Active Fund Management when ESG Matters: An Equilibrium Perspective*

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Abstract

This paper develops and applies an information acquisition model to analyze active management when ESG matters. In equilibrium, sustainable investing leads mutual fund managers to acquire information when cross-asset ESG attributes and cross-fund ESG preferences are dispersed. Sustainability-based information decisions magnify fund heterogeneities in stock holdings and tracking errors, amplify the scope of active management, as well as reduce discount rates and improve price informativeness for underlying assets with sustainability profiles that depart from the average. Enforcing ESG-perceptive funds to adopt the optimal policies of ESG-indifferent funds leads to substantial utility losses, illustrating the economic significance of nonpecuniary motives.

Keywords: ESG, Information acquisition, Mutual funds, Asset pricing

JEL classification: G11, G12, G23, M14, Q01

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1 Introduction

The managerial skill of active mutual funds has been of longstanding interest to financial economists. Fund managers have incentives to invest in research and information acquisition when the resulting superior performance allows them to attract capital flows and collect economic rents (Berk and Green, 2004; Stambaugh, 2014; Choi and Robertson, 2020). However, in recent years, with the growing awareness of Environmental, Social, and Governance (ESG) considerations, investment decisions are increasingly influenced by nonpecuniary motives beyond financial performance (Hartzmark and Sussman, 2019). At the start of 2020, global sustainable investment reached US$ 35.3 trillion, accounting for 36% of all professionally managed assets and an astonishing 55% increase from 2016 (source: GSIA, 2020).[1]

Despite the rapid growth of sustainable investing, to date, little attention has been devoted to addressing the following key questions from an equilibrium perspective. How does sustainable investing interact with mutual funds' information acquisition and attention allocation decisions? What are the implications of ESG-perceptive financial intermediaries for the cross-section of stock prices and price informativeness? How does sustainable investing affect the scope of the active fund management industry? Answers to these questions could be useful in understanding how intermediaries incorporate social objectives into their information acquisition and attention allocation mechanisms, which could potentially affect the price efficiency of the securities market and the allocation of resources in the economy.

The paper aims to address these key questions by developing an equilibrium model on active fund management when ESG matters. We formulate an economy consisting of multiple risky assets and a continuum of risk-averse agents. The assets differ in their ESG profiles, ranging from the most (i.e., green) to the least sustainable (i.e., brown). The agents are heterogeneous in two ways. First, their preferences for holding green assets range from ESG indifference to the most ESG perceptive. Second, each agent can purchase costly signals about random payoffs of risk factors, while some agents have a more favorable cost function.

In equilibrium, following Kacperczyk et al. (2016), active fund managers are agents who possess a strictly positive amount of information. For the remaining participants (e.g., households and passive funds), the marginal cost of information exceeds the marginal benefit

[1]For perspective, global sustainable investment was US$ 22.8 trillion, accounting for 28% of all professionally managed assets in 2016.

for each of the risk factors. Hence, they remain uninformed. Investors then form optimal portfolios conditioned on their private signals. In the rational equilibrium, the market clears, each investors' beliefs about the distribution of all observable variables are fulfilled, and the price depends on information through matching the demand for risky assets and the supply.

The model generates a set of predictions for the universe of active funds and individual stocks. In the first, an essential condition for ESG-induced information acquisition is the presence of dispersion in fund ESG preferences and asset ESG attributes. With such heterogeneities, the fund's signal precision improves with the departure of its own ESG preference from the aggregate, and the departure of the underlying assets' ESG attributes from green neutrality. Moreover, the size of the active fund industry rises due to sustainable investing. In particular, while ESG-perceptive (ESG-indifferent) funds acquire more information on green (brown) assets and less on brown (green), overall, there is more information purchased in equilibrium due to ESG motives. The increase in the signal precision (average across funds and assets) is proportional to the product of cross-fund dispersion in ESG preferences and cross-asset dispersion in ESG attributes, and it positively interacts with managerial skills. That is, when fund managers are more skilled, their ESG-induced signal precision improves.

Regarding the optimal policies, it is shown that mutual funds overweight assets with more precise signals and compatible ESG profiles. Thus, ESG-perceptive (ESG-indifferent) funds overweight green (brown) stocks, with the portfolio tilts more pronounced for low-volatility stocks. Notably, the optimal fund policies could significantly differ due to ESG motives. That is, enforcing an ESG-perceptive fund to adopt the optimal information and portfolio policies of an ESG-indifferent fund could lead to substantial utility losses.

The model also indicates that dispersion in portfolio holdings and tracking error increase when the assets held by the fund depart from green neutrality, and when the fund's ESG preferences depart from the aggregate. Moreover, fund performance is jointly determined by ESG considerations and managerial skills. As in Pástor et al. (2021), accounting for ESG preferences while muting skills, a passive ESG-perceptive (ESG-neutral) fund would deliver a negative (positive) alpha due to overweighting lower (higher) expected return green (brown) stocks. Accounting for skills, the integration of sustainable investing and information decisions leads to nontrivial effects on the optimal strategies of stock holdings. In response, the alpha spread between identically skilled ESG-perceptive and ESG-indifferent funds could be nonzero, even controlling for an ESG benchmark that prices passive investments.

Moving to individual stocks, we make two major predictions. The first characterizes the cross-section of asset prices. Information decisions deepen (weaken) the negative relation between the expected net payoff and the ESG rating for green (brown) assets. Specifically, the expected net payoff for green assets is lower due to two forces: (i) the nonpecuniary benefits from holding green investments, and (ii) the lower posterior variance of the green asset payoff due to higher signal precision. For brown assets, the two forces work in opposite directions (with the nonpecuniary channel likely to dominate based on calibration). Second, price informativeness improves for assets whose ESG profiles depart from green neutrality and whose mutual fund investors display higher dispersion in their ESG preferences.

We empirically test the model based on the universe of actively managed U.S. equity mutual funds and common stocks from 2001 to 2019. We collect monthly ESG rating data from three data vendors, i.e., MSCI KLD, MSCI IVA, and Sustainalytics, and compute the average rank across the raters to obtain the firm-level ESG rating. We then compute the fund-level ESG rating as the investment value-weighted average of the stock ESG ratings in a fund's most recently reported holding portfolio. ESG-perceptive (i.e., green) funds and ESG-indifferent (i.e., brown) funds are classified based on the ESG profiles of their stock holdings. While green (brown) funds naturally invest more in green (brown) stocks, we confirm the model prediction that both types of funds invest less in their preferred investment universe as the idiosyncratic volatility (or the total volatility) of the investable assets rises.

The evidence also shows that both portfolio dispersion and tracking error increase when funds hold assets that depart more substantially from green neutrality. For instance, a one-standard-deviation increase in the departure from green neutrality is associated with 37.4% higher portfolio dispersion and 14.0% higher tracking error. The analysis thus supports the model prediction that ESG considerations play an essential role in shaping fund managers' information decisions and investment strategies. That is, when mutual funds invest in stocks with more extreme ESG profiles, they are more likely to adopt distinct trading strategies and deviate from a benchmark, possibly due to their enhanced information acquisition activities.

We then test the implications for individual stocks. We employ green (brown) fund ownership, labeled Green IO (Brown IO), as a proxy for the information acquisition intensity for green (brown) stocks. We first sort stocks into quintile portfolios based on their green fund ownership. Within each green fund ownership group, we further sort stocks into quintile portfolios according to their ESG ratings. While equilibrium theory predicts a negative relation between the ESG rating and expected return due to the nonpecuniary benefits of holding green stocks, Pástor et al. (2022) document that U.S. green stocks outperform brown stocks in realized returns during the last decade due to an unexpected shift in investors' tastes for green holdings. Therefore, we divide the full sample into two subperiods, i.e., January 2001–October 2012 and November 2012–December 2019, following Pástor et al. (2022).

The first subperiod provides a cleaner setting to analyze equilibrium asset pricing implications. Over that period, the negative ESG-return relation holds only among stocks with high green fund ownership, because green stocks are associated with lower expected returns in the presence of information acquisition. In contrast, the negative return predictability of ESG ratings does not hold for the remaining firms. The high-Green-IO, high-ESG stocks generate a significant CAPM alpha of -0.280% per month and underperform the high-Green-IO, low-ESG stocks by 0.578% per month, while other high-ESG stocks deliver a higher payoff.

In a similar double-sort setting, first by brown fund ownership and then by stock ESG ratings, we document a significantly negative ESG-return relation among stocks with low brown fund ownership, and the negative return predictability of ESG ratings can be attributed to the outperformance of brown stocks. The negative return predictability of ESG ratings does not hold for most remaining firms. The low-Brown-IO, low-ESG stocks generate a significant CAPM alpha of 0.423% per month and outperform low-Brown-IO, high-ESG stocks by 0.569% per month, while other low-ESG stocks deliver a lower payoff.

Considering the implied cost of capital (ICC) as an alternative proxy for expected return, we confirm that green stocks exhibit lower ICC than brown stocks in both subperiods. Notably, the negative ESG-ICC relation is more pronounced among stocks with high green fund ownership and low brown fund ownership. Among high-Green-IO (low-Brown-IO) stocks, green stocks display 0.149% and 0.108% (0.061% and 0.078%) lower ICC per month than brown stocks in the first and second subperiods, respectively. The ICC spread between green and brown stocks is smaller in absolute magnitude and often statistically insignificant for the remaining firms. Overall, the empirical evidence supports the prediction that information decisions deepen (weaken) the negative ESG-return relation for green (brown) assets.

The empirical findings about price informativeness are also consistent with the proposed equilibrium. Stocks with substantial departure from green neutrality and those held by funds with more heterogeneous ESG preferences display higher price informativeness. To illustrate, a one-standard-deviation increase in the departure from green neutrality (heterogeneity in

ESG preferences) is associated with 26.3% (41.4%) higher price informativeness in the next year. The effects are also robust for longer horizons. Thus, sustainable investing not only provides capital to green firms but also improves the efficiency of the financial market due to information acquisition. The overall evidence supports the notion that asset managers consider ESG motives in making their information and portfolio policies, which subsequently affect the cross-section of asset prices and price informativeness of the financial market.

Beyond the empirical tests, we conduct calibration exercises to further quantify the model implications. We show that an ESG-perceptive fund encounters a large certainty equivalent loss if enforced to adopt the information decision and portfolio strategy that are optimal for an ESG-indifferent fund. The utility loss is exclusively attributed to the loss of nonpecuniary, rather than monetary, benefits. Second, by using the industry-wide information acquisition cost as a proxy for the size of the active fund industry, we find that the total information cost increases considerably due to ESG motives. Looking forward, the scope of the active management industry could grow with greater dispersion in the sustainability profiles of investable assets or higher dispersion in the preferences for sustainable investing.

This paper contributes to several strands of the literature. First, we further develop the information acquisition literature. Grossman and Stiglitz (1980) consider informed and uninformed agents who trade for their own accounts. Ross (2005) recognizes the possibility that the informed could offer wealth management services to the uninformed. That insight is adopted by Garcia and Vanden (2009) and Gârleanu and Pedersen (2018). Our framework is more closely related to Kacperczyk et al. (2016), who study the rational attention allocation of mutual funds. For instance, we follow their innovative approach that information decisions focus on risk factor payoffs. However, there are differences in the overall model and focus. In our setting, information is costly to acquire while equilibrium obtains when the marginal cost of information pars with the marginal benefit. Moreover, we emphasize the implications of ESG motives for both the active fund industry and the intermediary asset pricing.

Second, the paper is also associated with the growing literature on the asset pricing implications of sustainable investing. While theoretical work makes the premise that ESG-perceptive investors are willing to sacrifice financial payoffs for nonpecuniary benefits (e.g., Heinkel et al., 2001; Berk and van Binsbergen, 2021; Pástor et al., 2021; Pedersen et al., 2021; Avramov et al., 2022; Goldstein et al., 2022), there is mixed empirical evidence based on different ESG proxies (e.g., Gompers et al., 2003; Hong and Kacperczyk, 2009; Edmans, 2011; Bolton and Kacperczyk, 2021; Pedersen et al., 2021). Our model identifies a novel effect of sustainable investing: green firms can benefit from a lower cost of capital due to (i) the nonpecuniary benefits of holding green stocks, as proposed in prior literature and (ii) lower risk due to the information acquired by ESG-perceptive mutual funds. Thus, greener firms can make more socially responsible investments and generate higher social impact. Our empirical results confirm this prediction and show that the negative ESG-return relation mostly characterizes stocks with high green fund ownership and low brown fund ownership.

Finally, the paper is related to recent work on sustainable investing by institutional investors (e.g., Amel-Zadeh and Serafeim, 2018; Dyck et al., 2019). While existing work focuses on ESG scores as the driving force of sustainable investing, we expand this line of research by considering the departure of asset ESG attributes from green neutrality and the departure of fund ESG preferences from the aggregate. Both quantities are motivated in equilibrium, and supported by empirical tests based on a comprehensive sample of funds.

The remainder of this paper proceeds as follows. Section 2 presents the model. Section 3 describes the data. Section 4 empirically examines how ESG motives affect mutual fund investments. Section 5 tests the implications for individual stocks. Section 6 calibrates the model and explores its quantitative implications. The conclusion follows in Section 7.

2 Model

2.1 The economy

We start with the supply side of the economy. Following Kacperczyk et al. (2016), there are N investable risky assets whose payoffs load on N risk factors. The asset payoffs are formulated as

$$\begin{cases} f_i = \mu_i + b_i z_N + z_i, \quad i \in \{1, \dots, N-1\} \\ f_N = \mu_N + z_N, \end{cases} \tag{1}$$

where f_i, μ_i, and z_i, are the realized payoff, the expected value of the payoff, and the corresponding (demeaned) risk factor payoff, respectively. The N-th security represents a composite asset with a payoff that is driven only by the aggregate risk factor, where the mean payoff is given by μ_N and the shock is represented by z_N. The slope coefficient b_i stands for the asset exposure to the aggregate risk factor. It is assumed that $z_i \sim \mathcal{N}(0, \sigma_i)$

for both the individual and the composite assets, and moreover the shocks are uncorrelated.

Information decisions focus on risk factor payoffs. The risk factor supply is modeled as $\bar{\mathcal{X}}_i + \mathcal{X}_i$, where $\bar{\mathcal{X}}_i$ is the mean supply and $\mathcal{X}_i$ is assumed to obey the normal distribution, $\mathcal{X}_i \sim \mathcal{N}(0, \sigma_{\mathcal{X}})$. The random supply formulation aims to preclude the possibility that asset prices fully reveal the private signals. Then, there is a wedge in asset valuations across agents.[2] Considering the universe of investable assets, the implied supply is $\bar{x}_i + x_i$, where $\bar{x}_i = \bar{\mathcal{X}}_i - b_i \bar{\mathcal{X}}_N$ is the mean supply and x_i is a random draw from the normal distribution with zero mean and variance equal to $\sigma_{\mathcal{X}}(1 + b_i^2)$. To ease notation, the gross interest rate and the mean supply of each of the risk factors are all normalized to unity, while the Online Appendix A re-derives the setting for a generic interest rate and mean supplies.

From the perspective of sustainable investing, each of the risky assets has exogenous ESG attributes represented by the score g_i. Green (brown) assets have positive (negative) ESG scores. The ESG profile of the i-th risk factor is then given by $\mathcal{G}_i = g_i - b_i g_N$ for $i \neq N$ and $\mathcal{G}_N = g_N$. We assume that the composite asset is green neutral, namely, $g_N = 0$. Then, the ESG profile of the i-th risk factor is identical to that of the i-th risky asset, that is, $g_i = \mathcal{G}_i$. Empirically, the true color of the market is unobserved, and moreover, corporate ESG ratings are ordinal in nature. Thus, it is innocuous to assume that the composite asset indicates the cutoff between green and brown investments. To distill the incremental implications of sustainable investing, we remain agnostic about the possible dependencies between the asset ESG score and other attributes known to predict the cross-section of expected returns.

Moving to the demand side, it is assumed that the economy is populated by a continuum of risk-averse optimizing agents, which are indexed by j. As we show later in the text, in equilibrium, some agents are active funds, while others are passive funds or households. Each agent can purchase up to N costly signals about the random risk factor payoffs. A signal for an asset-agent pair is modeled as

$$\eta_{ij} = z_i + \varepsilon_{ij}, \qquad \varepsilon_{ij} \sim \mathcal{N}\left(0, S_{ij}^{-1}\right), \tag{2}$$

where S_{ij} denotes the signal precision of risk factor i, optimally selected by agent j. Following the literature, the cross-agent average of ε_{ij} is assumed to be zero for each of the risk factors.

[2] Random supply can be motivated through the presence of noise traders, trading triggered by life-cycle liquidity forces, and lack of perfect knowledge of the market structure. See, e.g., Admati (1985).

It is further assumed that individual agents have mean-variance preferences, which are given by

$$U_j\left(W_j, G_j, S_{1j}, S_{2j}, \ldots, S_{Nj}\right) = \mathrm{E}\left[W_j\right] - \frac{\rho}{2}\mathrm{Var}\left[W_j\right] + \delta_j \mathrm{E}\left[G_j\right], \tag{3}$$

where ρ is the risk aversion parameter, δ_j represents the preference for holding green assets (with a higher value reflecting stronger preference), $G_j = \sum_{i=1}^{N} q_{ij} g_i$ is the ESG score of the portfolio, q_{ij} denotes the portfolio position for the asset-agent pair, W_j stands for the agent's terminal wealth that satisfies the budget constraint $W_j = W_{0j} + \sum_{i=1}^{N} q_{ij}\left(f_i - p_i\right) - \sum_{i=1}^{N} c_{ij}\left(S_{ij}\right)$, p_i is the price of the risky asset, and $\sum_{i=1}^{N} c_{ij}\left(S_{ij}\right)$ is the total cost of information acquisition, with $c_{ij}\left(S_{ij}\right)$ standing for the cost per risk factor i. The ESG preference parameter δ_j is assumed to be nonnegative and strictly positive for a nonzero measure of the agents in the economy. The term $\delta_j \mathrm{E}\left[G_j\right]$ represents the expected nonpecuniary benefits from ESG investing. The expectation operator appears because the portfolio weights are formed based on random realizations of signals and asset supplies.

Accounting for ESG preferences directly in the investors' utility function is motivated by Pástor et al. (2021) in their study of ESG equilibrium. In addition, ESG preferences are likely to vary across different types of investors. For instance, Avramov et al. (2022) show that norm-constrained institutions such as pension funds favor green stocks, while hedge funds invest more heavily in brown stocks.

We turn to modeling the cost of information acquisition. The cost function reflects stock picking skills and is given by a continuous function $c_{ij}\left(s\right)$ defined for $s \geq 0$, where $c_{ij}\left(0\right) = 0$. As in Verrecchia (1982), the cost is assumed to be increasing and convex in the signal precision s. Furthermore, the signal precision S_{ij} is assumed to be nonnegative; thus, it is infeasible to forget information about one risk factor to enhance the set of information about other factors (see also Van Nieuwerburgh and Veldkamp, 2009, 2010).

The cost function is agent-dependent because distinct agents may possess various degrees of information processing skill. This is supported by the empirical evidence (e.g., Chevalier and Ellison, 1999; Berk and van Binsbergen, 2015; Gerakos et al., 2021) and considered in the equilibrium setting of Gârleanu and Pedersen (2018). The cost is also stock-specific, which is consistent with the notion that fund managers can gain an informational advantage about specific firms through industry expertise (Kacperczyk et al., 2005; Avramov and Wermers, 2006), the information flows within financial conglomerates (Irvine et al., 2006; Massa and Rehman, 2008), and social connections (Cohen et al., 2008). From the perspective of sustainability investing, in the absence of compelling evidence on how the information cost (or managerial skill) varies with the fund's tendency to hold green assets or with the ESG profile of an investable asset, we remain agnostic about such potential dependencies.

While the overall setting is static, the actions and realizations appear in a sequence that spans four periods. In period 0, agents are endowed with both the initial wealth and the cost function.[3] In period 1, each agent undertakes an information acquisition decision that translates into the precision of multiple signals with respect to the risk factor payoffs. As we show below, information decisions depend on both the ESG profile of the particular asset and the agent-specific cost function and preference for holding sustainable assets. Signals are realized at the end of period 1. In period 2, optimal portfolios are formed based on moments that condition on the signals, and the asset prices and trading volumes are set. In period 3, asset payoffs are delivered and utilities are realized. In the following, we provide the details.

2.2 Active asset management when ESG matters

We derive the equilibrium prices and optimal signals through backward induction. We first formulate the portfolio allocation in period 2 conditional on the optimal signal realized in period 1, and then solve for information acquisition decisions in period 1.

In period 2, each of the optimizing agents chooses the portfolio that maximizes the mean-variance utility

$$U_{2j}\left(W_j, G_j, S_{1j}, S_{2j}, \dots, S_{Nj}\right) = \mathrm{E}_{2j}\left[W_j\right] - \frac{\rho}{2}\mathrm{Var}_{2j}\left[W_j\right] + \delta_j G_j, \tag{4}$$

subject to the budget constraint, where $\mathrm{E}_{2j}[.]$ and $\mathrm{Var}_{2j}[.]$ denote the expectation and variance conditional on the information available in period 2 including the realizations of the signals acquired in period 1, respectively.

The period-2 prices are set by market clearing: the sum of the individual stock (risk factor) positions is equal to the supply of stocks (risk factors). The proposition below provides the details (the proof is shown in Online Appendix A.1).

[3]For perspective, in Grossman and Stiglitz (1980), agents are ex ante identical. Then, a fraction of agents purchases information, and this fraction is set in equilibrium, such that the expected utility of the informed is equal to that of the uninformed. In Hellwig (1980), and a large body of follow-up work, agents are endowed with varying degrees of information; hence, some agents have informational advantages over others, ex ante. In our setting, informational advantages come into play through a more favorable cost function.

Proposition 1. *The price of a risky asset is given by*

$$p_i = \underbrace{\mu_i + \zeta_i z_i + b_i \zeta_N z_N - \rho\left(\bar{\sigma}_i + b_i \bar{\sigma}_N\right)}_{\text{cross-agent risk-adjusted posterior payoff}} \\ \underbrace{- \rho\left(\frac{\zeta_i}{\bar{S}_i} x_i + b_i\left(\frac{\zeta_i}{\bar{S}_i} + \frac{\zeta_N}{\bar{S}_N}\right) x_N\right)}_{\text{random supply component}} + \underbrace{\bar{\delta}_i g_i}_{\substack{\text{nonpecuniary}\\ \text{motives}}}, \tag{5}$$

where $\bar{S}_i = \int_j S_{ij} \mathrm{d}j$ represents the cross-agent average signal precision per risk factor i, $\bar{\delta}_i = \bar{\sigma}_i \int_j \hat{\sigma}_{ij}^{-1} \delta_j \mathrm{d}j$ is the aggregate asset-specific ESG preference, $\hat{\sigma}_{ij}^{-1} = \sigma_i^{-1} + S_{ij} + \sigma_{pi}^{-1}$ stands for posterior payoff precision, as perceived by agent j, $\bar{\sigma}_i^{-1} = \sigma_i^{-1} + \bar{S}_i + \sigma_{pi}^{-1}$ is the corresponding cross-agent average, $\zeta_i = \frac{\bar{S}_i + \sigma_{pi}^{-1}}{\bar{\sigma}_i^{-1}}$ is the fraction of the posterior payoff precision attributed to the price and private signals, and $\sigma_{pi}^{-1} = \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}}}$ is the precision of the price signal.

The asset price increases with the cross-agent posterior payoff, adjusted for risk, while it diminishes with the random supplies of the asset-specific and aggregate risk factors, x_i and x_N. From the perspective of sustainable investing, the green (brown) asset price rises (falls) with the nonpecuniary motives. Indeed, the stock ESG profile and the preferences for holding green assets are important determinants of the cross-section of asset pricing and price informativeness, which we comprehensively analyze in Subsections 2.4 and 2.5, respectively. At this stage, we focus on understanding active management when ESG matters.

We proceed by deriving the optimal information decisions. In period 1, each agent chooses the precision of multiple signals to maximize[4]

$$U_{1j}\left(W_j, G_j, S_{1j}, S_{2j}, \ldots, S_{Nj}\right) = \mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[W_j\right] - \frac{\rho}{2}\mathrm{Var}_{2j}\left[W_j\right] + \delta_j G_j\right]. \tag{6}$$

The proposition below, which we prove in Online Appendix A.2, describes the signal precision for the asset-agent pair that maximizes the expected utility in period 1.

Proposition 2. *The optimal signal precision S_{ij} is given by*

$$S_{ij} = \max\left[0, s | c_{ij}'(s) = \psi_{ij}\right], \tag{7}$$

[4] Van Nieuwerburgh and Veldkamp (2010) show that maximizing $\mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[W_j\right] - \frac{\rho}{2}\mathrm{Var}_{2j}\left[W_j\right]\right]$ is equivalent to maximizing the time-1 expectation of the time-2 certainty equivalent for an investor endowed with constant absolute risk aversion utility, i.e., $\mathrm{E}_{1j}\left[-\rho^{-1}\log\left(\mathrm{E}_{2j}\left[e^{-\rho W_j}\right]\right)\right]$.

where the pre-cost marginal benefit of information acquisition is

$$\psi_{ij} = \frac{1}{2\rho}\left(\bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\sigma}_i + \left(\delta_j - \bar{\delta}_i\right)g_i\right)^2\right). \tag{8}$$

Equilibrium information decisions are obtained as the solution to a fixed-point problem. The signal precision in Equation (7) depends on the marginal benefit of information in Equation (8), which in turn depends on the aggregate signal precision via $\bar{S}_i$, $\bar{\sigma}_i$, and $\bar{\delta}_i$.

For some agents, the equilibrium marginal benefit exceeds the marginal cost of buying an infinitesimal unit of information, $c'_{ij}(S_{ij})$, for at least one risk factor. These agents would purchase a strictly positive amount of information, inversely associated with the convexity of their cost function. For other agents, the benefit-cost gap is nonpositive for all risk factors. These agents remain uninformed. The agents purchasing information are active mutual funds, while the uninformed are the households or the passive mutual funds.

As evident from Equations (7) and (8), beyond the essential (positive) dependence of the signal precision on managerial skills, information decisions also vary with the asset sustainability profile as well as with the individual and aggregate preferences for sustainable investing. ESG motives come into play through the $\left(\delta_j - \bar{\delta}_i\right)g_i$ term in Equation (8). Intuitively, ESG-perceptive mutual funds ($\delta_j > \bar{\delta}_i$) attribute higher valuations to green assets. Thus, they would make information decisions to improve their knowledge about green asset payoffs. Conversely, ESG-indifferent funds ($\delta_j < \bar{\delta}_i$) would be reluctant to pay the extra premium associated with green investing. Thus, they are likely to specialize in brown stocks, which incentivizes costly searches for brown asset payoffs. We formalize this intuition below.

For the remainder of this subsection, to analyze the implications of ESG motives for signal precisions, we control for managerial skills by considering a cost function that is identical across stocks and agents, and further make several simplifying assumptions. It is first assumed that the information cost is proportional to the square of the signal precision, i.e., $c_{ij}(s) = \kappa s^2$ with $\kappa > 0$. This cost function implies that each individual agent purchases information in equilibrium. It is then assumed that asset payoffs have identical posterior variances ($\sigma_i = \bar{\sigma}$) and the aggregate ESG preferences are identical across assets ($\bar{\delta}_i = \bar{\delta}$).

Then, let $\hat{\bar{S}}_{ESG}$ be the component in the average (across agents and assets) signal precision, $\hat{\bar{S}} = \sum_{i=1}^{N}\left(\int_j S_{ij}\mathrm{d}j\right)$, explicitly associated with ESG considerations. It follows that (the derivation is shown in Online Appendix A.3):

$$\hat{\hat{S}}_{ESG} = \frac{\sigma_\delta \sigma_g}{4\kappa\rho}, \tag{9}$$

where σ_δ denotes the cross-agent variance of ESG preferences and σ_g stands for the cross-stock variance of ESG scores. The analysis suggests that ESG motives contribute to the overall size of the active fund industry, as they lead mutual funds to purchasing incremental information in equilibrium. ESG-induced information acquisition only applies in the presence of cross-asset dispersion in ESG attributes and cross-fund dispersion in ESG preferences. The incremental information positively interacts with managerial skills. In particular, when the fund managers are more skilled (lower κ), the ESG-induced signal precision improves.

We also attempt to study how the fund signal precision varies with the fund ESG preference and how the asset signal precision varies with the asset ESG profile. The fund signal precision is defined as the cross-asset average of the signal precision, $\hat{S}_j = \frac{1}{N}\sum_{i=1}^{N} S_{ij}$, and the asset signal precision, $\bar{S}_i$, is defined in Proposition 1.

We show in Online Appendix A.4, that the sensitivity of the fund signal precision to the departure of its ESG preference from the aggregate, $\left|\delta_j - \bar{\delta}\right|$, is given by

$$\frac{\partial \hat{S}_j}{\partial \left|\delta_j - \bar{\delta}\right|} = \xi_F \sigma_g \left|\delta_j - \bar{\delta}\right|, \tag{10}$$

where $\xi_F = (2\rho\kappa)^{-1} > 0$. Thus, in the presence of cross-asset dispersion in the ESG profile ($\sigma_g > 0$), the departure of the fund ESG preference from the aggregate determines the sensitivity of the signal precision to the preference for holding green stocks. As the preference of an above-average ESG-perceptive investor rises, the average signal precision improves. Likewise, for a below-average ESG investor, as the preference for ESG investing diminishes, the average signal precision also improves.

The tractability of the derivative expression in Equation (10) is useful for illustrating how accounting for potential heterogeneities in managerial skills affects the implications of ESG motives for an individual fund. In particular, consider two funds with identical preferences (above the aggregate) for holding green stocks but different skills in stock picking. It follows that the more skilled (lower κ) fund would further improve the signal precision of green asset payoffs due to ESG motives.

Next, the sensitivity of the asset signal precision to the departure of the asset ESG score from green neutrality, $|g_i|$, is given by (Online Appendix A.5 provides the details)

$$\frac{\partial \bar{S}_i}{\partial |g_i|} = \xi_{Ai} \sigma_\delta |g_i|, \tag{11}$$

where $\xi_{Ai} = \left(\rho\kappa + \left(\left(\rho^2 (1 + \sigma_{\mathcal{X}}) + \bar{S}_i\right)\left(1 + \frac{2\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}}}\right)\bar{\sigma}_i + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}}}\right)\bar{\sigma}_i^2\right)^{-1} > 0$ for all assets. That is, in the presence of cross-fund dispersion in ESG preferences ($\sigma_\delta > 0$), the signal precision increases with the asset's departure from green neutrality (either green or brown). Thus, signal precisions would improve for assets that display more extreme ESG attributes.

In summary, ESG-perceptive funds attribute higher valuations to green assets. Thus, they acquire more information about green stocks and less about brown. Conversely, ESG-indifferent funds are likely to specialize in brown stocks, and they conduct more costly searches for brown asset payoffs and less for green. Still, the overall information purchased in equilibrium increases due to ESG motives, while the signal precision improves more strongly for assets whose ESG profiles display more substantial deviation from the average.

2.3 Stock holdings, tracking error, and performance

The mutual fund preference for ESG investing also affects its (i) stock holdings, (ii) tracking error, and (iii) net payoff in excess of the market. First, we describe the optimal portfolio and its expected ESG profile (the proof is shown in Online Appendix A.6).

Proposition 3. *The expected ESG tilt of the fund's optimal portfolio relative to the market is given by*

$$\mathrm{E}\left[q_{ij} - \bar{q}_i\right] = \Delta S_{ij} \bar{\sigma}_i + \left(\bar{\sigma}_i^{-1} + \Delta S_{ij}\right) \frac{\Delta \delta_{ij}}{\rho} g_i, \qquad i = 1, \ldots, N-1 \tag{12}$$

$$\mathrm{E}\left[q_{Nj} - \bar{q}_N\right] = \Delta S_{Nj} \bar{\sigma}_N - \sum_{i=1}^{N-1} b_i \mathrm{E}\left[q_{ij} - \bar{q}_i\right], \tag{13}$$

where $\bar{q}_i = \int q_{ij} \mathrm{d}j$, $\Delta\delta_{ij} = \delta_j - \bar{\delta}_i$, *and* $\Delta S_{ij} = S_{ij} - \bar{S}_i$. *The expected ESG score of the portfolio is*

$$\mathrm{E}\left[G_j\right] = \sum_{i=1}^{N-1} \left(\Delta S_{ij} \bar{\sigma}_i g_i + \left(\bar{\sigma}_i^{-1} + \Delta S_{ij}\right) \frac{\Delta \delta_{ij}}{\rho} g_i^2\right). \tag{14}$$

The first component in Equations (12) and (13) reflects the notion that agents overweight assets characterized by signals that are more precise than the average ($\Delta S_{ij} > 0$). Then, per Equation (12), agents who are more ESG perceptive than the average ($\Delta\delta_{ij} > 0$) overweight green assets. The degree of overweighting increases with the total signal precision, $\bar{\sigma}_i^{-1} + \Delta S_{ij}$. Agents with $\Delta\delta_{ij} < 0$ would implement the opposite strategy, underweighting green assets. Turning to the expected ESG profile of the optimal portfolio in Equation (14), the composition of stocks is obviously greener for ESG-perceptive agents. Importantly, this effect intensifies with increasing precision of the signal (ΔS_{ij}) and with increasing preference for sustainable investing ($\Delta\delta_{ij}$).

To derive an intuitive, more easily interpretable, expression for the expected spread in stock holdings between green and brown funds, we consider the following simplified setting. First, the economy consists of ESG-perceptive and ESG-indifferent funds with preference parameters $\delta_P > 0$ and $\delta_I = 0$, respectively. Second, funds can invest in two assets, green and brown, with scores $g_{gr} = \bar{g} > 0$ and $g_{br} = -\bar{g}$ and with identical posterior variances, i.e., $\bar{\sigma}_{gr} = \bar{\sigma}_{br} = \bar{\sigma}$. Third, for the green asset, the ESG-perceptive fund receives a signal with precision $\bar{S} + \Delta S$, while the ESG-indifferent fund receives a signal with precision $\bar{S} - \Delta S$. For the brown asset, the corresponding signal precisions are $\bar{S} - \Delta S$ and $\bar{S} + \Delta S$. The signal precisions reflect the inference from Proposition 2 that ESG-perceptive (ESG-indifferent) funds acquire more information about green (brown) asset payoffs. Finally, the groups of funds are equal in size. Then, the expected spread in portfolio positions is given by

$$\mathrm{E}\left[q_{grP} - q_{grI}\right] = \frac{\delta_P \bar{g}}{\rho \bar{\sigma}} + \frac{2\Delta S}{\bar{\sigma}^{-1}}. \tag{15}$$

The expected spread consists of two components. The first describes the ratio between two determinants of expected asset returns—the nonpecuniary motive of the ESG-perceptive fund, $\delta_P \bar{g}$, and the monetary item, $\rho\bar{\sigma}$.[5] As the nonpecuniary benefits become more pronounced, the expected portfolio spread increases. The second component describes the cross-fund difference in the signal precision, normalized by the posterior precision. Essentially, ESG-perceptive funds would overweight green stocks with higher signal precision, while underweight brown stocks, with stronger underweighting for lower-volatility stocks.[6]

[5] We derive the components of expected net asset payoffs in the next subsection.

[6] Observe from Equation (15) that the sensitivity of the expected portfolio spread to $\bar{\sigma}$ is $\frac{\partial \mathrm{E}[q_{grP} - q_{grI}]}{\partial \bar{\sigma}} =$

Because our derivations characterize the implications of optimal information and portfolio policies, an essential question arises: do optimal policies of the green and brown funds materially differ? To answer this question, we derive the expected utility loss perceived by an ESG-perceptive fund that is forced to employ the optimal information and portfolio decisions of an ESG-indifferent fund. To our knowledge, Geczy et al. (2021) are the first to assess the utility losses associated with socially responsible investing. Relative to their optimization experiments, we derive the utility loss based on our proposed equilibrium. Notably, the utility losses reported in a large body of past work are based on symmetric information. Then, the value function is evaluated at the deterministic optimal and suboptimal portfolio strategies. The utility loss is the gap between the evaluated utility measures.

With information acquisition, the value function depends on both the precision of multiple signals and the stochastic strategy that conditions on the signal realizations. Given the complexity of the utility loss expression, we leave the technical details to Online Appendix A.7. We assess the utility loss using calibration experiments, and confirm that the expected loss, which is attributable exclusively to nonpecuniary motives, can be substantial. For instance, the loss can exceed 20% of the expected net fund payoff.

As optimal policies could differ significantly, we proceed to derive the implications of ESG motives for dispersion in stock positions, tracking error, and fund performance. The portfolio dispersion is defined as the sum of the squared distances of the individual equity positions relative to the market portfolio: $\text{Disp}_j = \text{E}\left[\sum_{i=1}^{N-1} \left(q_{ij} - \bar{q}_i\right)^2\right]$. The dispersion in portfolio positions induces a tracking error for the optimal portfolio relative to the market. The tracking error is defined as the variance of the difference between the portfolio returns and the market returns: $\text{TE}_j = \text{Var}\left[\sum_{i=1}^{N} \left(q_{ij} - \bar{q}_i\right)\left(f_i - p_i\right)\right]$. The proposition below (the proof is shown in Online Appendix A.8) states the determinants of portfolio dispersion and tracking error.

Proposition 4. *The ESG-induced dispersion of portfolio positions across individual assets*

$-\frac{\delta_P \bar{g}}{\rho \bar{\sigma}^2} + 2\Delta S$, where the first term is negative and strongly dominant for reasonable parameter values. For perspective, according to our calibration results (see Section 6), the first term is equal to -36.82, while the second term is 0.11, leading to $\frac{\partial \text{E}[q_{grP} - q_{grI}]}{\partial \bar{\sigma}} \approx -36.71$.

($i = 1, \ldots, N-1$) is given by

$$\text{Disp}_j = \frac{1}{\rho^2} \sum_{i=1}^{N-1} \left(S_{ij} + \Delta S_{ij}^2 V_{ii} + \left(\rho \bar{\sigma}_i \Delta S_{ij} + \left(\bar{\sigma}_i^{-1} + \Delta S_{ij} \right) \Delta \delta_{ij} g_i \right)^2 \right), \tag{16}$$

where $V_{ii} = \bar{\sigma}_i \left(1 + \left(\rho^2 \sigma_{\mathcal{X}} + \bar{S}_i\right) \bar{\sigma}_i\right)$ is the unconditional variance of the net payoff of risk factor i. The tracking error of the optimal portfolio is given by

$$\text{TE}_j = \frac{1}{\rho^2} \sum_{i=1}^{N} \begin{pmatrix} \left((\rho \bar{\sigma}_i)^2 + V_{ii} \right) S_{ij} + 2 \left(V_{ii} \Delta S_{ij} \right)^2 \\ + \left(2 \rho \bar{\sigma}_i \Delta S_{ij} + \left(\bar{\sigma}_i^{-1} + \Delta S_{ij} \right) \Delta \delta_{ij} g_i \right)^2 V_{ii} \end{pmatrix}. \tag{17}$$

Each asset contributes to portfolio dispersion and tracking error through three components. The first is associated with the signal realization and is present even when agents have identical ESG preferences and identical signal precision (S_{ij}). This is because a random signal realized in period 1, even drawn from the same distribution, governs the optimal portfolio of period 2. The second component is driven by the squared difference between the agent's signal precision and the average market-wide precision, ΔS_{ij}^2. When an agent observes signals that are either more or less precise than the average signal, the optimal portfolio would depart more substantially from the market portfolio. The third component reflects the interaction between the monetary and the nonpecuniary components, where $\rho \bar{\sigma}_i \Delta S_{ij}$ and $\left(\bar{\sigma}_i^{-1} + \Delta S_{ij} \right)$ are risk-based components related to differential signal precision (ΔS_{ij}), and $\Delta \delta_{ij} g_i$ indicates the differential nonpecuniary benefits induced by the differential ESG preference ($\Delta \delta_{ij}$) and ESG profile (g_i).

Then, combining the expressions in Propositions 2 and 4, the analysis shows that portfolio dispersion and tracking error increase when the assets held by the funds depart from green neutrality, when the fund's ESG preference departs from the aggregate, and when the market-wide heterogeneity in ESG preferences widens.

Regarding performance, we compute the excess fund payoff, closely associated with alpha, following Kacperczyk et al. (2016), as $\text{EENP}_j = \text{E} \left[\sum_{i=1}^{N} \left(q_{ij} - \bar{q}_i \right) \left(f_i - p_i \right) \right]$. The proposition below (the proof is shown in Online Appendix A.9) provides the details.

Proposition 5. *The conditional expected net payoff in excess of the market is given by*

$$\text{EENP}_j = \sum_{i=1}^{N} \left(\begin{array}{l} \left(\left(\rho\bar{\sigma}_i - \bar{\delta}_i g_i\right) \bar{\sigma}_i + \frac{1}{\rho} V_{ii} \right) \Delta S_{ij} \\ + \frac{1}{\rho} \left(\rho\bar{\sigma}_i - \bar{\delta}_i g_i\right) \left(\bar{\sigma}_i^{-1} + \Delta S_{ij}\right) \Delta\delta_{ij} g_i \end{array} \right). \tag{18}$$

For perspective, we first consider the case of passive fund management. Abstracting from ESG considerations, the return spread between a passive fund and the market is equal to zero, because $\Delta\delta_{ij} = 0$ and $\Delta S_{ij} = 0$ for all assets and funds. Accounting for ESG preferences, a passive ESG-perceptive fund ($\Delta\delta_{ij} > 0$) would overweight green assets, characterized by an equilibrium expected net payoff, $\rho\bar{\sigma}_i - \bar{\delta}_i g_i$, that is lower. Conversely, brown assets, characterized by a higher expected net payoff, would be underweighted. Thus, the fund would deliver a negative expected excess net payoff. Similarly, a passive ESG-indifferent fund ($\Delta\delta_{ij} < 0$) would generate a positive payoff. The analysis on passive funds reflects inference from the symmetric information setting (e.g., Heinkel et al., 2001; Berk and van Binsbergen, 2021; Pástor et al., 2021; Pedersen et al., 2021; Avramov et al., 2022).

In the presence of managerial skills, an active ESG-perceptive fund can either underperform or outperform the market, depending upon the strength of its skills. In other words, the incremental positive expected return due to managerial skills, captured by the first term in Equation (18), can partially or fully offset the return reduction that is attributable to holding green assets. Moreover, controlling for the amount of information acquired, i.e., fixing ΔS_{ij} across agents and assets, ESG-indifferent funds would deliver higher expected returns relative to ESG-perceptive funds.

We note that Proposition 5 focuses on the expected net payoff in excess of the market, while our calibration experiments, reported below, suggest that the main results also apply to the CAPM alpha. Hence, when evaluating fund performance in the presence of ESG motives, a higher alpha may not indicate superior managerial skills. Instead, higher alpha might merely point to an ESG-indifferent fund specializing in higher expected return brown stocks.

In fact, in the presence of information decisions, a long-short ESG-based asset pricing factor may not eliminate the negative alpha spread between ESG-perceptive and ESG-indifferent funds that are equally skilled. To illustrate this point, we again consider the simplified setting that forms the basis for Equation (15). Then, the spread in expected net payoff between equally skilled ESG-perceptive and ESG-indifferent funds is given by

$$\mathrm{EENP}_P - \mathrm{EENP}_I = -\delta_P \bar{g} \left(\frac{\delta_P \bar{g}}{\rho \bar{\sigma}} + \frac{2\Delta S}{\bar{\sigma}^{-1}} \right). \tag{19}$$

The spread in Equation (19) is clearly negative, obtained by scaling the expected portfolio spread in Equation (15) by the nonpecuniary motive. Hence, information acquisition nontrivially affects portfolio strategies, so that the alpha spread between equally skilled ESG-perceptive and ESG-indifferent funds can be nonzero. In particular, controlling for an ESG benchmark that prices passive investments would only capture the first term in Equation (19), while the second term is left unexplained.

2.4 The cross-section of asset payoffs

We are now ready to derive and interpret the cross-section of the expected net stock payoffs. In particular, based on the price equations from Proposition 1, we express the expected net payoffs as follows.

Proposition 6. *The expected net payoffs for the composite and individual assets are*

$$E[f_N - p_N] = \rho \bar{\sigma}_N, \tag{20}$$

$$E[f_i - p_i] = b_i E[f_N - p_N] + \rho \bar{\sigma}_i - \bar{\delta}_i g_i. \tag{21}$$

According to Equation (20), the expected net payoff of the composite asset is equal to the product of the risk aversion and the posterior variance of the payoff, conforming to the CAPM-type representation, except that the valuation varies across agents, depending on the amount of information purchased about the composite asset.[7]

Turning to individual stocks, Equation (21) formulates the cross-section of the expected net payoffs in the presence of information acquisition and ESG motives. It extends Equation (6) in Pástor et al. (2021) by considering financial intermediaries who might have preferences

[7]Equation (20) assumes that the market is green neutral. As highlighted in Avramov et al. (2022), in a symmetric-equilibrium framework, when the market is not green neutral, there is an incremental component in the expected net payoff to capture the utility of holding a green market (negative contribution to the expected payoff) or the disutility of holding a brown market (positive contribution to the expected payoff).

for holding green assets. The presence of intermediaries modifies the asset pricing equation in two ways. The first is the asset-specific expected nonpecuniary payoff, captured by $\bar{\delta}_i g_i$. Specifically, $\bar{\delta}_i$ represents the weighted average of individual agents' preferences for sustainable investing, with weights reflecting the precision of the posterior distribution of the payoff. As ESG-perceptive agents are likely to acquire more information about green assets, higher precision is associated with higher δ_j values for green assets. This suggests that $\bar{\delta}_i$ and g_i are positively correlated, reinforcing the negative relation between the ESG profile and the expected net payoff due to the nonpecuniary benefits from green assets. For brown assets, a negative relation also holds, but it is weakened relative to the symmetric information case, as $\bar{\delta}_i$ diminishes when the asset becomes browner.

Second, the expected net payoff is directly affected by information acquisition decisions through the posterior variance ($\bar{\sigma}_i$). As noted earlier, in the presence of cross-agent heterogeneity in ESG preferences, costly information acquisition is more pronounced for higher values of green and brown, while no incremental acquisition applies to ESG-neutral assets.

Thus, the expected net payoff for green assets is lower due to two forces. The first is associated with the nonpecuniary benefits from holding green investments. The second originates from the lower posterior variance of the payoff of a greener asset, which is attributable to higher signal precision. Hence, the negative relation between the expected net payoff and the ESG rating deepens for green assets.

For brown assets, the two forces work in opposite directions. On the one hand, as the asset becomes browner, its expected payoff becomes higher due to the nonpecuniary channel. On the other hand, the signal precision is higher, triggering a reduced expected payoff.[8] Finally, for ESG-neutral assets, no information acquisition or nonpecuniary benefits are attributed to sustainable investing.

Equation (21) proposes an intermediary-based asset pricing model through the lens of an information acquisition setting. He and Krishnamurthy (2018) suggest that intermediary-based asset pricing builds on the presence of an intermediary sector and a household sector. Some households do not directly invest in some intermediated assets, thus delegating their investments to the intermediary sector. Intermediaries come into play in equilibrium due to

[8]An unreported calibration experiment suggests that, for reasonable parameter values, the nonpecuniary channel dominates. Hence, by integrating through the forces, brown assets earn higher returns on average, and the negative association between the ESG profile and the net expected payoff still applies.

frictions: there is a wedge between the household and intermediary valuations of assets.

Note that the uninformed agents in our setting, the households, do not *explicitly* delegate the informed to trade on their behalf. Instead the informed, the active funds, are proprietary traders. Nevertheless, in the presence of informational heterogeneity, there is a wedge in the valuation of securities between active funds and households. Thus, the informed investors qualify to be intermediaries and moreover, they are likely to be the marginal traders in risky assets.

Addressed from a different perspective, mutual funds in our setting can be viewed as a collection of individuals who collaborate to share the cost of information acquisition. Investing in complex assets requires the acquisition of costly information, making such assets difficult to access for individuals. The possibility of sharing the information cost through the formation of a fund allows pools of individuals to actively participate in trading risky assets. Thus, the households in our setting *implicitly* delegate the active funds to trade on their behalf.

2.5 The cross-section of price informativeness

We conclude the model section by exploring the cross-sectional relationship between price informativeness and the ESG profile. We define the price informativeness for asset i as $\mathrm{PI}_i = \frac{\mathrm{Cov}[f_i, p_i]}{\mathrm{Std}[p_i]}$, following Bai et al. (2016) and Farboodi et al. (2022). The proposition below provides the resulting expression for price informativeness.

Proposition 7. *The price informativeness for asset i is given by*

$$\mathrm{PI}_i = \frac{\sigma_i \zeta_i + b_i^2 \sigma_N \zeta_N}{\sqrt{\left(\sigma_i + \rho^2 \frac{\sigma_{\mathcal{X}}}{\bar{S}_i^2}\right) \zeta_i^2 + b_i^2 \left(\sigma_N + \rho^2 \frac{\sigma_{\mathcal{X}}}{\bar{S}_N^2}\right) \zeta_N^2}}. \tag{22}$$

As we show in Online Appendix A.10, the price informativeness of the risk factor is equal to $\frac{\sigma_i}{\sqrt{\sigma_i + \rho^2 \sigma_{\mathcal{X}} / \bar{S}_i^2}}$. When the average signal precision of the risk factor, $\bar{S}_i$, approaches zero, the risk factor price does not provide any information about the random payoff. In addition, price informativeness monotonically increases with the average signal precision, converging to $\sqrt{\sigma_i}$ as $\bar{S}_i$ grows arbitrarily large. Considering the price informativeness of a risky asset, rather than that of a risk factor, the variation with the signal precision is based on a rather complex expression that we analyze through calibration and report later in the text. We confirm the intuition that price informativeness grows when the average signal becomes more precise.

Because the signal precision depends on the various components analyzed earlier, the price informativeness improves for assets whose color departs (in both ways) from green neutrality and whose mutual fund investors display more heterogeneous ESG preferences.

In what follows, we take the model to data. As elaborated in the introduction, the model generates several testable predictions for both mutual funds and individual stocks. We empirically test the model predictions and further use calibration to assess some quantitative implications.

3 Data

3.1 Data sources

The sample of mutual funds consists of all U.S. actively managed equity mutual funds. Quarterly institutional equity holdings are acquired from the Thomson-Reuters mutual fund holdings database. The database contains quarter-end security holding information for all registered mutual funds that are required to report their holdings to the U.S. Securities and Exchange Commission (SEC). We match the holdings database with the Center for Research in Security Prices (CRSP) mutual fund database, which reports monthly net-of-fee returns and total net assets (TNAs), as well as other quarterly fund characteristics, such as the turnover and the expense ratio. We consolidate multiple share classes into portfolios by adding together share-class TNAs and by value weighting share-class characteristics (e.g., returns, fees) based on lagged share-class TNAs.

Equity funds are identified based on the objective codes from the CRSP following Kacperczyk et al. (2008). We exclude funds identified by the CRSP "index_fund_flag" as index funds as well as funds whose name contains the following strings: "INDEX", "IDX", "IX", "INDX", "NASDAQ", "DOW", "MKT", "DJ", "S&P", "500", "BARRA", "WILSHIRE", and "RUSSELL". The sample is further restricted to funds that have TNA of at least $15 million to avoid the survivorship bias problem (see, e.g., Elton et al., 1996; Pástor et al., 2015), and we exclude observations prior to the fund's starting date reported by CRSP to prevent incubation bias (Evans, 2010). The mutual fund benchmark is defined based on the Primary Prospectus Benchmark from the Morningstar mutual fund database.

The stock sample consists of all NYSE/AMEX/Nasdaq common stocks with share codes 10 or 11; daily and monthly stock data are obtained from the CRSP database. We collect monthly ESG rating data from three data vendors: MSCI KLD, MSCI IVA (also known as MSCI ESG Ratings), and Sustainalytics. These data providers represent the major players in the ESG rating market, and their ratings are widely used by both practitioners and a growing number of academic studies (e.g., Eccles and Stroehle, 2018). Quarterly and annual financial statement data come from the COMPUSTAT database. Analyst forecast data are provided by the Institutional Brokers' Estimate System (I/B/E/S).

The full sample spans the period 2001 through 2019. The sample begins in 2001 when MSCI KLD expanded coverage to Russell 1000 firms (Nofsinger et al., 2019) and institutional investors display a growing preference for ESG investing during that period (Starks et al., 2020). The final sample contains 4,761 unique equity funds and 5,744 unique stocks. On average, there are 2,084 funds and 2,235 stocks per month.

3.2 Main variables

We start with the firm-level ESG rating from each data provider. For the MSCI KLD data, we construct an aggregate ESG rating by summing all strengths and subtracting all concerns (e.g., Lins et al., 2017). Since the MSCI KLD data end in 2016, we complement them with the "ESG Rating" from MSCI IVA and "Total_ESG_Score" from Sustainalytics.[9] ESG rating agencies can differ in terms of their rating scale, e.g., MSCI KLD rating ranges from -11 to $+19$ in our sample, MSCI IVA uses a seven-tier rating scale from the best (AAA) to the worst (CCC), and Sustainalytics applies a scale from 0 to 100. To achieve comparability across the rating agencies, we proceed as follows. For each rater-month, we sort all stocks according to the original rating scale of the respective data provider and calculate the percentile rank (normalized between -0.5 and 0.5) for each stock-rater. Then, for each stock, we compute the average rank across all raters to obtain the firm-level ESG rating, labeled *Stock ESG*.[10]

[9] Our MSCI KLD, MSCI IVA, and Sustainalytics samples extend from 2001 to 2016, 2006 to 2019, and 2009 to 2019, respectively. Each data vendor covers an average of 2,242, 1,457, and 1,199 firms per month, respectively, during the sample period.

[10] Using the average rank allows us to examine a longer sample period and a larger number of firms. It also mitigates the concern that our results could be driven by the idiosyncrasies in a specific ESG rating,

Next, we define the fund-level ESG rating as the investment value-weighted average of *Stock ESG* in a fund's most recently reported holding portfolio, labeled *Fund ESG*. To capture the heterogeneous ESG preferences among mutual funds in stock investment, the dispersion in ESG preferences for a stock, labeled *Stock ESGDisp*, is defined as the standard deviation of the fund ESG rating of all funds that hold that stock. The standard deviation is investment value-weighted to account for the relative importance of individual mutual funds' ESG preferences.[11] Online Appendix Table B.1 provides a detailed definition for each variable.

3.3 Summary statistics

We report the summary statistics in Table 1. Panel A reports the means, medians, standard deviations, and quantile distributions of the monthly stock ESG ratings, rating dispersion, and other stock characteristics. The average stock ESG rating is -0.006 with a standard deviation of 0.253.[12]

Panel B reports similar statistics for the fund characteristics. Notably, the cross-sectional statistics of the ESG ratings at the fund level are quite similar to those at the stock level. The average fund ESG rating is -0.020 with a standard deviation of 0.271. In addition, the fund ESG is -0.250 at the 25^{th} percentile and 0.202 at the 75^{th} percentile of the distribution, indicating that mutual funds display dispersed preferences in ESG investing. This further motivates us to investigate the role of heterogeneous ESG preferences across funds, in addition to ESG levels such as firm ESG attributes and fund ESG preferences.

given the rating disagreement across different ESG data vendors (e.g., Avramov et al., 2022). In addition, investors may rely on ESG ratings from different data vendors; therefore, the average rating provides an approximate assessment of the perceived ESG profile among investors.

[11]Unreported analyses using equal-weighted standard deviation also confirm our findings.

[12]While we normalize the ESG ratings to be between -0.5 and 0.5 for the entire universe of covered firms, the summary statistics only include stocks used in later analyses that require additional data regarding other firm characteristics. Therefore, the average ESG rating is approximately zero (although not exactly zero), and the distribution of the stock ESG ratings may slightly deviate from a uniform distribution.

4 Mutual fund investment and performance

4.1 Stock holdings

The first prediction generated from the model is that ESG-perceptive (ESG-indifferent) funds overweight green (brown) stocks, and the degree of overweighting increases with the total signal precision (Proposition 3). In particular, the expected difference in portfolio positions between ESG-perceptive and ESG-indifferent funds increases with the stock ESG rating and signal precision and diminishes with return volatility, as formulated in Equation (15). The model predicts that ESG-perceptive funds overweight green stocks, especially those with low volatility. Similarly, ESG-indifferent funds overweight low-volatility brown stocks. In the presence of high volatility or low signal precision, both types of funds demand less risky assets in their preferred investment universe; hence, they are less affected by ESG considerations. Therefore, return volatility should attenuate the positive relationship between the stock ESG rating and the ownership gap, i.e., the difference in portfolio positions between ESG-perceptive and ESG-indifferent funds.

Because mutual funds' ESG preferences are not directly observed, we measure their revealed preferences through the stocks they hold. We identify ESG-perceptive funds as those holding greener assets (labeled green funds) and ESG-indifferent funds as those holding browner assets (labeled brown funds).[13] For each stock, we compute the percentage ownership from green funds and brown funds, as well as the spread between them. We then estimate the following monthly Fama and MacBeth (1973) regression:

$$IO_{i,t} = \alpha + \beta_1 ESG_{i,t-1} + \beta_2 IVOL_{i,t-1} + \beta_3 ESG_{i,t-1} \times IVOL_{i,t-1} + cN_{i,t-1} + \varepsilon_{i,t}, \quad (23)$$

where $IO_{i,t}$ is the mutual fund ownership of stock i in month t, measured by green fund ownership, brown fund ownership, and the difference in ownership between green and brown funds. We identify green (brown) funds as those with a fund-level ESG rating in the top (bottom) quintile across all funds at the end of each month. $ESG_{i,t-1}$ is the ESG rating,

[13] Note that in the model, we separately consider funds' ESG preferences (ESG-perceptive and ESG-indifferent) and portfolio ESG scores (positive for green and negative for brown). In the empirical section, we label ESG-perceptive funds as green funds and ESG-indifferent funds as brown funds for ease of definition. In our context, brown funds are not necessarily averse to ESG investing. They could be ESG-indifferent, thus optimally holding brown stocks due to their superior financial performance.

and $IVOL_{i,t-1}$ is the idiosyncratic volatility. Vector N stacks all other stock-level control variables: the *Log(Size)*, *Log(BM)*, *ROE*, *I/A*, *1M Return*, *12M Return*, *IO*, *Log(Illiquidity)*, *Log(Analyst Coverage)*, and *Analyst Dispersion*. Online Appendix Table B.1 provides a detailed definition for each variable. We also report Newey and West (1987) adjusted t-statistics.

Panel A of Table 2 presents the results. Several findings are worth noting. By construction, the stock ESG rating is positively (negatively) associated with green (brown) fund ownership. Then, consistent with the model prediction, idiosyncratic volatility is negatively related to ownership from both types of funds. A one-standard-deviation increase in $IVOL$ is associated with 23.6% lower green fund ownership in Model 1 and 7.9% lower brown fund ownership in Model 4 (scaled by the sample mean of the corresponding fund ownership).[14] The impact of idiosyncratic volatility (i.e., low signal precision) on mutual fund ownership is economically significant. For perspective, a one-standard-deviation increase in *Stock ESG* is associated with 39.6% higher green fund ownership and 18.1% lower brown fund ownership in Models 1 and 4, respectively (scaled by the sample mean of the corresponding fund ownership). Hence, our findings reinforce the notion that both signal precision and ESG considerations matter for mutual fund portfolio choices.

Next, we show that green (brown) funds invest less in green (brown) stocks in the presence of high idiosyncratic volatility, as implied by the opposite signs of *Stock ESG* and *Stock ESG*$\times$*IVOL* in Model 2 (Model 5). Finally, while the ownership gap between green and brown funds increases with stock ESG ratings (by construction), the positive ESG-ownership gap relation attenuates when idiosyncratic volatility is high (Model 8).

Our findings are also robust to controlling for a comprehensive set of stock characteristics (Models 3, 6, and 9). Consistent with the prior literature (e.g., Liang and Renneboog, 2017; Dyck et al., 2019; Hsu et al., 2022), large, growth firms tend to have better ESG performance and thus attract more green funds. In addition, green funds are more likely to hold stocks with low profitability and past returns, possibly due to their nonpecuniary motives. As expected, brown funds often specialize in stocks with opposite attributes.

In Panel B of Table 2, we replace idiosyncratic volatility with total return volatility

[14]The economic magnitude is computed as $-0.209 \times 1.350/1.198 = -23.6\%$, where -0.209 is the regression coefficient of *IVOL* in Model 1, 1.350 is the standard deviation of *IVOL* (Table 1 Panel A), and 1.198 is the sample mean of *Green IO* (Table 1 Panel A).

and our findings remain intact.[15] For instance, a one-standard-deviation increase in total return volatility ($RETVOL$) is associated with 26.1% lower green fund ownership and 6.7% lower brown fund ownership in Models 1 and 4, respectively (scaled by the sample mean of the corresponding fund ownership). In addition, the positive ESG-ownership gap relation attenuates when total return volatility increases (Model 8).

Overall, our findings support the model prediction that imprecise signals lower investor demand for risky assets, especially in their preferred investment universe. Therefore, mutual fund investment is less affected by ESG considerations when volatility is high. In the presence of unprecedented growth in sustainable investing, our findings highlight the interplay between ESG preferences and information acquisition in shaping the investment practices of active fund management.

4.2 Portfolio dispersion and tracking error

While the previous analysis focuses on mutual fund ownership in individual stocks, we move on to analyzing overall portfolio choices. As shown in Equations (8), (10), and (11), in the presence of heterogeneous ESG preferences across funds, active funds acquire more firm-specific information when the firm's ESG profile departs from green neutrality. This intuition leads to a testable hypothesis: the portfolio dispersion and tracking error increase when funds hold assets with more extreme ESG attributes, as implied by Proposition 4.[16]

To test this hypothesis, we estimate the following monthly Fama and MacBeth (1973) regression:

$$DISP_{j,t} = \alpha + \beta_1 ESGDev_{j,t-1} + cM_{j,t-1} + \varepsilon_{j,t}, \tag{24}$$

where $DISP_{j,t}$ refers to four measures, $HHIBMK_{j,t}$, $TEBMK_{j,t}$, $HHIMKT_{j,t}$, and $TEMKT_{j,t}$. $HHIBMK_{j,t}$ characterizes the portfolio dispersion of fund j in month t, indicating the deviation of the fund's investment strategy from its benchmark portfolio. $TEBMK_{j,t}$ is the tracking error, reflecting the deviation of fund returns from its benchmark portfolio returns. $HHIMKT_{j,t}$ and $TEMKT_{j,t}$ are similar measures that use the market portfolio as

[15] While the idiosyncratic volatility is more aligned with the model setup formulated in Equation (1), we nevertheless consider total volatility in the empirical analyses as a robustness check.

[16] Table 1 Panel B confirms the presence of market-wide heterogeneity in ESG preferences across funds, which is necessary for the model prediction.

a benchmark.[17] To measure the fund-level departure from green neutrality, $ESGDev_{j,t-1}$, we take the absolute value of the fund ESG rating. Vector M stacks all other fund-level control variables: the *Fund Return*, *Fund Flow*, *Log(Fund TNA)*, *Expense Ratio*, *Fund Turnover*, *Log(Fund Age)*, and *Flow Volatility.* We expect to see a positive value of β_1, as the model predicts. Online Appendix Table B.1 provides a detailed definition for each variable. We also report Newey and West (1987) adjusted t-statistics.

We tabulate the results in Table 3. Consistent with the model prediction, the departure from green neutrality is positively associated with portfolio dispersion and tracking error. In particular, a one-standard-deviation increase in *Fund ESGDev* is associated with 37.4% higher portfolio dispersion in Model 1 and 14.0% higher tracking error in Model 2 based on fund-specific benchmarks (scaled by the sample mean of the corresponding dispersion measures).[18] Our findings remain intact when benchmarking against the market portfolio. Specifically, a one-standard-deviation increase in *Fund ESGDev* is associated with 44.5% higher portfolio dispersion in Model 3 and 14.9% higher tracking error in Model 4 (scaled by the sample mean of the corresponding dispersion measures).

Overall, our findings support the model prediction that when mutual funds invest in stocks with more extreme ESG profiles (greater departure from green neutrality), they are more likely to adopt distinct trading strategies and deviate from a passive benchmark, possibly due to their enhanced information acquisition activities.

5 Asset pricing implications

Having shown that ESG considerations affect mutual fund stock holdings, portfolio and return dispersions through their information acquisition decisions, we now investigate how sustainable investing affects stock returns and price informativeness in the cross-section.

[17]Note that Proposition 4 formulates the portfolio dispersion and tracking error using the market portfolio as a benchmark. In the empirical analyses, we also employ a fund-specific benchmark from its prospectus to better capture the active deviations in mutual fund investment.

[18]The impact of portfolio dispersion is computed as $0.167 \times 0.139/0.062 = 37.4\%$, where 0.167 is the regression coefficient of *Fund ESGDev* in Model 1, 0.139 is the standard deviation of *Fund ESGDev* (Table 1 Panel B), and 0.062 is the sample mean of *HHIBMK* (Table 1 Panel B).

5.1 Cross-sectional return predictability

As shown in Proposition 6, the model predicts that the expected return (i) diminishes with the stock ESG rating and mutual funds' ESG preferences and (ii) increases with the posterior variance (inversely related to the signal precision). In addition, green funds acquire more information about green stocks, and brown funds acquire more information about brown stocks, as formulated in Equation (10). On the one hand, high green fund ownership implies more information acquisition and lower variance for green stocks, leading to lower expected returns for green stocks and amplifying the negative ESG-return relation. On the other hand, high brown fund ownership also indicates more information acquisition and lower variance for brown stocks, leading to lower expected returns for brown stocks and weakening the negative ESG-return relation. Taken together, we expect the negative ESG-return relation to be more pronounced among green stocks with high green fund ownership and brown stocks with low brown fund ownership, i.e., when information acquisition and the corresponding posterior variance, the ESG preference, and the ESG rating affect asset prices in the same direction.

The analysis proceeds as follows. At the end of month t, stocks are first sorted into quintiles according to their green fund ownership (*Green IO*). Within each green fund ownership group, stocks are further sorted into quintiles according to their ESG ratings to generate 25 (5×5) portfolios. The low- (high)-ESG-rating and green-fund-ownership portfolios comprise the bottom (top) quintile of stocks based on the ESG rating and green fund ownership, respectively. For each of the 25 portfolios, we compute the value-weighted return in month $t+1$ and rebalance the portfolios at the end of month $t+1$. Within each quintile of portfolios sorted by green fund ownership, we also implement a zero-cost trading strategy by taking long positions in the top quintile of stocks (highest ESG rating) and selling short stocks in the bottom quintile (lowest ESG rating). The payoff of the long-short investment strategy is computed as the high (top quintile) minus low (bottom quintile) portfolio return ("HML-R"), indicating the return predictability of ESG ratings after controlling for information acquisition. We then report the time-series averages of the monthly returns for each of the 25 portfolios and the long-short strategy. Similarly, within each quintile of portfolios sorted by stock ESG ratings, we implement an investment strategy of going long (short) the high- (low)-green-fund-ownership stocks ("HML-G"). Finally, we consider a univariate portfolio sort based on ESG ratings (green fund ownership) and report similar statistics in the column (row) titled "All".

In addition to the raw portfolio returns, we report the risk-adjusted returns from (i) the CAPM, i.e., only adjusting for the market factor (MKT, defined as the excess return on the value-weighted CRSP market index over the one-month Treasury bill rate); (ii) the Fama-French six-factor model (FF6), consisting of the market factor (MKT), the size factor (SMB, defined as small minus big firm return premium), the book-to-market factor (HML, defined as the high book-to-market minus the low book-to-market return premium), the profitability factor (RMW, defined as the robust minus weak return premium), the investment factor (CMA, defined as the conservative minus aggressive return premium), and the momentum factor (MOM) (Fama and French, 2018);[19] and the characteristic-adjusted returns from (iii) the Daniel et al. (1997) model (DGTW), that is, the stock returns are adjusted by the style average, where stock styles are created by triple-sorting stocks into 125 (5×5×5) size, book-to-market, and momentum portfolios. The standard errors in all estimations are corrected for autocorrelation using the Newey and West (1987) method.

One caveat is that while equilibrium asset pricing predicts a negative relation between the ESG rating and *expected* return due to the nonpecuniary benefits of holding green stocks, we only observe ex post *realized* returns. Furthermore, Pástor et al. (2022) document that U.S. green stocks outperformed brown stocks during the last decade, due to an unexpected shift in investors' tastes for green holdings. To ensure that the wedge between expected and realized returns does not distort our findings, we divide the full sample into two subperiods, January 2001–October 2012 and November 2012–December 2019.[20] We expect the results to be stronger in the first subperiod, which provides a cleaner setting to analyze the equilibrium asset pricing implications.

Table 4 reports the results of raw return and CAPM-adjusted return, with Panel A1 for the January 2001–October 2012 subperiod and Panel A2 for the November 2012–December 2019 subperiod. In the interest of brevity, we tabulate the results of FF6-adjusted return and DGTW-adjusted return in Online Appendix Table B.2 and only discuss the main findings in this subsection. Several findings are worth noting. First, the negative ESG-return

[19] We thank Kenneth French for making the common factor returns available via his website: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[20] We split the sample in October 2012 because MSCI's coverage increased dramatically in October 2012, when it began covering small U.S. stocks (Pástor et al., 2022). The ESG ratings reported in October 2012 are used to assess fund performance in November 2012 (the beginning of the second subperiod).

relation only holds among stocks with high green fund ownership during the first subperiod (Panel A1). Specifically, brown stocks (i.e., stocks in the bottom ESG rating quintile) outperform green stocks (i.e., stocks in the top ESG rating quintile) by 0.624% per month in raw return and 0.578% (0.560%, 0.511%) per month in CAPM-adjusted (FF6-adjusted, DGTW-adjusted) return. In contrast, the long-short portfolio ("HML-R") returns as well as the associated risk-adjusted and characteristic-adjusted returns are insignificant for the remaining firms.

Second, the negative ESG-return relation is concentrated in stocks with high green fund ownership because green stocks underperform more in the presence of information acquisition. The high-ESG, high-Green-IO stocks generate a significant CAPM alpha of -0.280% per month, while high-ESG stocks in other Green-IO quintiles deliver higher payoff. This confirms the model prediction that information acquisition makes investment less risky (i.e., with a lower posterior variance), lowering the expected returns.

Third, moving to the more recent subperiod, green stocks outperform brown stocks in CAPM alpha, and the outperformance is also stronger among stocks with high green fund ownership (Panel A2). While our model does not capture the unexpected shift in investors' ESG preferences during this period, green stocks heavily invested in by green funds could be most exposed to this shift in preferences, therefore experiencing more price appreciation and higher realized returns. Indeed, high-ESG, high-Green-IO stocks yield a significantly positive CAPM alpha of 0.300% per month during the second subperiod.

In Panels B1 and B2 of Table 4, we report similar statistics by replacing green fund ownership with brown fund ownership (*Brown IO*). As expected, we find a significantly negative ESG-return relation among stocks with low brown fund ownership during the first subperiod (Panel B1). For instance, the long-short portfolio ("HML-R") generates a monthly return of -0.551% and CAPM-adjusted (FF6-adjusted, DGTW-adjusted) return of -0.569% (-0.555%, -0.515%). Furthermore, the negative return predictability of ESG ratings can be attributed to the outperformance of brown stocks. The low-ESG, low-Brown-IO stocks generate a significant CAPM alpha of 0.423% per month, while low-ESG stocks in other Brown-IO quintiles deliver a lower payoff. Importantly, the long-short portfolio ("HML-R") does not generate a significant payoff for most remaining firms.

Finally, as shown in Panel B2, brown stocks underperform during the more recent subperiod, especially for those heavily invested by brown funds. For instance, low-ESG, high-

Brown-IO stocks deliver a significant CAPM alpha of -0.523% per month, while low-ESG, low-Brown-IO stocks generate an insignificant CAPM alpha. One possibility is that because brown stocks underperform green stocks during this subperiod, brown funds devote less effort to acquiring information about brown stocks and may face divestment pressure, which further drives down the return (rather than offsetting the high return in the original model setup).

In addition to the subperiod analysis, we consider the implied cost of capital (ICC) as an alternative proxy for the expected return. We follow Hou et al. (2012) and the adjustment by Pástor et al. (2022) to compute the ICC for each stock-month, and ICC is the discount rate that equates the stock's market value to the present value of its expected future cash flows.[21]

We repeat the analyses in Table 4 while replacing realized return with ICC during the holding period. Table 5 has a layout similar to Table 4, with Panels A1 and A2 for portfolios sorted by green fund ownership (*Green IO*) and stock ESG ratings and Panels B1 and B2 for portfolios sorted by brown fund ownership (*Brown IO*) and stock ESG ratings. Panels A1 and B1 focus on the January 2001–October 2012 subperiod, and Panels A2 and B2 focus on the November 2012–December 2019 subperiod. As a robustness check, we tabulate the results of FF6-adjusted ICC and DGTW-adjusted ICC in Online Appendix Table B.3.[22]

First, green stocks exhibit lower ICC (DGTW-adjusted ICC) than brown stocks in both subperiods, and the monthly difference in a univariate sort is 0.103% (0.074%) in the first subperiod and 0.052% (0.023%) in the second subperiod. The negative ESG-ICC relation is in line with the nonpecuniary benefits of ESG investing and supports our model setup. Consistent with Pástor et al. (2022), our findings suggest that, compared with the realized return, ICC is a better proxy for the expected return.

Second, as shown in Panels A1 and A2, the negative ESG-ICC relation is more pro-

[21]To obtain the future cash flows, we forecast earnings from the cross-sectional regressions for the first three years ahead. In addition, we assume that the expected return on equity (ROE) mean-reverts to the industry median ROE by the end of year 12 and forecast ROE from year 4 to year 12 using a linear interpolation. The residual income from year 12 onward is regarded as a perpetuity. Details on the ICC estimation can be found in Hou et al. (2012) and the Internet Appendix in Pástor et al. (2022). While the ICC estimated from this approach measures the annualized expected return, we divide it by 12 to obtain monthly ICC. Later, we construct monthly rebalanced portfolios with a one-month holding period.

[22]Note that the results using CAPM- and FF6-adjusted ICCs are qualitatively and quantitatively similar to ICC; therefore, we focus on ICC and DGTW-adjusted ICC when discussing the findings.

nounced among stocks with high green fund ownership. When green fund ownership is low, green stocks display 0.028% (0.036%) and an insignificant 0.019% (0.006%) lower ICC (DGTW-adjusted ICC) per month than brown stocks in the first and second subperiod, respectively. When green fund ownership is high, green stocks display 0.149% (0.105%) and 0.108% (0.055%) lower ICC (DGTW-adjusted ICC) per month than brown stocks in the first and second subperiod, respectively. The monthly difference in ICC (DGTW-adjusted ICC) spread between high- and low-green-fund-ownership portfolios is significant at −0.122% (−0.069%) in the first subperiod and −0.089% (−0.049%) in the second subperiod.

Third, the negative ESG-ICC relation is also stronger among stocks with low brown fund ownership (Panels B1 and B2). When brown fund ownership is low, green stocks display 0.061% (0.066%) and 0.078% (0.043%) lower ICC (DGTW-adjusted ICC) per month than brown stocks in the first and second subperiod, respectively. When brown fund ownership is high, the ICCs for green stocks and brown stocks are no longer significantly different in most cases. The monthly difference in ICC (DGTW-adjusted ICC) spread between high- and low-brown-fund-ownership portfolios is significant at 0.051% (0.042%) in the first subperiod and 0.066% (0.045%) in the second subperiod.

Collectively, consistent with the model prediction, we show that active investors' ESG preferences play a vital role in the cross-section of stock prices beyond the ESG profile of the firm, through their information acquisition decisions. The negative ESG-return relation is mainly confined to stocks with high green fund ownership and low brown fund ownership because information acquisition lowers the perceived riskiness of the stock, which enhances the low expected return for green stocks but offsets the high expected return for brown stocks. Therefore, our findings document a novel beneficial effect of sustainable investing: green firms can enjoy a lower cost of capital due to (i) the nonpecuniary benefits of holding green stocks as proposed in prior literature and (ii) lower risk due to enhanced information acquisition. This allows them to make more socially responsible investments and generate higher social impact.

5.2 Price informativeness

Our model also predicts that price informativeness increases with signal precision (Proposition 7). In addition, signal precision improves when a firm's ESG profile departs from green neutrality and its investors display dispersed ESG preferences, as shown in Equations (8), (10), and (11). Therefore, the model implies higher price informativeness in the presence of (i) a departure from green neutrality and (ii) heterogeneous ESG preferences.

To test the model predictions, we estimate the following annual Fama and MacBeth (1973) regression:

$$\frac{E_{i,y+h}}{A_{i,y}} = \alpha + \beta_1 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) + \beta_2 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) \times ESGDev_{i,y} + \beta_3 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) \times ESGDisp_{i,y} + \beta_4 ESGDev_{i,y} + \beta_5 ESGDisp_{i,y} + \beta_6 Log\left(\frac{E_{i,y}}{A_{i,y}}\right) + cN_{i,y} + \varepsilon_{i,y+h}, \tag{25}$$

where $E_{i,y+h}$ is the earnings before interest and taxes of stock i in year $y+h$, $A_{i,y}$ is the total assets, $M_{i,y}$ is the market capitalization, $ESGDev_{i,y}$ is the departure from green neutrality, and $ESGDisp_{i,y}$ is the stock-level heterogeneity in fund ESG preferences. Vector N stacks all other stock-level control variables: the *IO*, *Log(Asset)*, *Leverage*, *Tangibility*, *Log(Sales)*, *Cash*, *Log(Analyst Coverage)*, and *Analyst Dispersion*. The β_1 coefficient measures the extent to which the current stock market valuation predicts future earnings and proxies for the price informativeness at the market level (Bai et al., 2016). The β_2 and β_3 coefficients capture the incremental effect of departure from green neutrality and heterogeneous ESG preferences, respectively, allowing us to test the model prediction in the cross-section. This empirical specification and the choice of control variables closely follow Kacperczyk et al. (2021). Online Appendix Table B.1 provides a detailed definition for each variable. We also report Newey and West (1987) adjusted t-statistics.

We tabulate the results in Table 6. We focus on the one-year ($h = 1$, Models 1–4), three-year ($h = 3$, Models 5–8), and five-year ($h = 5$, Models 9–12) forecasting horizons. Consistent with the model prediction, the β_2 and β_3 coefficients are positive and statistically significant in all specifications, suggesting that stocks with extreme ESG profiles and those held by investors with heterogeneous ESG preferences display high price informativeness. As shown in Model 2 (Model 3), a one-standard-deviation increase in *Stock ESGDev* (*Stock ESGDisp*) is associated with 26.3% (41.4%) higher price informativeness in the next year.[23] The results are similar for the joint specification (Model 4) and robust for longer horizons

[23] The increase in price informativeness is computed as $(0.027 \times 0.134) / (0.008 + 0.027 \times 0.214) = 26.3\%$, where 0.008 and 0.027 are the regression coefficients of *Log(M/A)* and *Log(M/A)*×*Stock ESGDev* in Model 2, and 0.214 and 0.134 are the sample mean and standard deviation of *Stock ESGDev* (Table 1 Panel A).

(Models 5–12).

The evidence on stock-level price informativeness is in line with our fund-level analyses (Table 3), i.e., in the presence of departure from green neutrality and heterogeneous ESG preferences in aggregate, active mutual funds deviate more from a passive benchmark, possibly due to their enhanced information acquisition activities. In addition, our findings suggest that sustainable investing not only provides capital to green firms so they can generate greater social impact but also has broader implications for the financial market. To optimize the asset allocation with ESG considerations, active funds make information acquisition decisions according to their ESG preferences, firms' ESG profiles, and the heterogeneity in ESG preferences across all market participants. The informed trading from active funds further improves the price efficiency of the stocks in their desired investment universe.

Overall, our empirical results build a compelling case suggesting that sustainable investing plays a prominent role in determining the information acquisition decisions and investment strategies of active mutual funds, the cross-section of asset prices, and the price informativeness of the underlying assets. As more institutions seek sustainable investing, we will likely observe an even more substantial impact in the future.

6 Calibration

We calibrate the model to provide further quantitative perspectives regarding the model implications. The calibration considers an economy consisting of two types of active funds: ESG indifferent ($\delta_I = 0$) and ESG perceptive ($\delta_P > 0$). The latter funds attribute value to holding green assets and they represent a fraction φ of the total mass of agents. Each individual fund is assumed to be atomistic, having no independent impact on equilibrium. There are three types of investable assets, namely, a green asset, a brown asset, and the ESG-neutral composite asset.

The expected monetary payoff of all tradable assets is assumed, without loss of generality, to be equal to one dollar ($\mu_{gr} = \mu_{br} = \mu_{agg} = 1$). The prior variance of the aggregate asset payoff is set to be $\sigma_{agg} = 0.15^2$. Hence, the volatility of the composite asset is 15% of the expected payoff, approximately matching the annualized historical volatility of the U.S. equity market (15.19% during the extended sample period from July 1963 through December

2019). The observed annual equity premium during that period is 6.50%. Based on Equation (20), if the posterior variance $\bar{\sigma}_{agg}$ were equal to the prior variance σ_{agg}, the expected net payoff $\rho\bar{\sigma}_{agg}$ would be equal to 6.75% for $\rho = 3$. We retain the value of three for the risk aversion parameter, which translates to a market premium slightly below 6.75%, as information acquisition leads to higher posterior precision.

The green and brown assets are assumed to have a unit loading on the aggregate risk factor ($b_{gr} = b_{br} = 1$). The asset-specific shocks are assumed to have variance given by $\sigma_{gr} = \sigma_{br} = 0.15^2$. Hence, the total variance of the individual asset payoff is approximately equal to 0.21^2. Regarding the risk factors, we assume that the mean supply of all the risk factors is one unit, while the standard deviation of the supply is 10% of the mean. Hence, $\sigma_{\mathcal{X}} = 0.1^2$.

We next set the ESG preference parameter, δ_P, as well as the individual asset ESG scores, g_{gr} and g_{br}. The expression $\delta_P g_{gr}$ ($\delta_P g_{br}$) represents the nonpecuniary effects from holding the green (brown) asset. We choose $\delta_P = 1$ as the benchmark value for ESG preferences and consider $g_{gr} = 0.05$ and $g_{br} = -0.05$. With these parameter specifications, sustainable funds perceive 5% of the expected financial payoff as nonpecuniary benefit (loss) due to holding one unit of the green (brown) asset. Thus, the green and brown assets considered here can be perceived as members in the cross-section of individual stocks that considerably depart from green neutrality.

The cost function is given by $c_{ij} = \kappa S_{ij}^2$. As the fund-level cost of information acquisition is the sum of c_{ij} across stock holdings, the value κ determines the information cost and, hence, the amount of information purchased in equilibrium. In our sample, active and index funds display an average expense ratio of 1.18% and 0.56%, respectively. The difference in fees, i.e., 0.62%, could establish a plausible proxy for the information acquisition cost. Thus, we choose $\kappa = 0.01$, which, as we show later, implies that informed funds optimally spend between 50 and 60 basis points to purchase information.

Equilibrium information decisions are determined as the solution to a fixed-point problem. That is, the signal precision in Equation (7) depends on the marginal benefit of information acquisition in Equation (8), which, in turn, depends on the aggregate signal precision through $\bar{S}_i$, $\bar{\sigma}_i$, and $\bar{\delta}_i$. In the calibration, the equilibrium is determined by numerically solving Equation (7) jointly for the ESG-perceptive and ESG-indifferent funds.

6.1 Understanding the individual fund

In this subsection, we study the optimal information acquisition policy and the portfolio characteristics for the marginal, individual, fund when $\varphi = 0.5$ and the ESG preference parameter ranges between 0 and 1. Figure 1 describes the calibration results. There are altogether nine graphs. Graph (a) shows the fund's optimal signal precision. Based on Equations (7) and (8), the signal precision increases (decreases) in δ_j for the green (brown) risk factors. When ESG preferences are near 0.5, the average value in the economy, the risk factors have identical signal precision. Then, the total cost of information acquisition, shown in Graph (b), is convex in ESG preferences, growing for values of δ_j that depart from 0.5. The calibration result indicates that the optimal cost of information acquisition is approximately 55 basis points, compatible with the observed gap between active and passive mutual fund expense ratios, as noted earlier. Graph (c) shows the expected portfolio positions relative to the average position across agents. When ESG preferences are near 0.5, the expected portfolio positions are equal to the market portfolio. When $\delta_j = 1$, the expected position is approximately 0.4 units higher for the green asset and 0.4 units lower for the brown asset. Conversely, the brown asset dominates stock holdings when $\delta_j = 0$.

Graph (d) shows the expected nonpecuniary payoff from ESG investing, i.e., $\mathrm{E}[\delta_j G_j]$. As indicated by Equation (14), the expected portfolio ESG profile, $\mathrm{E}[G_j]$, increases with δ_j. The expected nonpecuniary benefits are then zero when the fund is ESG indifferent ($\delta_j = 0$). The nonpecuniary benefits are slightly negative when δ_j is below the average value in the economy, as the fund benefits from a more favorable financial profile of the assets it holds. The nonpecuniary benefits become positive when δ_j is greater than 0.5, reaching a maximum perceived value of 4% for $\delta_j = 1$.[24]

Next, Graph (e) displays the portfolio dispersion. The measure increases significantly when the fund ESG preference δ_j departs from the aggregate ESG preference, as described in Proposition 4. The portfolio dispersion is 0.095 for $\delta_j = 0.5$ and increases to 0.406 for δ_j that is equal to 0 or 1. Likewise, the tracking error, shown in Graph (f), substantially increases with the departure of the ESG preference from the average, ranging between 0.033 and 0.093.

[24] The nonpecuniary benefits are given by the ESG preference parameter, $\delta_j = 1$, times the product of the expected excess position in the green asset and its ESG score, 0.4×0.05, plus the product of the expected excess position in the brown asset and its ESG score, $(-0.4) \times (-0.05)$.

Proposition 5 implies that the expected net payoff diminishes with the fund's ESG preferences. Per the calibration results, the portfolio expected net payoff, reported in Graph (g), is approximately 0.2, decreasing by approximately 0.04 for a unit increase in δ_j. In Online Appendix A.6, we also derive the CAPM alpha of the portfolio, displayed in Graph (h). Similar to the expected net payoff, the CAPM alpha decreases by approximately 4% when δ_j increases from 0 to 1, turning from positive to negative, due to increasingly overweighting green assets.

Finally, we assess the welfare implications of ESG motives. Following the derivations in Online Appendix A.7, Graph (i) displays the expected certainty equivalent loss perceived by a fund with ESG preference δ_j that is enforced to adopt the information decisions and portfolio strategy that are optimal for a fund with ESG preference δ_{sub}. We experiment with three values for δ_{sub}, namely, zero, 0.5, and 1. The loss is expressed as a percentage of the optimal expected net payoff. The utility loss can be substantial when the distance between δ_j and δ_{sub} grows. For instance, an ESG-perceptive fund with $\delta_j = 1$ that implements the information acquisition and portfolio policies of a fund with $\delta_{\text{sub}} = 0$ perceives a certainty equivalent loss of approximately 21.5% of the expected net payoff.

6.2 Price informativeness and the size of the active fund industry

We next study the general equilibrium implications for the cross-section of price informativeness and the overall size of the active fund industry. As in our calibration the green and brown assets have identical characteristics other than the opposite ESG profiles, they should display symmetric implications for the average signal precision and price informativeness.

Graph (a) shows the average signal precision across funds as a function of δ_P when $\varphi = 0.5$. The corresponding graph in the bottom row displays the variation in the aggregate signal precision with the choice of φ when $\delta_P = 1$. When all funds are ESG indifferent ($\delta_P = 0$ or $\varphi = 0$), the average signal precision for the green and brown risk factors is 0.4275, which leads to a posterior variance equal to 0.146^2, lower than the prior value (0.15^2) by more than 5%.[25] The average signal precision for both green and brown assets grows with the dispersion in ESG preferences, with a higher δ_P, and with the heterogeneity across agents

[25] According to Proposition 1, the posterior precision is directly increased by the signal precision, as well as indirectly through the price signal precision, i.e., $\bar{\sigma}_{gr}^{-1} = \sigma_{gr}^{-1} + \bar{S}_{gr} + \frac{\bar{S}_{gr}^2}{\rho^2 \sigma_{\mathcal{X}}} = \frac{1}{0.15^2} + 0.4275 + \frac{0.4275^2}{3^2 \times 0.1^2} \approx \frac{1}{0.146^2}$.

(maximum heterogeneity obtains for $\varphi = 0.5$). Notably, the signal precision grows by 8.7% (from 0.4275 to 0.4649) when δ_P increases from 0 to 2. Furthermore, when $\delta_P = 1$, the signal precision grows by 2.2% (from 0.4275 to 0.4368) for $\varphi = 0.5$ relative to the case where there is no heterogeneity in ESG preferences ($\varphi = 0$ or 1).

Graph (b) in Figure 2 shows the variation of the price informativeness measure, introduced in Subsection 2.5, with δ_P. The price informativeness grows with δ_P for both the green and brown assets, increasing from 4.43 for $\delta_P = 0$, to 4.48 for $\delta_P = 1$, and to 4.62 for $\delta_P = 2$. The increase reflects the higher average signal precision shown in Graph (a). As the bottom graph shows, the presence of ESG-perceptive funds implies an increase in price informativeness only when there is heterogeneity in ESG preferences. Price informativeness records the minimum value (4.43) when ESG motives are absent or homogeneous.

The sensitivity of information decisions to dispersions in cross-stock ESG attributes and cross-fund ESG preferences points to the potential meaningful implications of ESG motives for the size of the active asset management industry. The scope of the active industry has been explored in earlier work, including Pástor and Stambaugh (2012) and Pástor et al. (2015). We show that sustainable investing has a positive effect on the overall scope of the active asset management industry, leading to a greater amount of information purchased in equilibrium. To quantify this effect, we use the aggregate cost of information acquisition as a proxy for the size of the active fund industry. The overall cost is given by $\varphi \cdot \sum_{i=1}^{N} \kappa S_{iP}^2 + (1-\varphi) \cdot \sum_{i=1}^{N} \kappa S_{iI}^2$, where S_{iP} and S_{iI} are the optimal signal precisions acquired by ESG-perceptive and ESG-indifferent agents for asset i, respectively. As shown in Graph (c) at the top, the total information cost grows with δ_P, from a minimum of 54.8 basis points for the case where all agents are ESG indifferent ($\delta_P = 0$), to 57.0 basis points for $\delta_P = 1$ (a 4% increase) and to 63.7 basis points for $\delta_P = 2$ (a 16% increase). The bottom graph confirms that the increase in information costs applies only when ESG preferences are dispersed, while the maximum dispersion reflects the $\varphi = 0.5$ case.

7 Conclusion

We comprehensively analyze the equilibrium implications of fund managers making information acquisition decisions based on financial and social objectives. The model produces a number of predictions regarding fund managers' portfolio choices, the scope of the active mutual fund industry, as well as the cross-section of asset prices.

In equilibrium, when active funds exhibit heterogeneous preferences for sustainable investing and when assets display heterogeneous ESG attributes, ESG-perceptive (ESG-indifferent) funds acquire more information about green (brown) assets and less information about brown (green) assets. Still, incremental information is purchased in equilibrium due to ESG motives, amplifying the size of the active fund industry. The incremental information characterizes any asset that departs from green neutrality. ESG-perceptive (ESG-indifferent) funds also overweight green (brown) assets, with the portfolio tilts more pronounced for low-volatility stocks. The optimal policies of ESG-perceptive and ESG-indifferent funds differ significantly due to nonpecuniary motives. In particular, enforcing ESG-perceptive funds to follow the optimal information and portfolio policies of ESG-indifferent funds triggers significant expected utility costs due to the loss of nonpecuniary benefits. Furthermore, the portfolio dispersion and tracking error increase when the assets held by the funds depart from green neutrality, when the fund preference for holding green stocks departs from the aggregate ESG preference, and when the market-wide heterogeneity in ESG preferences widens.

Regarding asset pricing implications, information acquisition deepens (weakens) the negative ESG-return relation for green (brown) assets. Specifically, the expected return for green assets is lower due to (i) the nonpecuniary benefits from holding green investments and (ii) the lower posterior variance of the green asset payoff due to higher signal precision. In contrast, the two forces act in opposite directions for brown assets. Finally, information acquisition improves the price informativeness of the underlying assets, when such assets depart from green neutrality and are held by active funds with heterogeneous ESG preferences.

Empirical tests provide supporting evidence. First, while green (brown) funds invest more in green (brown) stocks, both types of funds invest less in their preferred investment universe as the volatility of the investable assets rises. Second, mutual funds that invest in stocks with greater departure from green neutrality are more likely to adopt distinct trading strategies and deviate from a passive benchmark. Third, the negative ESG-return relation only holds among stocks with high green fund ownership (low brown fund ownership), as information acquisition implies even lower expected returns for green stocks, while offsets the high expected returns for brown stocks. Finally, stocks with greater departure from green neutrality and held by funds with more heterogeneous ESG preferences display higher price informativeness. The model predictions are further quantified in the calibration exercise.

Our findings highlight that ESG considerations play an essential role in shaping mutual funds' information acquisition decisions, their portfolio choices, and the size of the active fund industry. As a result, sustainable investing not only provides capital to green firms, but also improves the overall efficiency of the financial market due to ESG-induced information acquisition. Information acquisition also reduces the risk of sustainable investing and tilts the negative ESG-return relationship, indicating a potential channel to explain the mixed empirical evidence documented in prior studies.

The paper suggests avenues for future research. First, due to the lack of consistency in the ESG ratings provided by different rating agencies, it could be helpful to account for the rating uncertainty and the additional information acquired about assets' ESG profiles. Second, it could be useful to explicitly account for delegation, i.e., (uninformed) households delegate their investments to the (informed) intermediary sector. Then, testable equilibrium restrictions on fund flows and ESG motives can be derived.[26] Finally, while the ESG profile of an asset is exogenous in our setting, activist shareholders can engage in corporate ESG activities and improve the sustainability performance of targeted firms. We leave these and other extensions for future work.

[26]See, e.g., Dou et al. (2022) for the equilibrium asset pricing implications of fund flows.

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Table 1: Summary Statistics

This table presents the summary statistics for the data used in the paper during the period from 2001 to 2019. Panels A and B report the means, standard deviations, medians, and quantile distributions of stock and fund characteristics, respectively. Online Appendix Table B.1 provides a detailed definition for each variable.

	Mean	Std.Dev.	Quantile Distribution				
			10%	25%	Median	75%	90%
Panel A: Stock Characteristics							
Stock ESG	-0.006	0.253	-0.352	-0.221	-0.028	0.168	0.337
Stock ESGDev	0.214	0.134	0.051	0.093	0.195	0.316	0.415
Stock ESGDisp	0.151	0.068	0.067	0.107	0.150	0.197	0.240
Green IO	1.198	2.359	0.000	0.001	0.099	1.266	4.104
Brown IO	4.966	5.237	0.062	0.786	3.269	7.581	12.408
IVOL	1.774	1.350	0.678	0.945	1.410	2.148	3.221
RETVOL	2.479	1.726	1.038	1.409	2.017	2.981	4.376
Log(Size)	7.284	1.600	5.368	6.107	7.143	8.297	9.529
Log(BM)	-0.735	0.791	-1.759	-1.180	-0.648	-0.208	0.158
ROE	0.012	0.159	-0.064	0.002	0.025	0.046	0.079
I/A	0.141	0.382	-0.098	-0.011	0.061	0.171	0.400
1M Return	0.924	12.447	-12.500	-5.222	0.811	6.722	13.919
12M Return	0.118	0.478	-0.375	-0.139	0.077	0.299	0.592
IO	0.715	0.242	0.348	0.581	0.775	0.904	0.990
Log(Illiquidity)	-6.369	2.202	-9.228	-7.949	-6.445	-4.878	-3.437
Log(Analyst Coverage)	1.987	0.844	0.693	1.386	2.079	2.639	3.045
Analyst Dispersion	0.134	0.399	0.008	0.015	0.033	0.089	0.250
Log(M/A)	-0.108	1.076	-1.675	-0.731	-0.012	0.624	1.197
E/A	0.040	0.174	-0.085	0.019	0.063	0.114	0.175
Log(Asset)	7.330	1.917	4.904	5.943	7.257	8.569	9.904
Leverage	0.553	0.264	0.200	0.355	0.548	0.737	0.898
Tangibility	0.232	0.246	0.012	0.040	0.134	0.352	0.655
Log(Sales)	6.637	2.115	4.177	5.347	6.669	8.009	9.290
Cash	0.131	0.157	0.009	0.023	0.073	0.178	0.331
Panel B: Fund Characteristics							
Fund ESG	-0.020	0.271	-0.380	-0.250	-0.031	0.202	0.362
Fund ESGDev	0.233	0.139	0.045	0.113	0.227	0.347	0.433
HHIBMK	0.062	0.167	0.003	0.011	0.019	0.036	0.093
TEBMK	0.132	0.333	0.010	0.026	0.055	0.120	0.271
HHIMKT	0.064	0.162	0.008	0.013	0.021	0.038	0.095
TEMKT	0.230	0.545	0.033	0.059	0.118	0.233	0.448
Fund Return	0.588	4.628	-5.151	-1.593	0.925	3.228	5.711
Fund Flow	-0.001	4.731	-3.120	-1.508	-0.463	0.784	3.374
Log(Fund TNA)	5.840	1.696	3.608	4.514	5.765	7.036	8.132
Expense Ratio	1.182	0.395	0.737	0.933	1.147	1.403	1.690
Fund Turnover	0.781	0.767	0.170	0.310	0.570	0.980	1.580
Log(Fund Age)	4.793	0.849	3.664	4.317	4.905	5.347	5.727
Flow Volatility	4.424	10.408	0.506	0.910	1.819	3.889	8.417

Table 2: Stock ESG Rating, Return Volatility, and Mutual Fund Ownership

Panel A presents the results of the following monthly Fama-MacBeth regression and their corresponding Newey-West adjusted t-statistics:

$$IO_{i,t} = \alpha + \beta_1 ESG_{i,t-1} + \beta_2 IVOL_{i,t-1} + \beta_3 ESG_{i,t-1} \times IVOL_{i,t-1} + cN_{i,t-1} + \varepsilon_{i,t},$$

where $IO_{i,t}$ is the mutual fund ownership of stock i in month t, $ESG_{i,t-1}$ is the ESG rating, and $IVOL_{i,t-1}$ is the idiosyncratic volatility. $IO_{i,t}$ is measured by green fund ownership (Models 1-3), brown fund ownership (Models 4-6), and the difference in ownership between green and brown funds (Models 7-9). We identify the green (brown) funds as those with a fund-level ESG rating in the top (bottom) quintile across all funds at the end of each month. Vector N stacks all other stock-level control variables, namely, the Log(Size), Log(BM), ROE, I/A, 1M Return, 12M Return, IO, Log(Illiquidity), Log(Analyst Coverage), and Analyst Dispersion. Panel B reports similar statistics when we replace $IVOL_{i,t-1}$ with $RETVOL_{i,t-1}$, defined as the total return volatility of stock i in month t-1. Online Appendix Table B.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Panel A: Mutual Fund Ownership Regressed on Lagged Stock ESG Rating and Idiosyncratic Volatility

Dep. Var. =	Green IO			Brown IO			Green − Brown IO		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Stock ESG	1.873***	3.004***	2.047***	-3.558***	-5.671***	-2.513***	5.430***	8.675***	4.560***
	(11.69)	(10.84)	(13.86)	(-21.22)	(-15.50)	(-22.50)	(18.43)	(13.80)	(20.78)
IVOL	-0.209***	-0.241***	0.074***	-0.290***	-0.220***	-0.447***	0.081***	-0.021	0.521***
	(-8.24)	(-8.49)	(4.79)	(-11.55)	(-7.84)	(-10.53)	(3.59)	(-0.63)	(14.29)
Stock ESG × IVOL		-0.726***	-0.501***		1.354***	0.478***		-2.079***	-0.979***
		(-8.34)	(-7.30)		(7.62)	(6.62)		(-8.14)	(-7.53)
Log(Size)			0.773***			-0.912***			1.685***
			(12.24)			(-9.72)			(11.36)
Log(BM)			-0.213***			0.537***			-0.750***
			(-5.32)			(13.51)			(-13.72)
ROE			-0.429***			1.547***			-1.977***
			(-4.56)			(7.14)			(-8.16)
I/A			-0.125**			-0.018			-0.106
			(-2.17)			(-0.24)			(-0.96)
1M Return			-0.007***			0.011***			-0.018***
			(-10.84)			(7.17)			(-9.44)
12M Return			-0.425***			0.550***			-0.975***
			(-6.92)			(4.24)			(-5.73)
IO			1.055***			9.340***			-8.285***
			(7.77)			(19.38)			(-13.76)
Log(Illiquidity)			0.088***			0.068			0.020
			(3.01)			(1.17)			(0.33)
Log(Analyst Coverage)			0.231***			-0.556***			0.787***
			(7.34)			(-6.44)			(9.92)
Analyst Dispersion			0.102***			-0.645***			0.747***
			(4.60)			(-7.20)			(7.16)
Constant	1.600***	1.624***	-5.356***	5.246***	5.188***	7.722***	-3.646***	-3.564***	-13.078***
	(30.65)	(31.56)	(-22.56)	(24.18)	(24.60)	(8.23)	(-17.80)	(-18.35)	(-12.89)
Obs	509,482	509,482	419,014	509,482	509,482	419,014	509,482	509,482	419,014
R-squared	0.077	0.088	0.327	0.048	0.056	0.347	0.059	0.070	0.365

Panel B: Mutual Fund Ownership Regressed on Lagged Stock ESG Rating and Return Volatility

Dep. Var. =	Green IO			Brown IO			Green − Brown IO		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Stock ESG	1.865***	3.324***	2.317***	-3.515***	-6.104***	-2.670***	5.380***	9.427***	4.987***
	(11.74)	(10.79)	(12.96)	(-20.92)	(-14.58)	(-22.31)	(18.50)	(13.22)	(19.30)
RETVOL	-0.181***	-0.211***	0.055***	-0.193***	-0.129***	-0.350***	0.012	-0.082**	0.405***
	(-6.49)	(-6.85)	(2.94)	(-9.04)	(-4.96)	(-10.21)	(0.40)	(-2.03)	(14.00)
Stock ESG × RETVOL		-0.682***	-0.483***		1.222***	0.421***		-1.904***	-0.905***
		(-8.25)	(-7.19)		(7.45)	(6.52)		(-7.96)	(-7.43)
Log(Size)			0.764***			-0.848***			1.612***
			(12.68)			(-9.75)			(11.62)
Log(BM)			-0.210***			0.549***			-0.759***
			(-5.38)			(14.29)			(-14.73)
ROE			-0.410***			1.560***			-1.970***
			(-4.52)			(6.81)			(-7.50)
I/A			-0.119**			-0.017			-0.102
			(-2.08)			(-0.22)			(-0.92)
1M Return			-0.007***			0.010***			-0.017***
			(-11.06)			(6.59)			(-8.94)
12M Return			-0.424***			0.554***			-0.978***
			(-6.71)			(4.23)			(-5.62)
IO			1.036***			9.414***			-8.378***
			(7.73)			(19.28)			(-13.81)
Log(Illiquidity)			0.084***			0.110*			-0.026
			(2.87)			(1.78)			(-0.43)
Log(Analyst Coverage)			0.229***			-0.548***			0.777***
			(7.61)			(-6.33)			(9.44)
Analyst Dispersion			0.103***			-0.655***			0.757***
			(4.32)			(-7.11)			(6.93)
Constant	1.672***	1.708***	-5.297***	5.200***	5.119***	7.512***	-3.528***	-3.411***	-12.808***
	(24.32)	(24.72)	(-23.70)	(25.14)	(25.70)	(8.20)	(-19.85)	(-20.83)	(-13.25)
Obs	509,487	509,487	419,017	509,487	509,487	419,017	509,487	509,487	419,017
R-squared	0.081	0.093	0.329	0.046	0.054	0.346	0.061	0.073	0.364

Table 3: Mutual Fund Portfolio Dispersion and Tracking Error

Model 1 presents the results of the following monthly Fama-MacBeth regression and their corresponding Newey-West adjusted t-statistics:

$$HHIBMK_{j,t} = \alpha + \beta_1 ESGDev_{j,t-1} + cM_{j,t-1} + \varepsilon_{j,t},$$

where $HHIBMK_{j,t}$ is the portfolio dispersion of fund j in month t computed with respect to the fund's benchmark. $ESGDev_{j,t-1}$ is the fund-level departure from green neutrality, while vector M stacks all other fund-level control variables, namely, the Fund Return, Fund Flow, Log(Fund TNA), Expense Ratio, Fund Turnover, Log(Fund Age), and Flow Volatility. Model 2 reports similar statistics when we replace $HHIBMK_{j,t}$ with $TEBMK_{j,t}$, defined as the tracking error of fund j in month t and computed with respect to the fund's benchmark. Models 3-4 report similar statistics when the dependent variables are $HHIMKT_{j,t}$ and $TEMKT_{j,t}$, indicating the portfolio dispersion and tracking error, respectively, computed with respect to the market portfolio. Online Appendix Table B.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Portfolio Dispersion and Tracking Error Regressed on Lagged ESG Deviation				
Dep. Var. =	HHIBMK	TEBMK	HHIMKT	TEMKT
	Model 1	Model 2	Model 3	Model 4
Fund ESGDev	0.167***	0.133***	0.205***	0.247***
	(13.84)	(4.42)	(14.78)	(5.88)
Fund Return	-0.003***	-0.002	-0.003***	-0.004
	(-3.01)	(-1.06)	(-2.99)	(-1.11)
Fund Flow	0.000***	0.001**	0.000**	0.001*
	(3.59)	(2.36)	(2.12)	(1.76)
Log(Fund TNA)	0.001**	-0.005***	0.002***	-0.005***
	(2.26)	(-8.00)	(4.33)	(-4.56)
Expense Ratio	-0.011***	0.083***	-0.008***	0.103***
	(-5.42)	(10.64)	(-5.35)	(10.41)
Fund Turnover	0.007***	0.027***	0.004***	0.015***
	(4.55)	(10.18)	(4.99)	(4.05)
Log(Fund Age)	-0.008***	0.026***	-0.005***	0.017***
	(-6.35)	(8.62)	(-4.86)	(3.98)
Flow Volatility	0.000***	0.002***	0.000***	0.002***
	(3.52)	(8.30)	(6.04)	(10.94)
Constant	0.093***	-0.175***	0.067***	-0.143***
	(9.68)	(-7.50)	(9.04)	(-3.61)
Obs	475,228	475,180	475,233	488,966
R-squared	0.062	0.113	0.078	0.156

Table 4: Performance of Portfolios Sorted by Mutual Fund Ownership and ESG Rating

In Panels A1 and A2, at the end of month t, stocks are first sorted into quintiles according to their green fund ownership. Within each green fund ownership group, stocks are further sorted into quintiles according to their ESG ratings to generate 25 (5×5) portfolios. The low- (high)-ESG-rating and green-fund-ownership portfolios comprise the bottom (top) quintile of stocks based on the ESG rating and green fund ownership, respectively. For each of the 25 portfolios, we compute the value-weighted return in month $t+1$ and rebalance the portfolios at the end of month $t+1$. Panel A reports the time-series averages of the monthly returns for each of the 25 portfolios and for the investment strategy of going long (short) in the high- (low)-ESG-rating stocks ("HML-R") and the investment strategy of going long (short) in the high- (low)-green-fund-ownership stocks ("HML-G"). The column "All" reports similar statistics for the portfolios sorted only by the ESG ratings, and the row "All" reports similar statistics for the portfolios sorted only by green fund ownership. The portfolio returns are further adjusted by the CAPM. Panels A1 and A2 report the subperiod results for January 2001–October 2012 and for November 2012–December 2019, respectively. Panels B1 and B2 report similar statistics when we replace green fund ownership with brown fund ownership. We identify green (brown) funds as those with a fund-level ESG rating in the top (bottom) quintile across all funds at the end of each month. The Newey-West adjusted t-statistics are shown in parentheses. Online Appendix Table B.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

	Return							CAPM-adjusted Return						
Ownership	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel A1: Portfolios Sorted by Green Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.871	0.723	0.468	0.609	0.551	-0.319	0.755	0.464*	0.335	0.122	0.214	0.173	-0.291	0.357
	(1.40)	(1.26)	(0.89)	(1.15)	(1.07)	(-1.02)	(1.38)	(1.76)	(1.26)	(0.36)	(0.86)	(0.62)	(-0.97)	(1.66)
2	0.816	0.899	0.803	0.533	1.001**	0.184	0.738	0.419*	0.473	0.398	0.171	0.620***	0.201	0.345*
	(1.45)	(1.35)	(1.17)	(1.07)	(2.19)	(0.55)	(1.43)	(1.76)	(1.40)	(0.92)	(0.59)	(2.64)	(0.62)	(1.89)
3	0.603	0.342	0.560	0.131	0.533	-0.070	0.482	0.208	-0.063	0.175	-0.262	0.150	-0.059	0.087
	(1.09)	(0.63)	(1.06)	(0.24)	(1.19)	(-0.24)	(0.95)	(0.95)	(-0.35)	(0.83)	(-1.61)	(0.77)	(-0.20)	(0.65)
4	0.517	0.417	0.496	0.385	0.271	-0.246	0.412	0.148	0.021	0.121	-0.010	-0.143	-0.291	0.028
	(1.09)	(0.82)	(1.04)	(0.72)	(0.52)	(-0.89)	(0.92)	(0.85)	(0.08)	(0.76)	(-0.04)	(-0.79)	(-1.05)	(0.29)
High	0.706	0.356	0.496	0.216	0.083	-0.624***	0.236	0.298	-0.012	0.093	-0.168	-0.280**	-0.578**	-0.152
	(1.37)	(0.77)	(0.95)	(0.43)	(0.18)	(-2.65)	(0.50)	(1.46)	(-0.05)	(0.54)	(-0.86)	(-2.09)	(-2.48)	(-1.58)
HML-G	-0.165	-0.367	0.029	-0.393	-0.469	-0.304	-0.518**	-0.166	-0.346	-0.029	-0.381	-0.454	-0.287	-0.508**
	(-0.55)	(-1.04)	(0.07)	(-1.23)	(-1.46)	(-0.94)	(-2.10)	(-0.55)	(-0.98)	(-0.07)	(-1.16)	(-1.38)	(-0.87)	(-2.01)
All	0.594	0.277	0.377	0.225	0.305	-0.290		0.223*	-0.127	0.001	-0.147	-0.069	-0.292	
	(1.29)	(0.57)	(0.80)	(0.50)	(0.71)	(-1.51)		(1.74)	(-0.79)	(0.01)	(-1.25)	(-0.89)	(-1.51)	
Panel A2: Portfolios Sorted by Green Fund Ownership and ESG Rating (Nov 2012–Dec 2019)														
Low	0.736	0.820*	0.869**	0.786*	0.785*	0.049	0.802*	-0.771**	-0.594**	-0.461*	-0.580**	-0.614**	0.158	-0.592**
	(1.57)	(1.92)	(2.01)	(1.91)	(1.82)	(0.20)	(1.96)	(-2.37)	(-2.22)	(-1.74)	(-2.17)	(-2.21)	(0.59)	(-2.43)
2	0.786*	0.965***	1.132**	1.145***	0.969**	0.183	0.991**	-0.764***	-0.413*	-0.332	-0.393	-0.561**	0.203	-0.482**
	(1.71)	(2.74)	(2.37)	(2.83)	(2.23)	(0.70)	(2.49)	(-2.66)	(-1.81)	(-1.11)	(-1.55)	(-2.57)	(0.72)	(-2.49)
3	1.023**	1.477***	1.098**	0.871**	1.125***	0.102	1.134***	-0.402	0.129	-0.323	-0.539***	-0.318	0.083	-0.275
	(2.17)	(3.45)	(2.60)	(2.34)	(2.97)	(0.33)	(3.02)	(-1.35)	(0.48)	(-1.31)	(-2.98)	(-1.59)	(0.28)	(-1.66)
4	1.268***	1.836***	1.165***	0.932***	1.203***	-0.065	1.247***	-0.075	0.702***	-0.020	-0.299	-0.173	-0.097	-0.023
	(3.45)	(5.67)	(3.14)	(2.78)	(3.35)	(-0.23)	(4.00)	(-0.28)	(3.73)	(-0.10)	(-1.51)	(-0.80)	(-0.28)	(-0.17)
High	1.006***	1.079***	1.161***	1.229***	1.362***	0.357*	1.213***	-0.217	-0.040	-0.087	0.085	0.300***	0.517**	0.072
	(3.27)	(3.88)	(3.79)	(4.62)	(4.83)	(1.69)	(4.56)	(-1.56)	(-0.30)	(-0.84)	(0.76)	(2.65)	(2.41)	(1.29)
HML-G	0.270	0.259	0.292	0.444	0.578*	0.308	0.412	0.554	0.553	0.374	0.664**	0.914***	0.359	0.664**
	(0.79)	(0.77)	(0.96)	(1.35)	(1.87)	(1.07)	(1.49)	(1.57)	(1.65)	(1.26)	(2.01)	(2.81)	(1.14)	(2.36)
All	1.074***	1.397***	1.045***	1.120***	1.267***	0.193		-0.251	0.073	-0.156	-0.105	0.121**	0.372*	
	(3.11)	(4.22)	(3.36)	(3.92)	(4.68)	(1.07)		(-1.58)	(0.41)	(-1.65)	(-1.41)	(1.99)	(1.85)	
Panel B1: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.770**	0.373	0.482	0.682	0.219	-0.551*	0.354	0.423**	0.008	0.104	0.308	-0.146	-0.569*	-0.010
	(2.14)	(0.75)	(0.94)	(1.38)	(0.45)	(-1.68)	(0.83)	(2.00)	(0.03)	(0.32)	(1.17)	(-0.65)	(-1.77)	(-0.07)
2	0.565	0.282	0.220	0.241	0.230	-0.335	0.313	0.205	-0.107	-0.174	-0.136	-0.181	-0.386*	-0.080
	(1.29)	(0.57)	(0.44)	(0.47)	(0.47)	(-1.38)	(0.68)	(0.96)	(-0.44)	(-0.87)	(-0.58)	(-1.22)	(-1.69)	(-0.69)
3	0.643	0.394	0.232	0.313	0.506	-0.137	0.481	0.243	-0.021	-0.148	-0.090	0.118	-0.124	0.084
	(1.16)	(0.73)	(0.50)	(0.53)	(1.10)	(-0.55)	(0.97)	(1.22)	(-0.10)	(-1.11)	(-0.36)	(0.86)	(-0.51)	(0.82)
4	0.802	0.621	0.489	0.463	0.463	-0.339	0.615	0.413*	0.201	0.107	0.066	0.084	-0.329	0.219
	(1.51)	(1.08)	(0.94)	(0.84)	(0.95)	(-1.49)	(1.20)	(1.95)	(0.94)	(0.51)	(0.32)	(0.49)	(-1.42)	(1.51)
High	0.648	0.501	0.432	0.648	0.317	-0.332	0.504	0.259	0.100	0.019	0.233	-0.079	-0.338	0.102
	(1.12)	(0.89)	(0.69)	(1.10)	(0.59)	(-1.40)	(0.89)	(0.96)	(0.45)	(0.08)	(1.18)	(-0.39)	(-1.41)	(0.51)
HML-B	-0.122	0.129	-0.050	-0.033	0.097	0.219	0.150	-0.164	0.093	-0.085	-0.076	0.066	0.231	0.112
	(-0.32)	(0.42)	(-0.11)	(-0.09)	(0.29)	(0.56)	(0.51)	(-0.46)	(0.31)	(-0.19)	(-0.20)	(0.21)	(0.60)	(0.40)
All	0.594	0.277	0.377	0.225	0.305	-0.290		0.223*	-0.127	0.001	-0.147	-0.069	-0.292	
	(1.29)	(0.57)	(0.80)	(0.50)	(0.71)	(-1.51)		(1.74)	(-0.79)	(0.01)	(-1.25)	(-0.89)	(-1.51)	
Panel B2: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Nov 2012–Dec 2019)														
Low	1.227***	1.098***	1.054***	1.162***	1.370***	0.143	1.194***	-0.032	0.010	-0.142	-0.018	0.301**	0.333	0.048
	(3.57)	(3.84)	(3.57)	(4.31)	(4.82)	(0.61)	(4.46)	(-0.17)	(0.08)	(-1.30)	(-0.14)	(2.62)	(1.41)	(0.96)
2	1.222***	1.244***	1.119***	1.414***	1.181***	-0.041	1.244***	-0.113	-0.074	-0.161	0.097	-0.166	-0.054	-0.080
	(2.97)	(3.70)	(3.05)	(4.23)	(3.73)	(-0.16)	(3.92)	(-0.40)	(-0.41)	(-0.80)	(0.74)	(-1.51)	(-0.20)	(-0.70)
3	0.999**	1.014***	1.298***	1.165***	1.053***	0.054	1.128***	-0.532**	-0.380*	-0.098	-0.287	-0.308	0.224	-0.283*
	(2.26)	(2.70)	(3.45)	(2.99)	(2.79)	(0.24)	(3.08)	(-2.06)	(-1.69)	(-0.47)	(-1.49)	(-1.59)	(0.97)	(-1.74)
4	1.005**	1.203***	1.275***	1.293***	1.176***	0.171	1.188***	-0.444*	-0.261	-0.073	-0.168	-0.291	0.153	-0.245
	(2.50)	(3.19)	(3.19)	(3.20)	(3.00)	(1.07)	(3.16)	(-1.93)	(-1.18)	(-0.33)	(-1.00)	(-1.41)	(0.92)	(-1.39)
High	0.951**	1.238***	1.142***	1.028**	1.217***	0.265	1.118***	-0.523**	-0.077	-0.318	-0.415*	-0.275	0.248	-0.321
	(2.32)	(3.09)	(2.98)	(2.56)	(3.08)	(1.56)	(2.89)	(-2.23)	(-0.33)	(-1.37)	(-1.90)	(-1.43)	(1.40)	(-1.60)
HML-B	-0.276	0.140	0.089	-0.135	-0.153	0.123	-0.076	-0.491*	-0.088	-0.176	-0.397	-0.576**	-0.085	-0.369
	(-0.97)	(0.51)	(0.38)	(-0.48)	(-0.56)	(0.47)	(-0.33)	(-1.91)	(-0.29)	(-0.64)	(-1.29)	(-2.20)	(-0.32)	(-1.54)
All	1.074***	1.397***	1.045***	1.120***	1.267***	0.193		-0.251	0.073	-0.156	-0.105	0.121**	0.372*	
	(3.11)	(4.22)	(3.36)	(3.92)	(4.68)	(1.07)		(-1.58)	(0.41)	(-1.65)	(-1.41)	(1.99)	(1.85)	

Table 5: Implied Cost of Capital of Portfolios Sorted by Mutual Fund Ownership and ESG Rating

In Panels A1 and A2, at the end of month t, stocks are first sorted into quintiles according to their green fund ownership. Within each green fund ownership group, stocks are further sorted into quintiles according to their ESG ratings to generate 25 (5×5) portfolios. The low- (high)-ESG-rating and green-fund-ownership portfolios comprise the bottom (top) quintile of stocks based on the ESG rating and green fund ownership, respectively. For each of the 25 portfolios, we compute the value-weighted implied cost of capital (ICC) in month t+1 and rebalance the portfolios at the end of month t+1. We compute the ICC for each stock-month following Hou et al. (2012) and Pástor et al. (2022). Panel A reports the time-series averages of the monthly ICCs for each of the 25 portfolios and for the investment strategy of going long (short) in the high- (low)-ESG-rating stocks ("HML-R") and the investment strategy of going long (short) in the high- (low)-green-fund-ownership stocks ("HML-G"). The column "All" reports similar statistics for portfolios sorted only by the ESG ratings, and the row "All" reports similar statistics for portfolios sorted only by green fund ownership. The portfolio ICCs are further adjusted by the CAPM. Panels A1 and A2 report the subperiod results for January 2001–October 2012 and for November 2012–December 2019, respectively. Panels B1 and B2 report similar statistics when we replace green fund ownership with brown fund ownership. We identify green (brown) funds as those with a fund-level ESG rating in the top (bottom) quintile across all funds at the end of each month. The Newey-West adjusted t-statistics are shown in parentheses. Online Appendix Table B.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

	ICC							CAPM-adjusted ICC						
Ownership	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel A1: Portfolios Sorted by Green Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.754***	0.609***	0.554***	0.695***	0.727***	-0.028**	0.728***	0.603***	0.457***	0.401***	0.544***	0.574***	-0.029***	0.575***
	(55.65)	(15.41)	(11.08)	(24.75)	(56.30)	(-2.42)	(60.93)	(19.87)	(9.40)	(7.17)	(15.39)	(19.54)	(-2.63)	(19.73)
2	0.705***	0.654***	0.612***	0.617***	0.717***	0.013	0.692***	0.552***	0.502***	0.460***	0.464***	0.565***	0.013	0.539***
	(35.39)	(23.46)	(16.08)	(17.99)	(60.99)	(0.77)	(47.20)	(16.41)	(11.53)	(8.75)	(11.20)	(20.23)	(0.79)	(17.33)
3	0.699***	0.676***	0.643***	0.607***	0.721***	0.022	0.690***	0.547***	0.523***	0.491***	0.455***	0.568***	0.022	0.538***
	(32.73)	(28.84)	(24.81)	(19.02)	(53.95)	(1.17)	(49.01)	(15.24)	(13.46)	(11.45)	(11.33)	(20.33)	(1.15)	(17.07)
4	0.684***	0.630***	0.677***	0.643***	0.653***	-0.031*	0.648***	0.531***	0.477***	0.524***	0.491***	0.500***	-0.031*	0.495***
	(36.14)	(33.50)	(38.66)	(27.80)	(32.98)	(-1.79)	(40.35)	(14.32)	(16.07)	(15.46)	(13.18)	(14.37)	(-1.83)	(15.22)
High	0.703***	0.614***	0.647***	0.616***	0.554***	-0.149***	0.613***	0.551***	0.461***	0.495***	0.464***	0.401***	-0.149***	0.461***
	(35.28)	(16.97)	(42.33)	(47.03)	(55.17)	(-11.05)	(47.91)	(15.89)	(9.87)	(14.75)	(14.56)	(14.65)	(-10.92)	(14.90)
HML-G	-0.051**	0.004	0.094*	-0.079**	-0.173***	-0.122***	-0.114***	-0.052***	0.004	0.094*	-0.080**	-0.173***	-0.121***	-0.114***
	(-2.60)	(0.08)	(1.83)	(-2.52)	(-12.15)	(-6.91)	(-7.38)	(-2.63)	(0.06)	(1.83)	(-2.59)	(-12.27)	(-6.91)	(-7.42)
All	0.681***	0.608***	0.619***	0.581***	0.578***	-0.103***		0.528***	0.455***	0.467***	0.429***	0.425***	-0.103***	
	(37.33)	(19.29)	(19.01)	(18.19)	(56.78)	(-10.44)		(14.85)	(9.13)	(9.89)	(10.36)	(14.45)	(-10.39)	
Panel A2: Portfolios Sorted by Green Fund Ownership and ESG Rating (Nov 2012–Dec 2019)														
Low	0.505***	0.498***	0.497***	0.472***	0.486***	-0.019	0.491***	0.454***	0.449***	0.450***	0.419***	0.434***	-0.020	0.440***
	(14.01)	(13.77)	(14.02)	(13.58)	(14.10)	(-1.47)	(14.24)	(12.06)	(12.33)	(13.57)	(14.23)	(13.33)	(-1.39)	(13.44)
2	0.575***	0.576***	0.545***	0.547***	0.557***	-0.019	0.560***	0.519***	0.523***	0.488***	0.488***	0.499***	-0.020	0.503***
	(45.54)	(44.22)	(33.38)	(39.10)	(40.83)	(-1.28)	(50.39)	(22.37)	(22.52)	(19.51)	(23.20)	(29.75)	(-1.31)	(24.50)
3	0.575***	0.498***	0.551***	0.568***	0.604***	0.029***	0.559***	0.515***	0.438***	0.494***	0.512***	0.548***	0.033***	0.501***
	(35.80)	(39.59)	(60.19)	(52.16)	(48.58)	(3.16)	(52.84)	(16.69)	(18.00)	(25.34)	(27.13)	(23.07)	(3.14)	(21.58)
4	0.552***	0.503***	0.551***	0.533***	0.517***	-0.035	0.517***	0.490***	0.445***	0.492***	0.478***	0.458***	-0.033	0.458***
	(24.88)	(25.68)	(31.79)	(47.16)	(21.47)	(-1.09)	(36.34)	(14.12)	(16.78)	(17.57)	(31.31)	(22.50)	(-0.97)	(20.44)
High	0.577***	0.608***	0.599***	0.563***	0.469***	-0.108***	0.547***	0.518***	0.552***	0.541***	0.505***	0.410***	-0.108***	0.488***
	(24.94)	(63.00)	(51.80)	(39.74)	(25.74)	(-6.60)	(38.81)	(15.08)	(27.83)	(22.57)	(17.97)	(12.26)	(-6.57)	(17.21)
HML-G	0.072	0.110***	0.102**	0.091**	-0.017	-0.089***	0.055	0.064	0.103***	0.091**	0.085**	-0.024	-0.088***	0.048
	(1.42)	(3.02)	(2.53)	(2.21)	(-0.41)	(-4.08)	(1.36)	(1.37)	(3.09)	(2.50)	(2.24)	(-0.62)	(-3.76)	(1.29)
All	0.563***	0.526***	0.576***	0.585***	0.512***	-0.052***		0.503***	0.467***	0.519***	0.528***	0.453***	-0.050***	
	(31.18)	(28.88)	(42.88)	(80.74)	(36.04)	(-4.50)		(17.57)	(14.15)	(21.17)	(28.35)	(16.00)	(-4.43)	
Panel B1: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.610***	0.619***	0.540***	0.613***	0.548***	-0.061***	0.581***	0.457***	0.467***	0.386***	0.461***	0.396***	-0.061***	0.428***
	(26.72)	(18.41)	(14.81)	(40.67)	(51.97)	(-3.54)	(45.63)	(12.45)	(11.56)	(8.84)	(15.29)	(15.11)	(-3.54)	(14.58)
2	0.647***	0.618***	0.599***	0.635***	0.614***	-0.033***	0.634***	0.494***	0.465***	0.446***	0.482***	0.462***	-0.032***	0.481***
	(23.19)	(18.84)	(16.90)	(33.32)	(28.42)	(-2.99)	(28.00)	(12.17)	(11.03)	(8.07)	(13.93)	(13.10)	(-2.94)	(13.00)
3	0.668***	0.606***	0.601***	0.599***	0.657***	-0.011	0.657***	0.515***	0.454***	0.448***	0.447***	0.505***	-0.010	0.504***
	(30.52)	(18.46)	(17.85)	(19.24)	(39.33)	(-0.90)	(38.57)	(13.27)	(9.20)	(9.24)	(10.99)	(15.68)	(-0.86)	(14.99)
4	0.708***	0.690***	0.643***	0.648***	0.722***	0.014	0.694***	0.555***	0.538***	0.490***	0.496***	0.569***	0.014	0.541***
	(47.35)	(48.08)	(31.16)	(25.77)	(54.40)	(1.06)	(59.61)	(17.84)	(19.42)	(15.22)	(13.50)	(21.50)	(1.09)	(18.80)
High	0.743***	0.705***	0.678***	0.722***	0.732***	-0.011	0.720***	0.590***	0.553***	0.526***	0.570***	0.580***	-0.011	0.568***
	(54.47)	(50.28)	(31.27)	(56.58)	(54.89)	(-1.37)	(58.88)	(19.90)	(17.52)	(15.88)	(18.11)	(19.67)	(-1.36)	(18.87)
HML-B	0.133***	0.087**	0.138***	0.109***	0.184***	0.051***	0.140***	0.134***	0.086**	0.140***	0.109***	0.184***	0.050***	0.140***
	(5.04)	(2.52)	(3.24)	(6.42)	(11.06)	(2.80)	(8.17)	(5.08)	(2.51)	(3.25)	(6.38)	(11.08)	(2.78)	(8.20)
All	0.681***	0.608***	0.619***	0.581***	0.578***	-0.103***		0.528***	0.455***	0.467***	0.429***	0.425***	-0.103***	
	(37.33)	(19.29)	(19.01)	(18.19)	(56.78)	(-10.44)		(14.85)	(9.13)	(9.89)	(10.36)	(14.45)	(-10.39)	
Panel B2: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Nov 2012–Dec 2019)														
Low	0.545***	0.579***	0.594***	0.558***	0.467***	-0.078***	0.537***	0.486***	0.523***	0.536***	0.498***	0.408***	-0.077***	0.479***
	(21.62)	(42.57)	(73.88)	(42.40)	(25.45)	(-5.04)	(41.03)	(12.56)	(20.61)	(30.54)	(19.72)	(12.20)	(-5.01)	(17.55)
2	0.532***	0.559***	0.566***	0.562***	0.546***	0.014	0.552***	0.470***	0.500***	0.508***	0.501***	0.488***	0.018	0.493***
	(26.62)	(33.16)	(35.96)	(43.45)	(41.86)	(0.93)	(40.70)	(17.76)	(18.01)	(21.28)	(26.18)	(21.24)	(1.14)	(22.16)
3	0.551***	0.526***	0.560***	0.528***	0.523***	-0.028**	0.538***	0.497***	0.471***	0.502***	0.472***	0.465***	-0.031**	0.482***
	(38.18)	(39.14)	(32.09)	(41.62)	(46.05)	(-2.41)	(45.39)	(17.39)	(18.27)	(16.05)	(22.27)	(21.01)	(-2.42)	(19.51)
4	0.579***	0.542***	0.555***	0.553***	0.548***	-0.031***	0.556***	0.520***	0.483***	0.496***	0.495***	0.490***	-0.030**	0.497***
	(42.01)	(37.32)	(31.58)	(54.32)	(61.81)	(-2.66)	(47.13)	(20.23)	(18.19)	(16.43)	(21.73)	(24.40)	(-2.59)	(20.17)
High	0.607***	0.577***	0.582***	0.593***	0.596***	-0.012	0.590***	0.551***	0.521***	0.526***	0.535***	0.540***	-0.011	0.534***
	(48.49)	(35.34)	(35.97)	(48.22)	(95.72)	(-1.40)	(47.80)	(23.38)	(17.91)	(17.98)	(20.98)	(27.57)	(-1.34)	(21.12)
HML-B	0.062***	-0.002	-0.012	0.035***	0.128***	0.066***	0.052***	0.066***	-0.002	-0.010	0.037***	0.132***	0.066***	0.055***
	(2.82)	(-0.23)	(-0.66)	(4.13)	(8.75)	(3.39)	(8.26)	(3.00)	(-0.18)	(-0.55)	(4.50)	(8.72)	(3.29)	(9.06)
All	0.563***	0.526***	0.576***	0.585***	0.512***	-0.052***		0.503***	0.467***	0.519***	0.528***	0.453***	-0.050***	
	(31.18)	(28.88)	(42.88)	(80.74)	(36.04)	(-4.50)		(17.57)	(14.15)	(21.17)	(28.35)	(16.00)	(-4.43)	

Table 6: Stock Price Informativeness

This table presents the results of the following annual Fama-MacBeth regression and their corresponding Newey-West adjusted t-statistics:

$$\frac{E_{i,y+h}}{A_{i,y}} = \alpha + \beta_1 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) + \beta_2 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) \times ESGDev_{i,y} + \beta_3 Log\left(\frac{M_{i,y}}{A_{i,y}}\right) \times ESGDisp_{i,y}$$
$$+ \beta_4 ESGDev_{i,y} + \beta_5 ESGDisp_{i,y} + \beta_6 Log\left(\frac{E_{i,y}}{A_{i,y}}\right) + cN_{i,y} + \varepsilon_{i,y+h},$$

where $E_{i,y+h}$ is the earnings before interest and taxes of stock i in year $y+h$, $A_{i,y}$ is the total assets, $M_{i,y}$ is the market capitalization, $ESGDev_{i,y}$ is the departure from green neutrality, and $ESGDisp_{i,y}$ is the stock-level heterogeneity in the fund ESG preferences. Vector N stacks all other stock-level control variables, namely, the IO, Log(Asset), Leverage, Tangibility, Log(Sales), Cash, Log(Analyst Coverage), and Analyst Dispersion. Models 1-4, Models 5-8, and Models 9-12 report the results when $h = 1$, $h = 3$, and $h = 5$, respectively. Online Appendix Table B.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Dep. Var. =	$E_{i,y+1}/A_{i,y}$				$E_{i,y+3}/A_{i,y}$				$E_{i,y+5}/A_{i,y}$			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Log(M/A)	0.012***	0.008**	0.001	-0.001	0.016**	0.007	-0.006	-0.012	0.026**	0.017	-0.004	-0.008
	(4.94)	(2.73)	(0.40)	(-0.29)	(2.67)	(0.92)	(-0.89)	(-1.52)	(2.64)	(1.59)	(-0.35)	(-0.62)
Log(M/A) × Stock ESGDev		0.027***		0.022***		0.060***		0.049***		0.061***		0.050**
		(4.37)		(3.45)		(5.53)		(4.41)		(3.67)		(2.95)
Log(M/A) × Stock ESGDisp			0.075***	0.068***			0.150***	0.138***			0.201***	0.178***
			(7.18)	(6.18)			(6.65)	(6.48)			(6.87)	(5.62)
Stock ESGDev		-0.000		-0.001		0.008		0.007		-0.004		-0.005
		(-0.10)		(-0.24)		(0.56)		(0.52)		(-0.26)		(-0.37)
Stock ESGDisp			0.019*	0.019*			0.048**	0.049**			0.066**	0.068**
			(1.81)	(1.85)			(2.49)	(2.76)			(2.32)	(2.49)
E/A	0.827***	0.824***	0.822***	0.820***	0.822***	0.815***	0.811***	0.807***	0.839***	0.831***	0.826***	0.821***
	(26.77)	(26.52)	(26.55)	(26.44)	(17.82)	(17.69)	(17.39)	(17.38)	(17.88)	(17.91)	(17.51)	(17.69)
IO	0.002	0.003	0.003	0.003	-0.005	-0.003	-0.005	-0.003	-0.001	0.001	-0.002	-0.000
	(0.66)	(0.93)	(0.81)	(1.00)	(-0.46)	(-0.26)	(-0.44)	(-0.28)	(-0.08)	(0.05)	(-0.11)	(-0.02)
Log(Asset)	-0.008***	-0.008***	-0.008***	-0.008***	-0.016***	-0.016***	-0.016***	-0.016***	-0.015***	-0.015***	-0.016***	-0.016***
	(-4.50)	(-4.68)	(-4.82)	(-4.99)	(-4.49)	(-4.49)	(-4.72)	(-4.72)	(-4.27)	(-4.49)	(-4.61)	(-4.84)
Leverage	0.042***	0.042***	0.041***	0.041***	0.048***	0.049***	0.046***	0.048***	0.055***	0.057***	0.053***	0.055***
	(9.04)	(9.10)	(8.90)	(8.92)	(4.12)	(4.21)	(4.08)	(4.18)	(3.13)	(3.25)	(3.12)	(3.24)
Tangibility	-0.006	-0.006	-0.006	-0.006	-0.017	-0.015	-0.017	-0.015	-0.028	-0.027	-0.027	-0.027
	(-1.03)	(-0.98)	(-0.94)	(-0.91)	(-0.98)	(-0.91)	(-0.95)	(-0.89)	(-1.21)	(-1.16)	(-1.16)	(-1.14)
Log(Sales)	0.011***	0.011***	0.012***	0.012***	0.019***	0.018***	0.019***	0.019***	0.017***	0.018***	0.018***	0.018***
	(7.12)	(7.18)	(7.44)	(7.54)	(6.65)	(6.43)	(6.93)	(6.73)	(6.41)	(6.40)	(6.82)	(6.84)
Cash	-0.062***	-0.061***	-0.061***	-0.060***	-0.070**	-0.066**	-0.068**	-0.066**	-0.050	-0.048	-0.047	-0.046
	(-4.81)	(-4.77)	(-4.89)	(-4.88)	(-2.55)	(-2.45)	(-2.55)	(-2.48)	(-1.06)	(-1.01)	(-1.01)	(-1.00)
Log(Analyst Coverage)	-0.002	-0.002	-0.003	-0.003	0.002	0.002	0.001	0.001	0.006	0.007	0.005	0.006
	(-1.28)	(-1.20)	(-1.45)	(-1.39)	(0.48)	(0.50)	(0.33)	(0.35)	(1.39)	(1.42)	(1.19)	(1.25)
Analyst Dispersion	-0.009**	-0.009**	-0.009**	-0.009**	-0.004	-0.003	-0.004	-0.003	-0.003	-0.004	-0.004	-0.004
	(-2.86)	(-2.84)	(-2.87)	(-2.85)	(-1.27)	(-1.12)	(-1.29)	(-1.14)	(-0.80)	(-0.78)	(-0.90)	(-0.87)
Constant	-0.008	-0.010	-0.011	-0.012*	0.010	0.007	0.004	0.002	0.019	0.016	0.010	0.009
	(-1.24)	(-1.60)	(-1.73)	(-1.99)	(0.77)	(0.57)	(0.28)	(0.16)	(1.31)	(1.09)	(0.73)	(0.62)
Obs	51,699	51,699	51,699	51,699	41,104	41,104	41,104	41,104	32,266	32,266	32,266	32,266
R-squared	0.736	0.737	0.738	0.738	0.477	0.481	0.480	0.483	0.336	0.338	0.340	0.342

Figure 1: Calibration - Characteristics of the Marginal Fund

This figure shows the characteristics of the optimal information acquisition and the portfolio policy of an infinitely small agent in an economy where two masses of agents coexist: ESG indifferent and ESG perceptive. The ESG preference of the marginal agent δ_j is allowed to vary. Graphs (a) to (h) show the optimal signal precision, the total cost of information acquisition, the expected difference in the portfolio positions relative to the market, the expected nonpecuniary benefits of the portfolio, the expected dispersion of the portfolio positions, the tracking error, the expected net payoff, and the CAPM alpha of the portfolio. Graph (i) shows the certainty equivalent loss, relative to the expected net payoff, that is perceived by the marginal agent when forced to acquire the information and implement the conditional portfolio of an agent with ESG preferences δ_{sub}.

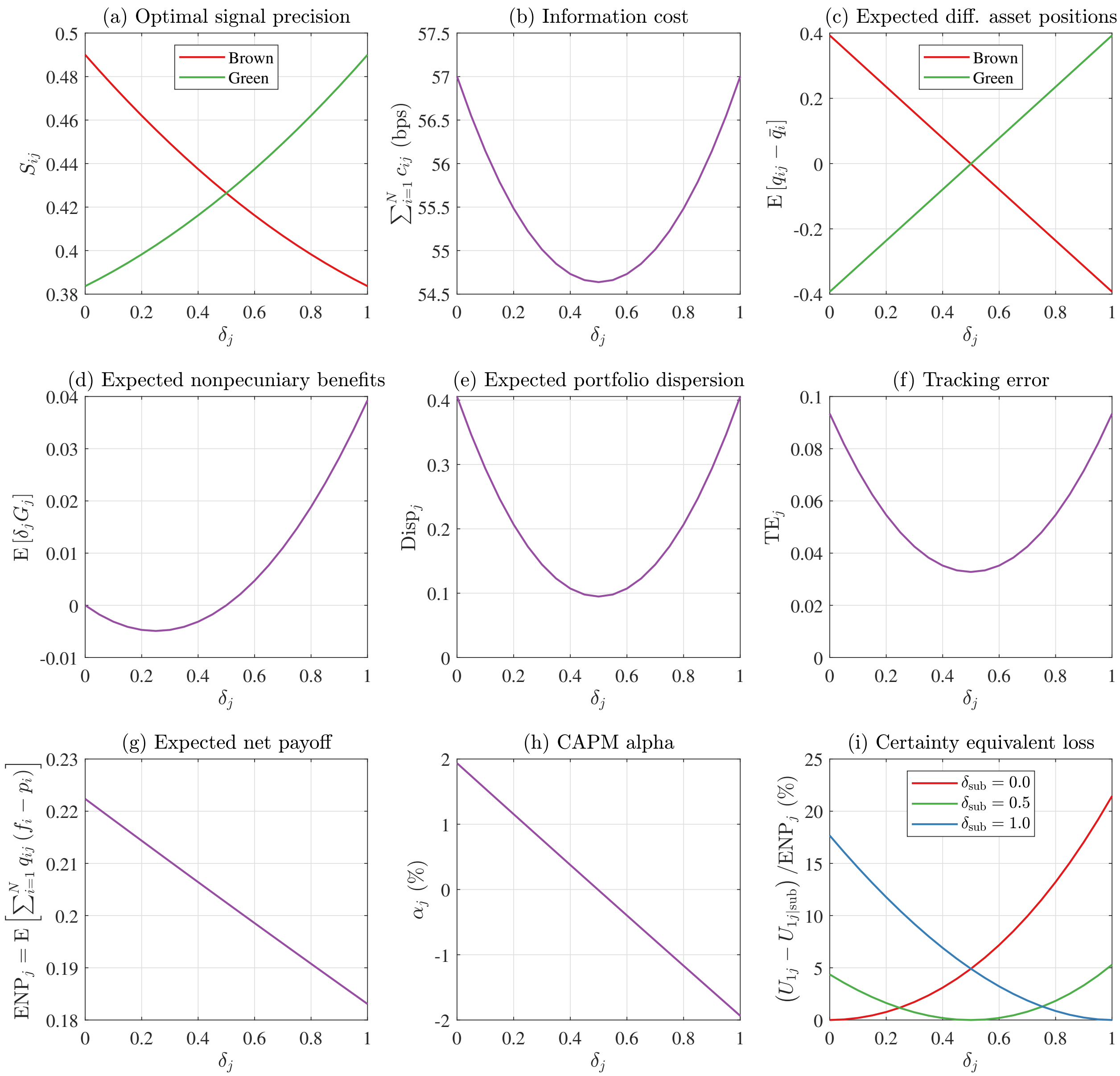
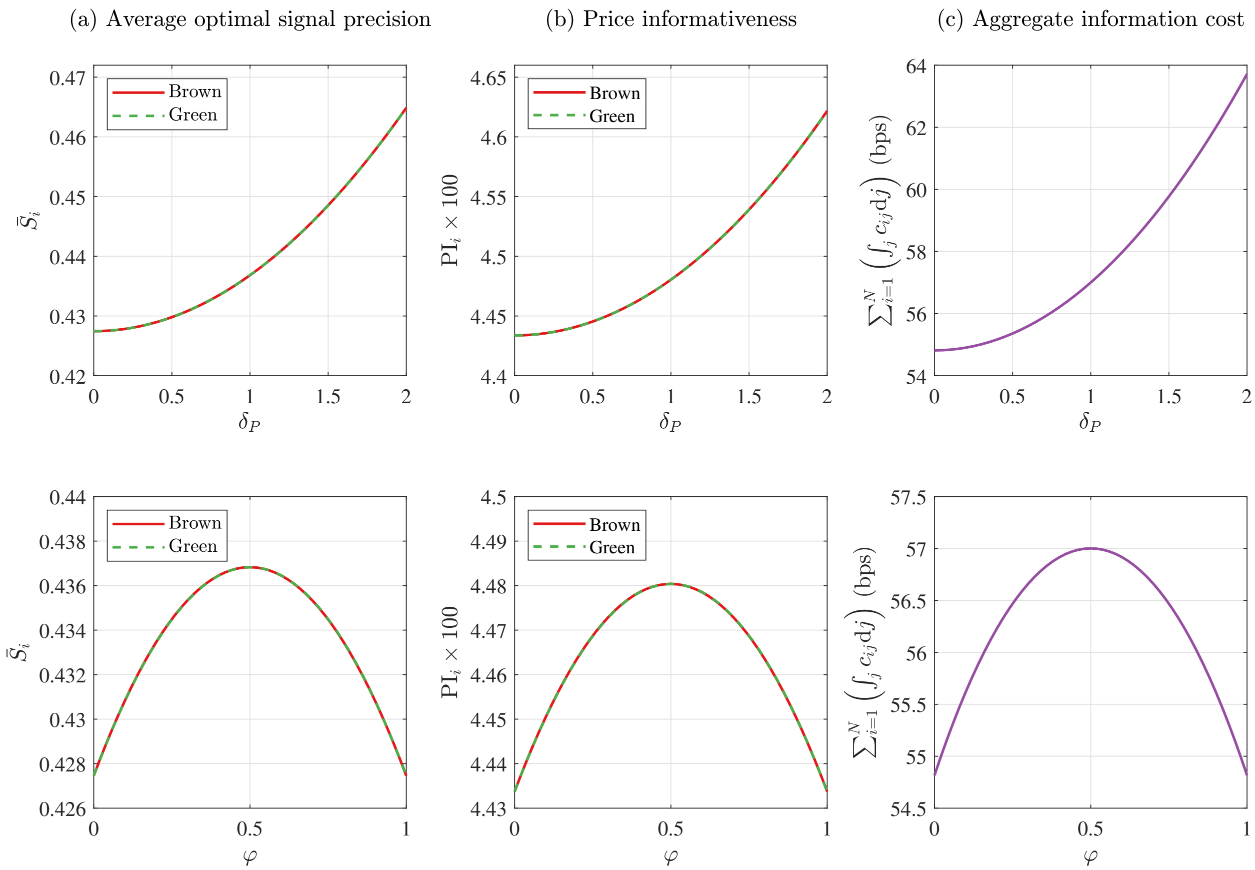


Figure 2: Calibration - Equilibrium Asset Pricing

Graphs (a) show the equilibrium aggregate signal precision for the green and brown assets in the economy. Graphs (b) show the price informativeness of the assets. Graphs (c) show the aggregate information acquisition cost. ESG-perceptive funds have ESG preferences of δ_P and represent a fraction φ of the total population, while ESG-indifferent funds have zero ESG preferences ($\delta_I = 0$). For the graphs in the top row, δ_P varies between 0 and 2, while $\varphi = 0.5$. For the graphs in the bottom row, $\delta_P = 1$, while φ varies between 0 and 1.



Active Fund Management when ESG Matters: An Equilibrium Perspective

Online Appendix

Doron Avramov Si Cheng Andrea Tarelli

This Online Appendix presents the proofs and derivations, as well as the supplementary empirical results discussed in the paper.

Section A. Derivations

- A.1. Solving for asset prices
- A.2. Solving for information decisions
- A.3. Total signal precision
- A.4. Sensitivity of the optimal signal precision to ESG preferences
- A.5. Sensitivity of the optimal aggregate signal precision to the ESG score
- A.6. Portfolio positions and ESG profile
- A.7. Expected utility loss from following a suboptimal strategy and information acquisition policy
- A.8. Portfolio dispersion and tracking error
- A.9. Expected net payoff and alpha
- A.10. Price informativeness

Section B. Supplementary material

- Table B.1. Variables Definitions
- Table B.2. Performance of Portfolios Sorted by Mutual Fund Ownership and ESG Rating
- Table B.3. Implied Cost of Capital of Portfolios Sorted by Mutual Fund Ownership and ESG Rating

A Derivations

Before proceeding with the derivations, we briefly describe the economic setting. Following Kacperczyk et al. (2016), asset payoffs are expressed in matrix form

$$\boldsymbol{f} = \boldsymbol{\mu} + \boldsymbol{\Gamma}\boldsymbol{z}, \tag{A.1}$$

where $\boldsymbol{f}$, $\boldsymbol{\mu}$, $\boldsymbol{z} \sim \mathcal{MN}(\mathbf{0}, \boldsymbol{\Sigma})$, and $\boldsymbol{\Sigma}$ are the matrix versions of f_i, μ_i, z_i and σ_i, respectively, while $\boldsymbol{\Gamma}$ is given by

$$\boldsymbol{\Gamma} = \begin{bmatrix} 1 & 0 & \cdots & 0 & b_1 \\ 0 & 1 & \cdots & 0 & b_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & b_{N-1} \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix}, \tag{A.2}$$

and its inverse is given by

$$\boldsymbol{\Gamma}^{-1} = \begin{bmatrix} 1 & 0 & \cdots & 0 & -b_1 \\ 0 & 1 & \cdots & 0 & -b_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & 1 & -b_{N-1} \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix}. \tag{A.3}$$

The risk factors can then be rewritten as

$$\boldsymbol{\mathcal{F}} = \boldsymbol{\Gamma}^{-1}\boldsymbol{f} = \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z}. \tag{A.4}$$

A risk factor supply is denoted by $\bar{\mathcal{X}}_i + \mathcal{X}_i$, where $\bar{\mathcal{X}}_i$ is the mean supply and $\mathcal{X}_i \sim \mathcal{N}(0, \sigma_{\mathcal{X}i})$ is the random supply noise. While in the text, the supply noise $\sigma_{\mathcal{X}i}$ is assumed to be constant across assets, in the derivations that follow, we consider the general case of heterogeneous supply noise. Let $\left(\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}}\right)$ denote the supply vector of the risk factors, where $\boldsymbol{\mathcal{X}} \sim \mathcal{MN}(\mathbf{0}, \boldsymbol{\Sigma}_{\mathcal{X}})$, and let $\bar{\boldsymbol{x}} + \boldsymbol{x}$ denote the supply of the risky assets. It follows that $\bar{\boldsymbol{x}} + \boldsymbol{x} = \boldsymbol{\Gamma}^{-1}\left(\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}}\right)$.

It is assumed that each of the agents has mean-variance preferences, given by

$$U_j(W_j, G_j, S_{1j}, S_{2j}, \ldots, S_{Nj}) = \mathrm{E}[W_j] - \frac{\rho}{2}\mathrm{Var}[W_j] + \delta_j \mathrm{E}[G_j], \tag{A.5}$$

where ρ is risk aversion, δ_j represents the preference for ESG with a higher value reflecting a stronger preference, $G_j = \sum_{i=1}^{N} q_{ij} g_i$ is the ESG score of the portfolio, W_j stands for the agent's terminal wealth that satisfies the budget constraint $W_j = W_{0j} + \sum_{i=1}^{N} q_{ij}(f_i - p_i) - \sum_{i=1}^{N} c_{ij}(S_{ij})$, p_i is the price of the risky asset, and $\sum_{i=1}^{N} c_{ij}(S_{ij})$ is the total cost of information acquisition, with $c_{ij}(S_{ij})$ standing for the cost per risk factor i. The ESG preference parameter δ_j is assumed to be nonnegative and strictly positive for a nonzero measure of agents in the economy.

The time-1 expected utility is

$$U_{1j}(W_j, G_j, \mathbf{S}_j) = \mathrm{E}_{1j}[U_{2j}(W_j, G_j, \mathbf{S}_j)] = \mathrm{E}_{1j}\left[\mathrm{E}_{2j}[W_j] - \frac{\rho}{2}\mathrm{Var}_{2j}[W_j] + \delta_j \mathrm{E}_{2j}[G_j]\right]. \tag{A.6}$$

The equilibrium is derived by backward induction, first optimizing the portfolio allocation in period 2 and then optimizing the information acquisition in period 1. At time 2, agent j chooses the portfolio that maximizes the expected utility

$$U_{2j}(W_j, G_j, \mathbf{S}_j) = \mathrm{E}_{2j}[W_j] - \frac{\rho}{2}\mathrm{Var}_{2j}[W_j] + \delta_j \mathrm{E}_{2j}[G_j], \tag{A.7}$$

where $\mathrm{E}_{2j}[.]$ and $\mathrm{Var}_{2j}[.]$ denote the expectation and variance conditional on the information available in period 2 that includes the signals acquired in period 1, respectively. Let $\boldsymbol{\mathcal{P}} = \boldsymbol{\Gamma}^{-1}\boldsymbol{p}$ denote the vector of risk factor prices, and let $\boldsymbol{\mathcal{Q}}_j = \boldsymbol{\Gamma}'\boldsymbol{q}_j$ denote the positions in the risk factors. As $\boldsymbol{f} = \boldsymbol{\Gamma}\boldsymbol{\mathcal{F}}$, $\boldsymbol{p} = \boldsymbol{\Gamma}\boldsymbol{\mathcal{P}}$, and $\boldsymbol{q}_j' = \boldsymbol{\mathcal{Q}}_j'\boldsymbol{\Gamma}^{-1}$, the budget constraint becomes $W_j = rW_{0j} + \boldsymbol{\mathcal{Q}}_j'(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r) - \sum_{i=1}^{N} c_{ij}(S_{ij})$, and the ESG scores of the risk factors are $\boldsymbol{\mathcal{G}} = \boldsymbol{\Gamma}^{-1}\boldsymbol{g}$. Hence, the individual ESG score of a risk factor is $\mathcal{G}_i = g_i - b_i g_N$ for $i < N$ and $\mathcal{G}_N = g_N$. Assuming that the composite asset is green neutral, the risk factors and the corresponding risky assets have the same ESG profile, $\mathcal{G}_i = g_i$.

A.1 Solving for asset prices

The equilibrium asset prices clear the market. The time-2 vector of prices is conjectured to be

$$\boldsymbol{\mathcal{P}} = \frac{1}{r}\left(\boldsymbol{A} + \boldsymbol{B}\boldsymbol{z} + \boldsymbol{C}\boldsymbol{\mathcal{X}} + \boldsymbol{D}\boldsymbol{\mathcal{G}}\right). \tag{A.8}$$

Our aim is to find the price coefficients.

To start, market clearing requires that

$$\int \boldsymbol{\mathcal{Q}}_j \mathrm{d}j = \bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}}. \tag{A.9}$$

Agent j acquires information represented by the collection of signals $\boldsymbol{\eta}_j$

$$\boldsymbol{\eta}_j = \boldsymbol{z} + \boldsymbol{\varepsilon}_j, \qquad \boldsymbol{\varepsilon}_j \sim \mathcal{MN}\left(\mathbf{0}, \mathbf{S}_j^{-1}\right), \tag{A.10}$$

where $\mathbf{S}_j$ is a diagonal matrix with nonnegative elements S_{ij}. At time 1, the agent chooses S_{ij} to maximize

$$U_{1j}\left(W_j, G_j, \mathbf{S}_j\right) = \mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[W_j\right] - \frac{\rho}{2}\mathrm{Var}_{2j}\left[W_j\right] + \delta_j \mathrm{E}_{2j}\left[G_j\right]\right]. \tag{A.11}$$

The signal from prices takes the form

$$\boldsymbol{\eta}_p = \boldsymbol{z} + \boldsymbol{\varepsilon}_p \qquad \boldsymbol{\varepsilon}_p \sim \mathcal{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_p\right), \tag{A.12}$$

where $\boldsymbol{\Sigma}_p$ is recovered below. In particular,

$$\begin{aligned}\boldsymbol{\eta}_p &= \boldsymbol{B}^{-1}\left(\boldsymbol{\mathcal{P}}r - \boldsymbol{A} - \boldsymbol{D}\boldsymbol{\mathcal{G}}\right)\\ &= \boldsymbol{B}^{-1}\left(\boldsymbol{B}\boldsymbol{z} + \boldsymbol{C}\boldsymbol{\mathcal{X}}\right)\\ &= \boldsymbol{z} + \underbrace{\boldsymbol{B}^{-1}\boldsymbol{C}\boldsymbol{\mathcal{X}}}_{\boldsymbol{\varepsilon}_p},\end{aligned} \tag{A.13}$$

where $\boldsymbol{\varepsilon}_p \sim \mathcal{N}\left(\mathbf{0}, \boldsymbol{\Sigma}_p\right)$ and $\boldsymbol{\Sigma}_p = \boldsymbol{B}^{-1}\boldsymbol{C}\boldsymbol{\Sigma}_{\mathcal{X}}\boldsymbol{C}'\boldsymbol{B}^{-1\prime}$ ($\boldsymbol{\Sigma}_p^{-1} = \boldsymbol{B}'\boldsymbol{C}^{-1\prime}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\boldsymbol{C}^{-1}\boldsymbol{B}$).

The posterior beliefs about $\boldsymbol{z}$ can then be represented by the normal density with moments

$$\hat{\boldsymbol{z}}_j = \hat{\boldsymbol{\Sigma}}_j\left(\mathbf{S}_j\boldsymbol{\eta}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p\right), \tag{A.14}$$

$$\hat{\boldsymbol{\Sigma}}_j^{-1} = \boldsymbol{\Sigma}^{-1} + \mathbf{S}_j + \boldsymbol{\Sigma}_p^{-1}. \tag{A.15}$$

As $\boldsymbol{\mathcal{F}} = \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z}$, the time-2 conditional expected payoff of the risk factors is

$$\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] = \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{z}}_j. \tag{A.16}$$

The posterior distribution of the risk factor payoffs is then

$$\boldsymbol{\mathcal{F}} \sim \mathcal{N}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right], \mathrm{Var}_{2j}\left[\boldsymbol{\mathcal{F}}\right]\right), \tag{A.17}$$

where $\mathrm{Var}_{2j}\left[\boldsymbol{\mathcal{F}}\right] = \hat{\boldsymbol{\Sigma}}_j$. The time-2 portfolio that optimally invests in the risk factors is given by

$$\boldsymbol{\mathcal{Q}}_j = \frac{1}{\rho}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right). \tag{A.18}$$

From Equation (A.8), we obtain

$$\boldsymbol{\mathcal{X}} = \boldsymbol{C}^{-1}\left(\boldsymbol{\mathcal{P}}r - \boldsymbol{A} - \boldsymbol{B}\boldsymbol{z} - \boldsymbol{D}\boldsymbol{\mathcal{G}}\right) = \boldsymbol{C}^{-1}\boldsymbol{B}\left(\boldsymbol{\eta}_p - \boldsymbol{z}\right). \tag{A.19}$$

Aggregating through the equations above yields

$$\begin{aligned}
\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}} = \bar{\boldsymbol{Q}} &= \int_j \boldsymbol{\mathcal{Q}}_j \mathrm{d}j \\
&= \int_j \frac{1}{\rho}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)\mathrm{d}j \\
&= \int_j \frac{1}{\rho}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \mathrm{E}_{2j}\left[\boldsymbol{z}\right] - \boldsymbol{A} - \boldsymbol{B}\boldsymbol{\eta}_p - \boldsymbol{D}\boldsymbol{\mathcal{G}} + \delta_j\boldsymbol{\mathcal{G}}\right)\mathrm{d}j \\
&= \frac{1}{\rho}\left(\int_j\left(\mathbf{S}_j\boldsymbol{\eta}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p\right)\mathrm{d}j + \left(\int_j \hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j\mathrm{d}j\right)\boldsymbol{\mathcal{G}} + \left(\int_j\hat{\boldsymbol{\Sigma}}_j^{-1}\mathrm{d}j\right)\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{A} - \boldsymbol{B}\boldsymbol{\eta}_p - \boldsymbol{D}\boldsymbol{\mathcal{G}}\right)\right) \\
&= \frac{1}{\rho}\left(\bar{\mathbf{S}}\boldsymbol{z} + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p + \left(\int_j\hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j\mathrm{d}j\right)\boldsymbol{\mathcal{G}} + \bar{\boldsymbol{\Sigma}}^{-1}\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{A} - \boldsymbol{B}\boldsymbol{\eta}_p - \boldsymbol{D}\boldsymbol{\mathcal{G}}\right)\right),
\end{aligned} \tag{A.20}$$

where $\bar{\boldsymbol{\Sigma}}^{-1} = \int_j \hat{\boldsymbol{\Sigma}}_j^{-1}\mathrm{d}j$ is a matrix with diagonal elements $\bar{\sigma}_i^{-1} = \int_j \hat{\sigma}_{ij}^{-1}\mathrm{d}j$, and $\bar{\mathbf{S}} = \int_j \mathbf{S}_j\mathrm{d}j$. In deriving the last expression, it is assumed that the average noise of the private signals is zero. Then, substituting Equation (A.19) into Equation (A.20) leads to

$$\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{C}^{-1}\boldsymbol{B}\left(\boldsymbol{\eta}_p - \boldsymbol{z}\right) = \frac{1}{\rho}\left(\bar{\mathbf{S}}\boldsymbol{z} + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p + \left(\int_j\hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j\mathrm{d}j\right)\boldsymbol{\mathcal{G}} + \bar{\boldsymbol{\Sigma}}^{-1}\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{A} - \boldsymbol{B}\boldsymbol{\eta}_p - \boldsymbol{D}\boldsymbol{\mathcal{G}}\right)\right). \tag{A.21}$$

By matching coefficients, we obtain

$$\begin{cases}
\bar{\boldsymbol{\mathcal{X}}} = \frac{1}{\rho}\bar{\boldsymbol{\Sigma}}^{-1}\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{A}\right) \\
\boldsymbol{C}^{-1}\boldsymbol{B} = \frac{1}{\rho}\left(\boldsymbol{\Sigma}_p^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\boldsymbol{B}\right) \\
-\boldsymbol{C}^{-1}\boldsymbol{B} = \frac{1}{\rho}\bar{\mathbf{S}} \\
\boldsymbol{D} = \bar{\boldsymbol{\Sigma}}\int_j\hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j\mathrm{d}j.
\end{cases} \tag{A.22}$$

The price coefficients then follow:

$$\begin{cases}
\boldsymbol{A} = \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} \\
\boldsymbol{B} = \bar{\boldsymbol{\Sigma}}\left(\boldsymbol{\Sigma}_p^{-1} + \bar{\mathbf{S}}\right) = \mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1} \\
\boldsymbol{C} = -\rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \boldsymbol{\Sigma}_p^{-1}\bar{\mathbf{S}}^{-1}\right) \\
\boldsymbol{D} = \bar{\boldsymbol{\Sigma}}\int_j\hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j\mathrm{d}j \equiv \bar{\boldsymbol{\delta}},
\end{cases} \tag{A.23}$$

where $\bar{\boldsymbol{\delta}}$ is a diagonal matrix with i-th element equal to $\bar{\delta}_i = \bar{\sigma}_i\int_j\hat{\sigma}_{ij}^{-1}\delta_j\mathrm{d}j$. As $\boldsymbol{B}^{-1}\boldsymbol{C} = -\rho\bar{\mathbf{S}}^{-1}$, we obtain

$$\boldsymbol{\Sigma}_p = \boldsymbol{B}^{-1}\boldsymbol{C}\boldsymbol{\Sigma}_{\mathcal{X}}\boldsymbol{C}'\boldsymbol{B}^{-1\prime} = \rho^2\bar{\mathbf{S}}^{-1}\boldsymbol{\Sigma}_{\mathcal{X}}\bar{\mathbf{S}}^{-1}. \tag{A.24}$$

It follows that $\boldsymbol{\Sigma}_p^{-1} = \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}$ and $\boldsymbol{C} = -\rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)$. Thus, the diagonal elements of $\bar{\boldsymbol{\Sigma}}^{-1} = \boldsymbol{\Sigma}^{-1} + \bar{\mathbf{S}} + \boldsymbol{\Sigma}_p^{-1}$ can be written as

$$\bar{\sigma}_i^{-1} = \sigma_i^{-1} + \bar{S}_i + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}. \tag{A.25}$$

Next, the vector of risk factor prices (multiplied by the gross rate) is given by

$$\boldsymbol{\mathcal{P}}r = \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{z} - \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}} + \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}. \tag{A.26}$$

The terms of the diagonal matrix $\mathbf{I}-\bar{\mathbf{\Sigma}}\mathbf{\Sigma}^{-1}$ are all positive, expressed by $1-\sigma_i^{-1}/\left(\sigma_i^{-1}+\bar{S}_i+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)$. Using the relations $\boldsymbol{\mathcal{P}}=\mathbf{\Gamma}^{-1}\boldsymbol{p}$ and $\boldsymbol{\mathcal{X}}=\mathbf{\Gamma}\boldsymbol{x}$, the equilibrium asset prices are then given by

$$\boldsymbol{p}r=\boldsymbol{\mu}-\rho\mathbf{\Gamma}\bar{\mathbf{\Sigma}}\mathbf{\Gamma}\bar{\boldsymbol{x}}+\mathbf{\Gamma}\left(\mathbf{I}-\bar{\mathbf{\Sigma}}\mathbf{\Sigma}^{-1}\right)\boldsymbol{z}-\rho\mathbf{\Gamma}\bar{\mathbf{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right)\mathbf{\Gamma}\boldsymbol{x}+\mathbf{\Gamma}\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}. \tag{A.27}$$

Proposition 1 follows by substituting $\mathbf{\Gamma}$ from Equation (A.2).

A.2 Solving for information decisions

Our aim is to derive the time-1 expected utility. Then, the information decision is based on equating the marginal benefit from information acquisition to the marginal cost. To start, the agent's wealth can be expressed as

$$W_j=rW_{0j}+\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\mathbf{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)-c_j\left(\mathbf{S}_j\right). \tag{A.28}$$

Then, the time-1 expected utility is

$$\begin{aligned}
U_{1j}=&\ \mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[rW_{0j}+\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\mathbf{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right]\right]\\
&-\frac{\rho}{2}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[rW_{0j}+\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\mathbf{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right]\right]\\
&+\frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\mathbf{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}}\right]-c_j\left(\mathbf{S}_j\right),\\
=&\ rW_{0j}+\mathrm{E}_{1j}\left[\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\mathbf{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r\right)\right]\\
&-\frac{\rho}{2}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\mathbf{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right]\right]\\
&+\frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right]-\boldsymbol{\mathcal{P}}r+\delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\mathbf{\Sigma}}_j^{-1}\right]\boldsymbol{\mathcal{G}}-c_j\left(\mathbf{S}_j\right).
\end{aligned} \tag{A.29}$$

To further characterize the above expression, we use Equations (A.4) and (A.26) to rewrite the net payoff as

$$\begin{aligned}
\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r&=\mathbf{\Gamma}^{-1}\boldsymbol{\mu}+\boldsymbol{z}-\left(\mathbf{\Gamma}^{-1}\boldsymbol{\mu}-\rho\bar{\mathbf{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}+\left(\mathbf{I}-\bar{\mathbf{\Sigma}}\mathbf{\Sigma}^{-1}\right)\boldsymbol{z}-\rho\bar{\mathbf{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}+\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}\right)\\
&=\rho\bar{\mathbf{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}+\bar{\mathbf{\Sigma}}\mathbf{\Sigma}^{-1}\boldsymbol{z}+\rho\bar{\mathbf{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}-\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}\\
&=\mathbf{w}+\mathbf{V}^{\frac{1}{2}}\mathbf{u},
\end{aligned} \tag{A.30}$$

where $\mathbf{u}\sim\mathcal{N}\left(\mathbf{0},\mathbf{I}\right)$, $\mathbf{w}=\rho\bar{\mathbf{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}-\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}$, $\mathbf{V}^{\frac{1}{2}}\mathbf{u}=\bar{\mathbf{\Sigma}}\mathbf{\Sigma}^{-1}\boldsymbol{z}+\rho\bar{\mathbf{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}$, and $\mathbf{V}$ is given by

$$\begin{aligned}
\mathbf{V}&=\bar{\mathbf{\Sigma}}\mathbf{\Sigma}^{-1}\bar{\mathbf{\Sigma}}+\rho^2\bar{\mathbf{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right)\mathbf{\Sigma}_{\mathcal{X}}\left(\mathbf{I}+\frac{1}{\rho^2}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\right)\bar{\mathbf{\Sigma}},\\
&=\bar{\mathbf{\Sigma}}\left(\mathbf{\Sigma}^{-1}+\rho^2\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\right)\mathbf{\Sigma}_{\mathcal{X}}\left(\mathbf{I}+\frac{1}{\rho^2}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\right)\right)\bar{\mathbf{\Sigma}},\\
&=\bar{\mathbf{\Sigma}}\left(\mathbf{\Sigma}^{-1}+\rho^2\mathbf{\Sigma}_{\mathcal{X}}+\bar{\mathbf{S}}+\underbrace{\bar{\mathbf{S}}+\frac{1}{\rho^2}\bar{\mathbf{S}}\mathbf{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}}_{\mathbf{\Sigma}_p^{-1}}\right)\bar{\mathbf{\Sigma}},
\end{aligned}$$

$$= \bar{\boldsymbol{\Sigma}}\left(\rho^2\boldsymbol{\Sigma}_{\mathcal{X}} + \bar{\mathbf{S}} + \bar{\boldsymbol{\Sigma}}^{-1}\right)\bar{\boldsymbol{\Sigma}}. \tag{A.31}$$

The matrix V is diagonal with elements $V_{ii} = \bar{\sigma}_i\left(1 + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i\right)$.

The time-2 expected net payoff is $\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r = \mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{F}} + \boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r$, while the time-1 variance is

$$\mathrm{Var}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right] = \mathrm{Var}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{F}}\right] + \mathrm{Var}_{1j}\left[\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right] + 2\mathrm{Cov}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{F}}, \boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right]. \tag{A.32}$$

We solve each of the variance components.

From Equations (A.4) and (A.16), we obtain

$$\begin{aligned}
\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{F}} &= \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{\Sigma}}_j\mathbf{S}_j\left(\boldsymbol{z} + \boldsymbol{\varepsilon}_j\right) + \hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}_p^{-1}\left(\boldsymbol{z} + \boldsymbol{\varepsilon}_p\right) - \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{z} \\
&= \hat{\boldsymbol{\Sigma}}_j\left(\left(\mathbf{S}_j + \boldsymbol{\Sigma}_p^{-1} - \hat{\boldsymbol{\Sigma}}_j^{-1}\right)\boldsymbol{z} + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\varepsilon}_p\right) \\
&= \hat{\boldsymbol{\Sigma}}_j\left(-\boldsymbol{\Sigma}^{-1}\boldsymbol{z} + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\varepsilon}_p\right).
\end{aligned} \tag{A.33}$$

The time-1 expected value of the above expression is zero. Then, as $\boldsymbol{z}$, $\boldsymbol{\varepsilon}_j$, and $\boldsymbol{\varepsilon}_p$ are independent, the time-1 variance is equal to

$$\mathrm{Var}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{F}}\right] = \hat{\boldsymbol{\Sigma}}_j\underbrace{\left(\boldsymbol{\Sigma}^{-1} + \mathbf{S}_j + \boldsymbol{\Sigma}_p^{-1}\right)}_{\hat{\boldsymbol{\Sigma}}_j^{-1}}\hat{\boldsymbol{\Sigma}}_j' = \hat{\boldsymbol{\Sigma}}_j. \tag{A.34}$$

From Equation (A.30), we obtain $\mathrm{Var}_{1j}\left[\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right] = \mathbf{V}$. To solve for the third term in Equation (A.32), we first express the net payoff as

$$\begin{aligned}
\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r &= \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z} - \boldsymbol{A} - \boldsymbol{B}\left(\boldsymbol{z} + \boldsymbol{\varepsilon}_p\right) - \boldsymbol{D}\boldsymbol{\mathcal{G}} \\
&= \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z} - \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\left(\boldsymbol{z} + \boldsymbol{\varepsilon}_p\right) - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}} \\
&= \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z} - \left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{\varepsilon}_p - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}.
\end{aligned} \tag{A.35}$$

Then, the third term is

$$\begin{aligned}
\mathrm{Cov}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{F}}, \boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right] &= \mathrm{Cov}_1\left[\hat{\boldsymbol{\Sigma}}_j\left(-\boldsymbol{\Sigma}^{-1}\boldsymbol{z} + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\varepsilon}_p\right), \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z} - \left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{\varepsilon}_p\right] \\
&= \mathrm{Cov}_1\left[-\hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}^{-1}\boldsymbol{z} + \hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}_p^{-1}\boldsymbol{\varepsilon}_p, \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z} - \left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{\varepsilon}_p\right] \\
&= -\hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}^{-1}\boldsymbol{\Sigma}\boldsymbol{\Sigma}^{-1}\bar{\boldsymbol{\Sigma}} - \hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}_p^{-1}\boldsymbol{\Sigma}_p\left(\mathbf{I} - \boldsymbol{\Sigma}^{-1}\bar{\boldsymbol{\Sigma}}\right) \\
&= -\hat{\boldsymbol{\Sigma}}_j\boldsymbol{\Sigma}^{-1}\bar{\boldsymbol{\Sigma}} - \hat{\boldsymbol{\Sigma}}_j\left(\mathbf{I} - \boldsymbol{\Sigma}^{-1}\bar{\boldsymbol{\Sigma}}\right) \\
&= -\hat{\boldsymbol{\Sigma}}_j.
\end{aligned} \tag{A.36}$$

Aggregating through the three terms, the time-1 variance in Equation (A.32) is

$$\begin{aligned}
\mathrm{Var}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right] &= \hat{\boldsymbol{\Sigma}}_j + \mathbf{V} - 2\hat{\boldsymbol{\Sigma}}_j = \mathbf{V} - \hat{\boldsymbol{\Sigma}}_j \\
&= \bar{\boldsymbol{\Sigma}}\left(\rho^2\boldsymbol{\Sigma}_{\mathcal{X}} + \bar{\mathbf{S}} + \bar{\boldsymbol{\Sigma}}^{-1}\right)\bar{\boldsymbol{\Sigma}} - \hat{\boldsymbol{\Sigma}}_j,
\end{aligned} \tag{A.37}$$

which is a diagonal matrix with elements

$$\left(\mathrm{Var}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right]\right)_{ii} = \bar{\sigma}_i\left(1 + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i\right) - \hat{\sigma}_{ij} = \left(\bar{\sigma}_i - \hat{\sigma}_{ij}\right) + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2. \tag{A.38}$$

The time-1 distribution of the expected excess payoff is

$$\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r \sim \mathcal{MN}\left(\mathbf{w}, \mathbf{V} - \hat{\mathbf{\Sigma}}_j\right). \tag{A.39}$$

Equation (A.29) can be rewritten as

$$\begin{aligned}
U_{1j} = {} & rW_{0j} + \frac{1}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)' \hat{\mathbf{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)\right] \\
& + \frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\boldsymbol{\mathcal{G}}'\hat{\mathbf{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)\right] \\
& - \frac{\rho}{2}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)' \hat{\mathbf{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right)\right]\right] \\
& + \frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)' \hat{\mathbf{\Sigma}}_j^{-1}\right]\boldsymbol{\mathcal{G}} \\
& + \frac{\delta_j^2}{\rho}\boldsymbol{\mathcal{G}}'\hat{\mathbf{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}} - c_j\left(\boldsymbol{S}_j\right) \\
= {} & rW_{0j} + \frac{1}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)' \hat{\mathbf{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)\right] \\
& + \frac{\delta_j}{\rho}\boldsymbol{\mathcal{G}}'\hat{\mathbf{\Sigma}}_j^{-1}\mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right] \\
& - \frac{1}{2\rho}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)' \hat{\mathbf{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right)\right]\right] \\
& + \frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)' \hat{\mathbf{\Sigma}}_j^{-1}\right]\boldsymbol{\mathcal{G}} \\
& + \frac{\delta_j^2}{\rho}\boldsymbol{\mathcal{G}}'\hat{\mathbf{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}} - c_j\left(\boldsymbol{S}_j\right).
\end{aligned} \tag{A.40}$$

Then, the first term in Equation (A.40) can be expressed as

$$\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)' \hat{\mathbf{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)\right] = \mathrm{E}_{1j}\left[\boldsymbol{m}_1'\boldsymbol{m}_1\right], \tag{A.41}$$

where $\boldsymbol{m}_1 = \hat{\mathbf{\Sigma}}_j^{-\frac{1}{2}}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)$, $\mathrm{E}_{1j}\left[\boldsymbol{m}_1\right] = \hat{\mathbf{\Sigma}}_j^{-\frac{1}{2}}\mathbf{w}$, and $\mathrm{Var}_{1j}\left[\boldsymbol{m}_1\right] = \hat{\mathbf{\Sigma}}_j^{-\frac{1}{2}}\left(\mathbf{V} - \hat{\mathbf{\Sigma}}_j\right)\hat{\mathbf{\Sigma}}_j^{-\frac{1}{2}} = \hat{\mathbf{\Sigma}}_j^{-1}\mathbf{V} - \mathbf{I}$. Then $\boldsymbol{m}_1 \sim \mathcal{MN}\left(\hat{\mathbf{\Sigma}}_j^{-\frac{1}{2}}\mathbf{w}, \hat{\mathbf{\Sigma}}_j^{-1}\mathbf{V} - \mathbf{I}\right)$. Hence,

$$\begin{aligned}
& \mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)' \hat{\mathbf{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)\right] \\
& = \mathrm{E}_{1j}\left[\boldsymbol{m}_1'\boldsymbol{m}_1\right] = \mathrm{tr}\left(\hat{\mathbf{\Sigma}}_j^{-1}\mathbf{V} - \mathbf{I}\right) + \mathbf{w}'\hat{\mathbf{\Sigma}}_j^{-1}\mathbf{w} \\
& = \sum_{i=1}^{N}\left(\bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\underbrace{\rho\bar{\mathcal{X}}_i\bar{\sigma}_i - \bar{\delta}_i\mathcal{G}_i}_{w_i}\right)^2\right)\left(\sigma_i^{-1} + S_{ij} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) - N,
\end{aligned} \tag{A.42}$$

where $w_i = \rho\bar{\mathcal{X}}_i\bar{\sigma}_i - \bar{\delta}_i\mathcal{G}_i$. The second term in Equation (A.40) is $\mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right] = \mathbf{w}$, while the third term is

$$\begin{aligned}
& \mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)' \hat{\mathbf{\Sigma}}_j^{-1}\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right)\right]\right] \\
& = \mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)' \hat{\mathbf{\Sigma}}_j^{-1}\underbrace{\mathrm{Var}_{2j}\left[\boldsymbol{\mathcal{F}}\right]}_{\hat{\mathbf{\Sigma}}_j}\hat{\mathbf{\Sigma}}_j^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)\right]
\end{aligned}$$

$$= \mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j \boldsymbol{\mathcal{G}}\right)' \hat{\boldsymbol{\Sigma}}_j^{-1} \left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j \boldsymbol{\mathcal{G}}\right)\right]$$
$$= \mathrm{tr}\left(\hat{\boldsymbol{\Sigma}}_j^{-1}\mathbf{V} - \mathbf{I}\right) + \left(\mathbf{w} + \delta_j \boldsymbol{\mathcal{G}}\right)' \hat{\boldsymbol{\Sigma}}_j^{-1} \left(\mathbf{w} + \delta_j \boldsymbol{\mathcal{G}}\right)$$
$$= \sum_{i=1}^{N} \left(\bar{\sigma}_i + \left(\rho^2 \sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i + \left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1} + S_{ij} + \frac{\bar{S}_i^2}{\rho^2\sigma_x}\right) - N. \tag{A.43}$$

The fourth term is

$$\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)' \hat{\boldsymbol{\Sigma}}_j^{-1}\right] = \mathbf{w}'\hat{\boldsymbol{\Sigma}}_j^{-1}. \tag{A.44}$$

Aggregating through the four terms, the time-1 expected utility in Equation (A.40) is given by

$$\begin{aligned}
U_{1j} &= rW_{0j} \\
&\quad + \frac{1}{\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i - \bar{\delta}_i\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1} + S_{ij} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) - \frac{N}{\rho} \\
&\quad + \frac{\delta_j}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_j^{-1}\mathbf{w} \\
&\quad - \frac{1}{2\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i + \left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1} + S_{ij} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) + \frac{N}{2\rho} \\
&\quad + \frac{\delta_j}{\rho}\mathbf{w}'\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}} + \frac{\delta_j^2}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}} - c_j\left(\boldsymbol{S}_j\right) \\
&= rW_{0j} \\
&\quad + \frac{1}{\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i - \bar{\delta}_i\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1} + S_{ij} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) - \frac{N}{\rho} \\
&\quad + \sum_{i=1}^{N} 2\frac{\delta_j}{\rho}\mathcal{G}_i\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i - \bar{\delta}_i\mathcal{G}_i\right)\left(\sigma_i^{-1} + S_{ij} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) \\
&\quad - \frac{1}{2\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i + \left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1} + S_{ij} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) + \frac{N}{2\rho} \\
&\quad + \frac{\delta_j^2}{\rho}\sum_{i=1}^{N}\mathcal{G}_i^2\left(\sigma_i^{-1} + S_{ij} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) - \sum_{i=1}^{N} c_{ij}\left(S_{ij}\right) \\
&= \text{constant} + \sum_{i=1}^{N}\psi_{ij}S_{ij} - \sum_{i=1}^{N} c_{ij}\left(S_{ij}\right),
\end{aligned} \tag{A.45}$$

where

$$\begin{aligned}
2\rho\psi_{ij} &= \bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + 2\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i - \bar{\delta}_i\mathcal{G}_i\right)^2 + 4\delta_j\mathcal{G}_i\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i - \bar{\delta}_i\mathcal{G}_i\right) - \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i - \bar{\delta}_i\mathcal{G}_i + \delta_j\mathcal{G}_i\right)^2 + 2\delta_j^2\mathcal{G}_i^2 \\
&= \bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + 2\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\right)^2 + 2\left(\bar{\delta}_i\mathcal{G}_i\right)^2 - 4\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\bar{\delta}_i\mathcal{G}_i + 4\delta_j\mathcal{G}_i\rho\bar{\mathcal{X}}_i\bar{\sigma}_i - 4\delta_j\bar{\delta}_i\mathcal{G}_i^2 - \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\right)^2 \\
&= -\left(\bar{\delta}_i\mathcal{G}_i\right)^2 - \left(\delta_j\mathcal{G}_i\right)^2 + 2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\bar{\delta}_i\mathcal{G}_i - 2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\delta_j\mathcal{G}_i + 2\bar{\delta}_i\delta_j\mathcal{G}_i^2 + 2\delta_j^2\mathcal{G}_i^2 \\
&= \bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\right)^2 - 2\delta_j\bar{\delta}_i\mathcal{G}_i^2 + \left(\bar{\delta}_i\mathcal{G}_i\right)^2 + \left(\delta_j\mathcal{G}_i\right)^2 - 2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\bar{\delta}_i\mathcal{G}_i + 2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\delta_j\mathcal{G}_i \\
&= \bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\right)^2 + \left(\delta_j - \bar{\delta}_i\right)^2\mathcal{G}_i^2 + 2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i \\
&= \bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i + \left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i\right)^2.
\end{aligned} \tag{A.46}$$

Accounting for the constraint $S_{ij} \geq 0$, the optimal signal precision is given by

$$S_{ij} = \max \left[0, s | c'_{ij}(s) = \psi_{ij}\right]. \tag{A.47}$$

A.3 Total signal precision

We evaluate the average signal precision across all assets and agents when $c_{ij}(s) = \kappa s^2$ with $\kappa > 0$. We assume, without loss of generality, that $\frac{1}{N}\sum_{i=1}^{N} g_i = 0$. Recall that ESG scores are ordinal in nature. We further assume that $\bar{\sigma}_i = \bar{\sigma}$, $\bar{\delta}_i = \bar{\delta} = \int_j \delta_j \mathrm{d}j$, $\bar{X}_i = 1$. The optimal signal precision is then given by

$$S_{ij} = \frac{\bar{\sigma} + \left(\rho^2 \sigma_{\mathcal{X}} + \bar{S}\right)\bar{\sigma}^2 + \left(\rho\bar{\sigma} + \left(\delta_j - \bar{\delta}\right) g_i\right)^2}{4\kappa\rho}. \tag{A.48}$$

The average signal precision across all assets and agents is then equal to

$$\begin{aligned}
\hat{\bar{S}} &= \frac{1}{N}\sum_{i=1}^{N}\left(\int_j S_{ij}\mathrm{d}j\right) \\
&= \frac{1}{N}\sum_{i=1}^{N}\int_j \frac{\bar{\sigma} + \left(\rho^2 \sigma_{\mathcal{X}} + \bar{S}\right)\bar{\sigma}^2 + \left(\rho\bar{\sigma} + \left(\delta_j - \bar{\delta}\right) g_i\right)^2}{4\kappa\rho}\mathrm{d}j \\
&= \frac{1}{N}\sum_{i=1}^{N}\int_j \frac{\bar{\sigma} + \left(\rho^2 \sigma_{\mathcal{X}} + \bar{S}\right)\bar{\sigma}^2 + \left(\rho\bar{\sigma}\right)^2 + 2\rho\bar{\sigma}\left(\delta_j - \bar{\delta}\right) g_i + \left(\delta_j - \bar{\delta}\right)^2 g_i^2}{4\kappa\rho}\mathrm{d}j \\
&= \frac{\bar{\sigma} + \left(\rho^2 \sigma_{\mathcal{X}} + \bar{S}\right)\bar{\sigma}^2 + \left(\rho\bar{\sigma}\right)^2 + \sigma_\delta \sigma_g}{4\kappa\rho},
\end{aligned} \tag{A.49}$$

where $\sigma_\delta = \int_j \left(\delta_j - \bar{\delta}\right)^2 \mathrm{d}j$ and $\sigma_g = \frac{1}{N}\sum_{i=1}^{N} g_i^2$. The last term in the numerator of Equation (A.49) is the only component that is explicitly originating from ESG considerations, leading to an incremental average signal precision equal to $\hat{\bar{S}}_{ESG} = \frac{\sigma_\delta \sigma_g}{4\kappa\rho}$.

A.4 Sensitivity of the optimal signal precision to ESG preferences

We differentiate ψ_{ij} in Equation (A.46) with respect to $\left|\delta_j - \bar{\delta}\right|$

$$\frac{\partial \psi_{ij}}{\partial\left|\delta_j - \bar{\delta}\right|} = \frac{\partial}{\partial \delta_j}\frac{\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i + \operatorname{sign}\left(\delta_j - \bar{\delta}_i\right)\cdot\left|\delta_j - \bar{\delta}_i\right|\mathcal{G}_i\right)^2}{2\rho} = \frac{\rho\bar{\mathcal{X}}_i\bar{\sigma}_i + \left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i}{\rho}\cdot\operatorname{sign}\left(\delta_j - \bar{\delta}_i\right)\cdot\mathcal{G}_i. \tag{A.50}$$

When $c_{ij}(s) = \kappa s^2$ with $\kappa > 0$, the optimal signal precision is strictly positive and equal to $S_{ij} = \frac{\psi_{ij}}{2\kappa}$. Then

$$\frac{\partial S_{ij}}{\partial\left|\delta_j - \bar{\delta}\right|} = \frac{\rho\bar{\mathcal{X}}_i\bar{\sigma}_i + \left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i}{2\kappa\rho}\cdot\operatorname{sign}\left(\delta_j - \bar{\delta}_i\right)\cdot\mathcal{G}_i. \tag{A.51}$$

Then,

$$\begin{aligned}
\frac{\partial \hat{S}_j}{\partial\left|\delta_j - \bar{\delta}\right|} &= \frac{\partial}{\partial\left|\delta_j - \bar{\delta}\right|}\frac{\sum_{i=1}^{N} S_{ij}}{N} = \frac{1}{N}\sum_{i=1}^{N}\frac{\partial S_{ij}}{\partial\left|\delta_j - \bar{\delta}\right|} = \frac{1}{N}\sum_{i=1}^{N}\frac{\rho\bar{\sigma} + \left(\delta_j - \bar{\delta}\right) g_i}{2\kappa\rho}\cdot\operatorname{sign}\left(\delta_j - \bar{\delta}\right)\cdot g_i \\
&= \operatorname{sign}\left(\delta_j - \bar{\delta}\right)\cdot\left(\frac{1}{N}\sum_{i=1}^{N}\frac{\bar{\sigma}}{2\kappa\rho}\cdot g_i + \frac{1}{N}\sum_{i=1}^{N}\frac{\delta_j - \bar{\delta}}{2\kappa\rho}g_i^2\right) = \frac{\sigma_g}{2\kappa\rho}\left|\delta_j - \bar{\delta}\right|.
\end{aligned} \tag{A.52}$$

A.5 Sensitivity of the optimal aggregate signal precision to the ESG score

Taking the derivative of ψ_{ij} in Equation (A.46) with respect to g_i, we obtain

$$\frac{\partial \psi_{ij}}{\partial g_i} = \frac{\bar{\sigma}_i^2 \frac{\partial \bar{S}_i}{\partial g_i} + \left(1 + 2\left(\rho^2 \sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i + 2\rho\bar{\mathcal{X}}_i\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i + \left(\delta_j - \bar{\delta}_i\right)g_i\right)\right)\frac{\partial \bar{\sigma}_i}{\partial g_i}}{2\rho} + \frac{\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i + \left(\delta_j - \bar{\delta}_i\right)g_i\right)\left(\delta_j - \bar{\delta}_i\right)}{\rho}. \tag{A.53}$$

It then follows that

$$\frac{\partial \bar{\sigma}_i}{\partial g_i} = \frac{\partial}{\partial g_i}\left(\sigma_i^{-1} + \bar{S}_i + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}}\right)^{-1} = -\left(\sigma_i^{-1} + \bar{S}_i + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}}\right)^{-2}\left(1 + \frac{2\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right)\frac{\partial \bar{S}_i}{\partial g_i}. \tag{A.54}$$

When $c_{ij}(s) = \kappa s^2$ for all assets and agents, the optimal signal precision is strictly positive and equal to $S_{ij} = \frac{\psi_{ij}}{2\kappa}$. Then,

$$\frac{\partial S_{ij}}{\partial g_i} = -\bar{\sigma}_i^2 \frac{\left(2\left(\rho^2 \sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i + 2\rho\bar{\mathcal{X}}_i\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i + \left(\delta_j - \bar{\delta}_i\right)g_i\right)\right)\left(1 + \frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right) + \frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}}{2\rho\kappa}\frac{\partial \bar{S}_i}{\partial g_i} + \frac{\rho\bar{\sigma}_i\bar{\mathcal{X}}_i + \left(\delta_j - \bar{\delta}_i\right)g_i}{\rho\kappa}\left(\delta_j - \bar{\delta}_i\right). \tag{A.55}$$

Integrating across agents allows one to obtain the sensitivity of the average signal precision with respect to the ESG score

$$\frac{\partial \bar{S}_i}{\partial g_i} = \frac{\frac{\rho\bar{\sigma}_i\bar{\mathcal{X}}_i}{\rho\kappa}\left(\int_j \delta_j \mathrm{d}j - \bar{\delta}_i\right) + \frac{g_i}{\rho\kappa}\int_j\left(\delta_j - \bar{\delta}_i\right)^2 \mathrm{d}j}{1 + \bar{\sigma}_i^2\frac{\left(2\left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i + 2\rho\bar{\mathcal{X}}_i\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i + \left(\int_j \delta_j \mathrm{d}j - \bar{\delta}_i\right)g_i\right)\right)\left(1 + \frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right) + \frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}}{2\rho\kappa}}. \tag{A.56}$$

Assuming $\bar{\delta}_i = \int_j \delta_j \mathrm{d}j$, it follows that $\int_j\left(\delta_j - \bar{\delta}_i\right)\mathrm{d}j = 0$, while $\sigma_\delta = \int_j\left(\delta_j - \bar{\delta}_i\right)^2\mathrm{d}j$ represents the variance of ESG preferences across agents. The sensitivity of the average signal precision can then be expressed as

$$\frac{\partial \bar{S}_i}{\partial g_i} = \frac{\sigma_\delta}{\rho\kappa + \left(\left(\rho^2\left(\sigma_{\mathcal{X}i} + \bar{\mathcal{X}}_i^2\right) + \bar{S}_i\right)\left(1 + \frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\sigma}_i + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\sigma}_i^2} g_i, \tag{A.57}$$

where the denominator is a positive quantity. Multiplying both sides by $\operatorname{sign}(g_i)$, the derivative can be rewritten as

$$\frac{\partial \bar{S}_i}{\partial |g_i|} = \frac{\sigma_\delta}{\rho\kappa + \left(\left(\rho^2\left(\sigma_{\mathcal{X}i} + \bar{\mathcal{X}}_i^2\right) + \bar{S}_i\right)\left(1 + \frac{2\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\sigma}_i + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\sigma}_i^2}|g_i|. \tag{A.58}$$

A.6 Portfolio positions and ESG profile

We first derive the portfolio that optimally invests in the risk factors. Substituting Equations (A.14) and (A.16) into Equation (A.18), the optimal portfolio is given by

$$\begin{aligned}
\boldsymbol{\mathcal{Q}}_j &= \frac{1}{\rho}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \hat{\boldsymbol{\Sigma}}_j\left(\mathbf{S}_j\boldsymbol{\eta}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p\right) - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right) \\
&= \frac{1}{\rho}\left(\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \mathbf{S}_j\boldsymbol{\eta}_j + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p - \hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{P}}r + \delta_j\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}}\right) \\
&= \frac{1}{\rho}\left(\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{z} + \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}\right) + \mathbf{S}_j\left(\boldsymbol{z} + \boldsymbol{\varepsilon}_j\right) + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\left(\boldsymbol{z} - \rho\bar{\mathbf{S}}^{-1}\boldsymbol{\mathcal{X}}\right) + \delta_j\hat{\boldsymbol{\Sigma}}_j^{-1}\boldsymbol{\mathcal{G}}\right)
\end{aligned}$$

$$= \frac{1}{\rho}\left(\rho\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}} + \left(\mathbf{S}_j - \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right) + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\right)\boldsymbol{z}\right.$$
$$\left. + \left(\rho\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) - \frac{1}{\rho}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}} + \mathbf{S}_j\boldsymbol{\varepsilon}_j\right). \tag{A.59}$$

The unconditional expectation of the portfolio is

$$\mathrm{E}\left[\boldsymbol{\mathcal{Q}}_j\right] = \frac{1}{\rho}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right). \tag{A.60}$$

From Equations (A.20) and (A.23), the cross-agent average portfolio is

$$\begin{aligned}
\bar{\boldsymbol{\mathcal{Q}}} &= \int_j \boldsymbol{\mathcal{Q}}_j \mathrm{d}j \\
&= \frac{1}{\rho}\left(\bar{\boldsymbol{\Sigma}}^{-1}\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \bar{\mathbf{S}}\boldsymbol{z} + \boldsymbol{\Sigma}_p^{-1}\boldsymbol{\eta}_p - \bar{\boldsymbol{\Sigma}}^{-1}\boldsymbol{\mathcal{P}}r + \bar{\boldsymbol{\Sigma}}^{-1}\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}\right) \\
&= \frac{1}{\rho}\left(\bar{\boldsymbol{\Sigma}}^{-1}\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{z} + \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right) + \bar{\mathbf{S}}\boldsymbol{z} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\left(\boldsymbol{z} - \rho\bar{\mathbf{S}}^{-1}\boldsymbol{\mathcal{X}}\right)\right).
\end{aligned} \tag{A.61}$$

Its unconditional expectation is $\mathrm{E}\left[\bar{\boldsymbol{\mathcal{Q}}}\right] = \bar{\boldsymbol{\mathcal{X}}}$. The difference between the risk-factor portfolio of investor j in Equation (A.18) and the average portfolio is

$$\begin{aligned}
\boldsymbol{\mathcal{Q}}_j - \bar{\boldsymbol{\mathcal{Q}}} &= \frac{1}{\rho}\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} - \boldsymbol{\mathcal{P}}r\right) + \left(\mathbf{S}_j - \bar{\mathbf{S}}\right)\boldsymbol{z} + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \left(\hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j - \bar{\boldsymbol{\Sigma}}^{-1}\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right) \\
&= \frac{1}{\rho}\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right) + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \left(\hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j - \bar{\boldsymbol{\Sigma}}^{-1}\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right) \\
&= \frac{1}{\rho}\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}\right) + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \left(\hat{\boldsymbol{\Sigma}}_j^{-1}\delta_j - \bar{\boldsymbol{\Sigma}}^{-1}\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right) \\
&= \frac{1}{\rho}\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}\right) + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right),
\end{aligned} \tag{A.62}$$

where the second equality follows from $\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1} = \mathbf{S}_j - \bar{\mathbf{S}}$ and $\boldsymbol{\mathcal{F}} = \boldsymbol{\Gamma}^{-1}\boldsymbol{\mu} + \boldsymbol{z}$, while the third equality follows from Equation (A.30). The unconditional expectation of the difference is

$$\mathrm{E}\left[\boldsymbol{\mathcal{Q}}_j - \bar{\boldsymbol{\mathcal{Q}}}\right] = \left(\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}} - \mathbf{I}\right)\bar{\boldsymbol{\mathcal{X}}} + \frac{1}{\rho}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}. \tag{A.63}$$

We next analyze the optimal portfolio of risky assets. As $\boldsymbol{q}_j = \boldsymbol{\Gamma}^{-1\prime}\boldsymbol{\mathcal{Q}}_j$, the expected portfolio positions are given by

$$\begin{aligned}
\mathrm{E}\left[\boldsymbol{q}_j\right] &= \boldsymbol{\Gamma}^{-1\prime}\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\boldsymbol{\Gamma}\bar{\boldsymbol{x}} + \frac{1}{\rho}\boldsymbol{\Gamma}^{-1\prime}\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}} \\
&= \boldsymbol{\Gamma}^{-1\prime}\begin{bmatrix} \vdots \\ \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(\bar{x}_i + b_i\bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho}\hat{\sigma}_{ij}g_i \\ \vdots \\ \frac{\hat{\sigma}_{Nj}^{-1}}{\bar{\sigma}_N^{-1}}\bar{x}_N \end{bmatrix}
\end{aligned}$$

$$
= \begin{bmatrix} \vdots \\ \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} \left(\bar{x}_i + b_i \bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho} \hat{\sigma}_{ij} g_i \\ \vdots \\ \frac{\hat{\sigma}_{Nj}^{-1}}{\bar{\sigma}_N^{-1}} \bar{x}_N - \sum_{k=1}^{N-1} b_k \left(\frac{\hat{\sigma}_{kj}^{-1}}{\bar{\sigma}_k^{-1}} \left(\bar{x}_k + b_k \bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_k}{\rho} \hat{\sigma}_{kj} g_k \right) \end{bmatrix}. \tag{A.64}
$$

It then follows that

$$
\begin{cases} \mathrm{E}\left[q_{ij}\right] = \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} \left(\bar{x}_i + b_i \bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho} \hat{\sigma}_{ij} g_i & i = 1, \ldots, N-1 \\ \mathrm{E}\left[q_{Nj}\right] = \frac{\hat{\sigma}_{Nj}^{-1}}{\bar{\sigma}_N^{-1}} \bar{x}_N - \sum_{k=1}^{N-1} b_k \mathrm{E}\left[q_{kj}\right]. \end{cases} \tag{A.65}
$$

The expected portfolio positions in excess of the market counterparts are

$$
\begin{aligned}
\mathrm{E}\left[\boldsymbol{q}_j - \bar{\boldsymbol{q}}\right] &= \boldsymbol{\Gamma}^{-1\prime} \left(\hat{\boldsymbol{\Sigma}}_j^{-1} \bar{\boldsymbol{\Sigma}} - \mathbf{I}\right) \bar{\boldsymbol{\mathcal{X}}} + \frac{1}{\rho} \hat{\boldsymbol{\Sigma}}_j^{-1} \left(\delta_j \mathbf{I} - \bar{\boldsymbol{\delta}}\right) \boldsymbol{\mathcal{G}} \\
&= \boldsymbol{\Gamma}^{-1\prime} \begin{bmatrix} \vdots \\ \left(\frac{\bar{\sigma}_i}{\hat{\sigma}_{ij}} - 1\right) \left(\bar{x}_i + b_i \bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho} \hat{\sigma}_{ij}^{-1} g_i \\ \vdots \\ \left(\frac{\bar{\sigma}_N}{\hat{\sigma}_{Nj}} - 1\right) \bar{x}_N \end{bmatrix} \\
&= \begin{bmatrix} \vdots \\ \left(\frac{\bar{\sigma}_i}{\hat{\sigma}_{ij}} - 1\right) \left(\bar{x}_i + b_i \bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho} \hat{\sigma}_{ij}^{-1} g_i \\ \vdots \\ \left(\frac{\bar{\sigma}_N}{\hat{\sigma}_{Nj}} - 1\right) \bar{x}_N - \sum_{i=1}^{N-1} b_i \left(\left(\frac{\bar{\sigma}_i}{\hat{\sigma}_{ij}} - 1\right) \left(\bar{x}_i + b_i \bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho} \hat{\sigma}_{ij}^{-1} g_i \right) \end{bmatrix}.
\end{aligned} \tag{A.66}
$$

Then,

$$
\begin{cases} \mathrm{E}\left[q_{ij} - \bar{q}_i\right] = \left(S_{ij} - \bar{S}_i\right) \bar{\sigma}_i \left(\bar{x}_i + b_i \bar{x}_N\right) + \frac{\delta_j - \bar{\delta}_i}{\rho} \hat{\sigma}_{ij}^{-1} g_i, & i = 1, \ldots, N-1 \\ \mathrm{E}\left[q_{Nj} - \bar{q}_N\right] = \left(S_{Nj} - \bar{S}_N\right) \bar{\sigma}_N \bar{x}_N - \sum_{i=1}^{N-1} b_i \mathrm{E}\left[q_{ij} - \bar{q}_i\right]. \end{cases} \tag{A.67}
$$

The first equation in Proposition 2 follows.

The expected ESG score of the portfolio is given by

$$
\begin{aligned}
\mathrm{E}\left[G_j\right] &= \mathrm{E}\left[\left(\boldsymbol{q}_j - \bar{\boldsymbol{q}}\right)' \boldsymbol{g}\right] \\
&= \mathrm{E}\left[\left(\boldsymbol{\mathcal{Q}}_j - \bar{\boldsymbol{\mathcal{Q}}}\right)' \boldsymbol{\mathcal{G}}\right] \\
&= \frac{1}{\rho} \mathrm{E}\left[\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right) \left(\rho \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} + \mathbf{V}^{\frac{1}{2}} \mathbf{u}\right) + \mathbf{S}_j \boldsymbol{\varepsilon}_j + \hat{\boldsymbol{\Sigma}}_j^{-1} \left(\delta_j \mathbf{I} - \bar{\boldsymbol{\delta}}\right) \boldsymbol{\mathcal{G}}\right)' \boldsymbol{\mathcal{G}}\right] \\
&= \frac{1}{\rho} \left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right) \rho \bar{\boldsymbol{\Sigma}} \bar{\boldsymbol{\mathcal{X}}} + \hat{\boldsymbol{\Sigma}}_j^{-1} \left(\delta_j \mathbf{I} - \bar{\boldsymbol{\delta}}\right) \boldsymbol{\mathcal{G}}\right)' \boldsymbol{\mathcal{G}} \\
&= \sum_{i=1}^{N} \bar{\mathcal{X}}_i \left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} - 1\right) \mathcal{G}_i + \frac{1}{\rho} \hat{\sigma}_{ij}^{-1} \left(\delta_j - \bar{\delta}_i\right) \mathcal{G}_i^2 \\
&= \sum_{i=1}^{N} \left(\bar{x}_i + b_i \bar{x}_N\right) \left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} - 1\right) g_i + \rho^{-1} \hat{\sigma}_{ij}^{-1} \left(\delta_j - \bar{\delta}_i\right) g_i^2.
\end{aligned} \tag{A.68}
$$

To prove Equation (15), we assume that $g_{gr} = \bar{g}$, $g_{br} = -\bar{g}$, $\Delta S_{grP} = \Delta S_{brI} = \Delta S$, $\Delta S_{grI} = \Delta S_{brP} = -\Delta S$, $\bar{\sigma}_{gr} = \bar{\sigma}_{br} = \bar{\sigma}$, and $\bar{\mathcal{X}}_{gr} = \bar{\mathcal{X}}_{br} = 1$. Additionally, as the two groups of funds are of the same size, we assume that

$\bar{\delta}_{gr} = \bar{\delta}_{br} = \bar{\delta} = \frac{\delta_p+\delta_I}{2}$. Then:

$$\begin{cases} \mathrm{E}\left[q_{grP} - q_{grI}\right] = \frac{\delta_P-\delta_I}{\rho}\bar{\sigma}^{-1}\bar{g} + 2\Delta S\bar{\sigma}, \\ \mathrm{E}\left[q_{brP} - q_{brI}\right] = -\frac{\delta_P-\delta_I}{\rho}\bar{\sigma}^{-1}\bar{g} - 2\Delta S\bar{\sigma}. \end{cases} \tag{A.69}$$

A.7 Expected utility loss from following a suboptimal strategy and information acquisition policy

If agent j follows the strategy and the information decision that are optimal for agent k, its terminal wealth can be expressed as

$$W_{j|k} = rW_{0j} + \frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_k\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right) - c_j\left(\mathbf{S}_k\right). \tag{A.70}$$

Then, the time-1 expected utility is

$$\begin{aligned}
U_{1j|k} &= rW_{0j} + \mathrm{E}_{1j}\left[\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_k\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)\right] \\
&\quad - \frac{\rho}{2}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\frac{1}{\rho}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_k\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right)\right]\right] \\
&\quad + \frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_k\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\right]\boldsymbol{\mathcal{G}} - c_j\left(\mathbf{S}_k\right) \\
&= rW_{0j} + \frac{1}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)\right] \\
&\quad + \frac{\delta_k}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_k^{-1}\mathrm{E}_{1j}\left[\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right] \\
&\quad - \frac{1}{2\rho}\mathrm{E}_{1j}\left[\mathrm{Var}_{2j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r + \delta_j\boldsymbol{\mathcal{G}}\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right)\right]\right] \\
&\quad + \frac{\delta_j}{\rho}\mathrm{E}_{1j}\left[\left(\mathrm{E}_{2j}\left[\boldsymbol{\mathcal{F}}\right] - \boldsymbol{\mathcal{P}}r\right)'\hat{\boldsymbol{\Sigma}}_k^{-1}\right]\boldsymbol{\mathcal{G}} \\
&\quad + \frac{\delta_j\delta_k}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_k^{-1}\boldsymbol{\mathcal{G}} - c_j\left(\boldsymbol{S}_k\right) \\
&= rW_{0j} \\
&\quad + \frac{1}{\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i - \bar{\delta}_i\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1} + S_{ik} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) - \frac{N}{\rho} \\
&\quad + \frac{\delta_k}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_j^{-1}\mathbf{w} \\
&\quad - \frac{1}{2\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i + \left(\delta_k - \bar{\delta}_i\right)\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1} + S_{ik} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) + \frac{N}{2\rho} \\
&\quad + \frac{\delta_j}{\rho}\mathbf{w}'\hat{\boldsymbol{\Sigma}}_k^{-1}\boldsymbol{\mathcal{G}} + \frac{\delta_j\delta_k}{\rho}\boldsymbol{\mathcal{G}}'\hat{\boldsymbol{\Sigma}}_k^{-1}\boldsymbol{\mathcal{G}} - c_j\left(\boldsymbol{S}_k\right) \\
&= rW_{0j} \\
&\quad + \frac{1}{\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i - \bar{\delta}_i\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1} + S_{ik} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) - \frac{N}{\rho} \\
&\quad + \sum_{i=1}^{N}\frac{\delta_j + \delta_k}{\rho}\mathcal{G}_i\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i - \bar{\delta}_i\mathcal{G}_i\right)\left(\sigma_i^{-1} + S_{ik} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) \\
&\quad - \frac{1}{2\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i + \left(\rho^2\sigma_{\mathcal{X}i} + \bar{S}_i\right)\bar{\sigma}_i^2 + \left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i + \left(\delta_k - \bar{\delta}_i\right)\mathcal{G}_i\right)^2\right)\left(\sigma_i^{-1} + S_{ik} + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right) + \frac{N}{2\rho}
\end{aligned}$$

$$+\frac{\delta_j\delta_k}{\rho}\sum_{i=1}^{N}\mathcal{G}_i^2\left(\sigma_i^{-1}+S_{ik}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)-\sum_{i=1}^{N}c_{ij}\left(S_{ik}\right). \tag{A.71}$$

The expected utility loss from following the suboptimal policy is equal to

$$\begin{aligned}
U_{1j}-U_{1j|k}=&\frac{1}{\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i\right)^2\right)\left(S_{ij}-S_{ik}\right)\\
&+\sum_{i=1}^{N}2\frac{\delta_j}{\rho}\mathcal{G}_i\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i\right)\hat{\sigma}_{ij}^{-1}\\
&-\sum_{i=1}^{N}\frac{\delta_j+\delta_k}{\rho}\mathcal{G}_i\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i-\bar{\delta}_i\mathcal{G}_i\right)\hat{\sigma}_{ik}^{-1}\\
&+\frac{1}{2\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i+\left(\delta_k-\bar{\delta}_i\right)\mathcal{G}_i\right)^2\right)\hat{\sigma}_{ik}^{-1}\\
&-\frac{1}{2\rho}\sum_{i=1}^{N}\left(\bar{\sigma}_i+\left(\rho^2\sigma_{\mathcal{X}i}+\bar{S}_i\right)\bar{\sigma}_i^2+\left(\rho\bar{\mathcal{X}}_i\bar{\sigma}_i+\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)^2\right)\hat{\sigma}_{ij}^{-1}\\
&+\frac{\delta_j^2}{\rho}\sum_{i=1}^{N}\mathcal{G}_i^2\hat{\sigma}_{ij}^{-1}-\frac{\delta_j\delta_k}{\rho}\sum_{i=1}^{N}\mathcal{G}_i^2\hat{\sigma}_{ik}^{-1}\\
&-\sum_{i=1}^{N}\left(c_{ij}\left(S_{ij}\right)-c_{ij}\left(S_{ik}\right)\right).
\end{aligned}\tag{A.72}$$

A.8 Portfolio dispersion and tracking error

The average dispersion of the portfolio positions in individual assets ($i=1,...,N-1$) per Proposition 4 is computed as

$$\begin{aligned}
&\mathrm{E}\left[\sum_{i=1}^{N-1}\left(q_{ij}-\bar{q}_i\right)^2\right]\\
&=\mathrm{E}\left[\sum_{i=1}^{N-1}\left(\mathcal{Q}_{ij}-\bar{\mathcal{Q}}_i\right)^2\right]\\
&=\mathrm{E}\left[\sum_{i=1}^{N-1}\left(\frac{1}{\rho}\left(S_{ij}-\bar{S}_i\right)\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i+V_{ii}^{\frac{1}{2}}u_i\right)+\frac{1}{\rho}S_{ij}\varepsilon_{ij}+\frac{1}{\rho}\hat{\sigma}_{ij}^{-1}\left(\delta_{ij}-\bar{\delta}_i\right)\mathcal{G}_i\right)^2\right]\\
&=\mathrm{E}\left[\sum_{i=1}^{N-1}\left(\left(S_{ij}-\bar{S}_i\right)\bar{\sigma}_i\bar{\mathcal{X}}_i+\frac{1}{\rho}\left(S_{ij}-\bar{S}_i\right)V_{ii}^{\frac{1}{2}}u_i+\frac{1}{\rho}S_{ij}\varepsilon_{ij}+\frac{1}{\rho}\hat{\sigma}_{ij}^{-1}\Delta\delta_{ij}\mathcal{G}_i\right)^2\right]\\
&=\sum_{i=1}^{N-1}\left(\left(\left(S_{ij}-\bar{S}_i\right)\bar{\sigma}_i\bar{\mathcal{X}}_i+\frac{1}{\rho}\hat{\sigma}_{ij}^{-1}\Delta\delta_{ij}\mathcal{G}_i\right)^2+\frac{1}{\rho^2}\left(S_{ij}-\bar{S}_i\right)^2V_{ii}+\frac{1}{\rho^2}S_{ij}\right)\\
&=\sum_{i=1}^{N-1}\left(\left(\left(S_{ij}-\bar{S}_i\right)\bar{\sigma}_i\bar{\mathcal{X}}_i+\frac{1}{\rho}\left(\sigma_i^{-1}+S_{ij}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\Delta\delta_{ij}\mathcal{G}_i\right)^2+\frac{1}{\rho^2}\left(S_{ij}-\bar{S}_i\right)^2V_{ii}+\frac{1}{\rho^2}S_{ij}\right)\\
&=\frac{1}{\rho^2}\sum_{i=1}^{N-1}\left(\left(S_{ij}\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i+\Delta\delta_{ij}\mathcal{G}_i\right)-\bar{S}_i\rho\bar{\sigma}_i\bar{\mathcal{X}}_i+\left(\sigma_i^{-1}+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\Delta\delta_{ij}\mathcal{G}_i\right)^2+\left(S_{ij}-\bar{S}_i\right)^2V_{ii}+S_{ij}\right).
\end{aligned}\tag{A.73}$$

The return spread relative to the average portfolio is

$$\left(\boldsymbol{q}_j-\bar{\boldsymbol{q}}\right)'\left(\boldsymbol{f}-\boldsymbol{p}r\right)$$

$$
\begin{aligned}
&= \left(\boldsymbol{\mathcal{Q}}_j - \bar{\boldsymbol{\mathcal{Q}}}\right)' (\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}} r) \\
&= \frac{1}{\rho}\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}\right) + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right)'\left(\mathbf{w} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}\right).
\end{aligned} \tag{A.74}
$$

The tracking error of the optimal portfolio relative to the market portfolio is then

$$
\begin{aligned}
\mathrm{TE}_j &= \mathrm{Var}\left[\left(\boldsymbol{q}_j - \bar{\boldsymbol{q}}\right)'(\boldsymbol{f} - \boldsymbol{p}r)\right] = \mathrm{Var}\left[\left(\boldsymbol{\mathcal{Q}}_j - \bar{\boldsymbol{\mathcal{Q}}}\right)'(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r)\right] \\
&= \mathrm{Var}\left[\frac{1}{\rho}\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}\right) + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right)'\left(\mathbf{w} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}\right)\right] \\
&= \frac{1}{\rho^2}\mathrm{Var}\left[\left(\Delta\mathbf{S}_j\mathbf{V}^{\frac{1}{2}}\mathbf{u} + \mathbf{S}_j\boldsymbol{\varepsilon}_j\right)'\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}\right) + \left(\Delta\mathbf{S}_j\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right)'\mathbf{V}^{\frac{1}{2}}\mathbf{u}\right] \\
&= \frac{1}{\rho^2}\mathrm{Var}\left[\rho\boldsymbol{\varepsilon}_j'\mathbf{S}_j\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \mathbf{u}'\mathbf{V}^{\frac{1}{2}}\Delta\mathbf{S}_j\mathbf{V}^{\frac{1}{2}}\mathbf{u} + \boldsymbol{\varepsilon}_j'\mathbf{S}_j\mathbf{V}^{\frac{1}{2}}\mathbf{u} + \left(2\rho\bar{\boldsymbol{\mathcal{X}}}'\bar{\boldsymbol{\Sigma}}\Delta\mathbf{S}_j + \boldsymbol{\mathcal{G}}'\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\hat{\boldsymbol{\Sigma}}_j^{-1}\right)\mathbf{V}^{\frac{1}{2}}\mathbf{u}\right] \\
&= \frac{1}{\rho^2}\sum_{i=1}^{N}\left[\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i\right)^2 S_{ij} + 2\left(\Delta S_{ij}V_{ii}\right)^2 + V_{ii}S_{ij} + \left(2\rho\bar{\mathcal{X}}_i\bar{\sigma}_i\Delta S_{ij} + \mathcal{G}_i\left(\delta_j - \bar{\delta}_i\right)\hat{\sigma}_{ij}^{-1}\right)^2 V_{ii}\right].
\end{aligned} \tag{A.75}
$$

In the last equality, the second term follows from $\mathrm{Var}\left[u_i^2\right] = 2$, while the third term follows from the independence of ε_{ij} and u_i, which implies $\mathrm{Var}\left[\varepsilon_{ij}u_i\right] = \mathrm{Var}\left[\varepsilon_{ij}\right]\mathrm{Var}\left[u_i\right] = S_{ij}^{-1}$.

A.9 Expected net payoff and alpha

The expected excess net payoff is

$$
\begin{aligned}
\mathrm{EENP}_j &= \mathrm{E}\left[\left(\boldsymbol{q}_j - \bar{\boldsymbol{q}}\right)'(\boldsymbol{f} - \boldsymbol{p}r)\right] \\
&= \frac{1}{\rho}\mathrm{E}\left[\left(\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}\right) + \mathbf{S}_j\boldsymbol{\varepsilon}_j + \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}\right)'\left(\mathbf{w} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}\right)\right] \\
&= \frac{1}{\rho}\left(\rho\bar{\boldsymbol{\mathcal{X}}}'\bar{\boldsymbol{\Sigma}}\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\mathbf{w} + \boldsymbol{\mathcal{G}}'\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\mathbf{w} + \mathrm{E}\left[\mathbf{u}'\mathbf{V}^{\frac{1}{2}}\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\mathbf{V}^{\frac{1}{2}}\mathbf{u}\right]\right) \\
&= \frac{1}{\rho}\left(\rho\bar{\boldsymbol{\mathcal{X}}}'\bar{\boldsymbol{\Sigma}}\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}\right) + \boldsymbol{\mathcal{G}}'\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}\right) + \mathrm{tr}\left[\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\mathbf{V}\right]\right) \\
&= \rho\bar{\boldsymbol{\mathcal{X}}}'\bar{\boldsymbol{\Sigma}}\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\mathcal{X}}}'\bar{\boldsymbol{\Sigma}}\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}} \\
&\quad + \frac{1}{\rho}\boldsymbol{\mathcal{G}}'\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)'\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}\right) + \frac{1}{\rho}\mathrm{tr}\left[\left(\hat{\boldsymbol{\Sigma}}_j^{-1} - \bar{\boldsymbol{\Sigma}}^{-1}\right)\mathbf{V}\right] \\
&= \sum_{i=1}^{N}\rho\bar{\sigma}_i\bar{\mathcal{X}}_i^2\left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} - 1\right) - \bar{\mathcal{X}}_i\left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} - 1\right)\bar{\delta}_i\mathcal{G}_i + \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i\left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i - \frac{1}{\rho}\hat{\sigma}_{ij}^{-1}\left(\delta_j - \bar{\delta}_i\right)\bar{\delta}_i\mathcal{G}_i^2 + \frac{1}{\rho}\left(\hat{\sigma}_{ij}^{-1} - \bar{\sigma}_i^{-1}\right)V_{ii} \\
&= \sum_{i=1}^{N}\rho\bar{\sigma}_i\bar{\mathcal{X}}_i^2\left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} - 1\right) - \bar{\mathcal{X}}_i\left(\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}} - 1\right)\bar{\delta}_i\mathcal{G}_i + \frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i\Delta\delta_{ij}\mathcal{G}_i - \frac{1}{\rho}\hat{\sigma}_{ij}^{-1}\left(\delta_j - \bar{\delta}_i\right)\bar{\delta}_i\mathcal{G}_i^2 + \frac{1}{\rho}\Delta S_{ij}V_{ii} \\
&= \sum_{i=1}^{N}\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i\right)\bar{\sigma}_i\bar{\mathcal{X}}_i\Delta S_{ij} + \left(1 + \frac{\Delta S_{ij}}{\bar{\sigma}_i^{-1}}\right)\bar{\mathcal{X}}_i\Delta\delta_{ij}\mathcal{G}_i - \frac{1}{\rho}\left(\bar{\sigma}_i^{-1} + \Delta S_{ij}\right)\Delta\delta_{ij}\bar{\delta}_i\mathcal{G}_i^2 + \frac{1}{\rho}\Delta S_{ij}V_{ii} \\
&= \sum_{i=1}^{N}\left(\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i\right)\bar{\sigma}_i\bar{\mathcal{X}}_i + \frac{1}{\rho}V_{ii}\right)\Delta S_{ij} + \frac{1}{\rho}\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i\right)\left(\bar{\sigma}_i^{-1} + \Delta S_{ij}\right)\Delta\delta_{ij}\mathcal{G}_i.
\end{aligned} \tag{A.76}
$$

To prove Equation (19), we assume that $g_{gr} = \bar{g}$, $g_{br} = -\bar{g}$, $\Delta S_{grP} = \Delta S_{brI} = \Delta S$, $\Delta S_{grI} = \Delta S_{brP} = -\Delta S$, $\bar{\sigma}_{gr} = \bar{\sigma}_{br} = \bar{\sigma}$, $V_{gr} = V_{br} = V$, $\bar{\mathcal{X}}_{gr} = \bar{\mathcal{X}}_{br} = 1$, and $\bar{\delta}_{gr} = \bar{\delta}_{br} = \bar{\delta} = \frac{\delta_p + \delta_I}{2}$. Then:

$$
\begin{aligned}
\mathrm{EENP}_P - \mathrm{EENP}_I &= \left(\left(\rho\bar{\sigma} - \bar{\delta}\bar{g}\right)\bar{\sigma} + \frac{1}{\rho}V\right)\Delta S + \frac{1}{\rho}\left(\rho\bar{\sigma} - \bar{\delta}\bar{g}\right)\left(\bar{\sigma}^{-1} + \Delta S\right)\left(\delta_P - \bar{\delta}\right)\bar{g} \\
&\quad - \left(\left(\rho\bar{\sigma} + \bar{\delta}\bar{g}\right)\bar{\sigma} + \frac{1}{\rho}V\right)\Delta S - \frac{1}{\rho}\left(\rho\bar{\sigma} + \bar{\delta}\bar{g}\right)\left(\bar{\sigma}^{-1} - \Delta S\right)\left(\delta_P - \bar{\delta}\right)\bar{g} \\
&\quad + \left(\left(\rho\bar{\sigma} - \bar{\delta}\bar{g}\right)\bar{\sigma} + \frac{1}{\rho}V\right)\Delta S - \frac{1}{\rho}\left(\rho\bar{\sigma} - \bar{\delta}\bar{g}\right)\left(\bar{\sigma}^{-1} - \Delta S\right)\left(\delta_I - \bar{\delta}\right)\bar{g} \\
&\quad - \left(\left(\rho\bar{\sigma} + \bar{\delta}\bar{g}\right)\bar{\sigma} + \frac{1}{\rho}V\right)\Delta S + \frac{1}{\rho}\left(\rho\bar{\sigma} + \bar{\delta}\bar{g}\right)\left(\bar{\sigma}^{-1} + \Delta S\right)\left(\delta_I - \bar{\delta}\right)\bar{g} \\
&= -2\frac{\bar{\delta}}{\rho}\bar{\sigma}^{-1}\left(\delta_P - \delta_I\right)\bar{g}^2 - 4\bar{\delta}\bar{g}\bar{\sigma}\Delta S. \qquad \text{(A.77)}
\end{aligned}
$$

We then evaluate the expected net payoff of agent j's portfolio, $\mathrm{ENP}_j = \mathrm{E}\left[\boldsymbol{q}_j'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right]$. As $\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r = \mathbf{w} + \mathbf{V}^{\frac{1}{2}}\mathbf{u}$, where $\mathbf{w} = \rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}$ and $\mathbf{V}^{\frac{1}{2}}\mathbf{u} = \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z} + \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}$, and given $\boldsymbol{\mathcal{Q}}_j$ in Equation (A.59), we can write

$$
\begin{aligned}
\mathrm{ENP}_j &= \mathrm{E}\left[\boldsymbol{q}_j'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right] = \mathrm{E}\left[\boldsymbol{\mathcal{Q}}_j'\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right)\right] \\
&= \mathrm{E}\left[\begin{array}{l} \frac{1}{\rho}\left(\begin{array}{l} \rho\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} + \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I} - \bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}} + \left(\mathbf{S}_j - \hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathbf{I} - \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right) + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\right)\boldsymbol{z} \\ + \left(\rho\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right) - \frac{1}{\rho}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}} + \mathbf{S}_j\boldsymbol{\varepsilon}_j \end{array}\right)' \\ \left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}} + \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z} + \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right) \end{array}\right] \\
&= \frac{1}{\rho}\sum_{i=1}^{N}\mathrm{E}\left[\begin{array}{l} \left(\begin{array}{l} \rho\hat{\sigma}_{ij}^{-1}\bar{\sigma}_i\bar{\mathcal{X}}_i + \hat{\sigma}_{ij}^{-1}\left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i + \left(S_{ij} - \hat{\sigma}_{ij}^{-1}\left(1 - \bar{\sigma}_i\sigma_i^{-1}\right) + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)z_i \\ + \left(\rho\hat{\sigma}_{ij}^{-1}\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right) - \frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i + S_{ij}\varepsilon_{ij} \end{array}\right) \\ \cdot\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i + \bar{\sigma}_i\sigma_i^{-1}z_i + \rho\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right) \end{array}\right] \\
&= \frac{1}{\rho}\sum_{i=1}^{N}\left[\begin{array}{l} \left(\rho\hat{\sigma}_{ij}^{-1}\bar{\sigma}_i\bar{\mathcal{X}}_i + \hat{\sigma}_{ij}^{-1}\left(\delta_j - \bar{\delta}_i\right)\mathcal{G}_i\right)\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i\right) + \left(S_{ij} - \hat{\sigma}_{ij}^{-1}\left(1 - \bar{\sigma}_i\sigma_i^{-1}\right) + \frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\sigma}_i \\ + \left(\rho\hat{\sigma}_{ij}^{-1}\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right) - \frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\rho\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\sigma_{\mathcal{X}i} \end{array}\right]. \qquad \text{(A.78)}
\end{aligned}
$$

Our aim is to study the alpha of agent j's portfolio, expressing it as

$$
\alpha_j = \mathrm{E}\left[\boldsymbol{q}_j'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right] - \underbrace{\frac{\mathrm{Cov}\left[\boldsymbol{q}_j'\left(\boldsymbol{f} - \boldsymbol{p}r\right), \bar{\boldsymbol{q}}'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right]}{\mathrm{Var}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right]}}_{\beta_j}\mathrm{E}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right], \qquad \text{(A.79)}
$$

where $\mathrm{E}\left[\boldsymbol{q}_j'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right]$ is the expected net payoff of portfolio j given in Equation (A.78), while the quantities $\mathrm{E}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right]$, $\mathrm{Var}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right]$, and $\mathrm{Cov}\left[\boldsymbol{q}_j'\left(\boldsymbol{f} - \boldsymbol{p}r\right), \bar{\boldsymbol{q}}'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right]$ are given by:

$$
\begin{aligned}
\mathrm{E}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f} - \boldsymbol{p}r\right)\right] &= \mathrm{E}\left[\bar{\boldsymbol{\mathcal{Q}}}'\left(\boldsymbol{\mathcal{F}} - \boldsymbol{\mathcal{P}}r\right)\right] \\
&= \mathrm{E}\left[\left(\bar{\boldsymbol{\mathcal{X}}} + \boldsymbol{\mathcal{X}}\right)'\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}} - \bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}} + \bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z} + \rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I} + \frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right)\right] \\
&= \sum_{i=1}^{N}\mathrm{E}\left[\left(\bar{\mathcal{X}}_i + \mathcal{X}_i\right)\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i + \bar{\sigma}_i\sigma_i^{-1}z_i + \rho\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right)\right] \\
&= \sum_{i=1}^{N}\left(\bar{\mathcal{X}}_i\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i - \bar{\delta}_i\mathcal{G}_i\right) + \rho\bar{\sigma}_i\left(1 + \frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\sigma_{\mathcal{X}i}\right), \qquad \text{(A.80)}
\end{aligned}
$$

$$
\begin{aligned}
\mathrm{Var}\left[\bar{\boldsymbol{q}}'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right] &= \mathrm{Var}\left[\bar{\boldsymbol{\mathcal{Q}}}'\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right] \\
&= \mathrm{Var}\left[\left(\bar{\boldsymbol{\mathcal{X}}}+\boldsymbol{\mathcal{X}}\right)'\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}-\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}+\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z}+\rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right)\right] \\
&= \sum_{i=1}^{N}\mathrm{Var}\left[\left(\bar{\mathcal{X}}_i+\mathcal{X}_i\right)\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i-\bar{\delta}_i\mathcal{G}_i+\bar{\sigma}_i\sigma_i^{-1}z_i+\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right)\right] \\
&= \sum_{i=1}^{N}\mathrm{Var}\left[\left(\bar{\sigma}_i\sigma_i^{-1}\bar{\mathcal{X}}_i z_i+\left(\rho\bar{\sigma}_i\left(2+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\mathcal{X}}_i-\bar{\delta}_i\mathcal{G}_i\right)\mathcal{X}_i+\bar{\sigma}_i\sigma_i^{-1}z_i\mathcal{X}_i+\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i^2\right)\right] \\
&= \sum_{i=1}^{N}\left(\bar{\sigma}_i^2\bar{\mathcal{X}}_i^2\sigma_i^{-1}+\left(\rho\bar{\sigma}_i\left(2+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\bar{\mathcal{X}}_i-\bar{\delta}_i\mathcal{G}_i\right)^2\sigma_{\mathcal{X}i}+\bar{\sigma}_i^2\sigma_i^{-1}\sigma_{\mathcal{X}i}+2\rho^2\bar{\sigma}_i^2\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)^2\sigma_{\mathcal{X}i}^2\right),
\end{aligned}
\tag{A.81}
$$

and

$$
\begin{aligned}
&\mathrm{Cov}\left[\boldsymbol{q}_j'\left(\boldsymbol{f}-\boldsymbol{p}r\right),\bar{\boldsymbol{q}}'\left(\boldsymbol{f}-\boldsymbol{p}r\right)\right] = \mathrm{Cov}\left[\boldsymbol{\mathcal{Q}}_j'\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right),\bar{\boldsymbol{\mathcal{Q}}}'\left(\boldsymbol{\mathcal{F}}-\boldsymbol{\mathcal{P}}r\right)\right] \\
&= \mathrm{Cov}\left[\begin{array}{l}
\frac{1}{\rho}\left(\begin{array}{l}\rho\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}+\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I}-\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}}+\left(\mathbf{S}_j-\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathbf{I}-\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\right)\boldsymbol{z} \\ +\left(\rho\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)-\frac{1}{\rho}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}+\mathbf{S}_j\boldsymbol{\varepsilon}_j\end{array}\right)' \\
\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}-\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}+\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z}+\rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right), \\
\left(\bar{\boldsymbol{\mathcal{X}}}+\boldsymbol{\mathcal{X}}\right)'\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}-\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}+\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z}+\rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right)
\end{array}\right] \\
&= \frac{1}{\rho}\mathrm{Cov}\left[\begin{array}{l}
\left(\rho\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}-\bar{\boldsymbol{\delta}}\boldsymbol{\mathcal{G}}\right)'\left(\left(\mathbf{S}_j-\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathbf{I}-\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\right)\boldsymbol{z}+\left(\rho\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)-\frac{1}{\rho}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right) \\
+\left(\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z}+\rho\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\right)'\left(\begin{array}{l}\rho\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\bar{\boldsymbol{\mathcal{X}}}+\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\delta_j\mathbf{I}-\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{G}} \\ +\left(\mathbf{S}_j-\hat{\boldsymbol{\Sigma}}_j^{-1}\left(\mathbf{I}-\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\right)+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\bar{\mathbf{S}}\right)\boldsymbol{z} \\ +\left(\rho\hat{\boldsymbol{\Sigma}}_j^{-1}\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)-\frac{1}{\rho}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}\end{array}\right), \\
\left(\rho\bar{\boldsymbol{\mathcal{X}}}'\bar{\boldsymbol{\Sigma}}-\boldsymbol{\mathcal{G}}'\bar{\boldsymbol{\delta}}\right)\boldsymbol{\mathcal{X}}+\boldsymbol{\mathcal{X}}'\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z}+\rho\boldsymbol{\mathcal{X}}'\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}+\bar{\boldsymbol{\mathcal{X}}}'\bar{\boldsymbol{\Sigma}}\boldsymbol{\Sigma}^{-1}\boldsymbol{z}+\rho\bar{\boldsymbol{\mathcal{X}}}'\bar{\boldsymbol{\Sigma}}\left(\mathbf{I}+\frac{1}{\rho^2}\bar{\mathbf{S}}\boldsymbol{\Sigma}_{\mathcal{X}}^{-1}\right)\boldsymbol{\mathcal{X}}
\end{array}\right] \\
&= \frac{1}{\rho}\sum_{i=1}^{N}\mathrm{Cov}\left[\begin{array}{l}
\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i-\bar{\delta}_i\mathcal{G}_i\right)\left(\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)z_i+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right) \\
+\left(\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}z_i+\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right)\left(\begin{array}{l}\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i+\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i \\ +\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)z_i \\ +\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\end{array}\right), \\
\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i\left(2+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\bar{\delta}_i\mathcal{G}_i\right)\mathcal{X}_i+\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i z_i+\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\mathcal{X}_i z_i+\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i^2
\end{array}\right] \\
&= \frac{1}{\rho}\sum_{i=1}^{N}\mathrm{E}\left[\begin{array}{l}
\left[\begin{array}{l}
\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i-\bar{\delta}_i\mathcal{G}_i\right)\left(\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)z_i+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right) \\
+\left(\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}z_i+\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right)\left(\begin{array}{l}\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i+\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i \\ +\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)z_i \\ +\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\end{array}\right)
\end{array}\right] \\
\cdot\left[\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i\left(2+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\bar{\delta}_i\mathcal{G}_i\right)\mathcal{X}_i+\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i z_i+\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\mathcal{X}_i z_i+\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i^2\right]
\end{array}\right] \\
&\quad -\frac{1}{\rho}\sum_{i=1}^{N}\mathrm{E}\left[\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)z_i^2+\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i^2\right] \\
&\quad \cdot\mathrm{E}\left[\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i^2\right]
\end{aligned}
$$

$$
\begin{aligned}
&= \frac{1}{\rho}\sum_{i=1}^{N}\left[\begin{array}{l}
\left(w_i\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i+\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i\sigma_i \\
+\left(w_i\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i+\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\right) \\
\cdot\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i\left(2+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\bar{\delta}_i\mathcal{G}_i\right)\sigma_{\mathcal{X}i} \\
+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\left(\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\right)^2 3\sigma_{\mathcal{X}i}^2 \\
+\left(2\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\sigma_i\sigma_{\mathcal{X}i}
\end{array}\right] \\
&\quad -\frac{1}{\rho}\sum_{i=1}^{N}\left(\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\sigma_i+\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\sigma_{\mathcal{X}i}\right) \\
&\quad \cdot\left(\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\sigma_{\mathcal{X}i}\right) \\
&= \frac{1}{\rho}\sum_{i=1}^{N}\left[\begin{array}{l}
\left(w_i\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i+\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)\bar{\mathcal{X}}_i\bar{\sigma}_i \\
+\left(w_i\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\bar{\mathcal{X}}_i+\hat{\sigma}_{ij}^{-1}\left(\delta_j-\bar{\delta}_i\right)\mathcal{G}_i\right)\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\right) \\
\cdot\left(\rho\bar{\sigma}_i\bar{\mathcal{X}}_i\left(2+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\bar{\delta}_i\mathcal{G}_i\right)\sigma_{\mathcal{X}i} \\
+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\left(\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\right)^2 2\sigma_{\mathcal{X}i}^2 \\
+\left(\left(S_{ij}-\hat{\sigma}_{ij}^{-1}\left(1-\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)+\frac{\bar{S}_i^2}{\rho^2\sigma_{\mathcal{X}i}}\right)\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)+\left(\rho\frac{\hat{\sigma}_{ij}^{-1}}{\bar{\sigma}_i^{-1}}\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)-\frac{\bar{S}_i}{\rho\sigma_{\mathcal{X}i}}\right)\frac{\sigma_i^{-1}}{\bar{\sigma}_i^{-1}}\right)\bar{\sigma}_i\sigma_{\mathcal{X}i}
\end{array}\right].
\end{aligned}
\tag{A.82}
$$

A.10 Price informativeness

Following Kacperczyk et al. (2020), we can evaluate the price informativeness for risk factor i as follows:

$$
\begin{aligned}
\mathcal{PI}_i &= \frac{\operatorname{Cov}\left[\mathcal{F}_i,\mathcal{P}_i\right]}{\operatorname{Std}\left[\mathcal{P}_i\right]} = \frac{\operatorname{Cov}\left[\mathcal{F}_i,\mathcal{P}_i r\right]}{\operatorname{Std}\left[\mathcal{P}_i r\right]} \\
&= \frac{\operatorname{Cov}\left[z_i,\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)z_i-\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right]}{\operatorname{Std}\left[\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)z_i-\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right]} \\
&= \frac{\sigma_i-\bar{\sigma}_i}{\sqrt{\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)^2\sigma_i+\rho^2\bar{\sigma}_i^2\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)^2\sigma_{\mathcal{X}i}}} \\
&= \frac{\sigma_i}{\sqrt{\sigma_i+\rho^2\frac{\sigma_{\mathcal{X}i}}{\bar{S}_i^2}}}.
\end{aligned}
\tag{A.83}
$$

The asset-level price informativeness is

$$
\begin{aligned}
\mathrm{PI}_i &= \frac{\operatorname{Cov}\left[f_i,p_i\right]}{\operatorname{Std}\left[p_i\right]} = \frac{\operatorname{Cov}\left[\mathcal{F}_i+b_i\mathcal{F}_N,\mathcal{P}_i r+b_i\mathcal{P}_N r\right]}{\operatorname{Std}\left[\mathcal{P}_i r+b_i\mathcal{P}_N r\right]} \\
&= \frac{\operatorname{Cov}\left[z_i,\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)z_i-\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i\right]+b_i^2\operatorname{Cov}\left[z_N,\left(1-\frac{\bar{\sigma}_N}{\sigma_N}\right)z_N-\rho\bar{\sigma}_N\left(1+\frac{\bar{S}_N}{\rho^2\sigma_{\mathcal{X}N}}\right)\mathcal{X}_N\right]}{\operatorname{Std}\left[\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)z_i-\rho\bar{\sigma}_i\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)\mathcal{X}_i+b_i\left(\left(1-\frac{\bar{\sigma}_N}{\sigma_N}\right)z_N-\rho\bar{\sigma}_N\left(1+\frac{\bar{S}_N}{\rho^2\sigma_{\mathcal{X}N}}\right)\mathcal{X}_N\right)\right]} \\
&= \frac{\sigma_i-\bar{\sigma}_i+b_i^2\left(\sigma_N-\bar{\sigma}_N\right)}{\sqrt{\left(1-\frac{\bar{\sigma}_i}{\sigma_i}\right)^2\sigma_i+\rho^2\bar{\sigma}_i^2\left(1+\frac{\bar{S}_i}{\rho^2\sigma_{\mathcal{X}i}}\right)^2\sigma_{\mathcal{X}i}+b_i^2\left(\left(1-\frac{\bar{\sigma}_N}{\sigma_N}\right)^2\sigma_N+\rho^2\bar{\sigma}_N^2\left(1+\frac{\bar{S}_N}{\rho^2\sigma_{\mathcal{X}N}}\right)^2\sigma_{\mathcal{X}N}\right)}}
\end{aligned}
$$

$$= \frac{\sigma_i - \bar{\sigma}_i + b_i^2 \left(\sigma_N - \bar{\sigma}_N\right)}{\sqrt{\bar{\sigma}_i^2 \left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right)^2 \left(\bar{S}_i^2 \sigma_i + \rho^2 \sigma_{\mathcal{X}i}\right) + b_i^2 \bar{\sigma}_N^2 \left(1 + \frac{\bar{S}_N}{\rho^2 \sigma_{\mathcal{X}N}}\right)^2 \left(\bar{S}_N^2 \sigma_N + \rho^2 \sigma_{\mathcal{X}N}\right)}}$$

$$= \frac{\frac{1}{\sigma_i^{-1}} - \frac{1}{\sigma_i^{-1} + \bar{S}_i + \frac{\bar{S}_i^2}{\rho^2 \sigma_{\mathcal{X}i}}} + b_i^2 \left(\frac{1}{\sigma_N^{-1}} - \frac{1}{\sigma_N^{-1} + \bar{S}_N + \frac{\bar{S}_N^2}{\rho^2 \sigma_{\mathcal{X}N}}}\right)}{\sqrt{\bar{\sigma}_i^2 \left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right)^2 \left(\bar{S}_i^2 \sigma_i + \rho^2 \sigma_{\mathcal{X}i}\right) + b_i^2 \bar{\sigma}_N^2 \left(1 + \frac{\bar{S}_N}{\rho^2 \sigma_{\mathcal{X}N}}\right)^2 \left(\bar{S}_N^2 \sigma_N + \rho^2 \sigma_{\mathcal{X}N}\right)}}$$

$$= \frac{\sigma_i \bar{\sigma}_i \bar{S}_i \left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right) + b_i^2 \sigma_N \bar{\sigma}_N \bar{S}_N \left(1 + \frac{\bar{S}_N}{\rho^2 \sigma_{\mathcal{X}N}}\right)}{\sqrt{\left(\sigma_i + \rho^2 \frac{\sigma_{\mathcal{X}i}}{\bar{S}_i^2}\right) \bar{\sigma}_i^2 \bar{S}_i^2 \left(1 + \frac{\bar{S}_i}{\rho^2 \sigma_{\mathcal{X}i}}\right)^2 + b_i^2 \left(\sigma_N + \rho^2 \frac{\sigma_{\mathcal{X}N}}{\bar{S}_N^2}\right) \bar{\sigma}_N^2 \bar{S}_N^2 \left(1 + \frac{\bar{S}_N}{\rho^2 \sigma_{\mathcal{X}N}}\right)^2}}$$

$$= \frac{\sigma_i \zeta_i + b_i^2 \sigma_N \zeta_N}{\sqrt{\left(\sigma_i + \rho^2 \frac{\sigma_{\mathcal{X}i}}{\bar{S}_i^2}\right) \zeta_i^2 + b_i^2 \left(\sigma_N + \rho^2 \frac{\sigma_{\mathcal{X}N}}{\bar{S}_N^2}\right) \zeta_N^2}}. \tag{A.84}$$

B Supplementary material

Table B.1: Variables Definitions

Variables	Definitions
A. ESG Rating Measures	
Stock ESG	We collect ESG rating data from three data vendors: MSCI KLD, MSCI IVA, and Sustainalytics. For each rater-month, we sort all stocks covered by this rater according to the original rating scale and calculate the percentile rank (normalized between -0.5 and 0.5) for each stock. We compute the firm-level ESG rating as the average rank across all raters.
Fund ESG	The investment value-weighted average of the stock ESG rating in a fund's most recently reported holding portfolio. The stock ESG rating is defined as in the *Stock ESG* above.
Stock ESGDev	The stock-level departure from green neutrality of stock i in a given month t is computed as follows: $\text{ESGDev}_{i,t} = \lvert\text{Stock ESG}_{i,t}\rvert$, where Stock $\text{ESG}_{i,t}$ is the ESG rating of stock i in month t, which is defined as in the *Stock ESG* above.
Fund ESGDev	The fund-level departure from green neutrality of fund j in a given month t is computed as follows: $\text{ESGDev}_{j,t} = \lvert\text{Fund ESG}_{j,t}\rvert$, where Fund $\text{ESG}_{j,t}$ is the ESG rating of fund j in month t, which is defined as in the *Fund ESG* above.
Stock ESGDisp	The heterogeneity in the ESG preferences of stock i in a given month t is the (investment value-weighted) standard deviation of the fund ESG rating of all funds that hold stock i in month t.
B. Other Fund Characteristics	
HHIBMK	The portfolio dispersion of fund j in a given month t is computed as follows: $\text{HHIBMK}_{j,t} = \sum_{i=1}^{N_{j,t}} \left(w_{i,j,t} - w^b_{i,j,t}\right)^2$, where $w_{i,j,t}$ is the investment weight of stock i by fund j in month t, $w^b_{i,j,t}$ is the investment weight of stock i in fund j's benchmark portfolio at the same time, and $N_{j,t}$ is the total number of stocks in the universe of fund j's holding portfolio and benchmark portfolio at the same time. We define the benchmark of the mutual funds based on the Primary Prospectus Benchmark from the Morningstar mutual fund database.
TEBMK	The tracking error of fund j in a given month t, $\text{TEBMK}_{j,t}$, is obtained from the following daily regression with a 6-month estimation period (month $t-5$ to month t): $R_{j,d} = \alpha + \beta R^b_{j,d} + \epsilon_{j,d}$, where $R_{j,d}$ is the excess return of fund j on day d, and $R^b_{j,d}$ is the excess return on fund j's benchmark index at the same time. $\text{TEBMK}_{j,t}$ is the variance of $\epsilon_{j,d}$, following Cremers and Petajisto (2009). We define the benchmark of the mutual funds based on the Primary Prospectus Benchmark from the Morningstar mutual fund database.
HHIMKT	The portfolio dispersion of fund j in a given month t is computed as follows: $\text{HHIMKT}_{j,t} = \sum_{i=1}^{N_{j,t}} (w_{i,j,t} - w_{i,m,t})^2$, where $w_{i,j,t}$ is the investment weight of stock i by fund j in month t, $w_{i,m,t}$ is the investment weight of stock i in the market portfolio at the same time, and $N_{j,t}$ is the total number of stocks in the universe of fund j's holding portfolio and the market portfolio at the same time, following Kacperczyk et al. (2016).
TEMKT	The tracking error of fund j in a given month t, $\text{TEMKT}_{j,t}$, is obtained from the following daily regression with a 6-month estimation period (month $t-5$ to month t): $R_{j,d} = \alpha + \beta R_{m,d} + \epsilon_{j,d}$, where $R_{j,d}$ is the excess return of fund j on day d, and $R_{m,d}$ is the excess return on the market portfolio at the same time. $\text{TEMKT}_{j,t}$ is the variance of $\epsilon_{j,d}$.
Fund Return	The monthly net-of-fee return reported by the CRSP survivorship bias-free mutual fund database. When a fund has multiple share classes, its total return is computed as the share class total net assets (TNA)-weighted return of all share classes, where the TNA values are lagged by one month.
Fund Flow	The flow of fund j in a given month t is computed as follows: $\text{Flow}_{j,t} = \frac{\text{TNA}_{j,t} - \text{TNA}_{j,t-1} \times (1 + r_{j,t})}{\text{TNA}_{j,t-1}}$, where $\text{TNA}_{j,t}$ is the TNA of fund j in month t, and $r_{j,t}$ is the fund return at the same time.
Log(Fund TNA)	The logarithm of the total net assets, as reported in the CRSP survivorship bias-free mutual fund database.
Expense Ratio	The annualized expense ratio, as reported in the CRSP survivorship bias-free mutual fund database.
Fund Turnover	The annualized turnover ratio, as reported in the CRSP survivorship bias-free mutual fund database.
Log(Fund Age)	The logarithm of the number of operational months since inception.
Flow Volatility	The standard deviation of the monthly fund flows in the previous 12 months.

Table B.1 (continued)

Variables	**Definitions**
C. Other Stock Characteristics	
Green IO	The number of shares held by green funds divided by the number of shares outstanding. Green funds refer to funds with *Fund ESG* in the top quintile across all funds.
Brown IO	The number of shares held by brown funds divided by the number of shares outstanding. Brown funds refer to funds with *Fund ESG* in the bottom quintile across all funds.
IVOL	The standard deviation of the residuals estimated from the Fama-French-Carhart four-factor model (Fama and French, 1993; Carhart, 1997) by using the daily returns in a month. More specifically, we regress the daily stock excess return on the market, size, book-to-market, and momentum factor returns and obtain the residuals.
RETVOL	The standard deviation of the daily stock returns in a month.
Log(Size)	The logarithm of the stock market capitalization, which is computed as the number of common shares outstanding times the share price as reported in CRSP.
Log(BM)	The logarithm of the book-to-market ratio, which is defined as the book value of equity divided by market capitalization at fiscal year-end. The book value of equity is computed as the stockholders' equity (COMPUSTAT annual item SEQ), plus deferred taxes and investment tax credit (item TXDITC), minus the book value of the preferred stock. Depending on availability, we use the redemption value (item PSTKRV), liquidation value (item PSTKL), or carrying value (item PSTK) to estimate the book value of the preferred stock, following Fama and French (1993) and Davis et al. (2000).
ROE	The return on equity of stock i in a given quarter q is computed as follows: $\text{ROE}_{i,q} = \text{INCOME}_{i,q}/\text{EQUITY}_{i,q-1}$, where $\text{INCOME}_{i,q}$ is the income before extraordinary items (COMPUSTAT quarterly item IBQ) of stock i in quarter q, and $\text{EQUITY}_{i,q-1}$ is the shareholders' equity. Depending on availability, we use stockholders' equity (item SEQQ), common equity (item CEQQ) plus redemption value (item PSTKRQ), common equity (item CEQQ) plus the carrying value of the preferred stock (item PSTKQ), or total assets (item ATQ) minus total liabilities (item LTQ) in this order as shareholders' equity, following Hou et al. (2015).
I/A	The investment-to-assets of stock i in a given quarter q is computed as follows: $\text{I/A}_{i,q} = \text{AT}_{i,q}/\text{AT}_{i,q-4} - 1$, where $\text{AT}_{i,q}$ is the total assets (COMPUSTAT quarterly item ATQ) of stock i in quarter q.
1M Return	The monthly stock return.
12M Return	The past return in a given month t is computed as the cumulative 11-month return from month $t-11$ to month $t-1$, following Jegadeesh and Titman (1993).
IO	The number of shares held by institutions divided by the number of shares outstanding.
Log(Illiquidity)	The logarithm of stock illiquidity. The illiquidity of stock i in a given month t is computed as follows: $\text{ILLIQ}_{i,t} = \left(\sum_{d\in t} \lvert R_{i,d,t} \rvert / \text{VOLD}_{i,d,t}\right)/D_{i,t} \times 10^6$, where $R_{i,d,t}$ refers to the return of stock i on day d of month t, $\text{VOLD}_{i,d,t}$ refers to the dollar trading volume at the same time, and $D_{i,t}$ is the number of trading days for stock i in month t, following Amihud (2002).
Log(Analyst Coverage)	The logarithm of the number of analysts following a firm as reported in I/B/E/S.
Analyst Dispersion	The standard deviation of analysts' earnings (earnings per share, EPS) forecasts divided by the absolute value of the average earnings forecast as reported in I/B/E/S.
Log(M/A)	The logarithm of the market capitalization-to-total assets ratio, where market capitalization is defined as in *Log(Size)*, and total assets is reported in COMPUSTAT (annual item AT).
E/A	The earnings before interest and taxes (COMPUSTAT annual item EBIT) divided by the total assets (item AT).
Log(Asset)	The logarithm of the total assets (COMPUSTAT annual item AT).
Leverage	The total liabilities (COMPUSTAT annual item LT) divided by the total assets (item AT).
Tangibility	The net property, plant, and equipment (COMPUSTAT annual item PPENT) divided by the total assets (item AT).
Log(Sales)	The logarithm of the sales (COMPUSTAT annual item SALE).
Cash	The cash holdings (COMPUSTAT annual item CH) divided by the total assets (item AT).

Table B.2: Performance of Portfolios Sorted by Mutual Fund Ownership and ESG Rating

In Panels A1 and A2, at the end of month t, stocks are first sorted into quintiles according to their green fund ownership. Within each green fund ownership group, stocks are further sorted into quintiles according to their ESG ratings to generate 25 (5×5) portfolios. The low-(high)-ESG-rating and green-fund-ownership portfolios comprise the bottom (top) quintile of stocks based on the ESG rating and green fund ownership, respectively. For each of the 25 portfolios, we compute the value-weighted return in month $t+1$ and rebalance the portfolios at the end of month $t+1$. Panel A reports the monthly Fama-French six-factor-adjusted returns (FF6) and characteristic-adjusted returns per Daniel et al. (1997) (DGTW) for each of the 25 portfolios and for the investment strategy of going long (short) in the high- (low)-ESG-rating stocks ("HML-R") and the investment strategy of going long (short) in the high- (low)-green-fund-ownership stocks ("HML-G"). The column "All" reports similar statistics for the portfolios sorted only by the ESG ratings, and the row "All" reports similar statistics for the portfolios sorted only by green fund ownership. Panels A1 and A2 report the subperiod results for January 2001–October 2012 and for November 2012–December 2019, respectively. Panels B1 and B2 report similar statistics when we replace green fund ownership with brown fund ownership. We identify green (brown) funds as those with a fund-level ESG rating in the top (bottom) quintile across all funds at the end of each month. The Newey-West adjusted t-statistics are shown in parentheses. Online Appendix Table B.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

	FF6-adjusted Return							DGTW-adjusted Return						
Ownership	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel A1: Portfolios Sorted by Green Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	-0.026	-0.227	-0.484*	-0.270	-0.323*	-0.298	-0.207	0.110	0.262	-0.125	0.012	-0.230	-0.340	0.011
	(-0.11)	(-0.78)	(-1.74)	(-1.60)	(-1.81)	(-0.95)	(-1.59)	(0.50)	(1.40)	(-0.37)	(0.06)	(-1.07)	(-1.30)	(0.07)
2	-0.146	0.195	-0.183	-0.281	0.190	0.336	-0.107	0.071	0.264	0.064	-0.047	0.338	0.268	-0.008
	(-0.64)	(0.42)	(-0.73)	(-1.02)	(0.93)	(0.97)	(-0.66)	(0.36)	(0.98)	(0.16)	(-0.17)	(1.44)	(0.87)	(-0.05)
3	-0.177	-0.149	-0.197	-0.380**	-0.194	-0.017	-0.204	-0.045	-0.086	-0.063	-0.309*	-0.025	0.020	-0.094
	(-0.76)	(-0.77)	(-0.91)	(-2.10)	(-1.01)	(-0.06)	(-1.45)	(-0.30)	(-0.46)	(-0.39)	(-1.92)	(-0.11)	(0.08)	(-0.85)
4	0.193	0.314	0.222	-0.071	0.027	-0.166	0.163*	0.061	0.022	-0.119	-0.113	-0.071	-0.132	-0.004
	(1.18)	(1.21)	(1.10)	(-0.31)	(0.14)	(-0.59)	(1.78)	(0.35)	(0.11)	(-0.83)	(-0.60)	(-0.45)	(-0.66)	(-0.03)
High	0.307	-0.076	0.308*	0.098	-0.253	-0.560**	-0.039	0.245	-0.071	0.053	-0.128	-0.266*	-0.511**	-0.130
	(1.59)	(-0.33)	(1.93)	(0.49)	(-1.55)	(-2.31)	(-0.37)	(1.29)	(-0.58)	(0.41)	(-0.80)	(-1.66)	(-2.12)	(-1.35)
HML-G	0.332	0.151	0.791**	0.369	0.070	-0.263	0.168	0.134	-0.332*	0.177	-0.140	-0.037	-0.171	-0.140
	(1.16)	(0.42)	(2.46)	(1.50)	(0.28)	(-0.72)	(0.99)	(0.65)	(-1.78)	(0.49)	(-0.64)	(-0.15)	(-0.59)	(-0.96)
All	-0.001	-0.007	0.022	-0.191	0.024	0.025		0.092	-0.005	-0.090	-0.131	-0.017	-0.109	
	(-0.01)	(-0.05)	(0.24)	(-1.41)	(0.27)	(0.13)		(0.70)	(-0.05)	(-1.01)	(-1.39)	(-0.18)	(-0.79)	
Panel A2: Portfolios Sorted by Green Fund Ownership and ESG Rating (Nov 2012–Dec 2019)														
Low	-0.396*	-0.237	-0.071	-0.165	-0.291	0.105	-0.225	0.236	0.058	0.200	0.004	0.057	-0.179	0.102
	(-1.67)	(-1.27)	(-0.40)	(-0.90)	(-1.62)	(0.40)	(-1.63)	(1.39)	(0.34)	(1.31)	(0.02)	(0.30)	(-0.78)	(0.97)
2	-0.506**	-0.128	-0.045	-0.061	-0.310**	0.196	-0.206**	-0.170	-0.068	0.012	0.125	0.056	0.226	0.007
	(-2.20)	(-0.63)	(-0.25)	(-0.38)	(-2.06)	(0.79)	(-2.01)	(-0.74)	(-0.35)	(0.06)	(0.74)	(0.38)	(0.89)	(0.07)
3	-0.134	0.266	-0.100	-0.364***	-0.080	0.053	-0.069	-0.101	0.242	0.031	-0.039	0.091	0.192	0.044
	(-0.45)	(1.46)	(-0.61)	(-2.91)	(-0.62)	(0.17)	(-0.81)	(-0.45)	(1.20)	(0.21)	(-0.33)	(0.60)	(0.66)	(0.59)
4	-0.097	0.646***	0.070	-0.257	-0.145	-0.048	-0.025	0.201	0.631***	-0.041	-0.089	0.142	-0.059	0.145
	(-0.36)	(3.73)	(0.44)	(-1.32)	(-0.69)	(-0.12)	(-0.27)	(0.99)	(3.24)	(-0.26)	(-0.48)	(0.88)	(-0.23)	(1.27)
High	-0.240	0.008	-0.031	0.031	0.188*	0.427*	0.038	-0.026	0.037	0.079	0.126	0.257***	0.283*	0.127***
	(-1.57)	(0.08)	(-0.35)	(0.35)	(1.77)	(1.87)	(1.54)	(-0.27)	(0.33)	(0.96)	(1.57)	(3.21)	(1.91)	(3.14)
HML-G	0.156	0.245	0.039	0.196	0.479**	0.323	0.263*	-0.262	-0.021	-0.122	0.122	0.200	0.462**	0.025
	(0.58)	(1.03)	(0.23)	(1.01)	(2.61)	(1.07)	(1.90)	(-1.50)	(-0.10)	(-0.86)	(0.66)	(1.20)	(2.11)	(0.26)
All	-0.142	0.098	-0.078	-0.044	0.060	0.203		0.071	0.240*	0.028	0.027	0.178***	0.107	
	(-1.03)	(0.68)	(-0.99)	(-0.57)	(1.33)	(1.28)		(0.57)	(1.77)	(0.34)	(0.38)	(3.44)	(0.70)	
Panel B1: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.387*	-0.195	0.249	0.357	-0.167	-0.555**	0.071	0.336	-0.104	0.043	0.167	-0.178	-0.515*	0.025
	(1.66)	(-0.95)	(0.80)	(1.26)	(-0.74)	(-2.00)	(0.49)	(1.50)	(-0.62)	(0.20)	(0.76)	(-0.96)	(-1.83)	(0.21)
2	0.143	-0.193	0.010	-0.040	-0.028	-0.170	0.032	0.029	-0.133	-0.158	-0.248	-0.134	-0.162	-0.110
	(0.66)	(-0.79)	(0.06)	(-0.16)	(-0.18)	(-0.67)	(0.27)	(0.16)	(-0.80)	(-1.04)	(-1.10)	(-1.24)	(-0.78)	(-1.31)
3	0.018	0.183	-0.206	-0.305	-0.005	-0.023	-0.007	0.113	0.095	-0.207*	-0.168	0.024	-0.089	-0.002
	(0.08)	(0.80)	(-1.47)	(-1.24)	(-0.03)	(-0.08)	(-0.06)	(0.61)	(0.55)	(-1.66)	(-0.84)	(0.17)	(-0.41)	(-0.03)
4	0.089	0.015	-0.200	-0.142	-0.299*	-0.388*	-0.047	0.143	0.125	-0.114	0.016	-0.014	-0.157	0.066
	(0.40)	(0.07)	(-0.99)	(-0.61)	(-1.87)	(-1.68)	(-0.32)	(0.92)	(0.84)	(-0.64)	(0.10)	(-0.07)	(-0.66)	(0.62)
High	-0.229	-0.266	-0.373	-0.077	-0.559**	-0.330	-0.310*	0.118	-0.117	-0.134	0.025	-0.316*	-0.434**	-0.061
	(-0.96)	(-1.34)	(-1.49)	(-0.37)	(-2.54)	(-1.36)	(-1.72)	(0.62)	(-0.62)	(-0.67)	(0.15)	(-1.66)	(-2.06)	(-0.43)
HML-B	-0.616*	-0.071	-0.622	-0.434	-0.392	0.224	-0.382	-0.219	-0.013	-0.177	-0.143	-0.138	0.081	-0.086
	(-1.66)	(-0.23)	(-1.41)	(-1.10)	(-1.16)	(0.67)	(-1.34)	(-0.84)	(-0.05)	(-0.53)	(-0.59)	(-0.55)	(0.25)	(-0.47)
All	-0.001	-0.007	0.022	-0.191	0.024	0.025		0.092	-0.005	-0.090	-0.131	-0.017	-0.109	
	(-0.01)	(-0.05)	(0.24)	(-1.41)	(0.27)	(0.13)		(0.70)	(-0.05)	(-1.01)	(-1.39)	(-0.18)	(-0.79)	
Panel B2: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Nov 2012–Dec 2019)														
Low	-0.117	0.014	-0.085	-0.088	0.184*	0.301	-0.005	0.163	0.022	-0.019	0.086	0.258***	0.095	0.109***
	(-0.65)	(0.11)	(-0.79)	(-0.78)	(1.71)	(1.39)	(-0.17)	(0.97)	(0.21)	(-0.22)	(1.14)	(3.19)	(0.50)	(3.05)
2	0.003	0.021	-0.017	0.210*	-0.054	-0.057	0.037	0.183	0.162	0.145	0.282**	0.097	-0.086	0.164*
	(0.01)	(0.11)	(-0.11)	(1.94)	(-0.48)	(-0.21)	(0.52)	(0.93)	(0.90)	(0.86)	(2.39)	(0.91)	(-0.40)	(1.93)
3	-0.204	-0.160	0.087	-0.082	-0.150	0.054	-0.074	-0.054	-0.137	0.184	0.074	0.057	0.110	0.043
	(-1.18)	(-1.14)	(0.45)	(-0.56)	(-1.12)	(0.26)	(-0.91)	(-0.38)	(-1.08)	(1.29)	(0.51)	(0.39)	(0.52)	(0.59)
4	-0.160	-0.009	0.163	0.049	-0.077	0.083	-0.006	-0.039	0.194	0.129	0.278**	0.294**	0.333*	0.180**
	(-1.20)	(-0.08)	(1.12)	(0.35)	(-0.62)	(0.50)	(-0.10)	(-0.26)	(1.60)	(1.01)	(2.17)	(2.08)	(1.96)	(2.19)
High	-0.232	0.207	-0.056	-0.136	0.060	0.292	-0.031	-0.005	0.145	0.132	0.009	0.190	0.195	0.097
	(-1.63)	(1.41)	(-0.49)	(-1.26)	(0.59)	(1.64)	(-0.45)	(-0.03)	(0.96)	(1.00)	(0.06)	(1.54)	(1.12)	(0.89)
HML-B	-0.115	0.193	0.028	-0.048	-0.124	-0.009	-0.027	-0.168	0.123	0.150	-0.077	-0.068	0.100	-0.011
	(-0.57)	(0.85)	(0.17)	(-0.27)	(-0.79)	(-0.04)	(-0.32)	(-0.80)	(0.70)	(1.14)	(-0.48)	(-0.51)	(0.44)	(-0.11)
All	-0.142	0.098	-0.078	-0.044	0.060	0.203		0.071	0.240*	0.028	0.027	0.178***	0.107	
	(-1.03)	(0.68)	(-0.99)	(-0.57)	(1.33)	(1.28)		(0.57)	(1.77)	(0.34)	(0.38)	(3.44)	(0.70)	

Table B.3: Implied Cost of Capital of Portfolios Sorted by Mutual Fund Ownership and ESG Rating

In Panels A1 and A2, at the end of month t, stocks are first sorted into quintiles according to their green fund ownership. Within each green fund ownership group, stocks are further sorted into quintiles according to their ESG ratings to generate 25 (5×5) portfolios. The low-(high)-ESG-rating and green-fund-ownership portfolios comprise the bottom (top) quintile of stocks based on the ESG rating and green fund ownership, respectively. For each of the 25 portfolios, we compute the value-weighted implied cost of capital (ICC) in month $t+1$ and rebalance the portfolios at the end of month $t+1$. We compute the ICC for each stock-month following Hou et al. (2012) and Pástor et al. (2022). Panel A reports the time-series averages of the monthly Fama-French six-factor-adjusted ICCs (FF6) and characteristic-adjusted ICCs per Daniel et al. (1997) (DGTW) for each of the 25 portfolios and for the investment strategy of going long (short) in the high- (low)-ESG-rating stocks ("HML-R") and the investment strategy of going long (short) in the high- (low)-green-fund-ownership stocks ("HML-G"). The column "All" reports similar statistics for portfolios sorted only by the ESG ratings, and the row "All" reports similar statistics for portfolios sorted only by green fund ownership. Panels A1 and A2 report the subperiod results for January 2001–October 2012 and for November 2012–December 2019, respectively. Panels B1 and B2 report similar statistics when we replace green fund ownership with brown fund ownership. We identify green (brown) funds as those with a fund-level ESG rating in the top (bottom) quintile across all funds at the end of each month. The Newey-West adjusted t-statistics are shown in parentheses. Online Appendix Table B.1 provides a detailed definition for each variable. Numbers with *, **, and *** are significant at the 10%, 5%, and 1% levels, respectively.

Ownership	FF6-adjusted ICC							DGTW-adjusted ICC						
	Stock ESG							Stock ESG						
	Low	2	3	4	High	HML-R	All	Low	2	3	4	High	HML-R	All
Panel A1: Portfolios Sorted by Green Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.594***	0.451***	0.361***	0.531***	0.566***	-0.028**	0.567***	0.058***	0.012	0.021**	0.031***	0.021**	-0.036***	0.031***
	(18.74)	(9.23)	(6.25)	(14.08)	(18.51)	(-2.40)	(18.54)	(6.40)	(1.55)	(2.50)	(2.91)	(2.38)	(-3.70)	(4.33)
2	0.558***	0.494***	0.442***	0.458***	0.567***	0.009	0.542***	0.034***	0.008	0.018**	0.010	0.030***	-0.004	0.018***
	(17.62)	(11.16)	(7.74)	(10.74)	(19.89)	(0.49)	(18.08)	(3.36)	(0.95)	(2.43)	(1.47)	(3.88)	(-0.32)	(3.81)
3	0.552***	0.510***	0.480***	0.449***	0.572***	0.021	0.540***	0.036***	0.029**	0.004	-0.000	0.051***	0.015	0.024***
	(16.14)	(12.84)	(10.02)	(11.15)	(19.99)	(1.20)	(17.36)	(3.50)	(2.57)	(0.61)	(-0.01)	(4.09)	(1.02)	(3.65)
4	0.528***	0.479***	0.525***	0.498***	0.508***	-0.020	0.500***	0.031***	0.003	0.022***	-0.006	-0.007	-0.038***	0.004
	(14.21)	(16.24)	(16.18)	(13.79)	(15.46)	(-1.13)	(16.17)	(3.64)	(0.29)	(2.95)	(-0.70)	(-0.66)	(-2.82)	(0.58)
High	0.545***	0.471***	0.492***	0.462***	0.396***	-0.148***	0.457***	0.035***	0.022***	0.001	-0.023***	-0.070***	-0.105***	-0.025***
	(16.35)	(10.38)	(14.67)	(14.58)	(14.14)	(-11.45)	(14.70)	(3.56)	(4.26)	(0.09)	(-4.31)	(-11.74)	(-9.77)	(-6.41)
HML-G	-0.050**	0.020	0.130**	-0.069**	-0.170***	-0.120***	-0.110***	-0.023*	0.010	-0.020*	-0.053***	-0.091***	-0.069***	-0.056***
	(-2.61)	(0.37)	(2.35)	(-2.14)	(-12.55)	(-7.22)	(-7.49)	(-1.75)	(1.02)	(-1.86)	(-4.30)	(-10.19)	(-4.69)	(-6.50)
All	0.527***	0.452***	0.449***	0.427***	0.425***	-0.103***		0.025***	0.011	0.014***	-0.015***	-0.049***	-0.074***	
	(15.54)	(8.87)	(8.56)	(10.35)	(14.48)	(-10.69)		(5.58)	(1.61)	(4.91)	(-2.97)	(-13.33)	(-10.65)	
Panel A2: Portfolios Sorted by Green Fund Ownership and ESG Rating (Nov 2012–Dec 2019)														
Low	0.454***	0.451***	0.450***	0.421***	0.436***	-0.018	0.442***	-0.024***	-0.018**	-0.028***	-0.047***	-0.030***	-0.006	-0.029***
	(11.80)	(12.06)	(13.23)	(13.67)	(12.75)	(-1.33)	(12.99)	(-2.75)	(-2.35)	(-5.02)	(-5.29)	(-4.40)	(-0.53)	(-9.18)
2	0.519***	0.525***	0.490***	0.489***	0.502***	-0.017	0.505***	-0.009	0.001	-0.033***	-0.032***	-0.035***	-0.026**	-0.022***
	(22.22)	(23.45)	(19.08)	(22.69)	(29.57)	(-1.21)	(24.17)	(-1.49)	(0.14)	(-4.29)	(-4.34)	(-4.12)	(-2.18)	(-7.72)
3	0.517***	0.439***	0.493***	0.512***	0.548***	0.032***	0.501***	0.016**	-0.058***	-0.028***	0.002	0.015***	-0.000	-0.011***
	(16.83)	(18.50)	(25.31)	(27.18)	(23.30)	(2.91)	(21.80)	(2.04)	(-9.88)	(-4.37)	(0.37)	(2.72)	(-0.03)	(-4.04)
4	0.490***	0.445***	0.493***	0.478***	0.457***	-0.033	0.457***	0.013	-0.037***	-0.003	-0.015	-0.050***	-0.063***	-0.023***
	(13.52)	(16.57)	(17.93)	(30.03)	(22.74)	(-0.95)	(20.00)	(1.13)	(-2.75)	(-0.39)	(-1.39)	(-8.82)	(-4.76)	(-4.17)
High	0.521***	0.553***	0.543***	0.506***	0.411***	-0.110***	0.490***	0.003	0.048***	0.036***	0.004	-0.053***	-0.055***	-0.003*
	(15.83)	(28.12)	(22.39)	(18.58)	(12.38)	(-6.73)	(17.52)	(0.29)	(9.65)	(6.88)	(0.81)	(-17.91)	(-5.53)	(-1.72)
HML-G	0.067	0.102***	0.092**	0.085**	-0.025	-0.092***	0.048	0.026**	0.066***	0.063***	0.051***	-0.023***	-0.049***	0.026***
	(1.40)	(2.96)	(2.48)	(2.24)	(-0.63)	(-3.96)	(1.27)	(2.63)	(7.95)	(9.52)	(5.24)	(-3.49)	(-3.81)	(8.59)
All	0.504***	0.469***	0.519***	0.529***	0.454***	-0.049***		-0.003	-0.022***	0.021***	0.024***	-0.027***	-0.023***	
	(17.81)	(14.47)	(20.98)	(27.90)	(16.28)	(-4.21)		(-0.53)	(-4.14)	(5.16)	(5.38)	(-11.23)	(-3.10)	
Panel B1: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Jan 2001–Oct 2012)														
Low	0.451***	0.455***	0.394***	0.451***	0.391***	-0.060***	0.424***	-0.017	-0.001	-0.027***	-0.032***	-0.083***	-0.066***	-0.050***
	(12.30)	(11.06)	(9.07)	(14.62)	(14.39)	(-3.50)	(14.11)	(-1.20)	(-0.08)	(-2.85)	(-4.46)	(-16.03)	(-4.69)	(-9.23)
2	0.497***	0.476***	0.446***	0.493***	0.463***	-0.034***	0.485***	0.009	0.010	-0.004	-0.015*	-0.029***	-0.038***	-0.009
	(13.18)	(12.27)	(8.12)	(14.74)	(14.02)	(-2.97)	(14.02)	(0.65)	(1.24)	(-0.50)	(-1.75)	(-3.23)	(-3.43)	(-1.07)
3	0.522***	0.453***	0.435***	0.445***	0.505***	-0.017	0.507***	0.010	0.004	-0.007	-0.020**	-0.003	-0.013	-0.001
	(13.82)	(9.20)	(8.21)	(11.24)	(16.30)	(-1.44)	(15.66)	(1.08)	(0.48)	(-0.98)	(-1.99)	(-0.44)	(-1.22)	(-0.13)
4	0.553***	0.538***	0.489***	0.490***	0.571***	0.018	0.540***	0.036***	0.018**	0.005	0.012**	0.038***	0.002	0.024***
	(18.15)	(20.24)	(15.28)	(13.22)	(21.71)	(1.40)	(19.01)	(3.94)	(2.40)	(0.48)	(2.34)	(4.30)	(0.22)	(3.79)
High	0.584***	0.547***	0.518***	0.562***	0.579***	-0.005	0.563***	0.061***	0.029***	0.019*	0.041***	0.037***	-0.024***	0.038***
	(19.59)	(17.43)	(15.30)	(17.33)	(19.59)	(-0.67)	(18.54)	(5.52)	(2.78)	(1.79)	(3.60)	(3.61)	(-3.68)	(3.84)
HML-B	0.133***	0.092**	0.124***	0.111***	0.188***	0.055***	0.139***	0.079***	0.030**	0.046***	0.073***	0.121***	0.042***	0.088***
	(5.09)	(2.53)	(2.79)	(6.54)	(10.71)	(3.17)	(7.83)	(3.46)	(2.20)	(3.05)	(5.72)	(10.03)	(2.87)	(6.50)
All	0.527***	0.452***	0.449***	0.427***	0.425***	-0.103***		0.025***	0.011	0.014***	-0.015***	-0.049***	-0.074***	
	(15.54)	(8.87)	(8.56)	(10.35)	(14.48)	(-10.69)		(5.58)	(1.61)	(4.91)	(-2.97)	(-13.33)	(-10.65)	
Panel B2: Portfolios Sorted by Brown Fund Ownership and ESG Rating (Nov 2012–Dec 2019)														
Low	0.488***	0.524***	0.538***	0.500***	0.409***	-0.079***	0.480***	-0.010	0.032***	0.041***	0.000	-0.053***	-0.043***	-0.005***
	(13.21)	(20.36)	(29.52)	(20.24)	(12.38)	(-5.30)	(17.78)	(-1.07)	(7.20)	(6.33)	(0.06)	(-17.54)	(-4.10)	(-4.97)
2	0.473***	0.502***	0.508***	0.500***	0.489***	0.016	0.493***	-0.014	-0.006	0.001	-0.010	-0.028***	-0.014	-0.015***
	(17.36)	(18.28)	(20.78)	(25.79)	(21.09)	(1.01)	(21.77)	(-1.36)	(-1.07)	(0.11)	(-1.03)	(-5.35)	(-1.31)	(-2.84)
3	0.498***	0.473***	0.501***	0.475***	0.466***	-0.032**	0.483***	-0.009	-0.047***	-0.020***	-0.045***	-0.050***	-0.041***	-0.035***
	(17.78)	(18.43)	(16.03)	(22.37)	(20.83)	(-2.55)	(19.57)	(-1.07)	(-8.08)	(-3.39)	(-7.30)	(-6.11)	(-2.96)	(-9.56)
4	0.519***	0.483***	0.498***	0.495***	0.491***	-0.028**	0.497***	0.016***	-0.028***	-0.026***	-0.023***	-0.022***	-0.038***	-0.017***
	(20.10)	(17.93)	(16.42)	(22.16)	(24.14)	(-2.43)	(20.13)	(2.76)	(-4.18)	(-4.32)	(-4.55)	(-3.52)	(-4.01)	(-4.95)
High	0.552***	0.521***	0.526***	0.534***	0.540***	-0.012	0.534***	0.015***	0.007	-0.001	0.010*	0.017***	0.002	0.009***
	(23.25)	(18.19)	(18.13)	(21.09)	(28.17)	(-1.49)	(21.29)	(4.16)	(0.94)	(-0.13)	(1.92)	(2.72)	(0.25)	(2.74)
HML-B	0.064***	-0.003	-0.012	0.035***	0.131***	0.066***	0.053***	0.024**	-0.026***	-0.041***	0.010*	0.069***	0.045***	0.014***
	(3.23)	(-0.31)	(-0.66)	(4.41)	(8.62)	(3.43)	(9.24)	(2.23)	(-2.98)	(-3.47)	(1.68)	(8.77)	(3.25)	(4.59)
All	0.504***	0.469***	0.519***	0.529***	0.454***	-0.049***		-0.003	-0.022***	0.021***	0.024***	-0.027***	-0.023***	
	(17.81)	(14.47)	(20.98)	(27.90)	(16.28)	(-4.21)		(-0.53)	(-4.14)	(5.16)	(5.38)	(-11.23)	(-3.10)	