FINM 35000 Final Project: ESG Trading Strategy

[redacted]

Introduction

ESG has become a popular term since it was first coined in 2005. ESG investing attracts socially responsible investors who want to see their investing result in a positive social impact. In 2021, US sustainable fund assets value was seven times the value of 2013, growing from under $100 billion to $357 billion. 51% of the growth happens between December 2020 and December 2021.

ESG includes three non-financial factors: Environmental, Social, and Governance. The environmental aspect concerns whether the firm is environmentally friendly by evaluating whether a firm takes action to conserve natural resources. The Social factor considers a firm's social responsibility, such as labor standards. Governance is a way to measure the structure of a firm in terms of incentivizing, compensation, etc. All three factors combined to convey the idea of sustainable investing. Firms with higher ESG scores are perceived to be more healthy and could survive longer in the financial market since they are less likely to be involved in negative social impacts.

Now that ESG attracts more and more investment inflows, we would like to see whether using ESG as a stock selection criterion could generate positive alpha. We would like to test whether a firm disclosing its ESG activities will affect its return, how much variation in stocks' return could be explained by the Environmental, Social, and Governance factors individually and mutually, and whether an upgrading or degrading in ESG score will lead to changes in stock returns.

Data

Bloomberg, CRSP, Kenneth French are the three major data resources that we use. We also collect search interests data about ESG from 2015 to 2022 on Google Trends.

Bloomberg provides its proprietary Environmental, Social, and Governance scores and their subdivision scores from 2015 to the present based on the extent of a company's data disclosure.

The score ranges from 0 to 10 evaluating the company's aggregated Environmental, Social or Governance performance. We collect the respective Environmental, Social, and Governance scores for each component in the S&P 500 index from 2015 to October 2022. However, we cannot get general ESG scores from Bloomberg since it does not provide historical data for such entries. Therefore, we combine the individual Environmental, Social, and Governance scores by taking average to get a representative for the general ESG score.

Since we are evaluating the relationship between ESG scores and securities' returns, we also download the monthly return of each security in the S&P 500 index between 2015 and 2022 from CRSP in WRDS. We could use Bloomberg to extract such data for consistency, but we are afraid that such behavior could result in more than the Bloomberg data limit. To test whether the alpha generated by our trading strategy is indeed brought by the ESG factors or by other embedded factors such as Fama-French three factors, we also gather the Fama-French three factors data and risk-free rate from Kenneth French data library.

To avoid selection bias, we only download the ESG scores and returns of a company in a particular year if the company is in the S&P 500 of that year. For example, if company A is included in the S&P 500 index in 2017, only its 2017 ESG scores and returns are downloaded. Data for company A in time periods between 2015 and 2022, excluding 2017, are not provided.

In the eight years data range, we use the first six years (2015 - 2020) as our training data to select our trading strategy. The following two years (2021 and 2020) will be used as a test set where we apply our strategy and get the return and alpha.

Methodology

To find the model relevant to ESG that could explain the most variation in stock returns, we first conduct seven simple regressions. We use the yearly stock returns for stocks in the S&P 500 index from 2015 to 2020 as the response variable in our regressions.

The first regression's explanatory variable is an indicator variable that equals 0 if the company does not provide any data on the Environmental, Social, and Governance score and one if all three scores are disclosed. We use this regression to test whether disclosing the ESG-related activities or not has an effect on the stock returns. Then we conduct regressions of each of the three scores to see how much variation could be explained by each score individually. We also test the average of the three scores' relationship with stock return and the rank of the average scores' relationship with the return.

The last regression is called ESG momentum, which uses the difference of average ESG cores between two adjacent years. In our expectation, if a company gets involved in certain events that significantly improve or decrease its ESG scores, this would be reflected in its stock return.

The formulas for all simple regression equations are listed below:

$r_{i,t} = \alpha + \beta * I_{i,t} + \varepsilon$, using the indicator variable as X;

$r_{i,t} = \alpha + \beta * E_{i,t} + \varepsilon$, using the Environmental Pillar Score as X;

$r_{i,t} = \alpha + \beta * S_{i,t} + \varepsilon$, using the Social Pillar Score as X;

$r_{i,t} = \alpha + \beta * G_{i,t} + \varepsilon$, using the Governance Pillar Score as X;

$r_{i,t} = \alpha + \beta * ESG_{i,t} + \varepsilon$, using the average ESG score as X;

$r_{i,t} = \alpha + \beta * Rank_{i,t} + \varepsilon$, using the rank of average ESG score as X;

$r_{i,t} = \alpha + \beta * Diff_{i,t} + \varepsilon$, using the difference of average ESG score between two adjacent years as X.

We also examined how much variations in stock return could be attributed to the three factors mutually by conducting a multiple linear regression which contains Environmental, Social, and Governance Pillar Sore as regressors. The formula for such multiple regression is provided as follows:

$r_{i,t} = \alpha + \beta_1 * E_{i,t} + \beta_2 * S_{i,t} + \beta_3 * G_{i,t} + \varepsilon$, using the Environmental Pillar Score, Social Pillar Score and Governance Pillar Score as X.

Among all the models, we choose the model with the highest R-squared and relatively significant factors as our trading model. We run a regression again using a two-year window (t0, t1), select stocks based on the ESG score of the next year (t2), and plot the ESG weighted average return of our selected stocks. In our strategy, we long the stocks with the top one-third ESG scores and short the bottom one-third.

Regression analysis

All the regressions' r-squared are not very significant since most of them are not different from 0. The most significant r-squared 0.01 is obtained from the multi-regression model with all three factors as independent variables. Even in the best model, only 1% of the change in stock returns could be explained by the ESG scores. It seems that ESG scores do not perform well in explaining the variations in stock returns because the ESG score related information does not capture most of the events that change returns.

In the first regression with the indicator variable, the r-squared is 0.001, and only the indicator is significant at a 10% significance level. This indicates that the regression with only the dummy variable is not a very good model in predicting stock returns.

OLS Regression Results

Dep. Variable:	Return	**R-squared:**	0.001
Model:	OLS	**Adj. R-squared:**	0.001
Method:	Least Squares	**F-statistic:**	3.341
Date:	Tue, 29 Nov 2022	**Prob (F-statistic):**	0.0677
Time:	14:09:15	**Log-Likelihood:**	-6612.2
No. Observations:	2978	**AIC:**	1.323e+04
Df Residuals:	2976	**BIC:**	1.324e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.1005	0.142	0.710	0.478	-0.177	0.378
ESG_Indicator	0.2702	0.148	1.828	0.068	-0.020	0.560

Omnibus:	5018.714	**Durbin-Watson:**	1.999
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2906516.254
Skew:	11.530	**Prob(JB):**	0.00
Kurtosis:	154.301	**Cond. No.**	6.79

Regression results for $r_{i,t} = \alpha + \beta * I_{i,t} + \varepsilon$

Among the Environmental Pillar Score, Social Pillar Score, and Governance Pillar Score, Governance plays the best role in explaining the variations in return since the regression with only the Governance Pillar score has the highest r-squared value (0.007) and both the intercept and the variable are significant with P-values almost equal to 0. However, the other two regressions have a very low r-squared, and the independent variable is not substantial (P-value near 0.2).

OLS Regression Results

Dep. Variable:	Return	**R-squared:**	0.001
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	1.648
Date:	Tue, 29 Nov 2022	**Prob (F-statistic):**	0.199
Time:	14:09:15	**Log-Likelihood:**	-6177.9
No. Observations:	2731	**AIC:**	1.236e+04
Df Residuals:	2729	**BIC:**	1.237e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.3020	0.070	4.341	0.000	0.166	0.438
ENVIRONMENTAL_SCORE	0.0281	0.022	1.284	0.199	-0.015	0.071

Omnibus:	4510.048	**Durbin-Watson:**	2.004
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2263725.022
Skew:	11.079	**Prob(JB):**	0.00
Kurtosis:	142.293	**Cond. No.**	5.28

Regression results for $r_{i,t} = \alpha + \beta * E_{i,t} + \varepsilon$

OLS Regression Results

Dep. Variable:	Return	**R-squared:**	0.001
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	1.766
Date:	Tue, 29 Nov 2022	**Prob (F-statistic):**	0.184
Time:	14:09:15	**Log-Likelihood:**	-6177.9
No. Observations:	2731	**AIC:**	1.236e+04
Df Residuals:	2729	**BIC:**	1.237e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.4535	0.077	5.921	0.000	0.303	0.604
SOCIAL_SCORE	-0.0325	0.024	-1.329	0.184	-0.081	0.015

Omnibus:	4510.453	**Durbin-Watson:**	2.005
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2260050.205
Skew:	11.082	**Prob(JB):**	0.00
Kurtosis:	142.176	**Cond. No.**	5.76

Regression results for $r_{i,t} = \alpha + \beta * S_{i,t} + \varepsilon$

OLS Regression Results

Dep. Variable:	Return	**R-squared:**	0.007
Model:	OLS	**Adj. R-squared:**	0.007
Method:	Least Squares	**F-statistic:**	21.16
Date:	Tue, 29 Nov 2022	**Prob (F-statistic):**	4.40e-06
Time:	14:09:15	**Log-Likelihood:**	-6435.7
No. Observations:	2882	**AIC:**	1.288e+04
Df Residuals:	2880	**BIC:**	1.289e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	2.1914	0.401	5.470	0.000	1.406	2.977
GOVERNANCE_SCORE	-0.2573	0.056	-4.600	0.000	-0.367	-0.148

Omnibus:	4804.692	**Durbin-Watson:**	2.010
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2615545.955
Skew:	11.283	**Prob(JB):**	0.00
Kurtosis:	148.849	**Cond. No.**	69.5

Regression results for $r_{i,t} = \alpha + \beta * G_{i,t} + \varepsilon$

We also compare the regression results between models using average ESG scores and using the rank of the average score. The regression results are almost identical. Both models have near 0 r-squared values and only have significant intercepts. The p-values for the models use rank or not are 26.1% and 34.5%, respectively. They cannot be used as a reliable model for predicting returns.

OLS Regression Results

Dep. Variable:	Return	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	-0.000
Method:	Least Squares	**F-statistic:**	0.8926
Date:	Tue, 29 Nov 2022	**Prob (F-statistic):**	0.345
Time:	14:09:15	**Log-Likelihood:**	-6176.6
No. Observations:	2730	**AIC:**	1.236e+04
Df Residuals:	2728	**BIC:**	1.237e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.5197	0.164	3.173	0.002	0.199	0.841
ESG_Score_Avg	-0.0369	0.039	-0.945	0.345	-0.113	0.040

Omnibus:	4507.512	**Durbin-Watson:**	2.004
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2254742.493
Skew:	11.076	**Prob(JB):**	0.00
Kurtosis:	142.037	**Cond. No.**	16.3

Regression results for $r_{i,t} = \alpha + \beta * ESG_{i,t} + \varepsilon$

Dep. Variable:	Return	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	1.267
Date:	Tue, 29 Nov 2022	**Prob (F-statistic):**	0.261
Time:	14:09:15	**Log-Likelihood:**	-6176.4
No. Observations:	2730	**AIC:**	1.236e+04
Df Residuals:	2728	**BIC:**	1.237e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.2809	0.091	3.075	0.002	0.102	0.460
ESG_Score_Ranking_Avg	0.0005	0.000	1.125	0.261	-0.000	0.001

Omnibus:	4507.651	**Durbin-Watson:**	2.005
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2255300.413
Skew:	11.076	**Prob(JB):**	0.00
Kurtosis:	142.054	**Cond. No.**	469.

Regression results for $r_{i,t} = \alpha + \beta * Rank_{i,t} + \varepsilon$

The final simple regression is the one that we expect would work best, however, the result is not inline with our expectation. The p-value for the coefficient of the ESG momentum model is 30.9%, which is not significant. Also, the r-squared is still near 0.

OLS Regression Results

Dep. Variable:	Return	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	-0.000
Method:	Least Squares	**F-statistic:**	0.9235
Date:	Wed, 30 Nov 2022	**Prob (F-statistic):**	0.337
Time:	13:40:49	**Log-Likelihood:**	-4819.8
No. Observations:	2197	**AIC:**	9644.
Df Residuals:	2195	**BIC:**	9655.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.3382	0.051	6.595	0.000	0.238	0.439
ESG_Diff_Avg	0.0879	0.091	0.961	0.337	-0.091	0.267

Omnibus:	3569.000	**Durbin-Watson:**	0.402
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	1501260.544
Skew:	10.702	**Prob(JB):**	0.00
Kurtosis:	129.260	**Cond. No.**	2.12

Regression results for $r_{i,t} = \alpha + \beta * Diff_{i,t} + \varepsilon$

As we mentioned above, the multi-regression model gives the best result in predicting return changes. It has the highest r-squared value among all the models (0.01). And this higher r-squared value is not only brought by adding more factors compared with the previous models, since the adjusted r-squared is 0.009, still the highest among all the models. The intercept, Environmental Pillar Score, and Governance Pillar Score are all significant at a 5% significance level. The only concern about this model is that the Social Pillar Score has a non-significant P-value of 19.1%.

OLS Regression Results

Dep. Variable:	Return	**R-squared:**	0.010
Model:	OLS	**Adj. R-squared:**	0.009
Method:	Least Squares	**F-statistic:**	9.000
Date:	Tue, 29 Nov 2022	**Prob (F-statistic):**	6.27e-06
Time:	14:09:15	**Log-Likelihood:**	-6163.5
No. Observations:	2730	**AIC:**	1.234e+04
Df Residuals:	2726	**BIC:**	1.236e+04
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	2.3174	0.423	5.478	0.000	1.488	3.147
ENVIRONMENTAL_SCORE	0.0562	0.024	2.390	0.017	0.010	0.102
SOCIAL_SCORE	-0.0346	0.026	-1.308	0.191	-0.086	0.017
GOVERNANCE_SCORE	-0.2802	0.060	-4.644	0.000	-0.399	-0.162

Omnibus:	4492.457	**Durbin-Watson:**	2.022
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	2240727.213
Skew:	10.997	**Prob(JB):**	0.00
Kurtosis:	141.618	**Cond. No.**	78.3

Regression results for $r_{i,t} = \alpha + \beta_1 * E_{i,t} + \beta_2 * S_{i,t} + \beta_3 * G_{i,t} + \varepsilon$

The p-values and adjusted r-squared values for each model are provided in the table below for easier comparison.

	Independent Variable	P-value	Adjusted R-squared
Simple Regression	$I_{i,t}$	0.068	0.001
	$E_{i,t}$	0.199	0.000
	$S_{i,t}$	0.184	0.000
	$G_{i,t}$	0.000	0.007
	$ESG_{i,t}$	0.345	-0.000
	$Rank_{i,t}$	0.261	0.000
	$Diff_{i,t}$	0.337	-0.000
Multiple Regression	$E_{i,t}$	0.017	0.009
	$S_{i,t}$	0.191	
	$G_{i,t}$	0.000	

Strategy

Since we know the multiple regression model could explain the stock return variations best among all the models, we build our strategy based on this model. We use a two-year window (t0, t1) of yearly Environmental, Social, and Governance scores and the annual returns of stocks in the S&P 500 to conduct regression and get the regression coefficients. Combining these coefficients with ESG scores of the following year (t2), we calculate the weighted ESG scores and use them as a criterion for stock selection (The weighted ESG scores calculation formula is provided below). Then in the following year (t3), we long the stocks whose weighted ESG scores are in the top one-third in t2 and short the stocks whose weighted ESG scores are in the bottom one-third in t2. There is a year lag because we cannot get the ESG scores at the beginning of each year since those scores are normally published in the latter half of each year.

Weighted ESG score formula:

$$r_{i,t_{0/1}} = \alpha + \beta_1 * E_{i,t_{0/1}} + \beta_2 * S_{i,t_{0/1}} + \beta_3 * G_{i,t_{0/1}} + \varepsilon$$

$$ESG_{weighted,i,t_2} = \alpha + \beta_1 * E_{i,t_2} + \beta_2 * S_{i,t_2} + \beta_3 * G_{i,t_2}$$

We believe the transaction cost is negligible in our strategy because we only trade those stocks listed in the S&P 500 index. These stocks are highly liquid, making them easy to buy and borrow. Many brokers offer free commission services for trading them.

Strategy performance

We plotted the monthly return and the cumulative monthly return of our strategy from 2018 to 2022. 2018 is the first year that we can get our strategy return using the historical data in 2015 and 2016 for regression coefficients and 2017's ESG score. Then we calculate the returns using a rolling window of 1 year. Therefore, we can back-test our strategy returns for 2018, 2019, and 2020. We also tested our strategy in 2021 and 2022. The combined plots for the training and validating period return are shown below:

We can see that the monthly return ranges from -0.1 to 0.1, and the cumulative return ranges from -0.1 to 0.3. During the year 2021, the cumulative return dramatically increases with a considerable return jump of 0.2. Both the monthly and cumulative returns achieved their lowest value in March 2020, following a rapid decrease within three months.

The annualized return and volatility are calculated below. Only the returns of 2018 and 2022 are slightly negative. We also compute the mean return, volatility, monthly and annually sharpe ratio over the period of training, testing and whole dataset. The strategy performs better over the training period since this period has higher mean return and Sharpe ratio compared with that of the testing period.

	Annualized total return	Annualized volatility
2018	-0.0125	0.0618
2019	0.0878	0.051
2020	0.1191	0.1842
2021	0.0995	0.0507
2022	-0.0593	0.1045

	Mean	Vol	SR(mth)	SR(annual)
Train	0.0044	0.0332	0.1338	0.4634
Validation	0.0014	0.0235	0.0607	0.2102
Full	0.0033	0.0297	0.111	0.3845

Testing alpha by CAPM and Fama-French models

Using our selected stocks' returns as dependent variables, we run regressions using market and Fama-French factors. We want to confirm whether our returns are really generated by the strategy, or they are driven by the whole market and other factors.

The regression results are shown below:

Dep. Variable:	excess_strategy_return	**R-squared:**	0.886
Model:	OLS	**Adj. R-squared:**	0.884
Method:	Least Squares	**F-statistic:**	436.3
Date:	Wed, 30 Nov 2022	**Prob (F-statistic):**	4.15e-28
Time:	00:12:19	**Log-Likelihood:**	185.26
No. Observations:	58	**AIC:**	-366.5
Df Residuals:	56	**BIC:**	-362.4
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0007	0.001	-0.555	0.581	-0.003	0.002
Mkt-RF	0.4992	0.024	20.888	0.000	0.451	0.547

Omnibus:	8.809	**Durbin-Watson:**	1.958
Prob(Omnibus):	0.012	**Jarque-Bera (JB):**	20.122
Skew:	-0.010	**Prob(JB):**	4.27e-05
Kurtosis:	5.885	**Cond. No.**	18.0

CAPM regression

Dep. Variable:	excess_strategy_return	**R-squared:**	0.920
Model:	OLS	**Adj. R-squared:**	0.915
Method:	Least Squares	**F-statistic:**	206.8
Date:	Wed, 30 Nov 2022	**Prob (F-statistic):**	1.42e-29
Time:	00:14:32	**Log-Likelihood:**	195.44
No. Observations:	58	**AIC:**	-382.9
Df Residuals:	54	**BIC:**	-374.6
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0004	0.001	-0.367	0.715	-0.003	0.002
Mkt-RF	0.4719	0.022	21.572	0.000	0.428	0.516
SMB	0.1309	0.043	3.046	0.004	0.045	0.217
HML	0.0722	0.026	2.746	0.008	0.020	0.125

Omnibus:	4.705	**Durbin-Watson:**	2.389
Prob(Omnibus):	0.095	**Jarque-Bera (JB):**	3.738
Skew:	0.580	**Prob(JB):**	0.154
Kurtosis:	3.449	**Cond. No.**	39.4

Fama-French 3 factor model

Dep. Variable:	excess_strategy_return	**R-squared:**	0.920
Model:	OLS	**Adj. R-squared:**	0.913
Method:	Least Squares	**F-statistic:**	120.0
Date:	Wed, 30 Nov 2022	**Prob (F-statistic):**	2.65e-27
Time:	00:15:46	**Log-Likelihood:**	195.55
No. Observations:	58	**AIC:**	-379.1
Df Residuals:	52	**BIC:**	-366.7
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0004	0.001	-0.355	0.724	-0.003	0.002
Mkt-RF	0.4675	0.024	19.338	0.000	0.419	0.516
SMB	0.1377	0.052	2.664	0.010	0.034	0.241
HML	0.0742	0.040	1.844	0.071	-0.007	0.155
RMW	0.0224	0.060	0.372	0.711	-0.098	0.143
CMA	-0.0144	0.062	-0.233	0.817	-0.138	0.109

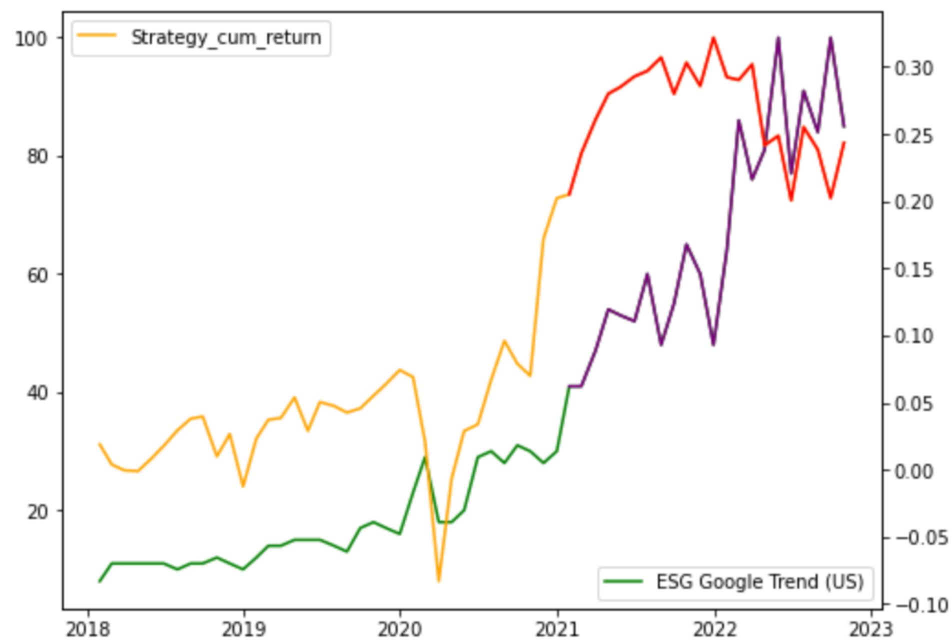
Omnibus:	5.857	**Durbin-Watson:**	2.389
Prob(Omnibus):	0.053	**Jarque-Bera (JB):**	4.870
Skew:	0.652	**Prob(JB):**	0.0876
Kurtosis:	3.561	**Cond. No.**	68.0

Fama-French 5 factor model

The above three regressions show quite high r-squared values, indicating that over 88.6% of variations in our strategy returns could be explained by the market and other factors. Also, the constant coefficients are all negative, which means that our strategy did not perform better than the CAPM and Fama-French models. However, the above conclusion should be built on a hypothesis that the P-value of these three regressions' constant coefficients should be small and significant, which is not the case in our regressions. Therefore, we cannot conclude that the alphas are significantly different from 0, or our strategy can generate higher or lower returns compared with CAPM and Fama.

Further exploration

Based on our previous strategy, we want to test a more aggressive method. Since the ESG topic is gaining popularity year by year, we would like to know whether the public's attention will contribute to ESG stocks' return. Google Trends provides data showing the search interests of a specific topic. "A value of 100 is the peak popularity for the term. A value of 50 means that the term is half as popular. A score of 0 means there was not enough data for this term." We find that the general trend of our previous strategy's cumulative return and ESG search time in google are similar. The graph is provided below.



Based on our previous strategy, we added constraints. If the growth rate of search time's maximum over a certain year is larger than 0.4, we add two times leverage to our strategy (the return of our chosen stocks doubled). If the growth rate of search time's maximum over a certain year is larger than 0.3, we add 1.5 times leverage to our strategy (the return of our chosen stocks doubled). In our examination, we find that the lowest value among the five years (2018 - 2022) maximum growth rate is 0.25. Therefore, the aggressive strategy almost adds leverage every year.

We plotted the new strategy's return and calculated the mean, volatility, monthly Sharpe ratio, and annualized Sharpe ratio for the previous strategy.

Because of the effect of leverage, the returns' range expanded from [-0.1,0.3] to [-0.2,0.6], and the extreme low and high returns were all doubled.

	Annualized total return_l	Annualized volatility_l
2018	-0.02	0.0927
2019	0.1334	0.0764
2020	0.2122	0.3685
2021	0.2051	0.1014
2022	-0.0905	0.1567

	Mean_l	Vol_l	SR(mth)_l	SR(annual)_l
Train	0.0091	0.0637	0.142	0.492
Validation	0.0045	0.0385	0.1171	0.4057
Full	0.0073	0.0552	0.1328	0.4601

The most significant change to our previous conservative strategy is that the difference of performance between training period and testing period is narrower. The performance during the validation period greatly improved with an increase of annualized sharpe ratio from 0.21 to 0.41.

We also conduct the CAPM regression and Fama-French models to test the alphas**.** The regression results are provided below:

Dep. Variable:	lev_excess_strategy_return	**R-squared:**	0.823
Model:	OLS	**Adj. R-squared:**	0.820
Method:	Least Squares	**F-statistic:**	260.1
Date:	Wed, 30 Nov 2022	**Prob (F-statistic):**	1.05e-22
Time:	13:40:52	**Log-Likelihood:**	136.42
No. Observations:	58	**AIC:**	-268.8
Df Residuals:	56	**BIC:**	-264.7
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	9.573e-05	0.003	0.031	0.976	-0.006	0.006
Mkt-RF	0.8944	0.055	16.126	0.000	0.783	1.006

Omnibus:	10.199	**Durbin-Watson:**	2.000
Prob(Omnibus):	0.006	**Jarque-Bera (JB):**	27.638
Skew:	0.023	**Prob(JB):**	9.96e-07
Kurtosis:	6.381	**Cond. No.**	18.0

CAPM regression

Dep. Variable:	lev_excess_strategy_return	**R-squared:**	0.866
Model:	OLS	**Adj. R-squared:**	0.859
Method:	Least Squares	**F-statistic:**	116.6
Date:	Wed, 30 Nov 2022	**Prob (F-statistic):**	1.42e-23
Time:	13:40:52	**Log-Likelihood:**	144.58
No. Observations:	58	**AIC:**	-281.2
Df Residuals:	54	**BIC:**	-272.9
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0008	0.003	0.277	0.783	-0.005	0.006
Mkt-RF	0.8386	0.053	15.954	0.000	0.733	0.944
SMB	0.2650	0.103	2.566	0.013	0.058	0.472
HML	0.1600	0.063	2.531	0.014	0.033	0.287

Omnibus:	6.150	**Durbin-Watson:**	2.374
Prob(Omnibus):	0.046	**Jarque-Bera (JB):**	5.245
Skew:	0.595	**Prob(JB):**	0.0726
Kurtosis:	3.869	**Cond. No.**	39.4

Fama-French 3 factor model

Dep. Variable:	lev_excess_strategy_return	R-squared:	0.867
Model:	OLS	Adj. R-squared:	0.855
Method:	Least Squares	F-statistic:	68.08
Date:	Wed, 30 Nov 2022	Prob (F-statistic):	1.32e-21
Time:	13:40:52	Log-Likelihood:	144.85
No. Observations:	58	AIC:	-277.7
Df Residuals:	52	BIC:	-265.3
Df Model:	5		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	0.0006	0.003	0.196	0.845	-0.005	0.006
Mkt-RF	0.8239	0.058	14.217	0.000	0.708	0.940
SMB	0.2997	0.124	2.419	0.019	0.051	0.548
HML	0.1518	0.096	1.574	0.122	-0.042	0.345
RMW	0.0939	0.144	0.652	0.517	-0.195	0.383
CMA	-0.0225	0.148	-0.152	0.880	-0.319	0.274

Omnibus:	7.470	Durbin-Watson:	2.376
Prob(Omnibus):	0.024	Jarque-Bera (JB):	6.807
Skew:	0.665	Prob(JB):	0.0333
Kurtosis:	4.024	Cond. No.	68.0

Fama-French 5 factor model

The results are not quite different from our previous strategy. All three regressions have high r-squared values and non-significant alphas. However, this time the alphas are positive rather than negative.

Conclusion

Both our aggressive and conservative trading strategies cannot produce a significant alpha over CAPM and Fama-French models. The r-squared values generated by regressions using ESG-related factors are always low. Therefore, we believe ESG alone cannot be used as a solid trading criterion. Combining it with other factors may work better.

References

1. *Google trends. (n.d.). Retrieved November 30, 2022, from https://trends.google.com/trends/explore?q*

2. *Can esg add alpha? MSCI. (n.d.). Retrieved November 30, 2022, from https://www.msci.com/www/blog-posts/can-esg-add-alpha-/0182820893*