Is ESG a Genuine Risk Factor?[1]

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Abstract

By applying the protocol for genuine risk factor identification proposed by Pukthuanthong et al. (2018), I examine whether ESG is a genuine risk factor for S&P 500 returns. According to this protocol, a genuine risk factor must meet three criteria: 1) be related to the co-variance of returns, 2) be priced in the cross-section of returns, and 3) yield a reward-to-risk ratio that is reasonable enough to be consistent with risk pricing. Using ESG data from June 2007 to June 2018, I find that ESG meets two of the three conditions. ESG is related to returns and exhibits a reasonable reward to-risk-rate, but it is not priced in the cross section of S&P 500 returns. Thus, we may regard ESG as a quasi-risk factor.

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1 – Introduction

It is unclear whether environmental, social, and governance (ESG) criteria taken together is genuinely a risk factor. In this paper, I will consider the question of whether ESG is a genuine risk factor that has an effect on portfolio returns.

Environmental, social, and governance (ESG) criteria cover a wide spectrum of issues that traditionally are not part of financial analysis, yet may have financial relevance. ESG investing is often used synonymously with sustainable investing, socially responsible investing, mission-related investing, or screening (MSCI 2019). However, ESG investing is distinct from these other investment techniques. Socially responsible investing and ESG investing both take into account ethical and moral criteria, but ESG investing does not rely on using mostly negative screens (such as not investing in alcohol, tobacco or firearms), rather ESG investing is based on the assumption that ESG factors have financial relevance. ESG factors could include how firms respond to climate change, how they manage their supply chains, how effective their health and safety policies are in the protection against accidents, how good they are with water management, how they treat their workers, and whether they have a corporate culture that builds trust and fosters innovation (Kell 2018).

Investors have become increasingly aware of the social and environmental consequences of the decisions that governments and companies make. Demand is increasing for integrating ESG criteria into investment decisions. In the beginning of 2018, $11.6 trillion of all professionally managed assets—nearly a quarter of all invested assets in the United States—were under ESG investment strategies, representing a sharp increase from 2010, when the amount was only $3 trillion overall (Connaker and Madsbjerg 2019).

While the popularity of ESG is undoubtedly growing, the focus of this paper is to discuss if ESG is a genuine risk factor. The rest of the paper is structured as follows: section 2 discusses the motivation for this study and presents a brief literature review; section 3 outlines the methodology of my analysis, which relies heavily on methods originally employed by Pukthuanthong et al. (2017) and Aguilar and Li (2019); section 4 describes the data used; section 5 displays the findings of my analysis; and section 6 concludes.

2 – Motivation and Prior Literature

In 2018, the U.S. Department of Labor (DOL) issued renewed guidance for fiduciaries under the Employee Retirement Income Security Act (ERISA). The DOL's Field Assistance Bulletin 2018-01 says that these fiduciaries "must not too readily treat ESG factors as economically relevant to the particular investment choices at issue when making a decision." Rather, ERISA fiduciaries "must always put first the economic interests of the plan in providing retirement benefits." This bulletin is a response to 2015 and 2016 guidance issued by the Obama administration that said the DOL should not discourage fiduciaries from considering ESG factors in selecting investment funds. However, this most recent 2018 guidance states that a decision to designate an investment alternative "may not be influenced by noneconomic factors unless the investment ultimately chosen for the plan, when judged solely on the basis of its economic value, would be equal to or superior to alternative available investments." Thus, if ESG is not a genuine risk factor, it may only be used as a "tie-breaker" between two or more equally competitive investment opportunities (Miller 2018).

The purpose of this paper is to determine if ESG criteria are in fact economically relevant and can be considered a genuine risk factor. My analysis will rely on a recently developed protocol for factor identification proposed by Pukthuanthon et al. (2018).

There is ample literature discussing whether ESG can be constructed as a genuine pricing risk factor. However, the relationship between ESG criteria and returns is not yet clear. Some studies suggest that exposure to ESG increases returns and reduces risk, while others indicate that

ESG has a statistically insignificant or even negative impact on portfolio performance. Further debate centers around whether ESG is truly a fundamental factor or merely a factor proxy that correlates with more traditional factors such as size and value (Dekhayser 2018).

Manescu (2011) used detailed data on seven environmental, social and governance (ESG) attributes for a long panel of large publicly traded U.S. firms during 1992 to 1998 and applied the Fama and French (1993) 3-factor model and the Carhart (1997) 4-factor model. She found that only community relations had a positive effect on risk-adjusted stock returns, but she noted that this effect was not compensation for risk but could be due to mispricing. Additionally, she identified a changing effect of employee relations, which switched from positive during the period of July 1992 to June 2003 to negative during the period of July 2003 to June 2008. She concluded that the positive effect could be due to mispricing, whereas there is some evidence that the negative effect was compensation for low non-sustainability risk. A weak negative effect of human rights and product safety indicators on risk-adjusted stock returns in the more recent period was also found to be likely due to mispricing. Manescu (2011) suggests that certain ESG attributes might be value relevant but they are not efficiently incorporated into stock prices.

Dorfleitner et al. (2013) used a zero-investment strategy to find that portfolios going long on stocks rated highly on the ESG dimensions and short on stocks rated lowly on ESG demonstrated significantly positive abnormal returns up to 20% in North America and Europe over a five-year period. They also identified regional differences in the effect of ESG on returns.

Girerd-Potin et al. (2014) used data from 2003 to 2014 and performed a principal component analysis to highlight three main independent socially responsible dimensions (which were similar to but not exactly the same as the ESG dimensions). For the three dimensions, they found that investors notably penalize large non-social firms and reward small social firms.

Other financial economists have found evidence supporting the conclusion that ESG is *not* a factor. Auer and Schumacher (2015) analyzed the effect of ESG on several portfolios screened on the industry level. Their results suggested that "regardless of geographic region, industry or ESG criterion, active selection of high- or low-rated stocks does not provide superior risk-adjusted performance in comparison to passive stock market investments." In the Asia-Pacific region and in the U.S., ESG investors obtained a performance similar to the broad market. Investors in Europe, however, tend to pay a price for socially responsible investing. Their results were robust among several dimensions.

Halbritter and Dorfleitner (2015) used ESG data from ASSET4, Bloomberg and KLD for the U.S. market from 1991 to 2012. They applied an ESG portfolio approach using the Carhart (1997) four-factor model as well as cross-sectional Fama and MacBeth (1973) regressions. They found that ESG portfolios do not show a significant return difference between companies with high and low ESG ratings. Although the Fama and MacBeth (1973) regressions revealed a significant influence of several ESG variables, their results show that investors are hardly able to exploit this relationship. The magnitude and direction of the impact are substantially dependent on the rating provider, the company sample, and the particular subperiod. Their results suggest that investors should no longer expect abnormal returns by trading a difference portfolio of high- and low-rated firms with regard to ESG criteria.

Sahut and Pasquini-Descomps (2015) investigated how news-based scores in ESG may have influenced monthly stock market returns in Switzerland, the U.S., and the U.K. from 2007 to 2011. They used a multifactor linear model, consisting of the classic four factors (Fama-French's three factors and momentum), plus a fifth factor, the ESG score, which represents the potential of the ESG score to explain monthly returns during the observed period. Through linear regression, they found that the variation of the overall ESG score is not significant in the U.S. and Switzerland for the observed stocks. In the U.K. however, the change in the overall ESG score is a significant and slightly negative factor for the observed stocks' monthly performance from 2007 to 2010. Using the same model, they also examined if the changes in sub-categories of ESG ratings (namely, governance, economic, environment, labor, human rights, society, and products) could explain the monthly market return. They found that the changes in sub-category ratings exhibit a small but significant impact on the stock's performance during limited periods or on limited sectors, which varies among the countries.

Aguilar and Li (2019) used the Pukthuanthong et al. (2018) protocol for factor identification to examine whether ESG is a factor on U.S. equity returns. They found that ESG met two of three conditions of the Pukthuanthong et al. (2018) protocol necessary to be classified a genuine risk factor. Their results suggested that ESG is related to returns and exhibits a reasonable reward-to-risk ratio, but it was not found to be priced in the cross-section of returns.

3 – Methodology

The aim of this paper is to identify whether ESG is a genuine risk factor. Pukthuanthong et al. (2018) recently proposed a method for factor identification that defines a genuine risk factor. This protocol, which I will hnceforth refer to as the PRS Protocol, specifies that a genuine risk factor 1) must be related to the covariance matrix of returns, 2) must be priced in the cross-section of returns, and 3) should yield a reward-to-risk ratio that is reasonable enough to be consistent with risk pricing. When the authors of the PRS Protocol developed it, they used the protocol to find that a market factor, a profitability factor, and traded versions of macroeconomic factors passed their protocol, but many characteristic-based factors did not. Several of the underlying characteristics, however, did command premiums in the cross-section.

A factor model can be expressed as:

$$R_t = E_{t-1}(\tilde{R}_t) + \beta_{t-1} f_t + \varepsilon_t \qquad (1)$$

where R is an N-asset column vector of securities' return in period t. Given K risk factors, f is a K × 1 mean zero column vector of factors that command risk premiums. These true risk factor loadings are in a matrix, β, with N rows and K columns. Finally, ε is an idiosyncratic N × 1 vector of errors whose covariance matrix is diagonal. Make note that the loadings of both the true risk factors and the unpriced factors have time subscripts $t – 1$. This allows for time variation. The loadings are assumed to be known one period in advance of the returns.

In an arbitrage-free economy with many assets, the expected returns at $t – 1$ conform to their own linear cross-sectional relation:

$$E_{t-1}(R_t) = R_{F,t-1} + \beta_{t-1} \lambda_{t-1} \qquad (2)$$

where the first term on the right is an N × 1 column vector with the risk-free rate at the beginning of the period in every position and λ is the factor premium. More exactly, λ can be specified as a possibly time-varying K × 1 column vector of nonzero risk premiums corresponding to the factor class f. Empirically, a true factor needs to be unpredictable and related to systemic volatility with a reasonable risk premium.

The PRS Protocol is one technique used to systematically check if a candidate attribute is a true factor. Equation 2 holds in a market where arbitrage is perfect and assets are not mispriced because of behavioral biases and arbitrage constraints. If there is asset mispricing, then deviations from Equation 2 are permissible, and such deviation will be associated with "characteristics" that proxy for investor biases (Pukthuanthong et al. 2018).

3.1 – Relating ESG to the Covariance Matrix of Returns

To perform the first step of the PRS Protocol, one must determine whether the factor candidates (in our case, ESG) are conditionally related to the covariance matrix of returns. This step allows one to satisfy the assumption that there are some underlying economic state variables driving returns. If the factors are indeed true factors, some linear combination of the factors should correlate strongly with the linear combination of the eigenvalues of the returns. A canonical correlation looks at the relationship between the two groups: a group of factors and a group of returns' principal components. This can be achieved using a principle components analysis (Aguilar and Li 2019). The procedure is outlined below:

1. Obtain return data R of N assets with T periods (N × T) and factors data F of K candidates with T periods (K × T).
2. Calculate the covariance matrix of asset returns: $\Omega = \frac{RR'}{T}(T \times T)$
3. Extract the first L eigenvectors that can explain 90% of the variation in Ω as principal components.
4. Calculate the canonical correlation of the L principal components and K factors.

3.2 – Determining if the ESG Factor is Priced in the Cross-Section

In order to perform the second step of the PRS Protocol, one uses a Fama-Macbeth (1973) approach to determine if the ESG factor is priced in the cross-section of returns. The two-step process of the Fama-Macbeth approach begins with a time series regression for each security *i*:

$$R_{it} - R_{Ft} = \alpha_i + F_t\beta_i + u_{it} \tag{3}$$

where $R_{it} - R_{Ft}$ is a (T × 1) matrix of excess returns, F is a (T × K) matrix of the factors, and β_i is a (K × 1) vector of factor loadings. This regression is run for each of the N number of assets being considered.

Following Fama-Macbeth (1973), once the N factor loadings (β_i) are estimated, a second regression is run to extract the factor premium at each time *t*. This regression is:

$$R_{it} - R_{Ft} = \gamma_{0t} + \gamma_{1t}\hat{\beta}_i + e_{it} \qquad (4)$$

where $\gamma_{0t}(T \times 1)$ is the pricing error and $\gamma_{1t}(T \times K)$ is the factor premium. The factor premium then has a mean $\gamma_1 = average(\gamma_{1t})$ and standard deviation $std(\gamma_{1t})$. The statistical significance of the factor premium can be determined based on the estimates and the standard deviation.

A particular shortcoming of the Fama-MacBeth approach is the large estimation error for β_i's in the first-pass regression. One potential soluation is replacing assets with portfolios. However, the PRS Protocol employs an Errors in Variables (EIV) technique to address the problem. The regression for the first pass is same as the normal Fama-MacBeth test. However, the β_i's for the second regression are not different from the result from the first. For each factor, a double sort on size and the estimated beta each June into 10 × 10 groups is performed. The β_i's are then averaged in each group as the beta for each asset *i* in the group for the year. This means that, for each asset *i*, β_i would change every June and remain constant throughout the rest of the year (Aguilar and Li 2019).

3.3 – Identifying a Reasonable Reward-to-Risk Ratio

The third and final step in the PRS Protocol is a simple test of Sharpe Ratio. As a "genuine" risk factor, the risk premium needs to be reasonably bounded. The Empirical Asset Pricing model possesses the property of having of no arbitrage or near arbitrage. The Sharpe Ratio as a standardized risk-reward ratio can provide evidence of near arbitrage opportunity. In a near arbitrage opportunity, one expects the risk to be very low relative to return. This would then lead to a high Sharpe Ratio. If a factor results in a sizable Sharpe Ratio, it might not be well-diversified, which would contradict the idea of price in the cross-section of returns. Following Lo and MacKinlay (1990), I set 0.6 to be the maximum Sharpe Ratio for each proposed factor's traded version.

The Sharpe Ratios I test here is a zero-invested long-short portfolio. Following the procedure of the example provided by Pukthuanthong et al. (2017), I also test the factor portfolio combined candidate with the market portfolio (Aguilar and Li 2019).

4 – Data Description

In this section, I describe the three datasets used in the paper: i) the universe of stock returns I am attempting to explain, ii) the Fama French five factors, and iii) the ESG scores.

4.1 – Stock Returns

The object of interest in this article is individual monthly stock returns. Specifically, I obtain the adjusted closing price from the CRSP data (2019) for the period June 29, 2007 through June 29, 2018. The assets selected are all members of the S&P 500 as of June 29, 2018. Additionally, in order to maintain a balanced panel of data, the universe of stock returns was restricted to include only companies which were surveyed and scored by RepRisk over the corresponding period. The universe included 440 stocks.

Table 1: Data description of S&P 500 stock returns

Simple daily returns from June 29, 2007 to June 29, 2018 for S&P 500 constituents are from the Center for Research in Security Prices (CRSP). This table provides summary statistics for all 440 stocks with RepRisk data over the entire June 29, 2007 to June 29, 2018 period.

	Stocks
Mean	0.0097385
Std	0.091199
Skew	0.98194
Kurt	24.097
Min	−0.84504
Q25	−0.035861
Q50	0.0099975
Q75	0.054487
Max	2.4498

Table 1 contains a statistical description of the monthly stock returns from all 440 RepRisk-scored S&P 500 assets in our sample. The high kurtosis indicates that our returns data has heavy tails and many outliers, and the data is skewed to the right. The maximum and minimum values indicate how extreme some of these outliers were, especially in comparison to the mean and the section of returns between the 25^{th}- and 75^{th}-percentiles.

4.2 – Fama French Factors

The first set of candidate factors are the commonly used five factors from Fama and French (2015). These factors can be found on Ken French's website (2019). They consist of the market factor ($R_m - R_f$), size factor (*SMB*), value/growth factor (*HML*), profitability factor (*RMW*), and the investment factor (*CMA*). I deviated from the PRS Protocol, using the ten-year treasury constant maturity rate as the risk-free rate gathered from the Fama and French factor data (2019) rather than the three-month treasury constant maturity rate used by the original authors of the PRS Protocol.

Table 2: Data description of the five Fama French factors

The Fama French five factors are from Ken French's Data Library.

	Mkt_Rf	SMB	HML	RMW	CMA
Mean	0.75329	0.13021	−0.231	0.27786	−0.031286
Std	4.2747	2.3984	2.6736	1.6017	1.4418
Skew	−0.74491	0.27747	0.14699	0.11794	0.20107
Kurt	4.8258	2.918	5.3438	3.2285	2.6992
Min	−17.23	−4.78	−11.1	−4	−3.34
Q25	−1.64	−1.745	−1.785	−0.715	−1.08
Q50	1.135	0.185	−0.3	0.285	−0.06
Q75	3.285	1.545	0.935	1.155	0.885
Max	11.35	6.87	8.32	4.82	3.63

Table 2 contains a statistical description of the Fama French five factors over our sample. In comparison to the extremely fat-tailed (leptokurtic) returns of the stocks (shown in Table 1), the market factor has a closer-to-normal kurtosis. The market factor is skewed to the left (although, this value too is closer to normal than the individual stock returns).

4.3 – ESG Scores

My ESG scores are collected from RepRisk, which includes data for companies that have been exposed to ESG risks. I used the RepRisk Index (RRI) to construct my ESG factor. RRI is a proprietary algorithm developed by RepRisk that "dynamically captures and quantifies a company's exposure to reputational risks related to ESG." The RRI denotes the current level of media and stakeholder coverage of a company related to ESG issues. It provides an assessment of the ESG and business conduct risks associated with financing, investing, or doing business with a particular company, and RRI scores roughly translate to measurements done by Thomson Reuters, Morningstar, and others.

The RRI is an integer value computed on a monthly basis that ranges from zero (lowest) to 100 (highest). The higher the value, the higher the risk exposure. More sustainable companies meeting many ESG criteria will have lower RRI scores, while companies with poor ESG practices will have higher RRI scores. A score in the range 0-25 indicates low risk exposure, 26-49 indicates medium risk exposure, 50-59 indicates high risk exposure, 60-74 indicates very high risk exposure, and 75-100 indicates extremely high risk exposure. RepRisk notes that it is expected that most large multinational corporations have scores in the range 26-49 (medium risk exposure) due to their global footprint and prominence in the media and amongst stakeholders. The RRI is calibrated in such a way that only a handful of companies with extremely high risk exposure earn scores above 75. RRI scores of zero are ambiguous, as they indicate either that a company was never exposed to ESG-related risks (RepRisk has not yet captured risk incidents for this company) or that the company was exposed to ESG risks before but the RRI has decayed to zero in the meantime (over a maximum period of two years).

Table 3: Data description of RRI scores

The RRI scores are computed over the balanced panel of data for 440 S&P 500 companies with RepRisk data for the period from June 29, 2007 to June 29, 2018.

	RRI
Mean	16.433
Std	14.935
Skew	0.85543
Kurt	3.7459
Min	0
Q25	0
Q50	18
Q75	24
Max	79

Looking at Table 3, it is clear that most companies in our sample have low risk exposure. Our mean and 75th-percentile value are all within the low risk exposure range. The fact that at least a quarter of the RRI scores are zero might indicate that our estimation is zero-inflated. This could be a potential source of bias, and this particular feature of the data should be examined carefully in future studies.

5 – Findings

Using ESG data from June 2007 to June 2018, I find that ESG meets two of the three conditions necessary to be considered a genuine risk factor. ESG is related to returns and exhibits a reasonable reward-to-risk rate, but it is not priced in the cross section of S&P 500 returns. Thus, we may regard ESG as a quasi-risk factor. I will retrace through the PRS Protocol, examining the results for each step along the way.

Before running through these three steps, I obtained the ESG factor by constructing an ESG factor portfolio and computing its returns based on the methodology from Fama and French (2015). Basically, I went long on stocks whose factor loadings are in the top 30th-percentile with equal weights and shorted the stocks whose factor loadings are in the bottom 30th-percentile with equal weights. The sum of weights for the long stocks is equal to the sum of weights for the short stocks.

5.1 – ESG is Related to the Covariance Matrix of Returns

For the first criterion, I extracted the first 61 principal components that can explain 90% of the variance in asset returns. Then I conducted a canonical correlation between these 61 eigenvectors and our ESG factor. The most meaningful results are the p-values. Note that all of the p-values for the factors are less than the alpha level, 0.05. So, the null hypothesis that the returns matrix and the factors are independent is rejected in favor of the alternative hypothesis that the proposed ESG factor is related to the covariance matrix of the asset returns.

Table 4: Canonical correlation test

All data pertains to the ESG scores and stock returns of interest for monthly returns June 2007 to June 2018. The entries are the χ^2 and p-values from a t-test with the null hypothesis of all canonical correlations jointly being zero.

	Chisq	P_Value
Mkt_Rf	504.97	3.8275e-71
SMB	148.58	2.8773e-09
HML	211.27	1.9156e-18
RMW	151.45	1.1922e-09
CMA	141.43	2.4725e-08
ESG	424.05	8.4721e-56

Table 4 lists the canonical correlation and p-value from an F-test with the null hypothesis that the canonical correlations are all zero. At the 0.05 significance level, we find that all factors, including our constructed ESG factor, reject the null and are related to the covariance matrix of returns.

3.2 – ESG Factor is Not Priced in the Cross-Section

I listed the annual risk premia (gamma) and their associated t-stats here. See in Table 5 that the magnitudes of the t-stats are all greater than 1.96 (the critical value indicating significance at 0.05 with more than ~30 degrees of freedom) except for ESG, which means that the risk premia of our candidate factor ESG are not significant.

Table 5: Fama-Macbeth Test

There are two passes of regressions in the Fama-Macbeth test (see Equations 3 and 4). The first pass is used to estimate the factor loadings, β's. The second applies the result from the first to estimate the factor premiums, γ's. If the factor is priced in the cross-sectional return, the premium should be significantly from 0.

	Mkt_Rf	SMB	HML	RMW	CMA	ESG
gamma1_07	0.0023035	0.0025111	-0.0046649	-0.0013305	-0.0037671	0.40697
tstat_07	2.5603	3.3549	-8.9249	-2.9268	-7.7992	1.0738
gamma1_08	0.0022604	0.0024998	-0.0046492	-0.0013434	-0.0037477	0.33621
tstat_08	2.5142	3.3381	-8.8882	-2.9561	-7.7558	0.87781
gamma1_09	0.0022497	0.0024918	-0.0046436	-0.0013419	-0.0037409	0.3098
tstat_09	2.5	3.3286	-8.8757	-2.9517	-7.7414	0.80988
gamma1_10	0.0022348	0.0024885	-0.004638	-0.0013429	-0.0037339	0.28176
tstat_10	2.4831	3.3232	-8.8602	-2.9534	-7.7233	0.73303
gamma1_11	0.002221	0.0024835	-0.0046317	-0.0013426	-0.003728	0.25377
tstat_11	2.4666	3.3166	-8.8461	-2.9517	-7.7026	0.65778
gamma1_12	0.0022089	0.0024852	-0.0046281	-0.001347	-0.0037218	0.2277
tstat_12	2.4544	3.3161	-8.8338	-2.9624	-7.6933	0.60391
gamma1_13	0.0022008	0.002485	-0.0046244	-0.0013484	-0.0037182	0.20965
tstat_13	2.4467	3.3144	-8.8294	-2.9657	-7.6866	0.56928
gamma1_14	0.0021899	0.0024812	-0.0046193	-0.0013495	-0.0037126	0.18565
tstat_14	2.4336	3.309	-8.8179	-2.968	-7.6719	0.50893
gamma1_15	0.002184	0.0024781	-0.0046164	-0.0013496	-0.0037094	0.17444
tstat_15	2.4258	3.3054	-8.8113	-2.9678	-7.663	0.47384
gamma1_16	0.002196	0.0024814	-0.0046216	-0.0013487	-0.0037147	0.19788
tstat_16	2.4392	3.3104	-8.8223	-2.966	-7.679	0.53435
gamma1_17	0.0021944	0.0024801	-0.0046211	-0.0013489	-0.0037139	0.19349
tstat_17	2.4368	3.309	-8.8191	-2.9665	-7.6757	0.52371
gamma1_18	0.0021897	0.0024902	-0.0046219	-0.0013553	-0.0037126	0.18044
tstat_18	2.4385	3.3152	-8.8204	-2.9818	-7.6861	0.53222

Disappointingly, Table 5 shows that the ESG factor is not priced into the cross-section of returns in any significant way.

3.3 – ESG has a Reasonable Reward-to-Risk Ratio

According to the PRS Protocol, a reasonable Sharpe Ratio should be less than 0.6 in magnitude. The pure ESG factor portfolio and the ESG factor portfolio incorporating the market have a Sharpe ratio lower than 0.6 in each portfolio. Thus, ESG has passed the third criterion.

Table 6: Sharpe Ratio for pure factor portfolio

These are the Sharpe Ratios for zero investment long-short portfolios. The pure factor portfolio for ESG shorts the worst 30th-percentile of ESG scores (high RRI) and longs the best 30th-percentile of ESG scores (low RRI). The other portfolios are computed according to Fama-French methodology. The Sharpe Ratio of each portfolio is:

$$Sharpe\,Ratio = \frac{E(R_p) - R_F}{\sigma(R_p)}$$

	Sharpe_Ratio
Mkt_Rf	0.03599
SMB	0.052357
HML	-0.070034
RMW	0.045805
CMA	-0.13061
ESG	0.046892

Table 7: Sharpe Ratio for factor portfolio incorporating market

These are the Sharpe Ratios of long-only portfolios combining each factor with the market portfolio, according to the following equation:

$$R_p = 0.5 \bullet R_{factor} + 0.5 \bullet R_M$$

As above, Sharpe Ratio of each portfolio is:

$$Sharpe\,Ratio = \frac{E(R_p) - R_F}{\sigma(R_p)}$$

	Sharpe_Ratio
Mkt_Rf	0.085947
SMB	0.11618
HML	0.043695
RMW	0.14598
CMA	0.035026
ESG	0.15906

Table 6 and Table 7 indicate that the Sharpe Ratios for both our ESG portfolios are within the reasonable bound (<0.6) specified by the PRS Protocol. Passing this test suggest that there is no arbitrage or near arbitrage opportunities with the ESG factor and that the ESG factor's premium is reasonable to capture a source of priced risk.

6 – Conclusion and possible extensions

This paper builds upon the pioneering work of Aguilar and Li (2019) in applying the PRS Protocol to determine if ESG is a genuine risk factor. In order to classify ESG as a genuine risk factor, the PRS Protocol requires one to:

1. Identify if the constructed ESG factor is related to the covariance matrix of returns
2. Apply the Fama-Macbeth method to test whether the factor is priced in the cross-section of returns
3. Test whether the Sharpe Ratio of the traded ESG factor portfolio is within the reasonable bound

Using ESG data from June 2007 to June 2018, I find that ESG meets two of the three conditions necessary to be considered a genuine risk factor. ESG is related to returns and exhibits a reasonable reward-to-risk rate, but it is not priced in the cross section of S&P 500 returns. Thus, we may regard ESG as quasi-risk factor.

This result means that ESG is not a genuine risk factor, but it leaves open the possibility of ESG being a proxy for some other more fundamental factor.

My analysis was limited by the incompleteness of the RepRisk ESG data and its short estimation period. The restricted universe and small sample period negatively impacted the precision of my estimates. The accuracy of the PRS Protocol can be improved by a larger sample and lengthier estimation period. Another potential problem, which Aguilar and Li (2019) also noted, is the inclusion of data from 2008 during the financial crisis. It could be that factor premia are unstable immediately before, during, and after a financial crisis.

However, the results suggest that, while not a genuine risk factor, ESG is a quasi-factor associated with asset risk. To bolster my results, future work should extend both the length and breadth of the estimation sample.

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