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Is Corporate Social Responsibility investing a free lunch? The relationship between ESG, tail risk, and upside potential of stocks before and during the COVID-19 crisis *

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Abstract

Did Corporate Social Responsibility investing benefit shareholders during the COVID-19 pandemic crisis? Distinguishing between downside tail risk and upside reward potential of stock returns, we provide evidence from 5,073 stocks listed on stock markets in ten countries. The findings suggests that better ESG ratings are associated with lower downside risk, but also with lower upside return potential. Thus, ESG ratings help investors to reduce their risk exposure to the market turmoil caused by the pandemic, while maintaining the fundamental trade-off between risk and reward.

Key Words: ESG; COVID 19; downside risk; upside potential; Sustainalytics; financial markets

JEL codes: D22, G11, G14; G32

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1 Introduction

There is a widespread perception that investors consider stocks with better Environmental, Social and Governance (ESG) ranking to be safer during market turmoil, and they expect them to exhibit a greater potential for future recovery from the crisis.

Research on the 2008–2009 financial crisis reveals that firms with high social capital, as measured by corporate social responsibility (CSR) intensity, were substantially less affected than firms with low social capital (Lins et al. 2017). The COVID-19 pandemic has reminded corporations and equity investors that markets suffer from rare but extreme negative shocks (Kantos et al. 2020). Did CSR investment also pay off in this global financial turbulence?

Early generations of measurement of CSR, captured by ESG ratings, were only indirectly connected with firms fundamentals and therefore also questioned by both investors and researchers (Christensen et al. 2021, Eccles et al. 2012, Kotsantonis et al. 2016, Porter et al. 2019). The new ESG generation, originally developed by Sustainalytics, is explicitly designed to help investors identify and understand financially relevant ESG risks at the security and portfolio level and how they might affect the long-term performance for equity and fixed income investments (Gaussel & Le Saint 2020). Contrary to traditional ESG approaches, a higher score reflect higher ESG risk exposure.

Although there is support in the literature that funds with lower ESG risks can be considered as safer investments during strong stock market turmoil, the overall evidence is somewhat ambiguous. For instance, Broadstock et al. (2021) explore the role of ESG performance in China before and during the pandemic and find that high ESG portfolios generally outperform low ESG portfolios. They also show that good ESG performance mitigates financial risk during the crisis. On the other hand, using a sample of 1750 U.S. firms and two alternative CSR ratings, MSCI ESG Stats and Thomson Reuters Refinitiv data, Bae et al. (2021) find no evidence that CSR affected stock returns during the crash period. However, also exploiting the Refinitiv data, Albuquerque et al. (2020) report that stocks with high ESG ratings are more resilient during a time of crisis and had significantly higher returns, lower return volatilities, and higher trading volumes than other stocks during the first quarter of 2020.

Basing their analysis on Morningstar data, Ferriani & Natoli (2020) find that equity funds with low ESG risk scores experienced positive investment inflows during and after the stock market collapse, while high risk ESG funds suffered sell-offs during the panic phase and afterwards. While all examined funds experienced negative cumulative returns, low risk funds scored significantly better than other funds. Exploiting data from MSCI, Singh (2020) studies the period May 2017-May 2020 and shows that risk averse investors sought shelter in CSR portfolios during the crisis period. Döttling & Kim (2020) apply a difference-in-differences framework using retail fund flow and ESG rating data from Morningstar, and show that investor demand for sustainability significantly weakens the economic stress induced by COVID-19. Also, using Morningstar ESG-ratings, Pástor & Vorsatz (2020) analyze flows of U.S. active equity mutual funds during the COVID-19 crisis in 2020 and report that investors favored funds with high sustainability ratings, while the performance results are less conclusive. Pavlova & de Boyrie (2021) use Morningstar-data to investigate risk-adjusted returns on 62 exchange trade funds before and during the COVID-19 market crash. They report that higher sustainability ratings of did not protect the funds from losses during the downturn 2020, but they did not perform worse than the rest of the market.

The current paper contributes by reporting evidence on ESG ratings and tail risks. We provide an answer to the question whether stocks with better ESG scores have been more resilient to higher financial market uncertainty. We study both the traditional and the new generation ESG ratings, and utilize a recent approach by Patton et al. (2019) to estimate tail returns as conditional Value-at-Risk (cVaR) and conditional Value-of-Return (cVoR) for a broad sample of 5,047 stocks from global stock markets.

Tail return measures for each stock are then combined with the ESG scores over the sample period January 2018 to October 2020 and correlated random effects regressions are employed to estimate the relationship between ESG and tail returns. We find that stocks with superior scores for both ESG generations have overall lower tail risks, but at the same time also a lower upside potential. A main conclusion is therefore that the ESG measures help investors to identify stocks with high risk exposure. The fundamental trade-off between risk and return still remains.

The rest of the paper is organized as follows. Section 2 presents the data and empirical methodology. Results are provided in Section 3. Section 4 reports robustness tests. Section 5 concludes.

2 Data and Methodology

Monthly ESG scores of various firms from different countries and industries are obtained from Sustainalytics which globally provides research and data related to ESG and corporate governance. The time frame of the collected ESG data is from January 2018 to October 2020 and includes a high number of stocks which are listed in ten countries: United States, Canada, Sweden, Germany, France, United Kingdom, Netherlands, Australia, China, and Japan.[1] Our motivation to choose stocks from these countries is that they represent markets with different CSR engagement, different regions and different markets sizes. While the traditional ESG measure is built on three individual pillars *Env*, *Soc* and *Gov*, the new measure, *ESG risk rating*, distinguishes between *overall risk exposure* (OES) and *overall managed risk* (OMS).

We obtain daily adjusted returns from Eikon Thomson Reuters. The return data expands from January 2006 to October 2020. Using an estimation window from January 2006 to December 2017, we obtain out-of-sample lower and upper tail forecasts at 1% level until October 2020. We include stocks that have at least 1000 returns during the estimation window. Then, we evaluate the accuracy risk models, from January 2018 to October 2020, and identify the best performing risk model for each stock. Finally, we investigate the impacts of the ESG scores on the tail forecasts during the 2018-2020 period.

We use Value-at-Risk (VaR) and conditional Value-at-Risk (cVaR) as financial risk measures. For an asset, the VaR is defined as the maximum loss given a probability level $\alpha \in (0, 1)$, and the cVaR, also known as expected shortfall, measures the expectation of losses beyond the VaR. Let $r_t \in \mathbb{R}$ be an asset return at time t, with distribution function F_t conditioned on information set $\mathbf{\Omega}_{t-1}$, s.t. $r_t|\mathbf{\Omega}_{t-1}\ F_t$, the $\alpha-$ level VaR and cVaR at time t are given as:

[1] Descriptive statistics for stocks in each country are provided in Table S1 in the online supplementary materials.

$$
\begin{cases}
\mathrm{VaR}_{\alpha t} = F_t^{-1}(\alpha; \mathbf{\Omega}_{t-1}), \\
\mathrm{cVaR}_{\alpha t} = \mathbb{E}[r_t | r_t \leqslant \mathrm{VaR}_{\alpha t}; \mathbf{\Omega}_{t-1}].
\end{cases}
\tag{1}
$$

To estimate these risk measures, we apply several risk models, including generalized autoregressive conditional heteroscedasticity (GARCH) and generalized autoregressive score (GAS). The latter is applied either to model VaR and cVaR jointly, as suggested in Patton et al. (2019), or to estimate VaR and cVaR from a conditional step-ahead distribution for returns, similar to Ardia et al. (2019). In the supplementary materials, Section I, we introduce the risk models. To describe the potential of upside returns, we use Value-of-Return (VoR_α) and conditional Value-of-Return (cVoR_α) at level α.

To test the link between ESG rating and stock tail returns, we use the correlated random effects (CRE) approach (Mundlak 1978, Wooldridge 2010, Schunck 2013, Schunck & Perales 2017) formulated as

$$
\widehat{\mathrm{cVaR}}_{it} = \beta_0 + \mu_i + \beta_w \mathrm{ESG}_{it} + \beta_b \overline{ESG}_i + \beta_c \mathrm{industry}_i + \lambda_t + e_{it} \tag{2}
$$

where $\widehat{\mathrm{cVaR}}_{it}$ is one-step ahead cVaR (or cVoR) forecast for stock i at time t, μ_i is a stock-specific effect, uncorrelated with the error term ϵ_{it}, β_w and β_b are within and between estimates, respectively, β_c are time-invariant industry and country variables, and λ_t denotes time effects. $\overline{ESG}_i$ denotes the average of ESG for stock i, and $\mathrm{industry}_i$ is a time-invariant industry effect. We apply the same model for the opposite upside tail measure cVoR.

3 Results

Table 1 displays the summary statistics of the variables used. There are more observations on ESG than ESG Risk Rating as the former starts January 2018 and the latter from December 2018. However, the new measure has a better coverage of its components.

Results of the CRE model regression on the relation between the old ESG and downside risk are presented in Table 2. We apply several risk models to forecast VaR, VoR, cVaR and cVor at each level of α, and select the best-performing model, with the lowest

Table 1: Summary Statistics (stock-month observations)

Variable	N	Mean	p50	SD	Min	Max
$cVaR_{0.01}$	191431	-7.7	-6.9	3.5	-25.1	-2.8
$cVoR_{0.01}$	197091	8.3	7.3	4.1	2.8	29.6
ESG (old)	150271	53.2	50.5	9.3	30.6	89.8
E	71887	57.5	56.3	14.1	9.8	97.7
S	71887	57.0	56.2	11.6	24.7	98.0
G	71887	61.4	61.0	10.2	26.2	92.9
ESG Risk Rating (new)	103840	28.8	27.7	10.8	5.7	72.2
Overall risk exposure (OES)	103840	40.1	38.8	13.4	14.1	96.2
Overall managed risk (OMS)	103840	29.8	27.5	13.6	1.0	78.4

Notes: $cVaR_{0.01}$ denotes 1% monthly conditional value-at-risk, $cVoR_{0.01}$ denotes 1% monthly conditional value-of-return, ESG has three pillars E, S, G, while the ESG Risk Rating contains two components, OMS and OES .

average loss computed from the Fissler and Ziegel (FZ) joint scoring function suggested in Fissler et al. (2016).[2] We further perform the goodness-of-fit test suggested in Patton et al. (2019).

Columns (1) and (3) of Table 2 report estimates for the pandemic crisis year 2020, while columns (2) and (4) show the estimates for pre-crisis years 2018 and 2019. Furthermore, columns (1) and (2) report the estimates for the ESG score, while columns (3) and (4) presents results for the pillars *Env*, *Soc* and *Gov*, separately.

Table 2: Correlated random effects model - ESG and downside risk ($cVaR_{0.01}$)

	Sample period			
	2020	2018/19	2020	2018/19
	(1)	(2)	(3)	(4)
ESG (w)	0.0247**	0.00374		
	(2.27)	(0.88)		
ESG (b)	0.0616***	0.0711***		
	(12.40)	(18.32)		
Env (w)			-0.00261	0.00393
			(-0.24)	(1.14)
Soc (w)			0.00695	-0.000178
			(0.61)	(-0.05)
Gov (w)			-0.00548	0.00161
			(-0.39)	(0.34)
Env (b)			0.0230***	0.0198***

[2]See Figures S4-S13 in the online supplementary materials which provide the p-values for each model across all stocks. In this test, a p-value higher than 10% suggests no indication of evidence against optimality, and therefore, a good fit for the corresponding risk model. We also compare the risk models using the Diebold-Mariano test. Those results are available upon request.

			(4.00)	(4.62)
Soc (b)			0.00827	0.00561
			(1.07)	(0.94)
Gov (b)			-0.0150*	0.0170**
			(-1.87)	(2.43)
Random stock effects	yes	yes	yes	yes
Fixed period effects	yes	yes	yes	yes
Fixed industry effects	yes	yes	yes	yes
Fixed country effects	yes	yes	yes	yes
Observations	45299	101719	21021	49212
No. stocks	4970	4899	2229	2342
R^2	0.378	0.247	0.419	0.222
rho	0.516	0.737	0.498	0.702

Notes: Full table reported in the supplementary materials, see Table S2. Cluster-robust t statistics in parentheses. (w) denotes the within, (b) denotes the between estimate. rho indicates the fraction of variance due to stock random effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Two main conclusions can be drawn from Table 2. First, the impact of the ESG scores on downside risk becomes more pronounced in the year 2020 during the pandemic crisis. Second, the between estimate is in most cases higher than the within estimate, and between estimates appear to be more statistically significant. This is largely explained by the low variation of the rating for the stocks over time. As many as 98% of companies maintained the same ESG rating during the peak of financial volatility in the spring of 2020. Conventional wisdom states that the between estimate measures the long-term impact, while the within estimate shows the short-term impact of the variable.

Considering the ESG pillars, for *Env* the between effect is positive and highly significant during both periods. The between estimate for *Gov* is positive and significant at the 5% level in column 4 (2018-2019), and weakly significant in column 3. The estimates for *Soc* are non-significant in both columns.

Table 3: Correlated random effects model - ESG Risk Rating and downside risk ($cVaR_{0.01}$)

	Sample period			
	2020	2018/19	2020	2018/19
	(1)	(2)	(3)	(4)
ESGR risk rating (w)	-0.0353***	0.00585		
	(-3.59)	(0.98)		
ESGR risk rating (b)	-0.0750***	-0.0774***		
	(-12.39)	(-14.69)		

Overall risk exposure (w)			-0.0185*	0.00266
			(-1.84)	(0.41)
Overall managed risk (w)			0.0271***	-0.00433
			(4.33)	(-1.33)
Overall risk exposure (b)			-0.0409***	-0.0318***
			(-6.52)	(-5.62)
Overall managed risk (b)			0.0425***	0.0504***
			(12.55)	(17.99)
Random stock effects	yes	yes	yes	yes
Fixed period effects	yes	yes	yes	yes
Fixed industry effects	yes	yes	yes	yes
Fixed country effects	yes	yes	yes	yes
Observations	46603	54881	46603	54881
No. stocks	4940	4821	4940	4821
R^2	0.379	0.245	0.382	0.256
rho	0.509	0.776	0.507	0.773

Notes: See Table 2. Full table with estimation results reported in supplementary materials, see Table S3.

Table 3 estimates Eq. (2) with the ESG Risk Rating measure where the sign is to be interpreted inversely because low rating indicates low risk. Surprisingly, the results for the aggregate measures are very similar to Table 2. In contrast to Table 2, the within estimate is statistically different from zero for the pandemic year 2020 and suggests lower downward risk, while being non-significant for the previous period. The between estimate shows that higher scores for the overall risk exposure increases the downward risk for both periods. Considering individual pillars, the between measure for overall managed risk is associated with reduced downside risk for both periods.

Table 4: Correlated random effects models - ESG and ESG risk and upside reward potential $cVoR_{0.01}$

	Sample period			
	2020	2018/19	2020	2018/19
	(1)	(2)	(3)	(4)
ESG (w)	-0.0258**	0.000448		
	(-2.02)	(0.09)		
ESG (b)	-0.0952***	-0.0978***		
	(-16.57)	(-21.53)		
ESGR risk rating (w)			0.0475***	-0.0202***
			(4.12)	(-2.88)
ESGR risk rating (b)			0.102***	0.101***
			(14.28)	(16.00)
Random stock effects	yes	yes	yes	yes

Fixed period effects	yes	yes	yes	yes
Fixed industry effects	yes	yes	yes	yes
Fixed country effects	yes	yes	yes	yes
Observations	46826	104428	48096	56286
No. stocks	5108	5037	5075	4956
R^2	0.341	0.257	0.336	0.247
rho	0.561	0.769	0.557	0.804

Notes: See Table 2. Full table reported in the supplementary materials, see Table S4.

Table 4 estimates whether ESG ratings also affect firms upside reward potential during the turmoil period. Results for the old ESG measure are presented in columns (1) and (2), and for the new measure in columns (3) and (4). Focusing on the between estimates, the results for $\mathrm{cVoR}_{0.01}$ show that higher ESG is associated with lower upside potential before and during the crisis. For *ESG Risk Rating*, however, higher scores imply higher upside potential.[3]

4 Robustness tests

Tables 5 (ESG) and 6 (ESG Risk Rating) consider sample splits below and above median values of selected stock characteristics: market capitalization, beta, dividend yields and P/E.

[3]We do not show the estimation results for VaR and VoR tail risk measures at various levels of α but overall those are quite similar to the reported ones.

Table 5: Robustness test sample splits: ESG and $\text{cVaR}_{0.01}$

	market cap		β		div yield		P/E	
	low	high	low	high	low	high	low	high
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESG (w)	0.0628***	0.00391	0.0195	0.0334**	0.0253	0.0284*	-0.00610	0.0413***
	(3.22)	(0.30)	(1.28)	(2.12)	(1.62)	(1.86)	(-0.36)	(2.59)
ESG (b)	-0.0122	0.0343***	0.0722***	0.0526***	0.0641***	0.0420***	0.0291***	0.0673***
	(-1.08)	(6.08)	(12.52)	(7.31)	(8.14)	(7.29)	(4.20)	(10.58)
Constant	-8.605***	-8.160***	-9.757***	-11.25***	-11.25***	-8.558***	-8.323***	-9.833***
	(-8.50)	(-13.54)	(-16.33)	(-14.76)	(-14.67)	(-8.85)	(-9.01)	(-16.58)
Observations	21446	23285	22566	21855	22026	22503	20104	19811
No. stocks	2453	2455	2443	2430	2446	2439	2205	2141
R^2	0.394	0.415	0.394	0.417	0.357	0.435	0.437	0.380
rho	0.483	0.478	0.485	0.473	0.561	0.414	0.431	0.488
p_{50}	7.017	9.922	0.777	1.439	0.140	3.400	10.63	30.13

Notes: Sample year 2020. Sample split below and above the median of stock characteristic. Cluster-robust t statistics in parentheses. Random stock effects and Fixed time effects included. Industry and country effects included. (w) denotes the within, (b) denotes the between estimate. rho indicates the fraction of variance due to stock random effects. p_{50} indicates the median values of the split variable in the subsample. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Robustness test sample splits: ESG risk and $cVaR_{0.01}$

	market cap		β		div yield		P/E	
	low	high	low	high	low	high	low	high
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ESG risk (w)	-0.0440***	-0.0385***	-0.0490***	-0.0280**	-0.0235	-0.0457***	-0.0328**	-0.0525***
	(-3.00)	(-2.92)	(-3.47)	(-2.08)	(-1.62)	(-3.46)	(-2.29)	(-3.74)
ESG risk (b)	-0.0193*	-0.0572***	-0.0701***	-0.0637***	-0.0730***	-0.0490***	-0.0541***	-0.0661***
	(-1.94)	(-7.30)	(-10.04)	(-7.08)	(-7.98)	(-6.82)	(-6.34)	(-8.15)
Constant	-8.357***	-3.839***	-2.687***	-5.563***	-4.527***	-4.105***	-4.465***	-3.348***
	(-8.78)	(-6.86)	(-5.12)	(-8.35)	(-6.65)	(-4.55)	(-5.29)	(-6.15)
Observations	22336	23693	23195	22535	22625	23160	20744	20382
No. stocks	2416	2462	2427	2418	2421	2431	2199	2129
R^2	0.393	0.418	0.389	0.418	0.361	0.432	0.441	0.373
rho	0.483	0.474	0.488	0.465	0.552	0.419	0.431	0.489
p_{50}	7.060	9.927	0.779	1.436	0.150	3.390	10.62	30.13

Notes: See Table 5.

The results confirm that the relationship between ESG and downside risk is not mediated by stock characteristics which are omitted in the regression models. Overall, the relationships are more pronounced for stocks with high P/E ratio and low dividend yield, which are typically considered as stocks with higher risk.

We also test whether including lags of ESG and ESG Risk Rating would affect the results for downside risk and upside potential. Lagging the CSR variables by one month, we find essentially the same results. The estimations are also robust when the number of country-specific COVID infections are included as regressors. The COVID cases variable exhibits a strong relationship with the forecasted downside tail risk of stocks.

Finally, one potential concern is whether reported standard errors are accurate. We report cluster robust standard errors at the stock level in all tables. Cross-stock correlations and dependencies could be a concern, which are not taken into account by the cluster robust standard errors. To analyze whether consideration of heteroscedasticity, autocorrelation and cross-sectional correlation could alter the conclusions we also estimate the models using Driscoll & Kraay (1998)'s robust standard errors.

Overall, these robust standard errors are smaller compared to cluster robust standard errors, and statistical inference gets even stronger.

5 Conclusions

The main finding of this paper is that stocks with higher ESG ratings have less downside risk, but also possess less upside potential. These relationships became more pronounced during the COVID-19 crisis compared to the period before. This implies that investors can reduce their risk exposure by investing in companies with superior CSR, but at the same time they reduce the likelihood to obtain higher upside returns. This conclusion applies to both the old and the new generation of ESG measures. Overall our results highlight that the fundamental trade-off between risk and return also holds for ESG investing.

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Supplementary Materials of "Is ESG investing a free lunch? ESG and stocks' tail returns during the pandemic financial crisis"

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In this document, we present supplementary materials. In Section I, we present the risk models including ARMA-GARCH, one-factor generalized autoregressive score (GAS), hybrid GAS/GARCH, and GAS Skewed Student-t models. In Section II, Figures S1-S3 present results of goodness-of-fit test for both the tail risk and upside potential. Figures S4-S13 provide average FZ scores across different countries. In addition, examples of tail risk and upside potential forecasts are plotted in Figures S14-S23.

I Risk Modeling

I.I ARMA-GARCH

To forecast stocks' returns, we use ARMA-GARCH(1,1) forecasting model, in which the conditional mean follows an ARMA process and the conditional variance follows a standard GARCH(1,1) process:

$$\begin{cases} r_t = c + \sum_{i=1}^{p} \varphi_{1i} r_{t-i} + \sum_{i=1}^{q} \varphi_{2i} \epsilon_{t-i} + \epsilon_t \\ \epsilon_t = \eta_t \sigma_t \\ \eta_t \approx (iid) \\ \sigma_t^2 = \omega + \gamma \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \end{cases} \tag{1}$$

where, r_t and η_t denote the stock returns and standardized residuals, c is a constant term and σ_t is the conditional standard deviation. The ARMA orders, p and q, can be selected using Akaike (AIC) or Bayesian (BIC) Information Criteira. The ARMA-GARCH(1,1) is estimated using Maximum Likelihood Estimation (MLE) with parameter restrictions, $\omega > 0$, $\gamma \geqslant 0$, $\beta \geqslant 0$, $\gamma + \beta < 1$.

To estimate step-ahead VaR and cVaR using, we apply several variants of the ARMA-GARCH model considering different standardized residuals' distribution F_η. Using mean and volatility forecasts, $\hat{\mu}_{t+1}$ and $\hat{\sigma}_{t+1}$, we define:

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$$
\begin{cases} \mathrm{VaR}_{\alpha,t+1} = \hat{\mu}_{t+1} + \hat{\sigma}_{t+1} F_{\eta}^{-1}(\alpha), \\ \mathrm{cVaR}_{\alpha,t+1} = \hat{\mu}_{t+1} + \hat{\sigma}_{t+1} \mathbb{E}[\eta_t | \eta_t \leqslant F_{\eta}^{-1}(\alpha)]. \end{cases} \tag{2}
$$

We narrow our choices for marginal distribution F_η to empirical, Gaussian, and skewed Student-t proposed in Hansen (1994). For further details on estimation of α-quantile and cVaR from skewed Student-t distribution, see Patton et al. (2019). We further apply extreme value theory (EVT) and use a semi-parametric method called peak over threshold (POT). In this approach, both upper and lower tails can be estimated and the marginal distribution, includes generalized Pareto distribution for the upper and lower tails, and Gaussian kernel for the middle part:

$$
F_\eta = \begin{cases} \frac{N_{u^L}}{N}\{1 + \xi^L \frac{u^L - \eta}{\beta^L}\}^{-\frac{1}{\xi^L}}, \eta < u^L, \\ \phi(\eta), u^L < \eta < u^R, \\ 1 - \frac{N_{u^R}}{N}\{1 + \xi^R \frac{u^R - \eta}{\beta^R}\}^{-\frac{1}{\xi^R}}, \eta > u^R, \end{cases} \tag{3}
$$

where ξ, β, u^R and u^L denote shape, scale, upper and lower thresholds, respectively.

I.II One-factor GAS

Patton et al. (2019) suggests modelling joint dynamics of VaR and cVaR using the GAS process. In this semi-parametric approach, parameters of interests are estimated by minimizing a scoring loss function, rather than the Maximum Likelihood (MLE) type of estimation which requires returns' distributional assumption. The one-factor GAS model for VaR and cVaR is based on the generalized autoregressive score (GAS) model introduced in Creal et al. (2013) and dynamic conditional score (DCS) model in Harvey (2013). Let VaR and cVaR follow a GAS(1,1) process, we have:

$$
\begin{bmatrix} \mathrm{VaR}_{\alpha,t+1} \\ \mathrm{cVaR}_{\alpha,t+1} \end{bmatrix} = \mathbf{W} + \mathbf{B} \begin{bmatrix} \mathrm{VaR}_{\alpha,t} \\ \mathrm{cVaR}_{\alpha,t} \end{bmatrix} + \mathbf{A}\mathbf{H}_t^{-1} \boldsymbol{\nabla}_t, \tag{4}
$$

where $\mathbf{A}$ and $\mathbf{B}$ are 2×2 matrices, $\mathbf{W}$ is a 2×1 vector, the scaling matrix $\mathbf{H}_t$ and $\boldsymbol{\nabla}_t$ are components of the forcing variable, with,

$$
\boldsymbol{\nabla}_t \equiv \begin{bmatrix} \partial L_{FZ0}(r_t, \mathrm{VaR}_{\alpha,t}, \mathrm{cVaR}_{\alpha,t}; \alpha)/\partial \mathrm{VaR}_{\alpha,t} \\ \partial L_{FZ0}(r_t, \mathrm{VaR}_{\alpha,t}, \mathrm{cVaR}_{\alpha,t}; \alpha)/\partial \mathrm{cVaR}_{\alpha,t} \end{bmatrix} = \begin{bmatrix} \lambda_{\mathrm{VaR},t}/\alpha \mathrm{VaR}_{\alpha,t} \mathrm{cVaR}_{\alpha,t} \\ -(\lambda_{\mathrm{VaR},t} + \alpha \lambda_{\mathrm{cVaR},t})/\alpha \mathrm{cVaR}_{\alpha,t}^2 \end{bmatrix}, \tag{5}
$$

where $\lambda_{\mathrm{VaR},t} \equiv -\mathrm{VaR}_{\alpha,t}(\mathbf{1}\{r_t \leqslant \mathrm{VaR}_{\alpha,t}\} - \alpha)$ and $\lambda_{\mathrm{cVaR},t} \equiv \alpha^{-1}\mathbf{1}\{r_t \leqslant \mathrm{VaR}_{\alpha,t}\} r_t - \mathrm{cVaR}_{\alpha,t}$, the loss function L_{FZ0}, suggested in Fissler et al. (2016), is given by:

$$
\begin{aligned} L_{FZ0}(r_t, \mathrm{VaR}_{\alpha,t}, \mathrm{cVaR}_{\alpha,t}; \alpha) = &-(\alpha \mathrm{cVaR}_{\alpha,t})^{-1} \mathbf{1}\{r_t \leqslant \mathrm{VaR}_{\alpha,t}\}(\mathrm{VaR}_{\alpha,t} - r_t) \\ &+ \mathrm{VaR}_{\alpha,t}/\mathrm{cVaR}_{\alpha,t} + \log(-\mathrm{cVaR}_{\alpha,t}) - 1. \end{aligned} \tag{6}
$$

Let VaR and cVaR be driven by a single variable κ_t, the one-factor GAS model is:

$$
\begin{cases} \mathrm{VaR}_{\alpha,t} = a e^{\kappa_t}, \\ \mathrm{cVaR}_{\alpha,t} = b e^{\kappa_t}, \\ \kappa_t = \omega + \beta \kappa_{t-1} + \gamma H_{t-1}^{-1} s_{t-1} = \omega + \beta \kappa_{t-1} + \gamma [b e^{\kappa_{t-1}}]^{-1} \left[\frac{1}{\alpha}\mathbf{1}\{r_t \leqslant a e^{\kappa_{t-1}}\} r_{t-1} - b e^{\kappa_{t-1}}\right], \end{cases} \tag{7}
$$

where $H_{t-1}^{-1}s_{t-1}$, s_t and I_t are the forcing variable, score and Hessian, respectively.

Let $\hat{\boldsymbol{\theta}}_T$ be a set of parameters to be estimated from Eq. (7), given the information set $\boldsymbol{\Omega}_{t-1}$, the FZ loss minimization corresponds to:

$$\hat{\boldsymbol{\theta}}_T = \arg\min_{\boldsymbol{\theta}} \frac{1}{T} \sum_{T}^{t=1} L_{FZ0}(r_t, \text{VaR}_{\alpha,t}(\boldsymbol{\Omega}_{t-1}; \boldsymbol{\theta}), \text{cVaR}_{\alpha,t}(\boldsymbol{\Omega}_{t-1}; \boldsymbol{\theta}); \alpha). \tag{8}$$

I.III GARCH FZ Minimization

As mentioned before, the FZ loss function can be used as an alternative to MLE. Patton et al. (2019) further suggest estimating the ARMA-GARCH model using FZ loss minimization. Assuming the conditional variance follows a GARCH(1,1) process, we have:

$$\begin{cases} r_t = \eta_t \sigma_t, \\ \eta_t \approx (iid), \\ \sigma_t^2 = \omega + \gamma r_{t-1}^2 + \beta \sigma_{t-1}^2, \\ \text{VaR}_{\alpha,t} = a\sigma_t, \ a = F_\eta^{-1}(\alpha) \\ \text{cVaR}_{\alpha,t} = b\sigma_t, \ b = \mathbb{E}[\eta_t | \eta_t \leqslant a], \end{cases} \tag{9}$$

with parameters $\boldsymbol{\theta} = (\gamma, \beta, a, b)$ that can be estimated using Eq. (8).

I.IV Hybrid GAS/GARCH

Following Patton et al. (2019), we also use a hybrid model which combines the forcing variable from the GAS process and conditional volatility from GARCH process, s.t., $\sigma_t = e^{\kappa_t}$. Considering log-volatility as the latent variable, we have:

$$\begin{cases} r_t = e^{\kappa_t} \eta_t, \\ \eta_t \approx (iid), \\ \kappa_t = \omega + \beta \kappa_{t-1} + \gamma \text{cVaR}_{\alpha,t-1}^{-1} \left[\frac{1}{\alpha} \mathbf{1}\{r_{t-1} \leqslant \text{VaR}_{\alpha,t-1}\} r_{t-1} - \text{cVaR}_{\alpha,t-1} \right] + \delta \log |r_{t-1}|, \end{cases} \tag{10}$$

with parameters $\boldsymbol{\theta} = (\gamma, \beta, \delta, a, b)$ that can be estimated using Eq. (8).

I.V GAS Skewed Student-t

Finally, we use the GAS process to model a predictive conditional skewed Student-t distribution. Given the estimated parameters for this distribution, we forecast VaR and ES, as suggested in Ardia et al. (2018). This model is different from the GAS one factor model as (i) we do not estimate VaR and cVaR jointly, and (ii) the parameters are estimated using MLE. Let $r_t | \boldsymbol{\Omega}_{t-1} \sim \mathcal{SKST}(r_t; \mu, \sigma_t, \xi, \nu)$, with a probability density function $f(r_t)$ conditioned on a set of time-varying parameters $\boldsymbol{\theta}_t$ and constant parameters Y. The dynamics in $\boldsymbol{\theta}_t$ can be estimated using a GASS process, s.t.

$$\boldsymbol{\theta}_{t+1} \equiv \mathbf{W} + \mathbf{B}\boldsymbol{\theta}_t + \mathbf{A}s_t. \tag{11}$$

In this model, we use the skewed Student-t distribution proposed by Fernández & Steel (1998). We set the time-Varying parameter to mean and log-volatility, $\boldsymbol{\theta}_t \equiv (\mu_t, \log\sigma_t)$, therefore, we have $\mathbf{Y} \equiv (\xi, \nu)$ (see Ardia et al. 2019, for further details on MLE for this model).

II Supplementary Figures

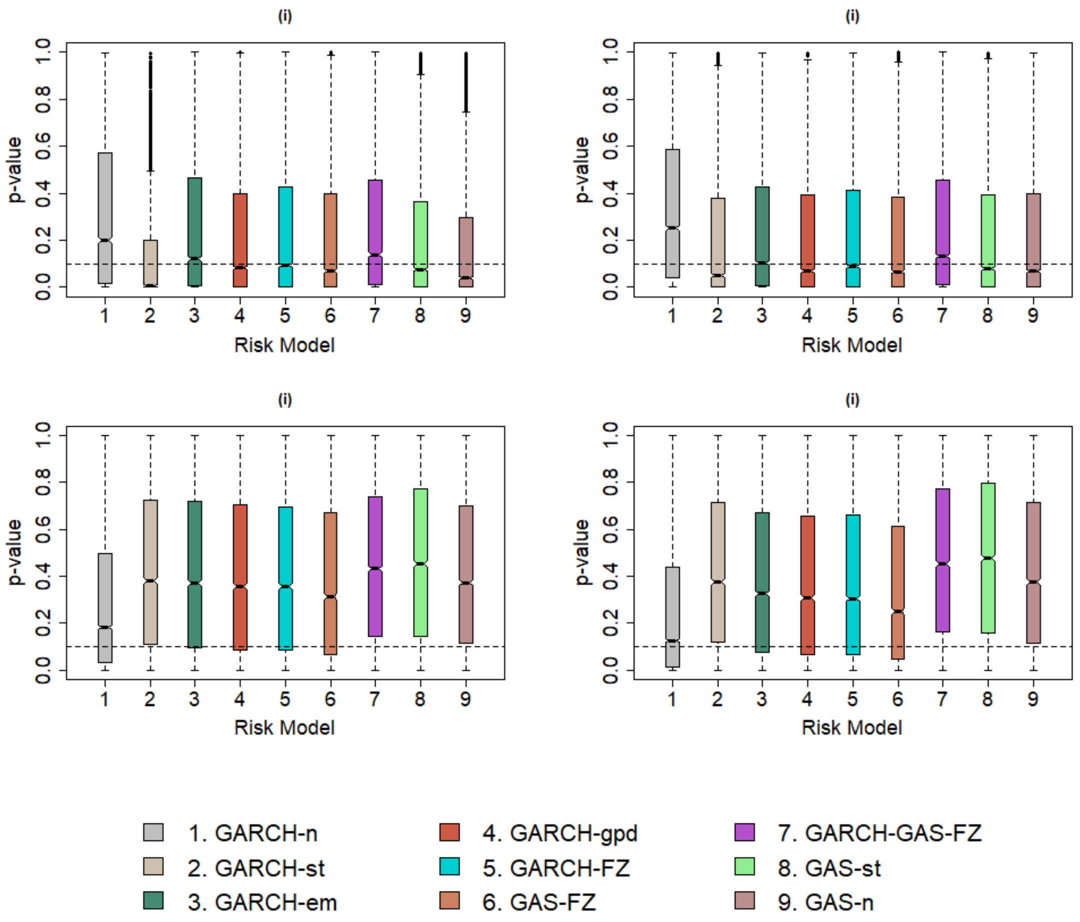

Figure S1: Goodness-of-fit for VaR at (i) 0.5%, (ii) 1%, (iii) 5%, (iv) 10%.

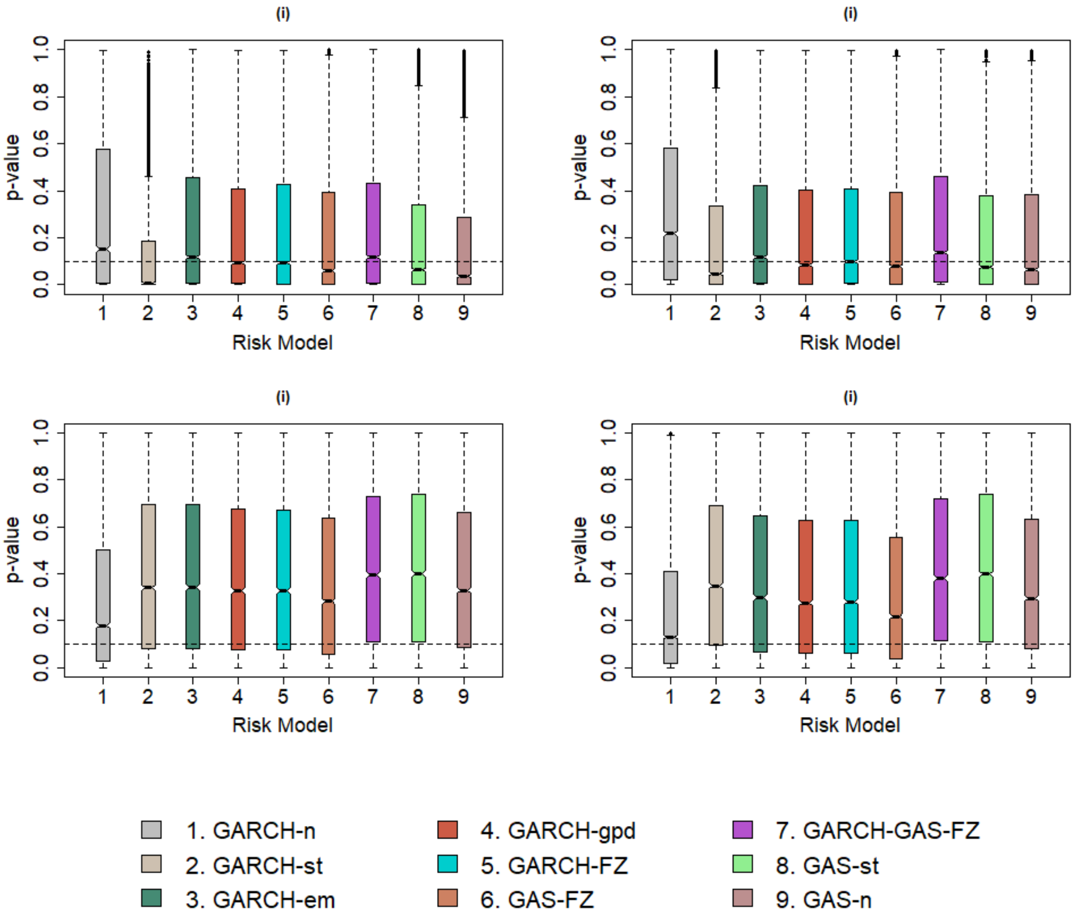

Figure S2: Goodness-of-fit for cVaR at (i) 0.5%, (ii) 1%, (iii) 5%, (iv) 10%.

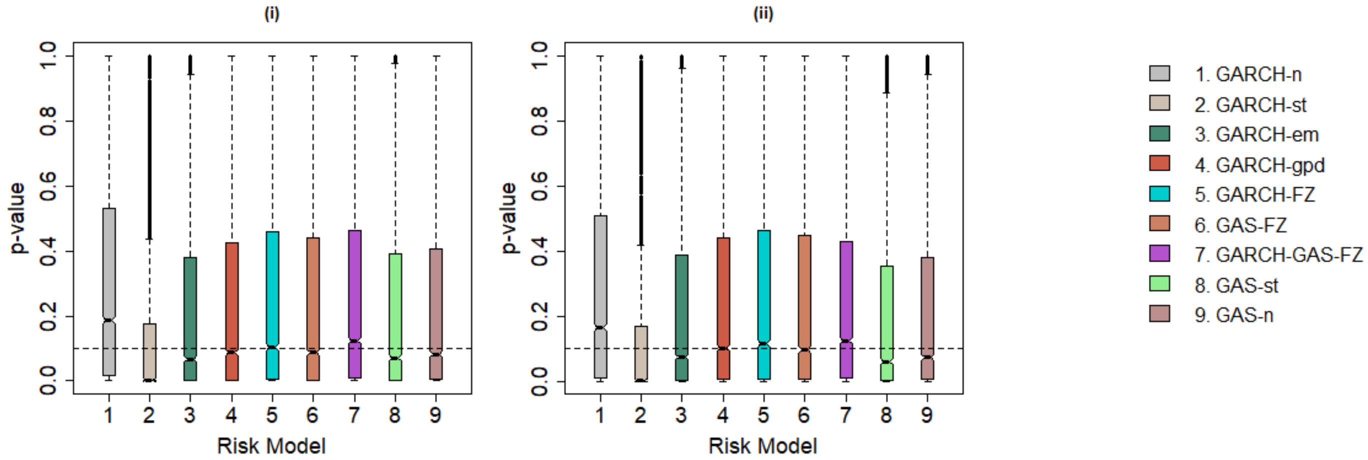

Figure S3: Goodness-of-fit for (i) VoR and (ii) CVoR at 1%.

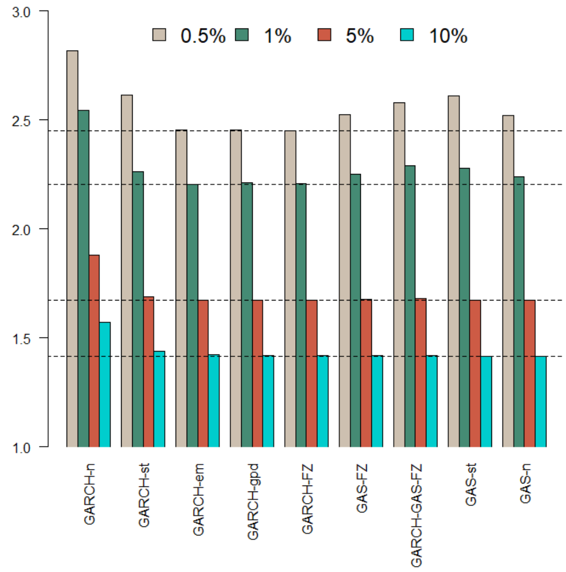

Figure S4: Average loss using FZ loss scoring function at different levels per risk model for Australia.

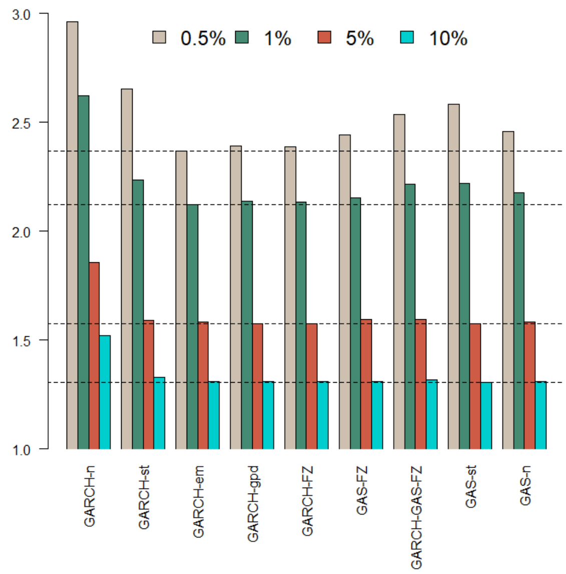

Figure S5: Average loss using FZ loss scoring function at different levels per risk model for Canada.

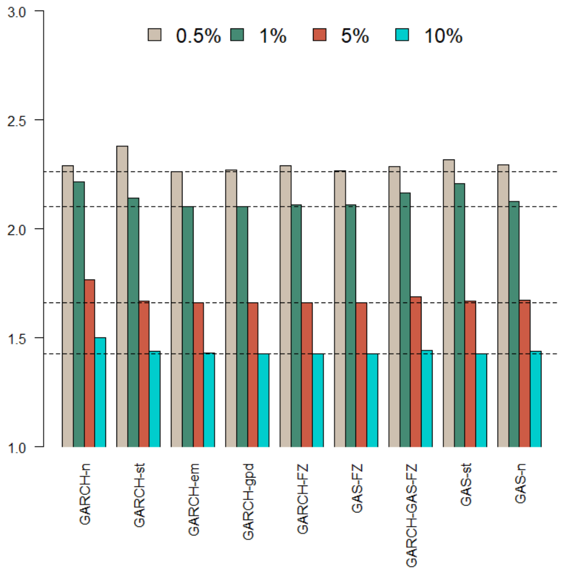

Figure S6: Average loss using FZ loss scoring function at different levels per risk model for China.

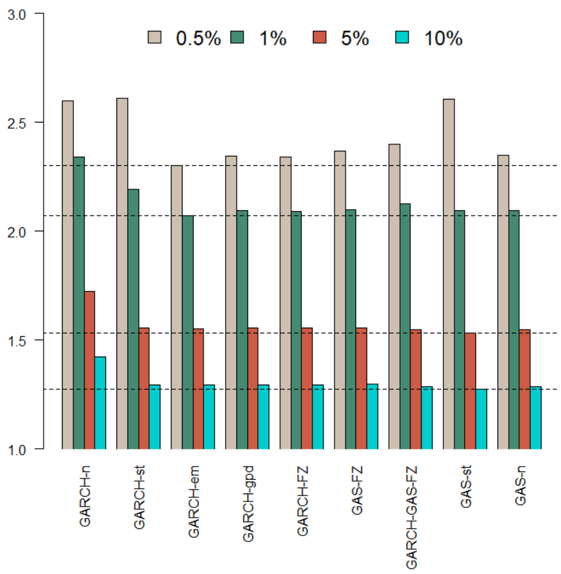

Figure S7: Average loss using FZ loss scoring function at different levels per risk model for France.

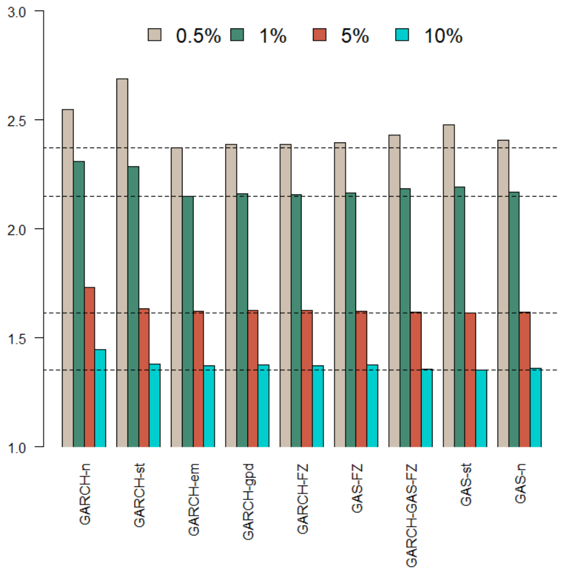

Figure S8: Average loss using FZ loss scoring function at different levels per risk model for Germany.

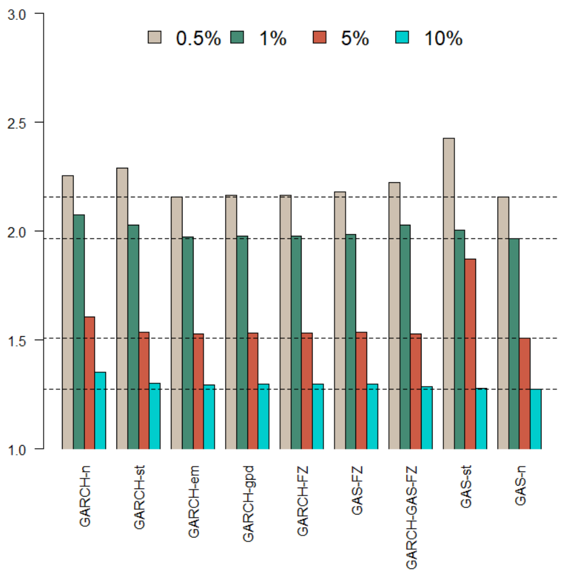

Figure S9: Average loss using FZ loss scoring function at different levels per risk model for Japan.

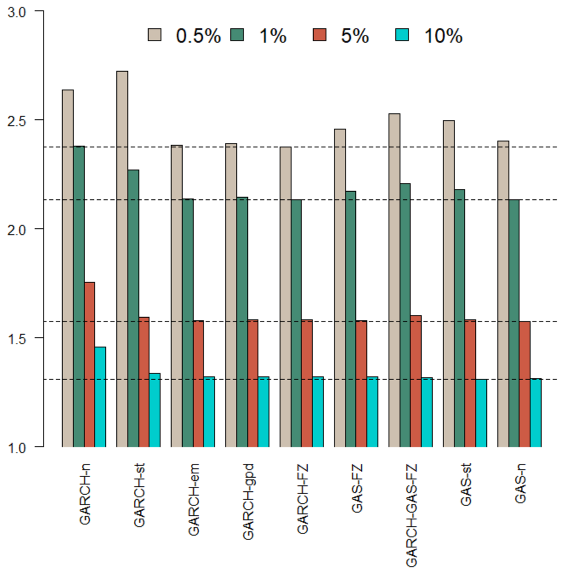

Figure S10: Average loss using FZ loss scoring function at different levels per risk model for Netherlands.

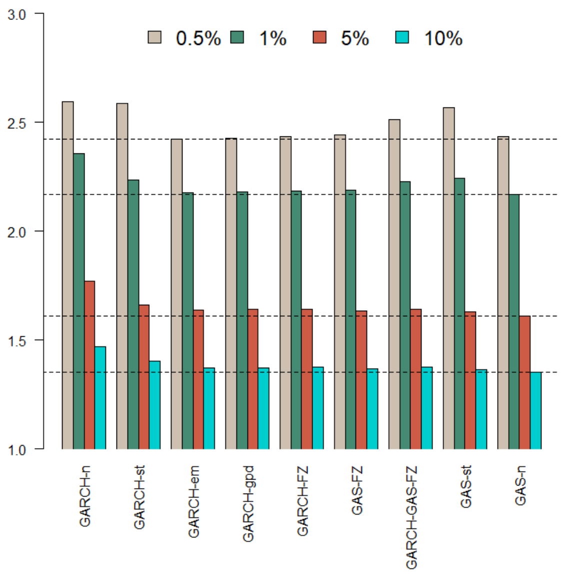

Figure S11: Average loss using FZ loss scoring function at different levels per risk model for Sweden.

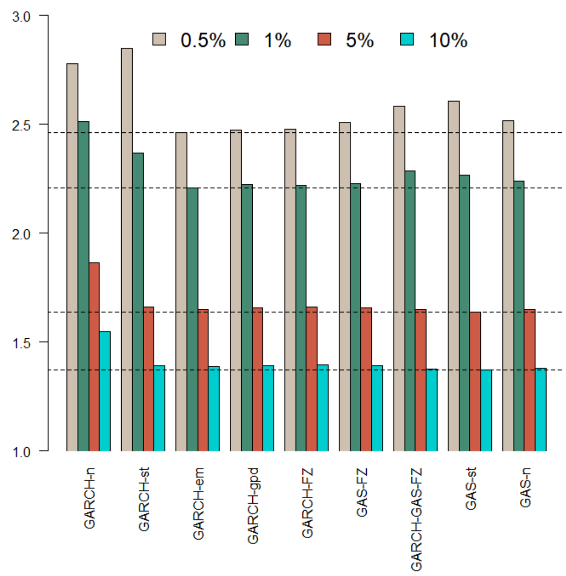

Figure S12: Average loss using FZ loss scoring function at different levels per risk model for UK.

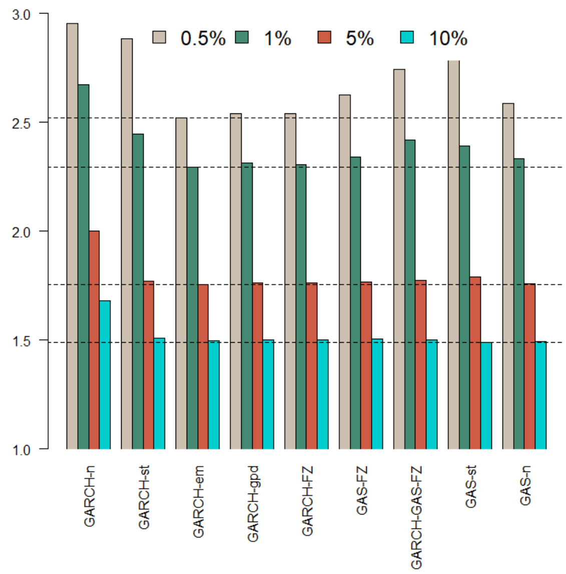

Figure S13: Average loss using FZ loss scoring function at different levels per risk model for USA.

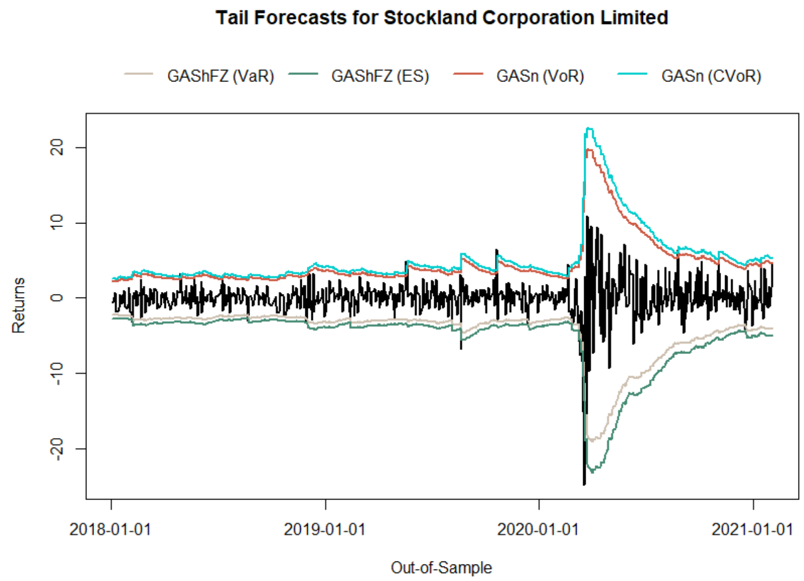

Figure S14: Example top ESG Australia (ESG = 85.8, ESGR = 10.1) forecasted tail measures.

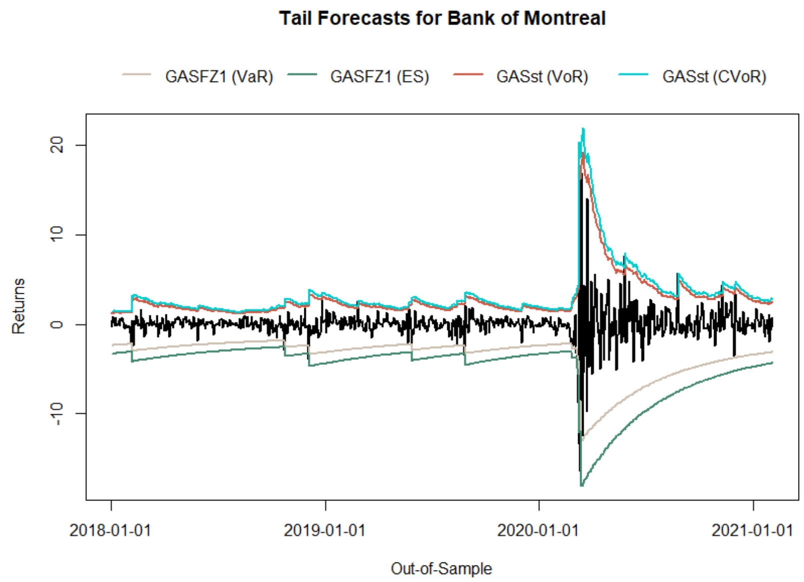

Figure S15: Example top ESG Canada (ESG = 74.7, ESGR = 20.9) forecasted tail measures.

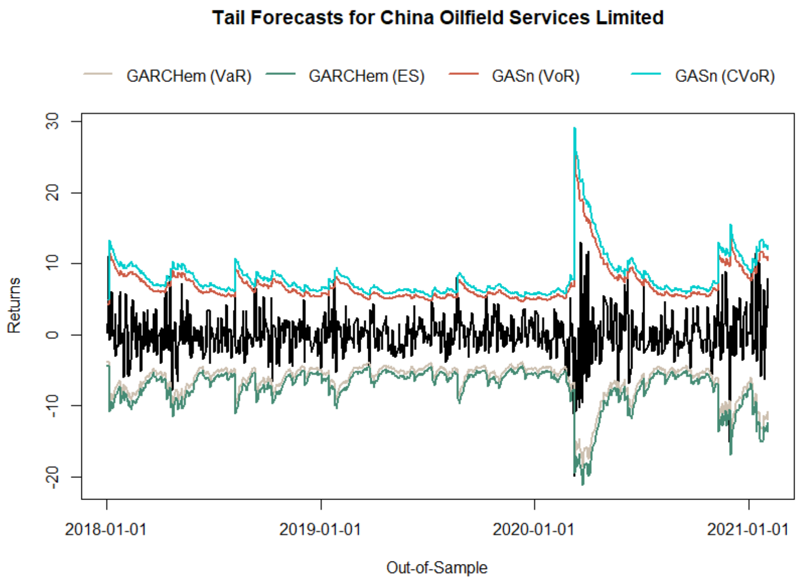

Figure S16: Example top ESG China (ESG = 65.9, ESGR = 27.8) forecasted tail measures.

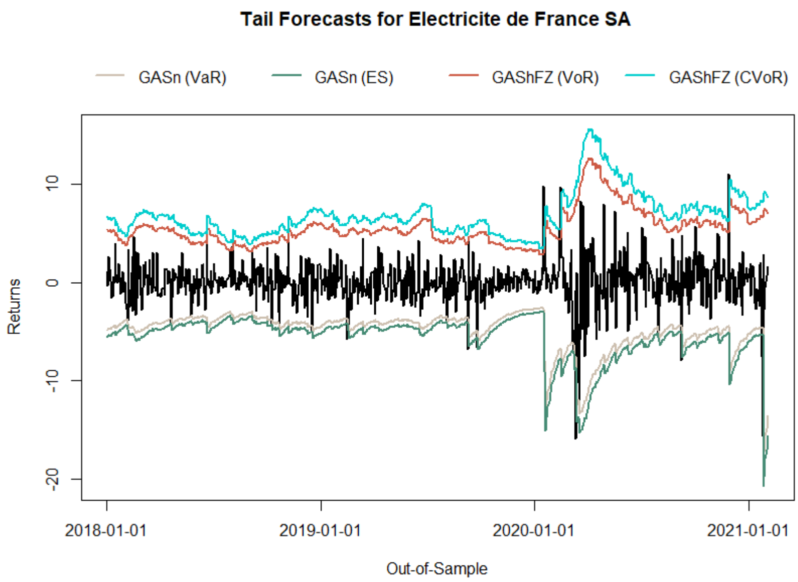

Figure S17: Example top ESG France (ESG = 83.9, ESGR = 22.2) forecasted tail measures.

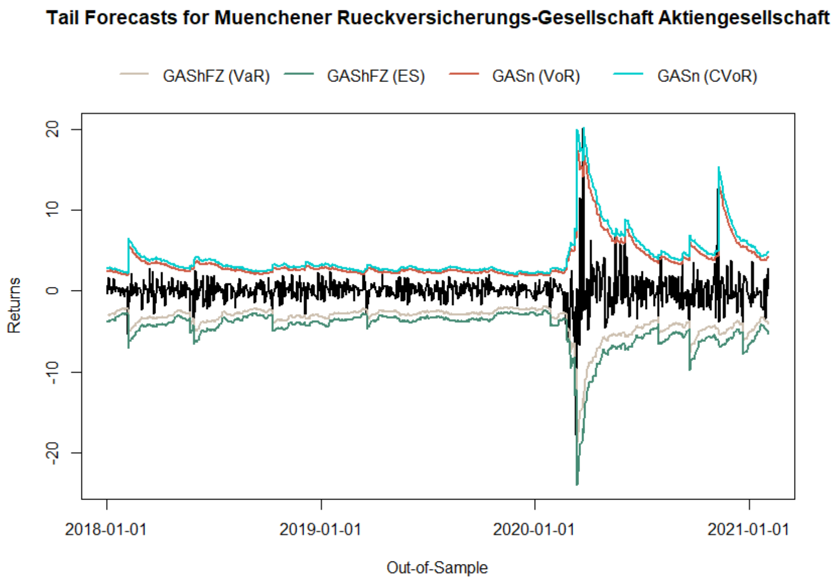

Figure S18: Example top ESG Germany (ESG = 84.7, ESGR = 16.1) forecasted tail measures.

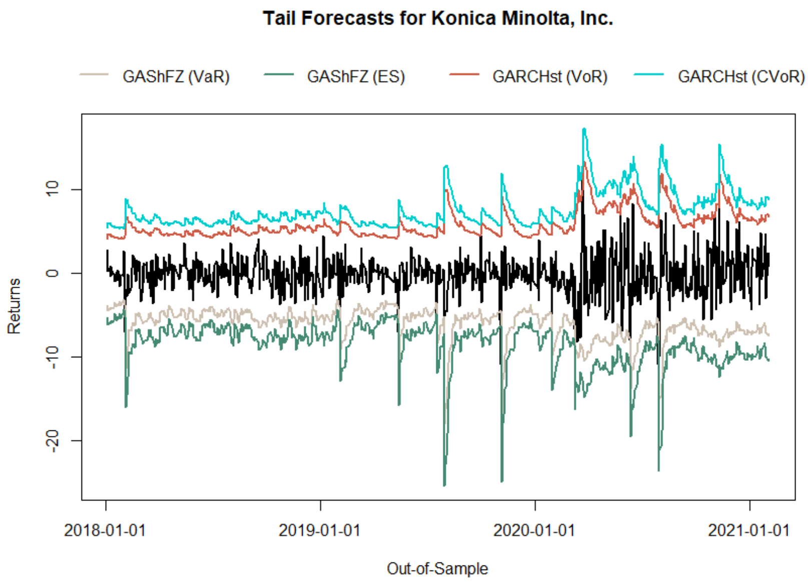

Figure S19: Example top ESG Japan (ESG = 81.5, ESGR = 13.5) forecasted tail measures.

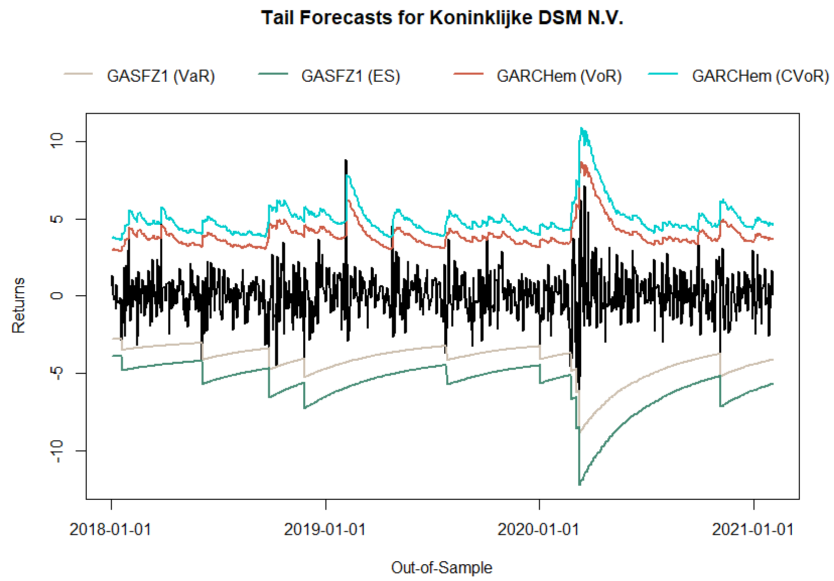

Figure S20: Example top ESG Netherlands (ESG = 85.7, ESGR = 18.5) forecasted tail measures.

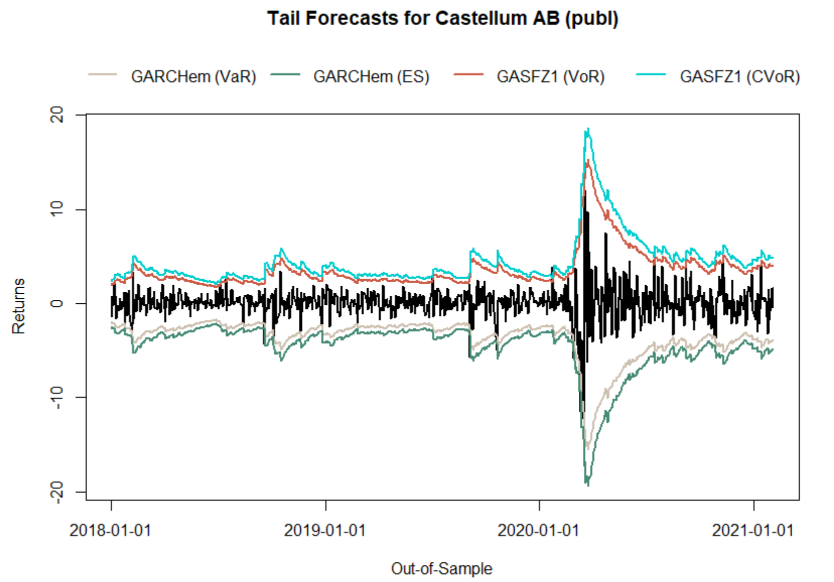

Figure S21: Example top ESG Sweden (ESG = 85.2, ESGR = 13.5) forecasted tail measures.

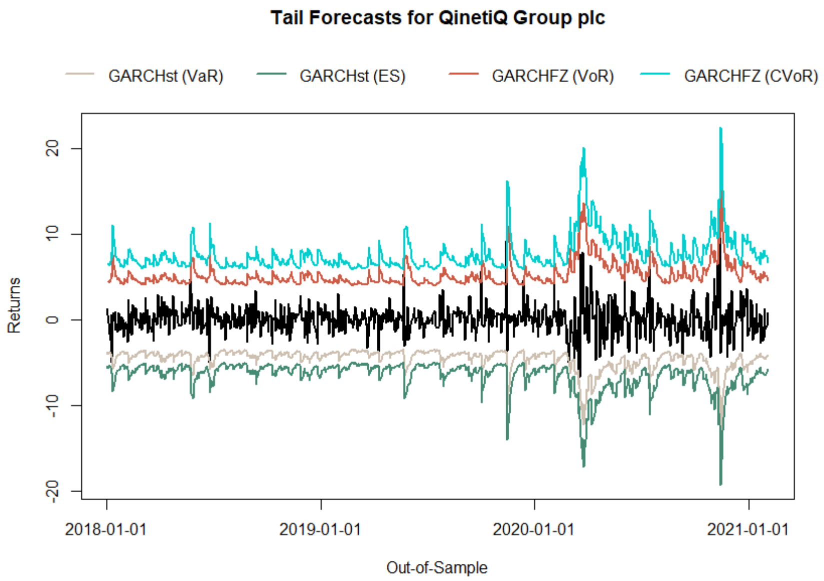

Figure S22: Example top ESG UK (ESG = 86.3, ESGR = 21.9) forecasted tail measures.

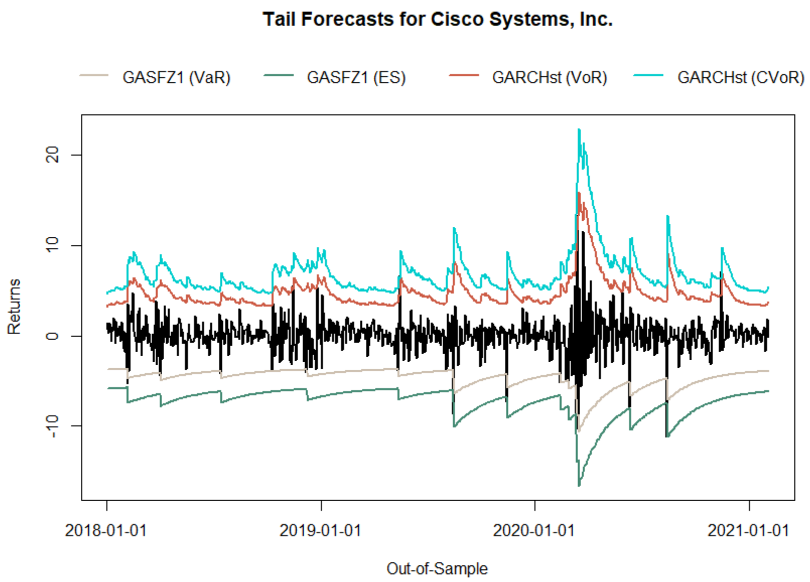

Figure S23: Example top ESG USA (ESG = 79.7, ESGR =12.7) forecasted tail measures.

III Supplementary Tables

Table S1: Means of stocks' ESG and ESGR ratings, $cVaR_{0.01}$ and $cVoR_{0.01}$ for each country, 2018-2020

Variable	ESG	Env	Soc	Gov	ESGR	OMS	OES	cVaR	cVoR	# stocks
Australia	57.6	56.5	60.0	67.7	28.5	36.2	42.8	-7.9	8.9	203
Canada	55.6	53.6	55.5	65.5	30.8	36.0	46.5	-7.7	8.3	255
China	46.8	48.4	48.9	49.3	35.8	18.3	43.1	-7.8	8.4	649
France	63.6	71.1	67.0	68.4	23.2	41.3	38.1	-6.5	7.1	145
Germany	60.2	64.1	63.5	65.0	25.7	39.3	41.2	-7.1	7.6	138
Japan	52.1	60.8	55.6	55.3	30.0	24.9	39.3	-6.7	7.3	1,176
Netherlands	65.0	68.3	66.2	71.9	21.5	47.0	39.4	-7.0	7.4	48
Sweden	58.2	65.0	65.6	68.7	24.4	33.9	36.0	-7.5	8.8	199
UK	60.6	62.3	62.2	65.4	23.7	41.4	38.9	-7.3	7.8	295
USA	51.3	53.7	54.6	61.4	28.5	29.6	39.4	-8.5	9.0	2,033
Total	53.2	57.5	57.0	61.4	28.8	29.8	40.1	-7.7	8.3	5,141

Notes: traditional ESG score and its components, ESGR denotes ESG risk rating with components OMS and OES. $cVaR_{0.01}$ denotes 1% monthly conditional value-at-risk, $cVoR_{0.01}$ denotes 1% monthly conditional value-of-return

Table S2: Correlated random effects model - ESG and downside risk ($cVaR_{0.01}$)

	Sample period			
	2020	2018/19	2020	2018/19
	(1)	(2)	(3)	(4)
ESG (w)	0.0247**	0.00374		
	(2.27)	(0.88)		
ESG (b)	0.0616***	0.0711***		
	(12.40)	(18.32)		
Env (w)			-0.00261	0.00393
			(-0.24)	(1.14)
Soc (w)			0.00695	-0.000178
			(0.61)	(-0.05)
Gov (w)			-0.00548	0.00161
			(-0.39)	(0.34)
Env (b)			0.0230***	0.0198***
			(4.00)	(4.62)
Soc (b)			0.00827	0.00561
			(1.07)	(0.94)
Gov (b)			-0.0150*	0.0170**
			(-1.87)	(2.43)
Auto Components	-0.359	-1.247***	0.462	-1.025**
	(-0.75)	(-3.91)	(0.69)	(-2.43)
Automobiles	-0.503	-0.143	-0.838	-0.617
	(-0.89)	(-0.38)	(-1.18)	(-1.43)
Banks	1.173***	1.783***	0.233	0.597
	(2.70)	(6.35)	(0.37)	(1.60)
Building Products	1.024**	-0.0590	1.745***	-0.550
	(2.16)	(-0.18)	(2.97)	(-1.24)

Chemicals	0.430	-0.432	1.043*	-0.385
	(0.95)	(-1.44)	(1.72)	(-1.07)
Commercial Services	0.555	-0.334	1.559**	-0.467
	(1.21)	(-1.10)	(2.42)	(-1.19)
Construction & Engineering	0.809*	-0.240	1.082*	-0.359
	(1.81)	(-0.79)	(1.71)	(-0.92)
Construction Materials	0.899*	0.149	0.830	-0.367
	(1.66)	(0.35)	(1.16)	(-0.79)
Consumer Durables	-0.0368	-0.990***	0.479	-1.405***
	(-0.08)	(-2.75)	(0.76)	(-3.22)
Consumer Services	0.213	0.326	0.318	-0.0277
	(0.44)	(1.03)	(0.46)	(-0.07)
Containers & Packaging	1.728***	0.374	1.926**	0.281
	(2.88)	(0.95)	(2.41)	(0.63)
Diversified Financials	1.031**	0.764***	1.165*	0.559
	(2.30)	(2.60)	(1.93)	(1.58)
Diversified Metals	-0.797	-1.702***	-0.331	-2.279***
	(-1.36)	(-3.89)	(-0.44)	(-4.30)
Electrical Equipment	0.516	-0.709**	1.222*	-0.430
	(1.09)	(-2.07)	(1.85)	(-1.02)
Energy Services	-3.088***	-1.974***	-2.480***	-2.193***
	(-4.74)	(-4.83)	(-3.03)	(-4.95)
Food Products	2.384***	0.735***	2.625***	0.276
	(5.34)	(2.58)	(4.35)	(0.80)
Food Retailers	1.919***	0.534	2.574***	0.131
	(3.90)	(1.56)	(4.01)	(0.31)
Healthcare	1.069**	-0.610*	1.603**	-0.701*
	(2.32)	(-1.95)	(2.58)	(-1.89)
Homebuilders	-0.710	-0.0383	-0.314	-0.243
	(-1.30)	(-0.11)	(-0.45)	(-0.64)
Household Products	2.105***	0.0652	3.108***	0.274
	(3.87)	(0.18)	(4.55)	(0.68)
Industrial Conglomerates	1.497***	0.453	0.998	0.413
	(2.61)	(1.09)	(1.27)	(0.93)
Insurance	1.579***	1.458***	1.383**	1.128***
	(3.12)	(4.48)	(2.12)	(3.09)
Machinery	0.614	-0.294	0.843	-0.625*
	(1.41)	(-1.05)	(1.39)	(-1.81)
Media	0.212	-0.110	1.017	-0.399
	(0.41)	(-0.32)	(1.48)	(-0.98)
Oil & Gas Producers	-1.839***	-1.513***	-1.988***	-1.856***
	(-3.57)	(-4.36)	(-2.81)	(-4.54)
Paper & Forestry	0.0757	-0.113	-0.290	-0.626
	(0.12)	(-0.30)	(-0.30)	(-1.29)
Pharmaceuticals	-0.352	-2.416***	1.251*	-1.689***
	(-0.74)	(-6.88)	(1.93)	(-3.83)
Precious Metals	-2.581***	-3.125***	-1.930***	-3.174***
	(-4.65)	(-6.38)	(-2.77)	(-5.77)
Real Estate	1.064**	1.917***	0.849	1.380***

	(2.43)	(6.90)	(1.42)	(4.12)
Refiners & Pipelines	-0.345	-0.227	0.415	-0.133
	(-0.62)	(-0.58)	(0.50)	(-0.32)
Retailing	0.109	-0.619*	0.658	-1.034***
	(0.23)	(-1.91)	(1.03)	(-2.67)
Semiconductors	-0.633	-2.365***	-0.301	-2.658***
	(-1.28)	(-6.87)	(-0.45)	(-5.55)
Software & Services	0.693	-0.858***	1.498**	-0.756**
	(1.55)	(-2.83)	(2.48)	(-2.10)
Steel	0.0954	-0.492	0.377	-1.062***
	(0.19)	(-1.51)	(0.59)	(-2.67)
Technology Hardware	-0.113	-1.534***	0.0714	-1.914***
	(-0.25)	(-4.94)	(0.11)	(-4.63)
Telecommunication Services	1.416**	-0.275	2.375***	-0.392
	(2.32)	(-0.62)	(3.51)	(-0.73)
Textiles &Apparel	-0.0999	-0.457	0.158	-0.746
	(-0.20)	(-1.25)	(0.20)	(-1.50)
Traders & Distributors	0.873*	0.0603	1.347*	-0.417
	(1.74)	(0.19)	(1.76)	(-0.97)
Transportation	0.738	0.260	0.613	-0.404
	(1.50)	(0.79)	(0.92)	(-0.98)
Transportation Infrastructure	1.537***	0.933**	1.660**	0.614
	(2.81)	(2.51)	(2.37)	(1.57)
Utilities	2.433***	1.340***	2.575***	0.919**
	(5.34)	(4.40)	(4.20)	(2.56)
Canada	0.333	0.917***	-0.121	0.358
	(1.12)	(3.88)	(-0.38)	(1.50)
China	2.205***	0.768***	1.445***	0.157
	(8.61)	(3.66)	(4.69)	(0.66)
France	0.915***	0.835***	0.0451	0.237
	(2.97)	(3.60)	(0.13)	(0.95)
Germany	0.712**	0.436*	0.128	0.00373
	(2.35)	(1.85)	(0.37)	(0.01)
Japan	2.475***	1.155***	1.583***	0.698***
	(10.42)	(6.13)	(5.79)	(3.40)
Netherlands	0.604	0.445	0.0745	-0.0391
	(1.16)	(1.25)	(0.13)	(-0.10)
Sweden	0.976***	0.159	0.736**	0.122
	(3.46)	(0.66)	(2.22)	(0.45)
UK	0.0664	0.321	-0.226	0.0400
	(0.24)	(1.57)	(-0.74)	(0.20)
USA	-1.034***	0.0216	-0.634**	0.188
	(-4.31)	(0.11)	(-2.49)	(1.05)
Constant	-10.69***	-10.18***	-7.396***	-7.693***
	(-18.86)	(-25.02)	(-9.24)	(-13.89)
Observations	45299	101719	21021	49212
No. stocks	4970	4899	2229	2342
R2	0.378	0.247	0.419	0.222

Random effects	yes	yes	yes	yes
rho	0.516	0.737	0.498	0.702

Notes: Cluster-robust t statistics in parentheses, Random stock effects. Fixed time effects included. Industry and country effects included. (w) denotes the within, (b) denotes the between estimate. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S3: Correlated random effects model - ESG risk measures and downside risk ($cVaR_{0.01}$)

	Sample period			
	2020	2018/19	2020	2018/19
	(1)	(2)	(3)	(4)
ESGR risk rating (w)	-0.0353***	0.00585		
	(-3.59)	(0.98)		
ESGR risk rating (b)	-0.0750***	-0.0774***		
	(-12.39)	(-14.69)		
Overall risk exposure (w)			-0.0185*	0.00266
			(-1.84)	(0.41)
Overall managed risk (w)			0.0271***	-0.00433
			(4.33)	(-1.33)
Overall risk exposure (b)			-0.0409***	-0.0318***
			(-6.52)	(-5.62)
Overall managed risk (b)			0.0425***	0.0504***
			(12.55)	(17.99)
Auto Components	-1.238***	-2.293***	-0.988**	-1.791***
	(-2.59)	(-6.65)	(-2.02)	(-5.05)
Automobiles	-1.229**	-1.139***	-1.055*	-0.811**
	(-2.15)	(-2.94)	(-1.83)	(-2.08)
Banks	0.221	0.688**	0.498	1.156***
	(0.52)	(2.39)	(1.14)	(3.88)
Building Products	-0.239	-1.403***	0.0105	-0.933***
	(-0.50)	(-4.11)	(0.02)	(-2.63)
Chemicals	0.134	-0.844***	0.103	-0.859***
	(0.30)	(-2.77)	(0.23)	(-2.78)
Commercial Services	-1.132**	-2.082***	-0.716	-1.333***
	(-2.41)	(-6.23)	(-1.47)	(-3.80)
Construction & Engineering	0.528	-0.427	0.563	-0.365
	(1.22)	(-1.38)	(1.29)	(-1.17)
Construction Materials	0.449	-0.374	0.509	-0.250
	(0.86)	(-0.89)	(0.96)	(-0.57)
Consumer Durables	-2.036***	-3.079***	-1.593***	-2.273***
	(-4.08)	(-7.87)	(-3.11)	(-5.57)
Consumer Services	-1.242***	-1.210***	-0.862*	-0.497
	(-2.58)	(-3.62)	(-1.74)	(-1.44)
Containers & Packaging	0.396	-0.949**	0.647	-0.379
	(0.64)	(-2.10)	(1.02)	(-0.83)
Diversified Financials	-0.101	-0.552*	0.147	-0.107
	(-0.23)	(-1.79)	(0.33)	(-0.34)

Diversified Metals	-0.282	-0.993**	-0.476	-1.381***
	(-0.49)	(-2.21)	(-0.82)	(-3.02)
Electrical Equipment	-0.439	-1.692***	-0.208	-1.291***
	(-0.93)	(-4.62)	(-0.43)	(-3.44)
Energy Services	-3.624***	-2.902***	-3.543***	-2.704***
	(-5.61)	(-5.90)	(-5.45)	(-5.41)
Food Products	1.849***	0.279	1.904***	0.437
	(4.23)	(0.95)	(4.31)	(1.48)
Food Retailers	0.639	-0.854**	1.014**	-0.204
	(1.33)	(-2.32)	(2.05)	(-0.54)
Healthcare	0.0133	-1.752***	0.383	-1.113***
	(0.03)	(-5.31)	(0.81)	(-3.23)
Homebuilders	-2.284***	-1.557***	-1.923***	-0.919**
	(-4.05)	(-3.73)	(-3.34)	(-2.11)
Household Products	1.549***	-0.513	1.678***	-0.238
	(2.84)	(-1.34)	(3.10)	(-0.63)
Industrial Conglomerates	1.652***	0.603	1.547***	0.390
	(2.82)	(1.43)	(2.64)	(0.92)
Insurance	0.540	0.482	0.750	0.872**
	(1.09)	(1.42)	(1.48)	(2.50)
Machinery	0.0736	-0.949***	0.242	-0.631**
	(0.17)	(-3.32)	(0.56)	(-2.16)
Media	-1.939***	-2.184***	-1.439***	-1.328***
	(-3.64)	(-5.92)	(-2.60)	(-3.39)
Oil & Gas Producers	-1.423***	-1.111***	-1.636***	-1.524***
	(-2.88)	(-3.15)	(-3.26)	(-4.21)
Paper & Forestry	-0.861	-1.330***	-0.785	-1.142***
	(-1.36)	(-3.09)	(-1.22)	(-2.63)
Pharmaceuticals	-1.178**	-3.297***	-0.886*	-2.776***
	(-2.54)	(-9.11)	(-1.88)	(-7.62)
Precious Metals	-2.066***	-2.521***	-2.184***	-2.799***
	(-3.82)	(-5.48)	(-4.00)	(-6.05)
Real Estate	-0.772*	0.0210	-0.321	0.858***
	(-1.72)	(0.07)	(-0.69)	(2.59)
Refiners & Pipelines	-0.364	-0.0684	-0.384	-0.0119
	(-0.68)	(-0.17)	(-0.71)	(-0.03)
Retailing	-1.978***	-2.896***	-1.481***	-2.012***
	(-4.08)	(-8.05)	(-2.89)	(-5.15)
Semiconductors	-1.346***	-2.915***	-1.189**	-2.639***
	(-2.72)	(-8.27)	(-2.39)	(-7.45)
Software & Services	-0.970**	-2.688***	-0.604	-2.020***
	(-2.15)	(-8.27)	(-1.29)	(-5.92)
Steel	0.440	-0.0569	0.248	-0.401
	(0.91)	(-0.17)	(0.51)	(-1.17)
Technology Hardware	-1.727***	-3.239***	-1.359***	-2.556***
	(-3.77)	(-9.70)	(-2.87)	(-7.23)
Telecommunication Services	0.471	-1.601***	0.642	-1.294**
	(0.82)	(-3.13)	(1.11)	(-2.56)
Textiles & Apparel	-2.075***	-2.561***	-1.656***	-1.784***

	(-3.91)	(-6.45)	(-3.01)	(-4.25)
Traders & Distributors	-0.210	-1.140***	0.113	-0.558
	(-0.42)	(-3.38)	(0.22)	(-1.60)
Transportation	-0.716	-1.207***	-0.547	-0.849**
	(-1.47)	(-3.48)	(-1.10)	(-2.41)
Transportation Infrastructure	-0.322	-0.972**	0.0796	-0.223
	(-0.59)	(-2.25)	(0.14)	(-0.52)
Utilities	2.526***	1.595***	2.520***	1.521***
	(5.71)	(5.06)	(5.64)	(4.77)
Canada	0.0541	0.613***	0.106	0.679***
	(0.19)	(2.58)	(0.37)	(2.88)
China	2.062***	0.869***	2.290***	1.209***
	(8.38)	(4.18)	(9.17)	(5.80)
France	1.138***	1.072***	1.034***	0.927***
	(3.79)	(4.58)	(3.45)	(4.01)
Germany	0.760***	0.531**	0.725**	0.457*
	(2.59)	(2.16)	(2.49)	(1.88)
Japan	2.412***	1.240***	2.593***	1.480***
	(10.50)	(6.51)	(11.22)	(7.82)
Netherlands	0.581	0.571*	0.486	0.414
	(1.17)	(1.67)	(0.98)	(1.19)
Sweden	0.943***	0.184	0.967***	0.231
	(3.38)	(0.74)	(3.51)	(0.95)
UK	0.0634	0.363*	-0.0125	0.234
	(0.23)	(1.71)	(-0.05)	(1.12)
USA	-1.222***	-0.217	-1.165***	-0.109
	(-5.29)	(-1.14)	(-5.07)	(-0.58)
Constant	-4.034***	-4.590***	-6.146***	-7.610***
	(-7.83)	(-12.20)	(-10.28)	(-16.40)
Observations	46603	54881	46603	54881
No. stocks	4940	4821	4940	4821
R2	0.379	0.245	0.382	0.256
rho	0.509	0.776	0.507	0.773

Notes: Cluster-robust t statistics in parentheses, Random stock effects. Fixed time effects included. Industry and country effects included. (w) denotes the within, (b) denotes the between estimate. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table S4: Correlated random effects models - ESG risk measures and upside potential ($cVoR_{0.01}$)

	Sample period			
	2020	2018/19	2020	2018/19
	(1)	(2)	(3)	(4)
ESG (w)	-0.0258**	0.000448		
	(-2.02)	(0.09)		
ESG (b)	-0.0952***	-0.0978***		
	(-16.57)	(-21.53)		
ESGR risk rating (w)			0.0475***	-0.0202***

			(4.12)	(-2.88)
ESGR risk rating (b)			0.102***	0.101***
			(14.28)	(16.00)
Auto Components	1.025**	1.557***	2.119***	2.787***
	(2.06)	(4.55)	(4.29)	(7.75)
Automobiles	1.029*	0.431	1.941***	1.556***
	(1.67)	(0.89)	(3.20)	(3.18)
Banks	-0.802*	-1.535***	0.484	-0.123
	(-1.84)	(-4.89)	(1.14)	(-0.39)
Building Products	-0.610	0.376	1.079**	2.136***
	(-1.17)	(0.92)	(2.05)	(5.09)
Chemicals	0.0640	0.930***	0.442	1.385***
	(0.14)	(2.65)	(0.98)	(3.97)
Commercial Services	-0.517	0.335	1.800***	2.622***
	(-1.12)	(1.00)	(3.78)	(7.30)
Construction & Engineering	-0.297	0.630*	0.0346	0.819**
	(-0.65)	(1.88)	(0.08)	(2.46)
Construction Materials	0.206	0.0910	0.729	0.748*
	(0.33)	(0.19)	(1.22)	(1.71)
Consumer Durables	0.0728	1.068**	2.799***	3.791***
	(0.14)	(2.52)	(5.11)	(8.32)
Consumer Services	0.322	-0.241	2.352***	1.791***
	(0.64)	(-0.70)	(4.64)	(4.96)
Containers & Packaging	-1.344**	-0.116	0.404	1.595***
	(-2.53)	(-0.29)	(0.74)	(3.65)
Diversified Financials	-0.844*	-0.633*	0.764*	0.994***
	(-1.82)	(-1.85)	(1.66)	(2.88)
Diversified Metals	1.945***	3.050***	1.163*	2.098***
	(3.00)	(5.23)	(1.83)	(3.56)
Electrical Equipment	0.500	1.376***	1.670***	2.596***
	(0.96)	(3.25)	(3.20)	(6.01)
Energy Services	4.057***	2.492***	4.721***	3.437***
	(5.44)	(5.44)	(6.40)	(6.71)
Food Products	-2.201***	-0.605*	-1.533***	0.0172
	(-4.96)	(-1.89)	(-3.58)	(0.05)
Food Retailers	-1.940***	-0.681**	-0.0811	1.195***
	(-4.02)	(-1.97)	(-0.17)	(3.21)
Healthcare	-0.864*	0.764**	0.589	2.222***
	(-1.83)	(2.17)	(1.25)	(6.15)
Homebuilders	0.635	0.144	2.806***	2.447***
	(1.07)	(0.34)	(4.73)	(4.61)
Household Products	-1.606***	0.379	-0.879	1.126**
	(-2.72)	(0.86)	(-1.47)	(2.43)
Industrial Conglomerates	-1.841***	-0.771	-2.056***	-0.963**
	(-3.04)	(-1.63)	(-3.43)	(-2.23)
Insurance	-1.371***	-1.362***	-0.0271	-0.186
	(-2.85)	(-4.01)	(-0.06)	(-0.54)
Machinery	-0.187	0.536*	0.522	1.350***
	(-0.43)	(1.70)	(1.23)	(4.34)

Media	0.663	0.529	3.587***	3.321***
	(1.24)	(1.36)	(6.42)	(7.92)
Oil & Gas Producers	2.749***	2.182***	2.126***	1.747***
	(5.11)	(5.45)	(4.16)	(4.25)
Paper & Forestry	0.386	0.167	1.631**	1.579***
	(0.53)	(0.38)	(2.20)	(3.53)
Pharmaceuticals	1.294**	3.264***	2.473***	4.410***
	(2.56)	(7.73)	(4.93)	(10.15)
Precious Metals	3.736***	3.633***	2.852***	3.112***
	(6.13)	(6.72)	(4.94)	(5.65)
Real Estate	-1.283***	-2.155***	1.255***	0.292
	(-2.93)	(-6.87)	(2.78)	(0.87)
Refiners & Pipelines	0.988*	0.762	1.006*	0.567
	(1.71)	(1.62)	(1.83)	(1.23)
Retailing	0.616	0.838**	3.449***	3.789***
	(1.24)	(2.31)	(6.77)	(9.63)
Semiconductors	0.991*	2.840***	1.951***	3.537***
	(1.80)	(6.60)	(3.57)	(7.87)
Software & Services	-0.234	1.292***	2.030***	3.680***
	(-0.51)	(3.72)	(4.33)	(10.07)
Steel	0.368	0.767*	-0.0805	0.178
	(0.68)	(1.91)	(-0.15)	(0.42)
Technology Hardware	0.323	1.672***	2.481***	3.852***
	(0.73)	(4.93)	(5.41)	(10.79)
Telecommunication Services	-1.724***	0.155	-0.0892	1.674***
	(-3.25)	(0.37)	(-0.16)	(3.51)
Textiles & Apparel	0.450	0.774*	3.046***	3.527***
	(0.82)	(1.77)	(5.28)	(7.52)
Traders & Distributors	-0.277	0.200	1.110**	1.703***
	(-0.52)	(0.56)	(2.16)	(4.81)
Transportation	-0.664	-0.232	1.346***	1.663***
	(-1.31)	(-0.65)	(2.70)	(4.55)
Transportation Infrastructure	-1.394**	-0.710	1.167**	1.854***
	(-2.39)	(-1.54)	(1.98)	(3.34)
Utilities	-2.352***	-1.322***	-2.576***	-1.640***
	(-5.16)	(-3.89)	(-5.85)	(-4.63)
Canada	-0.911***	-1.400***	-0.522	-1.106***
	(-2.64)	(-4.84)	(-1.52)	(-3.71)
China	-2.903***	-1.130***	-2.552***	-1.144***
	(-9.62)	(-4.28)	(-8.46)	(-4.22)
France	-1.212***	-0.928***	-1.494***	-1.286***
	(-3.37)	(-3.27)	(-4.22)	(-4.37)
Germany	-1.049***	-0.748***	-1.123***	-0.936***
	(-3.12)	(-2.69)	(-3.32)	(-3.31)
Japan	-2.777***	-1.507***	-2.627***	-1.575***
	(-9.85)	(-6.38)	(-9.24)	(-6.43)
Netherlands	-0.798*	-0.703*	-0.800*	-0.861**
	(-1.67)	(-1.95)	(-1.71)	(-2.50)
Sweden	-0.430	0.359	-0.393	0.232

	(-1.17)	(1.09)	(-1.03)	(0.68)
UK	-0.274	-0.656***	-0.264	-0.776***
	(-0.85)	(-2.61)	(-0.81)	(-2.93)
USA	0.614**	-0.587**	0.924***	-0.316
	(2.16)	(-2.49)	(3.26)	(-1.30)
Constant	13.02***	12.29***	3.298***	4.137***
	(21.37)	(25.61)	(6.00)	(9.55)
Observations	46826	104428	48096	56286
No. stocks	5108	5037	5075	4956
R2	0.341	0.257	0.336	0.247
rho	0.561	0.769	0.557	0.804

Notes: Cluster-robust t statistics in parentheses, Random stock effects. Fixed time effects included. Industry and country effects included. (w) denotes the within, (b) denotes the between estimate. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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