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Modelling Demand for ESG

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Abstract

Existing approaches have considered characteristics of Environmental, Social and Governance (ESG) focused investments from a return-oriented perspective, not paying due consideration to investors' utility and how ESG features impact utility. We contribute to this literature by providing a model that captures the implications for investment if ESG is valued by the investor as well as wealth. We first present the necessary theory and discuss the rather challenging problem of calibration of the various risk and preference parameters. Using Thomson Reuters ESG data from 2002 to 2018, we provide further empirical evidence that investors who value ESG factors have improved utilities which does not come at the cost of return performance.

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1. Introduction

Environmental, social and corporate governance (ESG) based investments have received a significantly rapid rise in interest across academics and practitioners in recent years as an increasing number of investors have widened their scope for company valuation to include criteria regarded extra-financial. ESG-friendly investment strategies can help investors, reliably and efficiently, avoid "sin" companies (alcohol, tobacco and gambling firms) that might pose a greater, perceived or real, financial risk due to their environmental, social or community practices.[1]

The increasing popularity of ESG-related investments has induced fund managers to introduce new financial products to meet this demand. Existing studies have argued that shareholders' as well as investors' risk exposures are related to ESG profiles of their firms, and consequently, stakeholders will benefit from investments incorporating elements of companies' ESG performance (see, Edmans (2011) and Jacobsen et al. (2019) for example). However, is there a framework that allows us to evaluate the trade-off between wealth and ESG? Are investors fully aware of the profits versus risks trade-off involved in ESG strategies? Particularly, will incorporating ESG into investment choices identifiably improve investors' wealth and/or utility? These are some of the unanswered questions that we aim to address in this article.

The existing literature, both theoretically and empirically, might be of limited help to investors in answering these questions as there is no consensus on whether ESG-motivated investments will result in performance optimization. Albuquerque et al. (2019), for instance, propose a theoretical industry equilibrium model that captures corporate social responsibility (CSR) activities and product differentiation. The authors' model forecasts that higher CSR investments come with lower risks and

[1] For academic evidence, see Starks et al. (2017), Giese et al. (2019), Henriksson et al. (2019), and Statman (2020) for further evidence. For practical evidence, see *2018 Global Sustainable Investment Review* issued by Global Sustainable Investment Alliance (GSIA) for example, which states that, sustainable investing assets in the five major markets grow rapidly in each of them with a more than 30% increase in total in two years, from $22.9 trillion in 2016 to $30.7 trillion in 2018. Details can be found in http://www.gsi-alliance.org/wp-content/uploads/2019/03/GSIR_Review2018.3.28.pdf. See *CFA Handbook on Sustainable Investments* for further evidence.

increasing firm value. Luo and Balvers (2017) on the other hand claim that ESG-unfriendly firms are expected to generate higher returns (even after controlling for various risks) under the assumptions that the market is segmented due to ESG-oriented investors boycotting such firms.

Empirical studies are equally divided; researchers have evaluated high-ESG score and low-ESG score (or sin) stocks on different dimensions including returns, volatilities, and other performance measures such as Sharpe ratios. Some, such as Hoepner et al (2018), have claimed that ESG-incorporated investments outperform various benchmarks. Hoepner et al. (ibid) argue that for shareholders, the involvement of ESG can lower firms' exposure to downside risks, particularly risks attributed to 'E' or environmental issues. This argument is supported by Albuquerque et al. (2020) who explore how firms with high ESG scores survive major crises, including the severe market turbulence during the on-going COVID-19 pandemic.

On the other spectrum however, others including Hong and Kacperczyk (2009) and Dorfleitner et al. (2020), argue that consideration of ESG will only weaken overall performance of portfolios as sin firms are typically recession-resistant and reduction in demand will make them cheap, thereby making them more attractive. Similarly, Cao et al (2020), postulate that stocks with high ESG underreact to mispricing signals and thereby make the market less efficient. Thus, the literature leaves an open question as to whether ESG improves performance.

Whatever the relationship between ESG and firm performance reveals itself to be in a more specific context, the question of whether there exists a trade-off between investor' wealth and ESG still remains unclear. Abstracting from purely return oriented analysis, we postulate a model that directly incorporates the impact of ESG-oriented investments in investors' utility function. In doing so, we include the increase in utility that each ESG-oriented investor directly derives from investing in high-ESG score assets.

This aspect has not had sufficient attention in existing literature which has primarily concentrated on post-optimisation aspects of low and high-ESG score portfolios, namely through forecasted returns or Sharpe ratios. Our theoretical framework builds and extends an approach derived by Ahmed and Satchell (2020), hereafter AS (2020). Adapting this approach, we assume that the investor's utility function depends explicitly on wealth and ESG. Note, that we do not consider the impact of a firm's ESG activities or performance on its share price, which would affect firm value and as a result investor wealth and utility. Cao et al (2020), among others consider such an analysis in a market efficiency framework but they do not consider the direct impact of ESG on utility.

Our main findings are summarized as follows. We prove that investors who directly derive utility from ESG oriented investments will enjoy higher utility from a portfolio considering both ESG and wealth aspects of investment assets compared to one that only focusses on wealth. Notwithstanding that the investors would face a fall in their expected returns, the Sharpe ratio of portfolios may increase as the variances are substantially reduced compared to the returns.

Furthermore, we prove that regardless of how one values ESG compared to wealth, once utility has been optimised with regards to ESG and wealth, the overall utility remains unchanged as increasing ESG certainty equivalence comes at the cost of the decreasing wealth certainty equivalence. However, if utility derived from a portfolio's ESG performance is not considered during optimisation (e.g. when optimisation only considers return and volatility characteristics), the resulting portfolio will unequivocally be inferior to the bi-variate optimisation procedure we propose.

Finally, we provide an empirical example using Thomson Reuters ESG data for 100 large US companies over a sample period of 2002 to 2018. The empirical application helps us provide a real-world example of our proposed methodology. While ex-ante we make no assumptions regarding the conditional return of the ESG portfolio, we in fact note that the ESG portfolio outperforms its mean variance counterpart not only in certainty equivalence terms (which is known ex-ante) but also in terms of conventional performance indicators such as returns and volatility.

Thus, we contribute to the literature by providing a unique model for investors' utility, incorporating ESG performance to fill the gap on an interesting but less researched question, 'how will investors' utility change when ESG is included explicitly alongside measures of wealth?' The implications of our model and the subsequent empirical example suggest that investors' utility improves no matter how they value ESG relative to their wealth, and more importantly, that there is no trade-off between investor ESG consumption and investors' portfolio returns. We also argue that ESG is not a factor of wealth or returns but a "consumption" good which gives utility in its own right. A recent study by Henriksson et al (2018). attempts to integrate ESG in a portfolio optimisation problem but their focus is primarily on constructing a measure for ESG and less on incorporating ESG as providing utility. Another study by Pedersen et al (2020) uses the utility optimisation framework but their methodology is different from ours. We distinguish our approach from theirs in Section 2.

The remaining paper is organised as follows. Section 2 presents the theoretical framework, Section 3 discusses our empirical findings, and Section 4 concludes.

2. Model

We assume that investors have bivariate utility of the form

$$U(C, Z) = \exp(-\lambda C - \phi Z)$$

where C is consumption (second period wealth) and Z is an attribute independent of C; in the current context, Z represents a measure of the portfolio's ESG performance. Such a specification can be considered a special case of Mixex utility which has been frequently analysed in the risk literature' e.g. see Tsetlin and Winkler (2009). We further assume that $C \sim N(\mu_p, \sigma_p^2)$ and $Z \sim N(0,1)$. Furthermore, there are N available assets which we can choose to invest in with returns r_n, an N by 1 vector, which are multivariate normal, $\mathrm{N}(\mu, \Omega)$, and with an ESG measure Z, an N by 1 vector. We invest in assets by holding portfolio weights, w_n.We do not constrain the portfolio weights to add to 1, largely to avoid some tiresome algebra. As a consequence, there is a residual riskless asset position. We also replace consumption/wealth by portfolio returns.

Under these assumptions,

$$V = E\big(U(C, Z)\big) = E(-\exp(\lambda C - \phi Z)) = E(-\exp(-\lambda w'r - \phi w'Z))$$

$$= -\exp\left(-\lambda w'\mu + \frac{1}{2}\lambda^2 w'\Omega w + \frac{1}{2}\phi^2 w'w\right)$$

To establish the certainty equivalence of this quantity, we need to be aware that certainty equivalents under this specification are bivariate; namely, we need to solve for $cerc$ as well as $cerz$ in the following equation where $cerc$ is the certainty equivalent for wealth and $cerz$ the certainty equivalent for ESG, Z.

$$-\exp(-\lambda cerc - \phi cerz) = -\exp\left(-\lambda w'\mu + \tfrac{1}{2}\lambda^2 w'\Omega w + \tfrac{1}{2}\phi^2 w'w\right)$$

Or,

$$\lambda cerc + \phi cerz = \lambda w'\mu - \tfrac{1}{2}\lambda^2 w'\Omega w - \tfrac{1}{2}\phi^2 w'w \qquad (1)$$

Identification of certainty equivalent quantities requires some assumptions. Following Kihlstrom and Mirman (1974), and Corbage (2001), we identify the wealth certainty equivalence $cerc$ by setting the attribute certainty equivalence $cerz$ to zero. Strictly this is return certainty equivalence. This is just one of the choices available, but one frequently assumed. Later in this section, we explore a different assumption for identifying certainty equivalent quantities.

This results in the following solution for $cerc$.

$$cerc = w'\mu - \frac{1}{2}\lambda w'\Omega w - \frac{1}{2}\delta w'w \qquad (2)$$

Where $\delta = \frac{\phi^2}{\lambda} > 0$.

We restate the following proposition from AS (2020).[2]

Proposition 1

Under the assumptions of bivariate utility if wealth and ESG are bivariate normal as described above and the investor is assumed to be wealth risk-averse ($\lambda > 0$), then the investor is necessarily ESG risk averse in terms of the determination of their wealth certainty equivalence $cerc$, assuming attribute certainty equivalence $cerz$ is zero (see equation 2).

Intuitively, Proposition 1 says that if investors prefer high ESG portfolios ($\phi > 0$), then $\frac{dcerc_{p*}}{d\phi}$ is decreasing in ϕ. If investors prefer low ESG portfolios ($\phi < 0$), then for larger enough ϕ, $\frac{dcerc_{p*}}{d\phi}$ is increasing in ϕ, where $cerc_{p^*}$ is the optimised wealth certainty equivalence.

At this point we should comment on the model by Pedersen et al (2020). Pedersen et al (ibid) consider a portfolio problem which is essentially a mean–variance utility problem with an additional term that captures preferences for ESG; the specific argument in the ESG utility being average portfolio ESG,

[2] Note, AS(2020) do not consider ESG specifically and their analysis is restricted to a generic attribute Z.

since they attempt to maximize sharpe ratios. Their framework involves treating ESG as either non-stochastic, or, alternatively, stochastic but independent of future asset wealth (see their equations 3 and 4). In their model, ESG becomes relevant once one considers market equilibrium as equilibrium prices will depend upon ESG in general. This is an interesting framework but different from our own. For instance, our framework offers analytical solutions and we make no assumptions regarding the pricing mechanism for assets.

We now turn to solving the investor's optimization problem. We first consider the traditional case where $\delta = 0$, which will correspond to the mean variance portfolio

$$\text{Max} \qquad w'\mu - \frac{1}{2}\lambda w'\Omega w \qquad (3)$$

The first order condition is $\mu - \lambda\Omega w = 0$; which gives us the following weights for the simple mean-variance portfolio:

$$w = \frac{\Omega^{-1}\mu}{\lambda}$$

$$\mu_p = \frac{\mu'\Omega^{-1}\mu}{\lambda}$$

The certainty equivalent quantity corresponding to this portfolio is given by:

$$cerc_p = \frac{\mu'\Omega^{-1}\mu}{2\lambda} - \frac{\delta\mu'\Omega^{-2}\mu}{2\lambda^2}$$

The investor can choose to invest in this portfolio if she only has preferences for maximising return for given volatility; however her true utility function, if she also has independent preferences for ESG, is given by equation (2) rather than equation (3) and the above mean-variance portfolio will not be utility maximizing as we will show below.

With the ESG component of utility included, the utility maximization problem becomes:

Max $$w'\mu - \frac{1}{2}\lambda w'\Omega w - \frac{1}{2}\delta w'w \tag{4}$$

where Proposition 1 ensures that the various Lagrange multipliers/risk aversion coefficients are both positive. We will denote optimal quantities by w^*, μ_p^* , $cerc_p^*$.

This can be rewritten as

$$\max \mathrm{V} = w'\mu - \frac{1}{2}\lambda(w'(\Omega + \frac{\delta I}{\lambda})w)$$

The first order condition is: $\mu - \lambda(\Omega + \frac{\delta I}{\lambda})w = 0$, yielding the following optimal portfolio weights and returns respectively:

$$w^* = \frac{\left(\Omega+\frac{\delta I}{\lambda}\right)^{-1}\mu}{\lambda}$$

$$\mu_p^* = \frac{\mu'\left(\Omega+\frac{\delta I}{\lambda}\right)^{-1}\mu}{\lambda}$$

The corresponding certainty equivalent return is:

$$cerc_p^* = \frac{\mu'\left(\Omega+\frac{\delta I}{\lambda}\right)^{-1}\mu}{2\lambda} \tag{5}$$

We can use the Woodbury matrix identity to analytically derive the difference between the two portfolio returns (with and without ESG). The Woodbury matrix identity is given by:

$$\left(\Omega + \frac{\delta I}{\lambda}\right)^{-1} = \Omega^{-1} - \Omega^{-1}(\frac{\lambda I}{\delta} + \Omega^{-1})^{-1}\Omega^{-1}$$

The implies the following difference in portfolio returns:

$$\mu_p^* - \mu_p = \frac{\mu'\left(\Omega+\frac{\delta I}{\lambda}\right)^{-1}\mu}{\lambda} - \frac{\mu'\Omega^{-1}\mu}{\lambda} = -\frac{\mu'\Omega^{-1}(\frac{\lambda I}{\delta}+\Omega^{-1})^{-1}\Omega^{-1}\mu}{\lambda} \tag{6}$$

This result shows us that the expected return of the bi-variate portfolio with ESG is less than the expected return of the mean-variance portfolio without ESG since the matrix in the numerator of the second term is positive definite. Using the Woodbury matrix identity again, we can derive a non-negative expression for the difference in certainty equivalent returns:

$$cerc_p^* - cerc_p = \frac{\delta\mu\prime\Omega^{-2}\mu}{2\lambda^2} - \frac{\mu\prime\Omega^{-1}(\frac{\lambda I}{\delta}+\Omega^{-1})^{-1}\Omega^{-1}\mu}{2\lambda}.$$

Furthermore we can prove that expected return falls for ESG loving investors(see above), variance is reduced (proof involves repeated analysis of positive definite matrices) and the standard deviation is reduced whilst overall utility is raised, based on our increase in certainty equivalence. The magnitude of the Sharpe ratio is ambiguous which is not surprising as the Sharpe ratio optimises expected utility in one dimension whilst here, we have two dimensions, wealth and ESG. This further differentiates our results from Pederson et al (2020), who attempt to maximize the Sharpe ratio.

We state the above results as Corollary 1.

Corollary 1. Under the assumptions of bivariate utility if wealth and ESG are bivariate normal as described above and the investor is assumed to be wealth risk-averse ($\lambda > 0$), the expected return of her ESG –based portfolio will be lower, its variance will be lower and the Sharpe ratio can increase or decrease.

If we wish to add constraints to any of the problems such as constraining the weights to add up to 1, we proceed as follows. The matrix A below can be any of the pre-existing matrices such as Ω in (3) or $\Omega + \frac{\delta I}{\lambda}$ in (4). The maximisation problem is:

Max $$w'\mu - \frac{1}{2}\lambda w'Aw - \theta(\ w'i - 1)$$

This leads to the following solution

$$w = \frac{A^{-1}(\mu - \frac{(\beta-\lambda)}{\gamma} i)}{\lambda}, \text{ where } \beta = \mu'(A^{-1})'i \; and \; \gamma = i'(A^{-1})'i$$

The standard assumption that *cerz* is zero sits uneasily with both the rhetoric and the reality of ESG investing. Generally, one sets *cerz* to 0 because the secondary attribute's utility is hard to quantify, but here we can readily ask the question, what proportion of wealth utility might one evaluate ESG utility at? A reasonable approach may be to consider $cerz$ as a proportion of $cerc$.

Consequently, we assume that

$$cerz = \psi cerc \text{ where } 0 \leq \psi \leq 1 \qquad (7)$$

Although we may not be able to observe ψ, we can propose sensible numbers. For example, we can postulate that the investor values ESG at say 20% of the value from expected utility of wealth on its own leading to $\psi = 0.20$.

We now consider the general case where $Z \sim N(\mu_z, \Omega_z)$and also assume that $Cov(r, Z') = H$, where H is an N by N (possibly diagonal) matrix. Thus, the returns are no longer independent of ESG as previously assumed.

As before,

$$E(-\exp(-\lambda C - \phi Z)) = E(-\exp(-\lambda w'r - \phi w'Z))$$

$$= -\exp\left(-\lambda w'\mu - \phi w'\mu_z + \frac{1}{2}\lambda^2 w'\Omega w + \frac{1}{2}\phi^2 w'\Omega_z w + \lambda\phi w'Hw\right)$$

Again, assuming that $cerz = 0$, we obtain the expression:

$$cerc = w'\mu + \delta w'\mu_z - \frac{1}{2}\lambda w'\Omega w - \frac{1}{2}\phi\delta w'\Omega_z w - \phi w'Hw$$

Maximising $cerc$ yields the optimal weights as follows:

$$w^{**} = \frac{\left((\Omega + 2\delta H + \delta^2\Omega_z)^{-1}(\mu + \delta\mu_z)\right)}{\lambda}$$

So the maximised value of $cerc$ is:

$$cerc^{**} = \frac{\left((\mu + \delta\mu_z)'(\lambda\Omega + 2\phi H + \delta^2\Omega_z)^{-1}(\mu + \delta\mu_z)\right)}{2\lambda}$$

The above result is for the most general case where we assume a non-zero mean and variance for the ESG attribute. On the other hand, if we normalise the ESG attribute so that it has a zero mean and an identity variance matrix, the optimum weights are:

$$w^{***} = \frac{(\Omega + 2\delta H + + \delta^2 I)^{-1}\mu}{\lambda} \tag{8}$$

Finally, we note the most general results when $cerz \neq 0$. The respective certainty equivalent quantities for return and ESG respectively can be derived as below:

$$(\lambda + \psi\phi)cerc = \lambda w'\mu - \frac{1}{2}\lambda^2 w'\Omega w - \frac{1}{2}\phi^2 w'w. - \lambda\phi w'Hw.$$

So $$cerc = \frac{\lambda w'\mu - \frac{1}{2}\lambda^2 w'\Omega w - \frac{1}{2}\phi^2 w'w. - \lambda\phi w'Hw}{(\lambda + \psi\phi)}$$

and $$cerz = \frac{\psi(\lambda w'\mu - \frac{1}{2}\lambda^2 w'\Omega w - \frac{1}{2}\phi^2 w'w. - \lambda\phi w'Hw)}{(\lambda + \psi\phi)}$$

The above structure has several consequences which we list as Proposition 2

Proposition 2:

Assuming the general case and assumption for *cerz* as in (7)

2.1: The above framework has expected utility increasing in *cerz* if one likes ESG and decreasing in ESG if one dislikes ESG.

2.2: The optimised utility is independent of ψ.

Proof. Let,

$$V = -\exp(-\lambda cerc - \phi cerz)$$

Then,

$$\frac{dV}{dcerz} = \phi V; \text{ (this is true in general)}$$

For proposition 2.2, we note that,

$$\text{V= -exp (-}(\lambda + \psi\phi)cerc\text{) from (7)}$$

But that $$cerc = \frac{\lambda w'\mu - \frac{1}{2}\lambda^2 w'\Omega w - \frac{1}{2}\phi^2 w'w. - \lambda\phi w'Hw}{(\lambda+\psi\phi)}$$

So that V and thus optimised V does not depend upon $\psi; QED.$

Proposition 2 says that no matter how much you value ESG relative to wealth, increasing ESG certainty equivalence via increasing ψ will come at the cost of decreasing wealth certainty equivalence so that overall utility is unchanged. Thus, assuming $cerz = 0$ does not change the overall certainty equivalent if the parameter values are fixed and known.

This is a consequence of our utility function with its CARA properties and our assumption in (7) than anything deeper. Note, the optimising $cerc$ incorporates ESG characteristics so that the inclusion of ESG has a non-trivial impact. Also note, that this certainty equivalent will continue to be larger than the certainty equivalent for the mean-variance portfolio as proved in (6). The certainty equivalent quantity and weights remain sensitive to the risk-aversion parameters, λ and ϕ.

One case that may aid intuition is where there is only one risky asset; then

$$w^{**} = \frac{\mu+\delta\mu_z}{\lambda(\sigma^2+2\delta h+\delta^2\sigma_z^2)}.$$

Here, all symbols are scalars. We see immediately that if h (the correlation between as asset's return and its own ESG score) is positive, then an increase in h leads to a reduction in w^{**}, assuming all other terms are positive. However, if h is negative, then if h becomes a larger negative number, the overall risk goes down and w^{**} goes up. In this context ESG is hedging the overall "risk" of the asset.

Of course, w^{**} is increasing in μ **and** μ_z.We do not explore the comparative statics of the risk parameters.

3. Empirical Results

The aim of this empirical exercise is to compare the characteristics of a simple wealth maximising, mean-variance portfolio to a portfolio derived from maximising bi-variate utility where ESG performance is also considered. The availability or lack thereof of ESG data determined the candidates for the portfolio. We use the largest 100 US companies by market capitalization (as at 31 Dec 2018), for which annual ESG data were available from at least 2005 till 2018 (often data are available from 2002). Note, that reliable and objective ESG data are not available monthly and any analysis requiring moments from the ESG data are unconditional moments.

Given our selection criteria we form two portfolios: a simple mean-variance portfolio which seeks to maximize returns while minimizing the variance of the portfolio and a portfolio which considers the ESG performance of each company in addition to its mean and variance. Thus, the latter portfolio seeks to balance the return on each company with its ESG score. Companies with higher ESG scores are more likely to have higher weights in the latter portfolio contingent on the relative risk-aversion parameters λ and ϕ.

We proved in section 2 that the certainty equivalence from the ESG portfolio will always be higher than that from a simple mean variance portfolio. Whilst this is true in theory, we need to take care when applying this strategy empirically. Firstly, the calculation of the certainty equivalent quantity would rely on conditional as opposed to unconditional equity returns and variance-covariance matrices. This is outlined in further detail below. Secondly, when comparing the certainty equivalent quantities of the mean-variance portfolio with the ESG portfolio, we did not consider the ESG position in the simple mean-variance portfolio although a sub-optimal ESG position is taken. Thus, for a like to like comparison we use the wealth certainty equivalent expression, $cerc$.

This ensures that we consider an investor's utility derived from ESG positions even though she initially optimises using only mean-variance characteristics. In essence, think of this as a situation with two investors, both caring about ESG positions of individual stocks but with only one able to optimise with regards to ESG performance as well as mean-variance while the other is only able to optimise with regards to mean-variance (due to unavailability of our proposed methodology). Thus, our approach allows the incorporation of ESG performance within a utility maximising portfolio optimisation framework, rather than picking the best performing ESG stocks on a somewhat ad-hoc basis. By selecting the ESG risk aversion parameter ϕ, we ensure that the selected portfolio correctly balances the investor's return and ESG preferences. Through our empirical exercise, we can analyse if the optimisation strategy will have worked in practice and compare the respective portfolio returns and certainty equivalents.

We use returns as opposed to levels data for optimisation, i.e. monthly/annual return on each company and the annual percentage change in the ESG score of the company.[3] While monthly stock price data on each of the 100 companies in the sample are available from January 2000 (and usually from before), ESG data are only available from 2002 and that too on an annual as opposed to monthly basis. We use a rolling window of 100 months to compute the weights for both portfolios. For the mean variance portfolio, the weights are derived using equation 3 and for the ESG portfolio, we use a general form of the portfolio maximisation problem based on equation 8.

As mentioned before, while the mean return vector and the variance-covariance matrix for stock returns are conditional and based on 100 monthly observations, the moments for the ESG portfolio in particular the variance-covariance matrix of ESG changes Ω_z, the covariance matrix of ESG and stock returns, H and the mean change in ESG μ_z, are unconditional moments calculated on data from 2002-2018 since ESG data is not yet available on a monthly or quarterly basis. Alternatively, we could have used a simpler version of the portfolio optimisation problem that relies only the ESG risk aversion parameter ϕ i.e. equation (5). This would not require using any of the unconditional

[3] Our model does allow us to use ESG levels after normalising– these results are available upon request.

moments; our approach ensures that we use all the first and second moment information contained in the ESG data to form our portfolio.

Note that the formulae derived in section 2 do not include a no-shorting condition. Inclusion of a no-shorting condition would require a numerical as opposed to an analytical solution, so we impose no-shorting and normalisation conditions as follows. All negative weights, once computed, are assumed to be 0 as we do not allow any short positions in the portfolio. The remaining positive weights are then normalised using the simple formula: $w_{i,norm} = w_i / \sum_{i=1}^{n} w_i$, where $w_{i,norm}$ is the normalised weight of stock i in the portfolio and w_i represents the non-normalised positive or 0 weight. Once the portfolio weights have been derived and normalised, we compute the forward-looking portfolio return using the 101st period's equity return and the variance-covariance matrix from the 53rd to 101st period. To enable comparison, the certainty equivalent value, $cerc$, for both portfolios is computed using the formula below:

$$cerc = w'\mu + \delta w'\mu_z - \frac{1}{2}\lambda w'\Omega w - \frac{1}{2}\phi\delta w'\Omega_z w - \phi w'Hw$$

The rolling window is then moved forward by 1 period and the steps repeated. Using the above steps for our 100 stocks and data for 228 months starting from January 2000, we are able to obtain portfolio weights for all 100 companies in each period, forward looking returns and certainty equivalents for 128 periods which form the basis of comparison across the two portfolios.

Since the portfolio weights for mean-variance portfolio only depend on the parameter λ, we fix the value of λ at 10 and change ϕ to analyse the impact of including ESG considerations while optimising our portfolio. Recall that λ represents the investor's risk aversion towards financial returns and ϕ represents their risk aversion towards ESG performance. For two different investors a change in ESG of say 10% would yield different portfolio weight changes if their respective ϕ parameters are different. If ϕ is high, the investor may change the portfolio weights more than if ϕ were low, assuming that λ and the return characteristics of the relevant company do not change. In table 1, we report the average monthly return over the 128 period rolling window, of both portfolios μ_{mv}, μ_{esg}, the risk aversion parameters λ and ϕ, the Herfindahl indices for both portfolios and the average difference in certainty equivalent returns across the 128 months. The Herfindahl indices tell us about the diversification within a portfolio and are computed using the expression: $HHI = \sum_{i=1}^{100} w_i^2$. The index has a value between 0 and 1 and a higher value implies a more concentrated portfolio.

Table 1: Certainty Equivalent difference and HHI for MV and ESG portfolios.

$\lambda; \phi$	μ_{mv}, μ_{ESG}	$HHI_{mv,} HHI_{ESG}$	$cerc_{esg} - cerc_{mv}$
$10; 2$	0.78%; 0.83%	0.0115; 0.0119	0.0017
$10; 5$	0.78%;0.85%	0.0115; 0.0113	0.0069
$10; 8$	0.78%; 0.85%	0.0115; 0.0121	0.0160
$10; 10$	0.78%; 0.77%	0.0115; 0.0118	0.0344
10;15	0.78%; 0.92%	0.0115; 0.0123	0.1136
$10; 20$	0.78%;0.87%	0.0115; 0.0131	0.2533

As evident from table 1, our theoretical results are strengthened by our empirical exercise. Despite using conditional values and forward-looking attributes, we note that the certainty equivalent difference is always positive implying that an investor who values both ESG performance and portfolio return, will derive a higher utility from an optimisation approach that incorporates both ESG performance and equity return characteristics rather than a simple mean-variance approach. We also note that the certainty equivalence difference increases as risk aversion towards ESG performance increases. This is in line with our expectations, as an investor starts caring more about ESG performance than portfolio return, portfolio weights formed on the basis of ESG performance will yield much higher utility than those that do not. Although we can interpret the difference as a return, it is worth noting that the computation of the certainty equivalents includes a measure for ESG performance growth and is not a conventional financial return.

A rather surprising outcome from our analysis is the average return performance of both portfolios. Although in proposition 1, While there is no clear pattern, we note that in all but one case, the ESG portfolio yields a higher average monthly return than the mean-variance portfolio.

This is in contrast to the theoretical predictions of Corollary 1 and suggests to us that including non-standardised measures of ESG, together with capturing the dependence of ESG and returns, leads to qualitatively different solutions. We return to this point in the conclusion. The effect is maximised when ϕ is 1.5 times λ but this may be specific to the data at hand rather than a more generalised result.

Thus, an investor using our optimisation strategy would have, on average, achieved a higher financial return as well as a higher certainty equivalent return. The Herfindahl indices do not show a pattern either although the mean-variance portfolio appears to be more diversified in most cases, suggesting that the ESG optimised portfolio tends to concentrate more in equities with better ESG and return performance. The differences, however, do not appear to be significant. Different values of λ do not alter the qualitative results although the quantitative results, only for the Certainty equivalent calculation are scaled differently. We do not report these but can make them available upon request for specific values of λ and ϕ.

In table 2 we report average portfolio weights for both portfolios for the 128-month period for the 10 largest companies in the sample (the full sample is reported in Appendix 1) when the return risk aversion parameter λ is set to a value of 10.[4] For the ESG portfolio, we report average weights for $\phi = 2, \phi = 10$ and $\phi = 20$ to understand how the average weights evolve as risk aversion towards ESG performance increases. To aid analysis, we also report the average annualized return and average ESG score growth of the stocks in columns 2 and 3. Column 4 reports the correlation between the

[4] Tables corresponding to different values of λ and ϕ are available upon request.

company's stock return and ESG score growth, h. Columns 5-8 report the optimised weights based on our analytical methodology. The reported weights are average weights of the stock over the 128-month period. μ_i represents the average annualised return of stock i over the sample period, $\mu_{i,esg}$ represent the average growth in ESG score (annual), $\overline{w}_{i,portfolio}$ represents the average weight in stock i over the 128 month period for the respectively portfolio.

It is worth mentioning that some very large US companies are missing from this analysis due to non-availability of their ESG data either due to reporting issues or because they were incorporated very late in the sample and thus did not meet the selection criteria. An overall pattern is difficult to decipher from the table below since our optimisation methodology prioritises both wealth and ESG attributes of a company. Their interaction is also important through the covariance matrix H and thus, clear patterns do not always emerge.

Analysis on the basis of return and ESG growth alone is not sufficient since our optimization strategy also considers cross-correlations between different companies' returns and ESG score growth respectively which are not reported below, but the results do allow us to make some general comments. Firstly, we note that a higher than average return (11.8%) and a higher than average growth in ESG score (3.4%) often corresponds to a higher weight in the ESG portfolios (e.g. Amazon, United Health Group, Thermo Fisher etc) although there are some exceptions (likely due to high volatility across returns or ESG scores).

Secondly, we notice the impact of incorporating ESG changes in the optimisation procedure. For some companies (e.g. J. P Morgan Chase, Verizon, Comcast) a lower mean return but a higher ESG score growth can translate into a higher portfolio share in the bi-variate, ESG portfolio. The opposite is also true, a higher mean return but slower ESG score growth, can lead to lower weights in the ESG portfolio compared to the wealth oriented, mean-variance portfolio (e.g. Procter & Gamble, Chevron, Caterpillar, Danaher to mention a few).

There is no general pattern indicating how the weight for each individual equity evolves in ESG portfolios as ϕ changes. The directional changes compared to the mean-variance portfolio are somewhat consistent, but across different ESG portfolios we do not see any particular patterns since there are other factors that play a role in determining weight (namely the volatility of each equity and the covariance between the equity's return and ESG score). Importantly however, we observe that the inclusion of ESG data while selecting stocks for investment can make a significant difference to the composition of the portfolio. For instance, we note an average weight difference of 0.33% for each equity in the ESG portfolio corresponding to $\phi = 2$. This increases to an average difference in weights of 0.48% when ϕ increases to 20. This can translate into significantly different return profiles as we noted earlier in this section.

Table 2: Average company weights in MV and ESG portfolios $\lambda = 10$

Name	μ_i	$\mu_{i,esg}$	h_{ii}	$\overline{w}_{i,mv}$	$\overline{w}_{i,esg,\phi=2}$	$\overline{w}_{i,esg,\phi=10}$	$\overline{w}_{i,esg,\phi=20}$
Apple	39.7%	2.2%	0.19	0.6%	0.5%	0.4%	1.0%
Microsoft	8.1%	3.3%	-0.08	1.3%	0.8%	1.1%	1.5%
Amazon	36.6%	5.5%	0.11	0.4%	0.7%	0.8%	0.9%
Johnson & Johnson	6.1%	0.7%	0.04	1.7%	1.0%	1.9%	0.9%
JP Morgan Chase	6.1%	4.5%	-0.01	1.1%	1.6%	1.5%	1.3%
Exxon Mobil	4.0%	1.4%	-0.40	0.8%	1.4%	1.6%	1.7%
Alphabet A	26.4%	2.5%	-0.09	0.3%	0.5%	0.6%	1.1%
Walmart	2.8%	5.8%	-0.22	1.0%	1.1%	0.5%	0.2%
United Health Group	26.0%	4.1%	-0.02	0.7%	0.8%	1.0%	1.0%
Pfizer	3.1%	1.6%	-0.26	0.8%	0.4%	0.6%	1.2%

In summary, we note a difference in optimal portfolio weights when ESG is considered as a direct source of utility in portfolio optimization. This results in a higher utility for investors who value ESG performance as shown in table 1; often, this does not come at the cost of return performance. While portfolio optimization is more complex and requires the inclusion of more considerations than the simple mean-variance problem that we have used here for comparison, our analysis does provide a framework for the explicit inclusion of ESG performance and analytical formulae that allows for additional analysis.

5. CONCLUSION:

Fund managers are typically interested in the attributes of various stocks which they normalise by setting the mean to zero and the variance to one and often relating rankings to a normal distribution curve. These are used to determine portfolio weights such that they feed either into expected rates of return, the risk of individual assets or both. However, the theory behind conventional asset management is based upon maximising the expected utility of wealth. Special cases of this approach lead to mean-variance analysis and this or some variant of this is the dominant approach in quantitative portfolio construction. Extra variables will enter the picture either as terms in expressions for conditional first or second moments or, occasionally via constraints in optimisation.

Our paper is among the first to empirically explore the role of ESG as a source of direct utility to investors through our methodology which forms the main contribution in this article. In our study, we treat ESG as an element of the bivariate utility function of the investor as opposed to an exogenous factor determining conditional moments of equity returns. This allowed us to disentangle the impact of risky ESG on certainty-equivalence from the impact of risky wealth. By so doing, we contribute to the literature by presenting a novel model for investors' utility when ESG is directly valued by investors as well as their own wealth.

In Section 2, we derived analytical results which show that considering ESG in a bivariate setting improves the utility of the optimising investor compared to the investor who does not incorporate

ESG directly. This approach may be of interest for investment and asset managers who have previously relied on indirect methods of including ESG in portfolio construction. When put to an empirical test for a US -based data set in Section 3, our empirical results supported our analytical approach.

The results confirm our analytical findings and, as expected, the certainty equivalent quantities for our bivariate utility always exceed the certainty equivalent quantity of a mean-variance utility. This is an important result in this literature as it highlights that investors may be holding sub-optimal portfolios even if the certainty equivalent derived from ESG is assumed to be zero. Additionally, the conditional average returns of a rolling portfolio constructed with the bivariate optimisation weights were often greater than the conditional average returns of a mean-variance portfolio. We recognize that this was not guaranteed by our analytical results and may vary for different samples. Since corollary 1 suggests the opposite, albeit in a simplified setting, this is a caveat that conclusions will depend upon the measurement of ESG and the modelling of its joint distribution with returns.

There remain challenges to adopting this approach on a wider scale coming from the recording and reporting of ESG data and more precise modelling of investor attitudes towards ESG. It will be valuable to have investor survey data with responses comparing the relative importance of returns versus ESG to better model bivariate utility, thereby allowing us to measure ϕ more accurately. We expect this to vary considerably by age, occupation, and political leaning. Similarly, ESG reporting needs to be standardised, made consistent and transparent to encourage its adoption by smaller companies; as has been advocated by the big four accounting firms (Tett, 2020). This will allow for approaches like ours to better capture investor sentiment and to form portfolios that are more representative of investor preferences, enabling truly responsible investments.

APPENDIX:

Table A-1: Average company weights in MV and ESG portfolios $\lambda = 10$

Name	μ_i	$\mu_{i,esg}$	$\overline{w}_{i,mv}$	$\overline{w}_{i,esg,\phi=2}$	$\overline{w}_{i,esg,\phi=10}$	$\overline{w}_{i,esg,\phi=20}$
Apple	39.7%	2.2%	0.6%	0.5%	0.4%	1.0%
Microsoft	8.1%	3.3%	1.3%	0.8%	1.1%	1.5%
Amazon	36.6%	5.5%	0.4%	0.7%	0.8%	0.9%
Johnson & Johnson	6.1%	0.7%	1.7%	1.0%	1.9%	0.9%
JP Morgan Chase	6.1%	4.5%	1.1%	1.6%	1.5%	1.3%
Exxon mobil	4.0%	1.4%	0.8%	1.4%	1.6%	1.7%
Alphabet A	26.4%	2.5%	0.3%	0.5%	0.6%	1.1%
Walmart	2.8%	5.8%	1.0%	1.1%	0.5%	0.2%
United Health Group	26.0%	4.1%	0.7%	0.8%	1.0%	1.0%
Pfizer	3.1%	1.6%	0.8%	0.4%	0.6%	1.2%
Bank of America	7.1%	1.0%	1.1%	0.8%	0.8%	0.8%
Verizon	1.2%	8.0%	0.7%	2.0%	1.3%	1.9%
Wells Fargo & Co	5.9%	11.5%	1.9%	1.4%	1.6%	1.8%
Procter & Gamble	3.5%	1.5%	1.8%	1.1%	0.4%	0.3%
Chevron	6.5%	0.7%	1.9%	1.0%	1.5%	0.9%
Berkshire Hathaway A	10.7%	2.0%	1.2%	1.0%	0.9%	2.0%
AT&T	-1.1%	6.0%	0.9%	0.7%	1.0%	1.1%
Intel	6.2%	0.6%	0.6%	0.8%	0.6%	0.8%
Coca Cola	3.7%	1.7%	1.4%	0.9%	1.5%	0.5%
Cisco	4.2%	2.2%	0.8%	0.9%	0.5%	0.3%
Merck & Company	4.2%	0.3%	1.2%	1.1%	0.8%	1.1%
Boeing	16.8%	2.0%	1.0%	0.7%	0.9%	1.7%
Home Depot	9.1%	2.3%	1.0%	0.7%	1.1%	1.0%
Oracle	5.8%	5.1%	0.9%	0.7%	0.5%	1.0%
Walt Disney	10.0%	0.9%	0.9%	1.3%	1.1%	0.7%
Comcast	7.6%	5.7%	0.6%	1.2%	1.2%	1.7%
Pepsi Co	7.2%	2.2%	1.9%	1.5%	1.9%	1.2%
Citigroup	-1.9%	3.7%	0.4%	0.7%	0.6%	0.7%
Mcdonald’s	10.7%	1.5%	1.1%	1.0%	1.2%	1.3%
Abbot Labs	9.8%	0.9%	1.0%	1.2%	1.5%	1.6%
Medtronic	7.3%	2.4%	1.2%	0.7%	0.7%	0.7%
AMGEN	8.2%	4.4%	0.8%	0.7%	1.1%	1.0%
Eli Lily	4.8%	3.1%	0.9%	1.2%	1.2%	2.2%
3M	9.4%	1.0%	1.1%	1.5%	1.6%	0.9%
Adobe (NAS)	21.4%	1.9%	0.5%	0.8%	0.8%	1.1%
International Bus.Mchs	2.9%	1.1%	1.3%	1.4%	2.0%	0.8%
Accenture Class A	11.9%	5.9%	0.9%	1.4%	0.9%	0.5%
Union Pacific	16.4%	3.2%	0.7%	1.4%	0.9%	1.6%
United Technologies	8.4%	0.9%	1.7%	0.8%	1.2%	0.5%
Altria Group	15.3%	2.0%	1.3%	1.5%	1.4%	1.1%
Honeywell International	8.0%	5.0%	1.1%	0.8%	0.6%	0.7%
CVS Health	10.1%	6.2%	1.0%	0.4%	1.2%	0.6%
Nike ‘B’	16.0%	3.3%	1.0%	0.5%	1.4%	0.5%
Costco Wholesae	9.9%	1.9%	0.8%	1.6%	1.0%	1.5%

Thermo Fisher Scientific	20.5%	5.2%	0.9%	1.0%	1.1%	2.7%
American Express	9.9%	1.9%	0.7%	0.6%	1.3%	1.8%
Nextera Energy	13.4%	1.8%	1.2%	1.9%	1.7%	1.7%
NVIDIA	51.3%	6.3%	0.5%	0.4%	0.6%	0.6%
Texas Instruments	10.2%	1.0%	1.0%	1.1%	0.8%	1.0%
Bristol Myers Squib	2.3%	-0.5%	1.7%	1.3%	1.4%	0.4%
Gilead Sciences	25.8%	5.8%	1.2%	0.9%	0.8%	0.5%
Lockheed Martin	16.2%	6.4%	0.8%	0.7%	0.8%	0.4%
Starbucks	25.9%	1.3%	0.7%	0.9%	0.7%	0.7%
US Bancorp	5.4%	3.8%	0.7%	1.2%	1.4%	0.7%
Conoco Philips	9.2%	2.8%	1.9%	1.5%	1.7%	1.6%
Morgan Stanley	5.7%	4.1%	1.0%	0.8%	0.8%	0.5%
Walgreens Boots Alliance	7.2%	3.7%	0.8%	0.9%	0.4%	0.5%
Anthem	18.6%	2.2%	0.8%	0.7%	0.6%	0.7%
Caterpillar	13.3%	0.8%	0.8%	0.7%	0.6%	0.5%
Qualcomm	1.8%	5.7%	0.6%	0.3%	0.3%	0.1%
United Parcel Ser B	3.1%	1.5%	1.9%	1.2%	1.1%	1.8%
American Tower	22.3%	3.4%	0.8%	0.7%	0.4%	0.3%
Goldman Sachs GP	10.0%	3.1%	1.1%	0.9%	1.3%	1.2%
Danaher	15.4%	1.9%	1.8%	0.6%	0.6%	0.5%
Lowe’s Companies	13.8%	3.8%	0.9%	1.0%	1.2%	1.4%
General Electric	-5.0%	4.5%	0.9%	1.6%	0.4%	0.3%
Becton Dickinson	13.1%	2.3%	1.0%	0.6%	0.9%	1.5%
CME Group	33.5%	7.6%	0.4%	0.5%	0.4%	0.3%
Mondelez International	4.8%	5.4%	0.8%	1.3%	0.9%	1.3%
Stryker	14.6%	2.3%	1.1%	0.9%	1.0%	0.8%
Biogen	19.2%	6.3%	0.6%	0.7%	0.5%	0.4%
Duke Energy	6.4%	4.1%	1.6%	1.4%	1.4%	2.2%
Chubb	15.4%	3.7%	0.9%	0.8%	1.1%	1.1%
Automatic Data Proc.	7.2%	3.9%	1.2%	1.6%	1.2%	1.5%
EOG Res	25.8%	5.7%	0.5%	1.1%	1.2%	0.7%
Schlumberger	7.4%	2.4%	0.7%	0.5%	0.6%	0.5%
PNC Finl.Svs.Gp.	7.5%	6.9%	0.9%	1.4%	1.0%	1.3%
Simon Property Group	13.7%	1.8%	1.3%	1.0%	0.7%	0.5%
CSX	17.0%	6.0%	1.2%	0.6%	0.5%	0.8%
Charles Schwab	7.0%	1.5%	0.9%	0.8%	0.4%	0.3%
Colgate-Palmolive	4.0%	3.0%	1.0%	1.8%	1.0%	1.3%
CIGNA	20.2%	5.5%	0.8%	1.0%	0.9%	0.5%
TJX	18.6%	3.5%	1.4%	1.5%	0.5%	0.1%
Allergan	12.9%	3.4%	0.6%	0.7%	1.0%	0.9%
FEDEX	10.2%	6.6%	1.1%	1.2%	1.2%	1.9%
INTUIT	12.6%	4.5%	0.5%	0.9%	0.5%	0.7%
Occidental PTL.	12.2%	1.5%	1.1%	1.4%	2.0%	2.7%
Boston Scientific	14.2%	5.6%	0.5%	0.6%	0.5%	1.1%
Dominion Energy	8.7%	4.7%	1.1%	0.8%	1.7%	1.2%
Raytheon ‘B’	11.1%	4.4%	0.9%	0.8%	1.1%	0.5%
S&P Global	12.6%	5.6%	0.8%	0.9%	1.7%	0.6%

Bank of New York Mellon	4.0%	4.1%	0.9%	0.9%	1.8%	1.6%
Celgene	26.0%	4.0%	0.5%	0.6%	0.5%	0.5%
General Dynamics	11.9%	2.7%	1.0%	1.3%	1.0%	1.3%
Southern	6.8%	1.7%	2.3%	3.4%	1.6%	1.6%
Crown Castle	21.4%	0.8%	1.0%	0.5%	0.5%	0.2%
Deere	15.8%	1.7%	0.9%	1.1%	1.0%	1.0%
Parker Hannifin	12.1%	4.6%	1.0%	1.2%	1.3%	0.9%
ECOLAB	12.4%	2.7%	1.0%	0.9%	0.8%	1.1%
EXELON	9.3%	1.6%	1.2%	0.8%	1.1%	0.9%

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