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Climate uncertainty and information transmissions across the conventional and ESG assets☆

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ABSTRACT

This paper examines the effect of climate uncertainty on the spillover effects across the European conventional and environmental, social, and governance (ESG) financial markets via novel measures of physical and transitional climate risk proxies obtained from textual analysis. Analyzing daily data for stocks in the MSCI Europe ESG Leaders Index and various Euro based ESG bond indexes over the period January 3, 2014–September 30, 2021, we show that the shock transmissions between the conventional and ESG assets are significantly lower during periods of high climate uncertainty, suggesting that ESG investments can offer conventional investors diversification benefits against climate-driven shocks. Further comparing a forward-looking investment strategy conditional on the level of climate risk against the passive investment strategy, we show that investors who are worried about physical climate risks could utilize ESG equity sector portfolios as a diversification tool against physical climate uncertainty. In contrast, ESG bonds are found to be particularly useful in managing transition risk exposures that are associated with policy uncertainty and/or business transitions with respect to environmental policies. The findings have important implications regarding the role of climate uncertainty as a driver of informational spillovers across the conventional and ESG assets with important insights to manage climate risk exposures.

1. Introduction

A growing strand of the literature on climate finance documents that investors care about climate risk in their investments and asset valuations reflect investors' risk preferences towards climate risk exposures. Accordingly, a rapidly growing number of studies in the asset pricing literature highlight the importance of climate risk as a long-run risk factor (e.g. Bansal et al. (2017)), while more recent works document that climate risk exposure serves as a systematic driver of equity returns (e.g. Faccini et al. (2021), Bolton and Kacperczyk (2021), Bua et al. (2021) and Hsu et al. (2022)), bond returns (e.g. Painter (2020) and Huynh and Xia (2021)) as well as real estate pricing dynamics (e.g. Baldauf et al. (2020), Murfin and Spiegel (2020) and Bernstein et al. (2019)). Despite the growing evidence that climate risk poses significant challenges for economic growth prospects (e.g. Stern and Stern (2007)) and firm profitability (e.g. Pankratz et al. (2019) and Addoum et al. (2020)), how to manage climate uncertainty in conventional, passive

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portfolios held by typical investors is still understudied with several exceptions including Andersson et al. (2016) and Engle et al. (2020) who propose procedures to construct de-carbonized portfolios, while other recent works focus on the hedging effectiveness of green-labeled investments against climate exposures (e.g. Yousaf et al. (2022) and Cepni et al. (2022)).

In a recent survey that focuses on portfolio managers, directors, and investment analysts in Europe and the U.S., Krueger et al. (2020) document that investors tend to adopt a risk management approach when it comes to dealing with climate risk in their investments rather than divestment of high climate risk exposure assets in their portfolios. This approach, however, requires a better understanding of the interactions between the conventional investments and hedge assets that are to be used as instruments in climate risk hedging strategies. More importantly, one needs a better understanding of the role played by climate uncertainty as a driver of the information spillovers between the conventional and sustainable investments in order to devise effective diversification strategies against climate risk exposures. Against this background, this paper explores the role of climate uncertainty on the information transmissions across the European conventional stock market index and various ESG (Environmental, Social, and Governance) assets by utilizing novel measures of physical and transitional climate risks obtained from textual analysis. We then examine the hedging benefits of ESG investments for passive investors against climate uncertainty by proposing a forward-looking procedure that is conditional on high climate uncertainty market states. Our results show that supplementing conventional portfolios with ESG investments can indeed help manage portfolio risks against climate-driven shocks; however, it is essential that the investor differentiates between the physical and transition climate risk exposures in their portfolios as the effectiveness of the hedging scheme and the ESG asset to be utilized as a part of the strategy depends on the nature of climate risk managed.

In a recent study on U.S. stock returns, Faccini et al. (2021) provide some evidence that transition climate risk might be a dominant driver of stock returns. Utilizing separate proxies to capture physical and transition climate risks that relate to natural disasters, global warming, international summits, and U.S. climate policy, the authors show that only the U.S. climate policy factor is priced in the cross-section of stock returns, suggesting that the imminent risk of government intervention, rather than the direct risks from climate change, serves as a more dominant driver of stock market returns. Given these considerations, it is imperative that risk managers take into account the nature of the climate risk exposure of investment portfolios by distinguishing between the effects of physical and transition climate risks in their hedging strategies. We contribute to this emerging literature from a novel context by examining the effect of physical and transition climate risks on the transmission of shocks across the conventional and ESG assets via novel measures of physical and transitional climate risk proxies obtained from textual analysis. While our results show that ESG assets are generally less connected with their conventional counterparts during periods of high climate uncertainty, suggesting that ESG investments can offer conventional investors diversification benefits against climate-driven shocks, we also find that the type of ESG asset to be utilized as a hedge depends on the nature of climate risk that is managed in the portfolio. We show that investors who are worried about physical climate risks could utilize ESG equity sector portfolios as a diversification tool during periods of high physical climate uncertainty. Interestingly, however, ESG bonds are found to be particularly useful in managing transition risk exposures that are associated with policy uncertainty and/or business transitions with respect to environmental policies. Accordingly, while our findings show that ESG assets can be useful tools to manage climate risk exposures, not taking into account the nature of climate exposure in an investment portfolio could hurt the effectiveness of hedging strategies, consistent with the evidence in Faccini et al. (2021) that transition climate risk might be a dominant driver of stock returns compared to physical climate risk.

The findings of our paper have significant implications for the implementation of diversification models to manage climate risk exposures of conventional equity portfolios. Given that the nature of climate risk plays an important role in the transmission of shocks across the ESG and conventional assets, our findings suggest that any diversification strategy aimed to mitigate the negative effects of climate risk in a conventional equity portfolio should first measure the risk exposure of the portfolio with respect to each type of climate risk in terms of how the risk exposure relates to physical or transition related climate factors. Furthermore, our findings also imply that the type of asset to be used in such diversification strategies will depend on the nature of the climate risk to be managed. Finally, from an asset pricing perspective, our findings suggest that valuation models should distinguish between asset betas with respect to transition and physical climate risks in order to avoid pricing risk exposures that are in fact diversifiable in nature.

The remainder of the paper is organized as follows. Section 2 presents a brief review of the rapidly growing literature on green and sustainable finance. Sections 3 and 4 describe the data and the methodology utilized to measure the spillover effects between the conventional and ESG assets in the sample. Section 5 presents the empirical findings on the role of climate uncertainty as a determinant of connectedness patterns and the economic analysis. Section 6 concludes with a discussion of the findings and directions for future research.

2. Literature review

Growing importance of climate-related risks for the global economy and public awareness regarding the environmental and social impact of production and business processes across the world have led to a boom in climate friendly investments with the market value of green debt securities rising from less than \$40 billion in 2014 to over \$1 trillion in 2021 (Yousaf et al., 2022) as investors shifted part of their asset allocation to these investments (Krueger et al., 2020). Accordingly, the academic literature on green and sustainable finance has been growing rapidly with numerous papers examining ESG investments from various angles. The general consensus in the literature is that climate risk serves as a determinant of investment decisions by firms (Engle et al., 2020) and uncertainty regarding climate policy changes influences firms' decisions to reduce the carbon footprint of their business processes (Rodriguez Lopez et al., 2017), while the literature argues that climate risk can affect stock returns from two distinct channels. The first channel relates to the literature that establishes a link between time-varying disaster risks and investment growth (Gourio, 2012), consumption shocks (Wachter, 2013) and excess returns and volatility in the stock market (see, for example, Barro (2006), Berkman et al. (2011) and Wachter (2013)). This type of climate risk belongs to the broader physical climate risk which in turn materializes in a physical form wherein either extreme weather events, e.g. floods/heat waves, or climate chronic hazards, e.g. rising sea levels/droughts, incur financial losses for the firm (Cepni et al., 2022) with widespread effects on the cross-section of the economy regardless of energy intensity in firms' operations and despite the firms' adaptation or coping ability. In a study that focuses on disaster events not only limited to physical climate risks, Berkman et al. (2011) show that this form of disaster risk is priced in the cross-section of stock returns, implied by higher returns observed for industries that are more crisis risk-sensitive. In contrast, the second channel that links climate risk to stock market dynamics deals more with the transitionary aspects of climate change on the economy and consequently on business profitability. The so-called transition climate risk channel is typically prompted by changes in climate-related policies, shift in public preferences, and technological advances, and materializes in additional costs for firms as they adjust their operations to align with the transition' aim to achieve a greener, de-carbonized, and climate-neutral economy (Bua et al., 2021). This form of climate uncertainty affects firms that operate in relatively more energy-intensive industries as these firms de-carbonize their production processes to comply with the new regulations. The U.S. (Financial Stability Oversight Council, 2021) provide the following definitions of the two types of climate-related financial risks:

"Physical risks refer to the harm to people and property arising from acute, climate-related disaster events such as hurricanes, wildfires, floods, and heatwaves as well as longer-term chronic phenomena such as higher average temperatures, changes in precipitation patterns, sea-level rise, and ocean acidification... Transition risks refer to stresses to certain institutions or sectors arising from the shifts in policy, consumer and business sentiment, or technologies associated with the changes necessary to limit climate change".

Given these aforementioned considerations, separate strands of the emerging literature on climate finance has focused on the management of climate risks by financial firms and supervisors (see Breitenstein et al. (2021) for a review), the role of climate uncertainty in macroeconomic models (see Giglio et al. (2021) for a review) and the pricing of financial assets (see Venturini (2022) and Campiglio et al. (2022) for a review). One of the most heavily researched topics in this strand of the literature, however, is the investment implications of green and sustainable investments and how climate related risks drive return and volatility dynamics in these assets. Of particular focus in this literature has been the risk and return transmissions across the conventional and ESG assets and how these transmissions relate to the diversification or hedging effectiveness of these assets for conventional portfolios. In a popularly cited study in this emerging literature, Reboredo (2018) provides the initial evidence of strong linkages among the green, corporate and treasury bond markets, while green bonds are found to be somewhat weakly connected to equity assets including their green counterparts and energy assets, suggesting that these assets can offer diversification benefits for investors in the energy and stock markets. This finding is later supported by various studies that suggest green bonds would not only be considered an effective and inexpensive hedge for carbon risk (Jin et al., 2020), but can also serve as a potential diversifier for conventional stock and commodity portfolios (e.g. Nguyen et al. (2021)). Extending these works to a dynamic context, Broadstock and Cheng (2019) show that the linkage between the green and brown assets is in fact time-varying and significantly affected by various factors including financial market volatility, uncertainty, and economic activity. While Reboredo et al. (2020) document that the connectedness of green bonds and conventional assets vary over the short and long runs, other studies document asymmetries in the transmission of risks across these markets with respect to the direction of the market (e.g. Naeem et al. (2021); Ferrer et al. (2021)).

Despite the multitude of studies that explore the linkages between green/sustainable assets and their conventional counterparts from various angles and using different methodologies including wavelets (Nguyen et al., 2021; Reboredo et al., 2020) or copulas (Reboredo, 2018), the evidence regarding the effectiveness of these assets as a hedge or diversifier against market uncertainty still remains uncertain. While the evidence in Pástor and Vorsatz (2020) and Albuquerque et al. (2020) suggests that environmental and social investments have been quite resilient during periods of rising uncertainty, there is ample evidence in the literature suggesting that green bonds tend to offer inferior risk-adjusted returns for investors (Pham, 2016; Hachenberg and Schiereck, 2018; Bachelet et al., 2019), while others show that green focused mutual funds yield similar returns as conventional funds, but with lower risk (e.g. Climent and Soriano (2011)). Indeed, in a critical review of these assets, Cornell (2021) argues that while ESG investing remains popular due to its social benefits, higher expected returns are not among them. Clearly, the effectiveness of green and sustainable investments as a viable diversification tool for conventional portfolios is of high importance, particularly considering the evidence that climate concerns play a significant role in the pricing and trading decisions of investors (Bolton and Kacperczyk, 2021; Hsu et al., 2022) and that the nature of climate uncertainty in the form of transition or physical risks can be a factor in how climate risk exposure is priced by investors (Faccini et al., 2021; Bua et al., 2021).

The main contribution of our study is to extend the emerging literature on green and sustainable finance in a novel direction by exploring the separate roles of physical and transition climate risks as a determinant of the linkages between the ESG and conventional asset markets. Specifically, we explore whether climate uncertainty plays a significant role in the transmission of shocks across the two markets and if yes, whether the nature of climate uncertainty with respect to physical or transition risk is a factor in the transmission mechanism. Although this issue is largely unexplored in the existing literature it is of high importance for portfolio decisions as the diversification or hedging benefits of ESG assets for conventional investments depend on strength of shock transmissions, particularly during periods of high uncertainty. As a second novelty, we examine the hedging and diversification benefits of ESG assets for conventional investments against each type of climate uncertainty, which is an important consideration for not only the pricing of these assets, but also for their utilization in practical portfolio applications. Specifically, we explore whether certain ESG assets provide superior diversification benefits during high uncertainty periods and unlike the existing studies in the literature, we create industry-based ESG equity portfolios and compare the diversification benefits of ESG industry portfolios during periods of high physical and transition climate risks. To the best of our knowledge, ours is the first in the literature to provide a comparative analysis of industry-based ESG portfolios with respect to the nature of climate risk.

Table 1
Summary statistics.

	Mean	Median	Max	Min	Std.Dev.	Skewness	Kurtosis	JB	ADF
ESG stock returns									
Comm. Services	−0.011	0.012	6.612	−11.773	1.053	11.540	−0.858	0.000	−30.76***
Consumer Discr.	0.030	0.054	9.218	−12.839	1.218	11.806	−0.475	0.000	−29.35***
Consumer Staples	0.024	0.021	6.724	−7.533	0.915	5.497	−0.167	0.000	−32.01***
Energy	0.010	0.055	12.817	−17.096	1.621	16.692	−0.769	0.000	−29.53***
Financials	0.008	0.042	11.876	−16.243	1.466	18.625	−1.142	0.000	−29.29***
Health Care	0.043	0.062	5.390	−8.641	1.032	3.890	−0.397	0.000	−31.50***
Industrials	0.051	0.097	9.607	−11.484	1.141	10.341	−0.713	0.000	−31.47***
Information Tech.	0.082	0.115	10.204	−9.344	1.523	4.310	−0.293	0.000	−31.74***
Materials	0.038	0.081	6.715	−11.074	1.096	8.087	−0.849	0.000	−30.85***
Real Estate	0.025	0.044	7.204	−16.476	1.174	22.919	−1.623	0.000	−30.31***
ESG bond returns									
Sovereign	−0.001	0.008	7.936	−2.668	0.451	51.631	2.521	0.000	−32.24***
Corporate	0.011	0.018	0.967	−2.231	0.146	35.639	−2.571	0.000	−16.88***
Climate risk indexes									
Physical risk	0.007	0.005	0.133	−0.053	0.020	2.239	0.896	0.000	−48.76***
Transition risk	0.006	0.004	0.148	−0.082	0.021	3.564	0.929	0.000	−47.05***

Note: * denotes 5% significance level; JB stands for the *p*-value of the Jarque–Bera test for normality and ADF stands for the Augmented Dickey Fuller unit root tests.

3. Data

Our data set consists of 192 member companies of the MSCI Europe ESG Leaders Index, which is a weighted average index consisting of firms with high Environmental, Social, and Governance (ESG) performance relative to their sector peers. The index consists of mid- and large-cap companies across 15 countries in Europe, offering a diversified sustainability benchmark for investors who focus on European stocks.[1] Considering that the typical assignment of financial analysts takes place at the industry level and many business managers make recommendations at the sector level (Demirer et al., 2010) in addition to the argument by Choi and Sias (2009) that investors may receive signals about a given firm based on information available regarding other firms in the same industry, we examine the role of climate uncertainty by focusing on industry portfolios comprised of ESG leaders. The industry focus also allows us to examine the time variation in industry betas in response to climate uncertainty in our subsequent analysis. To that end, using the weight and sector information of the 192 companies in the sample, we construct the sector-specific ESG Leaders indexes for Communication Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, and Real Estate. Furthermore, in addition to the ESG stock portfolios, we also collect data for the Solactive ISS ESG Screened Euro IG Corporate Bond Index, tracking the performance of EUR denominated corporate bond market with eligible issuers operating by market standards on ESG, as well as the S&P ESG Pan-Europe Developed Sovereign Bond Index, which extends the sample of ESG assets to sovereign bonds.[2] Our empirical analysis is based on daily returns computed by log-differencing the daily closing prices of each index.

Physical and transition climate risk data is sourced from Bua et al. (2021). These indexes are obtained from textual analysis of *Reuters News* that is widely used by financial investors to update their investment decisions. Compiling a list of authoritative and scientific texts on climate change published by governmental authorities and other institutions, Bua et al. (2021) first filter the content associated with physical and transition risk. Next, comparing the filtered content with the corpus of European daily news via the cosine-similarity approach of Engle et al. (2020), they generate physical and transition concern series representing the percentage of news coverage dedicated to each type of risk. Finally, the authors use the residuals from an autoregressive model of order 1 of the concerned series to construct the Physical Risk Index (PRI) and the Transition Risk Index (TRI) that represent the two aspects of climate risk. Based on the ESG sector data availability, our daily data spans the period January 3, 2014–September 30, 2021, obtained from the Bloomberg terminal. Examining the descriptive statistics reported in Table 1, we observe positive average daily returns for all ESG equity sectors except communication services. Not surprisingly, the IT sector experiences the highest average return coupled with the highest return volatility while ESG bonds experience lower return volatility compared to the equity investments. Interestingly, the kurtosis statistic is found to be negative for all ESG equity sectors, implying that these series have thinner tails than the normal distribution, indicating that ESG sector returns do not experience extreme returns relative to what one would expect from a normal distribution. The Jarque–Bera statistic rejects the null hypothesis of normality for all series. Finally, the ADF statistic shows that all return series are stationary.

[1] The countries include Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the UK.

[2] The index weights of the countries are based on their ESG scores.

4. Methodology

4.1. Climate risk and the connectedness between ESG and conventional assets

To identify the role of climate risk on the information transmissions between conventional and ESG investments, our empirical approach consists of two steps. First, we estimate a dynamic connectedness network based on the generalized forecast error decomposition of a time-varying vector auto-regression (TVP-VAR) model. Next, using quantile regression models, we analyze how climate risks influence the estimated connectedness series between conventional stock markets and ESG investments. To estimate the time-varying connectedness measures, we adopt the TVP-VAR spillover network approach of Antonakakis et al. (2020) and estimate the following TVP-VAR model[3]:

$$\boldsymbol{y}_t = \boldsymbol{B}_t \boldsymbol{z}_{t-1} + \boldsymbol{u}_t \qquad \boldsymbol{u}_t, \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{1}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t, \qquad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{R}_t) \tag{2}$$

where $\boldsymbol{y}_t$ is a vector of ESG and conventional assets, as listed in Table 1. $\boldsymbol{z}_{t-1}$ is a matrix of the lagged values of $\boldsymbol{y}_t$, with the optimal lag length determined by the Bayesian information criterion (BIC). $\boldsymbol{B}_t$ is a matrix of the time-varying coefficients, which follows a random walk process. $\boldsymbol{u}_t$ and $\boldsymbol{v}_t$ denote the error terms, while $\boldsymbol{S}_t$ and $\boldsymbol{R}_t$ denote their corresponding variance–covariance matrices.[4]

From the TVP-VAR model, we compute the H-step ahead generalized forecast error variance decomposition (GFEVD), which is independent of the variable ordering (Koop et al. (1996) and Pesaran and Shin (1998)). To this end, we rewrite the TVP-VAR as a vector moving average (VMA) process utilizing the following equation: $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{B}_{it} \boldsymbol{z}_{t-i} + \boldsymbol{u}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{jt} \boldsymbol{u}_{t-j}$. Considering that cross-variable and own variance shares do not necessarily add up to one, the (unscaled) GFEVD, $\phi^g_{ij,t}(H)$, is normalized so that, the (scaled) GFEVD, $\tilde{\phi}^g_{ij,t}(H)$, shows the effect of variable j has on variable i, which is defined as the share of the forecast error variance in variable i explained by variable j. These GFEVD measures are then given by,

$$\phi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\iota_i' \boldsymbol{A}_t \boldsymbol{S}_t \iota_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\iota_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{A}_t' \iota_i)} \qquad \tilde{\phi}^g_{ij,t}(H) = \frac{\phi^g_{ij,t}(H)}{\sum_{j=1}^{k} \phi^g_{ij,t}(H)}$$

where $\sum_{j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = k$, and ι_i corresponds to a selection vector with unity on the ith position and zero otherwise. $\tilde{\phi}^g_{ij,t}(H)$ captures the amount of forecast error variance in variable i that comes from variable j, thereby indicating the directional spillover from variable j to variable i.

Using the normalized GFEVD $\tilde{\phi}^g_{ij,t}(H)$, we can compute several spillover indexes to capture the overall dependence structure among all the variables:

$$TO_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^g_{ij,t}(H) \tag{3}$$

$$FROM_{jt} = \sum_{i=1, i\neq j}^{k} \tilde{\phi}^g_{ji,t}(H) \tag{4}$$

$$NET_{jt} = TO_{jt} - FROM_{jt} \tag{5}$$

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} \equiv k^{-1} \sum_{j=1}^{k} FROM_{jt}. \tag{6}$$

$$NPDC_{ij,t} = \tilde{\phi}^g_{ij,t}(H) - \tilde{\phi}^g_{ji,t}(H) \tag{7}$$

$$PCI_{ij,t} = 2 * \frac{\tilde{\phi}^g_{ij,t}(H) + \tilde{\phi}^g_{ji,t}(H)}{\tilde{\phi}^g_{ij,t}(H) + \tilde{\phi}^g_{ji,t}(H) + \tilde{\phi}^g_{ii,t}(H) + \tilde{\phi}^g_{jj,t}(H)} \tag{8}$$

where $\tilde{\phi}^g_{ij,t}(H)$ represents the effect of a shock in variable j has on variable i. Eq. (3) illustrates the overall impact of a shock in variable j has on all *other* variables which is defined as *total directional connectedness to others* whereas Eq. (4) indicates the aggregated influence all *other* variables have on variable j (*total directional connectedness from others*). Eq. (5) subtracts the influence of variable j has on others by the influence *others* have on variable j, giving us the *net total directional connectedness*. Positive net spillovers indicate a variable is a net transmitter of shocks while negative values indicate a variable is a net receiver of shocks. Eq. (6) represents the TCI_t, which indicates the average effect of one variable on all *others*. Higher values of this measure implies that the network becomes more connected, implying that a shock in one variable will have larger impact on others. Eq. (7) defines *net pairwise directional connectedness* ($NPDC_{ij,t}$). A positive (negative) value indicates variable $j(i)$ is driving variable $i(j)$. Finally,

[3] This approach is an extension of the Diebold and Yılmaz (2012, 2014) connectedness model, which has been extensively used in previous research on market spillovers. This method overcomes the burden of the arbitrarily chosen rolling window sizes (which could lead to erratic or flattened parameters) and avoids the loss of valuable observations.

[4] Following Antonakakis et al. (2020), we estimate the TVP-VAR model using the Kalman filter with the Primiceri (2005) and Del Negro and Primiceri (2015) priors and forgetting factors of 0.99. Our results are qualitatively similar when we consider other forgetting factors between 0.96 and 0.99.

Eq. (8) measures the *pairwise connectedness index* between variables i and j, where a higher PCI indicates a higher degree of shock exchange between the two variables.

Having generated the connectedness series following the procedure outlined above, in the second step, we examine the impact of climate uncertainty on the spillover effects across the conventional and ESG assets. The rationale behind the analysis is partially motivated by the growing evidence that climate uncertainty concerns serve as a systematic driver of equity market returns[5] and environmental and social investments have been quite resilient even during periods of higher market uncertainty.[6] Accordingly, one can expect the shock transmissions across the conventional and ESG assets to be less pronounced during periods of high climate uncertainty as investors will be more likely to hold steady on their ESG asset positions during such periods, thus dampening the spillover effects that could be emanating from conventional asset markets. Clearly, if this is indeed the case, the case for ESG investments as a diversification tool against climate uncertainty will strengthen as these investments would be relatively immune from climate driven market shocks. To empirically examine these arguments, we utilize quantile regressions in the form:

$$PCI_{i,STOXX,t}(\tau) = \beta_0(\tau) + \beta_1(\tau)ClimateRisk_t + e_t \tag{9}$$

where $PCI_{i,STOXX,t}$ denotes the pairwise connectedness index between the conventional stock index (STOXX 50) and ESG asset i, τ refers to the connectedness quantile and e_t is the robust error term. As opposed to standard linear regressions that show an average relationship between the dependent and independent variables, quantile regressions allow us to examine the role of climate risk at the high and low spillover states, thus providing a more complete picture of the climate risk effects on information spillovers. Note that, in our application, we alternatively use the physical and transition climate risk series for $ClimateRisk$ in order to capture climate uncertainty from different dimensions and these uncertainty series are used one at a time in the quantile regression model to avoid possible multi-collinearity. For further robustness checks, we include several financial and macroeconomic variables including stock market volatility, economic policy uncertainty, gold market volatility, euro currency rate volatility and month/year time dummies. In addition, we also use the climate physical and transition concern series of Bua et al. (2021), which are based on the percentage of daily news related to climate physical and transition concerns, as alternative measures of climate uncertainty. Although not reported to save space, our conclusions are qualitatively similar across the alternative specifications (available upon request).

4.2. Economic analysis

4.2.1. Asymmetric dynamic conditional correlation (ADCC) model

We examine the economic implications of our analysis by first estimating the dynamic correlations between the conventional stock market index and each ESG asset and next constructing a forward looking investment strategy that utilizes ESG assets as a hedging instrument against climate uncertainty. Kroner and Ng (1998) suggest that if the expected return on one asset changes owing to an asymmetric volatility impact, the correlation between that asset's returns and other assets' returns should likewise vary. There is a compelling economic argument for the requirement that one must take into consideration the asymmetric impact on conditional second moments. The conditional volatility that is projected to occur following a price decline will be far lower than expected. In a similar vein, the conditional volatility that is predicted to accompany a rise in price will be too high. The leverage effect theory, which was developed by Black (1976) and Christie (1982), and the volatility feedback effect, which was presented by Campbell and Hentschel (1992) are the two hypotheses that have been put forth as potential explanations for this asymmetric impact. Motivated by these studies, we assume a passive investor who is currently invested in the conventional stock market index proxied by STOXX 50 and then employ the ADCC model suggested by Cappiello et al. (2006) to estimate jointly the time-varying correlations between the returns on the STOXX 50 index and each ESG asset (i.e. sector-specific ESG Leaders indexes, ESG Corporate Bond Index, and ESG Sovereign Bond Index). Specifically, we specify the following mean equation on the information set I_{t-1} :

$$r_t = \mu + \psi r_{t-1} + \varepsilon_t \tag{10}$$

where r_t is the $\mathrm{n} \times 1$ vector of returns. We denote the residuals by $\varepsilon_t = \mathrm{H}_t^{1/2}\mathrm{z}_t$ where H_t is the conditional covariance matrix of r_t and z_t is a $\mathrm{n} \times 1$ vector of i.i.d errors. H_t can be rewritten as:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{11}$$

where $D_t = \mathrm{diag}\left(h_{i,t}, \ldots, h_{n,t}\right)$ defined as the diagonal conditional variances. The conditional correlation matrix R_t can be shown as:

$$\mathrm{R_t} = \mathrm{diag}\left(q_{1,t}^{-1/2}, \ldots, q_{n,t}^{-1/2}\right) \mathrm{Q_t}\, \mathrm{diag}\left(q_{1,t}^{-1/2}, \ldots, q_{n,t}^{-1/2}\right) \tag{12}$$

[5] For example, Bolton and Kacperczyk (2021) provide evidence of a carbon premium in the stock markets. Choi et al. (2020) find that stocks of carbon-intensive firms underperform firms with low carbon emission in abnormally warm weather and the return patterns are unlikely to be driven by changes in fundamentals. Pástor et al. (2022) find that news about environmental concerns increase the realized returns on green assets and that these returns are unexpected, reflecting news about environmental concerns rather than high expected returns.

[6] For example, Albuquerque et al. (2020) find that stocks with higher environmental/social (ES) ratings have significantly higher returns, lower return volatility, and higher operating profit margins during the beginning phase of the COVID-19 pandemic. ES firms with higher advertising expenditures had higher stock returns, and stocks held by more ES-oriented investors exhibit smaller volatility during the COVID-19 crash.

where Q_t is a symmetric positive definite matrix with $\mathrm{Q_t} = \left(1 - \theta_1 - \theta_2\right)\overline{\mathrm{Q}} + \theta_1 \mathrm{z_{t-1}} \mathrm{z'_{t-1}} + \theta_2 \mathrm{Q_{t-1}}$ and $\overline{\mathrm{Q}}$ represents the $\mathrm{n{\times}n}$ unconditional matrix of the standardized residuals $\mathrm{z_{i,t}}$. θ_1 and θ_2 are non-negative satisfying the condition $\theta_1 + \theta_2 < 1$. The correlation estimator is then formulated as:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}} \tag{13}$$

Cappiello et al. (2006) modify the symmetric DCC model of Engle (2002) with additional terms that capture the asymmetric effect of positive and negative shocks on volatility by modifying the conditional volatility model as:

$$h_{i,t} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{i,t-1} + \gamma_i \varepsilon_{i,t-1}^2 I\left(\varepsilon_{i,t-1}\right) \tag{14}$$

where the indicator function $I_{t-1} = 1$ if $\varepsilon_{i,t-1} < 0$ otherwise $I_{t-1} = 0$. Thus, a positive value for d implies that positive shocks tend to increase volatility less than negative shocks, capturing the "*asymmetric*" effect. The dynamics of Q_t in the asymmetric ADCC model is then defined as:

$$Q_t = \left(\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{Q} - G\right) + A' z_{t-1} z'_{t-1} A + B' Q_{t-1} B + G' z_t^- z_t'^- G \tag{15}$$

where z_t^- is the zero-threshold standardized errors with an unconditional matrix $\bar{Q}^-$ and A, B and G are $\mathrm{n} \times \mathrm{n}$ parameter matrices.[7]

4.2.2. Portfolio analysis

Having estimated the time-varying correlations between the conventional stock market index and each ESG asset, we next implement the optimal portfolio weight approach of Kroner and Ng (1998) to compute optimal portfolio weights for each ESG asset in a forward-looking manner. Assuming a passive stock market investor who is currently invested in the stock market index represented by STOXX 50, we use the conditional volatility and co-variance estimates obtained from the ADCC model in Eq. (16) to determine the optimal portfolio allocation for the conventional stock market index (x) and each ESG asset (y) as

$$w_t^{x/y} = \frac{h_t^y - h_t^{x/y}}{h_t^x - 2h_t^{x/y} + h_t^y}, \qquad w_t^{x/y} = \begin{cases} 0, \text{ if } w_t^{x/y} < 0 \\ w_t^{x/y}, \text{ if } 0 \le w_t^{x/y} \le 1 \\ 1, \text{ if } w_t^{x/y} > 1 \end{cases} \tag{16}$$

where $h_t^{x/y}$ denotes the conditional covariance between x and y and $w_t^{x/y}$ is the weight of asset x in a one-dollar portfolio of the two assets (x, y) at time t, while the portfolio allocation to the ESG asset is $1 - w_t^{x/y}$. When comparing the optimal portfolio to the passive portfolio, we track the percent reduction in the variance of the optimal portfolio using the formula:

$$HE = \left[\frac{\text{Variance}_{\text{passive}} - \text{Variance}_{\text{hedged}}}{\text{Variance}_{\text{passive}}}\right] \tag{17}$$

where $Variance_{hedged}$ and $Variance_{passive}$ indicate the variance of the hedged and passive portfolios, respectively. A higher value of HE implies a greater risk reduction provided by the hedge portfolio. Finally, the Sharpe ratio, defined as the ratio of the excess return on the portfolio to its standard deviation, is used to evaluate the risk-adjusted performance of the hedging strategy.[8]

Furthermore, we calculate the Information Ratio (IR), which allows us to compare different investment strategies by standardizing the returns. The Sharpe ratio and the information ratio are pretty comparable; nevertheless, the key distinction between them is that the Sharpe ratio uses the risk-free rate as its benchmark, while the information ratio uses the expected return as a benchmark. To put it another way, the information ratio measures the risk-adjusted return compared to the benchmark return. IR is computed using the formula:

$$IR = (HPR - BR)/TE \tag{18}$$

where HPR denotes the hedged portfolio return and similarly BR represents our benchmark STOXX 50 index return. TE is the tracking error computed as the standard deviation of the difference between STOXX 50 and the hedged portfolio returns.

5. Empirical results

5.1. Connectedness between the conventional and ESG investments

Fig. 1 presents the time-varying total connectedness index that captures the overall spillover effects across all the assets in the sample. The total connectedness estimates range between 65% and 88%, implying significant spillover effects across the conventional and ESG investments. This is not unexpected as the stocks included in the ESG category are subject to common systematic drivers

[7] Due to a high number of estimated parameters, we prefer not to present ADCC parameter estimates in the paper. However, the results are available on request from the authors.

[8] Our analysis is based on the in-sample calculation of portfolio weights and hedge ratios. As suggested by Basher and Sadorsky (2016) and Michańków et al. (2022), even though in-sample analysis helps determine how well a model fits the data, it might not be the most appropriate strategy to choose if a hedger is more concerned with how well a hedge performed outside of the testing period. In this case, using a rolling window analysis to estimate out-of-sample one-step-ahead forecasts of dynamic conditional correlations might be a better strategy. We left this exercise as future research.

Fig. 1. Time-varying total connectedness. Note: The figure shows the rolling total connectedness across quantiles. The x-axis indicates time while the y-axis indicates the spillover values.

as those listed in the conventional index. Examining the time variation in the series, we observe several episodes of a rising trend in the total connectedness estimates, most notably in 2014–2016 and later during the COVID-19 pandemic period in early 2020. The 2014–2016 period is characterized by highly volatile oil prices, during which oil prices dropped from a peak of $115 per barrel in June 2014 to $35 per barrel in February 2016. Moreover, this period coincides with the adoption of the Paris Climate Agreement by 196 countries at the end of 2015, which signaled an increase in the commitment of policymakers and other stakeholders to mitigate the impact of climate change. Likewise, we observe a similar rising trend in the total connectedness series at the beginning of 2018, which coincides with the release of the EU Commission Sustainable Finance Strategy.[9] It can thus be argued that uncertainty regarding climate policies has had a significant impact on the information spillovers across the ESG and conventional assets. These results echo the results in previous research, which find a significant impact of climate policies on environmentally friendly stock markets. For example, Fahmy (2022) shows an asymmetric impact of technology stock prices on clean energy stock prices during the post-Paris Agreement period. Antoniuk and Leirvik (2021) show that climate change policy events significantly impacted returns. Specifically, the Paris Agreement, Climategate, and Fukushima benefit the clean energy sector, while weakening climate change policy benefit the fossil fuel sectors. Finally, another surge in the total connectedness index is observed at the beginning of 2020 during the early phase of the COVID-19 pandemic, driven by rising concerns over contagion effects in the global financial markets. The increasing contagion during this period is consistent with the results of many recent studies, for example, Akyildirim et al. (2022), Pham and Do (2022) and Liu et al. (2022).

Fig. 2 displays the pairwise connectedness network among the variables throughout the entire sampling period. The arrows show the directions of spillovers between two variables, while the thickness of the edges shows the strength of the spillovers proxied by the sum of the directional spillovers between the variables. The red (blue) nodes indicate that an asset is a net shock transmitter (receiver) and the size of the nodes indicates the magnitude of the net spillovers. Not surprisingly, the conventional stock market index (proxied by the STOXX index) is the largest net shock transmitter as the aggregate market index reflects a broad spectrum of market uncertainties over and above those that are associated with environmental-, social-, and governance-related drivers of firm returns. This is also consistent with the fact that the STOXX index captures the movements of the overall equity market, while other indexes capture the movements of the ESG sub-sectors that are also a part of the aggregate stock market index. Interestingly, we find that the Corporate and Sovereign ESG bond indexes are strongly connected with each other, while, these assets, on average, are not connected to the other equity indexes in the model. Clearly, this is good news for the hedging role of ESG bonds for equity investments, consistent with the previous findings in the literature of weak connectedness between ESG bonds and the equity markets (e.g., Reboredo and Ugolini (2020), Reboredo et al. (2020)).

Figure A1 in the Appendix presents the time-varying directional connectedness estimates that capture the pairwise spillover effects between the conventional stock market index and each ESG asset. We observe that the conventional stock market index transmits more shocks to each ESG asset than the amount of shocks transmitted in the opposite direction, indicated by the orange lines that lie above the green lines in the plots. This means that the conventional stock market index generally drives the fluctuations in the ESG markets, which is consistent with our inferences in Fig. 2. We also observe that the orange and green lines in the graphs

[9] See https://ec.europa.eu/info/publications/sustainable-finance-renewed-strategy_en for more details.

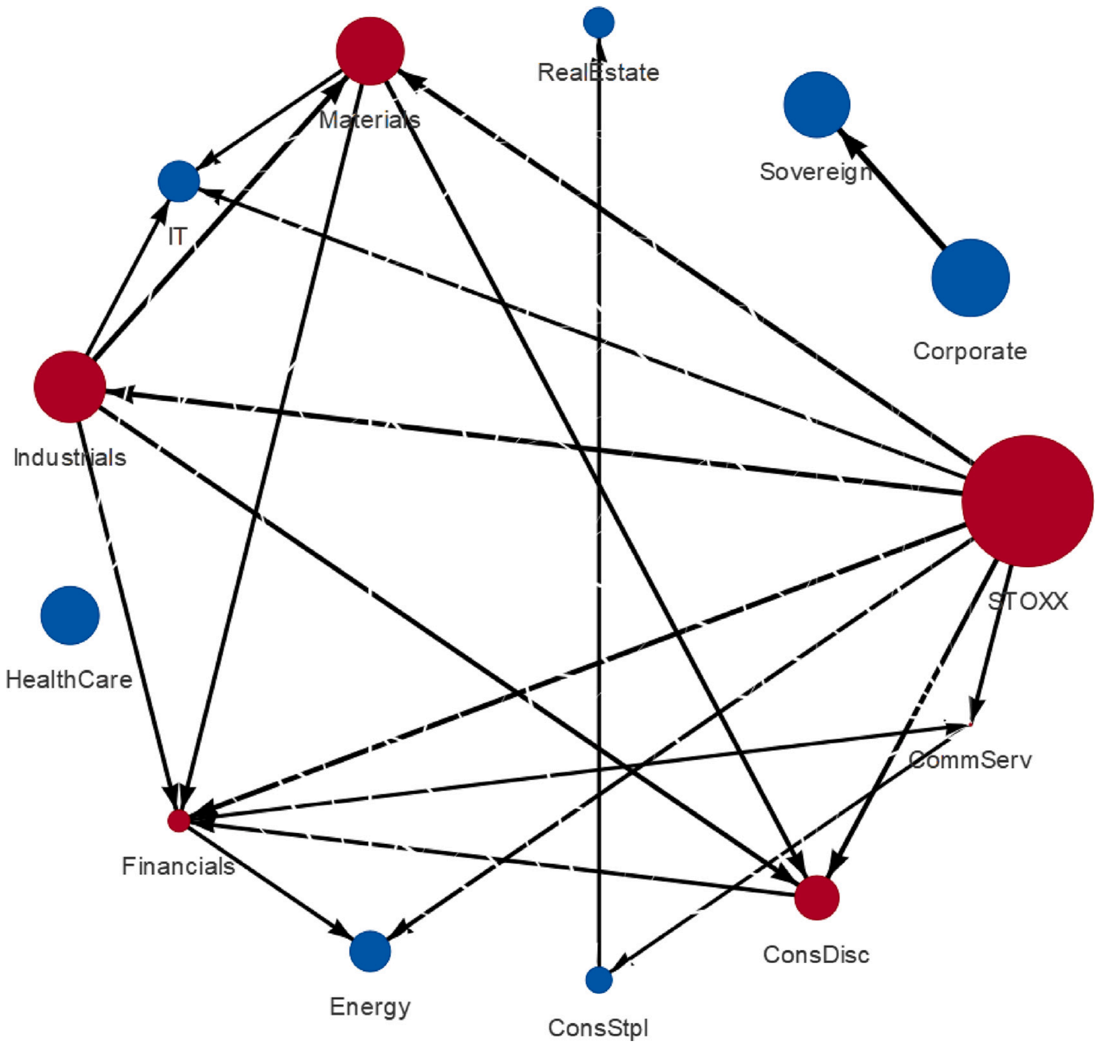

Fig. 2. Pairwise connectedness network. Note: The figure shows the average connectedness network among the conventional stock market index (STOXX 50 index) and various ESG investments. Red nodes indicate an asset is a net shock transmitter, while blue nodes indicate an asset is a net shock receiver. The size of the nodes captures the size of the net spillovers. The arrows show the directions of spillovers between two variables, while the thickness of the edges show the strength of the spillovers between two variables, which is proxied by the sum of the directional spillovers between the variables. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

tend to move in the same direction, indicating that directional spillovers from ESG markets to conventional stock markets generally co-move with the directional spillovers in the opposite direction. This implies the presence of common fundamental factors driving information spillovers in both directions. However, the spillover effects between each pair of assets do not change at the same rate, indicated by the gap between the green and orange lines in Figure A1 fluctuating over time. This pattern is more evident in the plot of net pairwise spillovers reported in Figure A2. While Energy, Information Technology, and Health Care sectors generally experience stronger information spillovers with the conventional stock market index, Industrials and Materials sectors are relatively less affected by the information transmissions. Most ESG equity sectors experience declines in the spillover effects from the conventional index during 2014–2016, with the exception of the ESG Energy equities and Sovereign/Corporate bonds. While the net connectedness between the Energy sub-sector and conventional stock market partly reflects the increasing contagion between energy prices and stock markets during this period, the rise in the spillover effects for bonds could be driven by the aftermath of the European debt crisis, thereby increasing the variability in the connectedness between the ESG fixed income markets and the conventional stock market. Similarly, most ESG sectors experience a gradual increase in the net pairwise connectedness with the conventional stock market index starting with the onset of the COVID-19 pandemic in early 2020, possibly due to rising concerns over the global economy and increasing risk aversion across market participants. In contrast, ESG bond markets experience an opposite pattern with a decline in the spillover effects during this period, consistent with the recent findings that green bonds and low-carbon stock returns move in the opposite direction or independently from conventional equities (for example, Reboredo et al. (2022), Cepni et al. (2022), Arif et al. (2022)).

Table 2
The impact of climate uncertainty on the pairwise connectedness between conventional stocks and ESG assets.

Dependent variable: Pairwise connectedness index						
Quantiles	Physical risks			Transition risks		
	5	50	95	5	50	95
	(1)	(2)	(3)	(4)	(5)	(6)
Communication Services	−0.115	−0.999***	−0.165	0.185*	−0.204	0.0501
	(−0.62)	(−6.11)	(−1.55)	(2.31)	(−1.48)	(1.02)
Consumer Discretionary	−0.115	−0.194*	−0.109	0.160	0.103*	−0.0303
	(−0.72)	(−2.54)	(−1.37)	(1.70)	(2.06)	(−0.33)
Consumer Staples	−1.423***	−1.065***	−0.121	1.035*	−0.270	0.0130
	(−4.10)	(−5.60)	(−0.44)	(2.36)	(−1.82)	(0.09)
Energy	−0.242*	−1.311***	−0.191***	−0.0336	−0.850***	−0.0265
	(−2.29)	(−11.48)	(−6.53)	(−0.33)	(−3.64)	(−0.28)
Financials	−0.400	−0.596***	−0.279***	0.206	−0.322**	−0.0695
	(−1.31)	(−7.38)	(−5.42)	(1.33)	(−3.19)	(−1.67)
Health Care	0.0311	−1.522***	−0.458***	0.0395	−0.0834	−0.0311
	(0.25)	(−6.08)	(−3.39)	(0.29)	(−0.30)	(−0.24)
Industrials	0.0338	−0.201***	−0.111**	0.0389	0.0215	−0.0719
	(1.07)	(−4.86)	(−2.84)	(0.84)	(0.59)	(−1.42)
Information Tech.	2.249***	0.0442	−0.259**	0.160	0.264*	−0.109
	(4.40)	(0.36)	(−2.69)	(0.29)	(2.44)	(−0.99)
Materials	0.00493	−0.111**	−0.186***	0.151*	0.0360	−0.0591
	(0.07)	(−2.72)	(−4.12)	(1.99)	(1.17)	(−1.03)
Real Estate	−0.365	−2.751***	−0.228	−0.445	−1.154*	0.0159
	(−1.42)	(−5.82)	(−1.93)	(−1.70)	(−2.27)	(0.19)
Sovereign	−0.00583	−0.555***	−0.813***	−0.0123*	−0.132	−0.220
	(−0.98)	(−6.39)	(−3.46)	(−2.32)	(−1.03)	(−1.30)
Corporate	−0.102*	−0.426***	−1.540**	0.160***	0.109	−0.950
	(−2.35)	(−4.67)	(−2.75)	(4.31)	(1.19)	(−1.52)

*, **, ***: Significant at 10, 5, 1% levels. t-statistics are in parentheses.
The pairwise connectedness index is defined in Eq. (8).

5.2. *Does climate uncertainty drive information spillovers between the conventional and ESG assets?*

In this section, we explore the role of climate risks on the pairwise connectedness between ESG investments and conventional stock markets via quantile regressions described in Section 4.1. Table 2 presents the estimated models based on the physical and transition climate risk series used as explanatory variables. Consistent with our visual inferences from the time-series plots for the connectedness series, we observe that climate uncertainty indeed has a significant effect on the information spillovers across the conventional and ESG markets. We find in general, that higher climate uncertainty makes the ESG markets less connected to the conventional stock market index, consistently across the different quantiles of connectedness and ESG equity sectors and bonds. This is good news from a diversification perspective as dampened shock transmissions across the ESG and conventional investments, particularly during periods of high climate uncertainty, will allow conventional, passive investors to find diversification or hedging benefits through ESG assets. However, we also observe that the effect of climate uncertainty depends on the type of climate risk, with stronger effects observed in the case of physical climate risk rather than transition risks. This implies that the performance of the ESG asset as a tool to hedge against climate uncertainty will depend on the type of climate exposure of the investor's portfolio, highlighting the importance of separating the physical and transition climate risk exposures of investment positions.

To further illustrate this point, we compute the time-varying betas between the aggregate market index (STOXX 50) and each ESG asset using time-varying correlations derived from the ADCC model described earlier in Section 4.2.1. Fig. 3 reports the plots for the time-varying ESG betas with respect to the aggregate stock market index captured by the STOXX 50 index. In line with the observations for the connectedness estimates, the time-varying betas generally follow an increasing trend for most sectors (except for Sovereign ESG bonds) around early 2020, which coincides with the outbreak of the COVID-19 pandemic. The estimated beta series reach their peaks in nearly all markets during 2020. Interestingly, many ESG sectors including Communication Services, Consumer Staples, Financial, Healthcare, Materials, and Real Estate experience market exposures well below unity, while, ESG-bonds have the lowest beta values close to zero, suggesting that these assets can provide a more robust option for investors who want to diversify the market risk exposure.

Examining the effect of climate uncertainty on the ESG betas, the results reported in Table 3 show that higher climate uncertainty is generally associated with lower betas across all ESG sectors, particularly at the upper extreme quantiles of market exposures. Once again, however, the climate effects on betas are stronger for physical climate uncertainty, in line with the results reported in Table 2. This implies that investors who are worried about physical climate risks, that is, the uncertainty associated with climate-related natural disasters and chronic physical hazards affecting business profitability, could utilize ESG equity sector portfolios as a diversification tool for conventional portfolios during periods of high physical climate uncertainty. The diversification role of ESG equities, however, does not necessarily extend to managing transition climate risks in conventional portfolios, as the results in Table 3 generally show insignificant transition climate risk effects on ESG equity betas. In the case of ESG bonds, however, the

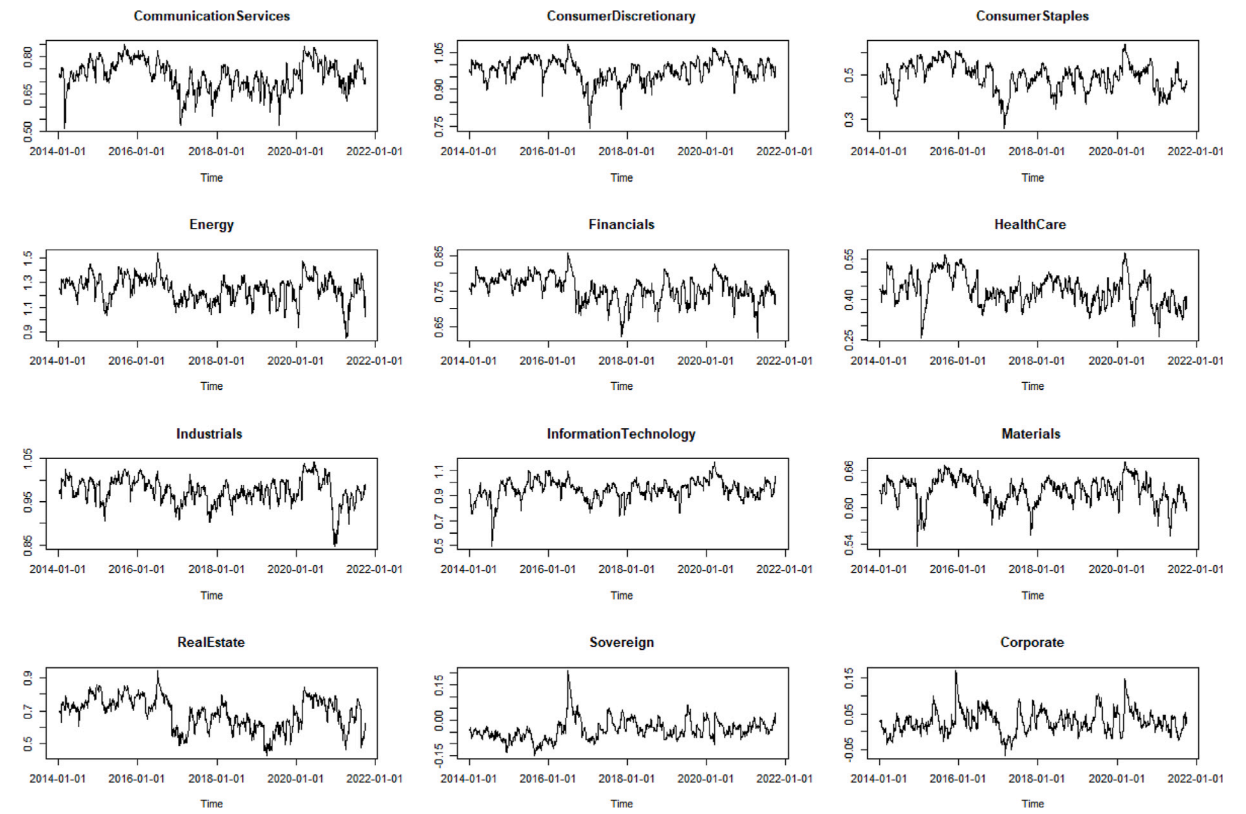

Fig. 3. Time varying betas between Stoxx 50 index and ESG assets (sector specific equity and bond indexes). Note: The figure presents the time-varying betas for various ESG assets with respect to aggregate market fluctuations proxied by the STOXX 50 index.

results show that fixed-income assets rated ESG could serve as a risk management tool against transition climate risks, implied by the negative and significant coefficients for both types of ESG bonds for high quantiles of transition risk (−0182 and −0.144 for ESG sovereign and corporate bonds, respectively). Coupled with the findings of near-zero beta estimates for these assets depicted in Fig. 3, the negative relation between the betas for these assets and the conventional market index suggests that ESG bonds could be useful to manage risk exposures with respect to climate policy uncertainty and/or business transitions towards a more regulated business setting with respect to environmental policies. Overall, our results suggest that while ESG assets can offer diversification and hedging benefits for conventional investment portfolios, it is essential to distinguish between physical and transition climate risk exposures in order to identify the best tool to mitigate climate risk effects in investment positions.

5.3. Economic implications

To provide an economic perspective to the findings presented so far, in the last part of our analysis, we examine several portfolio performance metrics that relate to the hedging ability of ESG assets for conventional investors. In this regard, we consider a passive investor who is currently invested in the STOXX 50 index, which we refer to as the unhedged portfolio. We then implement a forward-looking investment strategy in which the passive investor supplements the unhedged portfolio with a position in each ESG asset one at a time conditional on the market state with respect to climate uncertainty. More specifically, we follow Engle and Colacito (2006) and take a hedge position in the ESG asset during periods of high climate uncertainty defined by the climate risk index values above the sample average. During periods of low climate risk, however, the investor remains unhedged. We then compare the unhedged and hedged portfolios based on several performance metrics including the portfolio return, volatility, Sharpe ratio, and hedging effectiveness.

The results presented in Table 4 reveal several interesting insights. The most notable result is that the optimal portfolio strategy based on ESG bonds is highly effective in reducing portfolio risk, as the volatility of the hedged portfolios constructed by positions in ESG corporate/sovereign bonds is significantly lower than the volatility of the unhedged portfolio (1.063%). We find that supplementing the conventional portfolio with sovereign (corporate) ESG bonds yields a reduction in return volatility 17% (22%) and 25% (29%), respectively during periods of high physical and transition climate uncertainty, helping to reduce portfolio risk. This finding is consistent with the recent evidence by Yousaf et al. (2022) and Cepni et al. (2022) for green bonds and suggests that ESG-oriented bonds can be effectively utilized for risk management purposes during times of high climate uncertainty. In contrast,

Table 3
The impact of climate uncertainty on ESG betas.

Dependent variable: ESG sector market betas						
Quantiles	Physical risks			Transition risks		
	(1)	(2)	(3)	(4)	(5)	(6)
	5	50	95	5	50	95
Communication Services	−0.0968	−0.339***	−0.220***	0.345**	−0.169*	−0.0354
	(−0.56)	(−3.58)	(−3.81)	(2.88)	(−2.11)	(−0.66)
Consumer Discretionary	−0.0677	−0.154*	−0.145**	0.483**	0.100	−0.0512
	(−0.47)	(−2.51)	(−2.87)	(2.76)	(1.76)	(−0.72)
Consumer Staples	0.0348	−0.302***	−0.391***	0.214	−0.0215	−0.117
	(0.24)	(−3.51)	(−4.21)	(1.59)	(−0.27)	(−1.35)
Energy	−0.447*	−0.406**	−0.599*	−0.316	0.0926	−0.0565
	(−2.23)	(−2.91)	(−2.40)	(−1.15)	(0.75)	(−0.26)
Financials	−0.254**	−0.152***	−0.0574	−0.0340	−0.0115	−0.0220
	(−3.00)	(−3.42)	(−1.43)	(−0.33)	(−0.29)	(−0.63)
Health Care	0.0677	−0.0832	−0.220**	−0.0235	0.0284	−0.101
	(0.71)	(−1.29)	(−3.23)	(−0.26)	(0.47)	(−1.89)
Industrials	−0.0706	−0.166***	−0.0985*	0.131	0.0438	−0.0101
	(−0.75)	(−4.31)	(−2.33)	(1.51)	(0.94)	(−0.29)
Information Tech.	0.729**	−0.00779	−0.327**	0.746**	0.138	−0.0672
	(2.67)	(−0.08)	(−2.73)	(2.72)	(1.43)	(−0.63)
Materials	0.108*	−0.0891**	−0.0891*	0.0936	0.0634*	−0.0333
	(2.07)	(−2.63)	(−2.17)	(0.97)	(2.06)	(−1.15)
Real Estate	−0.135	−0.831***	−0.461**	0.0676	−0.271	−0.103
	(−1.09)	(−5.03)	(−3.04)	(0.34)	(−1.70)	(−0.62)
Sovereign	0.261*	0.136**	0.0396	0.0959	0.0983*	−0.230*
	(2.40)	(2.85)	(0.34)	(0.84)	(2.10)	(−2.26)
Corporate	−0.0603	−0.0312	−0.0158	0.0431	0.0424	−0.135
	(−1.02)	(−0.64)	(−0.17)	(1.30)	(0.91)	(−1.41)

*, **, ***: Significant at 10, 5, 1% levels. t-statistics are in parentheses.

Table 4
Hedging performance of ESG investments against climate risks.

	ComSrv	ConsDiscr	ConStap	Energy	Financial	HCare	Indust	IT	Materials	RealEst	Sovereign	Corporate	Unhedged
Physical risk													
Average	0.005%	0.018%	0.019%	0.019%	0.022%	0.038%	0.037%	0.071%	0.034%	0.031%	0.030%	0.031%	0.017%
Std.Dev	1.061%	1.140%	1.014%	1.283%	1.261%	1.054%	1.109%	1.275%	1.087%	1.095%	0.885%	0.825%	1.063%
Sharpe R.	0.477%	1.618%	1.906%	1.504%	1.748%	3.613%	3.305%	5.540%	3.119%	2.846%	3.404%	3.809%	1.579%
IR	−2.858%	0.443%	0.533%	0.382%	1.042%	3.649%	6.610%	8.065%	5.575%	2.645%	1.764%	2.221%	
HE	0.17%	−7.27%	4.56%	−20.71%	−18.63%	0.85%	−4.40%	−20.00%	−2.26%	−3.04%	16.74%	22.38%	
Transition risk													
Average	0.010%	0.028%	0.017%	−0.007%	0.025%	0.032%	0.040%	0.053%	0.027%	0.030%	0.020%	0.028%	0.017%
Std.Dev	1.060%	1.136%	0.978%	1.372%	1.277%	1.041%	1.097%	1.301%	1.083%	1.124%	0.793%	0.756%	1.063%
Sharpe R.	0.923%	2.422%	1.710%	−0.487%	1.933%	3.048%	3.646%	4.057%	2.528%	2.706%	2.584%	3.674%	1.579%
IR	−1.643%	2.869%	−0.011%	−3.265%	1.559%	2.535%	7.432%	5.113%	3.370%	2.356%	0.460%	1.505%	
HE	0.23%	−6.94%	7.96%	−29.13%	−20.16%	2.07%	−3.21%	−22.46%	−1.89%	−5.81%	25.37%	28.87%	

Note: HE indicates the hedging effectiveness ratio. Hence, a higher value of HE implies a greater risk reduction provided by the hedge portfolio compared to the unhedged portfolio. The Sharpe ratio is defined as the ratio of the excess return on the portfolio to its standard deviation.

we find that supplementing the conventional portfolio with positions in the ESG equity sectors leads to increased return volatility for hedged portfolios, with the exception of communication services, consumer staples, and health care, implied by negative hedge effectiveness values in the table. Thus, while ESG equities display some degree of heterogeneity regarding their climate risk hedging benefits, the findings clearly show that not all equity sector indexes, despite their ESG orientation, work as effective hedges against climate risk. Further examining the risk-adjusted returns in the table, we find that some specific ESG sector portfolios could instead help improve the risk-adjusted performance of unhedged portfolios during periods of high climate uncertainty despite their lack of risk reduction benefits for conventional investors. More interestingly, the biggest gain in risk-adjusted returns is offered by the ESG IT sector, closely followed by ESG bonds. Furthermore, a higher IR result indicates that the IT sector portfolio offers a higher return than the benchmark, considering the amount of risk being taken. Overall, the findings show that investors can still invest in equities with an ESG orientation in order to gain diversification benefits during periods of high climate uncertainty, however, the diversification benefits are not homogeneous across the different ESG sectors.

Considering the distinct patterns in the connectedness and time-varying beta series observed during the COVID-19 pandemic period in Figures A2 and 3, we break the sample into two periods and examine the economic results during the pre- and post-pandemic periods with January 1, 2020 as the cutoff date. The results in Table 5 show that, once again, supplementing the passive portfolio with positions in ESG assets yields a significant reduction in return volatility, particularly in the case of ESG bonds and some

Table 5
COVID-19 pandemic and the hedging performance of ESG investments against climate risks.

Pre-COVID (03/01/2014–31/12/2019)													
	ComSrv	ConsDiscr	ConStap	Energy	Financial	HCare	Indust	IT	Materials	RealEst	Sovereign	Corporate	Unhedged
Physical risk													
Average	0.010%	0.015%	0.027%	0.030%	0.018%	0.038%	0.030%	0.059%	0.038%	0.041%	0.031%	0.033%	0.016%
Std.Dev	0.934%	0.967%	0.915%	1.069%	1.084%	0.949%	0.972%	1.142%	0.966%	0.965%	0.801%	0.717%	0.933%
Sharpe R.	1.057%	1.530%	2.920%	2.797%	1.703%	3.957%	3.093%	5.139%	3.947%	4.225%	3.885%	4.535%	1.764%
IR	−1.655%	−0.520%	2.291%	2.527%	0.479%	3.939%	4.635%	6.739%	7.165%	4.736%	2.065%	2.703%	
HE	−0.13%	−3.62%	1.88%	−14.57%	−16.17%	−1.70%	−4.14%	−22.44%	−3.53%	−3.43%	14.12%	23.15%	
Transition risk													
Average	0.011%	0.025%	0.023%	−0.010%	0.029%	0.033%	0.031%	0.044%	0.027%	0.039%	0.022%	0.028%	0.016%
Std.Dev	0.927%	0.956%	0.890%	1.096%	1.038%	0.957%	0.972%	1.170%	0.973%	0.954%	0.737%	0.690%	0.933%
Sharpe R.	1.186%	2.629%	2.639%	−0.903%	2.755%	3.401%	3.218%	3.751%	2.819%	4.107%	2.937%	4.004%	1.764%
IR	−1.380%	2.833%	1.755%	−4.900%	3.296%	3.131%	5.065%	4.316%	3.756%	4.380%	0.712%	1.791%	
HE	0.64%	−2.45%	4.59%	−17.43%	−11.26%	−2.52%	−4.17%	−25.40%	−4.29%	−2.21%	20.99%	26.02%	
Post - COVID (01/01/2020–30/09/2021)													
Physical risk													
Average	−0.010%	0.033%	−0.005%	−0.015%	0.038%	0.040%	0.061%	0.116%	0.021%	0.000%	0.027%	0.028%	0.020%
Std.Dev	1.411%	1.596%	1.296%	1.835%	1.736%	1.352%	1.488%	1.653%	1.425%	1.455%	1.125%	1.118%	1.420%
Sharpe R.	−0.697%	2.040%	−0.419%	−0.798%	2.171%	2.980%	4.120%	6.999%	1.486%	0.034%	2.412%	2.506%	1.401%
IR	−6.629%	2.440%	−4.461%	−3.533%	2.451%	2.812%	12.769%	12.092%	0.397%	−3.050%	0.808%	0.958%	
HE	0.64%	−12.41%	8.72%	−29.22%	−22.23%	4.80%	−4.75%	−16.36%	−0.34%	−2.44%	20.82%	21.28%	
Transition risk													
Average	0.008%	0.038%	−0.004%	0.006%	0.013%	0.031%	0.072%	0.085%	0.029%	0.003%	0.019%	0.030%	0.020%
Std.Dev	1.426%	1.608%	1.233%	2.055%	1.877%	1.289%	1.445%	1.675%	1.395%	1.575%	0.961%	0.948%	1.420%
Sharpe R.	0.539%	2.344%	−0.352%	0.309%	0.709%	2.402%	4.968%	5.087%	2.092%	0.163%	1.931%	3.191%	1.401%
IR	−2.372%	3.253%	−3.676%	−1.191%	−0.805%	1.387%	13.974%	7.250%	2.438%	−2.309%	−0.130%	1.021%	
HE	−0.39%	−13.24%	13.18%	−44.68%	−32.19%	9.26%	−1.74%	−17.93%	1.77%	−10.89%	32.31%	33.28%	

Note: HE indicates the hedging effectiveness ratio. Hence, a higher value of HE implies a greater risk reduction provided by the hedge portfolio compared to the unhedged portfolio. The Sharpe ratio is defined as the ratio of the excess return on the portfolio to its standard deviation.

ESG sector portfolios, including consumer staples and health care. However, we observe that the pandemic, acting as a driver of tail risk, has significantly lowered the hedging benefits of ESG-related assets compared to the pre-COVID period, although they still offer improved Sharpe ratios compared to the unhedged portfolio in most cases. For the post-COVID period, the most considerable risk reduction is obtained when the unhedged portfolio is supplemented with corporate ESG bonds during high transition risk periods. On the other hand, the IT sector still yields the best Sharpe ratio during periods of high physical climate risk, consistently for the pre- and post-pandemic periods. The strong performance of the IT sector is most likely driven by the shift to a digital-first world, resulting in a boom in demand for digital services during the post-COVID period. Nevertheless, our findings show that ESG-related assets can serve as a good hedging instrument against climate risks even during the pandemic period, supporting the evidence by Yousaf et al. (2022).

6. Conclusion

The role of climate risk as a driver of return and volatility dynamics in financial markets is well established in the literature. According to the 2021 Weather, Climate and Catastrophe Insight by Aon (2021),[10] the economic losses caused by climate-related disasters in 2021 are estimated to be around $343b, the second largest in history, and an increasing number of central banks today plan to run climate transition stress tests on banks, insurers, and pension funds. Not surprisingly, rising concerns over climate change and its potential impact on the global economy have fueled a boom in sustainable and stakeholder-focused investments. According to Morningstar, investments pursuing environmental, social, and governance (ESG) standards constitute the fastest-growing segment of the asset management industry, with assets in ESG funds rising 53% from the previous year to $2.7tn in 2021. However, how effective these investments are as a risk management instrument against climate risk exposures in investment portfolios is still understudied in the literature. This paper contributes to the literature from a novel context by examining the effect of physical and transition climate risks on the transmission of shocks across the conventional and ESG assets via novel measures of physical and transitional climate risk proxies obtained from textual analysis. This is an important consideration as the effectiveness of hedging strategies depends on the interaction between ESG assets and their conventional counterparts during periods of high climate risk.

Examining a number of industry portfolios formed using ESG-focused equities as well as ESG-focused bond issues, our findings show that ESG assets are generally less connected with their conventional counterparts during periods of high climate uncertainty,

[10] Aon, Inc., is a multinational financial services firm that provides assessment on various risk factors affecting businesses globally including those that are climate related (see the 2021technicalreport).

suggesting that these assets can indeed offer conventional investors diversification benefits against climate-driven shocks. However, our findings also suggest that the type of ESG asset to be utilized as a hedging instrument depends on the nature of climate risk that is managed in the portfolio. More specifically, we find that investors who are worried about physical climate risks, that is, risks associated with the costly occurrence of both extreme and chronic climate-related hazards, could utilize ESG equity sector portfolios as a diversification tool during periods of high physical climate uncertainty. In contrast, ESG bonds are found to be particularly useful in managing transition risk exposures that are associated with policy uncertainty and/or business transitions with respect to environmental policies. Accordingly, our findings suggest that the effectiveness of climate hedging strategies and the hedging instrument that should be utilized as a part of the strategy will depend on the nature of climate exposure in an investment portfolio.

Our findings provide further support for the proponents of socially responsible investing as these investments not only provide non-financial benefits (psychological, public recognition, etc.) for investors and corporations but can also offer tangible benefits in terms of managing risk exposures with respect to climate uncertainty. From a policy-making perspective, our findings can be used as a guideline in the climate stress tests by regulators in their efforts to mitigate the negative effects of climate risks on the financial system. In future work, it will be interesting to reconcile our findings with the de-carbonization schemes offered in the literature and explore alternative de-carbonization strategies based on the risk exposure of investment portfolios with respect to physical and transition climate risks.

CRediT authorship contribution statement

Oguzhan Cepni: Conceptualization, Methodology, Sofware, Formal analysis, Data curation, Writing – original draft. **Riza Demirer:** Conceptualization, Writing – original draft, Writing – review & editing, Supervision. **Linh Pham:** Conceptualization, Methodology, Sofware, Formal analysis, Writing – original draft. **Lavinia Rognone:** Conceptualization, Data curation, Writing – original draft, Writing – review & editing.

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.intfin.2022.101730.

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