Master's Thesis

Erasmus University | Erasmus School of Economics

Preference of Moving Toward Sustainability in Oil & Gas Mutual Funds: Evidence from a Financial Perspective

Abstract

Since the need for increased awareness of sustainable energy is widely accepted, clean technology investments have experienced a steep rise. It is a widespread belief that sustainable investing did not generate higher returns compared to unsustainable investing. In this study, I investigate the relationship between financial performance and the movement toward sustainability in oil and gas mutual funds. Investors are reluctant to shift toward sustainability as they often worry about potential performance loss. This study provides empirical evidence on the impact of sustainability for oil and gas mutual fund financial performance for 7,166 unique mutual funds with monthly varying ESG ratings from 2016 to 2019. Employing a Carhart four-factor model with a sandwich variance estimator, the empirical results indicate significant evidence that it is financially attractive to move toward sustainability as an oil and gas mutual fund. I find that sustainability does not currently appear to be a drag on the performance of oil and gas mutual funds. Evidence suggests that recently sustainable oil and gas mutual funds tend to outperform oil and gas mutual funds.

Keywords: Sustainability, Mutual Fund, ESG, Oil & Gas industry, Cleantech
JEL Classification: G11, G23, Q01, Q42, Q21

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1. Introduction

Sustainable, responsible, and impactful investing, or socially responsible investing (SRI), is defined as "an investment discipline that considers environmental, social, and corporate governance (ESG) criteria to generate long-term competitive financial returns and positive societal impact" (US SIF SRI Basics, 2019). This type of investing is becoming more popular as investors are increasingly conscious of the environmental and social consequences of unsustainable investing. Questions asked are if it is natural to wonder whether sustainable investing might weaken returns. Furthermore, in which way the returns for sustainable investments differ yearly from unsustainable investments as their costs were decreasing and returns were increasing during the last several years. On top of that, the overarching question is to which degree are sustainable investments the future of investing. A rise in the number of investors should generally mean higher stock values for sustainable companies, thus making it easier for ESG-friendly mutual funds to raise money, leading to higher returns and expansion. However, academics such as Reboredo et al. (2017) and Renneboog et al. (2008) state that mutual funds are paying a "green premium" for investing in renewable energies (i.e., "going green"). The green premium is the higher price that the mutual fund has to pay to obtain the green stock. This premium has to be recouped in the long run. Additionally, the premium leads to lower financing costs. Furthermore, green stocks are accompanied by less risk, more stable cash flows and lower discount rates that lead to higher values.

However, the cleantech industry, mainly focused on solar, wind, and water related investments, is now mature enough that governmental help is not necessary for growth, as costs have come down rapidly during the last years. The energy transition is stimulated by the idea that in the long term clean technologies such as wind and solar power decrease in costs while fossil fuel energy will only get more expensive in the future. Another factor which can positively impact the energy transition are rising prices for emissions of carbon to encourage oil and gas (O&G) mutual funds to invest in clean technology and production processes. In this way, sustainable technologies, like cleantech, increase their competitiveness without any other policy needed (Bumpus et al., 2015). Furthermore, clean technology investments are increasing in popularity as O&G mutual funds seek investments in clean energy companies due to its environmental friendly character. Additionally, mutual funds remain exposure toward the oil and gas industry when investing in clean technology. These future perspectives make the clean technology sector attractive to invest in.

In this paper, my conducted research regarding sustainable investment performance focuses on the time-varying level of sustainability of oil and gas mutual funds. Specifically oil and gas industry focused, as there could be seen a true rise in these mutual funds adjusting their investments to more sustainable investments. This is because of more oil and gas mutual funds need to satisfy the demand of environmentally conscious stakeholders. The oil and gas sector needs to reduce its carbon footprint to survive. Another reason for this movement toward sustainable investments is the probably higher returns and lower costs of environmentally conscious investments. Moreover, given the increased number of sustainable investments over time, and the need of oil and gas funds to move toward sustainability and the improvement of returns, there is expected to discover that sustainable mutual funds are not underperforming unsustainable mutual funds and are likely outperforming them. Given the increased number of sustainable investment over the past years and the probable increase in experience of mutual funds in these investments we expect to analyze a steady improvement over time relative to unsustainable mutual funds. Accordingly, this study's research question is as follows: *"Do oil and gas mutual funds now generate higher returns when moving toward sustainability?"*

To my knowledge, this is the first research where sustainable mutual funds outperform unsustainable mutual funds, certainly with a focus on the oil and gas industry. One of the main contributions of this paper is that since last year investing in sustainable oil and gas mutual funds is better than investing in unsustainable oil and gas funds. There could be seen a clear tipping point last year. This is contrary to the before mentioned literature of for example Reboredo et al. (2017). The reason for this tipping point could be the disappearing green premium and the increase in the belief of stranded assets. A very important implication of the results is that we can approve that when oil and gas mutual funds are getting experienced with leading sustainable investments in this industry, we find risk adjusted-returns higher than those of the unsustainable oil and gas mutual funds. Moreover, this study is based on monthly varying ESG rating for a huge amount of self-selected mutual funds. This study uses a by far larger dataset than studies used before, which could be mainly attributed to the steep growth in availability of ESG ratings. Furthermore, this research find that sustainable mutual funds tend to experience a small cap effect. This funding is in line with the theory stating this type of stock faces less environmental risks and funds prefer to work with innovative environmental stocks.

The remainder of the paper is laid out as follows. In Section 2, I review the theoretical framework of my research subject. In Section 3, I introduce the data, and Section 4 lays out the details of the research methodology. The main empirical results are reported and elaborated on in Section 5. Finally, in Section 6, I draw conclusions from my research.

2. Theoretical Framework

This chapter contains a concise discussion and overview of current knowledge on the research subject. Section 2.1. starts with previous findings concerning the out- and underperformance of sustainable mutual funds and different sustainability ratings. Section 2.1.1. elaborates theoretically on green premia, 2.1.2. on stranded assets, and 2.1.3. discusses the view of managers and academics on the ongoing transition in the energy sector. In section 2.2 several hypotheses are developed and presented based on the relationship between sustainability and mutual fund performance.

2.1. Literature Review

A few decades ago, sustainable investing was believed to result in lower returns than unsustainable investing. Today, several academics are skeptical of this point of view. Some authors, such as Edmans (2011) and Kempf and Osthoff (2007), found empirical evidence supporting the idea that sustainable mutual funds outperform non-sustainable mutual funds. Durán-Santomil et al. (2019) discovered the positive relation of performance to the degree of a mutual fund's sustainability. This finding corresponds to mutual funds investing in higher rated assets generating better risk-adjusted and not-risk adjusted returns. Other studies, like Utz and Wimmer (2014), Kreander et al. (2002), and Kreander et al. (2005), provide no compelling evidence for outperformance or underperformance of Sustainable Responsible (SR) mutual funds. Climent and Soriano (2011) and El Ghoul and Karoui (2017) found that leading sustainable funds display poorer performance than unsustainable funds. A possible reason for this underperformance is that sustainable mutual funds investment decisions are based on higher quality, deeper and more complete information, resulting in a lower level of risk accompanied by their selected investments. From a theoretical viewpoint, environmental funds accompany higher risk, as the number of stocks available for investment are limited, which could cause the lower return. Another possible explanation is that sustainable funds have risen in value more quickly than unsustainable funds due to an increase in demand caused by more environmental, social and governmental awareness.

In this study, ESG scores were used to measure the level of social responsibility of the SR mutual fund. Wimmer (2012) demonstrated that ESG ratings approximately hold on for two years in SR mutual funds. This finding suggests that investors of these types of mutual funds, who are value driven, seeking ESG investments with high ratings cannot be sure of high ESG scores being retained in the long term. Thus, portfolios occasionally need to be rebalanced. Varying holdings of the SR mutual funds causes ESG scores holding on for the long-term. Furthermore, providing clear boundaries between the ESG scores to designate each fund to a specific score or group is difficult. Therefore, the portfolios are linked to the monthly varying ESG scores on a scale of zero to ten, where the mutual funds are categorized by the corresponding ESG score. Statman and Glushkov (2016) state the difficulty of defining the clear borders between the fund categories as a fund categorized as sustainable by the ESG score database could be one that only excludes tobacco company assets. The same category could count a fund that excludes tobacco company assets in addition to non-ethical assets, also known as “sin stocks”, like weapons, gambling and alcohol. Sin stocks are stocks of firms related to controversial activities that investors often leave alone. The former fund ranks relatively low on the social responsibility scale, while the latter ranks higher, but both are classified as sustainable funds. The difficulty of providing clear differences between the degrees of sustainability in mutual funds is obvious in the inconsistent list of research examining the performance of the different categories of sustainable funds. Gil-Bazo et al. (2010) used the Social Investment Forum to obtain a sample of SRI funds; Wimmer (2012) used this list as well and obtained from the Thomson Reuters Datastream ASSET4 database the ESG ratings for the securities of the fund holdings. Renneboog et al. (2008) used a modified Standard & Poor’s Fund list as their primary data source, while Ibikunle and Steffen (2017) use EIKON. Durán-Santomil et al. (2019) used Morningstar, and Statman and Glushkov (2016) used MSCI-ESG database. The MSCI-ESG is used in this research. In section 3.2 about ESG ratings is further elaborated on why this database is chosen. Contrary to research using a specific SRI list for the whole time period like Gil-Bazo et al. (2010), is that the sustainable mutual funds sample changes monthly with the corresponding ESG score and the enormous number of mutual funds used.

In this research, the sample consists of oil and gas mutual funds linked to their monthly level of sustainability. This is a logical approach as the assets held by sustainable mutual funds differ through time. Moreover, this approach allowed me to find sustainable funds even if they were not labelled specifically as SRI funds. Utz and Wimmer (2014) question the label SRI Mutual Fund, as their research show that sustainable mutual funds do not hold remarkably more ethical assets. Furthermore, the SRI mutual fund label does not ensure that unethical companies are excluded, meaning poor assets are not necessarily screened out. According to the results of Durán-Santomil et al. (2019), a large number of mutual funds are not announced as sustainable while the assets in their portfolio correspond to those of sustainable funds. I compiled my dataset manually and did not extracted it from US SIF or another given SRI mutual fund data list. While this SRI Mutual Fund label does not ensure the composition of the portfolio, the label is important for the value of the portfolio as Bilbao-Terol et al. (2017) indicated. They found a statistically significant and direct causality between the mutual fund's market value and the SRI label. On SRI labels will be elaborated in section 2.1.3. Energy Transition. In line with most research, the journal also provided evidence of the growth in sustainable investing.

2.1.1. Green premium

Bloemers et al. (2001) indicate that consumers are willing to pay a premium for clean energy and state that green premiums for energy prices could increase to more than 30% above the normal energy tariffs. Sustainable investing could also lead to better financial performance and a better risk profile, according to Reboredo et al. (2017), who agree with the concept that a premium is paid for shifting to renewable energy. Firm value is affected by an environmentally friendly image. Green companies are less susceptible to crises and environmental catastrophes, thus earning a premium compared to unsustainable companies (Chan and Walter, 2014). Green investments have more stable cash flows and tend to come with higher risk and a lower discount rate. This leads to a higher value. The green premium that is paid by mutual funds implies that mutual funds pay a higher price for the investment to include in the fund's portfolio. The premium paid will be regained in the long term.

Blumenshine and Wunnava (2010) describe the green premium as how a company's value is influenced by a sustainable representation. Their study suggests that high environmental rated companies have a market capitalization with relatively higher values than similar firms with lower environmental ratings. Thus, investors include environmental factors in the valuation of their stock prices or high environmental ratings add to a company's value. In addition, renewable energy has been achieving competitive and technological advantages against conventional oil and gas companies in the last decades. Energy prices are highly important for sustainable investment projects. Reboredo and Ugolini (2018) discovered a positive relationship between the impact of energy price movements and sustainable energy stock returns. They highlight that oil was crucial for sustainable energy stock returns.

Including renewable energy criteria when selecting portfolios could also negatively influence financial performance or possibly bring in lower risk and higher returns. Markowitz's (1952) portfolio theory suggests that the renewable energy's focus restricts diversification opportunities because the number of available stocks is limited. Thus, divesting fossil fuel stocks could impose inefficiency as the increased risk is not entirely compensated by higher returns. In other words, these funds' risk-adjusted performance are less than for broader focused corporate mutual funds. Furthermore, there are several distinctions in the sustainable mutual funds category. In general, green energy funds invest generally in smaller, newer, and more innovative environmental firms concentrated in several industries, which distinguish themselves from sustainable responsible funds. Sustainable responsible funds principally focus on companies with high ESG scores, and green mutual funds are typified by firms active in industries such as clean technology, renewable energies, and alternative fuels (Lesser et al., 2016).

As renewable energy investments are less appealing than conservative energy investments due to their poorer return and because of high production costs, profitability is required to gain investors' and entrepreneurs' attention. York and Venkataraman (2010) demonstrated that environmental issues clearly represent opportunities entrepreneurs are interested in. Moreover, they found that environmental entrepreneurship is most effective in profit-seeking, new ventures. Furthermore, the higher the uncertainty of the environmental problem, the more likely entrepreneurs contribute to resolving that problem. In addition, the industry focus is why some investors are reluctant to invest in sustainable mutual funds because the investment can lead to overexposure and underexposure in particular industries. Academics are skeptical these industry-focused disadvantages will continue to exist in the near future. A stream of academics is quite negative about the performance of oil and gas assets in the future; they believe the assets will be stranded which will be discussed in the next section.

2.1.2. Stranded assets

Ibikunle and Steffen (2017) argue that the impact of the risk factors on stranded assets will result in lower risk-adjusted returns for unsustainable mutual funds and those unsustainable mutual funds will be outperformed over time by sustainable mutual funds. Examples of risk factors which lead to asset stranding (Ansar et al., 2013) include changing resource landscapes, falling clean technology costs, new government policies, changing social norms, and consumer behavior and environmental challenges. More investors are demanding oil and gas firms to address the fact assets can become stranded. Multiple shareholders demand the relinquishment of the funds' fossil fuel assets in exchange for environmental-friendly alternatives. Jung et al. (2001) mention that the demand and interest of stakeholders in this industry are higher than in other industries. Thus, most of the large petroleum and refining companies have to make substantial sustainable investments, such as cleaning the operating process and technology. Consequently, fossil fuel assets will be converted to liabilities, revalued downward, or written off (Ansar et al., 2013). According to the Carbon Tracker Initiative (n.d.), the world's capital markets are carrying a "carbon bubble," highly related to the presence of unburnable carbon. The carbon bubble implies that fossil fuel shares are inflated for two reasons. First is a false assumption that all fossil fuel reserves will be used, while possibly most of those reserves (60% to 80%) must stay underground to avoid global warming. Second, the true costs of fossil fuels' carbon emissions are difficult to be determined. These circumstances improves the probability of those reserves becoming stranded assets in the future. The inflated fossil fuel shares lead to investors and markets are risking $2.2 trillion of stranded fossil fuel assets with the U.S. as the country with almost a quarter of the global exposure (Carbon Tracker, 2015). Stranded assets will lower portfolio values of institutional investors and thus private investors, as these institutional investors are strongly present in the oil and gas industry (Litterman, 2013).

2.1.3. Energy Transition

According to IRENA (2018), renewable power's way to meet the new generation's needs is increasing in competition. Since the beginning of this decade, the costs of several clean technologies as solar and wind technologies steeply declined in cost and are expected to remain decreasing in costs while the cost price of oil is increasing in the long run. Cleantech invests in both solar and wind power, as well in electric cars and batteries. For example, the global weighted average electricity cost from newly utilized solar PV plants fell by 73% from 2010 to 2017. (NextEra Energy, 2019 April 23). James L. Robo, the CEO of NextEra Energy, stated in January 2018 that solar power will be cheaper than coal and nuclear generation by the beginning of next decade. The energy transition is defined as a transformation of the worldwide energy sector from fossil energy to carbon free energy by the second half of this century, mainly empowered by policies, information technology and market instruments. The transition will be especially focused on the reduction of CO_2 emissions related to energy to restrict climate change. 90% of the needed decline in carbon could be achieved by energy efficiency measures and renewable energy. (IRENA, 2019). Thus, energy companies are changing to low-carbon energy sources and are spinning off and selling carbon-intensive assets and investing in renewable energies. The IEA confirms that renewables contributed to 24% of energy supply in 2017, where hydropower was the largest renewable resource, followed by wind (6%), photovoltaic (PV) solar panels (4%), and bioenergy (3%).

The oil and gas industry deals particularly with the energy transition, due to the nature of their business. There could be seen an enormous absolute increase of oil and gas mutual funds doing sustainable investments in clean technology (cleantech) during the last decade. Not a huge relative increase in sustainable investments could be seen. A possible explanation for this according to Ben van Beurden (2019), CEO of Shell, is that investing in oil will continue as long as the world demands this resource. Moreover, he states that the responsibility to comply with the Paris climate agreement, a UN agreement which deals with greenhouse-gas-emissions mitigation, adaption, and finance, also lies with the end users. As long as diesel cars are sold, diesel must be produced for those cars and not renewable energy. Van Beurden explains new energy activities with yields of 8% to 12% are worthwhile investing. However, in absolute numbers the number of sustainable investments did rise. In the oil and gas industry, investments in cleantech experienced a steep rise during the last several years. Via this route these investment companies buy higher sustainability ratings. According to the US SIF Trend Report (2018), investors considered ESG factors across USD 12 billion of professional managed assets in 2017, which is an increase of 38% since 2016. This number of investments suggests that sustainable investments yield financially competitive returns.

Fossil-free investments are growing in popularity, which reduces the demand for fossil fuel stocks relative to fossil-free stocks. As a result, fossil fuel stocks are underpriced, and fossil-free stocks are overpriced. Dam and Scholtens (2015) mention that the decrease in fossil fuel stock demand makes sharing risk of these stocks limited among funds investing in fossil fuel, which results in an increase in the return demanded for company-specific risk. This risk is accompanied by an increase in the fossil-free investments required rate of return and a decrease in the fossil-free investments required rate of return, suggesting the risk-adjusted returns of fossil-free investments are less than the unrestricted fossil fuel investments. Revelli and Viviani (2015) found sustainable investing does not cause extra costs compared to unsustainable investing. IRENA (2018) states that power from solar, wind, and other renewables are becoming steadily cheaper than the unsustainable oil and gas sources. At the time of the report (IRENA, 2018), the global weighted average costs for electricity from all clean technologies, except concentrated solar power (CSP), fell within the range of fossil fuels. As a result, investors should be aware of fossil-free stocks as a more attractive investment opportunity because they can both, generate high returns and focus on ESG criteria. Thus, investors obtain both financially and socially responsible performances. Revelli and Viviani (2015) noticed a “virtuous circle”, as savings in sustainable funds increase and sustainable companies’ access to financial resources increases. Accordingly, the cost of equity is reduced and the demand and prices for sustainable investments grows. Since the prices are higher for sustainable investments, the gap between sustainable and unsustainable investments increases, which discourages unsustainable investments to put effort in SRI developments (Revelli and Viviani, 2015).

From a cost perfective, onshore wind, if appropriate resources are available, is one of the cheapest sources of sustainable energy. The global weighted average costs of electricity from this type of renewable energy fell by 23% from 2010 to 2017. Wustenhagen and Bilharz (2006) explain the difference in green power purchases to other green product purchases. In contrast, green power clients do not substantially gain another product; the difference is the monetary flows. Green energy clients’ purchasing decisions are seen as a change in the electricity mix. Product characteristics are difficult to validate for clients. This information asymmetry will be overcome by signaling, specifically, the reputation of a supplier or via third-party certification to assure the quality of particular products and reduce complexity (Truffer et al., 2001). Third-party certification can occur through eco-labelling by environmental Non-Governmental Organizations (NGOs). Reduction of complexity and giving guidance via an eco-label could be improved as there are often several different labels used in the same areas, causing labels to compete. Therefore, the acceptance of one eco-label could help. Environmental NGOs in Europe developed highly sophisticated methods to differentiate green power from other types of energy, customers are then guaranteed to buy green power. But this guarantee is not the case for designed green products, also called “dark green” energy. This type of energy is not as green as thought of. These dark green designed energy products increase withholding positions to the belief in a certain eco-label.

Finally, Wustenhagen and Bilharz (2006) state several factors influencing renewable energy market development. First, power marketers seeking ways to distinguish themselves and to best fit customer needs. Via this renewable energy marketing, energy offerings can be differentiated where some of the incumbent utilities and start-ups are looking for. While

energy is a homogeneous product, green power has a relatively distinctive character, according to consumer minds. Second, consumers are willing to pay for renewable energy, but there is huge difference between the actual purchase decision and the declaration of willingness to pay (WTP). This gap identifies a huge green energy market potential. The actual purchase decision is affected by different factors, such as the general behavior of switching consumers in the electricity market. According to Sundt and Rehdanz (2015), the largest WTP per household and per month is in Finland and the US, a higher willingness to pay per household, but a lower willingness to pay per kwh. These countries have low energy prices and a high electricity consumption per capita. Third, the rising demand from non-residential customers, such as government authorities and businesses, is an important purchaser group for green energy. While this group is more sensitive to price changes, the volume of its purchases makes it an interesting market. Last, the absence of government policies strongly influences green power marketing, and policies like tax exemption on the demand-side support the renewable energy market (Wustenhagen and Bilharz, 2006).
Geels (2014) concludes that the resistance and resilience of unsustainable production regimes denies the benefits from expanding sustainable implementations. New technologies are commonly seen as the most important factor influencing the energy transition. Geels (2014) suggests that socio-political conflicts will be crucial for the transition as the fossil fuel companies in countries rich in natural resources are mostly state owned. The low-carbon transition does need to be solved with the state then. However, other researchers and policymakers believe the green innovation will be enough for the entire energy transition.

2.2. Hypothesis Development

The literature review extensively elaborated the relationship between mutual fund performance and sustainability. Several hypotheses were developed based on this relationship and are presented in this section. Previous research clearly states that sustainable investing results in lower returns than unsustainable investing for mutual funds, in particular oil and gas mutual funds. However, academics clearly did not prove the outperformance of sustainable oil and gas mutual funds over those more unsustainable while this relationship clearly developed overtime. I first formulated a general hypothesis to solve the more specific hypotheses afterwards.

> H1: Sustainable oil and gas mutual funds outperform unsustainable oil and gas mutual funds.

Ibikunle and Steffen (2017) could not establish a risk-adjusted performance difference between sustainable and unsustainable funds over the full sample period from 1991 to 2014. Kiernan (2001) confirms the first hypothesis and found an outperformance of environmental leaders by 12% from December 1997 to April 2000 due to environmental regulations, lawsuits against oil and gas companies, emission reductions, and strong growth in the renewable energy sector. The first hypothesis is consistent with the fact that the market values sustainable characteristics. The second hypothesis, which is displayed below, shows the relation between investing in oil and gas mutual funds with a high ESG score and in clean technology investments as wind and solar.

H2: Oil and gas mutual funds outperform Clean technology.

Investing in Clean technology has grown in popularity due to the increase in awareness of climate change and in the global need for energy, the possibility of fossil fuel assets being stranded, and the relative cost reduction of clean technology against fossil fuel investments and government subsidies and policies. Clean technology provides for oil and gas mutual funds the opportunity to invest in clean energy companies while remaining exposure toward the O&G industry. There could be seen a true turnaround in recent literature about clean technology as frequently these investment opportunities could be noted as lucrative investment opportunities. Bohl et al. (2012) analyzed the performance of renewable energy stocks between 2004 and 2011 in Germany by splitting the time period into two equal subperiods from 2004 to 2007 and from 2008 to 2011. In the first period, renewable energy stocks outperformed as the mean excess returns and alphas were positive and mostly significant. However, in the second period, the previously outperforming renewable energy stocks now underperformed in the German equity market. These alphas indicate that the renewable energy stocks lost 2% on average monthly on a risk-adjusted basis. According to Bohl et al. (2012), German clean technology seems profitable as the country has pledged to close its nuclear power reactors by the end of 2022 and the sustainable energy transition is highly encouraged. However, there is overcapacity in the German solar sector, which strongly reduces the profitability of the clean technology industry. Gaddy et al. (2017) used venture capital firms' investments in clean technology to compute the risk and returns by comparing the clean technology investments to investments in the medical and software technology sector. They stated that less than half of the $25 billion spent by venture capital firms to fund cleantech start-ups from 2006 to 2011 was returned. Furthermore, it warns that without new energy technologies climate change cannot be confronted cost-effectively. Thus, in case of technological innovation, it is important to decide whether innovations are within reason as Gaddy et al. (2017) find that cleantech offers high risk and low returns to investors. According to them, this low return and large required capital is mainly due to long associations with new hardware, materials, chemicals, and the manufacturing process. They believe that stimulating policies, corporations, and investors are necessary for innovation. De Cian et al. (2016) studied the relationship between energy investments and clean energy innovation. They found faster convergence of income across countries and economic growth are important matters for clean energy innovation. The analysis indicates that the availability of fossil fuel mainly drives low carbon energy improvement investments as the scarcity stimulates the innovation and non-fossil-fuel investments. Thus, innovation opportunities can be created by accommodating the prices of fossil fuels.

Inchauspe et al. (2014), Hofman and Huisman (2012), and Ortas and Moneva (2014) discovered the same turn in performance since the financial crisis, while using different indices. They found that before the crisis clean technology overperformed, but since the crisis, clean technology underperformed in the market indices. These results prove that renewable investments are cyclical during these periods: returns were low during the financial crisis and high during the non-crisis timeframe. Inchauspe et al. (2014) proved the renewable energy sector underperformed the stock market indices after the financial crisis, suggesting the renewable energy sector has decreased in attractiveness in the years after the financial crisis, from 2009 to 2013. As a result of a substantial lower oil price and subsidy post financial crisis, uncertainty regarding positive returns in the renewable energy sector rose (Inchauspe et al., 2014). However, renewable energy investments experienced immense growth during this decade. According to Inchauspe et al. (2014), this increase was caused by government policies, increases in oil prices, and growth in liquidity in renewable energy investments. Hofman and Huisman (2012) conducted research on the influence of the financial crisis on renewable energy investing, the same field as Inchauspe et al.'s (2014) research. They suggest that renewable energy might have become unpopular for private equity investors and venture capital firms as the financial crisis forced certain governments to cut subsidies. These developments will probably influence renewable energy investor preferences. Ortas and Moneva (2014) covered the primary worldwide energy market by measuring the financial performance of 21 primary clean technology equity indices. They suggest that during periods of market stability, clean technology financially outperforms the market portfolio. This outperformance is due to clean technology companies on average being associated with higher risk. Furthermore, the study suggests when investments in cleantech companies are restricted. their finances underperform in the market portfolio. However, according to Ortas and Moneva (2014), clean technology investments are likely to grow in the future given the development of low-carbon economies. They explain the underperformance is caused by geographically restricted investment indices being less profitable than more geographically diversified indices. Therefore, my study was conducted with U.S. factors and global factors for pricing the excess returns to compare the results to test both geographic investment scopes. The third hypothesis is similar to the first hypothesis but is evaluated over time. Ibikunle and Steffen (2017) state that the risk-adjusted return of sustainable funds improves progressively over time. Since the investment opportunity set is growing for this category, leading to a decrease in costs during recent years, returns may already be higher. Ibikunle and Steffen (2017) suggest that unsustainable funds are beginning to be significantly outperformed by sustainable funds, especially over the years from 2012 to 2014.

H3: Sustainable oil and gas mutual funds increased in performance during the last years relative to unsustainable oil and gas mutual funds.

The fourth hypothesis was developed based on the probable existence of the small cap effect. Gregory et al. (1997) examined the portfolio holdings of sustainable funds by analyzing their financial returns and found that sustainable investments were skewed toward smaller market capitalization companies, which indicates the small cap effect. They questioned whether the exposure of ethical trusts is greater to the small firm effect than non-ethical trusts. According to them, ethical trusts have greater exposure to the small firm risk than general trusts. Cortez et al. (2012) explains that sustainable mutual funds are strongly exposed to small capitalization companies due to their frequent investing in ESG friendly stocks and Clean technology stocks. Small cap stocks face fewer environmental risks and reasonably the funds' holdings are bent toward environmental innovative investments. Furthermore, their findings state that large firms are more likely to be excluded from the portfolios implied by the social screening process. Climent and Soriano (2011) observe that the average sustainable fund is heavily exposed to small capitalization stocks.

H4**:** Sustainable mutual funds experience a small cap effect.

3. Data

This chapter describes the selected sample criteria and the logic behind. The chapter is divided in four sections. First, in section 3.1. the portfolio composition and diversification of the portfolios is explained. Subsequently, in section 3.2. different sustainability rating providers are compared and characterized. Next, in section 3.3. elaborated is how I got to the final mutual fund dataset. Finally, in section 3.4. the market indices are chosen.

3.1. Portfolio composition

Derwall (2007) used the U.S. Social Investment Forum's institutional member firms provided by Bloomberg (US SIF Mutual Fund Performance Chart, 2019) to identify sustainable mutual funds. My study uses a far broader dataset of mutual funds stemming from several sources, while focusing on the oil and gas industry.

To evaluate oil and gas mutual fund performance, the funds were split into portfolios by matching them to the corresponding time-varying monthly ESG scores. The ESG portfolios were chosen by dividing the entire ESG rating dataset into three equal parts, given the return corresponding to the specific ESG rating was available. The portfolio of the lower third, the most unsustainable mutual funds, is labeled as "laggards." The middle portfolio is called "neutrals," and the highest, most sustainable portfolio, is named "leaders."

Table 1: *Sample construction*

Omitting criteria	**N**	**Omitted data**
	278,351	
CUSIP code unknown		74
	278,277	
May and June 2019 data unavailable for FF factors		15,042
	263,235	
If return unavailable		29,530
	233,705	

With 'omitting criteria' is meant the criteria due to which data has been omitted. 'N' represent the number of data points left over in the sample and 'Omitted data' gives the amount of data omitted due to the criteria. Before the 'start sample' of 278,351 only mutual fund data with an available ESG rating has been selected.

In table 1 the sample construction process from the start sample, consisting of all available oil and gas mutual funds with an available ESG rating in the MSCI ESG Research LLC (2019) database, to the final sample of 223,705 data points is shown. Funds with a life span of less than 12 months were omitted before the start sample. As could be seen in table 1, data has been omitted if returns were unavailable. This could be directly linked to dead mutual funds who were excluded from the dataset as soon as its returns were unavailable. It could also be the case that mutual funds were raised during the sample period, for these funds the returns were unavailable at the start. Every month there are added new available oil and gas mutual funds to this sample. The dataset of oil and gas mutual funds is refreshed per month based on the SIC codes for the oil and gas industry.

The mutual fund data was extracted from the CRSP Survivor Bias Free US Mutual Fund Database, containing holdings of the funds from May 2016 to April 2019. I started by extracting the entire mutual fund database for this time span, then linked the mutual funds to SIC codes per month by using CRSP/Compustat Merged. The SIC codes made it possible to narrow the selection of funds to the oil and gas industry. Funds with SIC codes containing the words “oil,” “(natural) gas,” and ”(renewable) energy” were selected from the entire dataset. Furthermore, the sample was narrowed down by another criterion. I classified the global funds by the Lipper asset type, equity, which filters the investing funds in the stock market. In addition, there were employed only open-ended funds as Climent and Soriano (2011) do. Moreover, the CRSP database is survivor bias free, and survivor bias was avoided in the final sample as liquidated and merged mutual funds were kept in the dataset, in addition to active funds. Thereafter, I acquired the funds’ CUSIP and ISIN codes, via CRSP and FactSet respectively, to find the related returns of the security’s price performance over the range requested. ESG ratings are linked to mutual funds and its returns via the corresponding ISIN codes and dates. Funds with a life span of less than 12 months were omitted from the dataset. The portfolios are constructed with equal weighted least squares where the weight, 1 divided by the total number of funds, is multiplied by the mutual fund return. Small funds tend to outperform large funds and a larger part of the leading sustainable mutual funds are small. It is likely to believe that if a value-weighted portfolio was constructed the returns would have been higher for the leading sustainable portfolio and for the laggards vice versa. Thus an equal-weighted portfolio outperforms a value-weighted portfolio in terms of mean return.

The dataset consisted of 7,166 unique mutual funds, and each portfolio had at least 2,000 mutual funds at any time. With more than 30 mutual funds per portfolio, the portfolio is perfectly diversified and there is no reduction in systematic risk anymore if the number of mutual funds will be increased (Fisher & Lorie, 1970). The portfolios varied monthly in number of mutual funds per portfolio and by the presence of the specific mutual funds per portfolio. Nevertheless, all three portfolios remained equally distributed through the whole time period.

3.2. ESG Rating

The MSCI ESG Research LLC (2019) database was chosen in this research due to its out of the ordinary large number of available ESG scores and extremely wide range of available mutual funds for the oil and gas industry. MSCI's ESG scores are revised monthly and its fund holdings (constituents and weights) are updated monthly. In addition, the metrics are fund-level instead of company-level, like most databases. Furthermore, the database provides access to a dataset of approximately 32,000 multi-asset class mutual funds. Approximately 24,000 funds were available as of March 2016, which is the start of the dataset used in this research and the database itself. MSCI ESG scores cover over 600,000 fixed income and equity securities globally, and its holdings data was sourced from Thomson Reuters Lipper and accessed via FactSet. The score evaluates the resilience of a fund's holding collection to long-term ESG risks. High ESG score rated fund holdings are characterized by leading or improving management of key ESG risks. These scores are based on a granular breakdown of the core product or business segments, the location of its revenues or assets and other measures as outsourced production. The leading ESG funds invest in companies that exhibit improving and/or strong management of relevant ESG issues in a financial way. These firms are more flexible to turmoil arising from ESG related issues (MSCI ESG Research LLC, 2019). The ESG scores range from zero to ten, with zero and ten being the smallest and largest possible fund rating, respectively. A mutual fund had to pass the following criteria to be included in the dataset: 65% of the gross weight of the fund must come from covered securities, the date of the fund holdings must be less than one year old, and funds must have at least ten securities. The top fund-level factor, the Fund ESG Quality Score, was calculated as the underlying holding's overall ESG scores' weighted average.

Many ESG rating providers entered the market in recent years. This study compares Morningstar Direct, Eikon, CSR Hub, ASSET4, Sustainalytics, and MSCI ESG Research. The latter two providers had the largest dataset. During my conducted research on the Morningstar Direct and Sustainanalytics databases I found three pros and one clear con. Firstly, Morningstar Direct, which includes the data of Sustainalytics, only allowed me to extract current sustainability scores and not time series data. Secondly, Morningstar measures its rating relative to portfolios within the same Morningstar category, but none of the categories exactly fit the oil and gas industry, which would lead to incorrect sustainability ratings. Thirdly, Sustainalytics's screening option was not precise enough for our industry focus. In contrast, Sustainalytics is not issuer based, but is investor based as investors pay a yearly subscription. This does not leads to rating inflation as the ratings offered are not influenced by incentives to gain business from the issuer. Wimmer (2012) used the ASSET4 ESG database for a comparable study. His dataset consists of 27 mutual funds, with a fund composition of totally 276 with yearly ESG ratings availability. Disadvantages of this database are that it provides ESG ratings for only circa 7000 companies and that the data was provided on company level instead of fund level. On the other hand, ASSETS4 ESG does provide longer time spans of data. Furthermore, the CSR Hub database does not contain mutual funds and only offered 1585 companies in the category "Utilities & Refining" which is not the focus of this research.

3.3. Market Indices

The monthly returns necessary for the four-factor model (R_{mkt}, R_{smb}, R_{hml}, R_{mom}), Kenneth R. French world, and U.S. market factors were obtained from Kenneth R. French's website (2019). The excess market return was calculated by subtracting from the market return the risk-free rate. The market return was calculated as the value-weighted return on all NASDAQ, AMEX, and NYSE stocks from CRSP. The one-month T-bill rate from Ibbotson Associates was used as the risk-free rate. The WilderHill Clean Energy Index (ECO) was used as a benchmark for a cleantech Index. This clean technology benchmark index was used in several studies related to cleantech, such as Ortas and Moneva (2014) and Inchauspe et al. (2014) and WilderShares (n.d.). The Clean Energy Index uses a modified equal dollar weighting methodology, and its priority is to define and track the clean energy sector, more specifically, businesses that stand to gain from a societal transition to the use of cleaner energy and zero CO_2 renewables. First, stocks within the index are based on the relevance to preventing pollution, their significance regarding technological influence and clean energy. The FTSE Global Small Cap was created to benchmark the performance of liquid small capitalization stocks. This specific benchmark was used to examine the tendency of sustainable oil and gas mutual funds toward small capitalization stock. Cortez et al. (2009) and Luther and Matatko (1994) found evidence of sustainable funds having greater exposure to small capitalization companies than the more conventional ones. Several specialty indices were used as benchmarks as well. For example, to benchmark the oil and gas index market factor, the CRSP US Oil and Gas Index was used. This index has industry-specific oil and gas characteristics of the companies listed in the CRSP US Total Market Index. The other oil and gas market indices used as robustness checks (Appendix B) are the FTSE US Oil & Gas, FTSE All Cap US Oil and Gas and the S&P/TSX Equal Weight Oil and Gas. The FTSE US Oil & Gas comprises all oil- and gas-related stocks trading on the FTSE index. FTSE All Cap US Oil and Gas is a weighted-market cap index representing the performance of large, medium, and small cap stocks. This index comprises around 8,000 stocks. The latter index, S&P TSX Equal Weight Oil and Gas, supports investors with an oil and gas industry related portfolio of securities. Members are in the following subindustries: storage, drilling, equipment and services, exploration and production, refining and marketing, and storage and transportation of oil and gas and integrated oil and gas. This index mostly concerns Canada and the U.S..

4. Methodology

This chapter provide measurement methods to test the different research hypotheses reviewed in Section 2.2. In section 4.1. I briefly discussed the robust variance estimate.

To estimate performance differences between fund categories, the empirical sustainable investing literature stream can be divided into three types. First is the matched-pair analysis approach used by Climent and Soriano (2011) and Kreander et al. (2005). This approach has several shortcomings, for example, the dataset consists of fewer funds because finding mutual funds that entirely match in fund age, fund size, and investment objective is difficult.

Ultimately, this matching procedure will lead to losses in return data (Climent and Soriano, 2011). Kreander et al. (2005) used the matched-pair analysis as well, which contributes to their sample suffering from survivorship bias. Furthermore, this method could overstate the average performance of the funds. Second, Capelle-Blancard and Laguna (2010) based their research on an event study, by examining the market valuation following news of an ESG-related event, which cannot be used for the research question in this paper as financial performances is not linked to specific events here but to a degree of sustainability. The last type of empirical sustainable investing literature compares different categories of funds by analyzing their financial return, alpha, and Sharpe ratio (Renneboog et al., 2008 and Ibikunle and Steffen, 2017). Ibikunle and Steffen (2017) conducted a comparative analysis using a dynamic mean-variance model to investigate financial performance between conventional funds and SRI. Ito et al. (2013) also employed the dynamic mean-variance model but used a shortage function approach to analyze the performance of environmentally friendly funds and SRI.

This research was conducted with monthly varying portfolios according to their ESG rating. This method has not been used to my knowledge, although it is logical for a large sample. However, the strategy has likely not been implemented before due to the lack of the granularity in the available ESG data. In this study, mutual fund performances were compared using several robustness checks and analyzing the risks and returns of mutual funds simultaneously. Different portfolios were analyzed to test whether they could deliver excess risk adjusted-returns by using the Sharpe ratio (1966), the one-factor CAPM model (Fama and French, 1992) and the four-factor augmented with the Carhart (1997) momentum factor

CAPM model. The performance of sustainable to unsustainable mutual funds was studied using time-series returns of an equally weighted mutual fund portfolio. The performance of the fund portfolios was analyzed with U.S. market benchmark factors as the mutual funds used in this sample are all U.S. funds. The mutual fund data set consisted of solely U.S. funds, so their returns were computed via dollar prices and the risk-free rate used was the one-month U.S. Treasury Bill.

Treynor (1965), Sharpe (1966), and Sand Jensen (1968) were some of the first successful academics in the field of performance measures. Now, risk-adjusted returns are widely accepted as a convenient measure to compare investment alternatives. The econometric methodology used is based on regressions from unbalanced random panel data. This approach stems from Michael Jensen, who examined the CAPM-based alpha measure. This alpha measure regresses the risk-adjusted abnormal return on the excess market return.
The following Jensen (1968) CAPM one-factor model was estimated:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,mkt}(R_{m,t} - R_{ft}) + \varepsilon_{i,t} \quad (1)$$

The excess return of fund *i* in month *t* corresponds to subtracting the risk-free rate in month *t* ($R_{f,t,}$) from the return of fund *i* in month *t* ($R_{i,t}$). α is the one-factor adjusted portfolio return, and $\beta_{i,mkt}$ measures the portfolio's exposure to the market risk. The one-factor portfolio was extended by implementing a dummy variable category to control for differences in performance of the sustainability portfolios. I controlled for the categories laggards, neutrals, and leaders to determine the overperformance or underperformance in one of the three categories implemented in the one-factor CAPM model:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,mkt}(R_{m,t} - R_{ft}) + \delta_{i,CAT} D_x^{cat} + \varepsilon_{i,t,} \quad (2)$$

where $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories on fund *i*, and D_x^{cat} is a dummy variable, which takes the value 1 if the mutual fund applies to category laggards, neutrals, or leaders and 0 otherwise. The one-factor CAPM model is often criticized because of its failure to explain the expected stock returns. Therefore, performance was also analyzed using the three-factor model from Fama French (1993) supplemented with the Carhart (1997) momentum factor:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,mkt}(R_{m,t} - R_{ft}) + \beta_{i,smb}R_{smb,t} + \beta_{i,hml}R_{hml,t} + \beta_{i,mom}R_{mom,t} + \varepsilon_{i,t} \qquad (3)$$

This four-factor model includes the factors for market (mkt), size (smb), book-to-market (hml), and momentum (mom), where $\beta_{i,mkt}$, $\beta_{i,smb}$, $\beta_{i,hml}$, and $\beta_{i,mom}$ are the coefficients measuring the market-risk, small firm effect, value premium. and the fund i momentum impact, respectively. $R_{smb,t}$ is the return spread between a small and large cap portfolio at time *t*, $R_{hml,t}$ is the return difference between a growth and value stock portfolio at time *t*, obtained by computing the difference between a high and low book-to-market ratio. $R_{hml,t}$ is the return difference between a last 12-month winners portfolio and a last 12-month losers portfolio at time *t*. As in the CAPM one-factor model, I controlled the four-factor model for the portfolio categories laggards, neutrals and leaders with the following equation:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_{i,mkt}(R_{m,t} - R_{ft}) + \beta_{i,smb}R_{smb,t} + \beta_{i,hml}R_{hml,t} + \beta_{i,mom}R_{mom,t} + \delta_{i,CAT}D_x^{cat} + \varepsilon_{i,t} \qquad (4)$$

Finally, the Sharpe (1966) ratio is used to measure the portfolio excess return relative to the risk which has been taken, it shows the reward to the risk of the portfolio. The higher the funds Sharpe ratio the better returns have been relative to the amount of investment risk it has taken. For example, if the Sharpe ratio is 1, the return on investment is proportional to the risk taken. A Sharpe ratio lower than 1 means that the return on investment is lower than the risk taken. The ratio focuses on the standard deviation (total risk) instead of the market risk which is measured by the beta of the mutual fund. The ratio is calculated by the excess return of fund *i*, which corresponds to subtracting the average risk-free rate ($\bar{R}_{f,}$) from the average return of fund *i* ($\bar{R}_i$), divided by the standard deviation of fund *i* (σi).

$$\text{Sharpe ratio} = \frac{\bar{R}i - \bar{R}f}{\sigma i} \qquad (5)$$

4.1. Sandwich Variance Estimator

The dataset is an unbalanced panel, as it is common for the mutual funds in this type of dataset to not exist throughout the entire sample period. First, I relied on Ordinary Least Square coefficient estimated with PCSE (Panel Corrected Standard Error). Ordinary least squares is used to estimate the unknown parameters in a linear regression model. The PCSE is used to deal with autocorrelation, heteroscedasticity, and cross sectional dependence in the panel data (Beck and Katz, 1995) as earlier studies applied this methodology. Beck and Katz (1995) also mention the Parks estimator as a substitute for the PCSE estimator; however, the PCSE estimator should have finite sample advantages. Nevertheless, it did not fit the research approach as this study uses an exceptional large N, which is uncommon in similar research. However, the dataset consists of a small T, similar to previous research, as ESG rating data is a recently developed concept. When the N is large compared to T, the PCSE estimator properties are poor. Beck and Katz's (1995) PCSE estimates the entire N x N covariance matrix and leads to an inaccurate estimate if N is large and T is small. Both the PCSE and the Parks method experience the same shortcoming, so neither can be used if the length of the time frame T is much smaller than the number of mutual funds N.

In the end, I obtained a robust variance estimate, which deals with correlation within clusters by using the sandwich estimate of variance from Huber (1967) and White (1980). White (1980) presents the conditions under which a consistent estimator of the OLS parameter covariance matrix can be achieved. Hereby, in favor of the model-agnostic robust variances I forgo model-based variance estimates. The model is heteroscedasticity-consistent and directly tests for heteroscedasticity. Besides, I checked for non-linearity and there has been checked for outliers to know if there were no wrong data points for example. The estimator is independent of the formal model of the structure of the heteroscedasticity. The estimate is named "sandwich" because the mathematical model calculates the estimate as the product of three matrices. The correction matrix is thus "sandwiched" between the model-based variance matrices. Williams (2000) presents a proof that states that this estimator is unbiased for cluster-correlated data regardless of where it is applied.

5. Results

The analysis and discussion on the empirical results of this research are included in the following section. This chapter is divided in three sections which each present and discuss different findings. For each of the fund categories is the CAPM regression presented, with different market indices used. This is done in section 5.1. for the one-factor CAPM regression and in section 5.2. for the Carhart four-factor model. Finally, in section 5.3. multiple robustness checks are conducted. Before diving into the statistical results, details of the dataset's descriptive statistics are provided in table 2.

When analyzing the average mean portfolio returns and the market returns there could be seen no surprises. The average portfolio mean returns are not systematically higher than the market indices. Moreover, the leaders portfolio shows a lower average return than the market indices in general, this shows that this portfolio is indeed a growth portfolio.

Table 2. *Descriptive data statistics for sample period 2016-2019*

Return

Portfolio	Mean(%)	Sd.(%)	Min.(%)	Max.(%)	Skewness	Kurtosis	Annualized Mean(%)	Sd. ann.(%)	N	Age (mo.)
Laggards	0.97	4.11	-33.77	35.74	-0.44	63.18	12.28	14.24	77,902	32.00
Neutral	0.96	3.34	-30.85	30.55	-0.79	71.72	12.15	11.57	77,902	31.83
Leaders	0.85	3.52	-26.85	27.70	-0.73	51.63	10.69	12.19	77,902	31.53

Excess portfolio return

Portfolio	Mean(%)	Sd.(%)	Min.(%)	Max.(%)	Sharpe ratio
Laggards	0.88	4.12	-33.96	35.55	0.21
Neutral	0.73	3.53	-27.04	27.59	0.21
Leaders	0.86	3.35	-31.04	30.34	0.26

ESG rating

Portfolio	Mean	Sd.	Min.	Max.
Laggards	4.12	0.36	1.41	4.82
Neutral	4.87	0.25	4.32	5.53
Leaders	5.60	0.47	4.75	8.73

Table 2 reports the descriptive statistics of the return, excess portfolio return and the ESG rating for each of the three portfolio categories. For the equally distributed portfolios the number of mutual funds are shown in column '*N*', comprising a total of 233,705 unique data points over the full sample period from May 2016 to April 2019. In the last column, the age is displayed in months calculated by taking the average of the funds in the portfolio, varying across the portfolios, with the corresponding ESG score. In the excess portfolio return part the Sharpe ratio is also shown besides the mean, standard deviation, min. and max. For the ESG rating, the mean, standard deviation, min and max are both presented in absolute numbers.

The annualized mean risk-free rate used in this study is 1.25% and monthly 0.1%. When comparing these descriptive data statistics to related literature as Ibikunle and Steffen (2017) and Kreander et al. (2005) there can be conclude that the data used is plausible. The standard deviation is slightly lower which could be due to the larger sample used.

The most unsustainable portfolio (laggards) with an ESG score mean of 4.12 and a standard deviation of 0.36 over the entire sample period indicates the largest mean return for the most unsustainable mutual funds. Relying on these statistics, the lower the ESG score, the higher the profitability. Thus, while the standard deviation of the ESG score is the largest for the most unsustainable portfolio, this portfolio may experience the largest movements. This research displayed in table 1 documents that the Sharpe (1966) ratio of the leaders portfolio is higher than for the laggards portfolio, respectively 0.26 and 0.21. This suggests that oil and gas investors who want to optimize the mean-variance prefer investing in leading sustainable mutual fund portfolios. The higher the funds' Sharpe ratio, the better the returns have been relative to the amount of investment risk taken.

Table 2.1. *Summary statistics market indices*

Market Index	**Mean(%)**	**Sd.(%)**	**Min.(%)**	**Max.(%)**	**Skewness**	**Kurtosis**	**Annualized Mean(%)**	**Sd. ann.(%)**
Value-weighted return on all stocks of the NYSE, AMEX and NASDAQ indices	1.22	3.32	-9.36	8.62	-1.13	5.56	15.72	11.51
S&P500	1.01	3.17	-9.18	7.87	-1.15	5.47	12.86	10.97
The WilderHill Clean Energy	1.23	5.41	-11.76	19.17	0.63	5.17	15.81	18.74
CRSP US Oil & Gas	0.72	3.61	-10.35	10.31	-0.90	5.97	8.94	12.49
FTSE Small Cap	0.96	3.00	-8.00	7.68	-1.12	5.44	12.09	10.40
SMB	0.00	0.03	-0.05	0.06	0.33	2.38	0.00	0.09
HML	0.00	0.03	-0.04	0.08	1.07	4.39	-0.05	0.09
MOM	0.00	0.03	-0.09	0.05	-0.42	3.89	0.00	0.10
FTSE US / Oil & Gas	0.06	5.60	-13.50	11.49	-0.33	3.49	0.76	19.41
FTSE All Cap US / Oil & Gas	-0.38	5.95	-12.81	14.87	0.13	3.40	-4.51	20.60
S&P/TSX Equal Weight Oil and Gas	-0.63	6.09	-12.81	14.87	0.18	3.20	-7.25	21.09

Table 2.1. shows per market index used in this study the data statistics. The data statistics comprises the mean, standard deviation, minimum, maximum, skewness, kurtosis, annualized mean and standard deviation.

In table 2.1 the market indices used are displayed. Also the specific oil and gas indices are added to the summary statistics table. By analyzing table 2 and comparing this to the standard U.S. stock market benchmark, the S&P 500 in table 2.1., we can see that neutral mutual funds have about the same average return as the S&P500 market return. Unsurprisingly, laggards have higher return than the market data and leaders have lower return than the market data. This is unsurprising as the average return over the entire sample period of three years is taken. In table 2.2. the three year sample period is broken up in years. For the period 2018 to 2019, I find an average higher return for leaders than for laggards. This is the opposite of the years before this sample period. This is because of the recent tipping point for the returns of leading sustainable mutual funds which is demonstrated in this study. This tipping point could be seen when analyzing table 2.2. The tipping point could be seen as well in table 14 which is later elaborated on.

Table 2.2. *Descriptive data statistics per year for 2016-2019*

Return 2016-2017									
Portfolio	**Mean(%)**	**Sd.(%)**	**Min.(%)**	**Max.(%)**	**Skewness**	**Kurtosis**	**Ann. Mean(%)**	**Sd. ann.(%)**	**N**
Laggards	1.21	3.12	-20.15	35.56	0.97	6.57	15.52	10.81	24,446
Neutral	1.23	2.11	-10.57	22.90	0.49	5.47	15.80	7.31	24,446
Leaders	1.20	2.13	-10.94	22.52	-0.07	5.47	15.38	7.38	24,446
ESG rating 2016-2017									
Portfolio	**Mean**	**Sd.**	**Min.**	**Max.**					
Laggards	4.13	0.33	2.07	4.56					
Neutral	4.82	0.16	4.56	5.13					
Leaders	5.61	0.39	5.13	8.01					
Return 2017-2018									
Portfolio	**Mean(%)**	**Sd.(%)**	**Min.(%)**	**Max.(%)**	**Skewness**	**Kurtosis**	**Ann. Mean(%)**	**Sd. ann.(%)**	**N**
Laggards	1.19	3.03	-20.77	20.96	-0.24	5.13	15.52	10.50	28,014
Neutral	1.07	2.45	-26.56	27.46	-0.28	6.56	13.62	8.49	28,014
Leaders	0.87	2.56	-13.53	27.70	-0.05	4.79	10.95	8.87	28,014
ESG rating 2017-2018									
Portfolio	**Mean**	**Sd.**	**Min.**	**Max.**					
Laggards	4.08	0.35	2.07	4.56					
Neutral	4.86	0.17	4.56	5.13					
Leaders	5.60	0.41	5.13	8.36					
Return 2018-2019									
Portfolio	**Mean(%)**	**Sd.(%)**	**Min.(%)**	**Max.(%)**	**Skewness**	**Kurtosis**	**Ann. Mean(%)**	**Sd. ann.(%)**	**N**
Laggards	0.28	6.17	-33.77	35.74	-0.42	3.52	3.41	21.37	25,442
Neutral	0.42	5.24	-30.85	30.55	-0.53	3.60	5.16	18.15	25,442
Leaders	0.71	4.50	-26.85	26.92	-0.70	3.68	8.86	15.59	25,442

ESG rating 2018-2019				
Portfolio	**Mean**	**Sd.**	**Min.**	**Max.**
Laggards	4.10	0.35	1.41	4.56
Neutral	4.85	0.16	4.56	5.13
Leaders	5.69	0.43	5.13	8.73

Table 2.2. shows for the sample periods 2016 until 2017, 2017 until 2018 and 2018 until 2019 the Returns and ESG rating data statistics. The data statistics comprises the mean, standard deviation, minimum, maximum, skewness, kurtosis, annualized mean and standard deviation and N (observations) for the returns. The statistics comprises the mean, standard deviation, minimum and maximum for the ESG rating.

As could been seen in table 2.2. there are many observations per category each year. Each portfolio has the same amount of observations at the start of the year as the entire dataset is divided in three equal parts. The dataset varying monthly but not per model which is why I only stated the amount of observations in table 2.2. and not per table.

5.1. One-Factor CAPM model

For each of the three portfolios, the CAPM regression results are presented in the tables displayed in this section using the Kenneth R. French U.S. market factors. In tables A1 to A5 from Appendix A the results are shown for the one-factor CAPM model with the Fama French world factors. In tables A6 to A12 from Appendix B the results are shown for the four factor CAPM model with the Fama French world factors. Panel A shows the results from the estimation of equation (1) for each portfolio category separately. Panel A is estimated without the dummy variable which controls for categories. Panel A uses the formula in equation (1), the Jensen (1968) CAPM one-factor model for each category separately. Panel B presents results found using equation (2) for each category separately, controlled for category dummies.

Table 3 indicates that the whole sample of oil and gas mutual funds, each of the three portfolios, significantly underperforms the U.S. stock market benchmark. The laggards portfolio has a larger underperformance than the underperformance of the leaders portfolio, which could be expected. But the least underperformance for the neutral portfolio was not to be expected. The high beta for laggards of 1.12 could be related to the broad market proxy used.

Table 3: *One-factor | Value-weighted return on all NYSE, AMEX, and NASDAQ stocks*

Panel A	α		β_{MKT}		R^2_{ADJ}
Laggards (1)	-0.38***	(-50.73)	1.12***	(259.65)	0.69

	α		β_{MKT}		δ_{LAGG}	δ_{NEUTR}	δ_{LEAD}	R^2_{ADJ}
Neutrals (2)	-0.26***	(-41.54)	0.95***	(262.20)				0.80
Leaders (3)	-0.31***	(-42.95)	0.82***	(201.76)				0.76
Panel B	α		β_{MKT}		δ_{LAGG}	δ_{NEUTR}	δ_{LEAD}	R^2_{ADJ}
Laggards vs. (2) and (3)	-0.31***	(-40.34)	0.94***	(318.14)	/	0.05*** (5.37)	0.01 (0.57)	0.73
Neutrals vs. (1) and (3)	-0.25***	(-40.78)	0.94***	(318.14)	-0.05*** (-5.37)	/	-0.05*** (-5.13)	0.73
Leaders vs. (1) and (2)	-0.30***	(-40.93)	0.94***	(318.14)	-0.01 (-0.57)	0.05*** (5.13)	/	0.73

This table reports the results for the CAPM unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A uses the formula in equation (1), the Jensen (1968) CAPM one-factor model. Panel B presents results found using equation (2), which controls for the categories with dummies as one of the three categories implemented in the one-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals, and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The questions are answered by examining the effect of all the excess mutual fund returns on the R_{mkt} and in Panel B, including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the value-weighted return on all stocks of the NYSE, AMEX and NASDAQ indices as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%.

As the dataset was restricted to U.S. mutual funds, the regression was also conducted for the S&P 500, which is considered a typical U.S. market benchmark (Table 4). The S&P 500 could still be too broad, and thus inappropriate, as the dataset is specifically the oil and gas industry. As could be seen in table 4 the most unsustainable mutual funds are still the most market sensitive category, besides this category is highly correlated with the S&P 500. In tables 3 and 4 the ESG-unfriendly funds worst fit the model based on their adjusted R^2, viz., an adjusted R^2 of 0.65. The outcome of this sensitivity and correlation with the market is likely to be true as these funds are highly influenced by other political and economic factors as well.

Table 4: *One-factor | S&P500*

Panel A	α		β_{MKT}		δ_{LAGG}	δ_{NEUTR}	δ_{LEAD}	R^2_{ADJ}
Laggards (1)	-0.12***	(-15.73)	1.14***	(264.55)				0.65
Neutrals (2)	-0.05***	(-8.05)	1.00***	(271.62)				0.80
Leaders (3)	-0.15***	(-19.05)	0.87***	(206.95)				0.77
Panel B	α		β_{MKT}		δ_{LAGG}	δ_{NEUTR}	δ_{LEAD}	R^2_{ADJ}
Laggards vs. (2) and (3)	-0.09***	(-12.05)	0.98***	(334.93)	/	0.04*** (4.25)	-0.03*** (-2.20)	0.71
Neutrals vs. (1) and (3)	-0.05***	(-7.86)	0.98***	(334.93)	-0.04*** (4.25)	/	-0.07*** (7.32)	0.71

Leaders vs. (1) and (2)	-0.12***	(-15.42)	0.98***	(334.93)	0.03*** (2.20)	0.07*** (-7.32)	/	0.71

This table reports the results for the CAPM unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A uses the formula in equation (1), the Jensen (1968) CAPM one-factor model. Panel B presents results found by equation (2), which controls for the categories with dummies as one of the three categories implemented in the one-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals, and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the S&P 500 index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%.

Regardless of the low adjusted R-squared of 0.45 for the leaders and laggards, Panel A in tables 5 and 9 presents negative significant alphas. These alphas will probably become more negative. Not only from an environmental point of view, but from a financial perspective as well. Wind and solar power decrease in costs while fossil fuel energy will only get more expensive in the future. The results of the second hypothesis are provided below. None of the portfolios outperformed the Clean technology index. Thus, the hypothesis "Oil and gas mutual funds outperform Clean technology" could be rejected. This outcome was expected due to the energy transition and efficiencies in clean technology for example.

Table 5: *One-factor | The WilderHill Clean Energy Index (Clean technology index)*

Panel A	α		β_{MKT}					R^2_{ADJ}
Laggards (1)	-0.08***	(-8.70)	0.58***	(207.92)				0.45
Neutrals (2)	-0.13***	(-13.82)	0.46***	(184.45)				0.46
Leaders (3)	-0.40***	(-55.17)	0.39***	(206.17)				0.45
Panel B	α		β_{MKT}		δ_{LAGG}	δ_{NEUTR}	δ_{LEAD}	R^2_{ADJ}
Laggards vs. (2) and (3)	-0.05***	(-5.52)	0.47***	(274.64)	/	-0.08*** (-5.68)	-0.35*** (-28.92)	0.44
Neutrals vs. (1) and (3)	-0.13***	(-14.25)	0.47***	(274.64)	0.08*** (5.68)	/	-0.27*** (-23.49)	0.44
Leaders vs. (1) and (2)	-0.40***	(-55.59)	0.47***	(274.64)	0.35*** -28.92	0.27*** (23.49)	/	0.44

This table reports the results for the CAPM unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A uses the formula in equation (1), the Jensen (1968) CAPM one-factor model. Panel B presents results found by equation (2), which controls for the categories with dummies as one of the three categories implemented in the one-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the WilderHill Clean Energy index as market return.

β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%

Research was conducted for several oil and gas market benchmarks, the FTSE US Oil and Gas Index, the FTSE All Cap US Oil and Gas Index and the S&P/TSX Equal Weight Oil and Gas and the CRSP US Oil and Gas Index (Appendix B). The latter oil and gas index, CRSP U.S. Oil and Gas, indicates the most significant results, which was therefore the only oil and gas index displayed (Table 6).

Table 6: *One-factor | CRSP US Oil & Gas Index*

Panel A	α		β_{MKT}					R^2_{ADJ}
Laggards (1)	0.45***	(55.35)	0.51***	(132.12)				0.44
Neutrals (2)	0.35***	(42.10)	0.38***	(115.01)				0.38
Leaders (3)	0.10***	(12.50)	0.38***	(171.00)				0.43
Panel B	α		β_{MKT}		δ_{LAGG}	δ_{NEUTR}	δ_{LEAD}	R^2_{ADJ}
Laggards vs. (2) and (3)	0.38***	(43.95)	0.42***	(221.73)	/	0.01 (0.36)	-0.23*** (-19.11)	0.41
Neutrals vs. (1) and (3)	0.39***	(42.91)	0.42***	(221.73)	-0.01 (-0.36)	/	-0.23*** (-19.69)	0.41
Leaders vs. (1) and (2)	0.16***	(19.95)	0.42***	(221.73)	0.23*** (19.11)	0.23*** (19.69)	/	0.41

This table reports the results for the CAPM unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A uses the formula in equation (1), the Jensen (1968) CAPM one-factor model. Panel B presents results found by equation (2), which controls for the categories with dummies as one of the three categories implemented in the one-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals, and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the CRSP US Oil & Gas Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%.

According to Table 6, leading sustainable funds have the least outperformance in the full sample period from 2016 to 2019. However, the measuring coefficient of the model fit is small (i.e., the adjusted R^2 is 0.43). In Table 7, the one-factor CAPM regression results obtained with the FTSE Small Cap index as market benchmark are provided. The dummy variables were not included as this analysis has been done to measure the small cap effect discovered by Gregory et al. (1997). The FTSE Small Cap index is used to acknowledge the Leaders portfolio tendency toward small capitalization stocks, which could not be seen as the β_{MKT} are lowest (0.74) for the leaders fund-portfolio and the highest (1.04) for the sustainable laggards. However, Panel B indicates sustainable mutual funds outperform unsustainable mutual funds with a small cap market proxy. Thus, sustainable mutual funds show a positive performance toward small cap stocks, meaning the fourth hypothesis can be accepted.

Table 7: *One-factor | FTSE Small Cap Index*

Panel A	α		β_{MKT}					R^2_{ADJ}
Laggards (1)	0.14***	(18.33)	1.04***	(259.58)				0.72
Neutrals (2)	0.16***	(24.43)	0.86***	(247.78)				0.77
Leaders (3)	0.12***	(13.76)	0.74***	(212.95)				0.73
Panel B	α		β_{MKT}		δ_{LAGG}	δ_{NEUTR}	δ_{LEAD}	R^2_{ADJ}
Laggards vs. (2) and (3)	0.13***	(16.82)	0.86***	(311.12)	/	0.03*** (2.97)	0.08*** (7.05)	0.72
Neutrals vs. (1) and (3)	0.16***	(24.71)	0.86***	(311.12)	-0.03*** (-2.97)	/	0.05*** (5.20)	0.72
Leaders vs. (1) and (2)	0.21***	(24.04)	0.86***	(311.12)	-0.08*** (-7.05)	-0.05*** (-5.20)	/	0.72

This table reports the results for the CAPM unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A uses the formula in equation (1), the Jensen (1968) CAPM one-factor model. Panel B presents results found by equation (2), which controls for the categories with dummies as one of the three categories implemented in the one-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the FTSE Small Cap Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%.

5.2. Carhart four-factor model

Tables 8 through 13 present the multi-factor regression results modeled by the framework proposed by Carhart (1997). For each of the three portfolios, the regression is presented in the tables presented in this section using the Kenneth R. French U.S. market factors. In tables A6 to A12 from Appendix B the results are shown for the four factor CAPM model with the Fama French world factors. According to Cortez et al. (2012), the SRI funds for the U.S. and the world have a tendency toward growth stocks. This finding is in line with the results, as the HML beta is significantly more negative with -0.15, which is logic because the sustainable energy investments have recently experienced a steep growth and the range of sustainable investment opportunities is growing during the last decade. According to Table 8, ESG-unfriendly oil and gas mutual funds invest more in value stocks and less in growth stocks, which could be concluded from the significant positive HML beta of 0.05. In addition, three additional factors increase the R^2_{ADJ} compared to table 3 where the one-factor CAPM was used. Furthermore, the unsustainable portfolio is most sensitive to market risk for the U.S. Fama French factors (β_{MKT} = 0.99) and global Fama French factors (β_{MKT} = 1.08), which is presented in Appendix A, Table A6.

Leading sustainable oil and gas mutual funds invest more in growth and less in value stocks shown by the negative significant β_{HML} of -0.15. This result confirms earlier studies (Kreander et al., 2015 and Gregory et al. 1997) who showed that sustainable funds experience a small cap effect. Panel B from table 7 indicates that sustainable mutual funds show a positive performance toward small cap stocks. This funding is in line with the theory stating this type of stock faces fewer environmental risks and funds prefer to work with innovative environmental characterized stocks. These findings in table 7 using the FTSE small cap index as market benchmark and the related literature (Kreander et al., 2015, Gregory et al. 1997 and Cortez et al., 2012) is in contrast to table 8 which shows that there is no small firm effect for leaders. Table 8 shows that laggards have incorporated more value firms that outperform and leaders more growth firms which underperform. These findings make this table doubtful as it contradicts table 7 and the related literature (Kreander et al., 2015, Gregory et al. 1997 and Cortez et al., 2012). Contrarily, Bauer et al. (2005) found a βHML of 0.2 for a similar benchmark and concluded that unsustainable mutual funds invest significantly in value stocks.

Table 8: *Four-factor | Value-weighted return on all NYSE, AMEX, and NASDAQ stocks*

Panel A	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
Laggards (1)	-0.36***	(-51.77)	0.99***	(-268.99)	0.39***	(-62.18)	0.05***	(-9.87)	-0.09***	(-26.84)				0.76
Neutrals (2)	-0.26***	(-46.25)	0.94***	(-281.74)	-0.01***	(-2.98)	-0.06***	(-13.74)	-0.09***	(-27.94)				0.80
Leaders (3)	-0.41***	(-57.10)	0.82***	(-195.71)	-0.10***	(-42.96)	-0.15***	(-36.89)	-0.09***	(-31.12)				0.77
Panel B	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs. (2) and (3)	-0.31***	(-41.79)	0.90***	(352.09)	10.44***	(27.59)	-2.51***	(-7.68)	-8.49***	(-50.49)	/	0.06*** (6.18)	0.01 (0.80)	0.74
Neutrals vs. (1) and (3)	-0.25***	(-42.41)	0.90***	(352.09)	10.44***	(27.59)	-2.51***	(-7.68)	-8.49***	(-50.49)	-0.06*** (-6.18)	/	-0.05*** (-5.51)	0.74
Leaders vs. (1) and (2)	-0.30***	(-40.36)	0.90***	(352.09)	10.44***	(27.59)	-2.51***	(-7.68)	-8.49***	(-50.49)	-0.01 (-0.80)	0.05*** -5.51	/	0.74

This table reports the results for the Carhart (1997) four-factor unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A uses the formula in equation (3), the Carhart four-factor model (1997). This four-factor model incorporates the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t and was obtained by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12-month winners portfolio and a last 12-month losers portfolio at time t. Panel B presents results found by equation (4), which controls for the categories with dummies as one of the three categories is implemented in Carhart four-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the value-weighted return on all NYSE, AMEX, and NASDAQ stocks as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of respectively, 1%, 5%, and 10%.

Using the four-factor model (Table 9) instead of the one-factor CAPM model (Table 6) improves the model fit for the R^2_{ADJ} of all three portfolios. The intercept of leaders turned negative in contrast to the one-factor model. This underperformance of the leading sustainable portfolio seems logical as this regression is based on data over the complete sample period, while sustainable oil and gas investments were not profitable in the past. This table, as the four-factor model fits more precisely than the one-factor model, presents the answer to the first hypothesis. The first hypothesis is rejected because sustainable oil and gas mutual funds do not outperform unsustainable oil and gas mutual funds.

Table 9: *Four-factor | CRSP US Oil & Gas Index*

Panel A	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
Laggards (1)	0.29***	(37.98)	0.42***	(115.20)	0.31***	(44.29)	-0.21***	(-40.17)	-0.23***	(-61.99)				0.50
Neutrals (2)	0.28***	(30.00)	0.42***	(156.39)	-0.09***	(-20.40)	-0.33***	(-73.48)	-0.17***	(-41.04)				0.43
Leaders (3)	-0.12***	(-14.25)	0.42***	(205.21)	-0.16***	(-55.24)	-0.41***	(-96.88)	-0.11***	(-32.78)				0.49
Panel B	**α**		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs.	0.31***	(34.07)	0.42***	(279.09)	3.72***	(9.46)	-28.74***	(-89.29)	-15.97***	(-96.57)	/	-0.02***	-0.32***	0.45
(2) and (3)												(-1.36)	(-25.81)	
Neutrals vs.	-0.29***	(29.91)	0.42***	(279.09)	3.72***	(9.46)	-28.74***	(-89.29)	-15.97***	(-96.57)	0.02	/	-0.30***	0.45
(1) and (3)											(1.36)		(-23,84)	
Leaders vs.	-0.02*	(-1.93)	0.42***	(279.09)	3.72***	(9.46)	-28.74***	(-89.29)	-15.97***	(-96.57)	0.32***	0.30***	/	0.45
(1) and (2)											(25.81)	(23,84)		

This table reports the results for the Carhart (1997) four-factor unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A uses the formula in equation (3), the Carhart four-factor model (1997). This four-factor model incorporates the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t and was obtained by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12-month winners portfolio and a last 12-month losers portfolio at time t. Panel B presents results found by equation (4), which controls for the categories with dummies as one of the three categories is implemented in Carhart four-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables α measures the relationship between the risk-adjusted abnormal return of the specific category and CRSP US Oil & Gas Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%.

According to table 10, the cleantech index outperforms O&G mutual funds, even the most ESG-friendly mutual funds. Cleantech gives investors the opportunity to gain exposure toward the O&G industry while investing in clean companies. This increases the demand for clean technology investments. Cleantech is an attractive market for mutual funds who are not willing to ignore the O&G industry completely as the investors in these mutual funds do not want the mutual funds to invest in oil and gas directly due to its environment-unfriendly character. By investing in cleantech, the mutual funds do gain exposure toward the oil and gas industry but without the polluting aspect. Additionally, there could be a small green premium. For example when an oil company invests in solar power to capture a green premium in its shares. The underperformance could be due to mutual funds with high ESG ratings avoiding the hidden costs of environmental disasters and corporate social crises. Clean technology characteristics create value apart from that for shareholders and stakeholders, as well for the environment, employees, customers, and local communities (Chan and Walter, 2014). The results of the second hypothesis are provided below in table 10. The hypothesis "Oil and gas mutual funds outperform Clean technology" could be rejected. An interesting result shown in table 10 is the significant negative alpha of -0.59 for the oil and gas mutual funds which are leading in terms of sustainability, as they do not outperform clean technology as well. This argument speaks in favor of the divestment movement, which is in line with the rest of my findings. All stocks in the clean technology index are highly related to clean energy and have relevant influence to avoid pollution (WilderShares, n.d.). This is not the case for the sustainable leaders of oil and gas funds as these funds do not have to be environmentally conscious in theory as their high ESG rating could also be due to high socially and governance scores. In this research we are actually most interested in the environmental aspect of the ESG rating and less in the social and governance aspects. Furthermore, the 'leading' mutual funds do not have to consist entirely of sustainable investments as the ESG rating is a weighted average of the investments of the mutual fund. Moreover, oil and gas mutual funds cannot completely remove their unsustainable oil and gas investments. This is due to institutional investors as mutual funds are strongly presented in the oil and gas industry. This divestment would have high negative impact on the share price and implies a huge loss in value for these mutual funds as the equity percentage in these energy companies held by institutional investors is large (Ansar et al., 2013). For ExxonMobile (NASDAQ, 2019a) this equity percentage is 56.13 % and for Peabody Energy this 91.19 % (NASDAQ, 2019b). Ansar et al. (2013) believe that a very small part of the invested value is to be regained when getting rid of the unsustainable oil and gas investments. Furthermore, they mention the difficulty of estimating the impact of for example institutional investors as mutual funds on the value of energy companies. Institutional investors could not get easily rid of their large oil and gas positions without losing much of its value. These positions are way too large compared to their positions in sin stock investments as gambling for example. When the mutual funds who are holding large oil and gas positions adjust their scope more toward Cleantech, these mutual funds show their environmental awareness and they show at the same time a signal toward the oil and gas industry to change. Table 10 shows thus results in line with the divestment movement of mutual funds in the oil and gas industry.

Table 10: *Four-factor | The WilderHill Clean Energy Index (Clean technology index)*

Panel A	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
Laggards (1)	-0.07***	(-8.80)	0.48***	(199.38)	0.36***	(57.19)	0.15***	(28.72)	-0.83***	(-22.09)				0.52
Neutrals (2)	-0.13***	(-12.57)	0.47***	(190.34)	-0.74***	(-15.94)	-0.09*	(-1.89)	-0.59***	(-16.13)				0.46
Leaders (3)	-0.59***	(-66.62)	0.45***	(179.51)	-0.22***	(-60.65)	-0.25***	(-49.43)	-0.13***	(-4.41)				0.49
Panel B	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs. (2) and (3)	-0.06***	(-6.09)	0.44***	(326.21)	6.23***	(15.77)	-0.63***	(-1.92)	-5.01***	(-29.44)	/	-0.07*** (-5.02)	-0.34*** (-27.34)	0.44
Neutrals vs. (1) and (3)	-0.13***	(-14.25)	0.44***	(326.21)	6.23***	(15.77)	-0.63***	(-1.92)	-5.01***	(-29.44)	0.07*** (5.02)	/	-0.27*** (-23.04)	0.44
Leaders vs. (1) and (2)	-0.40***	(-54.49)	0.44***	(326.21)	6.23***	(15.77)	-0.63***	(-1.92)	-5.01***	(-29.44)	-0.34*** (-27.34)	-0.27*** (-23.04)	/	0.44

This table reports the results the Carhart (1997) four-factor unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A uses the formula in equation (3), the Carhart four-factor model (1997). This four-factor model incorporates the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t and was obtained by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12-month winners portfolio and a last 12-month losers portfolio at time t. Panel B presents results found by equation (4), which controls for the categories with dummies as one of the three categories is implemented in Carhart four-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the WilderHill Clean Energy Index (Clean technology index) as market return. βMKT shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%.

Table 11 provides information on a sustainability trend during the last three years, chiefly in panels A and E. The significant negative β_{HML} explains the growth bias of leading sustainability score funds as sustainable funds tend to have a great exposure to growth stocks. Leaders had a highly significant β_{HML} of -0.27 between 2016 to 2017 and a significant β_{HML} of -0.20 between 2018 to 2019. The results could be related to the increase in economic, political, and social awareness to climate change (Bohl et al., 2012). In panels B, D and F could be seen that the sustainable portfolio performance slowly increases from 2016 until 2019 which is expected. This result is similar to Ibikunle and Steffen (2017) which demonstrates that from 2011 onwards sustainable mutual funds significantly outperform the unstainable funds and those unsustainable funds continuously decrease to considerably underperform the sustainable funds over the years untill 2014.

In this study there is migration between the different portfolios. As could be seen in table 2.2. unsustainable mutual funds are getting relatively more sustainable over time. There is an ongoing change in the ESG rating range per portfolio, which is changing monthly. The ESG rating range generally increased in value over time per portfolio and the number of funds per portfolio remained equally divided over time. This means the portfolios were increasing in sustainability, but the amount of observations in the leaders portfolio did not increase as the portfolios were equally divided. In the model used there needed to be kept the number of funds in the portfolio as equal as possible which is the reason why the portfolios were not tied to a specific ESG rating range over the entire period but were equally divided into three groups.

Table 11: *Four-factor | Value-weighted return on all NYSE, AMEX, and NASDAQ stocks yearly*

Panel A	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
2016-2017														
Laggards (1)	-0.29***	(-31.39)	0.89***	(119.78)	0.30***	(41.05)	0.08***	(13.77)	-0.07***	(-10.57)				0.59
Neutrals (2)	-0.09***	(-11.43)	0.87***	(140.99)	-0.04***	(-8.40)	-0.08***	(-15.41)	-0.03***	(-3.75)				0.53
Leaders (3)	0.21***	(16.86)	0.51***	(41.32)	-0.04***	(-8.26)	-0.27***	(-38.77)	-0.11***	(-7.04)				0.32
Panel B	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs.	-0.10***	(-11.26)	0.82***	(161.20)	0.11***	(25.95)	-0.05***	(-11.77)	-0.07***	(-13.05)	/	0.02	-0.02	0.45
(2) and (3)												(1.46)	(-1.00)	
Neutrals vs.	-0.09***	(-9.78)	0.82***	(161.20)	0.11***	(25.95)	-0.05***	(-11.77)	-0.07***	(-13.05)	-0.02	/	-0.03**	0.45
(1) and (3)											(-1.46)		(-2.27)	
Leaders vs.	-0.12***	(-9.55)	0.82***	(161.20)	0.11***	(25.95)	-0.05***	(-11.77)	-0.07***	(-13.05)	0.02	0.03**	/	0.45
(1) and (2)											(1.00)	(2.27)		

Panel C	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
2017-2018														
Laggards (1)	-0.03***	(-2.72)	0.95***	(203.43)	0.39***	(53.36)	0.05***	(5.82)	-0.19***	(-24.28)				0.58
Neutrals (2)	-0.05***	(-5.31)	0.90***	(256.86)	-0.03***	(-7.93)	0.04***	(5.76)	-0.10***	(-17.53)				0.72
Leader (3)	-0.15***	(-21.35)	0.81***	(156.79)	-0.11***	(-41.00)	0.00	(-0.63)	-0.08***	(-15.60)				0.65
Panel D	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs.	0.07***	(6.58)	0.88***	(315.04)	0.08***	(19.44)	0.05***	(12.34)	-0.12***	(-31.56)	/	-0.15***	-0.30***	0.59
(2) and (3)												(-10.57)	(-19.80)	
Neutrals vs.	-0.08***	(-8.33)	0.88***	(315.04)	0.08***	(19.44)	0.05***	(12.34)	-0.12***	(-31.56)	0.147***	/	-0.15***	0.59
(1) and (3)											(10.57)		(-11.26)	
Leaders vs.	-0.23***	(-24.04)	0.88***	(315.04)	0.08***	(19.44)	0.05***	(12.34)	-0.12***	(-31.56)	0.30***	0.15***	/	0.59
(1) and (2)											(19.80)	-11.26		
Panel E	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
2018-2019														
Laggards (1)	-0.44***	(-10.13)	1.00***	(202.06)	0.47***	(29.88)	0.03**	(2.21)	-0.14***	(-13.34)				0.87
Neutrals (2)	-0.58***	(-22.54)	0.93***	(216.64)	0.04***	(4.06)	-0.05***	(-5.46)	-0.16***	(-24.33)				0.88
Leaders (3)	-0.84***	(-47.30)	0.82***	(189.68)	-0.15***	(-38.45)	-0.20***	(-37.65)	-0.16***	(-38.63)				0.85
Panel F	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs.	-1.04***	(-45.36)	0.89***	(311.90)	0.05***	(9.27)	-0.10***	(-19.25)	-0.15***	(-39.89)	/	0.39***	0.54***	0.84
(2) and (3)												(20.20)	(30.25)	
Neutrals vs.	-0.65***	(-33.57)	0.89***	(311.90)	0.05***	(9.27)	-0.10***	(-19.25)	-0.15***	(-39.89)	-0.39***		0.15***	0.84
(1) and (3)											(-20.20)		(10.10)	
Leaders vs.	-0.50***	(-28.81)	0.89***	(311.90)	0.05***	(9.27)	-0.10***	(-19.25)	-0.15***	(-39.89)	-0.54***	-0.15***	/	0.84
(1) and (2)											(-30.25)	(-10.10)		

This table reports the results for the Carhart (1997) four-factor unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A, C and E use the formula in equation (3), the Carhart four-factor model (1997).

This four-factor model incorporates the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t and was obtained by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12-month winners portfolio and a last 12-month losers portfolio at time t. Panel B, D and F presents results found by equation (4), which controls for the categories with dummies as one of the three categories is implemented in Carhart four-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B, D and F including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the value-weighted return on all NYSE, AMEX, and NASDAQ stocks as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5% and 10%.

The 12-month time periods started in April instead of January due to the multicollinearity problem and the ESG rating data availability of 36 months starting at April. The HML beta declines overtime for the unsustainable, more fossil fuel holding mutual funds, as they probably have to adjust to smaller-valued and lower-growth investments to keep up with their level of returns. Table 11 provides the impact of sustainability scores on mutual fund returns. In 2016 to 2017, no significant effects can be observed, except a negative significant effect of dummy leaders versus neutrals funds. From 2017 to 2018, leaders and neutrals funds had a negative effect on laggards, changing to a significant positive sign of 0.52 in the last period of 2018 to 2019 accompanied with an R^2_{ADJ} of 0.84. This finding indicates that now higher sustainability scores impact mutual fund returns positively, although this relationship was previously negative. Notably, laggards (β_{SMB} = 1.51), neutrals (β_{SMB} = 0.97), and leaders (β_{SMB} = 0.66) had a significant exposure to small capitalized stocks. These results correspond for sustainable leaders with Gregory et al.'s (1997) theory, which states that ESG-friendly investments are more likely to prevent large capitalization stocks.

Table 12: *Four-factor | CRSP US Oil & Gas Index per year*

Panel A	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		R^2_{ADJ}
2016-2017											
Laggards (1)	0.38***	-43.19	0.01	(-1.50)	0.55***	(-66.78)	0.01*	(-1.67)	-0.47***	(-74.90)	0.47
Neutrals (2)	0.61***	-72.69	0.01	(-1.04)	0.17***	(-25.53)	-0.13***	(-36.20)	-0.44***	(-61.62)	0.26
Leaders (3)	0.57***	-43.98	-0.09***	(-10.28)	0.17***	(-17.98)	-0.25***	(-43.71)	-0.30***	(-31.80)	0.23

Panel B	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs.	0.51***	(57.91)	-0.01***	(-3.20)	0.33***	(73.44)	-9.84***	(-31.70)	0.43***	(-110.55)	/	0.06***	0.05***	0.29
(2) and (3)												(4.83)	(3.03)	
Neutrals vs.	0.57***	(67.47)	-0.01***	(-3.20)	0.33***	(73.44)	-9.84***	(-31.70)	0.43***	(-110.55)	-0.06***	/	-0.02	0.29
(1) and (3)											(-4.83)		(-0.93)	
Leaders vs.	0.55***	(42.62)	-0.01***	(-3.20)	0.33***	(73.44)	-9.84***	(-31.70)	0.43***	(-110.55)	-0.05***	0.02	/	0.29
(1) and (2)											(-3.03)	-0.93		
Panel C	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
2017-2018														
Laggards (1)	-0.35***	(-28.97)	0.37***	(-95.3)	0.05***	(-6.63)	0.01	(-1.34)	0.27***	(-43.63)				0.38
Neutrals (2)	-0.30***	(-31.01)	0.34***	(-162.46)	-0.35***	(-80.50)	0.03***	(-4.19)	0.32***	(-53.99)				0.44
Leaders (3)	-0.57***	(-75.42)	0.34***	(-155.39)	-0.42***	(-130.85)	-0.14***	(-19.17)	0.32***	(-47.53)				0.46
Panel D	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs.	-0.24***	(-20.88)	0.35***	(215.08)	-0.24***	(-64.39)	-0.01***	(-3.44)	0.30***	(82.36)	/	-0.12***	-0.41***	0.37
(2) and (3)												(-7.78)	(-26.53)	
Neutrals vs.	-0.36***	(-36.34)	0.35***	(215.08)	-0.24***	(-64.39)	-0.01***	(-3.44)	0.30***	(82.36)	0.12***	/	-0.28***	0.37
(1) and (3)											(7.78)		(-19.40)	
Leaders vs.	-0.64***	(-68.90)	0.35***	(215.08)	-0.24***	(-64.39)	-0.01***	(-3.44)	0.30***	(82.36)	0.41***	0.28***	/	0.37
(1) and (2)											(26.53)	(19.40)		
Panel E	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
2018-2019														
Laggards (1)	4.34***	(-87.04)	0.83***	(-186.96)	1.51***	(-90.62)	1.48***	(-88.07)	0.85***	(-75.84)				0.84
Neutrals (2)	3.65***	(-99.91)	0.76***	(-202.79)	0.97***	(-97.39)	1.21***	(-96.08)	0.73***	(-90.63)				0.85
Leaders (3)	2.94***	(-88.38)	0.68***	(-188.16)	0.66***	(-109.11)	0.93***	(-100.65)	0.63***	(-90.11)				0.81
Panel F	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs.	3.13***	(110.36)	0.74***	(305.60)	0.96***	(134.03)	1.13***	(151.26)	0.71***	(140.08)	/	0.34***	0.52***	0.80

(2) and (3)												(17.02)	(28.34)	
Neutrals vs.	3.47***	(130.28)	0.74***	(305.60)	0.96***	(134.03)	1.13***	(151.26)	0.71***	(140.08)	-0.34***	/	0.17***	0.80
(1) and (3)											(-17.02)		(11.08)	
Leaders vs.	3.65***	(141.33)	0.74***	(305.60)	0.96***	(134.03)	1.13***	(151.26)	0.71***	(140.08)	-0.52***	-0.17***	/	0.80
(1) and (2)											(-28.34)	(-11.08)		

This table reports the results for the Carhart (1997) four-factor unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A, C and E use the formula in equation (3), the Carhart four-factor model (1997). This four-factor model incorporates the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t and was obtained by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12-month winners portfolio and a last 12-month losers portfolio at time t. Panel B, D and F presents results found by equation (4), which controls for the categories with dummies as one of the three categories is implemented in Carhart four-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B, D and F including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the CRSP US Oil & Gas index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%.

The decrease in the significant negative coefficients of laggards could be caused by the widely spoken divestment of unsustainable oil and gas stocks. The decrease is from dummy variables $\delta_{LAGGARDS\ 16\text{-}19,\ 17\text{-}19,\ 18\text{-}19}$ versus leaders, -0.01, -0.07, -0.54, respectively. The opposite dummy coefficients in panel B for leaders, 0.01, 0.07, and 0.54, indicate the result of hypothesis three: "Sustainable oil and gas mutual funds increased in performance during the last years relative to unsustainable oil and gas mutual funds." This hypothesis could not be rejected as there was a clear increasing significant pattern in the dummy variables . Only the first laggards dummy coefficients from 2016 to 2019 were insignificant.

Luo and Balvers (2017) and Trinks et al. (2018) label this divestment of stocks as sin stocks. As a result, the demand for unsustainable oil and gas stocks are reduced and excess demand for sustainable oil and gas stocks could reduce prices of unsustainable oil and gas stocks and increase prices of the sustainable ones.

In contrast, Tables 13 and 14 indicate the leading sustainable mutual funds are outperforming the U.S. and the CSRP US Oil and Gas market. A clear sustainability trend over the last several years was apparent and is reflected in the significant upward sloping coefficients as there is adjusted more weight to the most recent time period in the dummy variables. The finding of the Leaders 18-19 dummy coefficient ($\delta_{LEADERS\ 18\text{-}19}$ = 0.54), which is significant at a 1% level, is the most important finding of this research.

Table 13: *Four-factor | Value-weighted return on all NYSE, AMEX, and NASDAQ stocks for different timeframes*

Panel 2016-2019	$\alpha_{16\text{-}19}$	$\beta_{mkt16\text{-}19}$	$\delta_{LAGGARDS\ 16\text{-}19}$	$\delta_{NEUTRALS\ 16\text{-}19}$	$\delta_{LEADERS\ 16\text{-}19}$	R^2_{ADJ}
Laggards vs.	-0.31***	0.90***	/	0.06***	0.01	0.74
(2) and (3)	(-41.79)	(352.09)		(6.18)	(0.80)	
Neutrals vs.	-0.25***	0.90***	-0.06***	/	-0.05***	0.74
(1) and (3)	(-42.41)	(352.09)	(-6.18)		(-5.51)	
Leaders vs.	-0.30***	0.90***	-0.01	0.05***	/	0.74
(1) and (2)	(-40.36)	(352.09)	(-0.80)	(5.51)		
Panel 2017-2019	$\alpha_{17\text{-}19}$	$\beta_{mkt17\text{-}19}$	$\delta_{LAGGARDS\ 17\text{-}19}$	$\delta_{NEUTRALS\ 17\text{-}19}$	$\delta_{LEADERS\ 17\text{-}19}$	R^2_{ADJ}
Laggards vs.	-0.35***	0.91***	/	0.094***	0.07***	0.78
(1) and (2)	(-39.06)	(348.68)		(8.00)	(6.08)	
Neutrals vs.	-0.25***	0.91***	-0.09***	/	-0.02*	0.78
(1) and (3)	(-36.11)	(348.68)	(-8.00)	(8.11)	(-1.86)	
Leaders vs.	-0.27***	0.91***	-0.07	0.02	/	0.78
(1) and (2)	(-34.56)	(348.68)	-6.08	1.86		
Panel 2018-2019	$\alpha_{18\text{-}19}$	$\beta_{mkt18\text{-}19}$	$\delta_{LAGGARDS\ 18\text{-}19}$	$\delta_{NEUTRALS\ 18\text{-}19}$	$\delta_{LEADERS\ 18\text{-}19}$	R^2_{ADJ}
Laggards vs.	-1.04***	0.89***	/	0.39***	0.54***	0.84
(1) and (2)	(-45.36)	(311.90)		(20.20)	(30.25)	
Neutrals vs.	-0.65***	0.89***	-0.39***	/	0.15***	0.84
(1) and (3)	(-33.57)	(311.90)	(-20.20)	(1.55)	(10.10)	
Leaders vs.	-0.50***	0.89***	-0.54***	-0.15***	/	0.84
(1) and (2)	(-28.81)	(311.90)	(-30.25)	(10.10)		

In this table, the results are reported for the Carhart (1997) four-factor unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. This four-factor model incorporates the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t and was obtained by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12-month winners portfolio and a last 12-month losers portfolio at time t. Panel A and B present results found by equation (4), which controls for the categories with dummies as one of the three categories is implemented in Carhart four-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel A and B including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the value-weighted return on all NYSE, AMEX, and NASDAQ stocks as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%.

Table 14: *Four-factor | CRSP US Oil & Gas Index for different for different timeframes*

Panel 2016-2019	$\alpha_{16\text{-}19}$	$\beta_{mkt16\text{-}19}$	$\delta_{LAGGARDS\ 16\text{-}19}$	$\delta_{NEUTRALS\ 16\text{-}19}$	$\delta_{LEADERS\ 16\text{-}19}$	R^2_{ADJ}
Laggards vs.	0.31***	0.42***	/	-0.02	-0.32***	0.45
(2) and (3)	(34.07)	(279.09)		(-1.36)	(-25.81)	
Neutrals vs.	0.29***	0.42***	0.02	/	-0.30***	0.45
(1) and (3)	(29.91)	(279.09)	(1.36)		(-23.84)	
Leaders vs.	-0.02*	0.42***	0.32***	-0.30***	/	0.45
(1) and (2)	(-1.93)	(279.09)	(25.81)	(-23.84)		
Panel 2017-2019	$\alpha_{17\text{-}19}$	$\beta_{mkt17\text{-}19}$	$\delta_{LAGGARDS\ 17\text{-}19}$	$\delta_{NEUTRALS\ 17\text{-}19}$	$\delta_{LEADERS\ 17\text{-}19}$	R^2_{ADJ}
Laggards vs.	-0.23***	0.47***	/	0.01	-0.02*	0.53
(1) and (2)	(-23.62)	(306.76)		(0.46)	(-1.87)	
Neutrals vs.	-0.22***	0.47***	-0.01	/	-0.031	0.53
(1) and (3)	(-25.94)	(306.76)	(-0.46)		(-2,53)	
Leaders vs.	-0.25***	0.47***	0.02*	0.031	/	0.53
(1) and (2)	(-31.26)	(306.76)	(1.87)	2.53		

Panel 2018-2019	$\alpha_{18\text{-}19}$	$\beta_{mkt18\text{-}19}$	$\delta_{LAGGARDS\ 18\text{-}19}$	$\delta_{NEUTRALS\ 18\text{-}19}$	$\delta_{LEADERS\ 18\text{-}19}$	R^2_{ADJ}
Laggards vs.	3.13***	0.74***	/	0.344	0.52***	0.80
(1) and (2)	(110.36)	(305.60)		17.02	(28.34)	
Neutrals vs.	3.47***	0.74***	-0.34***	/	0.17***	0.80
(1) and (3)	(130.28)	(305.60)	(-17.02)		(11.08)	
Leaders vs.	3.65***	0.74***	-0.52***	-0.17***	/	0.80
(1) and (2)	(141.33)	(305.60)	(-28.34)	(-11.08)		

This table reports the results for the Carhart (1997) four-factor unbalanced random panel data regression using the U.S. monthly Fama French three-factor model from the Kenneth R. French data library. All units of measurement are shown in percentages. This four-factor model incorporates the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t and was obtained by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12-month winners portfolio and a last 12-month losers portfolio at time t. Panel A and B presents results found by equation (4), which controls for the categories with dummies as one of the three categories is implemented in Carhart four-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel A and B including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the CRSP US Oil & Gas index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%.

For the last time period, April 2018 to April 2019, the leaders-fund portfolio significantly outperformed the laggards-fund portfolio with a percentage of 0.52% which is statistically significant at a 1% level. A very important implication of the results is that we can validate when mutual funds are getting more experienced with leading sustainable investments in the oil and gas industry, we find risk adjusted-returns higher compared to those of the unsustainable oil and gas mutual funds.

5.3. Robustness checks

One of the robustness investigations performed to account for potential distortions is provided in Appendix A. I initially thought that world factors could give more appropriate outcomes than U.S. factors in pricing excess returns. The one-factor CAPM and three- and four-factor model analyses are repeated for the world factors from Fama French to test for robustness. This robustness check was conducted because oil and gas companies originate from all over the world and U.S. oil and gas mutual funds invest in oil and gas companies worldwide, so also in Europe and the Middle East. Unless the investment scope of the mutual fund data set is worldwide, the U.S. Fama French factors presented better results when pricing excess returns, which is logic as the dataset consists entirely of U.S. mutual funds.

Another robustness check is presented in Appendix B. This investigation determined which oil and gas market return data to use in the research. As explained in the data section, the following oil and gas indices were used: CRSP US Oil and Gas Index, The FTSE US Oil & Gas, FTSE All Cap US Oil and Gas and the S&P/TSX Equal Weight Oil and Gas. After this analysis, the CRSP US Oil and Gas Index and the FTSE US Oil & Gas had the highest adjust R-squared: all above 0.38. I choose the CRSP return as it had more significant results, while the adjusted R-squared remained exactly the same.

6. Conclusion

6.1. Summary and discussion

This research analyzes whether the US oil and gas mutual funds moving toward sustainability should prefer this move from a financial perspective. Comparing unsustainable and sustainable oil and gas mutual funds, is it feasible for sustainable mutual funds to not compromise return goals and align risk-adjusted returns in the long term? Accordingly, this study's research question is as follows: *"Do oil and gas mutual funds now generate higher returns when moving toward sustainability?"*

Theoretically, sustainable investments face higher risks as the investment scope is tighter than the scope from unsustainable investments. This tighter investment scope is likely why sustainable mutual funds had lower returns than the returns of unsustainable mutual funds between 2016 and 2018. The lower returns occurred through the whole sample period (2016-2019). The first hypothesis, sustainable oil and gas mutual funds outperform unsustainable oil and gas mutual funds, is rejected as there could be seen a clear positive alpha for the laggards portfolio and a clear negative alpha for the leaders portfolio.

However, for 2018 to 2019, sustainable mutual funds outperformed, meaning the returns converged. The third hypothesis, sustainable oil and gas mutual funds increased in performance during the last years relative to unsustainable oil and gas mutual funds, could be accepted. This hypothesis is evaluated over time and showed a clear increasing pattern in the dummy coefficients. I found that sustainable investing in the oil and gas industry can be profitable without giving up risk-adjusted returns.

The result of hypothesis three is consistent with the theoretical work which suggests that demand differs between non-SRI and SRI stock (Galema et al., 2008). Demand is increasing for clean technology investments as investors are seeking opportunities to invest in clean companies while remaining exposure toward the oil and gas industry. Mutual funds do not want to neglect the entire oil and gas sector and at the same time they do not want to invest in oil related stocks due to its polluting character. This is probably the reason why we could reject hypothesis two: "Oil and gas mutual funds outperform Clean technology". Clean technology investments offer exposure toward oil but with an environmentally friendly character.

An important finding is that currently investing in sustainable oil and gas mutual funds is better than investing in unsustainable oil and gas funds. The reason could be the disappearing green premium and the increase in the belief of stranded assets. To my knowledge, this is the first study where unsustainable oil and gas mutual funds underperform sustainable oil and gas mutual funds. This finding implies that the sustainable characteristic is priced by the market. The beta market coefficient is the lowest for sustainability leaders using the S&P 500 or WilderHill Clean Energy Index, which is in line with the findings of Fulton et al. (2012). They analyzed over 100 academic studies of sustainable investing and found that generally sustainable investing generates a lower cost of capital. This link suggests that market notices these investments to have lower risk and therefor result in a lower cost of capital. In a long term perspective, energy costs for sustainable energies such as solar and wind power will continue to decrease while fossil fuel energy will only increase in cost price.

Furthermore, sustainable mutual funds outperform unsustainable mutual funds with a small cap market proxy. Thus, sustainable mutual funds show a positive performance toward small cap stocks. This means that the fourth hypothesis, sustainable mutual funds experience a small cap effect, can be accepted. This finding is in line with the theory stating this type of stock faces fewer environmental risks and sustainable mutual funds prefer to work with innovative environmental characterized stocks, although these stocks are much smaller in size than the large oil and gas companies. Sustainable leaders in the oil and gas mutual funds industry are flourishing during the energy transition in the last years. The conclusion could be drawn that the fossil fuel energy era is decreasing in popularity and sustainable energy movements are increasing in popularity. Especially from a financial perspective as fossil fuels as oil will increase in costs and clean technology such as solar and wind energy will keep decreasing in costs. Comparing fossil fuel to clean energy, clean energy will only become more attractive in the long term.

The most crucial finding is likely that the risk-adjusted return yielded at the most sustainable oil and gas mutual funds are now statistically greater than unsustainable oil and gas funds, possibly because of the lowered costs of sustainable projects. As of 2019, sustainable oil and gas funds outperform the oil and gas market benchmark. Therefore, oil and gas mutual funds are better when they are sustainable, not only for ethical reasons but also from a financial perspective. Finally, this means that the research question could be answered positively as oil and gas mutual funds now generate higher returns when moving toward sustainability. Oil and gas mutual funds generate higher returns when becoming more sustainable and the performance of lagging oil and gas mutual funds diminishes over time and even underperforms over the entire period of April 2017 to April 2019.

6.2. Limitations and recommendations for further research

In this section I will provide the reader with an acknowledgement of the limitations of my research. Unless the methodology of this research has been carefully constructed and tested with several robustness checks, there are still certain limitations which are presented in this section.

The portfolio composition could be debated, as it is subjective when a mutual fund could be called sustainable. I divided the entire dataset in three equal parts based on their ESG-score, but a mutual funds in the unsustainable portfolio could be sustainable, or vice versa. A suggestion for further research could be to use more precise definitions and portfolios.

In addition, the unbalanced three-year panel data set from this research uses the timeframe T. This length is restricted because MSCI only provides ESG ratings as of March 2016. There are other ESG providers who provide these ratings for a longer timeframe, such as ASSET4. However, these databases such as ASSET4 introduces more limitations as already mentioned in the data section. The data provider produces fewer different mutual funds or yearly data instead of monthly data and a smaller number of mutual funds. Future research could benefit from having a larger dataset for the monthly ESG ratings, instead of only 3 years used now.

Finally, the design of ESG ratings is widely discussed. Occasionally, there is a lack of focus on certain issues. For instance, a company involved in governance issues could still have a high ESG rating if it scores high in the environmental and social field. Mostly, the scores are purely based on reported data and company policies. This practice is likely to create biases. For example, larger companies have more capacity to make detailed sustainability reports, resulting in large unsustainable oil and gas companies having higher ESG ratings than a small sustainable Cleantech firm. Therefore, it is likely that ESG analysts cover too many stocks to perform truly in-depth research.

References

Abadie, A., and Imbens, G. (2006). Large Sample Properties of Matching Estimators of Average Treatment Effects. *Econometrica*, 74(1), 235-267.

Ansar, A., Caldecott, B., and Tilbury, J. (2013). Stranded assets and the fossil fuel divestment campaign: what does divestment mean for the valuation of fossil fuel assets? Smith School of Enterprise and the Environment, University of Oxford Retrieved from https://www.smithschool.ox.ac.uk/publications/reports/SAP-divestment-report-final.pdf

Ayling, J., and Gunningham, N. (2015). Non-state governance and climate policy: the fossil fuel divestment movement. *Climate Policy*, 17(2), 131-149.

Beck, N.L., and Katz, J. (1995). What to Do (and Not to Do) with Time-Series Cross-Section Data. *American Political Science Review*. 89(3), 634-647.

Bilbao-Terol, A., Alvarez-Otero, S., Bilbao-Terol, C., and Canal-Fernandez, V. (2017). Hedonic evaluation of the SRI label of mutual funds using matching methodology. *International Review of Financial Analysis*. 52, 213-227.

Bloemers, R., Magnani, F., and Peters, M. (2001). Paying a green premium. *The Mckinsey Quarterly*, 37(3), 15-17.

Blumenshine, N. T., and Wunnava, P. V. (2010). The value of green: The effect of environmental rankings on market cap. *Technology and Investment*, 1(4), 239-242.

Bohl, M., Kaufmann, P., and Stephan, P. (2012). From Hero to Zero: Evidence of performance reversal and speculative bubbles in German renewable energy stocks. *Energy Economics*, 37(C), 40-51.

Brulle, R. J., Carmichael, J., and Jenkins, J. C. (2012). Shifting public opinion on climate change: An empirical assessment of factors influencing concern over climate change in the U.S., 2002-2010. *Climatic Change*, 114(2), 169-188.

Bumpus, A., Tansey, J., Henriquez, B., and Okereke, C. (2015). Carbon Governance, Climate Change and Business Transformation (1st ed.). 2 Park Squaree, Milton Park, Abingdon, Oxon, OX14 4RN: Routledge.

Capelle-Blancard, G., and Laguna, M. (2010). How does the stock market respond to chemical disasters? *Journal of Environmental Economics and Management*, 59(2), 192-205.

Carbon Tracker Initiative. (n.d.). Terms List - Carbon Bubble. Retrieved August 28, 2019, from https://www.carbontracker.org/refs-and-resources/terms-list/#carbon-bubble.

Carbon Tracker Initiative. (2015, December 2). Investors and markets are at risk from $2.2 trillion of stranded fossil fuel assets. Retrieved September 18, 2019, from https://www.carbontracker.org/tools-and-insights/investors-and-markets-are-at-risk-from-2-2-trillion-of-stranded-fossil-fuel-assets/.

Carhart, M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, 52(1), 57-82.

Chan, P. T., and Walter, T. (2014). Investment performance of “environmentally-friendly” firms and their initial public offers and seasoned equity offers. *Journal of Banking and Finance*, 44(1), 177-188.

Climent, F., and Soriano, P. J. (2011). Green and Good? The Investment Performance of US Environmental Mutual Funds. *Journal of Business Ethics*, 103(2), 275-287.

Cortez, M.C., Silva, F., and Areal, N. (2009). The Performance of European Socially Responsible Funds. *Journal of Business Ethics*, 87(4), 573-588.

Cortez, M. C., Silva, F., and Areal, N. (2011). Socially responsible investing in the global market: The performance of US and European funds. *International Journal of Finance and Economics*, 17(3), 254-271.

Dam, L., and Scholtens, B. (2015). Toward a theory of responsible investing: On the economic foundations of corporate social responsibility. *Resource and Energy Economics*, 41(C), 103-121.

De Cian, E., Sferra, F., and Tavoni, M. (2013). The influence of economic growth, population, and fossil fuel scarcity on energy investments. *Climatic Change*, 136(1), 39-55.

Derwall, J. (2007). The Economic Virtues of SRI and CSR (Doctoral Dissertation). Erasmus Research Institute of Management, Erasmus University Rotterdam.

Dijk, B. (2019, June 5). Shell blijft vooral nog veel in olie, gas en chemie investeren. *Financieel Dagblad*, p. 20.

Durán-Santomil, P., Otero-González, L., Correia-Domingues, R., and Reboredo, J. (2019). Does Sustainability Score Impact Mutual Fund Performance? *Sustainability*, 11(10), 1-17

Edmans, A. (2011). Does the stock market value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics*, 101(3), 621-640.

El Ghoul, S., and Karoui, A. (2017). Does corporate social responsibility affect mutual fund performance and flows? *Journal of Banking and Finance*, 77(C), 53-63.

Evans, J.L., and Archer, S.H. (1968), Diversification and the Reduction of Dispersion: an Empirical Analysis. *Journal of Finance*, 23(5), 761-767.

Fama, E., and French, K. (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance*, 47(2), 427-465.

Fama, Eugene, F., and Kenneth R. French. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1), 3-56.

Fisher, L., and Lorie, J. H. (1970). Some Studies of Variability of Returns on Investments in Common Stocks. *The Journal of Business*, 43(2), 99-134.

French, K. (2019). Retrieved 15 July 2019, from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html/.

Fulton, M., Kahn, B., and Sharples, C. (2012). Sustainable Investing: Establishing long-term value and performance. Retrieved from https://www.db.com/cr/en/docs/Sustainable_Investing_2012.pdf.

Gaddy, B., Sivaram, V., Jones, T.and Wayman, L. (2017), Venture Capital and Cleantech: The wrong model for energy transition. *Energy Policy*, 102(C), 385-395.

Galema, R., Plantinga, A., and Scholtens, B. (2008). The stocks at stake: Return and risk in socially responsible investment. *Journal of Banking and Finance*, 32(12), 2646-2654.

Geels, F.W. (2014). Regime resistance against low-carbon transitions: Introducing politics and power into the multi-level perspective. *Theory, Culture and Society*, 31(5), 21-40.

Gil-Bazo, J., Ruiz-Verdu, P., and Santos, A. (2010). The Performance of Socially Responsible Mutual Funds: The Role of Fees and Management Companies. *Journal of Business Ethics*, 94(2), 243-263.

Goldreyer, E., and Diltz, J. (1999). The performance of socially responsible mutual funds: incorporating sociopolitical information in portfolio selection. *Managerial Finance*, 25(1), 23-36.

Gregory, A., Matatko, J., and Luther, R. (1997). Ethical unit trust financial performance: Small company effects and fund size effects. *Journal of Business Finance and Accounting*, 24(5), 705-725.

Hofman, D.M., and Huisman, R. (2012). Did the financial crisis lead to changes in private equity investor preference regarding renewable energy and climate policies? *Energy Policy*, 47(C), 111-116.

Huber, P. J. (1967). The behavior of maximum likelihood estimates under nonstandard conditions. In Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability. *Statistics*, 1(1), 221-233.

Ibikunle, G., and 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.

Inchauspe, J., Ripple, R. D., and Trück, S. (2014). The dynamics of returns on renewable energy companies: A state-space approach. *Energy Economics*, 48(C), 325-335.

IRENA. (2019). Global energy transformation: A roadmap to 2050 (2019 edition). Retrieved 13 August 2019 from https://www.irena.org/DigitalArticles/2019/Apr/-/media/652AE07BBAAC407ABD1D45F6BBA8494B.ashx.

IRENA. (2018). Renewable power: Climate-safe energy competes on cost alone. Abu Dhabi: International Renewable Energy Agency.

IRENA. (2018). Renewable power: Climate-safe energy competes on cost alone. Retrieved from https://www.irena.org/-/media/Files/IRENA/Agency/Publication/2018/Dec/IRENA_COP24_costs_update_2018.pdf.

Ito, Y., Managi, S., and Matsuda, A. (2013). Performances of socially responsible investment and environmentally friendly funds. *Journal of the operational research society*, 64(11), 1583-1594.

Jensen, M. (1968). The Performance of Mutual Funds in the Period 1945–1964. *Journal of Finance* 23(2), 389-415.

Jung, E. J., Kim, J. S., and Rhee, S. K. (2001). The measurement of corporate environmental performance and its application to the analysis of efficiency in oil industry. *Journal of Cleaner Production*, 9(6), 551-563.

Kempf, A., and Osthoff, P. (2007). The effect of socially responsible investing on portfolio performance. *European Financial Management*, 13(5), 908-922.

Kiernan, M. (2001). Eco-value, sustainability, and shareholder value: Driving environmental performance to the bottom line. *Environmental Quality Management*, 10(4), 1-12

Kreander, N., Gray, R.H., Power, D.M., and Sinclair, C.D. (2005). Evaluating the Performance of Ethical and Non-Ethical Funds: A Matched Pair Analysis. *Journal of Business Finance and Accounting*, 32(7) and (8),1465-1493.

Lesser, K., Rößle, F., and Walkshäusl, C. (2016). Socially responsible, green, and faith-based investment strategies: screening activity matters! *Finance Research Letters*, 16(C), 171-178.

Litterman, R. (2013, November 5). Opinion: The other reason for divestment. Retrieved September 23, 2019, from https://ensia.com/voices/the-other-reason-for-divestment/

Luo, H., and Balvers, R. (2017). Social Screens and Systematic Investor Boycott Risk. *Journal Of Financial And Quantitative Analysis*, 52(1), 365-399.

Luther, R. G., and Matatko, J. (1994). The Performance of Ethical Unit Trusts: Choosing an Appropriate Benchmark. *The British Accounting Review*, 26(1), 77-89.

Markowitz, H.M. (1952). Portfolio selection. *Journal of Finance*, 7(1), 77-91.

MSCI ESG Research LLC. (2019). MSCI ESG Fund Ratings Methodology (July). Retrieved from https://www.msci.com/documents/1296102/15388113/MSCI+ESG+Fund+Ratings+Exec+Summary+Methodology.pdf/ec622acc-42a7-158f-6a47-` ed7aa4503d4f?t=1562690846881

NASDAQ. (2019a, September 19). Exxon Mobil Corporation Common Stock (XOM) Institutional Holdings. Retrieved September 19, 2019, from https://www.nasdaq.com/market-activity/stocks/xom/institutional-holdings

NASDAQ. (2019b, September 19). Peabody Energy Corporation Common Stock (BTU) Institutional Holdings. Retrieved September 19, 2019, from https://www.nasdaq.com/market-activity/stocks/btu/institutional-holdings

NextEra Energy. (2019, April 23). NextEra Energy (NEE) Q4 2018 Earnings Conference Call Transcript [Press release]. Retrieved September 20, 2019, from https://www.fool.com/earnings/call- transcripts/2019/01/25/nextera-energy-nee-q4-2018-earnings-conference-cal.aspx?Cid=P2TkIF

Ortas, E., and Moneva, J. M. (2013). The Clean Techs equity indexes at stake: Risk and return dynamics analysis. *Energy*, 57(1), 259-269.

Reboredo, J. C., and Ugolini, A. (2018). The impact of energy prices on clean energy stock prices: A multivariate quantile dependence approach. *Energy Economics,* 76(C), 136-152.

Reboredo, J.C., Quintela, M., and Otero, L. A. (2017). Do investors pay a premium for going green? Evidence from alternative energy mutual funds. *Renewable and Sustainable Energy Reviews,* 73(C), 512-520.

Renneboog, L., Ter Horst, J., and Zhang, C. (2008). Socially responsible investments: Institutional aspects, performance, and investor behavior. *Journal of Banking and Finance*, 32(9), 1723-1742.

Revelli, C., and Viviani, J. (2015). Financial performance of socially responsible investing (SRI): what have we learned? A meta-analysis. *Business Ethics: A European Review*, 24(2), 158-185.

Sharpe, W. (1966), Mutual Fund Performance. *Journal of Business*, 39(1), 119-138.

Statman, M. (2004), ‘The Diversification Puzzle’. *Financial Analysts Journal*, 60(4), 44-53.

Statman, M., and Glushkov, D. (2016). Classifying and Measuring the Performance of Socially Responsible Mutual Funds. *The Journal Of Portfolio Management*, 42(2), 140-151.

Sundt, S., and Rehdanz, K. (2015). Consumers’ willingness to pay for green electricity: A meta-analysis of the literature. *Energy Economics*, 51(C), 1-8.

Treynor, J. L. (1965). How to Rate Management of Investment Funds. *Harvard Business Review*, 43(1), 63-75.

Trinks, A., Scholtens, B., Mulder, M., and Dam, L. (2018). Fossil Fuel Divestment and Portfolio Performance. *Ecological Economics*, 146, 740-748.

Truffer, B., Markard, J., and Wüstenhagen, R. (2001). Eco-labeling of electricity - Strategies and tradeoffs in the definition of environmental standards. *Energy Policy*, 29(11), 885-897.

U.S. Department of Energy, Energy Information Administration, Renewables. (2018). Market analysis and forecast from 2018 to 2023. (2019, July 23). Retrieved from https://www.iea.org/renewables2018/.

US SIF Mutual Fund Performance Chart. (2019). Retrieved 15 July 2019, from https://charts.ussif.org/mfpc/#.

US SIF SRI Basics. (2019). Retrieved 18 July 2019, from https://www.ussif.org/sribasics.

US SIF Trend Report. (2018). *Forum for Sustainable and Responsible Investment*. Retrieved 20 July 2019.

Utz, S., and 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.

White, H. (1980). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica*, 48(4), 817-838

WilderShares. (n.d.). About eco index: Philosophy Behind WilderHill Clean Energy Index (ECO). Retrieved July 15, 2019, from https://wildershares.com/about.php .

Williams, R. L. (2000). A note on robust variance estimation for cluster-correlated data. *Biometrics*, 56(2), 645-646.

Wimmer, M. (2012). ESG-persistence in Socially Responsible Mutual Funds. *Journal of Management and Sustainability*. 3(1), 9-15.

Wustenhagen, R., and Bilharz, M. (2006). Green energy market development in Germany: effective public policy and emerging customer demand. *Energy Policy*, 34(13), 1681-1696.

York, J., and Venkataraman, S. (2010). The entrepreneur–environment nexus: Uncertainty, innovation, and allocation. *Journal Of Business Venturing*, 25(5), 449-463.

Appendix

Appendix A: Fama French world market factors

The tables in this section report findings of Fama French world market factors to price excess returns. These outcomes are a robustness check for the U.S. market factors. As a result, the U.S. market factors fit the model better than the world market factors and provided more significant results.

Table A1: *One-factor | Fama French Global market return*

Panel A	α		β_{MKT}					R^2_{ADJ}
Laggards (1)	-0.19***	(-24.33)	1.13***	(249.26)				0.57
Neutrals (2)	-0.06***	(-9.53)	1.02***	(245.10)				0.75
Leaders (3)	0.08***	(-12.27)	0.92***	(209.78)				0.77
Panel B	α		β_{MKT}		$\delta_{LAGGARDS}$	$\delta_{NEUTRALS}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs.	-0.08***	(-10.33)	1.01***	(340.19)	/	0.03***	0.10***	0.68
(2) and (3)						(2.65)	(8.77)	
Neutrals vs.	-0.05***	(-8.59)	1.01***	(340.19)	-0.03***	/	0.07***	0.68
(1) and (3)					(-2.65)		(7.22)	
Leaders vs.	0.02	(2.36)	1.01***	(340.19)	-0.10***	-0.07***	/	0.68
(1) and (2)					(-8.77)	(-7.22)		

This table reports the results for the CAPM unbalanced random panel data regression using the global monthly Fama French three-factors model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A used the formula in equation (1), the Jensen (1968) CAPM 1-factor model. Panel B presents results found by equation (2), which controls for the categories with dummies as one of the three categories implemented in the one-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. *α* measures the relationship between the risk-adjusted abnormal return of the specific category and the Fama French global market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%.

Table A2: *One-factor | S&P500*

Panel A	α		β_{MKT}					R^2_{ADJ}
Laggards (1)	-0.22***	(-28.10)	1.13***	(251.16)				0.63
Neutrals (2)	-0.04***	(-6.68)	0.99***	(255.83)				0.78
Leaders (3)	0.01	(1.14)	0.86***	(200.40)				0.76
Panel B	α		β_{MKT}		$\delta_{LAGGARDS}$	$\delta_{NEUTRALS}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs.	-0.07***	(-8.88)	0.97***	(324.31)	/	0.04***	'-0.02**	0.70
(2) and (3)						(4.28)	(-1.83)	

Neutrals vs.	-0.03***	(-4.35)	0.97***	(324.31)	-0.04***	/	-0.06***	0.70
(1) and (3)					(-4.28)		(-7.01)	
Leaders vs.	-0.09***	(-13.85)	0.97***	(324.31)	0.02**	0.06***	/	0.70
(1) and (2)					(1.83)	(7.01)		

This table reports the results for the CAPM unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. Panel A used the formula in equation (1), the Jensen (1968) CAPM 1-factor model. Panel B presents results found by equation (2) which controls for the categories with dummies as one of the 3 categories is implemented in the 1-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables α measures the relation of the risk-adjusted abnormal return of the specific category and the S&P 500 Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table A3: *One factor | The WilderHill Clean Energy Index (Clean technology index)*

Panel A	α		β_{MKT}					R^2_{ADJ}
Laggards (1)	0.27***	(30.69)	0.57***	(204.56)				0.45
Neutrals (2)	0.34***	(40.44)	0.45***	(179.02)				0.46
Leaders (3)	0.28***	(44.28)	0.39***	(203.02)				0.45
Panel B	α		β_{MKT}		$\delta_{LAGGARDS}$	$\delta_{NEUTRALS}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs.	0.39***	(44.71)	0.45***	(274.13)	/	-0.06***	-0.19***	0.44
(2) and (3)						(-4.94)	(-16.99)	
Neutrals vs.	0.33***	(42.23)	0.45***	(274.13)	0.060***	/	-0.13***	0.44
(1) and (3)					(4.94)		(-13.06)	
Leaders vs.	0.21***	(-29.85)	0.45***	(274.13)	0.19***	0.13***	/	0.44
(1) and (2)					(16.99)	(13.06)		

This table reports the results for the CAPM unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. Panel A used the formula in equation (1), the Jensen (1968) CAPM 1-factor model. Panel B presents results found by equation (2) which controls for the categories with dummies as one of the 3 categories is implemented in the 1-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relation of the risk-adjusted abnormal return of the specific category and the WilderHill Clean Energy Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table A4: *One-factor | CRSP US Oil & Gas Index*

Panel A	α		β_{MKT}		R^2_{ADJ}
Laggards (1)	0.84***	(101.00)	0.50***	(126.78)	0.42
Neutrals (2)	0.87***	(114.24)	0.36***	(109.36)	0.36

Leaders (3)	0.79***	(105.86)	0.37***	(161.88)				0.41
Panel B	*α*		*β_{MKT}*		δLAGGARDS	δNEUTRALS	δLEADERS	R^2_{ADJ}
Laggards vs. (2) and (3)	0.85***	(103.33)	0.41***	(214.19)	/	0.03** (2.17)	-0.05*** (-4.80)	0.40
Neutrals vs. (1) and (3)	0.88***	(113.59)	0.41***	(214.19)	-0.03** (-2.17)	/	-0.08*** (-7.53)	0.40
Leaders vs. (1) and (2)	0.80***	(-107.64)	0.41***	(214.19)	0.05*** (4.80)	0.08*** (7.53)	/	0.40

This table reports the results for the CAPM unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. Panel A used the formula in equation (1), the Jensen (1968) CAPM 1-factor model. Panel B presents results found by equation (2) which controls for the categories with dummies as one of the 3 categories is implemented in the 1-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relation of the risk-adjusted abnormal return of the specific category and the CRSP US Oil & Gas Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table A5: *One-factor | FTSE Small Cap Index*

Panel A	*α*		*β_{MKT}*					R^2_{ADJ}
Laggards (1)	0.10***	(13.79)	1.05***	(246.71)				0.70
Neutrals (2)	0.28***	(45.58)	0.85***	(232.37)				0.75
Leaders (3)	0.42***	(60.66)	0.74***	(204.84)				0.72
Panel B	*α*		*β_{MKT}*		δLAGGARDS	δNEUTRALS	δLEADERS	R^2_{ADJ}
Laggards vs. (2) and (3)	0.24***	(32.22)	0.86***	(298.65)	/	0.03*** (3.49)	0.12*** (10.81)	0.70
Neutrals vs. (1) and (3)	0.28***	(44.86)	0.86***	(298.65)	-0.03*** (-3.49)	/	0.09*** (8.82)	0.70
Leaders vs. (1) and (2)	0.37***	(47.89)	0.86***	(298.65)	-0.12*** (-10.81)	-0.09*** (-8.82)	/	0.70

This table reports the results for the CAPM unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. Panel A used the formula in equation (1), the Jensen (1968) CAPM 1-factor model. Panel B presents results found by equation (2) which controls for the categories with dummies as one of the 3 categories is implemented in the 1-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relation of the risk-adjusted abnormal return of the specific category and the FTSE Small Cap Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table A6: *Four-factor | Fama French Global market return*

Panel A	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
Laggards (1)	-0.05***	(-6.33)	1.08***	(256.41)	0.62***	(-64.81)	0.11***	(14.83)	-0.14***	(-31.64)				0.61
Neutrals (2)	-0.05***	(-7.97)	1.01***	(263.30)	-0.01**	(-2.35)	-5.23***	(-9.18)	-0.07***	(-15.87)				0.75
Leaders (3)	-0.05***	(-10.55)	0.91***	(213.80)	-0.16***	(-33.60)	-0.18***	(-35.50)	-0.03***	(-9.94)				0.78
Panel B	**α**		**β_{MKT}**		**β_{SMB}**		**β_{HML}**		**β_{MOM}**		**$\delta_{LAGGARDS}$**	**$\delta_{NEUTRAL}$**	**$\delta_{LEADERS}$**	**R^2_{ADJ}**
Laggards vs. (2) and (3)	-0.08***	-10.33	0.98***	(360.56)	0.16***	(26.28)	-0.04***	(-8.69)	-0.09***	(-27.18)	/	0.03*** (3.35)	0.13*** (10.63)	0.72
Neutrals vs. (1) and (3)	-0.05***	-8.59	0.98***	(360.56)	0.16***	(26.28)	-0.04***	(-8.69)	-0.09***	(-27.18)	-0.03*** (-3.35)	/	0.09*** (8.80)	0.72
Leaders vs. (1) and (2)	0.09***	12.37	0.98***	(360.56)	0.16***	(26.28)	-0.04***	(-8.69)	-0.09***	(-27.18)	-0.13*** (-10.63)	-0.09*** (-8.80)	/	0.72

This table reports the results for the Carhart (1997) 4-factor unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. Panel A used the formula in equation (3), the Carhart 4-factor model (1997). This 4-factor model incorporates factors for the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12 months winners portfolio and a last 12 months losers portfolio at time t. Panel B presents results found by equation (4) which controls for the categories with dummies as one of the 3 categories is implemented in Carhart 4-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relation of the risk-adjusted abnormal return of the specific category and the Fama French Global market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table A7: *Four-factor | CRSP US Oil & Gas Index*

Panel A	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
Laggards (1)	0.87***	(102.09)	0.49***	(140.78)	0.37***	(41.42)	-0.61***	(-85.90)	-0.46***	(105.00)				0.52
Neutrals (2)	0.78***	(81.36)	0.39***	(146.53)	-0.16***	(-20.56)	-0.65***	(-104.86)	-0.29***	(-60.69)				0.47
Leaders (3)	0.36***	(45.34)	0.38***	(189.49)	-0.33***	(-51.36)	-0.75***	(-114.70)	-0.25***	(-61.65)				0.53
Panel B	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs. (2) and (3)	0.81***	(90.48)	0.42***	(250.44)	-0.02***	(-4.33)	-0.65***	(-159.83)	-0.34***	(-134.08)	/	-0.01 (-0.42)	-0.28*** (-23.16)	0.49
Neutrals vs. (1) and (3)	0.81***	(90.42)	0.42***	(250.44)	-0.02***	(-4.33)	-0.65***	(-159.83)	-0.34***	(-134.08)	0.01*** (0.42)	/	-0.28*** (-22.87)	0.49
Leaders vs. (1) and (2)	0.53***	(73.72)	0.42***	(250.44)	-0.02***	(-4.33)	-0.65***	(-159.83)	-0.34***	(-134.08)	0.28*** (23.16)	0.28*** (22.87)	/	0.49

This table reports the results for the Carhart (1997) 4-factor unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. Panel A used the formula in equation (3), the Carhart 4-factor model (1997). This 4-factor model incorporates factors for the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12 months winners portfolio and a last 12 months losers portfolio at time t. Panel B presents results found by equation (4) which controls for the categories with dummies as one of the 3 categories is implemented in Carhart 4-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relation of the risk-adjusted abnormal return of the specific category and CRSP US Oil & Gas Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table A8: *Four-factor | The WilderHill Clean Energy Index (Clean technology index)*

Panel A	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
Laggards (1)	0.35***	(42.83)	0.55***	(220.07)	0.21***	(24.03)	0.14***	(18.64)	-0.14***	(-36.81)				0.47
Neutrals (2)	0.26***	(24.48)	0.48***	(195.65)	-0.42***	(-49.99)	-0.07***	(-12.05)	-0.03***	(-7.25)				0.47
Leaders (3)	-0.13***	(-14.46)	0.44***	(194.10)	-0.65***	(-79.03)	-0.20***	(-39.43)	-0.14***	(-28.97)				0.51
Panel B	**α**		**β_{MKT}**		**β_{SMB}**		**β_{HML}**		**β_{MOM}**		**$\delta_{LAGGARDS}$**	**$\delta_{NEUTRALS}$**	**$\delta_{LEADERS}$**	**R^2_{ADJ}**
Laggards vs. (2) and (3)	0.35***	(39.43)	0.47***	(327.04)	-0.25***	(-43.38)	-0.05	(-11.86)	-0.04***	(-16.15)	/	-0.07*** (-5.02)	-0.27*** (-22.20)	0.45
Neutrals vs. (1) and (3)	0.29***	(35.23)	0.47***	(327.04)	-0.25***	(-43.38)	-0.05	(-11.86)	-0.04***	(-16.15)	0.07*** (5.02)	/	-0.20*** (-18.61)	0.45
Leaders vs. (1) and (2)	0.09***	(12.57)	0.47***	(327.04)	-0.25***	(-43.38)	-0.05	(-11.86)	-0.04***	(-16.15)	0.27*** (22.20)	0.20*** (18.61)	/	0.45

This table reports the results for the Carhart (1997) 4-factor unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. Panel A used the formula in equation (3), the Carhart 4-factor model (1997). This 4-factor model incorporates factors for the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12 months winners portfolio and a last 12 months losers portfolio at time t. Panel B presents results found by equation (4) which controls for the categories with dummies as one of the 3 categories is implemented in Carhart 4-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relation of the risk-adjusted abnormal return of the specific category and the WilderHill Clean Energy Index (Clean technology index) as market return. βMKT shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table A9: *Four-factor | Fama French Global market return* per year

Panel A	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
2016-2017														
Laggards (1)	-0.31***	(-28.26)	0.89***	(130.56)	0.63***	(41.31)	0.55***	(58.70)	(1.66)***	(3.23)				0.36
Neutral (2)	0.02*	(1.93)	0.82***	(127.69)	-0.10***	(-9.66)	0.10***	(16.26)	(-1.40)**	(-2.45)				0.37
Leader (3)	0.06***	(4.67)	0.80***	(102.18)	-0.15***	(-10.18)	-0.12***	(-14.69)	(8.25)***	(9.58)				0.40
Panel B	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs. (2) and (3)	-0.06***	(-6.54)	0.85***	(-204.98)	0.21***	(-22.08)	0.24***	(-41.20)	0.002	(0.56)	/	-0.02 (-1.48)	-0.07*** (-4.19)	0.30
Neutral vs. (1) and (3)	-0.08***	(-9.18)	0.85***	(-204.98)	0.21***	(-22.08)	0.24***	(-41.20)	0.002	(0.56)	0.02 (1.48)	/	-0.05 *** (-3.14)	0.30
Leaders vs. (1) and (2)	-0.13***	(-10.19)	0.85***	(-204.98)	0.21***	(-22.08)	0.24***	(-41.20)	0.002	(0.56)	0.07*** (4.19)	0.05 *** (3.14)	/	0.30
Panel C	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
2017-2018														
Laggards (1)	-0.14***	(-8.47)	1.14***	(167.52)	1.08***	(70.75)	-0.26***	(-35.33)	-0.29***	(-23.00)				0.49
Neutral (2)	-0.14***	(-13.29)	1.04***	(245.12)	0.20***	(22.45)	-0.21***	(-33.65)	-0.05***	(-6.31)				0.70
Leader (3)	-0.11***	(-13.94)	0.94***	(159.52)	-0.05***	(-5.51)	-0.21***	(-32.51)	-0.03***	(-4.54)				0.66
Panel D	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs. (2) and (3)	0.017	(1.33)	1.04***	(-290.07)	0.41***	-46.63	-0.21***	(-54.96)	-0.11***	(-31.74)	/	-0.15*** (-10.75)	-0.28*** (-18.50)	0.56
Neutral vs. (1) and (3)	-0.13***	(-12.73)	1.04***	(-290.07)	0.41***	-46.63	-0.21***	(-54.96)	-0.11***	(-31.74)	0.15*** (10.75)	/	-0.13*** (-9.52)	0.56
Leaders vs. (1) and (2)	-0.26***	(-30.04)	1.04***	(-290.07)	0.41***	-46.63	-0.21***	(-54.96)	-0.11***	(-31.74)	0.28*** (18.50)	0.13*** (9.52)	/	0.56
Panel E	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
2018-2019														
Laggards (1)	-0.52***	(-14.56)	1.09***	(183.46)	0.48***	(23.17)	-0.67***	(-44.88)	-0.52***	(-47.93)				0.86

Neutral (2)	-0.60***	(-22.57)	0.98***	(177.30)	-0.19***	(-11.20)	-0.52***	(-39.20)	-0.41***	(-44.82)				0.88
Leader (3)	-0.34***	(-19.93)	0.88***	(198.25)	-0.29***	(-27.10)	-0.33***	(-29.82)	-0.18***	(-27.54)				0.85
Panel F	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		$\delta_{LAGGARDS}$	$\delta_{NEUTRAL}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs.	-0.83***	(-38.14)	0.96***	-301.85	-0.07***	(-6.99)	-0.47***	(-60.87)	-0.33***	(-62.76)	/	0.43***	0.54***	0.84
(2) and (3)												(22.04)	(29.79)	
Neutral vs.	-0.40***	(-22.34)	0.96***	-301.85	-0.07***	(-6.99)	-0.47***	(-60.87)	-0.33***	(-62.76)	-0.43***	/	0.10***	0.84
(1) and (3)											(-22.04)		(7.00)	
Leaders vs.	-0.30***	(-21.82)	0.96***	-301.85	-0.07***	(-6.99)	-0.47***	(-60.87)	-0.33***	(-62.76)	-0.54***	-0.10***	/	0.84
(1) and (2)											-29.79	(-7.00)		

This table reports the results for the Carhart (1997) 4-factor unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. Panel A, C and E used the formula in equation (3), the Carhart 4-factor model (1997). This 4-factor model incorporates factors for the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12 months winners portfolio and a last 12 months losers portfolio at time t. Panel B, D and F presents results found by equation (4) which controls for the categories with dummies as one of the 3 categories is implemented in Carhart 4-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B, D and F including to the dummy variables. α measures the relation of the risk-adjusted abnormal return of the specific category and the Fama French Global market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table A10: *Four-factor | CRSP US Oil & Gas Index per year*

Panel A	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
2016-2017														
Laggards (1)	1.13***	(112.45)	0.35***	(58.55)	0.39***	(32.16)	-0.30***	(-44.34)	-0.49***	(-82.19)				0.34
Neutral (2)	1.23***	(150.08)	0.14***	(25.46)	0.03***	(2.22)	-0.42***	(-81.56)	-0.39***	(-66.53)				0.19
Leader (3)	1.09***	(87.94)	-0.05***	(-6.91)	0.33***	(13.97)	-0.40***	(-50.00)	-0.23***	(-24.53)				0.22
Panel B	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		δ_{LAGG}	δ_{NEUTR}	δ_{LEAD}	R^2_{ADJ}
Laggards vs.	1.19***	(127.53)	0.20***	(48.42)	0.24***	(27.41)	-0.38***	(-103.72)	0.41***	(-103.49)	/	0.03**	0.00	0.43
(2) and (3)												(2.34)	(-0.28)	
Neutral vs.	1.22***	(148.01)	0.20***	(48.42)	0.24***	(27.41)	-0.38***	(-103.72)	0.41***	(-103.49)	-0.03**	/	-0.03*	0.43
(1) and (3)											(-2.34)		(-1.70)	
Leaders vs.	1.20***	(94.48)	0.20***	(48.42)	0.24***	(27.41)	-0.38***	(-103.72)	0.41***	(-103.49)	0.00	0.03*	/	0.43
(1) and (2)											(-0.28)	(1.70)		
Panel C	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
2017-2018														
Laggards (1)	-0.53***	(-32.90)	0.42***	(118.46)	0.43***	(27.88)	-0.02***	(-2.93)	0.74***	(81.52)				0.47
Neutral (2)	-0.25***	(-18.70)	0.31***	(167.64)	-0.41***	(-42.45)	0.08***	(12.04)	0.80***	(99.49)				0.49
Leader (3)	-0.31***	(-30.64)	0.29***	(152.12)	-0.67***	(-73.43)	-0.01***	(-1.42)	0.72***	(75.06)				0.48
Panel D	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}		δ_{LAGG}	δ_{NEUTR}	δ_{LEAD}	R^2_{ADJ}
Laggards vs.	-0.19***	(-14.97)	0.34***	(207.22)	-0.21***	(-25.47)	0.03***	(8.76)	0.76***	(145.83)	/	-0.14***	-0.38***	0.43
(2) and (3)												(-9.13)	(-25.04)	
Neutral vs.	-0.33***	(-28.16)	0.34***	(207.22)	-0.21***	(-25.47)	0.03***	(8.76)	0.76***	(145.83)	0.14***	/	-0.24***	0.43
(1) and (3)											(9.13)		(-16.88)	
Leaders vs.	0.57***	(-58.75)	0.34***	(207.22)	-0.21***	(-25.47)	0.03***	(8.76)	0.76***	(145.83)	0.38***	0.24***	/	0.43
(1) and (2)											(25.04)	(16.88)		

Panel E	α		β_{MKT}		β_{SMB}		β_{HML}		β_{MOM}					R^2_{ADJ}
2018-2019														
Laggards (1)	-0.42***	(-12.73)	0.53***	(126.73)	0.45***	(20.94)	-1.55***	(-93.94)	-1.09***	(-91.58)				0.80
Neutral (2)	-0.38***	(-13.12)	0.49***	(147.05)	-0.10***	(-5.12)	-1.21***	(-88.72)	-0.81***	(-86.38)				0.81
Leader (3)	-0.17***	(-9.24)	0.43***	(204.17)	-0.21***	(-18.78)	-1.02***	(-87.45)	-0.61***	(-94.79)				0.78
Panel F	**α**		**β_{MKT}**		**β_{SMB}**		**β_{HML}**		**β_{MOM}**		**δ_{LAGG}**	**δ_{NEUTR}**	**δ_{LEAD}**	**R^2_{ADJ}**
Laggards vs. (2) and (3)	-0.61***	(-28.26)	0.47***	(261.28)	-0.01***	(-1.26)	-1.21***	(143.70)	-0.79***	(-140.78)	/	0.30*** (14.50)	0.48*** (25.77)	0.77
Neutral vs. (1) and (3)	-0.30***	(16.14)	0.47***	(261.28)	-0.01***	(-1.26)	-1.21***	(143.70)	-0.79***	(-140.78)	-0.30*** (-14.50)	/	0.17*** (10.94)	0.77
Leaders vs. (1) and (2)	-0.13***	(8.98)	0.47***	(261.28)	-0.01***	(-1.26)	-1.21***	(143.70)	-0.79***	(-140.78)	-0.48*** (-25.77)	-0.17*** (-10.94)	/	0.77

This table reports the results for the Carhart (1997) 4-factor unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. Panel A, C and E used the formula in equation (3), the Carhart 4-factor model (1997). This 4-factor model incorporates factors for the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12 months winners portfolio and a last 12 months losers portfolio at time t. Panel B, D and F presents results found by equation (4) which controls for the categories with dummies as one of the 3 categories is implemented in Carhart 4-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B, D and F including to the dummy variables. α measures the relation of the risk-adjusted abnormal return of the specific category and the CRSP US Oil & Gas Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table A11: *Four-factor | Fama French Global market return for different timeframes*

Panel 2016-2019	$\alpha_{16\text{-}19}$	$\beta_{mkt16\text{-}19}$	$\delta_{LAGGARDS\ 16\text{-}19}$	$\delta_{NEUTRALS\ 16\text{-}19}$	$\delta_{LEADERS\ 16\text{-}19}$	R^2_{ADJ}
Laggards vs.	-0.03***	0.98***	/	0.04***	0.12***	0.68
(2) and (3)	(-4.25)	(360.56)		(3.35)	(10.63)	
Neutral vs.	0.00	0.98***	-0.04***	/	0.03***	0.68
(1) and (3)	(0.10)	(360.56)	(-3.35)		(3.35)	
Leaders vs.	0.09***	0.98***	-0.12***	-0.03***	/	0.68
(1) and (2)	(12.37)	(360.56)	(-10.63)	(-3.35)		
Panel 2017-2019	$\alpha_{17\text{-}19}$	$\beta_{mkt17\text{-}19}$	$\delta_{LAGGARDS\ 17\text{-}19}$	$\delta_{NEUTRALS\ 17\text{-}19}$	$\delta_{LEADERS\ 17\text{-}19}$	R^2_{ADJ}
Laggards vs.	-0.01	0.99***	/	0.10***	0.10***	0.77
(1) and (2)	(-0.56)	(349.84)		(8.38)	(8.07)	
Neutrals vs.	0.09***	0.99***	-0.10***	/	0.00	0.77
(1) and (3)	(13.49)	(349.84)	(-8.38)		(-0.08)	
Leaders vs.	0.09***	0.99***	-0.10***	-0.00	/	0.77
(1) and (2)	(14.17)	(349.84)	(-8.07)	(0.08)		
Panel 2018-2019	$\alpha_{18\text{-}19}$	$\beta_{mkt18\text{-}19}$	$\delta_{LAGGARDS\ 18\text{-}19}$	$\delta_{NEUTRALS\ 18\text{-}19}$	$\delta_{LEADERS\ 18\text{-}19}$	R^2_{ADJ}
Laggards vs.	-0.83***	0.96***	/	0.43***	0.54***	0.84
(1) and (2)	(-38.14)	(301.84)		(22.04)	(29.79)	
Neutrals vs.	-0.40***	0.96***	-0.43***	/	0.10***	0.84
(1) and (3)	(-22.34)	(301.84)	(-22.04)		(7.00)	
Leaders vs.	-0.30***	0.96***	-0.54***	-0.10***	/	0.84
(1) and (2)	(-21.82)	(301.84)	(-29.79)	(-7.00)		

This table reports the results for the Carhart (1997) 4-factor unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. This 4-factor model incorporates factors for the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where $\beta_{i,mkt}$, $\beta_{i,smb}$, $\beta_{i,hml}$ and $\beta_{i,mom}$ are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. $R_{smb,t}$ is the return spread between a small and large cap portfolio at time t, $R_{hml,t}$ is the return difference between a value and a growth stock portfolio at time t by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12 months winners portfolio and a last 12 months losers portfolio at time t. Panel A and B presents results found by equation (4) which controls for the categories with dummies as one of the 3 categories is implemented in Carhart 4-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel A and B including to the dummy variables. α measures the relation of the risk-adjusted abnormal return of the specific category and the Fama French global market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table A12: *Four-factor | CRSP US Oil & Gas Index for different for different timeframes*

Panel 2016-2019	$\alpha_{16\text{-}19}$	$\beta_{mkt16\text{-}19}$	$\delta_{LAGGARDS\ 16\text{-}19}$	$\delta_{NEUTRALS\ 16\text{-}19}$	$\delta_{LEADERS\ 16\text{-}19}$	R^2_{ADJ}
Laggards vs.	0.81***	0.42***	/	-0.01	-0.28***	0.49
(2) and (3)	(90.48)	(250.44)		(-0.42)	(-23.16)	
Neutral vs.	0.81***	0.42***	0.01	/	-0.28***	0.49
(1) and (3)	(90.42)	(250.44)	(0.42)		(-22.87)	
Leaders vs.	0.53***	0.42***	0.28***	0.28***	/	0.49
(1) and (2)	(73.22)	(250.44)	(23.16)	(22.87)		
Panel 2017-2019	$\alpha_{17\text{-}19}$	$\beta_{mkt17\text{-}19}$	$\delta_{LAGGARDS\ 17\text{-}19}$	$\delta_{NEUTRALS\ 17\text{-}19}$	$\delta_{LEADERS\ 17\text{-}19}$	R^2_{ADJ}
Laggards vs.	0.23***	0.46***	/	0.04***	-0.08***	0.58
(1) and (2)	(22.20)	(295.73)		(2.72)	(-6.30)	
Neutrals vs.	0.27***	0.46***	-0.04***	/	-0.12***	0.58
(1) and (3)	(29.50)	(295.73)	(-2.72)		(-9.79)	
Leaders vs.	0.14***	0.46***	0.08***	0.12***	/	0.58
(1) and (2)	(20.70)	(295.73)	(6.30)	(9.79)		
Panel 2018-2019	$\alpha_{18\text{-}19}$	$\beta_{mkt18\text{-}19}$	$\delta_{LAGGARDS\ 18\text{-}19}$	$\delta_{NEUTRALS\ 18\text{-}19}$	$\delta_{LEADERS\ 18\text{-}19}$	R^2_{ADJ}
Laggards vs.	-0.61***	0.47***	/	0.30***	0.48***	0.77
(1) and (2)	(-28.26)	(261.28)		(14.50)	(25.77)	
Neutrals vs.	-0.30***	0.47***	-0.30***	/	0.17***	0.77
(1) and (3)	(-16.14)	(261.28)	(-14.50)		(10.94)	
Leaders vs.	-0.13***	0.47***	-0.48***	-0.17***	/	0.77
(1) and (2)	(-8.97)	(261.28)	(-25.77)	(-10.94)		

This table reports the results for the Carhart (1997) 4-factor unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. This 4-factor model incorporates factors for the market (mkt), size (smb), book-to-market (hml), and momentum (mom) factors, where βi,mkt, βi,smb, βi,hml and βi,mom are the coefficient measuring the market-risk, small firm effect, value premium and the fund i momentum impact, respectively. Rsmb,t is the return spread between a small and large cap portfolio at time t, Rhml,t is the return difference between a value and a growth stock portfolio at time t by computing the difference between a high and low book-to-market ratio, Rhml,t is the return difference between a last 12 months winners portfolio and a last 12 months losers portfolio at time t. Panel A and B presents results found by equation (4) which controls for the categories with dummies as one of the 3 categories is implemented in Carhart 4-factor model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel A and B including to the dummy variables. α measures the relation of the risk-adjusted abnormal return of the specific category and the CRSP US Oil & Gas Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Appendix B: Oil and Gas Index

The tables in this section report findings of several oil and gas indices analyzed with Fama French U.S. factors to price excess returns. This analysis was performed as a robustness check for the best oil and gas index to use as a specialty index. As a result, the CRSP O&G index fitted the model better and had more significant results than the other indices.

Table B1: *One-factor | CRSP US Oil & Gas Index*

Panel A	α		β_{MKT}					R^2_{ADJ}
Laggards (1)	0.45***	(55.35)	0.51***	(132.12)				0.44
Neutrals (2)	0.35***	(42.10)	0.38***	(115.01)				0.38
Leaders (3)	0.10***	(12.50)	0.38***	(171.00)				0.43
Panel B	α		β_{MKT}		δ_{LAGG}	δ_{NEUTR}	δ_{LEAD}	R^2_{ADJ}
Laggards vs. (2) and (3)	0.38***	(43.95)	0.42***	(221.73)	/	0.01 (0.36)	-0.23*** (-19.11)	0.41
Neutrals vs. (1) and (3)	0.39***	(42.91)	0.42***	(221.73)	-0.01 (-0.36)	/	-0.23*** (-19.69)	0.41
Leaders vs. (1) and (2)	0.16***	(19.95)	0.42***	(221.73)	0.23*** (19.11)	0.23*** (19.69)	/	0.41

This table reports the results for the CAPM unbalanced random panel data regression using the global monthly Fama French three-factors model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A used the formula in equation (1), the Jensen (1968) CAPM one-factor model. Panel B presents results found by equation (2), which controls for the categories with dummies as one of the three categories implemented in the one-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measures the relationship between the risk-adjusted abnormal return of the specific category and the CRSP US Oil & Gas Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, **, and * indicate the significance level of, respectively, 1%, 5%, and 10%.

Table B2: *One-factor | FTSE US / Oil & Gas*

Panel A	α		β_{MKT}					R^2_{ADJ}
Laggards (1)	0.45***	(55.35)	0.51***	(132.12)				0.44
Neutrals (2)	0.35***	(42.10)	0.38***	(115.01)				0.38
Leaders (3)	0.10***	(12.50)	0.38***	(171.00)				0.43
Panel B	α		β_{MKT}		$\delta_{LAGGARDS}$	$\delta_{NEUTRALS}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs. (2) and (3)	0.38***	(44.44)	0.43***	(223.34)	/	-0.01 (-0.30)	-0.23*** (-19.20)	0.42
Neutrals vs. (1) and (3)	0.39***	(43.32)	0.43***	(223.34)	-0.01 (-0.30)	/	-0.23*** (-19.72)	0.42
Leaders vs. (1) and (2)	0.16***	(20.93)	0.43***	(223.34)	0.23*** (19.20)	0.23*** (19.72)	/	0.42

This table reports the results for the CAPM unbalanced random panel data regression using the global monthly Fama French three-factors model from the Kenneth R. French data library. All units of measurement are shown in percentages. Panel A used the formula in equation (1), the Jensen (1968) CAPM one-factor model. Panel B presents results found by equation (2), which controls for the categories with dummies as one of the three categories implemented in the one-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relationship to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are answered by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables. α measure the relation of the risk-adjusted abnormal return of the specific category and the FTSE US / Oil & Gas Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table B3: *One-factor | FTSE All Cap US / Oil & Gas*

Panel A	α		β_{MKT}					R^2_{ADJ}
Laggards (1)	0.60	(75.15)	0.47	(134.33)				0.38
Neutrals (2)	0.45	(56.82)	0.33	(115.35)				0.31
Leaders (3)	0.18	(21.92)	0.32	(185.39)				0.34
Panel B	α		β_{MKT}		$\delta_{LAGGARDS}$	$\delta_{NEUTRALS}$	$\delta_{LEADERS}$	R^2_{ADJ}
Laggards vs. (2) and (3)	0.48***	(57.00)	0.37***	(215.41)	/	0.02* (1.65)	-0.23*** (-19.40)	0.34
Neutrals vs. (1) and (3)	0.51***	(57.95)	0.37***	(215.41)	-0.02* (-1.65)	/	-0.25*** (-22.10)	0.34
Leaders vs. (1) and (2)	0.26***	(32.92)	0.37***	(215.41)	0.23*** (19.40)	0.25*** (22.10)	/	0.34

This table reports the results for the CAPM unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. Panel A used the formula in equation (1), the Jensen (1968) CAPM 1-factor model. Panel B presents results found by equation (2) which controls for the categories with dummies as one of the 3 categories is implemented in the 1-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables α measures the relation of the risk-adjusted abnormal return of the specific category and the FTSE All Cap US / Oil & Gas Index as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.

Table B4: *One-factor | S&P / TSX Equal Weight Oil and Gas*

Panel A	α		β_{MKT}					R^2_{ADJ}
Laggards (1)	-0.02	(-1.45)	-0.06	(-41.5)				0.01
Neutrals (2)	-0.15	(-12.28)	-0.11	(72.98)				0.04
Leaders (3)	-0.62	(-74.84)	-0.11	(-100.86)				0.05
Panel B	α		β_{MKT}		δ_{LAGG}	δ_{NEUTR}	δ_{LEAD}	R^2_{ADJ}

Laggards vs. (2) and (3)	-0.07***	(-6.77)	-0.09***	(-141.22)	/	-0.06*** (-3.13)	-0.51*** (-37.22)	0.03
Neutrals vs. (1) and (3)	-0.13***	(-10.36)	-0.09***	(-141.22)	-0.06*** (3.13)	/	-0.46*** (-29.53)	0.03
Leaders vs. (1) and (2)	-0.58***	(-69.88)	-0.09***	(-141.22)	0.51*** (37.22)	0.46*** (29.53)	/	0.03

This table reports the results for the CAPM unbalanced random panel data regression using the global monthly Fama French 3 Factors from the Kenneth R. French data library. All measuring units are shown in percentages. Panel A used the formula in equation (1), the Jensen (1968) CAPM 1-factor model. Panel B presents results found by equation (2) which controls for the categories with dummies as one of the 3 categories is implemented in the 1-factor CAPM model for each estimation. $\delta_{i,CAT}$ measures the effect of the relation to one of the categories (laggards, neutrals and leaders) on fund i, and D_x^{cat} is the dummy variable of the specific category; laggards, neutrals or leaders. The hypotheses are solved by examining the effect of all the excess mutual fund returns together to the R_{mkt} and in Panel B including to the dummy variables α measures the relation of the risk-adjusted abnormal return of the specific category and the S&P / TSX Equal Weight Oil and Gas as market return. β_{MKT} shows the risk and effect of the market. '/' is inserted if no outcome could be calculated as the category could not be regressed against itself. The robust t-test values in parentheses are calculated by using the sandwich estimate of variance from Huber (1967). ***, ** and * indicate the significance level of respectively, 1%, 5% and 10%.