ESG-screening and factor-risk-adjusted performance: the concentration level of screening does matter

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Abstract

Constructing ESG-screened portfolios aims to reduce the aggregate ESG-risk at the portfolio level by excluding low ESG-score constituents from the selection universe. But ESG-screening imposes limits on potential diversification as well as alters risk exposures to systematic factors. To investigate ESG-screening's impact on the factor-risk-adjusted performance of portfolios, we construct ESG-screened portfolios consisting of US equity mutual funds according to their returns-based ESG-scores. The result of performance contribution analysis for the sample period from 1999 to 2018 suggests that investors need to treat the concentration level of ESG-screening as a search parameter to balance the costs and benefits of ESG-screening.

Keywords: ESG; ESG screening; ESG score; concentration level of screening; factor-risk-adjusted performance; specific risk; systematic risk; performance contribution; responsible investing; downside protection

JEL: C15, G11, G12, G13, G22, G33

Recently, many long-term institutional investors have integrated environmental, social, and governance (hereafter, ESG) considerations into their portfolios. As of 2018, US investors consider ESG-factors for $12 trillion of professionally managed assets (US SIF 2018). ESG-integration is a regular screening and selection process that investors practice based on ESG criteria (Hoepner and McMillan 2009). A survey result shows that ESG-integration is the most widespread responsible investment practice today (Hayat and Orsagh 2015). As more investors accept ESG-integration as their investment policy, an increasing number of studies have investigated essential questions: whether ESG-integration generates the investment performance differentiable from non-ESG investment policies, what are significant drivers to bring the differentiable investment performance, whether unintended risks accompany the implementation of ESG-integration, and what are viable approaches to implement ESG-integration.

First, most prior studies focus on investigating if the investment performance of ESG-integration is different from, or better than, that of non-ESG counterparts. Although the recent growth of ESG-integration is remarkable, the empirical evidence on the performance of ESG-integration is inconsistent from the perspective of realized performance. The difference in average performance between responsible investing and conventional investing peers or benchmark indexes is both small and statistically insignificant (Renneboog, Ter Horst, and Zhang 2011). In contrast, Friede, Busch, and Bassen (2015) report a non-negative relationship between corporate ESG and financial performance in roughly 90% of the research. Of course, even if the investment performance of ESG-investing turns out to be suboptimal, it does not necessarily mean that ESG-investing is not desirable. Some investors may still accept sub-optimal performance to pursue their investment objectives. However, Renneboog, Ter Horst, and Zhang (2008) conclude that the existing studies hint but do not unequivocally demonstrate that SRI investors are willing to accept suboptimal financial performance to pursue social or ethical objectives.

The next question commonly investigated in the literature is about the main drivers to bring the differentiable performance. Even when investors observe the significant difference in realized performance, it is difficult to reconcile the observation with the risk-return paradigm (Derwall et al. 2005). Thus, it remains a puzzle that investing in firms based on public information such as sound environmental performance or good corporate governance produces superior abnormal returns (Renneboog, Ter Horst, and Zhang 2008). Recent studies shed light on this issue by clarifying the potential contributions of ESG-investing on investment performance: higher return, lower risk, and diversification. While the empirical evidence on higher return is still mixed, the evidence that ESG-investing helps manage investment risks is growing. In principle, constructing ESG-screened portfolios aims to reduce the aggregate ESG-risk at the portfolio level by excluding low ESG-score constituents from the eligible selection universe. If investors implement the screening successfully, they can expect ESG-screened portfolios to be protected against losses by ESG-events and provide the potential for higher realized alpha compared to unscreened portfolios. For instance, responsible investing played an insurance role and outperformed conventional investing during the 2007 Global Financial Crisis (Becchetti et al. 2015). Kumar et al. (2016) assesses the risk performance of ESG-screening at the company level and demonstrates that companies that incorporate ESG-factors show lower volatility in their stock performances than their peers in the same industry. Sherwood and Pollard (2018) report significant outperformance based on ESG integration in various performance measures. As a result, investors who have goals closely associated with wealth protection would be willing to manage the degree to which their portfolio's economic value may be at risk driven by ESG-issues. According to the CFA Institute (2017), risk analysis and client demand are the main reasons for investors to consider ESG-integration. Another driver of ESG-investing often mentioned in the literature is to expand opportunities for diversification. After introducing a dynamic measure of risk performance, Chong, Her, and Phillips (2006) conclude that the Vice Fund (an antithesis of socially responsible funds) may not be a viable candidate to enhance portfolio diversification. Sherwood and Pollard (2018) indicate that integrating ESG emerging market equities into institutional portfolios could provide institutional investors with higher returns and lower downside risk than non-ESG equity investments. For diversification, ESG-screening can be extended to the portfolio level by introducing a measure of the ESG-risks in a portfolio relative to its peer group (Morningstar, 2019).

Next, there exists a concern that unintended risks may accompany ESG-investing. It is hard to deny that ESG-factors play an important role in predicting returns; hence they should not be ignored while considering investment decisions (Maiti 2020). However, since ESG-screening alters risk exposures to conventional factors, the impact of ESG-screening on the factor-risk-adjusted performance of equity fund portfolios need to be investigated more closely. In line with this view, Brière, Peillex, and Ureche-Rangau (2017) show that SR-screening does contribute to the variability of mutual fund performance, together with asset allocation decisions and active management. They also show that this contribution is, on average, roughly two times lower than the contribution made by active portfolio choices. Maiti (2020) finds that three-factor models with market, size, and ESG factors perform better than the Fama–French three-factor model.

The last but not least important question is how to implement ESG-screening at the portfolio level. The modern portfolio theory suggests that investors can mitigate the specific risk of portfolios to arbitrarily low levels through diversification and that a well-diversified portfolio is supposed to deliver returns proportional to its associated systematic risk only. It implies that ESG-screening at the portfolio level may be redundant if ESG-risk at the constituent level can be mitigated fully through diversification. Even worse, ESG-screening is accompanied by the increase in specific risk to some degree because ESG-screening inherently imposes limits to diversification. Some prior studies investigate whether excluding high ESG-risk constituents might end up with unintended high diversifiable risk at the portfolio level. Barnett and Salomon (2006) hypothesize that the financial loss borne by an SRI fund due to poor diversification is offset as social screening intensifies because better-managed and more stable firms are selected into its portfolio. ESG-screening at the constituent level based on sustainability criteria alone can introduce the additional risk to the portfolio (Morgan and Ground, 2019). A few studies analyze the link between screening intensity (the number of exclusion criteria used for ESG-screening) and risk. Lee et al. (2010) show that screening intensity has no effect on unadjusted (raw) returns or idiosyncratic risk, and finds that increased screening results in lower systematic risk. Gharghoril and Ooi (2016) show that there is a negative curvilinear relationship between screening intensity and financial performance, which can be explained by the combined effects of stakeholder theory and modern portfolio theory. Verheyden, Eccles, and Feiner (2016) report an unequivocally positive contribution to risk-adjusted returns when using a 10% best-in-class ESG screening approach (one that effectively removes companies with the lowest 10% of ESG rankings). One practical consideration to implement ESG-screening is that it is accompanied by the turnover of constituents and related transaction costs. It is widely recognized that transaction costs as a substantial determinant of the net performance of any investment. For example, Keim and Madhavan (1997) document variations in trading costs among institutions, investment styles, and markets. Hence, from the practitioner's point of view, ESG-integration can be a viable alternative to its conventional counterpart only when the excess return on the best-in-class portfolio remained statistically significant in the presence of transaction costs. Derwall et al. (2005) show that a simple best-in-class stock selection strategy historically earned a higher market risk-adjusted and style-adjusted return than a worst-in-class portfolio even in the presence of transaction costs.

Our research is part of the literature that discusses the implementation issues of ESG-investing and contributes to this area in a couple of aspects. This study investigates the pattern of factor-risk-adjusted performance according to the concentration level of ESG-screening, rather than screening intensity. Since it is an empirical matter whether aggregate ESG-risks remain significant even at the diversified portfolio level, this paper investigates how ESG-screening affects the specific risk (after adjusting for systematic factor risk) of a fund portfolio. Also, we apply the returns-based approach to derive a time-series of ESG-screened portfolios' returns. Our empirical findings suggest that excluding low returns-based ESG-score funds from the eligible universe reduces the total risk of a portfolio consisting of US equity funds. The decrease of total risk by ESG-screening mainly results from reduced systematic risk driven by the decline in risk exposures to conventional factors. One interesting observation is that the specific risk tends to decrease slightly until the concentration level of ESG-screening reaches about 50% but increases fast after the threshold. It implies that investors should treat the concentration level of ESG-screening as a search parameter to balance the costs and benefits of ESG-screening.

To our knowledge, prior studies have never entirely conducted a contribution analysis on the factor-risk-adjusted performance of fund portfolios in the context of the concentration level of ESG-screening. If investors observe any risk performance gap resulting from ESG-investing, the approach presented in this paper helps to clarify the nature of the performance gap. Investors may widely integrate our analysis into the usual process of manager selection, portfolio construction, risk management, and monitoring.

Methodology

Portfolio Construction based on returns-based ESG-score

This paper aims to investigate considerable time-series volatility of the returns on ESG-screened portfolios, and thus extend the coverage in the time-series dimension by deriving historical returns-based ESG-scores.[2] Riding on the growing interest of investors, an increasing number of third-party specialized rating companies produce ESG-scores at the company level. Among its various applications, introducing a measure of the ESG-risks in an equity mutual fund relative to its peer group can extend ESG-screening to the portfolio level (Morningstar 2019). Up to date, Morningstar is the only rating company that provides ESG-scores for US equity funds. Morningstar's rating is a historical holdings-based calculation using the company-level ESG Risk Ratings from Sustainalytics. Although Morningstar's rating offers an objective way to evaluate how portfolios meet ESG challenges, their holdings-based ESG-scores are available just for the most recent evaluation period. Thus, we introduce returns-based

[2] We can also extend our coverage in cross-sectional data through returns-based ESG-scores for funds whose holdings-based ESG-scores are not available. With 1,263 funds active at December 2018 (out of a total sample of 2,355 total sample funds), the Morningstar database contains ESG scores for 1,234 funds.

ESG scores to investigate whether the dynamic ESG-screening at the portfolio level can add value over time. Since returns-based scores are derived from purely quantitative analysis on fund returns only, they may be less precise than holdings-based ESG-scores. However, returns-based ESG-scores helps us to evaluate the performance of portfolios in terms of risk metrics and return metrics.

We estimate returns-based ESG-scores from ordinary least-squares regressions within a factor model. In line with Xiong et al. (2010), we subtracted the market-factor (excess market returns, *MKT*) from fund returns over the one-month Treasury bill rate. Then, we regress the excess market returns of each fund on a constant and on the ESG-factor (ESG-screened index returns minus unscreened parent index returns, *EMU*). Note that we construct aggregate ESG-score rather than individual pillar score (E, S, and G score individually). We take this approach because we require a widely accepted ESG-screened index to derive returns-based scores through time-series regression. Once we identify any index screened by an individual pillar, we may apply a similar approach explained below to analyze each E, S, and G score individually. Such research could potentially have even greater value than this study to focus on aggregate ESG-score. For these time-series regressions, we used 60 monthly returns on each fund. Formally, the returns-based ESG-score estimation model has the form:

$$(r_t - MKT_t) = a_i + b_i EMU_t + \varepsilon_t \qquad (1)$$

where r_t is the excess return on fund i in month t, a_i represents the constant term of regression, b_i measures fund *i*'s risk exposure to ESG-factor, and ε_t is the residual term of regression. We interpret b_i as fund i's returns-based ESG-score over the estimation period.[3]

Next, we construct fund portfolios with distinctive returns-based ESG-scores. Based on returns-based ESG-scores for all active equity mutual funds, we rank the funds annually on their most recent scores. We identify the deciles of scores and categorize all available funds into groups according to ESG-scores. We denote the best *k-th* portfolio (hereafter, *Pk*) consisting of funds whose returns-based ESG-scores are higher than the *k-th* percentile. Then we derive portfolio returns from the equal-weighted returns of funds belonging to each collection.[4] Using the average return of fund portfolios, we intend to mitigate the impact of sources unique to a particular fund on the analysis.

Note that the equal-weighted average returns of all investable funds are denoted as P100. P100 can be regarded as a market proxy in prior research (Xiong et al., 2010; Brière, Peillex, and Ureche-Rangau, 2017). The concentration level of ESG-screening heightens from P100 to P5, where P100 corresponds to the broadest coverage and P5 to the narrowest coverage. The annual re-ranking and portfolio re-balancing occur at the end of December. Funds for which no rankings are available at the re-balancing date are excluded automatically for the subsequent 12-month period.

Factor-risk-adjusted alphas of ESG-screened Portfolios

In line with previous research, we address the performance of ESG-screened portfolios

[3] A returns-based ESG-score of zero would indicate neutral to systematic ESG-risk, a positive score represents hedging systematic ESG-risk, and a negative score implies maintaining high exposure to systematic ESG-risk.
[4] For a robustness check, we consider an alternative portfolio construction methodology: value-weighting and return calculation. In such a case, the portfolio Pk consists of high ESG-score funds making up the k percent of total values (sum of fund sizes) of the eligible universe. We found that most results presented henceforth were not sensitive to changes in portfolio formation, although the outcome of using value-weighted portfolio returns is not reported here for brevity.

from the perspective of conventional risk factors. This paper compares the factor-risk-adjusted performance of ESG-screened portfolios, in line with prior studies (Bauer, Koedijk, and Otten 2005; Derwall et al. 2005; Bauer, Otten, and Rad 2006). To do so, we consider various performance-affecting characteristics of ESG-screened portfolios through a multifactor model. From this perspective, we investigate the performance of ESG-screening explained by systematic factors: market sensitivity, style tilts, and industry bias.

As for style tilts, the literature has considerably debated and well documented conventional return anomalies such as the size (Banz 1981), the value (Fama and French 1993), the momentum (Jegadeesh and Titman 1993), and the profitability and investment (Fama and French 2015). Those return premiums can be regarded as proxies for various risks (Fama and French 1993; Vassalou and Xing 2004; Pastor and Stambaugh 2003). Referring to previous studies (Sharpe 1964; Fama and French 1993; Fama and French 2015), we include five primary factors (hereafter, *PFs*). They are *MKT*, capitalization (small-cap stock returns minus large-cap stocks returns, *SMB*), valuation (high BV/MV stock returns minus low BV/MV stock returns, *HML*), profitability (robust profitability stock returns minus weak profitability stocks returns, *RMW*), and investment (conservatively low investment stock returns minus aggressively high investment stock returns, *CMA*).

Also, we take into account the potential industry biases. We construct three additional industry principal-components (hereafter, *IPs*) orthogonal to the five *PFs*, following prior studies (Pastor and Stambaugh 2002; Geczy, Stambaugh, and Levin 2005; Jones and Shanken 2004; Derwall et al. 2005). We first derive the residuals from a regression of Fama and French's 30 industry-sorted portfolio returns on five *PFs*. The remaining industry returns (i.e., the model's intercept plus the residuals) represent the portion of industry-sorted portfolio returns that the five *PFs* do not explain. Subsequently, we perform a principal-components analysis of these remaining industry returns. Then, we take the first three principal components to capture the residual industry return variation.

Formally, the performance attribution model consisting of five *PFs* (*MKT*, *SMB*, *HML*, *RMW*, and *CMA*) plus three *IPs* has the form:

$$r_{kt} = a_k + b_{\mathrm{k,MKT}} MKT_t + b_{\mathrm{k,SMB}} SMB_t + b_{\mathrm{k,HML}} HML_t$$

$$+ b_{\mathrm{k,RMW}} RMW_t + b_{\mathrm{k,CMA}} CMA_t + b_{\mathrm{k,IND1-3}} \boldsymbol{IP}_{1-3t} + \varepsilon_{kt}$$

(2)

where r_{kt} is the excess return on ESG-screened portfolio k in month t, and $\boldsymbol{IP}_{1-3t}$ represents three *IP*s capturing industry effects in month t. a_k represents the alpha, which is the average abnormal return over the return on five *PF*s and three *IP*s. ε_{kt} stands for residuals, the difference between the observed returns of the ESG-screened portfolio and the returns predicted by systematic factors. For each of the ESG-screened portfolios, we estimated Equation (2) for the full sample period of 180 months (January 2004 – December 2018) and the half sample period of 90 months (July 2011 – December 2018).

Performance Contribution of ESG-screened Portfolios

We conduct a performance contribution analysis to investigate what sources bring the performance difference among ESG-screened portfolios. The purpose is to disentangle the contribution of the portfolio-specific source from that of systematic factors. To do so, we decompose the mean return and the return variability of ESG-screened portfolios into sources of interest. This paper supposes that five PFs and three IPs in Equation (2) are the only sources of returns on ESG-screened portfolios.

For the return contribution, we compute the product of the factor mean return multiplied by the sensitivity of the portfolio returns to the factor. We use the estimated coefficient of Equation (2) as the sensitivities. The alpha (after adjusting factor-risk) can be regarded as the part due to specific fund selection; that is, the portion of the portfolio return not related to any systematic factors. Our focus is to quantify the impact of ESG-screening on the factor-risk-adjusted performance, showing how it can add or remove the value.

We also conduct a risk contribution analysis to understand the sources of the ESG-screened portfolio's total risk. The understanding of ESG-screening's risk aspects is essential in light of evidence that responsible funds cater to various responsible investing investor motives (Derwall, Koedijk, and Ter Horst 2011) and exhibit heterogeneous performances (Geczy, Stambaugh, and Levin 2005). Indeed, ESG-screening may be a detrimental source of performance during financial crises (Nofsinger and Varma 2014). In line with previous research (Menchero and Hu 2006; Davis and Menchero 2010), we express the portfolio volatility as a function of the factors' volatilities, the sensitivity of the portfolio to these factors, and the correlation of the portfolio with other factors. The function has the form:

$$\sigma_k = \sum_{\mathrm{j}=1}^{8} b_{\mathrm{k,j}}\sigma_{\mathrm{j}}\rho_{\mathrm{k,j}} + {\sigma^2_{\varepsilon,\mathrm{k}}}\Big/{\sigma_k} \qquad (3)$$

where σ_k is the return volatility of portfolio k, σ_j is the return volatility of factor k, $\rho_{\mathrm{k,j}}$ is the correlation between portfolio k and factor j, and the specific risk, $\sigma_{\varepsilon,k}$, is not attributed to movements of PFs and IPs but is unique to portfolio k. Thus, $b_{\mathrm{k,j}}\sigma_{\mathrm{j}}\rho_{\mathrm{k,j}}$ represents the marginal contribution of factor j, and $\sigma^2_{\varepsilon,\mathrm{k}}/\sigma_k$ represents a specific risk contribution to the total volatility of portfolio k. Equation (3) shows that the portfolio volatility is the sum of each factor's contribution plus a portfolio specific risk. Note that the portfolio specific risk is of our interest to quantify the combined contribution of both diversification and ESG-screening.

Data and Descriptive Statistics

The dataset for our study comprises a sample of 2,354 US equity mutual funds classified based on the nine Morningstar categories.[5] Focusing on the domestic equity funds belonging to the nine style categories provides more precision to our research results by enabling us to isolate investment strategies exposed to similar risk factors. Our data consist of the total monthly returns of mutual funds over 240 months (January 1999 - December 2018). We obtained our fund data from Morningstar. We included both active and inactive/dead funds over our sample period, thus removing survivorship bias. We removed duplicate-share classes and retained only the oldest class fund with the most extended history. Duplicate-share classes are created for regulatory and accounting reasons but are virtually identical to one another (Statman 2000; Climent and Soriano 2011). To obtain reliable returns-based ESG-scores through regressions of Equation (1), we focus on funds that have been investable at least 60 months and are still available at re-balancing dates.

Table 1 presents the summary statistics of sample funds investable in December 2018 as well as factors. We calculate the summary statistics using funds that have been investable at least 60 months, are still available in December 2018, and have holdings-based ESG-scores. The fourth column of Panel A shows the average of funds' holdings-

[5] Morningstar classifies funds as being large-cap, mid-cap, or small-cap based on the market capitalization of the fund's stock holdings and as value, blend, or growth based on the value-growth orientation of the stock holdings (Morningstar 2018).

based ESG-scores. We retrieved holdings-based ESG-scores at the end of January 2019. Note that the average holdings-based ESG-scores of Large-cap funds (53.22) is higher than that of Small-cap funds (41.05). Value-style funds are not much different from Growth-style funds in terms of average holdings-based ESG-scores: 49.98 vs. 47.67. The last column shows the dispersion among holdings-based ESG-scores of funds in each category. Holdings-based ESG-scores are less dispersed among capitalization-oriented groups (<2.5), compared with valuation-oriented groups (>5.0). Taken together, ESG-screening may result in potentially severe style tilts in fund portfolios: the market capitalization and value-growth orientation. In light of prior evidence (Gregory, Matatko, and Luther 1997; Bauer, Koedijk, and Otten 2005), this observation suggests that style tilts may account for a considerable portion of ESG-screened portfolios' performance.

Insert Panel A of Table 1 here

We obtained the data for five PFs (*MKT*, *SMB*, *HML*, *RMW*, and *CMA*), 30 industry-sorted portfolio returns, and the risk-free rate (the US 1 month T-bill return) from the Kenneth French Data Library. As for proxies for *EMU*, we used the return difference between the ESG-screened index and its unscreened parent index: the difference between MSCI KLD 400 Social index and MSCI USA IMI index. We obtained the monthly returns of indexes from Morningstar.

Panel B of Table 1 reports descriptive statistics of the five *PF*s and provides several interesting observations. The mean return on *MKT* is significantly positive at the 5 percent level, noting that funds with higher exposure to market-factor would outperform during the investigated period. Also, the mean returns of *SMB* and *RMW*, and *CMA* are statistically significantly positive. It means that the market condition has been favorable for small-cap style, robust-profitability style, and low-investment style during the sample period.

Insert Panel B of Table 1 here

Results

Holdings-based ESG-scores vs. Returns-based ESG-scores

First of all, we compare returns-based ESG-scores to holdings-based ESG-scores of Morningstar and investigate the relationship between them. We estimated returns-based ESG-scores of 1,262 funds that have been investable from 2014 to 2018 and are still alive at the re-balancing date of December 2018. We evaluated these returns-based ESG-scores from the regression of Equation (1). For comparison, we retrieved holdings-based ESG-scores of 1,233 funds from Morningstar Direct at the end of January 2019. Those holdings-based ESG-scores are the most recent value at the date retrieving date. For 1,231 funds, we computed pairwise correlation coefficients between two sets of ESG-scores. Pearson's correlation coefficient is 0.81, and Spearman's rank correlation coefficient is 0.77.

Figure 1 visualizes the relationship between two sets of ESG-scores. Also, for 1,231 funds, we draw a scatter plot of returns-based ESG-scores on the vertical line against holdings-based ESG-scores on the horizontal line. The figure shows that returns-based ESG-scores are by and large correlated with holdings-based ESG-scores. It confirms that both sets of ESG-scores are supposed to provide consistent information with some discrepancies. Both sets of ESG-scores are means to identify an individual fund's ESG-risk exposure as an essential return and risk driver. Discrepancies are well to be expected since holdings-based ESG-scores measure the risk exposures from the securities held in a fund at a point in time, whereas returns-based ESG-scores estimate a fund's sensitivities to a range of distinct factors.

Insert Figure 1 here

Descriptive Statistics for ESG-screened portfolios

Panel A of Table 2 reports descriptive statistics for ten ESG-screened portfolios during the full sample period of 180 months (January 2004 – December 2018). These statistics suggest that ESG-screening can affect the distribution of portfolio returns. Both the mean of returns and the standard deviation of returns decreased from P100 to P10. The outcome implies that ESG-screening can result in lower-risk and lower-return investments by selecting less risky funds. It confirms that ESG-scores have positive correlations with low volatility over the 2007-2016 period (Melas, Nagy, and Kulkarni 2016). Concerning the risk-adjusted returns, the Sharpe ratio slightly improved as ESG-screening becomes more concentrated from P100 to P10. In other words, the low-risk results of ESG-screening outweighed its low return results.

Panel B of Table 2 reports descriptive statistics during the half sample period, 90 months (July 2011 – December 2018). Compared to ESG-screened portfolios in Panel A, those in Panel B present better performance measures: higher mean, lower standard deviation, higher skewness, lower kurtosis, and higher Sharpe ratio. An outstanding observation is that the mean return increased from P100 to P10, which is different from the representation in Panel A. As a result, the pattern of the Sharpe ratio became more pronounced. The Sharpe ratio significantly improved for higher-ranked portfolios from P100 to P10, indicating that stricter ESG-screening leads to greater returns.

Panel C of Table 2 shows descriptive statistics during the quarter sample period, 45 months (April 2015 – December 2018). A general lack of ESG-investing before 2010 and significant uptake in ESG over the last decade may affect the performance during the half sample period. To consider it, we break the second period down further and look at the investment performance during the quarter sample period. Panel C presents that the more recent investment performance of US equity funds deteriorates relatively: lower mean, lower skewness, and lower Sharpe ratio. However, the performance differential among ESG-screened portfolios remains the same: the Sharpe ratio significantly improved for higher-ranked portfolios from P100 to P10, indicating that stricter ESG-screening leads to better performance.

Taken together, the performance of ESG-screening in realized risk-adjusted return measures depended on the choice of the evaluation period. Since the market may be unable to price risk factors in an efficient manner (Lakonishok, Shleifer, and Vishny 1994; Haugen and Baker 1996), the performance of ESG-screening may have originated from the market's inability and depends on the choice of the evaluation period. The empirical result in Table 2 suggests that investors have factored ESG-information into their decisions more actively and that the market has become more efficient concerning ESG-risk for the recent period.

Insert Table 2 here

Empirical Results of Multifactor Regressions

Table 3 reports performance estimates of ESG-screened portfolios and shows the performance difference among them. Note that the table does not report loadings on IPs because those coefficients are challenging to interpret straightforwardly. Table 3 shows results for the half sample period of 90 months (July 2011 – December 2018) and provides several prominent observations.

First, the adjusted R^2 for each of the ten ESG-screened portfolios is close to one. The observation confirms the explanatory power of the multifactor attribution model. Second, a comparison of the market betas reveals that the beta on *MKT* decreased from P100 to P10. It implies that the portfolio formed from narrower screening had lower exposure to market risk.

Third, the results for other PF loadings confirm that the difference in style factor exposure among ESG-screened portfolios is substantial. Thus, accounting for differences in style factor exposures is vital in light of the evidence that has been presented in the related literature. Since ESG-screening tends to alter the risk profile of a portfolio (Benson, Brailsford, and Humphrey 2006), investors can change the risk exposure of the portfolio to systematic factors by excluding low ESG-score assets from the eligible universe.

Insert Table 3 here

Performance Contribution: Alpha vs. Specific risk

We decompose the portfolio mean return into four sources: the part due to MKT, the part due to the other four PFs, the part due to three IPs, and the remaining part unique to the portfolio. Figure 2 presents each of the four sources' contribution to the returns and the risk of ESG-screened portfolios for the 90 months sample period. For the graph, we constructed twenty ESG-screened portfolios, from P100 to P5, at intervals of 5% percentile. Following the standard format of snail trails in the risk-return domain, we place the risk contribution on the horizontal line and the return contribution on the vertical line. The arrow represents the direction of movement from P100 that include all funds to P5 based on the narrowest screening.

Panel A provides intriguing observations on the contribution of market factors. First of all, most of the ESG-screened portfolios' performance is explained by the market factor. The dominance of the portion due to MKT in the time-series analysis is consistent with the result in prior studies (Vardharaj and Fabozzi 2007; Xiong et al. 2010; Aglietta et al. 2012, Brière, Peillex, and Ureche-Rangau 2017). Besides, both the return contribution and the risk contribution decreased from P100 to P5. The pattern reflects that of the beta on *MKT* (in Table 3) and the positive mean return of MKT for the evaluation period (in Panel B of Table 1). The result is consistent with the observation that responsible investing outperformed conventional investing during the 2007 Global Financial Crisis (Becchetti et al. 2015), and that ESG-scores have positive correlations with low volatility from 2007 to 2016 (Melas, Nagy, and Kulkarni 2016).

In Panel B, the contribution due to style factors tended to increase from P100 to P10. The return contribution of style factors was negative with P100 but changed to be positive with P5. The risk contribution of style factors changed from positive to negative as one ascends the spectrum from P100 to P5. The movement toward the top-left direction in the risk-return space means that ESG-screening contributed to the improvement of risk performance as well as return performance. In line with prior studies, the returns on style investment strategies account for a considerable portion of responsible investing portfolio performance (Gregory, Matatko, and Luther 1997).

ESG-screening tends to often alter risk exposure to styles (Benson, Brailsford, and Humphrey 2006), and stocks with high aggregate ESG-scores tend to be large-growth stocks (Statman and Glushkov 2009). Taken together, ESG-scores have positive correlations with size and quality from 2007 to 2016 (Melas, Nagy, and Kulkarni 2016).

In Panel C, the contribution due to industry factors did not change much according to the concentration level of screening. The industry factors explain a small portion of the total performance of ESG-screened portfolios. Also, the industry factors contributed negatively to both the return and the risk of ESG-screened portfolios. The result of industry factors is somewhat different from those of prior studies. Sector exposures drive responsible investing portfolio returns to a great extent (DiBartolomeo and Kurtz 1999). This evidence implies that ESG-screening does not have the same impact if they induce a sector reallocation or are sector-neutral (Capelle-Blancard and Monjon 2014).

In Panel D, the snail trail of source unique to each portfolio takes the form of a hyperbola like the efficient frontier in the risk-return space. The segment from P100 to P30 is negatively sloped, and the segment afterward is positively sloped. The return contribution on the vertical axis is negative but continues to increase from P100 to P5. It is consistent with the gradual increase in estimated alphas in Table 3. Note that the concentrated portfolios (P20 and P10) were not statistically significantly different from zero. It suggests that concentrated portfolios tend to provide higher factor-risk-adjusted returns compared to the market proxy, P100. In Panel D of Figure 2, the sign of alpha even switches to be positive at the far right of the spectrum, P5.

The risk contribution of source-specific to portfolios declines slightly from P100 to P50. It implies that the benefit of decreasing ESG risk seems to outweigh the cost of increasing diversifiable risk until about 50% of low score funds are excluded from the eligible universe. In this negatively sloped segment in the risk-return space, taking on diversifiable risk by moving away from the full diversification can be justified. However, the risk contribution rises rapidly after P30, implying that the cost of limited diversification grows fast with a higher concentration of ESG-screening. On the segment with the concentration level of 30 percent, the cost of increasing diversifiable risk seems to become large enough to dominate the benefit of decreasing aggregate ESG risk.

Insert Figure 2 here

In sum, the factor-risk-adjusted performance of ESG-screened portfolios can be substantial, and the contribution of portion specific to portfolios resembles the efficient frontier in risk-return space. In line with previous studies in the field, we can address the performance of ESG-screening from the perspective of latent risk factors and mispricing within the risk-return paradigm.

As for latent risk factors, the literature has considerably debated and well documented conventional return anomalies such as the size (Banz 1981), the value (Fama and French 1993), the momentum (Jegadeesh and Titman 1993), and the profitability and investment (Fama and French 2015). Those return premiums can be regarded as proxies for various forms of risk (Fama and French 1993; Vassalou and Xing 2004; Pastor and Stambaugh 2003). The observation that the alpha improves as the concentration level of ESG-screening escalates suggests that ESG-screening may capture an additional latent factor. However, the ESG-factor has not been accepted widely as systematic yet, although a few prior studies have investigated on if the ESG-factor is systematic (Jin 2018; Fiskerstrand et al. 2019).

Regarding mispricing, the market inefficiency would cause conventional return anomalies (Lakonishok, Shleifer, and Vishny 1994; Haugen and Baker 1996). Likewise, market inefficiencies can lead to the realized abnormal return of an ESG-screened portfolio. The expected performance of ESG-screening is likely to be determined to the extent to which the market efficiently prices the systematic ESG-risk (Jin 2018). The mixed empirical evidence on realized performance may result from such a comprehensive scope of ESG-investing. There are many criteria on what counts as ESG-investing, and the ESG-investing lacks universally accepted structure and standards. It suggests that the market may not always be able to price the cost and benefit of ESG-screening in a thoroughly efficient manner.

Practical Discussion

We found that excluding low ESG-score funds (with low exposure to ESG-risk) has a sizable impact on the performance of equity fund portfolios in a risk-return paradigm. Such a difference in performance depends on how many funds investors eliminate from the eligible universe through ESG-screening. The target concentration level may depend on the implementation cost of constructing ESG-screened portfolios. In the case of re-balancing, the transaction cost from turnover and expense ratio of funds are also of investors' concerns. So, we investigate how turnover and expense ratio of ESG-screened portfolios change as the screening becomes more narrowly concentrated.

Turnover of ESG-screened Portfolios

As funds periodically enter and exit ESG-screened portfolios, reconstitution creates a turnover, which is costly in terms of transaction costs. Thus, maintaining tolerable turnover is a practical consideration to determine the concentration level of ESG-screening. We investigate the pattern of turnover according to the concentration of ESG-screening.

Panel A of Table 4 shows the average of one-year migration probabilities calculated at eight re-balancing dates over eight years (2011-2018). At re-balancing date *T*, we estimate migration probabilities with two sets of returns-based ESG-scores: the one set is for the 12 months before *T,* and the other set is for the following 12 months after *T*. For each of the ten ESG-screened portfolios, we calculate the migrating probability as the ratio of the number of funds falling into one of three states after a re-balancing date *T* over the number of funds belonging to the portfolio before the re-balancing date *T*. A given row denotes the probability of migrating from the portfolio Pk before *T* to one of three states after *T*: staying in the portfolio (hereafter, S_S), leaving the portfolio (henceforth, S_L), or being terminated (subsequently, S_T). Each row sums up to 100% by design. For instance, 131 funds (100%) belong to P10 during 2018. While we reconstitute P10 at the end of December 2018, 102 funds of those 131 funds stay in P10 by being classified into the same portfolio (S_S = 77.9%), 27 funds leave P10 and migrate to other portfolios (S_L = 20.6%), and 2 funds are terminated and dropped from the sample (S_T = 1.5%). Once one-year migration probabilities are calculated for eight re-balancing dates, we measure the average probability by the time-series average of eight one-year migration probabilities for each cell in Panel A of Table 4.

Migration probabilities of ESG-screened portfolios show several typical features. The likelihood of leaving escalates from P100 to P10: 2.6% for P90 versus 22.3% for P10. It confirms that more concentrated screening correlates with higher turnover. As an extreme case, no funds leave P100 because it includes all investible funds at the re-balancing date. In contrast, as for P10, more than one-fifth of the total constituent funds have been replaced by new constituents at every annual re-balancing date. Next, the probability of being terminated remained similar across ESG-screened portfolios. For each of the ten ESG-screened portfolios, about 4% of funds are terminated over one year. The result implies that the empirical probability of being terminated was not materially affected by the concentration level of ESG-screening. Taken together, transaction costs from high turnover can partly offset the benefit of ESG-screening for more concentrated portfolios.

Insert Panel A of Table 4 here

Expense Ratio

As another practical consideration, the expense ratio may differ across ESG-screened portfolios for several reasons. Funds in concentrated portfolios may spend more expense in gathering ESG-information and pass on higher costs to investors. Top score funds may charge a premium for strictly complying with ESG-mandate and ESG-analysis services. Therefore, we investigated whether the choice of concentration level can balance the possible benefits of ESG-screening against the level of fees charged.

Panel B of Table 4 shows the average expense ratio of funds falling into each of the ten ESG-screened portfolios. Note that the average expense ratio experienced a decrease from P100 to P30 and then went up from P30 to P10. The observed pattern underlines the importance of considering the effect of expense since there is a risk associated with the costs paid for ESG-screening. The costs of an ESG-screening have to be paid for sure, whereas the value-added of screened portfolios over unscreened ones is uncertain. A typical example is greenwashing.

Insert Panel B of Table 4 here

Conclusion

This paper aims to improve our understanding of the impact of ESG-screening on the performance of equity fund portfolios. We collected data on 2,354 US open-end equity funds over 20 years (1999-2018), constructed screened portfolios to returns-based ESG-scores, and then applied the multifactor attribution model to those portfolios' returns. Our primary interest was to examine whether the factor-risk-adjusted performance (either alpha or specific risk) of ESG-screened portfolios significantly respond to the concentration level of screening.

The empirical analysis provides some key takeaways for practitioners. First, more concentrated portfolios tend to deliver less risky performances relative to the unscreened one over the sample period of 2004 to 2018. The performance difference among ESG-screened portfolios was explained mainly by differences in market sensitivity. Second, the style factor exposures altered by ESG-screening contributed to improving both risks and return performance during the subperiod of July 2011 to December 2018. Third, the specific risk of portfolios slightly decreases with the material increase of alpha to the extent that we eliminate about 50% of low ESG-score funds from the eligible universe. Last, portfolios that are more concentrated tend to suffer from a high turnover rate. The pattern of the average expense ratio takes the form of a U-shape curve according to the concentration level of screening.

The findings of this study are mostly consistent with the body of research over the past decade. They have material implications for the field both theoretically and practically. On the theoretical side, our finding shows that ESG-screening can substantially affect the investment performance even at the portfolio level (in other words, even after the individual ESG-risk at the constituent level have been mitigated through diversification). The observation that ESG-screening significantly impacts the specific risk of well-diversified portfolios justifies ESG-screening at the portfolio level to manage the systematic ESG-risk. Now, we can more consistently reconcile the observed performance differential between ESG-investing and its counterpart within the well-established risk-return paradigm. A practical implication of this analysis is to decide a manageable size of the eligible universe regarding the implementation of ESG-screening. The limited diversification imposed by ESG-screening amounts to the cost of obtaining the downside protection. If the available universe is too narrow, investors are likely to face the high specific risk by strictly limiting the diversification among funds. An excessively broad universe may lead to dysfunctional downside protection by including greenwashed funds. This trade-off implies that investors should regard the concentration level of ESG-screening as a search parameter. In conclusion, the optimal concentration of ESG-integration depends on an investor's willingness to deviate from the unscreened counterpart.

Despite its contribution to the field, this study has some limitations. As far as the market is efficient, investors would determine the concentration level of ESG-screening based on their expectation of the probability and severity of ESG-events. Once investors strategically choose risk exposures against conventional systematic factors, the realized factor-risk-adjusted performance of ESG-screened portfolios would turn out to be positive (adverse) when ESG-events trigger more (less) severe losses than initially expected. Accordingly, the optimal choice of ESG-screening concentration relies on whether the efficient market hypothesis can fully explain the costs and benefits of ESG-screening. Testing an efficient market hypothesis, however, is beyond the scope of this article. Besides, this study employs returns-based ESG-scores. Although it is an unavoidable choice to derive a time-series of ESG-screened portfolios' returns, returns-based ESG-scores are less precise than holdings-based ESG-scores. We expect the findings of this paper to be verified once we accumulate holdings-based ESG-scores over a sufficiently long period. Moreover, the results of this study may be affected by the approach in which investors construct ESG-screened portfolios. This study creates ESG-screened portfolios based on a best-in-class process that practitioners commonly use. We also consider part of experimental conditions (such as turnover, expense-ratio). However, future research needs to double-check the robustness of results under more practical configurations.

With specifying the limitations, we leave our findings open to interpretation and encourage future research. As for investors who want to achieve competitive performances and compliance with the ESG-mandate, it would be one of the essential tasks to figure out how the concentration level of screening affects the factor-risk-adjusted performance of ESG-screened portfolios. From that perspective, additional research is required to explore various ESG-screening criteria, to verify the validity of returns-based ESG-screening, and to present complementary evidence from different countries. Especially, stressing that financial performance varies with the types of social screens used (Barnett and Salomon, 2006), we suggest moving toward an in-depth examination of the merits of different ESG-screening criteria.

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The authors report no conflicts of interest.

REFERENCE

Aglietta, M., M. Brière, S. Rigot, and O. Signori. 2012. "Rehabilitating the Role of Active Management for Pension Funds." *Journal of Banking & Finance*, vol. 36, no. 9 (September): 2565–2574.

Banz, R. 1981. "The Relationship between Return and Market Value of Common Stocks." *Journal of Financial Economics*, vol. 9, no. 1 (March):3–18.

Barnett, M. L., and R. M. Salomon. 2006. "Beyond dichotomy: The curvilinear relationship between social responsibility and financial performance." *Strategic Management Journal* 27:1101–22.

Bauer, R., K. Koedijk, and R. Otten. 2005. "International Evidence on Ethical Mutual Fund Performance and Investment Style." *Journal of Banking & Finance*, vol. 7, no. 29 (July): 1751–1767.

Bauer, R., R. Otten, and A.T. Rad. 2006. "Ethical Investing in Australia: Is There a Financial Penalty?" *Pacific-Basin Finance Journal*, vol. 14, no. 1 (January): 33–48.

Becchetti, L., R. Ciciretti, A. Dalò, and S. Herzel. 2015. "Socially Responsible and Conventional Investment Funds: Performance Comparison and the Global Financial Crisis." *Applied Economics* 47 (25): 2541–2562.

Benson, K.L., T.J. Brailsford, and J.E. Humphrey. 2006. "Do Socially Responsible Fund Managers Really Invest Differently?" *Journal of Business Ethics*, vol. 65, no. 4 (June): 337–357.

Brière, M., J. Peillex, and L. Ureche-Rangau. 2017. "Do Social Responsibility Screens Matter When Assessing Mutual Fund Performance?" *Financial Analysts Journal*, vol. 73, no. 3 (May/June): 53–66.

Capelle-Blancard, G., and S. Monjon. 2014. "The Performance of Socially Responsible Funds: Does the Screening Process Matter?" *European Financial Management*, vol. 20, no. 3 (June): 494–520.

CFA Institute. 2017. "Environmental, Social and Governenace (ESG) Survey."

Chong, J., M. Her, and G.M Phillips. 2006. "To Sin or Not to Sin? Now That's the Question." *Journal of Asset Management*, 6(6), pp. 406–417.

Climent, F., and O. Soriano. 2011. "Green and Good? The Investment Performance of US Environmental Mutual Funds." *Journal of Business Ethics*, vol. 103, no. 2 (October): 275–286.

Davis, B., and J. Menchero. 2010. “Risk Contribution is Exposure times Volatility times Correlation.” Research Insights. MSCI Barra Research.

Derwall, J.N., N. Guenster, R. Bauer, and K. Koedijk. 2005. “The Eco-Efficiency Premium Puzzle.” *Financial Analysts Journal*, vol. 61, no. 2 (March/April): 51–63.

Derwall, J.N., K. Koedijk, and J. Ter Horst. 2011. “A Tale of Values-Driven and Profit-Seeking Social Investors.” *Journal of Banking & Finance*, vol. 35, no. 8 (August): 2137–2147.

DiBartolomeo, D., and L. Kurtz. 1999. “Managing Risk Exposures of Socially Screened Portfolios.” Working paper, Northfield Information Services.

Fama, E., and K. French. 1993. “Common Risk Factors in the Returns on Stocks and Bonds.” *Journal of Financial Economics*, vol. 33, no. 1 (January):3–56.

Fama, E., and K. French. 2015. “A Five-factor Asset Pricing Model.” *Journal of Financial Economics*, 116: 1–22.

Fiskerstrand, S., S. Fjeldavli, T. Leirvik, Y. Antoniuk, and O. Nenadić. 2019. “Sustainable investments in the Norwegian stock market.” *Journal of Sustainable Finance & Investment* 0:0, pages 1-17.

Friede, G., T. Busch, and A. Bassen. 2015. “ESG and Financial Performance: Aggregated Evidence from More Than 2000 Empirical Studies.” *Journal of Sustainable Finance & Investment* 5 (4): 210–233.

Geczy, C.C., R. Stambaugh, and D. Levin. 2005. “Investing in Socially Responsible Mutual Funds.” Working paper, University of Pennsylvania (October).

Gharghori1, P., and E. Ooi. 2016. “Chapter 16 - The Relationship between Screening Intensity and Performance of Socially Responsible Investment Funds.” Handbook of Environmental and Sustainable Finance, 335-357.

Gil-Bazo, J., P. Ruiz-Verdú, and A.A.P. Santos. 2010. “The Performance of Socially Responsible Mutual Funds: The Role of Fees and Management Companies.” *Journal of Business Ethics*, vol. 94, no. 2 (June): 243–263.

Gregory, A., J. Matatko, and R. Luther. 1997. “Ethical Unit Trust Financial Performance: Small Company Effects and Fund Size Effects.” *Journal of Business Finance and Accounting*, vol. 24, no. 5 (June):705–725.

Hamilton, S., H. Joe, and M. Statman. 1993. “Doing Well While Doing Good? The Investment Performance of Socially Responsible Mutual Funds.” *Financial*

Analysts Journal, vol. 49, no. 6 (November/December):62–66.

Haugen, R., and N. Baker. 1996. "Commonality in the Determinants of Expected Stock Returns." *Journal of Financial Economics*, vol. 41, no. 3 (July):401–439.

Hayat, U., and M. Orsagh. 2015. Environmental, Social, and Governance Issues in Investing: A Guide for Investment Professionals. CFA Institute.

Hoepner, A., and D. McMillan. 2009. "Research on 'Responsible Investment': An Influential Literature Analysis Comprising a Rating, Characterisation, Categorisation, and Investigation." *SSRN Electronic Journal*, 1–84. doi:10.2139/ssrn.1454793.

Jegadeesh, N., and S. Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance*, vol. 48, no. 1 (March):65–91.

Jin, I. 2017. "Is ESG a Systematic Risk Factor for US Equity Mutual Funds?" *Journal of Sustainable Finance & Investment*, 8 (1): 72-93.

Jones, C., and J. Shanken. 2004. "Mutual Fund Performance with Learning across Funds." Unpublished working paper.

Keim, Donald B., and Ananth Madhavan. 1997. "Transactions Costs and Investment Style: An Inter-Exchange Analysis of Institutional Equity Trades." *Journal of Financial Economics*, vol. 46, no. 3 (December):265–292.

Kreander, N., R.H. Gray, DM Power, and C.D. Sinclair. 2005. "Evaluating the Performance of Ethical and Non-Ethical Funds: A Matched Pair Analysis." *Journal of Business Finance & Accounting*, vol. 32, no. 7–8 (September): 1465–1493.

Kumar, A., N. C., Smith, C., Badis, L., Wang, N., Ambrosy, P., & Tavares, R. 2016. "ESG factors and risk-adjusted performance: a new quantitative model." *Journal of Sustainable Finance & Investment*, 6(4), 292-300.

Lakonishok, J., A. Shleifer, and R. Vishny. 1994. "Contrarian Investment, Extrapolation, and Risk." *Journal of Finance*, vol. 49, no. 5 (December):1541–78.

Lee, D., J. Humphrey , K. Benson, and J. Ahn. 2010. "Socially responsible investment fund performance: the impact of screening intensity." *Accounting & Finance*, vol. 50, no. 2, 351-370.

Mackintosh, J. 2018. "Is Tesla or Exxon More Sustainable? It Depends Whom You Ask," the Wall Street Journal.

Maiti, M. (2020). "Is ESG the succeeding risk factor?" *Journal of Sustainable Finance & Investment*, 1-15.

Melas, D., Z. Nagy, and P. Kulkarni. 2016. Factor Investing and ESG Integration. MSCI Research Insight (November):1-34.

Menchero, J., and J. Hu. 2006. "Portfolio Risk Attribution." *The Journal of Performance Measurement*, vol. 10, no. 3, pp. 22–33.

Morgan, L., and J. Ground. 2019. Managing sustainability from a total portfolio perspective. Schroders Multi-asset investments.

Morningstar. 2018. Morningstar Style BoxTM Methodology. Morningstar Methodology Paper (February):1-39.

Morningstar. 2019. Morningstar Sustainability Rating. Morningstar Methodology Paper (June):1-6.

Nofsinger, J., and A. Varma. 2014. "Socially Responsible Funds and Market Crises." *Journal of Banking & Finance*, vol. 48, no. 11 (November): 180–193.

Pastor, L., and R. Stambaugh. 2002. "Mutual Fund Performance and Seemingly Unrelated Assets." *Journal of Financial Economics*, vol. 63, no. 3 (March):313–349.

Pastor, L., and R. Stambaugh. 2003. "Liquidity Risk and Expected Stock Returns." *Journal of Political Economy*, vol. 111, no. 3 (June):642–685.

Renneboog, L., J. Ter Horst, and C. Zhang. 2008. "Socially responsible investments: Institutional aspects, performance, and investor behavior." *Journal of Banking and Finance* 32:1723–42.

Renneboog, L., J. Ter Horst, and C. Zhang. 2011. "Is Ethical Money Financially Smart? Nonfinancial Attributes and Money Flows of Socially Responsible Investment Funds." *Journal of Financial Intermediation*, vol. 20, no. 4 (October): 562–588.

Sharpe, W. 1964. "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *Journal of Finance*, vol. 19, no. 3 (September):425–442.

Sherwood, M. W., & Pollard, J. L. 2018. "The risk-adjusted return potential of integrating ESG strategies into emerging market equities." *Journal of Sustainable Finance & Investment*, 8(1), 26-44.

Statman, M. 2000. "Socially Responsible Mutual Funds." *Financial Analysts Journal*, vol. 56, no. 3 (May/June):30–39.

Statman, M., and D. Glushkov. 2009. "The Wages of Social Responsibility." *Financial*

Analysts Journal, vol. 65, no. 4 (July/August): 33–46.

US SIF. 2018. "Report on US Sustainable, Responsible and Impact Investing Trends." US SIF Foundation Press Release.

Vassalou, M., and Y. Xing. 2004. "Default Risk in Equity Returns." *Journal of Finance*, vol. 59, no. 2 (April):831–868.

Vardharaj, R., and F.J. Fabozzi. 2007. "Sector, Style, Region: Explaining Stock Allocation Performance." *Financial Analysts Journal*, vol. 63, no. 3 (May/June): 59–70.

Verheyden, T., R. G. Eccles, and A. Feiner. 2016. "ESG for All? The Impact of ESG Screening on Return, Risk, and Diversification." *Journal of Applied Corporate Finance*, Vol. 28, Issue 2, pp. 47-55.

Xiong, J.X., R.G. Ibbotson, T.M. Idzorek, and P. Chen. 2010. "The Equal Importance of Asset Allocation and Active Management." *Financial Analysts Journal*, vol. 66, no. 2 (March/April): 1–9.

APPENDIX: TABLES

Table 1. Summary statistics

Panel A: Cross-sectional Average of Fund Attributes, December 2018

The table reports cross-sectional averages over funds that belong to each of the nine Morningstar categories in December 2018. No. of funds includes funds which have been investable at least 60 months, are still available in December 2018, and have holdings-based ESG-scores. We retrieved the data from Morningstar Direct on January 31, 2019.

Morningstar Category		No. of funds	Average size	holdings-based ESG-scores	
				Mean	S.D.
Capital-ization	Large	671	6.10	53.22	2.22
	Mid	242	2.48	45.66	2.30
	Small	318	1.51	41.05	1.05
Valuation	Value	316	3.04	50.01	5.48
	Blend	432	6.02	48.58	5.99
	Growth	483	3.35	47.67	5.32
Total		1,231	4.20	48.59	5.67

Panel B: Descriptive Statistics for Factors, 1999-2018

The table reports descriptive statistics for returns on Fama and French (2015) 's five factors: *MKT* is the excess return on market proxy, *SMB*, *HML*, *RMW*, and *CMA* are factor-mimicking portfolios for capitalization, valuation, profitability, and investment factor, respectively. *EMU* is a proxy of ESG-factor. The table also shows both t-values and p-values about t-tests for Mean=0.

Factor	Mean	S.D.	Skewness	Kurtosis	t-test for Mean=0	
					t-value	p-value
MKT	0.45	4.34	-0.61	3.91	1.59	0.06
SMB	0.34	3.18	0.45	8.56	1.64	0.05
HML	0.14	3.19	0.21	5.60	0.66	0.25
RMW	0.31	2.99	-0.38	11.67	1.61	0.05
CMA	0.26	2.16	0.69	5.71	1.89	0.03
EMU	-0.06	0.93	0.20	7.89	-0.95	0.17

Table 2. Descriptive Statistics for ESG-screened Portfolios

The table reports descriptive statistics for the ten ESG-screened portfolios. *Pk* represents the portfolio consisting of funds with returns-based ESG-score higher than the *k-th* percentile. Note that P100 denotes the equal-weighted average returns of all investable funds and can be regarded as a market proxy. The full sample period represents 180 months (January 2004 – December 2018), and the half sample period represents 90 months (July 2011 – December 2018), and the quarter sample period represents 45 months (April 2015 – December 2018). As for monthly returns of ESG-screened portfolios, the Sharpe ratio is the ratio of the mean excess return to the standard deviation of return. We annualized the mean return, the standard deviation, and the Sharpe ratio.

Panel A: Full Period

Portfolio	Mean	S.D.	Skewness	Kurtosis	Sharpe
P100	7.98	14.81	-0.78	5.23	0.46
P90	8.00	14.60	-0.79	5.30	0.47
P80	8.01	14.38	-0.79	5.36	0.47
P70	7.97	14.18	-0.79	5.37	0.48
P60	7.93	13.96	-0.80	5.35	0.48
P50	7.85	13.79	-0.81	5.35	0.48
P40	7.86	13.65	-0.82	5.36	0.49
P30	7.80	13.54	-0.85	5.44	0.49
P20	7.83	13.46	-0.88	5.53	0.49
P10	7.69	13.40	-0.92	5.74	0.48

Panel B: Half Period

Portfolio	Mean	S.D.	Skewness	Kurtosis	Sharpe
P100	9.18	12.93	-0.44	4.28	0.68
P90	9.32	12.69	-0.43	4.28	0.70
P80	9.49	12.47	-0.41	4.27	0.73
P70	9.62	12.28	-0.40	4.24	0.75
P60	9.82	12.09	-0.40	4.20	0.78
P50	9.99	11.95	-0.40	4.14	0.80
P40	10.17	11.81	-0.40	4.11	0.83
P30	10.27	11.65	-0.42	4.08	0.85
P20	10.48	11.49	-0.43	4.09	0.88
P10	10.49	11.26	-0.44	4.21	0.90

Panel C: Quarter Period

Portfolio	Mean	S.D.	Skewness	Kurtosis	Sharpe
P100	5.13	12.21	-0.91	4.28	0.36
P90	5.30	11.99	-0.90	4.28	0.38
P80	5.52	11.77	-0.88	4.25	0.41
P70	5.77	11.63	-0.84	4.22	0.43
P60	6.16	11.53	-0.80	4.19	0.47
P50	6.49	11.50	-0.78	4.18	0.50
P40	6.92	11.49	-0.76	4.18	0.54
P30	7.25	11.48	-0.74	4.19	0.57
P20	7.88	11.51	-0.73	4.27	0.62
P10	8.63	11.57	-0.71	4.42	0.68

Table 3. Empirical Results of Multifactor Regressions

We estimate the performance attribution model in Equation (2) for each of the ten ESG-screened portfolios based on returns-based ESG-scores. *Pk* represents the portfolio consisting of funds with returns-based ESG-score higher than *k-th* percentile. Note that P100 denotes the equal-weighted average returns of all investable funds and can be regarded as a market proxy. The estimation period is 90 months (July 2011 – December 2018). Although the model includes three *IP*s ($IP_{1\text{–}3t}$), we do not report coefficients on them. We derived P-values from Newey-West (1987) heteroscedasticity- and autocorrelation-consistent standard errors.

Portfolio		P100	P90	P80	P70	P60
MKT	Coef.	1.006	1.005	1.003	1.002	0.998
	P-value	0.000	0.000	0.000	0.000	0.000
SMB	Coef.	0.196	0.140	0.083	0.029	-0.010
	P-value	0.000	0.000	0.000	0.042	0.438
HML	Coef.	0.029	0.019	0.010	0.003	-0.009
	P-value	0.062	0.204	0.527	0.825	0.510
RMW	Coef.	-0.024	-0.024	-0.028	-0.029	-0.029
	P-value	0.126	0.122	0.070	0.062	0.049
CMA	Coef.	-0.082	-0.070	-0.058	-0.047	-0.043
	P-value	0.001	0.002	0.005	0.015	0.016
ALPHA	Coef.	-0.136	-0.134	-0.127	-0.122	-0.109
	P-value	0.000	0.000	0.000	0.000	0.000
Adjusted R^2		0.996	0.997	0.997	0.997	0.997

Portfolio		P50	P40	P30	P20	P10
MKT	Coef.	0.992	0.986	0.976	0.962	0.941
	P-value	0.000	0.000	0.000	0.000	0.000
SMB	Coef.	-0.034	-0.055	-0.068	-0.073	-0.076
	P-value	0.008	0.000	0.000	0.001	0.039
HML	Coef.	-0.026	-0.044	-0.060	-0.087	-0.117
	P-value	0.024	0.001	0.001	0.000	0.004
RMW	Coef.	-0.026	-0.021	-0.011	0.004	0.027
	P-value	0.072	0.222	0.641	0.899	0.600
CMA	Coef.	-0.042	-0.042	-0.037	-0.035	-0.023
	P-value	0.006	0.004	0.038	0.203	0.624
ALPHA	Coef.	-0.097	-0.081	-0.069	-0.044	-0.020
	P-value	0.000	0.000	0.015	0.269	0.739
Adjusted R^2		0.998	0.997	0.995	0.991	0.974

Table 4. Turnover and Expense ratio of ESG-screened Portfolios

Panel A: Turnover, 2011 – 2018 (8 years)

For each of the ten ESG-screened portfolios, the migrating probability is calculated as the ratio of the number of funds falling into one of three states after a re-balancing date *T* over the number of funds belonging to the portfolio before the re-balancing date *T*. We measure the average turnover by the time-series average of one-year turnovers over eight years (2011 – 2018). S_S represents the state of staying in the same portfolio, S_L stands for the state of leaving the portfolio, and S_T denotes the state of being terminated in the following 12 months. Each row sums to 100% by design. The table shows the average turnover of portfolios.

	S_S	S_L	S_T	Sum
P100	96.0	0.0	4.0	100
P90	93.5	2.6	4.0	100
P80	92.1	4.0	3.9	100
P70	91.2	5.0	3.9	100
P60	89.8	6.2	4.0	100
P50	87.7	8.5	3.8	100
P40	85.6	10.7	3.7	100
P30	82.3	14.0	3.7	100
P20	77.0	19.1	3.9	100
P10	73.5	22.3	4.2	100

Panel B: Expense Ratio, 2004 –2018 (15 years)

For each of the ten ESG-screened portfolios, we computed the portfolio's expense ratio by the cross-fund average of expense ratios for the following 12 months at every re-balancing date. We then calculated the time-series descriptive statistics of the portfolio's expense ratios over 15 years: Mean, SD, Min, and Max. The second row titled as No. of funds represents the number of funds investable at the re-balancing date. The third row titled as Missing represents the number of funds whose expense ratios Morningstar Direct does not report.

Portfolio	Mean	SD.	Min	Max
No. of funds	1,547	163	1,290	1,772
Missing	57	34	17	154
P100	1.19	0.08	1.06	1.35
P90	1.16	0.07	1.04	1.28
P80	1.14	0.07	1.02	1.26
P70	1.13	0.08	1.00	1.25
P60	1.10	0.08	0.97	1.23
P50	1.07	0.08	0.96	1.22
P40	1.06	0.07	0.94	1.19
P30	1.04	0.07	0.94	1.20
P20	1.05	0.07	0.95	1.19
P10	1.18	0.11	1.01	1.42

Figure 1. Comparison between returns-based and holdings-based ESG-scores

We estimated returns-based ESG-scores of 1262 funds that have been investable from 2014 to 2018 and are still alive at the re-balancing date of December 2018. We retrieved holdings-based ESG-scores of 1233 funds from Morningstar Direct on 31 January, 2019. For 1231 funds in stock, we draw a scatter plot with returns-based ESG-scores (RB ESG) on the vertical line against holdings-based ESG-scores (HB ESG) on the horizontal line.

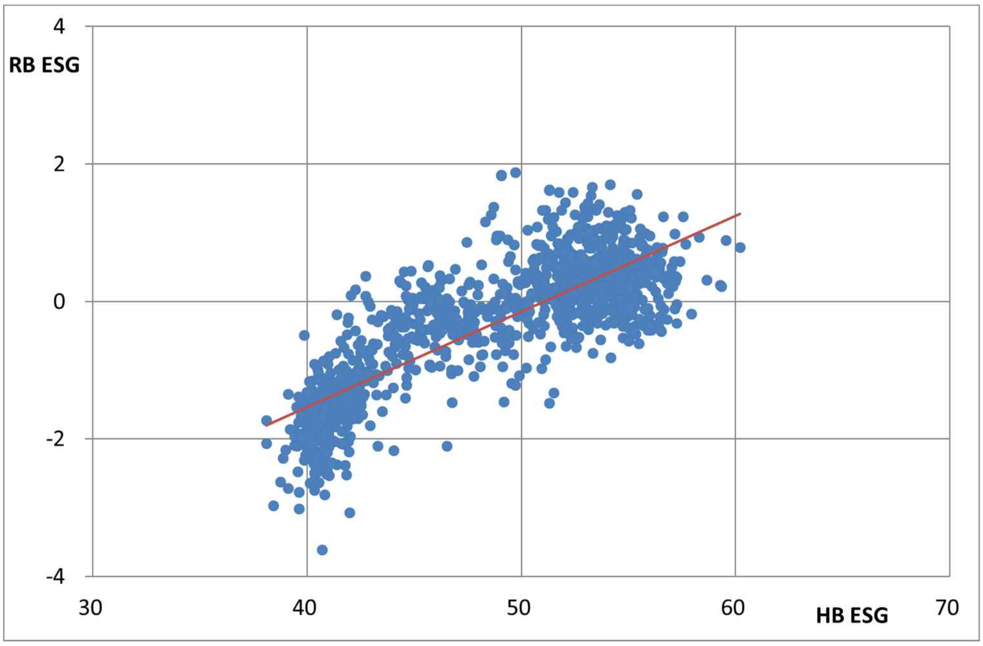
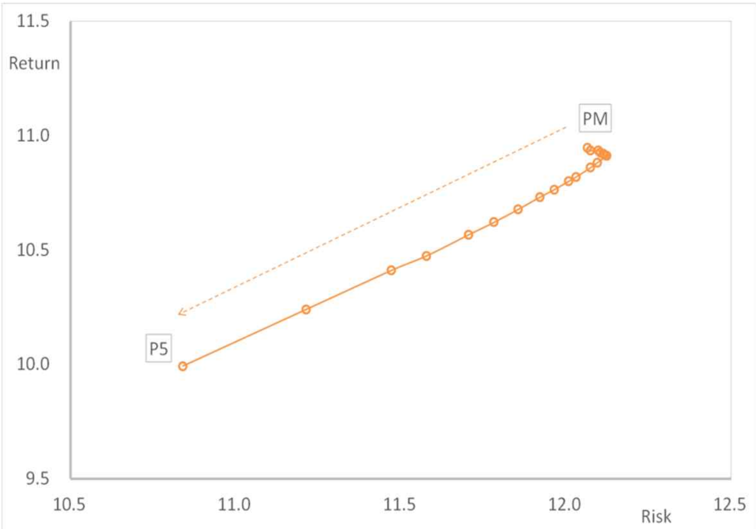


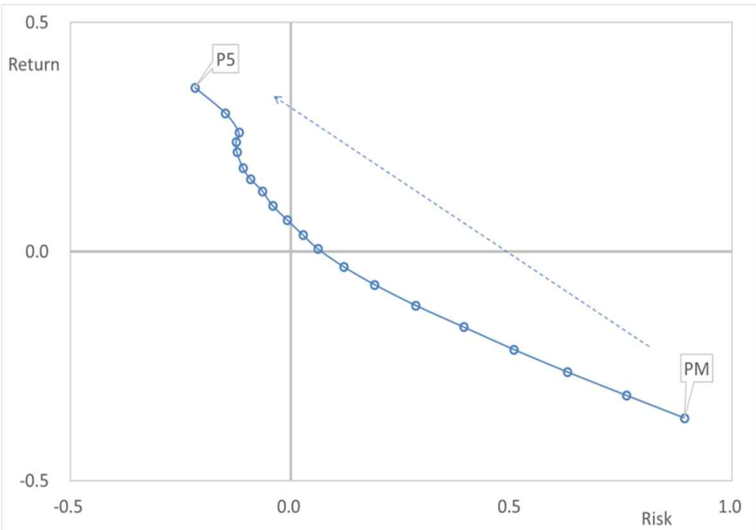
Figure 2. Contribution of Four Sources to Portfolio Return

The vertical line shows the contribution to portfolio returns, and the horizontal line presents the contribution to portfolio return variability. Circles represent each of twenty ESG-screened portfolios, at an interval of 5% percentile. The arrow represents the direction of movement from P100 including all funds to P5 based on the narrowest screening. Return and risk contributions are computed for the sample period of 90 months (July 2011 – December 2018) and are annualized.

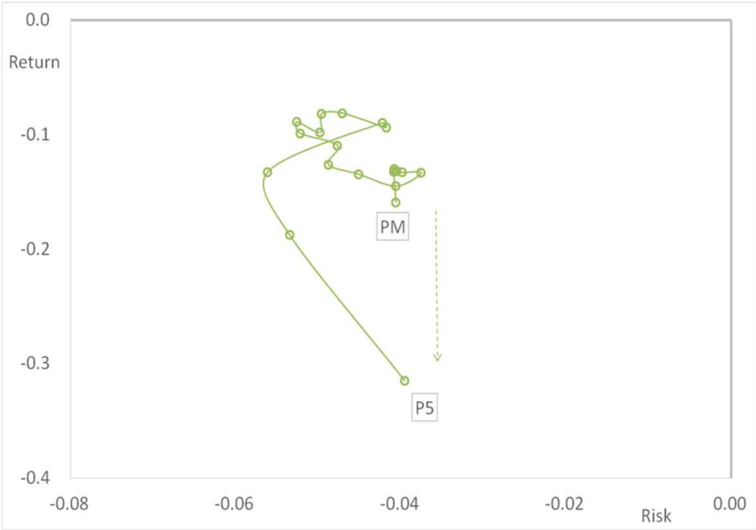
Panel A: Contribution of Market Factor



Panel B: Contribution of Style Factor



Panel C: Contribution of Industry Factor



Panel D: Alpha and the Specific Risk