Optimizing Portfolio Construction with ESG Considerations

ORIE 5253: Asset Management

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ABSTRACT

ESG (Environmental, Social and Governance) investing has become a priority among investors seeking sustainable investment ideas. The study focuses on including ESG considerations when optimizing a portfolio with ESG parameters as constraints and objectives in the traditional mean-variance setting. We compare each strategy using traditional metrics and analyze the returns/risk and ESG scores tradeoff for the portfolio. The effectiveness of ESG parameters is demonstrated by trading on S&P 100 universe. Moreover, the study compares traditional factors with ESG Good minus Bad factor and their correlations to understand the impact of ESG considerations in a portfolio.

1. INTRODUCTION

ESG stands for Environment, Social, and Governance, and many investors seek companies that incorporate all three of these elements. Investors, for instance, want to see that a business cares about the environment by reducing carbon emissions, and social issues by providing employees with secure workplaces, and governance by having ethical, transparent, and accountable practices.

Institutional investors have argued over last 20 years if accounting for Environmental, Social, and Governance (ESG) aspects can improve financial returns. Because ESG variables address long-term risks that the economy has not yet fully absorbed, proponents contend that markets do not efficiently price them and that alpha generation is feasible as markets start to identify these underappreciated aspects. Both sides of this debate have been supported by academic research and industry analyses, but overall they come to the conclusion that using ESG factors does not significantly harm an investor's performance and that using certain ESG strategies may even help investors outperform those using non-ESG tilted strategies in terms of risk-adjusted returns.

In this study, we analyze the effect of ESG Risk score by RepRisk on Portfolio Optimization for the period of January 2016 to December 2020 with stocks in S&P 100. We optimize the stock weights using two methods: 1) Maximize returns using the risk aversion parameter and 2) Minimize risk such that the portfolio tracks the benchmark (beta=1 with S&P 100). Further description of the strategies and approach with ESG parameters is mentioned in the ESG Strategies and Portfolio Optimization Analysis section respectively. Secondly, we analyze the ESG Good minus Bad factor constructed using the RepRisk rating in combination with the traditional size, value and momentum factors. The details of this analysis are mentioned in the ESG Factor Analysis section. Lastly, we conclude our study with results and recommendations on using ESG parameters for portfolio construction.

2. DATA

The data* used here ranges from January 2015 to December 2020 for all companies in the S&P 100 point in time universe. It is important to note that the point in time universe is considered in order to remove the survivorship bias. So at any time instance, we trade on only those companies that are present in the universe at that time instance. For this we consider the constituents of S&P 100 index rebalanced monthly and use the universe for each month accordingly, with the assumption that the universe for a specific month is known at the end of the last day of the previous month. The overall universe is a set of all companies that have appeared in the index at least once.

Apart from the point in time universe, the data includes three main components:

1. Daily price data for all companies in the universe and the S&P 100 (OEX) index
2. Monthly ESG data for all companies in the universe
3. Monthly factor data for all companies in the universe

The ESG data is from Wharton Research Data Services. The data vendor used is RepRisk, which gives the ESG Risk score denoting the current level of reputational risk exposure of a company related to ESG issues. Its values are between 0 to 100. There are also corresponding letter grades as shown in Table 1. It shows that the lower the ESG Risk score, the better the company is from ESG point of view. The data also includes the percentage contribution of each of the E, S and G parts in the ESG Risk score. Additionally, it provides an ESG Trend score, which is the difference in the ESG Risk Score between the current date and the date 30 days ago, emphasizing the direction of ESG Risk score movement. Its values are between -100 to 100.

	Low risk	Medium risk	High risk	Very high risk
Letter grade	AAA, AA, A	BBB, BB, B	CCC, CC, C	D
ESG Risk Score	0 to 25	26 to 49	50 to 74	75 to 100

Table 1: RepRisk ESG Risk score description

For the factor data, book-to-market ratio as a proxy for size factor, market capitalization as a proxy for size factor and average lagged returns of the past 12 months barring the last month due to short term reversal as a proxy for momentum factor. In addition to all these, data of the sectors corresponding to each company in the universe is also used for sector based analysis.

3. ESG STRATEGIES

For building strategies focused on ESG, it is important to consider how to incorporate ESG in the process to construct a robust and adaptable portfolio. For this, different levels of importance are placed on ESG Risk score in the portfolio construction process. We focus on three different levels and multiple strategies within each, as shown in Table 2.

<table>
<tr><td colspan="2">No ESG</td><td>ESG Risk score is neither used in company selection nor in company weight allocation. Markowitz optimization is applied to all companies in the point in time universe.</td></tr>
<tr><td rowspan="2">Semi ESG</td><td>Top ESG</td><td>ESG Risk score is used in company selection, but not in company weight allocation. Markowitz optimization is applied to the top 25 companies with the lowest ESG Risk score in the point in time universe.</td></tr>
<tr><td>Bottom ESG</td><td>ESG Risk score is used in company selection, but not in company weight allocation. Markowitz optimization is applied to the bottom 25 companies with the highest ESG Risk score in the point in time universe.</td></tr>
<tr><td rowspan="3">Full ESG</td><td>ESG in objective</td><td>ESG Risk score is not used in company selection, but used in company weight allocation. Modified Markowitz optimization is applied to all companies in the point in time universe with the objective being minimizing ESG Risk score and constraint on minimum returns required at constant risk (referred to as Obj1) or maximum risk allowed at constant returns (referred to as Obj2).</td></tr>
<tr><td>ESG as constraint</td><td>ESG Risk score is not used in company selection, but instead used in company weight allocation. Markowitz optimization is applied to all companies in the point in time universe with an extra constraint on maximum aggregate ESG Risk score allowed.</td></tr>
<tr><td>ESG for scaling</td><td>ESG Risk score is not used in company selection, but instead used in company weight allocation. Markowitz optimization is applied to all companies in the point in time universe and weights are scaled up or down based on ESG Risk score or ESG Trend score</td></tr>
</table>

Table 2: ESG strategies description

4. PORTFOLIO OPTIMIZATION ANALYSIS

We use the past one year daily returns data of the companies in the current point in time universe to calculate the mean and covariance matrix for optimization. For ESG parameters in the optimization, we use the ESG Risk score from the past month. The portfolios are rebalanced monthly and out of sample returns and ESG scores are calculated to compare all the strategies. We consider two optimization methods: 1) Classical Markowitz and 2) Index Tracking Markowitz. The methodology and results are described in the following sections. To test and compare the performance of all these strategies, following performance metrics are used, as described in Table 3.

	Description
Return	Compounded annual growth rate of daily returns
Volatility	Annualized standard deviation from daily returns
Sharpe Ratio	Annualized risk adjusted returns
Tracking Error	Annualized standard deviation of excess returns to benchmark
Information Ratio	Annualized excess returns compared to volatility of excess returns
Max Drawdown	Maximum decline from previous peak
Calmar Ratio	Annualized returns given maximum drawdowns
Sortino Ratio	Annualized downside risk adjusted returns
95% VAR	Maximum annual loss with 95% confidence
ESG Risk score	Average ESG Risk score
Sharpe/ESG Risk score	Annualized Sharpe ratio for a unit ESG Risk score

Table 3: Performance metrics

4.1. CLASSICAL MARKOWITZ OPTIMIZATION

Classical Markowitz portfolio optimization for long only portfolio solves the following optimization problem to allocate weights to companies within the portfolio, where γ is the risk aversion parameter and the optimal weights selected are corresponding to the γ that gives the highest Sharpe Ratio:

$$max\ \mu^T w - \gamma w^T \Sigma w \quad st.\ 1^T w = 1,\ w > 0,\ w \in W$$

For No ESG strategies, we simply use this optimization function on the entire point in time universe to find optimal weights.

For Semi ESG Top and Bottom strategies, we filter our current point in time universe based on last month's ESG Risk score and run this optimization problem on the selected universe of the top 25 companies with least ESG Risk score or the bottom 25 companies with most ESG Risk score to find optimal weights respectively.

For Full ESG Scaling strategies, we run this optimization function on the entire point in time universe to find optimal weights and then scale the weights by multiplying them with the ESG Risk score or ESG Trend score and dividing by the sum of weights to make them sum up to 1. For the Full ESG Constraint strategy, we run similar optimization on the entire point in time universe but with an added constraint that the portfolio ESG Risk score should be lower than the ESG Risk score of the No ESG portfolio denoted by *esg*, by a factor of *k*, where *k* < 1 (here *k* = 0.95 is used). The optimization is as follows:

$$max\ \mu^T w - \gamma w^T \Sigma w \quad st.\ 1^T w = 1,\ w > 0, ESG\ Risk\ score < k\ .\ esg\ \ w \in W$$

Finally, for Full ESG Objective strategies, the portfolio ESG Risk score is minimized by either keeping the constraint on maximum risk constant (equal to the risk of the No ESG portfolio, i.e. var, where *var* is used below) and varying the constraint on minimum returns by a factor k_1 (< 1, here = 0.95 i.e. allow 5% less returns) of the returns of No ESG portfolio or by keeping constraint on minimum returns constant (equal to the returns of the No ESG portfolio, i.e. ret, where *ret* is used below) and varying constraint on maximum risk by a factor k_2(> 1, here = 1.05 i.e. allow 5% more risk) of the risk of No ESG portfolio. The optimization is as follows:

$$min\ \ ESG\ Risk\ score \quad st.\ 1^T w = 1,\ w > 0,\ \mu^T w > k_1 .\ ret,\ w^T \Sigma w < k_2 .\ var,\ \ w \in W$$

The performance of all the above mentioned strategies is as shown in Table 4.

	No ESG	Semi ESG		Full ESG					Index
		Top ESG	Bottom ESG	ESG Objective		ESG Cons.	ESG Scaling		
				Min returns cons.	Max risk cons.		Tilt Scale	Mom. scale	
Return (%)	24.69	16.34	34.84	21.08	22.16	24.25	19.14	24.60	13.54
Volatility (%)	25.74	23.15	27.48	24.96	25.90	25.55	23.86	25.81	19.20
Sharpe Ratio	0.98	0.77	1.22	0.89	0.90	0.97	0.85	0.98	0.75
Tracking Error (%)	17.96	14.29	18.99	16.21	17.13	17.59	15.56	18.04	NA
Information Ratio	0.60	0.22	1.00	0.47	0.51	0.59	0.37	0.59	NA
Max Drawdown (%)	32.39	32.90	25.36	33.08	32.97	32.57	32.44	32.48	31.53
Calmar Ratio	0.78	0.54	1.32	0.67	0.70	0.76	0.62	0.78	0.46
Sortino Ratio	1.16	0.89	1.52	1.04	1.07	1.14	0.99	1.15	0.84
95% VAR (%)	-17.05	-20.36	-11.63	-18.90	-19.34	-17.14	-18.98	-17.23	-17.10
ESG Risk score	35.97	18.25	54.68	26.99	27.31	34.25	33.24	35.90	NA
Sharpe/ESG Risk score	0.027	0.042	0.022	0.033	0.033	0.028	0.025	0.027	NA

Table 4: Classical Markowitz results summary

Here we observe that for all strategies, the volatility remains almost constant. If we look closely at both the ESG Objective strategies we see that the ESG Risk score reduces noticeably without losing much on returns compared to No ESG strategy. So there is a clear trade-off here that we explore in Section 4.1.1. The cumulative returns of all strategies using Classical Markowitz optimization are illustrated in Figure 1.

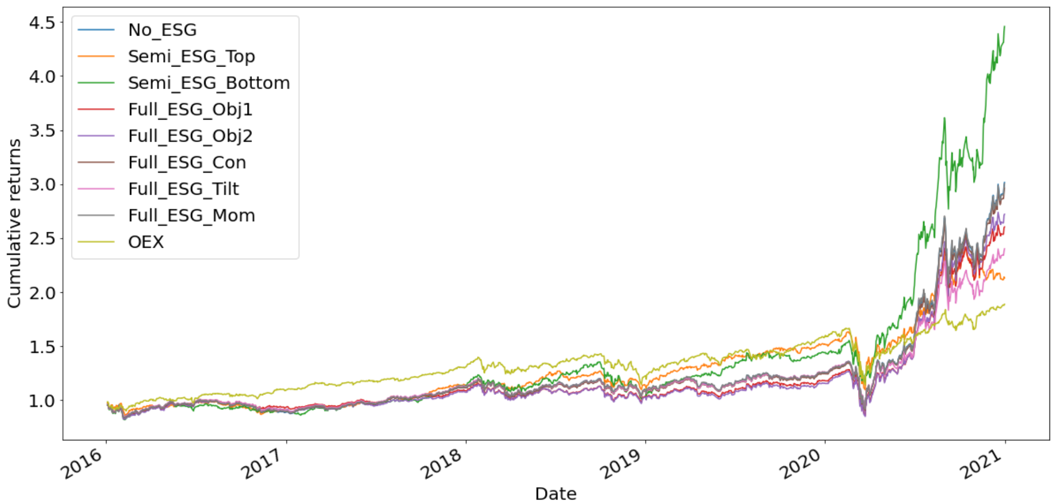

Figure 1: Cumulative returns of Classical Markowitz with ESG strategies

Here we see that pre covid, all strategies underperform the index and a sudden boom is observed post covid. The potential reasons for this shift due to covid are discussed further in Section 4.1.2. The Semi ESG Bottom strategy experiences the maximum boom and outperforms all others. To understand the reason for this behavior, we look into the market sectors of the companies chosen by the Semi ESG Bottom strategy in Section 4.1.3. The ESG Risk scores of each strategy are illustrated in Figure 2.

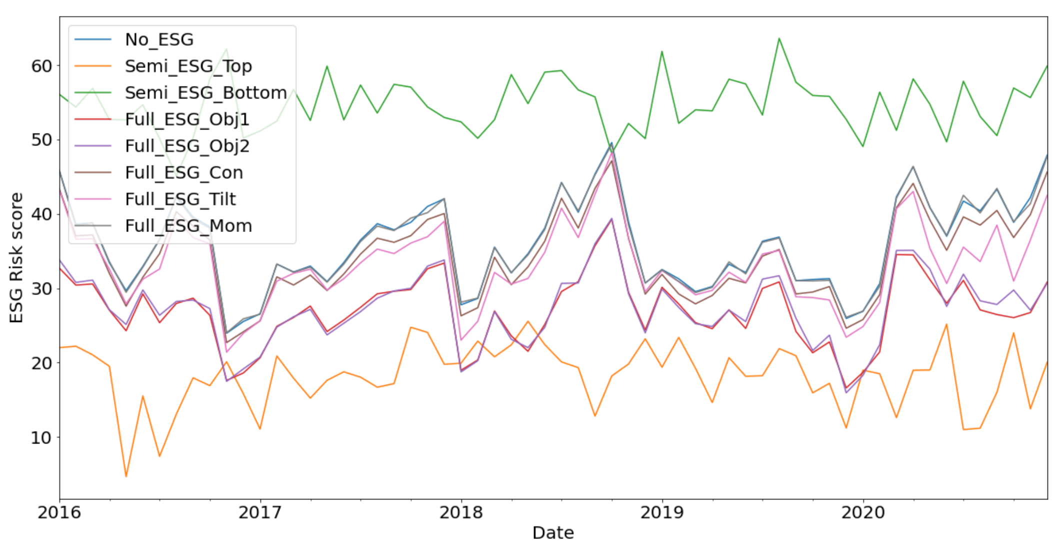

Figure 2: ESG Risk scores of Classical Markowitz with ESG strategies

Here we see as expected, the Semi ESG Top strategy has the lowest ESG Risk score (A grade) while the Semi ESG Bottom strategy has the highest ESG Risk score (C grade). All the other ESG favored strategies fall in the medium risk category and have lower ESG Risk score than No ESG strategy (B grade), again as expected. Another important observation is that the ESG Risk score is very volatile for all the strategies.

4.1.1. RETURNS/RISK VS. ESG PERFORMANCE TRADEOFF

ESG Objective Strategies allows to give different constraints on minimum returns needed or maximum risk allowed. This is a good way to calibrate the values in these constraints and check the tradeoff between ESG performance and risk/returns performance i.e. how much ESG performance can we boost by giving up how much returns or taking how much more risk. We conduct the analysis by taking the minimum returns needed as a certain percentage of No ESG portfolio return and by taking the maximum risk allowed as a certain percentage of No ESG portfolio risk. Table 5 shows how the performance varies as we allow the minimum returns needed to decrease or the maximum risk needed to increase.

	No ESG	Allow 5% less return than No ESG	Allow 10% less return than No ESG	Allow 15% less return than No ESG	Allow 5% more risk than No ESG	Allow 10% more risk than No ESG	Allow 15% more risk than No ESG
Return (%)	24.69	21.08	18.45	16.18	22.16	20.97	20.21
Volatility (%)	25.74	24.96	24.63	24.30	25.90	26.45	27.02
Sharpe Ratio	0.98	0.89	0.81	0.73	0.90	0.85	0.81
ESG Risk score	35.97	26.99	23.53	20.96	27.31	24.59	22.98
Sharpe/ESG Risk score	0.027	0.033	0.034	0.035	0.033	0.034	0.035

Table 5: Performance tradeoff by varying minimum returns needed or maximum risk allowed in Full ESG Objective strategies (Obj1 and Obj2)

We observe that by allowing 5% less returns or 5% more risk than No ESG strategy, the returns do not drop significantly but the ESG Risk score does. In fact the improvement in ESG takes the portfolio from B grade to almost A grade, making it lucrative to investors willing to give up little performance for favoring ESG. The improvement with respect to ESG is not as significant as performance hurt in terms of returns by allowing further lower returns or taking further more risk. However, investors can use this trade-off analysis and calibrate their portfolios based on their risk/return preferences.

4.1.2. COVID AS A CATALYST FOR ESG STRATEGIES

Historically, it is evident that times of financial crisis have been turning points for certain strategies. The dotcom bubble increased the importance of mean variance portfolio optimization while quality factor and low volatility factor became full fledged beta strategies post 2008 financial crisis. Recently, there have been discussions around ESG being an alpha strategy or smart beta strategy. While it is a fully developed smart beta strategy in Europe, that is not so evident in the USA yet. However, there have been some important changes post covid that can possibly explain the outperformance of ESG strategies in that period.

While earlier only the environmental pillar contributed majorly to ESG Risk score, post covid the importance of social and governance pillars increased. With this, the ESG criteria is reweighted with more emphasis on the public health system and inequalities and social issues are reconsidered at corporate level for defining ESG Risk scores in the light of labor practices, workplace safety, employee benefits, etc. Besides, there is a change in view for measurement of economic performance. Companies dependent on out of control factors like supply chain management, foreign workforce, workplace safety, etc. shut down in covid. It became important to focus on sustainable long-term economic performance integrating financial and extra-financial criteria with anticipated increase in supervision and regulation. Besides all of this, there has been a reinforcement of shared common values, which might even lead to a market for social bonds, like green bonds apart from benefiting ESG based equity strategies. So in all, it is very likely that covid will prove as a catalyst for ESG strategies developing into smart beta strategies in near future.

4.1.3. SECTOR ANALYSIS

According to the Global Industry Classification Standard, there are 11 broad market sectors in which we can categorize all the companies. These sectors are as shown in Figure 3. As a whole, each sector is likely to perform differently with respect to ESG.

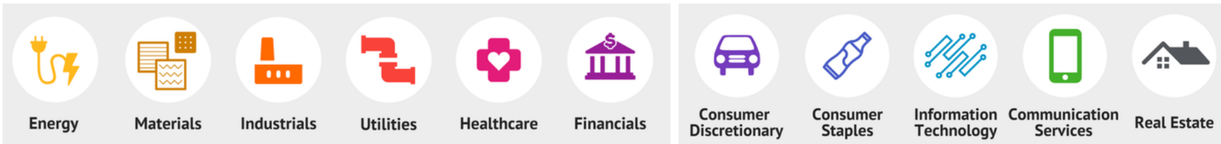

Figure 3: Broad classification of market sectors

Looking into the sectors chosen by Semi ESG Bottom Strategy, it turns out that these sectors are mostly Healthcare, Technology, Financial and Consumer Discretionary. Healthcare was majorly penalized by governance factor in ESG Risk score while Technology and Financial were penalized by social and governance factors in ESG Risk score post covid. Consumer Discretionary in general has a high ESG Risk score and that behavior continued post covid too. It is totally believable that the Healthcare sector performed well during a pandemic-induced recession. Many companies in the Technology sector also benefited from the new working environments during the pandemic. The Financial sector had mixed behaviors with certain segments within it benefiting while certain segments hurt by the unprecedented market volatility during the pandemic crisis, so it was not a clear winner, it was at least not a clear loser when considered as a whole sector. The Consumer Discretionary sector included products that are nonessential, so initially this sector dropped but as pandemic restriction lifted and people's economic conditions improved to start spending on these items heavily. This clearly explains why Semi ESG bottom strategy outperformed all others post covid.

4.2. INDEX TRACKING MARKOWITZ OPTIMIZATION

With Classical Markowitz, the issue is that it is difficult to compare it with the index benchmark because there is no common ground between the portfolios and the index benchmark. Index tracking Markowitz portfolio optimization for long only portfolio solves the following optimization problem to allocate weights to companies within the portfolio, where β is the list of betas (the covariance of the return of a company with the return of the index divided by the variance of the return of the index over past one year) of all companies in the point in time universe with respect to the index S&P 100.

$$min\ w^T \Sigma w \quad st.\ 1^T w = 1,\ w > 0,\ \beta^T w = 1,\ w \in W$$

For No ESG strategies, we simply use this optimization function on the entire point in time universe to find optimal weights.

For Semi ESG Top and Bottom strategies, we filter our current point in time universe based on last month's ESG Risk score and run this optimization problem on the selected universe of top 25 companies with least ESG Risk score or bottom 25 companies with most ESG Risk score to find optimal weights respectively.

For Full ESG Scaling strategies, we run this optimization function on the entire point in time universe to find optimal weights and then scale the weights by multiplying them with the ESG Risk score or ESG Trend score and dividing by the sum of weights to make them sum up to 1. For the Full ESG Constraint strategy, we run similar optimization on the entire point in time universe but with an added constraint that the portfolio ESG Risk score should be lower than the ESG Risk score of the No ESG portfolio denoted by *esg*, by a factor of *k*, where *k* < 1 (here *k* =0.95 is used). The optimization is as follows:

$$min\ w^T \Sigma w \quad st.\ 1^T w = 1,\ w > 0,\ \beta^T w = 1,\ \ ESG\ Risk\ score < k\,.\,esg,\ \ w \in W$$

Finally, for the Full ESG Objective strategy, the portfolio ESG Risk score is minimized without any constraints on minimum returns needed or maximum risk allowed. So here Obj1 and Obj2 refer to the same strategy. The optimization is as follows:

$$min\ \ ESG\ Risk\ score \quad st.\ 1^T w = 1,\ w > 0,\ \beta^T w = 1,\ \ w \in W$$

The performance of all the above mentioned strategies is shown in Table 6.

From there we see that the ESG Objective strategy performs poorly because, for index tracking, its objective is just to minimize the ESG Risk score along with the constraint of $\beta = 1$ with respect to the index and no other constraints on minimum return needed or maximum risk allowed. This is because those two constraints along with index tracking make it a very strict optimization that does not converge. Semi ESG Bottom strategy performs the best with the highest Sharpe Ratio but has the worst ESG Risk score while Semi ESG Top strategy underperforms the index but has the best ESG Risk score. It is important to note that the ESG Constraint strategy outperforms the No ESG strategy and has a relatively lower ESG risk score too, so that seems to be a good option for investors who want ESG focused portfolios while tracking the index.

The cumulative returns of all strategies using Index tracking Markowitz optimization are illustrated in Figure 4. The ESG Risk scores of each strategy are illustrated in Figure 5. The cumulative returns for ESG Objective strategy are poor as discussed above. All the other strategies do a decent job of tracking the index. The Semi ESG Top portfolio lies in the top quartile in terms of returns pre covid, but post covid drawdown, it lies in the bottom quartile thereafter. Again, sector bias in the filtered Semi ESG Top universe is the reason for this trend reversal as was seen with the Semi ESG Bottom strategy in Classical Markowitz Optimization.

	No ESG	Semi ESG		Full ESG				Index
		Top ESG	Bottom ESG	ESG Objective	ESG Constraint	ESG Scaling		
						Tilt Scale	Mom. scale	
Return (%)	13.50	12.83	14.25	-3.39	13.79	13.52	13.52	13.54
Volatility (%)	18.71	20.09	18.99	28.49	18.74	18.73	18.69	19.20
Sharpe Ratio	0.77	0.70	0.79	0.02	0.78	0.77	0.77	0.76
Tracking Error	1.5	5.7	3.4	20.08	1.7	1.6	1.5	NA
Information Ratio	-0.08	-0.07	0.16	-0.69	0.07	-0.06	-0.07	NA
Max Drawdown (%)	31.85	39.25	33.42	48.01	31.49	31.69	31.82	31.53
Calmar Ratio	0.45	0.36	0.45	0.01	0.46	0.45	0.45	0.46
Sortino Ratio	0.85	0.77	0.89	0.02	0.87	0.85	0.85	0.84
95% VAR (%)	-16.44	-19.03	-16.19	-46.35	-16.23	-16.45	-16.39	-17.10
ESG Risk score	32.78	17.87	53.92	3.68	28.30	29.70	32.68	NA
Sharpe/ESG Risk score	0.023	0.039	0.014	0.006	0.027	0.025	0.023	NA

Table 6: Index Tracking Markowitz results summary

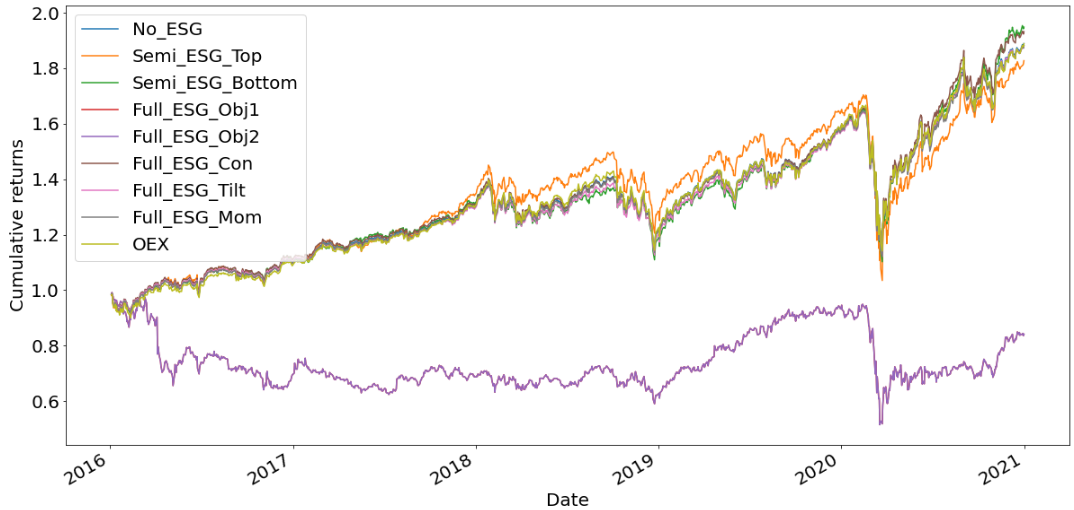

Figure 4: Cumulative returns of Index tracking Markowitz with ESG strategies

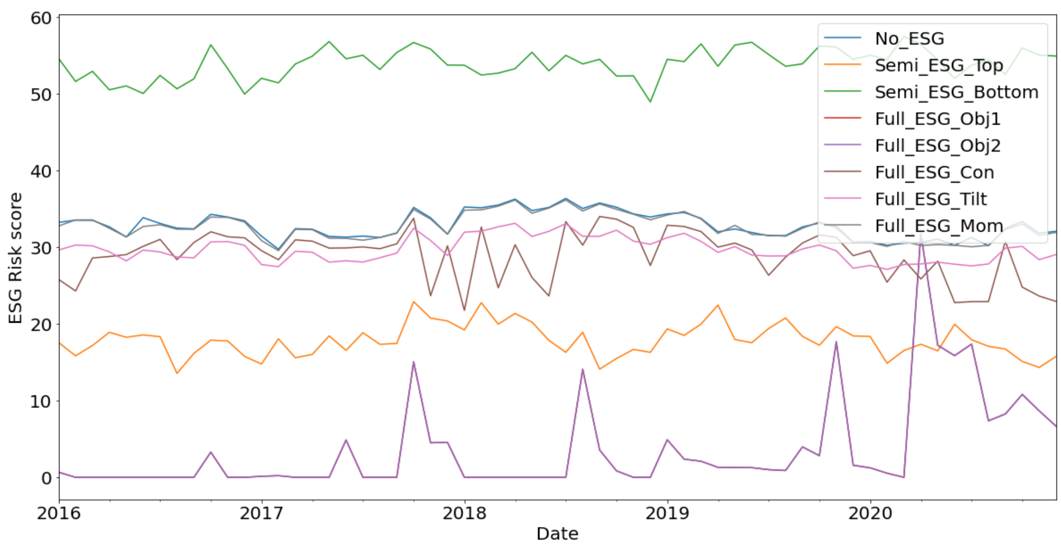

Figure 5: ESG Risk scores of Index tracking Markowitz with ESG strategies

The results for ESG Risk scores are again intuitive, with Semi ESG Bottom strategy having the highest ESG Risk score (C grade) and ESG Objective strategy having the lowest ESG Risk score (A grade), since that was the objective there without any constraints on minimum returns needed or maximum risk allowed. All the ESG favoring strategies have lesser ESG risk scores than No ESG strategy. Also, unlike the Classical Markowitz optimization results, their ESG Risk scores are less volatile and lie in the lower medium risk category (B grade).

5. INDIVIDUAL E, S AND G PORTFOLIOS ANALYSIS

Having analyzed in depth the performance of different strategies, we now look further into each of the individual components of ESG and analyze the E, S and G specific portfolios. For constructing these portfolios, instead of the ESG Risk score, we use the E Risk score, S Risk score and G Risk score individually. These individual risk scores are obtained by multiplying the percentage contributions of E, S and G parts in the ESG Risk score respectively. The performance for E, S and G portfolios are shown in Table 7.

	No ESG	E in objective	E as constraint	S in objective	S as constraint	S in objective	S as constraint
Return (%)	24.67	25.50	23.86	23.94	24.45	19.61	24.63
Volatility (%)	25.74	25.12	25.46	25.01	25.42	24.47	25.71
Sharpe Ratio	0.98	1.03	0.96	0.96	0.98	0.84	0.98
Maximum Drawdown (%)	32.39	32.88	32.42	32.38	32.43	33.02	32.58
E/S/G Risk score	32.97	2.1	4.86	9.33	14.34	10.01	15.00

Table 7: E, S, G Risk scores in classical Markowitz optimization summary

We observe that the returns, volatility and maximum drawdowns yield almost similar values for the E, S, G specific portfolio using them in objective or constraint. This is an indication that the inherent portfolios might be very similar if there is a noticeable correlation among the E, S, G Risk scores themselves. To investigate this further, we look at the cosine similarities of the weight vectors for the E, S, G portfolios for both objective and constraint strategies. For the objective strategies, the correlation among the portfolio weights is 77% between E-S, 69% between E-G and 67% between S-G. This indicates that the portfolios are indeed very similar, with G being slightly different and hence the minor difference in performance too. For the constraint strategy, there is 99% correlation in all E-S, E-G and S-G so again the portfolios are almost the same, hence yielding the same results. These results indeed suggest that on average, the individual E, S, G Risk scores could be highly correlated in our data universe. For instance, when businesses try to abide by environmental rules and more general sustainability concerns, social criteria might overlap with environmental criteria and governance. In order to understand in depth which of the E, S, G has the potential to generate superior alpha, it might make sense to go a level deeper and use individual theme scores within each of the E, S, G categories instead of the aggregate E, S, G Risk scores (pillar scores) for building a more flexible model for constructing E, S, G specific portfolios.

6. FAMA FRENCH AND ESG FACTOR ANALYSIS

With the performance boost in portfolios with ESG consideration, it becomes important to analyze if ESG can be used as a factor for smart beta strategies and if it augments or replaces the Fama French factors. Here, Value (proxied by book-to market ratio), Size (proxied by market capitalisation) and Momentum (proxied by average returns of past 12 months barring last month) factors are used. The way factor portfolios are constructed is by considering the factor values in the past month and constructing long short portfolios as shown in Table 8.

	Long Portfolio	**Short Portfolio**
ESG	Top 10 Good ESG companies (low ESG Risk score)	Bottom 10 Bad ESG companies (high ESG Risk score)
Value	Top 10 High Value companies (high book-to-market ratio)	Bottom 10 Low Value companies (low book-to-market ratio)
Size	Top 10 Small Size companies (low market capitalisation)	Bottom 10 Big Size companies (high market capitalisation)
Momentum	Top 10 Up Momentum companies (high momentum)	Top 10 Down Momentum companies (low momentum)

Table 8: Factor portfolios construction

The correlations among all these factors are shown in Table 9. We can observe a low correlation of ESG factor with all these factors, which indicates potential diversification benefits by incorporating ESG, along with the added advantage of boosted ESG score.

	ESG	Value	Size	Momentum
ESG	1	0.39	0.49	0.25
Value	0.39	1	0.73	0.41
Size	0.49	0.73	1	0.40
Momentum	0.25	0.41	0.40	1

Table 9: Factor Correlations

In order to capture any possible synergies among these factors, all combinations of Value, Size and Momentum factors with and without ESG factor are tried. While constructing a portfolio using multiple factors, a union of companies in long portfolios of all those factors is considered to make the long portfolio and a union of companies in short portfolios of all those factors is considered to make the short portfolio. A slightly modified version of equal weighted portfolio is used here. Then all the companies are weighted according to their occurrence frequency in these union portfolios so that if multiple factors suggest to long (or short) a specific company then that company will receive higher in magnitude positive (or negative) weight. Table 10 summarizes the results.

One thing to note here is that the relative performance of Value, Size and Momentum factors follows the same pattern as the benchmark Fama-French factors available in Kenneth R. French data library formulated on a much larger universe in our considered time frame. For these benchmark factors, the momentum factor performs best with 1.98% annualized returns while the value factor performs worst with -15.48% annualized returns, with the size factor in between with -2.34% annualized returns. This shows that our factor models work as expected on S&P 100 universe too in terms of relative performance. We observe that adding ESG Good minus Bad factor to traditional factor models yields better returns with the exception of adding ESG to momentum factor. The volatility on the other hand always decreases on adding ESG. Additionally, ESG factor by itself gives better returns than almost all combinations except momentum and size & momentum with or without ESG. However in terms of volatility, it has lower volatility than all combinations without ESG and most combinations with ESG, again except momentum and size & momentum. This shows that ESG has the potential to augment existing factor models and sometimes even completely replace them, hence making a very strong case of it becoming a smart beta strategy in near future.

	Returns (%)		Volatility (%)	
	Without ESG	With ESG	Without ESG	With ESG
ESG	-10.29		13.12	
Value	-19.51	-14.60	21.33	14.57
Size	-14.45	-12.11	17.82	13.43
Momentum	-2.30	-5.90	19.22	12.95
Value, Size	-16.79	-14.42	25.84	23.94
Value, Momentum	-10.79	-10.34	17.08	13.71
Size, Momentum	-8.61	-8.11	15.54	12.91
Value, Size, Momentum	-11.84	-11.26	16.05	13.86

Table 10: Comparison of factor models with and without ESG factor

7. CONCLUSIONS

This study presented several strategies of incorporating ESG considerations in the classical as well as index tracking Markowitz portfolio optimization process and compared performances. Going further, these performances were justified using in depth sector analysis of the portfolios and potential effects of covid crisis on ESG strategies performance in the post covid era. Analysis on tradeoff between better risk/return performance and better ESG performance is shown that can be useful to investors for choosing an ideal portfolio based on their risk/returns preferences. Further individual E, S, G portfolios are constructed which show significant correlations among themselves and hence the need to further theme scores to search alpha. Finally, ESG is studied as a factor along with traditional factors to conclude how it can augment them and even replace them to a certain extent.

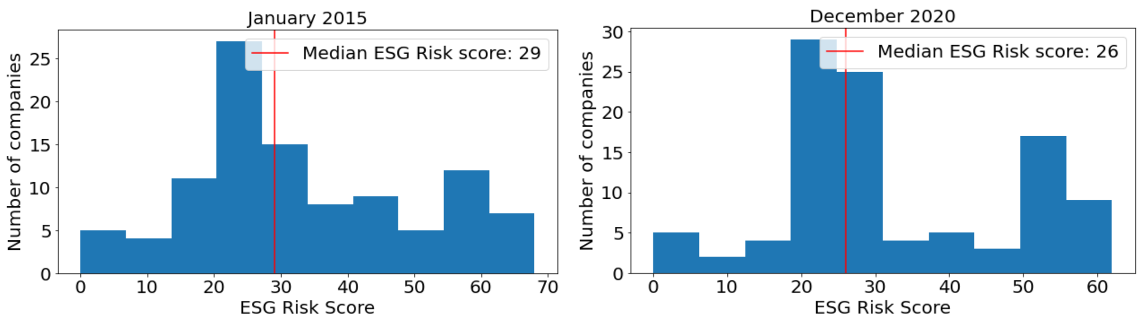

Figure 6: Shift is ESG Risk score over time

To sum it all up, ESG strategies do seem to have a bright future with investor interest in ESG based portfolios growing rapidly over time, especially after the importance of taking into account environmental, social and governance factors in investment decisions has become important with the covid crisis acting as a catalyst for development of ESG focused strategies. Several companies have started making ESG considerations and we see a shift in overall ESG Risk scores in our data universe. As seen in Figure 6, the median ESG Risk score shifted from 29 i.e. medium risk (B grade) to 26 i.e. almost the boundary of low risk (A grade) which means about 50% of the universe has low risk in terms of ESG. Also, companies with extreme ESG Risk scores shifted to relatively lower ESG Risk scores with the maximum ESG Risk score in the universe changing from 68 to 62. These are promising observations that show how over time companies will start taking ESG considerations more and more seriously, allowing investors to hold portfolios with purpose. It's time to switch gears to Responsible Investing!

8. REFERENCES

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*Please find data/code here - https://github.com/DN612/Portfolio-Optimization-using-ESG