
# Risk Exposure in ESG-Driven Portfolios: A Wavelet Study within the Tail-Concerned Insurance Sector

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## Highlights

- Wavelet analysis to study ESG rating changes' effect on insurance portfolio risks.
- ESG upgrades affect portfolio risk, suggesting potential for lower volatility.
- Separate risk (upside and downside) analysis of ESG factors highlights need to look beyond total volatility.
- Findings aid policymakers in ESG-aligned, sustainable risk management strategies.

# Risk Exposure in ESG-Driven Portfolios: A Wavelet Study within the Tail-Concerned Insurance Sector

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## Abstract

This paper employs wavelet analysis methodology to examine the pairwise time-frequency connectedness and lead-lag relationships between ESG rating changes and insurance equity portfolios' risk exposure. Focusing on the influence of ESG rating changes rather than absolute levels, it contributes to existing research, shedding light on the nuanced dynamics within the insurance sector. The findings underscore the importance of incorporating ESG considerations into portfolio risk assessments for policymakers and portfolio managers alike. Notably, the study reveals the impact of ESG upgrades on portfolio risk exposure, suggesting potential higher returns but also higher total volatility. Moreover, disaggregate risk (total, downside and upside) analysis uncovers insights into environmental, social, and governance factors, emphasizing the relevance of navigating beyond the total volatility and the overall ESG ratings. These insights inform adaptive risk management strategies aligned with evolving ESG standards, contributing to sustainable and risk-conscious economic and investment decisions within the insurance sector.

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## 1. Introduction

The relationship between Environmental, Social, and Governance (ESG) scores and insurance sector is a complex area of study. This analysis goes beyond correlations to understand how ESG rating fluctuations affect insurance equity portfolio risks. With global sustainable investments hitting $5.8 trillion in 2023 (KPMG, 2023), insurers are increasingly integrating ESG into risk management, emphasizing responsible underwriting and environmental/social impact assessment.

Building on Shanaev & Ghimire's (2022) research, which analyze the incorporation of ESG factors into financial mainstream, revealing mixed findings on their impact on investment and stock performance, this study dives into the relationships between ESG rating variations and risk exposure in insurance equity portfolios. It adds to a growing body of research examining the impact of ESG elements on stock performance and investment decisions (Saci et al., 2024; Said and ElBannan, 2023; Wang et al., 2024).

For instance, Saci et al. (2024) highlight that highly rated ESG Chinese firms exhibit lower systemic risk due to enhanced consumer loyalty and robust institutional investor support, particularly benefiting smaller companies as evidenced by beta coefficients from the capital asset pricing model. Moreover, Said and ElBannan (2023) demonstrate in emerging markets that superior environmental and social performance positively impacts stock behavior, though they do not find a clear link to price-to-sales ratios. In contrast, Wang et al. (2024) reveal significant discrepancies in ESG ratings across agencies adversely affecting stock returns in China's A-share market, underscoring the critical need for consistent and reliable ESG ratings to bolster investor confidence and sustain market development.

Furthermore, building on the research by Di Tommaso and Mazzuca (2023) regarding the impact of ESG rating changes and stock prices of European insurance companies – demonstrating significant influence where upgrades correlate with stock price rise and downgrades with declines – our analysis provides insights into both downside and upside risks associated with ESG ratings, contributing to a comprehensive understanding of ESG implications for insurance investments globally.

Analyzing how ESG ratings affect total, downside, and upside risks in insurance portfolios yield significant insights. Firstly, given the insurance industry's historical exposure to downside risk, understanding ESG's impact on components like underwriting, market, regulatory, and catastrophe risk is vital for risk management and investment decisions. Secondly, assessing ESG's influence on both downside and upside risks offers a comprehensive view of the portfolio's risk profile, including tail risks. These insights can identify hidden vulnerabilities and opportunities.

By integrating ESG criteria into risk analysis, investment strategies are harmonized with long-term sustainability goals, helping insurers mitigate losses and seize value creation opportunities. However, Landi et al. (2022) found that, despite these efforts, higher ESG scores did not improve market performance but increased investor uncertainty and systemic risk. This contrasts with findings by Oikonomou et al. (2012) and Godfrey et al. (2009), who showed that higher corporate social performance and strong CSR practices are associated with lower financial risk and milder market penalties during crises, respectively. Portfolio analyses by Czerwińska and Kaźmierkiewicz (2015) also support the notion that ESG-compliant portfolios perform better with lower risk in volatile markets. However, theoretical models by Godfrey (2005) and Diamond and Verrecchia (1991) suggest that CSR activities can reduce perceived risk by building reputation and reducing information asymmetry. On the other hand, Aupperle et al. (1985) and Camodeca et al. (2018) found neutral impacts of CSR on financial performance and risk, and arguments by Hill (2001) and Palazzo and Richter (2005) propose that CSR initiatives may increase financial risk by being perceived as unnecessary costs or legitimizing questionable practices. Thus, while some studies support a beneficial relationship between ESG factors and financial risk, others present conflicting or neutral findings, highlighting the complexity and variability in these relationships.

This study posits three key questions: 1) How do E, S, and G ratings relate to risk exposure in insurance portfolios? 2) How do E, S, and G portfolio ratings impact risk exposure in globally based ESG portfolios? 3) Is there a correlation between the scoring trends of different E, S, and G strategies? The aim is to uncover the complex relationships between shifts in ESG ratings and risk exposure in insurance portfolios. Utilizing wavelet analysis, the study examines time-frequency connections and lead-lag relationships between the ESG rating changes and risk exposure, focusing changes rather than absolute levels, contributing to the extant research (Shanaev and Ghimire, 2022).

## 2. Data and methods

This study relies on data from two main sources: (I) OWL ESG Analytics, a privately-owned database providing monthly ESG ratings for insurance companies from March 2009 to October 2022, and (II) Bloomberg, which supplies monthly equity trading prices for these companies during the same period, resulting in 164 monthly data points for each dataset. Company selection involves evaluating their E, S, and G performance and overall ESG ratings within the insurance sector, following Esparcia *et al.'s* (2023) methodology. This process includes identifying companies with consistent monthly ratings, narrowing down to those quoted on Bloomberg, applying a liquidity criterion (exclude firms with over 5% zero returns), and constructing equal weight portfolios, each comprising the 20 most highly capitalized companies (to ensure fair comparison) per pillar (E, S, G, and ESG), resulting in four distinct passive management strategies. We exclude E, S, and G pillar-based portfolios due to significant correlation with ESG portfolio returns. Initially, our study encompassed a global selection, including companies from North America, Europe, Asia-Pacific, and other regions worldwide (see Esparcia *et al.'s*, 2023 for further details regarding the database scope). However, after applying the liquidity and capitalization screens for portfolio construction, the final exposure of the considered strategies is purely United States-based. This refined focus ensures that the selected companies meet stringent liquidity and capitalization criteria, enhancing the robustness and comparability of our findings. This geographical specification provides a clearer basis for analyzing the impact of ESG ratings on risk exposure within the U.S. insurance sector, offering valuable insights for domestic investors and portfolio managers.

In contrast to conventional risk metrics rooted in standard deviation, which encompass both upward and downward risk, some research focuses solely on quantifying downside risk. This approach assumes investors prioritize avoiding losses, as highlighted by seminal contributions (see Roy, 1952; Markowitz, 1959; Klemkosky, 1973; Ang and Chua, 1979; Balzer, 1994). Bawa (1975) and Fishburn (1977) introduced Lower Partial Moments (LPMs) to capture negative deviations of returns from a minimum acceptable return, $h$.[1] Another segment of the literature (Keating and Shadwick, 2002), emphasizes

[1] The LPM of order $m$ can be expressed as follows:
$LPM_{\tau,m} = E[Max(\tau - r_{P,t}, 0)^m] = \int_{-\infty}^{\tau}(\tau - r_{P,t})^m f(r_{P,t}) dr_{p,t}$, where E[·] denotes expectations, $\tau$ is the minimum acceptable return or threshold, $r_{P,t}$ is the portfolio's return, and $f(r_{P,t})$ is the probability density function of returns.

the speculative inclinations of certain investors, exposing them to both downside and upside risk. This involves assessing a greater proportion of returns in the right tail of the distribution, commonly gauged through Upper Partial Moments (UPMs) estimation (Farinelli and Tibiletti, 2008; Esparcia and López, 2024).[2]

Thus, we analyze portfolio returns using three different measures: total returns (standard log returns), $r_t = ln(p_t/p_{t-1})$, upside returns (returns above the mean or right tail), $\text{Max}(r_t - E(r_t), 0)$, and downside returns (returns below the mean or left tail), $\text{Max}(E(r_t) - r_t, 0)$. In addition, we model the conditional variance using the seminal AR(1)-GARCH(1,1) process (Bollerslev, 1986) for each daily series of portfolio returns observed at day $t$, $y_t$, with conditional variance $\sigma_t^2$:

$$\begin{aligned} y_t &= \phi_0 + \phi_1 y_{t-1} + \varepsilon_t \\ \varepsilon_t &= \sigma_t z_t \quad z_t \sim N(0,1) \\ \sigma_t^2 &= \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2, \end{aligned} \tag{1}$$

The model constant, $\omega$, affects current volatility process as it becomes more negative. $\alpha$ captures the sign effect, while $\beta$ reflects the persistence of volatility. The residuals from the previous period, $\varepsilon_{t-1}$, refer to each asset under consideration. In addition, $\varepsilon_t$ represents dynamic intraday residuals from the AR(1) model. The random variables $z_t$ are $i.i.d.$ and follow a standard univariate normal distribution for each portfolio series. Finally, $\phi_0$ and $\phi_1$ correspond to the AR constant and lag-1 autocorrelation parameters, respectively.

Subsequently, we examine volatility connectedness and lead-lag relationships using wavelet coherency and phase difference measures (Esparcia and Gubareva, 2024).[3] These measures explore both total volatility and partial upside and downside risk. Wavelet coherency captures local correlations between two stationary time series in the time-frequency domain, using the cross-wavelet spectrum $W_{xy}(\tau, s) = W_x(\tau, s)W_x^*(\tau, s)$, together with the individual auto-wavelet spectrums $(W_x(\tau, s), W_y(\tau, s))$:

[2] The Upper Partial Moment (UPM) of order $q$ is defined as:

$$UPM_{\tau,q} = E[Max(r_{P,t} - \tau, 0)^q] = \int_{\tau}^{\infty} (r_{P,t} - h)^q f(r_{P,t}) dr_{P,t}.$$

[3] More details regarding these analyses are provided in the Supplementary Materials file.

$$R_{x,y}^2 = \frac{\left|S(W_{xy}(\tau,s))\right|^2}{S(|W_x(\tau,s)|^2)S(\left|W_y(\tau,s)\right|^2)} \quad (2)$$

In the context of achieving convolution in both time and scale, the smoothing operator, $S$, ensures that the squared wavelet coherence measure, $R_{xy}^2$, falls within the interval $0 \leq R_{xy}^2 \leq 1$.

Phase difference analysis explores both positive and negative correlations, as well as lead-lag relationships between two time series (Jiang *et al.* 2015):

$$\phi_{xy} = \tan^{-1}\left(\frac{\Im\{S(s^{-1}W_{xy})\}}{\Re\{S(s^{-1}W_{xy})\}}\right), \quad with\ \phi_{xy} \in [-\pi,\pi] \quad (3)$$

In the context of the Continuous Wavelet Transform, $\Im$ and $\Re$ correspond to the imaginary and real components, respectively. Eq. (2) allow us to assess the movement and fluctuation of the time series. If $\phi_{xy} = 0$, both time series show a common motion at the given time and frequency. For $\phi_{xy}\ \epsilon(0,\pi/2)$, time series fluctuate in phase, with $x$ leading the movement of $y$. Conversely, if $\phi_{xy}\ \epsilon(-\pi/2,0)$, $y$ leads the fluctuation of $x$. A phase difference of $\pi$ or $-\pi$ indicates an anti-phase movement. Finally, if $\phi_{xy}\ \epsilon(\pi/2,\pi)$, y leads x, while $\phi_{xy}\ \epsilon(-\pi,-\pi/2)$ shows $x$ leading $y$.

## 3. Empirical analysis

Our study, inspired by Maghyereh *et al.* (2019), implements the Maximal Overlap Discrete Wavelet Transform to decompose insurance portfolio risk exposure (total, downside and upside risk) and rating changes into different scales. These scales represent various investment horizons. Specifically, the short-term horizon (D1) captures the connection between portfolio risk exposure and rating changes influenced by shocks within 0 to 5 months (short-run or high decomposition frequencies). The medium-term horizon (D2) reflects variations due to shocks occurring between 6 to 23 months (mid-run). Lastly, the long-term horizon (D3) accounts for fluctuations occurring from 24 months onwards (long-run or low decomposition frequencies).

Referring to Figure 1, we observe weak links across the sample but find significant implications for insurance portfolio managers and broader market participants. Specifically, there's a stronger interaction between total ESG risk exposure in insurance portfolios and ESG rating downgrades compared to its connection with upgrades. This highlights investors' prioritization of loss avoidance, contrary to Gao *et al*. (2022), who

treat upside and downside risks equally. Moreover, we note a negative relationship between ESG ratings and insurance portfolio risk exposure for total and downside risks, shifting to a positive relationship for upside risk exposure. This suggests that rating upgrades may increase right tail risk, while downgrades could decrease total and left-tail risks, offering insights into managing downside risk exposure in insurance portfolios.

*FIGURE* 1 *HERE*

Figure 1 highlights significant differences among the three subgraphs in the time-frequency domain. Stronger relationships emerge in medium- and long-term planning horizons for total risk exposure, with minor irregularities in the short term. Medium-term planning shows a negative relationship, while long-term planning exhibits leading behaviors in response to ESG rating changes. The downside risk exposure demonstrates the highest connectivity, with negative interdependencies across the medium-term planning range. Conversely, the link between ESG rating changes and the right tail of risk exposure appears in both short and medium-term planning, indicating a dominant positive relationship driven by upside risk. These findings suggest a more robust relationship for medium-term planning, with statistically significant connectedness across various horizons. Portfolio managers can gain insights by considering different types of risk exposure based on the investment horizon.

Over the analyzed sample period, differences in risk levels emerge. Total and right tail show increased connectedness during stress periods like COVID-19 pandemic and the Russia-Ukraine war. In contrast, left tail risks shows higher interdependence with ESG rating changes during the aftermath of the global financial crisis and the European sovereign debt crisis. From 2015 to 2017, short-term planning horizons reveals interconnections for upside and downside risk exposure, likely influenced by environmental guidelines from the Task Force on Climate Financial Disclosures (TCFD) and growing investor environmental awareness (Esparcia and Gubareva, 2024). These findings underscore the evolving nature of connectedness over time, crucial for portfolio managers' investment planning.

The connectedness between rating changes (E, S, and G) and total/downturn risks of ESG portfolios (Figure 2) is lower than in Figure 1 for disaggregated ESG portfolios. Especially negative is the connection when assessing S and G ratings for total volatility and E rating for downturn risk. These results emphasize the importance of focusing on environmental practices rather than overall ESG for risk mitigation, as higher E ratings correlate with reduced left-tail risk. Evaluating rating changes' relationships with

portfolio upside risk based on global ESG factors, we find a broader spectrum of in-phase connections across frequencies and time intervals, though with higher vulnerability than Figure 1's peaks. This insight is valuable for speculative insurance portfolio managers or those concerned with portfolio return distribution's right tail, emphasizing the significance of examining E, S, and G subpillar breakdowns over the aggregate rating. Additionally, evidence reveals bidirectional relationships over time and frequency, indicating ratings influence risk and vice versa. Notwithstanding, lead-lag relationships are negligible concerning upside risk and subpillar rating changes, implying managers should focus on managing downside risk rather than potential gains.

*FIGURE 2 HERE*

In Figure 3, it is demonstrated that there exists a high degree of interconnection among the various pillars of ESG ratings, typically maintaining synchronization (in-phase). The interrelations among E-S, S-G, and E-G operate in both directions, mutually influencing each other. Particularly noteworthy are the strong positive connections observed between the E and S pillars, notably evident from 2015 onwards, coinciding with the growing awareness among investors regarding climate-related factors subsequent to the advent of the TCFD. As for the association between the S and G pillars, it tends to be generally in phase but low. Additionally, there exists a moderate to high level of positive correlation between the E and G pillars, with the influence of G predominantly leading over E in terms of lead-lag.

*FIGURE 3 HERE*

## 4. Conclusions

The research has important economic and policy implications for market participants, particularly policy makers and portfolio managers. The study highlights the importance of incorporating changes in ESG (Environmental, Social, Governance) ratings into portfolio risk assessments. In particular, the stronger interaction observed between ESG risk exposure and rating downgrades in the insurance sector suggests that investors are more sensitive to potential losses, which could guide policymakers in designing regulations that encourage more sustainable practices to mitigate downside risks. This heightened sensitivity to ESG downgrades in the insurance sector is driven by factors such as the central role of insurers in sustainable investment, the integration of sustainability criteria into insurance products, and policyholder decisions in favor of climate-friendly and sustainable companies. Thus, the asymmetry in investor responses to ESG upgrades and downgrades is driven by a combination of behavioral finance

principles, market dynamics and sector-specific characteristics. Understanding these factors provides valuable insights into investor behavior and highlights the importance of integrating ESG considerations into risk management strategies. For the insurance sector in particular, the heightened sensitivity to ESG downgrades underscores the need for robust ESG risk assessment and proactive management to mitigate potential adverse impacts. Our analysis acknowledges variations in risk levels during specific crises, such as the COVID-19 pandemic and the Russia-Ukraine war, and extends this examination to consider the broader influence of prevailing market conditions. We find that during bull markets and periods of economic growth, the positive sentiment and increased investment flows tend to amplify the impact of ESG rating upgrades on upside risk exposure, as investors are more inclined to reward higher-rated portfolios. Conversely, in bear markets and recessions, the heightened risk aversion and market stress accentuate the importance of downside risk management, leading to a stronger negative impact of ESG rating downgrades on total and left-tail risks. This conditional nature of ESG impacts highlights the need for dynamic risk management strategies that account for the broader economic environment, providing critical insights for portfolio managers in both favorable and adverse market conditions. Incorporating this broader market perspective reinforces the importance of adaptive strategies in managing ESG-related risks across different economic cycles.

In addition, the negative relationship between ESG ratings and overall downside risk, which becomes positive for upside risk, highlights the potential impact of ESG changes on portfolio risk profiles. This finding suggests that ESG rating upgrades may lead to increased right-tail risk, signaling the potential for higher returns but also higher volatility. Portfolio managers can use these insights to strategically manage risk and optimize performance. The study's emphasis on medium-term planning horizons as the most relevant period for understanding these relationships underscores the importance of adaptive investment strategies that align with evolving ESG standards and investor preferences. Ultimately, these findings contribute to a more nuanced understanding of how ESG considerations intersect with portfolio risk dynamics, guiding both economic policy and investment decisions towards sustainable and risk-conscious outcomes.

From the disaggregate subpillar analysis, we reveal some interesting insights, thus demonstrating the pertinency of navigating beyond the scope of the overall ESG ratings. Frist, increases in the E rating result in a further decrease in left-tail risk, suggesting a focus on enhancing environmental practices by part of insurance firms. Second,

speculative insurance portfolio managers should pay closer attention to the breakdown of E, S, and G subpillars rather than the aggregate rating itself, particularly for concerns with the right tail of the return distribution. Third, bidirectional relationships exist between ratings and risk, implying that changes in one influence the other over different periods and frequencies. Fourth, traditional insurance portfolio managers (risk averse by nature) should prioritize managing downside risk exposure over potential windfall gains, as indicated by the lack of lead-lag relationships between upside risk and rating changes by subpillar. Lastly, high in-phase interconnection among ESG subpillars is demonstrated, particularly between the E and S pillars, coinciding with increased investor awareness of climate-related factors post-TCFD.

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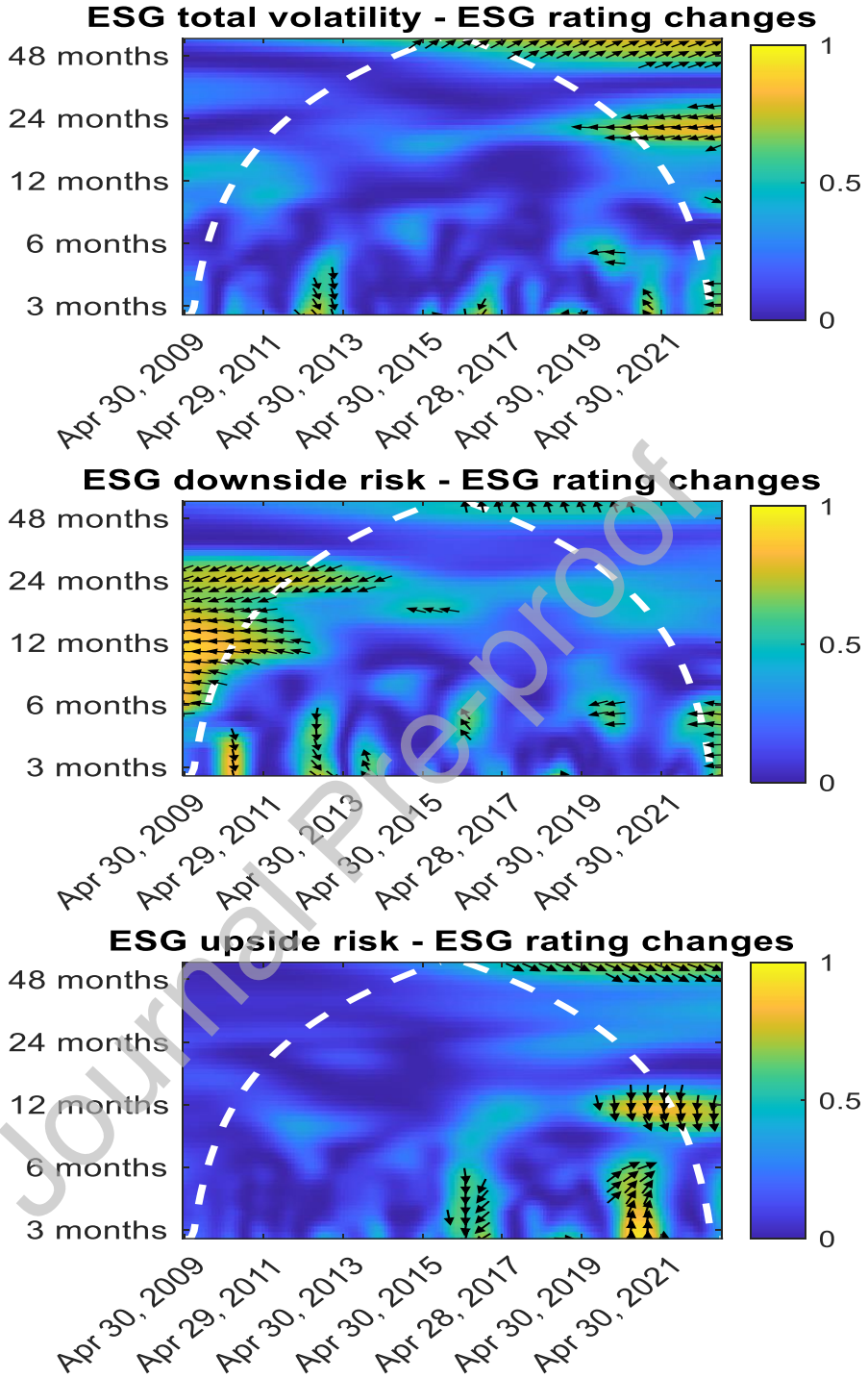
**Figure 1. Wavelet coherence & phase difference between ESG portfolio risk exposure (total, downside & upside) and their respective ratings**




General note for all the data representations: To ensure accurate interpretation of wavelet coherence and phase difference visuals, it is essential to follow established conventions (e.g., Umar and Gubareva, 2021 or Esparcia and Gubareva, 2024). Within wavelet coherence analysis, it is important to observe the fluctuation of co-movements across both time (horizontal axis) and frequencies (vertical axis), with the vertical axis signifying investors' time horizons. Strong correlations are depicted in red, while weaker dependencies are represented in blue. The presence of arrows indicates phase disparities: → and ← suggest in phase and out-of-phase movements respectively, while ↗ and ↙ indicate leading behaviors of the first series, and ↘ and ↖ imply delays. Caution is advised in proximity to the cone of influence (marked by a dashed white line) due to potential boundary effects.

**Figure 2. Relationship between ratings of different pillar portfolios and ESG portfolio risk exposure (total, downside & upside)**

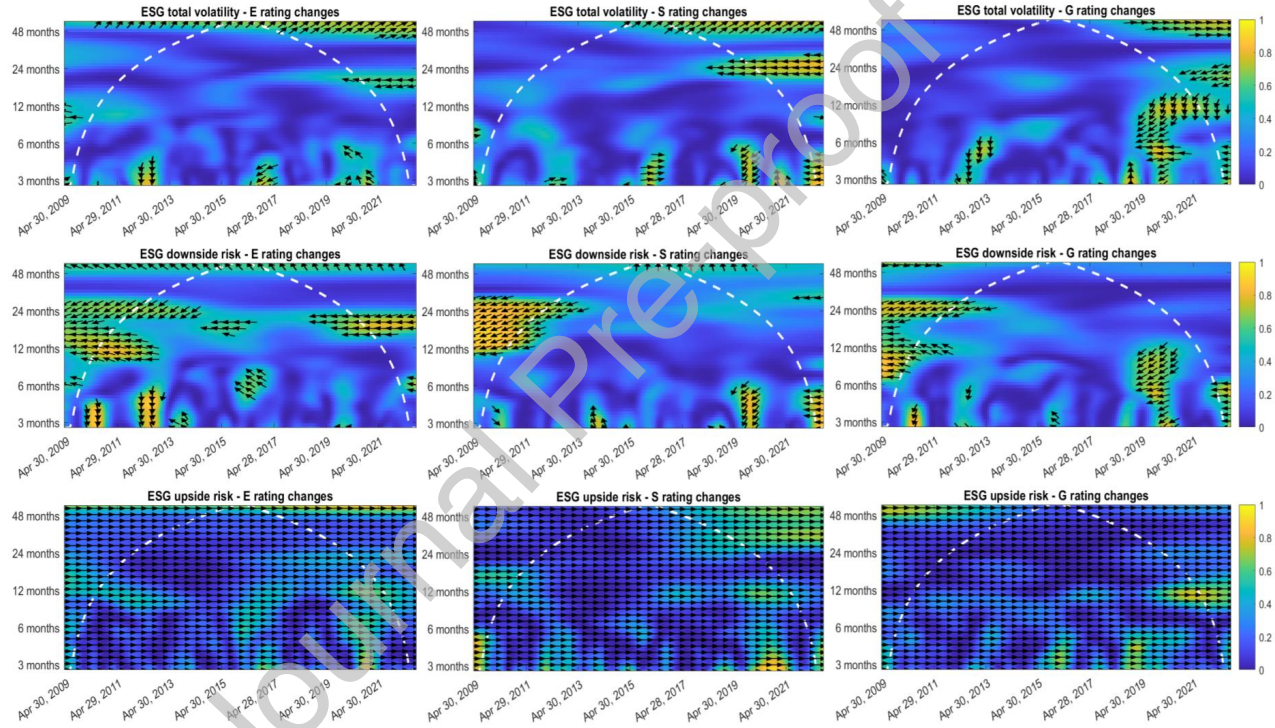
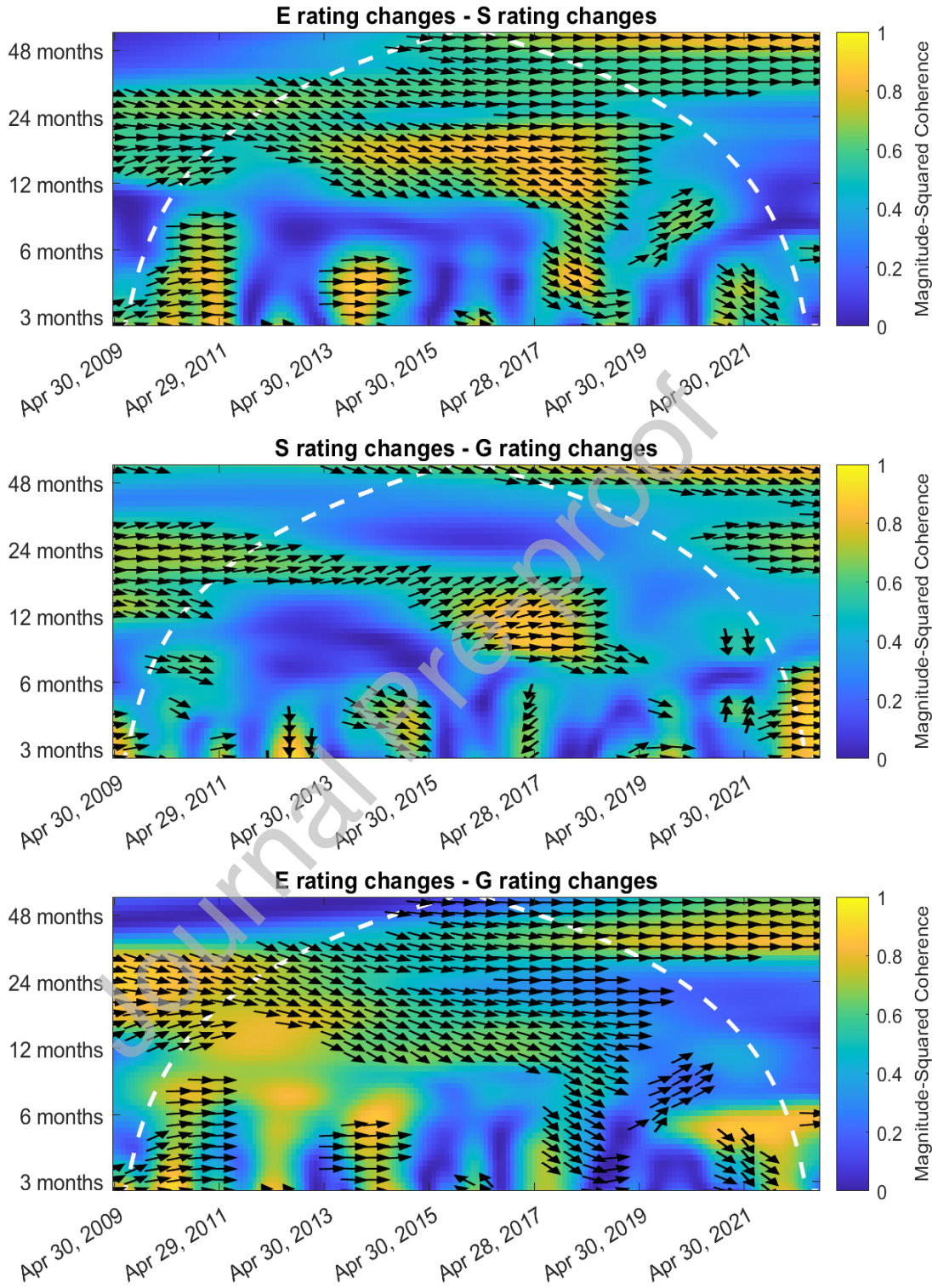


**Figure 3. Relationship between ratings of E, S & G pillar portfolios**



**Author statement**

**Fran Jareño:** Formal analysis, Funding acquisition, Project administration, Writing – review & original draft. **Carlos Esparcia:** Data curation, Formal analysis, Investigation, Methodology, Software, Writing – original draft, review and editing. **Giulia Fantini:** Formal analysis, Investigation, Validation, Writing – original draft.