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Spectral Climate Risk[*]

Andrea Cipollini[†] Iolanda Lo Cascio[‡] Fabio Parla[§]

Abstract

In this study, we analyze the role played by shocks to climate concern in driving the return performance of a green-minus-brown (GMB) portfolio designed to hedge climate risk. While previous studies conduct their analysis in the time domain, we use the extended Wold decomposition, which allows us to work in the time-frequency domain, and we explore, after controlling for traditional market risk factors, how the sensitivity of portfolio returns to shocks to climate concern varies across investment horizons of different lengths. The empirical evidence, based on a U.S. portfolio, shows an outperformance of green stocks larger than the one suggested by time-domain analysis and occurring with a delay that manifests over a four- to eight-day horizon. Moreover, our findings suggest that, among the three main categories of climate change risk (physical, transition, and liability), heightened concern about transition risk is the most important factor driving the observed outperformance of the green portfolio.

Keywords: Green-minus-brown portfolio, climate risk, structural VAR, extended Wold decomposition, multiresolution analysis

JEL: C32, C51, C58, G11

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1 Introduction

Existing studies on the performance of green versus brown stocks primarily analyze the expected return component of green and brown assets, linking differences in expected returns to firms' exposure to climate risk (see the seminal studies of Bolton and Kacperczyk, 2021 and Pástor et al., 2021, 2022). In contrast, we focus on the unexpected component of returns, namely the portion driven by shocks to climate concern (see Pástor et al., 2022 and Ardia et al., 2023). Rather than studying whether green and brown firms earn different expected returns due to their carbon exposure, we examine whether innovations in climate concern are a potential source of the observed outperformance of green stocks over short- to medium-term horizons. Using daily returns, and after controlling for traditional market risk factors, we rely on multiresolution analysis to assess how the impact of shocks to climate concern on risk-adjusted green-minus-brown (GMB) portfolio returns varies across frequency bands corresponding to horizons of different lengths, ranging from the short to the medium term. We argue that our approach sheds light on the dynamic response of green-brown return spreads to climate-related news. The preference for multiresolution analysis over regressions with time lags (see Pástor et al., 2022) to examine the dynamic response of green-minus-brown portfolio returns to shocks to climate concern is motivated as follows. First, multiresolution analysis allows us to isolate the noisy component of shocks to climate concern and, hence, to detect the fundamental component that triggers investor reactions leading to an outperformance of green stocks. Moreover, unlike regressions with time lags, multiresolution analysis avoids multicollinearity, due to the decomposition of shocks to climate concern into orthogonal components.

Our dataset combines information on the MSCI USA Low Carbon Target Index, used as a proxy for a portfolio of green stocks, and a market-capitalization-weighted index of U.S. thermal coal companies, used as a proxy for a portfolio of brown stocks. As a proxy for climate-related shocks, we rely on unanticipated changes in the Media Climate Change Concerns (MCCC) index developed by Ardia et al. (2023), a news-based index available at a daily frequency that captures the level of concern about climate change in the United States. Frequency-domain approaches provide an insightful representation of time-series dynamics by decomposing them into sinusoidal components at various frequencies, with the intensity of each component varying across the frequency spectrum. Dew-Becker and Giglio (2016) study asset pricing in the frequency domain using the discrete Fourier transform. The main limitation of Fourier analysis is related to the assumption that spectral intensities remain constant over time. This makes Fourier methods ineffective for analyzing signals containing local irregularities, such as spikes or discontinuities, which are typical of financial time series. To address this issue, multiresolution analysis based on wavelets can be a particularly useful tool for studying signals that are localized in both time and frequency. Recently, Bandi et al. (2021) employed both parametric and non-parametric multiresolution methods based on the Haar discrete wavelet filter to study how the contribution of systematic risk proxies (e.g., market risk factors) to portfolio returns varies across frequency bands. In this study, we use the parametric approach and examine, through the extended Wold decomposition developed by Bandi et al. (2021), how the delayed impact of climate concern shocks on GMB portfolio returns manifests across different investment horizons. The empirical evidence points to an outperformance of the green portfolio (driven by innovations in climate concern) over a four- to eight-day horizon, which is longer than the horizon documented in Ardia et al. (2023), who focus only on contemporaneous shocks to climate concern. Moreover, we find that this outperformance of green stocks is primarily driven by increases in concern about transition risk rather than physical or liability risk.

The remainder of the paper is organized as follows. Section 2 describes the empirical methodology. Section 3 discusses the empirical analysis: data and main results. Section 4 presents robustness checks. Finally, Section 5 concludes.

2 Empirical Methodology

The empirical strategy proceeds in three stages. In the first stage, we filter out the role played by traditional market risk factors by computing the market risk-adjusted returns of the GMB portfolio as the residuals from a Fama-French three-factor model. In the second and third stages, we investigate the impact of climate risk on GMB risk-adjusted returns using multiresolution analysis. First (see Sections 2.1 and 2.2), following Ortu et al. (2020) and Bandi et al. (2021), we use a multivariate extended Wold decomposition to jointly decompose risk-adjusted returns and a proxy for climate risk into orthogonal components with different degrees of persistence. This decomposition incorporates restrictions on the underlying multivariate process, allowing us to isolate the cycles associated with climate-related shocks. Then (see Section 2.3), we run regression analysis in which the frequency-specific components of the climate risk factor are used to explain the GMB portfolio return dynamics. This procedure yields a set of spectral climate risk betas, which capture the sensitivity of the GMB portfolio to climate shocks across different frequency bands.

2.1 Classic Wold Decomposition

Consider the market risk-adjusted return of the GMB portfolio, $\tilde{r}_t$, and the innovation in the MCCC index developed by Ardia et al. (2023), $\Delta MCCC_t$, and let the 2×1 vector of endogenous variables $x_t = (\tilde{r}_t, \Delta MCCC_t)'$ denote a covariance-stationary bivariate process, which admits the following classical Wold decomposition:

$$x_t = \sum_{k=0}^{\infty} \gamma_k \eta_{t-k} \tag{1}$$

As shown in equation (1), x_t is an infinite linear combination of current and past mutually uncorrelated error terms, where γ_k, for $k = 0, \ldots, \infty$, are 2×2 coefficient matrices, and η_t is a 2×1 vector of orthogonal structural form shocks such that $\mathbb{E}[\eta_t] = 0$ and $\mathbb{E}[\eta_t \eta_t'] = I_2$. The coefficients and shocks in equation (1) are obtained by estimating a structural VAR (SVAR) model:

$$x_t = c + \sum_{k=1}^{p} A_k x_{t-k} + P\eta_t \tag{2}$$

where c is a 2×1 vector of intercepts, and A_k, for $k = 1, \ldots, p$, are 2×2 slope coefficient matrices. The matrix P is the 2×2 structural impact multiplier matrix capturing the contemporaneous effect of the mutually uncorrelated structural shocks η_t on the endogenous variables. We focus on the following overidentified SVAR model:

$$\begin{pmatrix} \tilde{r}_t \\ \Delta MCCC_t \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \sum_{k=1}^{p} \begin{pmatrix} a_{11,k} & a_{12,k} \\ 0 & a_{22,k} \end{pmatrix} \begin{pmatrix} \tilde{r}_{t-k} \\ \Delta MCCC_{t-k} \end{pmatrix} + \begin{pmatrix} p_{11} & p_{12} \\ 0 & p_{22} \end{pmatrix} \begin{pmatrix} \eta_{1t} \\ \eta_{2t} \end{pmatrix} \tag{3}$$

We first impose a zero restriction on the impact multiplier matrix P, namely $p_{21} = 0$, such that shocks to $\tilde{r}_t$ do not contemporaneously affect $\Delta MCCC_t$. The overidentifying restrictions rule out dynamic feedback from $\tilde{r}_t$ to $\Delta MCCC_t$. i.e., $a_{21,k} = 0$ for $k = 1, \ldots, p$. The SVAR model is estimated by maximum likelihood (ML). More specifically, the concentrated log-likelihood for the impact multiplier matrix P is given by:

$$\log\, l_c(P) = -\frac{KT}{2}\log(2\pi) - \frac{T}{2}\log(\det(P)^2) - \frac{T}{2}\mathrm{tr}(P'^{-1}P^{-1}\hat{\Sigma}_\varepsilon) \tag{4}$$

where K is the number of endogenous variables (equal to two), $\hat{\Sigma}_\varepsilon = T^{-1}\sum_{t=1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_t'$ and $\hat{\varepsilon}_t = x_t - \hat{c} - \sum_{k=1}^{p} \hat{A}_k x_{t-k}$ is a 2×1 vector of residuals estimated using restricted generalized least squares (GLS) (see Kilian and Lütkepohl, 2017). The zero restrictions $a_{21,k} = 0$ for

$k = 1, \ldots, p$ imply p overidentifying restrictions, which are tested using a likelihood ratio (LR) test (see Section 3.2). The structural form shocks η_t are obtained from the following relationship $\eta_t = P^{-1}\hat{\varepsilon}_t$. Finally, the structural moving-average coefficients γ_k (i.e., the coefficients of the classical Wold decomposition) in equation (1) are obtained recursively from the structural VAR parameters.[1]

2.2 Extended Wold Decomposition

After estimating the classical Wold decomposition in equation (1), we proceed to estimate the extended Wold decomposition model specification, given by:

$$x_t = \sum_{j=1}^{\infty} \sum_{k=0}^{\infty} \Psi_k^{(j)} \eta_{t-k2^j}^{(j)} = \sum_{j=1}^{\infty} x_t^{(j)} \tag{5}$$

where $\Psi_k^{(j)}$ are the unique discrete Haar transforms (DHT) of the Wold coefficients γ_k, defined as:

$$\Psi_k^{(j)} = \frac{1}{\sqrt{2^j}} \left(\sum_{i=0}^{2^{j-1}-1} \gamma_{k2^j+i} - \sum_{i=0}^{2^{j-1}-1} \gamma_{k2^j+2^{j-1}+i} \right) \tag{6}$$

and $\eta_t^{(j)}$ denotes the corresponding DHT of the structural form shocks η_t:

$$\eta_t^{(j)} = \frac{1}{\sqrt{2^j}} \left(\sum_{i=0}^{2^{j-1}-1} \eta_{t-i} - \sum_{i=0}^{2^{j-1}-1} \eta_{t-2^{j-1}-i} \right) \tag{7}$$

As shown by Bandi et al. (2021), the coefficients and shocks entering the extended Wold decomposition allow multiresolution analysis: the vector of time series x_t can be decomposed into an infinite sum of orthogonal components indexed by the scale parameter j, denoted by $x_t^{(j)}$ in equation (5). Each $x_t^{(j)}$ captures fluctuations in x_t that are localized in both time and frequency, corresponding to cycles with lengths between 2^{j-1} and 2^j periods (see Bandi et al., 2021).

2.3 Spectral Climate Risk Model

Following the extended Wold decomposition of the market risk-adjusted return on the GMB portfolio ($\tilde{r}_t$) and the innovation in the MCCC index ($\Delta MCCC_t$), we analyze the relationship between these series across different frequency bands. Let $x_t^{(j)} = (\tilde{r}_t^{(j)}, \Delta MCCC_t^{(j)})'$

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[1] The 2×2 coefficient matrices of the classical Wold decomposition in equation (1) are computed from the recursion $\gamma_k = A_1\gamma_{k-1} + A_2\gamma_{k-2} + \ldots + A_p\gamma_{k-p}$, with $\gamma_0 = P$ and $\gamma_k = 0$ for $k < 0$.

denote the j-th orthogonal component of the decomposition, with $j \geq 1$, corresponding to cycles of specific length $[2^{j-1}, 2^j]$. The spectral climate risk factor model is specified as follows:

$$\tilde{r}_t = \beta_0 + \sum_{j=1}^{J} \beta^{(j)} \Delta MCCC_t^{(j)} + \beta^{(J+1)} \xi_t^{(J)} + u_t \tag{8}$$

where $\beta^{(j)}$ captures the sensitivity of returns to climate shocks at the j-th frequency band, and $\xi_t^{(J)} = \Delta MCCC_t - \sum_{j=1}^{J} \Delta MCCC_t^{(j)}$ denotes the residual smooth component, capturing the dynamics of the time series at low frequencies associated with scales $j > J$ (see equation 18 in Bandi et al., 2021). Equation (8) is estimated by ordinary least squares (OLS). As shown by Bandi et al. (2021), the time-domain coefficient β, obtained from a regression of $\tilde{r}_t$ on $\Delta MCCC_t$, can be expressed as a variance-weighted average of the spectral betas $\beta^{(j)}$:

$$\beta = v^{(1)} \beta^{(1)} + \ldots + v^{(J)} \beta^{(J)} + v^{(J+1)} \beta^{(J+1)} \tag{9}$$

where $v^{(j)} = \mathbb{V}(\Delta MCCC_t^{(j)}) / \mathbb{V}(\Delta MCCC_t)$ denotes the share of the total variance of $\Delta MCCC_t$ explained by its j-th component, and the last addend is the one associated with the residual smooth component $\xi_t^{(J)}$. This decomposition shows that the aggregate exposure to climate risk reflects contributions across multiple frequency bands, thereby providing a framework for distinguishing short-, medium-, and long-term risk effects.

3 Empirical Evidence

3.1 Data

We use daily U.S. stock market data spanning the period from 30 November 2010 to 28 June 2024. Our analysis focuses on two representative equity portfolios: the MSCI USA Low Carbon Target Index (used as a proxy for the green portfolio) and a market-capitalization-weighted index of the thermal coal industry (used as a proxy for the brown portfolio). The MSCI USA Low Carbon Target Index is a weighted portfolio that includes large- and mid-cap U.S. equities, constructed by assigning larger weights to firms that aim to reduce carbon emissions, based on MSCI ESG Carbon Metrics data. Data for this index are available starting on 30 November 2010, and we obtain end-of-day price series from the MSCI website. As for the brown portfolio, we construct a market-value-weighted portfolio using the daily closing price series of four U.S. companies operating in the thermal coal industry: "*Alliance Resource Partners, L.P.*" (ARLP), "*Hallador Energy Company*" (HNRG), "*NACCO Industries, Inc.*" (NC), and "*Natural Resource Partners, L.P.*" (NRP).[2] Figure 1, which reports the prices of the green and brown portfolios, highlights the outperformance of the green portfolio relative to the brown one over the entire sample period.

For both portfolios, daily returns are computed as log differences of the corresponding price series. The daily return on the GMB portfolio is then obtained as the difference between the returns on the green and brown legs. To account for systematic risk factors, we compute market risk-adjusted returns for the GMB portfolio. Specifically, we estimate a Fama-French three-factor regression in which the dependent variable is the GMB portfolio return, and use the estimated residuals (augmented by the intercept) as a proxy for market risk-adjusted returns. This adjustment isolates the component of the GMB portfolio's returns not explained by standard market, size, and value factors.

Climate-related risk is proxied by innovations in the Media Climate Change Concerns (MCCC) index developed by Ardia et al. (2023). The MCCC index is obtained through text-based analysis of news articles on climate change published by major U.S. newspapers and is available at a daily frequency over the period from January 2003 to June 2024. Specifically, the MCCC innovation is defined as the residual from an AR(1) model fitted to the daily level of the MCCC index. Following Pástor et al. (2022) and Ardia et al. (2023), the MCCC innovation on day t corresponds to the one-step-ahead prediction error computed using the AR(1) parameters estimated over a rolling window of 1096 days ending at time $t-1$. Moreover, Ardia et al. (2023) construct 30 MCCC subindices capturing different climate-related topics. These subindices are grouped into four broader themes: (*i*) business impact, (*ii*) environmental impact, (*iii*) social debate, and (*iv*) research.[3] For each subindex, we construct the corresponding innovation following the same procedure.

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[2] The brown portfolio is constructed as follows. First, we retrieve the list of the largest companies in the thermal coal industry from the Yahoo Finance database. Among the nine U.S. companies identified, we select four stocks that satisfy the following criteria: (*i*) data are available over the entire sample period (i.e., 30 November 2010 - 28 June 2024), and (*ii*) the stocks are continuously traded over the sample period. We then compute a market-value-weighted average of their closing prices. The weights are based on market capitalizations as of May 2025 and they are as follows (rounded): ARLP (0.61), HNRG (0.11), NC (0.04), and NRP (0.23).

[3] The MCCC subindices constructed by Ardia et al. (2023) are the following (grouped by theme): (*Business impact*) Climate summits, Agreements/actions, Climate legislation/regulations, Legal actions, Renewable energy, Carbon reduction technologies, Carbon credits market, Carbon tax, Government programs, Corporations/investments, Car industry, and Airline industry; (*Environmental impact*) Extreme temperatures, Food shortage/poverty, Hurricanes/floods, Glaciers/ice sheets, Ecosystems, Forests, Water drought, Tourism, Arctic wildlife, Marine wildlife, and Agriculture shifts; (*Social debate*) Political campaign, Social events, Controversies, and Cities; (*Research*) Global warming, UN/IPCC reports, and Scientific studies. See Ardia et al. (2023) for further details.

Fig. 1 Green and brown portfolio legs. Price indices (base = 100)

Notes. Prices of the green (green solid line) and brown (brown solid line) equity portfolios. Both series are normalized to 100 at the beginning of the sample period. Sample period: 30 November 2010 - 28 June 2024.

The empirical analysis described in Section 2 is conducted both for the aggregate MCCC index and for each individual subindex. Table 1 reports descriptive statistics for the main variables. The green portfolio exhibits a mean daily return of 0.045% with a standard deviation of 1.097%, whereas the brown portfolio has a mean return of -0.026% and a standard deviation of 2.228%. The mean and standard deviation of the GMB risk-adjusted returns are 0.048% and 1.929%, respectively. The aggregate MCCC index has an average value of 0.843 and a standard deviation of 0.457, while its innovation (ΔMCCC) has an average value of 0.085 and a standard deviation of 0.357.

As a robustness check, and in line with Ardia et al. (2023), we augment the autoregressive model used to estimate innovations in the MCCC index with a set of exogenous variables, available at a daily frequency, to control for potential confounding effects related to macroeconomic conditions, financial markets, and energy sector developments. In particular, we estimate an ARX(1) model in which the exogenous variables include the first lag of: (i) the Fama-French factors, namely the excess market return ($Mkt - Rf$, where Rf denotes the risk-free rate), size (SMB), and value (HML); (ii) the U.S. Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016); (iii) natural gas spot prices based on delivery at the Henry Hub, Louisiana ($Henry\ Hub$); (iv) propane prices based on delivery

Table 1 Descriptive statistics

	Mean	Median	Max	Min	Std dev
Green leg	0.045	0.063	8.925	-12.813	1.097
Brown leg	-0.026	0.003	28.480	-22.058	2.228
	Constituents				
ARLP	-0.006	0.000	54.218	-33.056	2.899
HNRG	-0.013	0.000	31.508	-22.206	3.709
NC	0.040	0.019	51.019	-21.572	2.884
NRP	-0.036	-0.038	28.484	-22.242	3.166
GMB	0.071	0.094	16.756	-27.872	2.060
GMB risk-adjusted	0.048	0.042	13.748	-23.711	1.929
MCCC	0.843	0.781	3.052	0.000	0.457
ΔMCCC	0.085	0.046	1.733	-1.125	0.357

Notes. Descriptive statistics for daily returns of the green (green leg), brown (brown leg), and green-minus-brown (GMB) portfolios, as well as for the MCCC index and its corresponding innovation (ΔMCCC). GMB risk-adjusted returns are obtained as the residuals (augmented by the intercept) from a Fama-French three-factor regression in which the dependent variable is the GMB portfolio return. Descriptive statistics for the individual constituents of the thermal coal (brown) portfolio are also reported: ARLP (*Alliance Resource Partners, L.P.*), HNRG (*Hallador Energy Company*), NC (*NACCO Industries, Inc.*), and NRP (*Natural Resource Partners, L.P.*). Descriptive statistics for daily returns are expressed in percent. Sample period: 30 November 2010 - 28 June 2024.

at Mont Belvieu, Texas (*Mont Belvieu*); (*v*) West Texas Intermediate (WTI) crude oil prices; (*vi*) the CBOE Volatility Index (VIX); (*vii*) the market yield on U.S. Treasury securities at 10-year constant maturity, used as a proxy for the term factor ($Term$); and (*viii*) the spread between Moody's Seasoned Baa Corporate Bond Yield and the 10-year Treasury yield, used as a proxy for the default factor ($Default$). The Fama-French factors ($Mkt - Rf$, SMB, and HML), the EPU index, and VIX enter the ARX model in levels. Energy prices (*Henry Hub*, *Mont Belvieu*, and WTI) are expressed in returns. The term factor enters in first differences, while the default factor is computed as the first difference of the spread between Moody's Seasoned Baa Corporate Bond Yield and the 10-year Treasury yield. The Fama-French factors are obtained from Kenneth R. French's data library, the *EPU* index is downloaded from the Economic Policy Uncertainty website, and the remaining variables are retrieved from the Federal Reserve Bank of St. Louis (FRED) database.

3.2 Results

As described in Section 2, we first compute the market risk-adjusted returns of the GMB portfolio as the residuals from a time-series regression in which GMB portfolio returns are regressed on the three Fama-French factors, namely the excess market return, size, and value.[4] In the second stage of the analysis, we estimate the bivariate structural VAR described in equations (2)-(3) to recover the coefficients underlying the extended Wold decomposition, which are used to construct the frequency-specific components of GMB risk-adjusted returns and innovations in the aggregate MCCC index (see Sections 2.1 and 2.2). The Akaike Information Criterion (AIC) suggests a lag of order seven.[5] In addition, a likelihood-ratio (LR) test fails to reject the overidentifying restrictions implied by the restricted specification, supporting its use relative to the unrestricted (reduced-form) VAR. The number of overidentifying restrictions is seven, and the LR statistic is 10.264, with a p-value of 0.174.

We now turn to the third stage of the analysis, which examines the exposure of GMB risk-adjusted returns to climate risk across frequency bands using the spectral regression framework. Table 2 reports the estimates from the regression model described in equation (8), which quantifies the contribution of the spectral climate risk factor. Specifically, we present results from the spectral beta regression based on $J = 4$ orthogonal frequency components. As shown in Table 2, the estimated variances of GMB risk-adjusted returns ($\sigma^2_{\tilde{r}}$) and of innovations in the aggregate MCCC index ($\sigma^2_{\Delta MCCC}$) decay across frequency bands. Our primary interest lies in the slope coefficients $\beta^{(j)}$. As shown in Table 2, the estimates are positive for the first three frequency bands, suggesting an outperformance of the green portfolio relative to the brown one at higher-frequency cycles. However, statistical significance is only observed for the frequency band corresponding to cycles between four and eight days (i.e., $J = 3$), where the estimated coefficient is 0.655%, larger than the corresponding time-domain estimate (0.155%) (see the top-right element of Table 2, reported in bold).[6] The bottom-right element of Table 2 (reported in bold) shows the

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[4] Results from the Fama-French three-factor model are available upon request.

[5] As a robustness check, we re-estimate the SVAR model using alternative lag lengths. The corresponding results are reported in Section 4.

[6] Evidence (in a time-domain framework) of an outperformance of green stocks driven by innovations in climate concern indices has been documented for the U.S. (see Pástor et al., 2022 and Ardia et al., 2023).

Table 2 Spectral climate risk factor model

	$J=1$	$J=2$	$J=3$	$J=4$	$J>4$	Time domain
β	0.082	0.144	**0.655****	-0.019	0.251	**0.155***
	(0.682)	(0.623)	(2.012)	(-0.066)	(1.046)	(1.723)
$\sigma^2_{\tilde{r}}$	1.862	0.976	0.440	0.228	0.230	
$\sigma^2_{\Delta MCCC}$	0.065	0.021	0.011	0.011	0.020	
v (weight)	0.511	0.162	0.082	0.089	0.157	
						$\sum_{j=1}^{J+1} v^{(j)}\beta^{(j)} = \mathbf{0.157}$

Notes. The table reports estimates from the spectral climate risk regression (see equation 8) in which GMB risk-adjusted returns are the dependent variable and the J frequency-specific components of the innovations to the aggregate MCCC index are used as regressors, for $J = 1, \ldots, 4$, with an additional residual smooth component ($J > 4$). The top-right element (in bold) reports the coefficient on the aggregate MCCC innovations obtained from a time-domain regression with GMB risk-adjusted returns as the dependent variable. The spectral betas (β) on the J components are reported in the first row, with robust t-statistics in parentheses. The variances of the GMB risk-adjusted returns ($\sigma^2_{\tilde{r}}$) and of the aggregate MCCC innovations ($\sigma^2_{\Delta MCCC}$) are reported in the third and fourth rows, respectively. The fifth row reports the relative variances (v). The bottom-right element (in bold) reports the variance-weighted average of the spectral betas, computed using the relative variances as weights. The decomposition is based on a structural VAR with seven lags. GMB risk-adjusted returns are expressed in percent. Significance levels: *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01. Estimation sample: 30 November 2010 - 28 June 2024.

variance-weighted average of the spectral betas (including the one associated with the residual smooth component, i.e., $J > 4$), equal to 0.157%, where the weights are given by the relative variances. Overall, the results suggest that green stocks outperform brown stocks over short-term horizons, specifically for cycles shorter than eight days.[7]

Moreover, we investigate which climate change-related topics drive the outperformance of the green portfolio relative to the brown one over short horizons. To this end, we estimate the spectral climate risk model separately for each MCCC subindex, regressing GMB risk-adjusted returns on the orthogonal frequency-band components of the innovation in the corresponding subindex. Each subindex captures a specific climate-related topic, for

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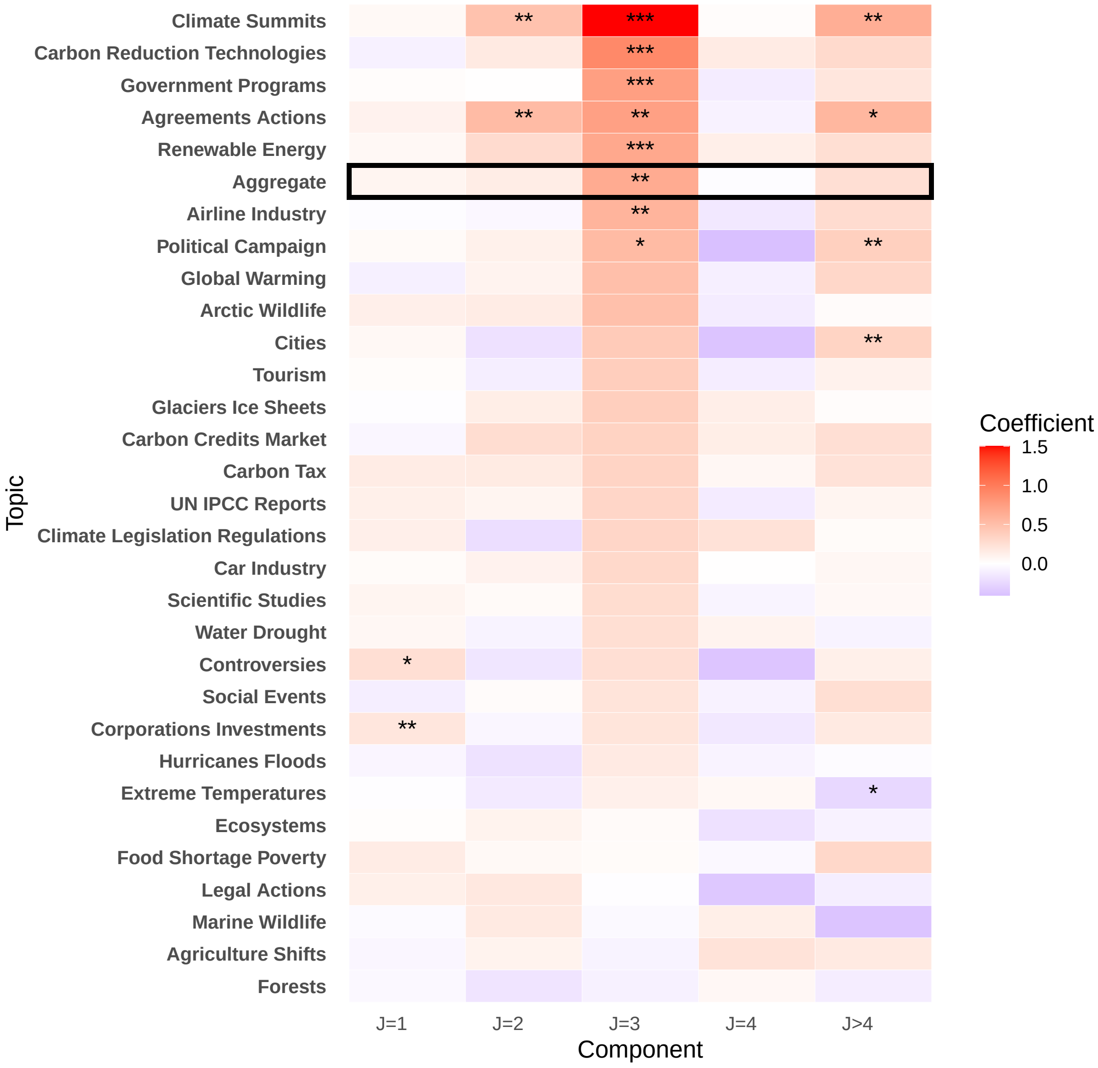
As for Europe, the study of Bua et al. (2024) finds that this effect is limited to the period following the Paris Agreement.

[7] We also estimate the spectral beta regression using $J = 8$ components. This extension neither improves the reconstruction of the time-domain beta nor yields statistically significant coefficients beyond $J = 4$ (results are available upon request).

Fig. 2 Spectral climate risk across different climate-change-related topics



Notes. The figure displays a heatmap of the spectral beta coefficients across frequency components for different climate-change-related topics. The MCCC topics on the vertical axis are ordered in decreasing magnitude according to the coefficient associated with the component $J = 3$ (see Section 3.2 for details). Shading reflects the value of the spectral beta for each component (red indicates positive coefficients, while blue indicates negative coefficients). The black box highlights the spectral betas associated with the aggregate MCCC innovations (i.e., corresponding to the estimates reported in Table 2). Coefficients are obtained from the spectral climate risk model (see equation 8) estimated for $J = 1, \ldots, 4$, with an additional residual smooth component ($J > 4$). The decomposition is based on a structural VAR with seven lags. GMB risk-adjusted returns are expressed in percent. Significance levels: *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01. Estimation sample: 30 November 2010 - 28 June 2024.

a total of thirty topics (see Section 3.1).[8] The results are summarized in the heatmap reported in Figure 2, where the magnitude and sign of the estimated spectral betas across frequency bands are represented by color intensity (red for positive coefficients and blue for negative ones). The MCCC topics are sorted according to the magnitude of the spectral beta at scale $J = 3$, which is the only frequency band yielding a statistically significant coefficient at the aggregate level. Consistent with the evidence for the aggregate MCCC index, scale $J = 3$ exhibits the largest number of statistically significant coefficients, all of which are positive. The topics contributing most to the green portfolio outperformance are related to transition risk, particularly climate policy. For instance, the spectral beta at $J = 3$ for *Climate summits* is 1.503%, while those for *Government programs* and *Agreements/actions* are 0.746% and 0.736%, respectively. Other transition risk topics that play an important role in driving the green portfolio outperformance are those related to technological innovation, such as *Carbon reduction technologies* (0.904%) and *Renewable energy* (0.680%). This evidence is consistent with Ardia et al. (2023), which document in a time-domain framework that concerns related to the transition to a low-carbon economy are among the main drivers of the relative performance of green firms. At the same time, we find evidence of outperformance of the green stock portfolio occurring with a delay of four- to eight-day horizon, which is longer than the one (contemporaneous) documented in Ardia et al. (2023).

Finally, we argue that the delayed response of stock returns to shocks in climate concern is grounded in the literature on informational frictions and gradual information diffusion. In settings where investors cannot instantaneously observe or process all relevant information, new signals are incorporated into prices only gradually over time. Building on this framework, Hong and Stein (1999) and Hong et al. (2000) show that when information about fundamentals diffuses slowly across heterogeneous investors, who receive different private signals at different times, stock prices exhibit underreaction in the short run and only gradually reflect the signal component of information shocks. In this context, investors may initially attribute observed market movements following a climate concern shock to noise rather than to information, and therefore delay substantive trading until the informational content of the shock becomes clearer. This mechanism generates a lagged adjustment in returns as the signal is gradually assimilated by the market, consistent with models of gradual information diffusion and limited attention.

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[8] Consistent with the analysis based on the aggregate MCCC innovations, we estimate a structural VAR fitted to the GMB risk-adjusted returns and the innovations in the corresponding MCCC subindex, using seven lags for each specification.

4 Robustness Checks

This section presents three sets of robustness checks. First, we consider alternative lag-length specifications in the estimation of the structural VAR. Second, we augment the autoregressive model used to identify innovations in the MCCC index by including a set of exogenous control variables. Third, we use an alternative weighting scheme (namely, equal weights) in the construction of the brown thermal coal portfolio.

Alternative SVAR lag-length specification. We re-estimate the spectral climate risk factor model described in equation (8) using orthogonal frequency components obtained from a structural VAR, as specified in equations (2)-(3), with twenty-two lags (corresponding to approximately one month of trading days).[9] Table 3 (panel A) reports the resulting spectral beta estimates based on the decomposition of innovations in the aggregate MCCC index. Consistent with the baseline specification (see Section 3.2), statistical significance across spectral betas emerges only at the third frequency band, with an estimated coefficient of 0.609%.[10] Figure 3 (panel A) summarizes the corresponding climate change topic-level results. Both the magnitude and the pattern of the coefficients closely mirror those obtained under the baseline structural VAR(7): the short-horizon (approximately one week) outperformance of the green portfolio remains primarily associated with transition-risk-related news.

ARX model. To account for potential confounding factors affecting the MCCC index (both aggregate and topic-specific), we estimate innovations as residuals from an ARX(1) model augmented with exogenous regressors. These include the first lag of: (*i*) the Fama-French factors ($Mkt - Rf$, SMB, and HML); (*ii*) the U.S. EPU index proposed by Baker et al. (2016); (*iii*) natural gas spot prices at the Henry Hub, Louisiana ($Henry\ Hub$); (*iv*) propane prices at Mont Belvieu, Texas ($Mont\ Belvieu$); (*v*) WTI crude oil prices; (*vi*) the CBOE Volatility Index (VIX); (*vii*) the market yield on U.S. Treasury securities at 10-year constant maturity ($Term$); and (*viii*) the spread between Moody's Seasoned Baa Corporate Bond Yield and the 10-year Treasury yield ($Default$).[11] The results are consistent with those in Section 3.2. More specifically, for the aggregate index, the spectral

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[9] As in Section 3.2, the spectral climate risk factor model is estimated using GMB risk-adjusted returns as the dependent variable and the frequency-specific components of the MCCC innovations (including the residual smooth component) as regressors.

[10] The LR statistic for the restricted VAR(22) is 24.127 (p-value 0.341), indicating that the overidentifying restrictions cannot be rejected.

[11] See Section 3.1 for additional details on the set of exogenous variables.

beta is statistically significant only at the third frequency band ($J = 3$), with an estimate of 0.673%, compared to 0.171% in the time domain (see Table 3, panel B).[12] At the climate change topic level, positive and statistically significant coefficients are found for topics associated with transition risk, with news to *Climate summits* playing the largest role in driving the outperformance of green stocks relative to brown stocks (see Figure 3, panel B).

Equally weighted brown portfolio. Finally, we repeat the empirical exercise by replacing the market-value-weighted brown portfolio with an equally weighted portfolio of U.S. thermal coal firms. Panel C of Table 3 reports the corresponding estimates based on aggregate MCCC innovations. In line with previous specifications, statistical significance is limited to the third frequency band, where the coefficient is 0.645% (compared to a time-domain estimate of 0.132%, which is not statistically significant).[13] Panel C of Figure 3 presents the results of the spectral multiresolution analysis applied to each specific climate-change-related topic. These findings are both quantitatively and qualitatively consistent with the previous robustness exercises.

Overall, the three robustness checks confirm the main findings discussed in Section 3.2: (*i*) green stocks outperform brown stocks at short horizons (i.e., cycles shorter than eight days), and (*ii*) this outperformance is driven by transition-risk-related news, particularly those associated with climate policy events such as climate summits.

5 Conclusions

In this work, unlike previous studies relying on time-domain analysis, we employ the extended Wold decomposition proposed by Bandi et al. (2021) to examine whether, for the U.S., the response of risk-adjusted returns on a green-minus-brown portfolio to innovations in climate concern differs across frequency bands associated with cycles of varying lengths. We find evidence that shocks to climate concern contribute to the outperformance of green stocks. Moreover, this effect materializes with a delay of four to eight days, which is longer than the horizon considered by Ardia et al. (2023). Finally, among the three categories of climate change concern, transition risk emerges as the primary driver of green stock out-

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[12] The LR test for the restricted VAR(7), where the MCCC innovation is obtained from the ARX specification described above, yields a statistic of 10.460 (p-value 0.164), supporting the restricted specification.

[13] The LR statistic is 8.492 (p-value 0.291), supporting the restricted VAR specification.

performance within the short-term horizon supported by our empirical results, particularly through components related to climate policy and technological innovation. The delayed response of stock returns to climate concern shocks points to inefficiencies arising from limited transparency about firms' environmental characteristics. Strengthening disclosure standards on corporate "greenness" could accelerate the incorporation of information into prices and speed up the allocation of capital toward sustainable investments.

Table 3 Spectral climate risk factor model: robustness checks

***Panel A*: Alternative SVAR lag-length**

	$J=1$	$J=2$	$J=3$	$J=4$	$J>4$	Time domain
β	0.102	0.153	**0.609***	-0.109	0.239	**0.155***
	(0.848)	(0.662)	(1.922)	(-0.319)	(1.014)	(1.723)
$\sigma^2_{\tilde{r}}$	1.867	0.977	0.441	0.216	0.237	
$\sigma^2_{\Delta MCCC}$	0.066	0.021	0.011	0.009	0.021	
v (weight)	0.514	0.165	0.087	0.067	0.167	

$\sum_{j=1}^{J+1} v^{(j)}\beta^{(j)} = \mathbf{0.164}$

***Panel B*: ARX model**

	$J=1$	$J=2$	$J=3$	$J=4$	$J>4$	Time domain
β	0.118	0.107	**0.673****	0.005	0.237	**0.171***
	(0.952)	(0.460)	(2.034)	(0.016)	(0.952)	(1.849)
$\sigma^2_{\tilde{r}}$	1.861	0.977	0.440	0.228	0.230	
$\sigma^2_{\Delta MCCC}$	0.064	0.021	0.011	0.012	0.020	
v (weight)	0.499	0.166	0.087	0.092	0.156	

$\sum_{j=1}^{J+1} v^{(j)}\beta^{(j)} = \mathbf{0.173}$

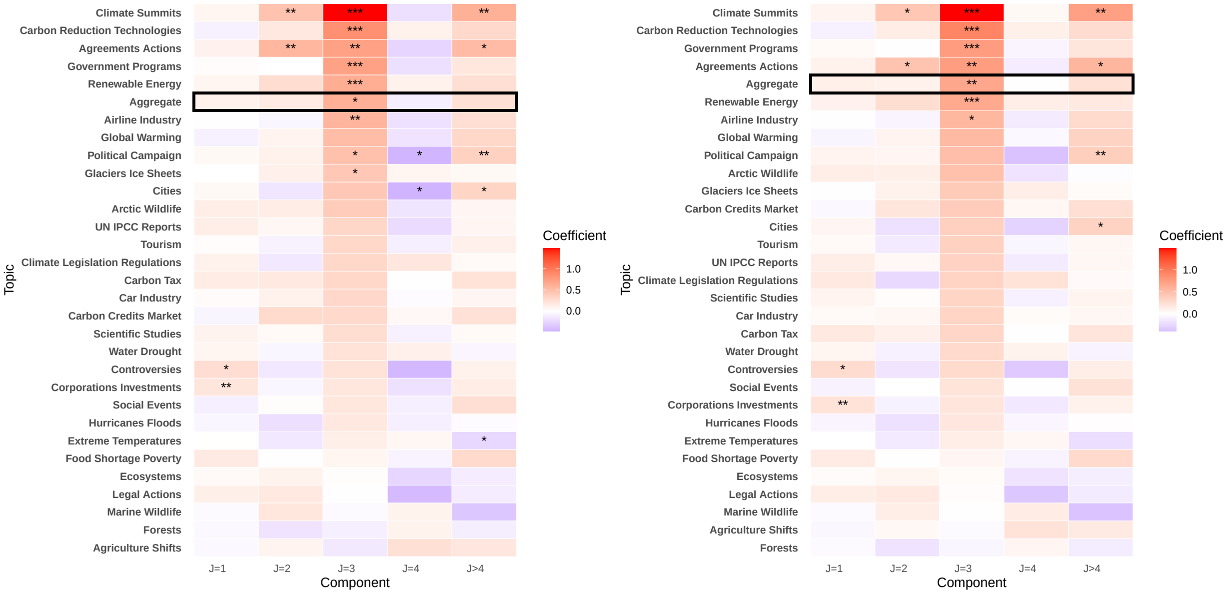
***Panel C*: Equally-weighted brown portfolio**

	$J=1$	$J=2$	$J=3$	$J=4$	$J>4$	Time domain
β	0.101	0.104	**0.645****	0.121	0.025	**0.132**
	(0.855)	(0.480)	(2.199)	(0.414)	(0.117)	(1.538)
$\sigma^2_{\tilde{r}}$	1.644	0.914	0.390	0.220	0.232	
$\sigma^2_{\Delta MCCC}$	0.065	0.021	0.011	0.011	0.020	
v (weight)	0.511	0.162	0.082	0.089	0.157	

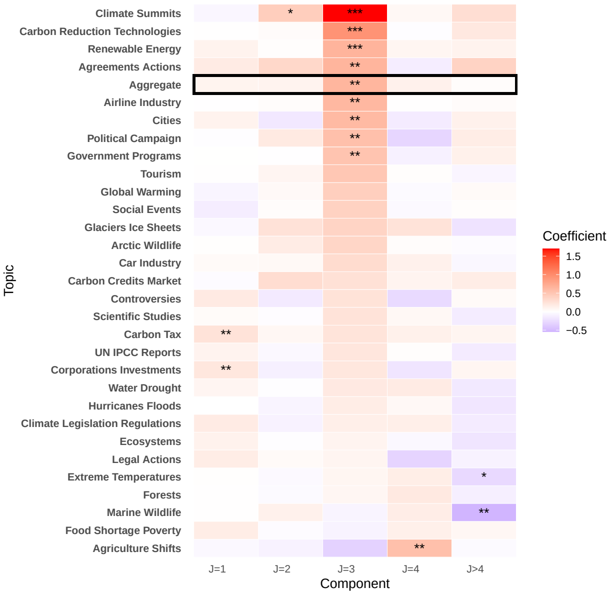
$\sum_{j=1}^{J+1} v^{(j)}\beta^{(j)} = \mathbf{0.136}$

Notes. The table reports estimates from the spectral climate risk regression (see equation 8) in which GMB risk-adjusted returns are the dependent variable and the J frequency-specific components of the innovations to the aggregate MCCC index are used as regressors, for $J = 1, \ldots, 4$, with an additional residual smooth component ($J > 4$), across the robustness exercises described in Section 4. Panel A shows estimates obtained by using frequency components from a structural VAR with twenty-two lags. Panel B reports estimates based on MCCC innovations obtained as residuals from an ARX model. Panel C shows results using a GMB portfolio in which the brown leg is constructed as an equally weighted portfolio of U.S. thermal coal firms. GMB risk-adjusted returns are expressed in percent. For additional details on the table entries, see the notes to Table 2. Significance levels: *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01. Estimation sample: 30 November 2010 - 28 June 2024.

Fig. 3 Spectral beta regressions across different MCCC topics: robustness checks



(a) Alternative SVAR lag-length **(b)** ARX model



(c) Equally-weighted brown portfolio

Notes. The figure presents heatmaps of the spectral beta coefficients across climate change-related topics for the robustness exercises described in Section 4. Panel A shows estimates obtained by using frequency components from a structural VAR with twenty-two lags. Panel B reports estimates based on MCCC innovations obtained as residuals from an ARX model. Panel C shows results using a GMB portfolio in which the brown leg is constructed as an equally weighted portfolio of U.S. thermal coal firms. GMB risk-adjusted returns are expressed in percent. For additional details on the figure, see the notes to Figure 2. Significance levels: *p-value < 0.1; **p-value < 0.05; ***p-value < 0.01. Estimation sample: 30 November 2010 - 28 June 2024.

Statements and Declarations

Competing Interests

The authors have no competing interests to declare.

Data Availability

Data are available upon request from the authors.

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