FINM 35000 Final Project

[redacted]

ESG TRADING STRATEGY

CONTENT

- **Data:**
  ESG scores, CRSP returns, Fama-French factors,
  Google Trends search interest

- **Methodology:**
  determine trading strategy by various regression

- **Regression:**
  explore both single and multiple regressions with ESG scores

- **Strategy Performance:**
  monthly and cumulative return over both the testing and validation sets
  Mean return, volatility and Sharpe ratio for different time period
  alpha comparison with Fama-French models

- **Exploration**
  use google trend data to capture the popularity of ESG and adjust leverage

DATA

Bloomberg

Yearly data from 2015 to 2022

- S&P 500 components and closing prices

Yearly Bloomberg score ranging from 0 to 10 evaluating each company's aggregated sector performance from 2015 to 2022

- Environmental Pillar Score
- Social Pillar Score
- Governance Pillar Score

Scores above are only available since 2015 in yearly frequency from Bloomberg

WRDS

- Monthly holding period returns of S&P 500 companies from 2015 to 2022

Kenneth French

- Monthly Fama-French 5 factors returns from 2015 to 2022

Google Trends

- Google Trends search interests about ESG from 2015 to 2022

METHODOLOGY

- **7 Simple regression:**

$$r_{i,t} = \alpha + \beta * I_{i,t} + \varepsilon$$
$$r_{i,t} = \alpha + \beta * E_{i,t} + \varepsilon$$
$$r_{i,t} = \alpha + \beta * S_{i,t} + \varepsilon$$
$$r_{i,t} = \alpha + \beta * G_{i,t} + \varepsilon$$
$$r_{i,t} = \alpha + \beta * \mathrm{Rank}_{i,t} + \varepsilon$$
$$r_{i,t} = \alpha + \beta * ESG_{,i,t} + \varepsilon$$
$$r_{i,t} = \alpha + \beta * Diff_{,i,t} + \varepsilon$$

Note:
$I_{i,t}$ = indicator variable;
$E_{i,t}$ = Environmental Pillar Score;
$S_{i,t}$ = Social Pillar Score;
$G_{i,t}$ = Governance Pillar Score;
$Rank_{i,t}$ = average ESG score;
$ESG_{i,t}$ = rank of average ESG score;
$Diff_{i,t}$ = difference of average ESG score between two adjacent years.

- **1 Multiple regression:**

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

Trading strategy

The best model captures the most variability in return

Highest R-square with low P-value

Strategy: Long stocks with the top 1/3 scores

Short stocks with the bottom 1/3 scores

Rebalance every year

Regression results

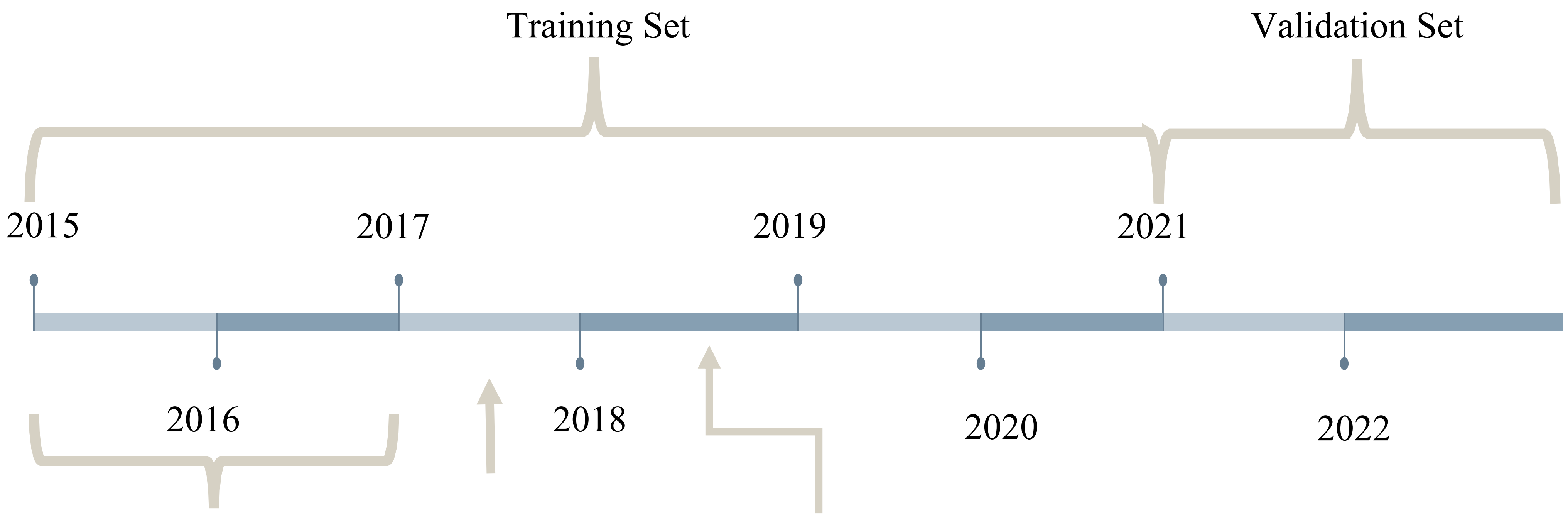
	Independent Variable	P Value	Adjusted R-squared		Independent Variable	P Value	Adjusted R-squared
1	ESG Indicator $I_{i,t}$	0.068	0.001	5	Average ESG score $Rank_{i,t}$	0.345	0.000
2	Environmental Pillar Score $E_{i,t}$	0.199	0.000	6	Rank of Average ESG Score $Diff_{i,t}$	0.261	0.000
3	Social Pillar Score $S_{i,t}$	0.184	0.000	7	Difference of Yearly ESG Score $ESG_{i,t}$	0.337	0.000
4	Governance Pillar Score $G_{i,t}$	0.000	0.007	8	Environmental, Social, Governance (Multiple)	0.017 ,0.191 , 0.000	0.009

Our strategy

Formula:

$$r_{i,t0/1} = \alpha + \beta_1 * E_{i,t0/1} + \beta_2 * S_{i,t0/1} + \beta_3 * G_{i,t0/1} + \varepsilon \quad \text{(i)}$$

$$ESG\_weigted_{i,t2} = \alpha + \beta_1 * E_{i,t2} + \beta_2 * S_{i,t2} + \beta_3 * G_{i,t2} + \varepsilon \quad \text{(ii)}$$



- Regression to get coefficients using formula (i)

- Get Environmental, Social, Governance Scores
- Plug into the formula (ii) to get weighted ESG score

- Rank weighted ESG score
- Long top 1/3
- Short bottom 1/3

Moving forward by 1 year each time
Transaction cost negligible

Strategy performance

	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

Alpha comparison – Fama-French models

CAPM

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

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

3 - Factor model

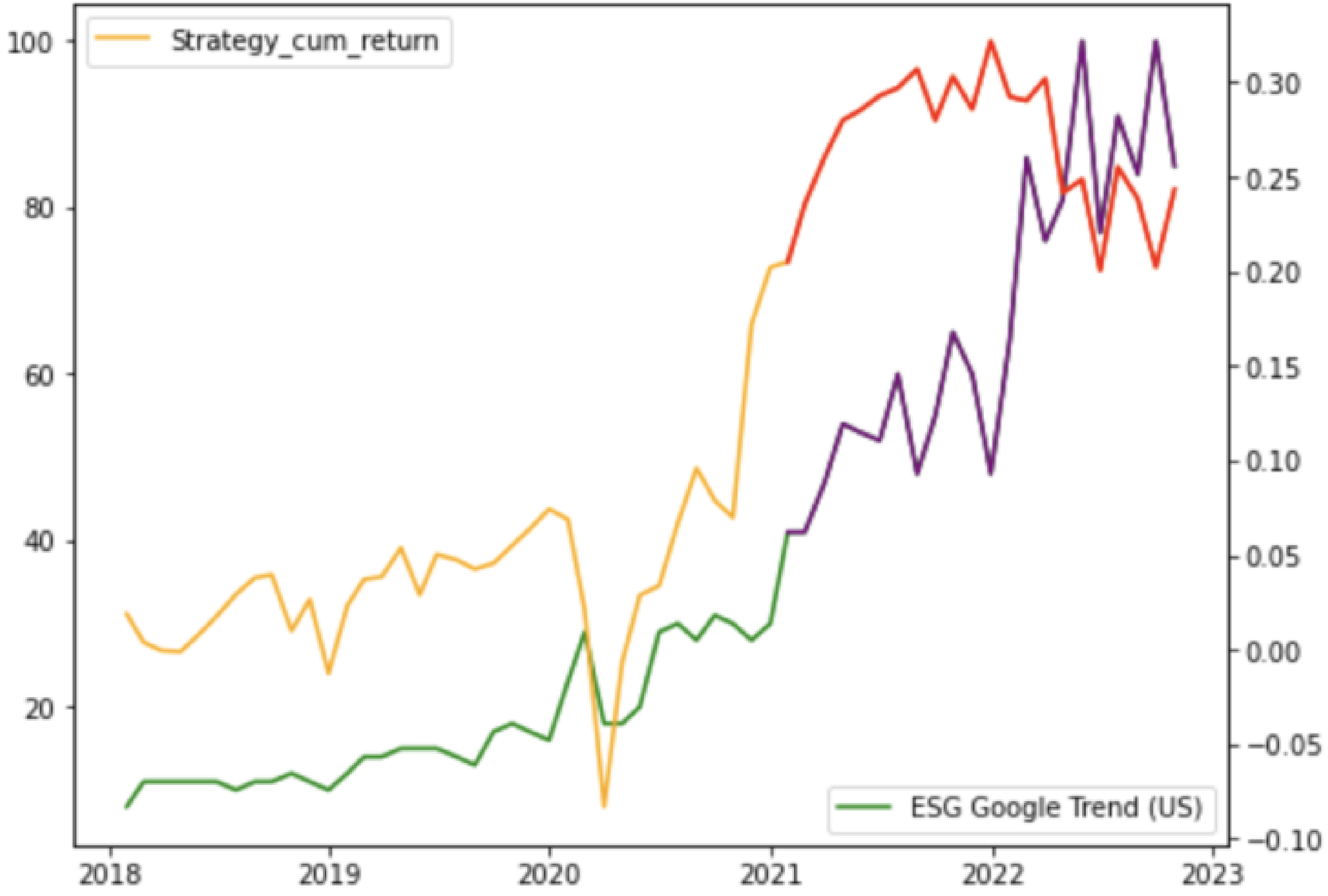
Dep. Variable:	excess_strategy_return	R-squared:	0.920
Model:	OLS	Adj. R-squared:	0.913
Method:	Least Squares	F-statistic:	120.0
Date:	Wed, 30 Nov 2022	Prob (F-statistic):	2.65e-27
Time:	00:15:46	Log-Likelihood:	195.55
No. Observations:	58	AIC:	-379.1
Df Residuals:	52	BIC:	-366.7
Df Model:	5		
Covariance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

5 - Factor model

Further exploration – Google Trends

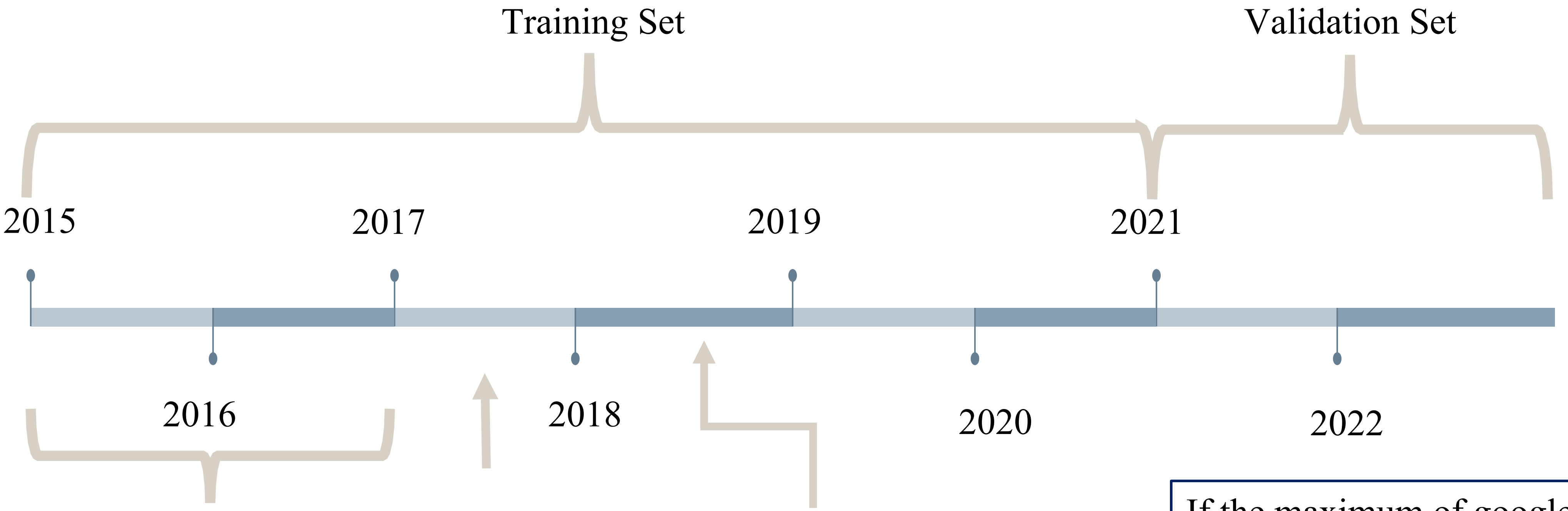


Our strategy with leverage

Formula:

$$r_{i,t0/1} = \alpha + \beta_1 * E_{i,t0/1} + \beta_2 * S_{i,t0/1} + \beta_3 * G_{i,t0/1} + \varepsilon \quad \text{(i)}$$

$$ESG\_weigted_{i,t2} = \alpha + \beta_1 * E_{i,t2} + \beta_2 * S_{i,t2} + \beta_3 * G_{i,t2} + \varepsilon \quad \text{(ii)}$$



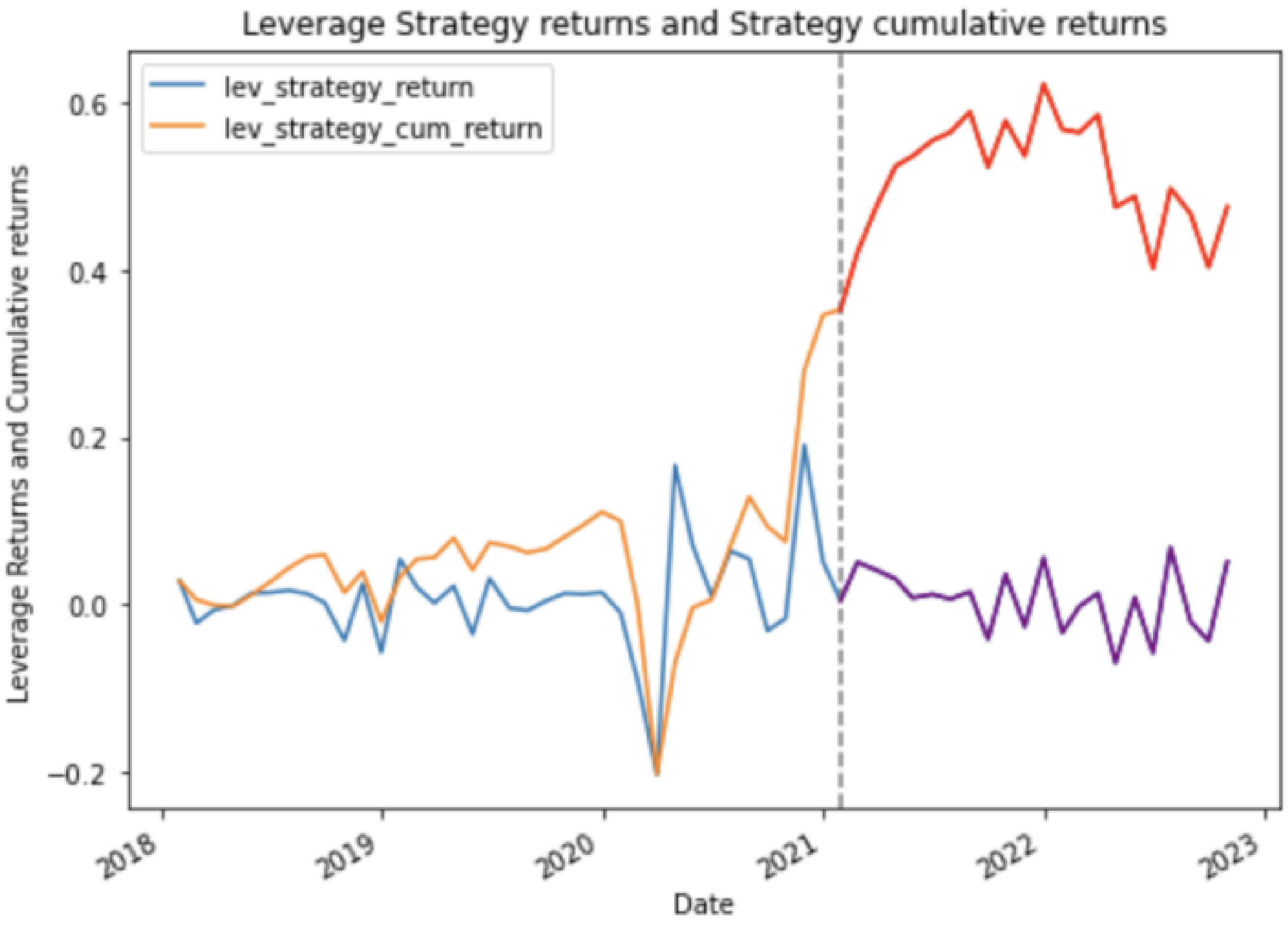
- Regression to get coefficients using formula (i)

- Get Environmental, Social, Governance Scores
- Plug into the formula (ii) to get weighted ESG score

- Rank weighted ESG score
- Long top 1/3
- Short bottom 1/3

If the maximum of google trend growth rate > 0.4,
⇒ Add 2 times leverage
If the maximum of google trend growth rate > 0.3,
=> Add 1.5 times leverage

Strategy with leverage performance



	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

Conclusion

Model	R-squared	Alpha	Strategy
Multiple regression is better than a single regression on ESG scores	Cannot explain most variations in stock returns	Not significantly different from CAPM and Fama-French models	ESG alone is not a very solid trading criteria. Combining it with other factors might work better

Thank you!

Appendix

Alpha comparison again

CAPM

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

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

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

5 - Factor model

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*