Journal of Behavioral and Experimental Finance 39 (2023) 100824

Contents lists available at ScienceDirect

Journal of Behavioral and Experimental Finance

journal homepage: www.elsevier.com/locate/jbef

Full length article

A flexible estimation of sectoral portfolio exposure to climate transition risks in the European stock market

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ARTICLE INFO

Article history:
Received 3 October 2022
Received in revised form 26 May 2023
Accepted 27 May 2023
Available online 30 May 2023

JEL classification:
C1
G12
Q50

Keywords:
Asset pricing model
Climate transition risk
Green-minus-brown factor
Flexible modelling framework

ABSTRACT

I investigate the exposure of sectoral equity portfolios to climate transition risks by augmenting a three-factor asset pricing model with a green-minus-brown (GMB) factor as a proxy. I estimate the relationship between risk factors and excess returns within an additive mixed model representation, which flexibly captures possible changes in investors' subjective beliefs as reflected in the determinants of asset pricing. Empirical evidence is provided based on European sectoral portfolios covering the 2016–2021 period. Compared to classic linear models, the results show an improvement in model goodness-of-fit when flexibly estimating the relationship between risk factors and excess returns. I confirm previous studies that exposure to climate transition risks particularly affects high-energy-intensity sectors. I also find heterogeneity in exposure between firms within each sectoral portfolio in terms of the sign and/or magnitude of estimates. Moreover, some firms still have no statistically significant exposure to climate transition risks.

1. Introduction

There is a rising awareness that the increase in extreme climate events, induced mainly by global warming, is causing damage to biodiversity, the economy, society and financial systems (e.g. Calabrese et al., 2023; Magnan et al., 2021; Mandel et al., 2021; Huynh and Xia, 2021; Ma et al., 2022). The European Environmental Agency reports that in the EU-27 countries, the economic losses from extreme climate-related events occurring between 1980 and 2020 are estimated at 487 billion euros (about 11.9 billion euro per year).[1] Analogously, in the US the National Centers for Environmental Information registered 332 weather and climate disasters between 1980 and mid-2022, with an estimated total cost exceeding 2.275 trillion dollars.

One prominent global challenge of this century is limiting global temperature increases and mitigating damage from extreme weather events. Policymakers are considering climate action plans to reduce the greenhouse gases responsible for global warming and to adapt to climate impacts. However, from the last Conference of the Parties (COP), it emerged that the convergence of countries on a common path to achieving a global environmentally friendly economy by 2050 is still an ambitious goal. European countries are working to draw a roadmap to make Europe the first continent to achieve carbon neutrality by 2050. For example, one-third of the 1.8 trillion euro investment from the NextGenerationEU Recovery Plan is slated to finance the European Green Deal.[2]

Public funds alone will not be sufficient to support the transition to a sustainable world, however, and as specified in article 2.1 (c) of the Paris Agreement (2015),[3] private investors can play a crucial role in mobilising capital to support the transition to a climate-friendly future (see also the Glasgow Financial Alliance for Net Zero (GFANZ) initiative[4]). Since climate risks (physical and transition-related) are recognised as a new source of financial risk (e.g. Battiston et al., 2021), investors are integrating them into their investment decision processes and risk-management evaluations. This includes the assessment of (direct and indirect) firm exposure to damages from physical risks, as well as (direct and indirect) costs of transitioning to a low-carbon economy as a consequence of a carbon pricing policy, new investment in clean capital, and reputational and legal risks, to name just a few. These risks may affect firms' balance sheets (especially of the most polluting ones) and represent a source of financial risk for participants in capital markets (e.g. Nguyen and Chaiechi,

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1 https://www.eea.europa.eu/ims/economic-losses-from-climate-related; information retrieved July 30, 2022.

2 https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en

3 https://unfccc.int/sites/default/files/english_paris_agreement.pdf

4 https://www.gfanzero.com/

https://doi.org/10.1016/j.jbef.2023.100824

2021; Shimbar, 2021b; Prosperi and Zanin, 2022; Ma et al., 2022; Makridis and Schloetzer, 2023; Xia, 2022).

In 2020, Mark Carney launched the COP26 *Private Finance Agenda*, with the aim of ensuring '*that every professional financial decision takes climate change into account*'.[5] Improving knowledge of the integration of climate risks in the stock market plays a crucial role in enabling participants in capital markets to identify, measure and manage risks and opportunities in the transition to a low-carbon economy. An emerging field of studies in finance has proposed several methodologies and empirical case studies to investigate how investors are integrating climate risks into their portfolios. Here, I focus on the literature exploring the issue of environmental matters and climate transition risks in the equity market.

Some studies have investigated the impact of environmental or sustainability risks on stock price returns by using firm sustainability performance scores released by rating agencies specialising in sustainability (e.g. Zhang et al., 2021; Naffa and Fain, 2022; Shanaev and Ghimire, 2022). Mixed evidence has emerged using performance scores, however. For instance, Naffa and Fain (2022) observed that environmental, social and governance (ESG) factors do not provide sufficient evidence to complement Fama and French asset pricing models. In contrast, Zhang et al. (2021) showed that good ESG profiles contribute to higher returns, especially after the Paris Agreement of 2015. Ford et al. (2022) instead explored the relationship between ESG factors and short-term investor sentiment derived from option markets. They found that the 'E' score and the ESG controversies score have a significant impact on trader sentiment. Typically, green assets have lower expected returns than brown assets because they are less risky (Hübel and Scholz, 2020). Nevertheless, Pástor et al. (2021) found that green assets outperform brown assets. Moreover, they demonstrated a shift in investors' tastes in green assets in the period analysed. Evidence that green stocks outperform brown stocks has also been documented by Bauer et al. (2022).

Other studies have proposed evaluating the integration of environmental or climate transition risks in stock pricing by constructing a risk factor defined as a portfolio return spread between green and brown firms (also known as green-minus-brown (GMB)). In the context of the societal and economic transition towards a more climate-friendly future, due to their business models brown businesses are more exposed to transition risks than green businesses (e.g. Battiston et al., 2022). The aim of adding the GMB factor to asset pricing models is thus to capture the exposure of a portfolio or firm to climate transition risks. In the literature, several proposals have been advanced for the identification and construction of green and brown portfolios (e.g. Hübel and Scholz, 2020; Alessi et al., 2021; Bernardini et al., 2021; Pastor et al., 2022; Prosperi and Zanin, 2022). Pastor et al. (2022) identified green and brown firms by combining the environmental pillar score and the MSCI environmental pillar weight. These scores are designed to capture a firm's overall resilience to long-term environmental risks. They observe that in recent years, green stocks have outperformed brown stocks. They explain the realised returns over the last years in relation to an increase in investor attention to environmental concerns, rather than high expected returns from green assets. This attention and concern for the climate is driven not only by climate shock events but also by the increasing recommendations by regulators to integrate and evaluate climate risks into the investment decision-making processes (e.g. Principles for Responsible Investment[6]).

Bernardini et al. (2021) focus on the electric utility sector and propose disentangling the carbon risk by constructing a long–short portfolio with a long position in the low-carbon portfolio and a short position in the high-carbon portfolio. Specifically, carbon risk is represented by a score including, among other things, the carbon emissions equivalent, energy consumption and investments in technology associated with emission reductions. Alessi et al. (2021) suggest a greenness and transparency factor, labelling green and brown firms based on their carbon intensity and the quality of their environmental disclosures. Prosperi and Zanin (2022) propose identifying brown and green firms using multiple screening criteria. Specifically, brown firms are identified using the Climate Policy Relevant Sectors (CPRS) classification developed in Battiston et al. (2017) and are further screened based on a minimum carbon-intensity threshold. Green firms are identified as the non-brown firms with the best environmental pillar scores (that is, firms demonstrating a better management of environmental matters than their peers), a maximum carbon-intensity threshold (lower than that defined for brown firms) and the absence of environmental controversies. In considering environmental controversies among the screening criteria, the aim is to minimise including in the green portfolio firms that violate the principle of 'Do no significant harm', according to the six environmental objectives considered by the EU Taxonomy.[7] In an opposite approach, Hübel and Scholz (2020) construct an environmental risk factor with long positions in listed firms with low environmental ratings (brown) and short positions in listed firms with high environmental ratings (green).

These studies test the relationship between the GMB risk factor and stock price returns mainly by extending the Fama and French asset pricing models (e.g. Fama and French, 1993). Exploring how and whether transition risks are incorporated into the financial market is important for several reasons. One reason is that investors are called on to support the transition to a more sustainable economy by financing companies that foster it. Evaluating how and to what extent these risks are currently being priced into the market is thus crucial for investors and policymakers. Another reason is that the financial market might not yet reflect or only partially price climate transition risks. As stated by Bolton and Kacperczyk (2021), this is because institutional investors have not formed a consensus regarding climate risk matters.

The main evidence from the literature suggests that the proposed GMB factors help capture such risks in the stock market, with stronger evidence of greater exposure to climate transition risks (e.g. climate policy risks, technological, stranded assets, litigation) for the most polluting firms/sectors compared to less polluting firms/sectors. These findings have generally been obtained by applying classic linear models, such as ordinal least squares (OLS) regression. This modelling framework is widely employed in the literature on asset pricing due to its simplicity in estimation and interpretability. However, it is likely to result in some biased conclusions because linear models are not suited to exploring the presence of some (a priori unknown) non-linear patterns between risk factors and excess returns. These non-linearities capture changes in investors' subjective beliefs, which are reflected in the determinants of asset pricing.

This paper contributes to the literature on the effect of climate transition risk on stock pricing from an empirical and methodological perspective.

From an empirical perspective, I provide evidence of the exposure to climate transition risks on European sector-level equity portfolios. In contrast to the large body of literature mentioned

5 https://ukcop26.org/wp-content/uploads/2020/11/COP26-Private-Finance-Hub-Strategy_Nov-2020v4.1.pdf

6 https://www.unpri.org/about-us/what-are-the-principles-for-responsible-investment

7 https://ec.europa.eu/info/business-economy-euro/banking-and-finance/sustainable-finance/eu-taxonomy-sustainable-activities_en

above, I investigate the risk factors-outcome relationship using daily rather than monthly observations, in order to better evaluate all of the information from the market (see also Prosperi and Zanin, 2022; Ardia et al., 2022; Boungou and Urom, 2023). More specifically, the analysis covers the 2016–2021 period. A sector-level study is interesting because it explores how investors are pricing climate transition risks for different economic activities. I evaluate the exposure of sectoral portfolios to climate transition risks using the GMB factor proposed by Prosperi and Zanin (2022) as a proxy and incorporating it into a Fama and French (1993) three-factor asset pricing model augmented by the momentum factor (Carhart, 1997). The time series of portfolio returns starts from 2016, as several studies have shown that investors increased their attention to climate risks following the Paris Agreement of 2015 and the recent documents put forward by regulators (for instance, the EU Taxonomy and the European Green Deal) that aim to guide investors towards orienting investments to support the low-carbon transition (e.g. Monasterolo and de Angelis, 2020; Zhang et al., 2021; Pastor et al., 2022; Prosperi and Zanin, 2022). I also estimate the models for the sub-periods of 2016–2018 and 2019–2021 to investigate potential differences across these timeframes. As compared to the 2016–2018 period, the three years of 2019–2021 are characterised by (a) an increase in the percentage of firms that disclose information on environmental matters,[8](b) increasing investor attention on environmental matters (e.g. Abate et al., 2021; Kleimeier and Viehs, 2021; Marshall et al., 2021; Semieniuk et al., 2021; Basse Mama and Mandaroux, 2022; Campiglio et al., 2022), and (c) the COVID-19 pandemic. The pandemic represents a natural experiment to assess sensitivity to climate transition risks in periods of the stock market being under pressure and to investigate how different sectors are affected. However, as a caveat, this market stress was not strictly correlated to climate policies. I also explore differences in the exposure to climate transition risk between firms within each sector. A firm-level analysis is important to evaluate whether diversification within portfolios masks heterogeneity in the exposure to climate risk across firms from the same peer group.

From a methodological perspective, I propose comparing the results of linear models to those obtained from a modelling approach that allows for relaxing the assumption of linearity. The assumption of a linear relationship between outcome and risk factors might be too stringent and may not allow for capturing aspects of changes in investor beliefs and market efficiency (e.g. Neslihanoglu et al., 2017). To capture nonlinearities, Dittmar (2002) proposed using a polynomial pricing kernel approach. However, this requires defining the degree of polynomials. Moreover, the possible issue of autocorrelation needs to be addressed. To overcome these limitations, I propose relaxing the assumption of linearity by estimating the asset pricing model within an additive mixed model (AMM) framework. The AMM is an extension of the linear mixed model representation (Berridge and Crouchley, 2011) in which part of the linear predictor is specified using smooth functions. This modelling specification is appealing because it is well-suited to flexibly handling the estimation of covariates using penalised splines and jointly deals with autocorrelation in the residuals (e.g. Zanin and Marra, 2012a; Wood, 2017). Penalised splines are helpful when a functional shape is not known a priori, and the penalty prevents the drawback of overfitting. In this way, the estimation is entirely data-driven, minimising specification errors and allowing the data to determine whether the functional form of the relationship is linear or non-linear (e.g. Zanin and Marra, 2012a,b; Wood, 2017).

Among the main empirical findings, I confirm that the high energy-intensity sectors are the most exposed to climate transition risks. However, in estimating the asset pricing models for each firm, I note a heterogeneous exposure to climate transition risks within sectors in terms of the sign of the relationship, statistical significance and the magnitude of estimates. This result is probably linked to a firm's business model and investor perceptions of the risks. Moreover, I also find that in some portfolios the percentage of firms with a statistically significant exposure to climate transition risks is relatively low (particularly for health care and information technology). This evidence may raise questions about whether a sharp re-pricing may occur as climate transition risks materialise.

From a methodological point of view, relaxing the assumption of linearity in the risk factors-outcome relationship contributes to improving the goodness-of-fit of the estimated models. Compared to linear models, the flexible estimation of asset pricing models allows capturing linear and non-linear patterns in the relationship of interest. Moreover, for some sectors I note a quite relevant enlargement of confidence intervals around the estimated smooth effects for the values of the GMB factor in the distribution's tails. These extreme values were observed during the pandemic, when investors panicked and triggered an increase in market volatility. Effects other than climate transition risks were likely to be incorporated into prices, affecting the robustness of the GMB-outcome relationship. Thus, some caution is required in interpreting smooth function patterns at the points where confidence intervals tend to enlarge notably. An enlargement of confidence intervals around estimated smooth effects is observed mainly in the utilities, materials, industrials and health care sectors, whereas the relationship appears to be more robust for energy and consumer staples than for other sectors. In summary, the use of AMM helps reveal a more transparent pattern regarding the GMB-outcome relationship, as well as for other risk factors included in the model.

The remainder of the paper is organised as follows. Section 2 describes the asset-pricing modelling framework. Section 3 presents the data sources and time series, while in Section 4 I describe the main empirical results. In Section 5, I outline the main conclusions.

2. Methodology

2.1. Linear model

I estimate the exposure to climate transition risk of sectoral equity portfolios by using as a proxy the GMB factor proposed by Prosperi and Zanin (2022). The GMB factor is added into the Fama and French (1993) three-factor asset pricing model augmented by the momentum factor (Carhart, 1997). Specifically, the model is as follows:

$$\begin{aligned} R_{it} - Rf_t = {} & \alpha_i + \beta_i^{GMB} GMB_t + \beta_i^{MKT}(MKT_t - Rf_t) + \beta_i^{SMB} SMB_t \\ & + \beta_i^{HML} HML_t + \beta_i^{WML} WML_t + \epsilon_{it}, \end{aligned} \tag{1}$$

where R_{it} is the return of portfolio i on day t, with $i = 1, \ldots, N$ sectors and $t = 1, \ldots, T$. Defining Rf as the daily risk-free rate (Euribor 1 month), $R_{it} - Rf_t$ is the excess return of portfolio i at time t. The parameter α_i is the intercept, which should be zero in an efficient market, while ϵ_{it} is the idiosyncratic risk. β_i^{GMB} is the parameter of interest, which aims to capture the exposure to climate transition risks. $MKT_t - Rf_t$ is the factor of the excess return of the market, while the associated β_i^{MKT} is the parameter to be estimated, interpreted as systemic risk. β_i^{SMB}, β_i^{HML} and β_i^{WML} are the Fama and French parameters to be estimated, associated with the risk factors SMB (small-minus-big, a size factor), HML (high-minus-low, a value factor) and WML

[8] See, for example, Fig. 6 in Appendix.

(winners-minus-losers, referring to momentum), as described in Section 3. A common practice in the asset pricing literature is to estimate model (1) using an ordinary least squares (OLS) estimator. To overcome the potential issue of outliers or extreme events, I also estimate (1) by applying a robust linear model (RLM) as in Prosperi and Zanin (2022). Specifically, I apply an M-estimator to reduce the influence of outliers in the model estimation (Wilcox, 2017).

2.2. A flexible estimation using an additive mixed model

In asset pricing model (1), the assumption is that risk factors have a linear relationship to the excess return ($R_{it} - Rf_t$) of the ith portfolio. Suppose the data do not support the assumption of a linear relationship. In that case, we risk incurring a potentially biased interpretation of the results by masking patterns of interest for investors. In the literature, several empirical studies in different disciplines have proposed relaxing the assumption of a linear relationship by applying regression spline models (e.g. Zanin and Marra, 2012a,b; McKeown and Sneddon, 2014; Zanin, 2015; Calabrese et al., 2016; Zanin, 2017; Calabrese and Zanin, 2022). In general, regression spline models aim to minimise specification errors using a data-driven approach, by avoiding including a priori assumptions regarding the functional form of the relationships.

The simplest way to achieve this aim is to estimate (1) within an additive modelling framework specified as

$$R_t - Rf_t = \alpha + s(GMB_t) + s(MKT_t - Rf_t) + s(SMB_t) + s(HML_t) + s(WML_t) + \epsilon_t, \tag{2}$$

For notational simplicity, I removed the subscript i. The fundamental difference between Eqs. (1) and (2) is that the β parameter is replaced by a one-dimensional smooth function $s(\bullet)$, which is represented by a linear combination of basis functions and parameters (Zanin and Marra, 2012a). The basis functions are chosen based on good numerical stability and convenient mathematical properties. A generic smooth function $s(\bullet)$ can be replaced by the following representation

$$s(x) = \gamma_0 + \gamma_1 x + \sum_{k=1}^{K} u_k (x - k_k)_+, \tag{3}$$

where γ_0, γ_1 and u_k are regression spline coefficients, k_k are K fixed knots and $(x - k_k)_+ = max(x - k_k, 0)$ (Ruppert, 2002). I drop the subscript t for convenience. The classic approach to regression spline parameters estimation is to consider a penalised likelihood maximisation, allowing the control of the trade-off between fit and smoothness. This avoids over-fitting of the smooth components, which is a risk if a classic maximum likelihood approach is used instead. Further methodological details can be found in Wood (2017).

A drawback of the estimation method mentioned above is that since data for the time series in the asset pricing model (1) are at a daily frequency, smooth parameter selection can be sensitive to the presence of autocorrelation in residuals (e.g. Opsomer et al., 2001; Krivobokova and Kauermann, 2007; Zanin and Marra, 2012a).

As a solution, the mixed model representation of penalised spline regression is well-suited to flexibly estimating the response-risk factor relationships and jointly dealing with serial correlation in residuals.

Model (2) with substitution (3) can be viewed as a linear mixed model (LMM) by treating the coefficients u_t as random effects (Zanin and Marra, 2012a). Thus, the model in matrix form can be written as follows:

$$\mathbf{y} = \mathbf{X}\boldsymbol{\gamma} + \mathbf{Z}\mathbf{u} + \boldsymbol{\varepsilon}, \tag{4}$$

where $\mathbf{y}$ is the response vector, $\mathbf{X}$ is the design matrix including the intercept and the risk factors, $\boldsymbol{\gamma}$ is the vector of the fixed parameters, $\mathbf{Z}$ is a model matrix of random effects, and $\mathbf{u}$ includes the random effects vector. $\boldsymbol{\varepsilon}$ is a vector of residuals. Analogously to (2), model (4) is estimated using penalised likelihood maximisation. Specifically, a restricted maximum likelihood (REML) method is employed to estimate the variance components and the auto-correlation parameters defined as an autoregressive process of order one (AR1). Extensive descriptions of the mixed-model-based penalised spline (or the additive mixed model) representation can be found in Ruppert et al. (2003), Zanin and Marra (2012a) and Wood (2017).

3. Data

3.1. The construction of European sectoral portfolios

I construct sectoral portfolios considering firms listed on the European market and using the Global Industry Classification Standard (GICS) to identify the sector to which each company belongs. The sectors considered are the following: communication services, consumer discretionary, consumer staples, energy, health care, industrials, information technology, materials and utilities. Coherently with other studies in literature, I exclude the financial, insurance and real estate sectors (e.g. Alessi et al., 2021; Prosperi and Zanin, 2022).

The portfolios are constructed including firms listed for the entire period of 2016–2021. The observations on stock returns are available at a daily frequency and are sourced from Refinitiv. Previous studies have demonstrated that the estimation of asset pricing models using daily rather than monthly data fits better with the assumption of market efficiency (Pham and Phuoc, 2020). In considering monthly data, there is a risk of masking some patterns in the relationship between risk factors and excess returns that might interest capital market participants.

Finally, the constituents are equally weighted to avoid some specific stocks influencing the performance of portfolios. In Table 1, I report descriptive statistics for the sectoral portfolios.

From the descriptive analysis, it can be noted that the portfolio of firms in the energy sector registers a higher value-at-risk (VAR) at confidence intervals of 99% (−4.01%) and 95% (−1.89%) than the other sectors. The materials, industrials and consumer discretionary sectors follow in terms of rank. The portfolio of the energy sector is also characterised by the highest volatility across the time series (with a standard deviation of 1.28). In contrast, the portfolio of consumer staples firms is less volatile and risky in terms of VAR than other sectors.

3.2. Risk factors

3.2.1. The green-minus-brown factor

To explore whether climate transition risks are reflected in equity performance, I include the GMB factor proposed by Prosperi and Zanin (2022) in the asset pricing models described in Section 2. The GMB factor is a spread between a portfolio with long positions in firms labelled as green and short positions in firms identified as brown. Previous studies have shown that green assets outperform brown assets in the medium-long run (e.g. Bernardini et al., 2021; Bauer et al., 2022; Pastor et al., 2022; Prosperi and Zanin, 2022).

The GMB factor proposed by Prosperi and Zanin (2022) is defined as

$$GMB_t = \frac{1}{2}(sG_t + lG_t) - \frac{1}{2}(sB_t + lB_t) \tag{5}$$

where the symbols G and B identify firms labelled as green and brown, respectively. The symbols s and l identify firm size

Table 1
Descriptive statistics for European sectoral portfolio returns based on daily observations from 2016 to 2021. SD stands for standard deviation.

GICS sectors	No. of equities in PTF	Mean	SD	Percentiles of the distribution						
				1th	5th	25th	50th	75th	95th	99th
Energy	144	−0.07	1.28	−4.01	−1.89	−0.57	−0.01	0.55	1.60	2.75
Utilities	94	0.03	0.82	−2.26	−1.16	−0.27	0.08	0.44	1.07	1.80
Materials	264	0.02	0.91	−3.04	−1.30	−0.34	0.07	0.48	1.19	2.04
Industrials	728	0.02	0.88	−2.89	−1.21	−0.29	0.09	0.43	1.09	2.05
Consumer Discretionary	398	0.01	0.94	−2.80	−1.26	−0.30	0.07	0.41	1.11	2.14
Consumer Staples	193	0.01	0.64	−1.94	−0.84	−0.21	0.05	0.31	0.80	1.45
Health Care	343	−0.02	0.84	−2.58	−1.31	−0.34	0.06	0.40	1.04	1.83
Information Technology	409	0.03	0.86	−2.71	−1.25	−0.24	0.11	0.43	1.09	1.84
Communication Services	226	−0.01	0.77	−2.60	−1.10	−0.29	0.05	0.35	0.94	1.62

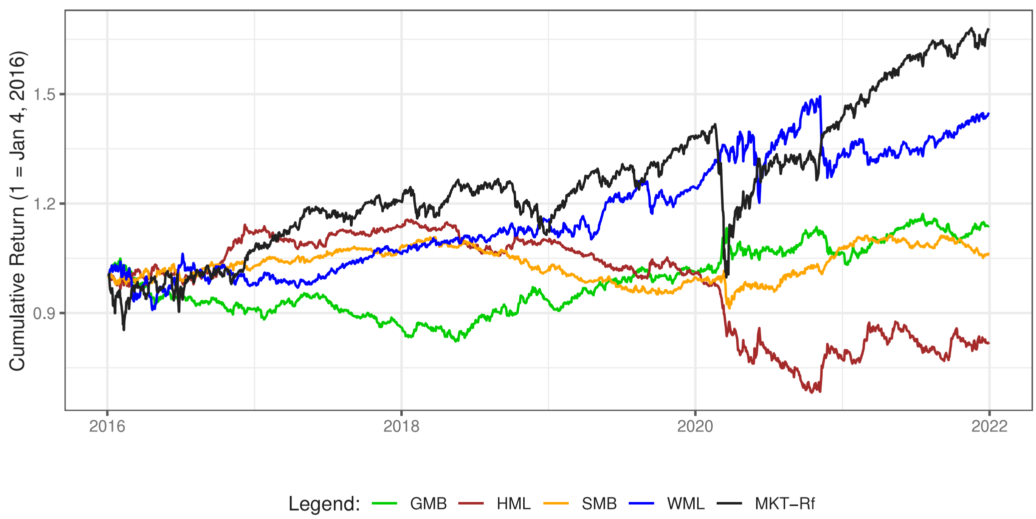

Fig. 1. Cumulative returns of the Fama and French factors and of the GMB factor (5).

(small-medium (s) and medium-large (l)) in terms of market capitalisation. The firms that are neither G nor B are labelled neutral (N). Moreover, all six portfolios (sG, lG, sB, lB, sN, lN) are balanced in terms of the number of equities (and sector) in order to reduce the issue of asymmetry in the size of portfolios.

Brown firms are identified using the Climate Policy Relevant Sectors (CPRS)[9] classification as in Battiston et al. (2017) and are further screened by identifying firms with a carbon intensity value above 50 tonnes per million US dollars of revenue.[10]

Green firms are identified as non-brown firms with an environmental pillar score[11] above 75,[12] a carbon intensity below or equal to 50 tonnes per million US dollars of revenue and the absence of environmental controversies.[13] Refinitiv is the data source used to select European listed firms with information on environmental matters.

The risk factor is constructed considering the same countries as the Fama and French risk factors.[14] For further methodological details on the GMB (5), please refer to Prosperi and Zanin (2022).

In Fig. 1, the green line shows the cumulative daily returns for the GMB (5) from January 2016 to December 2021. The time series shows a positive trend over the last few years, which means that the green portfolio outperformed the brown portfolio in the medium-long run. This may be partly driven by increasing investor attention to climate-risk matters, as observed by Pastor et al. (2022). In particular, green assets outperformed brown assets during the COVID-19 pandemic, when the stock market suffered substantial losses (e.g. Mukanjari and Sterner, 2020; Alexakis et al., 2021; Aljughaiman et al., 2021; Fernandez-Perez et al., 2021; Pastor et al., 2022; Prosperi and Zanin, 2022). Several explanations have been suggested for the outperformance during pandemic. For example, (i) green assets are less volatile than brown assets, (ii) there is an increased appetite for green assets, and (iii) an effort has been made to revitalise the economy by avoiding subsidising brown assets and accelerating the demand for clean-energy technologies (Mukanjari and Sterner, 2020). Moreover, green assets are more resilient to long-term transition risks than brown assets (Zanin, 2022).

Compared to alternative GMB factors available in the literature, the proposal by Prosperi and Zanin (2022) has the advantage of considering multiple indicators for screening green and brown firms by incorporating some indications from the regulator regarding the EU Taxonomy. However, the literature on climate

9 This is a classification of economic activities to assess climate transition risk and is compatible with the EU Taxonomy of sustainable activities (https://www.finexus.uzh.ch/en/projects/CPRS.html). See also Battiston et al. (2022).

10 This threshold is defined based on the median value among CPRS sector firms in the 2008–2020 period (Prosperi and Zanin, 2022).

11 The environmental score is based on a best-in-class criterion. For details, please refer to the methodology: https://www.refinitiv.com/content/dam/marketing/en_us/documents/methodology/refinitiv-esg-scores-methodology.pdf.

12 Scores range from 0 to 100, with 0 being the worst in class and 100 being the best in class.

13 This is to reduce the risk of labelling as green firms that are best in class but which violate the 'Do no significant harm (DNSH)' principle included in article 17 of the EU Taxonomy.

14 https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_3developed.html

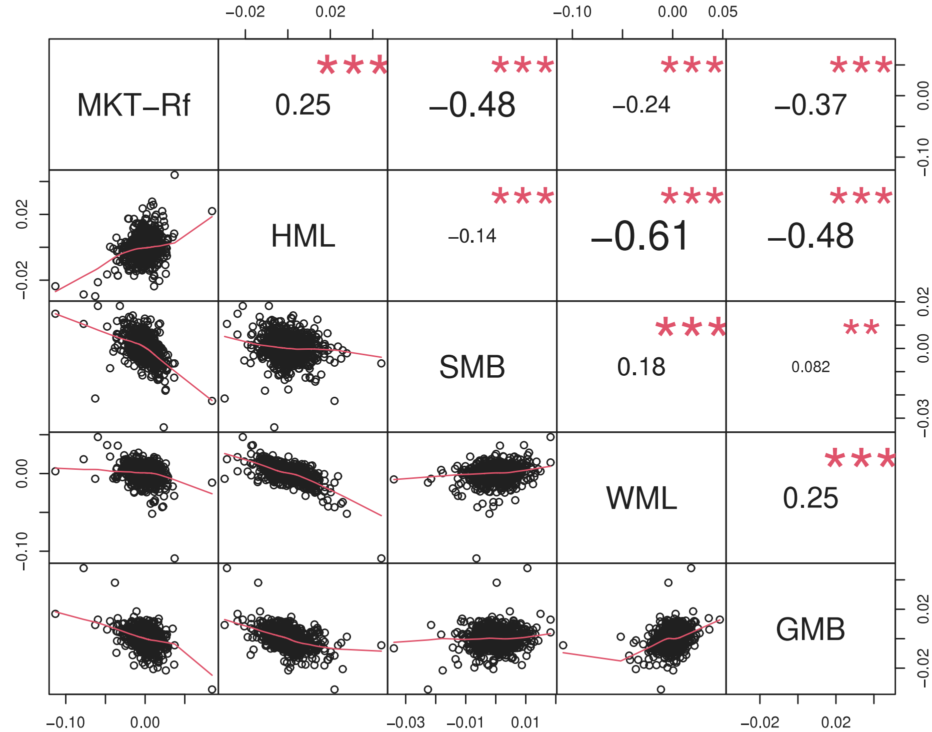

Fig. 2. Pearson correlations between risk factor returns. P-value: *** < 0.01; ** < 0.05; * < 0.1.

risk factors is still in its infancy. As of yet, there is no consensus regarding what risk factor can best capture the climate transition risk in asset pricing. Despite some differences in the criteria for identifying green and brown firms, the evidence from several studies mentioned in the previous sections indicates that green assets outperform brown assets in the long run.

3.2.2. Fama and French factors

In estimating the models described in Section 2, I also include the following Fama and French factors:[15] the excess return of the market (MKT-Rf), the factors capturing the size effect (small-minus-big, SMB) and the value effect (high-minus-low, HML), and the momentum factor (winners-minus-losers, WML). Since the analysis takes the perspective of a European investor, I convert the Fama and French factors to euro returns using the approach described in Glück et al. (2020).

Fig. 1 reports the daily cumulative returns of the risk factors over the sample period. The impact of the COVID-19 outbreak on the risk factors can clearly be observed. The national and local lockdowns imposed by governments to mitigate the spread of the virus fuelled expectations of a negative impact on the economy (e.g. in terms of business survival, shifts in consumer spending patterns with implications for production, and so on), resulting in volatility and a negative market performance (black line). The observed negative shock for the HML factor suggests that portfolios of firms with a high book-to-market ratio under-performed with regard to those with a low book-to-market ratio (red line). Analogously for the SMB factor, the portfolios of firms with small capitalisation under-performed with regard to those with large capitalisation (orange line), while outperforming them in the period following the shock.

Fig. 2 shows the correlations between the risk factors. Note that the most significant correlations are between WML and HML (−0.61), GMB and HML (−0.48) and SMB and MKT-Rf (−0.48). All correlations are statistically significant. As observed in other studies (Pastor et al., 2022; Prosperi and Zanin, 2022), the negative correlation between the GMB and HML factors might be motivated by value stocks more often being brown than green.

As a further descriptive analysis, I evaluate the variance inflation factor (VIF) to check for possible multicollinearity issues. The VIF values reported in Table 8 in the Appendix are well below the critical threshold of 5 (Hair et al., 2010). This suggests that multicollinearity is not an issue in the estimation of the asset pricing models described in Section 2.

4. Empirical results

Below, I present the main results from models (1) and (3), described in Section 2. In Section 4.1, I describe the results of the sectoral portfolio analyses, and Section 4.2 presents evidence from a firm-level analysis by sectoral portfolio.

4.1. Results of the sectoral portfolios analysis

4.1.1. Estimation results from linear models

In the estimation of model (1), $\widehat{\beta}_i^{GMB}$ is the parameter of interest, which aims to capture, through the GMB (5), investor perceptions regarding the exposure of sectoral portfolio i to climate transition risks. A challenge for investors in pricing climate transition risks is the difficulty of adequately quantifying such risks. The poor quality (or lack) of disclosures of non-financial information from firms (such as carbon emissions, investment in clean technology, and so on) and the uncertainty about the timing and magnitude of future climate policies may represent an obstacle for investors in adequately pricing climate transition risks in the stock market. Several studies suggest that the most polluting firms will be negatively impacted in terms of their balance sheets (for instance, for the stranding of fossil fuel assets) if a stringent climate policy materialises, with cascading effects on the economy and the financial system (e.g. Sen and von Schickfus, 2020; van der Ploeg and Rezai, 2020; Bocken and Short,

15 See footnote 14.

Table 2
Estimated parameters of model (1) using an OLS estimator. Standard errors are adjusted for autocorrelation and heteroskedasticity (Newey and West, 1987, 1994). The 95% confidence intervals are reported in square brackets. The stock market performances of firms in the portfolios are observed for the entire reference period.

GICS Sectors	$\widehat{\alpha}(\times 100)$	$\widehat{\beta}_{MKT}$	$\widehat{\beta}_{HML}$	$\widehat{\beta}_{SMB}$	$\widehat{\beta}_{WML}$	$\widehat{\beta}_{GMB}$	$R^2 adj$
Period: 2016–2021							
Energy	−0.100***	0.916***	0.452***	0.662***	−0.070**	−0.470***	0.748
	[−0.133;−0.066]	[0.852;0.979]	[0.348;0.555]	[0.541;0.784]	[−0.132;−0.008]	[−0.590;−0.350]	
Utilities	0.008	0.631***	−0.064	0.020	0.030	−0.149***	0.665
	[−0.017;0.033]	[0.538;0.723]	[−0.162;0.034]	[−0.086;0.126]	[−0.033;0.093]	[−0.229;−0.069]	
Materials	−0.013	0.788***	0.124***	0.460***	0.028	−0.244***	0.808
	[−0.033;0.006]	[0.739;0.837]	[0.058;0.190]	[0.383;0.538]	[−0.024;0.079]	[−0.311;−0.178]	
Industrials	−0.014	0.832***	0.057**	0.564***	−0.057***	−0.077***	0.859
	[−0.029;0.002]	[0.784;0.879]	[−0.004;0.119]	[0.473;0.655]	[−0.093;−0.020]	[−0.147;−0.023]	
Consumer Discretionary	−0.030***	0.883***	0.149***	0.700***	−0.116***	0.048	0.837
	[−0.049;−0.011]	[0.818;0.948]	[0.057;0.241]	[0.558;0.842]	[−0.166;−0.066]	[−0.030;0.127]	
Consumer Staples	−0.014	0.582***	−0.019	0.197***	−0.046***	0.086***	0.761
	[−0.029;0.002]	[0.531;0.632]	[−0.079;0.041]	[0.126;0.269]	[−0.088;−0.004]	[0.027;0.145]	
Health Care	−0.062***	0.795***	−0.320***	0.489***	0.025	−0.066*	0.762
	[−0.083;−0.041]	[0.732;0.858]	[−0.392;−0.247]	[0.403;0.575]	[−0.029;0.078]	[−0.138;0.006]	
Information Technology	−0.007	0.829***	−0.117***	0.637***	0.025	−0.122***	0.824
	[−0.024;0.011]	[0.772;0.886]	[−0.190;−0.043]	[0.36;0.737]	[−0.019;0.068]	[−0.186;−0.057]	
Communication Services	−0.041***	0.705***	0.094***	0.416***	−0.053**	0.024	0.794
	[−0.058;−0.023]	[0.60;0.761]	[0.028;0.160]	[0.334;0.499]	[−0.093;−0.012]	[−0.039;0.086]	
Period: 2016–2018							
Energy	−0.081***	0.774***	0.307***	0.521***	−0.164***	−0.446***	0.599
	[−0.127;−0.035]	[0.693;0.855]	[0.161;0.453]	[0.354;0.688]	[−0.262;−0.065]	[−0.578;−0.314]	
Utilities	0.006	0.472***	−0.116*	−0.129*	−0.111***	−0.133**	0.562
	[−0.023;0.036]	[0.414;0.530]	[−0.235;0.003]	[−0.264;0.006]	[−0.194;−0.029]	[−0.238;−0.028]	
Materials	−0.006	0.617***	−0.004	0.248***	−0.099***	−0.379***	0.722
	[−0.031;0.019]	[0.571;0.663]	[−0.089;0.082]	[0.154;0.342]	[−0.156;−0.042]	[−0.466;−0.292]	
Industrials	−0.014	0.649***	−0.068***	0.329***	−0.101***	−0.127***	0.743
	[−0.035;0.007]	[0.600;0.697]	[−0.132;−0.004]	[0.240;0.417]	[−0.156;−0.045]	[−0.196;−0.060]	
Consumer Discretionary	−0.019	0.661***	−0.099***	0.361***	−0.186***	−0.087***	0.729
	[−0.041;0.003]	[0.605;0.717]	[−0.173;−0.026]	[0.269;0.453]	[−0.265;−0.108]	[−0.156;−0.018]	
Consumer Staples	−0.005	0.473***	−0.246***	0.045	−0.108***	0.002	0.675
	[−0.024;0.015]	[0.431;0.514]	[−0.308;−0.185]	[−0.029;0.118]	[−0.159;−0.058]	[−0.063;0.068]	
Health Care	−0.055***	0.690***	−0.30***	0.373***	−0.050	−0.062	0.687
	[−0.083;−0.028]	[0.631;0.749]	[−0.387;−0.222]	[0.251;0.495]	[−0.105;0.004]	[−0.147;0.024]	
Information Technology	−0.010***	0.659***	−0.150***	0.420***	−0.031	−0.163***	0.699
	[−0.034;0.014]	[0.607;0.710]	[−0.221;−0.078]	[0.327;0.14]	[−0.091;0.028]	[−0.238;−0.089]	
Communication Services	−0.033***	0.614***	−0.037	0.249***	0.127***	−0.019	0.694
	[−0.057;−0.010]	[0.65;0.664]	[−0.114;0.041]	[0.153;0.347]	[−0.187;−0.066]	[−0.094;0.057]	
Period: 2019–2021							
Energy	−0.118***	0.998***	0.518***	0.737***	−0.016	−0.468***	0.827
	[−0.167;−0.069]	[0.927;1.070]	[0.398;0.638]	[0.598;0.877]	[−0.086;0.053]	[−0.627;−0.308]	
Utilities	0.006	0.729***	0.032	0.125*	0.090**	−0.126**	0.740
	[−0.032;0.044]	[0.614;0.843]	[−0.146;0.081]	[−0.009;0.260]	[0.012;0.169]	[−0.230;−0.022]	
Materials	−0.027**	0.904***	0.186***	0.614***	0.085***	−0.122***	0.872
	[−0.053;−0.001]	[0.859;0.948]	[0.118;0.253]	[0.535;0.693]	[0.025;0.145]	[−0.199;−0.045]	
Industrials	−0.018***	0.950***	0.089***	0.716***	−0.036***	−0.033	0.933
	[−0.036;0.000]	[0.916;0.984]	[0.042;0.136]	[0.641;0.791]	[−0.067;−0.006]	[−0.099;0.033]	
Consumer Discretionary	−0.046***	1.027***	0.239***	0.915***	−0.072***	0.162***	0.915
	[−0.069;−0.022]	[0.980;1.075]	[0.169;0.308]	[0.793;1.036]	[−0.117;−0.028]	[0.082;0.242]	
Consumer Staples	−0.021	0.645***	0.088***	0.271***	0.005	0.145***	0.833
	[−0.043;0.000]	[0.595;0.696]	[0.033;0.144]	[0.186;0.356]	[−0.041;0.052]	[0.075;0.216]	
Health Care	−0.073***	0.866***	−0.331***	0.584***	0.047	−0.041	0.815
	[−0.104;−0.042]	[0.788;0.945]	[−0.419;−0.244]	[0.485;0.682]	[−0.021;0.114]	[−0.141;0.057]	
Information Technology	−0.010	0.944***	−0.126***	0.797***	0.037*	−0.062*	0.904
	[−0.032;−0.011]	[0.893;0.996]	[−0.192;−0.059]	[0.705;0.890]	[−0.006;0.080]	[−0.135;0.012]	
Communication Services	−0.048***	0.761***	0.156***	0.520***	−0.010	0.062	0.859
	[−0.072;−0.024]	[0.698;0.824]	[0.090;0.223]	[0.428;0.612]	[−0.054;0.034]	[−0.018;0.141]	
No. of observations per portfolio							
Period: 2016–2021	1,525						
Period: 2016–2018	762						
Period: 2019–2021	763						

P-value: *** < 0.01; ** < 0.05; * < 0.1.

2021; Shimbar, 2021a; Semieniuk et al., 2022; Prosperi and Zanin, 2022).

In pricing the exposure of firms/sectors to climate transition risks, the assumption is that investors are making evaluations with the best information available, namely information from non-financial disclosures, multi-year industrial investment plans, stewardship and engagement activities and from (expected) government policies, to name a few.

The GMB (5) is a spread between the returns of a green and brown portfolio, where brown firms are expected to be more exposed to climate transition risks than green firms, due to their business models. When interpreting the results, the $\widehat{\beta}_i^{GMB}$ follows the behaviour of the brown portfolio if the parameter is of a negative sign and is statistically significant. Otherwise, it follows the behaviour of the green portfolio. When $\widehat{\beta}_i^{GMB}$ is not statistically

Table 3
Estimated parameters of model (1) using an M-estimator. Standard errors are adjusted for autocorrelation and heteroskedasticity (Newey and West, 1987, 1994). The 95% confidence intervals are reported in square brackets. The stock market performance of firms in the portfolios is observed for the entire reference period.

GICS sectors	$\widehat{\alpha}(\times 100)$	$\widehat{\beta}_{MKT}$	$\widehat{\beta}_{HML}$	$\widehat{\beta}_{SMB}$	$\widehat{\beta}_{WML}$	$\widehat{\beta}_{GMB}$
Period: 2016–2021						
Energy	−0.106***	0.894***	0.436***	0.642***	−0.080***	−0.417***
	[−0.138;−0.073]	[0.831;0.959]	[0.340;0.533]	[0.528;0.755]	[−0.138;−0.023]	[−0.510;−0.324]
Utilities	0.019*	0.559***	−0.113***	0.003	−0.004	−0.139***
	[−0.003;0.040]	[0.514;0.605]	[−0.177;−0.049]	[−0.079;0.086]	[−0.045;0.036]	[−0.196;−0.083]
Materials	−0.011***	0.754***	0.098***	0.426***	0.001	−0.246***
	[−0.029;0.008]	[0.711;0.796]	[0.041;0.156]	[0.354;0.499]	[−0.042;0.044]	[−0.306;−0.186]
Industrials	−0.005	0.801***	0.031	0.519***	−0.072***	−0.077***
	[−0.020;0.009]	[0.762;0.840]	[−0.018;0.079]	[0.447;0.590]	[−0.103;−0.041]	[−0.127;−0.026]
Consumer Discretionary	−0.015*	0.819***	0.081***	0.93***	−0.140***	0.024
	[−0.032;0.002]	[0.772;0.865]	[0.023;0.140]	[0.509;0.677]	[−0.176;−0.103]	[−0.032;0.080]
Consumer Staples	−0.003	0.25***	−0.060***	0.151***	−0.069***	0.089***
	[−0.017;0.011]	[0.491;0.559]	[−0.10;−0.015]	[0.09;0.206]	[−0.103;−0.035]	[0.046;0.133]
Health Care	−0.050***	0.738***	−0.341***	0.438***	−0.013	−0.072***
	[−0.070;−0.031]	[0.695;0.781]	[−0.394;−0.287]	[0.362;0.515]	[−0.053;0.026]	[−0.132;−0.012]
Information Technology	0.001	0.780***	−0.163***	0.568***	−0.000	−0.124***
	[−0.015;0.018]	[0.737;0.822]	[−0.210;−0.117]	[0.500;0.635]	[−0.031;0.030]	[−0.174;−0.075]
Communication Services	−0.025***	0.644***	0.01**	0.372***	−0.076***	0.019
	[−0.041;−0.008]	[0.608;0.681]	[0.004;0.097]	[0.304;0.440]	[−0.106;−0.047]	[−0.026;0.065]
Period: 2016–2018						
Energy	−0.082***	0.732***	0.273***	0.466***	−0.164***	−0.458***
	[−0.127;−0.037]	[0.648;0.812]	[0.128;0.417]	[0.281;0.652]	[−0.259;−0.069]	[−0.593;−0.324]
Utilities	0.015***	0.467***	−0.103**	−0.087	−0.084**	−0.113***
	[−0.014;0.044]	[0.410;0.525]	[−0.199;−0.006]	[−0.203;0.028]	[−0.147;−0.022]	[−0.193;−0.033]
Materials	−0.006	0.603***	0.000	0.241***	−0.090***	−0.379***
	[−0.031;0.019]	[0.559;0.648]	[−0.083;0.083]	[0.144;0.338]	[−0.149;−0.032]	[−0.459;−0.300]
Industrials	−0.009	0.625***	−0.061*	0.297***	−0.086***	−0.128***
	[−0.030;0.013]	[0.564;0686]	[−0.126;0.003]	[0.197;0.398]	[−0.138;−0.033]	[−0.194;−0.062]
Consumer Discretionary	−0.010	0.631***	−0.102***	0.326***	−0.149***	−0.089***
	[−0.032;0.012]	[0.77;0.686]	[−0.174;−0.031]	[0.228;0.424]	[−0.208;−0.090]	[−0.15;−0.024]
Consumer Staples	−0.005	0.452***	−0.257***	0.029	−0.097***	0.007
	[−0.013;0.023]	[0.409;0.496]	[−0.318;−0.196]	[−0.052;0.111]	[−0.141;−0.053]	[−0.056;0.0070]
Health Care	−0.040***	0.642***	−0.316***	0.291***	−0.045	−0.076*
	[−0.066;−0.014]	[0.584;0.701]	[−0.399;−0.234]	[0.172;0.410]	[−0.100;0.009]	[−0.155;0.003]
Information Technology	−0.003	0.625***	−0.133***	0.380***	−0.018	−0.165***
	[−0.029;0.023]	[0.567;0.683]	[−0.207;−0.058]	[0.280;0.479]	[−0.075;0.039]	[0.240;−0.080]
Communication Services	−0.020*	0.584***	−0.061	0.222***	−0.111***	−0.035
	[−0.043;0.003]	[0.537;0.631]	[−0.137;0.016]	[0.125;0.319]	[−0.165;−0.057]	[−0.108;0.038]
Period: 2019–2021						
Energy	−0.137***	1.003***	0.526***	0.743***	−0.022	−0.382***
	[−0.183;−0.091]	[0.916;1.091]	[0.400;0.651]	[0.613;0.873]	[−0.091;0.048]	[−0.503;−0.261]
Utilities	0.012	0.66***	−0.083	0.11*	0.052	−0.127***
	[−0.023;0.046]	[0.79;0.733]	[−0.181;0.016]	[−0.005;0.235]	[−0.025;0.129]	[−0.214;−0.040]
Materials	−0.029*	0.893***	0.184***	0.597***	0.062**	−0.113***
	[−0.053;−0.005]	[0.853;0.933]	[0.123;0.245]	[0.522;0.671]	[0.010;0.115]	[−0.176;−0.049]
Industrials	−0.012	0.941***	0.099***	0.689***	−0.031*	−0.016
	[−0.030;−0.006]	[0.897;0.985]	[0.041;0.156]	[0.591;0.786]	[−0.063;0.001]	[−0.078;0.046]
Consumer Discretionary	−0.037***	1.001***	0.223***	0.848***	−0.074***	0.151***
	[−0.061;−0.013]	[0.938;1.065]	[0.149;0.296]	[0.712;0.984]	[−0.117;−0.031]	[0.074;0.228]
Consumer Staples	−0.017	0.601***	0.068***	0.248***	−0.011	0.154***
	[−0.037;0.004]	[0.552;0.651]	[0.015;0.122]	[0.168;0.327]	[−0.057;0.035]	[0.098;0.210]
Health Care	−0.065***	0.823***	−0.343***	0.569***	0.006	−0.033
	[−0.093;−0.036]	[0.760;0.886]	[−0.424;−0.261]	[0.473;0.664]	[−0.053;0.065]	[−0.119;0.054]
Information Technology	−0.003	0.904***	−0.160***	0.739***	0.009	−0.051
	[−0.023;0.018]	[0.851;0.957]	[−0.220;−0.101]	[0.662;0.815]	[−0.032;0.050]	[−0.115;0.013]
Communication Services	−0.033***	0.700***	0.121***	0.490***	−0.037*	0.062**
	[−0.057;−0.000]	[0.647;0.754]	[0.062;0.180]	[0.406;0.574]	[−0.076;0.000]	[0.005;0.119]
No. of observations per portfolio						
Period: 2016–2021	1,525					
Period: 2016–2018	762					
Period: 2019–2021	763					

P-value: *** $<$ 0.01; ** $<$ 0.05; * $<$ 0.1.

significant, this indicates that climate risks are not (yet) reflected in stock portfolio returns.

However, this interpretation does not mean that when the relationship is statistically significant and $\widehat{\beta}_i^{GMB}$ is of a negative (positive) sign, all the constituents in the portfolio follow the behaviour of the brown (green) portfolio. Nor does a not statistically significant $\widehat{\beta}_i^{GMB}$ at the portfolio level mean that none of the portfolio constituents are exposed to climate transition risks in a significant way. Nevertheless, sectoral portfolio analysis is interesting because it offers insights into the exposure of different economic sectors to climate transition risks.

Table 2 reports the estimated parameters for the standard linear model (1) widely applied in the literature on asset pricing. Table 3 reports the results when applying an M-estimator (robust regression).

In considering the entire period of observation (2016–2021), it emerges that the negative sign and the highest magnitudes (in absolute terms) of $\widehat{\beta}_i^{GMB}$ are observable among the most polluting sectors, such as energy and materials. This result is coherent with the expectation that these sectors likely suffer the most if events of climate policy materialise (see, for example, Pham et al., 2019; Antoniuk and Leirvik, 2021; Prosperi and Zanin, 2022).

These sectors are followed by utilities ($\widehat{\beta}_i^{GMB} = -0.149$) and information technology ($\widehat{\beta}_i^{GMB} = -0.122$) . While firms in the utility sector are recognised as being brown (e.g. Bernardini et al., 2021; Battiston et al., 2022), the results regarding information technology may seem surprising. However, these might reflect an evaluation of risks deriving from supply chains (indirect channel) rather than from direct exposure of the firm to climate transition risks. For example, the manufacturing of computer chips, which information technology firms in various fields use extensively, might represent a source of indirect vulnerability to climate risks. This is because their production requires a large amount of energy, water and different gases, and also generates hazardous waste, with an environmental and climate impact that is not negligible (e.g. Williams, 2003; Ruberti, 2023).

The portfolio of consumer staples firms is the only one that shows a statistically significant and positive $\widehat{\beta}_i^{GMB}$. This means that performance correlates to a green rather than a brown portfolio. Consumer staples firms represent a sector that aims to satisfy the necessities of daily life, in contrast to discretionary products. Moreover, the industry tends to be characterised by low cyclicality, contributing to a certain stability in the portfolio. From a climate policy-related perspective, investors do not likely expect regulators to impose fast and stringent environmental requirements on this sector as for energy-intensive industries. During the COVID outbreak, few restrictions on this sector were in place given its importance in satisfying the necessities of daily life. This may have contributed to strengthening such expectations.

The portfolio of industrials shows a negative relationship and a low magnitude of $\widehat{\beta}_i^{GMB}$ (-0.077). However, the low magnitude of the coefficient might reflect an effect of portfolio diversification. The sector, indeed includes firms with very different business models and, plausibly, for some of them, non-negligible exposure to direct and indirect climate transition risks.

The consumer discretionary and communication services sectors do not show a statistically significant $\widehat{\beta}_i^{GMB}$. At the same time, I estimate a weak statistical significance the health care portfolio.

To further explore the relationships over time, I split the analysis into two sub-periods (2016–2018 and 2019–2021). Immediately following the Paris Agreement signed at the end of 2015, the 2016–2018 period is characterised by increasing investor attention to climate risks (Monasterolo and de Angelis, 2020). This attention increased even further in the following years, and especially during the exogenous shock of the COVID-19 pandemic (see, for example, Ramelli and Wagner, 2020).

Some interesting results are observed for the materials and consumer discretionary sectors. For the materials sectoral portfolio, I estimate a decrease in the magnitude (in absolute terms) of $\widehat{\beta}_i^{GMB}$ from -0.379 in the 2016–2018 period to -0.113 in 2019–2021. Instead, estimates for the consumer discretionary portfolio show a change in the sign of the relationship from -0.087 in the 2016–2018 period to 0.162 in 2019–2021. For both portfolios, when comparing the two sub-periods the confidence intervals associated with estimates do not show an overlap. This suggests that differences are statistically significant. Further evidence emerges for the consumer discretionary portfolio when carrying out some sensitivity analyses. Specifically, the sign of the relationship changes from negative (2016–2018 period) to positive (2019–2021) when the size factor (that is, the SMB factor) and value factor (HML factor) are included in the last three-year period of the estimate. If these two factors are excluded, the $\widehat{\beta}_i^{GMB}$ is statistically significant and equals -0.10.

For the industrials sector portfolio, which includes manufacturers and distributors of capital goods, commercial and professional services and transportation services, there is a loss of statistical significance in $\widehat{\beta}_i^{GMB}$ in the last three years of the sample period. Similar to the consumer discretionary portfolio, a loss in statistical significance occurs when the size factor (SMB) is included in the model (see also Guo, 2023).

The exposure of portfolios to climate transition risks is not statistically significant in either sub-period for the health care and communication services portfolios.

Some differences between the two sub-periods also emerge for the other risk factors included in the model (1), namely for the market, size, value and momentum. In particular, over the last three years of observation I estimate an increase in systemic risk across sectors ($\widehat{\beta}_i^{MKT}$), which was influenced by the COVID-19 event (see, for example, Ashraf, 2020; Abuzayed et al., 2021; Ahmad et al., 2021; Padhan and Prabheesh, 2021). The highest statistically significant $\widehat{\alpha}$ (%) is estimated for the energy and health care sectors. The overlap in the associated confidence intervals suggests no statistical difference in estimates between the two sub-periods. Finally, I note that estimates obtained using the OLS and the M-estimator are qualitatively similar.

4.1.2. Estimation results for the additive mixed model

The *a priori* assumption of a linear relationship between risk factors and portfolio excess returns in Eq. (1) might be too stringent and be unable to capture potential non-linearities regarding the exposure of sectoral portfolios to climate transition risks. The non-linearities capture changes in investors' subjective beliefs, which are reflected in the determinants of asset pricing (e.g. Neslihanoglu et al., 2017). To relax the assumption of linearity, I propose rewriting Eq. (1) as a semiparametric model (4). As documented in several papers (Zanin and Marra, 2012b,a), applying a flexible modelling technique through penalised smoothing splines allows for the use of a data-driven approach to determine the typology of the relationship (linear or non-linear). At the same time, the penalty prevents overfitting.

Table 4 reports the in-sample mean absolute error (MAE) calculated for the different estimated models. The most evident reduction in the MAE emerges when moving from the estimation of the classic linear model to a mixed additive model, rather than versus the M-estimator, and especially for the 2019–2021 sample period. This finding is also reflected in the R^2 reported in the last columns of Tables 2 and 5 and suggests an increase in the goodness-of-fit of models when relaxing the linearity assumption in the risk factors-response relationship.

Table 5 reports the estimated degrees of freedom (*edf*) and the approximate significance of the risk factors included in the asset pricing model (4) by sectoral portfolio and sub-period. A linear relationship between risk factors and portfolio return is captured when the *edf* equals one. Fig. 3 shows the estimated smooth effects of the GMB (5) on portfolio excess returns.[16] Table 9 in the Appendix reports the temporal error structure modelled using an AR1 process.

From Table 5, it emerges that the linear relationship between the GMB (5) and portfolio excess returns is, in most cases, confirmed when the model (4) is estimated for 2016–2018 sub-period. Some non-linearities are instead observed in the 2019–2021 period. Increased market volatility characterised the last three years of the sample period, due to the pandemic. Despite relaxing the assumption of linearity by estimating an AMM, I confirm most of the not statistically significant relationships observed in the estimated linear models (Section 4.1.1).

Table 4
Mean absolute error (MAE). Values are calculated on excess returns in percentages. In the round brackets, I report the difference in MAE compared to the linear model (OLS estimator), which is standard practice in the literature estimating asset pricing models.

GICS sectors	Linear model (OLS)	M-estimator	Additive mixed model
Period: 2016–2021			
Energy	0.485	0.484 (−0.001)	0.468 (−0.012)
Utilities	0.351	0.347 (−0.004)	0.330 (−0.021)
Materials	0.302	0.301 (−0.001)	0.291 (−0.011)
Industrials	0.248	0.248 (0.000)	0.239 (−0.009)
Consumer Discretionary	0.281	0.278 (−0.003)	0.266 (−0.015)
Consumer Staples	0.234	0.229 (−0.005)	0.219 (−0.015)
Health Care	0.306	0.303 (−0.003)	0.293 (−0.013)
Information Technology	0.268	0.265 (−0.003)	0.235 (−0.033)
Communication Services	0.262	0.257 (−0.005)	0.247 (−0.015)
Period: 2016–2018			
Energy	0.488	0.488 (0.000)	0.485 (−0.003)
Utilities	0.319	0.317 (−0.002)	0.306 (−0.013)
Materials	0.288	0.288 (0.000)	0.281 (−0.007)
Industrials	0.255	0.254 (−0.001)	0.252 (−0.003)
Consumer Discretionary	0.272	0.271 (−0.001)	0.267 (−0.005)
Consumer Staples	0.221	0.220 (−0.001)	0.216 (−0.005)
Health Care	0.294	0.292 (−0.002)	0.288 (−0.006)
Information Technology	0.274	0.273 (−0.001)	0.265 (−0.009)
Communication Services	0.267	0.266 (−0.001)	0.262 (−0.005)
Period: 2019–2021			
Energy	0.465	0.464 (−0.001)	0.439 (−0.026)
Utilities	0.369	0.364 (−0.005)	0.340 (−0.029)
Materials	0.287	0.286 (−0.001)	0.276 (−0.011)
Industrials	0.206	0.205 (−0.001)	0.194 (−0.012)
Consumer Discretionary	0.251	0.249 (−0.002)	0.230 (−0.021)
Consumer Staples	0.228	0.225 (−0.003)	0.208 (−0.020)
Health Care	0.308	0.306 (−0.002)	0.287 (−0.030)
Information Technology	0.238	0.235 (−0.003)	0.216 (−0.022)
Communication Services	0.247	0.242 (−0.005)	0.222 (−0.025)

Table 5
Estimated degrees of freedom (*edf*) and the approximate significance from the estimation of the model (4). The stock market performance of firms in the portfolios is observed for the entire reference period. The graphical representation of the smooth functions is reported in the supplementary material.

GICS sectors	$\widehat{\alpha}(\times 100)$	$s(MKT)$	$s(HML)$	$s(SMB)$	$s(WML)$	$s(GMB)$	$R^2 adj$
Period: 2016–2021							
Energy	-0.069^{***}	6.615^{***}	2.705^{***}	5.380^{***}	1.000^{**}	4.128^{***}	0.769
Utilities	0.035	6.731^{***}	2.778	3.838	2.976	3.375^{***}	0.723
Materials	0.020^{**}	6.501^{***}	1.000^{***}	3.548^{***}	5.649	3.254^{***}	0.822
Industrials	0.022^{***}	7.462^{***}	1.000	4.973^{***}	4.474^{***}	2.37^{***}	0.872
Consumer Discretionary	0.007	7.022^{***}	3.254^{***}	5.877^{***}	5.460^{***}	3.010^{***}	0.860
Consumer Staples	0.012^{*}	7.357^{***}	2.474^{**}	3.813^{***}	5.194^{***}	1.000^{***}	0.796
Health Care	-0.021^{**}	6.787^{***}	1.000^{***}	2.585^{***}	4.894^{***}	1.267^{**}	0.784
Information Technology	0.034^{***}	6.957^{***}	3.675^{***}	3.648^{***}	4.880	1.000^{***}	0.843
Communication Services	−0.010	6.637^{***}	3.214^{*}	4.145^{***}	1.388^{***}	2.996	0.819
Period: 2016–2018							
Energy	-0.064^{***}	3.529^{***}	1.000^{***}	2.889^{***}	1.000^{***}	1.000^{***}	0.605
Utilities	0.010	4.434^{***}	2.792^{*}	5.557^{*}	1.000^{***}	1.000^{**}	0.599
Materials	0.005	4.537^{***}	1.000	3.180^{***}	3.869^{***}	1.000^{***}	0.734
Industrials	−0.006	4.349^{***}	2.871^{*}	1.000^{***}	1.923^{***}	1.000^{***}	0.748
Consumer Discretionary	−0.013	4.935^{***}	1.000^{***}	2.670^{***}	1.000^{***}	1.627^{**}	0.742
Consumer Staples	−0.003	4.991^{***}	1.000^{***}	3.073^{**}	1.000^{***}	1.000	0.690
Health Care	-0.049^{***}	4.272^{***}	1.000^{***}	1.000^{***}	3.369	1.722	0.692
Information Technology	0.000	4.475^{***}	1.000^{***}	1.000^{***}	5.452	2.080^{***}	0.712
Communication Services	-0.027^{**}	4.534^{***}	1.000	1.000^{***}	3.269^{***}	1.000	0.705
Period: 2019–2021							
Energy	-0.073^{***}	6.748^{***}	2.361^{***}	4.568^{***}	1.000	3.399^{***}	0.850
Utilities	0.061^{***}	6.223^{***}	1.000	3.948^{*}	2.486^{*}	3.717^{**}	0.794
Materials	0.035^{**}	7.028^{***}	2.771^{***}	2.775^{***}	4.243^{***}	2.883^{***}	0.883
Industrials	0.050^{***}	7.687^{***}	1.000^{***}	4.018^{***}	3.841^{***}	3.087	0.941
Consumer Discretionary	0.027^{*}	6.826^{***}	1.529^{***}	4.562^{***}	5.866^{***}	2.98^{***}	0.928
Consumer Staples	0.028^{**}	7.328^{***}	2.094^{*}	4.787^{***}	5.204	1.126^{***}	0.867
Health Care	0.007	6.491^{***}	1.000^{***}	2.218^{***}	5.147^{***}	2.256	0.841
Information Technology	0.067^{***}	7.249^{***}	3.686^{***}	5.063^{***}	4.888^{***}	1.000^{***}	0.920
Communication Services	0.006	7.485^{***}	1.000^{***}	5.297^{***}	1.000^{***}	3.592^{***}	0.889
No. of observations per portfolio							
Period: 2016–2021	1,525						
Period: 2016–2018	762						
Period: 2019–2021	763						

P-value: $^{***} < 0.01$; $^{**} < 0.05$; $^{*} < 0.1$.

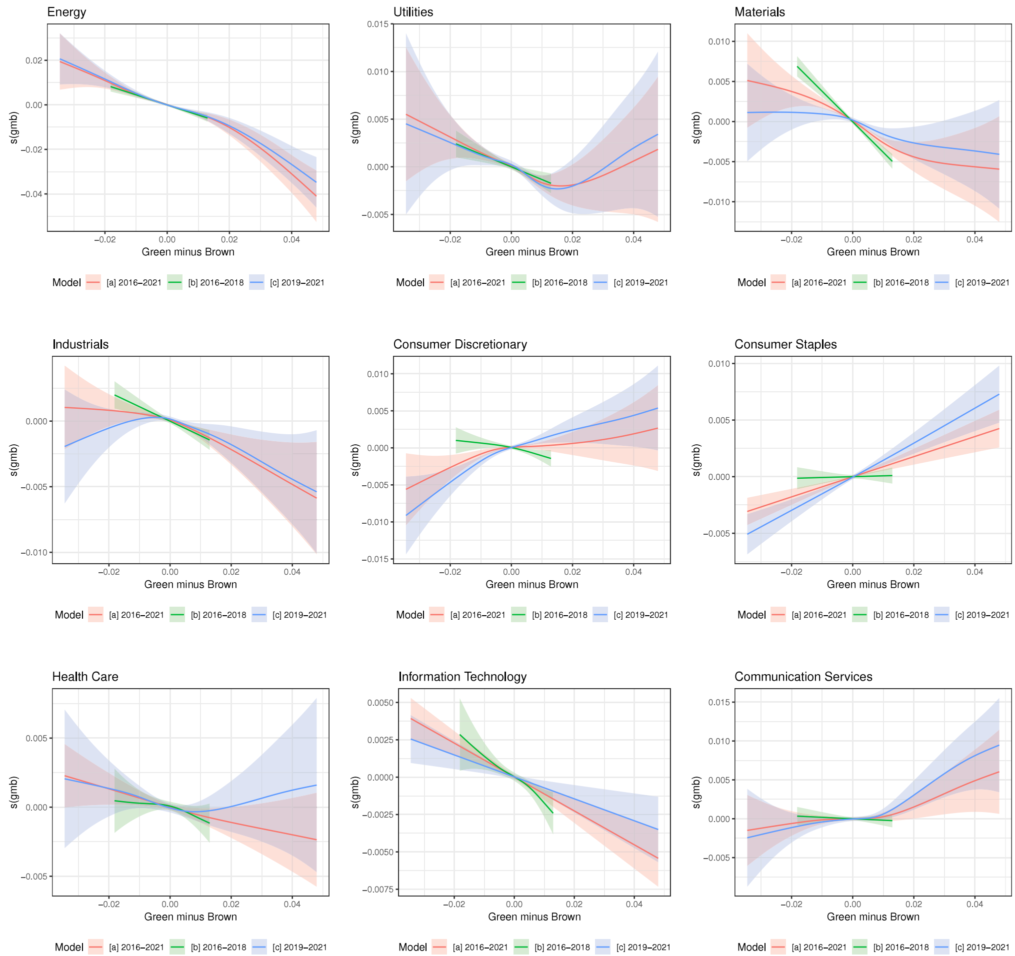

Fig. 3. Estimated smooth effects of the GMB (5) by sectoral portfolio and the associated 95% confidence intervals. The estimated smooth functions are centred around zero due to centring identifiability constraints. The stock market performance of firms in the portfolios is observed for the entire reference period.

Fig. 5 reports the estimated smooth effects of the GMB (5) at the firm level by sectoral portfolio over 2016–2021. The joint graphical representation of the estimated smooth functions for each firm has some limitations in identifying single paths. However, the plots confirm the heterogeneity of the exposure to climate transition risks observed from linear models (positive or negative correlation with GMB (5)).

Compared to linear models, the plots in Fig. 3 offer some additional insights into the patterns of the relationship of interest. An increased uncertainty (larger confidence intervals) around the smooth function estimates is observable for the values of the GMB (5) in the tails of the distribution (the distribution of the GMB (5) is reported in Fig. 7 in the Appendix); values that materialised at the beginning of the COVID-19 outbreak.[17] The largest confidence intervals are accentuated for the utilities, materials, industrials and health care sectors. Some caution is required in interpreting results when estimates return large confidence intervals. This is because the pattern of the smooth function cannot be interpreted as robust and statistically significant for these points. The results from the portfolio of the utility sector are an interesting case study in this regard. From the estimated linear models (Tables 2 and 3), it emerges that this portfolio is in line with a brown portfolio in both sub-periods. This finding is also confirmed in Fig. 3, particularly in the 2016–2018 period. In 2019–2021, the smooth function is always statistically significant. However, the large confidence intervals for values of the GMB in the distribution's tails (see also Fig. 8 in the Appendix) suggest caution in interpreting the inverted U-shaped pattern. Due to their business models, firms in the utility sector are typically recognised as brown; we would therefore expect a relationship similar to that observed for the energy sector. However, Ramelli and Wagner (2020) observed that during the incubation and outbreak period of COVID-19, the utilities performed quite well because firms suffered little in terms of demand (and expected demand) for their products. Thereby, increased market volatility and many effects other than climate transition risks may have contributed to affecting the GMB–outcome relationship during the pandemic. Some similar considerations can also be applied, for instance, to explain the uncertainty and patterns of the estimated smooth effects for the health care portfolio.

The relationship appears more robust for the energy and consumer staples sectors. Specifically, the energy sector shows a non-linear decreasing pattern with an increasingly steep slope for realised returns beyond 2% for the GMB factor; that is, when green firms outperformed brown firms during the pandemic. This pattern cannot be captured from the OLS estimates, with

[16] The plots of the smooth effects of the remaining risk factors included in the models are reported in the supplementary material.

[17] The rigorous restriction policies adopted by governments to mitigate the spread of the virus and the uncertainty regarding the duration of the pandemic fuelled market volatility and losses. Economic operators expected a deep impact of these policies on firm balance sheets (for instance, in terms of business survival, change in consumer behaviour, and so on) and on economic and social systems (Zaremba et al., 2020; Mussida and Zanin, 2023).

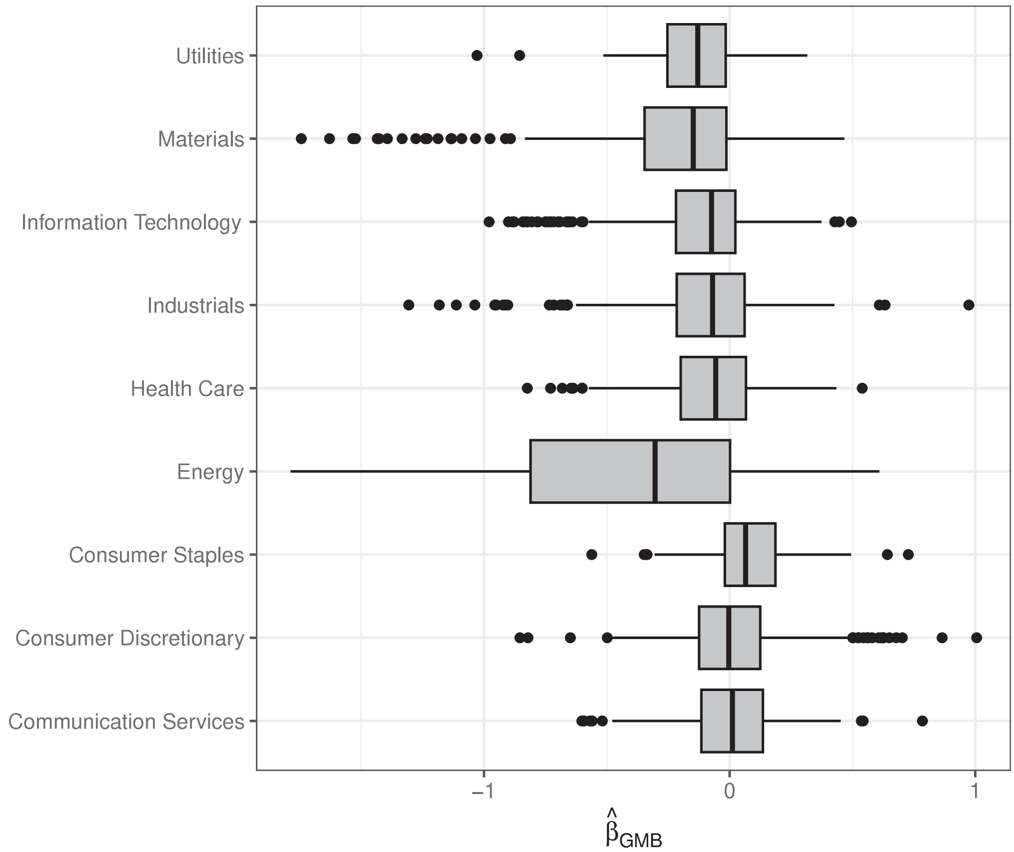

Fig. 4. Boxplot distributions of the estimated $\hat{\beta}_{GMB}$ at the firm level. Estimates are from model (1), applying the M-estimator. Only the statistically significant parameters are shown. The stock market performance of firms is observed for the entire reference period.

the risk of masking an important insight (a priori unknown) for investors. Further interesting evidence emerges for consumer staples. Specifically, the relationship is confirmed to be substantially linear and statistically significant, mainly for the 2019–2021 period. However, when focusing on the 2016–2018 period, the relationship only shows a statistically significant non-linear increasing pattern when the HML factor is excluded from the regression.

In general, the estimates from this flexible modelling approach can help provide more transparent information than a linear model in terms of the relationship between risk factors and the excess returns of a portfolio.

4.1.3. Robustness analyses

Robustness analyses can shed some additional light on the GMB–outcome relationship at the portfolio level. First, I explore whether the estimated patterns are robust to changes in sectoral portfolio composition. To this aim, I construct 100 new portfolios for each sector by randomly selecting half of the equities available from each. Then I estimate the AMM (4) for the whole sample period. Fig. 9 in the Appendix reports the estimated smooth effects of the GMB (5) for 100 portfolios, with the median path marked in red. The statistical significance of the estimates is confirmed, with some cases of a not statistically significant relationship for communication services (about 15% of the new portfolios) and health care (about 8% of the new portfolios). The plots highlight that the median pattern is coherent with the results reported in Fig. 3.

Second, I explore the contribution of the GMB (5) compared to a classic capital asset pricing model. Table 10 in the Appendix reports the R^2 from the estimated AMM (4) for 2016–2021. Augmenting the classic asset pricing model with the GMB (5), the greatest increase in R^2 is observable for the energy and materials portfolios. This confirms this factor's contribution in the sectors most exposed to climate transition risks.

Third, I evaluate whether there is an improvement in the goodness-of-fit of the estimated models when augmenting the AMM (4) of other Fama and French factors such as the investment factor (conservative-minus-aggressive, CMA) and the profitability factor (robust-minus-weak, RMW). From the last two columns of Table 10 in the Appendix, we can see that including the two additional factors does not improve the results discussed in the previous sections.[18] In terms of $\hat{\alpha}$, I found no relevant differences between the various specifications (see Table 11 in the Appendix).

Fourth, I also estimate the models using observations at a monthly frequency, rather than daily. The results are not reported here, but the most relevant evidence is that most non-linearities disappear in favour of a linear relationship.

4.2. Firm-level analysis

The sector-level analysis is interesting to explore how exposure to climate transition risks differs across economic activities. However, the diversification within portfolios may mask some heterogeneity in exposure across firms from the same peer group. I further investigate this point by providing some results regarding estimates at the firm level. First, I carry out estimates using the parametric model (1), and then using the semi-parametric specification (2).

18 In estimating the model with all the factors (last column of Table 10 in the Appendix), I remove the HML factor because of a multicollinearity issue (see also Prosperi and Zanin, 2022).

Table 6
Firm-level analysis applying the M-estimator. GMB^{ns} and GMB^{sign} refer to not statistically significant (ns) and statistically significant (*sign*) at a confidence level of 5%, respectively. The statistics regarding coverage refer to the percentage of constituents in the group with an environmental pillar score (ENV score) available. The statistics regarding means refer to the constituents in the group for which an ENV score is available. The statistics regarding the coverage and mean value of the ENV score refer to the indicated observational period. The stock market performance of firms in the portfolios is observed for the entire reference period.

GICS Sectors	No. of Equities	% $\hat{\beta}_{GMB}^{sign}$	Coverage ENV score (%)		Mean ENV score	
			$\hat{\beta}_{GMB}^{ns}$	$\hat{\beta}_{GMB}^{sign}$	$\hat{\beta}_{GMB}^{ns}$	$\hat{\beta}_{GMB}^{sign}$
Period: 2016–2021						
Energy	144	50.00	19.68	73.61	44	60
Utilities	94	42.55	50.31	87.92	58	71
Materials	264	41.28	26.67	83.03	48	68
Industrials	728	29.94	41.83	65.93	46	54
Consumer Discretionary	398	26.13	42.12	64.70	56	51
Consumer Staples	193	28.49	41.74	79.82	54	72
Health Care	343	17.78	35.40	61.48	41	46
Information Technology	409	23.71	22.86	51.20	42	43
Communication Services	226	26.10	39.88	63.56	45	62
Period: 2016–2018						
Energy	144	43.05	17.48	85.22	39	61
Utilities	94	20.21	60.67	88.60	63	73
Materials	264	40.90	25.00	85.96	49	68
Industrials	728	23.21	42.07	72.12	46	57
Consumer Discretionary	398	25.87	41.65	66.34	52	58
Consumer Staples	193	15.02	50.56	64.20	61	69
Health Care	343	9.91	38.24	56.37	38	66
Information Technology	409	20.29	21.32	62.05	36	50
Communication Services	226	13.71	41.33	75.81	49	58
Period: 2019–2021						
Energy	144	46.52	22.94	73.88	43	61
Utilities	94	29.78	58.08	85.71	62	71
Materials	264	23.86	40.05	81.48	59	67
Industrials	728	19.50	46.08	61.31	49	51
Consumer Discretionary	398	17.83	43.81	67.45	56	51
Consumer Staples	193	27.97	42.46	78.77	56	70
Health Care	343	13.70	37.16	58.16	42	45
Information Technology	409	15.16	26.37	47.58	41	45
Communication Services	226	22.12	43.52	55.00	49	60

Fig. 4 reports the boxplot distributions of the estimated firm-level $\hat{\beta}_{GMB}$ that are statistically significant, obtained by applying the M-estimator for the 2016–2021 period.[19] As a general overview, I confirm that a granular analysis at the firm level helps to explore the heterogeneity of firms in a sectoral portfolio in terms of the sign of the relationship and statistical significance. For example, the analysis at the sectoral level discussed previously showed that the portfolio of the industrials sector has a $\hat{\beta}_{GMB}$ with a negative sign. Detailing the analysis at the firm level, there is evidence that some firms in this sector have a $\hat{\beta}_{GMB}$ with a negative sign, and others with a positive sign of the relationship, by reflecting different investor perceptions of exposure to climate transition risk. Moreover, I note that in several other cases, the $\hat{\beta}_{GMB}$ is not statistically significant (see Table 6). A similar interpretation can be extended to the other sectors explored. These results are coherent with evidence from Prosperi and Zanin (2022).

Table 6 provides additional details regarding a firm's exposure to climate transition risks. These are reported for the whole sample period examined (2016–2021) and by sub-period (2016–2018 and 2019–2021). As a guideline for reading Table 6, I comment on the results from the energy sector. From the estimation of model (1) for 2016–2021, I obtain that $\hat{\beta}_{GMB}$ is statistically significant for 50% of the firms in the portfolio, a percentage that is still limited considering that the sector is characterised by firms particularly exposed to transition risks. Of this 50%, 73.61% have an environmental pillar score (ENV score), with a mean value of 60.[20] For the remaining 50% of firms with a not statistically significant $\hat{\beta}_{GMB}$, only 19.68% have an ENV score, with a mean value of 44. Similar interpretations can be extended to the remaining sectors.

In general, dividing the time series into sub-periods reveals a more or less accentuated reduction in the percentage of statistically significant $\hat{\beta}_{GMB}$ compared to the entire observation period. This evidence is consistent with Pham and Phuoc (2020) and demonstrates that medium-term estimates better fit the market efficiency hypothesis than short-term estimates. Despite this, when comparing the three years of 2019–2021 with 2016–2018, in some sectors I observe an increase in the percentage of firms with a $\hat{\beta}_{GMB}$ that becomes statistically significant, and especially for firms in the consumer staples and communication services sectors. In contrast, I observe a reduction for firms in materials, information technology, discretionary consumer products and industrials. The lower percentage of statistically significant $\hat{\beta}_{GMB}$ compared to the previous three-year period suggests a reduction in firms for which investors are pricing climate transition risks. This last result appears to be quite controversial as environmental issues are increasingly the focus of investor attention. Further investigation is thus required in this regard.

As a common finding between the two sub-periods, I find that firms with a not statistically significant $\hat{\beta}_{GMB}$ have, on average, a lower ENV score than those with a statistically significant $\hat{\beta}_{GMB}$. This suggests that investors tend to incorporate an evaluation of the exposure to climate risks into their decision-making, and especially when it comes to firms in the sector that are demonstrating better management regarding environmental matters (see also Zanin, 2022). Another interesting interpretation of this result is that this evaluation of the exposure to climate transition risks is not confined to firms with an ENV score (at least from the data provider used here). This suggests that other

19 The analysis by sub-period (2016–2018 and 2019–2021) reveals qualitatively similar evidence.

20 The score ranges from 0 to 100, with 0 being the worst in class and 100 the best in class.

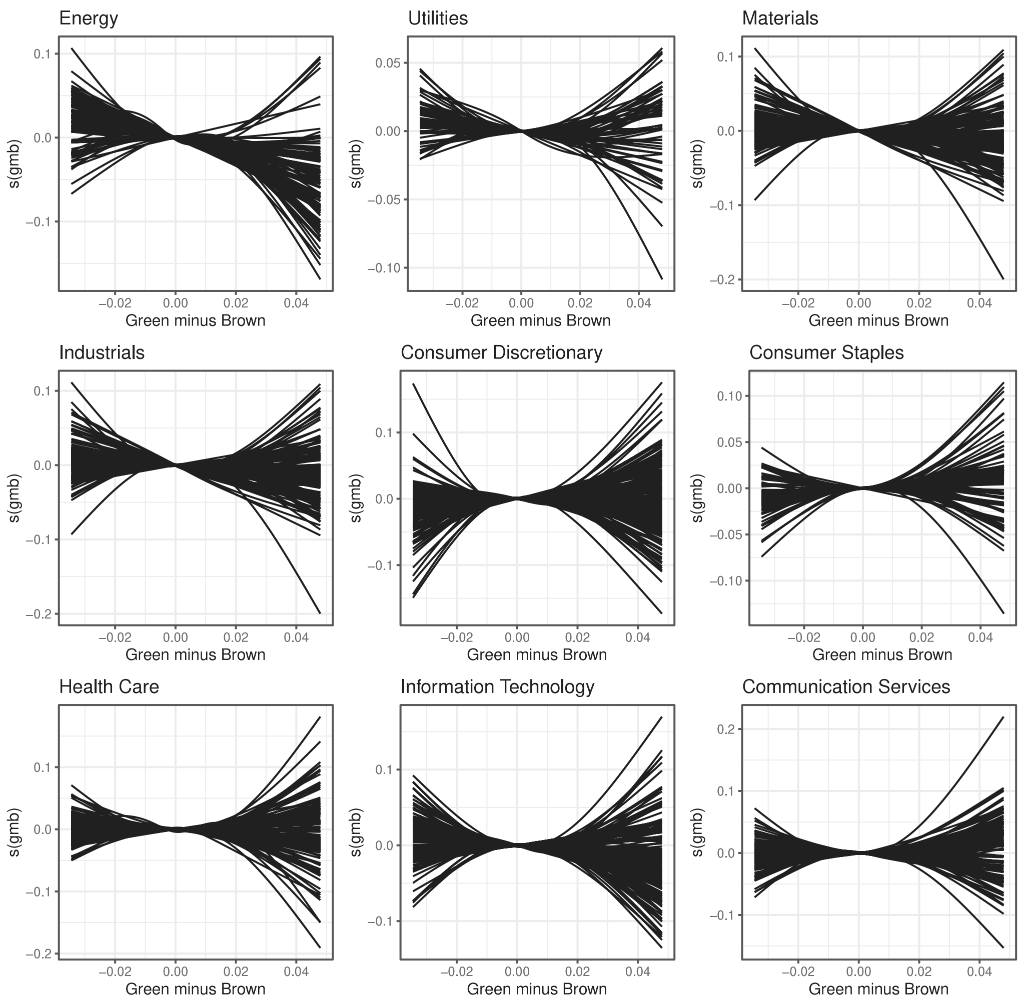

Fig. 5. Estimated smooth effects of the GMB (5) at the firm level for each sectoral portfolio. Only the smooth functions that are statistically significant at a confidence level of 5% are reported. The estimated smooth functions are centred around zero due to centring identifiability constraints. The performance of firms in the portfolios is observed for the entire period (2016–2021).

sources of information likely contribute to the evaluation of a firm's exposure to climate transition risks.

Table 7 reports analogous descriptive statistics to Table 6. Compared to statistics from estimates obtained by applying a linear M-estimator, when relaxing the assumption of linearity, all sectors show an increase in the percentage of firms for which the GMB (5) is statistically significant. This evidence is observed for the entire observational period and for each sub-periods examined. In particular, contrary to what is observed in Table 6, we can note a general increase in the percentage of estimated smooth effects that are statistically significant when moving from 2016–2018 to 2019–2021. This evidence confirms the importance of capturing non-linearities in the risk factors-outcome relationship in order to improve the estimates. Moreover, it suggests that investors are increasing their evaluations of climate transition risks. However, these results do not provide information on demand shifts to green stocks, as in Pastor et al. (2022). Future extensions of this work should investigate this matter.

5. Conclusions

I explore whether climate transition risks are incorporated into equity returns at both the sectoral portfolio level and at the firm level. I capture climate transition risks using the GMB factor constructed following the methodology proposed by Prosperi and Zanin (2022) and incorporating it into a three-factor Fama and French asset pricing model augmented by the momentum factor. In the literature, the relationship between risk factors and equity returns is assumed to be linear. However, this assumption might be too stringent and unable to flexibly capture changes in investors' subjective beliefs reflected in the determinants of asset pricing.

To overcome this potential limitation of linear models, I propose estimating the risk factors-excess returns relationship using a flexible modelling technique: the additive mixed model. This modelling framework allows for relaxing the assumptions of specific functional forms not known a priori to the researcher, allowing the data to determine the typology of the relationship (linear or non-linear) by applying a penalised smoothing spline approach (Zanin and Marra, 2012b,a). I compare these results with those obtained by estimating the traditional linear models.

For the empirical analysis, I construct industrial sectoral equity portfolios considering firms listed on the European market. The portfolios are constructed using firms listed for the entire period of 2016–2021. The observations on stock returns are available at a daily frequency. Moreover, I also split the analysis into sub-periods (2016–2018 and 2019–2021) to capture potential differences in the estimates across time.

The results contribute to improving knowledge from both an empirical and a methodological perspective. From an empirical point of view, the estimates suggest that high energy-intensity sectors are the most exposed to climate transition risks, and

Table 7
Firm-level analysis applying the AMM (4) reveals some additional insights for single constituents in the sectoral portfolio. $s(GMB)^{ns}$ and $s(GMB)^{sign}$ refer to not statistically significant (ns) and statistically significant (*sign*) smooth functions at a confidence level of 5%, respectively. The statistics regarding coverage refer to the percentage of constituents in the group with an environmental pillar score (ENV score) available. The statistics regarding mean refer to the constituents in the group for which an ENV score is available. The statistics regarding the coverage and mean value of the ENV score refer to the relative observational period. The performance of firms in the portfolios is observed for the entire period (2016–2021).

GICS sectors	No. of Equities	% $s(GMB)^{sign.}$	Coverage ENV score (%)		Mean ENV score	
			$s(GMB)^{ns}$	$s(GMB)^{sign}$	$s(GMB)^{ns}$	$s(GMB)^{sign}$
Period: 2016–2021						
Energy	144	65.97	10.20	65.44	33	59
Utilities	94	58.51	39.32	85.45	53	69
Materials	264	51.52	23.44	74.88	45	67
Industrials	728	49.31	36.45	62.00	44	53
Consumer Discretionary	398	47.24	35.40	62.12	59	51
Consumer Staples	193	45.59	35.66	72.83	54	68
Health Care	343	34.99	33.11	52.92	38	47
Information Technology	409	37.65	22.61	41.13	39	45
Communication Services	226	48.67	35.01	57.73	40	58
Period: 2016–2018						
Energy	144	44.44	18.54	81.77	43	60
Utilities	94	26.59	60.39	82.67	62	72
Materials	264	42.80	24.39	84.07	48	67
Industrials	728	25.41	40.36	74.53	45	57
Consumer Discretionary	398	24.87	41.20	68.69	52	59
Consumer Staples	193	21.24	47.59	71.08	62	62
Health Care	343	15.45	36.90	57.23	38	58
Information Technology	409	22.98	20.79	59.04	36	49
Communication Services	226	20.35	40.52	67.75	49	57
Period: 2019–2021						
Energy	144	61.81	18.18	64.23	37	60
Utilities	94	55.32	47.22	81.73	54	71
Materials	264	45.45	32.52	70.83	56	65
Industrials	728	43.81	40.67	59.79	47	51
Consumer Discretionary	398	44.22	38.59	59.92	55	54
Consumer Staples	193	46.63	38.77	68.45	54	67
Health Care	343	30.32	32.85	56.57	36	51
Information Technology	409	33.25	24.24	40.32	37	48
Communication Services	226	44.24	35.80	59.00	41	59

Table 8
Variance inflation factor.

Factors	Period: 2016–2021	Period: 2016–2018	Period: 2019–2021
MKT	1.540	1.428	1.669
HML	1.971	1.550	2.329
SMB	1.331	1.354	1.359
WML	1.646	1.245	1.961
GMB	1.479	1.407	1.558

particularly energy and materials. Interesting evidence emerges from estimates at the firm level. Specifically, I find heterogeneous exposure to climate transition risks within sectors regarding the sign and statistical significance of the relationship. This is probably linked to the firm's business model and investor perceptions of the risks. I also highlight that the percentage of firms with a statistically significant exposure to climate transition risks is relatively low in some portfolios (particularly in health care and information technology). This evidence may raise questions about whether a sharp re-pricing may occur as climate transition risks materialise. Moreover, I find that statistical significance of the exposure to climate transition risk is typically among firms that manage environmental matters better than their sectoral peers.

From a methodological point of view, relaxing the assumption of linearity of the risk factors–outcome relationship contributes to improving the goodness-of-fit of the estimated models. Moreover, it allows a more transparent interpretation of the relationship than linear models. For example, it is possible to note an increase in uncertainty around the estimated smooth effects for values of the GMB (5) in the tails of the distribution. These extreme values were observed during the pandemic outbreak when investors panicked and triggered an increase in market volatility. This uncertainty around estimates likely reflects other effects than just climate transition risks. Therefore, some caution is required in interpreting smooth function patterns at the points where confidence intervals enlarge the most, suggesting a less robust estimated relationship. This evidence is accentuated mainly in the utilities, materials, industrials and health care sectors,

Table 9
Estimated AR1 parameters by sectoral portfolio.

GICS sectors	Period: 2016–2021	Period: 2016–2018	Period: 2019–2021
Energy	0.032	−0.007	0.093
Utilities	−0.019	0.010	−0.028
Materials	−0.134	−0.112	−0.109
Industrials	−0.321	−0.308	−0.271
Consumer Discretionary	−0.236	−0.283	−0.145
Consumer Staples	−0.135	−0.189	−0.063
Health Care	−0.003	−0.011	0.021
Information Technology	−0.198	−0.182	−0.139
Communication Services	−0.131	−0.162	−0.084

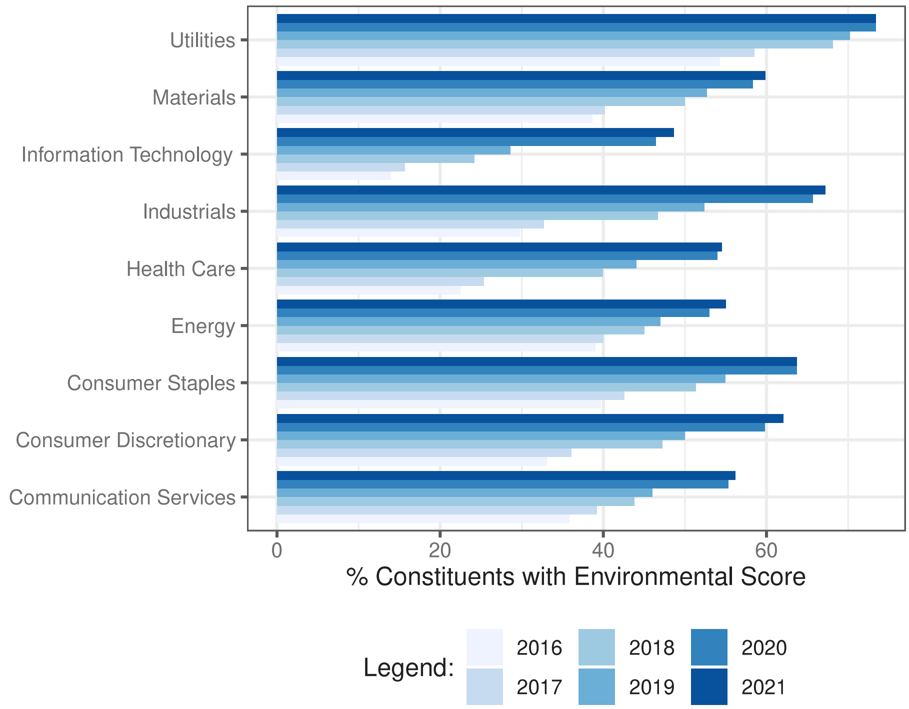

Fig. 6. Percentage of constituents with an environmental pillar score in each sectoral portfolio (on a yearly basis).

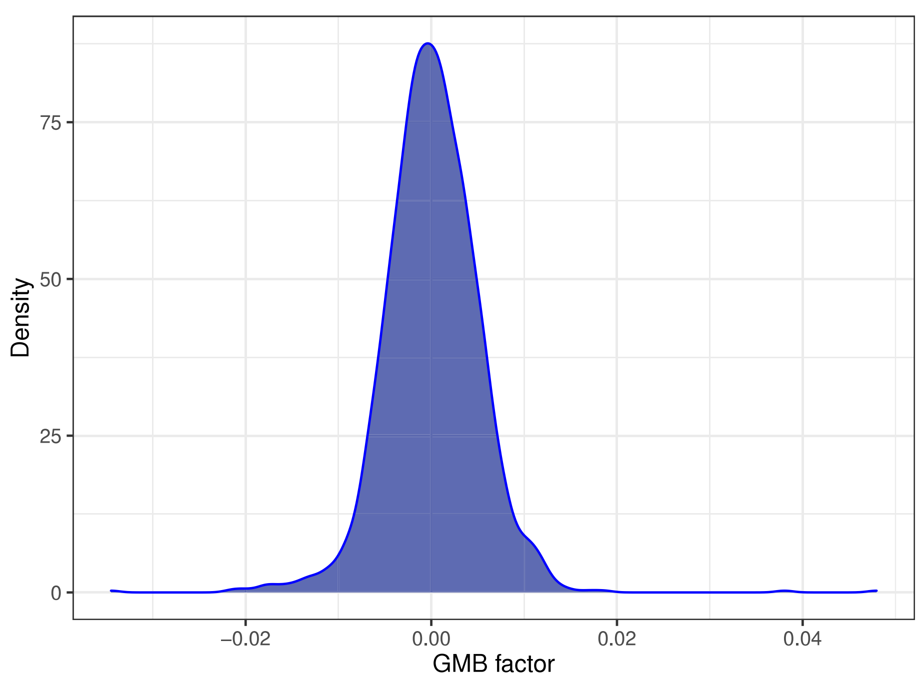

Fig. 7. Density distribution of the GMB (5).

whereas the relationship appears more robust for the energy and consumer staples.

Future research might consider extending the application of model (4) to other geographical areas. Moreover, further extensions of this paper may address (a) whether firm-specific characteristics can explain why for some firms the exposure to climate transition risks is statistically significant while for others it is not, and (b) the role of informative channels other than non-financial disclosure reflected in ESG metrics (e.g. stewardship and engagement activities).

CRediT authorship contribution statement

Luca Zanin: Conceptualization, Methodology, Formal analysis, Writing – review & editing.

Declaration of competing interest

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

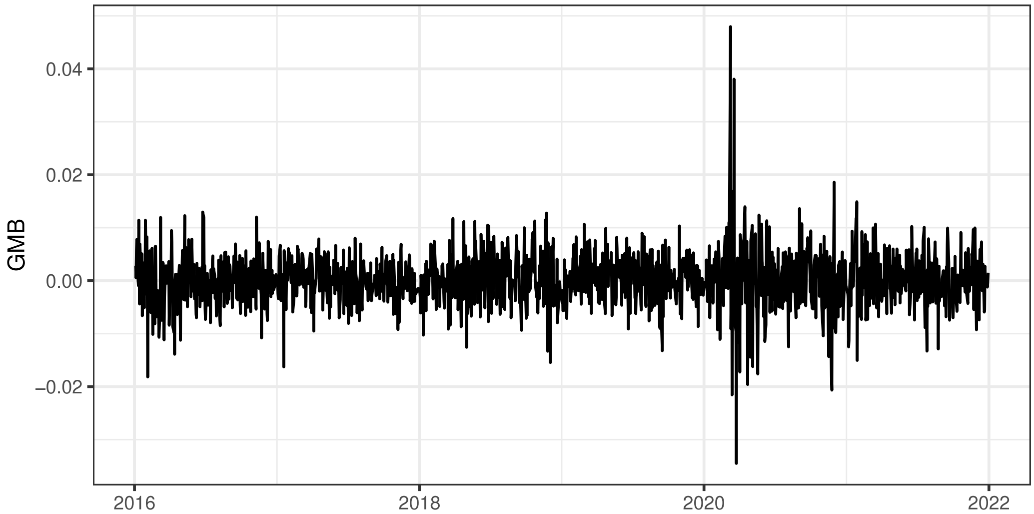

Fig. 8. Time series of the GMB (5). Values are not in percentages.

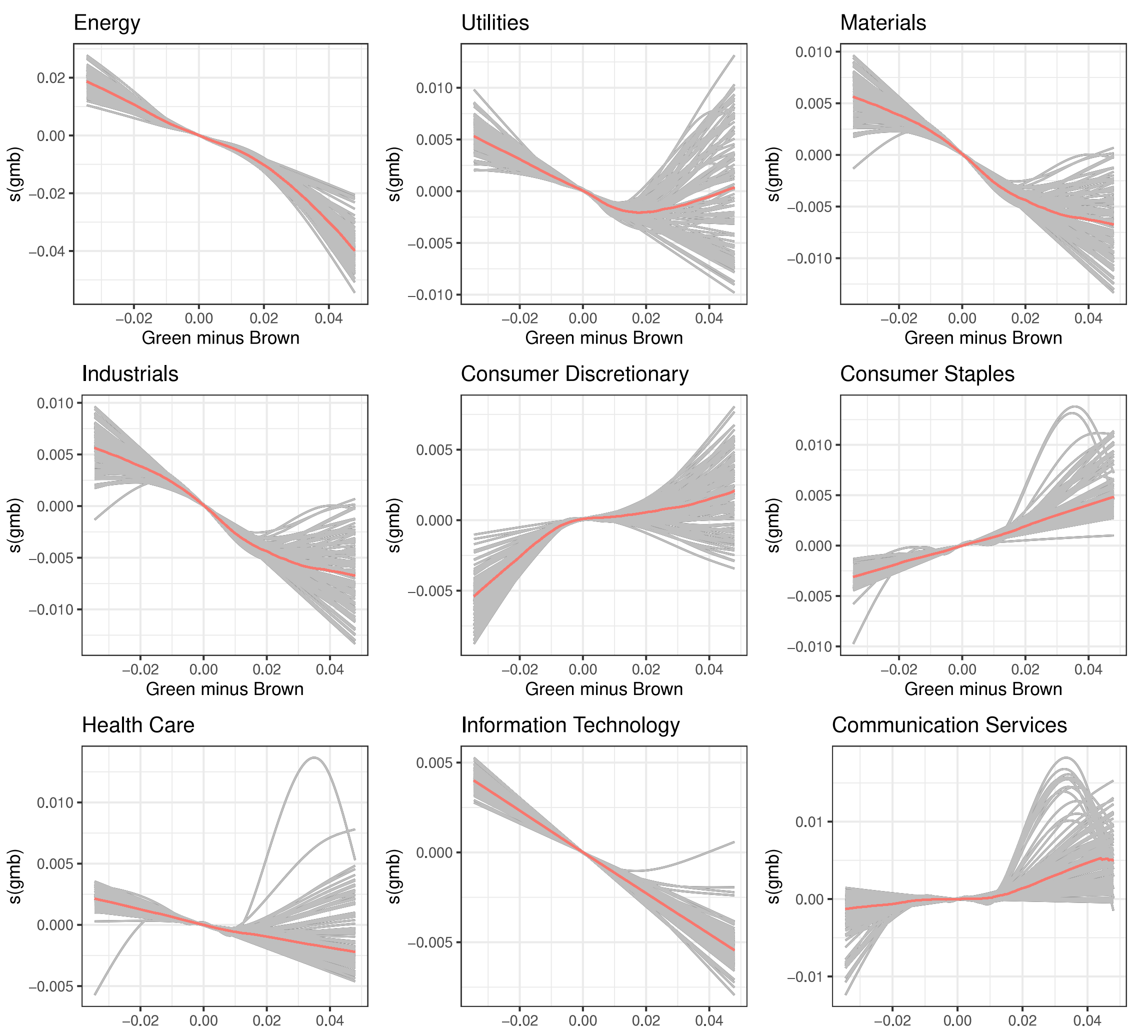

Fig. 9. Estimated smooth effects of the GMB (5) for 100 portfolios constructed randomly by selecting half of the equities available for each sectoral portfolio. The red line represents the median of the estimated smooth functions. The estimated smooth functions are centred around zero due to centring identifiability constraints. The stock market performance of firms in the portfolios is observed for the entire reference period.

Table 10
The R^2 from the estimated AMM for 2016–2021.

GICS sectors	MKT-Rf	MKT-Rf + GMB	MKT-Rf + GMB + SMB + HML + WML	MKT-Rf + GMB + SMB + WML + CMA + RMW
Energy	0.633	0.707	0.769	0.773
Utilities	0.708	0.710	0.723	0.723
Materials	0.763	0.792	0.822	0.821
Industrials	0.821	0.828	0.872	0.873
Consumer Discretionary	0.784	0.788	0.860	0.861
Consumer Staples	0.777	0.781	0.796	0.801
Health Care	0.689	0.691	0.784	0.769
Information Technology	0.767	0.769	0.843	0.844
Communication Services	0.786	0.788	0.819	0.818

Table 11
The $\hat{\alpha}(\times 100)$ from the estimated AMM for 2016–2021.

GICS sectors	MKT-Rf	MKT-Rf + GMB	MKT-Rf + GMB + SMB + HML + WML	MKT-Rf + GMB + SMB + WML + CMA + RMW
Energy	-0.068^{***}	-0.068^{***}	-0.068^{***}	-0.068^{***}
Utilities	0.035^{***}	0.035^{***}	0.035^{***}	0.035^{***}
Materials	0.020^{*}	0.020^{*}	0.020^{*}	0.020^{*}
Industrials	0.022^{*}	0.022^{*}	0.022^{***}	0.022^{***}
Consumer Discretionary	0.007	0.007	0.007	0.007
Consumer Staples	0.012^{*}	0.012^{*}	0.012^{*}	0.012^{*}
Health Care	−0.020	−0.020	-0.021^{*}	-0.021^{*}
Information Technology	0.033^{***}	0.033^{***}	0.033^{***}	0.033^{***}
Communication Services	−0.010	−0.010	−0.010	−0.010

Acknowledgements

I would like to thank the Editor and an anonymous reviewer for their constructive suggestions. The opinions expressed herein are those of the author and do not necessarily reflect those of the institution of affiliation.

Appendix A

See Figs. 6–9, Tables 8–11.

Appendix B. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jbef.2023.100824.

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