

© Copyright 2019
Sunayna Rangarajan

Impact Investing: Performance Analysis and Comparison Across Themes

Sunayna Rangarajan

A thesis

submitted in partial fulfillment of the

requirements for the degree of

Master of Science in Computational Finance & Risk Management

University of Washington

2019

Committee:

Tim Leung

Daniel Hanson

Program Authorized to Offer Degree:

Applied Mathematics

University of Washington

Abstract

Impact Investing: Performance Analysis and Comparison Across Themes

Sunayna Rangarajan

Chair of the Supervisory Committee:

Tim Leung

Applied Mathematics

Social impact themes prioritized by the United Nations’ “The 2030 Agenda for Sustainable Development” such as clean energy, workplace equality, and industrial innovation share similar characteristics in terms of correlation with the market and volatility over time. However, they have striking differences in their performance characteristics as measured by annualized return, annualized risk, and the MSCI ESG (Environmental, Social, and Governance) Quality Score for Funds. Thus, creating equally weighted portfolios with monthly rebalancing, for Exchange Traded Funds (ETFs) in different themes leads to very different results. In this paper, we develop investment strategies based on the Flexible Asset Allocation model by Keller and Putten (2012). We also expand our definition of themes and observe differences in portfolios of socially responsible ETFs, chosen based on factors including momentum, volatility, correlation and the MSCI ESG Quality Score for Funds. All chosen strategies yield a higher sharpe ratio than just investing in the market index indicating that thematic impact investing typically leads to a higher return than the market for the level of risk taken. In simple terms, it is possible to make good money by doing good.

TABLE OF CONTENTS

| | |
|---|----|
| List Of Figures..... | v |
| List Of Tables | vi |
| Chapter 1. Introduction..... | 1 |
| 1.1 Thematic Impact Investing..... | 2 |
| 1.2 Literature Review..... | 4 |
| Chapter 2. Characteristics and Similarities Of The Themes..... | 6 |
| 2.1 Clean Energy..... | 6 |
| 2.2 Fossil fuel reserve free | 8 |
| 2.3 Low Carbon..... | 10 |
| 2.4 Clean Water | 12 |
| 2.5 Workplace Equality..... | 14 |
| 2.6 Global Impact | 16 |
| 2.7 Industrial Innovation..... | 17 |
| 2.8 Comparison Across Themes | 19 |
| Chapter 3. Why Impact Investing Themes Are Actually Different..... | 20 |
| 3.1 Performance Differences | 20 |
| 3.2 Portfolio Optimization and Efficient Frontier Analysis..... | 28 |
| Chapter 4. Another Approach To Thematic Impact Investing: Flexible Asset Allocation | 30 |
| 4.1 Background..... | 30 |
| 4.2 Results..... | 32 |
| Chapter 5. Conclusions and Future Work | 35 |
| Bibliography..... | 36 |
| Appendix..... | 38 |

LIST OF FIGURES

| | |
|--|----|
| Figure 2-1: Clean Energy ETF's Correlation with the SPY & XLE..... | 7 |
| Figure 2-2: Volatility of returns of Clean Energy ETFs | 8 |
| Figure 2-3: Fossil Fuel Reserve Free ETF's Correlation with the SPY & XLE..... | 9 |
| Figure 2-4: Volatility of returns of Fossil Fuel Reserve Free ETFs | 10 |
| Figure 2-5: Low Carbon ETF's Correlation with the SPY & XLE | 11 |
| Figure 2-6: Volatility of returns of Low Carbon ETFs..... | 11 |
| Figure 2-7: Clean Water ETF's Correlation with the SPY & XLU..... | 13 |
| Figure 2-8: Volatility of returns of Clean Water ETFs..... | 13 |
| Figure 2-9: Workplace Equality ETF's Correlation with the SPY..... | 15 |
| Figure 2-10: Volatility of returns of Workplace Equality ETFs..... | 15 |
| Figure 2-11: Global Impact ETF's Correlation with the SPY | 16 |
| Figure 2-12: Volatility of returns of Global Impact ETFs..... | 17 |
| Figure 2-13: Industrial Innovation ETF's Correlation with the SPY and XLK..... | 18 |
| Figure 2-14: Volatility of returns of Industrial Innovation ETFs | 18 |
| Figure 2-15: Correlation among themes | 19 |
| Figure 3-1: Performance of a \$1000 investment across themes and benchmarks..... | 26 |
| Figure 3-2: A comparison of themes across risk, return, and ESG scores. | 29 |
| Figure 4-1: R Shiny view of the Flexible Asset Allocation (FAA) dashboard..... | 32 |
| Figure 4-2: Performance Chart of FAA Strategies..... | 34 |

LIST OF TABLES

| | |
|--|----|
| Table 3-1: Performance Statistics across themes and benchmarks..... | 24 |
| Table 3-2: Social Impact Data..... | 27 |
| Table 4-1: Performance Statistics of Flexible Asset Allocation (FAA) Strategies..... | 35 |

ACKNOWLEDGEMENTS

First and foremost, I would like to thank my advisor, Tim Leung. His attention to detail and dedicated focus to research inspired me to do better work. Despite his heavy workload, he always made himself available to discuss ideas and provide valuable feedback. I am very grateful to Tim for teaching me to be a better researcher.

Next, I would like to thank Daniel Hanson for being a member of my committee. I appreciate him for taking time to sit for my defense presentation as well as carefully reading over my thesis and providing feedback.

I have had some incredible teachers, advisors and professors in my academic journey in the University of Washington, University at Buffalo, New York, Singapore Institute of Management, and Jaigopal Garodia Vivekananda Vidyalaya. My gratitude for their kindness and guidance while encouraging me to strive for excellence in my pursuits is immeasurable.

Balancing a master's thesis on top of coursework and internship has not been easy and I am grateful for my friends for always believing in me and making the process a lot more fun. Finally, I would like to thank my family, especially my parents and my brother for their unconditional love and support. I could not have done any of this without you.

Chapter 1. INTRODUCTION

Impact Investing means investing in companies or funds to generate social, governance and environmental benefits, in addition to making a financial return. Such investing is crucial because it provides the resources to address the most pressing challenges in areas including clean energy, clean water, affordable housing, healthcare and education. As [Simon \(2017\)](#) rightly notes, “Rather than playing with the \$46 billion that constitutes the annual spending of philanthropy, we can leverage the \$196 trillion that circulates in the global economy every day for social justice” (p.31). Thus, impact investing is a simple but very powerful concept that can help with long-term systemic change.

One of the more interesting approaches to impact investing is thematic impact investing. In this method, the focus is on macro themes, i.e., market sectors or regions. It helps us identify the most effective use of our capital from a financial return, risk and social impact perspective. For example, let us consider the issue of gender parity in the workplace. Facebook’s chief operating officer – Shery Sandberg and other senior leaders ([Seetharaman & Glazer, 2018](#)) said that, “Women remain underrepresented within companies at every level”. According to the fourth annual Women in the Workplace survey from LeanIn.Org and McKinsey & Co., only about 1 in 5 senior leaders is a woman and only 1 in 25 is a woman of color (p.1). This is a serious economic and social problem because businesses are much less likely to get the best solutions to problems when there is a lack of diversity in the workplace. As individuals, we can invest in companies including non-profits that have strong workplace equality policies together with programs that encourage young girls to enter and lead industries such as Tech, Finance etc. This sends a powerful message to the industry that people really care about workplace equality. Additionally, when many people believe in the same theme and investment is driven in the direction of such companies, investors are very likely to benefit from superior financial returns in a thematic portfolio if the companies in the index benefit from the business.

Selecting the themes for impact investing is a challenging process because multiple factors need to be taken into consideration. [Bérubé, Ghai, & Tétrault \(2014\)](#) state the following four key questions that must be asked about each theme before including it in our portfolio ([p.55](#)).

- Is the theme investable?
- What is the risk that the theme will not materialize?
- Does the institution have the capabilities to differentiate itself?
- Does the theme fit within the current portfolio construction and investment policies?

Keeping these questions in mind, I tried to identify impact investing themes that are consistent with the United Nations' Envision 2030 – Sustainable development goals. According to the United Nations, “The Sustainable development Goals are the blueprint to achieve a better and more sustainable future for all. They address the global challenges we face, including those related to poverty, inequality, climate, environmental degradation, prosperity, peace and justice. The Goals interconnect and in order to leave no one behind, it is important that we achieve each Goal and target by 2030” ([United Nations, 2015](#)). Since these goals will be prioritized by institutions and investors alike in the coming years, I believe they are relevant impact investing themes. The chosen themes include Clean Energy, Fossil Fuel Reserve Free, Low Carbon, Clean Water, Workplace Equality, Global Impact, and Industrial Innovation. Some combinations of multiple themes have also been used to demonstrate the benefits of portfolio diversification.

1.1 THEMATIC IMPACT INVESTING

In this paper, we focus on thematic impact investing using an equally weighted portfolio of Exchange Traded Funds (ETFs). ETFs are very popular and affordable investment vehicles for individual investors and these days many financial institutions are developing socially responsible ETFs (Example: iShares MSCI USA ESG Select ETF (SUSA), iShares MSCI ACWI Low Carbon Target ETF (CRBN), SPDR SSGA Gender Diversity Index ETF (SHE)) that address various issues. ETFs also offer greater trading flexibility, incur lower costs, provide tax benefits and help with

portfolio diversification. Implementing an equally weighted strategy on this portfolio of ETFs means that the same weight or importance is assigned to each ETF in the portfolio. In other words, the number of shares purchased is higher for lower-priced ETFs, such that, the total dollar value invested in every ETF is the same.

Mathematically, this can be represented as follows: Let us suppose that the total value of the portfolio consisting of N ETFs is represented by V_P . The value of each ETF i in the portfolio is a product of the number of shares of each ETF – λ_i and the price of each ETF – P_i .

$$\begin{aligned} V_P &= \sum_{i=1}^N V_i \\ &= \sum_{i=1}^N \lambda_i P_i \end{aligned}$$

When we create an equally weighted portfolio, equal % weight w_i of the total portfolio value V_P is invested in each ETF. This can also be written as follows.

$$\begin{aligned} w_i &= \frac{V_i}{V_P} \\ &= \frac{\lambda_i P_i}{V_P} \\ &= \frac{1}{N} \text{ for } i \in 1, \dots, N \end{aligned}$$

Every month, we rebalance the portfolio V_P such that we equalize the position sizes in dollar amounts among all the ETFs. This strategy gives us a more diversified exposure to various ETFs and a greater growth potential. In this paper, we have selected ETFs for each theme based on Assets Under Management (AUM) and the relevance of the ETF within the theme. Consistent 2 years and 1 month of price data (Feb 15th, 2017 – Mar 29th, 2019) has been used for our analysis across all themes and ETFs. Transaction costs have been assumed to be zero for the purpose of our analysis.

BlackRock projects that by 2028, there will be \$400-billion-plus in ESG ETFs, up from \$25 billion today – a 1500% increase (Norton, 2018). Thus, analyzing the characteristics and

performance of various themes of ETFs would be valuable for investors looking to diversify their portfolio and make responsible investments. A comparison of these themes would help highlight the point that, not all themes are created equal from a return, risk and social impact perspective. Also, it would help provide useful recommendations on when to invest in each theme or a combination of themes.

1.2 LITERATURE REVIEW

According to [Berry & Junkus \(2013\)](#), one of the biggest problems faced by investors in socially responsible investing is that there is no underlying financial framework that relates the marginal social responsibility of an investment with the investment's performance. In other words, investors are looking for the optimal tradeoff between social impact, risk and return. By identifying and comparing ETF themes based on the above tradeoff, this challenge can be minimized.

[Basdekidou & Styliadou \(2017\)](#) computed the correlation between the firm's trading performance of four Corporate Social Responsibility (CSR) categories (Activism, Community Development, Corporate Governance and Environment) and the underlined market volatility. They had useful results such as, Environment CSR firms had better results during less volatile markets while it is better to trade Community Development and Corporate Governance CSR firms during more volatile markets. For future research, they suggested that exploring other CSR/Social impact categories and when they generate better returns will be very useful ([pg. 36](#)). This paper will aim to move in that direction with socially responsible ETFs.

Based on aggregated evidence from more than 2000 empirical studies, [Friede, Busch, & Bassen \(2015\)](#) note that the business case for ESG investing is empirically very well founded. About 90% of the studies find a non-negative relation between ESG and Corporate Financial Performance (CFP) and majority of the 90% are in fact positive ([p.210](#)). This shows us that impact

investing might not just be good for the society and investors but also makes business and financial sense.

[Kempf & Osthoff \(2006\)](#) also support the above point by using KLD Ratings data from 1991-2004 to confirm that the performance of socially responsible portfolios is never significantly negative. KLD ratings are performance ratings of companies developed by KLD Research & Analytics, Inc, a leading authority on social research for institutional investors. Therefore, investors do not suffer performance loss by trying to reach their ethical goals and in contrast, companies with low social responsibility often have poor performance over time ([p.13](#)).

However, [Galema, Plantinga, & Scholtens \(2008\)](#) note that socially responsible investing (SRI) impacts stock returns by lowering book-to-market ratios and not by generating positive alphas. In other words, they claim that SRI is reflected in the demand differences between SRI and non-SRI stocks. According to them, most empirical studies that contradict this result, incorrectly calculate financial performance by controlling for systematic risk while systematic risk is a part of this tradeoff. Also, using aggregate measures of SRI tends to have confounding effects, because of aggregation over different dimensions ([p.2646-2647](#)). In this paper, we will not ignore systematic risk when calculating financial performance as well as use peer-level ESG metrics to test our results.

Chapter 2. CHARACTERISTICS AND SIMILARITIES OF THE THEMES

Since all themes under consideration are combinations of socially responsible ETFs, some ETFs might even have many of the same stocks. For example, Johnson & Johnson (JNJ) stock is a major holding of the *Workplace Equality ETF - SPDR® SSGA Gender Diversity Index ETF (SHE)*. However, it is also a part of other themes such as Global Impact since it is a top 10 holding of the *iShares ESG MSCI USA ETF (ESGU)*.

Therefore, we can expect that the different themes are likely to be generally positively correlated with each other over time and with market-level benchmark such as the SPY. It is also probable that their volatility trends are similar. In this chapter, we will explore characteristics of each of the themes and understand their correlation and volatility trends. It is important to note that these similarities do not mean that there is no potential for diversification and this idea will be examined further in [Chapter 3](#).

2.1 CLEAN ENERGY

Under the Clean Energy theme, we include ETFs that invest in renewable energy sources such as solar power, wind energy as well as clean technology. This theme relates directly to the United Nations' Envision 2030 – Sustainable development goal: Ensure access to affordable, reliable, sustainable and modern energy. Energy is crucial to almost every global challenge today. According to [Rehman et al. \(2012\)](#), 1.5 billion people globally lack access to modern electricity. Among those that do have access, not everyone uses renewable energy sources. The United Nations estimates that if people worldwide switch to energy efficient lightbulbs, the world would save \$120 billion annually ([United Nations, 2015](#)). Therefore, investment in clean energy is not only vital for a better future but also makes good financial sense.

In our Clean Energy theme, an equally weighted portfolio strategy with monthly rebalancing has been employed for the ETFs: Invesco Clean Tech ETF (PZD), iShares Global Clean Energy ETF (ICLN), Invesco Wilderhill Clean Energy ETF (PBW), First Trust NASDAQ Clean Edge Energy Index Fund (QCLN), Invesco Solar ETF (TAN), VanEck Vectors Global Alternative Energy ETF (GEX), First Trust Global Wind Energy ETF (FAN), Invesco Global Clean Energy ETF (PBD) and Global X YieldCo & Renewable Energy Income ETF (YLCO). We used both SPDR S&P 500 ETF Trust (SPY) and Energy Select Sector SPDR (XLE) as our benchmark to evaluate the performance of our theme. Below are the rolling 60-day correlation and the rolling 60-day volatility charts of the different ETFs with benchmarks. Lower correlation indicates potential for diversification.

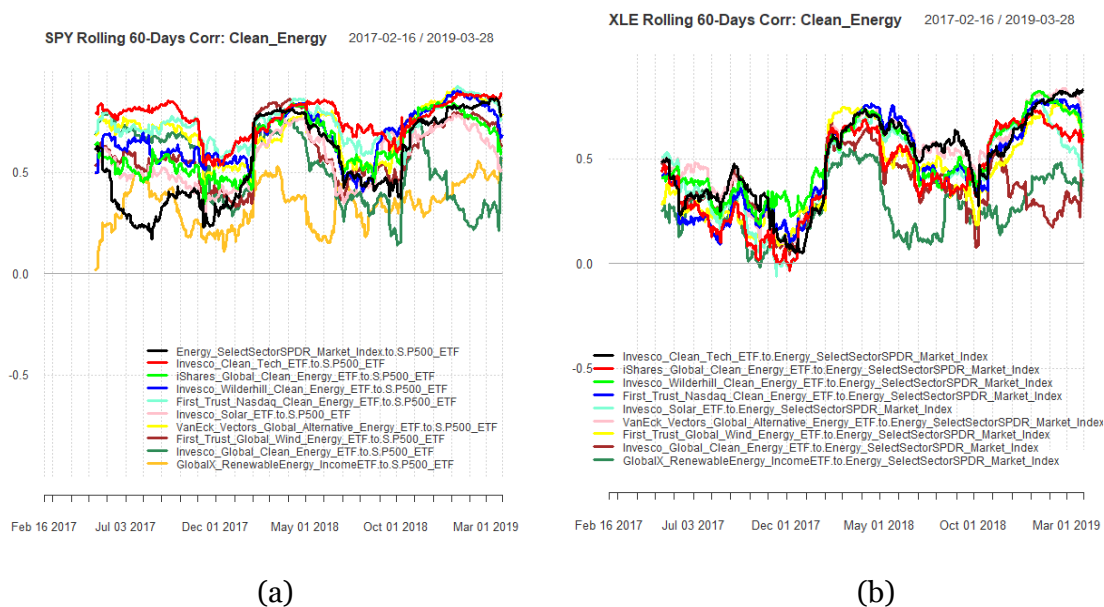


Figure 2-1: (a) All Clean Energy ETFs are moderately positively correlated with the SPY. Global X Renewable Energy Income ETF typically has the lowest correlation with the SPY & Invesco Clean Tech ETF typically has the highest correlation with the SPY. (b) All Clean Energy ETFs are moderately positively correlated with the XLE. Last year, Global X Renewable Energy Income ETF & Invesco Global Clean Energy ETF have exhibited lower correlation with the XLE.

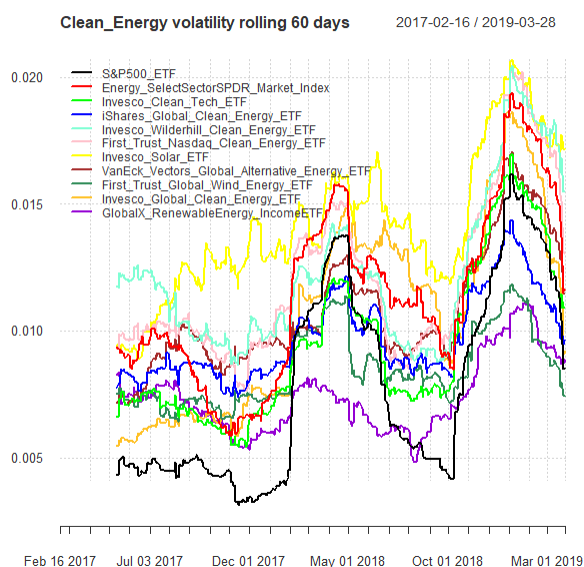


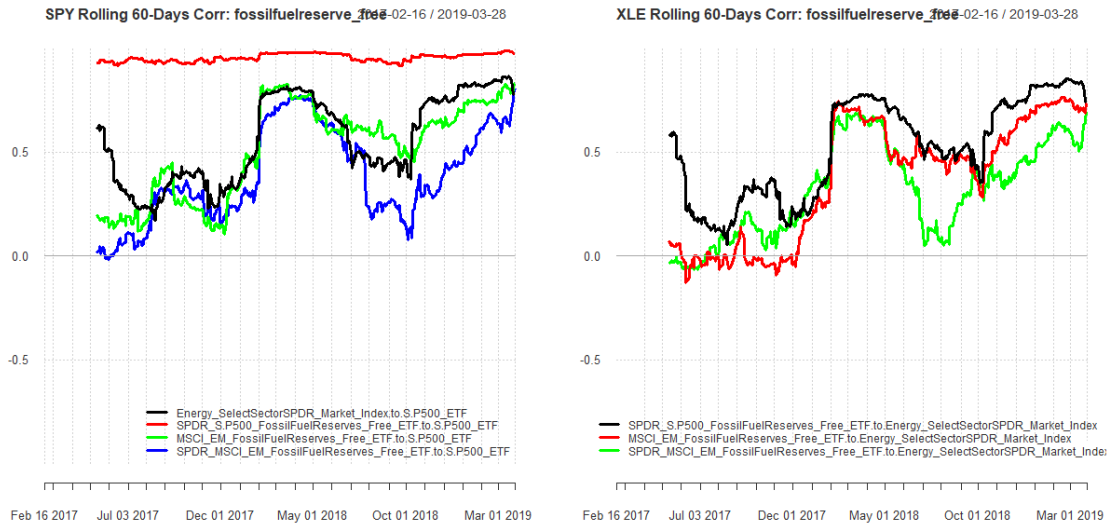
Figure 2-2: Volatility of returns of Clean Energy ETFs have been increasing in the past 2 years but the trend shows that it is declining in the recent times. Most Clean Energy ETFs are riskier than the SPY but less risky than the XLE benchmark. In the past few months, iShares Global Clean Energy ETF, First Trust Global Wind Energy ETF and Global X Renewable Energy Income ETF have been less volatile than both the SPY and XLE.

2.2 FOSSIL FUEL RESERVE FREE

Under the Fossil Fuel Reserve Free theme, we exclude companies that produce or process or burn fossil fuels, from the portfolio. Like the Clean Energy (2.1) theme, this theme relates to the United Nations' goal of ensuring access to affordable, reliable, sustainable and modern energy. The use of fossil fuels contributes to a major share of greenhouse gases (GHG) emissions, in particular CO₂ and thus affect climate change (Bauer et al., 2015). Thus, there is a need to invest in renewable energy sources like solar, wind, and thermal.

In the Fossil Fuel Reserve Free theme, an equally weighted portfolio strategy with monthly rebalancing has been employed for the ETFs: SPDR S&P 500 Fossil Fuel Reserves Free ETF (SPYX), SPDR MSCI Emerging Markets Fossil Fuel Reserves Free ETF (EFAX), and SPDR MSCI Emerging Markets Fossil Fuel Reserve Free ETF. We used both SPDR S&P 500 ETF Trust (SPY) and Energy Select Sector SPDR (XLE) as our benchmark to evaluate the performance of our

theme. Below are the rolling 60-day correlation and the rolling 60-day volatility charts of the different ETFs with benchmarks. Lower correlation indicates potential for diversification.



(a)

(b)

Figure 2-3: (a) Most Fossil Fuel Reserve Free ETFs are moderately positively correlated with the SPY but SPDR SP500 Fossil Fuel Reserve Free ETF has a much stronger positive correlation because it is derived from the SPY. (b) All Fossil Fuel Reserve Free ETFs are moderately positively correlated with the XLE.

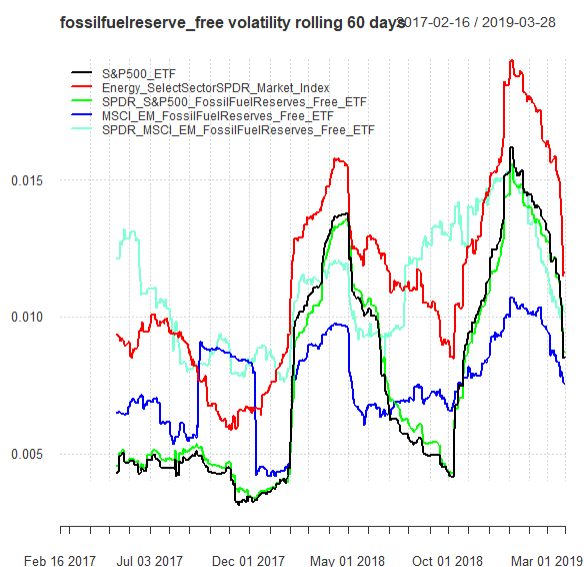


Figure 2-4: Volatility of returns of Fossil Fuel Reserve Free ETFs have been increasing in the past 2 years but have been declining in the recent months. Fossil Fuel Reserve Free ETFs are typically riskier than the SPY but less risky than XLE. In the past few months (Oct 1st, 2018 – Mar 29th, 2019), all the Fossil Fuel Reserve Free ETFs are less volatile than both the SPY & XLE.

2.3 LOW CARBON

Under the Low Carbon theme, we invest in ETFs that includes companies having a low carbon footprint. This theme is important because it is a major aspect of the United Nations' Envision 2030 - Sustainable Development Goal on Climate Action – *Take Urgent Action to Combat Climate Change and its impact*. Atmospheric methane and other-short lived greenhouse gases are expected to keep the global sea-levels rising for several centuries ([Sea-level rise for centuries to come, 2017](#)). As a result of the urgency required to combat climate change, the Paris Agreement was signed by 195 countries in December 2015. Thus, achieving low-carbon levels in the economy is the need of the hour and more investment needs to be made towards that goal.

In the Low Carbon theme, an equally weighted portfolio strategy with monthly rebalancing has been employed for the ETFs: MSCI ACWI Low Carbon Target ETF (CRBN) and, SPDR MSCI ACWI Low Carbon Target ETF (LOWC). Once again, SPDR S&P 500 ETF Trust (SPY) and Energy Select Sector SPDR (XLE) were used as our benchmark. Below are the rolling 60-day correlation

and the rolling 60-day volatility charts of the different ETFs with benchmarks. Lower correlation indicates potential for diversification.

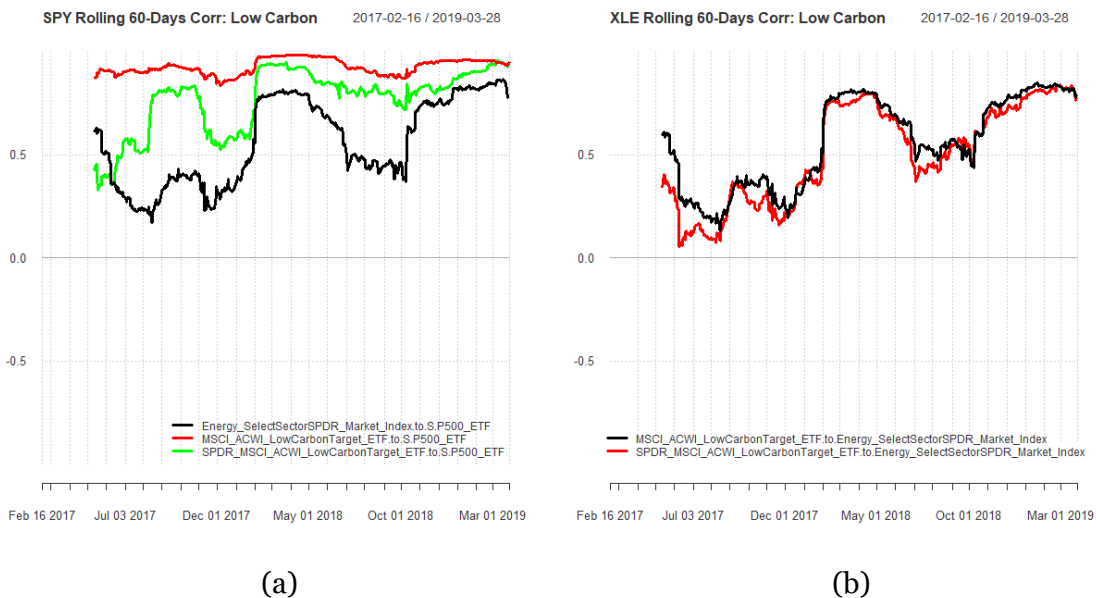


Figure 2-5: a) All Low Carbon ETFs are moderately positively correlated with the SPY except the SPDR MSCI ACWI Low Carbon ETF (CRBN) which has a high positive correlation. This is because CRBN tracks many same companies as the SPY & just excludes the ones with a high carbon exposure. b) All Low Carbon ETFs are moderately positively correlated with the XLE.

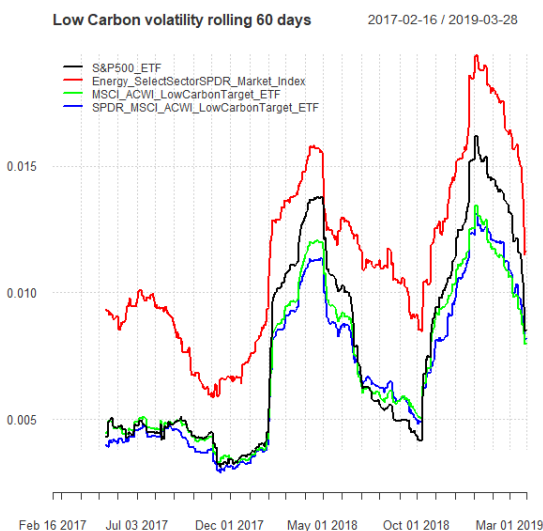


Figure 2-6: Volatility of returns of Low Carbon ETFs have been rising in the past 2 years but declining in the past months. Low Carbon ETFs have been generally less volatile than both the SPY and XLE.

2.4 CLEAN WATER

Under the Clean Water theme, we invest in companies that conserve and purify water for homes, businesses and industries. Ensuring access to clean water and sanitation for all is one of United Nations' Envision 2030 Sustainable Development Goals. According to the UN, 3 in 10 people lack access to safely managed drinking water services and 6 in 10 people lack access to safely managed sanitation services ([United Nations, 2015](#)). Having access to clean water is a very basic human need and therefore it is important to consider the Clean Water theme while evaluating impact investing ETF portfolios.

In the Clean Water theme, an equally weighted portfolio strategy with monthly rebalancing has been employed for the ETFs: Invesco Water Resources ETF (PHO), Invesco Global Water ETF (PIO), Invesco S&P Global Water ETF (CGW), First Trust Water ETF (FIW), and Tortoise Global Water ESG Fund (TBLU). We used both SPDR S&P 500 ETF Trust (SPY) and the Utilities Select Sector SPDR (XLU) as our benchmark to evaluate the performance of our theme. Below are the rolling 60-day correlation and the rolling 60-day volatility charts of the different ETFs with benchmarks. Lower correlation indicates potential for diversification.

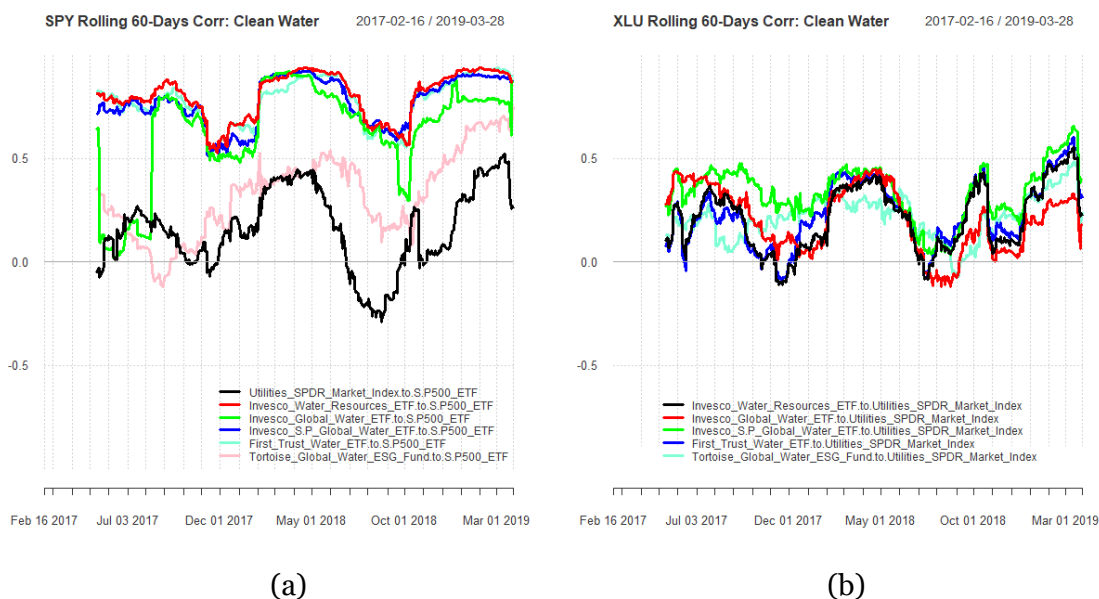


Figure 2-7: (a) All Clean Water ETFs are moderately positively correlated with the SPY. Tortoise Global Water ESG Fund (TBLU) and the Utilities SPDR Market Index (XLU) exhibit comparatively lower correlation with the SPY than other Clean Water ETFs. (b) All Clean Water ETFs are moderately positively correlated with the XLU.

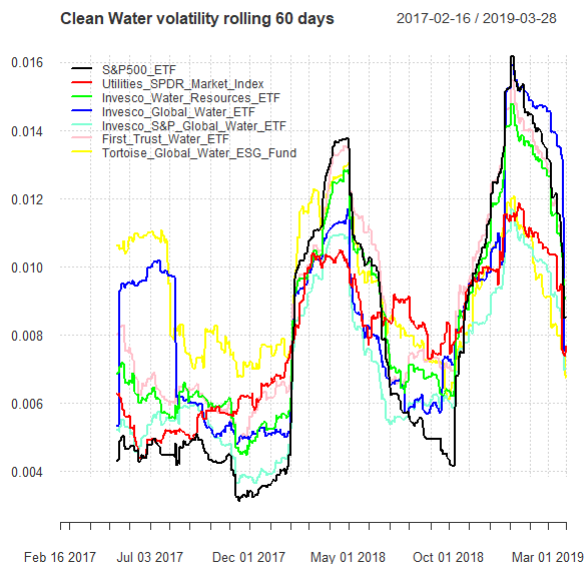


Figure 2-8: Volatility of returns of Clean Water ETFs have been increasing in the past 2 years but decreasing in the recent months. They have been typically more volatile than the SPY in the past but in the recent months (Oct 1st, 2018 – Mar 29th, 2019), they were less risky than the SPY.

2.5 WORKPLACE EQUALITY

Under the Workplace Equality theme, we invest in companies that have a higher gender diversity in senior leadership and support LGBTQ equality in the workplace. This theme relates to 2 of the United Nations' Envision 2030 Sustainable Development Goals: i) Gender Equality: *Achieve gender equality and empower all women and girls*, ii) Decent Work & Economic Growth: *Promote inclusive and sustainable economic growth, employment and decent work for all*. Women are lagging behind globally in terms of both labor force participation rate and pay. They also continue to do 2.6 times the unpaid and domestic work that men do ([United Nations, 2015](#)). Investing in Workplace Equality will not only help women but everyone who has been undervalued because of gender, race, ethnicity or any other reason.

In this theme, an equally weighted portfolio strategy with monthly rebalancing has been employed for the ETFs: Workplace Equality ETF (EQLT), Barclays Women in Leadership ETN (WIL) and SPDR SSGA Gender Diversity (SHE). Since, a market-level benchmark could not be identified, only SPDR S&P 500 ETF Trust (SPY) was used as the benchmark for comparison in the below rolling 60-day correlation and rolling 60-day volatility charts.

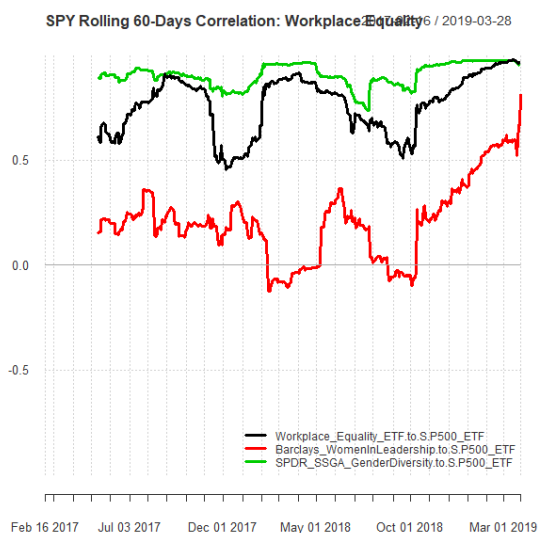


Figure 2-9: Most Workplace Equality ETFs are moderately positively correlated with the SPY but Barclays Women in Leadership ETN (WIL) exhibits very low correlation with the SPY and sometimes even negative correlation indicating potential for diversification

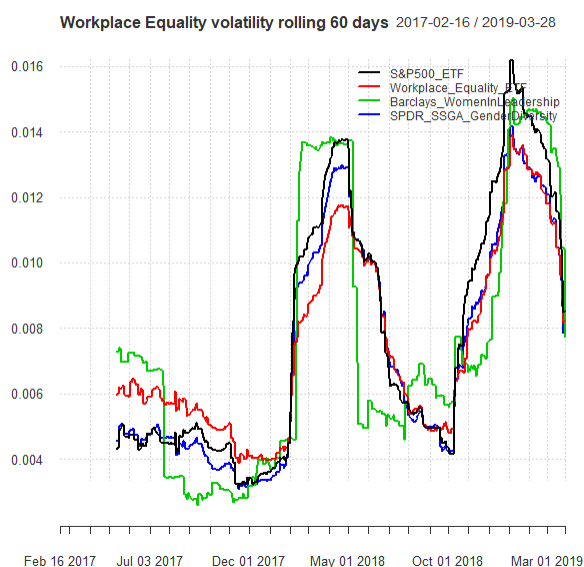


Figure 2-10: Volatility of returns of Workplace Equality ETFs have been increasing in the past 2 years but are declining in recent months (Oct 1st, 2018 – Mar 29th, 2019). In these recent months, they have also been less volatile than the SPY benchmark.

2.6 GLOBAL IMPACT

Under the Global Impact theme, we invest in companies that not only employ strong ESG practices but also build their businesses around products and services that leads to a positive change. Since this theme covers a broad spectrum of socially responsible ETFs, it relates directly or indirectly to all of the United Nations' Envision 2030 Sustainable Development Goals.

In this theme, an equally weighted portfolio strategy with monthly rebalancing has been employed for the ETFs: iShares MSCI EM ESG Optimized ETF (ESGE), iShares ESG MSCI EAFE ETF (ESGD), iShares MSCI KLD 400 Social ETF (DSI), iShares MSCI U.S.A. ESG Select ETF (SUSA), iShares ESG MSCI U.S.A. ETF (ESGU), and FlexShares STOXX Global ESG Impact Index Fund (ESGG). Once again, since a market-level benchmark could not be identified, only SPDR S&P 500 ETF Trust (SPY) was used as the benchmark for comparison.

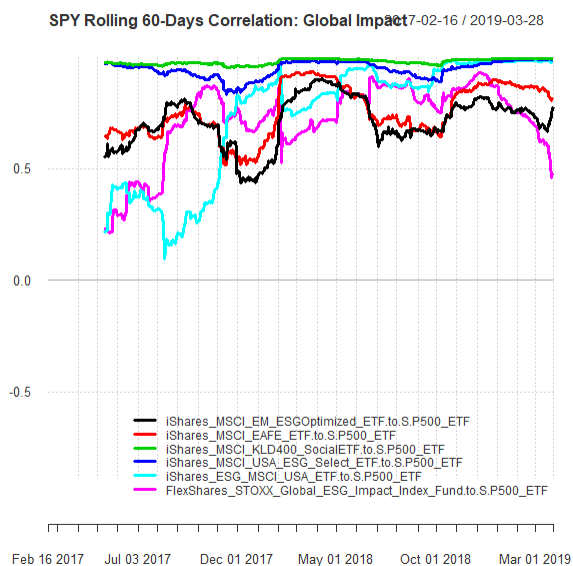


Figure 2-11: Most Global Impact ETFs are moderately positively correlated with the SPY. iShares MSCI KLD400 ETF (DSI) and iShares MSCI USA ESG Select ETF (SUSA) exhibit a consistently strong positive correlation with the SPY because they contain many socially responsible large-cap and mid-cap stocks which are also a part of the SPY.

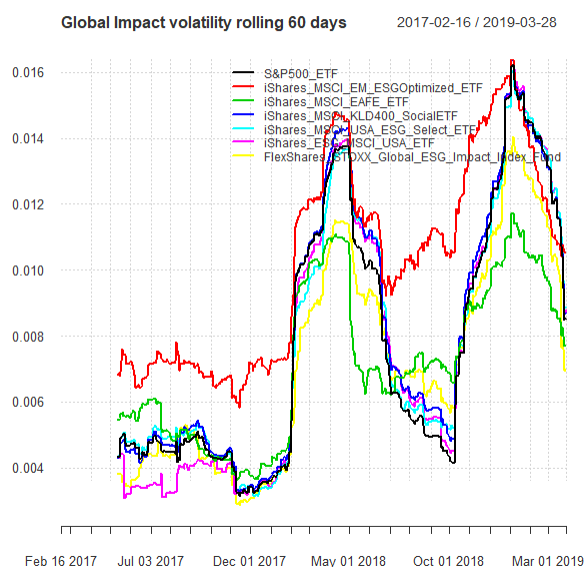


Figure 2-12: Volatility of returns of Global Impact ETFs have been increasing in the past 2 years but are declining in recent months (Oct 1st, 2018 – Mar 29th, 2019). In these recent months, they have also been less volatile than the SPY benchmark.

2.7 INDUSTRIAL INNOVATION

Under the Industrial Innovation theme, we invest in the latest advancements in robotics, artificial intelligence, cloud computing and other innovations. *Building resilient infrastructure, promoting inclusive and sustainable industrialization, and fostering innovation* is one of the UN Envision 2030 Sustainable Development Goals (United Nations, 2015). When used effectively, industrial innovation has the potential to lift nations out of poverty and thus it is an important theme for this paper.

In this theme, an equally weighted portfolio strategy with monthly rebalancing has been employed for the ETFs: ARK Industrial Innovation ETF (ARKQ), Global X Robotics & Artificial Intelligence Thematic ETF (BOTZ), iShares Exponential Technologies ETF (XT), OBO Global Robotics and Automation Index ETF (ROBO), SPDR FactSet Innovative Technology ETF (XITK), First Trust Cloud Computing ETF (SKYY), Global X FinTech ETF (FINX), ARK Web x.o ETF (ARKW), ARK Innovation ETF (ARKK), ETFMG Prime Mobile Payments ETF (IPAY), and 3D Printing ETF (PRNT). We used both SPY and Technology Select Sector SPDR (XLK) as our

benchmark to evaluate the performance of our theme in the below 60-day rolling correlation & 60-day rolling volatility charts.

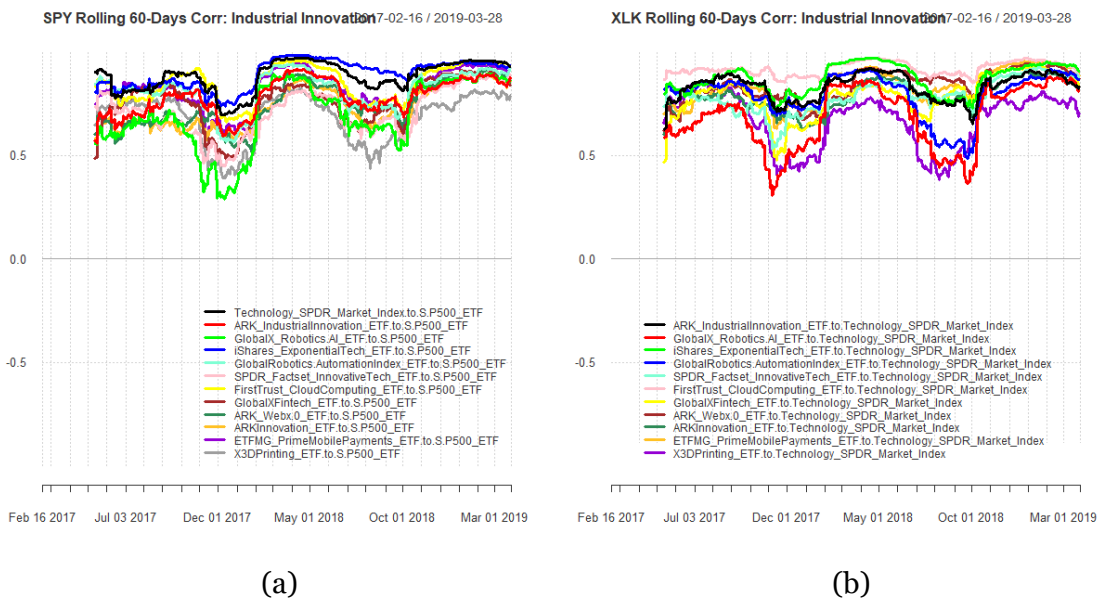


Figure 2-13: All Industrial Innovation ETFs are moderately positively correlated with both the SPY and XLK.

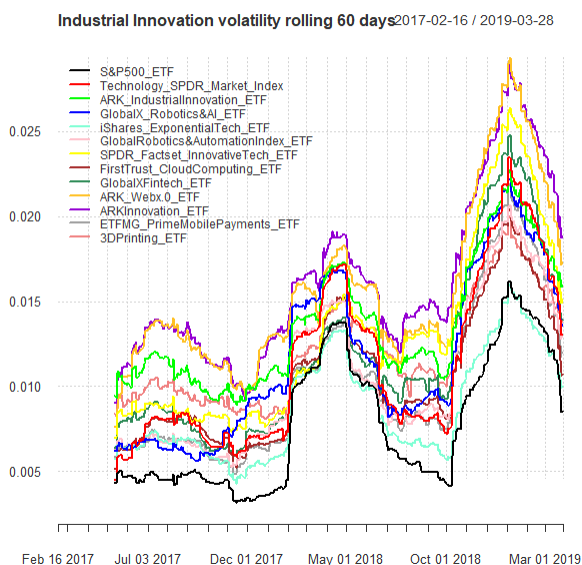


Figure 2-14: Volatility of returns of Industrial Innovation ETFs have been increasing in the past 2 years. Industrial Innovation ETFs have been consistently more volatile than the SPY. About half of the industrial innovation ETFs are more volatile than the benchmark XLK.

2.8 COMPARISON ACROSS THEMES

When we create an equally weighted portfolio of ETFs under each theme, it is also important to understand the correlation between themes such as the correlation between industrial innovation portfolio and workplace equality portfolio. The correlation matrix (calculated using the 2 years 1 month data: Feb 15th, 2017 – Mar 29th, 2019) below shows us that the daily portfolio returns of most themes are generally positively correlated.

Thus, on face value, it may seem as though investing in either of the themes (equally weighted portfolios with monthly rebalancing) would yield similar results.

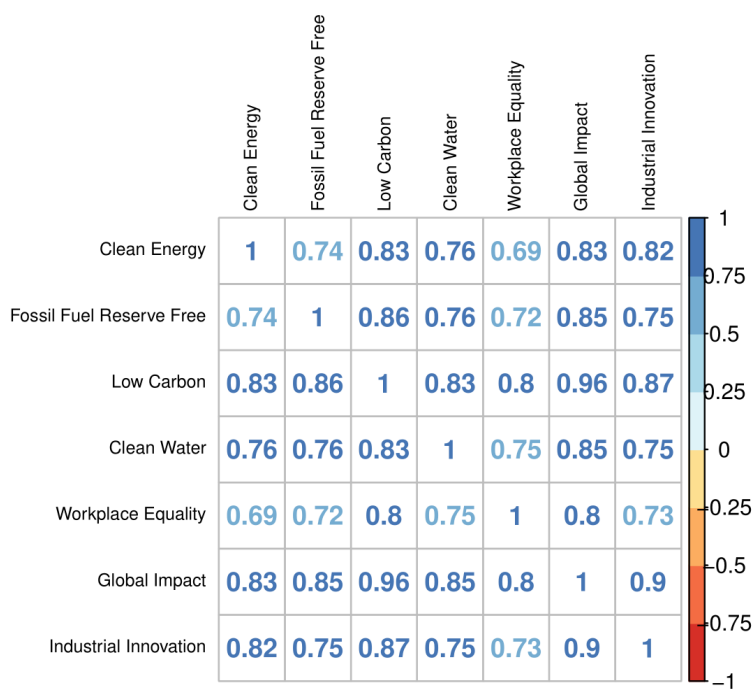


Figure 2-15: All themes are positively correlated. The correlation between Clean Energy and Workplace Equality is the lowest at 0.68. The highest correlation of 0.96 is the correlation between Global Impact and Low Carbon.

Chapter 3. WHY IMPACT INVESTING THEMES ARE ACTUALLY DIFFERENT

Despite the similarities observed in [Chapter 2](#), upon further introspection, it becomes clear that the story is completely different, and the themes are in fact, unequal performers. This becomes evident when we start to look at the performance statistics especially risk, return and MSCI ESG scores. Also, investing a fixed amount such as \$1000 in each of the themes leads to very different results when compared to the benchmark (E.g.: SPY, XLE, XLU, XLK).

3.1 PERFORMANCE DIFFERENCES

For each theme, different number of ETFs were a part of the overall equally-weighted portfolio based on Assets under Management (AUM) and relevance to the theme. We used both SPDR S&P 500 ETF Trust (SPY) and a relevant ETF based on the sector (Energy Select Sector SPDR (XLE), Utilities SPDR (XLU), and Technology Select Sector SPDR Fund (XLK)) as benchmarks to evaluate our results. ETFs in the Workplace Equality and the Global Impact themes are relatively new to the market and thus don't have a sector-specific ETF yet as a benchmark. Therefore, only SPDR S&P 500 ETF Trust (SPY) was used to evaluate their performance.

Below are the performance metrics that we used to evaluate the performance of each theme and [table 3-1](#) provides a summary of our results. In addition to the themes discussed in [Chapter 2](#), we also used a Combination theme which is an equally weighted portfolio with monthly rebalancing of the ETFs in the Industrial Innovation and Workplace Equality themes. This is an interesting combination because both themes relate to "G - Governance" aspect of ESG and workplace equality in tech is a topic of growing interest. Most investors in the Socially Responsible ETF space would like to invest in more than just one theme and this combination portfolio would demonstrate the performance of one such strategy. Many other strategies can also be tested.

- **Total return:** This metric provides the total financial return over the 2 year and 1-month period (Feb 15th, 2017 – Mar 29th, 2019). Industrial Innovation (44.2%) has the highest total return followed by the Combination (37.7%) portfolio and Clean Water (21.9%). Fossil Fuel Reserve Free (14.2%) portfolio has the lowest total return over this period. Among the benchmarks, XLK (45.9%) has the highest total return and this is higher than any of our themes for this period. XLE (-3.1%) on the other hand has a negative total return during this period due to high volatility in the clean energy theme.
- **Annualized return:** This metric compares the financial return across themes on an annualized basis. The results look similar to Total return with Industrial Innovation (19%) having the highest annualized return followed by the Combination (16.4%) portfolio and Clean Water (9.9%). Fossil Fuel Reserve Free (6.5%) portfolio has the lowest annualized return. The benchmarks also demonstrates similar results with XLK having the highest annualized return (19.6%) and XLE (-1.5%) having the lowest annualized return during this period.
- **Annualized volatility:** This metric compares the annualized standard deviation or risk across themes. Industrial Innovation (18.2%) has the highest annualized volatility followed by the Combination (15.9%) portfolio and Clean Energy (13.8%). Workplace Equality (10.3%) has the lowest annualized volatility. Among the benchmarks, both XLK (18.8%) and XLE (18.6%) have very high annualized volatilities but unlike XLE, XLK also has high returns.
- **Sharpe Ratio:** Sharpe Ratio measures excess return per unit of risk/deviation. We assume a risk free rate of 2% approximately equal to U.S T-Bill rate. Industrial Innovation has the highest Sharpe Ratio of 0.915 followed by the Combination theme (0.884), Global Impact (0.548) and Clean Water (0.657). Even though the Clean Energy theme has a higher annualized return than the Low Carbon theme, it has a lower Sharpe ratio because of higher annualized volatility (Clean Water – 0.477, Clean Energy – 0.453). The XLK benchmark has a Sharpe Ratio that is equally high as the Industrial Innovation theme (0.91) implying that it gives the same excess return for the risk taken. The SPY index (0.66) has an above average Sharpe Ratio during this period.

- **Correlation with SPY:** As discussed in [Chapter 2](#), all themes are highly positively correlated with the benchmark SPY, with Global Impact exhibiting the highest correlation of 0.956 and Clean Energy & Fossil Fuel Reserve Free exhibiting the lowest correlation of 0.794.
- **Beta with SPY:** Beta determines volatility of the theme in relation to the volatility of the benchmark – SPY. In other words, it captures the overall market risk or systematic risk which cannot be diversified away. SPY or the market has a beta of 1. The Industrial Innovation theme with a beta of 1.214 is more volatile than the market and so is the Combination theme with a beta of 1.09. All other themes are less volatile than the market and the Workplace Equality theme has the lowest beta of 0.639.
- **Jensen Alpha with SPY:** Jensen’s Alpha determines the excess return of the theme over the theoretical expected return. In this case, we measure the excess return over the benchmark SPY. As expected, the Industrial Innovation theme has the highest positive excess return (0.068) over SPY followed by the Combination theme (0.055). The Fossil Fuel Reserve Free and Low Carbon theme have negative Jensen Alphas of -0.004 each respectively.
- **Skewness:** Skewness measures the risk that the returns are not spread symmetrically around the mean. It helps highlight the variance in the data and the presence of a skewed distribution. The returns are negatively skewed in all themes indicating the mean and median of returns are less than the mode of the returns. Low Carbon is most negatively skewed at -0.685 and Clean Energy is least negatively skewed at -0.237. Among the benchmarks, XLU (-0.58) is the most negatively skewed and XLE (-0.23) is the least negatively skewed. The market index SPY has a skewness of -0.48.
- **Kurtosis:** Kurtosis measures how heavily the tails of the distribution of returns differ from the tails of a normal distribution. We use the “fisher” method (ratio of unbiased moment estimators) to compute excess Kurtosis. Kurtosis is a measure of financial risk since a large kurtosis implies the presence of more extreme values. Workplace Equality has the largest Kurtosis of 4.516 and Clean Energy has the smallest Kurtosis of 1.316. Among the benchmarks,

interestingly, the SPY has a higher kurtosis (more extreme returns) of 5.87 than the Technology benchmark XLK which has a kurtosis of 3.95.

- **Maximum relative drawdown:** Maximum relative drawdown measures the largest single drop in returns from a peak before a new peak value is achieved. Therefore, a higher value suggests presence of more volatility. The Industrial Innovation theme has the largest maximum relative drawdown of 26.7% while the Clean Water has the smallest value of 17.5%. XLE (30%) has the largest maximum relative drawdown among benchmarks while XLU has the smallest value of 15%.
- **Correlation with index:** All themes that have a relevant sector ETF index are positively correlated with it. Industrial Innovation and Combination themes have the largest positive correlation of 0.919 with the benchmark XLK. Clean Water has the lowest positive correlation of 0.298 with the benchmark XLU.
- **Beta with index:** Assuming that the benchmark index has a beta of 1, beta helps measure the systematic or non-diversifiable risk of the theme. All themes are less volatile than their respective benchmark since they have a value lower than 1. Industrial Innovation has the highest beta of 0.885 with benchmark XLK while Clean Water has the lowest beta of 0.273 with the benchmark XLU.
- **Jensen Alpha with Index:** The Clean Energy theme has the highest Jensen's Alpha/excess return over benchmark XLE of 0.098. The Combination (Industrial innovation + Workplace Equality) theme has the lowest Jensen Alpha over the benchmark XLK of 0.028. This is an interesting observation because it demonstrates that while the Clean Energy theme might not be the most profitable among themes, it makes sense from a financial return perspective to invest in it rather than the market-level benchmark XLE.

Table 3-1: a) Performance Statistics of themes – The themes differ in their risk-return characteristics. The Industrial Innovation theme has the highest Sharpe Ratio of 0.915 but it also has the largest systematic risk with the SPY as indicated by the beta value of 1.214. b) Benchmark performance statistics – XLK (0.91) has the highest Sharpe Ratio and XLE (-0.18) has the lowest.

| (a) | | | | | | | | | |
|-------------------------|--------------|--------------------------|------------|-------------|--------------------|---------------|-----------------------|--|--|
| Statistic | Clean Energy | Fossil Fuel Reserve Free | Low Carbon | Clean Water | Workplace Equality | Global Impact | Industrial Innovation | Combination (Industrial Innovation + Workplace Equality) | |
| Number of ETFs | 9 | 3 | 2 | 5 | 3 | 6 | 11 | 14 | |
| Index | XLE | XLE | XLE | XLU | - | - | XLK | XLK | |
| Total return | 18.5% | 14.2% | 16.7% | 21.9% | 15.1% | 19.3% | 44.2% | 37.7% | |
| Annualized return | 8.4% | 6.5% | 7.6% | 9.9% | 6.9% | 8.7% | 19% | 16.4% | |
| Annualized volatility | 13.8% | 11.6% | 11.5% | 11.7% | 10.3% | 12% | 18.2% | 15.9% | |
| Sharpe Ratio | 0.453 | 0.379 | 0.477 | 0.657 | 0.464 | 0.548 | 0.915 | 0.884 | |
| Correlation with SPY | 0.794 | 0.794 | 0.925 | 0.845 | 0.831 | 0.956 | 0.892 | 0.913 | |
| Beta with SPY | 0.818 | 0.689 | 0.796 | 0.740 | 0.639 | 0.861 | 1.214 | 1.09 | |
| Jensen Alpha with SPY | 0.001 | -0.004 | -0.004 | 0.024 | 0.004 | 0.001 | 0.068 | 0.055 | |
| Skewness | -0.237 | -0.428 | -0.685 | -0.47 | -0.614 | -0.639 | -0.616 | -0.603 | |
| Kurtosis | 1.316 | 2.3 | 4.136 | 4.24 | 4.516 | 3.651 | 2.804 | 2.956 | |
| Max relative drawdown | 21.1% | 22.1% | 20.3% | 17.5% | 19.2% | 20.5% | 26.7% | 24.9% | |
| Correlation with index | 0.627 | 0.596 | 0.682 | 0.298 | - | - | 0.919 | 0.919 | |
| Beta with index | 0.462 | 0.371 | 0.420 | 0.273 | - | - | 0.885 | 0.777 | |
| Jensen Alpha with index | 0.098 | 0.076 | 0.089 | 0.068 | - | - | 0.035 | 0.028 | |

| (b) | | | | |
|-----------------------|--------|--------|--------|-------|
| Statistic | SPY | XLE | XLU | XLK |
| Total return | 24.7% | -3.1% | 27.01% | 45.9% |
| Annualized return | 11.03% | -1.51% | 12.01% | 19.6% |
| Annualized volatility | 13.32% | 18.6% | 12.76% | 18.8% |
| Sharpe Ratio | 0.66 | -0.18 | 0.76 | 0.91 |
| Skewness | -0.48 | -0.23 | -0.58 | -0.42 |
| Kurtosis | 5.87 | 2.26 | 2.23 | 3.95 |
| Max relative drawdown | 19% | 30% | 15% | 23% |

As we can see in table 3-1, some themes (E.g.: Industrial Innovation) have been historically more volatile than others and this can be attributed to the characteristics of the industry/product. Therefore, a risk-averse investor should pay attention to metrics such as average annualized standard deviation and maximum relative drawdown before choosing a theme. The Clean Water theme has a comparatively low annualized volatility of 11.7% and a similarly low maximum relative drawdown of 17.5% and thus would be one potentially good investment choice for risk-averse investors. While past information might not necessarily indicate future trends, it serves a guideline in choosing a theme.

Similarly, when we compare returns, investing \$1000 separately in each theme typically leads to similar results as investing in a benchmark such as the SPY, XLK, and XLU. However, few like the Industrial Innovation and Global Impact theme have performed much better financially than the benchmark. Recent advancements in robotics, AI etc, can be attributed for the excellent performance of the industrial innovation theme. Companies that employ strong ESG practices and build products that drive positive change are also generating higher returns as evidenced by the Global Impact theme (19.3%).

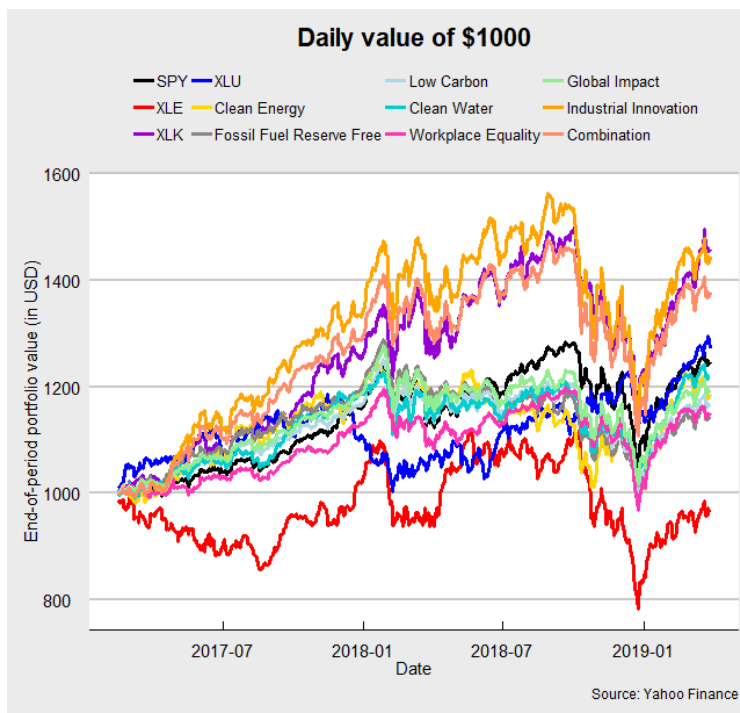


Figure 3-1: Performance of a \$1000 investment across themes and benchmarks: The industrial innovation theme has the highest end-of-period portfolio value over time while the XLE benchmark has the lowest end-of-period portfolio value over time. The Industrial Innovation, Combination theme and XLK always outperform the SPY and other themes.

Another important performance difference is the **social impact potential**. In this paper, we'll be using the MSCI ESG Fund Quality Score (Data obtained from: www.etf.com) as our metric. This is a top-level fund factor and is calculated as the weighted average of the underlying holdings' overall ESG score. It is on a scale of 0-10 with 10 being the highest possible score. Since every fund is universally given this score based on the same methodology, it facilitates comparison across themes. MSCI uses both qualitative and quantitative data of companies (100+ datasets, company disclosure, 1600+ media sources) to assess the key risks and/or opportunities the companies are exposed to and how well the companies are managing those risk and opportunities. The final ESG score is a measure of the overall picture of the company based on these criteria compared to its global peers.

Table 3-2: Social Impact Data - Different ESG scores affect the themes' social impact potential. Global Impact has the highest overall ESG score of 6.89 while Industrial Innovation has the lowest overall ESG score of 5.19. While comparing within peer group, Global Impact theme falls in the 95th percentile of peer ETFs (highest) and the Combination theme falls in the 30th percentile of peer ETFs (lowest).

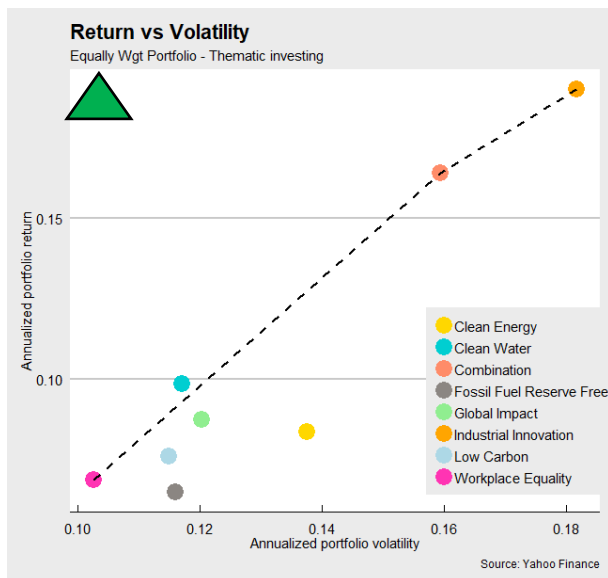
| Themes | MSCI ESG Fund Quality Score (Average) | MSCI ESG Peer Group Percentile Rank (Average) |
|--|---------------------------------------|---|
| SPY | 5.57 | 62 |
| Clean Energy | 6.14 | 77.87 |
| Clean Water | 5.69 | 82.75 |
| Combination (Workplace Equality + Industrial Innovation) | 5.23 | 30 |
| Fossil Fuel Reserve Free | 5.55 | 73.5 |
| Global Impact | 6.89 | 95.33 |
| Industrial Innovation | 5.19 | 35.45 |
| Low Carbon | 5.77 | Not Available |
| Workplace Equality | 5.5 | Not Available |

The Global Impact theme is especially impressive being in the 95th percentile for peer ESG score. Since the industrial innovation theme includes many ETFs and some of them have a very low peer-ESG percentile (Eg: XT – 17th percentile, IPAY – 5th percentile), they skew the average to 36th percentile. However, this is still low compared to other themes. Most other themes are above the 50th percentile in terms of their ESG/social impact score indicating that they have above average social impact potential. The S&P500 benchmark (SPY) has an ESG score of 5.57 which is higher than a few of the themes under consideration except Clean Energy, Clean Water, Global Impact, and Low Carbon.

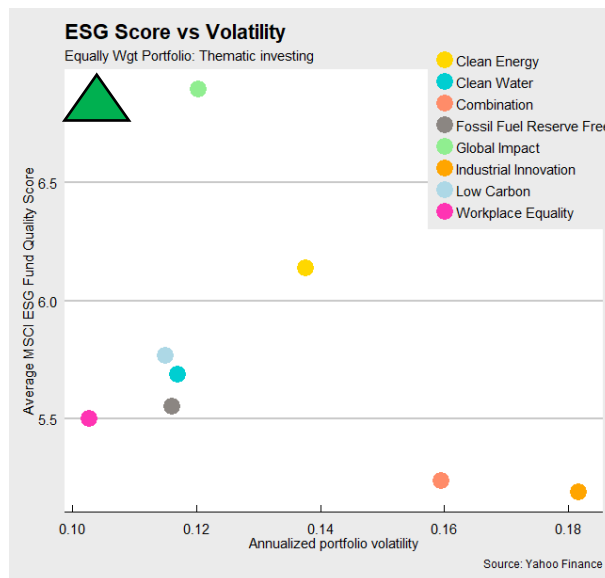
3.2 PORTFOLIO OPTIMIZATION AND EFFICIENT FRONTIER ANALYSIS

In section 3.1, several performance metrics were viewed individually. However, when an investor is deciding which theme to invest, all of them must be taken into consideration at once. In other words, we need to find the optimal portfolio that maximizes return, maximizes social impact, and minimizes risk.

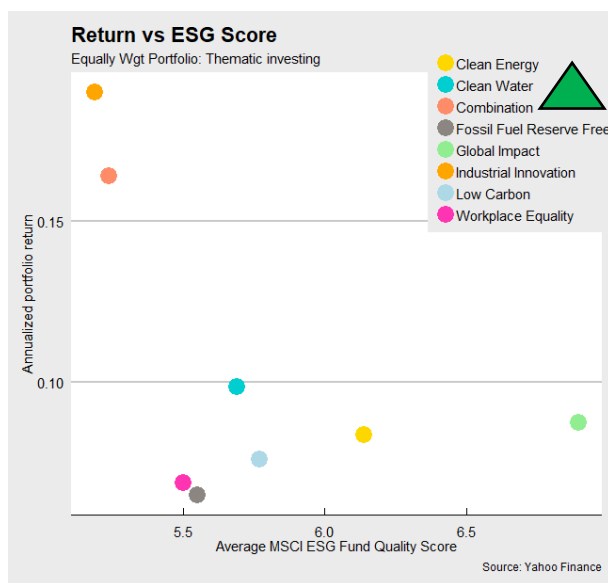
We can visualize the differences across the themes below and also view an efficient frontier that performs the desired optimization. There is always a tradeoff between risk, return and social impact. For instance, Global Impact theme has a very high ESG score and relatively low volatility in comparison with other themes. However, it is not a leader in terms of financial return. Similarly, the Industrial innovation theme has excellent financial return, but it has a high volatility and relatively low ESG scores. On the other hand, the combination theme (Workplace Equality + Industrial innovation) has a return higher than the Workplace Equality theme, a volatility lower than the Industrial Innovation theme and an ESG score higher than the Industrial Innovation theme. The Clean Water theme also stands out in terms of the risk-return combination as can be observed in figure 3-2. The combination of Clean Water and Industrial Innovation is another interesting combination theme that can be tested to balance risk, return and social impact. Therefore, investing in a combination of themes is a worthwhile strategy since it helps meet different investment preferences and in some cases yields unexpected benefits due to diversification.



(a)



(b)



(c)

Figure 3-2: Comparing themes across risk, return, and ESG scores leads to better portfolio choices. The green triangle represents the direction of the preferred scenarios, i.e., regions with high return, low risk, and high ESG scores. (a) Themes that have a high return and low volatility are preferred. The black efficient-frontier line suggests different possibilities of risk and return by investing in a combination of themes. (b) Themes that have a low volatility and high ESG scores are preferred. (c) Themes that have a high return and high ESG scores are preferred.

Chapter 4. ANOTHER APPROACH TO THEMATIC IMPACT INVESTING: FLEXIBLE ASSET ALLOCATION

In [Chapter 2](#) & [Chapter 3](#), we looked at themes based on the social impact cause that they were catering to such as: clean energy, workplace equality etc. These themes were different but not necessarily always profitable than their respective benchmarks. Also, our choice of themes need not be limited to this definition of themes. Investors would be more interested in choosing a portfolio of socially responsible ETFs that address their specific concerns like their need for minimum risk or equal balance between return and social impact potential. The Flexible Asset Allocation model helps with this objective since a portfolio of socially responsible ETFs can now be chosen based on characteristics such as momentum, volatility, correlation and ESG scores.

4.1 BACKGROUND

The Flexible Asset Allocation (FAA) model was developed by [Keller & Putten](#) in [2012](#). It extends time series momentum model to a more generalized momentum model consisting of four new factors - Absolute momentum (A), Volatility momentum (V) and Correlation momentum (C) apart from traditional relative momentum factor (R). These factors are defined as follows:

- Absolute momentum (A): Absolute momentum or time-series momentum was calculated as the most recent price of an ETF over its first price in the dataset.
- Relative momentum (R): Relative momentum analyzes the changes in price of each ETF relative to other ETFs in our universe.
- Volatility momentum (V): Volatility momentum analyzes the annualized standard deviation of returns of each ETF relative to other ETFs in our dataset.
- Correlation momentum (C): Correlation momentum ranks ETFs based on their total correlation with other ETFs in our universe.

In this paper, each ETF is ranked based on momentum R, volatility V, correlation C and an additional factor - *MSCI Total ESG score E* to account for the social impact potential of the ETF. This can be defined as:

- **ESG Score Momentum (E):** ESG Score Momentum ranks ETFs in our universe based on the total MSCI ESG score.

Let L_i represent the loss function for each ETF i in our universe U . Our universe includes all the socially responsible ETFs discussed in [Chapter 2](#) & [Chapter 3](#) as well as the respective sector benchmarks – XLE, XLU, and XLK. This results in a comprehensive universe of 40 ETFs and our investment choices can be made based on the above factors (A, R, V, C,E). The function L_i is a summation of the weighted ranks of the relative momentum, volatility momentum, correlation momentum and ESG momentum strategies respectively. w_R, w_V, w_C & w_E respectively refer to the weight or importance assigned to the relative momentum, volatility momentum, correlation momentum and ESG momentum strategies respectively. For the purposes of this paper, we will assume that the weights range from 0 to 1, where a higher weight for a strategy implies higher importance is given to that strategy. The weights of all ETFs in the portfolio need not necessarily add up to 1, i.e., the total weights can range from 0 to number of ETFs in the portfolio. The $rank(r_i), rank(v_i), rank(c_i),$ and $rank(e_i)$ respectively provide the rank of ETF i relative to other ETFs in the universe U based on return (higher is better \rightarrow higher rank), volatility (lower is better \rightarrow higher rank), correlation (lower is better \rightarrow higher rank), and ESG score (higher is better \rightarrow higher rank). Below is the loss function L_i and a lower value indicates that the ETF i is better based on the weighted ranking of relative momentum, volatility momentum, correlation momentum and ESG momentum strategies:

$$L_i = w_R * rank(r_i) + w_V * rank(v_i) + w_C * rank(c_i) + w_E * rank(e_i)$$

Each month, an equally-weighted portfolio of the best N ETFs out of the U – 40 ETFs in the universe is created, sorting ETFs by relative momentum (higher is better), while replacing ETFs by Vanguard Short Term Treasury ETF (VGSH) when their absolute momentum is less than

-10%. While the -10% threshold has been used consistently in all the strategies in this paper, it is an input in the [R Shiny](#) dashboard and can be modified according to the user's preferences. It must be noted that all ranking has been performed without taking absolute momentum into account, and only removing negative absolute momentum securities at the very end, after allocating weights. For the flexible asset allocation strategy, all ETFs were ranked based on momentum, annualized volatility, correlation and MSCI ESG Score. Since volatility and correlation are worse at higher values, they were multiplied by -1. Once total ranks were calculated using the formula above, an investment was made in the top N ETFs every period and if there were less than N ETFs with positive momentum, the remaining amount was invested in the VGSH.

4.2 RESULTS

As a first step, I created an equal-weight strategy with 25% assigned to each factor and compared it to the performance of the SPY. This and many other strategies can be viewed and tested interactively using the RShiny server ([Kipnis, 2014](#)) mentioned in the Appendix.

Flexible Asset Allocation for Socially Responsible ETF portfolio

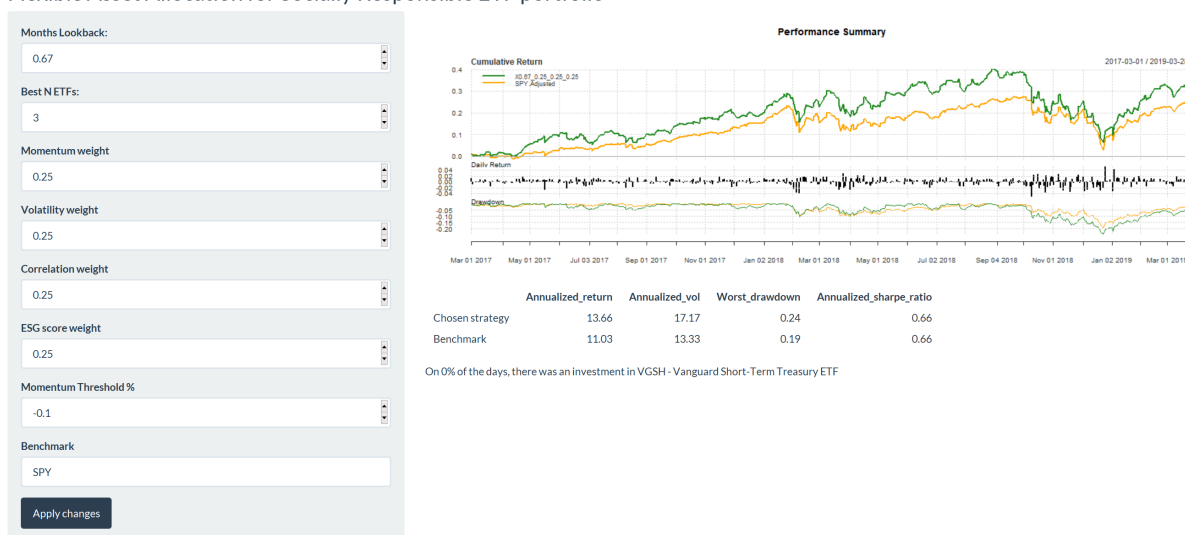


Figure 4-1: R Shiny view of the FAA dashboard. Lookback period: 20 days, Best N ETFs: 3, Relative Momentum Weight: 0.25, Volatility Weight: 0.25, Correlation Weight: 0.25, ESG Score Weight: 0.25, Benchmark: SPY. This strategy has an annualized return of 13.66% which is higher than SPY's annualized return of 11% but the Sharpe Ratio of 0.66 is equal to SPY's value.

Below are 5 important strategies that were tested using a lookback period of 20-days to understand their performance:

- **Pure momentum strategy:** Here the weights were assigned as 1 for momentum and 0 across all the other factors (*Lookback period: 20 days, Best N ETFs: 3, Relative Momentum Weight: 1, Volatility Weight: 0, Correlation Weight: 0, ESG Score Weight: 0*). This strategy demonstrated that when only high relative momentum is objective, one could invest in any of the 3 ETFs in the universe.
- **N4:** We invest in top 4 ETFs instead of top 3 (*Lookback period: 20 days, Best N ETFs: 4, Relative Momentum Weight: 0.25, Volatility Weight: 0.25, Correlation Weight: 0.25, ESG Score Weight: 0.25*). This led to an equally weighted portfolio with the 4 ETFs – iShares MSCI USA ESG Select ETF (SUSA), Technology Select Sector SPDR Fund (XLK), Cloud Computing ETF (SKYY), and the 3D Printing ETF (PRNT).
- **Momentum & Correlation strategy:** Here, a weight of 1 was assigned to momentum and correlation respectively and a weight of 0 was assigned across other factors (*Lookback period: 20 days, Best N ETFs: 3, Relative Momentum Weight: 1, Volatility Weight: 0, Correlation Weight: 1, ESG Score Weight: 0*). This resulted in an equally weighted portfolio with the 3 ETFs – ARK Innovation ETF (ARKK), ETFMG Prime Mobile Payments ETF (IPAY), 3D Printing ETF (PRNT).
- **Overweight ESG strategy:** In this strategy, we assign a weight of 1 to the ESG score while the weights of other factors are 0.25 (*Lookback period: 20 days, Best N ETFs: 3, Relative Momentum Weight: 0.25, Volatility Weight: 0.25, Correlation Weight: 0.25, ESG Score Weight: 1*). This resulted in an equally weighted portfolio with the 3 ETFs – iShares ESG MSCI EAFE ETF (ESGD), iShares MSCI USA ESG Select ETF (SUSA) and Technology Select SPDR Fund (XLK)
- **Uniform strategy:** This is an equal-weight strategy where all factors have a weight of 1 each (*Lookback period: 20 days, Best N ETFs: 3, Relative Momentum Weight: 1,*

Volatility Weight: 1, Correlation Weight: 1, ESG Score Weight: 1). Our portfolio consisted of the 3 ETFs - Technology Select Sector SPDR Fund (XLK), Cloud Computing ETF (SKYY), and the 3D Printing ETF (PRNT).

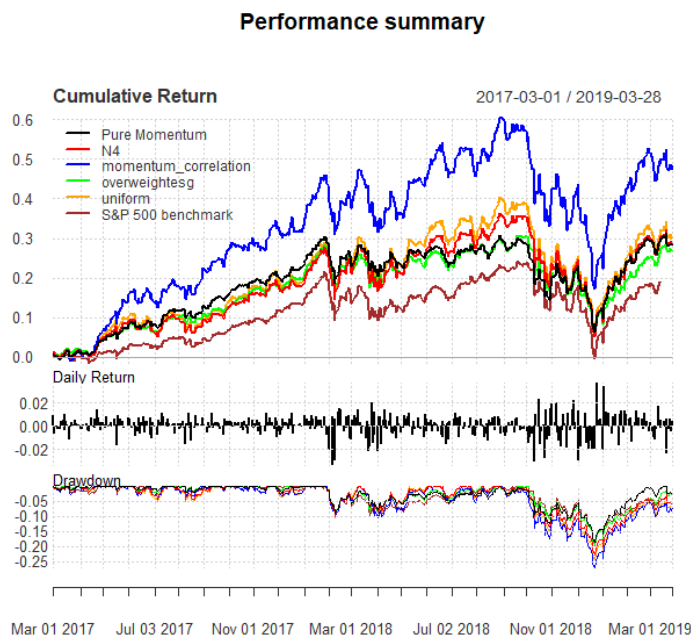


Figure 4-2: Performance Chart of FAA Strategies: It pays off to invest in these strategies rather than just the S&P500 benchmark because all strategies have a higher cumulative return in comparison to S&P 500. Momentum & Correlation has the highest cumulative return among the strategies tested. Also, most strategies have a lower drawdown over time compared to the S&P500 benchmark.

Upon analyzing the performance of these 5 strategies in comparison with the benchmark SPY, we can observe that all strategies perform much better in terms than the benchmark. The momentum & correlation strategy especially stands out in terms of Sharpe Ratio and gives investors more return for each unit of risk taken. The overweight ESG strategy also does very well in terms of risk, return and Sharpe Ratio and this indicates that ESG score is also an important factor to consider making a profit, while investing in socially responsible ETF portfolios.

Table 4-1: Performance Statistics of FAA Strategies: All chosen strategies consistently outperform the S&P500 benchmark. Momentum & Correlation strategy has the highest Sharpe Ratio followed by Pure Momentum and ESG momentum strategy. Pure momentum and the S&P500 benchmark respectively, have the lowest drawdown of 18.57% and 19.35% respectively.

| Strategy | Sharpe Ratio | Annualized return | Annualized standard deviation | Worst Drawdown |
|------------------------|--------------|-------------------|-------------------------------|----------------|
| Momentum & Correlation | 0.97 | 20.99% | 19.11% | 27.06% |
| Pure Momentum | 0.85 | 12.96% | 12.66% | 18.52% |
| Overweight ESG | 0.73 | 12.26% | 13.77% | 19.52% |
| N=4 | 0.68 | 13.06% | 15.95% | 22.80% |
| Uniform | 0.67 | 13.65% | 17.16% | 24.28% |
| S&P 500 Benchmark | 0.66 | 11.03% | 13.33% | 19.35% |

Chapter 5. CONCLUSIONS AND FUTURE WORK

Since our themes were chosen based on the United Nations' 2030 Sustainable Development goals, all of them have a very strong potential to grow in the future. In this paper, we reviewed how each of these themes might seem similar based on correlation and volatility but vary significantly in their risk-return, and social impact characteristics. Using the Flexible Asset Allocation models enabled us to expand our definition of a "theme" and analyze combinations of socially responsible ETFs based on factors including momentum, volatility, correlation and ESG scores. This helped us choose better combinations of ETFs based on current market conditions and led to results that were consistently more profitable for the risk taken than investing in the SPY benchmark. As a next step, it would be interesting to test these strategies and other hypotheses for different time periods, different ETF combinations and incorporate transaction costs for a more realistic picture.

BIBLIOGRAPHY

- Basdekidou, V. A., & Styliadou, A. A. (2017). Corporate Social Responsibility Performance & ETF Historical Market Volatility. *International Journal of Economics and Finance*, 9(10), 30. doi: <http://dx.doi.org/10.5539/ijef.v9n10p30>
- Bauer, N., Bosetti, V., Hamdi-Cherif, M., Kitous, A., McCollum, D., Méjean, A., . . . Van Vuuren, D (2015). CO2 emission mitigation and fossil fuel markets: Dynamic and international aspects of climate policies. *Technological Forecasting & Social Change*, 90 PA, 243-256. doi:<https://doi.org/10.1016/j.techfore.2013.09.009>
- Berry, T. C., & Junkus, J. C.(2013). Socially Responsible Investing: An investor perspective. *Journal of Business Ethics*, 112(4), 707-720. doi:<http://doi.org/10.1007/s10551-012-1567-0>
- Bérubé, V., Ghai, S., & Tétrault, J. (2014, December). From indexes to insights: The rise of thematic investing. Retrieved from McKinsey & Company:<https://www.mckinsey.com/industries/private-equity-and-principal-investors/our-insights/from-indexes-to-insights-the-rise-of-thematic-investing>
- Friede, G., Busch, T., & Bassen, A. (2015). ESG and Financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment*, 5(4), 210-233. doi:<http://doi.org/10.1080/20430795.2015.1118917>
- Galema, R., Plantinga, A., & Scholtens, B. (2008). The stocks at stake: Return and risk in socially responsible investment. *Journal of Banking & Finance*, 32(12), 2646-2654. doi:<http://doi.org/10.1016/j.jbankfin.2008.06.002>
- Rehman, I. H., Kar, A., Banerjee, M., Kumar, P., Shardul, M., Mohanty, J., & Hossain, I. (2012). Understanding the political economy and key drivers of energy access in addressing national energy access priorities and policies. *Energy Policy*, 47 (Supplement 1), 27–37. doi:<https://doi.org/10.1016/j.enpol.2012.03.043>
- Keller, W. J., & van Putten, H. (2012). Generalized Momentum and Flexible Asset Allocation (FAA): An Heuristic Approach. *SSRN Electronic Journal*. doi:[10.2139/ssrn.2193735](https://doi.org/10.2139/ssrn.2193735)
- Kempf, A. & Osthof, P. (2006). The Effect of Socially Responsible Investing on Financial Performance.

- Kipnis, I. (2014, October 28). QuantStrat TradeR. Retrieved from An Attempt At Replicating Flexible Asset Allocation (FAA): <https://quantstrattrader.wordpress.com/2014/10/20/an-attempt-at-replicating-flexible-asset-allocation-faa/>
- Kipnis, I. (2014, November 25). *QuantStrat TradeR*. Retrieved from An Update on Flexible Asset Allocation: <https://quantstrattrader.wordpress.com/2014/11/25/an-update-on-flexible-asset-allocation/>
- Norton, L. P. (2018, October 26). Sustainable Investing Is at a “Tipping Point,” BlackRock Says. Retrieved from Barron's: <https://www.barrons.com/articles/blackrock-sustainable-investing-funds-1540523163>
- Sea-level rise for centuries to come. (2017). *Nature*, 541(7637), 262-263. Retrieved from <https://search.proquest.com/docview/1861002866?accountid=14784>
- Seetharaman, D., & Glazer, E. (2018, October 25). Gender Equality Stalls in Corporate America Despite #MeToo. Retrieved from Wall Street Journal : <https://www.wsj.com/articles/gender-equality-stalls-in-corporate-america-despite-metoo-1540375203>
- Simon, M. (2017). *The new economics of social change* (First ed.). New York: Nation Books.
- United Nations: Sustainable Development Goals. (2015). Retrieved from <https://www.un.org/sustainabledevelopment/sustainable-development-goals/>

APPENDIX

- **R Shiny – Flexible Asset Allocation for Socially Responsible ETFs:** <https://github.com/SunaynaRangarajan/FAA-Socially-Responsible-ETFs> . This can be run in R using `runGitHub("FAA-Socially-Responsible-ETFs", "SunaynaRangarajan")` after the `shiny` package is installed and loaded. *Note: This dashboard will be continuously modified to improve functionality for the user.*
- **Summarized sample R code for comparison across themes and computing performance statistics**

```
library(quantmod)

library(xts)
library(PerformanceAnalytics)

library(zoo)
library(tseries)
library(ggplot2)

#Thematic Impact Investing with a Sector/Market Index (Comment out beta charts if there is no benchmark)
#Benchmark must always be first or second value

Thematic_Impact_Investing ETF <- function(theme, ETF_symbols, ETF_names, start_date, end_date, market_index= NULL)
{
  #Data structure that contains stock quote objects
  ETF_Data <- new.env()

  data <- getSymbols(ETF_symbols, src="yahoo", env=ETF_Data, from=start_date, to=end_date)
  data <- na.omit(na.locf(do.call(merge, eapply(ETF_Data, Ad)[data])))
  colnames(data) <- ETF_names

  #Daily Log returns
  log_returns <- na.omit(diff(log(data)))

  #60-day rolling correlation
  cor_plot = chart.RollingCorrelation(log_returns[, -1, drop=FALSE],
                                     log_returns[, 1, drop=FALSE],
                                     legend.loc="bottomright",
                                     width=60, main =
```

```

paste("SPY Rolling 60-Days Corr:", theme), lwd=3, colorset = c("black", "
red", "green", "blue", "aquamarine1", "pink", "yellow", "brown", "seagreen", "goldenrod1", "darkviolet", "gray62", "lightcoral", "olivedrab1", "plum2", "wheat2", "skyblue"))
print(cor_plot)

cor_plot_market_index = chart.RollingCorrelation(log_returns[,c(-1,-2), drop
=FALSE], log_returns[,2, drop=FALSE], legend.loc="bottom", width=60, main =
paste(ETF_symbols[2], "Rolling 60-Days Corr:", theme), lwd=3, colorset = c("black", "red", "green", "blue", "aquamarine1", "pink", "yellow", "brown", "seagreen", "goldenrod1", "darkviolet", "gray62", "lightcoral", "olivedrab1", "plum2", "wheat2", "skyblue"))

print(cor_plot_market_index)

#60-day rolling volatility
roll.sigmahat = rollapply(log_returns, width=60, FUN=sd, align="right")
vol_plot = chart.TimeSeries(roll.sigmahat, legend.loc="topleft",
main = paste(theme, "volatility rolling", 60, "days"),
ylab="rolling volatility of daily log returns",
colorset = c("black", "red", "green", "blue", "aquamarine1", "pink", "yellow", "brown", "seagreen", "goldenrod1", "darkviolet", "gray62", "lightcoral", "olivedrab1", "plum2", "wheat2", "skyblue"))
print(vol_plot)

#60-day rolling beta
beta_plot = chart.RollingRegression(log_returns[,c(-1,-2), drop=FALSE],
log_returns[,2, drop=FALSE], legend.loc="topright", width=60, Rf = 0, attribute = "Beta", main = paste("Rolling 60-Days Beta:", theme), lwd=3,
colorset = c("black", "red", "green", "blue", "aquamarine1", "pink", "yellow", "brown", "seagreen", "goldenrod1", "darkviolet", "gray62", "lightcoral", "olivedrab1", "plum2", "wheat2", "skyblue"))
print(beta_plot)

#Constructing an equally weighted portfolio with monthly rebalancing
portfolio = log_returns[,c(-1,-2)]
equal_weight = rep(1/ncol(portfolio), ncol(portfolio))
pf_rebal <- Return.portfolio(portfolio, weights = equal_weight, rebalance_on = "months", verbose=TRUE)
EOP_Portfolio = rowSums(pf_rebal$EOP.Value)
EOP_return = pf_rebal$return

#Equity curve
normalized_SPY = cumprod(na.omit(data[,1]/lag(data[,1],1)))
normalized_market_index = cumprod(na.omit(data[,2]/lag(data[,2],1)))

plot(x=index(log_returns), y=EOP_Portfolio*1000, type="l", col="green",
lwd=2,

```

```

    ylab="EOP Portfolio Value", xlab="Year", main="Daily Value of $1000", ylim=c(700, 2000))
    par(new=TRUE)

    plot(x=index(normalized_SPY), y=normalized_SPY*1000, type="l", lwd=2, col="black", ylab="EOP Portfolio Value", xlab="Year", main="Daily Value of $1000", ylim=c(700,2000))
    par(new=TRUE)

    plot(x=index(normalized_market_index), y=normalized_market_index*1000, type="l", lwd=2, col="orange", ylab="EOP Portfolio Value", xlab="Year", main="Daily Value of $1000", ylim=c(700,2000))

    legend("topleft", legend=c(paste(theme), "SPY", c(paste(ETF_symbols[2]))), col=c("green", "black", "orange"), lty=1, lwd=2)

    #Performance statistics
    performance_stat = data.frame(

Total_return = c(Return.cumulative(pf_rebal$returns, geometric=TRUE)),
Annualized_return = c(Return.annualized(pf_rebal$returns, geometric = TRUE, scale = 252)),
Sd = c(StdDev.annualized(pf_rebal$returns, scale = 252)),
Sharpe_Ratio = c(SharpeRatio.annualized(pf_rebal$returns, Rf=0.02/252, scale=252)),
cor_etf = c(cor(pf_rebal$returns, log_returns[,1])),
beta_etf = CAPM.beta(pf_rebal$returns, log_returns[,1], Rf=0.02/25),
jensenAlpha_etf = CAPM.jensenAlpha(pf_rebal$returns, log_returns[,1], Rf=0.02/25),
skewness_etf = skewness(pf_rebal$returns),
kurtosis_etf = kurtosis(pf_rebal$returns),
Max_relative_drawdown = max((cummax(EOP_Portfolio)-(EOP_Portfolio))/cummax(EOP_Portfolio)),
cor_market_index = c(cor(pf_rebal$returns, log_returns[,2])),
beta_market_index = CAPM.beta(pf_rebal$returns, log_returns[,2], Rf=0.02/25),
jensenAlpha_market_index = CAPM.jensenAlpha(pf_rebal$returns, log_returns[,2], Rf=0.02/25),
returns = EOP_return)

t_performance_stat = t(performance_stat[1,-ncol(performance_stat)])
row.names(t_performance_stat) = c("Total return", "Annualized return", "Annualized standard deviation", "Sharpe Ratio", "Correlation with SPY", "Beta with SPY", "Jensen Alpha with SPY", "Skewness", "Kurtosis", "Maximum Relative Drawdown", "Correlation with market index", "Beta with market index", "Jensen Alpha with Market Index")

```

```

result = cbind(index(log_returns),EOP_Portfolio*1000)
return(result)
}

```

- **Summarized sample R code for Portfolio Optimization Plot**

```

library(ggplot2)
library(ggthemes)
library(reshape)
library(dplyr)

ggplot() +
  geom_point(data=mean_variance_esg, aes(x=variance, y=mean, col=portfolio),
size=6) +
  geom_line(data=eff_frontier, aes(x=variance, y=mean), lwd=1, lty=2) +
  labs(subtitle="Equally Wgt Portfolio - Thematic investing",
y="Annualized portfolio return",
x="Annualized portfolio volatility",
title="Return vs Volatility",
caption = "Source: Yahoo Finance") +
  scale_colour_manual(values=c("gold", "darkturquoise","salmon1", "seashell4"
,"lightgreen","orange","lightblue","maroon1","black")) +
  theme_economist_white() +
  theme(legend.title=element_blank(), legend.text=element_text(size=11), lege
nd.position = c(0.85,0.25))

```

- **Summarized sample R code for FAA including ESG ETFs**

- *#References*

#Keller, W. J. (2012). Generalized Momentum and Flexible Asset Allocation (FAA):

#An Heuristic Approach. SSRN Electronic Journal. doi:10.2139/ssrn.2193735

#Kipnis, I. (2014, October 28). QuantStrat TradeR. Retrieved from An Attempt At Replicating Flexible Asset Allocation (FAA):

#https://quantstrattrader.wordpress.com/2014/10/20/an-attempt-at-replicating-flexible-asset-allocation-faa/

#Kipnis, I. (2014, November 25). QuantStrat TradeR. Retrieved from An Update on Flexible Asset Allocation:

#https://quantstrattrader.wordpress.com/2014/11/25/an-update-on-flexible-asset-allocation/

```

packages <- c("PerformanceAnalytics", "quantmod","xts","scales")
new.packages <- packages[!(packages %in% installed.packages()[,"Package"])
]
if(length(new.packages)>0) {install.packages(new.packages)}

```

```
library(PerformanceAnalytics)
```

- `library(quantmod)`
- `library(xts)`
- `library(scales)`

```
adPrices <- read.csv("adPrices.csv")
adPrices$Index <- as.Date(adPrices$Index)
adPrices <- xts(adPrices[, -1], order.by=adPrices[, 1])
```

```
esg_data <- read.csv("ESG_Score.csv")
esg_data <- esg_data[, c(1, 2)]
esg <- esg_data[, 2]
names(esg) <- esg_data[, 1]
```

```
FAA <- function(prices, monthsLookback = 1,
                weightMom = 1, weightVol = .5, weightCor = .5, weightesg =
0.5,
                riskFreeName = "VGSB", bestN = 3, momentum_threshold = -0.1)
{
```

```
  returns <- Return.calculate(prices)
  monthlyEps <- endpoints(prices, on = "months")
  riskFreeCol <- grep(riskFreeName, colnames(prices))
  tmp <- list()
  dates <- list()
```

```
  for(i in 2:(length(monthlyEps) - monthsLookback)) {
```

```
    priceData <- prices[monthlyEps[i]:monthlyEps[i+monthsLookback],]
    returnsData <- returns[monthlyEps[i]:monthlyEps[i+monthsLookback],]
```

```
    momentum <- data.frame(t(t(priceData[nrow(priceData),])/t(priceData[1,
])) - 1))
```

```
    momentum <- momentum[, !is.na(momentum)]
    priceData <- priceData[, names(momentum)]
    returnsData <- returnsData[, names(momentum)]
```

```
    momRank <- rank(momentum)
    vols <- data.frame(StdDev(returnsData))
    volRank <- rank(-vols)
    cors <- cor(returnsData, use="complete.obs")
    corRank <- rank(-rowSums(cors))
    esg <- esg
    esgRank <- rank(esg)
```

```

    totalRank <- rank(weightMom*momRank + weightVol*volRank + weightCor*co
rRank + weightesg*esgRank)
    topNvals <- as.vector(totalRank[order(totalRank, decreasing = TRUE)][1
:bestN])

    #compute weights
    longs <- totalRank %in% topNvals #invest in ranks Length - bestN or hi
gher (in R, rank 1 is lowest)
    longs[momentum < momentum_threshold] <- 0
    longs <- longs/sum(longs) #equal weight all candidates
    longs[longs > 1/bestN] <- 1/bestN #in the event that we have fewer tha
n top N invested into, lower weights to 1/top N
    names(longs) <- names(totalRank)

    #append removed names (those with momentum < momentum_threshold)
    removedZeroes <- rep(0, ncol(returns))
    names(removedZeroes) <- names(returns)[!names(returns) %in% names(long
s)]
    longs <- c(longs, removedZeroes)

    #reorder to be in the same column order as original returns/prices
    longs <- data.frame(t(longs))
    longs <- longs[, names(returns)]

    #append lists
    tmp[[i]] <- longs
    dates[[i]] <- index(returnsData)[nrow(returnsData)]
  }

  weights <- do.call(rbind, tmp)
  dates <- do.call(c, dates)
  weights <- xts(weights, order.by=as.Date(dates))
  weights[, riskFreeCol] <- weights[, riskFreeCol] + 1-rowSums(weights)
  strategyReturns <- Return.rebalancing(R = returns, weights = weights, ge
ometric = TRUE)
  colnames(strategyReturns) <- paste(monthsLookback, weightMom, weightVol,
weightCor, sep="_")
  return(strategyReturns)
}

Cash_inv <- function(prices, monthsLookback = 1,
                    weightMom = 1, weightVol = .5, weightCor = .5, weight
esg = 0.5,
                    riskFreeName = "VGSH", bestN = 3, momentum_threshold=-0.1 )
{
  returns <- Return.calculate(prices)

```

```

monthlyEps <- endpoints(prices, on = "months")
riskFreeCol <- grep(riskFreeName, colnames(prices))
tmp <- list()
dates <- list()

for(i in 2:(length(monthlyEps) - monthsLookback)) {
  #subset data
  priceData <- prices[monthlyEps[i]:monthlyEps[i+monthsLookback],]
  returnsData <- returns[monthlyEps[i]:monthlyEps[i+monthsLookback],]

  #perform computations
  momentum <- data.frame(t(t(priceData[nrow(priceData),])/t(priceData[1,
]) - 1))
  momentum <- momentum[,!is.na(momentum)]
  #momentum[is.na(momentum)] <- -1 #set any NA momentum to negative 1 to
keep R from crashing
  priceData <- priceData[,names(momentum)]
  returnsData <- returnsData[,names(momentum)]

  momRank <- rank(momentum)
  vols <- data.frame(StdDev(returnsData))
  volRank <- rank(-vols)
  cors <- cor(returnsData, use="complete.obs")
  corRank <- rank(-rowSums(cors))
  esg <- esg
  esgRank <- rank(esg)

  totalRank <- rank(weightMom*momRank + weightVol*volRank + weightCor*co
rRank + weightesg*esgRank)
  topNvals <- as.vector(totalRank[order(totalRank, decreasing = TRUE)][1
:bestN])

  #compute weights
  longs <- totalRank %in% topNvals #invest in ranks length - bestN or hi
gher (in R, rank 1 is lowest)
  longs[momentum < momentum_threshold] <- 0
  longs <- longs/sum(longs) #equal weight all candidates
  longs[longs > 1/bestN] <- 1/bestN #in the event that we have fewer tha
n top N invested into, lower weights to 1/top N
  names(longs) <- names(totalRank)

  #append removed names (those with momentum < momentum_threshold)
  removedZeroes <- rep(0, ncol(returns))
  names(removedZeroes) <- names(returns)[!names(returns) %in% names(long
s)]
  longs <- c(longs, removedZeroes)

  #reorder to be in the same column order as original returns/prices
  longs <- data.frame(t(longs))

```

```

longs <- longs[, names(returns)]

#append lists
tmp[[i]] <- longs
dates[[i]] <- index(returnsData)[nrow(returnsData)]
}

weights <- do.call(rbind, tmp)
dates <- do.call(c, dates)
weights <- xts(weights, order.by=as.Date(dates))
weights[, riskFreeCol] <- weights[, riskFreeCol] + 1-rowSums(weights)
strategyReturns <- Return.rebalancing(R = returns, weights = weights, geometric = TRUE)
colnames(strategyReturns) <- paste(monthsLookback, weightMom, weightVol, weightCor, sep="_")
return(percent(sum(weights$VGSH>0)/nrow(weights)))
}

benchmark <- function (stock_symbol) {
  benchmark_Data <- new.env()
  benchmark = getSymbols(toString(stock_symbol), src="yahoo", env=benchmark_Data, from="2017-02-15", to="2019-03-29")
  benchmark = na.omit(na.locf(do.call(merge, eapply(benchmark_Data, Ad))))
  benchmark_return = Return.calculate(benchmark)
  return(benchmark_return)
}

```