Market Price of Systematic ESG Risk

Ick Jin[1]

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[1] Jin is at the National Assembly Budget Office. The views in this paper are the responsibility of the author, not the institution the author is affiliated with.

Abstract

As institutional investors utilize ESG investing, ESG indices may account for joint movement in security prices and act as a systematic ESG risk factor. We identify the systematic ESG risk factor through the orthogonal spread between a broad market and an ESG-screened index. We suggest the double-index model, apply it to US equity mutual funds, and show that exposures to the systematic ESG risk correlate significantly with the sorted portfolio's expected returns. It implies that the double-index model helps investors estimate the market price of systematic ESG risk and use the information for their investment decisions.

Keywords

ESG investing, ESG integration, systematic ESG risk, index model, asset pricing model, portfolio construction, risk management

JEL codes

C15; G11; G12; G13; G22; G33

ESG (environmental, social, and governance) investing is an investment approach that considers both financial and ESG objectives. Although the scope of ESG investing has expanded significantly in recent years, the method initially started with imposing negative screens. Considering that ESG investing has grown so fast and seems to grow further, it is vital to understand its aggregate impact on asset prices.

We analyze the effects of synchronized ESG investing through a systematic risk factor lens. Although investors may differ in their preferences for ESG, which have multiple dimensions, investors may unintentionally herd on their ESG investment 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 at the same time.

The synchronized response among ESG investors can emerge in many cases. Investors may employ a common approach: they first omit unwanted securities from a diversified benchmark. Then, they weigh remaining securities in proportion to their market capitalizations or minimize tracking error relative to its benchmark. Or they may over(under)-weigh individual securities that match a particular ESG orientation in an optimized tilt. The synchronized response may result from balancing the competing priorities of enhancing a portfolio's ESG score and minimizing its tracking error relative to its benchmark.

One of the recent market movements to enforce the herding response among ESG investors is that passive ESG investing has been a critical trend in asset management over the last ten years (Belsom et al. 2019; Blitz and Groot 2019; Hoque 2020). As US retail investors have shifted from stock picking to indexed investing, institutional investors' ownership of US companies has now reached an extraordinary level. At the same time, as large institutional investors become more insisting on ESG investing, the AUM of passive ESG strategies significantly grows. For example, 2020 marked the fourth consecutive year that passive fund flows outpaced actively managed ones among sustainable funds (Hale 2021).

Some highly relevant papers recently noted the aggregated impact of ESG investing (Bolton and Kacperczyk 2021; Koijen and Yogo 2019; Gibson, Krueger, and Mitali 2020; Pástor, Stambaugh, and Taylor 2021; Pedersen, Fitzgibbons, and Pomorski 2021). Bolton and Kacperczyk (2021) study whether carbon emissions affect the cross-section of US stock returns. They conclude that investors are already demanding compensation for their exposure to carbon emission risk. Koijen and Yogo (2019) develop an asset pricing model that implies characteristics-based demand when returns have a factor structure and expected returns and factor loadings depend on the assets' characteristics. Gibson, Krueger, and Mitali (2020) show the positive effect of sustainability footprints on the risk-adjusted performance of 13F institutions' equity portfolios. They explain the outperformance by growing investor preferences for sustainable investing over time and the resulting price pressure that institutions exert on stocks with good environmental scores. Pástor, Stambaugh, and Taylor (2021) present a model of investing based on ESG criteria. They find that green assets can outperform brown ones when the ESG factor captures shifts in customers' tastes for green products and investors' tastes for green holdings. Pedersen, Fitzgibbons, and Pomorski (2021) introduce an ESG-efficient frontier that shows the highest attainable Sharpe ratio for each ESG level. Their ESG-adjusted capital asset pricing model determines equilibrium asset prices when ESG raises or lowers the required return.

These papers share a similar perspective: as institutional investors' awareness of ESG risks increases, the size of ESG investment surges could lead to price pressure and price comovement among the low-ESG-risk stocks. This phenomenon suggests that ESG risks (at least a part of them) can be systematic. Recent academic and industry research can back up this conjecture by showing that ESG risks can be universal, and we need to control them even at the level of well-diversified portfolios (Fiskerstrand et al. 2020; Jin 2018).

Based on the view that the systematic ESG risk factor exists, we suggest a double-index model in which the comovement between securities is due to two systematic risk factors. Diversified institutional investors can stick to the basic principle of maximizing risk-adjusted returns with the double-index model. According to MPT, investors can diversify unsystematic risk through diversification and thus should pay attention to only systematic risk.[2] Especially, institutional investors with a diversified portfolio have exposure to only systematic risks, so their interest should be to manage systematic ESG risk. Our double-index model can help investors incorporate the systematic ESG risk factor into their portfolio optimization in a manner more consistent with MPT (Modern Portfolio Theory).

For the double-index model, we partition the overall market risk factor that causes securities to move together into two parts: the adjusted market risk factor and the ESG risk factor. The adjusted market risk factor captures the broad market movement after netting off the comovement triggered by systematic ESG events. The ESG risk factor 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. Considering the current industry practice that ESG-screened indices utilize negative exclusion, we use an ESG-screened index as the adjusted market risk factor and take the orthogonal spread between a broad market index and an ESG-screened index as the ESG risk factor.

The paper's main point is to propose a framework for assessing the market price of the systematic ESG risk. Our empirical evidence shows that exposures to a systematic ESG

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[2] Systematic ESG risks may include but be not limited to the following examples: legislation for corporate governance, a change in social norm for labor and gender, a pandemic, or sudden and irreversible climate change.

risk factor are associated with out-of-sample excess returns, and thus investors should consider it when making investment decisions. The proposed double-index model suggests a practical framework that is intuitive and easy to compute the market price of systematic ESG risk. The approach reveals valuable insights regarding formalizing the prospect on systematic ESG risk and measuring and incorporating its market price into the investment process.

This study provides contributions to the existing literature on ESG investing. We explicitly decompose the overall market risk factor into two parts (the adjusted market risk factor and the ESG risk factor), rather than treating the ESG risk factor separated from and additional to the overall market risk factor. Applying the double-index model allows us to attribute the performance of an ESG integrated portfolio to the sources regarding two systematic risk factors. This approach helps us better understand the nature of ESG investing within the modern portfolio theory.

In addition, the result of our analysis is essential for several practical applications. Most of all, identifying a proxy of systematic ESG risk is a critical task in practice when investors want to manage the systematic ESG risk factor. Investors can use the double-index model to form return expectations, optimize portfolios,[3] predict correlation coefficients among securities, and attribute the sources of portfolio performance. Unveiling individual assets' responsiveness to the systematic ESG risk factor could provide investors with a theoretical base to develop smart-beta strategies integrating with ESG investing.

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-index 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

[3] For example, Jin (2021) extends the simple criteria for optimal portfolio constructin developed originally by Elton, Gruber, and Padberg (1976) for a single-index model, and suggests a decision criteria based on the double-index model for optimal portfolio selection.

MacBeth (1973) to US equity mutual funds. We finalize the article by presenting concluding remarks and directions for future research.

Analytical Framework for ESG Integration

Single-index model

As a starting point, we first introduce the single-index model Elton, Gruber, and Padberg (1976), with some notations modified by adding sub-scripts "o" for comparative purposes. Suppose that the single-index model adequately reflects the correlation structure between securities. That is:

(1-1) $R_i = \alpha_{o,i} + \beta_{o,i} I_{o,m} + e_{o,i}$ for i = 1, ..., N

(1-2) $I_{o,m} = \alpha_{o,m} + e_{o,m}$

(1-3) $\mathrm{E}\left(e_{o,m} e_{o,i}\right) = 0$ for i = 1, ..., N

(1-4) $\mathrm{E}\left(e_{o,i} e_{o,j}\right) = 0$ for i = 1, ..., N ; j = 1, ..., N ; and $j \neq i$

where R_i = the rate of return on security i (a random variable)

$I_{o,m}$ = the rate of return on a market index (a random variable)

$\beta_{o,i}$ = a measure of the responsiveness of security i to changes in the market index

$\alpha_{o,i}$ = the return on security i that is independent of changes in the market index

$e_{o,i}$ = a variable with a mean of zero and variance $\sigma^2_{o,ei}$

$\alpha_{o,m}$ = the mean of the market index

$e_{o,m}$ = a variable with a mean of zero and variance $\sigma^2_{o,m}$

$\sigma^2_{o,m}$ = the variance of the market index

In this setting, the last two equations characterize the approximation of the single-index model to the covariance structure. These equations imply that the only joint movement between securities comes about because of a common response to a market index ($I_{o,m}$).

Systematic risk factors

We depart from the single-index model by modifying the return generating process of a conventional market index ($I_{o,m}$). For an unscreened broad market index (hereafter, IM), we change the equation as follows:

(2-1) $$I_{o,m} = \alpha_{o,m} + e_m + e_s$$

A basic premise of the modification is to decompose a random variable ($e_{o,m}$) into the adjusted market risk component (e_m) and the ESG risk component (e_s). With this equation, we separate random shocks attributable to the aggregate ESG news (CSR events, changes in ESG-screened index constituents, or ESG rating changes) from those attributable to the market movement other than ESG news. Then, we assume that the ESG risk component follows a distribution independent of the adjusted market risk component's distribution. That is, two random features are independent of each other as follows:

(2-2) $$E(e_m e_s) = 0$$

Next, we are paying attention to that ESG screening aims to hedge the systematic ESG risk. Thus, we treat an ESG-screened index (hereafter, IE) as a proxy for the adjusted market risk factor (netting the systematic ESG risk factor). Under the postulation, we define the adjusted market risk factor as follows:

(2-3) $$I_m = \alpha_m + e_m$$

where α_m = the mean of the adjusted market risk factor (ESG-screened index)

e_m = a variable with a mean of zero and variance σ_m^2

σ_m^2 = the variance of the adjusted market risk factor

Last, we capture the behavior of the systematic ESG risk through the spread of IM returns over IE returns. By subtracting Eq. (2-3) from Eq. (2-1), we obtain the systematic ESG risk factor as follows:

(2-4) $I_s = \alpha_s + e_s$

where α_s = the mean of the ESG risk factor (the spread of IM returns over IE returns)

e_s = a variable with a mean of zero and variance σ_s^2

σ_s^2 = the variance of the systematic ESG risk factor

Note that $\alpha_s = \alpha_{o,m} - \alpha_m$. Introducing the ESG risk factor relies on the standard industry practice regarding IEs (Jin 2022). The construction of IE generally begins with its parent IM that acts as the initial universe of potential constituents. A set of ESG screening rules is then applied to select securities so that IE provides investors with exposure to the aggregate of the highest ESG-rated firms in IM. In the midst of that, major index providers try to mitigate overconcentration risk to certain factors. They aim to achieve the dual goal of tilting towards a higher ESG score at the index level while maintaining a risk-return profile close to its IM. In the end, IE can proxy the market risk factor after netting off the systematic ESG risk factor. We name IE the adjusted market risk factor, pointing out that IE hedges the systematic ESG risk from IM. In addition, we can capture the movement of the ESG risk factor through the orthogonal spread of IM returns over IE returns. Thus, the ESG risk factor (I_s) stands for the market movement triggered by the aggregate of ESG-issues only, orthogonal to the adjusted market risk factor (I_m). Note that the assumption of zero covariance between two systematic risk factors holds by construction.

It is worth clarifying how the introduction of the ESG risk factor helps us understand the nature of ESG investing. To stay as close as possible to the original MPT framework, we hypothesize the existence of a systematic ESG risk factor. Although introducing a priced ESG risk factor is still not settled in the emerging ESG asset pricing literature, we can back up the assumption by referring to recent empirical work on the implications of ESG risk for asset prices (Bansal, Ochoa, and Kiku 2016; Bolton and Kacperczyk 2021; Engle et al. 2019; Hoepner et al. 2021; H. G. Hong, Li, and Xu 2017; Ilhan, Sautner, and Vilkov 2020; Jin 2018; Krueger, Sautner, and Starks 2019; Luo and Balvers 2017). While some studies focus on climate risk, others have identified multiple other aspects of ESG-related risk. We complement these studies with a construction of a systematic ESG risk factor that may capture unexpected shifts in ESG concerns of investors. In addition, our assumption that the systematic ESG risk exists has a fair amount of empirical support in the mutual fund literature (Białkowski and Starks 2016; Bollen 2007; Hartzmark and Sussman 2017; Renneboog, Ter Horst, and Zhang 2011; Riedl and Smeets 2017). Table 1 summarizes the relevant arguments in this previous research.

Insert Table 1 here

Our treatment of systematic ESG risk is also related to a widespread practice. The most common approach of passive ESG investing is replicating ESG screened indices. As more institutional investors follow ESG screened indices like one another, ESG issues may drive comovement among securities included in those indices. Securities with high ESG scores tend to increase (decrease) in price when ESG indices go up (down). It suggests that once passive ESG investing becomes large enough, an ESG-screen index can account for joint movement in security prices beyond that accounted for by a broad market index. Hence, a challenge for ESG investing is to clarify how they consider the comovement of securities induced by ESG concerns during their valuation.

Double-index model

Incorporating the ESG risk factor allows us to extend the single-index model for our analysis on ESG investing. We assume that the following double-index model is an adequate description of reality:

(3-1) $R_i = \alpha_i + \beta_i I_m + \gamma_i I_s + e_i$ for i = 1, ..., N

(3-2) $I_m = \alpha_m + e_m$

(3-3) $I_s = \alpha_s + e_s$

(3-4) $\mathrm{E}(e_m e_s) = 0$

(3-5) $\mathrm{E}(e_m e_i) = 0$ for i = 1, ..., N

(3-6) $\mathrm{E}(e_s e_i) = 0$ for i = 1, ..., N

(3-7) $\mathrm{E}(e_i e_j) = 0$ for i = 1, ..., N ; j = 1, ..., N ; and $j \neq i$

where I_m = the rate of return on an adjusted market risk factor (a random variable)

I_s = the rate of return on an ESG risk factor (a random variable)

β_i = a measure of the responsiveness of security i to changes in the adjusted market risk factor

γ_i = a measure of the responsiveness of security i to changes in the ESG risk factor

α_i = the return on security i that is independent of both changes in the adjusted market risk factor and changes in the ESG risk factor

e_i = a variable with a mean of zero and variance σ_{ei}^2

e_m = a variable with a mean of zero and variance σ_m^2

e_s = a variable with a mean of zero and variance σ_s^2

σ_m^2 = the variance of the adjusted market risk factor

σ_s^2 = the variance of the ESG risk factor

In our setting, the last four equations characterize the approximation of the double-index model to the covariance structure. The assumption implied by these equations is that the only joint movement between securities comes about because of common responses to the adjusted market risk factor and the ESG risk factor.

While the double-index model mimics the single-index model in notations, definitions, and critical assumptions, it has differences in two aspects. First, the apparent difference relates to the number of systematic risk factors that define the joint movements among securities. As its name suggests, the single-index model assumes only one systematic risk factor: overall market risk factor ($I_{o,m}$) represented by a broad market index. In contrast, the double-index model takes two systematic risk factors: adjusted market risk factor (I_m) and ESG risk factor (I_s).

Second, although the double-index model contains more than one factor, like a multi-index model, the way we identify systematic risk factors distinguishes the double-index model from the multi-index models.[4] We break down the overall market risk factor into two mutually independent components in the double-index model. To do so, we decompose the general market risk factor (IM) into two mutually separate pieces: IE and the orthogonal spread (hereafter, OS) between IM and IE. We first set IE as the adjusted market risk factor, regress its parent IM to IE, and then take the residuals as the ESG risk factor. By the techniques of estimation used in regression analysis, the residual is uncorrelated with the

[4] For example, the multi-index model in chapter 8 of Elton et al. (2014) includes an industry index to explain the residual movement of securities that the movement of a broad market index can not explain. The multi-index model removes the correlation from the industry index by regressing the industry index on the broad market index and taking the residuals.

regressor. In this way, we derive uncorrelated factors from a set of correlated indexes: IM and IE.

Empirical Analysis

We follow three basic steps: estimating the first-pass time-series regression, combining funds into portfolios, and estimating the second-pass cross-sectional regression.

First-pass time-series regression

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

(3-1) $R_i = \alpha_i + \beta_i I_m + \gamma_i I_s + e_i$ for i = 1, ..., N

We collect the following statistics over the 60 observations at each rolling estimation window to use in later analysis:

β_i = Sample estimates of the adjusted market risk measure for each of the 1117 funds

γ_i = Sample estimates of the ESG risk measure for each of the 1117 funds

We take the values of coefficients ($\hat{\beta}_i$ and $\hat{\gamma}_i$) are estimates of the accurate systematic risk measure for the 1117 funds during the sample period.

Grouping strategy

We take the approach of using portfolios in place of individual funds to alleviate the errorsin-variables problem, following the standard in the empirical asset pricing literature (Jensen, Black, and Scholes 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-index model that deviates from earlier studies to accommodate the systematic ESG risk factor.

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

The choice of portfolio numbers balances computation costs against maintaining the statistical significance. At each last month of the risk exposure estimation period, we divide 1117 sample funds into 40 groups based on their rank by beta and gamma. We form an equally weighted portfolio of the funds that comprise each group. A strategy consisted of holding the funds of a particular group over the next 12 months. Notice that an investor could follow the approach outlined here. Each month the investor divides funds into groups by beta and gamma based on the previous five years (60 months) returns. If investors want to pursue the high-risk strategy, they divide their money equally among the funds in the highest risk group. They do this every month and observe the outcomes.

We examine three cases where the grouping criteria vary in detail for robustness check. For the first alternate, 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 $\hat{\beta}_i$. We compute the overall systematic risk metric in the double index model as:

(4) $$\hat{\kappa}_i = \sqrt{\left(\hat{\beta}_i^2 \hat{\sigma}_m^2 + \hat{\gamma}_i^2 \hat{\sigma}_s^2\right) / \left(\hat{\sigma}_m^2 + \hat{\sigma}_s^2\right)}$$

where $\hat{\kappa}_i = 1$ when $\hat{\beta}_i = \hat{\gamma}_i = 1$.[5] 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. For the second alternate, we modify the number of the group at each layer by forming 20 portfolios based on the rank of beta estimates ($\hat{\beta}_i$) at the first layer. Then, at the second layer, we divide individual funds within the k-th portfolio sorted by betas into two sub-portfolios based on the rank of $\hat{\gamma}_i$. Through the alternative two-layer procedure, we still 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 third alternate, we alter the length of the performance evaluation period for grouped portfolios by 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.

Following each of the grouping criteria, we average the systematic risk metrics across funds within each portfolio j to obtain $\hat{\beta}_j$ (or $\hat{\kappa}_j$) and $\hat{\gamma}_j$ for the second-pass cross-sectional regression during the performance evaluation period.

Second-pass cross-sectional regression

We then perform one second-pass cross-sectional regression each month of the performance evaluation period.[6] The equation we test is:

[5] In the single-index model, $\hat{\kappa}_i = \hat{\beta}_i$ for since $\hat{\sigma}_s^2$ is restricted to zero, which is the same as previous studies.
[6] If we estimate this cross-sectional equation for each month, it is possible to investigate how the parameters change over

(5) $$\bar{R}_j = a_\beta \hat{\beta}_j + a_\gamma \hat{\gamma}_j + \varepsilon_j$$

where we obtain risk exposure estimates of portfolio j ($\hat{\beta}_j$ and $\hat{\gamma}_j$) from the first-pass time-series regression.[7] Regarding parameters of the model, a_β shows a risk premium against the adjusted market risk in the capital markets, and a_γ represents a risk premium against the systematic ESG risk. Note that we compute sample averages of the excess return on every portfolio ($\bar{R}_j$) over the next 12 months by default or 24 months in the third alternate for robustness check. It allows us to test the out-of-sample risk-return trade-offs generated by our grouping criteria.

We have estimates of $\hat{a}_{\beta,t}$ and $\hat{a}_{\gamma,t}$ for each month over the performance evaluation period. Then we find the average value of any $\hat{a}_{k,t}$ $(k = \beta, \gamma)$ simply by averaging the individual values and denote them by a_k^*. We test this mean to see if it is significantly different from zero and interpret a_γ^* as a market price of the systematic ESG risk. Following Fama and MacBeth (1973), we compute t-statistics for testing the hypothesis that $a_k^* = 0$ as:

(6) $$t(a_k^*) = \frac{a_k^*}{s(\hat{a}_k)/\sqrt{n}}$$

where $s(\hat{a}_k)$ is the standard deviation of the monthly estimates, and n is the number of months in the period. Note that n is also the number of estimates $\hat{a}_{k,t}$ used to compute a_k^* and $s(\hat{a}_k)$. Finally, we use the t-distribution with the degree of freedom of n to compute p-values.

Equity Index Data

time. This form of the equation also allows us to test a series of hypotheses regarding the double-index model.

[7] 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.

Our index dataset comprises US equity indices, IM, IE, and OS. We obtain their monthly returns for 138 months (January 2010 - June 2021) from Morningstar. We use three pairs of IE and corresponding IM to derive two systematic factors: the adjusted market risk factor and the ESG risk factor. We use a pair of indices supplied by MSCI (hereafter, CI): MSCI USA ESG Leaders for IE and MSCI USA IMI for I.M. Dow-Jones (hereafter, DJ) provides DJ Sustainability US Composite as IE, and its IM is DJ US Broad Stock Market. We get Morningstar Sustainability as IE and Morningstar US Market as IM provided from Morningstar (hereafter, MS).

Although each IE has some differences in the detailed screening procedure, IEs share the common principle. IEs employ negative screening to exclude equities that have low ESG scores. Each IE targets 50% coverage by float market capitalization of large- and mid-capitalization stocks in its corresponding IM Index providers use the security ESG scores supplied by in-house research departments or third-party consulting companies. Table 2 shows the information on three pairs of IM and IE used in our analysis.

Insert Table 2 here

We use the average risk exposures against the systematic risks derived by averaging risk exposures that we estimate using indexes of three providers: CI, DJ, and MS. ESG rating disagreement among the leading ESG data vendors has been widely documented (Berg, Kölbel, and Rigobon 2020). It makes the construction of an index based on one ESG rating data provider debatable because this ignores ESG rating disagreement risk, which is priced in stock returns (Gibson, Krueger, and Schmidt 2021). Using average values over three major index providers can mitigate the ESG rating disagreement risk. We also provide the analysis results based on indexes of the individual provider.

Table 3 presents the descriptive statistics for IM, IE, and OS returns for three index providers: CI, DJ, and MS. 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 IM and IE In contrast, annualized means of OS are much smaller, resulting from how we construct OS from the regression residual plus the constant. In the next column, standard deviations for IM and IE indicate that the dispersion in return volatility is not considerable across indices. On the contrary, standard deviations for OS imply that the orthogonal spread's return volatility is much smaller. Table 3 also presents that monthly returns' skewness is negative for IM and IE, in contrast to positive skewness for OS. In addition, monthly returns' kurtosis of OS is marginally lower than IM and IE[8] Furthermore, return distributions of IMs and IEs 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 IM and IE 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 OS.

Insert Table 3 here

Equity mutual fund data

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

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

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.

Empirical Results

Characteristics of sorted portfolios

Table 3 shows characteristics 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 beta-portfolios based on beta estimates ($\hat{\beta}_i$). Each beta-portfolio is subdivided into five gamma-portfolios using funds' gamma estimates ($\hat{\gamma}_i$). 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. Table 3 shows the time-series average of portfolio characteristics for every month. The first column (G0) shows equal-weighted averages of all funds in each beta-portfolio. The top row (B0) shows equal-weighted averages of all funds with the same gamma rank.

The evidence that our grouping strategy provides is a positive relationship between exposure to systematic risk factors and subsequent average returns. Table 3 best illustrates this point. We find that both beta and gamma exposures positively correlate with the following average returns.

Panel A of Table 3 shows the portfolio gamma across 40 sorted portfolios. The top row shows that the portfolio gamma steadily increases from G1 (lowest) to G5 (highest). It is a natural result of the grouping criteria on gamma-portfolios. Interestingly, the first column shows the portfolio gamma monotonically increases from B1 (lowest) to B8 (highest). It implies that estimated exposures to two systematic risks are positively correlated, reflecting the specification on our double-index model with the overall market risk partitioned into two parts.[9]

Panel B of Table 3 shows the portfolio beta across 40 sorted portfolios. The first column indicates that the portfolio beta increases from B1 (lowest) to B8 (highest). It is a natural result of the grouping criteria on beta-portfolios. What is noteworthy is that the portfolio beta is almost identical among five gamma-portfolios within each beta-portfolio, as shown in the top row. This aspect is because we design the systematic ESG risk factor orthogonal to the adjusted market factor. Also, since we form five gamma sub-portfolios within every beta-portfolio, the pattern shows the effect of gamma after isolating the impact of beta.

Panel C of Table 3 shows the ex-post portfolio returns across 40 sorted portfolios and reveals two notable points. 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 gamma on portfolio returns is positive with portfolio beta 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 non-linear relation with portfolio betas. The highest ex-post returns occur in the fourth beta-portfolio (B4).

In the double-index model, the expected return of an asset depends on its beta (exposure to the market risk factor) and gamma (exposure to the systematic ESG risk factor). Consequently, the exposure to the systematic ESG risk affects assets' expected returns. When

[9] This is different from the specification of Pástor, Stambaugh, and Taylor (2020) where green and brown assets have opposite exposures to the market risk factor.

the ESG risk premium is positive, the higher the asset's exposure to the systematic ESG risk, the higher is its expected return in equilibrium. Ex-ante, high-gamma portfolios earn higher expected returns than low-gamma portfolios.[10]

Insert Table 3 here

The market price of ESG risk

Table 4 shows the second-pass regression estimates based on the double-index model 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). We present results for three different index providers (CI, DJ, MS) and their average (AV). For each period and index provider, the table shows the average (a_k^*) of the month-by-month regression coefficient estimates ($\hat{a}_{k,t}$), and the mean (r^{2*}) of the month-by-month coefficients of determination (r^2) adjusted for degrees of freedom. P-values for testing the hypothesis that $a_k^* = 0$ are presented. Finally, we offer results for four different specifications we design for robustness check.

Panel A shows the result based on the base specification: 8-by-5 grouping criteria, one-year evaluation period, and exposure to the adjusted market risk factor ($\hat{\beta}_j$). Examining results over the entire period, $a_\gamma^*(AV)$ is smaller relative to $a_\beta^*(AV)$ but is statistically different from zero. When we examine it over the first subperiod, it becomes even smaller

10 (Choi, Gao, and Jiang 2019; Engle et al. 2019) suggests such evidence in the context of climate risk.

and is not statistically different from zero. The pattern repeats itself when examing $a_{\gamma}^{*}(DJ)$ or $a_{\gamma}^{*}(MS)$ while it becomes more prominent than $a_{\gamma}^{*}(AV)$. It remains large enough to be significantly different from zero in the second subperiod. In contrast, $a_{\gamma}^{*}(CI)$ exhibits negative signs over the entire period and for each subperiod, although they are not statistically different from zero. Note that absolute values of $a_{\gamma}^{*}(CI)$ and $a_{\beta}^{*}(AV)$ are more prominent than results with other index providers. From Panel A, 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. 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-gamma (hereafter, green) assets have lower expected returns because of their ability to better hedge the systematic ESG risk. High-gamma (hereafter, brown) assets offer higher expected returns.

Panel B shows the result based on the second specification: 20-by-2 grouping criteria with anything else equal. Results in Panel B are close to those in Panel A. A notable difference is that negative $a_{\gamma}^{*}(CI)$'s become statistically significant over the entire period and for each subperiod. A three-fund separation illuminates how the systematic 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-gamma portfolios can have higher expected returns because investors' tastes for green holdings continue. Brown portfolios are on the brink of losing value as investors dislike them and thus can offer lower expected returns.

Panel C shows the result based on the third specification: a two-year evaluation period with anything else equal. The results in Panel C are also similar. We see that $a_{\gamma}^{*}(DJ)$ or $a_{\gamma}^{*}(M\,S)$ become significantly positive even for the first subperiod. Note that the mean of the month-by-month coefficients of determination is larger in Panel C than in other panels. It implies that our double-index model has more explanatory power in the second subperiod. The more profound explanatory power may result from the market condition where the consensus on ESG integration becomes stronger. Note that the double-index model designed in this paper lies in an intermediate position between the full historical performance and the single-index model to reproduce the historical performance. Adding the systematic ESG risk factor makes things more complex and reproduces the historical correlation matrix more accurately. It does not guarantee that the double-index model accurately forecasts future performance. However, the estimation results of Table 4 reveal how well the double-index model estimates the future returns of sorted portfolios. The statistical significance of the systematic ESG risk market price suggests the potential to improve economic effectiveness by employing the double-index model.

Panel D shows the result based on the fourth specification: grouping based on exposure to the systematic risk factor ($\hat{\kappa}_j$) with anything else equal. Although $a_{\gamma}^{*}(AV)$ is not significantly positive for the entire period, other results are still similar. We see that $a_{\gamma}^{*}(DJ)$

or $a_{\gamma}^{*}(MS)$ is larger than $a_{\gamma}^{*}(CI)$. 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-index asset model. And gammas of sorted portfolios positively correlate with betas of sorted portfolios, as shown in Table 3. As a result, the estimated market price of the systematic ESG risk is robust to the change in risk metrics used in the second-pass regression. In general, a multi-factor approach may be necessary to capture the risk associated with ESG investing when investors' tastes may also shift for reasons unrelated to systematic ESG risk.

Insert Table 4 here

Implications of empirical findings

A novel insight of our analysis is that the double-index 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. Since our double-index model captures those ingredients, risk-adjusted-return-maximizing investors make ESG investments voluntarily when reducing the exposure to the systematic ESG risk is rewarded. 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 ESG concerns strengthen unexpectedly, green assets can outperform brown ones. Since investors dislike unexpected deteriorations in the aggregate ESG characteristics, if the systematic ESG risk factor worsens suddenly due to new government regulations, brown assets underperform green ones.

Our findings on the 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, Morse, and Yasuda 2021; Chava 2014; El Ghoul et al. 2011; H. Hong and Kacperczyk 2009; Zerbib 2019) report that green assets underperform brown assets in various contexts. These results are consistent with our analysis' positive risk premium for the systematic ESG risk factor. In contrast, other studies (Edmans 2011; Gompers, Ishii, and Metrick 2003; Kempf and Osthoff 2007) find the opposite result, compatible with the negative risk premium for a systematic ESG risk factor in our model. These contradictory conclusions seem to result from using different definitions of green and brown. Table 5 summarizes the significant finding and relevant interpretations of each study.

Insert Table 5 here

Our analysis highlights that ESG investing might underperform (overperform) going forward, mainly because the systematic ESG risk is priced at a premium (discount) today. The result based on the systematic ESG risk shares similar characteristics with recent theoretical studies (Pástor, Stambaugh, and Taylor 2021; Pedersen, Fitzgibbons, and Pomorski 2021). Pástor, Stambaugh, and Taylor (2021) show that positive (negative) realizations of ESG factor, which result from shifts in customers' and investors' tastes, can result in green assets outperforming (underperforming) brown ones. Pedersen, Fitzgibbons, and Pomorski (2021) suggest a model in which stocks with higher ESG scores can have either higher or lower expected returns, depending on the wealth of the ESG motivated investors. Our double-index model is also related to other prior theoretical studies of ESG investing (Albuquerque, Koskinen, and Zhang 2019; Baker et al. 2018; Heinkel, Kraus, and Zechner 2001). Table 6 summarizes the feature and notable results of each study.

Insert Table 6 here

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 2020). While some ESG investors use passive portfolio strategies that rely on the ESG-screened indexes, others use other styles: engagement strategies, thematic strategies, and impact investing. Any ESG investing style caters to investors with distinct ESG preferences. Thus, it is essential to note that 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.

Conclusion

As the size of ESG investing has grown so fast, the 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 comovement among the low-ESG-risk assets. The current proliferation of ESG investing among institutional investors can drive comovement among assets and make ESG risks (at least a part of them) systematic. This phenomenon suggests the existence of systematic ESG risk.

Based on the view that the systematic ESG risk factor exists, we suggest a double-index model. In the model, the comovement between assets is due to two systematic risk factors: the adjusted market risk factor and the ESG risk factor. We focus on the industry practice that ESG indices utilize negative screening intending to eliminate ESG risk of individual assets. We use an ESG-screened index as a proxy for the adjusted market risk factor and take the orthogonal spread between a broad market index and an ESG-screened index as a proxy for the systematic ESG risk factor. The approach is highly tractable, yielding simple and intuitive expressions for the return generating process, including the systematic ESG risk.

Our empirical evidence on the monthly returns on US equity mutual funds shows that the exposure to systematic ESG risk is associated with out-of-sample excess returns. Thus investors should consider it when making investment decisions to improve future performance. It indicates that investors can incorporate the systematic ESG risk factor into the investment decision process consistent with MPT. Variations depend on which provider's indexes we use to construct systematic risk factors and the period. We see that the risk premium with DJ or MS is more significant than that with CI, and the risk premium is more effective for the second subperiod than for the first subperiod. Overall, the risk premium is significantly different from zero.

The integration of the systematic ESG risk may be suitable for ESG investors willing to align portfolio construction with their ESG motives. The challenge for those investors is to verify how the portfolio optimization with ESG incorporated can effectively improve the ESG quality of the overall market.

The practice that maximizes ESG quality while maintaining factor exposures within stated limits can help improve the long-term investment performance by incorporating ESG issues that conventional investing ignores.

Overall, using the existing IE may be suitable for ESG investors willing to accept the performance comparable to the broad market portfolio. The double-index approach can contribute to enhancing long-term investment performance. As far as investors want to reduce the departure of IE from IM, the divergence in exposure to the ESG risk factor would remain within the limited range. It remains to be studied how the active share of IE from IM could increase return, lower risk, or enhance diversification of optimal portfolio. The change may give rise to many investment decisions regarding the choice of the universe, portfolio construction, rebalancing method, rebalancing frequency, constituent weights, risk controls, etc. On such an occasion, ESG investing may require investors to utilize portfolio optimization, risk management, and performance evaluation techniques: such as the double-index model suggested in this paper.

A few directions for future research include the following. A basic assumption of our analysis is that OS (orthogonal spread calculated by regressing IM returns on IE returns) accurately identifies the systematic ESG risk factor. Future research needs to validate this assumption by investigating the impact of including other factors. Next, the influence of the systematic ESG risk factor has increased over time during the sample period. Future research can verify whether the observation holds during another sampling period. Next, the significant risk premium to the systematic ESG risk may depend on sample funds. Future research can apply the double-index model to equity funds in different regions.

This analysis suggests a clear direction with rigorous explanation and thus intuitive interpretations about incorporating the ESG risk factor to portfolio optimization. We hope that this could be a step in the long process of improving the understanding of ESG integration with portfolio optimization for asset owners, asset managers, and other service providers.

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APPENDIX: TABLES

Table 1. Recent studies on ESG risk factor

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

Research	Relevant argument
ESG risk factor	
Bansal, Ochoa, and Kiku (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.
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. (2018)	ESG engagement reduces firms' downside risk and exposures to a downside-risk factor.
Hong, Li, and Xu (2019)	Food stock prices respond to climate risks.
Ilhan, Sautner, and Vilkov (2019)	Firms with higher carbon emissions exhibit more tail risk and more variance risk.
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.
Krueger, Sautner, and Starks (2019)	Institutional investors consider climate risks to be significant investment risks.
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.
Renneboog, ter Horst, and Zhang (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.

Table 2. ESG screened indices and parent indices

The table briefs three pairs of indices used in our analysis: three broad market indices (IM) as parent indices and three ESG-screened indices (IE). Each IE targets 50% coverage by float market capitalization of large- and mid-capitalization stocks in its corresponding IM IE aims to provide exposure to equities with low-ESG-risk by employing negative screening.

Index Provider	Type	Index Name
Dow-Jones (DJ.)	IM.	DJ US Broad Stock Market TR USD
	IE	DJ Sustainability US Composite TR USD
Morningstar (MS.)	IM.	Morningstar US Market TR USD
	IE	Morningstar US Sustainability TR USD
MSCI (CI)	IM	MSCI USA IMI GR USD
	IE	MSCI USA ESG Leaders GR USD

Table 3. Descriptive statistics: IM, IE, and OS.

This table presents descriptive statistics for three broad market indices (IM), three ESG screened indices (IE), and three orthogonal spreads (OS). OS is computed by regressing IM returns on IE returns and taking the residual plus the constant. We treat IE as the adjusted market risk factor and OS as the systematic ESG risk factor. We derive these two systematic risk factors using pairs of broad market index and ESG-screened index from three providers: MSCI (CI), Dow-Jones (DJ), Morningstar (MS).
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.

Index		Mean	SD	Skew	Kurt	SW test	
DJ	IM	17.76	15.66	-0.65	2.55	0.93	**
	IE	18.27	14.83	-0.56	1.82	0.94	**
	OS	1.70	2.54	0.71	1.97	0.95	**
MS	IM	17.78	15.53	-0.64	2.47	0.93	**
	IE	17.17	14.53	-0.63	1.95	0.94	**
	OS	0.67	1.85	0.69	1.54	0.97	
CI	IM	17.87	15.66	-0.65	2.54	0.93	**
	IE	17.66	14.61	-0.67	2.29	0.93	**
	OS	1.12	1.84	0.52	2.11	0.96	

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

Table 3. Characteristics of Sorted Portfolios

Panel A. Average of exposures to the systematic ESG risk ($\hat{\gamma}_j$)

The table shows the portfolio gamma 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 beta-portfolios based on beta estimates ($\hat{\beta}_i$): B1 (lowest) to B8 (highest). Each beta-portfolio is subdivided into five gamma-portfolios using funds' gamma estimates ($\hat{\gamma}_i$): G1 (lowest) to G5 (highest). The table shows the time-series average of portfolio characteristics obtained for every month. The first column (G0) shows equal-weighted averages of all funds in each beta-portfolio. The top row (B0) shows equal-weighted averages of all funds with the same gamma rank.

	G0	G1	G2	G3	G4	G5
B0	1.75	0.47	1.17	1.72	2.25	3.14
B1	0.68	-0.49	0.11	0.58	1.12	2.06
B2	1.18	0.10	0.65	1.05	1.61	2.50
B3	1.29	0.28	0.71	1.09	1.74	2.64
B4	1.59	0.46	0.98	1.53	2.08	2.88
B5	1.86	0.59	1.29	1.87	2.33	3.22
B6	2.14	0.70	1.53	2.21	2.70	3.57
B7	2.43	0.88	1.85	2.54	2.96	3.94
B8	2.82	1.22	2.22	2.86	3.47	4.33

Table 3. Characteristics of Sorted Portfolios (Continue)

Panel B. Average of exposures to the adjusted market risk ($\hat{\boldsymbol{\beta}}_j$)

The table shows the portfolio beta 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 beta-portfolios based on beta estimates ($\hat{\beta}_i$): B1 (lowest) to B8 (highest). Each beta-portfolio is subdivided into five gamma-portfolios using funds' gamma estimates ($\hat{\gamma}_i$): G1 (lowest) to G5 (highest). The table shows the time-series average of portfolio characteristics obtained for every month. The first column (G0) shows equal-weighted averages of all funds in each beta-portfolio. The top row (B0) shows equal-weighted averages of all funds with the same gamma rank.

	G0	G1	G2	G3	G4	G5
B0	1.06	1.05	1.06	1.06	1.06	1.06
B1	0.87	0.81	0.86	0.88	0.89	0.90
B2	0.97	0.97	0.97	0.97	0.97	0.97
B3	1.01	1.01	1.00	1.01	1.01	1.01
B4	1.04	1.03	1.03	1.04	1.04	1.04
B5	1.07	1.07	1.07	1.07	1.07	1.07
B6	1.10	1.10	1.10	1.10	1.11	1.11
B7	1.15	1.15	1.15	1.15	1.15	1.15
B8	1.25	1.24	1.25	1.24	1.24	1.26

Table 3. Characteristics of Sorted Portfolios (Continue)

Panel C. Average of the excess returns ($\bar{R}_j$)

The table 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 beta-portfolios based on beta estimates ($\hat{\beta}_i$): B1 (lowest) to B8 (highest). Each beta-portfolio is subdivided into five gamma-portfolios using funds' gamma estimates ($\hat{\gamma}_i$): G1 (lowest) to G5 (highest). 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 table shows the time-series average of portfolio characteristics obtained for every month. The first column (G0) shows equal-weighted averages of all funds in each beta-portfolio. The top row (B0) shows equal-weighted averages of all funds with the same gamma rank.

	G0	G1	G2	G3	G4	G5
B0	0.98	0.80	0.93	0.97	1.05	1.16
B1	0.86	0.79	0.80	0.81	0.89	1.01
B2	0.97	0.79	0.93	1.00	1.07	1.05
B3	1.02	0.82	1.03	1.02	1.10	1.14
B4	1.05	0.85	1.01	1.08	1.15	1.17
B5	1.03	0.84	0.96	1.08	1.15	1.11
B6	0.99	0.81	0.95	1.04	1.00	1.14
B7	0.97	0.80	0.96	0.92	0.91	1.25
B8	0.96	0.72	0.78	0.84	1.07	1.40

Table 4. Second-pass Regression Estimates

Panel A. Base specification

The table represents results from the base specification when applying the approach proposed by Fama and MacBeth (1973). The table 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 ($\hat{\beta}_i$) and the exposure to the systematic ESG risk factor ($\hat{\gamma}_i$). Risk exposures are computed from the first-pass time-series regression during previous 60 months. Portfolios are formed by ranking funds firt on beta ($\hat{\beta}_i$) into eight portfolios and then on gamma ($\hat{\gamma}_i$) within each beta group into five portfoios. Average excess returns of 40 portfolios are computed for 12 months subsequent to the portfolio formation. The estimated figures ($\hat{a}_\beta$ and $\hat{a}_\gamma$) represent the risk premium on each of 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.

Parameter		AV		CI		DJ		MS	
		Ave.	p-val.	Ave.	p-val.	Ave.	p-val.	Ave.	p-val.
Entire Period	$\hat{a}_\beta$	0.818	0.000	0.958	0.000	0.748	0.000	0.728	0.000
	$\hat{a}_\gamma$	0.056	0.015	-0.042	0.105	0.130	0.001	0.133	0.000
	R^2	0.842	0.000	0.877	0.000	0.830	0.000	0.829	0.000
1st Sub-period	$\hat{a}_\beta$	0.855	0.000	0.924	0.000	0.829	0.000	0.815	0.000
	$\hat{a}_\gamma$	0.005	0.839	-0.055	0.147	0.044	0.314	0.048	0.106
	R^2	0.902	0.000	0.910	0.000	0.904	0.000	0.881	0.000
2nd Sub-period	$\hat{a}_\beta$	0.782	0.000	0.997	0.000	0.662	0.001	0.640	0.001
	$\hat{a}_\gamma$	0.113	0.003	-0.024	0.482	0.226	0.000	0.225	0.000
	R^2	0.782	0.000	0.846	0.000	0.757	0.000	0.779	0.000

Table 4. Second-pass Regression Estimates (continue)

Panel B. 20-by-2 grouping criteria

The table represents results from the alternative grouping criteria when applying the approach proposed by Fama and MacBeth (1973). The table 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 ($\hat{\beta}_i$) and the exposure to the systematic ESG risk factor ($\hat{\gamma}_i$). Risk exposures are computed from the first-pass time-series regression during previous 60 months. Portfolios are formed by ranking funds firt on beta ($\hat{\beta}_i$) into 20 portfolios and then on gamma ($\hat{\gamma}_i$) within each beta group into two portfoios. Average excess returns of 40 portfolios are computed for 12 months subsequent to the portfolio formation. The estimated figures ($\hat{a}_\beta$ and $\hat{a}_\gamma$) represent the risk premium on each of 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.

Parameter		AV		CI		DJ		MS	
		Ave.	p-val.	Ave.	p-val.	Ave.	p-val.	Ave.	p-val.
Entire Period	$\hat{a}_\beta$	0.847	0.000	0.981	0.000	0.790	0.000	0.755	0.000
	$\hat{a}_\gamma$	0.039	0.080	-0.058	0.025	0.101	0.005	0.114	0.000
	R^2	0.860	0.000	0.889	0.000	0.848	0.000	0.837	0.000
1st Sub-period	$\hat{a}_\beta$	0.869	0.000	0.950	0.000	0.845	0.000	0.829	0.000
	$\hat{a}_\gamma$	-0.004	0.886	-0.075	0.052	0.033	0.444	0.038	0.199
	R^2	0.912	0.000	0.914	0.000	0.916	0.000	0.882	0.000
2nd Sub-period	$\hat{a}_\beta$	0.826	0.000	1.018	0.000	0.732	0.000	0.680	0.001
	$\hat{a}_\gamma$	0.087	0.018	-0.038	0.275	0.178	0.001	0.198	0.000
	R^2	0.810	0.000	0.867	0.000	0.782	0.000	0.795	0.000

Table 4. Second-pass Regression Estimates (continue)

Panel C. Two-year evaluation period

The table represents results from the longer evaluation period when applying the approach proposed by Fama and MacBeth (1973). The table 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 ($\hat{\beta}_i$) and the exposure to the systematic ESG risk factor ($\hat{\gamma}_i$). Risk exposures are computed from the first-pass time-series regression during previous 60 months. Portfolios are formed by ranking funds firt on beta ($\hat{\beta}_i$) into eight portfolios and then on gamma ($\hat{\gamma}_i$) within each beta group into five portfoios. Average excess returns of 40 portfolios are computed for 24 months subsequent to the portfolio formation. The estimated figures ($\hat{a}_\beta$ and $\hat{a}_\gamma$) represent the risk premium on each of two risk factor exposures during each period, respectively. We report the average value of those risk premiums over 54 months for the entire period and 27 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.

Parameter		AV		CI		DJ		MS	
		Ave.	p-val.	Ave.	p-val.	Ave.	p-val.	Ave.	p-val.
Entire Period	$\hat{a}_\beta$	0.806	0.000	0.937	0.000	0.724	0.000	0.743	0.000
	$\hat{a}_\gamma$	0.055	0.000	-0.029	0.076	0.136	0.000	0.120	0.000
	R^2	0.916	0.000	0.940	0.000	0.910	0.000	0.919	0.000
1st Sub-period	$\hat{a}_\beta$	0.887	0.000	0.945	0.000	0.850	0.000	0.843	0.000
	$\hat{a}_\gamma$	0.021	0.254	-0.024	0.350	0.060	0.051	0.083	0.001
	R^2	0.970	0.000	0.977	0.000	0.967	0.000	0.972	0.000
2nd Sub-period	$\hat{a}_\beta$	0.716	0.000	0.925	0.000	0.586	0.000	0.636	0.000
	$\hat{a}_\gamma$	0.092	0.000	-0.032	0.082	0.217	0.000	0.158	0.000
	R^2	0.860	0.000	0.902	0.000	0.851	0.000	0.865	0.000

Table 4. Second-pass Regression Estimates (continue)

Panel D. Alternative systematic risk metric

The table represents results from the alternative systematic risk metric when applying the approach proposed by Fama and MacBeth (1973). The table 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 overall market risk factor ($\hat{\kappa}_i$) and the exposure to the systematic ESG risk factor ($\hat{\gamma}_i$). Risk exposures are computed from the first-pass time-series regression during previous 60 months. Portfolios are formed by ranking funds firt on the overall market risk factor ($\hat{\kappa}_i$) into eight portfolios and then on gamma ($\hat{\gamma}_i$) within each beta group into five portfoios. Average excess returns of 40 portfolios are computed for 12 months subsequent to the portfolio formation. The estimated figures ($\hat{a}_\kappa$ and $\hat{a}_\gamma$) represent the risk premium on each of 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.

Parameter		AV		CI		DJ		MS	
		Ave.	p-val.	Ave.	p-val.	Ave.	p-val.	Ave.	p-val.
Entire Period	$\hat{a}_\kappa$	0.835	0.000	0.981	0.000	0.800	0.000	0.740	0.000
	$\hat{a}_\gamma$	0.034	0.131	-0.069	0.007	0.074	0.045	0.119	0.000
	R^2	0.840	0.000	0.871	0.000	0.832	0.000	0.831	0.000
1st Sub-period	$\hat{a}_\kappa$	0.881	0.000	0.949	0.000	0.902	0.000	0.827	0.000
	$\hat{a}_\gamma$	-0.023	0.329	-0.082	0.031	-0.031	0.460	0.034	0.244
	R^2	0.902	0.000	0.911	0.000	0.906	0.000	0.881	0.000
2nd Sub-period	$\hat{a}_\kappa$	0.791	0.000	1.019	0.000	0.694	0.001	0.653	0.001
	$\hat{a}_\gamma$	0.097	0.010	-0.051	0.125	0.191	0.001	0.211	0.000
	R^2	0.778	0.000	0.833	0.000	0.760	0.000	0.783	0.000

Table 5. Previous studies on performance of ESG investing

This table summarizes the relevant argument of previous studies on the ESG risk factor. The f irst column (Research) shows authors and publication year. The second column (Relevant arg ument) presents the main argument to regard ESG information as risk factor.

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, Morse, and Yasuda (2018)	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 tastes for green holdings affect 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, Ishii, and Metrick (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.

Table 6. Previous theoretical studies on ESG investing

This table summarizes the feature and primary results of previous theoretical studies on the E SG investing. The first column (Research) shows authors and publication year. The second co lumn (Feature) summarizes the main assumptions of each model for the comparison among p apers. The third column (Primary result) presents the material effect of ESG investing predict ed by the model.

Research	Feature	Primary result
Albuquerque, Koskinen, and Zhang (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.
Dimson, Karakas, and Li (2015)	Investors conduct shareholder engagement with management.	ESG investing can potentially increase market value.
Heinkel, Kraus, and Zechner (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 (2020)	Investors face financing constraints and coordination among agents.	ESG investing has a positive social impact.
Pástor, Stambaugh, and Taylor (2020)	Some investors derive nonpecuniary benefits from green holdings.	Positive (negative) realizations of ESG factor, which result from shifts in customers' and investors' tastes, can result in green assets outperforming (underperforming) brown ones.
Pedersen, Fitzgibbons, and Pomorski (2019)	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 investors.