite Index which is a market-capitalization weighted index, that represents more small cap stocks. This index moved similar than the S&P 500 but stronger when investors prefer small cap stocks and tend to move worse when demand for large cap stocks is higher. This benchmark was used in several mutual fund performance studies, also by Fama and French (1993). As always it is up to the individual data, which benchmark is the most appropriate one. My hedge fund data consist mainly of global and emerging markets investing hedge funds, also a smaller amount of only Europe or only US is included. Hence the most appropriate one is a global benchmark; I have chosen the MSCI World index. In addition, I calculated an own hedge fund index (HFI) by equally weighting all my hedge funds returns, both SRI and non-SRI.

Another robust benchmark for my risk-adjusted analysis of hedge funds is the MSCI KLD 400 Social Index. Among the 3.000 largest U.S. companies, the 400 best companies in terms of ESG scores are selected. Also, FTSE4Good developed index provides a good benchmark for measuring the global ESG standards in developed markets with more than 20 countries. The Stoxx Global ESG leaders index put the focus on global companies with leading positions in ESG indicators provided by Sustainalytics. This index will be later chosen in my robustness section. In order to see how the portfolio of hedge funds performed against a broad market of hedge funds, I use the free to access Credit Suisse database and download monthly data for the Credit Suisse Hedge fund index and the Long/Short Equity index.[7]

For my following study I will use the MSCI World as the market benchmark and also an own calculated HFI. Not all calculated results and the other mentioned benchmarks can be included in this master thesis but are available upon request.

5.6 Fama and MacBeth (1973) regressions

Both developed an approach which is widely used in asset-pricing. Their regression procedure regresses monthly cross-sectional returns against independent variables in a two-step procedure. This master thesis will not put too much weight on explanation and background on statistical models, but because of the importance of this procedure, I will short summarize the main ideas. As I said, the regression is based on two steps, first it estimates the betas and then the risk-premias for the chosen risk-factors.

First stage: time-series regression – to find the betas

$$R_t = \alpha + \beta F_t + \varepsilon_t \tag{10}$$

[7] https://lab.credit-suisse.com/#/en/index-nav

Where R_t is the hedge funds return, α is the time-series intercept and is not equal to the pricing error, βF_t are the betas, ε_t are residuals; each hedge funds return is regressed against the risk factors to determine the hedge funds beta for the respective risk factor.

Second stage: cross-sectional regression at each time

$$R_t = \lambda_{0t} + \hat{\beta}\lambda_t + \alpha_t \tag{11}$$

The intercept is included to denote the zero-beta rate in excess over the risk-free rate λ_{0t}, the lamda coefficients λ_t are the risk premiums estimates of the risk factors $\hat{\beta}$. Thus, the average of these lambdas are the price of risk for the risk factor. α_t are the errors of that regression.
All hedge fund returns are regressed for the decided time period against the estimated betas. For example, if you have 500 observations, you have to run 500 different cross-sectional regressions at each time. Finally, you will get the average risk premium for each factor, respectively. The OLS betas coming from the time-series regression, the cross-section can be done with GLS or OLS, I use the latter one.

I use several risk factors for my FMB regression as in equation 10. Therefore, I have to run several time-series regressions for each risk factor in stage 1 or I can use panel data. Because I want to exploit time-series variation in the risk-factors and how that relates to my dependent variable hedge fund returns, I have to do panel data and correct for standard errors, following Petersen (2009). The big question is are the error terms independent of each other and they are almost always not independent of each other. For example, if in one month a hedge fund has high returns, the other hedge fund typically also has in the same direction returns. Especially in the 2020-year, similar high negative returns in March and April and high positive returns in September, October and November can be seen over the most hedge funds. So, we have to correct for the correlation in the error terms. But during the time Fama and MacBeth (1973) was writing their paper, nobody knew how to correct OLS regressions for cross correlation of the error terms. But interestingly also many papers nowadays ignore this fact; Petersen (2009, p.435) found in a sample of finance papers that 42% simply ignored cross-sectional correlation of the error terms. I will adjust by using the Newey-West procedure (Newey and West, 1987), where the bias will be small (Petersen, 2009, p.437).

A really big advantage of this approach is that you can also use it for unbalanced panels. This means according to my table 24 I don't need data over the whole-time span for every hedge fund. However, I selected only hedge funds with complete data und fund characteristics, so that I have a balanced panel.

Nevertheless, you have to prepare your data in a way, that you can perform your regression, which was quite challenging. I haven't had access to SAS where you can simply change your data structure with the "proc transpose" command, so in one click reshape your data from long to wide format and work with it for further analysis in Stata. After all, I changed my data in Excel with the command "Paste special" and "transpose" in a way, that I have panel data. I structured my data in the following way: Column 1 and 2 are created for arranging the data to panel data in Stata. I used Stata, because it was more straightforward to implement than with R. With the "xtset" command I tell Stata that I have panel data: "xtset name column 1 name column 2", where the first column is the panel variable and the second column the time variable.

The FMB regressions can now easily be estimated with the "asreg" package, using the "fmb" option. My dependent variable is the monthly return of the single hedge funds, where the independent variables are all hedge fund characteristic variables, I collected over Eurekahedge ("asreg dependant independent, fmb"). Adjusting for standard errors during the second stage regression is done with Newey and West (1987) with the command "newey(3)" using three monthly lags. The data structure how I read in the data into Stata is shown at table 24. The data is in the long format, beginning with hedge fund 1 in column 1 and the 12 months in year 2020 in column 2. Because of the long data preparation time when extending to 48 months[8] (7200 observations) or even 11years[9] (19800 observations), I computed Fama and MacBeth (1973) regressions for the most recent year 2020 (1800 observations) on equation 12 and 13.

$$R_t = \alpha + \beta_1 FundAge_{i,t} + \beta_2 FundAssets_{i,t} + \beta_3 SRI_{i,t} + \varepsilon_{i,t} \tag{12}$$

$$R_t = \alpha + \beta_1 FundAge_{i,t} + \beta_2 FundAssets_{i,t} + \beta_3 SRI_{i,t} + \beta_4 ManagementFee_{i,t} + \beta_5 PerformanceFee_{i,t} + \beta_6 Leveraged_{i,t} + \beta_7 HWM_{i,t} + \varepsilon_{i,t} \tag{13}$$

[8] 150*48 = 7200

[9] 150*132= 19800

5.7 Propensity Score Matching (Rosenbaum and Rubin, 1983)

This method is not only popular in the mutual fund literature, but also in medicine (Morgan, 2001), epidemiology (Normand et al., 2001), psychology (Jones et al., 2004), social work (Barth et al., 2007) and many more fields. This technique can unfold differences in hedge funds with similar characteristics (DeFond et al., 2015) and has a big advantage when a relatively small sample is compared to a large sample. This is true for 36 SRI HF and 3607 non-SRI HF in the Filbeck et al. (2016) paper, whose ratio is nearly 1 percent and in the Abadie and Imbens paper (2006, p.6) with 185 treated to 2490 untreated observations. For this reason, in the PSM always a treated and a control (untreated) group must exist, where the variable of interest must be a treatment dummy. However, my sample size is not as big and the ratio of SRI to non-SRI HF is much higher.

The main motivation of all matching methods is based on the Rubin causal model (Rubin, 1974). I will shortly summarize the idea theoretically. The equation 14 of the average treatment effect (ATE) can be estimated as follows:

$$\mu = E(Y_{i1} | T_i = 1) - E(Y_{i0} | T_i = 0) \qquad (14)$$

Y_{i1} is the outcome of unit i if the unit receives treatment and Y_{i0} is the the outcome for unit i if the unit don't receive treatment, so to speak is in the control group. The treatment effect is the difference between Y_{i1} and Y_{i0}. This underlies the assumption that the individuals in both groups have the same probability to receive the treatment. However, normally the covariates are not balanced across treatment and control groups, thus we have to look on the average treatment effect for the treated (ATT) in equation 15.

$$\mu \mid (T=1) = E(Y_{i1} | T_i = 1) - E(Y_{i0} | T_i = 1) \qquad (15)$$

A propensity score is the "conditional probability of assignment to a particular treatment given a vector of observed covariates" (Rosenbaum and Rubin, 1983, p.41). That works as follows: "First by matching on the covariates and then by matching on the estimated propensity score" (Abadie and Imbens, 2006, p.6)

Again, this method is working in 2 steps:

First a propensity score is calculated for every hedge fund, which include all important characteristics. These characteristics are my hedge fund typical variables like HWM, lock-up and so on. This is done by a logistic or probit regression, where all characteristics are bundled into covariates.

In the second step as much as possible hedge funds will be matched between both groups the treated and the control group with the most similar propensity score. The estimates of the effect of treatment can be computed on the one hand through a weighting scheme (Imbens, 2004; King et al., 2011) or on the other hand by matching on the fitted values from the first step (Stuart, 2010; De Fond et al., 2015). For my analysis I will use fitted values and a probit regression.

But there is no clear consensus about how exactly matching should be performed and finally to measure the success of the respective matching method, because matching with many variables and 100% consistency is not realistic. The following methods do not require a perfect match with respect to the hedge fund characteristic variables but are rather based on distance calculation of treated and control observations, with the aim of matching those with the smallest possible distance. With regard to the choice of the distance dimension there are again a variety of approaches and the "Matching" package in R implements many different ones[10].

There are two widely used methods, namely PSM by Rosenbaum and Rubin (1983) and multivariate matching based on the Mahalanobis distance by Cochran and Rubin (1973), I will use the first one. A drawback of both methods is that they make the balance worse, if the EPBR doesn't hold. To overcome this issue an algorithmically genetic matching approach imposes more properties, implemented by the R-package "rgenoud"[11]. This matching algorithm maximizes the balance of the covariates between treated and non-treated groups, first written by Diamond and Sekhon (2005) and it is also used in my master thesis. The algorithm "GenMatch" written in C++ enhances covariate balance and possibly can reduce bias when distribution assumptions hold. This approach is a generalization of PSM and Mahalanobis distance matching. Interestingly this method doesn't use the propensity scores estimated in step

[10] http://sekhon.berkeley.edu/matching/
[11] http://sekhon.berkeley.edu/rgenoud/

1, which can be also seen in the R-script file. The generalization is done through an additional weight matrix, which is called in R: "Weight.matrix". It is shown by Diamond and Sekhon (2005) that genetic matching has better properties both when EPBR holds or not.

I have performed the PSM with R and the package "Matching" and the three main functions "Match", "MatchBalance" and "GenMatch" (Sekhon, 2011). The first and the second command is used combined in order to check if the results of "Match" have reached balance on the set of covariates. This technique will find the closest match between variables of SRI and non-SRI hedge funds with a minimization of the standardized distances (Friedman et al., 2001). I have used the glm[12] function in R to estimate a probit regression model. First step is to decide what is your treatment status, which must be a zero/one variable. This is clearly the fact if a hedge fund is pursuing SRI strategies or not. Secondly you have to identify the control group, or no treatment group, which is the non-SRI HF sample. The independent variables are all hedge fund typical variables on which we match and the monthly return is the outcome variable or dependent variable. So, based on the fact if hedge funds get this treatment, so to speak SRI treatment, will it have an effect on their outcome, so to speak their performance.

In the second step of PSM we can match the propensity scores either on the Average Treatment on the treated effect (ATT) or on the Average treatment effect (ATE). The ATT is the average of the slope over the subset of the population for hedge funds pursuing SRI strategies, whereas ATE is the average of the slope over the entire population of hedge funds (Stuart, 2010, p.6). So ATE tries to find a causal effect for both treated and untreated groups. It is able to do so, because each treated is matched with a non-treated with the highest degree of similarity in the covariates.

Finally, sensitivity tests are performed with the package "rbounds"[13] written by Keele (2009). The matched and unmatched data is used for calculating the Rosenbaum bounds for the treatment effect. I calculated bounds for the Hodges-Lehmann point estimates ("hlsens") and for the Wilcoxon signed-rank test for matched data ("psens"). The results are available upon request or by running the R-script file.

[12] GLM stands for generalized linear model
[13] https://cran.r-project.org/web/packages/rbounds/index.html

6 Empirical results with discussion

This chapter reports the empirical results by applying the above methodology and is organized as follows: The first section displays the results of the summary statistics, followed by correlation results and a pairwise comparison of means test. The second section is turned into two parts. The first part discusses the results of the CAPM and 4-factor models with 2 different benchmarks. The second part is looking on multi-factor models and discusses the results with different benchmarks and timespans. The third section tests my null hypothesis with Fama and MacBeth regressions (1973). Finally, I use propensity score matching to determine if SRI hedge funds result in superior returns.

6.1 Summary statistics

Summary statistics for my sample are displayed in Table 6. Panel 1 includes all collected statistics for the HF-SRI funds, while Panel 2 includes statistics for the HF-conv. funds. Panel 3 includes a first comparison of both hedge funds groups.

The mean monthly returns are similar among SRI hedge funds and non-SRI hedge funds at 0,76% and 0,69%, respectively. The standard deviation of SRI hedge funds and non-SRI hedge funds are also similar at 13,67 and 13,36 respectively. The SRI hedge funds are younger on average with a mean age of 15,55 years compared with 17,42 years for the non-SRI hedge funds. Hedge funds pursuing SRI strategies are also smaller with a mean of $513,38 million compared to $716,3 million for non-SRI hedge-funds. On average, SRI hedge funds have lower management and performance fees, 1,495% and 14,25% respectively, compared with 1,513% and 14,83% for non-SRI hedge funds. Despite the similar monthly averages, the performance fee of the SRI hedge funds have bigger variation with a standard deviation of 8,33 compared to 7,45 for non-SRI hedge funds. Management fees are quite similar in variation.

SRI hedge funds are slightly more likely to use a dividend policy (28%) than non-SRI hedge funds (24%) based on the dummy-variable dividend policy. SRI hedge funds are less likely to use leverage (36%) than non-SRI hedge funds (41%). SRI hedge funds are also less likely to employ a lock-up period (18%) compared to 26% of non-SRI hedge funds. Quite similar numbers are shown for the penalty with 26% and 25% respectively. SRI hedge funds are also less likely to employ a high-water mark (70%), compared to 80% of non-SRI funds. The Min and Max column in table 6 shows, that not only positive average monthly returns were possible during my 11-year timespan. The biggest monthly loss for SRI hedge funds is -10,75% and for non-SRI hedge funds -10,99%, whereas the biggest average monthly gain is 7,87% and 7,35% respectively. Interestingly both highest gains and losses occurred in the same year 2020. During this 11-year timespan the market was in a 10-year long bull market, stopping in last year 2020, when a pandemic forced the global market quick down[14], followed by an exceptionally fast recovery in the same year (US News, 2020). This period will be considered separately in detail.

Correlation

Table 7, 8 and 9 reports correlation coefficients between hedge fund strategies and between passive investment strategies. Fung and Hsieh (1997) report a low correlation between hedge fund return and standard asset classes returns, compared to mutual funds returns, whereas mine are higher for MSCI World with 0,87 and 0,93 respectively for SRI HF and non-SRI HF (Table 7). Table 7 reports correlation coefficients between the two HF portfolios, the market factor and three Fama-French factors. The three Fama-French factors range are between -0,44 and 0,41. The market factor and hedge fund portfolio range are between 0,87 to 0,95.

Table 8 reports correlations of my sample among the 2 main hedge fund strategies, both SRI HF and non-SRI HF and the combined portfolio strategy. Because these two different strategies are not very strongly different, no high variability can be seen, ranging from 0,98 to 0,83. This is different to Cappocci and Hübner (2004, p.71) where high variability of -0,80 to 0,97 is detected, but with much more hedge fund strategies in the sample. The reason is, that Short selling is the only fund category which is negatively correlated with all other strategies. My long/short hedge funds are less strongly correlated than the long-only hedge funds within the full sample hedge funds.

Table 9 reports the correlation results for the passive investment strategies, which range is much wider with -0,52 to 0,83. Most coefficients are below 0,4 and higher than -0,52. Except the Emerging market coefficient with 0,83. Nearly 95% are below 0,4; too low to raise serious multicollinearity concerns.

[14] Many global indices crashed by around 20-35% in a few weeks.

Pairwise comparisons of means

I performed a pairwise comparison of means test for all my collected hedge fund variables, in order to see if there is a first answer to my research question. As proved in Panel 3 of table 6, the difference in age and HWM are both statistically significant with p-values less than 0,1 and absolute t-statistics greater than 1,30 in both cases. However, the monthly returns are not significantly different between SRI hedge funds and the sample of non-SRI hedge funds. That's the reason to further analyze the return data with different statistical approaches, which will be proposed in the next chapter. Also differences in management and performance fee, as well as assets, leveraged, lock-up, dividend policy and penalty are not statistically significant.

6.2 Factor model results

I compute all following regression estimations with Newey and West (1987) standard errors to adjust for any autocorrelation and heteroskedasticity in the error terms.

Do SRI hedge fund perform better than non-SRI HF? The overall results show statistically significant alphas for both portfolios and strategies.

Results of the CAPM, 3- and 4-factor model

Table 10 shows the outcome of the CAPM, 3-factor Fama/French and 4-factor Carhart regressions with the MSCI world as the market benchmark. The table shows significant loading on the market factor on all three models. The market loading is the traditional beta of the hedge fund. Most typical equity only mutual funds show betas close to 1, hedge funds vary more and depending a lot on the strategy. Over all three models the beta factor is around 0,5 and highly significant on the 0,01 level. The beta is quite similar to the results found by Capocci and Hübner (2004, p.72). Although they run regressions for every subcategory of hedge funds, most betas are rather low between 0,2 and 0,5 except for the long-only leveraged and US opportunistic growth funds. Moreover, all alphas are significant with 0,4% and 0,3% respectively for SRI and non-SRI hedge funds on the 0,01 level, also the difference portfolio is significant on the 0,1 level. This is a first answer to my research question. I can reject my null hypothesis on the 0,1 level and conclude SRI hedge funds outperform their conventional peers with 0,1% monthly during the 11-year period after adjusting for the four risk-factors.

The model fit is with a R^2 of 0,77 and 0,89 for the 4-factor model for both hedge fund sample quite good. We have also a fairly decent fit for the 1-factor model with 0,76 and 0,87. This tells that 76% and 87% of the hedge fund return are explained by one factor. The SMB loading is 0,091 and 0,135 in the 4-factor model and show that my hedge funds reacting more to large caps. Finally, the HML loading is 0,040 and 0,022 in the 4-factor model, indicating a growth portfolio rather than a value one. Momentum doesn't increase the explanatory power of the model and is positive and negative with 0,001 and -0,002 which means that past winners are also winners in this period and not when they are negative respectively.

Table 11 reports the results from 2013 to 2019. A significant outperformance of 0,3% per month or about 3,6% per year for SRI hedge funds. A highly significant monthly outperformance of 0,2% or about 2,4% per year for non-SRI hedge funds. The difference between both is not significant. Like in the model of total period, the SMB factor is only significant for non-SRI hedge funds in the 4-factor model, but now on the 0,1 level. Its value of 0,068 indicate that it cannot primarily said if it loads more on a large or a small cap but tend to be more a large cap. A zero value signifies a large cap, whereas a value of 0,5 and greater a small cap. SRI hedge funds are smaller in size, but it cannot be shown that these funds are primarily investing into smaller companies. This is also determined by the lower correlation coefficient to the SMB factor for SRI hedge funds in table 7. For the slightly negative HML loading, the non-SRI hedge funds react more on a growth portfolio, than a value one. It can be said that a number around zero is growth, a number greater than 0,3 a value portfolio. The momentum factor shows no improvement in the power of the model. SRI hedge funds have on average lower R^2 values than their counterparts. The difference portfolios show no evidence of any outperformance adjusted by the risk factors.

On table 12 I isolate the time period to the most recent crisis-year 2020. The pandemic has affected the alpha with no significant monthly outperformance in all three models. The difference portfolio indicates small significance on the 0,1 level for the CAPM model. I can reject my null hypothesis $H1_a$ and $H2_a$ and conclude that the SRI hedge funds outperform in a more recent period and in a period of economic downturn with 0,3%.

The market beta is in the range of 0,49 to 0,63 in all three models. Interestingly the SMB factor reacts now much stronger with 0,76 and 0,62 for the 4-factor than for the 3-factor model. This highly significant number indicates that in the pandemic year, the fund manager is more invested into small cap stocks. The relation to the HML factor is again small positive, the manager is rather buying growth than value stocks. Momentum factor is still not significant and the R^2 is for all models really high. In general, it can be said that the Fama/French (1993) 3-factor model produces similar results to the Carhart (1997) 4-factor model.

Table 13 put the focus on the sovereign debt crisis in the Eurozone, which took mainly place between 2010 and 2012. SRI managers can outperform the market with 0,5%, while conventional fund managers with 0,4%. Their difference is not statistically significant. The factors SMB and HML haven't improved the model R^2, only conventional hedge funds SMB is significant on the 0,05 level. The loading with 0,171 and 0,185 signifies rather a large cap than a small cap. HML and MOM factors are not significant.

Finally, I present in table 14 an overview about the total 132-month period, the before mentioned two crisis-periods and a longer pre-crisis period with a focus on the difference portfolios. I computed for all the difference portfolios.
From table 14, several main conclusions can be drawn. First, all alpha coefficients for the difference-portfolio besides the total period are insignificant, but not for Market and HML coefficient. Second as indicated by the differences in exposure to market betas, all periods are significant and SRI hedge funds are less market sensitive than their non-SRI hedge funds.
Third SRI hedge funds are more exposed to small caps while non-SRI hedge funds less.
Fourth, all momentum and HML coefficients are insignificant. Fifth the high adjusted R^2 results show that these risk-factors have significant explanatory power over both hedge funds strategies returns. But significant alphas for both portfolios show that hedge fund manager can outperform the market over the 11-year period, a 7-year pre-crisis period and during the debt crisis. By looking only on the CAPM a significant difference in return between SRI and non-SRI hedge funds can be detected, after controlling for several risk factors namely size (SML), book-to market (HML) and momentum (MOM) only in the full time period.

To further enlarge my findings, I calculated an own hedge fund index (HFI), consisting of equally weighted returns of both SRI and non-SRI hedge fund samples. As shown in table 15 no significant alpha in all different time periods can be detected. SRI hedge funds follow really close the HFI, because the market beta is close to 1 in all four periods.
In order to isolate a pure hedge fund strategy, I calculated the equally weighted returns for long/short and for long-only strategies respectively, shown in Table 16a and 16b. A highly on the 1%-level significance alpha of 0,2% for the whole 11-year period indicates that long/short hedge funds following SRI strategies clearly outperform their conventional peers (table 16a).

Also, in a shorter 36-month pre-crisis period from 2017-2019 SRI hedge funds outperform on the 0,1 level with 0,2%. It can be seen that the market beta is around 0,8, whereas for long-only hedge funds (Table 16b) closer to 1. This is not surprising because my HFI consist of more hedge funds in the long-only category than long/short.

The HML coefficient shows that for the pre-crisis and the total period the previously described investment behavior, that the SRI hedge fund manager tends to invest more in growth stocks. In the total period this is undoubted, but in the pre-crisis period the factor is with 0,158 clearly higher and closer to 0,3 and hence also loads to a value portfolio. Moreover, the SRI long-only hedge funds show insignificant alphas.

Therefore, my null hypothesis is rejected for long/short hedge funds. To further investigate hedge fund returns, the following traditional Fung and Hsieh (2004) model is introduced.

7- and 8-factor model

Table 17 and 18 show the results for the 7- and 8-factor model of equation 8 with the MSCI World as the market factor for the 11-year period and for the last 4 years, respectively. Both portfolios are exposed to many risk factors and both to at least one factor of equity-oriented, bond-oriented, trend-following and emerging markets factors.

It reveals that both market betas are in all cases significantly positive, but in general rather low but higher for the 7-factor model and for the non-SRI hedge fund returns. This was one reason for using a more detailed model in the Capocci and Hübner (2004, p.74) study, that better explains variations in hedge fund returns than the before mentioned models. The authors found that 25% of the funds analyzed account for significant excess returns. The market beta in my model is slightly reduced by adding an eight factor for emerging markets, but the explanatory power Adjusted R^2 is increasing from 81,7% to 82,7%. The emerging markets factor is highly significant in all models, almost all managers from the SRI and non-SRI part prefer emerging markets. Only for non-SRI hedge funds the size spread is highly significant positive for both time periods.

Both fixed income factors are highly significant, namely the credit spread and the 10-year treasury yield. This suggests that on average the SRI hedge funds have exposure to both equity and interest rate. For non-SRI hedge funds both fixed income factors are highly significant on the 0,01 level.

Even after adjusting for these risk factors, investors can earn on average 0,4% and 0,3% per month with both investment strategies SRI and non-SRI respectively. The recent 48-month period in table 18 show only a significant alpha for non-SRI hedge funds with 0,2%. The explanatory power is even higher for the non-SRI hedge funds sample with 96,6% (table 18).

Surprisingly the portfolios of lookback straddles have no significance in all models for bonds and currencies, but they have for commodities. This means both portfolios are significantly negative exposed to a commodity trend following risk-factor. For a shorter time span of 4 years the SRI hedge funds returns are significantly negative exposed to a trend following currency risk factor (table 18). These 3 factors are only risk-factors for a very few hedge fund types; Fung and Hsieh (2004, p.71) account them for only 5-10 % in total hedge funds.

Another big difference is the significant spread between small-cap and large-cap stock returns on the 1% level for non-SRI hedge funds. Thus, both equity risk factors are significant and non-SRI hedge fund managers prefer also smaller stocks, whereas both prefer emerging market stocks, with a stronger premium for non-SRI hedge funds. This is in line with Capocci and Hübner (2004, p.75) where more than half of all managers invested into emerging markets. Interestingly by looking on the shorter 4-years period, the emerging market risk-factor loads stronger on SRI hedge funds.

Own multi-factor model

Table 21 shows my own multi-factor model of equation 9. I validate that non-SRI hedge fund managers don't prefer growth stocks. Both models with and without an emerging factor included are highly significant on the HML factor and show opposite finding towards Carhart (1997) but confirm the results of Capocci and Hübner (2004, p.77). The emerging market factor can improve the model quality adjusted R^2 from 91,3% to 93,3%. Both fixed-income risk factors are on the 0,01 and 0,05-level significant in both models with and without the emerging markets factor. Both hedge fund managers deliver significant monthly excess return with 0,40% and 0,30% respectively after adjusting for the emerging markets factor. Like on the 11-year period in the model before, the emerging markets factor loads again stronger on the non-SRI hedge funds.

As a big difference is the significant negative factor loading on the lookback straddle portfolio for bonds and SRI hedge fund managers. It seems that the exposure on these bonds is less when adding the emerging markets factor in the model. The commodity trend risk-factor is negatively exposed to both hedge funds managers portfolios.

Another major difference is the significant negative alpha for non-SRI hedge funds at table 22 and 23[15]. In the 8-factor (table 19 and 20) and extended multifactor model a significant negative alpha determines an underperformance of non-SRI hedge funds of -0,1% and -0,05% respectively. Hence the reverse conclusion can be drawn that no significance on SRI hedge funds must be at least a better risk-adjusted performance.

Overall, it seems that the multi-factor model, as well as the Carhart (1997) and Fung and Hsieh (2004) model can explain hedge funds investing behavior. Both type of models have high R^2 and they could deliver significant excess returns.

6.3 Fama and MacBeth (1973) regression results

I will first regress the monthly hedge fund returns on the hedge fund specific control variables like in equation 12, namely fund age and AUM. Table 25 shows the average coefficient numbers and standard errors of these 12 monthly estimations. The natural log of estimated assets and the fund age is not statistically significant in the full sample and both sub samples. I find statistically significant difference in returns due to SRI in the full sample and in the long-only hedge funds sample, at the 10 percent and on the 5 percent level respectively. I do not find a statistically significant difference towards SRI when looking directly at long/short hedge funds. I fail to reject the null hypothesis for the long/short category, since SRI doesn't result in statistically significant superior returns. However, I reject the null hypothesis for the full sample and long-only category and conclude that SRI hedge funds result in statistically significant superior returns. The coefficient on the dummy variable for ESG indicates that this monthly outperformance is 31,2 basis points, or 3,74% annually for the full sample. Long-only hedge funds dummy variable indicates a monthly outperformance of 0,8% or 9,6% annually.

The levels of R^2 are quite low, but similar to the Filbeck et al. (2016) study. It is typical in financial time series data because many factors contribute to the returns which are not included in my model. However, the level of R^2 is also similar in other studies using a similar

[15] Fung & Hsieh 8-factor and extended multifactor model regression results for SRI and non-SRI strategies on the own constructed HFI are shown in the appendix, on the total period and the last 4 years respectively.

methodology, for example like in the Ammann and Moerth (2005) study who tried to explain different hedge fund sizes on excess return and alpha.

The Eurekahedge database includes variables that have been researched historically in literature. For example, Ackermann et al. (1999, p.855) explained hedge fund performance and volatility by isolating their individual characteristics with six different dummy variables and four characteristics. Their main finding was that performance fee rates and risk-adjusted returns were positively correlated, also supported by Liang (1999).

Hence, I have included into the equation 13 performance and management fee as a hedge fund characteristic variable and the two dummy variables for Leverage and HWM. The results of this FMB two-step procedure are displayed in table 26.

At first glance, it can be seen that these variables added some extra explanatory power. The coefficients are similar to the reduced model, but also add some more statistically significant results. The ESG dummy variable has the same statistically significant results as in the first regression but is now for both the full and long-only sample significant on the 5% level. Management fee is now significant on the 5% level for the full sample and on the 10% level for the long-only sample.

The newly introduced variables performance fee and HWM are only significant for the long/short hedge funds on the 5% and 1% level. Moreover, for the natural log of assets, fund age and leveraged I do not find any statistically significance.

The SRI exhibit superior monthly performance of 0,35 % in the full sample and 0,914% for the long-only category. In summary I can reject my null hypothesis for the full sample and the long-only hedge funds category and provide evidence that some SRI hedge funds do outperform their conventional peers in the 2020 crisis period. To summarize I fail to reject my null hypothesis for the long/short category.

6.4 Propensity Score matching results

The probit model result (table 28) can be interpreted like for normal probit models. Funds with higher assets, more years and higher management fees are less likely to be in the treated group. Only years is significant on the 5% level. But the purpose of this model is not really looking on this result, it’s more important to calculate the propensity scores, or the predictive probabilities of this model, that are used in the second step for matching. However, misspecification of propensity scores is not as problematic as when the outcome model is debatable with biased treatment effects (Stuart, 2010, p.14).

Each of the treated group gets a match from the control group and then we can compare the average treatment effect of SRI hedge funds on the control group non-SRI hedge funds (table 27). For this final step the "Match" command is used. My results on table 30 use the two variables of equation 12 and can be interpreted as follows: if you are investing into a SRI hedge fund then you will have 0,098% more return compared to a non-SRI hedge fund each month during the 11-year period, but not statistically significant.

On Panel 1 of table 27 I reproduce for a better comparison the results of Panel 1 on table 6. Matched SRI hedge funds don't remain on average younger with a mean age of 15,55 years and 15,382 years, respectively. But SRI hedge funds are still smaller after matching with \$513,4 million and \$669,36 million respectively. However, both matches have reduced the differences between the original data. Before matching a difference -1,86 years occurred and after matching the difference was 0,17 years. For the assets the difference could be reduced from -202,9 to -155,98. This matching was done through "MatchBalance" command in R[16]. If the matching results are not good enough, Sekhon (2011) proposes to change the PSM and some parameter with which the matching is done.

Since this analysis haven't provide any probative findings, I go ahead with the matching procedure on some more variables and equation 13 variables.

Interestingly by adding the variable HWM (table 31) the results get statistically significant on the 5% level (t-stat: 1,97). This positive coefficient indicates 0,18% higher return for SRI-hedge funds on a monthly basis. Thus, I can reject my null hypothesis from the PSM using the equation 12 plus the HWM variable that SRI result in significant superior performance. The standard error is 0,0009 which is the Abadie and Imbens (2006) standard error. The summary function output also provides the number of observations in total (150), the number of treated observations (50), the number of matched pairs with weighted ties (150) and the number of matched pairs without using the ties (155). Results for "ties" equal to false are available upon request. In this case, the sum of the weighted observations will be the same than the original number of observations, but this is not recommended because it underestimates the variance of hedge fund returns. Only within larger datasets, this bias is not worth to consider (Sekhon, 2011, p.9). Results for the "ATT" are also available upon request or by running the R-script.

[16] More R- output results like in table 29 for PSM matching and Genetic Matching are available upon request

However, only by using “ties” equal to false, significant positive results can be discovered for the equation 12 variables and HWM and for the equation 13 variables without leveraged and without both fee variables respectively.

When including the equation 13 variables (table 32) I find a positive but not statistically significant coefficient. The ATE is 0,11%. Interestingly by excluding both fee variables (table 33) I get significant results again on the 5% level (t-stat 1,97) with a 0,18% outperformance on a monthly basis for SRI hedge funds. This can be explained on panel 2 table 27, by looking at Equation 13 (column 4): the matching of both fee variables (management and performance fee) hasn’t been improved well, instead got even slightly worse for the management fee. Without running PSM on these two variables the results are significant. Leveraged is smaller for non-SRI-HF but closer that before and HWM is with 0,74 almost the same than in the HF-SRI sample. The difference in HWM could be reduced from -0,1 to -0,06 and the leveraged from -0,08 to 0,02. Hence my matching results are quite decent, and I don’t have to change the PSM on some parameters. Moreover, this justifies my exclusion as pointed out by Stuart (2010, p.10) that it is not reasonable to include many variables in smaller samples. She proposes to give variables more weight that are believed to be more related to the outcome variable. The Genetic matching approach as pointed out in panel 3 of table 27 have better results for the matching on assets with only $83 million difference. The leveraged and HWM variable are a perfect match, so to speak have the same values using the equation 13. Both fee variables got no closer match. All p-values of equation 12 and 13 (table 27) are not significant. But, highly probably because of the lower number of observations my results are not significant. It would be interesting to see how the results are changing when we have several hundred of hedge funds in the control group like in the Filbeck et al. (2016) paper. Matching became the tool of choice as Keele (2009) claimed. When estimating treatment effects in observational data he mentioned several advantages over regression-based models. It reduces the dependency on functional form and take into account larger transparency in the modelling process.

However, if the number of matches will be increased the quality of matches goes down, because the treated group will not be matched exactly anymore. The QQ-plot can compare the distribution of the variables in the treated and untreated group, by examining their quantiles. I will show the empirical QQ-plot for the variable age in order to check the balancing property (see figure 2). The red line indicates a perfect match, meaning that the two groups have identical empirical distributions. We see that matches are better for younger ages of hedge funds, because the matches are closer to the 45-degree red line. The empirical QQ-plot for age looks good, notably when compared with figure 3 in the appendix. The balance is now improved and not made worse after matching (table 27 for the variable age). This QQ-plot can be displayed for any variable included in my PSM model.

Filbeck et al. (2016) mentioned some drawbacks of this method but immediately refute them. The concern questions the effectiveness of this methodology in explaining the research question. So let me cut to the chase: the covariates and the dependent variables are not randomly distributed (King and Nielsen, 2016). But however, security returns are assumed to be efficient and hence represent a “random walk”. This concern wasn’t troublesome for my research. Moreover, Filbeck et al. (2016) uses the k:1 nearest neighbor matching, one of the easiest implementable and understandable methods with an estimation of the ATT. This 1:1 matching approach can drop a large number of observations and k:1 matching can lead to poor matches without using a caliper (Stuart, 2010, p.16). With using a caliper of for instance 0,3 only matching occurs when the difference in the propensity scores of treated and control group are at most 0,3. However, they used 1:1 nearest neighbor matching, but also 1:2 and 1:3 matching. 1:1 means that exactly one control observation is matched with the treatment observation, whereas 1:2 means that 2 control observations are matched with one treatment observation. As an advantage of 1:k matching is that the power is increasing because of the bigger number of matches. The obvious disadvantage on the other hand is that matches are poorer with respect to their fund characteristics.

By looking on the matching results of the Filbeck et al. (2016) study, the non-SRI hedge funds are matched closer on equation 12 and 13 respectively. Like in my results the non-SRI hedge funds are older. The matching has reduced the differences in years from -1,32[17] over -0,894 (equation 12) to -0,06 (equation 13). Also, the size variable in million dollars can be reduced from -31,1 over -21,1 to -3,1. Interestingly the incentive fee has only improved for the equation 13 variables. HWM and Leveraged improved for both equations. The only variable which hasn’t improved during matching for both equations is the management fee variable, but this variable was by chance really close before matching with 1,347% and 1,35% for SRI hedge funds and non-SRI hedge funds respectively. In general, it can be seen that the gap fell by

[17] Filbeck et al. (2016) on page 412, table 1 panel C, third column for variable age: -0,324 is a typo, after deducting 6,489 from 5,168.

including more variables for matching. The differences attenuated much the same as in my research. As a result, Filbeck et al. (2016) show that statistical significance has disappeared. But they only found statistically significance for superior SRI hedge fund returns in the extended set of variables in equation 13. Additional results of their study have already been discussed in the Literature section.

7 Robustness tests

Purpose of the robustness check is to see if my results found in the empirical results section are still valid when using different data. Hence the robust test should answer the following question: Do SRI hedge funds still outperform non-SRI funds using the 3F Fama/French, 4F Carhart model and 8-factor Fung Hsieh model. Are differences around several subperiods similar and face the same significance levels?

First, I perform the robust test on the same data with two other benchmarks. The Stoxx Global ESG leaders index comprises 402 worldwide companies which are carefully selected by the swiss company Stoxx Ltd. a subsidiary of the german Deutsche Börse AG (Pressebox, 2020). The choice of these 402 companies is made from a range of 1800 ESG rated companies by the dutch company Sustainalytics. The Dow Jones global World index provide 95% of global market coverage selected by Dow Jones editors, both in emerging and developed markets. Second, I use a new sample of long/short hedge funds that have a more recent inception date. I select between January 2010 to January 2017. Hence, hedge funds both SRI and non-SRI from my main data are not listed twice. The new sample is tested in addition with two indices from Credit Suisse database. Moreover, the MSCI KLD400 Social Index and the FTSE4 Good developed Index were also tested. Third I will contribute to existing literature by ranking each hedge fund company's 13F data in relation to their companies ESG scores. My excel tool can be adjusted in several ways which I explain afterwards. I provide the drawbacks of this method, as well as more suggestions for developments in future research.

7.1 Stoxx Global ESG Leaders Index

In order to account for the SRI hedge funds, an ESG index is used as a benchmark, instead of the MSCI world index in the main analysis. Again, all market betas have significant loadings and are around 0,5 (table 34). It is supposed that for SRI hedge funds the loading is higher than for non-SRI hedge funds or closer to 1, but this couldn't be identified. Only in the 12-month period in table 35 the market beta is with 0,62 higher in the four-factor model for SRI hedge funds. The alphas are all significant for the full time period besides the difference portfolios not. However, for the 1-factor CAPM, SRI hedge funds outperform non-SRI hedge funds with 0,3% during the 2020 year. The model fit is for the four-year period in table 34 slightly lower than for the 2020 year. The SMB coefficients are now for both models significant, but higher for SRI hedge funds in 2020. A much greater value for the 2020-year period justifies the higher return in 2020, that investing into smaller companies lead to higher returns. Both HML loadings are not significant, but the MOM loading is significant in the 2020 year and improves the overall model R^2. The positive momentum shows that winners of the last period are also winners in this period. However, during the full time period no significant outperformance can be detected. The own multifactor model on table 36 show similar results than before. The HML loadings are now also significant for the SRI hedge funds. Other variables like Size Spread, bond market factor and credit spread, as well as the bond trend following risk factor show similar results. Interestingly the emerging markets factor loads stronger. It implies that my estimation results are fairly robust against the change into an alternate ESG related benchmark. I observed similar patterns for the Dow Jones Global World index, the results are available upon request.

7.2 New sample long/short hedge funds

The time period is from January 2017 to December 2020, shorter than the main sample data used in this master thesis. I looked on shorter track records, because it was easier to find more hedge funds, but also to see if the sample suffers from survivorship bias. My new sample consist of 94 long/short hedge funds, namely 47 SRI and non-SRI hedge funds respectively. Both samples contain hedge funds investing into global, European, US and emerging markets countries. Filbeck et al. (2016, p.414) couldn't find any significant outperformance for SRI long-short hedge funds. I could find one using my own calculated HFI for several subperiods and the total period (table 16). However, during the 2020 pandemic crisis not. I will short summarize the hedge fund statistics (table 37), followed by 4-factor model regressions with the MSCI world index, an own calculated HFI and finally the combined multifactor model.

The mean monthly return is lower for SRI hedge funds in the full sample time span 2017-2020, with 0,657% against 0,844%. By only looking on the 2020 time span the monthly return is now higher for SRI hedge funds with 1,1% against 1,03%. Both highest monthly losses and gains occurred like in my main data in the year 2020 (table 6). Most other variables are quite similar, indicating by the negative sign in Panel 3 on table 37. After performing a pairwise comparison of means test, the HWM and the Lock-up variable are now highly significant on the 5 % and 1 % level respectively. Non-SRI hedge funds using in 95% of all cases a HWM (85% SRI HF) and in 25% of all cases a lock-up period (4% SRI HF). The differences in Leveraged, dividend policy and Penalty are quite similar, like in the main data. Again, the management and performance fee are both higher for non-SRI hedge funds, but the differences are now stronger with around 0,05% and 1,06% respectively.

The factor models in table 38 show no significant performance differences between both sample of hedge funds. Only without adjusting for hedge fund typical risk factors higher returns in 2020 can be found for SRI hedge funds. It can be also seen that the emerging markets factor is now for the first time not significant for the SRI hedge funds in the multi-factor model on table 39. Alphas are not significant and smaller compared with that one in the empirical part. One possible reason for the diminishing of alphas is that the time period is recent and short for these hedge fund returns.

Second, from the Credit Suisse database, their calculated Hedge Fund index is used, which is a broader track of hedge funds than my own calculated HFI. It tracks around 9.000 hedge funds with AUM bigger than $50 million. By the way, this index is asset-weighted, opposed to my calculated HFI. However, they argue that asset-weighted is a more accurate depiction when investing in this asset-class. Indeed, this is reasonable, because they only include funds greater than $50 million under AUM, which wasn't the case in my sample. It is also more representative of the whole hedge fund universe because they haven't removed funds until they were liquidated due to minimizing survivorship bias. Both type of hedge funds outperform the broad hedge fund index in the 4-year period with 0,2% and 0,4%, for SRI and non-SRI respectively in the 4-factor model. The difference portfolios are not significant, but they are in the 2020-year period with 0,8% on the 5% level using the 3-factor model. Interestingly they do not outperform the hedge fund index during the 2020 year.

Credit Suisse also include several individual strategy indices; hence I downloaded the returns for the long/short hedge fund index. Again, I can confirm the outperformance of long/short hedge funds during the 2020 year for SRI hedge funds with 0,7%. using the 4-factor model. In the 8-factor model the results changed to an outperformance of non-SRI hedge funds with 0,3% for the 4-year period and no significance for SRI hedge funds.

Last but not least, when using the MSCI KLD400, during the 2020 year, a significant outperformance of 0,7% and 0,9% in the 3- and 4-factor model is visible. The FTSE4Good developed index show no significance at all. The last 3 benchmark results are not shown in the appendix and are available upon request.

In summary, it implies that my estimation results are fairly robust against the change in the length of track records and the hedge fund category.

7.3 ESG scores matching with 13F data

The starting point is data on the individual hedge fund company level. All institutional investment managers who exercise investment discretion over $100 million are required by the SEC to file the form 13F at the end of each calendar quarter (SEC, 2020, Question 2). 13F securities include equity securities and options, as well as ETF's and certain convertible debt securities (SEC, 2020, Question 7). The 13F filing data is obtained through Eurekahedge database. To construct the individual hedge fund company ESG score I use the database Thomson Reuters. My search criteria were an ESG score of at least 30, a social pillar score of at least 20, a governance pillar score of at least 20 and an environmental pillar score of at least 20. This gave me an output of 4283 hits. The idea was not giving place to bad rated companies in total ESG score, but also not to companies who neglect one of the three pillars. For example, the E and G are really high, but the social pillar score is quite low because the company reject labor unions, can't prevent child labor or pay their main workforce below minimum wages. Of course, if I haven't set this restriction, I would have much more ESG companies hits, namely 8513. This is the total number of rated companies by Thomson Reuters by the way. Brandon et al. (2020, p.14) rated companies are much bigger, because they merged two data providers.

My calculations are twofold, first an individual ESG score is calculated, second return data is matched.

As a first step the total AUM value of the hedge fund company is calculated (sum of column 2 in the excel file[18]), which is divided by the individual stock holding to get a fraction from the whole AUM (column 3). With "vlookup" the 4283 companies are screened and matched with column 1 of my 13F data. This output is on column 4. If a company is matched, I display the ESG score, if no match is found a #N/A occurs. Finally in column 5 I sum up the fraction I calculated in column 3 with the ESG score in column 4 to get weighted scores. This is important because it makes a difference if for example 0,2% or 3% of the total AUM is invested in one company. In order to get the calculation done with #N/A values in column 4, I use the "if(is number(…))" command. In a last step I sum up all ESG numbers in column 5 to obtain a final

[18] The excel file with all calculations is available upon request

ESG score for the individual hedge fund company. This procedure is done for all 42 hedge fund companies.

To answer my research question, I need in the second step return data for each hedge fund company. I included only HF companies with return data available for at least one hedge fund. I made three groups of ESG scores, group 1, group 2 and group 3 with high, middle and low ESG scores respectively. This was done through the "Sort" function in Excel. For example, group 1 average ESG score is 23,9, whereas group 3 has only a 12,8 average ESG score. Moreover, not only the ESG scores, but also the return of the last 4 years and the 2020 year is included. This is crucial, because now the very last step is to compare the average returns in group 1, 2 and 3 against each other.

My results confirm the past finding that SRI hedge funds outperform their conventional peers. During the most recent year 2020 the first group consisting of 14 hedge fund companies within the highest ESG group earned on average 19,7%, followed by the second group with 16,5% and far behind is the third group with 5,5%. This clearly confirm table 12 CAPM results and table 25 and 26 FMB results. However as pointed out in the upcoming drawback section, for the full 4-year period my results are no longer robust against biases in the portfolio holdings. This can be the main reason that the return in the first group is with 6,52% only slightly higher than in the third group with 5,99% and even smaller than in the second group with 9,95%.

Drawbacks

Although I found a quite nice and decent fit, several drawbacks and improvements can be made for further research.

First of all, I had only access to the fourth Quarter 13F data of 2020. This means that for a more accurate research Quarter 1-3 is needed for matching with the 2020 returns. If the years 2017-2019 are included, I recommend 12 more quarter data to get less biased results. The reason is simple, holdings can change more or less fast depending on the hedge fund strategy. But the possibility is higher to have more different company holding's structure three or four years earlier than only a few months. If hedge funds make only a few trades, their holding can be similar to the 13F holding even after a few months later. Therefore my 2020 years result can be seen as much more valid than 2017-2020, but still can be improved by Quarter 1-3.

Moreover, in the 13F file only long-positions are mentioned (SEC, 2020, Question 41). This means that no short positions are included and also no offsetting between long and short is allowed. Therefore, hedge funds pursuing short strategies are more biased within this approach, whereas long-only hedge funds not. Further research can use this fact as a starting point.

In addition, hedge fund companies put several funds on the market. The 13F data comprise all holdings in all single hedge funds together. Hence, for a less biased consideration all hedge fund returns should be weighted according to their size. I haven't had access to all single hedge funds returns on every of these 42 hedge fund companies. So, my data would be biased in either way, I decided to include for simplification one hedge fund respectively. A list of these 42 hedge funds is displayed in the excel file, as well as the respective management company.

Different type of ETF's, indicated by Ishares Inc and Ishares Tr are on the 13F data, however because I have only ESG scores for companies I cannot match any ESG score with them. Otherwise, it would be also not possible to get ESG scores if the exact ETF name is not displayed. One solution is to exclude the Ishares amount from calculation, which reduces the total assets in column 2 and hence the ratio is higher for other companies. Another way is to include it, which gives relatively less weight to the other companies/ scores and hence decrease the overall final ESG score, I decided for the latter one.

A much better robustness check would definitely be to look on hedge fund companies of my main sample of this master thesis. However, I couldn't access 13F data on these companies. If that would have worked, I can identify the skill of the hedge fund manager. When I can confirm a positive alpha in the factor models, FMB regressions or PSM but nothing is observed in the 13F long equity holdings, it must be bred by the unobserved actions of hedge funds managers. These are actions that are not disclosed in the 13F holdings which can be addressed to the skill of the manager. However, drivers of the skill can be identified afterwards (e.g., HF strategies, fee incentives, geographical, smaller/larger firms). In order to isolate the manager skill, Agarval et al. (2020) calculated the difference of hedge fund returns and a theoretical long equity portfolio with buy- and hold- returns of the 13F quarterly data. This difference is up to the manager skill and should be researched further. Agarval et al. (2020) tries to explain this difference with active intraquarter trading of long-equity positions, derivative usage, shortselling and confidential trading.

Finally, to address one last concern about the ESG rating by Thomson Reuters. Like the 13F data, the ESG ratings should adjusted for time as well (see literature section; J.P. Morgan, 2016). Companies who are rated in 2017 with a high ESG score, can have a changed score in 2020. I retrieved the scores in one point of time, namely 28 of February 2021. ESG ratings share both characteristics of time series and cross-sectional data. My downloaded list contains the companies rating at one point in time, which is cross-sectional data, but the evolvement for one firm rating is a time-series. This can be linked to my FMB regression with panel data; however, the determinants of ESG rating can be discussed in a whole research topic separately.

Adjustments and improvements

One of the biggest advantages is that the ranking of individual holdings can be adjusted by the researcher and evaluated afterwards. This is not the case for ESG frameworks made by Eurekahedge and other data vendors. Therefore, this approach is much more precise and less biased, hence a few papers in 2020 (see literature section) measured the performance based on the companies ESG valuation of hedge fund holdings and their commitment for SRI indicating by joining the PRI.

The search criteria for ESG companies could also depend upon other scores. Thomson Reuters provides more than the 4 scores I used for my company list. The selected ESG score in my robustness analysis is the weighted average score of the three pillars, whereas the ESG combined score is adjusted by a controversy factor. The controversy score measures company exposure to 23 ESG controversies topics and negative events reflected in global media. If no controversies occur, the ESG combined score is equal to the ESG score. If controversies occur, the ESG combined score is the weighted average of both scores. For example, the very well-known FAANG companies highlight a 26,9-point difference in ESG scores and ESG controversy scores (ESG score: 59,31 and ESGC Score: 32,43) (Refinitiv, 2021). To give relatively more weight to some pillars, Thomson Reuters provide 10 not equally weighted subcategories of the overall ESG score, namely resource use, emissions, innovation, workforce, human rights, community, product responsibility, management, shareholders and CSR strategy score (Thomson Reuters, 2017). These scores can be researched for another robustness test and can be weighted by the researcher accordingly.

The decision to give one factor relatively more weight can be challenging. But it is important and fundamental for further conclusions, because institutional investors give some factors more relevance. Of the $6,2 trillion managed ESG assets in the U.S., social criteria has been applied to slightly more than 92 percent of assets (9% increase to 2018), followed by environmental criteria roughly 70% (24% increase to 2018) and the governance criteria with around 62% (12% increase to 2018). This clearly shows that the strongest momentum is on the environmental factor. My excel tool can be on the one hand easily adjusted on the company side by increasing the E score and decreasing the S and G score (e.g. E score at least 40 and S and G score at least 20). But on the other hand, the final ESG score calculation procedure can be changed in a way, that companies with higher E scores above a predefined threshold will get relatively more weight into the final ESG score (e.g. with factor 2).

Last but not least the inclusion of PRI signatories brings new opportunities. First it can be compared in two groups HF-signatory and HF-non-signatory respectively. In addition, SRI-HF-signatory and SRI-HF-non-signatory, comparable to the study of Liang et al. (2020). Second PRI signatories can be grouped in low, high or/and middle ESG ratings. Besides it can be compared among several pillars. This means are returns more affected by bad human rights scores or rather by emission scores. Does it cost more return when having a low social score or rather environmental or governance scores? If the PRI is questioned, because it is easy to get the membership after paying a fee and by making a reporting process, the alternative of so-called stewardship codes for good corporate governance can be applied. These codes got an ESG renewal, meaning that hedge fund companies in the UK promote higher consideration on ESG factors under the principle 7 which is called ESG integration. Codes have different names but exist worldwide. For example, in the US it is called ISG Stewardship Framework for Institutional investors (Klettner, 2017; Responsible Investor, 2019; PRI, 2019).

More robustness tests can be done by dividing into two separated portfolios of small and large hedge funds. It has been shown that hedge funds that are smaller in size can earn easier their high predefined annual returns. For example, a hedge fund with 1 billion in year 0 and a 25% performance target for 20 years in a row must have a capitalization at the end of year 20 approximately to 86,7 billion, which is quite unrealistic. For a hedge fund with 20 million it is approximately 1,7 billion. So high performance can be rather sustained on a relatively small AUM. Furthermore, the significant difference in age and HWM (table 6, panel 3) can tested in further research. In the reduced long-short sample the significant difference in lock-up period and how this effects on performance can be tested with two separated portfolios.

The ratio of fund management fee to performance fee is researched under the incentive alignment on a very recent paper by Fung et al. (2021). It can be further researched whether hedge funds with smaller ratio of management fee to performance fee have higher ESG scores and yield superior return. In a second step it can be determined whether high ESG scores allow the manager to charge higher performance-based fees.

Coming back to the critique from KPMG (2020, p.48) one can compare the use of different data vendors under several methodology constraints. Interestingly ESG rating agencies are paid by investors, which is contrary to credit rating business (Novethic, 2013, p.4). With over 150 vendors, only a few are mostly used in research, namely Thomson Reuters, MSCI, Bloomberg and Sustainalytics. For example, RobecoSam whose ESG rating business was aquired in 2019 and operates now under S&P Global. It is said that RobecoSam uses one of the most advanced ESG scoring methodologies with over 20 years of experience, currently analyzing and assessing over 4.700 companies (RobecoSAM, 2019). However, the ESG landscape is evolving, and data vendors have to be still innovative, in order to maintain business relations with various customer segments. This proves another time the high takeover activity in this industry; in the last year 2020 Morningstar aquired Sustainalytics (Sustainalytics, 2020).

8 Conclusion and outlook

As in the introduction named, the climate summit promises ambitious goals. The current U.S. administration call the last 4 years wasted years for the climate. As announced on the global earth day 2021, by end of 2030 they want to reduce their CO_2 level to at least 50% of the year 2005. However, many legal requirements will be imposed to reach this target, for example the oil and gas industry will get stricter regulations. The decisions made by the current administration will also have an impact on the U.S. ESG regulation. Interestingly only 7 out of 700 U.S. energy companies report the total renewable energy they have purchased and produced. To reach the 1,5°C goal in the Paris agreement, the CO_2 emissions have to decrease by 7,6% annually till 2030 (Refinitiv, 2020). The climate change brings $2,5 trillion of global assets value at risk estimated by Dietz et al. (2016) or another estimation by the Economist (2015) accounts for $4,2 trillion.

Moreover, the Swiss Re Group, the second largest reassurer worldwide announced on the global earth day that the climate change will lead to a significant slump in GDP. If no countermeasures are taken, there is a threat of a global temperature rise more than 3 degrees Celsius in the next 30 years and the world economy would shrink by 18%. China's GDP would shrink by almost a quarter (24%) by mid-century. According to the resinsurer the US would suffer a decline in GDP of 10% and Europe almost 11%. However mitigating climate change would require a whole range of measures. More carbon-pricing regulations are needed combined with an alignment on a taxonomy of green and sustainable investments (Swiss Re, 2021).

As Reuters announced in April 2021, the global hedge fund AUM reached their best quarter performance with an average gain of 6% for 21 years. It is slightly distorted by a huge 120% gain on cryptocurrency hedge funds. However more traditional strategies like event driven or equity focused made 8,2% and 7,1% respectively, while the S&P 500 made 5,8% (Reuters, 2021). Further research can tackle these developments and look if it's driven by hedge funds pursuing SRI strategies. First which type of hedge funds get more investment inflow and second is investing into SRI also financially rewarded.

The main danger of the whole ESG trend is that financial information disclosure is well established, while SRI disclosures are not standardized. This can be problematic for the reliability of ESG ratings; what data basis can be used. As pointed out earlier, the ESG agencies use different SR indicators and methodologies. Hence hedge funds can do a good job by hiring their own ESG research team and using ESG vendors only to narrow down their choices. The ESG rating can be strong if many different publicly available data are reported. On the regulatory side, governments want the development of a joint disclosure. To illustrate, the SASB is developing standardized sustainability accounting standards, which is easily comparable among industries and countries (SASB, 2021). The trend can only become dangerous if the focus by investors is primary set on ESG. As Ammann et al. (2018) demonstrated, investors are shifting money according to Morningstar Sustainability rating from low to high rated funds. But these findings were stronger for retail investors than for institutional ones.

Moreover, the question of whether the environment is actually less damaged by investing into SRI assets has not been “sustainably” resolved. The german DekaBank had a lawsuit in Frankfurt in 2021 due to misleading positive effects of its impact equity fund. The investment company of the local saving banks developed an online tool by which an investor can see how much positive impact is generated. By investing 10.000€ into the Deka-Nachhaltigkeit Impact Aktien fund, the impact is a saving of 6,71 tons of waste and 42.837 liters of water treatment. However, these calculations are problematic and investing only in shares of one company will not cause this saving at all (Responsible Investor, 2021). The underlying intuition behind is shares are typically acquired on the secondary market, thus the investment goes to a seller, not the company itself. But if enough people invest themselves of the stock, the stock price will go up, leading to significant gains to the management of the company who hold most likely shares themselves.

This master thesis sheds light on socially responsible investing thoughts by analyzing hedge fund returns while using different statistical approaches with an own collected recent dataset. To my best knowledge, no previous study has examined SRI hedge fund returns using so many different statistical approaches.

I started with a simple comparison of means test with no significant differences. Factor model results are manifold. I find statistically significant SRI hedge fund outperformance of 0,1% monthly between 2010 and 2020. When I include only the time period of the ongoing pandemic, the results are even stronger. After controlling for an own constructed hedge fund index, I prove that long/short hedge funds outperforming their conventional peers on the 0,01 level with 0,2% monthly. This can be seen not only for the full time period, but also for a shorter 36-month pre-crisis period. In the 7- and 8 factor model, both hedge funds portfolios outperformed the market, while results are stronger for the full time period. After using the HFI an underperformance of conventional hedge funds for the full and shorter time period can be seen and again in the own multi-factor model.

When using the FMB (1973) regressions I find statistically significant SRI hedge fund outperformance when using the reduced set of hedge fund characteristics, but stronger evidence when using the extended set. SRI hedge fund monthly returns outperform non-SRI by 0,35% monthly. After breaking down into strategies, long-only hedge funds pursuing SRI strategies outperform with 0,91%, while long/short hedge funds have no significance at all. I also find a statistically significant impact of the SRI hedge funds using PSM with the two variables of the equation 12 and the HWM variable. The full hedge fund characteristics without both fee variables lead to 0,18% monthly outperformance of SRI hedge funds. To see how robust my results actually are, I rolled up the whole procedure from the back. I started on individual company holdings of each hedge fund company. The results are distinct and confirm my past results, that SRI strategies yield superior performance.

Collectively, I can reject all my research questions. Thus, SRI hedge funds have experienced rather higher returns compared to non-SRI hedge funds. However, the results are ambiguous for the long/short and long-only strategies.

These results shed light on the investment performance for SRI hedge funds as well as the different regulatory pressure through different ESG frameworks (e.g. PRI and stewardship codes). However, the adoption of standardized codes will help and boost hedge fund manager with internalizing investors preferences for socially responsible investments (Preqin, 2019).

To my best knowledge research between hedge funds and SRI is quite limited, absolutely contrary to mutual funds or traditional hedge funds studies. The only study I found, which directly addresses hedge funds performance within two samples is the Filbeck et al. (2016) paper. More research is definitely required in the field of hedge funds and ESG/SRI investing. In both cases, investors can decide if they invest for ethical reasons or for significant outperformance. Neither assumption has been conclusively verified. Moreover, I hope I can provide with my excel tool a good starting point for further research.

Outlook

In the alterative assets field, hedge funds are far behind and have clearly a way to go in adopting ESG considerations and policies. However, the appetite is apparently visible among institutional investors (GSIR, 2018; Preqin, 2019; Morgan Stanley, 2020 and KPMG, 2020). I believe that more hedge fund managers should be thinking about incorporating ESG policies today, in order to be successful tomorrow.

Admittedly, Preqin (2018) makes it easier for me to see in the future. They jumped five years ahead and estimated the total AUM in 2023 for hedge funds and private capital on $14 trillion. What are the drivers for this tremendous forecast? - Technology (especially with blockchain), ESG, emerging markets and affluent individuals. In general, all asset classes expand over the next five years. Hedge funds are estimated with $4,7 trillion (31% increase from end of 2017). Combined with the private equity industry they represent 75% of the total $8,8 trillion alternative assets industry by end of 2017 and are estimated for 2023 a little bit smaller in relative terms with 69%. However, the hedge funds and private equity industry is undisputed the number 1 and 2 in the alternative assets industry. Interestingly private equity is estimated to grow faster in the coming years with 58% (31% hedge funds), passing the hedge funds industry in absolute terms. Probably a bit unsurprisingly, managers believe that the biggest source of growth within the next five year is organic growth (Preqin, 2018, p.21). Fund managers will target stronger emerging markets, China, India and Africa by 2023.

The Covid-19 crisis is a rule changing event and has shown that it destroys old business models and creates new ones. Moreover, it is a turning point for ESG investments (US SIF, 2020). This means that ESG increased before the crisis and continued to increase during and after the crisis. The momentum is expected to continue in the aftermath of the crisis even stronger. This positive view of expectations is shared among 50 global institutions representing $12,9 trillion AUM polled by J.P. Morgan (2020). They looked even further in the future and expect the global sustainable market by end of 2030 reaching $45 trillion AUM.

Finally, ESG factors are important for balancing risk and producing superior returns. If the mandate is more on risk management, I propose to exclude companies or sectors, or whatever seems to be risky, to minimize ESG risks. If the value creation has a stronger focus, then hedge funds should target companies with high ESG related factors. It’s up to the strategy what expertise is needed for carrying out sustainable investing. For example, if more environmental factors are considered, more specialists in this topic are needed, whereas hedge funds that are using screening approaches need quantitative analysis experts in their team.

The institutional investor group creates transparency by adopting many prioritized challenges of humankind, by shaping the change for a more sustainable future (PRI, 2020). With respect to ESG factors, the sustainable market has grown significantly and as demand has surged, many of the leading institutional investors are at the forefront of implementing sustainable strategies (AAM, 2021; ABP, 2021). As well as punishing companies with bad ESG disclosure by divesting themselves of the stock.

Is sustainability a risk factor? – on top of the traditional ones, like value, quality, size and momentum. For example, the size factor is associated with large stocks, it relies on metrics like market capitalization. In contrast there is no metrics for environment, social or governance. How can sustainability be used as a factor for a long defensive investment horizon? Five European countries, namely Switzerland, UK, Italy, Germany and France have implemented carbon pricing. It would be interesting to see if companies in these countries performed better since this implementation. For further research, I propose to enlarge the Carhart 4-factor model with an ESG-related factor. This factor relates to the difference between SRI and non-SRI hedge fund returns. It also allows a closer look at whether you can lower your risk with a SRI portfolio.

To conclude, this master thesis has the purpose to enhance our perception about the performance of sustainable investing in the hedge funds industry and it provides several key takeaways. First, the prevalent objection against SRI is that SRI give up financial benefit to some extent because it imposes frontiers to diversification. This objection was revalued with a recent dataset under several time periods and couldn’t prove to be true. Second the hedge fund industry is on a good way to catch up in SRI. Third, ESG research can be done inhouse or with buying the data from external vendors. Fourth, the strong demand after ESG assets can give price pressure like Pedersen et al. (2020) showed in their equilibrium model, at least on the short run. Nowadays type U investors were outnumbered and on the long run the cost and benefit analysis will justify higher valuations driven by type A and M investors. This can also be applied on hedge funds investors.

Finally, the main drivers I found during my research, which speaks for SRI in the future are: First, SRI outperformed not only in the wake of the pandemic sell-off, but also in normal time-periods. Hence it is highly possible, that the gap in performance between SRI and non-SRI will continue to widen. ESG research and investing will become more complex and the awareness of the public on sustainability risks will change the investor sentiment towards SRI investments. Second, institutional managers have pressure from many stakeholder groups, thus fund repurposing, divesting in response to ESG factors and the rising AUM in SRI are clearly visible. Third, policymakers put pressure in recent years, from voluntary to binding legislations.

My results contribute to past literature on the relation between institutional investors and the strength of their ESG investment policies on financial performance. I highlighted that one of the drivers behind a better risk-adjusted performance is pursuing SRI strategies. I also used the holdings of each hedge fund company to show that higher ESG scores are rewarded with more returns.

In my view, striving to be ESG aligned, institutional investors can conquer new investment opportunities by realizing financial and non-financial value at the same time. This is meaningful not only for regulators, but also to the society as a whole. However, as an idiom goes “you cannot have your cake and eat it too”; this sounds logical for institutional investors who must decide SRI or non-SRI.

9 References

AAM. (2021). *Japan's GPIF seeks ESG research providers.* Retrieved on 23 April 2021 from https://www.asiaasset.com/post/24208-gpif-0121

ABP. (2021). *Investments.* Retrieved on 23 April 2021 from https://www.abp.nl/english/investments/

Abadie, A., & Imbens, G. (2006). Large Sample Properties of Matching Estimators for Average Treatment Effects. *Econometrica*, 74, 235-267. https://doi.org/10.1111/j.1468-0262.2006.00655.x

Abadie, A., & Imbens, G. (2011). Bias-corrected matching estimators for average treatment effects. *Journal of Business & Economic Statistics*, 29(1), 1-11. https://doi.org/10.1198/jbes.2009.07333

Ackermann, C., McEnally, R., & Ravenscraft, D. (1999). The performance of hedge funds: risk, return, and incentives. *Journal of Finance*, 54(3), 833-874. https://doi.org/10.1111/0022-1082.00129

Agarval, V., & Naik, N.Y. (2001). Characterizing hedge fund risks with buy-and-hold and option-based strategies. *Working Paper, London Business School*.

Agarval, V., Ruenzi, S., & Weigert, F. (2020). Unobserved Performance of Hedge Funds. *University of St.Gallen, School of Finance Research Paper* No. 2018/25. Available at SSRN: https://ssrn.com/abstract=3288468 or http://dx.doi.org/10.2139/ssrn.3288468

Ammann, M., & Moerth, P. (2005). Impact of fund size on hedge fund performance. *Journal of Asset Management*, 6(3), 219–238. https://doi.org/10.1057/palgrave.jam.2240177

Ammann, M., Bauer, C., Fischer, S., & Müller, P. (2018). The impact of the Morningstar Sustainability Rating on mutual fund flows. *European Financial Management*, 25(3), 520– 553. https://doi.org/10.1111/eufm.12181

Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2020). Climate Change Concerns and the Performance of Green Versus Brown Stocks. *National Bank of Belgium*, Working Paper Research, October 2020 No 395. Available at SSRN: https://ssrn.com/abstract=3717722 or http://dx.doi.org/10.2139/ssrn.3717722

Barber, B.M., Morse, A., & Yasuda, A. (2020). Impact investing. *Journal of Financial Economics*, 139, 162-185. https://doi.org/10.1016/j.jfineco.2020.07.008

Barclayhedge. (2021). *Hedge Fund Industry Assets Under Management.* Retrieved on 23 April 2021 from https://www.barclayhedge.com/solutions/assets-under-management/hedge-fund-assets-under-management/

Banz, R.W. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3-18. https://doi.org/10.1016/0304-405X(81)90018-0

Barth, R. P., Greeson, J. K., Guo, S., & Green, B. (2007). Outcomes for youth receiving intensive in-home therapy or residential care: A comparison using propensity scores. *American Journal of Orthopsychiatry*, 77, 497–505. https://doi.org/10.1037/0002-9432.77.4.497

Bauer, R., Koedijk, K., & Otten, R. (2005). International evidence on ethical mutual fund performance and investment style. *Journal of Banking & Finance*, 29(7), 1751-1767. https://doi.org/10.1016/j.jbankfin.2004.06.035

Bello, Z.Y. (2005). Socially responsible investing and portfolio diversification. *The Journal of Financial Research*, 28(1), 41-57. https://doi.org/10.1111/j.1475-6803.2005.00113.x

Bialkowski, J., & Starks, L.T. (2016). *SRI Funds: Investor Demand, Exogenous Shocks and ESG Profiles.* Business and Law. BlackRock Research Conference, 6 Jan 2016.

BlackRock. (2020). *Sustainable Investing: resilience amid uncertainty*. Retrieved on 24 March from https://www.blackrock.com/corporate/literature/investor-education/sustainable-investing-resilience.pdf

Bollen, N. P. B. (2007). Mutual fund attributes and investor behavior. *Journal of Financial and Quantitative Analysis*, 42(3), 683–708.

Brandon, R.G., Krueger, P., & Mitali, S.F. (2020). The Sustainability Footprint of Institutional Investors: ESG driven price pressure and performance. *Swiss Finance Institute Research Paper* No. 17-05, European Corporate Governance Institute (ECGI) - Finance Working Paper No. 571/2018, Available at SSRN: https://ssrn.com/abstract=2918926 or http://dx.doi.org/10.2139/ssrn.2918926

Capocci, D., & Hübner, G. (2004). Analysis of hedge fund performance. *Journal of Empirical Finance*, 11(1), 55-89. https://doi.org/10.1016/j.jempfin.2002.12.002

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, 52(1), 57-82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Climent, F., & Soriano, P. (2011). Green and Good? The Investment Performance of US Environmental Mutual Funds, *Journal of Business Ethics*, 103(2), 275-287. https://doi.org/10.1007/s10551-011-0865-2

CNBC. (2021). *Melvin Capital, hedge fund that bet against GameStop, lost more than 50% in January,* Retrieved on 24 April 2021 from https://www.cnbc.com/2021/01/31/melvin-capital-lost-more-than-50percent-after-betting-against-gamestop-wsj.html

Cochran, W.G., & Rubin, D.B. (1973). Controlling Bias in Observational Studies: A Review. *The Indian Journal of Statistics*, 35, 417–446.

DeFond, M. L., Erkens, D. H., & Zhang, J. (2015). Does PSM really eliminate the big n audit quality effect? *Working Paper* No. ACC 02.14, Marshall School of Business. Available at SSRN: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2472092

Demski, C., Capstick, S., Pidgeon, N., Sposato, R.G., & Spence, A. (2017). Experience of extreme weather affects climate change mitigation and adaptation responses. *Climatic Change*, 140(2), 149-164. https://doi.org/10.1007/s10584-016-1837-4

Derwall, J., Koedijk, K., & ter Horst, J. (2011). A tale of value-seeking versus profit-driven investors. *Journal of Banking and Finance*, 35(8), 2137-2147.

Diamond, A., & Sekhon, J.S. (2005). Genetic Matching for Estimating Causal Effects: A General Multivariate Matching Method for Achieving Balance in Observational Studies. *The Review of Economics and Statistics*, 95(3), 932-945. https://doi.org/10.1162/REST_a_00318

Dietz, S., Bowen, A., Dixon, C., & Gradwell, P. (2016). Climate value at risk of global financial assets. *Nature Climate Change*, 6, 676-679. https://doi.org/10.1038/nclimate2972

Diltz, J.D. (1995). The private cost of socially responsible investing. *Applied Financial Economics*, 5, 69–77. https://doi.org/10.1080/758529174

Economist. (2015). *The cost of inaction.* Retrieved on 6 May 2021 from https://eiuperspectives.economist.com/sustainability/cost-inaction

EU. (2021). *2050 long-term strategy.* Retrieved on 24 March 2021 from https://ec.europa.eu/clima/policies/strategies/2050_en

Eurekahedge. (2020). *The Eurekahedge Report – November 2020*. Retrieved on 3 March 2021 from https://www.eurekahedge.com/Research/News/2076/Hedge-Fund-Report-November-2020

Eurekahedge. (2021). *Glossary*. Retrieved on 3 March 2021 from https://www.eurekahedge.com/FundProfile/Glossary/GHF

Fama, E.F., & French, K.R. (1992). The Cross-Section of Expected Stock Returns. *Journal of Financial Economics*, 47(2), 427-465.

Fama, E.F., & French, K.R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, 3-56. https://doi.org/10.7208/9780226426983-018

Fama, E.F., & French, K.R. (1998). Value versus growth: the international evidence. *Journal of Finance*, 53(6), 1975-1999. https://doi.org/10.1111/0022-1082.00080

Fama, E.F., & French, K.R. (2010). Luck versus Skill in the Cross-Section of Mutual Fund Returns. *Journal of Financial Economics,* 65(5), 1915-1947. https://doi.org/10.7208/9780226426983-014

Fama, E.F., & Macbeth, J.D. (1973). Risk, return, and equilibrium: empirical tests. *Journal of Political Economy*, 81(3), 607–636.

Filbeck, G., Krause, T.A., & Reis, L. (2016). Socially responsible investing in hedge funds. *Journal of Asset Management,* 17(6), 408-421. https://doi.org/10.1057/s41260-016-0022-7

Financial Times. (2017). *The ethical investment boom.* Retrieved on 8 April from https://www.ft.com/content/9254dfd2-8e4e-11e7-a352-e46f43c5825d

Fung, W., & Hsieh, D.A. (2000). Performance characteristics of hedge funds and commodity funds: natural vs spurious biases. *The Journal of Quantitative and Financial Analysis*, 35(3), 291–307. https://doi.org/10.2307/2676205

Fung, W., & Hsieh, D.A. (2004). Hedge fund benchmarks: A Risk-Based Approach. *Financial Analysts Journal*, 60(5), 65-80. https://doi.org/10.2469/faj.v60.n5.2657

Fung, W., Hsieh, D.A., Naik, N., & Teo, M. (2021). Hedge fund franchises. *Management Science*, 67(2), 1199-1226. https://doi.org/10.1287/mnsc.2019.3516

Gregory, A., & Whittaker, J. (2007). Performance and Performance Persistence of 'Ethical' Unit Trusts in the UK. *Journal of Business Finance & Accounting,* 34(7-8), 1327-1344. https://doi.org/10.1111/j.1468-5957.2007.02006.x

Grossman, B.R., & Sharpe, W.F. (1986). Financial implications of South African divestment. *Financial Analysts Journal*, 42, 15–29. https://doi.org/10.2469/faj.v42.n4.15

GSI. (2018). *2018 global sustainable investment review.* Retrieved on 24 March from http://www.gsi-alliance.org/wp-content/uploads/2019/03/GSIR_Review2018.3.28.pdf

Hamilton, S., Jo, H., & Statman, M. (1993). Doing well while doing good? The investment performance of socially responsible mutual funds. *Financial Analysts Journal,* 49(6), 62-67. https://doi.org/10.2469/faj.v49.n6.62

HFR. (2020). *HFRI gains drive hedge fund inflows.* Retrieved on 18 March 2021 from https://www.hfr.com/sites/default/files/articles/2020.Q3.HFR_GIR.pdf

Ibikunle, G., & Steffen, T. (2017). European Green Mutual Fund Performance: A Comparative Analysis with Their Conventional and Black Peers. *Journal of Business Ethics,* 145(2), 337- 355. https://doi.org/10.1007/s10551-015-2850-7

Imbens, G. (2004). Nonparametric Estimation of Average Treatment Effects under Exogeneity: A Review. *The Review of Economics and Statistics,* 86(1), 4-29. https://doi.org/10.1162/003465304323023651

Ito, Y., Managi, S., & Matsuda, A. (2013). Performances of socially responsible investment and environmentally friendly funds. *Journal of the Operational Research Society*, 64(11), 1583–1594. https://doi.org/10.1057/jors.2012.112

Jensen, M.C. (1968). Problems in selection of security portfolios. *Journal of Finance*, 23(2), 389-419.

Jones, A. S., D'Agostino, R. B., Gondolf, E. W., & Heckert, A. (2004). Assessing the effect of batterer program completion on reassault using propensity scores. *Journal of Interpersonal Violence*, 19, 1002–1020. https://doi.org/10.1177/0886260504268005

J.P. Morgan. (2016). *ESG – Environmental, Social & Governance Investing. Equity Quantitative Strategy*. Available at: https://yoursri.com/media-new/download/jpm-esg-how-esg-can-enhance-your-portfolio.pdf/view

J.P. Morgan. (2020). *Why COVID-19 Could Prove to Be a Major Turning Point for ESG Investing.* Retrieved on 27 April 2021 from https://www.jpmorgan.com/insights/research/covid-19-esg-investing

Keele, L.J. (2009). An overview of rbounds: An R Package For Sensitivity Analysis with Matched Data. Available at: https://www.researchgate.net/publication/251969933_An_Overview_of_Rbounds_An_R_Package_for_Rosenbaum_Bounds_Sensitivity_Analysis_with_Matched_Data

King, G., Nielsen, R., Coberley, C., & Pope, J. (2011). Comparative effectiveness of matching methods for causal inference. *Working paper*, Harvard University. Available at: https://gking.harvard.edu/publications/comparative-effectiveness-matching-methods-causal-inference

King, G., & Nielsen, R. (2016). Why propensity scores should not be used for matching. *Political Analysis*, 27(4), 435-454. Available at: https://gking.harvard.edu/publications/why-propensity-scores-should-not-be-used-formatching

Klettner, A. (2017). The Impact of Stewardship Codes on Corporate Governance and Sustainability. *New Zealand Business Law Quarterly*, 23, 259-275. http://hdl.handle.net/10453/124342

KPMG. (2020). *Sustainable Investing – fast forwarding its evolution.* Retrieved on 16 March 2021 from https://home.kpmg/xx/en/home/insights/2020/02/sustainable-investing.html

Kurtz, L., & diBartolomeo, D. (2011). The long-term performance of a social investment universe. *Journal of Investing*, 20(3), 95–102. https://doi.org/10.3905/joi.2011.20.3.095

Lean, H. H., Ang, W. R., & Smyth, R. (2015). Performance and performance persistence of socially responsible investment funds in Europe and North America. *The North American Journal of Economics and Finance*, 34, 254-266. https://doi.org/10.1016/j.najef.2015.09.011

Liang, B. (1999). On the performance of hedge funds. *Financial Analysts Journal*, 55(4), 72-85. https://doi.org/10.2469/faj.v55.n4.2287

Liang, B. (2000). Hedge funds: the living and the dead. *Journal of Financial and Quantitative Analysis*, 35(3), 309-325. https://doi.org/10.2307/2676206

Liang, H., Sun, L., & Teo, M. (2020). Greenwashing. Available at SSRN: https://ssrn.com/abstract=3610627 or http://dx.doi.org/10.2139/ssrn.3610627

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *The Review of Economics and Statistics*, 47(1), 13-37.

Mallin, C.A., Saadouni, B., & Briston, R.J. (1995). The financial performance of ethical investment funds. *Journal of Business Finance and Accounting*, 22(4), 483-496.

Marketwatch. (2019). *Norway sovereign-wealth fund aims to dump a swath of oil and gas stocks*. Retrieved on 9 March 2021 from https://www.marketwatch.com/story/norway-sovereign-wealth-fund-aims-to-dump-a-swath-of-oil-and-gas-stocks-2019-03-08

Marketwatch. (2021). *The Greening of the S&P 500: 7 charts for Earth Day.* Retrieved on 22 April 2021 from https://www.marketwatch.com/story/the-greening-of-the-s-p-500-7-charts-for-earth-day-11619029602

Medium. (2018): *Alfred Winslow Jones: The Father of the Hedge Fund Industry*, retrieved 9 March 2021 from https://rainfundai.medium.com/alfred-winslow-jones-the-father-of-the-hedge-fund-industry-698d069c0d53

Minor, D. B. (2007). Finding the [financial] cost of socially responsible investing. *Journal of Investing*, 16(3), 54–70. https://doi.org/10.3905/joi.2007.694762

Morgan, S. L. (2001). Counterfactuals, causal effect, heterogeneity, and the Catholic school effect on learning. *Sociology of Education*, 74, 341–374.

Morgan Stanley. (2020). *Sustainable Signals: Asset owners see sustainability as core to the future of investing*. Available at: https://www.morganstanley.com/content/dam/msdotcom/sustainability/20-05-22_3094389%20Sustainable%20Signals%20Asset%20Owners_FINAL.pdf

Morningstar. (2020). *Sustainable Funds weather the first quarter better than conventional funds*. Retrieved on 25 March 2021 from https://www.morningstar.com/articles/976361/sustainable-funds-weather-the-first-quarter-better-than-conventional-funds

MSCI. (2020). *MSCI ESG Indexes during the coronavirus crisis.* Retrieved on 25 March 2021 from https://www.msci.com/www/blog-posts/msci-esg-indexes-during-the/01781235361

Muñoz, F., Vargas, M., & Marco, I. (2014). Environmental Mutual Funds: Financial Performance and Managerial Abilities. *Journal of Business Ethics*, 124(4), 551-569. https://doi.org/10.1007/s10551-013-1893-x

Newey, W.K., & West, K.D. (1987). A simple positive semi-definite heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55, 703-798.

Nofsinger, J., & Varma, A. (2014). Socially responsible funds and market crises. *Journal of Banking & Finance*, 48, 180-193. https://doi.org/10.1016/j.jbankfin.2013.12.016

Normand, S. T., Landrum, M. B., Guadagnoli, E., Ayanian, J. Z., Ryan, T. J., & Cleary, P. D. (2001). Validating recommendations for coronary angiography following acute myocardial infarction in the elderly: A matched analysis using propensity scores. *Journal of Clinical Epidemiology*, 54, 387–398. https://doi.org/10.1016/S0895-4356(00)00321-8

Novethic. (2013). *Overview of ESG rating agencies.* Retrieved on 29 March 2021 from https://www.novethic.com/fileadmin/user_upload/tx_ausynovethicetudes/pdf_complets/2013_overview_ESG_rating_agencies.pdf

Pastor, L., Stambaugh, R., & Taylor L.A. (2020). Sustainable investing in equilibrium. *Journal of Financial Economics*. https://doi.org/10.1016/j.jfineco.2020.12.011

Petersen, M. A. (2009). Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, *The Review of Financial Studies*, 22(1), 435-480. https://doi.org/10.1093/rfs/hhn053

Pedersen, L. H., Fitzgibbons, S., & Pomorski, L. (2020). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics*. https://doi.org/10.1016/j.jfineco.2020.11.001

Preqin. (2018). *The future of Alternatives*. Retrieved on 27 April 2021 from https://docs.preqin.com/reports/Preqin-Future-of-Alternatives-Report-October-2018.pdf

Preqin. (2019). *Will hedge funds ever truly embrace ESG principles?* Retrieved on 18 March 2021 from https://docs.preqin.com/reports/Preqin-Will-Hedge-Funds-Ever-Truly-Embrace-ESG-Principles-May-19.pdf

Pressebox. (2020). *Bridgestone zum zweiten Mal in Folge im STOXX Global ESG Leaders Index gelistet*. Retrieved on 1 April from https://www.pressebox.de/inaktiv/bridgestone-deutschland-gmbh/Bridgestone-zum-zweiten-Mal-in-Folge-im-STOXX-Global-ESG-Leaders-Index-gelistet/boxid/1024642

PRI. (2019). *Active-Ownership 2.0: The evolution Stewardship urgently needs.* Retrieved on 18 April 2021 from https://www.unpri.org/download?ac=9721

PRI. (2020). *Enhance our global footprint.* Retrieved on 15 April 2021 from https://www.unpri.org/annual-report-2020/how-we-work/building-our-effectiveness/enhance-our-global-footprint

Refinitiv. (2019). *Are S&P 500 companies prioritizing environmental sustainability?* Retrieved on 15 April 2021 from https://www.refinitiv.com/perspectives/future-of-investing-trading/are-sp-500-companies-prioritizing-environmental-sustainability/

Refinitiv. (2020). *U.S. Climate change policy: Do we need a new approach?* Retrieved on 22 April 2021 from https://www.refinitiv.com/perspectives/future-of-investing-trading/u-s-climate-change-policy-do-we-need-a-new-approach/

Refinitiv. (2021). *Understanding how ESG scores are measured, their usefulness and how they will evolve.* Retrieved on 22 April 2021 from https://www.refinitiv.com/perspectives/future-of-investing-trading/understanding-how-esg-scores-are-measured-their-usefulness-and-how-they-will-evolve/

Renneboog, L., Ter Horst, J., & Zhang, C. (2008). The price of ethics and stakeholder governance: The performance of socially responsible mutual funds, *Journal of Corporate Finance,* 14(3), 302-322. https://doi.org/10.1016/j.jcorpfin.2008.03.009

Responsible Investor. (2019). *UK stewardship code becomes a de facto ESG code – but it needs teeth.* Retrieved on 22 April 2021 from https://www.responsible-investor.com/articles/analysis-uk-stewardship-code-becomes-a-de-facto-esg-code-but-it-needs-teeth

Responsible Investor. (2021). *DekaBank sued over 'misleading' fund impact calculator.* Retrieved on 24 April 2021 from https://www.responsible-investor.com/articles/dekabank-sued-over-misleading-fund-impact-calculator

Reuters. (2021). *Hedge fund assets hit record $3.8 trillion in first quarter.* Retrieved on 24 April 2021 from https://www.reuters.com/business/hedge-fund-assets-hit-record-38-trillion-first-quarter-2021-04-21/

RobecoSAM. (2019). *S&P Global to acquire the ESG ratings business from RobecoSAM.* Retrieved on 15. April 2021 from https://www.robeco.com/media/5/8/f/58f2708943b460a1e32b72df93adc4a7_191121-media-release-robecosam-spglobal-esg-ratings-vdef_tcm17-21925.pdf

Roll, R. (1981). A Possible Explanation of the Small Firm Effect. *The Journal of Finance*, 36 (4), 879–888. https://doi.org/10.1111/j.1540-6261.1981.tb04890.x

Rosenbaum, P., & Rubin, D. (1983) The central role of the propensity score in observational studies for casual effects. *Biometrika*, 70(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive Evidence of Market Inefficiency. *The Journal of Portfolio Management,* 11(3), 9–16. https://doi.org/10.3905/jpm.1985.409007

Rubin, D. B. (1974). Estimating Causal Effects of Treatments in Randomized and Nonrandomized Studies. *Journal of Educational Psychology,* 66, 688–701. https://doi.org/10.1037/h0037350

Rudd, A. (1981). Social responsibility and portfolio performance. *California Management Review,* 23(4), 55–61. https://doi.org/10.2307/41164931

SASB. (2021). *SASB connects business and investors on the financial impacts of sustainability.* Retrieved on 25 April 2021 from https://www.sasb.org/about/

SEC. (2020). *Frequently asked questions about Form 13F.* Retrieved on 25. March from https://www.sec.gov/divisions/investment/13ffaq.htm

Sekhon, J.S. (2011). Multivariate and Propensity Score Matching Software with Automated Balance Optimization: The Matching package for R. *Journal of Statistical Software,* 42(7), 1-52. Available at SSRN: https://ssrn.com/abstract=1009044

Sharpe, W. F. (1963). A simplified model for portfolio analysis. *Management science,* 9(2), 277-293. https://doi.org/10.1287/mnsc.9.2.277

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425-442.

Silva, F., & Cortez, M.C. (2016). The performance of US and European green funds in different market conditions. *Journal of Cleaner Production,* 135, 558-566. https://doi.org/10.1016/j.jclepro.2016.06.112

Statman, M. (2006). Socially Responsible Indexes. *The Journal of Portfolio Management,* 32(3), 100-109. https://doi.org/10.3905/jpm.2006.628411

Steiner, M., & Ammann, M. (2008). Risk Factors for the Swiss Stock Market. *Swiss Journal of Economics and Statistics*, 144 (1), 1–35. https://doi.org/10.1007/BF03399247

Stuart, E. A. (2010). Matching Methods for Causal Inference: A Review and a Look Forward. *Statistical Science,* 25(1), 1–21. https://doi.org/10.1214/09-STS313

Sustainalytics. (2020). *Morningstar to aquire Sustainalytics and expand access to ESG research, data and analytics for investors worldwide*. Retrieved on 25 March 2021 from https://www.sustainalytics.com/esg-news/news-details/2020/04/20/morningstar-to-acquire-sustainalytics-and-expand-access-to-esg-research-data-and-analytics-for-investors-worldwide

Swiss Re. (2021). *World economy set to lose up to 18% GDP from climate change if no action taken, reveals Swiss Re Institute's stress-test analysis.* Retrieved on 23 April 2021 from https://www.swissre.com/media/news-releases/nr-20210422-economics-of-climate-change-risks.html

Thomson Reuters. (2017). *Thomson Reuters ESG scores.* Retrieved on 25 April 2021 from https://www.esade.edu/itemsweb/biblioteca/bbdd/inbbdd/archivos/Thomson_Reuters_ESG_Scores.pdf

US News. (2020). *Coronavirus Sell-Off Sends Plunging Dow Into Bear Territory After 11-Year Bull Market.* Retrieved on 20 March from https://www.usnews.com/news/economy/articles/2020-03-11/dows-bull-market-ends-after-11-year-run-amid-coronavirus-related-sell-off

US SIF. (2010). *Report on US sustainable and impact investing trends 2010.* Retrieved on 25 March 2021 from https://www.ussif.org/files/Publications/10_Trends_Exec_Summary.pdf

US SIF. (2018). *Report on US sustainable and impact investing trends 2018.* Retrieved on 25 March 2021 from https://www.ussif.org/store_category.asp?id=4

US SIF. (2020). *Report on US sustainable and impact investing trends 2020.* Retrieved on 25 March 2021 from https://www.ussif.org/trends

Utz, S., & Wimmer, M. (2014). Are they any good at all? A financial and ethical analysis of socially responsible mutual funds. *Journal of Asset Management,* 15(1), 72–82. https://doi.org/10.1057/jam.2014.8

Wall Street Journal. (2016). *Does socially responsible investing make financial sense?* Retrieved on 28 February 2021 from https://www.wsj.com/articles/does-socially-responsible-investing-make-financial-sense-1456715888

Wall Street Journal. (2019). *ESG funds draw SEC Scrutiny.* Retrieved on 20 March 2021 from https://www.wsj.com/articles/esg-funds-draw-sec-scrutiny-11576492201

10 Appendix

Figure 1: Investors and fund managers that believe ESG will become more important over the next five years

Source: Preqin Investor and Fund Manager Interviews, November 2018 (Preqin 2019)

Figure 2: QQ-plot with matching on the variable age for the control and treated group

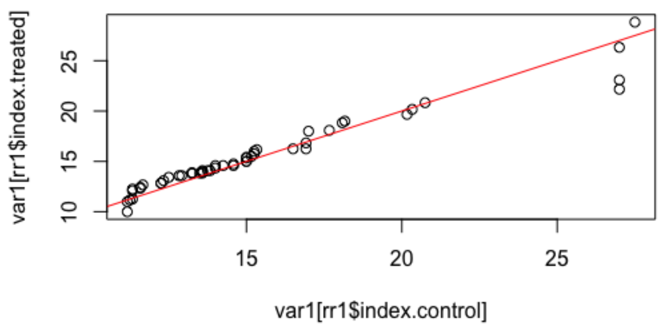

Figure 3: QQ-plot without matching on the variable age for the control and treated group

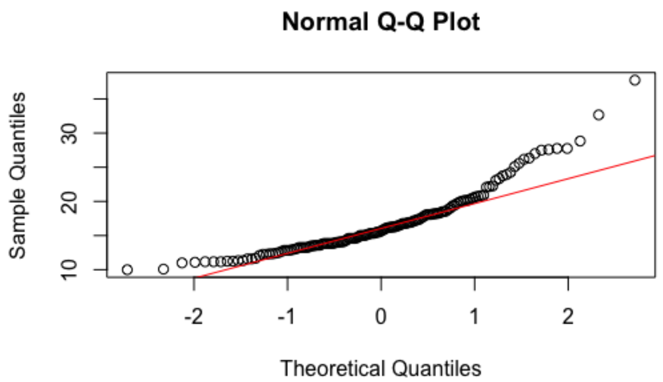

Table 1: Summary of previous studies on sustainable investing

Author	Findings for SRI
Pastor et al. (2020)	Green assets have lower CAPM alphas than brown assets
Pedersen et al. (2020)	Assets with high ESG scores have lower CAPM returns
Barber et al. (2020)	Impact funds achieved 4,7% lower IRR than VC funds

Table 2: Summary of previous corporate studies on sustainable investing

Company	Period	Findings for SRI
J.P. Morgan (2016)	2007-2016	Companies with high ESG scores carry less risk and lead to better long-term performance ESG indices returns are higher than their non-SRI benchmarks
BlackRock (2020)	01/2020-04/2020 2015-2020	88% of ESG mutual funds and ETF's outperformed their 32 non-sustainable indices outperformance of ESG in market-downturns
Morgan Stanley (2020)	Dec. 2019	95% of asset owners integrate or consider ESG
KPMG (2020)	Dec. 2019	15% of managers have embedded ESG factors across their hedge fund strategies 85% of institutional investors are the biggest driver for ESG oriented hedge fund demand. 55% ESG hedge funds target alpha returns.

Table 3: Summary of previous studies on SRI hedge funds

Author	Country	Period	Findings for SRI hedge funds
Filbeck et al. (2016)	US	2005-2015	Positive significant alphas for some subcategories and different time periods using PSM and FMB
Liang et al. (2020)	global	2006-2019	Greenwashing leads to a significant underperformance (tested with different scoring providers and by decomposing ESG into E&S and G)
Brandon et al. (2020)	US	2002-2015	Outperformance, strongly driven by factor E and in recent time period
		2002-2013	Alpha significant positive for sustainable footprint in the natural disaster model

Table 4: Eurekahedge description of 3 examples of sustainable hedge funds

Arisaig Global Emerging Markets Consumer Fund BV
Manager Profile: Given the brand-owning nature of our businesses, the nascent regulatory environment in emerging markets, and the long term nature of our investment horizon, the **assessment of Environmental, Social and Governance ("ESG") issues is particularly important to us.** We carry out **sustainability assessments on all of our target companies,** engage with our holdings to share insights gleaned from our research, and encourage improved disclosure and the adoption of best practices. We see **ESG analysis and engagement as integral to our investment process**: only those businesses which are generating value in a truly sustainable way will be able to successfully navigate the vast growth runway ahead in the emerging market consumer sector. Funds Strategy: (…) The Fund invests in best-in-class consumer franchises with a bias towards aligned ownership structures and businesses with a **strong approach to ESG issues** (…).
CARN Latitude NOK-R-OPA3
Funds Strategy: (…) CARN Long Short received the Nordic Swan Ecolabel (the official ecolabel of the Nordic countries) in March 2020, as the first Nordic hedge fund to be awarded this certification. The Nordic Swan Ecolabel ensures that CARN Long Short is managed within a **proven sustainability framework** and consequently **meets the high environmental and ethical standards for sustainable investing.**
Sycomore Partners Fund I
Manager Profile: (…) The role of its team of 24 fund manager-analysts, including **9 ESG (Environment, Social, and Governance) specialists**, is to assess the overall performance of a company in relation to its stakeholders: shareholders, clients, employees, suppliers, civil society and the environment. Driven by its ambition to combine purpose and performance, Sycomore AM has become a **leading player in the field of socially responsible investment**.

Table 5: sub-sample categories

	(1) HF-SRI	(2) HF-conv.
Long/Short	15	30
Long only	24	48
Others	11	22
Total	50	100

Notes: This table summarizes the characteristics of hedge funds of the Eurekahedge database of socially responsible (1) and not socially responsible (2) hedge funds. The long-only category includes bottom-up, diversified debt and dual-approach funds. Whereas the Others category includes multi-strategy, relative value, fixed income and CTA funds.

Table 6: Hedge fund summary statistics

variable	Mean	SD	Min	Max
Panel (1)HF-SRI				
Monthly return	0,767	13,678	-10,75	7,87
Age (years)	15,55	3.7703	10	28,83
Assets (in m$)	513,38	1239,45	8	7550
Management fee	1,495	0.5148	0,0	3,0
Performance fee	14,25	8.3337	0	25
Leveraged	0,36	0.4848	0	1
Dividend policy	0,28	0.4535	0	1
HWM	0,70	0.4629	0	1
Lock-up	0,18	0.3880	0	1
Penalty	0,26	0.4430	0	1
Panel (2)HF-conv.				
Monthly return	0,698	13,363	-10,99	7,35
Age (years)	17,42	4.9972	10,08	37,75
Assets (in m$)	716,3	1180.18	6	7453
Management fee	1,513	0.4591	0,5	3
Performance fee	14,84	7.4525	0	25
Leveraged	0,41	0.4943	0	1
Dividend policy	0,24	0.4292	0	1
HWM	0,8	0.4020	0	1
Lock-up	0,26	0.4408	0	1
Penalty	0,25	0.4351	0	1
variable	difference	t-stat	p-value	
Panel (3)= (1)-(2)				
Monthly return	*0,0689*	*0,8683*	*0,1938*	
Age (years)	*-1,8633*	*-2,5498*	*0,0059 ****	
Assets (in m$)	*-202,9*	*1,6625*	*0,1838*	
Management fee	*-0,0179*	*-0,2079*	*0,4178*	
Performance fee	*-0,5850*	*-0,4195*	*0,3379*	
Leveraged	*-0,050*	*-0,5914*	*0,5555*	
Dividend policy	*0,04*	*0,5182*	*0,3027*	
HWM	*-0,10*	*-1,3016*	*0,0982**	
Lock-up	*-0,08*	*-1,1364*	*0,1291*	
Penalty	*0,01*	*0,13107*	*0,4479*	

Notes: This table summarizes the characteristics of hedge funds of the Eurekahedge database of socially responsible (1) and not socially responsible (2) hedge funds. Mean is the average monthly return over the full sample period, Age is the number of years the fund has been in existence, assets are measured in millions of dollars, management and performance fee are measured in annual percentages and leveraged, dividend policy, HWM, lock-up and penalty are dummy variables. The sample contains 132 months from January 2010 to December 2020. *p <0,1, **p<0,05, ***p<0,01.

Table 7: Correlation – Fama/French Factors and SRI and non-SRI HF-strategies

	HF-SRI	HF-conv	MSCI	SMB	HML	MOM
HF-SRI	1					
HF-conv	0,95	1				
MSCI	0,87	0,93	1			
SMB	0,36	0,41	0,31	1		
HML	0,24	0,24	0,21	0,19	1	
MOM	-0,33	-0,35	-0,35	-0,22	-0,44	1

Table 8: Correlation between SRI and non-SRI hedge fund strategies

	HF_ SRI	HF_conv	HF_SRI_l ongonly	HF_conv_ longonly	SRI_lon gshort	HF_conv_lo ngshort
HF_SRI	1					
HF_conv.	0,95	1				
HF_SRI_longonly	0,98	0,93	1			
HF_conv_longonly	0,95	0,98	0,94	1		
HF_SRI_longshort	0,90	0,86	0,83	0,86	1	
HF_conv_longshort	0,91	0,96	0,89	0,93	0,85	1

Table 9: Correlation between passive investment strategies

	MSCI	HML	MOM	Size	10Y	Cred	Bd	Fx	Com	Em
MSCI	1									
HML	0,21	1								
MOM	-0,35	-0,45	1							
SizeSpr	0,25	0,34	-0,17	1						
10Y	0,35	0,46	-0,13	0,34	1					
CredSpr	-0,21	-0,04	0,14	0,06	0,39	1				
BdOpt	-0,52	-0,39	0,31	-0,15	-0,43	0,15	1			
FxOpt	-0,36	-0,28	0,31	-0,11	-0,22	0,22	0,58	1		
ComOpt	-0,29	-0,27	0,18	-0,19	-0,32	0,09	0,36	0,42	1	
Em	0,83	0,21	-0,38	0,14	0,21	-0,29	-0,48	-0,30	-0,31	1

Table 10: Results CAPM/3F Fama/French/ 4F Carhart Model

Panel A	Alpha	Market	SMB	HML	MOM	R^2
SRI-HF	0,004**	0,481***				0,76
Conventional	0,003***	0,529***				0,87
Difference	0,001*	-0,048***				0,08
Panel B						
SRI-HF	0,004***	0,460***	0,091**	0,040		0,77
Conventional	0,003**	0,502***	0,135***	0,022		0,89
Difference	0,001*	-0,042**	-0,044*	0,017		0,11
Panel C						
SRI-HF	0,004***	0,460***	0,091**	0,040	0,001	0,77
Conventional	0,003***	0,501***	0,135***	0,022	-0,002	0,89
Difference	0,001*	-0,041***	-0,044*	0,019	0,003	0,11

Note: *p <0,1, **p<0,05, ***p<0,01. Panel A contains the results from the CAPM of the equally weighted portfolios. Panel B contains the results from the 3-factor Fama/French model. Panel C contains the results from the 4-factor Carhart Model. The regressions were estimated with robust estimators, alphas are monthly. 132 monthly observations from 2010-2020, the Market factor is MSCI World Index.

Table 11: Results CAPM/ 3-F Fama/French/ 4-F Carhart Model for pre-crisis

Panel A	Alpha	Market	SMB	HML	MOM	R^2
SRI-HF	0,003***	0,443***				0,71
Conventional	0,002***	0,494***				0,85
Difference	0,001	-0,051**				0,038
Panel B						
SRI-HF	0,003***	0,444***	-0,011	-0,026		0,71
Conventional	0,002***	0,486***	0,068*	-0,049*		0,87
Difference	0,001	-0,041*	-0,079**	0,023		0,084
Panel C						
SRI-HF	0,003***	0,464***	-0,008	0,015	0,055	0,71
Conventional	0,002***	0,488***	0,068*	-0,044	0,007	0,87
Difference	0,001	-0,024	-0,077**	0,059	0,048	0,101

Note: *p <0,1 , **p<0,05, ***p<0,01. Panel A contains the results from the CAPM. Panel B contains the results from the 3-factor Fama/French model. Panel C contains the results from the 4-factor Carhart Model. The regressions were estimated with robust estimators, alphas are monthly. 84 monthly observations from 2013-2019, the Market factor is MSCI World Index.

Table 12: Results CAPM/ 3-F Fama/French/ 4-F Carhart Model for pandemic crisis

Panel A	Alpha	Market	SMB	HML	MOM	R^2
SRI-HF	0,007	0,625***				0,85
Conventional	0,004	0,612***				0,89
Difference	0,003*	0,013				0,03
Panel B						
SRI-HF	0,008	0,498***	0,371	0,111		0,90
Conventional	0,007	0,494***	0,270	0,157		0,95
Difference	0,001	0,005	0,101	-0,046		0,16
Panel C						
SRI-HF	0,002	0,543***	0,767*	0,078	0,272	0,92
Conventional	0,001	0,533***	0,620**	0,128	0,240	0,97
Difference	0,0001	0,010	0,147	-0,050	0,032	0,18

Note: *p <0,1 , **p<0,05, ***p<0,01. Panel A contains the results from the CAPM. Panel B contains the results from the 3-factor Fama/French model. Panel C contains the results from the 4-factor Carhart Model. The regressions were estimated with robust estimators, alphas are monthly. 12 monthly observations in 2020, the Market factor is MSCI World Index.

Table 13: Results CAPM/ 3-F Fama/French/ 4-F Carhart Model for debt crisis

Panel A	Alpha	Market	SMB	HML	MOM	R^2
SRI-HF	0,005***	0,405***				0,78
Conventional	0,004***	0,498***				0,89
Difference	0,001	-0,093***				0,47
Panel B						
SRI-HF	0,005***	0,376***	0,136	0,035		0,79
Conventional	0,004***	0,467***	0,171**	0,007		0,90
Difference	0,001	-0,091***	-0,035	0,028		0,46
Panel C						
SRI-HF	0,005***	0,370***	0,148	0,039	-0,040	0,78
Conventional	0,004***	0,461***	0,185**	0,011	-0,046	0,90
Difference	0,001	-0,090***	-0,037	0,027	0,005	0,45

Note: *p <0,1 , **p<0,05, ***p<0,01. Panel A contains the results from the CAPM. Panel B contains the results from the 3-factor Fama/French model. Panel C contains the results from the 4-factor Carhart Model. The regressions were estimated with robust estimators, alphas are monthly. 36 monthly observations from 2010-2012, the Market factor is MSCI World Index.

Table 14: Differences of HF-SRI and HF-Conv. for 3 sub-periods

	Alpha (SRI)	Alpha (conv)	Alpha (diff)	Market (diff)	SMB (diff)	HML (diff)	MOM (diff)	R^2 (diff)	n
Debt-crisis	0,005***	0,004***	0,001	-0,090***	-0,037	0,027	0,005	0,45	36
Pre-crisis	0,003***	0,002***	0,001	-0,024	-0,077**	0,059	0,048	0,10	84
Virus crisis	0,002	0,001	0,0001	0,010	0,147	-0,050	0,032	0,18	12
Total	0,004***	0,003***	0,001*	-0,041***	-0,044*	0,019	0,003	0,11	132

Note: *p <0,1, **p<0,05, ***p<0,01. The table shows the intercepts of the 4-factor Carhart model from the SRI HF portfolio (SRI), conventional HF portfolio (conv) and all results from the difference portfolios (diff). The regressions were estimated with robust estimators and all alphas are monthly. Debt-crisis: Jan.2010-Dec.2013, Pre-crisis: Jan.2013-Dec.2019, Virus crisis: Jan.2020-Dec.2020, Total: Jan.2010-Dec.2020, the Market factor is MSCI World Index.

Table 15: Results 4-factor model with HFI

	Alpha	Market	SMB	HML	MOM	R^2	n
Total	0,001	0,987***	-0,053***	0,017	0,016	0,96	132
debt	0,001	0,911***	-0,023	-0,003	0,002	0,97	36
Pre-crisis	0,001	1,041***	-0,075***	0,061***	0,060***	0,95	84
corona	-0,001	1,030***	0,10	-0,050	0,026	0,99	12

Note: *p <0,1, **p<0,05, ***p<0,01. The table shows the intercepts of the 4-factor Carhart model from the SRI hedge funds portfolio. The regressions were estimated with robust estimators and all alphas are monthly. Debt-crisis: Jan.2010-Dec.2013, Pre-crisis: Jan.2013-Dec.2019, Virus crisis: Jan.2020-Dec.2020, total: Jan.2010-Dec.2020, the Market factor is the HFI.

Table 16a: Results 4-factor model with HFI and SRI long/short HF

	Alpha	Market	SMB	HML	MOM	R^2	n
Total	0,002***	0,738***	-0,007	0,078***	0,020	0,86	132
Debt	0,003***	0,645***	0,034	0,052	0,020	0,87	36
Pre-crisis	0,002*	0,786***	-0,016	0,158***	0,048	0,79	36
Corona	0,002	0,790***	0,138	0,049	0,069	0,93	12

Note: *p <0,1, **p<0,05, ***p<0,01. Table shows the intercepts of the 4-factor Carhart model from the SRI long/short hedge funds portfolio. The regressions were estimated with robust estimators and all alphas are monthly. Debt crisis: Jan.2010-Dec.2012, Pre-crisis: Jan.2017-Dec.2019, Virus crisis: Jan.2020-Dec.2020, total: Jan.2010-Dec.2020, the Market factor is own HFI.

Table 16b: Results 4-factor model with HFI and SRI long-only HF

	Alpha	Market	SMB	HML	MOM	R^2	n
Total	0,001	1,064***	-0,039	-0,035	0,013	0,95	132
Debt	-0,0002	1,031***	-0,064	-0,059	-0,010	0,96	36
Pre-crisis	0,001	0,986***	-0,069	-0,010	-0,040	0,86	36
Corona	-0,0004	1,088***	0,179	-0,113	0,034	0,98	12

Note: *p <0,1, **p<0,05, ***p<0,01. Table shows the intercepts of the 4-factor Carhart model from the SRI long-only hedge funds portfolio. The regressions were estimated with robust estimators and all alphas are monthly. Debt crisis: Jan.2010-Dec. 2012, Pre-crisis: Jan.2017-Dec.2019, Virus crisis: Jan.2020-Dec.2020, Total: Jan.2010-Dec.2020, the Market factor is the HFI.

Table 17: Results for 7 and 8-factor Fung & Hsieh model

	Dependent variable:			
	SRI		non-SRI	
	(1)	(2)	(3)	(4)
MKT	0.393***	0.317***	0.461***	0.351***
	(0.029)	(0.040)	(0.017)	(0.024)
Size_Spread	0.042	0.051	0.088***	0.099***
	(0.036)	(0.034)	(0.027)	(0.022)
DGS10	0.011*	0.013**	0.014***	0.016***
	(0.006)	(0.006)	(0.005)	(0.004)
DBAAMDGS10	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0003)	(0.0003)	(0.0002)	(0.0003)
PTFSBD	-0.010	-0.008	-0.002	0.001
	(0.007)	(0.007)	(0.005)	(0.005)
PTFSFX	0.003	0.002	0.006	0.004
	(0.006)	(0.007)	(0.004)	(0.004)
PTFSCOM	-0.017***	-0.015**	-0.011**	-0.007
	(0.006)	(0.006)	(0.004)	(0.005)
Emerging		0.079**		0.115***
		(0.034)		(0.022)
Constant	0.004***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	132	132	132	132
R^2	0.827	0.837	0.916	0.933
Adjusted R^2	0.817	0.827	0.912	0.929
Residual Std. Error	0.010 (df = 124)	0.009 (df = 123)	0.007 (df = 124)	0.006 (df = 123)

Note: *p <0,1, **p<0,05, ***p<0,01. The table shows the intercepts of the 7 and 8-factor Fung & Hsieh model. The regressions were estimated with robust estimators, alphas are monthly. 132 monthly observations from January 2010 to December 2020, the Market factor is the MSCI world.

Table 18: Results for 7 and 8-factor Fung & Hsieh model in a shorter time period

	Dependent variable:			
	SRI		non-SRI	
	(1)	(2)	(3)	(4)
MKT	0.414***	0.302***	0.438***	0.339***
	(0.046)	(0.051)	(0.027)	(0.027)
Size_Spread	-0.006	0.023	0.081*	0.094***
	(0.055)	(0.050)	(0.041)	(0.027)
DGS10	0.026**	0.025**	0.027***	0.028***
	(0.011)	(0.012)	(0.008)	(0.007)
DBAAMDGS10	-0.001***	-0.001***	-0.002***	-0.001***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
PTFSBD	0.001	0.005	0.006	0.010*
	(0.012)	(0.012)	(0.006)	(0.006)
PTFSFX	-0.014**	-0.017**	-0.002	-0.005
	(0.006)	(0.007)	(0.006)	(0.005)
PTFSCOM	-0.0004	0.005	-0.005	-0.001
	(0.012)	(0.011)	(0.009)	(0.007)
Emerging		0.134***		0.123***
		(0.046)		(0.030)
Constant	0.001	0.001	0.002*	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	48	48	48	48
R^2	0.904	0.918	0.954	0.972
Adjusted R^2	0.888	0.901	0.946	0.966
Residual Std. Error	0.009 (df = 40)	0.008 (df = 39)	0.006 (df = 40)	0.005 (df = 39)

Note: *p <0,1, **p<0,05, ***p<0,01. The table shows the intercepts of the 7 and 8-factor Fung & Hsieh model. The regressions were estimated with robust estimators, alphas are monthly. 48 monthly observations from January 2017 to December 2020, the Market factor is the MSCI world.

Table 19: Results for 7 and 8-factor Fung & Hsieh model with HFI

	Dependent variable:			
	SRI		non-SRI	
	(1)	(2)	(3)	(4)
MKT	0.966***	1.097***	1.025***	0.968***
	(0.032)	(0.039)	(0.014)	(0.018)
Size_Spread	-0.028*	-0.043**	0.017**	0.022***
	(0.017)	(0.017)	(0.008)	(0.007)
DGS10	-0.001	-0.005*	0.0005	0.002
	(0.003)	(0.003)	(0.002)	(0.001)
DBAAMDGS10	-0.00000	0.0001	0.00002	-0.00002
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
PTFSBD	-0.003	-0.005	0.001	0.002
	(0.004)	(0.003)	(0.002)	(0.001)
PTFSFX	0.001	0.001	0.0003	-0.00002
	(0.004)	(0.003)	(0.002)	(0.001)
PTFSCOM	-0.006*	-0.006*	0.002	0.002*
	(0.003)	(0.003)	(0.001)	(0.001)
Emerging		-0.065***		0.028***
		(0.014)		(0.007)
Constant	0.0004	-0.0003	-0.001***	-0.0005**
	(0.0004)	(0.0005)	(0.0002)	(0.0002)
Observations	132	132	132	132
R^2	0.964	0.968	0.992	0.993
Adjusted R^2	0.962	0.966	0.992	0.992
Residual Std. Error	0.004 (df = 124)	0.004 (df = 123)	0.002 (df = 124)	0.002 (df = 123)

Note: *p <0,1, **p<0,05, ***p<0,01. The table shows the intercepts of the 7 and 8-factor Fung & Hsieh model. The regressions were estimated with robust estimators, alphas are monthly. 132 monthly observations from January 2010 to December 2020, the Market factor is the HFI.

Table 20: Results for 7 and 8-factor Fung & Hsieh model with HFI in a shorter time period

	Dependent variable:			
	SRI		non-SRI	
	(1)	(2)	(3)	(4)
MKT	1.071***	1.078***	0.999***	0.983***
	(0.145)	(0.084)	(0.034)	(0.034)
Size_Spread	-0.055	-0.053	0.026	0.028*
	(0.064)	(0.043)	(0.019)	(0.016)
DGS10	-0.0003	-0.002	-0.0002	0.0004
	(0.013)	(0.010)	(0.004)	(0.004)
DBAAMDGS10	0.0002	0.0002	-0.00002	-0.00003
	(0.0003)	(0.0002)	(0.0001)	(0.0001)
PTFSBD	-0.003	-0.005	0.001	0.001
	(0.013)	(0.011)	(0.004)	(0.004)
PTFSFX	-0.003	-0.004	0.004	0.004
	(0.012)	(0.008)	(0.003)	(0.003)
PTFSCOM	0.006	0.007	-0.003	-0.003
	(0.013)	(0.011)	(0.004)	(0.004)
Emerging		-0.013		0.009
		(0.039)		(0.015)
Constant	-0.001	-0.001	-0.001***	-0.001**
	(0.001)	(0.001)	(0.0004)	(0.0004)
Observations	48	48	48	48
R^2	0.975	0.972	0.994	0.994
Adjusted R^2	0.970	0.966	0.993	0.992
Residual Std. Error	0.004 (df = 40)	0.005 (df = 39)	0.002 (df = 40)	0.002 (df = 39)
Note:				*p**p***p<0.01

Note: The table shows the intercepts of the 7 and 8-factor Fung & Hsieh model. The regressions were estimated with robust estimators, alphas are monthly. 48 monthly observations from January 2017 to December 2020, the Market factor is the HFI.

Table 21: Results for own multi-factor model

	Dependent variable:			
	SRI		non-SRI	
	(1)	(2)	(3)	(4)
MKT	0.386***	0.300***	0.453***	0.335***
	(0.027)	(0.040)	(0.019)	(0.026)
HML	-0.056	-0.060	-0.064**	-0.070**
	(0.044)	(0.043)	(0.031)	(0.027)
momentum	-0.012	0.001	-0.024	-0.007
	(0.030)	(0.030)	(0.021)	(0.019)
Size_Spread	0.072**	0.083**	0.105***	0.120***
	(0.035)	(0.034)	(0.025)	(0.022)
DGS10	0.016**	0.018**	0.018***	0.021***
	(0.007)	(0.007)	(0.005)	(0.005)
DBAAMDGS10	-0.002***	-0.001***	-0.001***	-0.001***
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
PTFSBD	-0.013**	-0.011*	-0.004	-0.001
	(0.007)	(0.006)	(0.005)	(0.004)
PTFSFX	0.005	0.003	0.007*	0.004
	(0.006)	(0.006)	(0.004)	(0.004)
PTFSCOM	-0.013**	-0.011*	-0.009**	-0.005
	(0.006)	(0.006)	(0.005)	(0.004)
Emerging		0.088***		0.122***
		(0.031)		(0.020)
Constant	0.004***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	132	132	132	132
R^2	0.828	0.839	0.919	0.938
Adjusted R^2	0.816	0.825	0.913	0.933
Residual Std. Error	0.010 (df = 122)	0.010 (df = 121)	0.007 (df = 122)	0.006 (df = 121)
F Statistic	65.363*** (df = 9; 122)	62.914*** (df = 10; 121)	154.034*** (df = 9; 122)	182.671*** (df = 10; 121)

Note: *p <0,1, **p<0,05, ***p<0,01. The table shows the intercepts of the own multi-factor model. The regressions were estimated with robust estimators, alphas are monthly. 132 monthly observations from January 2010 to December 2020, the Market factor is the MSCI world index.

Table 22: Results for own multi-factor model with HFI

	Dependent variable:			
	SRI		non-SRI	
	(1)	(2)	(3)	(4)
MKT	0.964***	1.114***	1.023***	0.960***
	(0.027)	(0.041)	(0.013)	(0.020)
HML	0.017	0.029	-0.004	-0.008
	(0.021)	(0.020)	(0.010)	(0.010)
momentum	0.018	0.009	-0.006	-0.003
	(0.014)	(0.014)	(0.007)	(0.007)
Size_Spread	-0.022	-0.044***	0.014*	0.023***
	(0.017)	(0.017)	(0.008)	(0.008)
DGS10	-0.003	-0.007**	0.001	0.003
	(0.004)	(0.003)	(0.002)	(0.002)
DBAAMDGS10	-0.00002	0.0001	0.00003	-0.00002
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
PTFSBD	-0.005	-0.006**	0.001	0.002
	(0.003)	(0.003)	(0.001)	(0.001)
PTFSFX	-0.001	0.0005	0.001	0.0003
	(0.003)	(0.003)	(0.001)	(0.001)
PTFSCOM	-0.003	-0.004	0.001	0.002
	(0.003)	(0.003)	(0.001)	(0.001)
Emerging		-0.071***		0.030***
		(0.015)		(0.007)
Constant	0.0003	-0.0004	-0.001***	-0.001**
	(0.0005)	(0.0005)	(0.0002)	(0.0002)
Observations	132	132	132	132
R^2	0.961	0.967	0.992	0.993
Adjusted R^2	0.958	0.964	0.991	0.992
Residual Std. Error	0.005 (df = 122)	0.004 (df = 121)	0.002 (df = 122)	0.002 (df = 121)
F Statistic	336.279*** (df = 9; 122)	354.266*** (df = 10; 121)	1,642.082*** (df = 9; 122)	1,656.018*** (df = 10; 121)

Note: *p <0,1, **p<0,05, ***p<0,01. The table shows the intercepts of the own multi-factor model. The regressions were estimated with robust estimators, alphas are monthly. 132 monthly observations from January 2010 to December 2020, the Market factor is the HFI.

Table 23: Results for own multi-factor model with HFI and shorter time-period

	Dependent variable:			
	SRI		non-SRI	
	(1)	(2)	(3)	(4)
MKT	1.042***	1.099***	1.002***	0.969***
	(0.114)	(0.162)	(0.037)	(0.040)
HML	-0.008	0.007	-0.007	-0.014
	(0.047)	(0.063)	(0.020)	(0.021)
momentum	-0.015	-0.013	0.005	0.004
	(0.026)	(0.022)	(0.011)	(0.011)
Size_Spread	-0.051	-0.071	0.029	0.035*
	(0.053)	(0.075)	(0.020)	(0.019)
DGS10	-0.0003	0.001	0.0001	0.001
	(0.009)	(0.009)	(0.004)	(0.004)
DBAAMDGS10	0.0001	0.0002	-0.00001	-0.00004
	(0.0004)	(0.0005)	(0.0001)	(0.0001)
PTFSBD	-0.004	-0.001	0.0005	0.001
	(0.011)	(0.018)	(0.004)	(0.004)
PTFSFX	-0.004	-0.0001	0.003	0.003
	(0.008)	(0.014)	(0.003)	(0.003)
PTFSCOM	0.007	0.004	-0.003	-0.003
	(0.012)	(0.018)	(0.004)	(0.004)
Emerging		-0.008		0.017
		(0.035)		(0.016)
Constant	-0.001	-0.001	-0.001**	-0.001**
	(0.001)	(0.002)	(0.0005)	(0.0004)
Observations	48	48	48	48
R^2	0.973	0.978	0.994	0.994
Adjusted R^2	0.966	0.972	0.992	0.992
Residual Std. Error	0.005 (df = 38)	0.004 (df = 37)	0.002 (df = 38)	0.002 (df = 37)

Note: *p <0,1, **p<0,05, ***p<0,01. The table shows the intercepts of the own multi-factor model. The regressions were estimated with robust estimators, alphas are monthly. 48 monthly observations from January 2017 to December 2020, the Market factor is the HFI.

Table 24: Panel data structure for Fama and MacBeth regressions (1973)

HF	Month	Return	Age	Ln(assets)	Mgt.	Perf.	Leveraged	Dividend	ESG
1	1	0,56	12,83	5,53	2	20	0	0	1
1	2	0,54	12,83	5,53	2	20	0	0	1
1	3	0,51	12,83	5,53	2	20	0	0	1
1	4	0,52	12,83	5,53	2	20	0	0	1
1	5	0,47	12,83	5,53	2	20	0	0	1
1	6	0,42	12,83	5,53	2	20	0	0	1
1	7	0,46	12,83	5,53	2	20	0	0	1
1	8	0,38	12,83	5,53	2	20	0	0	1
1	9	0,42	12,83	5,53	2	20	0	0	1
1	10	0,4	12,83	5,53	2	20	0	0	1
1	11	0,36	12,83	5,53	2	20	0	0	1
1	12	0,38	12,83	5,53	2	20	0	0	1
2	1	0,89	20,16	3,40	1,54	0	0	1	1
2	2	-0,56	20,16	3,40	1,54	0	0	1	1

Table 25: Fama and MacBeth (1973) regressions of monthly returns

	Full sample (t-stat)	Long-only (t-stat)	Long/short (t-stat)
Ln(assets)	-0,053 (-0,35)	-0,253 (-1,00)	0,248 (1,06)
Age	0,0023 (0,05)	0,069 (0,93)	-0,116 (-1,17)
ESG	0,312* (2,03)	0,800** (2,65)	-0,041 (-0,20)
Constant	1,493 (0,78)	1,674 (0,68)	1,927** (2,57)
N	150	72	45
Avg. R-squared	0,02	0,06	0,07

Notes: This table presents the results of FMB (1973) monthly cross-sectional regressions. Newey and West (1987) t-statistics using 3 monthly lags are reported in parentheses. (*), (**) and (***) indicate statistically significant factors at 10 per cent, 5 per cent and 1 per cent levels, respectively. Sample data contain results for 12 months from January 2020 to December 2020.

Table 26: Fama and MacBeth (1973) regressions of monthly returns

	Full sample (t-stat)	Long-only (t-stat)	Long/short (t-stat)
Ln(assets)	-0,035 (-0,25)	-0,198 (-0,83)	0,264 (0,98)
Age	0,003 (0,06)	0,062 (0,75)	-0,151 (-1,33)
ESG	0,351** (2,54)	0,914** (2,61)	-0,279 (-1,75)
Management fee	0,421** (2,75)	1,113* (2,14)	0,474 (0,69)
Performance fee	-0,025 (-0,96)	0,032 (1,21)	-0,146** (-2,98)
Leveraged	0,035 (0,11)	0,427 (0,62)	0,035 (0,07)
HWM	0,305 (0,57)	-0,379 (-0,95)	2,772*** (3,65)
Constant	0,863 (0,46)	-0,316 (-0,13)	1,859 (1,05)
N	150	72	45
Avg. R-squared	0,04	0,13	0,14

Notes: This table presents the results of FMB (1973) monthly cross-sectional regressions. Newey and West (1987) t-statistics using 3 monthly lags are reported in parentheses. (*), (**) and (***) indicate statistically significant factors at 10 per cent, 5 per cent and 1 per cent levels, respectively. Sample data contain results for 12 months from January 2020 to December 2020.

Table 27: Matched samples based on equation 12 and 13 hedge funds characteristics

variable	Mean	SD	Min	Max
Panel (1)HF-SRI				
Monthly return	0,767	13,678	-10,75	7,87
Age (years)	15,55	3.7703	10	28,83
Assets (in m$)	513,38	1239,456	8	7550
Management fee	1,495	0.5148	0,0	3,0
Performance fee	14,25	8.3337	0	25
Leveraged	0,36	0.4848	0	1
Dividend policy	0,28	0.4535	0	1
HWM	0,70	0.4629	0	1
Lock-up	0,18	0.3880	0	1
Penalty	0,26	0.4430	0	1
Panel (2)HF-conv.	Equation 12	p-value	Equation 13	p-value
Age (years)	15.382	0.64385	15.115	0.33793
Assets (in m$)	669.36	0.54946	618.84	0.70272
Management fee			1.4675	0.52633
Performance fee			14.22	0.9838
Leveraged			0.34	0.37
HWM			0.74	0.56505
Panel (3)HF-conv.	Equation 12	p-value	Equation 13	p-value
Age (years)	15.723	0.62588	15.5	0.80179
Assets (in m$)	430.38	0.34533	513.22	0.99717
Management fee			1.482	0.80249
Performance fee			13.95	0.53732
Leveraged			0.36	1
HWM			0,7	1

Notes: Panel 2 and 3 is after matching. Panel 1 is the original data from table 6. Panel 2 is matching with MatchBalance and Panel 3 is Genetic matching. The p-value gets 1 when values of both groups are identical. Dividend policy and Penalty are not matched.

Table 28: First step: propensity scores

	Estimate	SD	P-value
intercept	1.108e+00 *	6.270e-01	0.0772
Assets	-8.055e-05	9.707e-05	0.4067
Years	-6.601e-02 **	2.644e-02	0.0125
Management fee	-9.152e-02	2.325e-01	0.6938
Performance fee	1.187e-02	2.129e-02	0.5771
leveraged	-2.670e-02	2.460e-01	0.9136
HWM	-5.684e-01	3.685e-01	0.1230

Table 29: MatchBalance R-output results

> MatchBalance(Tr ~ X, match.out = rr1, nboots=0, data=data_funds_11years)

	***** (V1) Xassets *****	
	Before Matching	After Matching
mean treatment........	513.38	513.38
std mean diff.........	-15.068	-11.583
mean raw eQQ diff.....	313.52	283.66
med raw eQQ diff.....	135	169
max raw eQQ diff.....	2438	2438
mean eCDF diff........	0.15088	0.17206
med eCDF diff........	0.17	0.20755
max eCDF diff........	0.27	0.32075
var ratio (Tr/Co).....	1.3019	1.3186
T-test p-value........	0.36761	0.54946
KS Naive p-value......	0.015501	0.0085683
KS Statistic..........	0.27	0.32075
After Matching Minimum p.value: 0.0085683		
Variable Name(s): Xassets Number(s): 1		

Notes: the control group variable X consist of the equation 12 variables, but only the variable asset is displayed (the R-output for variable age is excluded)

Table 30: standard matching "ATE" on equation 12 variables

Estimate	0.00098967
AI SE	0.00092485
T-stat	1.0701
p.val	0.28458
Original number of observations	150
Original number of treated observations	50
Matched number of observations	150
Matched number of observations (unweighted)	155

Table 31: R-Output: standard matching "ATE" on equation 12 variables and HWM

Estimate	0.0017954
AI SE	0.00090868
T-stat	1.9758
p.val	0.048172
Original number of observations	150
Original number of treated obs	50
Matched number of observations	150
Matched number of observations (unweighted)	155

Table 32: standard matching "ATE" on equation 13 variables

Estimate	0.0011225
AI SE	0.0010469
T-stat	1.0723
p.val	0.28361
Original number of observations	150
Original number of treated observations	50
Matched number of observations	150
Matched number of observations (unweighted)	154

Table 33: standard matching "ATE" on equation 13 variables without fee variables

Estimate	0.0017991
AI SE	0.00090946
T-stat	1.9782
p.val	0.047908
Original number of observations	150
Original number of treated observations	50
Matched number of observations	150
Matched number of observations (unweighted)	151

Table 34: Results CAPM/ 3-F Fama/French/ 4-F Carhart Model - Stoxx ESG Index

Panel A	Alpha	Market	SMB	HML	MOM	R^2
SRI-HF	0,004**	0,502***				0,77
Conventional	0,004***	0,520***				0,78
Difference	0,001	-0,018				0,01
Panel B						
SRI-HF	0,004***	0,494***	0,070	-0,031		0,78
Conventional	0,004**	0,501***	0,132***	-0,041		0,79
Difference	0,001	-0,007	-0,062**	0,009		0,05
Panel C						
SRI-HF	0,004***	0,499***	0,072	-0,022	0,021	0,78
Conventional	0,003***	0,502***	0,133***	-0,038	0,005	0,80
Difference	0,001	-0,004	-0,060*	0,017	0,016	0,05

Note: *p <0,1, **p<0,05, ***p<0,01. Panel A contains the results from the CAPM. Panel B contains the results from the 3-factor Fama/French model. Panel C contains the results from the 4-factor Carhart Model. The regressions were estimated with robust estimators, alphas are monthly. 132 monthly observations from 2010-2020, the Market factor is Stoxx Global ESG Leaders Index.

Table 35: Results CAPM/ 3-F Fama/French/ 4-F Carhart Model in 2020

Panel A	Alpha	Market	SMB	HML	MOM	R^2
SRI-HF	0,015**	0,570***				0,88
Conventional	0,012**	0,555***				0,90
Difference	0,003*	0,015				0,05
Panel B						
SRI-HF	0,015	0,487***	0,215	0,075		0,90
Conventional	0,014	0,480***	0,118	0,124		0,91
Difference	0,001	0,007	0,097	-0,049		0,16
Panel C						
SRI-HF	0,003	0,622***	0,949*	-0,034	0,553**	0,96
Conventional	0,003	0,604***	0,792**	0,024	0,507***	0,97
Difference	-0,0001	0,019	0,157	-0,058	0,046	0,19

Note: *p <0,1, **p<0,05, ***p<0,01. Panel A contains the results from the CAPM. Panel B contains the results from the 3-factor Fama/French model. Panel C contains the results from the 4-factor Carhart Model. The regressions were estimated with robust estimators, alphas are monthly. 12 monthly observations in 2020, the Market factor is Stoxx Global ESG Leaders Index.

Table 36: Results for own multi-factor model - Stoxx Global ESG Index

	Dependent variable:			
	SRI		non-SRI	
	(1)	(2)	(3)	(4)
MKT	0.415***	0.304***	0.429***	0.269***
	(0.030)	(0.030)	(0.030)	(0.023)
HML	-0.104**	-0.082**	-0.135***	-0.103***
	(0.044)	(0.038)	(0.045)	(0.029)
momentum	0.007	0.037	-0.021	0.022
	(0.031)	(0.027)	(0.032)	(0.020)
Size_Spread	0.055	0.069**	0.099***	0.119***
	(0.036)	(0.031)	(0.036)	(0.023)
DGS10	0.016**	0.016**	0.022***	0.022***
	(0.007)	(0.006)	(0.008)	(0.005)
DBAAMDGS10	-0.001***	-0.001***	-0.001***	-0.001***
	(0.0003)	(0.0003)	(0.0003)	(0.0002)
PTFSBD	-0.018***	-0.010*	-0.013*	-0.001
	(0.007)	(0.006)	(0.007)	(0.004)
PTFSFX	0.003	-0.001	0.004	-0.001
	(0.006)	(0.005)	(0.006)	(0.004)
PTFSCOM	-0.005	-0.002	-0.001	0.004
	(0.007)	(0.006)	(0.007)	(0.004)
Emerging		0.151***		0.218***
		(0.021)		(0.016)
Constant	0.004***	0.004***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	132	132	132	132
R^2	0.821	0.873	0.829	0.931
Adjusted R^2	0.808	0.862	0.816	0.925
Residual Std. Error	0.010 (df = 122)	0.009 (df = 121)	0.010 (df = 122)	0.007 (df = 121)
F Statistic	62.167*** (df = 9; 122)	83.158*** (df = 10; 121)	65.660*** (df = 9; 122)	163.421*** (df = 10; 121)
Note:				*p**p***p<0.01

The table shows the intercepts of the own multi-factor model. The regressions were estimated with robust estimators, alphas are monthly. 132 monthly observations from January 2010 to December 2020, the Market factor is the Stoxx Global Leaders Index.

Table 37: Long/short hedge fund summary statistics

variable	Mean	SD	Min	Max
Panel (1)HF SRI				
Return 2017-2020	0,657	11,75	-6,60	4,94
Return 2020	1,107	16,37	-6,60	4,94
Age (years)	7,07	2.0953	4,08	11
Assets (in m$)	383,7	633.66	3	3170
Management fee	1,39	0.5793	0,5	4,0
Performance fee	16,61	6.3570	0	25
Leveraged	0,659	0.4789	0	1
Dividend policy	0,23	0.4279	0	1
HWM	0,85	0.3598	0	1
Lock-up	0,04	0.2040	0	1
Penalty	0,21	0.4136	0	1
Panel (2)HF-conv.				
Return 2017-2020	0,844	12,74	-7,38	5,60
Return 2020	1,03	18,73	-7,38	5,60
Age (years)	7,37	2.0324	4,08	11
Assets (in m$)	427	1092.88	10	7321
Management fee	1,439	0.4777	0,25	2,4
Performance fee	17,67	4.2160	0	25
Leveraged	0,70	0.4622	0	1
Dividend policy	0,25	0.4407	0	1
HWM	0,95	0.2040	0	1
Lock-up	0,25	0.4407	0	1
Penalty	0,28	0.4521	0	1
variable	difference	t-stat	p-value	
Panel (3)= (1)-(2)				
Return 2017-2020	-0,1873	-1,2327	0,1104	
Return 2020	0,077	0,2212	0,4126	
Age (years)	-0,3032	-0,7120	0,2391	
Assets (in m$)	-43,27	-0,2348	0,4074	
Management fee	-0,049	-0,4506	0,3266	
Performance fee	-1,063	-0,9561	0,1709	
Leveraged	-0,042	-0,4382	0,3311	
Dividend policy	-0,021	-0,2374	0,4064	
HWM	-0,106	-1,762	0,0410**	
Lock-up	-0,212	-3,003	0,0019***	
Penalty	-0,063	-0,7140	0,2385	

Notes: This table summarizes the characteristics of hedge funds of the Eurekahedge database of socially responsible (1) and not socially responsible (2) long/short hedge funds. Mean is the average monthly return over the full sample and 2020 period, Age is the number of years the fund has been in existence, assets are measured in millions of dollars, management and performance fee are measured in annual percentages and leveraged, dividend policy, HWM, lock-up and penalty are dummy variables. The sample contains 48 months from January 2017 to December 2020. *p <0,1, **p<0,05, ***p<0,01.

Table 38: Results CAPM/ 3-F Fama/French/ 4-F Carhart Model – long/short sample

Panel A	Alpha	Market	SMB	HML	MOM	R^2
SRI-HF	0,002	0,422***				0,86
Conventional	0,004***	0,426***				0,86
Difference	-0,002	-0,005				0,01
Panel B						
SRI-HF	0,002	0,401***	0,077	0,040		0,87
Conventional	0,004**	0,389***	0,139***	-0,013		0,90
Difference	-0,002	-0,012	-0,122**	0,031		0,10
Panel C						
SRI-HF	0,002	0,409***	0,089*	0,035	0,030	0,88
Conventional	0,004***	0,408***	0,219***	0,028	0,073**	0,91
Difference	-0,002	0,001	-0,129**	0,007	-0,044	0,12

Note: *p <0,1, **p<0,05, ***p<0,01. Panel A contains the results from the CAPM. Panel B contains the results from the 3-factor Fama/French model. Panel C contains the results from the 4-factor Carhart Model. The regressions were estimated with robust estimators, alphas are monthly. 48 monthly observations from 2017-2020, the Market factor is MSCI World Index and an equally weighted long-short portfolio.

Table 39: Results for own multi-factor model – long/short sample

	Dependent variable:			
	SRI		non-SRI	
	(1)	(2)	(3)	(4)
MKT	0.288***	0.216***	0.482***	0.392***
	(0.052)	(0.071)	(0.043)	(0.055)
HML	-0.045	-0.062	-0.260***	-0.282***
	(0.078)	(0.078)	(0.064)	(0.061)
momentum	-0.040	-0.023	-0.121**	-0.100*
	(0.064)	(0.064)	(0.052)	(0.050)
Size_Spread	0.047	0.070	0.203***	0.233***
	(0.070)	(0.071)	(0.057)	(0.055)
DGS10	0.018	0.017	0.031**	0.031**
	(0.016)	(0.015)	(0.013)	(0.012)
DBAAMDGS10	-0.001**	-0.001**	-0.001**	-0.001**
	(0.001)	(0.001)	(0.0004)	(0.0004)
PTFSBD	-0.008	-0.006	-0.008	-0.005
	(0.011)	(0.011)	(0.009)	(0.009)
PTFSFX	0.016	0.012	0.007	0.002
	(0.011)	(0.011)	(0.009)	(0.009)
PTFSCOM	0.015	0.018	-0.004	-0.001
	(0.014)	(0.014)	(0.011)	(0.011)
Emerging		0.093		0.117**
		(0.063)		(0.049)
Constant	0.002	0.002	0.002	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	48	48	48	48
R^2	0.767	0.780	0.939	0.947
Adjusted R^2	0.712	0.720	0.924	0.932
Residual Std. Error	0.011 (df = 38)	0.011 (df = 37)	0.009 (df = 38)	0.008 (df = 37)
F Statistic	13.885*** (df = 9; 38)	13.106*** (df = 10; 37)	64.674*** (df = 9; 38)	65.890*** (df = 10; 37)
Note:				*p**p***p<0.01

The table shows the intercepts of the own multi-factor model. The regressions were estimated with robust estimators, alphas are monthly. 48 monthly observations from 2017 to 2020, the Market factor is the MSCI World index.

11 Executive summary

Sustainable investing is mainly driven by institutional investors, but hedge funds are still the lowest percentage among institutional implementing SRI strategies (Morgan Stanley, 2020). The AUM proliferated during the last years (GSIR, 2018; PRI 2020; US SIF, 2020) which is mainly driven by the ambitious plans of governments (EU, 2021, Refinitiv, 2020), but also of the awareness of the general public and institutional investors (AAM, 2021; ABP, 2021). However, also the hedge fund industry AUM is increasing (HFR, 2020; Barclayhedge, 2021), even if hedge funds haven't a clear tendency to invest socially responsible (Preqin, 2019).

Socially responsible investing has gained recognition in recent years, but the evidence on whether SRI positively affects investor returns is mixed. The research question of this master thesis is to investigate whether hedge funds pursuing SRI strategies are compensated with higher returns than their non-SRI counterparts. I make use of several empirical methods at the level of hedge funds, but also on companies each hedge fund is invested in. Using factor models with different risk-factors, I find evidence that SRI hedge funds do significantly outperform non-SRI hedge funds on average by 0,1% monthly from 2010 to 2020 with even stronger results in the pandemic year 2020. Moreover, SRI long/short hedge funds outperforming their conventional peers among several periods. Using FMB (1973) regressions for the 2020 year, I find similar outperformance of SRI hedge funds and after breaking down into categories I find that SRI long-only hedge funds outperform. Working with PSM technique, I find similar SRI hedge fund findings for the whole time period. After investigating the performance of company holdings of hedge funds I confirm my past return-based methodology findings.

So far, literature about SRI in hedge funds is undoubtedly rare. This thesis sheds mainly light on performance differences among SRI- and non-SRI hedge funds, but also raises concerns about ESG frameworks. Investors are attributing increased importance to sustainability and quality of ESG data and SRI becomes more and more entrenched in the investment landscape. The rise of SRI in the hedge fund industry and ESG investing in general is poised to continue.

Keywords: sustainable investing, socially responsible investing, ESG investing, hedge funds, multi-factor models, ESG, SRI, risk-adjusted performance, institutional investors, 13F