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Measuring climate-related and environmental risks for equities

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ABSTRACT

Financial regulators and investors are increasingly concerned about the effects of climate change on investments and seek to capture the climate-related and environmental risks of investments. Whilst energy companies have attracted most of the attention due to the contribution of the Energy sector to environmental degradation, climate-related and environmental risks actually affect companies in every sector. In this paper, we propose novel measures termed as climate Value-at-Risk (VaR) and climate Expected Shortfall (ES) that capture the risk attributed to transition risk factors proxied by environmental scores. We compare the average ratio of climate VaR and ES to total risk in various equity sectors, which enables us to identify the sectors in which climate and environmental risk factors contribute most to the total risk. Our analysis considers different risk measurements and various significance levels. Our findings show heterogeneity in sensitivity to climate and environmental risk factors in various sectors. The Health Care sector is the least cost-effective in reducing climate-related and environmental risks, and the Energy sector benefits most from improving the firms' environmental scores.

1. Introduction

As one of the most critical global challenges on this planet, climate change potentially impacts every individual, with health and social implications, but also affecting the economy and the financial system. Fossil fuels are a crucial input to production, and economic growth increases greenhouse gas emissions. The climate change attributes to those emissions and the literature shows that climate change has become a prominent risk that will potentially create substantial costs to the economy (Burke et al., 2015; Dietz et al., 2016; Lesk et al., 2016). Nonetheless, if the economic effects of climate change are as large as some studies have suggested, then, given that financial assets are ultimately supported by economic activities, the impact of climate change on financial assets could also be substantial.

Research on the interaction between climate change and financial economics is termed climate finance (Giglio et al., 2021). In this field, one of the important topics at the moment is to understand the effect of climate on various financial indicators. As highlighted by the Bank of England (2021), there is a research gap in incorporating climate risks into capital requirements. Additionally, the Basel Committee on Banking Supervision (2021) explores how climate-related risk factors arise and impact portfolios as well as levels of risk, providing the theoretical background on climate-related risk drivers and their transmission channels. From an EU perspective, the European Central Bank (2020) expects the financial institutions to continuously monitor the effects of climate-related and environmental risk factors on their holdings and future investments. To act on that, the European Central Bank (2022) put forward a framework for annual climate risk stress test. To address the research gap and meet regulatory demands, our study contributes to the climate finance literature that investigates the impact of climate-related and environmental risks on financial markets and firms.

We introduce new measures of climate-related and environmental risks, specifically *climate Value-at-Risk* and *climate Expected Shortfall* which capture the risk in equities that stems from climate-related and environmental risk factors proxied by environmental scores. Also, we compare the average ratios of climate Value-at-Risk and climate Expected Shortfall to total risk in several equity sectors, and we identify the sectors in which climate-related and environmental risk factors contribute most to total risk.

In this study, we use the terminology "climate-related and environmental risks" following European Central Bank (2020) and Network for Greening the Financial System (2020, 2023) to capture the impact from climate change and environmental degradation in companies, and perform a comparative analysis of the various industry sectors. Climate-related and environmental impact has two main drivers, physical risk and transition risk. The former refers to the mainly negative

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Table 1
Summary statistics.

Sector	*Return* (%)	*Environment*	*Emission*	*Innovation*	*Resource*	*Size*	*M/B**	*ROE**	*Leverage**	*Investment*	*NumComp*
Basic Materials	1.061	42.591	41.739	44.426	44.950	7.837	2.652	0.029	1.423	4.231	62
Consumer Discretionary	1.107	49.103	44.379	45.990	50.110	8.609	4.608	0.050	1.531	4.671	125
Consumer Staples	0.972	48.954	43.753	45.655	53.314	8.873	7.192	0.068	1.690	4.608	61
Energy	0.989	63.171	57.855	53.369	56.901	8.761	1.126	0.001	0.558	5.472	28
Financials	1.403	53.045	52.106	41.627	49.021	9.298	5.905	0.066	1.444	2.895	65
Health Care	1.620	56.791	56.961	46.748	63.459	9.624	7.770	0.020	0.740	4.523	31
Industrials	1.238	43.642	38.535	45.510	42.599	8.258	5.316	0.054	1.764	3.942	188
Real Estate	1.018	51.928	53.844	43.738	51.257	8.467	2.497	0.019	1.374	0.738	74
Technology	2.089	52.050	52.124	52.157	54.933	9.008	4.670	0.032	0.446	4.200	88
Telecommunications	0.617	46.841	48.230	46.677	53.289	8.947	2.424	0.011	1.174	4.968	22
Utilities	1.200	49.931	56.083	44.952	49.158	8.827	2.015	0.025	1.263	6.038	58

Note: This table reports averages (for monthly frequency) of the variables employed in the regressions in this study reported for 11 different sectors listed in the first column. The sample period is from January 2003 to December 2019. *Return* represents average monthly return of the sector (in percentages). *Emission*, *Innovation*, and *Resource* indicate, respectively, the Emission score, Innovation score, and Resource Use score. *Size* is the natural logarithm of market capitalization in $ million. *M/B* denotes the market value of equity divided by its book value. *ROE* is the return on equity. *Leverage* is the total debt (long-term and short-term) divided by the total stockholders' equity. *Investment* is the natural logarithm of the capital expenditures in $ million. *NumComp* represents the number of companies in the sector. Variables followed by * are winsorized at 1%.

Table 2
Panel regression results for returns and environmental scores at various quantiles.

	Quantiles								
Variable	1%	5%	10%	30%	50%	70%	90%	95%	99%
Environment	−0.057***	−0.032***	−0.021***	−0.008***	−0.003**	0.004*	0.013**	0.015	0.021
	(0.011)	(0.006)	(0.005)	(0.002)	(0.001)	(0.002)	(0.006)	(0.010)	(0.018)
Size	3.575***	2.437***	1.794***	0.773***	0.263***	−0.249***	−1.288***	−2.077***	−4.225***
	(0.268)	(0.181)	(0.128)	(0.057)	(0.029)	(0.053)	(0.156)	(0.223)	(0.382)
M/B	0.027***	0.010	0.001	0.002	0.000	0.000	−0.002	−0.001	−0.003
	(0.007)	(0.006)	(0.006)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.015)
ROE	−0.979**	−0.725	−0.037	−0.180	0.034	0.023	0.081	−0.046	−0.606
	(0.420)	(0.584)	(0.375)	(0.226)	(0.188)	(0.165)	(0.132)	(0.236)	(0.514)
Leverage	−0.230**	−0.010	0.001	−0.001	−0.001	0.000	0.010	0.008	0.289*
	(0.101)	(0.028)	(0.013)	(0.008)	(0.005)	(0.003)	(0.013)	(0.034)	(0.168)
Investment	−0.686***	−0.492***	−0.395***	−0.250***	−0.186***	−0.119***	0.024	0.157	0.379**
	(0.144)	(0.112)	(0.098)	(0.047)	(0.030)	(0.031)	(0.076)	(0.100)	(0.193)

Note: This table presents the results of the quantile regression with penalized sector fixed effects for the panel data of returns and environmental pillar under the Refinitiv ESG scores during the sample period from January 2003 to December 2019. The quantiles considered are 1%, 5%, 10%, 30%, 50%, 70%, 90%, 95%, and 99%. All control variables are lagged by one month. The standard errors are reported in parenthesis, *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively.

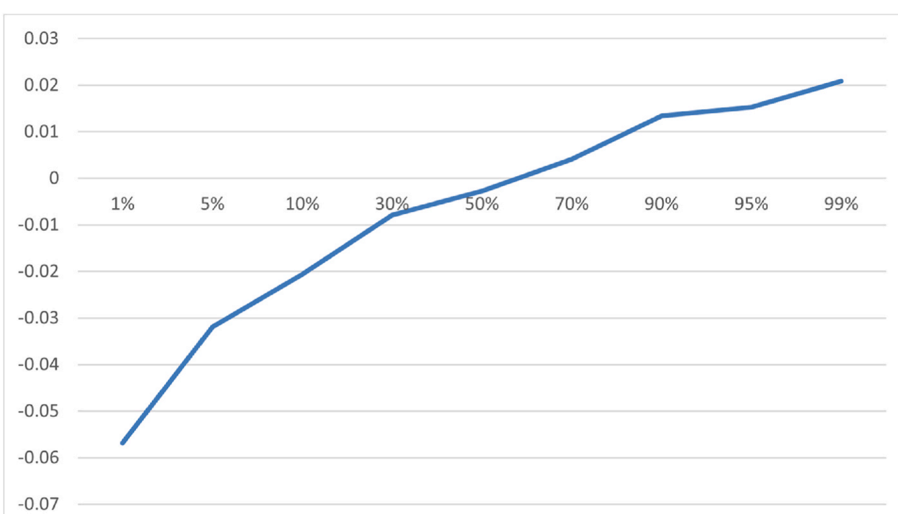

Fig. 1. Effect of the environmental pillar under Refinitiv ESG scores on returns at different quantiles.

impact of climate and weather-related events on business operations, society, and supply chains (Tankov and Tantet, 2019). There are two sub-categories within the class of physical risks: acute risk and chronic risk. Extreme weather events including extreme drought and precipitation, floods, hurricanes, heatwaves, and wildfires are defined as acute risks. Chronic risks are generally considered to include: rising sea levels, rising average temperatures, and ocean acidification. The latter refers to the risk associated with a path to a low carbon economy and all

Table 3
Summary statistics for VaR and ES estimates at 1% level.

Sector	VaR	ES	Climate VaR	Climate ES
Basic Materials	−27.998	−37.971	0.377	0.577
Consumer Discretionary	−28.306	−39.501	−0.258	−0.784
Consumer Staples	−22.031	−31.454	2.217	3.186
Energy	−30.231	−40.293	6.642	9.346
Financials	−21.000	−27.844	0.372	0.201
Health Care	−21.370	−30.283	−4.928	−7.134
Industrials	−25.150	−34.762	−0.583	−0.684
Real Estate	−17.069	−22.258	−0.329	−0.430
Technology	−27.349	−38.528	2.040	2.797
Telecommunications	−28.696	−41.374	−1.656	−2.368
Utilities	−16.920	−22.357	1.210	1.681

Note: This table reports the average firm-month total VaR and ES as well as climate VaR and ES (in percentages) for 11 sectors during the period from January 2003 to December 2019. In columns 1 and 2, average VaR and ES estimates at 1% level are presented. Average climate VaR and ES calculated using Eq. (6) are reported in columns 3 and 4. The negative coefficients of environmental scores in Tables 4 and 5 may lead to positive Climate VaR or ES estimates. A positive (negative) Climate VaR or ES means that the environmental scores contribute to a reduction (increase) in the total risk.

related implications of fossil fuels and dependent sectors (Curtin et al., 2019).[1]

Climate-related and environmental risks are growing concern for the financial sector, and they are affecting the prices of various assets, including stocks, bonds, real estate, and more (see Bernstein et al., 2019; Goldsmith-Pinkham et al., 2019; Hong et al., 2019; Baldauf et al., 2020; Painter, 2020; Bolton and Kacperczyk, 2021; Giglio et al., 2021). Also, they are long-term risks that pose significant challenges to investors, as it is often not effectively priced in financial markets (Andersson et al., 2016; Bansal et al., 2016). To mitigate these risks, investors need to consider the potential impact of climate change on the returns of assets. The implementation of carbon pricing can play an important role in reducing CO_2 emissions (Best et al., 2020), but it is also important to consider other factors, such as firm-level risk exposure to climate regulation (Seltzer et al., 2022), to climate change news shocks (Ardia et al., 2023), to the attention paid by market participants in earnings calls related to a firm's climate risks (Sautner et al., 2023), and the effects of weather conditions with abnormal temperatures (Anttila-Hughes, 2016; Kumar et al., 2019; Choi et al., 2020). On the one hand, companies with high carbon emissions are more likely to be exposed to climate-related and environmental risks, and their stock prices may be more likely to be affected by climate-related factors (Bolton and Kacperczyk, 2021). On the other hand, companies with higher environmental scores on ESG scores are likely to perform better when climate-related events occur (Engle et al., 2020; Huynh and Xia, 2021). Furthermore, climate policy uncertainty is reflected in the option price and can influence the social cost of carbon, as well as affecting the stock prices of firms with high exposure to climate policy (Barnett, 2023; Barnett et al., 2020; Ilhan et al., 2021). The hot debate of the climate change also arises the concerns of the impact of climate change on the financial risk management. Dietz et al. (2016) propose a climate risk measure by taking into account effects of climate damages on the present value of global assets. Acharya et al. (2023) provide a climate risk measure exploring a climate stress testing characterization of risk for financial firms and banks.

Risk measures such as Value-at-Risk (VaR) and Expected Shortfall (ES) have been widely used in academics and practice. VaR is one of the most popular tail risk measures that is employed to assess and manage financial risk. VaR is an estimate of the quantile of the distribution of profit and losses, and it can be measured at different levels. Due to its conceptual simplicity, VaR has become a popular risk measure of market risk and is frequently investigated (see Duffie and Pan, 1997; Dowd, 1998; Jorion, 2000; Dempster, 2002; Allen, 2012). However, since VaR ignores the shape and structure of the tail of the returns' distribution and is not a coherent risk measure (i.e. it is not subadditive), ES, as an alternative, has been proposed (Artzner, 1997; Artzner et al., 1999). It measures the expected value of the observations provided that they exceed VaR and is a coherent risk measure (Roccioletti, 2015). Due to its favourable properties, ES has consistently increased in popularity (see e.g. Chen et al., 2012; Patton et al., 2019; Taylor, 2019; Gerlach and Wang, 2020). However, the measurement of ES is inherently dependent on the value of the VaR estimate. As such, ES is not elicitable by itself, and only the (VaR, ES) tuple is elicitable (Ziegel, 2016). There is no doubt that in recent years climate-related and environmental risks have become some of the most important components of total financial risks, as highlighted by the European Central Bank (2020) and the Network for Greening the Financial System (2020, 2023). One important question that arises is to what extent climate-related and environmental risks contribute to the total financial risks, and this is the central research question we address here. Additionally, it has been well documented that different sectors have heterogeneity in the climate and environmental-factors (e.g. Giese et al., 2021). Thus, we extend our analysis by investigating the relationship between market risks and climate-related and environmental risk factors in various sectors.

This paper makes three main contributions. First, we pioneer in investigating the relationship between stock returns and transition climate-related and environmental risk factors in different return quantiles. The existing literature focuses on the link between environmental risk factors and the stock returns in the mean (Giese et al., 2019; Cornell, 2021; Luo, 2022), without paying attention to possible variations in the different quantiles of the stock returns. Based on firm-level environmental scores constructed by the ESG ("Environmental, Social, and Governance") scores data provided by Refinitiv to proxy the firms' climate-related and environmental risk exposure, we find a significant negative relationship between them in the lower quantiles of stock returns, implying that companies that face financial difficulties are affected negatively by the costs of improvements made to their environmental scores.

Our second contribution is to propose novel measures (climate VaR and climate ES) that capture the market risk attributed to climate-related and environmental risk factors proxied by environmental scores. Some institutions have proposed risk measures that they labelled "Climate Value-at-Risk" (e.g. MSCI, 2020). However, there is no publicly available documentation on how their measure is computed.[2] In addition, we introduce climate risk ratios for VaR and ES, which show the proportion of market risk which is due to climate-related and environmental risk factors. These novel measures can be useful tools for other researchers, investors and policymakers.

Our third contribution is to highlight how companies in various sectors respond to climate-related and environmental risks. As far as we know, there is no literature on sectoral analysis for climate VaR/ES. Our results indicate the heterogeneity in the sensitivity of different sectors to climate-related and environmental risk variables. In particular, companies in the Energy sector gain the most from improving environmental scores, whereas companies in the Health Care sector are the least cost-effective in decreasing their climate-related and environmental risk. Our results are robust to changes to the models used to capture risk and to the levels of risk significance.

The rest of the paper is organized as follows. Section 2 discusses the methodology to estimate the climate-related and environmental risk

[1] Also see Basel Committee on Banking Supervision (2021) for a regulatory perspective on climate-related risk drivers in the banking system.

[2] The commercial product illustrated by MSCI (2020) reports the climate VaR spread by different sectors of activity found within a portfolio, whereas our study provides a new measure on climate VaR/ES based on the relationship between market risks and climate-related and environmental risk factors.

Table 4
Environmental scores and VaR.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Basic Materials	Consumer Discretionary	Consumer Staples	Energy	Financials	Health Care	Industrials	Real Estate	Technology	Telecommunications	Utilities
Emission	−0.028***	0.014**	0.002	0.014	0.009	−0.053***	0.015***	−0.016***	0.044***	0.050***	0.006
	(0.007)	(0.006)	(0.005)	(0.014)	(0.014)	(0.010)	(0.004)	(0.006)	(0.007)	(0.011)	(0.006)
Innovation	−0.004	−0.001	0.014***	0.031***	−0.030***	−0.006	−0.017***	0.020***	0.004	0.018**	0.016***
	(0.006)	(0.005)	(0.003)	(0.008)	(0.010)	(0.011)	(0.004)	(0.005)	(0.006)	(0.008)	(0.004)
Resource	0.038***	−0.017***	0.028***	0.074***	0.023**	−0.026***	−0.010**	−0.007	−0.008	−0.092***	0.003
	(0.007)	(0.006)	(0.005)	(0.013)	(0.011)	(0.010)	(0.004)	(0.005)	(0.008)	(0.018)	(0.005)
Size	4.273***	5.801***	4.236***	6.510***	7.632***	6.602***	5.479***	3.670***	2.477***	1.030**	8.209***
	(0.657)	(0.290)	(0.382)	(0.575)	(0.808)	(0.704)	(0.353)	(0.582)	(0.269)	(0.448)	(1.915)
M/B	0.527***	−0.022**	0.003	−0.016	−0.007	0.053***	−0.005*	1.681***	−0.039***	0.531***	−0.352
	(0.080)	(0.011)	(0.003)	(0.081)	(0.017)	(0.012)	(0.003)	(0.196)	(0.012)	(0.112)	(0.223)
Leverage	−0.518***	0.014	−0.019	0.047	−0.575***	−0.910***	0.003	−3.456***	0.102**	−1.494***	0.434
	(0.07)	(0.031)	(0.020)	(0.091)	(0.106)	(0.142)	(0.003)	(0.378)	(0.045)	(0.254)	(0.430)
ROE	1.866**	0.869*	0.211***	1.429	4.752***	4.809***	0.103	0.481	−0.521	4.957***	4.229**
	(0.861)	(0.524)	(0.071)	(1.281)	(1.646)	(1.287)	(0.203)	(3.705)	(0.321)	(1.679)	(1.970)
Investment	−0.543***	0.061	−0.115	0.775**	−0.251**	−0.742***	0.074	0.571**	−0.160	−1.754***	−0.519**
	(0.189)	(0.112)	(0.097)	(0.344)	(0.098)	(0.183)	(0.094)	(0.272)	(0.098)	(0.338)	(0.259)
Constant	−59.430***	−79.160***	−60.890***	−104.100***	−98.490***	−76.470***	−71.030***	−49.790***	−51.450***	−23.140***	−89.160***
	(5.229)	(2.614)	(3.639)	(5.858)	(8.051)	(6.659)	(3.040)	(5.204)	(2.289)	(4.267)	(17.830)
Observations	4009	8590	5092	1789	4699	2125	13,280	3680	7574	1742	5489
Adjusted R-squared	0.766	0.738	0.792	0.871	0.866	0.800	0.761	0.870	0.711	0.793	0.619
Year-Month F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table provides panel regression estimates for the impact of environmental scores on VaR. Regressions are estimated at sector level. The independent variables are *Emission*, *Innovation*, and *Resource*. All control variables are lagged by one month. The sample duration extends from January 2003 to December 2019. All regressions include the year-month fixed effect and firm fixed effect. Huber-White robust standard errors are used in the regression and reported in parentheses. ** and *** denote statistical significance at 5% and 1% levels, respectively.

measures. Section 3 introduces the firm-level data used in the empirical analysis. Section 4 presents the estimation results from panel data regressions. Section 5 reports the results of several robustness checks. Section 6 concludes. The online Supplemental Appendix contains additional results.

2. Methodology

2.1. Risk measures

The downside risk is captured by the left tail of stock returns' distribution. Two prevalent measures are employed to identify such risk. The first measure, VaR, is an estimate of the quantile of the distribution of profit and losses and it can be measured at different levels. Due to its conceptual simplicity, VaR has become a popular risk measure of market risk. However, VaR ignores the shape and structure of the tail of the returns' distribution and is not a coherent risk measure (i.e. it is not subadditive) (Artzner et al., 1999). Thus, a second risk measure has been introduced, ES, which measures the expected value of the observations provided that they exceed VaR; this is a coherent risk measure (Roccioletti, 2015).

VaR provides banks and financial institutions with an estimate of the minimum loss level that occurs in the worst outcomes at a given level $\alpha \in (0,1)$. Let $F_Y(\cdot|\Omega_{t-1})$ denote the cumulative distribution function of asset return Y_t over a time horizon (such as one day or one week) conditional on the information set Ω_{t-1}. The VaR at level α can be written directly in terms of the inverse cumulative distribution function (Duffie and Pan, 1997):

$$VaR_t^{\alpha} = F_Y^{-1}(\alpha|\Omega_{t-1}), \tag{1}$$

where VaR_t^{α} denotes the α-quantile of the underlying return distribution at time t. As such, Following Ziegel (2016), Nolde and Ziegel (2017), and Chen (2018), the VaR at level α at time t can be defined as:

$$VaR_t^{\alpha} = \inf\{Y_t | F_Y(Y_t|\Omega_{t-1}) \geq \alpha\}. \tag{2}$$

ES measures the expectation of return conditional on its value being less than VaR. As a coherent risk measure and due to its superior properties, ES has become increasingly popular in the risk management of banks and financial institutions. Recently, the Basel Committee on Banking Supervision (2013) proposed a transition from VaR at 1% level to ES at 2.5% level motivated by the global financial crisis in 2008. ES at level α at time t can be formally defined as (see Acerbi and Tasche, 2002):

$$ES_t^{\alpha} = \mathbb{E}\left[Y_t \middle| Y_t \leq VaR_t^R, \Omega_{t-1}\right]. \tag{3}$$

Since the generalized autoregressive conditional heteroskedastic (GARCH) model of Bollerslev (1986) and its variants (Nelson, 1991) capture the time-varying volatility feature, they are widely used to forecast VaR and ES in the literature. We also employ the GARCH model with skewed t distribution of Hansen (1994) for our estimation of risk measures. The model is specified as follows:

$$v_t = \mu_t + a\sigma_t, \ \text{ where } \ a = F_\eta^{-1}(\alpha),$$

$$e_t = \mu_t + b\sigma_t, \ \text{ where } \ b = \mathbb{E}[\eta_t | \eta_t \leq a],$$

$$Y_t = \sigma_t \eta_t, \ \ \eta_t \sim iid\, F_\eta(0,1),$$

$$\sigma_t^2 = \omega + \delta\sigma_{t-1}^2 + \gamma Y_{t-1}^2 \tag{4}$$

where σ_t^2 is the conditional variance which follows a GARCH(1,1) process, η_t is the standardized residual that follows the skewed t distribution $F_\eta(0,1)$ and Y_t is the de-meaned daily returns. This model is based on a strong link between VaR/ES and equity returns, which has been widely discussed in the early literature (e.g. Duffie and Pan, 1997; Dowd,

Table 5
Environmental scores and ES.

Variable	(1) Basic Materials	(2) Consumer Discretionary	(3) Consumer Staples	(4) Energy	(5) Financials	(6) Health Care	(7) Industrials	(8) Real Estate	(9) Technology	(10) Telecommunications	(11) Utilities
Emission	−0.037***	0.019**	0.004	0.025	0.006	−0.072***	0.021***	−0.022***	0.064***	0.072***	0.009
	(0.010)	(0.008)	(0.008)	(0.019)	(0.020)	(0.014)	(0.006)	(0.007)	(0.010)	(0.016)	(0.008)
Innovation	−0.004	−0.007	0.020***	0.036***	−0.042***	−0.010	−0.021***	0.026***	0.007	0.026**	0.022***
	(0.008)	(0.007)	(0.004)	(0.010)	(0.015)	(0.016)	(0.005)	(0.006)	(0.00844)	(0.012)	(0.006)
Resource	0.052***	−0.026***	0.039***	0.105***	0.033**	−0.040***	−0.013**	−0.008	−0.016	−0.133***	0.004
	(0.010)	(0.008)	(0.008)	(0.018)	(0.015)	(0.014)	(0.006)	(0.007)	(0.011)	(0.026)	(0.006)
Size	5.879***	8.120***	6.145***	8.632***	9.975***	9.500***	7.557***	4.942***	3.538***	1.629**	11.000***
	(0.908)	(0.409)	(0.555)	(0.789)	(1.104)	(1.010)	(0.500)	(0.773)	(0.394)	(0.645)	(2.560)
M/B	0.690***	−0.031**	0.005	−0.026	−0.013	0.076***	−0.006	2.199***	−0.056***	0.780***	−0.458
	(0.107)	(0.015)	(0.005)	(0.111)	(0.027)	(0.018)	(0.004)	(0.257)	(0.017)	(0.161)	(0.298)
Leverage	−0.675***	0.018	−0.030	0.069	−0.702***	−1.295***	0.004	−4.562***	0.150**	−2.200***	0.564
	(0.097)	(0.042)	(0.028)	(0.123)	(0.137)	(0.204)	(0.005)	(0.495)	(0.066)	(0.368)	(0.576)
ROE	2.338**	1.230*	0.304***	1.837	6.250***	6.865***	0.148	1.137	−0.750	7.183***	5.675**
	(1.129)	(0.728)	(0.0994)	(1.732)	(2.196)	(1.846)	(0.279)	(4.693)	(0.476)	(2.400)	(2.631)
Investment	−0.686***	0.020	−0.162	0.916**	−0.306**	−1.042***	0.071	0.738**	−0.266*	−2.474***	−0.757**
	(0.253)	(0.153)	(0.140)	(0.465)	(0.130)	(0.256)	(0.125)	(0.354)	(0.141)	(0.478)	(0.351)
Constant	−81.600***	−109.700***	−87.650***	−137.700***	−128.900***	−109.100***	−97.620***	−66.050***	−72.420***	−34.640***	−118.60***
	(7.205)	(3.663)	(5.280)	(8.005)	(10.99)	(9.527)	(4.307)	(6.914)	(3.321)	(6.094)	(23.840)
Observations	4009	8590	5092	1789	4699	2125	13,280	3680	7574	1742	5489
Adjusted R-squared	0.770	0.767	0.812	0.882	0.863	0.816	0.770	0.872	0.716	0.813	0.631
Year-Month F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm F.E.	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table provides estimates of the effect of environmental scores on ES based on panel regressions. Regressions are estimated at sector level. The independent variables are *Emission*, *Innovation*, and *Resource*. All control variables are lagged by one month. The sample period is from January 2003 to December 2019. All regressions include the year-month fixed effect and firm fixed effect. Huber-White robust standard errors are used in the regression and reported in parentheses. ** and *** denote statistical significance at 5% and 1% levels, respectively.

1998). We transform the daily VaR and ES to monthly estimates by multiplying average daily risk measures in the given month by the square root of 21. There are many other ways to estimate VaR and ES. We provide the robustness checks using alternative estimation of VaR and ES in Section 5.

2.2. Climate VaR and ES

We employ the Environmental component (denoted as E-score) of the ESG score in our study, given that it is related to the environmental factors and captures the effects of climate-related issues on companies. The E-score is comprised of three sub-scores: the *Emission* score, the *Innovation* score, and the *Resource Use* score. Specifically, the *Emission* score reflects the extent to which a firm is committed to reducing environmental emissions in its production and operational processes; the *Innovation* score measures a firm's capacity to create new market opportunities through environmental technologies and processes, or eco-designed products; the *Resource Use* score reflects a firm's performance and capacity to reduce the amount of natural resources it uses and improve its supply chain management. Taken together, these sub-components provide a comprehensive view of a firm's environmental performance and can help investors make informed decisions about the long-term sustainability and financial performance of a company. Thus, instead of directly revealing the link between this environmental pillar and the downside risks, we consider these three sub-components of the E-score in order to quantify the market risks attributed to the climate-related and environmental risk factors.

To determine the extent to which the risk presented by climate-related and environmental factors affects the VaR and ES of the equity returns, we begin our analysis by investigating the link between market risk measures and environmental scores in various sectors. For every sector, we estimate the following panel data regression:

$$\begin{aligned} \textit{Downside Risk}_{i,t} &= \beta_0 + \beta_1 \textit{Emission}_{i,t} + \beta_2 \textit{Innovation}_{i,t} + \beta_3 \textit{Resource}_{i,t} \\ &+ \beta_4 \textit{Controls}_{i,t-1} + \delta_i + \gamma_t + \epsilon_{i,t}, \end{aligned} \tag{5}$$

where the $\textit{Downside Risk}_{i,t}$ represents one of the two risk measures ($VaR_{i,t}$ and $ES_{i,t}$) of the firm i in month t at 1% level; $\textit{Emission}_{i,t}$, $\textit{Innovation}_{i,t}$ and $\textit{Resource}_{i,t}$ measure the Emission, Innovation and Resource Use scores, respectively, of firm i in month t; $\textit{Controls}_{i,t-1}$ is a vector of control variables that may affect downside risk, including size, M/B, leverage, ROE, and investment.[3] We include firm fixed effect (δ_i) and year-month fixed effect (γ_t). We obtain $\widehat{\beta}_1$, $\widehat{\beta}_2$, and $\widehat{\beta}_3$, and these capture the effects of the climate-related and environmental risk factors on VaR and ES. Also, we report the heteroskedasticity-consistent standard errors of White (1980).

In the following, we provide the definition for Climate VaR and ES, which are the VaR and ES of the stock returns of a firm, attributed to environmental scores. Based on Eq. (5), the Climate VaR and ES of firm i in month t are calculated as:

$$\textit{Climate Downside Risk}_{i,t} = \widehat{\beta}_1 \textit{Emission}_{i,t} + \widehat{\beta}_2 \textit{Innovation}_{i,t} + \widehat{\beta}_3 \textit{Resource}_{i,t}. \tag{6}$$

If the β is negative (positive), an increase in the Emission score, Innovation score, or Resource Use score increases (decreases) the risk.[4] Additionally, we define the portion of VaR or ES attributable to environmental scores as follows:

[3] Following the approach in Bolton and Kacperczyk (2021), we run these regressions for firm-months observations. The firm-level control variables are updated quarterly, so in our regressions, we use the most recent observation for these variables. The emission score variables are updated annually, and for these as well we use the most recent observations in our regressions.

[4] The environmental scores are between 0 and 100, and the risk is typically expressed as a negative number.

Fig. 2. Heatmaps of the Statistical significance (left) and Economic significance (right) of the Emission score, Innovation score, and Resource Use score for VaR from 11 sectors during the sample period from January 2003 to December 2019. The statistical significance is represented by the coefficients of environmental scores in Table 4. *, **, and *** denote statistical significance at 10%, 5%, and 1% levels, respectively. Economic significance is defined as the percentage change in total VaR associated with an increase of one standard deviation in the specified environmental score. In both heatmaps, red (green) boxes indicate that an improvement in the specified environmental score increases (decreases) risk.

Table 6
Summary statistics of climate risk ratio for VaR and ES at 1% level.

Sector	Mean		Std		Max		Min	
	(1) VaR	(2) ES	(3) VaR	(4) ES	(5) VaR	(6) ES	(7) VaR	(8) ES
Basic Materials	−1.703	−1.861	3.090	3.081	3.825	3.791	−10.870	−10.268
Consumer Discretionary	1.026	2.249	1.301	1.744	6.161	9.259	−1.092	−0.679
Consumer Staples	−12.382	−12.771	7.997	8.515	−1.240	−1.217	−32.989	−36.480
Energy	−26.996	−29.397	18.960	21.607	−4.905	−5.120	−76.727	−86.979
Financials	−1.896	−0.805	4.032	4.084	6.510	9.748	−11.419	−10.604
Health Care	26.499	27.671	15.638	16.909	69.415	75.364	1.987	2.130
Industrials	2.585	2.223	2.139	2.020	9.570	8.892	−2.476	−2.753
Real Estate	1.879	1.900	3.590	3.660	10.070	10.118	−8.939	−8.909
Technology	−8.086	−7.954	4.949	4.972	−0.410	−0.264	−23.312	−23.123
Telecommunications	7.141	7.382	8.882	9.614	29.765	33.169	−9.396	−9.684
Utilities	−7.776	−8.314	3.672	3.997	−1.459	−1.606	−15.918	−17.169

Note: This table presents the summary statistics of the climate risk ratio for VaR and ES (in percentages) for 11 sectors from January 2003 to December 2019. The mean values and standard deviations of the ratio appear in columns 1–2 and 3–4, while the maximum and minimum values of the ratio appear in columns 5–6 and 7–8.

$$\textit{Climate Risk Ratio}_{i,t} = \frac{\textit{Climate Downside Risk}_{i,t}}{\text{Downside Risk}_{i,t}}. \tag{7}$$

When the sign of the ratio is negative, the effort spent on the improvement of these three environmental scores reduces the riskiness of the firm. When it is positive, the cost associated with the improvement of the environmental scores leads to an increase in the firm's downside risk.

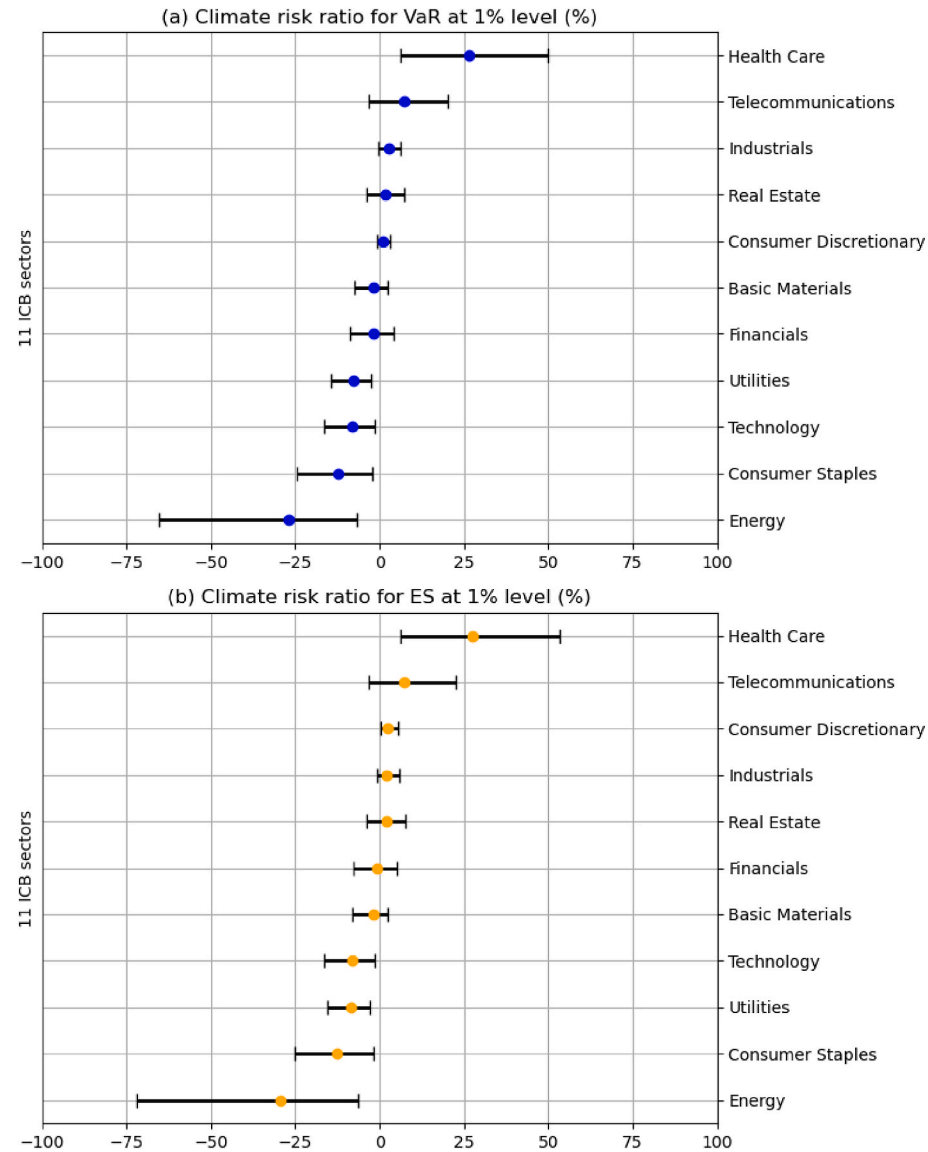

Fig. 3. Climate risk ratio (in percentages) for 11 sectors at 1% level. The ratios for Var and ES are displayed in (a) and (b), respectively. The left and right boundaries of the error bar for each sector are the 5 percent and 95 percent quantiles of the ratio, while the coloured marker represents the mean value. The sectors in the panel are ordered in descending order of the average climate risk ratio.

2.3. *Quantile regression with penalized fixed effect for panel data*

In the recent literature, several environmental proxies have been shown to affect stock returns (Engle et al., 2020; Bolton and Kacperczyk, 2021; Hsu et al., 2023). Here we employ the quantile regression proposed by Koenker (2004) using panel data to discover the relationship between stock returns and environmental scores at various quantiles. To determine how environmental scores influence returns at different quantiles of their distribution, we first investigate the following standard linear panel regression model:

$$y_{i,t} = x_{i,t}^{\top}\beta + \delta_i + \epsilon_{i,t}, \quad t = 1, \dots, T_i, \quad i = 1, \dots, n, \tag{8}$$

where $y_{i,t}$ indicates the firm's stock return, $x_{i,t}$ is a vector of variables including the environmental pillar of the ESG score and the lagged one-month size, M/B, leverage, ROE, and investment. δ_i represents the firm fixed effect, and $\epsilon_{i,t}$ is the error term. The subscript i indexes the firm, while the subscript t indexes the time. The following model is then considered for the conditional quantile functions (at quantile) of the returns in month t of the i^{th} firm $y_{i,t}$:

$$Q_{y_{i,t}}\left(\tau | x_{i,t}\right) = x_{i,t}^{\top}\beta(\tau) + \delta_i, \quad t = 1, \dots, T_i, \quad i = 1, \dots, n, \tag{9}$$

To simultaneously estimate Eq. (9) for several quantiles, we perform the following optimization:

$$\min_{(\beta,\delta)} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{T_i} w_k \rho_{\tau_k}\left(y_{i,t} - x_{i,t}^{\top}\beta(\tau_k) - \delta_i\right), \tag{10}$$

where $\rho_{\tau}(\epsilon) = \epsilon(\tau - I(\epsilon < 0))$ denotes the piecewise linear quantile loss function of Koenker and Bassett Jr (1978). The weights w_k control the relative impact of the q quantiles $\{\tau_1, \dots, \tau_q\}$ on the estimation of the parameters.

The estimation of β and the firm fixed-effect δ_i can be improved by reducing the unconstrained δ_i's toward a common value. To achieve that, we employ the ℓ_1 penalty, $P(\delta) = \sum_{i=1}^{n} |\delta_i|$ in addition to Eq. (10). Then, we obtain the estimators by solving the penalized version of Eq. (10):

Table 7
The climate risk ratios and ratio rankings.

Sector	Climate risk ratio				Rank			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	G-SKT	GJR-G-SKT	G-FZ	CARE	G-SKT	GJR-G-SKT	G-FZ	CARE
Basic Materials	−1.703	−0.410	1.351	3.031	6	6	7	7
Consumer Discretionary	1.026	1.951	1.265	2.361	7	7	6	6
Consumer Staples	−12.382	−16.257	−11.202	−10.786	2	2	2	3
Energy	−26.996	−28.556	−27.457	−17.976	1	1	1	1
Financials	−1.896	−1.355	−3.521	−5.484	5	5	5	5
Health Care	26.499	27.649	20.652	17.795	11	11	11	11
Industrials	2.585	4.126	2.018	3.790	9	9	8	8
Real Estate	1.879	1.964	2.149	4.630	8	8	9	9
Technology	−8.105	−8.248	−7.668	−7.601	3	3	4	4
Telecommunications	7.141	8.699	12.404	5.460	10	10	10	10
Utilities	−7.776	−6.516	−8.355	−11.218	4	4	3	2

Note: This table presents the average climate risk ratios (in percentage) and the rankings for 11 sectors (the model with the lowest ratio is ranked 1 and the model with the highest ratio is ranked 11) based on the climate risk ratio for VaR estimates at 1% level from January 2003 to December 2019 for 3 risk model specifications. The negative (positive) ratio refers to a reduction (increase) in the total risk due to environmental scores. G-SKT, GJR-G- SKT, G-FZ, and CARE correspond to the GARCH model with skewed *t* distribution, the GJR-GARCH model with skewed *t* distribution, the GARCH model estimated with the FZ0 loss function from Fissler and Ziegel (2016), and the CARE model based on Taylor (2008), respectively.

$$\min_{(\beta,\delta)} \sum_{k=1}^{q} \sum_{i=1}^{n} \sum_{t=1}^{T_i} w_k \rho_{\tau_k}\left(y_{i,t} - x_{i,t}^{\top}\beta(\tau_k) - \delta_i\right) + \lambda \sum_{i=1}^{n} |\delta_i|, \quad \lambda > 0, \tag{11}$$

where λ is the penalty term. For $\lambda \mapsto 0$ we obtain the fixed effects estimator described in Eq. (10), while as $\lambda \mapsto \infty$ the $\widehat{\delta} \mapsto 0$ for all $i = 1, \dots, n$ and we obtain an estimate of the model with the fixed effects eliminated.

3. Data

In this section, we describe all datasets used in the empirical analysis. Detailed definitions of the variables are provided in Table SA.1 of the Supplemental Appendix. We focus on U.S. companies in this study. To avoid the potential structural break during the COVID-19 period, our primary database ranges from January 2003 to December 2019 and is primarily comprised of three datasets obtained from Refinitiv, Compustat, and CRSP. Refinitiv provides data on environmental scores, Compustat provides data on corporate fundamentals, and CRSP provides data on stock returns. We implement the matching using CUSIP as the main identifier, and the ultimate matching produces 802 unique firms and 58,290 firm-month observations.[5]

According to Section 2.2, we measure firm-level environmental performance using the *Emission* scores, the *Innovation* scores, and the *Resource Use* scores under the environmental pillar of the Refinitiv ESG scores. Calculated at the firm-quarter level, our control variables are defined as follows. *Size* is the natural logarithm of the firm's market capitalization. *M/B* is the firm's market capitalization divided by its book value. *Leverage* is the book leverage of the firm. *ROE is* the firm's earning performance. *Investment* is the natural logarithm of the firm's capital expenditure plus one (to avoid the natural logarithm of zero). To mitigate the impact of outliers, *M/B*, *Leverage*, and *ROE* are winsorized at 1% level. We note that firms in various sectors have diverse responses to environmental scores. Hence, we report the summary statistics of the sample with respect to the FTSE/DJ Industry Classification Benchmark (ICB) in Table 1. Telecommunications has the lowest average return with a value of 0.617%, while Technology has the highest average return (2.089%), followed by Health Care (1.620%). The Energy sector has the greatest overall environmental score, Emission score and Innovation score, with respective values of 63.171, 57.855 and 53.339. The Health Care sector has the highest Resource Use score (63.459), but the lowest Innovation score (41.626). The lowest Emission and Resource Use scores are reported for Industrials, which are 38.535 and 42.599, respectively.

[5] The correlations of the environmental scores and control variables are reported in the Supplemental Appendix.

4. Results

4.1. Quantile regression results

We begin our analysis by investigating the relationship between stock returns in different quantiles and the environmental pillar of the Refinitiv ESG scores, by employing the quantile regression described in Section 2.3. Table 2 reports the panel regression results for quantiles $\tau \in \{1\%, 5\%, 10\%, 30\%, 50\%, 70\%, 90\%, 95\%, 99\%\}$, where all quantiles are assigned with equal weights when estimating using Eq. (11). For the quantiles below 95%, significant coefficients are observed for the environmental score.

The overall trend is that the effect is negative for lower quantiles and positive for higher quantiles and is more pronounced for lower quantiles. The signs of the control variables are generally consistent with the literature. Fig. 1 illustrates the values of the coefficient of the environmental score, for the above quantiles between $\tau = 1\%$ to $\tau = 99\%$. At the 1% quantile, the environmental scores have the most negative effect on the stock returns. This effect diminishes when the quantile reaches the 50% quantile, at which point this effect switches to positive. When companies struggle, then the costs associated with improving their E-score bring additional burdens and so improving the E-score reduces overall returns. The effect is opposite when companies do well, in such instances improving the E-score increases company returns.

4.2. Climate VaR and ES results

The quantile regression results of Section 4.1 show that there is a differential effect of the environmental scores on the returns, depending on which quantile the returns falls into. This subsection examines the relationship between downside risk (VaR and ES) and environmental scores. We collect daily stock returns from January 2003 to December 2019 using CUSIP from CRSP as described in Section 3. Then, the firm-month VaR and ES at 1% level are estimated using the specification in Section 2.1. We present the average monthly VaR and ES across several sectors in columns 1 and 2 of Table 3. Real Estate and Utilities are the sectors with the lowest average VaR and ES, whereas Energy is the sector with the highest total risk.

To reveal the effects of environmental scores on downside risk, we regress the VaR and ES at 1% level on the *Emission* score, the *Innovation* score, the *Resource Use* score, along with firm-level control variables. The results are presented in Table 4 and Table 5 for VaR and ES,

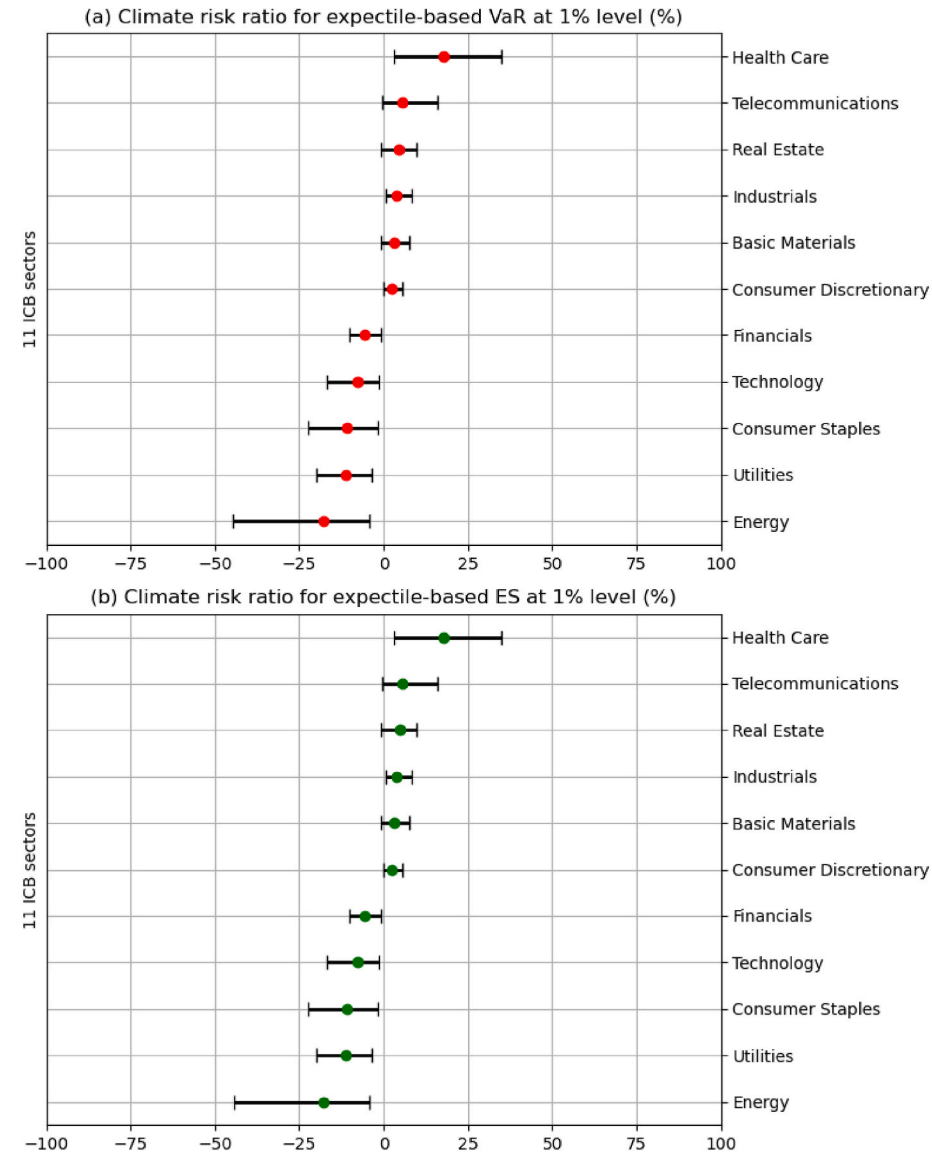

Fig. 4. Expectile-based climate risk ratio (in percentages) for 11 sectors at 1% level. The ratios for expectile-based Var and ES are displayed in (a) and (b), respectively. The left and right boundaries of the error bar for each sector are the 5 percent and 95 percent quantiles of the ratio, while the coloured marker represents the mean value. The sectors in the panel are ordered in descending order of the average expectile-based climate risk ratio.

respectively. The Energy and Utilities sectors have only positive coefficients across all scores, indicating that an improvement in any one of these environmental scores of firms in these two sectors leads to a reduction in the total risk of the firms. Health Care, however, has solely negative coefficients on the environmental scores, which indicates that as the environmental scores increase, the firms' total risks increase proportionally. In other words, the companies' investments in improving their environmental scores reduce their total risk in the Energy and Utilities sectors, whilst it increases their total risk in the Health Care sector. This might be related to the link between medical services and emissions, as also argued by Pichler et al. (2019). Building low carbon strategies requires considerable effort, given the complexities of medical supply chains and health treatments, and can be very costly for health companies, which makes emission reductions hard to achieve. Other sectors have coefficients with mixed signs associated with the three environmental scores. Due to the differences of sectors, some sectors benefit from increases in the individual scores but are negatively affected by others. For instance, firms in the Industrials sector have their risk affected positively by their Emission score but negatively by their Innovation score and Resource Use score.

The left panel of Fig. 2 displays the heatmaps of the statistical significance of VaR with respect to the three environmental scores. According to the value of the coefficients, sectors including Consumer Staples, Energy, and Utilities benefit from the improvement in all of the three environmental scores. The Innovation score has a positive and statistically significant effect on the total risk of the companies in these three sectors. This effect is also observed for Resource Use Score in the Consumer Staples and Energy sectors. However, the negative signs of the coefficients of the three environmental scores in the Health Care sector indicate that the additional expenditures made by companies to improve their environmental scores raise their total risk. The right panel of Fig. 2 reports the economic significance of the results. Several key observations are worth noting.[6] First, an one-standard-deviation increase in the Resource Use score of companies in the Energy sector leads to a worsening of 2.042% in their total risk. Second, companies in the Health Care sector suffer a deterioration of 1.490% in their total risk due to an one-

[6] To our knowledge, there is no existing literature of performing such a sectoral analysis to compare our results against.

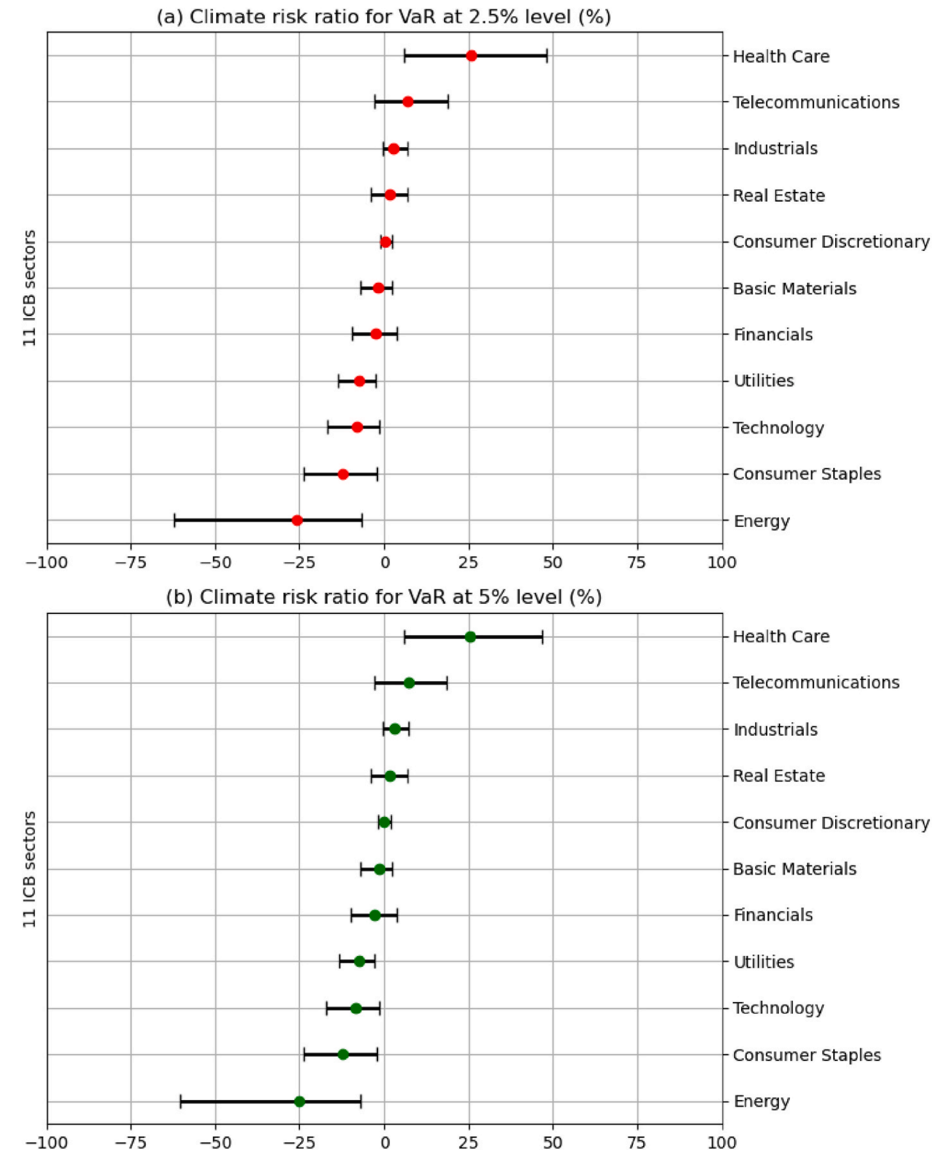

Fig. 5. Summary statistics of the climate risk ratio (in percentages) for VaR at 2.5% (a) and 5% (b) levels for 11 sectors. The left and right boundaries of the error bars are the 5 percent and 95 percent quantiles of the ratio, while the coloured marker represents the mean value. The sectors in both panels are ordered in descending order of the average climate risk ratio.

standard-deviation increase in the Emission score. Third, an one-standard-deviation increase in the Resource Use score of companies in the Telecommunication sector is associated with a 2.392% improvement in their total risk. Lastly, companies in the Technology sector benefit an improvement of 1.159% in their total risk via an one-standard-deviation increase in the Emission score.

Climate VaR and ES are computed[7] based on Eq. (6), and the results are presented in columns 3 and 4 in Table 3. In the Energy sector, the average Climate VaR (ES) is the most positive at 6.642% (9.346%), which implies that the environmental scores lead to a reduction of total VaR (ES). On the contrary, the VaR and ES of firms in Health Care attributed to environmental scores are the highest in absolute value. The cost associated with improving the environmental scores leads to an increase in the firms' downside risk in this sector. A similar effect can be seen in the Telecommunication sector.

We employ the climate-related and environmental risk measure proposed in Eq. (7) to demonstrate the extent to which the environmental scores affect the total downside risk of the firms. The summary statistics of the climate risk ratio for VaR and ES for different sectors are reported in Table 6. A negative (positive) sign in the mean value of the climate risk ratio indicates that, on average, improvements in the environmental scores reduce (increase) the total risk of the firm. Sectors including Basic Materials, Consumer Staples, Energy, Financials, Technology, and Utilities benefit from the effort spent on increasing the companies' environmental scores, and the proportion of total VaR reduced by environmental scores ranges from 1.703% to 26.996%. Sectors such as Consumer Discretionary, Health Care, Industrials, Real Estate, and Telecommunications are negatively affected by the increases in the companies' environmental scores, but the effect on their total VaR is less than 7.2%, with the exception of Health Care, which is characterized by VaR increases of 26.499% on average, due to the companies' environmental scores. Similar results can be found for ES.

To visually illustrate the fraction of VaR and ES that is attributable to the environmental scores, we display summary statistics of the climate risk ratio of VaR and ES in Fig. 3, and sort the climate risk ratio of different sectors in descending order in both panels. We would like to highlight three points. First, in four sectors (particularly the Energy

[7] As far as we know, there is no backtest for climate VaR/ES developed yet.

sector), the climate risk ratio is negative, as expected, showing that climate-related and environmental risks are reduced when companies improve their environmental performance. In the Energy sector, the climate-related and environmental risk factors can reduce VaR or ES by about 28% on average and the 5% quantile of the ratio for VaR is −65.294% and for ES it is −71.872%. Second, the climate risk ratio in six sectors is not significant on average. The ranking of sectors including Health Care, Telecommunication, Consumer Staples, and Energy are the same in both Fig. 3(a) and (b). Third, the only outlier is the Health Care sector where the effect is inversed, which means by improving environmental performance, the VaR and ES of the companies increases.

In the Health Care sector, the climate-related and environmental risk factors contribute approximately 27% on average to the total VaR and ES, the 95% quantile of the ratio for VaR is 49.956% and for ES it is 53.454%. In this sector, emissions can result from medical treatments and low emission alternatives are often expensive, making it difficult to reduce emissions, the priority being improvements in health and reducing the risks to the patients; see Pichler et al. (2019) for further deliberation.

5. Robustness checks

5.1. Asymmetric VaR and ES models

To account for the possibility of asymmetry in the volatility, we repeat our previously presented climate-related and environmental risks estimation methodology using the GJR-GARCH model (Glosten et al., 1993) with skewed *t* innovations. Table 7 (column 2) depicts the climate risk ratios for the GJR- GARCH model. We notice that it yields similar but slightly different values for the climate risk ratio. When it comes to the ranking of the sectors based on the climate risk ratios (Table 7, column 6), there is a high degree of consistency, with the ratios remaining mostly unaffected.

5.2. Semi-parametric VaR and ES models

Recently, Patton et al. (2019) introduced semi-parametric models for VaR and ES. In the following, we check whether our results are affected if the risk measures are obtained via one of the semi-parametric models, namely the GARCH-FZ model. Table 7 (columns 3) shows the climate risk ratios obtained with this model, which is similar to the previous results. The ranking of the sectors based on the GARCH-FZ model (Table 7, column 7) is consistent with our earlier rankings.

5.3. Expectile-based climate VaR and ES

In this section, we explore expectile-based climate risk measures as an alternative. This is motivated by the fact that expectiles have a different dependence on the form of the distribution, as compared to quantiles. Whilst a change in the shape of the distribution will not alter the quantile, it will modify the expectile. Taylor (2008) developed the Conditional Autoregressive Expectile (CARE) model to compute expectile-based risk measures. Using the CARE model, we obtain the expectile-based VaR and ES, which is further used to calculate climate VaR and ES (as well as risk ratios). Fig. 4 shows the expectile-based climate risk ratios for various sectors. Table 7 (columns 4 and 8) provides the expectile-based climate risk ratios as well as sector ranks. It can be noted that the results obtained from the expectile-based measures are in line with the quantile-based values reported in Section 4.2, demonstrating the robustness of our findings to expectile-based risk measures.

5.4. Alternative risk levels

After the 2007–2008 financial crisis, the Basel Committee on Banking Supervision (2013) proposed a transition from 1% VaR to 2.5% ES. In addition to VaR and ES at 1%, different risk levels are therefore explored in this robustness check. We employ VaR at 2.5% and 5% levels estimated from the GARCH model with skewed *t* distribution, as dependent variables in Eq. (5).[8] Fig. 5 presents the summary of the climate risk ratio for VaR at 2.5% and 5% levels for the 11 sectors previously considered. Figs. 3 and 5 are similar, in that the ranking position of all sectors corresponds between the two figures. The 5% (95%) quantile of the climate risk ratio for companies in the Energy (Health Care) sector at 1% risk level is on average −65.293 (49.956), and at the 5% risk level, it is −60.268 (46.893). By shifting 1% risk levels to less extreme risk levels, the influence of environmental scores on downside risk is reduced, with the exception of companies in the Financials, Industrials, and Technology sectors, which have 5% risk levels on average more impacted by the companies' environmental scores.

6. Conclusion

In this study, we propose new measures of climate downside risk that reveal to what extent the firm-level environmental scores influence the downside risk of the firms. We reveal the statistically significant negative relationship between stock returns and environmental pillar of the Refinitiv ESG scores at low quantiles of the returns. We employ the Emission score, Innovation score, and Resource Use score of the environmental pillar to explain the downside risk of the firms in various sectors. Our definitions of climate VaR and ES capture the market risk components associated to climate-related and environmental risks. We document that there is heterogeneity in the sensitivity of the firm-level risk to environmental scores. Our framework shows that firms in some sectors, notably Energy and Utilities, can reduce their downside risk by improving their firms' environmental scores, while for companies in sectors such as Health Care, improving the environmental scores is not cost-effective. These results are consistent with various risk assessments and levels of risk. These findings have important implications for investors and business managers to capture sensitivities to climate-related risk factors. Future research could consider a more nuanced decomposition of climate-related and environmental risks, in addition to the investigation of the relationship between downside risks and physical risk factors (e.g. rising sea levels or hurricane-prone regions).

CRediT authorship contribution statement

Emese Lazar: Writing – review & editing, Methodology, Conceptualization. **Jingqi Pan:** Writing – original draft, Software, Methodology, Formal analysis, Conceptualization. **Shixuan Wang:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2024.123393.

Data availability

Data will be made available on request.

[8] Analogous results for ES are available in the Supplemental Appendix.

References

Acerbi, C., Tasche, D., 2002. Expected shortfall: a natural coherent alternative to Value at Risk. Econ. Notes 31 (2), 379–388. https://doi.org/10.1111/1468-0300.00091.

Acharya, V.V., Berner, R., Engle, R., et al., 2023. Climate stress testing. Annual Review of Financial Economics 15, 291–326.

Allen, S.L., 2012. Financial Risk Management: A Practitioner's Guide to Managing Market and Credit Risk. John Wiley & Sons.

Andersson, M., Bolton, P., Samama, F., 2016. Hedging climate risk. Financ. Anal. J. 72 (3), 13–32. https://doi.org/10.2469/faj.v72.n3.4.

Anttila-Hughes, J., 2016. Financial market response to extreme events indicating climatic change. Eur. Phys. J. Spec. Top. 225 (3), 527–538. https://doi.org/10.1140/epjst/e2015-50098-6.

Ardia, D., Bluteau, K., Boudt, K., et al., 2023. Climate change concerns and the performance of green vs. brown stocks. Manag. Sci. 69 (12), 7607–7632. https://doi.org/10.1287/mnsc.2022.4636.

Artzner, P., 1997. Thinking coherently. Risk 10, 68–71.

Artzner, P., Delbaen, F., Eber, J.M., et al., 1999. Coherent measures of risk. Math. Finance 9 (3), 203–228. https://doi.org/10.1111/1467-9965.00068.

Baldauf, M., Garlappi, L., Yannelis, C., 2020. Does climate change affect real estate prices? Only if you believe in it. Rev. Financ. Stud. 33 (3), 1256–1295. https://doi.org/10.1093/rfs/hhz073.

Bank of England, 2021. Bank of England report on climate-related risks and the regulatory capital frameworks. Available at: https://www.bankofengland.co.uk/prudential-regulation/publication/2023/report-on-climate-related-risks-and-the-regulatory-capital-frameworks. (Accessed 16 October 2024).

Bansal, R., Kiku, D., Ochoa, M., 2016. Price of Long-Run Temperature Shifts in Capital Markets. National Bureau of Economic Research. Technical Report, Available at: https://papers.ssrn.com/sol3/papers.cfm?abstractid=2827447. (Accessed 15 January 2023).

Barnett, M., 2023. Climate Change and Uncertainty: An Asset Pricing Perspective. Management Science 69 (12), 7562–7584. https://doi.org/10.1287/mnsc.2022.4635.

Barnett, M., Brock, W., Hansen, L.P., 2020. Pricing uncertainty induced by climate change. Rev. Financ. Stud. 33 (3), 1024–1066. https://doi.org/10.1093/rfs/hhz144.

Basel Committee on Banking Supervision, 2013. Fundamental review of the trading book: a revised market risk framework. available at: http://www.bis.org/publ/bcbs265.pdf. (Accessed 15 January 2023).

Basel Committee on Banking Supervision, 2021. Climate-related risk drivers and their transmission channels. Available at: https://www.bis.org/bcbs/publ/d517.pdf. (Accessed 12 April 2024).

Bernstein, A., Gustafson, M.T., Lewis, R., 2019. Disaster on the horizon: the price effect of sea level rise. J. Financ. Econ. 134 (2), 253–272. https://doi.org/10.1016/j.jfineco.2019.03.013.

Best, R., Burke, P.J., Jotzo, F., 2020. Carbon pricing efficacy: Cross-country evidence. Environ. Resour. Econ. 77 (1), 69–94. https://doi.org/10.1007/s10640-020-00436-x.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. J. Econom. 31 (3), 307–327. https://doi.org/10.1016/0304-4076(86)90063-1.

Bolton, P., Kacperczyk, M., 2021. Do investors care about carbon risk? J. Financ. Econ. 142 (2), 517–549. https://doi.org/10.1016/j.jfineco.2021.05.008.

Burke, M., Hsiang, S.M., Miguel, E., 2015. Global non-linear effect of temperature on economic production. Nature 527, 235–239. https://doi.org/10.1038/nature15725.

Chen, J., 2018. On exactitude in financial regulation: value-at-risk, expected shortfall, and expectiles. Risks 6 (2), 61. https://doi.org/10.3390/risks6020061.

Chen, Q., Gerlach, R., Lu, Z., 2012. Bayesian Value-at-Risk and expected shortfall forecasting via the asymmetric Laplace distribution. Comput. Stat. Data Anal. 56 (11), 3498–3516. https://doi.org/10.1016/j.csda.2010.06.018.

Choi, D., Gao, Z., Jiang, W., 2020. Attention to global warming. Rev. Financ. Stud. 33 (3), 1112–1145. https://doi.org/10.1093/rfs/hhz086.

Cornell, B., 2021. ESG preferences, risk and return. Eur. Financ. Manag. 27 (1), 12–19.

Curtin, J., McInerney, C., Gallach'oir, B.O., et al., 2019. Quantifying stranding risk for fossil fuel assets and implications for renewable energy investment: a review of the literature. Renew. Sustain. Energy Rev. 116, 109402. https://doi.org/10.1016/j.rser.2019.109402.

Dempster, M.A.H., 2002. Risk Management: Value at Risk and beyond. Cambridge University Press.

Dietz, S., Bowen, A., Dixon, C., et al., 2016. 'Climate value at risk' of global financial assets. Nat. Clim. Change 6 (7), 676–679. https://doi.org/10.1038/nclimate2972.

Dowd, K., 1998. Beyond Value at Risk: the New Science of Risk Management, vol. 96. Wiley.

Duffie, D., Pan, J., 1997. An overview of value at risk. J. Deriv. 4 (3), 7–49. https://doi.org/10.3905/jod.1997.407971.

Engle, R.F., Giglio, S., Kelly, B., et al., 2020. Hedging climate change news. Rev. Financ. Stud. 33 (3), 1184–1216. https://doi.org/10.1093/rfs/hhz072.

European Central Bank, 2020. Guide on climate-related and environmental risks: supervisory expectations relating to risk management and disclosure. Available at: https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.202011finalguideonclimate-relatedandenvironmentalrisks~58213f6564.en.pdf. (Accessed 12 April 2024).

European Central Bank, 2022. 2022 climate risk stress test. Available at https://www.bankingsupervision.europa.eu/ecb/pub/pdf/ssm.climatestresstestreport.20220708~2e3cc0999f.en.pdf. (Accessed 16 October 2024).

Fissler, T., Ziegel, J.F., 2016. Higher order elicitability and Osband's principle. Ann. Stat. 44 (4), 1680–1707. https://doi.org/10.1214/16-AOS1439.

Gerlach, R., Wang, C., 2020. Semi-parametric dynamic asymmetric Laplace models for tail risk forecasting, incorporating realized measures. Int. J. Forecast. 36 (2), 489–506. https://doi.org/10.1016/j.ijforecast.2019.07.003.

Giese, G., Lee, L.E., Melas, D., et al., 2019. Foundations of ESG investing: how ESG affects equity valuation, risk, and performance. J. Portfolio Manag. 45 (5), 69–83.

Giese, G., Nagy, Z., Lee, L.E., 2021. Deconstructing ESG ratings performance: Risk and return for e, s, and g by time horizon, sector, and weighting. J. Portfolio Manag. 47 (3), 94–111.

Giglio, S., Kelly, B., Stroebel, J., 2021. Climate finance. Annual Review of Financial Economics 13, 15–36. https://doi.org/10.1146/annurev-financial-102620-103311.

Glosten, L.R., Jagannathan, R., Runkle, D.E., 1993. On the relation between the expected value and the volatility of the nominal excess return on stocks. J. Finance 48 (5), 1779–1801.

Goldsmith-Pinkham, P., Gustafson, M., Lewis, R., et al., 2019. Sea level rise and municipal bond yields, Jacobs Levy equity management center for quantitative financial research paper. https://dx.doi.org/10.2139/ssrn.3478364. (Accessed 15 January 2023).

Hansen, B.E., 1994. Autoregressive conditional density estimation. Int. Econ. Rev. 35 (3), 705–730. https://doi.org/10.2307/2527081.

Hong, H., Li, F.W., Xu, J., 2019. Climate risks and market efficiency. J. Econom. 208 (1), 265–281. https://doi.org/10.1016/j.jeconom.2018.09.015.

Hsu, P.H., Li, K., Tsou, C.Y., 2023. The pollution premium. J. Finance. https://doi.org/10.1111/jofi.13217, 78, 1343-1392.

Huynh, T.D., Xia, Y., 2021. Climate change news risk and corporate bond returns. J. Financ. Quant. Anal. 56 (6), 1985–2009. https://doi.org/10.1017/S0022109020000757.

Ilhan, E., Sautner, Z., Vilkov, G., 2021. Carbon tail risk. Rev. Financ. Stud. 34 (3), 1540–1571. https://doi.org/10.1093/rfs/hhaa071.

Jorion, P., 2000. Risk management lessons from long-term capital management. Eur. Financ. Manag. 6 (3), 277–300. https://doi.org/10.1111/1468-036X.00125.

Koenker, R., 2004. Quantile regression for longitudinal data. J. Multivariate Anal. 91 (1), 74–89. https://doi.org/10.1016/j.jmva.2004.05.006.

Koenker, R., Bassett, Jr G., 1978. Regression quantiles. Econometrica: J. Econom. Soc. 46 (1), 33–50. https://doi.org/10.2307/1913643.

Kumar, A., Xin, W., Zhang, C., 2019. Climate Sensitivity, Mispricing, and Predictable Returns. University of Miami Working Paper. doi:10.2139/ssrn.3331872. (Accessed 15 January 2023).

Lesk, C., Rowhani, P., Ramankutty, N., 2016. Influence of extreme weather disasters on global crop production. Nature 529, 84–87.

Luo, D., 2022. Esg, liquidity, and stock returns. J. Int. Financ. Mark. Inst. Money 78 (101), 526.

MSCI, 2020. Climate value-at-risk. Available at: https://www.msci.com/documents/1296102/16985724/MSCI-ClimateVaR-Introduction-Feb2020.pdf. Accessed on October 2024.

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: a new approach. Econometrica: J. Econom. Soc. 59 (2), 347–370. https://doi.org/10.2307/2938260.

Network for Greening the Financial System, 2020. Guide for Supervisors Integrating climate-related and environmental risks into prudential supervision Available at: https://www.ngfs.net/sites/default/files/medias/documents/ngfsguideforsupervisors.pdf. (Accessed 12 April 2024).

Network for Greening the Financial System, 2023. NGFS Scenarios for central banks and supervisors. Available at: https://www.ngfs.net/sites/default/files/medias/documents/ngfsclimatescenariosforcentralbanksandsupervisorsphaseiv.pdf. (Accessed 12 April 2024).

Nolde, N., Ziegel, J.F., 2017. Elicitability and backtesting: perspectives for banking regulation. Ann. Appl. Stat. 11 (4), 1833–1874. https://doi.org/10.1214/17-AOAS1041.

Painter, M., 2020. An inconvenient cost: the effects of climate change on municipal bonds. J. Financ. Econ. 135 (2), 468–482. https://doi.org/10.1016/j.jfineco.2019.06.006.

Patton, A.J., Ziegel, J.F., Chen, R., 2019. Dynamic semiparametric models for expected shortfall (and Value-at-Risk). J. Econom. 211 (2), 388–413. https://doi.org/10.1016/j.jeconom.2018.10.008.

Pichler, P.P., Jaccard, I.S., Weisz, U., et al., 2019. International comparison of health care carbon footprints. Environ. Res. Lett. 14 (6). https://doi.org/10.1088/1748-9326/ab19e1, 064,004.

Roccioletti, S., 2015. Backtesting Value at Risk and Expected Shortfall. Springer. https://doi.org/10.1007/978-3-658-11908-9.

Sautner, Z., Van Lent, L., Vilkov, G., et al., 2023. Pricing climate change exposure. Manag. Sci. 69 (12), 7540–7561.

Seltzer, L.H., Starks, L., Zhu, Q., 2022. Climate Regulatory Risk and Corporate Bonds. National Bureau of Economic Research. https://doi.org/10.2139/ssrn.3563271. Technical Report. (Accessed 15 January 2023).

Tankov, P., Tantet, A., 2019. Climate data for physical risk assessment in finance. SSRN 3480156. https://dx.doi.org/10.2139/ssrn.3480156. (Accessed 15 January 2023).

Taylor, J.W., 2008. Estimating value at risk and expected shortfall using expectiles. J. Financ. Econom. 6 (2), 231–252. https://doi.org/10.1093/jjfinec/nbn001.

Taylor, J.W., 2019. Forecasting Value at Risk and expected shortfall using a semiparametric approach based on the asymmetric Laplace distribution. J. Bus. Econ. Stat. 37 (1), 121–133. https://doi.org/10.1080/07350015.2017.1281815.

White, H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. Econometrica: J. Econom. Soc. 48 (4), 817–838. https://doi.org/10.2307/1912934.

Ziegel, J.F., 2016. Coherence and elicitability. Math. Finance 26 (4), 901–918. https://doi.org/10.1111/mafi.12080.