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Research article

Systematic ESG risk and hedge fund

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Abstract: We present a framework for linking hedge funds to environmental, social, and governance (ESG) investments based on systematic ESG risk. We proposed a double-factor model to explain the co-movement of asset returns due to two systematic risk factors: Adjusted market risk and systematic ESG risk. Complementing prior work that introduces ESG characteristic indicators as determinants of agents' utility functions, this framework leverages modern portfolio theory by establishing a channel through which systematic ESG shocks affect asset risk and, in turn, equilibrium expected returns. This approach enabled us to estimate empirical market prices for systematic ESG risk from real-world observations and derive the relationship between equilibrium expected returns and the loadings on systematic risk factors. Applying this framework to U.S. equity mutual funds, we found that the loadings of systematic ESG risk were significantly correlated with the expected return of the sorted portfolios. These results suggested that it is possible to design hedge fund strategies that capitalize on systematic ESG risk that varies over time.

Keywords: ESG investing; systematic ESG risk; market price; index model; hedge fund

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

1. Introduction

ESG (environmental, social, and governance) investing is an investment approach that considers both financial and ESG objectives. At least in the traditional perception, hedge funds are focused solely on maximizing financial returns. From this perspective, hedge funds and ESG investing seem like an unlikely pairing. However, just as the rapid spread of ESG investing has impacted various sectors of the financial market, it is likely to impact hedge funds as well. Incorporating ESG considerations into their investment decisions could become a new strategy for hedge funds, especially if it can provide new opportunities to generate returns. What we highlight is the possibility that hedge funds can find strategies to improve risk-adjusted returns while balancing the dual priorities of improving the ESG quality of their portfolios and maximizing returns.

The popular method with negative screens is to omit unwanted securities from the universe of interest and then weigh the remaining securities in proportion to their market capitalizations. To optimize the Markowitz objective function, investors may modify optimization problems by adding ESG performance metrics of individual securities and preference parameters as constraints or utility function arguments. Based on this approach, can we design a long-short strategy that sells stocks with low ESG scores and buys stocks with high ESG scores? Market participants' preferences for ESG issues may change over time, and such changes may affect the equilibrium expected return of assets. This implies that the market price for the systematic ESG risk factor will fluctuate. Then, is it possible to develop a market timing strategy that captures these flows and adjusts portfolio composition? The purpose of this paper is to investigate this possibility in modern portfolio theory (henceforth MPT).

Because ESG investing has grown so rapidly, investors need a framework to manage systematic ESG risk in their investment decisions. We focus on the effect of synchronized ESG investing through a systematic risk factor lens, on the premise that investors may unintentionally herd on their decisions. Investors who may derive utility (disutility) from holdings of low (high)-ESG-risk assets are likely to respond similarly to unexpected changes in ESG concerns. Those concerns may lead many investors to shift their demands for low-ESG-risk purchases or to change their appreciation for low-ESG-risk holdings. One of the recent market movements to enforce the herding response is that passive ESG investing has been a critical trend in asset management over the last ten years (Belsom et al., 2019). As more institutional investors replicate ESG-screened indices, an ESG-screen index can account for joint movement in security prices beyond that accounted for by a broad market index. Some highly relevant papers note the aggregated impact of ESG investing. Bolton and Kacperczyk (2021) show that investors are already demanding compensation for their exposure to carbon emission risk. Koijen and Yogo (2019) suggest an asset pricing model that expected returns and factor loadings depending on the assets' characteristics-based demand. Gibson et al. (2020) show the positive effect of growing investor preferences for sustainable investing on the risk-adjusted performance of institutional investors' portfolios. Pástor et al. (2021) find that green assets can outperform brown ones when the ESG factor captures shifts in investors' tastes for green holdings. Pedersen et al. (2021) introduce an ESG-efficient frontier to show when the ESG score raises or lowers the required return. These papers share a similar perspective: As institutional investors' awareness of ESG risks increases, the surges of ESG investment could lead to price pressure and price co-movement among the low-ESG-risk stocks. Hence, a challenge for hedge funds is to clarify how the comovement of securities induced by ESG issues affects the equilibrium expected returns of assets.

Hedge fund managers can also explore approaches to gauge the market price of systematic ESG risk through real-world observations. We suggest a double-factor model in which the co-movement between securities is due to two systematic risk factors. According to the MPT, diversified portfolios are only exposed to systemic risk and should therefore be concerned with systematic ESG risk management. From this perspective, we divide total market risk into adjusted market risk and systematic ESG risk factors. The first captures the broad market movement after netting off the comovement triggered by systematic ESG events. The latter accounts for joint movement in security prices beyond that accounted for by the adjusted market risk factor. We use a pair of a broad market index and an ESG-screened index to derive these two factors. Then, we derive the relation between equilibrium expected returns and loadings on systematic risk factors. This approach makes it possible to estimate the market price of the systematic ESG risk through data observed in reality. The empirical outcome on US equity mutual funds shows that loadings on the systematic ESG risk correlate significantly with the sorted portfolio's expected returns. Since the correlation is significant, it is possible to design a hedge fund strategy using it.

This study contributed to the literature. Most of all, identifying a proxy of systematic ESG risk is a critical task in practice when investors want to develop a hedge fund strategy. Managers can use the double-factor model to estimate the empirical market price of the systematic ESG risk. The information helps managers form return expectations, optimize portfolios, predict correlation coefficients among securities, and attribute the sources of portfolio performance. For instance, Pedersen et al. (2021) assume that the conditional expectation for investors who use ESG scores to update their views on risk and the expected return has a linear relation with a metric of ESG characteristics. Our framework can complement the study by showing how the systematic ESG risk can affect future risks or returns within the MPT framework. The pathway by which a company's non-financial characteristics are transmitted through its financial performance to the risk and expected return of the securities issued by the company combines considerable noise. As a result, even if a company's ESG metrics improve (deteriorate), the change does not immediately translate into higher (lower) security returns. This is the rationale behind our attempt to determine the materiality of various ESG metrics. The double-factor model identifies systematic ESG risk factors through the changes in returns observed in the capital market and estimates individual stocks' risk and expected return through their sensitivity to systematic risk factors. This approach can help hedge funds organize their strategies by detouring materiality issues.

For another example, Pástor et al. (2021) propose a theoretical model with the market portfolio and the ESG factors to show that a stock's market beta depends on the stock's loading on the ESG factor times that factor's loading on the market. In their model, ESG-related shocks directly affect the expected return while the risk of assets remains unchanged. Our framework can enrich the study by relating the systematic ESG risk to asset risks and thereby to equilibrium expected returns. Changing investor preferences for ESG values is one of the fundamental drivers that can lead to structural changes in the financial performance of equity portfolios. However, timely capturing these preferences and translating them into a security's risk or expected return is a difficult process in practice. The double-factor model allows hedge funds to identify systematic ESG risk factors and estimate relevant expected returns based on market-observed returns. For hedge funds looking to capture and capitalize on dynamic changes in capital markets, the double-factor model can be an attractive and practical tool.

The paper proceeds as follows. First, we introduce two systematic risk factors (the adjusted market risk factor and the ESG risk factor) and the double-factor model. Next, we describe the design for empirical analysis and present the data. Then the paper provides empirical results resulting from applying the two-step procedure proposed by Fama and MacBeth (1973) to US equity mutual funds. We finalize the article by presenting concluding remarks and directions for future research.

2. Materials and methods

2.1. Double-factor model

We assume that the following double-factor model is an adequate description of reality. We consider a single-period model from time 0 to time 1. There are N assets, n=1, …, N. Let $\tilde{r}_n$ denote the return on asset n's shares above the riskless rate, r_f. Let $\tilde{r}$ be the $N \times 1$ vector whose nth element is $\tilde{r}_n$. We assume $\tilde{r}$ is normally distributed:

$$\tilde{r} = \mu + m\tilde{\varepsilon}_m + g\tilde{\varepsilon}_g + \tilde{\eta} \tag{1}$$

where μ contains equilibrium expected excess returns. The random variables $\tilde{\varepsilon}_m$ and $\tilde{\varepsilon}_g$ have zero means. The shock $\tilde{\varepsilon}_m$ can be viewed as the adjusted market risk factor, with the elements of m being assets' sensitivities to that shock. The shock $\tilde{\varepsilon}_g$ represents the systematic ESG risk factor, with the elements of g being assets' sensitivities to that shock. $\tilde{\eta}$ is a mean-zero vector that is uncorrelated with $\tilde{\varepsilon}_m$ and $\tilde{\varepsilon}_g$ and has a diagonal covariance matrix, Λ. In our setting, the only joint movement between assets comes about because of common responses to two systematic risk factors.

The theoretical foundation of the double-factor model is the multi-factor model. Multifactor models of security market returns can be divided into three types: macroeconomic, fundamental, and statistical factor models (Connor, 1995). Macroeconomic factor models use observable economic time series, such as inflation and interest rates, to measure the pervasive shocks to security returns. APT (arbitrage pricing theory) of Ross (1976) is a multi-factor model that relates various macroeconomic systematic risk variables to the pricing of financial assets. Including Fama and French (2015)'s five-factor model, fundamental factor models use the returns to portfolios associated with observed security attributes such as dividend yield, the book-to-market ratio, and industry identifiers. Statistical factor models derive their pervasive factors from factor analysis of the security returns panel data set. The double-factor model can be viewed as an extension of multi-factor models. The double-factor model is related to macroeconomic factor models in that they attempt to identify systematic risk factors by focusing on the co-movement of multiple stock returns. It is also similar to the fundamental factor model in that it utilizes an index built on ESG performance, which assesses the non-financial characteristics of individual stocks. It can also be interpreted as a statistical factor model in that it follows the decomposition of market portfolio returns into two orthogonal systematic risk factors.

The existence of a systematic ESG risk factor within the MPT framework can be backed up by recent empirical work on the implications of ESG risk for asset prices (Bansal et al., 2016; Bolton and Kacperczyk, 2021; Cohen, 2023a, 2023b; Engle et al., 2019; Hoepner et al., 2021; Hong et al., 2017;

Ilhan et al., 2020; Krueger, 2019; Luo and Balvers, 2017). While some studies focus on climate risk, others have identified multiple other aspects of ESG-related risk. In addition, the specification may have a fair amount of empirical support in the mutual fund literature (Białkowski and Starks, 2016; Bollen, 2007; Hartzmark and Sussman, 2019; Renneboog et al., 2011; Riedl and Smeets, 2017). We complement previous studies by explicitly introducing a systematic ESG risk factor that may capture unexpected shifts in the ESG concerns of investors. Table 1 summarizes the relevant arguments in this previous research.

Table 1. Recent studies on ESG risk factors.

Research	Relevant argument
ESG risk factor	
Bansal et al. (2016)	Climate change is a long-run risk factor.
Bolton and Kacperczyk (2021)	Investors demand compensation for exposure to carbon risk in the form of higher returns on carbon-intensive firms.
Cohen (2023a)	Sustainability risk and especially social risk is important to a firm's survival chances and therefore mitigating those risks can dramatically improve corporates' financial stability.
Cohen (2023b)	The traditional CAPM "Beta" carries environmental and corporate governance risks for the S & P500 stocks, but it totally neglects social risks.
Engle et al. (2019)	Investors can dynamically hedge climate risk by constructing mimicking portfolios that hedge innovations in climate news series obtained by textual analysis of news sources.
Hoepner et al. (2021)	ESG engagement reduces firms' downside risk and exposures to a downside risk factor.
Hong et al. (2017)	Food stock prices respond to climate risks.
Ilhan et al. (2020)	Firms with higher carbon emissions exhibit more tail risk and more variance risk.
Krueger et al. (2020)	Institutional investors consider climate risks to be significant investment risks.
Jin (2018)	US open-end equity funds tend to hedge the systematic ESG risk, and the fund market prices the exposure to systematic ESG risk.
Kim et al. (2022)	ESG performance acts as a moderator or a mediator between NPF's shareholding and financial performance.
Luo and Balvers (2017)	There exists a premium for boycott risk.
Mutual fund flows	
Bialkowski and Starks (2016)	Mutual fund flows respond to environmental disasters.
Bollen (2007)	Flows to SRI mutual funds are less volatile than flows to non-SRI funds.
Hartzmark and Sussman (2019)	Being categorized as low (high) sustainability resulted in net outflows (inflows).
Renneboog et al. (2011)	Flows to SRI mutual funds are less responsive to negative past performance.
Riedl and Smeets (2017)	Investors in SRI funds also indicate a willingness to forgo financial performance to accommodate their social preferences.

Note: This table summarizes the relevant argument of previous studies on the ESG risk factor. The first column (Research) shows the authors and publication year, and the second column (Relevant argument) presents the main view regarding ESG information as a risk factor.

2.2. Test hypotheses

Under the MPT framework, we can express expected excess returns in equilibrium as their capital asset pricing model (CAPM) values:

$$\mu = \beta\mu_M \tag{2}$$

where the notations are as follows:
the weight vector in asset n $(N \times 1)$: x,
the total risk of assets: $\tilde{\varepsilon} = m\tilde{\varepsilon}_m + g\tilde{\varepsilon}_g + \tilde{\eta}$ and $\tilde{\varepsilon} \sim N(0, \Sigma)$,
the variance of the market return: $\sigma_M^2 = x'\Sigma x$,
the market equity premium: $\mu_M = x'\mu$, and
the vector of market betas: $\beta = (1/\sigma_M^2)\Sigma x$.

In our double-factor model, the systematic ESG risk factor affects returns ex-ante by influencing market betas. The vector of market betas is:

$$\beta = m\beta_m + g\beta_g + (1/\sigma_M^2)\Lambda x \tag{3}$$

where $\beta_m \equiv \mathrm{Cov}(\tilde{\varepsilon}_m, \tilde{\varepsilon}_M)/\sigma_M^2$, $\beta_g \equiv \mathrm{Cov}(\tilde{\varepsilon}_g, \tilde{\varepsilon}_M)/\sigma_M^2$. Weighted error terms ($\tilde{\varepsilon}_M \equiv x'\tilde{\varepsilon}$, $\tilde{\varepsilon}_m \equiv x'\tilde{\varepsilon}_m$, and $\tilde{\varepsilon}_g \equiv x'\tilde{\varepsilon}_g$) represent the unexpected returns for the total risk, adjusted market risk, and weighted ESG risk, respectively. In words, an asset's market beta depends on the asset's loading on the adjusted market risk factor (m) times the factor's loading on the market (β_m), plus the asset's loading on the systematic ESG risk factor (g) times the factor's loading on the market (β_g), plus a term reflecting idiosyncratic risk. From these formulations, we immediately obtain

$$\mu = \mu_m m + \mu_g g + (\mu_M/\sigma_M^2)\Lambda x \tag{4a}$$

$$\beta_m = m_M(\sigma_m^2/\sigma_M^2) + g_M(\sigma_{mg}/\sigma_M^2) \tag{4b}$$

$$\beta_g = g_M(\sigma_g^2/\sigma_M^2) + m_M(\sigma_{mg}/\sigma_M^2) \tag{4c}$$

where $\mu_m \equiv \beta_m\mu_M$, $\mu_g \equiv \beta_g\mu_M$, $m_M \equiv x'm$ and $g_M \equiv x'g$. If we assume $\sigma_{mg} = 0$, then the second term in equations (4b) and (4c) drops out.[1] The overall market surely loads positively on the adjusted market risk factor, $\tilde{\varepsilon}_m$, meaning $m_M > 0$. The sign of g_M is less clear. The role of the systematic ESG risk factor depends on the market portfolio's overall loading on the factor. Whether the systematic ESG risk premium (μ_g) is positive is an interesting question for empirical research.

2.3. Empirical analysis

We follow four basic steps: identifying proxies for systematic risk factors, estimating the first-pass time-series regression, combining funds into portfolios, and estimating the second-pass cross-sectional regression.

[1] The multi-index model of Elton et al. (1976) and the double-factor model of Jin (2022b) adopt this assumption.

2.3.1. Proxies for systematic risk factors

Our double-factor model sets up two systematic risks: an adjusted market risk and a systematic ESG risk. To identify proxies for those factors, we begin with the return on an unscreened broad market index ($\tilde{I}_M$) as a proxy for the overall market risk:

$$\tilde{I}_M = \alpha_M + \tilde{\varepsilon}_m + \tilde{\varepsilon}_g \tag{5}$$

where α_M is the mean of an unscreened broad market index. Next, we take the returns on an ESG-screened index as a proxy for the adjusted market risk netting the systematic ESG risk. As pointed out by Jin (2022a), it reflects the standard industry practice regarding the ESG-screened index. Its construction generally begins with its parent index, the initial universe of potential constituents. A set of ESG screening rules is then applied to select securities so that the ESG-screened index provides investors with exposure to the aggregate of the highest ESG-rated firms in the parent index. Amid that, the risk-return profile of the ESG-screened index remains close to its parent index. In essence, the systematic ESG risk inherent in the parent index is removed. Under the postulation, we define the adjusted market risk factor as follows:

$$\tilde{I}_E = \alpha_E + \tilde{\varepsilon}_m \tag{6}$$

where $\tilde{I}_E$ is the return on an ESG-screened index and α_E is the mean of its returns. Last, we capture the behavior of the systematic ESG risk through the spread of $\tilde{I}_M$ over $\tilde{I}_E$. We suppose that the systematic ESG risk stands for the market movement triggered by the aggregate of ESG issues only. If we assume $\sigma_{mg} = 0$, we can make the systematic ESG risk risk orthogonal to the adjusted market risk by construction.[2] By subtracting equation (6) from equation (5), we obtain the systematic ESG risk factor as follows:

$$\tilde{I}_S = \alpha_S + \tilde{\varepsilon}_g \tag{7}$$

where $\tilde{I}_S$ is the spread between two returns, α_S is the mean of the spread, and $\alpha_S = \alpha_M - \alpha_E$.

Note that the basic structure delineated above is close to the multi-index case simple criteria for optimal portfolio selection of Elton et al. (1977). However, the double-factor model identifies two systematic risk factors by decomposing the total market return instead of industry-specific indices. This approach is based on the premise that systemic ESG risk differs from traditional market risk. ESG investing aims to improve a company's financial performance over the medium to long term through non-financial attributes. If these strategies are properly designed, the risk-return profile of ESG investments can be different from the risk-return profile of a market portfolio. This is evidenced by the fact that the underlying statistics for the adjusted market risk factor return and the systematic ESG risk factor return, discussed later, are different. In this regard, Jin (2022b)shows that the empirical result of the index model for the sample period from 2011 to 2020 shows that the daily returns of ESG-screened indices (constructed through negative screening without portfolio skews) have a beta coefficient lower

[2] We regress its parent broad market index to ESG-screened index, and then take the residuals as the systematic ESG risk factor. By the techniques of estimation used in regression analysis, the residual is uncorrelated with the regressor. In this way, we derive uncorrelated factors from a set of correlated indexes: broad market index and ESG-screened index (Jin, 2022c).

than one. The EGARCH analysis confirms that ESG factor surprise has a lower long-run level, higher persistence, and minor asymmetry than market factor surprise.

2.3.2. First-pass time-series regression

We estimate the systematic risk metric as the coefficient of a first-pass time-series regression. For each rolling window during the systematic risk exposure estimation period, we estimate the empirical version of equation (1) for each fund i of 1117 sample funds:

$$\tilde{r}_i = \mu_i + m_i\tilde{r}_m + g_i\tilde{r}_g + \tilde{\eta}_i \tag{8}$$

where $\tilde{r}_m = \tilde{I}_E - \alpha_E$ and $\tilde{r}_g = \tilde{I}_S - \alpha_S$. We collect the following statistics over the 60 observations at each rolling estimation window to use in later analysis:

$\widehat{m}_i$= Sample estimates of the adjusted market risk metric for each of the 1117 funds

$\hat{g}_i$= Sample estimates of the ESG risk metric for each of the 1117 funds

We take the values of coefficients ($\widehat{m}_i$ and $\hat{g}_i$) are estimates of the accurate systematic risk metric for the 1117 funds during the sample period.

The way we construct the systematic ESG factor, using a simple regression between the ESG and broad market indices, is simple and easy to implement. While the approach is practical, it is subject to potential methodological bias. While ESG indices are designed according to common principles, the specific screening procedure may vary from provider to provider. ESG rating disagreement among the leading ESG data vendors has been widely documented (Berget al., 2020). It makes the construction of an index based on one ESG rating data provider debatable because this approach ignores ESG rating disagreement risk, which is priced in stock returns (Gibson et al., 2021). To address this potential limitation, hedge funds may use three pairs of ESG-screened indexes and corresponding broad market indexes to derive two systematic factors: $\tilde{r}_m$ and $\tilde{r}_g$. Specifically, in addition to Morningstar's indices, we calculate the systematic risk factor which is based on indices provided by MSCI (MSCI USA ESG Leaders and MSCI USA IMI), and Dow Jones (DJ Sustainability US Composite and DJ US Broad Stock Market), respectively. Then, hedge funds may take the average risk exposure values estimated using each pair of indexes provided by three providers.

2.3.3. Grouping strategy

We take the approach of using portfolios in place of individual funds to alleviate the errors-in-variables problem, following the standard in the empirical asset pricing literature (Jensen et al., 2006; Fama and MacBeth, 1973). We first form portfolios of funds based on systematic risk parameters estimated from a first-pass time-series regression. We begin by illustrating the grouping strategy in the double-factor model that deviates from Jin (2022c) to accommodate the systematic ESG risk factor.

We employ two-layer grouping criteria to get portfolios with different systematic risks in the double-factor model. The specifics of the approach are as follows. We divide the 1117 sample funds into eightm-sorted portfolios at the first layer. We form these eight m-sorted portfolios based on the rank of individual fund's m-loading estimates ($\widehat{m}_i$). We divide funds within the k-th m-sorted portfolio into five g-sorted sub-portfolios at the next layer. We form five sub-portfolios based on the rank of g-loading estimates ($\hat{g}_i$) within the k-th m-sortedportfolio. Through the two-layer procedure, we end up with 40 portfolios.

We examine three cases where the grouping criteria vary in detail for robustness check. For the first alternative, we modify the number of the group at each layer by forming 20 portfolios based on the rank of the m-loading estimate $\hat{m}_i$ at the first layer. Then, at the second layer, we divide individual funds within the k-th m-sorted portfolio into two sub-portfolios based on the rank of the g-loading estimate $\hat{g}_i$. Through the alternative two-layer procedure, we end up with 40 portfolios. The purpose of this variation is to see if the risk premium related to systematic ESG risk responds materially to the change in the grouping criteria. For the second alternative, we alter the length of the performance evaluation period for grouped portfolios using a more extended evaluation period of 2 years instead of 1 year. The purpose of this variation is to examine whether the strategy of constructing a portfolio based on systematic risk indicators can maintain discriminatory performance when the performance evaluation period is prolonged. For the third alternative, we change the systematic risk metric by forming eight portfolios based on the rank of the overall systematic risk metric $\hat{\kappa}_i$ instead of $\hat{m}_i$. We compute the overall systematic risk metric in the double index model as:

$$\hat{\kappa}_i = \sqrt{\left(\hat{m}_i^2 \hat{\sigma}_m^2 + \hat{g}_i^2 \hat{\sigma}_g^2\right) / \left(\hat{\sigma}_m^2 + \hat{\sigma}_g^2\right)} \tag{9}$$

where $\hat{\kappa}_i = 1$ when $\hat{m}_i = \hat{g}_i = 1$.[3] Reviewing this variation aims to investigate whether adjusting systematic risk indicators, which are the basis for grouping, can significantly impact the risk premium associated with systematic ESG risk.

As an advantage of this grouping strategy, hedge funds can easily extend the current set-up to accommodate multi-layers when investors want to include exposure to various other factors like styles or sectors. Like the relevant papers (Görgen et al., 2020; Henriksson et al., 2019), hedge funds may construct an ESG factor as a zero-cost portfolio at the first layer and then add grouping layers based on the Carhart four-factor or Fama-French five-factor model. Jin (2018; 2022a) derives an ESG factor from indexes and combines it with the Fama-French five-factor model. Currently, ESG investing in the global financial market encompasses many strategies. Estimating the ESG factor based on market indexes can be a concise and inexpensive alternative for investors willing to utilize ESG investment with a comprehensive investment philosophy. On the other hand, the double-index model is compatible with employing a zero-cost ESG portfolio whenever it might be better suited to sophisticated investors who want to control risk exposure to other factors (Jin, 2022c).

2.3.4. Second-pass cross-sectional regression

We then perform a second-pass cross-sectional regression each month of the performance evaluation period.[4] We estimate the empirical version of equation (4a):

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[3] In the single-index model, $\hat{\kappa}_i = \hat{\beta}_i$ since $\hat{\sigma}_s^2$ is restricted to zero, which is the same as previous studies.

[4] If we estimate this cross-sectional equation for each month, it is possible to investigate how the parameters change over time. This form of the equation also allows us to test a series of hypotheses regarding the double-factor model.

$$\hat{\mu}_j = \mu_m \widehat{m}_j + \mu_g \hat{g}_j + \epsilon_j \tag{10}$$

where $\hat{\mu}_j$ is expected excess return estimate of portfolio j, and $\widehat{m}_j$ and $\hat{g}_j$ are risk exposure estimates of portfolio j from the first-pass time-series regression.[5] Here, based on each grouping criterion described above, we average the estimates across funds within each portfolio j to obtain $\hat{\mu}_j$, $\widehat{m}_j$, $\hat{g}_j$, and $\hat{\kappa}_j$ for the second-pass cross-sectional regression during the performance evaluation period. Regarding parameters of equation (10), μ_m shows a risk premium against the adjusted market risk in the capital markets, and μ_s represents a risk premium against the systematic ESG risk. Note that we compute sample averages of the excess return on every portfolio (μ_j) over the next 12 months by 12 or 24 months. It allows us to test the out-of-sample risk-return trade-offs generated by our grouping criteria.

We have estimates of $\hat{\mu}_{\mathrm{m},t}$ and $\hat{\mu}_{\mathrm{g},t}$ for each month over the performance evaluation period. Then we find the average value of any $\hat{\mu}_{k,t}$ $(k = m, g)$ simply by averaging the individual values and denote them by μ_k^*. We test this mean to see if it is significantly different from zero and interpret μ_{g}^* as a market price of the systematic ESG risk. Following Fama and MacBeth (1973), we compute t-statistics to test the hypothesis that $\mu_k^* = 0$. The same number of estimates $\hat{\mu}_{\mathrm{k,t}}$ are used to compute μ_k^* and $s(\hat{\mu}_{\mathrm{k}})$ in a similar manner. Finally, we use the t-distribution with the degree of freedom of T to compute p-values.

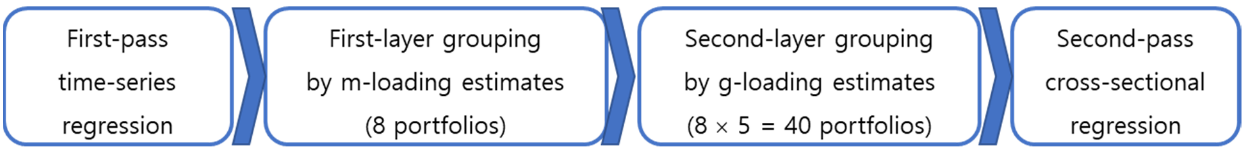

Figure 1. Workflow.

Note: Figure 1 symbolizes the workflow we have described so far. First, we estimate the adjusted market risk factor exposure ($\widehat{m}_i$) and systematic ESG risk factor exposure ($\hat{g}_i$) from the first time series regression. Next, we construct 40 portfolios based on these risk exposures. For the "base" case, we construct eight m-sorted portfolios by ranking funds according to their m-loading estimates ($\widehat{m}_i$). Then, within each m-sorted group, we construct five g-sorted sub-portfolios according to their g-loading estimates ($\hat{g}_i$). Next, we estimate the risk premiums for the two systematic risk factors via a second cross-sectional regression on the average excess returns of the 40 portfolios.

2.4. Data

2.4.1. Equity index

Our index dataset comprises a pair of US equity indices: Morningstar US Market for a broad market index and Morningstar Sustainability for an ESG-screened index. The Morningstar Sustainability targets 50% coverage by float market capitalization of large- and mid-capitalization stocks in the Morningstar US Market. We obtained their monthly returns for 138 months (January

[5] Note that the second-pass cross-sectional regression does not have a constant term because R_j is in excess returns of portfolio j and the purpose of our analysis is to measure the size of risk premium against systematic risks.

2010–June 2021) from Morningstar. Table 2 shows the pair of indices used in our analysis.

Table 2A. Market indices.

Index Provider	Type	Index Name
Panel A.Parent indexand ESG-screened index		
Morningstar	Broad market index	Morningstar US Market TR USD
	ESG-screened index	Morningstar US Sustainability TR USD

Note: Table 2A briefs a pair of indices used in our analysis: a broad market index as parent indices and an ESG-screened index. The ESG-screened index targets 50% coverage by float market capitalization of large- and mid-capitalization stocks in the broad market index. The ESG-screened index aims to provide exposure to equities with low-ESG risk by employing negative screening.

Panel B presents the descriptive statistics for index returns. We annualize means of monthly returns via $[(1 + r)^{12} - 1]$, and monthly standard deviations via $\sigma\sqrt{12}$. The first column shows no material difference in annualized mean between the broad market index and the ESG-screened index. In contrast, the annualized means of the spread are much smaller, resulting from how we construct it from the regression residual plus the constant. In the next column, standard deviations for two indices indicate that the dispersion in return volatility is not considerable across indices. On the contrary, standard deviations for the spread imply that the return volatility of the orthogonal spread is much smaller. The table also presents that monthly returns' skewness is negative for two indices, in contrast to positive skewness for the spread. In addition, monthly returns' kurtosis of the spread is marginally lower than the two indices.[6] Furthermore, return distributions of the two indices are non-normal. We use the Shapiro-Wilk test, whose null hypothesis is that the returns have a normal distribution. In the last column, the Shapiro-Wilk test statistics are significant at the 1% level across the two indices. The rejection of the normality hypothesis is compatible with negative skewness and excess kurtosis. Note that the Shapiro-Wilk test statistics are less significant for the spread.

[6] We use Fisher's definition of kurtosis, and thus the kurtosis of a normal distribution is zero. Kurtosis figures are normalized by N-1.

Table 2B. Market indices.

Index	Mean	SD	Skew	Kurt	SW test	
Panel B. Descriptive statistics						
Broad market index	17.78	15.53	−0.64	2.47	0.93	**
ESG−screened index	17.17	14.53	−0.63	1.95	0.94	**
Spread	0.67	1.85	0.69	1.54	0.97	

** (*) denotes statistical significance at the 1% (5%) level.

Note: Table 2B presents descriptive statistics for a broad market index, an ESG-screened index, and an orthogonal spread. The spread is computed by regressing the broad market index returns on the ESG-screened index returns and taking the residual plus the constant. We treat the ESG-screened index as the adjusted market risk factor and the spread as the systematic ESG risk factor. We derive these two systematic risk factors using a pair of indices from Morningstar. The table shows the annualized mean (Mean), annualized standard deviation (SD), skewness (Skew), and kurtosis (Kurt) of monthly returns. We annualize means of monthly returns via $[(1 + r)^{12} - 1]$, and standard deviations of monthly returns via $\sigma\sqrt{12}$. We use Fisher's definition of kurtosis, and thus the kurtosis of a normal distribution is zero. The table also presents the Shapiro-Wilk (SW) normality. We retrieve monthly returns data from Morningstar, ranging from January 2010 through June 2021.

2.4.2. Equity mutual fund

The fund data for our study comprises a sample of 1117 US equity mutual funds classified based on the nine Morningstar categories in June 2021. Focusing on the domestic equity funds belonging to the nine style categories provides more precision to our research results by isolating investment strategies exposed to similar risk factors. Our data consist of the total monthly returns over 138 months (January 2010–June 2021) for mutual funds that have been investable for at least 60 months, are still available in June 2021, and have Morningstar's ESG scores.

3. Results and discussion

3.1. Characteristics of sorted portfolios

Table 3 shows the characteristics of 40 portfolios sorted by previously described grouping criteria. We calculate the equal-weighted monthly returns on the resulting 40 portfolios for the evaluation period with the subsequent 12 months. The average returns are the time-series averages of the monthly returns, in percent. The first column (G0) shows equal-weighted averages of all funds in each m-sorted portfolio. The top row (M0) shows equal-weighted averages of all funds with the same g-sorted rank.

The evidence that our grouping strategy provides is a positive relationship between exposure to both systematic risk factors and subsequent average returns. The top row shows that the ex-post portfolio returns increase linearly from G1 (lowest) to G5 (highest). The pattern suggests that the net effect of portfolio g-loading on portfolio returns is positive with portfolio m-loading fixed. In other words, the market price of systematic ESG risk is positive, for which we will investigate its significance through a formal test later. The first column shows that the ex-post portfolio returns may have a non-linear relation with portfolio betas. The highest ex-post returns occur in the fourth m-sorted portfolio (M4).

In the double-factor model, the expected return of an asset depends on its m-loading on the adjusted market risk factor and g-loading on the systematic ESG risk factor. Consequently, the g-loading on the systematic ESG risk affects assets' expected returns. When the ESG risk premium is positive, the higher the asset's exposure to the systematic ESG risk, the higher its expected return in equilibrium. Ex-ante, high g-loading portfolios earn higher expected returns than low g-loading portfolios.[7]

Table 3. Characteristics of sorted portfolios.

	G0	G1	G2	G3	G4	G5
M0	0.98	0.80	0.93	0.97	1.05	1.16
M1	0.86	0.79	0.80	0.81	0.89	1.01
M2	0.97	0.79	0.93	1.00	1.07	1.05
M3	1.02	0.82	1.03	1.02	1.10	1.14
M4	1.05	0.85	1.01	1.08	1.15	1.17
M5	1.03	0.84	0.96	1.08	1.15	1.11
M6	0.99	0.81	0.95	1.04	1.00	1.14
M7	0.97	0.80	0.96	0.92	0.91	1.25
M8	0.96	0.72	0.78	0.84	1.07	1.40

Note: Table 3 shows the ex-post portfolio returns of 40 portfolios sorted by previously described grouping criteria. At the end of every estimation period with 60 monthly returns, we assign the sample funds to eight m-sorted po rtfolios based on beta estimates ($\widehat{m}_i$): M1 (lowest) to M8 (highest). Each m-sorted portfolio is subdivided into fiv e gamma-portfolios using funds' gamma estimates ($\hat{g}_i$): G1 (lowest) to G5 (highest). We calculate the equal-weig hted monthly returns on the resulting 40 portfolios for the evaluation period with the subsequent 12 months. The average returns are the time-series averages of the monthly returns, in percent. The table shows the time-series av erage of portfolio characteristics obtained for every month. The first column (G0) shows equal-weighted averages of all funds in each m-sorted portfolio. The top row (M0) shows equal-weighted averages of all funds with the sa me gamma rank.

3.2. The empirical market price of ESG risk

Table 4 shows the second-pass regression estimates based on the double-factor model in equation (10). Our focus is to investigate whether the market price of systematic ESG risk is significant. We present results for the overall period from January 2016 to June 2021 (66 months), the first subperiods from January 2016 to September 2018 (33 months), and the second subperiod from October 2018 to June 2021 (33 months). For each period, the table shows the average $\boldsymbol{\mu}_k^*$ of the month-by-month regression coefficient estimates $\widehat{\boldsymbol{\mu}}_{k,t}$, and the mean $\overline{\boldsymbol{R}}^2$ of the month-by-month coefficients of determination $\boldsymbol{R}^2$ adjusted for degrees of freedom. P-values for testing the hypothesis that $\boldsymbol{\mu}_k^* = \mathbf{0}$ are presented. Finally, we offer results for four different specifications we designed for robustness check.

The second column ("Base") shows the result based on the base specification: 8-by-5 grouping criteria, one-year evaluation period, and m-loading on the adjusted market risk factor $\widehat{m}_j$. Examining results over the entire period, μ_g^* is smaller relative to μ_m^* but is statistically different from zero.

[7] Some previous studies (Choi et al., 2020; Engle et al., 2019) suggest such evidence in the context of climate risk.

When we examine it over the first subperiod, it becomes even smaller and is not statistically different from zero. From this, we can safely conclude that systematic ESG risk affects the expected returns of sorted portfolios. The risk premium for the systematic ESG risk corresponds to the maximum certain return ESG investors are willing to forego in exchange for hedging the systematic ESG risk. We can illustrate the market price of the systematic ESG risk in the context of a three-fund separation.[8] Each investor holds the ESG portfolio, the risk-free asset, and the non-ESG portfolio (essentially long market and short ESG portfolios). The price-adjustment mechanism affects the risk premium that investors are willing to sacrifice to invest in the ESG portfolio instead of the market portfolio or the aggregate ESG tilt away from the market portfolio. In the end, low g-loading assets have lower expected returns because of their ability to better hedge the systematic ESG risk. High g-loading assets offer higher expected returns.

The third column("Grouping") shows the result based on the second specification: 20-by-2 grouping criteria with anything else equal. Results in the case are close to those in "Base". The fourth column ("Period") shows the result based on the third specification: a two-year evaluation period with anything else equal. While most results are also similar, we see that μ_g^* become significantly positive even for the first subperiod. Note that the mean of the month-by-month coefficients of determination is larger in the fourth column than in other columns. It implies that our double-factor model has more explanatory power in the second sub-period. The more profound explanatory power may result from the market condition where the consensus on ESG integration becomes stronger. The statistical significance of the systematic ESG risk market price suggests the potential to improve economic effectiveness by employing the double-factor model. The last column ("Metric") shows the result based on the last specification: Grouping based on exposure to the systematic risk factor ($\hat{\kappa}_j$) with anything else equal. Most results are similar. The market price of the systematic ESG risk is more significant for the second subperiod than for the first subperiod. Note that two components (the adjusted market risk factor and the systematic ESG risk factor) make up the whole (the systematic risk factor) in our double-factor asset model. This result indicates that the estimated market price of the systematic ESG risk is robust to the change in risk metrics used in the second-pass regression.

[8]Similarly, a three-fund separation can also illuminate that thesystematic ESG risk can bear a negative market price. Investors with average tastes hold the market portfolio, investors with stronger-than-average tastes go long the ESG portfolio, and investors with weaker preferences go short the ESG portfolio. The extent to which a market portfolio satisfies investors depends on how strong the demand for the ESG portfolio is. If many investors derive a large amount of utility from the ESG portfolio, asset prices adjust to reflect those tastes. Suppose market prices slowly adjust to the synchronized demand shift from the market portfolio toward the ESG portfolio. In that case, low g-loading portfolios can have higher expected returns because investors' tastes for low g-loading holdings continue. Portfolios with high g-loading are on the brink of losing value as investors dislike them and thus can offer lower expected returns.

Table 4. Second-pass regression estimates.

Specification		Base		Grouping		Period		Metric	
		Ave.	p-val.	Ave.	p-val.	Ave.	p-val.	Ave.	p-val.
Entire Period	$\hat{\mu}_m$	0.728	0.000	0.755	0.000	0.743	0.000	0.740	0.000
	$\hat{\mu}_g$	0.133	0.000	0.114	0.000	0.120	0.000	0.119	0.000
	R^2	0.829	0.000	0.837	0.000	0.919	0.000	0.831	0.000
1st Sub-period	$\hat{\mu}_m$	0.815	0.000	0.829	0.000	0.843	0.000	0.827	0.000
	$\hat{\mu}_g$	0.048	0.106	0.038	0.199	0.083	0.001	0.034	0.244
	R^2	0.881	0.000	0.882	0.000	0.972	0.000	0.881	0.000
2nd Sub-period	$\hat{\mu}_m$	0.640	0.001	0.680	0.001	0.636	0.000	0.653	0.001
	$\hat{\mu}_g$	0.225	0.000	0.198	0.000	0.158	0.000	0.211	0.000
	R^2	0.779	0.000	0.795	0.000	0.865	0.000	0.783	0.000

Note: Table 4 shows average estimated coefficients from the regressions of average excess returns of 40 portfolios on two systematic risk factor exposure estimates: The exposure to the adjusted market risk factor ($\widehat{m}_i$) and the exposure to the systematic ESG risk factor ($\hat{g}_i$). Risk exposures are computed from the first-pass time-series regression during the previous 60 months.

For the "Base" case, we form eight m-sorted portfolios by ranking funds first on m-loading estimates ($\widehat{m}_i$). Then, we form five g-sorted sub-portfolios on g-loading estimates ($\hat{g}_i$) within each m-sorted group. The average excess returns of 40 portfolios are computed for 12 months after the portfolio formation. The estimated figures ($\hat{\mu}_m$ and $\hat{\mu}_g$) represent the risk premium on each of the two risk factor exposures during each period, respectively. We report the average value of those risk premiums over 66 months for the entire period and 33 months for each sub-period. Corresponding p-values are computed from t-distribution, and the degree of freedom is set to the number of estimates used to compute t-statistics. We also present the average value of adjusted R-squares for each period.

For the "Grouping" case, we form 20 m-sorted portfolios by ranking funds first on m-loading estimates ($\widehat{m}_i$). Then, we form two g-sorted sub-portfolios on g-loading estimates ($\hat{g}_i$) within each m-sorted group. Anything else remains unchanged from the "Base" case.

For the "Period" case, the average excess returns of 40 portfolios are computed for 24 months after the portfolio formation. Anything else remains unchanged from the "Base" case.

For the "Metric" case, we sort 40 portfolios on two systematic risk factor exposure estimates: the exposure to the overall market risk factor ($\hat{\kappa}_i$) and the exposure to the systematic ESG risk factor ($\hat{g}_i$). Anything else remains unchanged from the "Base" case.

3.3. Implications for hedge fund strategy

A novel insight of our analysis is that the double-factor model can capture a significant risk premium on the systematic ESG risk, which emerges through various channels: The extent to which ESG characteristics signal profitability, ESG information is incorporated into prices, and ESG-investors' demand pressure affects required returns, etc. Our double-factor model enables hedge funds to measure and strategically manage their exposure to systematic ESG risk. The systematic ESG risk factor realization affects the relative performance of green and brown assets ex-post. When the systematic ESG risk premium is positive, a positive realization of the factor results in the outperformance of brown assets. If the systematic ESG risk factor worsens suddenly due to new government regulations, brown assets underperform green ones.

Our findings on the empirical market price of the systematic ESG risk carry practical implications for the future performance of ESG investing. Some prior studies (Baker et al., 2018; Barber et al., 2021; Chava, 2014; El Ghoul et al., 2011; Hong and Kacperczyk, 2009; Zerbib, 2019) report that green assets underperform brown assets in various contexts.[9] These results are consistent with our analysis' positive risk premium for the systematic ESG risk factor. Table 5 summarizes the significant findings and relevant interpretations of each study.

Table 5. Previous studies on the performance of ESG investing.

Research	Finding	Interpretation
Green assets underperform brown assets.		
Baker et al. (2018) Zerbib (2019)	Green bonds tend to be priced at a premium, offering lower yields than traditional bonds.	The premium is driven by investors' environmental concerns.
Barber et al. (2021)	Venture capital funds that aim not only for financial return but also for social impact earn lower returns than other funds.	Investors derive nonpecuniary utility from investing in dual-objective funds.
Chava (2014) El Ghoul et al. (2011)	Greener firms have a lower implied cost of capital.	The taste for green holdings affects the cost of capital.
Hong and Kacperczyk (2009)	Sin stocks (stocks of public firms producing alcohol, tobacco, and gaming) outperform non-sin stocks.	Social norms lead investors to demand compensation for holding sin stocks.
Green assets outperform brown assets.		
Edmans (2011)	Firms perform better if they have higher employee satisfaction.	Firms are better governed.
Gompers et al. (2003)	Firms perform better if they have strong shareholder rights.	Firms are better governed.
Kempf and Ostho (2007)	Firms perform better if they have higher ESG ratings in the 1992–2004 period.	Firms are better governed.

Note: Table 5 summarizes the relevant argument of previous studies on the ESG risk factor. The first column (Research) shows the authors and publication year. The second column (Relevant argument) presents the main argument regarding ESG information as a risk factor.

Hedge fund managers may be mindful that ESG investments may underperform (outperform) in the future because systematic ESG risk is currently priced at a premium (discount). The result based on the systematic ESG risk shares similar characteristics with recent theoretical studies (Pástor,

[9] Other studies (Edmans, 2011; Gompers et al., 2003; Kempf and Osthoff, 2007) find the opposite result, i.e. green assets underperform brown assets. Those ex-post observations may be compatible with the positive (negative) risk premium for a negative (positive) realization of systematic ESG risk factor.

Stambaugh, and Taylor 2021; Pedersen, Fitzgibbons, and Pomorski 2021). Pástor, Stambaugh, and Taylor (2021) show that positive (negative) realizations of ESG factors, which result from shifts in customers' and investors' tastes, can result in green assets outperforming (underperforming) brown ones. Pedersen et al. (2021) suggest a model in which stocks with higher ESG scores can have either higher or lower expected returns, depending on the wealth of ESG-motivated investors. Our double-factor model is also related to other prior theoretical studies of ESG investing (Albuquerque et al., 2019; Baker et al., 2018; Heinkel et al., 2001). Table 6 summarizes the features and notable results of each study.

Table 6. Previous theoretical studies on ESG investing.

Research	Feature	Primary result
Albuquerque et al. (2019)	A firm's socially responsible investments increase customer loyalty, giving the firm more pricing power.	The pricing power makes the firm less risky and thus more valuable.
Baker et al. (2018)	One of two types of investors with mean-variance preferences has tastes for green assets.	Green assets have lower expected returns and more concentrated ownership.
Heinkel et al. (2001)	One of two types of investors refuses to hold shares in polluting firms.	The reduction in risk-sharing increases the cost of capital of polluting firms, depressing their investment.
Oehmke and Opp (2024)	Investors face financing constraints and coordination among agents.	ESG investing has a positive social impact.
Pástor et al. (2021)	Some investors derive nonpecuniary benefits from green holdings.	Positive (negative) realizations of ESG factors, which result from shifts in customers' and investors' tastes, can result in green assets outperforming (underperforming) brown ones.
Pedersen et al. (2021)	One of three types of investors with mean-variance preferences is unaware of firms' ESG scores.	Stocks with higher ESG scores can have either higher or lower expected returns, depending on the wealth of the third type of investor.

Note: Table 6 summarizes the features and primary results of previous theoretical studies on ESG investing. The first column (Research) shows the authors and publication year. The second column (Feature) summarizes the main assumptions of each model for the comparison among papers. The third column (Primary result) presents the material effect of ESG investing predicted by the model.

We have mainly discussed negative screening while at least eight different ESG investment styles exist in reality. According to the institutional investors' survey, although negative screening is prevalent, investors perceive it as the least efficient regarding risk-return trade-offs (Amel-Zadeh and Serafeim, 2018). Indeed, too concentrated screening could restrict the diversification benefit and deteriorate the risk-adjusted rate of return (Jin, 2022a). ESG investors use various styles: engagement strategies, thematic strategies, and impact investing. The risk-return trade-off comes second for some ESG investors (such as impact investors) since they want primarily to generate a positive ESG impact with their investments. Even for such ESG investors, the analysis of this paper would help them recognize the opportunity cost of ESG investing and make their informed decision.[10] For instance, an ESG integration framework for portfolio optimization reflects that the systematic ESG risk can account for joint movement in security prices.

Another practical implication of our findings is that hedge fund managers and investors can establish a long-short strategy to hedge against systematic ESG risk. Most discussions of ESG investing focus on strategies that exclude stocks with high individual ESG risk from a portfolio based on stock-specific ESG characteristics. However, such negative screening strategies may not be sufficient in situations where investors recognize that systematic ESG risk factors may commonly affect the stocks that comprise an investment universe and wish to construct a neutral portfolio to those risk factors. Hedge funds can utilize the double-factor model presented in this paper to identify stocks to sell and buy in their investment universe and implement a long-short strategy to meet the needs of investors seeking systematic ESG risk-neutral portfolios.

The findings in this paper also have potential policy implications that regulators and policymakers can use to set new standards for ESG investing. One of the main policy instruments for ESG investing is ESG disclosure for companies, financial instruments, etc. Much of the current disclosure debate focuses on standardization to ensure that as much information about ESG issues is disclosed as possible and that it is comparable across companies and financial instruments. The more accurate and standardized ESG information is provided, the easier it is expected to facilitate rational investment decisions. However, in addition to ESG information for individual stocks, some investors may also be interested in systemic ESG risk exposure across the capital markets and how sensitive their portfolio's financial performance may be to such risk factors. If time or cost constraints make it difficult for investors to fully digest information on individual stocks, information on systemic ESG risk factors may be more appropriate for them. The double-factor model presented in this paper can provide a tool for the average materiality of several ESG risks that are recognized as material by capital markets and reflected in asset prices. Policymakers reviewing ESG disclosure standards may want to consider including relevant information on the scope and content of disclosures.

4. Conclusions

As the size of ESG investing has grown so fast, a synchronized response among ESG investors can emerge in many cases. For instance, institutional investors' awareness of ESG risks increases, and institutional investors may employ a common approach. The surge of ESG investment could lead to price pressure and price co-movement among the low-ESG-risk assets. This collective movement has made it possible to identify and manage systemic ESG risks as a potential basis for hedge fund strategies.

Based on this view, we suggest a double-factor model. In the model, the co-movement between assets is due to two systematic risk factors: the adjusted market risk factor and the systematic ESG risk factor. We use an ESG-screened index as a proxy for the adjusted market risk factor, then take the orthogonal spread between a broad market index and an ESG-screened index as a proxy for the

[10] For instance, private climate finance can be scaled up by linking it to ESG investments (Jin, 2023, 2024a, 2024b).

systematic ESG risk factor. This approach enables hedge funds to more easily estimate the empirical market price of the systematic ESG risk through data observed in reality.

The empirical evidence on the monthly returns on US equity mutual funds shows that the loading on systematic ESG risk is associated with out-of-sample excess returns. The results show that ESG risk premiums that are significantly different from zero have become more effective in recent years. It indicates that hedge funds can incorporate the systematic ESG risk factor into the investment decision process consistent with MPT. Our double-factor framework provides an effective tool to measure the opportunity cost of maximizing ESG quality while maintaining factor exposures within comfortable limits. Identifying the empirical market price of the systematic ESG risk that conventional investing ignores can help hedge funds develop strategies regarding portfolio optimization, risk management, performance evaluation, etc. This analysis could be a step in the long process of improving the understanding of ESG investing for hedge funds.

Some directions for future research include the following. The basic premise of our analysis is that the orthogonal spread (calculated by regressing the broad market index return on the ESG-screened index return) accurately identifies systematic ESG risk. This assumption takes into account the practice of major ESG index providers to exclude stocks with high ESG risk but keep the risk-return profile close to the broad market index. For hedge funds to remove different systematic risk factors from the orthogonal spread between the two indices, they may need to regress the broad market index returns on the returns of the ESG-selected index as well as other risk factors. To address this situation, future research could extend this analysis to include other factors, such as Fama and French's (2015) five factors.

Second, the influence of systematic ESG risk factors has increased over time during our sample period. If the increase in flows into ESG investments over the past few years was purely a reflection of a shift in investor preferences, the relative financial performance of ESG investments relative to traditional investments would not change much once the inflows slowed. If, on the other hand, as we suggest, the performance of financial assets can vary in response to changes in systematic ESG risk factors and their sensitivity to such changes, then the relative financial performance of ESG investments may continue to change in the future. Future research could determine whether our observations hold over longer sample periods.

Finally, the significant risk premium for systematic ESG risk may vary across the sample funds. Future research could apply the double-factor model to equity funds in other regions. For regions with mature ESG indices, it may be possible to derive systematic ESG risk from two indices, as is the approach in this paper. If we analyze regions without active ESG indices in their capital markets, the double-factor model can be applied by creating a zero-cost portfolio after sorting the universe of stocks by ESG characteristics.

Use of AI tools declaration

The author declares that they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The author declares no conflicts of interest in this paper. The views in this paper are the responsibility of the author, not the institution the author is affiliated with.

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