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A factor approach to the performance of ESG leaders and laggards

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ABSTRACT

We introduce a factor approach to performance measurement of global ESG equity investments. We construct ESG pure factor portfolios (PFP) following Fama-MacBeth; then, applying Fama-French (FF) spanning regressions that simultaneously test performance and the validity of adding new ESG factors to the FF 5-factor model. To address endogeneity, we use a GMM-IV estimator. Our ESG portfolios do not generate significant alphas during 2015-2019, corroborating the literature's neutrality argument. We find no sufficient evidence for ESG factors to complement FF5. PFPs, nevertheless, may serve as ESG indices to quantify investment portfolio sustainability risks via performance attribution of the ESG factor tilt.

1. Introduction

ESG investing is becoming mainstream in global equity markets[1] driven by rising demand for investments that promote sustainability[2]. Regulators[3] require disclosure to evaluate the extent to which ESG alignment impacts portfolio performance. This paper contributes to the literature by introducing a factor methodology to quantify the impact of ESG alignment on investment performance. Hence, we construct *pure* ESG equity factor portfolios (PFP), rated on a five-point scale[4], filtering out secondary factor effects. Then, we measure the risk-adjusted performance of the pure ESG factors. These ESG PFPs may function as *sustainability indices* used for the calculation of investment portfolio tilt to ESG factors; and for the quantification of the performance attribution of the ESG factor tilt. Further, our approach simultaneously tests ESG strategy performance and serves to validate ESG as new factors in the Fama-French (FF) 5-factor model (FF5).

Literature on ESG investment performance covers three arguments. First, the neutral relationship contends that markets are informationally efficient, hence, it is not possible to achieve superior risk-adjusted returns (Fama, 1970). Studies by Hartzmark and Sussman (2019) and Managi et al. (2012) support neutrality. In contrast, Adler and Kritzman (2008), Bauer et al. (2005) and Berlinger

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[1] According to the GSIA (2018), sustainable investments accounted for 33 per cent of total assets under management globally in 2018 compared to 21 per cent two years earlier.

[2] Tucker and Jones (2020) found that 85 per cent of millennials have a high demand for ESG. Amel-Zadeh and Serafeim (2018) argue that the second most important motivation of investment professionals for using ESG is client demand.

[3] In the EU, Regulation 2019/2088 (SFDR) requires sustainability-related disclosures.

[4] The five categories cover ESG leaders, followers, loungers, laggards, and not rated in line with Triguero et al. (2016).

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Table 1
Grouping scheme of ESG exposures

Group code	Classification	Classification rules
A	Leader in E/S/G	$\text{NormESG}_i \geq 60$
B	Follower in E/S/G	$60 > \text{NormESG}_i \geq 50$
C	Lounger in E/S/G	$50 > \text{NormESG}_i \geq 40$
D	Laggard in E/S/G	$\text{NormESG}_i < 40$
NR	Not rated	ESG scores are not disclosed

Notes:
We classify ESG scores into four plus one groups. The first four groups are in decreasing order of ESG quality, and the group codes A, B, C and D are analogous to credit ratings. Companies that do not have scores belong to a separate class and are labelled 'not rated'. The classification (leader, follower, lounger and laggard) follows the naming convention of Triguero et al. (2016). The classification rules are as follows: 60 = one standard deviation above the average score, 50 = average score, 40 = one standard deviation below the average score.

and Lovas (2015) argue that ESG investments result in potential underperformance; one explanation is that ESG investments are a subset of the market, hence have lower diversification capability; another is that sustainability aspects sacrifice short-term growth. Finally, Consolandi et al. (2009) and Renneboog et al. (2008) attest to superior returns emphasising 'doing well while doing good'. We contribute to the literature by testing if, at least, a neutral relationship exists.

The investment literature follows two distinct approaches to evaluate ESG investments. One compares ESG funds' performance with their non-ESG counterparts (Lesser et al., 2016; Nofsinger and Varma, 2014; Pástor and Vorsatz, 2020). Another approach is to identify ESG as new risk factors similarly to the original FF factors (Hübel and Scholz, 2020; Jin, 2018; Maiti, 2020). We apply the right-hand-side (RHS) method, popularised by FF (2018), which combines the two approaches with the benefit of capturing specific factors' pure performance (Bali et al., 2016) while testing whether they are valid new factors (FF, 1996, 2015, 2017). This paper's novelty lies in applying the RHS approach to ESG factors.

Portfolio managers who integrate sustainability in their investment portfolios undertake a dual optimisation process that combines ESG strategies with fundamental valuation. To measure the impact of sustainability risk on portfolio returns, we propose using our ESG PFPs as indices to measure ESG tilt to different ESG factors from leaders to laggards. This method is superior to calculating the overall ESG rating of investment portfolios currently commonly used by asset managers, as it separates the performance contribution of the ESG tilt from the secondary factors such as geographical, industry or style effects. Menchero (2010) and Menchero and Ji (2017) present a similar technique; our comprehensive approach controls for 98 different style, industry and country factors.

ESG PFPs rest on constrained WLS cross-sectional regressions derived from the Fama – MacBeth (1973) (FM) approach. In FF5 time-series spanning regressions, we test whether ESG factors achieve superior risk-adjusted returns. FF (2020 p. 1913) argue that the application of FM cross-sectional factors in an FF-type time series regression context explain average asset returns a bit better than the traditional FF time-series factors. Despite its advantages, this combination of methods is still not widespread in the literature; bar the applications presented in Back et al. (2013, 2015).

According to Jahmane and Gaies (2020 p. 2), endogeneity remains a largely unaddressed problem in the sustainability literature. In the time-series analysis, we control for endogeneity by using a GMM distance IV estimator.

The paper details PFPs formation and the GMM-IV_d approach in section 2; then introduces the database in section 3; while section 4 presents empirical results; we conclude our findings in section 5.

2. Methodology

We begin by constructing PFPs following Back et al. (2013), Clarke et al. (2014, 2017), Menchero (2010), and Walter and Berlinger (1999). From a mathematical perspective, PFPs rest on constrained WLS cross-sectional regressions. We calculate pure factor (PF) returns as follows:

$$r_{it+1} = r_{Mt+1} + \sum_k \beta_{kt+1} z_{kit} + \varepsilon_{it+1} \tag{1}$$

where r_{it+1} is the return of security i at time $t+1$; the regressors are the market-weight standardised factor exposures, z_{kit}. Regression betas are the market-relative excess returns of PFPs.

We note that the beta coefficients in (1) could be measured as the returns to factor-mimicking long-short portfolios. The critical step is to calculate stock weights. Formula (2) derives from matrix algebra:

$$W = R(R'Z'VZR)^{-1}R'Z'V \tag{2}$$

where W is the $(m+1) \times N$ matrix for active security weights, Z is the $N \times (m+1)$ matrix of standardised exposures, V is a $N \times N$ diagonal matrix with market capitalisations in the diagonal. Variable m represents the number of PFs, '+1' indicates the market factor. R is the $(m+1) \times (m+1\text{-}3)$ constraint matrix (Heston – Rouwenhorst, 1994), which manages exact multicollinearity due to ESG, countries and industries.

We construct ESG dummy variables based on Sustainalytics scores to obtain PFPs. Environmental, social, and governance scores are

Table 2
Pure style factors and factor-related descriptors

Factor	Descriptor
Beta	Market-relative beta: $Beta_i$ - $Beta_M$
Value	E/P, CF/P, BV/P
Momentum	Return, price, and Sharpe-momentum
Size	-ln(MCap), -ln(Assets), -ln(Sales)
Volatility	Total & residual volatility, price range
Liquidity	Amihud (2002) liquidity ratio
Profitability	ROE, ROA, ROIC/WACC, Profit margin
Growth	Profit before tax, net income, and sales growth
Investment	Assets growth
Leverage	Book & market leverage, Debts/Assets
Earnings variability	Sales, net income, FCFF variability
Environment (E), Social (S), Governance (G)	E, S, G scores from Sustainalytics

Notes: We neutralise the effects of 11 well-known style, 24 industry and 48 country factors when constructing Fama-MacBeth-based E, S and G factor portfolios (due to limited space, we do not report sectors and countries). The size, value, investment, and profitability factors are applied in the FF 5-factor model. The momentum factor is often attributed to Carhart (1997). Most of the factors consist of more than one firm characteristics as descriptors. Descriptors are merged into factors via principal component analysis (PCA).

treated separately and categorised into four rated groups, in decreasing order of ESG quality, in addition to a fifth group of unrated companies[5]. Table 1 summarises our grouping scheme.

Industry-specific scores are not comparable across sectors; therefore, we follow Morningstar's approach allowing for cross-sectorial comparison via standardisation (Justice and Hale, 2016):

$$zESG_i = \frac{ESG_i - \mu_{peer}}{\sigma_{peer}}, \tag{3}$$

where ESG_i is the company-level score, μ_{peer} and σ_{peer} are the mean and standard deviation of the peer scores. Next, we transform z-scores into normalised scores on a 0-100 scale, with a mean and standard deviation of 50 and 10, respectively:

$$NormESG_i = 50 + (zESG_i \ x \ 10) \tag{4}$$

The derivation of the GMM-IV_d formula presented below can be found in Racicot (2015), Racicot et al. (2019), Roy and Shijin (2018), and Naffa and Fain (2020):

$$argmin_{\widehat{\beta}} \left\{ n^{-1} \left[d'(Y - X\widehat{\beta}) \right]' Wn^{-1} \left[d'(Y - X\widehat{\beta}) \right] \right\} \tag{5}$$

The d matrix in (5) is a 'distance' matrix that corresponds to the robust instruments and defined as:

$$d = X - \widehat{X} = X - P_Z X = (I - P_Z)X \tag{6}$$

The elements of d in (6) can be expressed in a deviation form as:

$$d_{it} = x_{it} - \widehat{x}_{it} \tag{7}$$

where x_{it} and $\widehat{x}_{it}$ are matrix X_{it} and $\widehat{X}_{it}$ taken in deviation from their means. Intuitively, d_{it} is a filtered version of the endogenous variables. Variable $\widehat{x}_{it}$ in (7) is obtained by applying OLS on the z_t instruments:

$$x_{it} = \widehat{\gamma}_0 + z_t\widehat{\phi} + \varsigma_t = \widehat{x}_{it} + \varsigma_t \tag{8}$$

We define the z_t instruments as $z_t = \{z_{0t}, z_{1t}, z_{2t}\}$, where z_{0t} is a vector of one $(Tx1)$, $z_{1t} = x_{it} \odot x_{it}$ and $z_{2t} = x_{it} \odot x_{it} \odot x_{it} - 3x_{it}[D(x_{it}'x_{it}/T)]$. The symbol $\odot$ is the Hadamard product, $D(x_{it}'x_{it}/T) = (x_{it}'x_{it}/T) \odot I_n$ is a diagonal matrix, and I_n is an identity matrix of dimension $(k \ x \ k)$, where k is the number of regressors. These instruments are consistent with Dagenais and Dagenais (1997).

In the empirical section, we test the alphas of the FF5:

$$RP_{it} = \alpha_i + b_{1i} MRP_t + b_{2i} R_{SIZEt} + b_{3i} R_{VALUEt} + b_{4i} R_{PROITt} + b_{5i} R_{INVt} + u_{it}, \tag{9}$$

where RP_{it} is the excess return[6] of E, S, and G, α_t is the alpha, MRP_t is the market risk premium, R_{SIZEt}, R_{VALUEt}, $R_{PROFITt}$, and R_{INVt} are the

[5] We use dummy variables to handle the issue of missing scores, hence we can include unrated firms. Another statistical issue could be the sample selection bias. Wong et al. (2021) argue that adopting ESG rating is not randomly distributed across firms: their sample firms with ESG score tend to be more mature, high performing and carry lower tangible assets. In this paper, the FM procedure overcomes this bias as it neutralises numerous firm characteristics while constructing ESG portfolios.

[6] The risk-free rate is the 1-year T-Bill return.

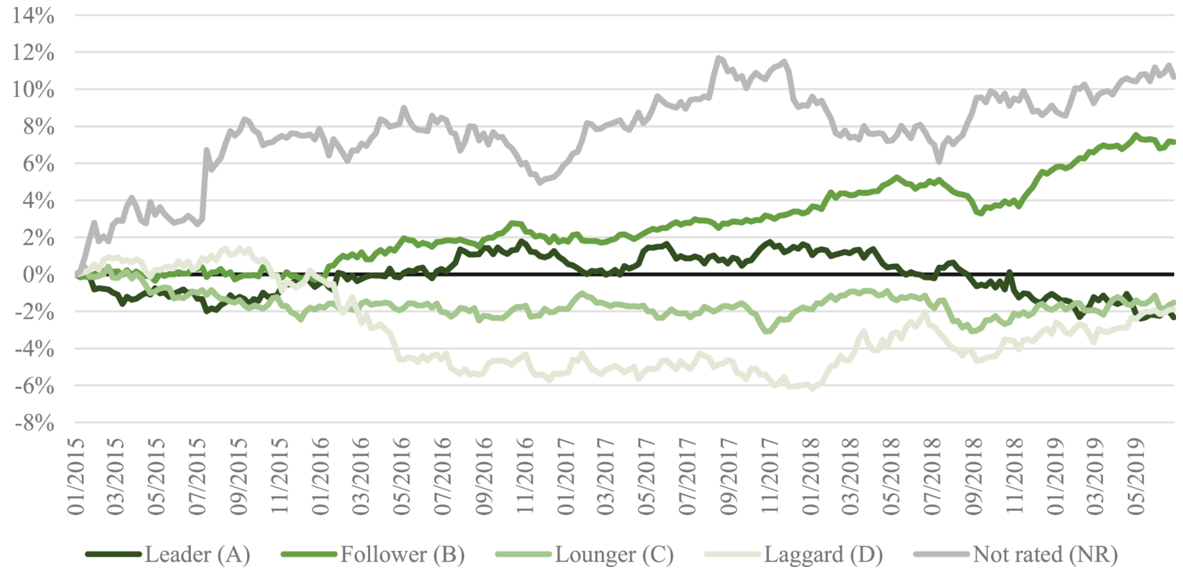

Fig. 1. Cumulative market-relative returns of environment (E) factor portfolios, 2015-2019. The figure depicts the cumulative market-adjusted performance of pure environmental portfolios classified according to Table 1. Returns are total log returns.

market-relative returns of size, value, profitability, and investment PFPs, respectively. Variables b_{1i}, b_{2i}, b_{3i}, b_{4i}, and b_{5i} are sensitivities to factor returns. We calculate (9) applying OLS with Newey – West (1987) standard errors and GMM-IV$_d$ approach.

3. Database

We assess ESG investing from a global equity investor perspective; hence, we select the MSCI ACWI Index as the investment universe[7]. We calculate weekly total returns, 15 ESG, 28 raw style descriptors, 24 industry, and 48 country exposures based on Bloomberg data for 2015-2019[8]. Raw style descriptors are the inputs to compute style factor exposures with principal component analysis (PCA). As a result of PCA, we have eleven style factors (Table 2).

All stocks traded between 2015-2019 are analysed, controlling survivorship bias. For statistical inference, data cleansing procedures are performed. First, we excluded companies that did not have, for any reason, price, total return, or market capitalisation. Second, the penny stocks (maximum price below USD 5) were excluded. We dealt with missing values, as well: instead of removing observations, we employed multiple imputations (MI). After MI, we specified winsorisation rules based on the 1st and the 99th percentiles to manage extreme values.

Altogether, we compiled a uniquely organised database including approximately 15 million data points, covering ca. 2,700 individual stocks, for a period spanning 234 weeks and measuring 98 factors.

4. Results

Figs. 1-3 depict the market-relative returns of ESG PFPs. Fig. 1 shows environmental portfolio returns, not accounting for risk at this stage.

The leaders resulted in a negative cumulative market-relative return (-2.32 per cent). The follower outperformed (7.15 per cent) while loungers (-1.53 per cent) and laggards (-1.88 per cent) underperformed the market. Unrated companies outperformed each PFP (10.65 per cent).

Social factor portfolios are presented in Fig. 2. The leaders realised a negative market-relative return (-1.61 per cent). The followers outperformed the market (2.24 per cent), the loungers also added 6.60 per cent, while the laggards realised a negative return of -2.75 per cent. Unrated companies accumulated 10.86 per cent.

Governance portfolio returns are in Fig. 3. The leader portfolio was up merely 0.87 per cent. The follower portfolio outperformed the market by 4.50 per cent, but loungers underperformed (-1.61 per cent). The laggards resulted in a 0.82 per cent surplus. Similarly to the previous cases, the NR portfolio outperformed the most, by 11.07 per cent.

Below, we present results from the risk-adjusted performance measures; findings are summarised in Table 3.

[7] The index serves as a proxy for the global equity market and as our benchmark.

[8] The great majority of firms did not disclose sustainability reports until recent years, meaning that ESG scores from earlier periods are not reliable: in 2017, 85 per cent of S&P 500 Index companies published sustainability reports, up from 11 per cent in 2011 (Matos, 2020). The shortage of reliable scores is the reason for the relatively short timeframe.

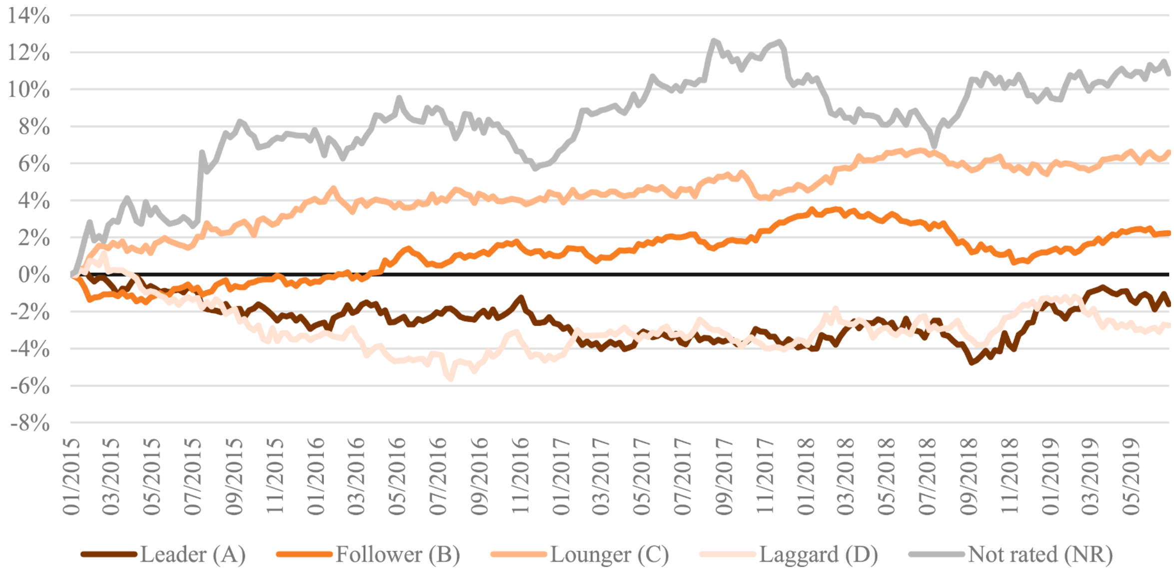

Fig. 2. Cumulative market-relative return of social (S) factor portfolios, 2015-2019. The figure depicts the cumulative market-adjusted performance of pure social portfolios classified according to Table 1. Returns are total log returns.

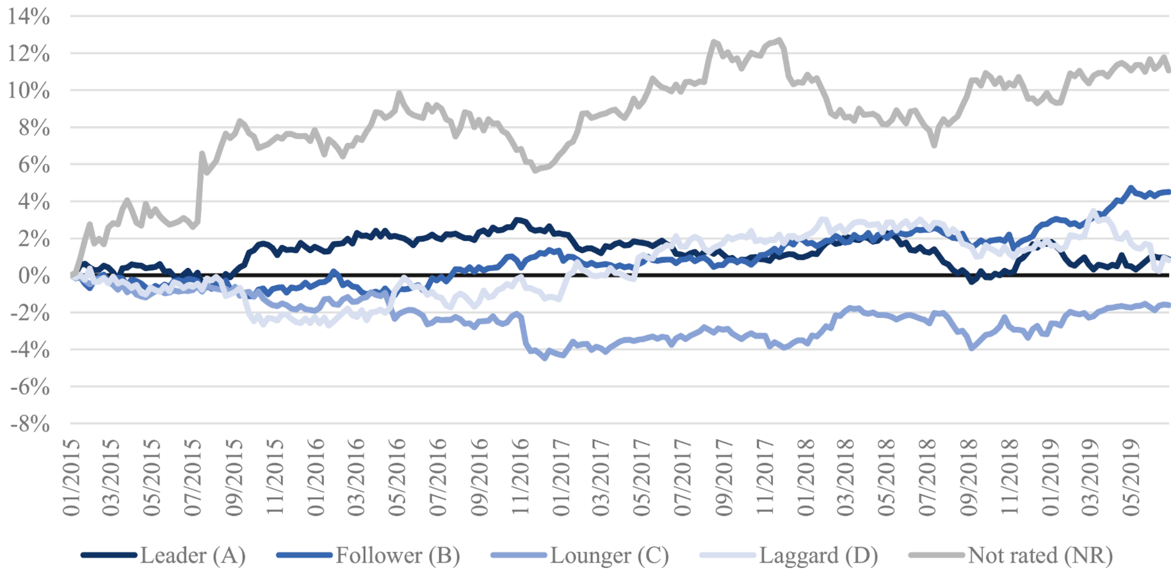

Fig. 3. Cumulative market-relative return of governance (G) factor portfolios, 2015-2019. The figure depicts the cumulative market-adjusted performance of pure governance portfolios classified according to Table 1. Returns are total log returns.

The leader portfolios generated negative alphas; however, only the environmental portfolio's results were significant at 10 per cent, achieving -1.19 and -1.18 per cent p.a. for both OLS and GMM-IV$_d$. Unrated portfolio across ESG were not significant in any instance after risk-adjustment, despite their high returns. Follower E and G portfolios had positive alphas; the former is significant at 10.00 per cent in both estimation methods (1.15 and 1.14 per cent p.a.). The lounger S portfolio realised a marginally significant 1.09 per cent alpha, according to GMM-IV$_d$.

We also examined the Sharpe-ratio and two alternative alpha estimation methods as robustness tests (Table 4.). Instead of the GMM, we apply the two-stage least squares (TSLS) estimator. The IVs are (1) the 'z' instruments from Equation (8) also used by Racicot and Théoret (2014), and (2) the higher-order moments up to three of the regressors. The latter approach is consistent with Cragg (1997) and Lewbel (1997). Lewbel contends that these instruments are appropriate for estimation when no other alternative IVs are easily available.

The Sharpe ratios support alpha results, though the leader environmental portfolio's negative performance is no longer significant. Concurrently, the follower governance portfolio has become a marginally significant outperformer. The follower environmental and

Table 3
Financial performance of ESG PFPs

PFPs		(A) α (OLS HAC)	t-stat	p-value		(B) α (GMM-IV$_d$)	t-stat	p-value	
E	Leader (A)	**-1.19%**	**-1.84**	**0.067**	*	**-1.18%**	**-1.81**	**0.071**	*
	Follower (B)	**1.15%**	**1.94**	**0.054**	*	**1.14%**	**1.79**	**0.073**	*
	Lounger (C)	-0.78%	-1.53	0.126		-0.73%	-1.31	0.189	
	Laggard (D)	-0.42%	-0.33	0.743		-0.33%	-0.27	0.786	
	Not rated (NR)	1.07%	0.84	0.402		1.13%	0.89	0.373	
S	Leader (A)	-0.97%	-1.20	0.231		-0.94%	-1.14	0.256	
	Follower (B)	0.02%	0.03	0.977		0.01%	0.02	0.987	
	Lounger (C)	1.06%	1.62	0.107		**1.09%**	**1.73**	**0.083**	*
	Laggard (D)	-0.80%	-0.83	0.406		-0.73%	-0.84	0.402	
	Not rated (NR)	1.13%	0.84	0.404		1.18%	0.87	0.386	
G	Leader (A)	-0.18%	-0.29	0.775		-0.15%	-0.22	0.823	
	Follower (B)	0.65%	1.25	0.213		0.67%	1.28	0.200	
	Lounger (C)	-0.90%	-1.30	0.194		-0.94%	-1.35	0.178	
	Laggard (D)	-0.41%	-0.43	0.670		-0.30%	-0.31	0.757	
	Not rated (NR)	1.03%	0.76	0.448		1.07%	0.79	0.428	

Notes: Alphas (log returns) are annualised figures. Both Panels (A) and (B) apply risk factors from Equation 9 (FF5), which rest on (1) and (2). In Panel (A), alphas are calculated, applying OLS with Newey-West standard errors. In Panel (B), alphas are the GMM-IV$_d$ method outcomes using the HAC weighting matrix and HAC standard errors. To test for weak and endogenous instruments, as well as measurement errors, we followed Racicot et al. (2019) as well as Olea and Pflueger (2013). We found that the IVs are robust and exogenous, and there are some measurement errors based on OLS; hence GMM-IV$_d$ is a more appropriate method for measuring performance than OLS.

Table 4
Robustness tests of ESG PFPs' financial performance

PFPs		(A) α (TSLS-IV$_z$)	t-stat	p-value	(B) α (TSLS-IV$_m$)	t-stat	p-value		(C) Sharpe$_{i\text{-}M}$	t-stat	p-value	
E	Leader (A)	-1.63%	-1.29	0.199	-1.33%	-1.16	0.246		-0.049	-0.81	0.420	
	Follower (B)	1.25%	1.24	0.215	**1.19%**	**1.70**	**0.090**	*	**0.119**	**2.30**	**0.023**	**
	Lounger (C)	-0.45%	-0.28	0.778	-0.21%	-0.26	0.799		-0.032	-0.57	0.568	
	Laggard (D)	-1.53%	-0.66	0.512	-0.91%	-0.59	0.553		-0.013	-0.16	0.875	
	Not rated (NR)	1.07%	0.35	0.726	1.58%	1.03	0.305		0.16	1.30	0.196	
S	Leader (A)	-0.87%	-0.70	0.483	-1.65%	-1.35	0.179		-0.042	-0.60	0.546	
	Follower (B)	0.24%	0.25	0.805	-0.11%	-0.14	0.892		0.031	0.60	0.548	
	Lounger (C)	0.70%	0.73	0.468	1.57%	1.55	0.122		**0.118**	**2.19**	**0.030**	**
	Laggard (D)	-2.90%	-1.35	0.178	-0.43%	-0.28	0.782		-0.035	-0.44	0.658	
	Not rated (NR)	1.67%	0.70	0.481	1.48%	1.00	0.316		0.16	1.30	0.193	
G	Leader (A)	-0.83%	-0.67	0.505	-0.06%	-0.05	0.958		0.013	0.23	0.817	
	Follower (B)	0.30%	0.37	0.710	0.87%	1.18	0.240		**0.077**	**1.65**	**0.100**	*
	Lounger (C)	0.29%	0.18	0.861	-0.34%	-0.24	0.812		-0.027	-0.42	0.672	
	Laggard (D)	-1.11%	-0.45	0.654	-0.84%	-0.58	0.564		-0.004	-0.05	0.962	
	Not rated (NR)	0.30%	0.11	0.912	0.94%	0.66	0.507		0.164	1.33	0.186	

Notes: Alphas (log returns) and Sharpe-ratios are annualised figures. Sharpe$_{i\text{-}M}$ refers to the i^{th} portfolio's Sharpe ratio over the market's (M) Sharpe-ratio. Both Panel (A) and (B) apply risk factors from Equation 9 (FF5), which rest on (1) and (2). In Panel (A), alphas are calculated, applying TSLS with the 'z' instruments based on (8) and proposed by Dagenais and Dagenais (1997) in line with Durbin (1954) and Pal (1980). In Panel (B), alphas are the TSLS method outcomes using higher-order moments (m) as instruments (further details on why higher moments are proper IVs are in Cragg, 1997; and Lewbel, 1997). In both cases, HAC standard errors are applied.

the lounger social portfolios also beat the market but now at a 5 per cent significance level. Based on the IV$_z$ and IV$_m$ approaches, the leader environmental portfolio's negative alpha is not significant any more at the usual significance levels. No further results are significant, except for the follower environmental portfolio that has a marginally significant alpha based on TSLS-IV$_m$.

Our results have the following implications: ESG leader portfolios realised significant negative risk-adjusted returns, though the results are not robust. The environmental follower portfolio showed positive risk-adjusted performance as results were significant for four model specifications, yet the model failed in the robustness checks. All ESG laggard portfolios underperformed, however, results remain statistically not significant.

We conclude that our factor portfolios did not have robust significant alphas. This result supports literature findings that the FF5 effectively explains stock returns (Guo et al., 2017; Zaremba and Czapkiewicz, 2017).

Another conclusion comes from the applied FF spanning regression technique as it tests if ESG factors are viable new factors in the FF5. Harvey et al. (2016, p. 37) argue that a newly discovered factor requires a t-statistic of at least 3.0. Although our ESG portfolios are suitable to measure the performance attribution of ESG factors, the low t-statistics do not justify them as complementary new factors to the FF5, in line with Xiao et al. (2013). In contrast, Hübel and Scholz (2020) and Díaz et al. (2021) find evidence in support of ESG as valid additional factors.

We propose another application for our results for the asset management industry. The PFPs may be used as ESG indices to capture sustainability risks of investment portfolios. Asset managers may regress their portfolios on the ESG PFPs to find their portfolios' ESG tilt, and hence, quantify the performance attribution of the ESG factor tilt while excluding secondary factor impacts.

5. Conclusion

We examined the risk-adjusted performance of ESG pure factor portfolios in global equity markets from 2015 to mid-2019, covering ESG leaders, followers, loungers, and laggards. Our ESG portfolios did not generate significant alphas, corroborating literature findings on neutrality. The applied spanning regression approach following *Fama and French* also served to test the validity of ESG factors to explain the cross-section of expected returns. We found no sufficient evidence for our ESG factors to be considered as additional factors in the FF5. The ESG PFPs, however, may serve as indices to capture sustainability risks by quantifying the performance attribution of the ESG factor tilt while excluding secondary factor impacts.

Author statement

Both authors shared in the conceptualisation, analysis, writing, reviewing, and editing of this paper.

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References

Adler, T., Kritzman, M., 2008. The cost of socially responsible investing. J. Portf. Manag. 35, 52–56. https://doi.org/10.3905/JPM.2008.35.1.52.

Amel-Zadeh, A., Serafeim, G., 2018. Why and how investors use ESG information: evidence from a global survey. Financ. Anal. J. 74, 87–103. https://doi.org/10.2469/faj.v74.n3.2.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. J. Financ. Mark. 5, 31–56. https://doi.org/10.1016/S1386-4181(01)00024-6.

Back, K., Kapadia, N., Ostdiek, B., 2015. Testing Factor Models on Characteristic and Covariance Pure Plays (SSRN Scholarly Paper No. ID 2621696). Social Science Research Network, Rochester, NY. https://doi.org/10.2139/ssrn.2621696.

Back, K., Kapadia, N., Ostdiek, B., 2013. Slopes as Factors: Characteristic Pure Plays (SSRN Scholarly Paper No. ID 2295993). Social Science Research Network, Rochester, NY. https://doi.org/10.2139/ssrn.2295993.

Bali, T.G., Engle, R.F., Murray, S., 2016. Empirical Asset Pricing: The Cross Section of Stock Returns. John Wiley & Sons, Inc., Hoboken, N.J.

Bauer, R., Koedijk, K., Otten, R., 2005. International evidence on ethical mutual fund performance and investment style. J. Bank. Finance 29, 1751–1767. https://doi.org/10.1016/j.jbankfin.2004.06.035.

Berlinger, E., Lovas, A., 2015. Sustainability and growth: the Stern review and the model of directed technical change (IEHAS Discussion Papers No. MT-DP-2015/1; ISBN 978-615-5447-59-4). Hungarian Academy of Sciences, Institute of Economics, Centre for Economic and Regional Studies, Budapest.

Carhart, M.M., 1997. On Persistence in Mutual Fund Performance. J. Financ. 52, 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x.

Clarke, R., de Silva, H., Thorley, S., 2017. Pure factor portfolios and multivariate regression analysis. J. Portf. Manag. 43, 16–31. https://doi.org/10.3905/jpm.2017.43.3.016.

Clarke, R., de Silva, H., Thorley, S., 2014. The not-so-well-known three-and-one-half-factor model. Financ. Anal. Journal 70, 13–23. https://doi.org/10.2469/faj.v70.n5.3.

Consolandi, C., Jaiswal-Dale, A., Poggiani, E., Vercelli, A., 2009. Global standards and ethical stock indexes: the case of the Dow Jones sustainability stoxx index. J. Bus. Ethics 87, 185–197. https://doi.org/10.1007/s10551-008-9793-1.

Cragg, J.G., 1997. Using higher moments to estimate the simple errors-in-variables model. RAND J. Econ. 28, S71–S91. https://doi.org/10.2307/3087456.

Dagenais, M.G., Dagenais, D.L., 1997. Higher moment estimators for linear regression models with errors in the variables. J. Econom. 76, 193–221. https://doi.org/10.1016/0304-4076(95)01789-5.

Díaz, V., Ibrushi, D., Zhao, J., 2021. Reconsidering systematic factors during the Covid-19 pandemic – the rising importance of ESG. Financ. Res. Lett. 38, 101870 https://doi.org/10.1016/j.frl.2020.101870.

Durbin, J., 1954. Errors in Variables. Revue de l'Institut International de Statistique /Review of the international statistical institute 22, 23–32. doi:10.2307/1401917.

Fama, E.F., 1970. Efficient capital markets: a review of theory and empirical work. J. Financ. 25, 383–417. https://doi.org/10.2307/2325486.

Fama, E.F., French, K.R., 2020. Comparing cross-section and time-series factor models. Rev. Financ. Stud. 33, 1891–1926. https://doi.org/10.1093/rfs/hhz089.

Fama, E.F., French, K.R., 2018. Choosing factors. J. Financ. Econ. 128, 234–252. https://doi.org/10.1016/j.jfineco.2018.02.012.

Fama, E.F., French, K.R., 2017. International tests of a five-factor asset pricing model. J. Financ. Econ. 123, 441–463. https://doi.org/10.1016/j.jfineco.2016.11.004.

Fama, E.F., French, K.R., 2015. A five-factor asset pricing model. J. Financ. Econ. 116, 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010.

Fama, E.F., French, K.R., 1996. Multifactor explanations of asset pricing anomalies. J. Financ. 51, 55–84. https://doi.org/10.1111/j.1540-6261.1996.tb05202.x.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: empirical tests. J. Polit. Econ. 81, 607–636. https://doi.org/10.1086/260061.

GSIA, 2018. Global Sustainable Investment Review 2018. GSIA.

Guo, B., Zhang, W., Zhang, Y., Zhang, H., 2017. The five-factor asset pricing model tests for the Chinese stock market. Pac.-Basin Financ. J. 43, 84–106. https://doi.org/10.1016/j.pacfin.2017.02.001.

Hartzmark, S.M., Sussman, A.B., 2019. Do investors value sustainability? a natural experiment examining ranking and fund flows. J. Financ. 74, 2789–2837. https://doi.org/10.1111/jofi.12841.

Harvey, C.R., Liu, Y., Zhu, H., 2016. … and the cross-section of expected returns. Rev. Financ. Stud. 29, 5–68. https://doi.org/10.1093/rfs/hhv059.

Heston, S.L., Rouwenhorst, K.G., 1994. Does industrial structure explain the benefits of international diversification? J. Financ. Econ. 36, 3–27. https://doi.org/10.1016/0304-405X(94)90028-0.

Hübel, B., Scholz, H., 2020. Integrating sustainability risks in asset management: the role of ESG exposures and ESG ratings. J. Asset. Manag. 21, 52–69. https://doi.org/10.1057/s41260-019-00139-z.

Jahmane, A., Gaies, B., 2020. Corporate social responsibility, financial instability and corporate financial performance: linear, non-linear and spillover effects – The case of the CAC 40 companies. Financ. Res. Lett. 34, 101483 https://doi.org/10.1016/j.frl.2020.101483.

Jin, I., 2018. Is ESG a systematic risk factor for US equity mutual funds? J. Sustain. Financ. Invest. 8, 72–93. https://doi.org/10.1080/20430795.2017.1395251.

Justice, P., Hale, J., 2016. Morningstar Sustainability Rating. Morningstar.

Lesser, K., Rößle, F., Walkshäusl, C., 2016. Socially responsible, green, and faith-based investment strategies: screening activity matters! Financ. Res. Lett. 16, 171–178. https://doi.org/10.1016/j.frl.2015.11.001.

Lewbel, A., 1997. Constructing instruments for regressions with measurement error when no additional data are available, with an application to patents and R&D. Econometrica 65, 1201–1213. https://doi.org/10.2307/2171884.

Maiti, M., 2020. Is ESG the succeeding risk factor? J. Sustain. Financ. Invest. 0, 1–15. https://doi.org/10.1080/20430795.2020.1723380.

Managi, S., Okimoto, T., Matsuda, A., 2012. Do socially responsible investment indexes outperform conventional indexes? Appl. Financ. Econ. 22, 1511–1527. https://doi.org/10.1080/09603107.2012.665593.

Matos, P., 2020. ESG and Responsible Institutional Investing Around the World: A Critical Review (SSRN Scholarly Paper No. ID 3668998). Social Science Research Network, Rochester, NY. https://doi.org/10.2139/ssrn.3668998.

Menchero, J., 2010. The characteristics of factor portfolios. J. Perform. Meas. 15, 52–62.

Menchero, J., Ji, L., 2017. Pure Factor Returns in Real Time. Bloomberg White Papers 1–14.

Naffa, H., Fain, M., 2020. Performance measurement of ESG-themed megatrend investments in global equity markets using pure factor portfolios methodology. PLoS One 15, e0244225. https://doi.org/10.1371/journal.pone.0244225.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703–708. https://doi.org/10.2307/1913610.

Nofsinger, J., Varma, A., 2014. Socially responsible funds and market crises. J. Bank. Financ. 48, 180–193. https://doi.org/10.1016/j.jbankfin.2013.12.016.

Olea, J.L.M., Pflueger, C., 2013. A robust test for weak instruments. J. Bus. Econ. Stat. 31, 358–369. https://doi.org/10.1080/00401706.2013.806694.

Pal, M., 1980. Consistent moment estimators of regression coefficients in the presence of errors in variables. J. Econom. 14, 349–364. https://doi.org/10.1016/0304-4076(80)90032-9.

Pástor, Ľ., Vorsatz, M.B., 2020. Mutual fund performance and flows during the COVID-19 crisis. Rev. Asset Pric. Stud. 10, 791–833. https://doi.org/10.1093/rapstu/raaa015.

Racicot, F.-É., 2015. Engineering robust instruments for GMM estimation of panel data regression models with errors in variables: a note. Appl. Econ. 47, 981–989. https://doi.org/10.1080/00036846.2014.985373.

Racicot, F.-E., Rentz, W.F., Kahl, A., Mesly, O., 2019. Examining the dynamics of illiquidity risks within the phases of the business cycle. Borsa Istanbul Rev. 19, 117–131. https://doi.org/10.1016/j.bir.2018.12.001.

Racicot, F.-É., Rentz, W.F., Tessier, D., Théoret, R., 2019. The conditional Fama-French model and endogenous illiquidity: a robust instrumental variables test. PLoS One 14, e0221599. https://doi.org/10.1371/journal.pone.0221599.

Racicot, F.-É., Théoret, R., 2014. Cumulant instrument estimators for hedge fund return models with errors in variables. Appl. Econ. 46, 1134–1149. https://doi.org/10.1080/00036846.2013.868591.

Renneboog, L., Ter Horst, J., Zhang, C., 2008. Socially responsible investments: institutional aspects, performance, and investor behavior. J.Bank. Financ. 32, 1723–1742. https://doi.org/10.1016/j.jbankfin.2007.12.039.

Roy, R., Shijin, S., 2018. A six-factor asset pricing model. Borsa Istanbul Rev. 18, 205–217. https://doi.org/10.1016/j.bir.2018.02.001.

Triguero, A., Moreno-Mondéjar, L., Davia, M.A., 2016. Leaders and laggards in environmental innovation: an empirical analysis of SMEs in Europe. Bus. Strateg. Environ. 25, 28–39. https://doi.org/10.1002/bse.1854.

Tucker III, J.J., Jones, S., 2020. Environmental, social, and governance investing: investor demand, the great wealth transfer, and strategies for ESG investing. J. Financ. Serv. Prof. 74, 56–75.

Walter, G., Berlinger, E., 1999. Factor models in the securities market. The Arbitrage Pricing Theory (APT). Faktormodellek az értékpapírpiacon. Az arbitrált árfolyamok modellje (APT). Bankszemle 43, 34–43.

Wong, W.C., Batten, J.A., Ahmad, A.H., Mohamed-Arshad, S.B., Nordin, S., Adzis, A.A., 2021. Does ESG certification add firm value? Financ. Res. Lett. 39, 101593 https://doi.org/10.1016/j.frl.2020.101593.

Xiao, Y., Faff, R., Gharghori, P., Lee, D., 2013. An empirical study of the world price of sustainability. J. Bus. Ethics 114, 297–310. https://doi.org/10.1007/s10551-012-1342-2.

Zaremba, A., Czapkiewicz, A., 2017. Digesting anomalies in emerging European markets: a comparison of factor pricing models. Emerg. Mark. Rev. 31, 1–15. https://doi.org/10.1016/j.ememar.2016.12.002.