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Incorporating ESG into Optimal Stock Portfolios for the Global Timber & Forestry Industry

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ABSTRACT

This paper investigates how optimal portfolios of timber & forestry stocks perform relative to the global S&P timber & forestry index when corporate social responsibility (CSR) is considered. We incorporate CSR in the construction of optimal portfolios by utilizing combined environmental, social, and governance (ESG) scores. Historical as well as copula-augmented predictive models and ESG-constrained optimization are used to analyze out-of-sample performance of various portfolio strategies over the period 2018–2021. The results of copula-based portfolio strategies are better than of the historical models. Another insight gained by his study is that socially responsible investments in forestry stocks are feasible without sacrificing risk-adjusted returns.

Keywords: Portfolio optimization, ESG, forestry stocks, return, risk, vine copula

JEL Codes: G11, G12, G17, G32

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1 Introduction

Total investment in the global forestry industry has increased tenfold since the early 2000s.[1] Features like good prospects for risk-adjusted returns, high risk diversification potential, and the ability to hedge inflation risks are considered to be main reasons for the increased attractiveness of timberland & forestry stocks (Wan *et al.*, 2015; Mei, 2019; Chudy and Cubbage, 2020).

In addition, the 2015 Paris Climate Agreement emphasizes the important role of forests for climate change mitigation. Wood biomass has become an alternative renewable energy source (Favero and Mendelsohn, 2014), and forest-based building and construction materials are attractive alternatives to carbon intensive materials. Sustainable forest management practices are also crucial for maintaining the vitality of the earth's complex biological diversity by avoiding deforestation and forest degradation (Hunter and Hunter Jr, 1999). This comes into play as investors become increasingly concerned with the environmental, social, and governance (ESG) aspects of their investments. Companies aiming for corporate social responsibility (CSR) are expected to be able to anticipate future risks and opportunities, to be more disposed to longer-term strategic thinking, and to be more focused on long-term value creation instead of short-term profit maximization.

The main purpose of this paper is to analyze the impact of incorporating CSR concerns into portfolio construction using timber & forestry stocks. For the implementation of optimal portfolios we focus on stocks from the constituent list of the S&P Global Timber & Forestry (GTF) index. This list entails 25 of the worldwide largest timber & forestry stocks. A fundamental question related to investing based on CSR considerations is the following: how does incorporating ESG target values (bounds) into the portfolio construction affect the performance of (risk-return) optimal timber & forestry stock portfolios? One common concern with ESG investing is the potentially lower portfolio performance in terms of risk-adjusted returns of socially responsible investments (Boffo and Patalano, 2020; Pedersen *et al.*, 2020; Lööf *et al.*, 2021).

To improve the portfolios' level of social responsibility, we propose a combined portfolio optimization approach that includes (i) modeling the dependence structure between fat-tailed non-Gaussian asset returns[2] and (ii) imposing boundaries (constraints) on the portfolio stocks' ESG ratings. In particular, we utilize vine copulas that have gained popularity in portfolio optimization as they can describe multivariate conditional distributions capturing both symmetric and asymmetric tail dependence (see e.g., Low *et al.*, 2013; Sahamkhadam, 2021; Sahamkhadam *et al.*, 2022). Using 29

[1] https://www.unpri.org/investment-tools/private-markets/infrastructure-and-other-real-assets/forestry, retrieved on 22 June 2021.

[2] For another application of dependence modeling using copulas, see Sun (2013).

timber & forestry stocks,[3] we construct socially responsible copula-based portfolios with either risk minimization or reward/risk maximization. The latter is used to obtain optimal portfolios in terms of both expected return and risk.

To construct socially responsible portfolios, we apply the minimum risk and maximum reward/risk optimization and impose lower boundaries for the level of traditional ESG ratings and upper boundaries for the recently developed ESG risk (ESGR) scores. It is worth noting that while the traditional ESG rating lies in the range from 0 to 100, where a higher ESG means a better rating, the newer ESGR rating uses the same range of values, but a lower ESGR value implies less ESG risk, and is therefore better. As regards the traditional ESG ratings, we obtain the ESG scores for each stock both from Sustainalytics (thereafter ESG I) and from Thomson Reuters Refinitiv Eikon (thereafter ESG II). This enables us to analyze the consistency of ESG ratings from different providers. We investigate three portfolio methods, i.e., unconstrained, ESGR-constrained, and multi-ESG-constrained. The latter includes constraints on all ESG scores available for this study, i.e., ESGR, ESG I, and ESG II. The results for the multi-ESG-criteria portfolio strategy are in particular valuable for investors as they demonstrate that a combination of consistently top ESG-performing forestry stocks may also provide good reward-to-risk prospects.

The outcomes of the various portfolio strategies are evaluated in two steps. First, out-of-sample backtesting is used and performance measures for each strategy are computed. In a second step, regression models are applied to investigate whether there are significant differences in copula-based portfolio strategies compared to historical ones, and also whether there are significant differences with regard to imposing ESG constraints in the portfolio optimizations. The regression results confirm the advantage of copula-based portfolio strategies over historical ones, and also reveal that ESG-constrained portfolios do, contrary to common belief, not imply significantly lower Sortino, Sharpe, or STARR ratios. Thus, the results highlight that it is possible to improve the average ESG, and thereby the sustainability of investments in forestry stocks, by using the proposed methods without sacrificing risk-adjusted returns.

The current study's contribution is twofold. First, we construct and investigate sustainable (socially responsible) portfolio investments in the timber & forestry industry using ESG scores. We provide evidence of the usefulness of the proposed portfolio strategies to achieve sustainable investments. Second, we incorporate dependence structure modeling into the suggested socially responsible portfolio optimization. We extend previous, related work (for

[3] The number of stocks in the sample is higher than 25 because of past changes in the S&P GTF constituents list.

instance, Busby *et al.*, 2020), by estimating returns' predictive multivariate distribution using vine copula modeling. In sum, this study documents the advantages of imposing sustainability restrictions on copula-based portfolio optimization, and to our knowledge, this is the first study to provide such a result. Third, to obtain socially responsible optimal (reward/risk maximization) portfolios, we combine fractional programming techniques with ESG constraints, which makes this study the first to suggest and use such a method for socially responsible portfolios.

The rest of the paper is organized as follows. Section 2 presents the empirical methodology including portfolio optimization. Section 3 presents information on the data. Results are provided in Section 4. Section 5 concludes.

2 Methodology

In this section, we present and compare the copula-based approach with the historical model. Furthermore, we introduce both unconstrained and ESG-constrained portfolio optimization models.

2.1 Copula-based Portfolio Approach

The copula-based portfolios are comparable to the classical Markowitz's mean-variance type portfolios. In both approaches, we define the investor's utility function as either risk minimization or reward/risk maximization. Indeed, the portfolio optimization problem is similar for both methods. However, the difference is how to obtain a predictive multivariate distribution for asset returns denoted by $\hat{r}_t$. In the classical mean-variance analysis, we use past observations and estimate expected portfolio return and variance. In the copula-based approach, a copula-augmented risk model is used to estimate step-ahead conditional multivariate distribution. In this paper, we refer to portfolios obtained via the former approach as historical-based portfolios and provide an empirical comparison between the two approaches. In particular, we compare the two approaches when constructing the socially responsible portfolios. A detailed comparison of the two approaches can also be found in Sahamkhadam *et al.* (2018). In the copula-based approach, we first estimate the step-ahead expected returns and standard deviations for individual assets and obtain their marginal distribution using the VAR-GARCH model. Following that, we transform standardized residuals into uniform marginals and estimate the dependence structure between asset returns using truncated R-vine copula models. Then, we draw simulations from the step-ahead joint distribution, and finally, perform portfolio optimization using returns' forecasts. In Appendices A and B, we present the R-vine copula model and steps involved in constructing copula-based portfolios.

2.2 Portfolio Optimization Methods

For a portfolio that consists of d assets with excess returns $\hat{\mathbf{r}}_t = (\hat{r}_{1t}, \hat{r}_{2t}, \ldots, \hat{r}_{dt})$, asset weights $\hat{\mathbf{w}}_t = (\hat{w}_{1t}, \hat{w}_{2t}, \ldots, \hat{w}_{dt})$, a $d \times d$ positive-definite covariance matrix $\hat{\mathbf{\Sigma}}_t$, and a $d \times 1$ vector of asset means $\hat{\boldsymbol{\mu}}_t = (\hat{\mu}_{1t}, \hat{\mu}_{2t}, \ldots, \hat{\mu}_{dt})$ at time (out-of-sample iteration) t, Markowitz (1952) suggests that the portfolio's expected return and variance are $\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t$ and $\hat{\mathbf{w}}_t^\intercal \hat{\mathbf{\Sigma}}_t \hat{\mathbf{w}}_t$, respectively. Furthermore, he proposes that an investor should invest in optimal portfolios according to the mean-variance *Efficient Frontier*. Among these portfolios are the Min-Variance and Max-Sharpe Ratio (Max-SR). While the former is suitable for a risk-averse investor with the objective of reducing the portfolio risk, the latter, as suggested in Sharpe (1966), is an alternative for a risk-averse investor who seeks a maximum reward/risk ratio, which entails maximizing the compensation for any accepted unit of risk.

To extend the Markowitz-type portfolios, we also include the ESG (risk) scores. Let $\mathbf{ESGR}_t = (ESGR_{1t}, ESGR_{2t}, \ldots, ESGR_{dt})$, $\mathbf{ESG}_t^I = (ESG_{1t}^I, ESG_{2t}^I, \ldots, ESG_{dt}^I)$, and $\mathbf{ESG}_t^{II} = (ESG_{1t}^{II}, ESG_{2t}^{II}, \ldots, ESG_{dt}^{II})$ be $d \times 1$ vectors of assets' ESGR, ESG I and ESG II scores, respectively. Then, the socially responsible multi-ESG-constrained Min-Variance portfolio is obtained as:

$$\begin{aligned}
\underset{\hat{\mathbf{w}}_t}{\text{minimize}} \quad & \hat{\mathbf{w}}_t^\intercal \hat{\mathbf{\Sigma}} \hat{\mathbf{w}}_t && \text{portfolio risk} \\
\text{subject to} \quad & \hat{\mathbf{w}}_t^\intercal \mathbf{ESGR}_t \leq U_{ESGR_t} \\
& \hat{\mathbf{w}}_t^\intercal \mathbf{ESG}_t^I \geq L_{ESG_t^I} \\
& \hat{\mathbf{w}}_t^\intercal \mathbf{ESG}_t^{II} \geq L_{ESG_t^{II}} \\
& \hat{\mathbf{w}}_t^\intercal \mathbf{1} = 1 && \text{full investment} \\
& \hat{w}_{jt} \geq 0, \forall j \in \{1, 2, \ldots, d\} && \text{long position,}
\end{aligned} \tag{1}$$

where $\hat{\mathbf{w}}_t^\intercal \mathbf{ESGR}_t$ and U_{ESGR_t} denote the portfolio's ESGR score and its upper boundary at time t. To identify proper lower boundaries for portfolio ESG I and ESG II, we use the third quartiles of these scores across assets s.t. $L_{ESG_t^I} = Q_3(ESG_{1t}^I, ESG_{2t}^I, \ldots, ESG_{dt}^I)$ and $L_{ESG_t^{II}} = Q_3(ESG_{1t}^{II}, ESG_{2t}^{II}, \ldots, ESG_{dt}^{II})$, where $Q_k(.)$ is the k^{th} empirical quartile. We set the upper boundaries for portfolio ESGR to the first quartile such that $U_{ESGR_t} = Q_1(ESGR_{1t}, ESGR_{2t}, \ldots, ESGR_{dt})$.[4]

For the Max-SR portfolio, the objective function $\frac{\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t}{\sqrt{\hat{\mathbf{w}}_t^\intercal \hat{\mathbf{\Sigma}}_t \hat{\mathbf{w}}_t}}$, is a non-linear term and to obtain a convex optimization, we apply fractional programming (see e.g., Charnes and Cooper, 1962; Dinkelbach, 1967).[5]

[4]This portfolio optimization problem is comparable to that in Qi and Li (2020), where equality constraints are imposed on individual pillars, i.e., environmental, social, and governance scores.

[5]For both the Sharpe and STARR ratios, we use the 3-month US T-bill rate as the risk-free rate.

The risk measure in the Max-SR portfolio problem is the portfolio standard deviation, $\sqrt{\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\Sigma}}_t \hat{\mathbf{w}}_t}$. Since the covariance matrix, $\hat{\boldsymbol{\Sigma}}_t$, is positive semi-definite and portfolio variance, $\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\Sigma}}_t \hat{\mathbf{w}}_t$, is strictly monotonic, the minimization of the portfolio variance corresponds to the minimization of the portfolio standard deviation. Assuming (i) the portfolio's expected return, $\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t$, is a (quasi-)concave function and strictly positive, and (ii) the portfolio variance is convex (i.e., non-singular) and strictly positive, then the ratio $\frac{\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\Sigma}}_t \hat{\mathbf{w}}_t}{\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t}$ is quasi-convex and its minimization corresponds to the maximization of $\frac{\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t}{\sqrt{\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\Sigma}}_t \hat{\mathbf{w}}_t}}$ (see Stoyanov *et al.*, 2007, for more details). Therefore, the Max-SR optimization problem can be written as:

$$
\begin{aligned}
\underset{\hat{\mathbf{w}}_t}{\text{minimize}} \quad & \frac{\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\Sigma}}_t \hat{\mathbf{w}}_t}{\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t} & \\
\text{subject to} \quad & \hat{\mathbf{w}}_t^\intercal \mathbf{1} = 1 & \text{full investment} \\
& 0 \leq \hat{w}_{jt} \leq 1, \forall j \in \{1, 2, \ldots, d\} & \text{long positions only}
\end{aligned}
\tag{2}
$$

To transform Problem (2) into a quadratic programming optimization, let $\tilde{\mathbf{w}}_t$ be a vector of unbounded weights, ν be an auxiliary variable capturing the inverse of the denominator of the objective function s.t. $\nu = [\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t]^{-1}$. Since the portfolio variance is a positively homogeneous function, by setting $\hat{\mathbf{w}}_t = \tilde{\mathbf{w}}_t/\nu$, we have $\sqrt{\tilde{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\Sigma}}_t \tilde{\mathbf{w}}_t} = \nu\sqrt{\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\Sigma}}_t \hat{\mathbf{w}}_t} = \sqrt{\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\Sigma}}_t \hat{\mathbf{w}}_t}[\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t]^{-1}$. Therefore, the Max-SR portfolio problem is equivalent to:

$$
\begin{aligned}
\underset{\tilde{\mathbf{w}}_t, \nu}{\text{minimize}} \quad & \tilde{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\Sigma}}_t \tilde{\mathbf{w}}_t & \text{portfolio risk} \\
\text{subject to} \quad & \tilde{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t \geq 1 & \text{portfolio return} \\
& \tilde{\mathbf{w}}_t^\intercal \mathbf{1} = \nu & \text{full investment} \\
& 0 \leq \tilde{w}_{jt} \leq \nu, \forall j \in \{1, 2, \ldots, d\} & \text{long positions only} \\
& \nu > 0, &
\end{aligned}
\tag{3}
$$

where the portfolio return constraint, $\tilde{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t \geq 1$, is equivalent to the condition that $\nu = [\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t]^{-1}$, due to the positively homogeneous property of portfolios' expected return, i.e., $\tilde{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t = \nu[\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t] = [\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t]^{-1}\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t = 1$. Since $\hat{w}_{jt} = \frac{\tilde{w}_{jt}}{\nu}$, both the full investment and long positions constraints are equivalent to those from Problem (2). The last constraint ensures that the portfolio return is positive.

To construct a socially responsible multi-ESG-constrained optimal portfolio, we suggest to add constraints for portfolio ESGR, ESG I, and ESG II scores.

In this case, the socially responsible Max-SR portfolio is defined as:

$$\begin{aligned}
\underset{\tilde{\mathbf{w}}_t,\nu}{\text{minimize}} \quad & \tilde{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\Sigma}}_t \tilde{\mathbf{w}}_t && \text{portfolio risk} \\
\text{subject to} \quad & \tilde{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t \geq 1 && \text{portfolio return} \\
& \tilde{\mathbf{w}}_t^\intercal \mathbf{ESGR}_t \leq \nu U_{ESGR_t} \\
& \tilde{\mathbf{w}}_t^\intercal \mathbf{ESG}_t^I \geq \nu L_{ESG_t^I} \\
& \tilde{\mathbf{w}}_t^\intercal \mathbf{ESG}_t^{II} \geq \nu L_{ESG_t^{II}} \\
& \tilde{\mathbf{w}}_t^\intercal \mathbf{1} = \nu && \text{full investment} \\
& 0 \leq \tilde{w}_{jt} \leq \nu, \forall j \in \{1, 2, \ldots, d\} && \text{long positions only} \\
& \nu > 0,
\end{aligned} \tag{4}$$

where ν denotes an auxiliary scaling variable, $\tilde{\mathbf{w}}_t$ is a vector of the unconstrained weights with the final optimal weights obtained as $\hat{w}_{jt} = \frac{\tilde{w}_{jt}}{\nu}$.

To protect the investor from extreme losses during a bearish market, tail risk measures are widely applied in portfolio optimization (for an application, see Restrepo *et al.*, 2020). Among these measures is the conditional Value-at-Risk (CVaR), also known as the expected shortfall. CVaR is defined as average losses beyond VaR, and for a portfolio it can be minimized by using linear programming (see Rockafellar and Uryasev, 2000, for more details on the linear transformation of CVaR).

Let $\mathfrak{f}(\hat{\mathbf{w}}_t, \hat{\mathbf{r}}_{mt}) = -\hat{\mathbf{w}}_t^\intercal \hat{\mathbf{r}}_{mt}$ be a loss function and set $l = \mathrm{VaR}_\alpha(\hat{\mathbf{w}}_t)$. Let $\boldsymbol{\upsilon}_t = (\upsilon_{1t}, \upsilon_{2t}, \ldots, \upsilon_{Mt})$ be an auxiliary variable that captures losses beyond the VaR s.t. $\boldsymbol{\upsilon}_{mt} = \big[- \hat{\mathbf{w}}_t^\intercal \hat{\mathbf{r}}_{mt} - \mathrm{VaR}_\alpha(\hat{\mathbf{w}}_t) \big]^+$. The multi-ESG-constrained Min-CVaR portfolio can be imposed as a linear system:

$$\begin{aligned}
\underset{\hat{\mathbf{w}}_t, l, \boldsymbol{\upsilon}_t}{\text{minimize}} \quad & l + \frac{1}{M(1-\alpha)} \sum_{m=1}^{M} \upsilon_{mt} && \text{portfolio tail risk} \\
\text{subject to} \quad & \hat{\mathbf{w}}_t^\intercal \hat{\mathbf{r}}_{mt} + l + \upsilon_{mt} \geq 0, \forall m \in \{1, 2, \ldots, M\} \\
& \hat{\mathbf{w}}_t^\intercal \mathbf{ESGR}_t \leq U_{ESGR_t} \\
& \hat{\mathbf{w}}_t^\intercal \mathbf{ESG}_t^I \geq L_{ESG_t^I} \\
& \hat{\mathbf{w}}_t^\intercal \mathbf{ESG}_t^{II} \geq L_{ESG_t^{II}} \\
& \hat{\mathbf{w}}_t^\intercal \mathbf{1} = 1 && \text{full investment} \\
& \hat{w}_{jt} \geq 0, \forall j \in \{1, 2, .., d\} && \text{long position,}
\end{aligned} \tag{5}$$

where l is the VaR at α level, and M is the total number of simulated returns from the step-ahead multivariate distribution.

Similar to the Max-SR optimization in Equation (4), one could maximize the mean/CVaR (also known as the stable tail-adjusted return ratio or STARR).

Since the risk measure, $\text{CVaR}(\hat{\mathbf{w}}_t)$, is convex, the maximization of STARR, i.e., $\hat{\boldsymbol{\mu}}_t \text{CVaR}(\hat{\mathbf{w}}_t)^{-1}$, corresponds to the minimization of $\text{CVaR}(\hat{\mathbf{w}}_t)\hat{\boldsymbol{\mu}}_t^{-1}$. By setting $\hat{\mathbf{w}}_t = \tilde{\mathbf{w}}_t/\nu$, we have $\text{CVaR}(\tilde{\mathbf{w}}_t) = \nu\text{CVaR}(\hat{\mathbf{w}}_t) = \text{CVaR}(\hat{\mathbf{w}}_t)[\hat{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t]^{-1}$. We use $\boldsymbol{\upsilon}_t$ as an auxiliary variable and define $\text{CVaR}(\tilde{\mathbf{w}}_t) = l + \frac{1}{M(1-\alpha)} \sum_{m=1}^{M} \upsilon_{mt}$. In this case the optimization system is given by:

$$
\begin{aligned}
\underset{\tilde{\mathbf{w}}_t, l, \boldsymbol{\upsilon}_t, \nu}{\text{minimize}} \quad & l + \frac{1}{M(1-\alpha)} \sum_{m=1}^{M} \upsilon_{mt} && \text{portfolio tail risk} \\
\text{subject to} \quad & \tilde{\mathbf{w}}_t^\intercal \hat{\boldsymbol{\mu}}_t \geq 1 && \text{portfolio return} \\
& \tilde{\mathbf{w}}_t^\intercal \hat{\mathbf{r}}_{mt} + l + \upsilon_{mt} \geq 0, \forall m \in \{1, 2, .., M\} \\
& \tilde{\mathbf{w}}_t^\intercal \mathbf{ESGR}_t \leq \nu U_{ESGR_t} \\
& \tilde{\mathbf{w}}_t^\intercal \mathbf{ESG}_t^{I} \geq \nu L_{ESG_t^I} \\
& \tilde{\mathbf{w}}_t^\intercal \mathbf{ESG}_t^{II} \geq \nu L_{ESG_t^{II}} \\
& \tilde{\mathbf{w}}_t^\intercal \mathbf{1} = \nu && \text{full investment} \\
& 0 \leq \tilde{w}_{jt} \leq \nu, \forall j \in \{1, 2, .., d\} && \text{long positions only} \\
& \upsilon_{mt} \geq 0 \\
& \nu > 0.
\end{aligned}
\tag{6}
$$

To estimate the ESGR-constrained portfolios, we remove the constraints for ESG I and ESG II from Equations (1), (4), (5), and (6).

3 Data

In this paper, we use international stocks that are constituents of the S&P GTF index which represents the 25 largest global timber & forestry stocks. An investor has the possibility to participate in the development of the S&P GTF index by investing in the iShares S&P GTF exchange traded fund (ETF). We will label this investment in the following as the GTF ETF benchmark. Note that this benchmark represents a passive investment strategy, in which the included stocks are weighted with their market capitalization as suggested by the CAPM. The S&P GTF index updates its constituent list and their respective weights twice each year. Since the historical constituents of S&P GTF have changed during the sample period due to delisting of stocks or market capitalization changes, the sample contains 29 stocks in total.

As we are particularly interested in socially responsible investments, we employ ESG I and ESGR scores obtained from Sustainalytics, and also the ESG II scores obtained from Refinitiv Eikon database. Only stocks which have data available on all ESG measures are considered for the analysis. As mentioned above, we explore two different versions of ESG measures retrieved from Sustainalytics. The first, which we refer to as ESG I, is considered as the standard ESG measure, while the second, which is labeled as ESG Risk (ESGR) rating, focuses on materiality and risk issues. This revised ESG was launched in 2018 by Sustainalytics as a new generation of ESG measurement. The ESGR approach sorts companies into five risk categories: negligible, low, medium, high, severe. These risk categories are absolute, meaning that a "high risk" assessment reflects a comparable degree of unmanaged ESG risk across the economy, whether it refers to a manufacturing company, an agriculture company, an utility company, or any other type of company. To be considered relevant in the ESGR, an issue must have a potentially substantial impact on the economic value of a company and, hence, the financial risk and return profile of an investor. Compared to traditional ESG I and II measures, ESGR consists of one single currency of risk. One point of risk is equivalent, no matter which company or which issue it applies to, and points of risk add up across issues to create overall scores. The ESGR is composed of three building blocks that contribute to the overall rating score for a company. These building blocks include Corporate Governance, material ESG issues, and idiosyncratic issues. We also obtain the adjusted (total) daily returns and the 3-month US T-bill rate from Thomson Reuters's Eikon database from January 2015 to December 2021, resulting in 1793 trading days.

Table A1 in the appendix presents the descriptive statistics of asset returns. Most return series are positively skewed and show positive kurtosis. Considering the results of Jarque–Bera's normality test, we can conclude that all series have non-Gaussian empirical distributions. The results of the ARCH test with one lag indicate volatility clustering and autocorrelation in the squared residuals for most series. The test statistics for the Ljung–Box test with ten lags suggest serial correlation for most of the series.

Not only do we estimate the copula-based portfolios, but we also take a simple historical approach where we use the historical asset returns in the portfolio optimization (as an example, see Redmond and Cubbage, 1988). As the ESGR data is only available from December 2018, we consider a 3-year period, from December 2018 to December 2021, to investigate how CSR measures affect portfolio performance.[6] To understand the impact of CSR consideration on portfolio performance, we also show the results for unconstrained portfolios. As benchmark for portfolio strategies, we compare the results with the passive investment into the iShares S&P GTF ETF.

[6]Our choice of the time period 2018–2021 is further motivated by the severe market turmoil caused by the pandemic crisis, which made investors' trade-off between risk and reward particularly challenging and, therefore, important to study.

4 Results

In this section, we analyze the out-of-sample performance of optimal timber & forestry portfolios, with and without imposing constraints on CSR measures, using the GTF ETF as benchmark. Finally, we compare performance results between unconstrained and constrained historical and copula-based optimal portfolios.

4.1 ESG-constrained and unconstrained portfolios

Table 1 reports the results for the unconstrained, ESGR-constrained, and multi-ESG-constrained timber & forestry portfolios during the 2018–2021 period. The GTF ETF benchmark achieves a higher average return (0.098%) than the historical-based optimal portfolios, and consequently, results in better risk-adjusted ratios. However, the ETF has higher downside risk (6.95%) than the other portfolio strategies.

The CSR measures reported for the ETF, i.e., an ESG I of 63.6, indicates the average level of social responsibility anticipated when investing in the timber & forestry stocks using a passive diversification strategy following the S&P GTF index.

Panel (B) presents the results for historical-based optimized portfolios. In regard to risk minimization, both Min-Variance and Min-CVaR portfolios have lower volatility and tail risk compared to the benchmark. In particular, the Min-CVaR portfolio results in a CVaR of 4.02%. Considering the reward/risk maximization, both the Max-SR and Max-STARR portfolios also reduce the tail risk but fail to increase the average return. Overall, these unconstrained historical portfolios provide better downside risk than the benchmark portfolios and show similar levels of social responsibility as the GTF ETF.

As we can see in Panel (C), the ESGR constraint results in portfolios with better ESG I and ESGR scores than the average values from the benchmark. Moreover, the ESGR constraint leads to Min-Variance, Min-CVaR, and Max-STARR historical-based portfolios with higher average returns. Panels (E) and (F) show that the Min-Variance and Min-CVaR copula-based portfolios, i.e., ESGR-constrained and unconstrained, have lower downside risk (CVaR) compared to the benchmark. In general, the copula-based portfolios with risk minimization achieve lower downside risk, higher average return, and better risk-adjusted performance compared to those from the historical approach. This is due to incorporating tail dependency when modeling the predictive multivariate distribution for asset returns via vine copulas. For instance, the historical-based Min-CVaR portfolio in Panel (B) results in an average return of 0.042% and a CVaR of 4.02%, while its copula-based counterpart in Panel (E) has an average return of 0.087% and a CVaR of 3.83%. Although, the Max-SR and Max-STARR copula-based portfolios achieve higher average returns, they fail to reduce both the volatility and downside risk compared

Table 1: Portfolio out-of-sample performance using S&P GTF stocks.

Portfolio strategy	Ave. return	St. deviation	CVaR	Sortino	SR	STARR	ESGR	ESG I	ESG II	Wealth	Turnover
Panel A: Benchmarks											
iShares S&P GTF index	0.098	1.48	6.95	0.082	0.066	0.014	19.5	63.6	62.9	199	0.000
Panel B: Historical-based unconstrained optimal portfolios											
Min-Variance	0.046	1.14	5.26	0.050	0.040	0.009	22.8	63.8	53.1	136	0.024
Min-CVaR	0.042	1.09	4.02	0.053	0.038	0.010	24.0	64.1	55.0	133	0.021
Max-SR	0.056	1.19	4.16	0.068	0.047	0.013	21.5	66.8	62.4	147	0.068
Max-STARR	0.030	1.15	4.27	0.037	0.026	0.007	22.2	66.5	61.4	120	0.137
Panel C: Historical-based ESGR-constrained optimal portfolios											
Min-Variance	0.054	1.26	6.01	0.050	0.043	0.009	16.9	70.0	59.1	144	0.024
Min-CVaR	0.044	1.31	5.94	0.040	0.034	0.007	16.9	72.3	60.0	133	0.030
Max-SR	0.048	1.31	5.18	0.051	0.037	0.009	16.9	72.2	71.1	137	0.074
Max-STARR	0.037	1.39	5.67	0.036	0.027	0.007	16.9	72.5	74.1	124	0.131
Panel D: Historical-based multi-ESG-constrained optimal portfolios											
Min-Variance	0.041	1.30	5.90	0.038	0.032	0.007	16.9	75.6	76.6	129	0.027
Min-CVaR	0.037	1.32	5.96	0.035	0.028	0.006	16.9	75.6	76.6	125	0.031
Max-SR	0.063	1.41	5.50	0.062	0.045	0.011	16.4	75.7	77.6	152	0.058
Max-STARR	0.057	1.43	5.67	0.054	0.040	0.010	16.4	75.8	77.4	145	0.084

Note: This table reports out-of-sample performance measures for portfolios obtained based on a rolling window of 1000 trading days with an out-of-sample period from December 2018 to December 2021. Except for the average turnover and ESG scores, all performance measures are obtained using daily out-of-sample portfolio returns and are expressed in percentages. ESG I and ESGR are based on the scores from Sustainalytics. ESG II is based on scores from Refinitiv Eikon (Thomson Reuters) database. The CVaR is shown at the 1% level. The average turnover is computed based on a proportional transaction cost of 1 basis point.

Table 1: Continued.

Portfolio strategy	Ave. return	St. deviation	CVaR	Sortino	SR	STARR	ESGR	ESG I	ESG II	Wealth	Turnover
Panel E: Copula-based unconstrained optimal portfolios											
Min-Variance	0.050	0.971	3.41	0.074	0.052	0.015	22.6	63.4	53.0	144	0.279
Min-CVaR	0.087	1.04	3.83	0.113	0.084	0.023	22.1	64.2	52.3	190	0.688
Max-SR	0.173	1.74	5.58	0.147	0.100	0.031	21.9	63.4	52.8	351	1.615
Max-STARR	0.172	1.83	6.39	0.130	0.094	0.027	21.7	63.4	53.5	344	1.668
Panel F: Copula-based ESGR-constrained optimal portfolios											
Min-Variance	0.065	1.17	4.82	0.071	0.056	0.014	16.9	69.6	57.2	159	0.247
Min-CVaR	0.096	1.22	4.99	0.101	0.079	0.019	16.9	70.0	56.4	202	0.586
Max-SR	0.152	1.58	5.87	0.133	0.096	0.026	16.8	71.0	55.8	303	1.303
Max-STARR	0.157	1.64	6.33	0.129	0.096	0.025	16.8	70.9	56.3	313	1.349
Panel G: Copula-based multi-ESG-constrained portfolios											
Min-Variance	0.054	1.31	5.85	0.050	0.041	0.009	16.9	75.6	76.6	143	0.195
Min-CVaR	0.063	1.35	6.08	0.058	0.046	0.010	16.9	75.6	76.6	153	0.395
Max-SR	0.125	1.45	5.30	0.118	0.086	0.024	16.3	75.8	77.6	248	1.109
Max-STARR	0.127	1.51	6.08	0.114	0.084	0.021	16.2	75.8	77.5	250	1.168

to their historical counterparts. For instance, the Max-SR and Max-STARR portfolios in Panel (E) result in the highest average returns, i.e., 0.17%, which is due to the VAR model used in the mean equation, while achieving lower CVaR compared to the benchmark. Panels (D) and (G) provide the results for constrained portfolios when imposing boundaries on all types of ESG scores. While imposing multi-ESG constraints for the Max-SR and STARR portfolios in Panel (D) leads to higher average returns and higher CVaR, the multi-ESG constraints in Panel (G) reduce both volatility and CVaR for these portfolios. This indicates that multi-ESG constraints restrict investment only in assets with the best CSR performance, and therefore, using these assets results in optimal portfolios with lower risk compared to both the benchmarks. We notice all the multi-ESG-constrained portfolios in Panels (D) and (G) achieve similar ESG I, ESGR, and ESG II scores. This indicates that the optimization cannot find a solution with better scores than the upper (lower) boundaries and better objective value. It is noteworthy that the average turnover reported for the copula-based portfolios indicates a higher volume of trades required to hold these strategies compared to those from the historical-based approach.[7]

In Table 2, we report the average weights for the top ten assets in the copula-based timber & forestry portfolios. Daio Paper Co. has a high weight, in particular, in unconstrained portfolio strategies that minimize portfolio risk. However, it has a high ESGR score, i.e., 35.1, and therefore, it is not among the top assets in the constrained portfolios in Panels (B) and (C). Other examples of assets that are not included in the ESGR-constrained portfolios include Holmen Aktiebolag and Oji Holdings Corporation. Most of the assets included in Panel B have an average ESGR score below 20 (see Table C). For instance, BillerudKorsnas AB and Mondi plc. are not included in the top ten assets of the unconstrained portfolios and have an average ESGR score of 11.6 and 12.2, respectively. Obviously, more weights are allocated to the assets with low ESGR when applying the ESGR-constrained optimization. Although Sumitomo Forestry Co. is already among the top ten assets in the unconstrained portfolios, it receives even more weight in the socially responsible portfolios (ESGR-constrained) because its average ESGR score, i.e., 13.8, is below the average of the timber & forestry industry.

To understand how the portfolios perform over the 2016–2021 sample period, we plot cumulative realized returns for the Max-SR and Min-CVaR portfolios. Figure 1 illustrates the results for the Max-SR portfolios. Both the unconstrained and multi-ESG-constrained historical-based Max-SR portfolios do not perform better than the benchmark ETF during 2021. However, the copula-based portfolios achieve higher cumulative returns, in particular, during the post Covid-19 market crash in March 2020. This result corresponds to those in Table 1.

[7]These results are following those in Sahamkhadam *et al.* (2018) and Sahamkhadam (2021).

Table 2: Top asset weights (in %) for copula-based portfolio strategies.

Stock	Min Variance	Min CVaR	Max SR	Max STARR
Panel (A): Unconstrained portfolios				
Daio Paper Corporation	17.1	17.1	9.06	8.28
Nippon Paper Industries Co.	13.2	8.14	5.10	3.41
Klabin S.A.	13.0	16.7	6.60	7.34
Holmen Aktiebolag	6.97	4.27	3.97	2.74
Sumitomo Forestry Co.	6.86	8.13	9.34	9.53
CatchMark Timber Trust Inc.	6.48	6.45	5.79	5.57
Rayonier Inc.	6.39	4.79	3.21	2.93
Svenska Cellulosa Aktiebolaget	5.02	4.72	4.11	3.44
Sappi Limited	2.79	3.60	4.17	5.12
Oji Holdings Corporation	2.65	3.96	9.67	10.3
$\sum$	80.5	77.9	61.0	58.7
Panel (B): ESGR-constrained portfolios				
Sumitomo Forestry Co.	18.3	18.8	19.4	18.8
Klabin S.A.	17.8	23.0	12.7	14.8
Rayonier Inc.	10.2	7.73	6.34	5.90
BillerudKorsnäs AB	8.77	5.17	6.30	4.73
Mondi PLC	6.84	6.29	5.21	5.44
UPM-Kymmene Oyj	5.32	4.89	6.88	5.63
CatchMark Timber Trust Inc.	4.10	4.44	2.77	2.60
Smurfit Kappa Group PLC	3.76	5.25	5.13	6.59
Sappi Limited	2.75	3.54	4.37	5.32
Metsa Board Oyj	0.92	1.49	7.56	7.16
$\sum$	78.8	80.6	76.7	77.0
Panel (C): multi-ESG-constrained portfolios				
Klabin S.A.	19.7	25.7	17.3	21.1
UPM-Kymmene Oyj	13.7	14.0	16.4	14.2
Nippon Paper Industries Co.	13.0	11.3	5.18	4.10
Mondi PLC	12.2	10.6	13.1	13.6
BillerudKorsnäs AB	11.3	7.26	10.5	7.94
Metsa Board Oyj	7.21	6.65	6.84	6.29
Sappi Limited	4.20	6.07	4.45	5.87
Smurfit Kappa Group PLC	3.88	5.01	6.32	8.36
Svenska Cellulosa Aktiebolaget	2.15	1.69	5.89	4.76
West Fraser Timber Co.	2.07	3.06	1.90	2.39
$\sum$	89.4	91.3	87.9	88.6

Note: This table reports average weight (in %) for top ten assets in the copula-based portfolio strategy in the respective column, see results reported in Table 1.

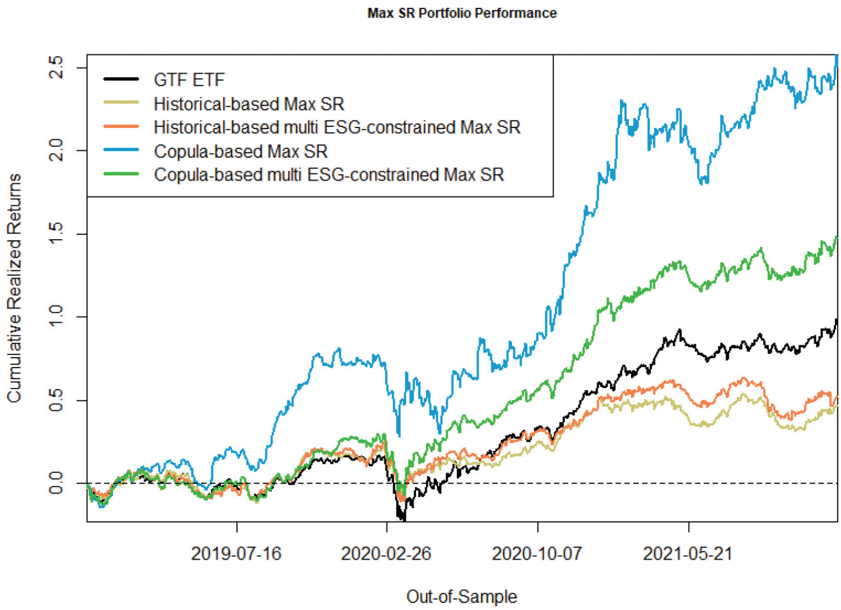

Figure 1: Cumulative out-of-sample returns for the Max-SR portfolios.

In addition to the cumulative returns, we also investigate short-term investments with a holding period of 252 trading days. By rolling this holding period over the out-of-sample, we record the realized SR and CVaR for the Max-SR and Min-CVaR portfolios and compare them with those from the benchmarks. Figure 2 shows the realized SR from the Max-SR portfolios. For most holding periods, both the constrained and unconstrained copula-based Max-SR portfolios achieve higher SR compared to the benchmark. Figure 3 plots the realized CVaR for the different strategies. In general, the ETF results in higher CVaR than the copula-based portfolios. For the Min-CVaR portfolios in Figure 3, we see an increase in the realized CVaR due to the market crash in March 2020. Interestingly, both the constrained and unconstrained Min-CVaR portfolio optimizations reduce the extreme losses during the short-horizon holding periods during and after the market crash.

4.2 Evaluation of portfolio strategies

Table 3 presents an evaluation of the outcomes of the various portfolio strategies presented in Table 1 and those that are obtained using only ESG I or ESG II scores. Using dummy variables, the quantile regression models[8] test whether

[8]Quantile regression was preferred in this case as the sample is small and quantile regression is robust with regard to outliers.

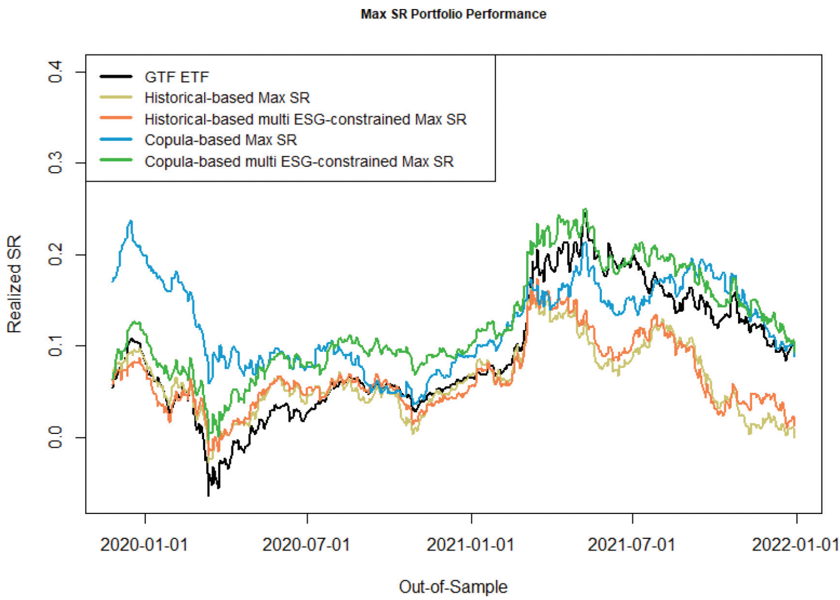

Figure 2: This figure illustrates the realized out-of-sample SR for the Max-SR portfolio strategies computed for each holding period consisting of 252 days.

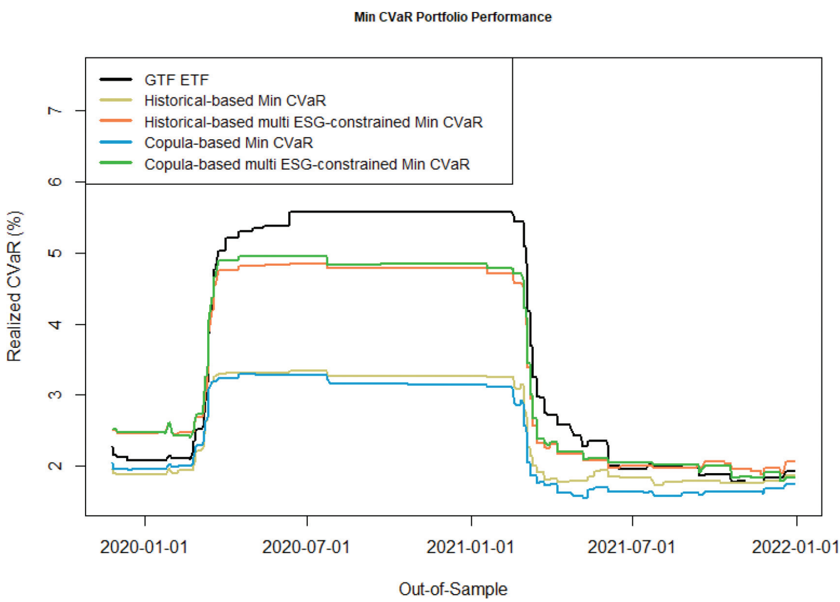

Figure 3: This figure illustrates the realized out-of-sample CVaR for the Min-CVaR portfolio strategies computed for each holding period consisting of 252 days.

Table 3: Quantile regression models to evaluate portfolio strategies

	(1) Sortino	(2) SR	(3) STARR	(4) Turnover
Copula-based	0.0530***	0.0400***	0.0110***	0.664***
	(4.84)	(5.38)	(5.19)	(4.04)
ESG-constrained	−0.0170	−0.0100	−0.00400	0.00800
	(−1.28)	(−1.11)	(−1.56)	(0.04)
Constant	0.0600***	0.0440***	0.0120***	0.0240
	(4.74)	(5.12)	(4.91)	(0.13)
N	41	41	41	41
pseudo R^2	0.371	0.410	0.370	0.377

Note: t statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. Reference categories are historical-based strategies for copula-based, and unconstrained for constrained portfolio strategies. In total, we estimate five types of portfolios including unconstrained, ESG I-constrained, ESG II-constrained, ESGR-constrained, and multi-ESG-constrained. Including the four portfolio optimizations and the ETF benchmark, we have 41 portfolios.

outcomes differ significantly between (1) copula-based vis-à-vis historical, (2) ESG-constrained vis-à-vis unconstrained portfolio strategies.[9]

The first column shows that portfolio strategies imposing constraints on ESG do not have a statistically significant lower Sortino ratio. The results also show that the copula-based approach yields portfolios with significantly better risk-adjusted performance than the historical approach. Likewise, columns 2 and 3 consider additional measures that describe risk-adjusted returns. In accordance with column 1, no significant negative impact from incorporating ESG constraints in the optimization can be found. Column 4 shows that the inclusion of ESG constraints has no impact on the portfolio average turnover. Similar to the risk-adjusted measures, the copula-based portfolios yield higher turnover compared to the historical-based ones.

In Table 4 we investigate the impact of imposing constraints on the achieved average level of portfolios' ESG outcomes. The three final columns show that using ESG constraints significantly increases the level of social responsibility for each ESG measure. Using the traditional ESG I and II measures, where higher score corresponds to better performance, we notice a highly significant and positive estimate for the ESG-constrained portfolios (columns (2) and (3)). This holds also for the new ESG risk measure in column (1) (with reversed sign as it applies an inverted rank scale). One can also see the impact from imposing a constraint on a different ESG measure, as those ESG measures are correlated. For instance in column (2) we can see that imposing the constraint

[9] Another application of this approach to evaluate different portfolio strategies can be found in Sahamkhadam *et al.* (2018).

Table 4: Quantile regression models to evaluate the impact of imposing ESG constraints on average portfolio ESG.

	(1) ESGR	(2) ESG I	(3) ESG II	(4) ESGR	(5) ESG I	(6) ESG II
Copula-based	−0.0880	0.001000	−2.885	−0.582	−0.163	−3.811
	(−0.12)	(0.00)	(−0.73)	(−0.55)	(−0.09)	(−0.87)
ESGR-constrained	−2.594**	4.072*	−2.890	—	—	—
	(−2.58)	(1.82)	(−0.53)			
ESG I-constrained	−1.882*	7.811***	−1.337	—	—	—
	(−1.87)	(3.50)	(−0.25)			
ESG II-constrained	0.0360	2.300	14.18**	—	—	—
	(0.04)	(1.03)	(2.61)			
multi-ESG-constrained	—	—	—	−2.009	5.993**	15.20***
				(−1.50)	(2.60)	(2.74)
Constant	19.47***	66.84***	62.93***	18.91***	69.78***	62.42***
	(29.31)	(45.28)	(17.48)	(24.18)	(51.77)	(19.21)
N	41	41	41	41	41	41
pseudo R^2	0.289	0.292	0.354	0.108	0.289	0.338

Note: t statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$. See notes Table 3. Dependent variables are the average ESG scores of the 41 portfolios including the benchmark.

regarding ESG I also positively affects ESGR (reduces the score), though this effect is only weakly significant. In columns (4) to (6) we investigate the effect of applying constraints on all ESG measures at the same time in the optimization labeled multi-ESG-constrained. We can see that by imposing this constraint we can improve all ESG measures, but the effect is most pronounced for ESG II followed by ESG I, and it is not significant for ESGR. These results prove that by imposing constraints on the least acceptable level of portfolio ESG the investor can achieve higher levels of social responsibility while using optimal portfolio strategies.

In summary, our results indicate that (i) there are advantages of using optimal portfolio strategies for investments in timber & forestry stocks, both in terms of portfolio returns and risks, compared to the iShares GTF ETF reflecting a passive investment strategy, (ii) the copula-based portfolios achieve higher returns and better risk-adjusted performance compared to the historical strategies, (iii) the suggested combined approach, with both copula modeling and ESG- or ESGR-constrained optimization, achieves higher social responsibility while providing the investors with the same level of risk-adjusted returns as the unconstrained strategy.

5 Conclusions

This paper examines the impact of corporate social responsibility (CSR) on stock market investments in the global timber & forestry (GTF) industry, and tests how optimal portfolios considering CSR perform relative to the S&P GTF index. We suggest a combined optimal portfolio approach that includes (both symmetric and asymmetric) tail dependence and CSR. To construct the socially responsible portfolios, the paper utilizes ESG scores from Sustainalytics and Refinitiv Eikon. We forecast asset returns using vine copula-augmented risk models and perform both risk minimization and reward/risk maximization, while imposing minimum threshold ESG constraints. We apply this empirical approach to 29 timber & forestry stocks which are current or past constituents of the S&P GTF index and analyze the portfolios' out-of-sample performance.

The overall results show a better performance of copula-based portfolio strategies in comparison to historical ones, and provide evidence to financial investors that socially responsible investments in forestry stocks are feasible without sacrificing risk-adjusted returns. This finding is important since forestry firms which focus on CSR can be expected to better anticipate future risks and opportunities, and are more dedicated to long-term value creation.

As more and better ESG information for companies becomes available, future studies might be able to analyze even longer time periods for investments in GTF stocks. One promising avenue for future research is to incorporate ESG information for predicting returns' multivariate distribution, which can be used for portfolio optimization. Moreover, ESG ratings typically also contain rich qualitative information about the respective company. Future research should try to utilize this qualitative information as a form of sentiment for the optimal portfolio construction.

Acknowledgements

Hans Lööf and Andreas Stephan thank The Swedish Agency for Growth Policy Analysis for financial support for the project "ESG ratings and the downside risk of stock returns".

Appendices

A Regular vine copula

According to Sklar's (1959) theorem, any multivariate cumulative distribution function F for a random variable set $(Z_1, \ldots, Z_d)$ consists of a d-dimensional copula C and marginal distributions $F_1, \ldots, F_d$, such that:

$$\begin{aligned} \forall \mathbf{z} \in \mathbb{R}^d : F(z_1, z_2, \ldots, z_d) &= C(F_1(z_1), F_2(z_2), \ldots, F_d(z_d)) \\ &= C(u_1, u_2, \ldots, u_d), \end{aligned} \tag{7}$$

where $z_j = F_j^{-1}(u_j),\ u_j \sim U[0,1]^d, \forall j \in \{1, 2, \ldots, d\}$.

Given that the marginals F_j are continuous, C is unique and defined as the joint distribution of $(U_1, \ldots, U_d) = (F_1(Z_1), \ldots, F_d(Z_d))$. Let $\mathbf{\Omega}$ be the parameter set in the copula multivariate distribution function $C(u_1, u_2, \ldots, u_d|\mathbf{\Omega})$, and f_j be the derivative of the univariate marginal distribution F_j. The d-dimensional joint distribution's density function is given as:

$$\begin{aligned} f(z_1, z_2, \ldots, z_d) &= \frac{\partial^d C(F_1(z_1), F_2(z_2), \ldots, F_d(z_d)|\mathbf{\Omega})}{\partial z_1, \partial z_2, \ldots, \partial z_d} \\ &= c(F_1(z_1), F_2(z_2), \ldots, F_d(z_d)|\mathbf{\Omega}) \times \prod_{j=1}^{d} f_j(z_j), \end{aligned} \tag{8}$$

where c is the copula density function, with the log-likelihood function:

$$\mathcal{L}((z_1, z_2, \ldots, z_d)|\mathbf{\Omega}) = \sum_{t=1}^{T} \left[\sum_{j=1}^{d} \log f_j(z_{tj}) + \log\big[c(u_{t1}, u_{t2}, \ldots, u_{td}|\mathbf{\Omega})\big] \right]. \tag{9}$$

Drawing upon the idea of Joe (1996) to decompose the joint density function to several pair-copula densities, Bedford and Cooke (2001) and Bedford and

Cooke (2002) derive a graphical representation of the pair-copula construction (PCC) in the form of nested trees called vine copulas. See Joe (2014) and Czado (2019) for properties and statistical inference of vine copulas.

For a d-dimensional set of continuous random variables, there exist $d(d-1)/2$ pair-copulas, and the copula density c can be decomposed into a product of these pair-copulas' densities. Using a sequence of $i = 1, 2, \ldots, d-1$ linked trees, the decomposition can be presented in a graphical PCC, known as the regular vine (Rvine). Let $e \in E_i$ be the edge between two nodes, n_e and k_e represent a pair-copula $c_{n_e,k_e;D_e}$ conditioned on D_e, with the copula parameter(s) $\mathbf{\Omega}_{n_e,k_e|D_e}$. Let $\boldsymbol{u}_{D_e} = \{u_i | i \in D_e\}$ be the variables in the conditioning set D_e, and $C_{n_e|D_e}$ is the conditional distribution of $U_{ne}|\boldsymbol{U}_{D_e}$. The copula density for a simplified Rvine copula is:

$$c\left(u|\mathbf{\Omega}\right) = \prod_{i=1}^{d-1} \prod_{e \in E_i} c_{n_e,k_e;D_e} \left(C_{n_e|D_e}(u_{n_e}|\boldsymbol{u}_{D_e}), C_{k_e|D_e}(u_{k_e}|\boldsymbol{u}_{D_e}) | \mathbf{\Omega}_{n_e,k_e|D_e} \right), \tag{10}$$

with the corresponding log-likelihood function:

$$\mathcal{L}(\mathbf{\Omega}|u) = \sum_{j=1}^{d} \sum_{i=1}^{d-1} \sum_{e \in E_i} \ln \Big[c_{n_e,k_e;D_e} \Big(C_{n_e|D_e}(u_{j,n_e}|u_{j,D_e}), C_{k_e|D_e}(u_{j,k_e}|u_{j,D_e}) | \mathbf{\Omega}_{n_e,k_e|D_e} \Big) \Big]. \tag{11}$$

Due to the complexity and computational difficulties in estimating the dependence structure in high-dimensional settings, truncated and simplified vine structures have been developed. Following Brechmann *et al.* (2012), a truncation can be applied to the number of trees in the vine by setting an independence copula at each edge from a specific tree $I \in \{1, 2, \ldots, d-1\}$ to the final tree.[10] In this case, the density of an I-level truncated Rvine is given as:

$$c^{Truncated}\left(u\right) = \prod_{i=1}^{I} \prod_{e \in E_i} c_{n_e,k_e|D_e} \Big(C_{n_e|D_e}\left(u_{n_e}|u_{D_e}\right), C_{k_e|D_e}\left(u_{k_e}|u_{D_e}\right) | \mathbf{\Omega}_{n_e,k_e|D_e} \Big). \tag{12}$$

B Copula-based Portfolios

To construct copula-based portfolios, a step-ahead multivariate conditional return distribution is obtained through a copula-augmented forecasting model.

[10] To select the truncation level I as well as the copula families in a mixed vine copula structure, we apply the modified version of the Bayesian Information Criteria (BIC) for vine copulas as suggested by Nagler *et al.* (2019).

To do so, set the following parameters: L = the estimation window length (here 1,000 trading days), $\forall \iota \in [L+1, T] : t_\iota$ = out-of-sample iteration, M = the total number of drawings from the step-ahead multivariate conditional return distribution, and d = the total number of assets in the portfolio. In the next step, repeat the following steps for all out-of-sample iterations t_ι:

Step 1. Initialize by setting $\forall t \in [t_{\iota-L}, t_{\iota-1}]$: $\mathbf{r}_t = (r_{1t}, r_{2t}, \ldots, r_{dt}), r_{jt} = [\frac{p_{jt}}{p_{j,t-1}} - 1] \times 100$ as the excess returns computed based on the observed adjusted total returns and the risk-free rate.

Step 2. $\forall j \in [1, d]$: obtain standardized residuals $\hat{\mathbf{z}}_j = (\hat{z}_{jt_{\iota-L}}, \ldots, \hat{z}_{jt_{\iota-1}})$, conditional mean $\hat{\mu}_{jt_\iota}$, and volatility $\hat{\sigma}_{jt_\iota}$ forecasts assuming, w.l.o.g., the returns follow an VAR-GARCH process:

$$\begin{cases} \mathbf{r}_t = \mathbf{c} + \boldsymbol{\phi}_1 \mathbf{r}_{t-1} + \boldsymbol{\epsilon}_t \\ \epsilon_{jt} = \sqrt{h_{jt}} z_{jt} \\ z_{jt} \approx (iid), \\ \sigma^2_{jt} = \alpha_{0j} + \alpha_{1j}\epsilon^2_{j,t-1} + \beta_{1j}\sigma^2_{j,t-1}, \\ \alpha_{0j} > 0,\ \alpha_{1j} \geq 0,\ \beta_{1j} \geq 0,\ \alpha_{1j} + \beta_{1j} < 1,\ \forall t \in [t_{\iota-L}, t_{\iota-1}]. \end{cases} \tag{13}$$

Step 3. Obtain uniform marginals $\hat{u}_{jt} = F_j(\hat{z}_{jt}),\ j \in [1, d],\ t \in [t_{\iota-L}, t_{\iota-1}]$ from the cumulative marginal distribution function s.t. $\hat{u}_{jt} \sim U[0, 1]^d$.

Step 4. Insert the estimated marginal uniform $(\hat{U}_1, \ldots, \hat{U}_d)$ of step 3 into the Rvine copula model in Equations (10)–(12) and estimate the copula parameter vector $\hat{\boldsymbol{\Omega}}$ using maximum likelihood estimation.

Step 5. Draw M uniform random numbers from the estimated multivariate Rvine copula distribution in step 4. Convert the simulated random numbers into standardized residuals $\hat{\boldsymbol{\nu}}_t = \{\hat{\boldsymbol{\nu}}_{mt},\ m = 1, \ldots, M,\ t = t_\iota\}$ using the inverse of the marginal distribution for each asset.

Step 6. Obtain return forecasts as $\hat{r}_{jmt_\iota} = \hat{\mu}_{jt_\iota} + \hat{\sigma}_{jt_\iota}\hat{\nu}_{jmt_\iota}$, $\forall j \in [1, d]$, $\forall m \in [1, M]$.

Step 7. Insert the return forecasts $\hat{\mathbf{r}}_{t_\iota} = \{\hat{\mathbf{r}}_{mt_\iota},\ m = 1, \ldots, M\}$ into the chosen portfolio optimization, Equations (1)–(6), and estimate optimal asset weights $\hat{\mathbf{w}}_{t_\iota} = (\hat{w}_{1t_\iota}, \hat{w}_{2t_\iota}, \ldots, \hat{w}_{dt_\iota})$.

Step 8. Given the proportional transaction cost Γ and realization of asset returns from observed prices, compute the portfolio return $R_{t_\iota} = [1 - \Gamma \sum_{j=1}^{d}(|\hat{w}_{jt_\iota} - \hat{w}^*_{jt_\iota}|)](1 + \hat{\mathbf{w}}^\intercal_{t_\iota}\mathbf{r}_{t_\iota}) - 1$, where $\hat{w}^*_{jt_\iota}$ denotes the realized asset weights at the end of the previous re-balancing interval.[11]

[11] We set the proportional transaction cost Γ to 1 basis point.

C Tables

Table A1: Descriptive statistics.

Entity name	Country	Ave. return	St. Dev.	Skewness	Kurtosis	JB	ARCH	Ljung-Box	ESGR	ESG I	ESG II
Smurfit Kappa Group PLC	Ireland	0.125	2.08	0.408	5.11	2844***	53.6***	11.3	13.8	78.2	79.4
International Paper Company	United States	0.051	1.78	0.159	8.14	6976***	574***	71.2***	24.8	61.7	–
Packaging Corporation of America	United States	0.093	1.71	0.205	9.00	8522***	37.1***	59.5***	18.7	59.7	57.9
Weyerhaeuser Co	United States	0.064	1.93	−0.088	30.6	98240***	382***	181***	18.6	63.7	76.2
Plum Creek Timber Company Inc.	United States	0.023	1.25	2.21	37.5	62060***	0.300	6.70	–	–	56.8
Potlatch Corporation	United States	0.066	1.94	−0.073	33.4	117415***	676***	220***	20.5	45.2	47.0
Rayonier Inc.	United States	0.037	1.70	−0.160	34.1	122121***	1028***	151***	17.3	43.9	43.6
Sappi Limited	South Africa	0.061	2.53	0.347	5.17	2837***	125***	28.4***	18.0	71.1	75.9
UPM-Kymmene Oyj	Finland	0.090	1.79	0.055	5.72	3428***	19.9***	13.9	15.5	79.0	82.9
Svenska Cellulosa Aktiebolaget	Sweden	0.107	1.58	0.699	8.14	7147***	35.4***	28.0***	19.3	68.7	84.4
West Fraser Timber Co. Ltd.	Canada	0.103	2.43	0.413	7.29	5640***	183***	19.0**	20.3	65.9	59.9
Stora Enso Oyj	Finland	0.084	1.96	−0.178	3.36	1197***	29.8***	15.0	19.2	76.9	85.4
Western Forest Products Inc.	Canada	0.083	2.68	0.396	4.80	2474***	54.2***	18.6**	22.9	54.2	33.9
Interfor Corporation	Canada	0.131	2.80	0.265	6.19	4038***	207***	28.0***	21.6	55.8	34.4
Holmen Aktiebolag (publ)	Sweden	0.082	1.39	−0.017	5.63	3321***	83.7***	13.8	19.6	73.7	57.3
Suzano Papel e Celulose S.A.	Brazil	0.147	2.83	0.515	6.09	1631***	22.2***	19.5**	20.6	70.5	63.8
Oji Holdings Corporation	Japan	0.041	1.93	0.142	2.20	500***	24.7***	10.7	29.3	52.4	52.7
Canfor Corporation	Canada	0.080	2.86	6.69	174	3172827***	0.100	10.4	25.1	52.3	44.2
Daio Paper Corporation	Japan	0.073	1.88	−0.100	5.75	3378***	29.8***	23.6***	35.1	54.4	18.2
Sumitomo Forestry Co., Ltd.	Japan	0.074	1.84	0.442	4.28	1951***	40.7***	6.10	16.5	73.7	–
Klabin S.A.	Brazil	0.071	1.92	−0.042	5.60	2569***	74.7***	32.5***	15.5	75.4	65.1
BillerudKorsnäs AB	Sweden	0.080	1.79	0.056	8.40	7396***	12.2***	24.0***	11.6	84.2	81.8
Metsa Board Oyj	Finland	0.108	2.07	−0.076	4.10	1765***	42.9***	17.6*	16.4	85.6	63.9
Nippon Paper Industries Co., Ltd.	Japan	0.012	1.81	0.165	3.05	843***	42.4***	4.30	27.9	61.9	69.8
KapStone Paper And Packaging Corp	United States	0.129	2.53	−0.046	30.3	65977***	1.20	15.00	–	–	56.8
CatchMark Timber Trust Inc	United States	0.019	2.13	−0.761	30.6	79554***	315***	89.6***	22.3	43.5	36.6
Domtar Corporation	United States	0.050	2.25	1.44	18.8	37823***	49.4***	33.6***	24.9	63.6	68.4
Mondi PLC	United Kingdom	0.083	1.70	−0.242	2.66	771***	34.9***	14.7	12.2	79.3	87.8
WestRock Co.	United States	0.026	2.42	−0.145	8.21	4635***	305***	61.2***	17.9	63.6	51.3

Note: This table provides the descriptive statistics for the daily returns of S&P GTF stocks. The sample period runs from February 2012 to March 2021. The average daily return is expressed as a percentage. JB shows the result of Jarque–Bera's normality test. The test statistic for the Ljung—Box Q test with 10 lags is presented. The ARCH test is reported with 1 lag. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. ESGR and ESG I have been obtained from Sustainalytics, while ESG II is taken from the Refinitiv Eikon database (Thomson Reuters).

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