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by Andrea Cipollini and Fabio Parla

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CEFIN – Centro Studi di Banca e Finanza www.cefin.unimore.it
Dipartimento di Economia Marco Biagi – Università di Modena e Reggio Emilia

Viale Jacopo Berengario 51, 41121 MODENA (Italy) tel. 39-059.2056711

(Centralino) fax 39-059 205 6927

Climate risk and investment in equities in Europe: a Panel SVAR approach*

Andrea Cipollini† Fabio Parla‡

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Abstract

In this study, we use data on European stocks to construct a green-minus-brown portfolio hedging climate risk and to evaluate its performance in terms of cumulative expected and unexpected returns. More specifically, we estimate a Structural Panel VAR fitted to one month return and realized volatility computed for 40 constituents of a green portfolio (i.e., the low carbon emission portfolio monitored by Refinitiv) and for 41 constituents of a brown portfolio (underlying the Oil&Gas and Utilities industry sectors of the STOXX Europe 600). The common shocks underlying the cross-sectional averages, interpreted as portfolio shocks, are retrieved in a first stage of the analysis and they are used to control for cross-sectional dependence. We compute the historical decomposition (for cumulative returns) in a second stage of the analysis and we find, in line with Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics*, *146*(2), 403–424, an out-performance of the expected component of the brown portfolio relative to the one for the green portfolio, and an out-performance of the green portfolio when we turn our focus on the unexpected component. We also extend the analysis of Pástor et al. (2022), assessing, for the top 5 constituents of the green portfolio (e.g., those which are found to have the worst performance in terms of expected return), the role played by idiosyncratic shocks in shaping their out-performance in terms of unexpected component. Finally, after exploiting the non-gaussian time series properties of the financial time series considered for the purpose of statistical identification, we are able to interpret ex post the idiosyncratic shocks in terms of financial leverage and risk aversion.

Keywords: Climate risk, green and brown portfolios, portfolio shocks, Panel VAR

JEL: C33, C58, Q54

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†Department of Economics, Business and Statistics, University of Palermo, V.le delle Scienze, 90128 Palermo, Italy. Email: andrea.cipollini@unipa.it. ReCent and Cefin.

‡Department of Economics, Business and Statistics, University of Palermo, V.le delle Scienze, 90128 Palermo, Italy. Email: fabio.parla@unipa.it. (Corresponding author)

1 Introduction

The role of investment in equities to hedge climate risk has recently gained popularity. Stock prices reflect expectations about the future impact of climate change on the macroeconomy. In particular, cash flow effects of temperature shocks arise given their impact on labour productivity and labour supply (especially in some sectors) and they are discounted in stock prices. While the study of Bansal et al. (2019) shows that growth stocks are those mostly vulnerable to climate risk since they are exposed to long-run risk, a number of studies rely on environmental scores, carbon emission or industry classification in detecting the stocks (e.g., green and brown) more vulnerable to climate risk. In particular, while the study of Bolton and Kacperczyk (2021) finds that stocks of firms with higher carbon emissions (but not with high emission intensity) earn higher risk-adjusted returns, Görgen et al. (2020) find an insignificantly negative carbon premium when they combine multiple carbon-emission-related measures. Pástor et al. (2022) disentangle the expected and unexpected components of a green-minus-brown, climate risk hedging portfolio, and find evidence of a switch in the sign (from negative to positive) of the risk premium when turning the focus from the expected component of (cumulative) returns to the unexpected one associated with news arrival.[1] More specifically, according to Pástor et al. (2021), the excess return of a climate hedging portfolio (green-minus-brown) is the sum of a risk premium and a taste premium. The former is associated with the hedging properties of investors and the latter is associated with the appetite for green assets. While the hedging properties of the green portfolio lead to a negative expected excess return, increasing climate concerns can raise investors' demand for green assets, driving up green asset prices. Moreover, environmental regulations can boost demand for green products, driving up green firms' profits and thus their stock prices. While the previous studies focus on the US, the study of Bua et al. (2022) focuses on Europe and the authors find an increasing role played by physical and transition climate risk since the Paris Agreement (December 2015) on climate change. More specifically, the authors find a relatively higher required return is asked for stocks which provide a bad hedge against climate risk. In this study, we focus on European stocks, and in particular, we consider a sample of 40 constituents of a portfolio with a high environmental score monitored by Refinitiv and another one given by 41 constituents underlying the Oil&Gas and Utilities industry sectors of the

[1]Shocks to an index of climate concern developed by Ardia et al. (2022) are the main driver of the unexpected component of stock return. While Pástor et al. (2022) use the Ardia et al. (2022)'s index computed on a monthly basis (see also Engle et al., 2020), the study of Ardia et al. (2022) relies on a daily index of climate concern, disentangling the role of climate change transition and physical risk.

STOXX Europe 600. The main contributions of our study are as follows. First, we rely on an information set to compute the expected and the unexpected component of returns which is given by a relatively large panel of one month return and realized volatilities of stocks examined over the sample period $2010m6 - 2022m5$. Second, we share with Ludvigson and Ng (2007) the use of common factors (underlying two large datasets of macro and financial variables) to investigate the model predictive performance for the stock market return and, more generally, the risk-return relationship in the US. While Ludvigson and Ng (2007) use a dynamic factor model to extract the aforementioned common factors, we estimate a Panel VAR using the methodology put forward by Cesa-Bianchi et al. (2020) which does not rely on the estimation of principal components but on structural shocks underlying the dynamics of cross-sectional averages, to control for cross-sectional dependence. In particular, the analysis of Cesa-Bianchi et al. (2020) is split into two stages, where, in the first one, the contemporaneous values of the common shocks (interpreted as portfolio shocks) are obtained through Structural VAR analysis fitted to the cross-sectional averages of the two endogenous variables considered. The Panel VAR is, then, estimated in the second stage, using, as exogenous variables, the lagged values of the cross-sectional averages of the endogenous variables and the contemporaneous common shocks retrieved in the first stage of the analysis. We find that the use of the aforementioned exogenous variables to control for cross-sectional dependence improves the predictive performance of the model for the return (and realized volatility) of each portfolio constituent. The third contribution is the use of historical decomposition from Panel VAR to retrieve the expected and unexpected components of portfolio returns and the one for the constituents. In particular, in the second stage of the estimation analysis, we obtain, through historical decomposition of the return series, the expected component, showing, in line with Pástor et al. (2022), an out-performance of the cumulative return on the brown portfolio relative to the green portfolio. The empirical findings suggest that the green companies under investigation play a climate risk hedging role according to the stock market. Moreover, in line with the theoretical and empirical findings of Pástor et al. (2022), we find, through historical decomposition, an out-performance of the unexpected component of the green portfolio (in terms of cumulative returns). Our final contribution is related to the marginal contribution of the constituents to the green portfolio performance (in terms of expected and unexpected cumulative returns). More specifically, we focus on the top five constituents of the green portfolio in terms of climate risk hedging (e.g., those with the largest negative expected cumulative return relative to the brown portfolio) and we examine, after controlling for common shocks, the role played by idiosyncratic shocks underlying their unexpected component. Finally, we are able to statistically identify the idiosyncratic shocks (through the non-gaussian time series properties according to the methodology put forward by Lanne et al., 2017): we interpret them, ex-post, as risk aversion and financial leverage and we examine their contribution to the evolution over time of the unexpected component.

The paper is organized as follows. Section 2 describes the empirical methodology. Section 3 discusses the data. Section 4 discusses the empirical evidence and Section 5 concludes.

2 Empirical model

Following Cesa-Bianchi et al. (2020), we estimate a structural Panel Factor-Augmented Vector Autoregressions (VAR) fitted to monthly return (r_{it}) and realized volatility (RV_{it}) of the N constituents entering either the green or the brown portfolio. The model is estimated for each of the two portfolios, separately:

$$y_{it} = \mu_i + \sum_{\ell=1}^{p} \Phi_{i\ell} y_{it-\ell} + \Delta_i \hat{\varepsilon}_t + \sum_{\ell=1}^{q} \Theta_{i\ell} \bar{y}_{t-\ell} + B_{i0}\xi_{it} \tag{1}$$

where $y_{it} = (r'_{it}, RV'_{it})'$ is a 2×1 vector of endogenous variables observed for the $i-th$ constituent, with $i = 1, \ldots, N$, at month t, μ_i is a 2×1 vector of intercept terms, $\Phi_{i\ell}$, for $\ell = 1, \ldots, p$, is a 2×2 matrix of slope coefficients. Moreover, we include in the model specification a set of exogenous variables: (i) $\hat{\varepsilon}_t$ is a 2×1 vector of estimated orthogonal shocks extracted from common factors hitting the green and brown portfolios, whose loadings are contained in the 2×2 matrix Δ_i; (ii) $\bar{y}_{t-\ell}$, for $\ell = 1, \ldots, q$, are the lagged cross-sectional averages computed among the return and realized volatility of the N constituents, with the associated coefficients contained in the 2×2 matrix $\Theta_{i\ell}$.[2] Finally, B_{i0} is a 2×2 matrix containing the effects of the idiosyncratic structural shocks (ξ_{it}) on the endogenous variables, such that $u_{it} = B_{i0}\xi_{it}$, where u_{it} is a 2×1 vector of serially uncorrelated idiosyncratic reduced-form innovations.

In line with Cesa-Bianchi et al. (2020), to estimate the model in equation (1), we follow a two-step approach. In the first step, we identify the structural common shocks ($\hat{\varepsilon}_t$) by estimating an aggregated (i.e., portfolio-wide) VAR fitted to the cross-sectional averages of the N constituents' one month return and realized volatility ($\bar{y}_t$):

[2]As discussed in Cesa-Bianchi et al. (2020), since $\hat{\varepsilon}_t$ are estimated using the lagged observations of the cross-sectional averages ($\bar{y}_{t-\ell}$) (see equation 2), it is important to filter out their effect.

$$\bar{y}_t = \mu + \sum_{\ell=1}^{p} A_\ell \bar{y}_{t-\ell} + B_0 \varepsilon_t \tag{2}$$

where $\bar{y}_t = (\bar{r}_t', \bar{RV}_t')'$ is a 2×1 vector of aggregated one month return and realized volatility. These are computed as the cross-sectional weighted average of one month return, i.e., $\bar{r}_t = \sum_{i=1}^{N} w_i r_{it}$, and of realized volatility, i.e., $\bar{RV}_t = \sum_{i=1}^{N} w_i RV_{it}$, where w_i is a vector of weights, reflecting the importance of each i-th constituent within the two portfolios. For both the green and brown portfolios, we set $w_i = 1/N$, for $i = 1, \ldots, N$.[3] Furthermore, μ is a 2×1 vector of constant terms, A_ℓ, for $\ell = 1, \ldots, p$, is a 2×2 matrix of slope coefficients, B_0 is the 2×2 structural impact multiplier matrix and ε_t is a 2×1 vector of structural shocks.

In the second step, for each of the N constituents entering either the green or brown portfolio, we estimate the VAR augmented with the exogenous variables (VARX) (see equation 1). Then, we compute impulse response functions (to both common and idiosyncratic shocks) and historical decomposition of r_{it} and RV_{it}. Both the aggregate SVAR and the constituent-specific SVARX are estimated through maximum likelihood (ML) estimation by assuming that the structural shocks are non-Gaussian.

2.1 Maximum likelihood estimation of the non-Gaussian SVAR

Both the aggregate SVAR and the Panel Factor-Augmented VAR are estimated by ML under the non-Gaussianity assumption. For the sake of simplicity, we only describe the ML estimator of the structural- and reduced-form parameters entering the aggregate SVAR (see equation 2). However, the estimation approach discussed in the rest of this section can be easily extended to the Panel Factor-Augmented VAR described in equation (1).

Given the data $y_{-p+1}, \ldots, y_0, y_1, \ldots, y_T$ (where $y_{-p+1}, \ldots, y_0$ is the initial condition) and assuming a Student's t-distribution of the error terms, the parameters of the SVAR in equation (2), $\theta = (\pi, \beta, \sigma, \lambda)$, can be estimated by maximizing the following log-likelihood:

$$L_T(\theta) = T^{-1} \sum_{t=1}^{T} l_t(\theta) \tag{3}$$

where $\pi = vec\big([\mu, A_1, \ldots, A_p]\big)$ is a $2(2p+1) \times 1$ vector of the reduced-form VAR parameters,

[3] As described in Section 3, the Refinitiv Eurozone Low Carbon Select Index (i.e., the green portfolio) is constructed by using an equally-weighted scheme, hence we assign equal weights to each constituent. Moreover, since in our analysis, the brown portfolio is constructed by aggregating constituents from two different industry sectors (i.e., Oil&Gas and Utilities sectors), we set their weights (w_i) equal to $1/N$.

$\beta = vecd^o(\tilde{B}_0)$ is a 2×1 vector containing the off-diagonal elements of $\tilde{B}_0$, that is B_0 with its main diagonal entries being normalized to unity, $\sigma = (\sigma_1, \sigma_2)$ are the standard deviations of the structural shocks and $\lambda = (\lambda_1, \lambda_2)$ are the degree of freedom of the two independent Student's t-distributions. The log density $l_t(\theta)$ is defined as follows:

$$l_t(\theta) = \sum_{i=1}^{2} \log\, f_i\big(\sigma_i^{-1} e_i' \tilde{B}_0(\beta)^{-1} u_t; \lambda_i\big) - \log\, \Big(\det\big(\tilde{B}_0(\beta)\big)\Big) - \sum_{i=1}^{2} \log\, \sigma_i \tag{4}$$

where f_i is the density function of the Student's t-distribution, u_t are the reduced form VAR residuals, such that $u_t = B_0 \varepsilon_t = \tilde{B}_0 \Omega^{1/2} \varepsilon_t$, where $\Omega^{1/2} = \mathrm{diag}(\sigma_1, \sigma_2)$, and e_i is the i-th selection vector.[4] In line with Lanne et al. (2017), we estimate the SVAR using a three-step ML estimation.[5] In the first step, we estimate the reduced form of VAR parameters associated with the structural specification in equation (2) using OLS estimation ($\hat{\pi}^{LS}$). In the second step, we estimate the normalized structural impact multiplier ($\tilde{B}_0$), the standard deviation of the structural shocks (σ) and the degree of freedom (λ), using the OLS residuals obtained from the previous step. In particular, the structural parameters are estimated by maximizing the following log-likelihood function:

$$L_T(\beta, \sigma, \lambda) = L_T(\hat{\pi}^{LS}, \beta, \sigma, \lambda) = T^{-1} \sum_{t=1}^{T} l_t(\hat{\pi}^{LS}, \beta, \sigma, \lambda) \tag{5}$$

where the log density $l_t(\hat{\pi}^{LS}, \beta, \sigma, \lambda)$ is obtained by replacing u_t with the estimated reduced-form residuals $\hat{u}_t^{LS}$ in equation (4). Maximizing the log-likelihood function in equation (5) leads to the estimates of the structural parameters: $\hat{\beta}$, $\hat{\sigma}$ and $\hat{\lambda}$. Finally, in the third step, we estimate the reduced form of VAR parameters $\pi = vec\big([\mu, A_1, \ldots, A_p]\big)$, by using the estimates of the structural parameters obtained in the previous step and by maximizing the following log-likelihood function:

$$L_T(\pi) = L_T(\pi, \hat{\beta}, \hat{\sigma}, \hat{\lambda}) = T^{-1} \sum_{t=1}^{T} l_t(\pi, \hat{\beta}, \hat{\sigma}, \hat{\lambda}) \tag{6}$$

with respect to π. This leads to the ML estimate of the reduced form of VAR parameters, that is $\hat{\pi} = vec\big([\hat{\mu}, \hat{A}_1, \ldots, \hat{A}_p]\big)$.[6]

[4] See Lanne et al. (2017) for further details on the ML estimation for non-Gaussian SVAR.

[5] Our choice of Student's t-distributed error terms is along the line of Lanne et al. (2017), which describe how the three-step estimation approach is asymptotically efficient under the assumption of symmetry in the error distribution.

[6] The codes used in our study are an adaptation of the R package `svars` developed by Lange et al. (2021).

The identification through non-Gaussianity has two desirable features for our empirical analysis. First, as discussed by Lanne et al. (2017), this methodology allows computing unique impulse responses without imposing any theory-driven restrictions (such as short- or long-run zero exclusion restrictions, or sign-restrictions) on the response of the endogenous variables to the structural shocks. However, identification through non-Gaussian errors is a statistical tool, hence to give an economic interpretation of the structural shocks we use ex-post theory-driven sign restrictions. Second, our empirical methodology involving fat-tailed error distributions (i.e., independent Student's t-distributions) is suitable for financial market series showing potential outlier observations.[7]

Once obtaining the ML estimates of both the reduced and structural form of VAR parameters, that is $\hat{\theta} = (\hat{\pi}, \hat{\beta}, \hat{\sigma}, \hat{\lambda})$, we retrieve the structural shocks as follows $\hat{\varepsilon}_t = \hat{B}_0^{-1}\hat{u}_t$. Then, we include $\hat{\varepsilon}_t$ as an exogenous term in the constituent-specific VARX, together with the lagged cross-sectional averages of endogenous variables (see equation 1).[8] The Panel Factor-Augmented VAR is estimated by running ML estimation for each constituent-specific VARX, separately.

2.2 Structural analysis

For both the green and brown portfolios, we compute the impulse responses to common and idiosyncratic shocks and the historical decomposition of one month return and realized volatility. Given a lag of order 2 (i.e., $p = q = 2$), let us re-write each i-th constituent-specific VARX in equation (1) in its companion representation:

$$Y_{it} = \boldsymbol{\mu}_i + \mathbf{\Phi}_i Y_{it-1} + \mathbf{\Delta}_i \hat{\mathcal{E}}_t + \mathbf{\Theta}_{i1} \bar{Y}_{t-1} + \mathbf{\Theta}_{i2} \bar{Y}_{t-2} + \mathbf{B}_{i0} \Xi_{it} \tag{7}$$

where Y_{it} and Y_{it-1} are the 4×1 vector containing the endogenous variables observed for each constituent i, $\hat{\mathcal{E}}_t$ is a 4×1 vector containing the common factors, $\bar{Y}_{t-1}$ and $\bar{Y}_{t-2}$ are the 4×1 vector of lagged cross-sectional averages ($q = 2$) and Ξ_{it} is the 4×1 vector containing the idiosyncratic structural shocks. Moreover, $\mathbf{\Phi}_i$ is the 4×4 matrix containing the slope coefficients, $\mathbf{\Delta}_i$ is the 4×4 matrix containing the loadings associated with the common factors, $\mathbf{\Theta}_{i1}$ and $\mathbf{\Theta}_{i2}$ are the 4×4 matrices containing the coefficients associated

[7] Recently, a number of studies have shown the importance of using Student's t-distributed errors in VAR models to tackle large shocks, such as the recent Covid-19 pandemic, both for structural identification and forecasting evaluation exercises (see e.g., Bobeica & Hartwig, 2023; Carriero et al., 2022, among others).

[8] As described above, given that the common factors are identified also using lagged cross-sectional averages of the endogenous variables, Cesa-Bianchi et al. (2020) point at the importance of including $\bar{y}_{t-\ell}$ in equation (1).

with the lagged cross-sectional averages, $\mathbf{B}_{i0}$ is the 4×4 matrix containing the impact multiplier coefficients, and $\boldsymbol{\mu}_i$ is the 4×1 vector containing the intercept terms.
The structural impulse response functions can be computed from the Moving Average (MA) representation of the constituent-specific VARX (see Appendix A). More specifically, for each i-th constituent, the impulse response to both common (Γ_{ih}) and idiosyncratic (Υ_{ih}) shocks, for $h = 0, 1, 2, \ldots$, can be computed as follows:

$$\Gamma_{ih} = J\mathbf{\Phi}_i^h J'\Delta_i \qquad \Upsilon_{ih} = J\mathbf{\Phi}_i^h J' B_{i0} \tag{8}$$

where Δ_i is the 2×2 matrix containing the loadings associated with the common factors, B_{i0} is the 2×2 impact multiplier matrix, and $J = [I_2 : 0 : \cdots : 0]$ is a 2×4 selection matrix. Moreover, we also compute the historical decomposition of the one month return and realized volatility for each i-th constituent as follows:[9]

$$y_{it} = JY_{it} = \underbrace{J\sum_{j=0}^{t-1}\mathbf{\Phi}_i^j\boldsymbol{\mu}_i + J\mathbf{\Phi}_i^t Y_{i0} + J\sum_{j=0}^{t-1}\mathbf{\Phi}_i^j\mathbf{\Theta}_{i1}\bar{Y}_{t-j-1} + J\sum_{j=0}^{t-1}\mathbf{\Phi}_i^j\mathbf{\Theta}_{i2}\bar{Y}_{t-j-2} +}_{\text{Total expected component}} \tag{9}$$
$$+ \underbrace{J\sum_{j=0}^{t-1}\mathbf{\Phi}_i^j\mathbf{\Delta}_i\hat{\mathcal{E}}_{t-j} + J\sum_{j=0}^{t-1}\mathbf{\Phi}_i^j\mathbf{B}_{i0}\Xi_{it-j}}_{\text{Total unexpected component}}$$

where the one month return (r_{it}) and the realized volatility (RV_{it}) contained in $y_{it} = (r_{it}', RV_{it}')'$ can be decomposed into an anticipated (expected) and an unanticipated (unexpected) component. In particular, the total expected component to the dynamics of r_{it} and RV_{it} is computed as the sum of the contribution of the constant terms (μ_i), the initial condition (y_{i0}), and the lagged cross-sectional averages ($\bar{y}_{it-1}$ and $\bar{y}_{it-2}$), while the contribution of the total unexpected component is obtained by summing up the contribution of the common ($\hat{\varepsilon}_t$) and idiosyncratic (ξ_{it}) shocks.

3 Data

In this paper, we use monthly returns and realized volatility of two European green and brown portfolios of stocks over the period $2010m6 - 2022m5$. As for the green portfolio,

[9] See Appendix A, for further details on the construction of the MA representation.

we select the Eurozone Low Carbon Select Index maintained by Refinitiv, which measures the performance of the stocks of 50 European companies that actively support and invest in environmental, social, and governance (ESG) values and principles in the operation of their companies, particularly by aiming to lessen their carbon emissions.[10] The index is computed by aggregating the information of its 50 constituents using an equally-weighted scheme.[11] Due to data availability, as well as to avoid overlapping between green and brown portfolios, we discard 10 constituents from the estimation sample.[12] This enables us to span over a relatively long time horizon and, at the same time, to cover the 80% of the original portfolio sample size.[13] The list of 40 green portfolio's constituents used in our study, together with their environment score provided by Refinitiv, is reported in Table 1 (Panel A). As can be seen in Table 1 (Panel A), most of the constituents (around 78% of the total portfolio) show an environment score greater than 75.[14] As for the brown portfolio, we construct an equally-weighted portfolio underlying the Oil&Gas and Utilities industry sectors of the STOXX Europe 600, that is the iShares STOXX Europe 600 Oil&Gas UCITS ETF and the iShares STOXX Europe 600 Utilities UCITS ETF, both monitored by BlackRock. We select 41 companies (out of the 51 available) whose observations start from June 2010.[15] The list of the companies entering the brown portfolio is reported in Table 1 (Panel B). As shown in Table 1 (Panel B), only 24 out of 41 constituents report an environment score greater than 75.

For both the green and brown portfolios, the monthly return and realized volatility series

[10]The ESG score provided by Refinitiv measures the performance of a company in terms of three pillars: (*i*) environment, (*ii*) social and (*iii*) governance. Refinitiv assigns a score to each pillar that results from the aggregation of ten different category scores. The environment pillar includes emissions, resource use and innovation. The social pillar includes human rights, product responsibility, workforce and community. Finally, the governance pillar includes management, shareholders and CSR strategy.

[11]Technical details on the construction and calculation methodology are reported in the Refinitiv website.

[12]In detail, we remove the following companies, whose observations are available for less than 10 years (the first date available is reported in brackets): *ASR Nederland N.V.* (10 June 2016), *CNH Industrial N.V.* (30 September 2013), *KION GROUP AG* (8 July 2013), *Signify N.V.* (27 May 2016), *NN Group N.V.* (2 July 2014), *Vonovia SE* (11 July 2013), *Worldline SA* (27 June 2014) and *Zalando SE* (1 October 2014). Moreover, we remove *Electricité de France S.A.* and *Red Eléctrica Corporación, S.A.* as they are also included in the constructed brown portfolio.

[13]In the selected sample, we replace the missing observations with the value observed the day before.

[14]According to Refinitiv, companies with a score greater than 75 show excellent relative ESG performance as well as a high level of transparency in publicly reporting material ESG data.

[15]We discard the following companies from the estimation sample (the first available observation is reported in brackets): *Corporación Acciona Energías Renovables, S.A.* (2 July 2021), *BKW AG* (12 December 2011), *Energean plc* (16 March 2018), *Siemens Energy AG* (29 September 2020), *Gaztransport & Technigaz SA* (27 February 2014), *Harbour Energy plc* (1 April 2021), *Italgas S.p.A.* (7 November 2016), *Ørsted A/S* (9 June 2016). Furthermore, the two companies entering the green portfolio (*Electricité de France S.A.* and *Red Eléctrica Corporación, S.A.*) are also discarded.

Table 1: Constituents of the green and brown portfolios

Panel A: Green portfolio

Security name	Ticker	Country	Env. score	Security name	Ticker	Country	Env. score
ALSTOM SA	ALO	France	99	KESKO	KESKOB	Finland	78
ALLIANZ SE	ALV	Germany	95	KONINKLIJKE KPN NV	KPN	Netherlands	76
AMADEUS IT HOLDING SA	AMS	Spain	73	MEDIOBANCA BANCA CRED. FIN. SPA	MB	Italy	47
BANCO BILBAO VIZCAYA ARGENTARIA S.A.	BBVA	Spain	95	MÜNCHENER RÜCK*	MUV2	Germany	94
BAYERISCHE MOTOREN WERKE AG	BMW	Germany	81	NOKIA OYJ	NOKIA	Finland	70
BNP PARIBAS SA	BNP	France	95	ORANGE SA	ORA	France	86
CAIXABANK SA	CABK	Spain	85	KONINKLIJKE PHILIPS NV	PHIA	Netherlands	81
CAP GEMINI SA	CAP	France	77	KERING SA	KER	France	96
CARREFOUR SA	CA	France	91	PUMA SE	PUM	Germany	85
COMMERZBANK AG	CBK	Germany	93	RANDSTAD NV	RAND	Netherlands	63
DASSAULT SYSTEMES SA	DSY	France	77	BANCO SANTANDER SA	SAN	Spain	90
DEUTSCHE BOERSE AG	DB1	Germany	66	SCHNEIDER ELECTRIC SA	SU	France	68
DEUTSCHE TELEKOM AG	DTE	Germany	85	SIEMENS AG	SIE	Germany	88
ELISA OYJ	ELISA	Finland	71	SOCIETE GENERALE	GLE	France	96
ASSICURAZIONI GENERALI SPA	G	Italy	96	STMICROELECTRONICS NV	STM	Netherlands	95
HENKEL AG & CO KGAA	HEN3	Germany	70	SYMRISE AG	SY1	Germany	64
ING GROEP NV	INGA	Netherlands	86	TELEFONICA SA	TEF	Spain	82
INTESA SANPAOLO SPA	ISP	Italy	97	UCB SA	UCB	Belgium	77
INDITEX S.A.	ITX	Spain	96	UNIBAIL RODAMCO WESTFIELD	URW	France	88
KBC GROUPE SA	KBC	Belgium	93	VIVENDI SA	VIV	France	81

Panel B: Brown portfolio

Security name	Ticker	Country	Env. score	Security name	Ticker	Country	Env. score
A2A	A2A	Italy	84	NESTE	NESTE	Finland	74
AKER BP	AKRBP	Norway	60	NATIONAL GRID PLC	NG.	United Kingdom	62
BP PLC	BP	United Kingdom	91	NATURGY ENERGY SA	NTGY	Spain	89
CENTRICA PLC	CNA	United Kingdom	71	OMV AG	OMV	Austria	76
DRAX GROUP PLC	DRX	United Kingdom	63	POLSKI KONCERN NAFTOWY ORLEN SA	PKN	Poland	57
ENCAVIS AG	ECV	Germany	42	PENNON GROUP PLC	PNN	United Kingdom	89
EDP ENERGIAS DE PORTUGAL SA	EDP	Portugal	89	REPSOL SA	REP	Spain	89
EDP RENOVAVEIS SA	EDPR	Portugal	90	RWE AG	RWE	Germany	79
ENDESA SA	ELE	Spain	82	SHELL PLC	SHELL	United Kingdom	91
ELIA GROUP SA	ELI	Belgium	55	SNAM	SRG	Italy	96
ENEL	ENEL	Italy	96	SSE PLC	SSE	United Kingdom	92
ENAGÁS SA	ENG	Spain	84	SUBSEA SA	SUBC	Norway	86
ENGIE SA	ENGI	France	67	SEVERN TRENT PLC	SVT	United Kingdom	72
ENI	ENI	Italy	72	TENARIS SA	TEN	Italy	78
E.ON N	EOAN	Germany	58	TERNA RETE ELETTRICA NAZIONALE	TRN	Italy	75
EQUINOR	EQNR	Norway	75	TOTALENERGIES	TTE	France	91
FORTUM	FORTUM	Finland	85	UNITED UTILITIES GROUP PLC	UU.	United Kingdom	82
GALP ENERGIA SGPS SA	GALP	Portugal	75	VERBUND AG	VER	Austria	90
HERA	HER	Italy	99	VEOLIA ENVIRON. SA	VIE	France	79
IBERDROLA SA	IBE	Spain	96	VESTAS WIND SYSTEMS	VWS	Denmark	75
NEL	NEL	Norway	36				

Notes. List of constituents entering the Refinitiv Eurozone Low Carbon Select Index (namely the green portfolio) (Panel A) and the brown portfolio constructed by aggregating the companies' stocks from the iShares STOXX Europe 600 Oil&Gas UCITS ETF and iShares STOXX Europe 600 Utilities UCITS ETF (Panel B). For each constituent, the table reports the following information: full security name, ticker, the headquarter (at a country level) and the environment score (out of 100) provided by Refinitiv. *Abbreviation of Münchener Rückversicherungs-Gesellschaft Aktiengesellschaft in München.

of the N constituents are computed by using their close price series downloaded from the Yahoo Finance database. We compute the return over a one-month horizon (r_{it}) as the log changes of the monthly close price: $r_{it} = \log(P_{it}) - \log(P_{it-1})$, for $t = 1, \ldots, T$, where P_{it} is the close price of the i-th constituent observed at the end of month t. In line with Cesa-Bianchi et al. (2020), the monthly realized volatility (RV_{it}) is computed as the sum of the squared daily return (r_{id}):

$$RV_{it} = \sqrt{\sum_{d=1}^{D} (r_{id} - \bar{r}_i)^2}\,, \qquad \text{for } t = 1, \ldots, T \tag{10}$$

where D is the number of trading days in month t, $r_{id} = \log(P_{id}) - \log(P_{id-1})$ is the daily return computed for the i-th constituent, and P_{id} is the daily closing price. Descriptive statistics for the monthly return and for the realized volatility of the 40 green portfolio's

Table 2: Descriptive statistics for the monthly return of the green portfolio.

Constituent	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
ALO	-0.003	-0.002	0.398	-0.258	0.089	0.357	5.932
ALV	0.006	0.006	0.269	-0.239	0.069	-0.278	4.820
AMS	0.011	0.014	0.338	-0.385	0.072	-0.748	10.454
BBVA	-0.003	0.001	0.468	-0.397	0.097	0.268	7.720
BMW	0.005	0.008	0.234	-0.242	0.083	-0.035	3.920
BNP	0.001	0.013	0.364	-0.465	0.098	-0.679	6.771
CA	-0.004	0.005	0.148	-0.318	0.070	-0.676	4.809
CABK	-0.000	0.003	0.318	-0.311	0.097	0.085	4.060
CAP	0.011	0.014	0.170	-0.254	0.076	-0.586	3.388
CBK	-0.012	0.002	0.339	-0.454	0.120	-0.313	4.109
DB1	0.008	0.011	0.139	-0.220	0.060	-0.726	4.688
DSY	0.015	0.020	0.161	-0.209	0.059	-0.370	3.784
DTE	0.005	0.007	0.145	-0.222	0.059	-0.453	4.714
ELISA	0.009	0.014	0.154	-0.174	0.050	-0.237	3.644
G	0.001	-0.003	0.261	-0.270	0.078	-0.197	4.657
GLE	-0.002	0.004	0.360	-0.511	0.119	-0.654	5.297
HEN3	0.004	0.004	0.161	-0.155	0.056	-0.187	3.394
INGA	0.003	0.012	0.333	-0.588	0.105	-1.122	9.287
ISP	-0.000	0.010	0.305	-0.390	0.108	-0.736	4.477
ITX	0.006	0.007	0.273	-0.192	0.068	0.090	4.627
KBC	0.004	0.014	0.398	-0.671	0.113	-1.264	12.584
KER	0.012	0.002	0.210	-0.175	0.072	0.101	2.899
KESKOB	0.009	0.014	0.215	-0.187	0.074	-0.092	3.279
KPN	-0.004	0.000	0.215	-0.461	0.078	-1.416	10.565
MB	0.003	0.009	0.283	-0.488	0.110	-0.764	5.420
MUV2	0.005	0.011	0.151	-0.226	0.059	-0.673	4.062
NOKIA	-0.004	-0.001	0.507	-0.408	0.116	-0.092	6.008
ORA	-0.002	-0.004	0.189	-0.158	0.060	0.429	3.613
PHIA	0.000	0.003	0.156	-0.267	0.069	-0.395	3.806
PUM	0.008	0.003	0.249	-0.241	0.075	-0.029	4.105
RAND	0.003	0.004	0.192	-0.373	0.085	-0.938	5.788
SAN	-0.007	0.000	0.388	-0.405	0.094	-0.222	6.308
SIE	0.004	0.005	0.151	-0.218	0.063	-0.419	3.713
STM	0.012	0.020	0.227	-0.358	0.100	-0.445	3.491
SU	0.008	0.017	0.155	-0.144	0.063	-0.358	2.575
SY1	0.013	0.021	0.148	-0.207	0.056	-0.739	4.095
TEF	-0.008	-0.007	0.265	-0.250	0.075	-0.106	4.002
UCB	0.008	0.003	0.196	-0.277	0.068	-0.412	4.509
URW	-0.005	-0.002	0.533	-0.749	0.101	-1.801	27.238
VIV	-0.003	0.006	0.145	-1.086	0.107	-7.308	74.780

Notes. Descriptive statistics computed for the monthly return (in decimals) of the selected 40 constituents entering the Refinitiv Eurozone Low Carbon Select Index, over the period spanning from June 2010 to May 2022. The first column shows the ticker of each constituent (see Table 1, panel A).

Table 3: Descriptive statistics for the monthly realized volatility of the green portfolio.

Constituent	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
ALO	0.079	0.068	0.237	0.021	0.041	1.463	5.292
ALV	0.061	0.057	0.300	0.020	0.036	3.169	18.431
AMS	0.070	0.061	0.305	0.024	0.037	2.684	14.606
BBVA	0.089	0.079	0.308	0.035	0.041	1.996	8.842
BMW	0.073	0.068	0.286	0.025	0.033	2.495	14.253
BNP	0.088	0.074	0.357	0.032	0.050	2.553	11.641
CA	0.074	0.065	0.234	0.032	0.031	1.702	7.342
CABK	0.088	0.082	0.286	0.036	0.035	2.146	10.825
CAP	0.075	0.066	0.269	0.024	0.034	2.102	10.360
CBK	0.111	0.097	0.357	0.043	0.051	1.755	6.770
DB1	0.062	0.057	0.248	0.018	0.029	3.103	17.146
DSY	0.061	0.054	0.262	0.022	0.029	2.627	16.638
DTE	0.057	0.051	0.196	0.019	0.025	1.722	8.263
ELISA	0.056	0.051	0.212	0.020	0.025	2.319	12.984
G	0.068	0.060	0.225	0.022	0.033	1.962	8.815
GLE	0.103	0.088	0.412	0.033	0.059	2.277	9.724
HEN3	0.057	0.051	0.157	0.022	0.022	1.751	7.437
INGA	0.091	0.079	0.378	0.023	0.051	2.354	10.856
ISP	0.097	0.085	0.308	0.022	0.051	1.658	6.398
ITX	0.068	0.064	0.209	0.028	0.026	1.856	9.104
KBC	0.096	0.081	0.350	0.026	0.056	1.833	6.823
KER	0.074	0.068	0.264	0.023	0.031	1.979	11.245
KESKOB	0.068	0.061	0.274	0.024	0.032	2.228	13.056
KPN	0.070	0.060	0.237	0.022	0.035	1.926	7.812
MB	0.091	0.084	0.346	0.029	0.045	2.275	12.122
MUV2	0.058	0.050	0.320	0.020	0.034	3.894	27.570
NOKIA	0.100	0.085	0.292	0.036	0.051	1.649	5.512
ORA	0.061	0.054	0.197	0.020	0.026	1.316	6.770
PHIA	0.068	0.061	0.187	0.024	0.027	1.643	7.116
PUM	0.075	0.069	0.309	0.028	0.034	2.862	17.809
RAND	0.079	0.071	0.236	0.025	0.034	1.898	8.091
SAN	0.089	0.076	0.304	0.038	0.041	2.005	9.134
SIE	0.063	0.057	0.256	0.019	0.028	3.047	19.356
STM	0.103	0.095	0.329	0.042	0.039	1.793	9.963
SU	0.075	0.067	0.251	0.024	0.033	2.023	9.461
SY1	0.060	0.056	0.199	0.020	0.023	2.143	11.867
TEF	0.067	0.057	0.286	0.027	0.036	2.514	13.184
UCB	0.065	0.058	0.228	0.022	0.030	2.501	12.051
URW	0.079	0.060	0.426	0.021	0.060	2.997	13.907
VIV	0.068	0.056	0.912	0.021	0.076	9.772	108.464

Notes. Descriptive statistics computed for the monthly realized volatility (in decimals) of the selected 40 constituents entering the Refinitiv Eurozone Low Carbon Select Index, over the period spanning from June 2010 to May 2022. The first column shows the ticker of each constituent (see Table 1, panel A).

Table 4: Descriptive statistics for the monthly return of the brown portfolio.

Constituent	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
A2A	0.002	0.011	0.254	-0.329	0.086	-0.708	4.828
AKRBP	0.020	0.026	0.566	-0.514	0.134	0.260	6.401
BP	-0.001	-0.001	0.241	-0.439	0.079	-0.692	9.412
CNA	-0.009	-0.004	0.235	-0.639	0.086	-2.651	21.949
DRX	0.005	0.008	0.306	-0.563	0.105	-1.060	8.411
ECV	0.017	0.008	0.213	-0.247	0.072	0.134	4.171
EDP	0.004	-0.003	0.163	-0.251	0.061	-0.294	4.572
EDPR	0.011	0.010	0.250	-0.220	0.071	0.095	4.070
ELE	0.001	0.008	0.135	-0.700	0.083	-4.286	36.920
ELI	0.012	0.011	0.164	-0.103	0.045	0.260	3.593
ENEL	0.003	0.002	0.203	-0.191	0.068	-0.257	3.353
ENG	0.003	0.007	0.163	-0.257	0.058	-0.640	5.342
ENGI	-0.005	-0.001	0.175	-0.468	0.075	-1.503	11.896
ENI	-0.000	0.003	0.323	-0.191	0.067	0.686	6.216
EOAN	-0.006	0.001	0.223	-0.275	0.073	-0.662	4.930
EQNR	0.007	0.005	0.187	-0.168	0.062	0.040	3.345
FORTUM	-0.000	0.007	0.173	-0.366	0.073	-1.202	6.881
GALP	0.000	0.006	0.263	-0.211	0.076	-0.052	3.667
HER	0.006	0.006	0.163	-0.175	0.065	-0.417	3.509
IBE	0.005	0.002	0.190	-0.232	0.067	-0.428	4.282
NEL	-0.009	-0.002	0.903	-0.749	0.226	0.367	5.709
NESTE	0.016	0.005	0.296	-0.185	0.094	0.308	3.194
NG	0.005	0.006	0.089	-0.154	0.045	-0.732	3.895
NTGY	0.006	0.005	0.192	-0.266	0.069	-0.362	4.418
OMV	0.005	0.008	0.366	-0.408	0.092	-0.389	6.248
PKN	0.005	0.002	0.373	-0.255	0.091	0.219	4.124
PNN	0.002	0.007	0.117	-0.287	0.058	-1.072	6.619
REP	-0.001	0.006	0.411	-0.264	0.088	0.282	6.367
RWE	-0.002	-0.006	0.221	-0.347	0.098	-0.597	4.335
SHEL	0.002	0.005	0.275	-0.183	0.064	0.495	5.409
SRG	0.003	0.010	0.115	-0.282	0.051	-1.556	9.577
SSE	0.004	0.001	0.122	-0.158	0.049	-0.098	2.944
SUBC	0.000	0.003	0.316	-0.511	0.106	-0.597	6.218
SVT	0.006	0.013	0.119	-0.210	0.050	-0.753	5.050
TEN	0.000	0.008	0.466	-0.381	0.102	0.198	6.514
TRN	0.007	0.008	0.110	-0.224	0.048	-0.800	5.680
TTE	0.003	0.006	0.327	-0.140	0.063	0.835	6.863
UU	0.005	0.010	0.121	-0.171	0.051	-0.379	3.324
VER	0.009	0.012	0.225	-0.261	0.085	-0.192	3.433
VIE	0.002	0.003	0.303	-0.311	0.083	-0.331	5.440
VWS	0.008	0.009	0.548	-0.342	0.127	0.391	5.044

Notes. Descriptive statistics computed for the monthly return (in decimals) of the selected 41 constituents entering the brown portfolio, that is the equally-weighted portfolio constructed by combining the iShares STOXX Europe 600 Oil&Gas UCITS ETF and iShares STOXX Europe 600 Utilities UCITS ETF, over the period spanning from June 2010 to May 2022. The first column shows the ticker of each constituent (see Table 1, panel B).

Table 5: Descriptive statistics for the monthly realized volatility of the brown portfolio.

Constituent	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis
A2A	0.076	0.071	0.280	0.029	0.035	2.273	11.433
AKRBP	0.109	0.092	0.450	0.038	0.061	2.972	15.135
BP	0.070	0.060	0.390	0.018	0.042	3.729	26.016
CNA	0.072	0.061	0.330	0.019	0.044	2.740	12.946
DRX	0.087	0.078	0.360	0.026	0.046	2.691	13.604
ECV	0.080	0.065	0.334	0.019	0.048	2.307	11.076
EDP	0.064	0.061	0.262	0.017	0.028	2.798	19.045
EDPR	0.071	0.066	0.228	0.017	0.032	1.153	6.238
ELE	0.064	0.058	0.642	0.019	0.055	8.288	85.288
ELI	0.048	0.041	0.306	0.013	0.029	5.061	43.283
ENEL	0.069	0.064	0.284	0.022	0.030	2.961	20.079
ENG	0.058	0.055	0.239	0.025	0.025	2.987	20.143
ENGI	0.066	0.060	0.244	0.027	0.028	2.379	12.994
ENI	0.067	0.058	0.379	0.022	0.038	4.335	33.978
EOAN	0.069	0.062	0.194	0.028	0.033	1.887	6.929
EQNR	0.070	0.066	0.309	0.019	0.033	3.023	21.094
FORTUM	0.066	0.057	0.228	0.026	0.030	2.112	9.409
GALP	0.076	0.068	0.276	0.026	0.036	1.866	9.423
HER	0.063	0.057	0.288	0.024	0.028	4.136	30.512
IBE	0.059	0.052	0.237	0.017	0.031	2.318	11.117
NEL	0.204	0.177	0.614	0.058	0.114	1.606	5.508
NESTE	0.088	0.081	0.306	0.031	0.038	1.947	10.021
NG	0.049	0.045	0.218	0.022	0.022	3.596	26.638
NTGY	0.063	0.054	0.271	0.023	0.032	2.595	14.452
OMV	0.079	0.073	0.451	0.030	0.041	5.563	48.889
PKN	0.088	0.083	0.211	0.037	0.027	2.014	9.345
PNN	0.057	0.050	0.367	0.024	0.033	5.992	53.167
REP	0.080	0.069	0.328	0.033	0.043	2.278	11.040
RWE	0.082	0.073	0.254	0.031	0.038	1.819	6.934
SHEL	0.064	0.056	0.388	0.016	0.040	4.190	30.841
SRG	0.057	0.052	0.305	0.024	0.030	4.622	35.659
SSE	0.056	0.049	0.299	0.023	0.030	4.215	32.655
SUBC	0.099	0.091	0.441	0.033	0.046	3.207	22.927
SVT	0.053	0.048	0.198	0.026	0.021	2.948	17.971
TEN	0.089	0.082	0.316	0.038	0.037	2.281	12.358
TRN	0.055	0.050	0.249	0.021	0.025	3.781	26.685
TTE	0.064	0.057	0.366	0.023	0.036	4.562	36.518
UU	0.054	0.052	0.228	0.028	0.022	3.699	28.358
VER	0.078	0.068	0.331	0.037	0.036	3.263	20.156
VIE	0.074	0.065	0.291	0.022	0.039	2.373	11.787
VWS	0.118	0.110	0.322	0.036	0.056	1.332	4.927

Notes. Descriptive statistics computed for the monthly realized volatility (in decimals) of the selected 41 constituents entering the brown portfolio, that is the equally-weighted portfolio constructed by combining the iShares STOXX Europe 600 Oil&Gas UCITS ETF and iShares STOXX Europe 600 Utilities UCITS ETF, over the period spanning from June 2010 to May 2022. The first column shows the ticker of each constituent (see Table 1, panel B).

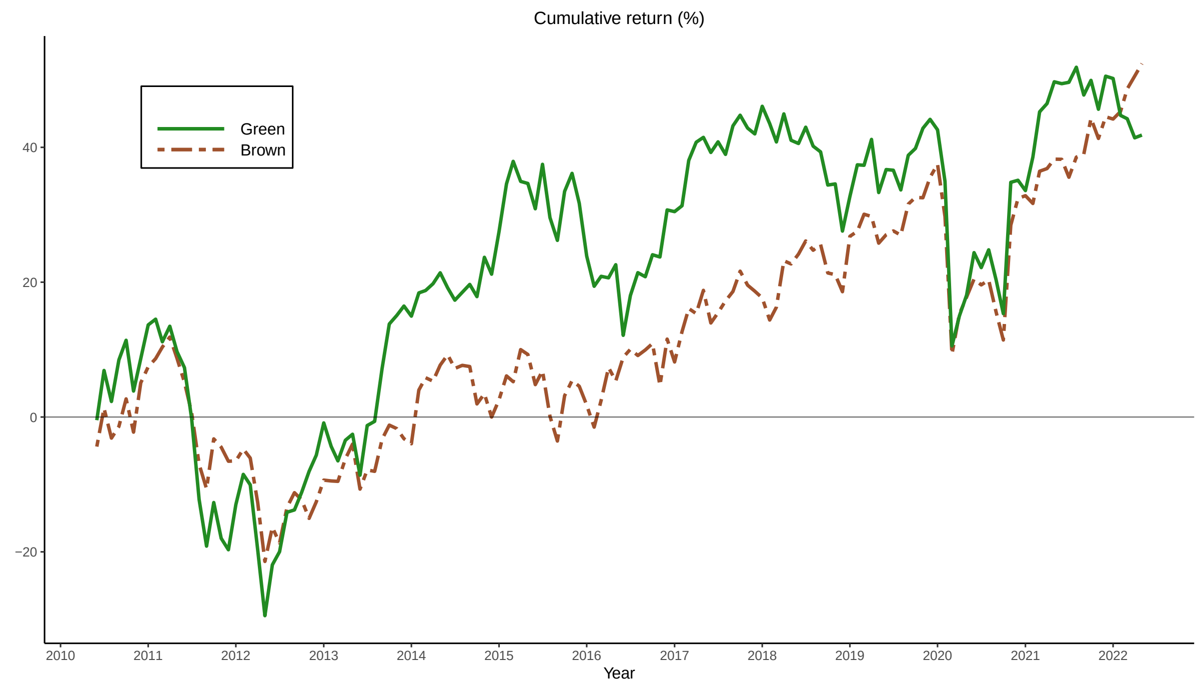
constituents are reported in Table 2 and Table 3, respectively, while the corresponding descriptive statistics for the 41 brown portfolio's constituents are reported in Tables 4-5. In line with Pástor et al. (2022), we focus on the return-based portfolio performance. The mean of the one month return on the green and brown portfolios considered is equal to 0.29% and 0.36%, respectively. The comparison between the one month returns sample mean shows a negative risk premium driving the unconditional expectation return on the green-minus-brown portfolio, suggesting a climate risk hedging role played by green stocks. The standard deviation of the one month return on the green and brown portfolios are equal, respectively to 5.07% and to 4.12%, respectively. The large values of the skewness and kurtosis reported by both the monthly return and realized volatility of the green (see Tables 2-3) and brown (see Tables 4-5) portfolios' constituents support the assumption of non-gaussianity we use to identify the structural shocks.

Figure 1 shows the cumulative return of green (solid line) and brown (dashed line) portfolios computed, for each portfolio, as the cumulative sum of the cross-sectional average of the constituents' one month return, over the period $2010m6 - 2022m5$. In line with the empirical findings of Pástor et al. (2022) we observe, for European stocks, an out-performance of the green portfolio by 10.4%, on average, relative to the brown portfolio. However, the green portfolio out-performance is milder than the one observed by Pástor et al. (2022) for the US over the $2012 - 2020$ sample period. More specifically, Figure 1 shows an out-performance of the green portfolio especially over the period $2013 - 2019$. The green-minus-brown (GMB) cumulative return becomes negligible during the first months of the Covid-19 pandemic, and, after a rebound during 2021, the GMB cumulative return becomes negative over the last months of the sample (i.e., from February 2022).

4 Empirical evidence

Panel SVAR estimation. In the first stage of the analysis, we estimate the SVAR described in equation (2) to retrieve the common shocks, that is the structural shocks hitting the cross-sectional averages of return and realized volatility of the green and brown portfolios. Both the reduced- and structural-form parameters of the aggregate SVAR are estimated through ML by assuming that the error terms are non-gaussian, using the three-step approach discussed in Section 2.1 (see Lanne et al., 2017). Both for the green and brown portfolios, the Aikake information criterion (AIC) suggests a lag order of 2. A multivariate Portmanteau test for residual autocorrelation supports the

Figure 1: Cumulative return of the green and brown portfolios.



Notes. Cumulative return (in percent) of the green (green solid line) and brown (brown dashed line) portfolios observed over the period $2010m6 - 2022m5$. For both the green and brown portfolios, the portfolio's return is computed as the cross-sectional average of the portfolio constituents' return.

choice of a lag length equal to 2.[16] Given the assumption of non-gaussianity, we run a Multivariate Jarque-Bera test on the reduced form residuals obtained from the estimation of the aggregate VAR. The test strongly rejects the null hypothesis of normality for both the green and brown portfolios.

Thus, we estimate a structural VAR using a lag length equal to two ($p = 2$) for both the green and brown portfolios. The ML estimates of the standardized structural impact multiplier $\tilde{B}_0$ (i.e., the one with its main diagonal entries normalized to unity), the standard deviation of the structural shocks σ_i and the degree of freedom λ_i, for $i = 1, 2$, are shown in Table 6. In panel A of Table 6, we report the results for the green portfolio, while those related to the brown portfolio are reported in panel B of Table 6. The relatively large estimates of the parameter λ_i (both for the green and brown portfolios) suggest evidence of deviation from the normality assumption. In Table 6 (panels A and B), we also report the ML estimates of the non-standardized structural impact multiplier matrix $B_0 = \tilde{B}_0\Omega^{1/2}$, where $\Omega^{1/2} = \text{diag}(\sigma_1, \sigma_2)$ is the diagonal matrix containing the standard

[16]We run the multivariate Portmanteau test using twelve lags.

Table 6: ML estimation of the aggregate non-gaussian SVAR.

Panel A: Green							
		ε_1	ε_2			ε_1	ε_2
$\tilde{B}_0$	$\bar{r}_t$	1.000	-1.443	B_0	$\bar{r}_t$	0.038	-0.029
		(-)	(0.171)				
	$\bar{RV}_t$	0.032	1.000		$\bar{RV}_t$	0.001	0.020
		(0.050)	(-)				
σ_i		0.038	0.020				
		(0.004)	(0.003)				
λ_i		6.782	3.500				
		(3.000)	(0.985)				

Panel B: Brown							
$\tilde{B}_0$	$\bar{r}_t$	1.000	-1.069	B_0	$\bar{r}_t$	0.032	-0.019
		(-)	(0.128)				
	$\bar{RV}_t$	0.033	1.000		$\bar{RV}_t$	0.001	0.018
		(0.049)	(-)				
σ_i		0.032	0.018				
		(0.003)	(0.003)				
λ_i		7.010	3.336				
		(3.182)	(0.905)				

Notes. Maximum likelihood (ML) estimation of the aggregate SVAR (see equation 2) under the non-Gaussianity assumption of the error terms. The table shows the estimates of the standardized impact multiplier $\tilde{B}_0$ (i.e., with its main diagonal entries normalized to unity), the standard deviation of the structural shocks σ_i, and the degree of freedom λ_i, for $i = 1, 2$ (left panel). The corresponding standard errors are reported in brackets. The table also shows the non-standardised impact multiplier matrix $B_0 = \tilde{B}_0\Omega^{1/2}$ (right panel), where $\Omega^{1/2} = \text{diag}(\sigma_1, \sigma_2)$ is the diagonal matrix containing the standard deviation of the structural shocks (ε_t). Results in decimals. Estimation sample: $2010m6 - 2022m5$.

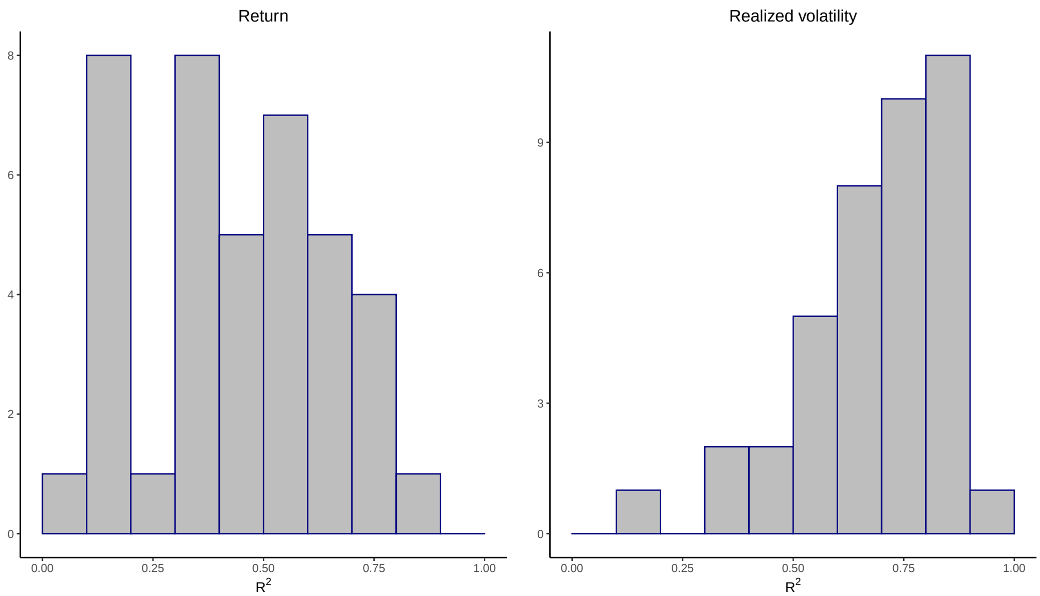
deviation of the structural shocks (ε_t). As discussed by the study of Lanne et al. (2017), the evidence of non-gaussianity for the financial time series considered allows us to rely only on a statistical exact identifying scheme. We now comment on the point estimate of the coefficients entering the columns of B_0 (see Table 6, right panel) which are then used to retrieve the common shocks, used in a second stage of the analysis, to control for cross-sectional dependence. The magnitude of the estimates is similar for both the green and brown portfolios. In particular, the first structural shock yields positive responses of $\bar{r}_t$ and $\bar{RV}_t$: it is equal to 3.8% and 0.1%, (respectively) for the green portfolio, and it is equal to 3.2% and 0.1% (respectively) for the brown portfolio. The response to the second structural shock drives the endogenous variables in opposite directions: the impact on $\bar{r}_t$ and $\bar{RV}_t$ is equal to -2.9% and to 2% for the green portfolio, and it is equal to -1.9% and to 1.8% for the brown portfolio.

In the second stage of the analysis, the common shocks (ε_t) estimated from the aggregate SVAR enter the Panel Factor-Augmented VAR as exogenous variables (see equation 1) together with the lagged values of the cross-sectional averages of the endogenous variables. The Panel Factor-Augmented VAR is estimated through ML by assuming that the error terms are not Gaussian, for each of the two portfolios, separately. We use the same lag structure for the two portfolios, that is the lag length is set equal to two for both the endogenous variables ($y_{it-\ell}$) (i.e., $p = 2$) and the lagged cross-sectional averages ($\bar{y}_{t-\ell}$) (i.e., $q = 2$). The predictive performance of the Panel VAR for the return and realized volatility series is assessed, first, by inspecting Figure 2 showing the distribution of the R^2 obtained by estimating the VARX for each of the 40 constituents entering the green portfolio (Figure 2, panel A) and for each of the 41 constituents entering the brown portfolio (Figure 2, panel B). In the left column of Figure 2, we report the R^2 associated with the equation of the one month return, while the right column shows those associated with the equation of the realized volatility. Inspection of Figure 2 reveals that the average R^2 computed from the estimation of the one month return equation and of the realized volatility equation are equal, respectively, to 0.44 and 0.69, for the green portfolio (i.e., average across the green portfolio's constituents), while the corresponding R^2 computed for the brown portfolio (i.e., average across the brown portfolio's constituents) are equal to 0.36 (for one month return) and 0.67 (for realized volatility).

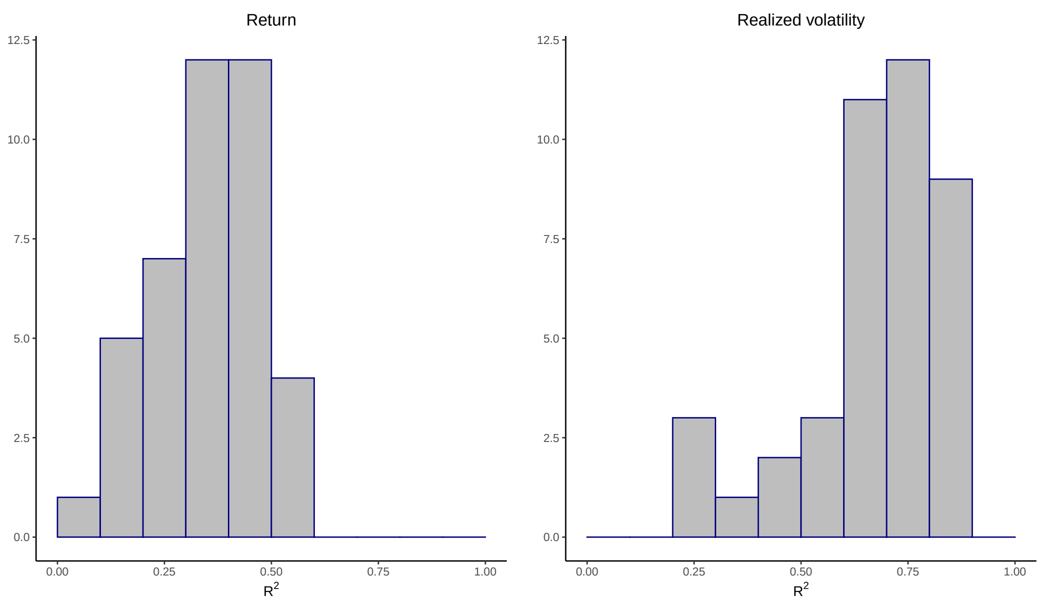
Moreover, in line with Cesa-Bianchi and Ferrero (2021), we measure the cross-sectional dependence among shocks by computing the average pairwise cross-section correlations associated with the VARX residuals (u_{it}).[17] As reported in Table 7, the average pairwise cross-section correlation of one month return (r_{it}) and realized volatility (RV_{it}) in the

[17] As discussed in Cesa-Bianchi et al. (2020) and Cesa-Bianchi and Ferrero (2021), evidence of weak cross-sectional dependence of the VARX residuals is crucial for the identification of the common factors (i.e., the structural shocks).

Figure 2: R^2 from the Panel Factor-Augmented VAR.



(a) Green constituents



(b) Brown constituents

Notes. Distribution of the R^2 computed from the constituent-by-constituent estimation of the Panel Factor-Augmented VAR described in equation (1). Panel A shows the distribution of the R^2 related to the VARX fitted to the one month return and realized volatility of the 40 constituents entering the green portfolio, while panel B shows the distribution of the R^2 related to the VARX fitted to the one month return and realized volatility of the 41 constituents entering the brown portfolio. Estimation sample: $2010m6 - 2022m5$.

raw data is equal to, respectively, 0.35 and 0.57 for the green portfolio and equal to, respectively, 0.27 and 0.53, for the brown portfolio. The average pairwise cross-section correlation of the associated reduced-form residuals becomes almost zero when controlling for the common factors, for both the green and brown portfolios.[18]

4.1 Impulse Response analysis

Impulse response analysis shows that we can rely only on statistical identification when the focus is on the response to common shocks. More specifically, Figure 3 shows the distribution of the response, at horizon zero, of one month return and realized volatility of each constituent entering the green and brown portfolios (panel A and B, respectively), where the impact response of the top five green constituents, in terms of climate hedging (see Section 4.2), is highlighted by green colour. An inspection of Figure 3 confirms the results discussed for the aggregate SVAR: while there is clear evidence of the opposite response of one month return and realized volatility to the second structural shock (negative for the former and positive for the latter), the response of realized volatility to the first structural common shock displays large dispersion around the mean. The evidence of high uncertainty in the identification of the first structural shock is confirmed when reporting the large error bands (we plot those associated with 68% and 90% confidence intervals in Figure 4) around the mean-group impulse response of the endogenous variables to the first common shock, computed over the 12-month forecast horizon for both green and brown portfolios. The analysis of the responses to idiosyncratic shocks allows relying not only on statistical identification but to give, ex-post, an economic interpretation of the structural shocks. Panel A of Figure 5 shows the impact responses for the 40 green portfolio's constituents, while panel B displays those for the 41 constituents entering the brown portfolio. As shown in Figure 5, with the only exception of a few constituents (that is for three constituents entering the green portfolio), in all the remaining constituent-specific VARX we can interpret ex post the shocks as risk aversion (the one underlying a positive co-movement of return and volatility motivated by a return compensation for higher risk) and financial leverage (the one underlying a negative co-movement of return and volatility motivated by negative shocks to return leading a total equity decrease, hence a rise in

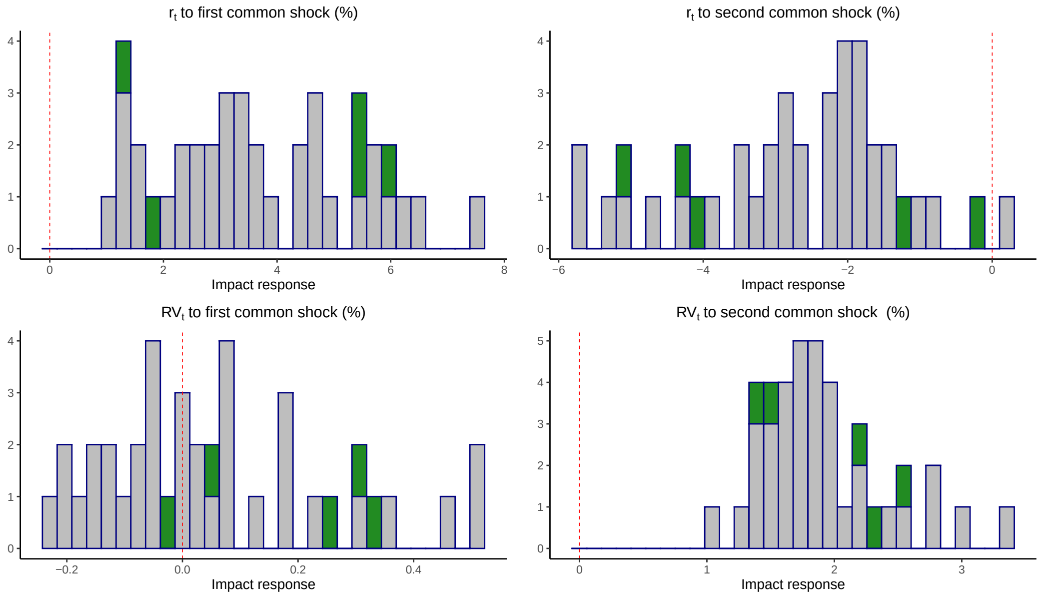
[18] As for the green portfolio, the mean of the average pairwise cross-section correlations is equal to -0.02 for the residuals associated with the equation for r_{it} and to -0.01 for the residuals associated with the equation for RV_{it} (see Table 7, left panel). As for the brown portfolio, the mean of the average pairwise cross-section correlations is equal to -0.01 for the residuals associated with the equation for r_{it} and equal to 0.01 for the residuals associated with the equation for RV_{it} (see Table 7, right panel).

Table 7: Average pairwise cross-section correlations for the green and brown portfolios

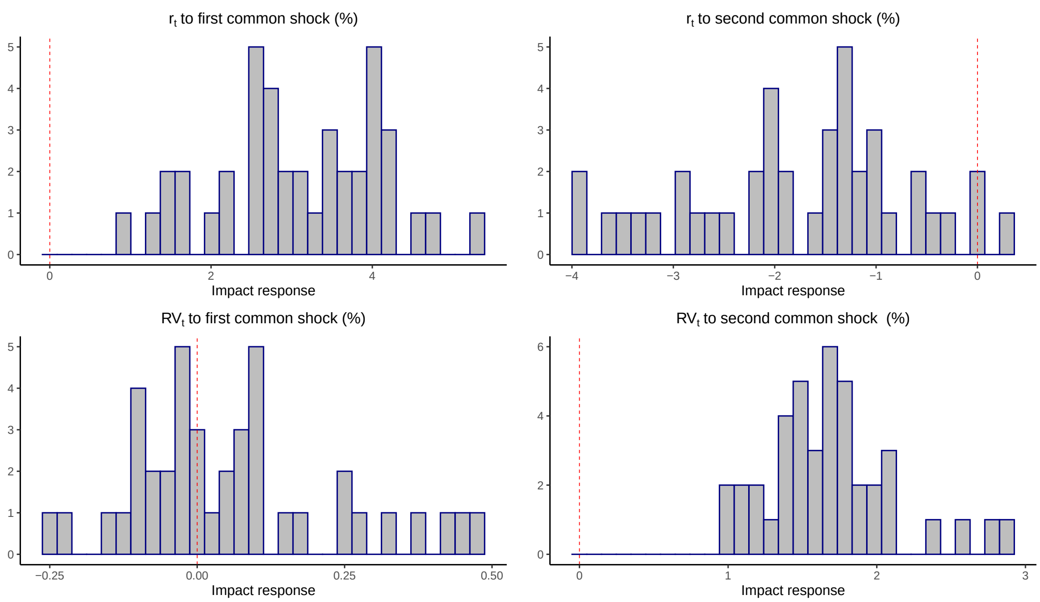
Green portfolio					Brown portfolio				
Constituent	r_t	RV_t	$u_t^{(r)}$	$u_t^{(RV)}$	Constituent	r_t	RV_t	$u_t^{(r)}$	$u_t^{(RV)}$
ALO	0.320	0.563	-0.032	-0.020	A2A	0.305	0.467	-0.012	0.000
ALV	0.497	0.688	-0.003	0.018	AKRBP	0.216	0.555	-0.061	-0.036
AMS	0.358	0.574	-0.012	-0.001	BP	0.321	0.633	-0.002	0.061
BBVA	0.455	0.657	-0.024	-0.002	CNA	0.270	0.470	-0.008	-0.016
BMW	0.398	0.668	-0.015	0.006	DRX	0.230	0.416	-0.028	-0.034
BNP	0.510	0.666	-0.016	0.013	ECV	0.117	0.426	-0.031	-0.044
CA	0.326	0.538	-0.029	-0.037	EDP	0.316	0.584	0.000	0.022
CABK	0.393	0.554	-0.024	-0.025	EDPR	0.229	0.474	-0.028	0.004
CAP	0.441	0.663	-0.021	-0.017	ELE	0.257	0.288	-0.012	-0.070
CBK	0.355	0.600	-0.039	-0.016	ELI	0.158	0.590	0.011	0.061
DB1	0.363	0.648	-0.007	0.000	ENEL	0.361	0.603	0.016	0.009
DSY	0.218	0.553	-0.017	-0.031	ENG	0.341	0.562	0.021	0.014
DTE	0.362	0.555	-0.013	0.001	ENGI	0.357	0.617	-0.003	-0.017
ELISA	0.104	0.475	-0.020	-0.034	ENI	0.369	0.678	-0.005	0.038
G	0.468	0.566	-0.012	0.000	EOAN	0.248	0.485	-0.009	-0.006
GLE	0.483	0.683	-0.023	0.008	EQNR	0.273	0.616	-0.020	-0.006
HEN3	0.298	0.497	-0.012	0.004	FORTUM	0.303	0.561	-0.029	-0.005
INGA	0.487	0.701	-0.022	0.011	GALP	0.310	0.610	-0.021	0.010
ISP	0.465	0.598	-0.022	-0.011	HER	0.311	0.608	0.014	0.046
ITX	0.344	0.576	-0.020	-0.001	IBE	0.326	0.524	0.007	0.004
KBC	0.380	0.628	-0.036	-0.004	NEL	0.057	0.076	-0.103	-0.152
KER	0.300	0.564	-0.018	-0.029	NESTE	0.229	0.522	-0.038	-0.041
KESKOB	0.191	0.554	-0.032	-0.010	NG	0.151	0.552	0.035	0.036
KPN	0.089	0.358	-0.025	-0.046	NTGY	0.350	0.587	0.013	-0.004
MB	0.439	0.570	-0.026	-0.015	OMV	0.336	0.639	-0.026	0.073
MUV2	0.438	0.676	-0.002	0.013	PKN	0.218	0.479	-0.042	0.033
NOKIA	0.224	0.343	-0.048	-0.059	PNN	0.147	0.313	0.001	-0.011
ORA	0.237	0.513	-0.023	-0.007	REP	0.337	0.604	-0.014	0.026
PHIA	0.329	0.532	-0.020	-0.011	RWE	0.300	0.481	-0.009	-0.011
PUM	0.200	0.472	-0.029	-0.014	SHEL	0.293	0.638	-0.009	0.057
RAND	0.461	0.651	-0.017	-0.010	SRG	0.324	0.597	0.026	0.045
SAN	0.452	0.645	-0.029	-0.003	SSE	0.276	0.589	0.004	0.042
SIE	0.432	0.631	-0.009	-0.007	SUBC	0.273	0.601	-0.046	0.010
STM	0.326	0.567	-0.034	-0.028	SVT	0.170	0.476	0.010	0.026
SU	0.412	0.672	-0.017	-0.003	TEN	0.273	0.609	-0.031	0.006
SY1	0.211	0.562	-0.023	-0.001	TRN	0.303	0.642	0.037	0.045
TEF	0.406	0.624	-0.024	0.010	TTE	0.323	0.665	-0.011	0.053
UCB	0.124	0.452	-0.021	-0.032	UU	0.190	0.516	0.017	0.033
URW	0.385	0.505	-0.023	0.003	VER	0.271	0.559	-0.023	0.017
VIV	0.190	0.181	-0.042	-0.096	VIE	0.301	0.548	0.002	-0.006
					VWS	0.161	0.256	-0.057	-0.073

Notes. The table shows the average pairwise cross-section correlations of the endogenous variables, that is of one-month return (r_t) and realized volatility (RV_t), and of the reduced-form residuals obtained from the estimation of the Panel Factor-Augmented VAR (see equation 1), for both the green (left panel) and brown (right panel) portfolios. Estimation sample: $2010m6 - 2022m5$.

Figure 3: Impact response of one month return and realized volatility to common shocks for the green and brown portfolio's constituents.



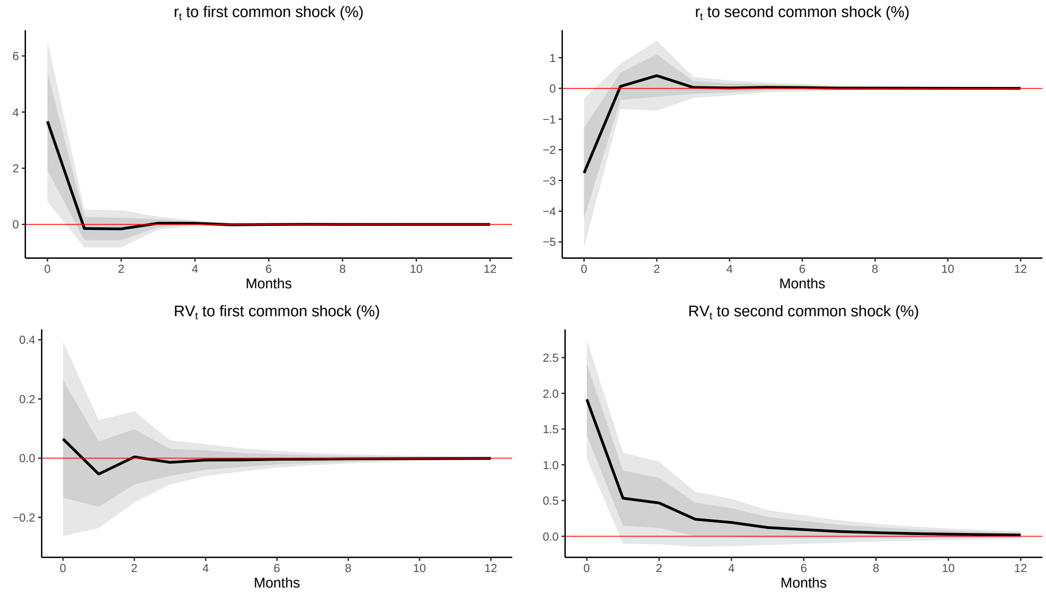
(a) Green portfolio



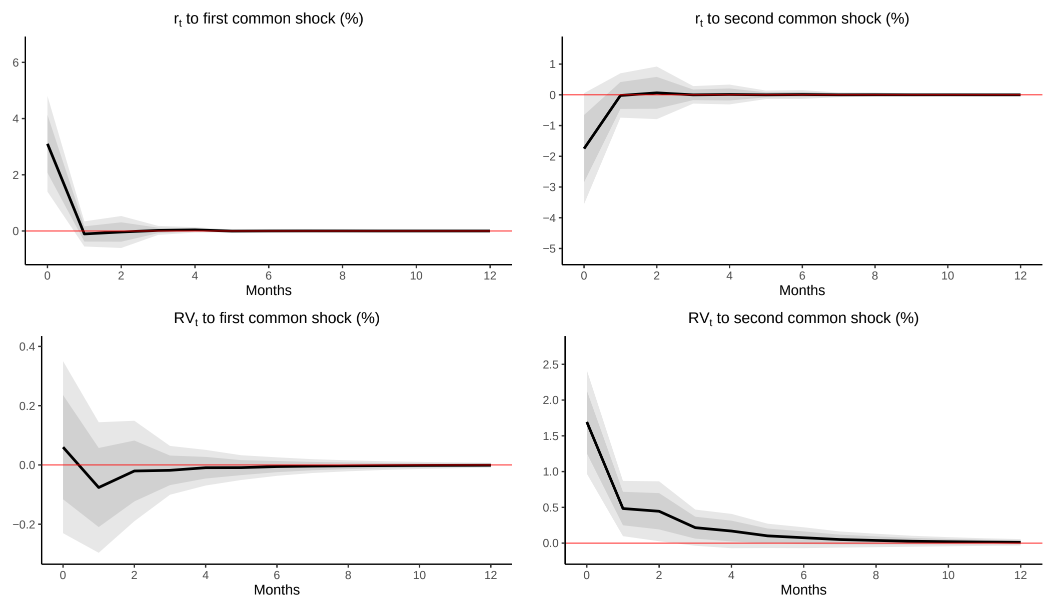
(b) Brown portfolio

Notes. Impulse response functions (in percent) of one month return (r_t) and realized volatility (RV_t) to common shocks at horizon zero, computed for the green portfolio's constituents (panel A) and for the brown portfolio's constituents (panel B). The size of the shocks is one standard deviation. The point estimates of the impact response are reported on the horizontal axis. The impact response computed for the top 5 green constituents is coloured in green. Estimation sample: $2010m6 - 2022m5$.

Figure 4: Impulse response profile of one month return and realized volatility to common shocks for the green and brown portfolio's constituents.



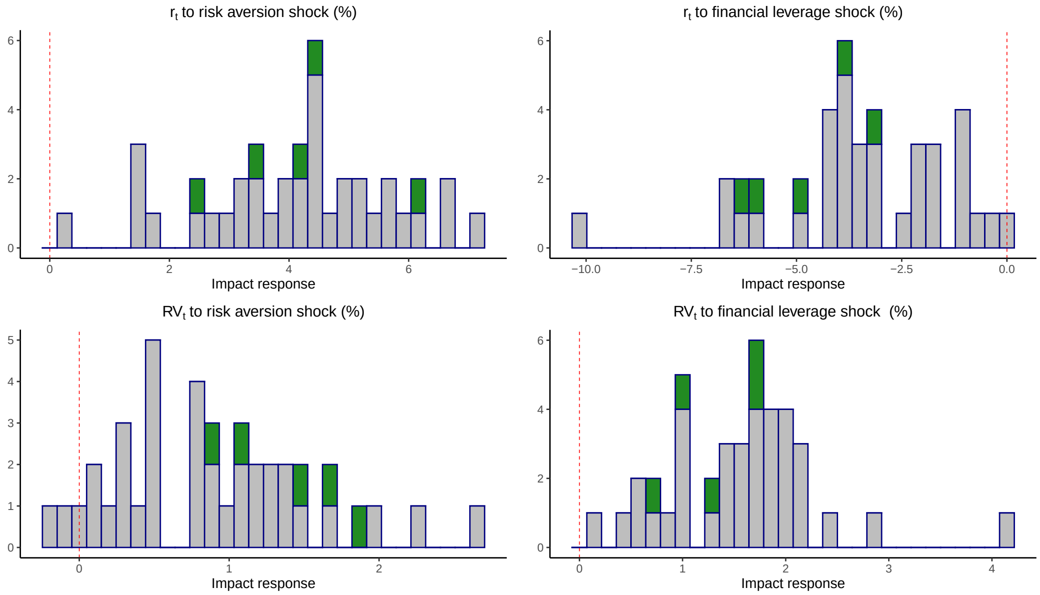
(a) Green portfolio



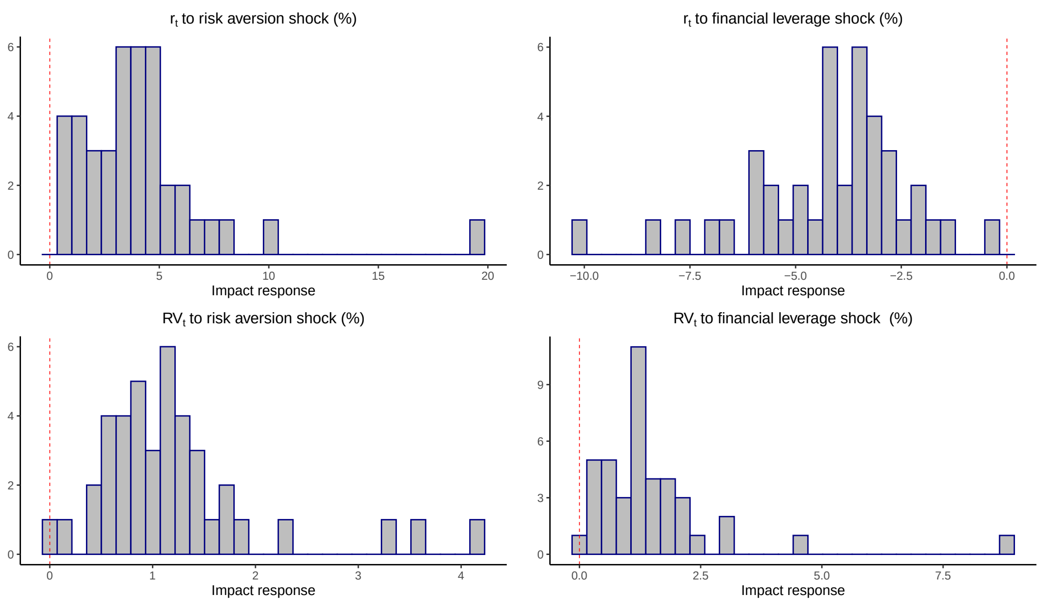
(b) Brown portfolio

Notes. Impulse response functions (in percent) of one month return (r_t) and realized volatility (RV_t) to common shocks, computed for the green portfolio's constituents (panel A) and for the brown portfolio's constituents (panel B) over a 12-month forecast horizon. The size of the shocks is one standard deviation. Each chart displays the arithmetic average of the constituent-specific impulse responses (black solid line) and the corresponding 68% (1σ) and 90% (1.65σ) confidence bands (grey shaded areas). Estimation sample: $2010m6 - 2022m5$.

Figure 5: Impact response of one month return and realized volatility to idiosyncratic shocks for the green and brown portfolio's constituents.



(a) Green portfolio



(b) Brown portfolio

Notes. Impulse response functions (in percent) of one month return (r_t) and realized volatility (RV_t) to idiosyncratic shocks (i.e., risk aversion and financial leverage idiosyncratic shocks) at horizon zero, computed for the green portfolio's constituents (panel A) and for the brown portfolio's constituents (panel B). The size of the shocks is one standard deviation. The point estimates of the impact response are reported on the horizontal axis. The impact response computed for the top 5 green constituents is coloured in green. Estimation sample: $2010m6 - 2022m5$.

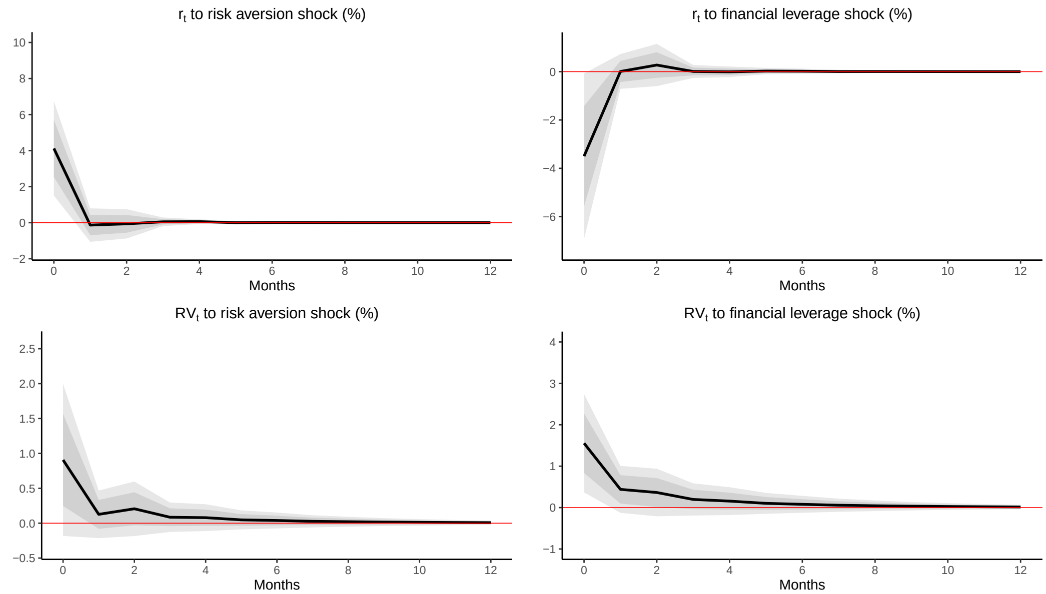
financial leverage and risk).[19] Similarly to the charts reporting the responses to common shocks, in Figure 5 we also highlight the responses to idiosyncratic shock reported by the top five green constituents (see Section 4.2). Figure 6 shows the average estimates of impulse responses across constituents (mean-group estimator) together with the 68% and 90% confidence intervals, computed for the green (panel A) and brown (panel B) portfolios. The average responses are qualitatively and quantitatively similar for both portfolios, however, the uncertainty around the mean-group estimates tends to be larger for the brown portfolio's constituents (see also Figure 5).

4.2 Historical decomposition

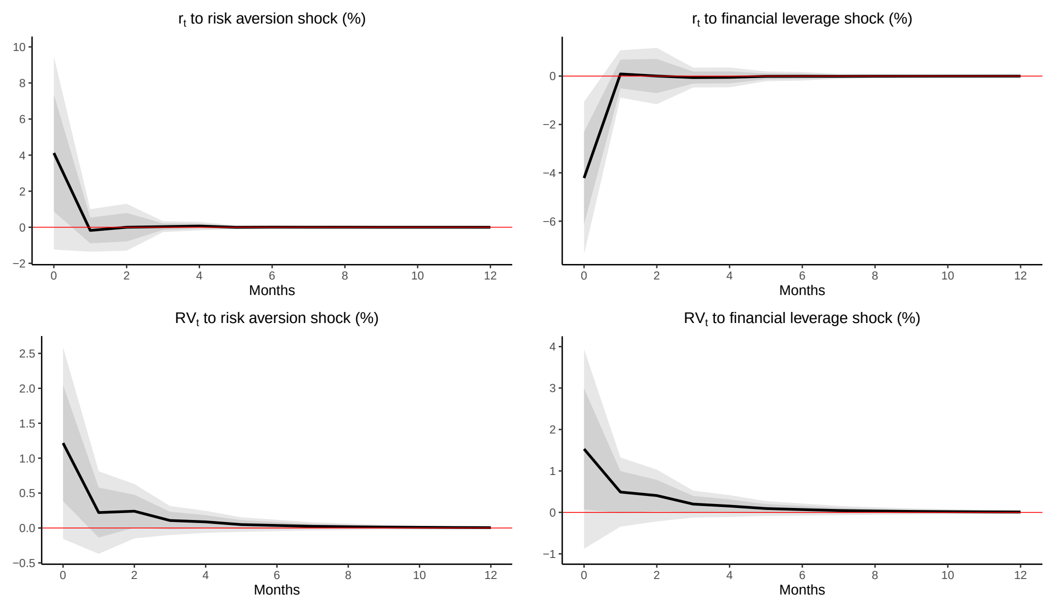
Figure 7 shows the historical decomposition of the cumulative return computed for the green-minus-brown (GMB) portfolio. The time series data for the cumulative return of the GMB portfolio are displayed through a black solid line and it is computed as the cumulative sum of the difference between the cross-sectional average of one month return computed across the 40 green portfolio's constituents and the one computed across the 41 constituents entering the brown portfolio. The GMB cumulative return is decomposed into the expected (blue solid line) and unexpected (red solid line) components and they are obtained by computing the cumulative sum of the expected and unexpected one month return obtained from the historical decomposition described in equation (9). The time-varying anticipated components of the green and brown portfolios are computed by taking the average of the historical decomposition of the green portfolio constituents as well as the one for the constituents of the brown portfolio. There is evidence of the out-performance of the brown portfolio with respect to the green portfolio in terms of cumulative expected return over the whole sample period (the mean value of the green-minus-brown difference between the expected cumulative return component is equal to -7%). These findings are in line with Pástor et al. (2022): stock markets acknowledge the climate risk hedging properties of the green portfolio, hence the expected return on the GMB portfolio (which investors hold to hedge climate risk) is negative. The unanticipated component of the GMB portfolio's cumulative return, computed as the difference between the unanticipated component of the green portfolio and the one of the brown portfolio, is reported in Figure 7 and it shows findings similar to those observed for US stocks by Pástor et al. (2022): there is evidence of an out-performance of the green portfolio over the brown one.

[19]The idiosyncratic structural shocks are not identified for the following green portfolio's constituents (the ticker is reported in brackets): *Allianz SE* (ALV), *BNP Paribas SA* (BNP), and *KBC Group SA* (KBC).

Figure 6: Impulse response profile of one month return and realized volatility to idiosyncratic shocks for the green and brown portfolio's constituents.



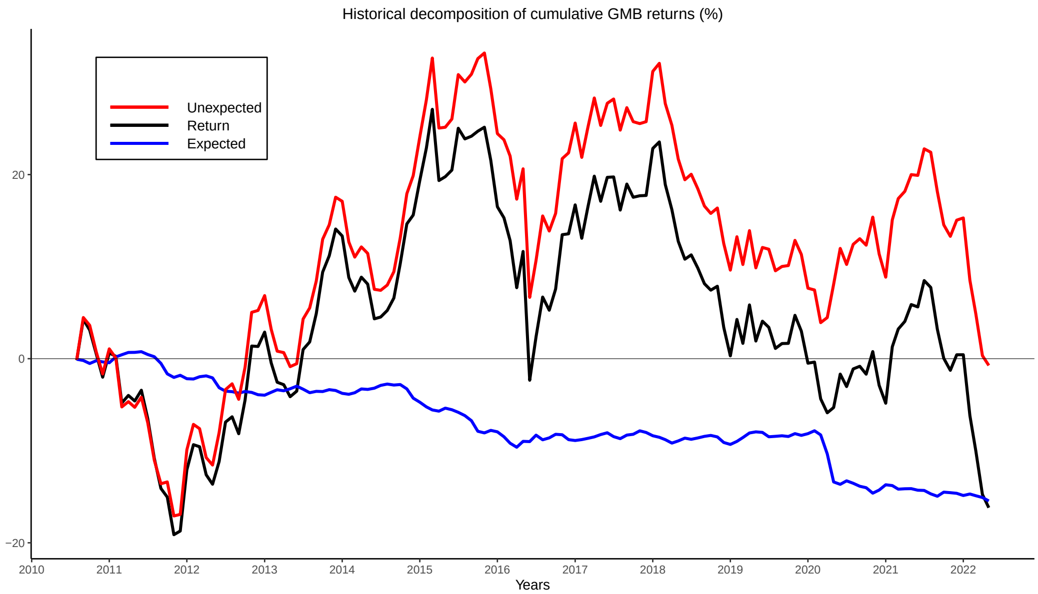
(a) Green portfolio



(b) Brown portfolio

Notes. Impulse response functions (in percent) of one month return (r_t) and realized volatility (RV_t) to idiosyncratic shocks (i.e., risk aversion and financial leverage idiosyncratic shocks), computed for the green portfolio's constituents (panel A) and for the brown portfolio's constituents (panel B) over a 12-month forecast horizon. The size of the shocks is one standard deviation. Each chart displays the arithmetic average of the constituent-specific impulse responses (black solid line) and the corresponding 68% (1σ) and 90% (1.65σ) confidence bands (grey shaded areas). Estimation sample: $2010m6 - 2022m5$.

Figure 7: Historical decomposition of the green-minus-brown (GMB) portfolio's cumulative returns.



Notes. Contribution of the expected and unexpected components to the green-minus-brown (GMB) portfolio's cumulative return in percent. The GMB portfolio's cumulative return (black line) is computed as the difference between the cumulative sum of the one-month return of the green portfolio and the one of the brown portfolio. The contributions of each component (expected and unexpected) to the cumulative return are obtained through the cumulative sum of the contributions computed for the one month return. The contribution of the expected component (blue line) is constructed as the difference between the expected component computed for the green portfolio's return and the one computed for the brown portfolio's return. For both the green and brown portfolios, the expected return is computed by averaging out the expected components obtained from the historical decomposition of the return across the portfolio constituents, over the observed sample. In each month, the expected component is computed as the sum of the contributions of the constant term, initial condition and lagged cross-sectional averages of return and realized volatilities. The contribution of the unexpected component (red line) is constructed as the difference between the unexpected component computed for the green portfolio's return and the one computed for the brown portfolio's return. For both the green and brown portfolios, the unexpected component is computed by averaging out the total unexpected components obtained from the historical decomposition of the return across the portfolio constituents, over the observed sample. In each month, the total unexpected component is computed as the sum of the contributions of the common shocks and the idiosyncratic shocks. Estimation sample: $2010m6 - 2022m5$.

Moreover, we extend the analysis of Pástor et al. (2022) by focusing (through historical decomposition) on the contribution of the top 5 constituents to the green portfolio performance. These are the constituents regarded by the financial markets as the best hedge for climate risk (i.e., their expected return exhibits the largest negative difference relative to the expected return for the brown portfolio) (see Table 8). Figure 8 (panels

Table 8: Average expected return of the green constituents in percent deviation from the brown average constituent.

Rank	Constituent	Deviation	Env. score	Rank	Constituent	Deviation	Env. score
1	CBK	-2.132	93	21	INGA	-0.050	86
2	SAN	-1.509	90	22	BNP	-0.046	95
3	KPN	-1.252	76	23	SIE	-0.037	88
4	ORA	-1.187	86	24	PUM	0.083	85
5	BBVA	-1.155	95	25	BMW	0.101	81
6	TEF	-0.988	82	26	KESKOB	0.102	78
7	CA	-0.967	91	27	RAND	0.132	63
8	CABK	-0.778	85	28	VIV	0.207	81
9	ALO	-0.554	99	29	ALV	0.229	95
10	DTE	-0.545	85	30	SU	0.268	68
11	G	-0.543	96	31	ITX	0.353	96
12	KBC	-0.443	93	32	DB1	0.493	66
13	NOKIA	-0.422	70	33	UCB	0.515	77
14	GLE	-0.417	96	34	MUV2	0.519	94
15	ISP	-0.355	97	35	KER	0.762	96
16	URW	-0.347	88	36	STM	1.030	95
17	HEN3	-0.147	70	37	DSY	1.090	77
18	PHIA	-0.125	81	38	SY1	1.206	64
19	ELISA	-0.095	71	39	CAP	1.277	77
20	MB	-0.066	47	40	AMS	1.441	73

Notes. Expected component of each of the 40 constituents entering the Refinitiv Eurozone Low Carbon Select Index (i.e., green portfolio) computed as the deviation from the expected component of the brown average constituent (i.e., obtained by computing the mean across the brown portfolio's constituents) and averaged across the full sample $2010m6 - 2022m5$, in percent. In each month, the expected component is computed as the sum of the contributions of the constant term, initial condition and lagged cross-sectional averages of return and realized volatilities. Estimation sample: $2010m6 - 2022m5$.

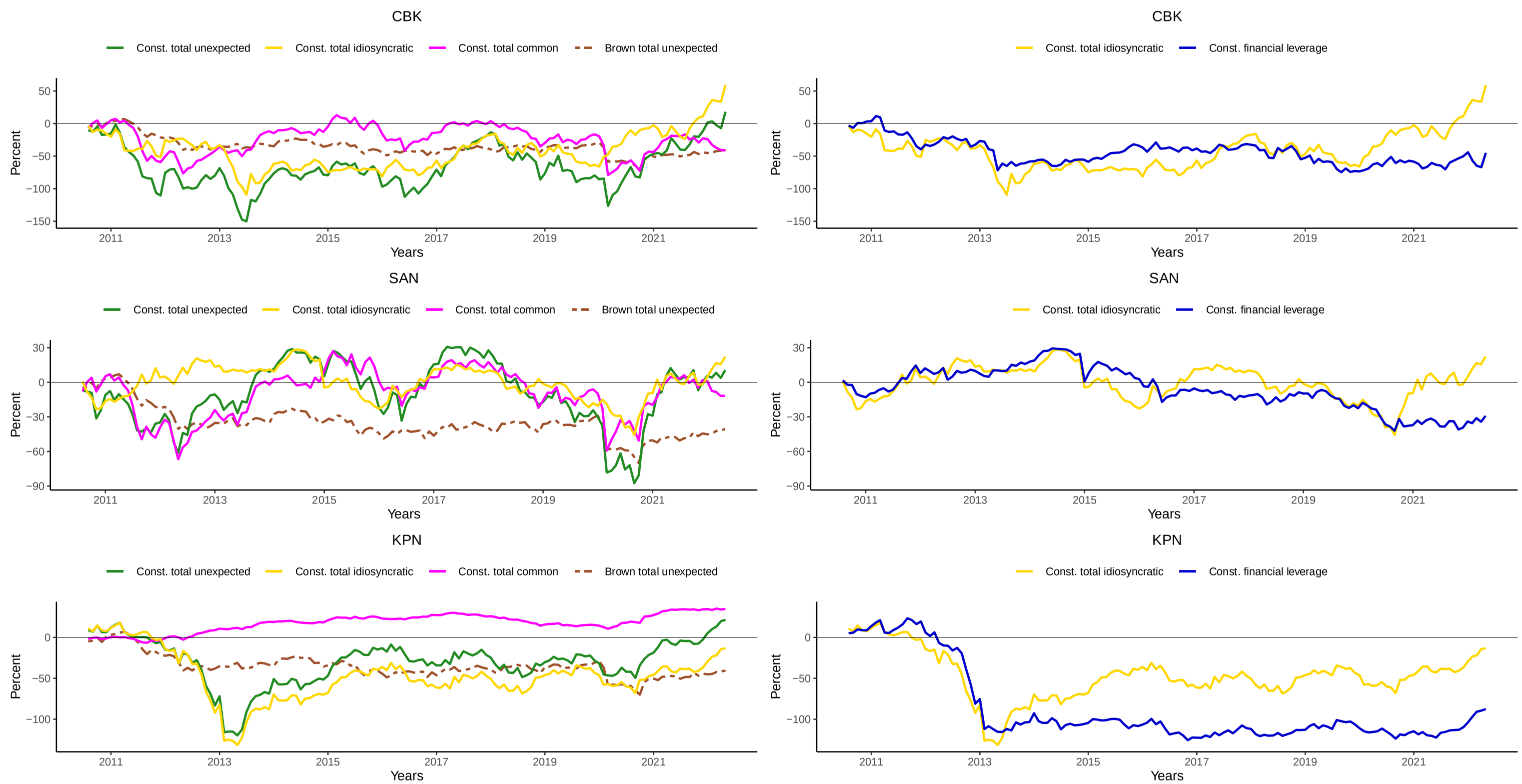
A and B) shows the historical decomposition of the cumulative return observed for the aforementioned green portfolio's constituents (the ticker and the industry are reported in brackets): *Commerzbank AG* (CBK, Banks), *Banco Santander S.A.* (SAN, Banks), *Koninklijke KPN N.V.* (KPN, Telecom Services), *Orange S.A.* (ORA, Telecom Services), and Banco Bilbao Vizcaya Argentaria S.A. (BBVA, Banks). The left column of Figure 8 shows the time-varying contribution of the total unexpected component (green solid line) computed as the sum of the contribution of the total common shocks (magenta solid line) and of the total idiosyncratic shocks (yellow solid line) to the dynamics of the top five green portfolio's constituents. For comparison, we also report the time-varying contribution of the total unexpected components to the dynamics of the brown portfolio (i.e., average across the brown portfolio's constituents) (brown dashed line). The right column of Figure 8 shows the role of the financial leverage shock (blue solid line) to the time-varying contribution of the total idiosyncratic shocks (yellow solid line).

The empirical evidence confirms an out-performance (in terms of the unanticipated component) of the top five 5 green portfolio's constituents relative to the brown portfolio. In particular, the empirical findings show (see Figure 8, left column of panels A and B) that, once we control for common shocks, the unanticipated component of SAN, ORA, and BBVA constituents (e.g., the one explained by idiosyncratic shocks) out-performs the brown portfolio's total unexpected component over the whole sample period. However, the out-performance of the idiosyncratic component for the CBK and KPN constituents (see Figure 8, left column of panels A) occurs only during the last few months of the sample. Finally, we turn the focus on the contribution of the two identified idiosyncratic shocks to the dynamics of the cumulative return observed for the top five green constituents (see the right column of Figure 8, panels A and B). Figure 8 (panels A and B) shows that while for the constituents belonging to the banking sector, i.e., CBK, SAN, and BBVA, the financial leverage shocks explain most of the variation observed in the total idiosyncratic component (with the only exception of the last part of the sample), the total idiosyncratic component estimated for the Telecommunication services' constituents (KPN and ORA) is mainly driven by the risk aversion shock (at least from the 2013 onward).

5 Conclusions

In this study, we compute the expected and unexpected components of the cumulative return on a climate risk hedging portfolio (green-minus-brown portfolio) using European stock market data. The information set used is given by the one month return and realized volatility of 40 constituents of the green portfolio (i.e., the low carbon emission portfolio monitored by Refinitiv) and, separately, of 41 constituents for a brown portfolio (underlying the Oil&Gas and Utilities industry sectors of the Eurostoxx 600). We fit a Panel Structural VAR to the constituents of the green portfolio and, separately, those for the brown portfolio. In line with Cesa-Bianchi et al. (2020), we control for cross-sectional dependence including, as exogenous variables, the common shocks to the cross-sectional averages of return and volatilities estimated in a first stage of the analysis and the lagged values of the cross-sectional averages for the two endogenous variables. The common shocks are retrieved in a first stage through Structural VAR and they are interpreted as portfolio shocks. Using the historical decomposition, we find, in line with Pástor et al. (2022), an out-performance of the expected component of the brown portfolio cumulative return relative to the one for the green portfolio and the out-performance of the unexpected component of the cumulative return on the green portfolio. Our findings suggest that, as

Figure 8: Historical decomposition of the top 5 green constituents' cumulative return.



(a) Commerzbank AG (CBK) (upper panel), Banco Santander S.A. (SAN) (middle panel), and Koninklijke KPN NV (KPN) (lower panel)

Figure 8: Historical decomposition of the top 5 green constituents' cumulative return. (cont'd)

(b) Orange S.A. (ORA) (upper panel) and Banco Bilbao Vizcaya Argentaria S.A. (BBVA) (lower panel)

Notes. Historical decomposition of the top 5 green constituent's cumulative return (in percent): Commerzbank AG (CBK), Banco Santander S.A. (SAN), and Koninklijke KPN NV (KPN) (panel A), Orange S.A. (ORA) and Banco Bilbao Vizcaya Argentaria S.A. (BBVA) (panel B). For each of the top 5 green constituents, the left panel shows the contribution of the total unexpected component (green solid line), computed as the sum of the contribution of the idiosyncratic shocks (yellow solid line) and the contribution of the common shocks (magenta solid line), to the cumulative returns. In the left panel, the contribution of the total unexpected component to the cumulative returns for the brown portfolio is also reported (brown dashed line). This is computed by averaging out the contribution of the total unexpected component to the cumulative returns across the constituents entering the brown portfolio. For each of the top 5 green constituents, the right panel shows the contribution of the green constituent's total idiosyncratic shocks (yellow solid line) and the contribution of the idiosyncratic financial leverage shock (blue solid line) to the cumulative returns. The top 5 green constituents are selected on the basis of their average expected return in percent deviation from the brown average constituent (see Table 8). Estimation sample: $2010m6 - 2022m5$.

for Europe, green stocks play the role, according to the market, of climate risk hedging (implying a small risk premium driving their expected return relative to the one associated with brown stocks). However, during the sample period examined, there is evidence of a rise in investors' demand for green assets, driving up green asset prices and motivated by rising climate concerns. We also extend the analysis of Pástor et al. (2022), exploring the performance of the top 5 constituents of the green portfolio in terms of climate hedging (that is, those which are found to have the largest negative premium relative to the brown portfolio). In particular, we focus on the role played by idiosyncratic shocks in shaping the dynamics of the unexpected component of the aforementioned constituents. Finally, we are able to identify statistically (exploiting the non-gaussian time series properties of both endogenous variables) the idiosyncratic shocks underlying the dynamics of the constituents and, then, to interpret them as risk aversion and financial leverage innovations.

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Appendices

Appendix A. Moving Average representation

Consider the Panel Factor-Augmented VAR model described in equation (1), which is estimated by using a lag length equal to two for both the lagged endogenous variables $y_{it-\ell}$ and the lagged cross-sectional averages $\bar{y}_{t-\ell}$, for $\ell = 1, 2$ (see Section 4):

$$y_{it} = \mu_i + \sum_{\ell=1}^{2} \Phi_{i\ell} y_{it-\ell} + \Delta_i \hat{\varepsilon}_t + \sum_{\ell=1}^{2} \Theta_{i\ell} \bar{y}_{t-\ell} + B_{i0} \xi_{it} \tag{A.1}$$

where $y_{it} = (r'_{it}, RV'_{it})'$ is the 2×1 vector of endogenous variables observed for the i-th constituent, with $i = 1, \ldots, N$, at month t (see equation 1, for further details). As described in Section 2.2, the model in equation (A.1) can be re-written as a VARX(1,2) using its companion representation as follows:

$$Y_{it} = \boldsymbol{\mu}_i + \boldsymbol{\Phi}_i Y_{it-1} + \boldsymbol{\Delta}_i \hat{\mathcal{E}}_t + \boldsymbol{\Theta}_{i1} \bar{Y}_{t-1} + \boldsymbol{\Theta}_{i2} \bar{Y}_{t-2} + \mathbf{B}_{i0} \Xi_{it} \tag{A.2}$$

where Y_{it} and Y_{it-1} contains the endogenous variables for the i-th constituent, $\hat{\mathcal{E}}_t$ contains the common factors, $\bar{Y}_{t-1}$ and $\bar{Y}_{t-2}$ contains the lagged cross-sectional averages, and Ξ_{it} contains the idiosyncratic structural shocks. Moreover, $\boldsymbol{\mu}_i$, $\boldsymbol{\Phi}_i$, $\boldsymbol{\Delta}_i$, $\boldsymbol{\Theta}_{i1}$, $\boldsymbol{\Theta}_{i2}$ and $\mathbf{B}_{i0}$ are the matrices containing respectively the constituent-specific intercepts, slope coefficients, loadings associated with the common factors, coefficients associated with the lagged cross-sectional averages, and impact multiplier coefficients. Under the stability condition, each VARX in equation (A.2) admits the following Moving Average (MA) representation:

$$\begin{aligned} Y_{it} = &\sum_{j=0}^{\infty} \boldsymbol{\Phi}_i^j \boldsymbol{\mu}_i + \boldsymbol{\Phi}_i^{\infty} Y_{i0} + \sum_{j=0}^{\infty} \boldsymbol{\Phi}_i^j \boldsymbol{\Delta}_i \hat{\mathcal{E}}_{t-j} + \sum_{j=0}^{\infty} \boldsymbol{\Phi}_i^j \boldsymbol{\Theta}_{i1} \bar{Y}_{t-j-1} + \sum_{j=0}^{\infty} \boldsymbol{\Phi}_i^j \boldsymbol{\Theta}_{i2} \bar{Y}_{t-j-2} + \\ &+ \sum_{j=0}^{\infty} \boldsymbol{\Phi}_i^j \mathbf{B}_{i0} \Xi_{it-j} \end{aligned} \tag{A.3}$$

Moreover, the MA representation of the vector of endogenous variables (y_{it}) can be computed by premultiplying equation (A.3) by the 2×4 selection matrix $J = [I_2 : 0 : \cdots : 0]$:

$$y_{it} = JY_{it} = \sum_{j=0}^{\infty} J\mathbf{\Phi}_i^j \boldsymbol{\mu}_i + J\mathbf{\Phi}_i^{\infty} Y_{i0} + \sum_{j=0}^{\infty} J\mathbf{\Phi}_i^j \mathbf{\Delta}_i \hat{\mathcal{E}}_{t-j} + \sum_{j=0}^{\infty} J\mathbf{\Phi}_i^j \mathbf{\Theta}_{i1} \bar{Y}_{t-j-1} + \\ + \sum_{j=0}^{\infty} J\mathbf{\Phi}_i^j \mathbf{\Theta}_{i2} \bar{Y}_{t-j-2} + \sum_{j=0}^{\infty} J\mathbf{\Phi}_i^j \mathbf{B}_{i0} \Xi_{it-j} \tag{A.4}$$

Given that $\boldsymbol{\mu}_i = J'J\boldsymbol{\mu}_i$, $Y_{i0} = J'JY_{i0}$, $\mathbf{\Delta}_i\hat{\mathcal{E}}_{t-j} = J'J\mathbf{\Delta}_i\hat{\mathcal{E}}_{t-j}$, $\mathbf{\Theta}_{i1}\bar{Y}_{t-j-1} = J'J\mathbf{\Theta}_{i1}\bar{Y}_{t-j-1}$, $\mathbf{\Theta}_{i2}\bar{Y}_{t-j-2} = J'J\mathbf{\Theta}_{i2}\bar{Y}_{t-j-2}$, and $\mathbf{B}_{i0}\Xi_{it-j} = J'J\mathbf{B}_{i0}\Xi_{it-j}$, the MA representation defined in equation (A.4) can be written as follows:

$$\begin{aligned} y_{it} &= \sum_{j=0}^{\infty} J\mathbf{\Phi}_i^j J'J\boldsymbol{\mu}_i + J\mathbf{\Phi}_i^{\infty} J'JY_{i0} + \sum_{j=0}^{\infty} J\mathbf{\Phi}_i^j J'J\mathbf{\Delta}_i \hat{\mathcal{E}}_{t-j} + \sum_{j=0}^{\infty} J\mathbf{\Phi}_i^j J'J\mathbf{\Theta}_{i1} \bar{Y}_{t-j-1} + \\ &+ \sum_{j=0}^{\infty} J\mathbf{\Phi}_i^j J'J\mathbf{\Theta}_{i2} \bar{Y}_{t-j-2} + \sum_{j=0}^{\infty} J\mathbf{\Phi}_i^j J'J\mathbf{B}_{i0} \Xi_{it-j} \\ &= \sum_{j=0}^{\infty} \Psi_{ij}\mu_i + \Psi_{i\infty} y_{i0} + \sum_{j=0}^{\infty} \Psi_{ij}\Delta_i\hat{\varepsilon}_{t-j} + \sum_{j=0}^{\infty} \Psi_{ij}\Theta_{i1}\bar{y}_{t-j-1} + \sum_{j=0}^{\infty} \Psi_{ij}\Theta_{i2}\bar{y}_{t-j-2} + \\ &+ \sum_{j=0}^{\infty} \Psi_{ij} B_{i0}\xi_{it-j} \end{aligned} \tag{A.5}$$

where $\Psi_{ij} = J\mathbf{\Phi}_i^j J'$ is the MA coefficients matrix, for $j = 0, 1, \ldots, \infty$, and $\mu_i = J\boldsymbol{\mu}_i$, $\Delta_i\hat{\varepsilon}_{t-j} = J\mathbf{\Delta}_i\hat{\mathcal{E}}_{t-j}$, $\Theta_{i1}\bar{y}_{t-j-1} = J\mathbf{\Theta}_{i1}\bar{Y}_{t-j-1}$, $\Theta_{i2}\bar{y}_{t-j-2} = J\mathbf{\Theta}_{i2}\bar{Y}_{t-j-2}$, and $B_{i0}\xi_{it-j} = J\mathbf{B}_{i0}\Xi_{it-j}$. From the MA representation in equations (A.3)-(A.5) we derive structural impulse response functions and historical decomposition (see Section 2.2).

Appendix B. Different lag structure

In this section, we estimate the Panel Factor-Augmented VAR described in equation (1) by using a different lag structure. In particular, both in the aggregate SVAR (see equation 2) and in the constituent-specific VARX, we set the number of lags equal to six.[20] Figure B.1 shows the historical decomposition of the cumulative return of the green-minus-brown

[20]Specifically, in the constituent-specific VARX (see equation 1), the lag length of the endogenous variables ($y_{it-\ell}$) and that of the cross-sectional averages ($\bar{y}_{t-\ell}$) are both set to six, i.e., $\ell = 1, \ldots, 6$. We also replicate the empirical analysis using twelve lags. The results, which are qualitatively similar to those discussed both in Section 4 and in this Appendix, are available upon request.

(GMB) portfolio into the expected and unexpected components.[21] Similarly to the results obtained by estimating the model using a lag of order two (discussed in Section 4), the evidence of the out-performance of the expected component of brown stocks' cumulative return and of the out-performance of the green portfolio in terms of unexpected components is confirmed also when using a larger lag order. Moreover, we also compute the ranking of the green portfolio's constituents in terms of their climate risk hedging properties. In line with the analysis described in Section 4.2, in Table B.1, we report the historical mean of the expected return of the green portfolio's constituents (deviation from the expected return of the brown portfolio). As shown in Table B.1, 4 out of the top 5 green constituents obtained from the estimation of the baseline model specification (see Table 8) are ranked in the top 5 positions: CBK, SAN, ORA, BBVA. Overall, these results suggest that the empirical evidence discussed in Section 4 is robust to alternative lag lengths.

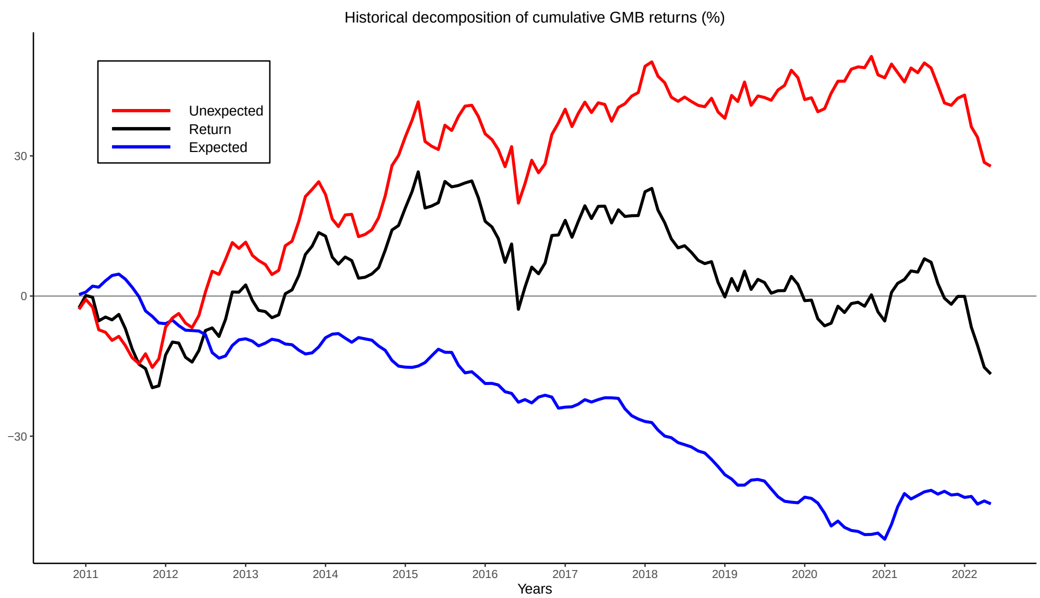
[21] See Section 4.2, for more details on the construction of the historical decomposition of the GMB portfolio's cumulative return.

Table B.1: Average expected return of the green constituents in percent deviation from the brown average constituent: different lag structure.

Rank	Constituent	Deviation	Env. score	Rank	Constituent	Deviation	Env. score
1	CBK	-2.143	93	21	ELISA	-0.386	71
2	SAN	-1.592	90	22	BMW	-0.283	81
3	ORA	-1.567	86	23	KBC	-0.168	93
4	BBVA	-1.561	95	24	PHIA	-0.137	81
5	TEF	-1.542	82	25	RAND	-0.103	63
6	CABK	-1.507	85	26	MB	-0.101	47
7	KPN	-1.195	76	27	VIV	0.017	81
8	NOKIA	-1.186	70	28	ALV	0.113	95
9	DTE	-0.907	85	29	SU	0.164	68
10	CA	-0.872	91	30	ITX	0.221	96
11	GLE	-0.802	96	31	KESKOB	0.249	78
12	ALO	-0.654	99	32	STM	0.306	95
13	HEN3	-0.640	70	33	DB1	0.422	66
14	ISP	-0.576	97	34	MUV2	0.455	94
15	URW	-0.523	88	35	UCB	0.480	77
16	G	-0.511	96	36	KER	0.768	96
17	INGA	-0.497	86	37	SY1	0.818	64
18	PUM	-0.487	85	38	DSY	1.176	77
19	SIE	-0.410	88	39	CAP	1.238	77
20	BNP	-0.388	95	40	AMS	1.414	73

Notes. Expected component of each of the 40 constituents entering the Refinitiv Eurozone Low Carbon Select Index (i.e., green portfolio) computed as the deviation from the expected component of the brown average constituent (i.e., obtained by computing the mean across the brown portfolio's constituents) and averaged across the full sample $2010m6 - 2022m5$, in percent. In each month, the expected component is computed as the sum of the contributions of the constant term, initial condition and lagged cross-sectional averages of return and realized volatilities. The lag length of the Panel Factor-Augmented VAR (see equation 1) is set equal to six. Estimation sample: $2010m6 - 2022m5$.

Figure B.1: Historical decomposition of the green-minus-brown (GMB) portfolio's cumulative return: different lag structure.



Notes. Contribution of the expected (blue solid line) and unexpected (red solid line) components to the green-minus-brown (GMB) portfolio's cumulative return (black solid line) in percent. For more details on the chart, see the notes in Figure 7. The lag length of the Panel Factor-Augmented VAR (see equation 1) is set equal to six. Estimation sample: $2010m6 - 2022m5$.

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Viale Jacopo Berengario 51, 41121 MODENA (Italy) tel. 39-059.2056711