Are ESG factors truly unique?☆

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ABSTRACT

The growing popularity of ESG investing raises questions about whether ESG and carbon factors represent unique sources of systematic risk or are absorbed by traditional equity factors. We find that the systematic components of recently proposed carbon and ESG risk factors are linear combinations of well-known risk factors. The ESG factor has a positive exposure to large firms, high beta firms and to the safety factor (a subcomponent of the quality factor). The carbon factor has positive exposure to the market and safety factors and negative loadings on the size and profitability factors. Furthermore, investors who follow well-known ESG indexes are exposed to market and size factor risks, and not always to the ESG and carbon factors. Such indexes are nevertheless closely related to the "long leg" of the ESG factor. Overall, the evidence suggests that the ESG and carbon factors are subordinated to other factors, highlighting the importance of leveraging established risk factors to account for ESG and carbon risks.

1. Introduction

The surge in demand for Environmental, Social and Governance (ESG) investment has led to investors and portfolio managers tilting their holdings towards ESG-aligned assets, reflecting a shift in investment practices that prioritize ESG criteria, including carbon metrics. This evolving approach is increasingly evident in academic literature, where researchers explore how the growing preference for green assets influences financial market equilibria (Pástor et al., 2021; Pedersen et al., 2021; Zerbib, 2022). The work of Pedersen et al. (2021) introduces the concept of the ESG-efficient frontier, demonstrating the optimal Sharpe ratio achievable at various ESG levels. Similarly, Pástor et al. (2021) present a model suggesting that, in equilibrium, green assets yield lower expected returns, attributed to both the desirability of holding such assets and their ability to mitigate climate risk. Additionally, Zerbib (2022) develops an asset pricing model that accounts for market segmentation and investor heterogeneity, revealing two distinct risk premiums: one related to underfollowed stocks and another, a taste premium, elucidating the link between ESG considerations and financial performance.

This study contributes to the burgeoning interest in ESG and green investments. It differentiates itself by focusing on the relationship between new and established risk factors within the U.S. asset pricing framework and addressing the question of whether ESG and carbon risk factors represent unique sources of systematic risk or are simply absorbed by traditional, well-established risk factors. We specifically examine whether incorporating ESG and green investment factors into asset pricing models composed of traditional

financial factors enhances their explanatory power. Our findings indicate that ESG and carbon-related factors can be effectively explained by existing, well-established risk factors, thereby challenging the notion that these new factors provide additional explanatory power. This suggests that the established risk factors already account for the carbon and ESG risk exposures. More precisely, the systematic components of carbon and ESG risks can be represented as linear combinations of established risk factors. Specifically, both carbon and ESG risk factors exhibit strong negative associations with the size factor and strong positive associations with the safety component of the quality factor. This suggests that low carbon and low ESG risk companies tend to be larger and safer. Furthermore, there is a strong positive association between the carbon factor and the market factor and a negative association of the former with the profitability factor. Thus, companies with low profitability or high market beta tend to have a better carbon footprint and lower carbon emissions. Finally, the ESG factor is negatively associated with the "Betting Against Beta" factor, implying that investing in companies with high ESG scores is an implicit bet on high market beta companies.

We proceed to analyze the factor exposure of the family of MSCI ESG indexes, since ESG equity indexes are a common means for investors to gain exposure to the ESG factor. The results show that ESG indexes have a positive exposure to the market, with a beta around one, meaning that investors have similar exposure to market risk as the market portfolio, and a negative exposure to the size factor, thus having exposure to large firms' risk. Furthermore, our analysis investigates the exposure of ESG indexes to the long legs of carbon and ESG factors, which involve investing in stocks of companies that score well on carbon emissions and ESG criteria, respectively. As ESG indexes are designed to capture the performance of these ESG strategies, the ESG indexes align with the long leg of the ESG factor. More precisely, they aim to reflect the returns from investing in firms with, for instance, high ESG ratings. Empirical tests reveal a strong relationship between MSCI ESG indexes and the long leg of the ESG factor, a connection further validated through robustness analyses with ESG stock indexes from other providers.

Our results align with the empirical findings of Naffa and Fain (2022), who use stock data to build ESG-focused portfolios categorized as Leaders, Followers, Loungers, Laggards, and Not Rated. In their study, they find no statistically significant abnormal returns when these portfolios were assessed against the Fama and French five-factor model. While their research centers on analyzing the alphas generated by these portfolios, our paper provides evidence that ESG and carbon factors discussed in the literature can be adequately explained by common equity factors. Furthermore, we examine the relationships between carbon and ESG factors and specific common equity factors, thus providing new insights into the dynamics between sustainability-related risks and conventional sources of risks.[1]

Moreover, our study also connects with research examining the factor exposure of "green" and "brown" investment strategies, such as the work by Ardia et al. (2023). They observe that green stocks tend to have less diversity in their factor exposures compared to brown stocks across most traditional equity factors. However, they also note an increase in the diversity of factor exposure for both green and brown stocks over time, indicating evolving market dynamics.

Contrary to our results, the works of Hübel and Scholz (2020), Díaz et al. (2021) and Maiti (2021) suggest that ESG factors significantly improve the predictive capability of standard asset pricing models. However, we acknowledge that the divergence in findings may be attributed to variations in data periods and frequencies used in the analyses. For example, Hübel and Scholz (2020) analyze data from 2003 to 2016, while Díaz et al. (2021) focus on a much shorter period from January to April 2020, and Maiti (2021) examines the 2010–2018 period. Additionally, differences in data frequency are notable, particularly in Díaz et al. (2021), which uses daily data. Furthermore, the studies differ in their focus, with Díaz et al. (2021) specifically analyzing the returns of industry portfolios.

Our conclusions are relevant for investors, asset managers and regulators to understand the significance of the ESG factor in driving returns and to establish the associated risk exposures. As many equity risk factors have been identified,[2] understanding whether ESG risks drive returns is of practical importance. Our findings reveal that ESG risks can largely be accounted for with existing risk factors. This has significant implications for portfolio construction, risk management and the design of ESG-focused financial strategies.

2. Literature review

Recent studies focus on the idea that investor preferences for sustainability or ESG factors influence asset pricing, exploring how these preferences impact financial markets and asset valuation (Pástor et al., 2021; Pedersen et al., 2021; Zerbib, 2022). They incorporate ESG factors or carbon risk measures into their asset pricing models, extending traditional frameworks such as the CAPM or multi-factor models, by adding new variables related to environmental and social metrics. This integration aims to better capture variations in stock returns driven by sustainability considerations.

Despite the consensus that brown firms should provide a risk premium as compensation for higher risk relative to green firms, the anticipated risk premium associated with brown assets has been challenged by empirical findings, with various studies indicating that green assets have yielded higher returns than expected (e.g., Karolyi et al., 2023; Ashwin Kumar et al., 2016; Lioui & Tarelli, 2022; Pástor et al., 2021, 2022). This phenomenon of green assets outperforming is attributed by Pástor et al. (2021) to changes in consumer preferences for green products and a parallel shift in investor preferences towards green investments. Karolyi et al. (2023) explore this topic by analyzing the market-based equity "greenium" across a broad dataset covering 21,902 firms from 96 countries. Their findings reveal that globally, green stocks have consistently outperformed their brown counterparts, with the most significant "greenium" effects observed in North America and predominantly before 2016, which is consistent with the results of Ashwin Kumar et al. (2016)

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[1] In addition, our analysis spans from 2003 to 2021, thus covering a significantly longer horizon than the Naffa and Fain (2022) study, including the start of the recent COVID-19 pandemic. Naffa and Fain (2022) limit their analysis to the 2015–2019 period to mitigate data reliability issues.

[2] See Harvey et al. (2016) for a survey of literature.

for the 2014–2015 period. Intriguingly, they also conclude that this outperformance of green stocks is largely unexplained by the traditional return factors recognized in the asset pricing literature, suggesting the presence of unique drivers behind the green premium.

In contrast with the findings on green assets' outperformance, research by Bolton and Kacperczyk (2021) demonstrates a connection between firms' carbon intensity and higher financial returns, suggesting a "carbon premium" that cannot be adequately accounted for by traditional equity pricing models. Similarly, Zhang (2022) investigates the market premium associated with carbon-transition risk across 89 countries from 2010 to 2021, discovering that companies with carbon-intensive operations tend to achieve significantly higher future returns. Zerbib (2022) identifies a distinct premium on stocks that are least favored by green investment funds. Additionally, the study by Görgen et al. (2020) introduces a "brown minus green" factor, acknowledging that while carbon risk may influence systematic return variations, there appears to be no direct evidence supporting a carbon risk premium.

The overall evidence is not conclusive, raising the question of the validity of the ESG (green) factor. Our paper draws on the literature that analyzes the usefulness and relevance of factors in pricing assets. Despite the extensive array of identified factors—often referred to as the "factor zoo"—scholarly consensus suggests that only a select few exhibit significant relevance (e.g., Chen et al., 2023; Feng et al., 2020; Hwang & Rubesam, 2019; Harvey & Liu, 2021; Harvey et al., 2016). Within this context, our study examines whether incorporating ESG and green investment factors into asset pricing models, alongside traditional financial factors, enhances their explanatory power.

3. Data

3.1. Common risk factors

We use well-established US equity factors in the literature and industry at monthly frequency. We use Fama and French's five factors, namely, market (*MKT*), size (*SMB*), value (*HML*), profitability (*RMW*) and investment (CMA), which are described in detail in Fama and French (2015), and the Carhart (1997) momentum factor (*MOM*). The Betting Against Beta factor (*BAB*) is based on buying leveraged low-beta portfolios and short-selling high-beta portfolios as a market-neutral investment strategy (Frazzini & Pedersen, 2014). The quality factor introduced by Novy-Marx (2013) aggregates three different components. We choose to focus on two of its components, namely, growth (*QMJ_GROWTH*) and safety (*QMJ_SAFETY*) (Asness et al., 2019). The profitability component is excluded due to its similarity with the Fama and French (2015) profitability factor. The factors are based on the high–minus–low portfolio approach, which uses the returns of hedged zero-cost portfolios, following the examples of the Fama and French factors (e.g., Fama & French, 2015).

3.2. The carbon and ESG factors

In this subsection, we explain the different ESG and Carbon factors we use and their sources. First, from Pedersen et al. (2021), we use the carbon (*CARBON*) and ESG (*ESG*) factors. The authors construct the factors from one-way sort quintile portfolios by taking the difference between the returns of the top and bottom equal-weighted (value-weighted) portfolios. Pedersen et al. (2021) use MSCI ESG scores to proxy for the ESG factor.[3] These scores try to capture a company's resilience to long-term material ESG risks. The carbon factor is sorted on carbon intensity, which is measured as carbon emissions as a fraction of dollar sales. Carbon intensity is negated (a minus sign is added in front), thus ensuring that the top-minus-bottom portfolio is long on the greenest companies and short on the brownest ones. Pedersen et al. (2021) obtain carbon emissions (scope 1 and 2) from S&P's Trucost.

We use the long-minus-short Pollutive-Minus-Clean (*PMC*) portfolios of Huij et al. (2021) that the authors use as proxies for carbon risk. The authors obtain the carbon emissions of companies by adding scope 1 and scope 2 greenhouse gas emissions from Trucost, as in Pedersen et al. (2021), and compute their carbon emission intensities by dividing the total emissions of each firm by its revenues. Firms are sorted based on carbon emissions and size to form value-weighted, size-adjusted long and short portfolios. The long portfolio consists of high-emissions companies, while the short portfolio contains low-emissions firms. The *PMC* factor return is the difference between the returns of these two portfolios.

Bauer et al. (2022) use a different source of carbon emissions data to construct their carbon factors. More precisely, they obtain carbon emissions from Refinitiv's Asset4/ESG database. Another notable difference is the inclusion of companies from all G7 countries (Canada, France, Germany, Italy, Japan, United Kingdom and United States). Similarly to Huij et al. (2021), Bauer et al. (2022) use two measures of the pollution of a firm—the sum of scope 1 and 2 emissions, and this sum divided by firm revenue, known as emission intensity. The latter helps to control for firm size. The authors then use each measure in a one-way sort to construct factor-mimicking Brown-Minus-Green (*BMG*) portfolios.[4] We denote the long-minus-short portfolio based on total emissions as *BMG* and the one based on carbon intensity as *BMG_IN*, and only utilize their value-weighted versions for consistency with other factors and conciseness.

Lioui and Tarelli (2022) construct ESG factors based on ESG scores obtained from the Asset4 database. The authors utilize two

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[3] MSCI uses a proprietary rules-based methodology to identify industry leaders and laggards according to their exposure to ESG risks, and how well they manage those risks relative to peers. Details on the methodology can be found on https://www.msci.com/our-solutions/indexes/esg-indexes.

[4] Here we refer to the second and third portfolio construction methods of Bauer et al. (2022). The authors refer to the resulting portfolios as "simple spreads".

different approaches for constructing their ESG factors—the time-series and cross-sectional approaches. The former involves sorting firms and placing them into responsible and irresponsible "buckets" (portfolios) based on their ESG ratings. Value-weighted returns are then calculated for these portfolios, and their return "spread" (responsible portfolio return–irresponsible portfolio return) is the proxy for the ESG factor return under this approach. We employ the output of the time-series approach for consistency with the other factors in our study and denote it as *ESG_LT*. Table 1 provides a description of the common risk factors, and carbon and ESG factors used as well as their sources.

3.3. ESG indexes

Our dataset also includes US ESG indexes for the purpose of establishing their factor exposures. The MSCI ESG Universal (*ESG_UNIVERSAL*) is the most general index that excludes companies found to be in violation of international norms (e.g., companies facing very severe controversies related to human rights, labor rights or the environment) and companies involved in controversial weapons (e.g. landmines, cluster munitions, depleted uranium, and biological and chemical weapons). Companies are either over-weighted or underweighted based on an ESG metric. The MSCI ESG Leader (*ESG_LEADERS*) targets companies that have the highest environmental, social and governance (ESG) ratings in each sector of the parent index and uses a best-in-class approach. It also ex-cludes companies involved in severe controversies. The MSCI USA ESG FOCUS and SELECT indexes target companies with positive environmental, social and governance characteristics while closely representing the risk and return profile of the parent index.[5] Both use optimization methods that aim to maximize their exposure to ESG, subject to a target tracking error and other constraints. The indexes are sector diversified and are designed to overweight companies with high MSCI ESG Ratings and underweight companies with low ratings. Both indexes also apply exclusion criteria.

3.4. Data sources and scope

The main data sources are the AQR's online data library[6] and the Kenneth French online data library.[7] In addition, the Bryan Kelly data library's Global Factor Data is accessed to obtain the quality factor components.[8] The *PMC*, *BMG* and *BMG_IN*, and *ESG_LT* factors are obtained from the respective authors. Finally, the ESG indexes are obtained from Morningstar Direct.

The final sample for the main analysis spans from June 2009 to March 2019, containing a total of 118 months, to ensure the availability of all factors.[9] For the regression analysis of the Pedersen ESG factor, the sample period is extended to start in February 2007, resulting in a total of 146 months. Additionally, the sample period is further extended to January 2003 for the analysis of the *ESG_LT* factor. For the Pedersen *CARBON* and *ESG* factors, both value and equally-weighted versions are presented.

3.5. Summary statistics

Table 2, Panel A, shows the summary statistics of the factors described in Table 1 from June 2009 (January 2010 in the case of BMG and BMG_IN due to limited data availability) to March 2019. The equal-weighted and value-weighted versions of the *CARBON* and *ESG* factors are both used (*CARBON_equal*, *CARBON_value*, *ESG_equal* and *ESG_value*, respectively). Inspecting the mean and median of monthly returns, the *HML*, *PMC*, *BMG* and *ESG_LT* factors have the lowest returns, while the *MKT*, *BAB* and *CARBON* factors have the highest returns. Regarding risk, the *ESG* (both value-weighted and equal-weighted), *QMJ_GROWTH, CMA* and *RMW* factors have the lowest volatility (SD), while the *MKT*, *MOM* and the carbon factors have the highest. The factors *MOM*, *MKT* and *BMG_IN* have negative skewness, while *CMA*, *BAB*, *QMJ_SAFETY*, *HML*, *BMG* and the *ESG* factors have positive skewness. The BAB, QMJ_GROWTH, HML, carbon factors, and ESG_LT exhibit the highest kurtosis. Panel B presents summary statistics of the MSCI ESG indexes. The indexes and the market factor in Panel A have similar returns.

Table 3 presents the correlations among factors. It reveals a strong correlation among ESG factors: 0.67 between *ESG_Equal* and *ESG_Value*, with *ESG_LT* also showing strong correlations with these metrics. Negative correlations among the carbon factors emerge as they are constructed in different ways. *CARBON_Value* and *CARBON_EQUAL* are long on the "clean" companies and short the polluters, while *PMC*, *BMG* and *BMG_IN* are the inverse. Among the carbon-related metrics, *BMG* and *PMC* have a significant correlation of 0.64, and an even stronger correlation of 0.69 exists between *BMG* and *BMG_IN*.

Correlations are moderate between the carbon and ESG factors. *CARBON_Equal* moderately correlates with *ESG_Equal*, and *BMG* shows a similar moderate correlation with *ESG_LT*. However, the long legs of these factors, *CARBON_Value (Long Leg)* and *ESG_Value (Long Leg)*, exhibit a high correlation of 0.96.

Regarding common financial factors, the ESG metrics negatively correlate with *MKT*, *SMB*, and *HML* but positively correlate with *RMW* and *QMJ*, the profitability and quality factors, respectively. Similarly, the carbon metrics positively correlate with *RMW*, *BAB* and *QMJ_SAFETY*, representing the profitability, Betting Against Beta and quality factors, respectively, but negatively correlate with

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[5] We also utilize the iShares MSCI USA ESG Select ETF to determine its factor exposures. This ETF tracks the MSCI USA ESG Select Index and is directly investible, unlike the index itself. Thus, this ETF is of practical importance to investors who wish to obtain exposure to the index.
[6] https://www.aqr.com/Insights/Datasets.
[7] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[8] https://jkpfactors.com/.
[9] We extend the sample for a subset of the analysis to December 2021 as a robustness check in Section 4.3.

Table 1

Factors Descriptions.

Variable Name	Description	Source
MKT	Market factor	Fama and French (2015)
SMB	Size factor	Idem
HML	Value factor	Idem
RMW	Robust Minus Weak is an operating profitability factor	Idem
CMA	Conservative Minus Aggressive (corporate investments factor)	Idem
BAB	Betting Against Beta factor	Frazzini and Pedersen (2014)
MOM	Momentum factor	Carhart (1997)
QMJ_GROWTH	Subcomponent Management of the Quality factor	https://jkpfactors.com/
QMJ_SAFETY	Subcomponent Safety of the Quality factor	Idem
CARBON	Carbon factor (includes equal-weighted and value-weighted versions)	Pedersen et al. (2021)
PMC	Pollutive-Minus-Clean factor (value-weighted)	Huij et al. (2021)
BMG	Brown-Minus-Green value-weighted spread (constructed using level of carbon dioxide emissions)	Bauer et al. (2022)
BMG_IN	Brown-Minus-Green value-weighted spread (constructed using intensity of carbon dioxide emissions)	Idem
ESG	ESG factor (includes equal-weighted and value-weighted versions)	Pedersen et al. (2021)
ESG_LT	ESG factor (time-series and value-weighted version)	Lioui and Tarelli (2022)

Table 2

Factors Descriptive Statistics.

Variable	Mean	Median	SD	Max	Min	Skew	Kurt
Panel A: Factors							
MKT	0.0118	0.0133	0.0373	0.1135	−0.0955	−0.34	3.52
SMB	0.0007	0.0029	0.0245	0.0703	−0.0492	0.16	2.73
HML	−0.0014	−0.0032	0.0234	0.0821	−0.0470	0.79	4.14
RMW	0.0012	0.0019	0.0157	0.0417	−0.0388	−0.03	2.86
CMA	0.0004	0.0001	0.0146	0.0370	−0.0323	0.31	2.73
BAB	0.0080	0.0076	0.0193	0.0910	−0.0599	0.33	6.03
MOM	0.0013	0.0026	0.0303	0.0649	−0.0907	−0.65	3.59
QMJ_GROWTH	0.0005	0.0013	0.0131	0.0443	−0.0354	−0.06	4.15
QMJ_SAFETY	0.0005	−0.0022	0.0229	0.0661	−0.0498	0.34	3.25
CARBON_equal	0.0043	0.0036	0.0293	0.0899	−0.1017	−0.14	3.97
CARBON_value	0.0041	−0.0002	0.0234	0.0673	−0.0499	0.26	2.69
CARBON_value (Long Leg)	0.0123	0.0155	0.0413	0.1148	−0.0990	−0.36	3.21
PMC	−0.0031	−0.0027	0.0187	0.0499	−0.0517	0.02	3.14
BMG	−0.0046	−0.0085	0.0303	0.0878	−0.0776	0.45	3.74
BMG_IN	−0.0037	0.0002	0.0317	0.0737	−0.0771	−0.19	2.79
ESG_equal	0.0001	0.0009	0.0114	0.0382	−0.0335	0.01	3.32
ESG_value	0.0008	0.0011	0.0178	0.0552	−0.0374	0.29	3.02
ESG_value (Long Leg)	0.0115	0.0129	0.0356	0.0897	−0.0840	−0.33	3.14
ESG_LT	−0.0026	−0.0025	0.0213	0.0755	−0.0688	0.48	4.49
Panel B: MSCI ESG Indexes							
ESG_UNIVERAL	0.0108	0.0148	0.0357	0.1072	−0.0890	−0.32	3.50
ESG_FOCUS	0.0120	0.0147	0.0363	0.1118	−0.0911	−0.33	3.56
ESG_LEADERS	0.0117	0.0151	0.0356	0.1133	−0.0847	−0.26	3.46
ESG_SELECT	0.0116	0.0125	0.0367	0.1178	−0.0922	−0.28	3.61

Factors descriptions are available in Table 1. Summary descriptive statistics include Mean, Media, standard deviation (SD), maximum (Max), minimum (Min), skewness (Skew) and kurtosis (Kurt). The sample period is June 2009 to March 2019.

MKT and *SMB*.

4. Empirical analysis

4.1. Carbon and ESG factors uniqueness

The main method used to examine the relationships between the *CARBON* and *ESG* factors and the remaining factors is a standard OLS time-series regression.[10] As stated in Section 3, the dependent variables capture zero-cost portfolio returns. The regression equation is:

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[10] We do not make adjustments to the standard errors. However, we have verified that using standard errors robust to heteroskedasticity and up to third-order autocorrelation has a negligible impact.

Table 3
Factor Correlations.

	ESG_equal	ESG_value	ESG_LT	CARBON_equal	CARBON_value	PMC	BMG	BMG_IN	ESG value (Long Leg)	CARBON value (Long Leg)
ESG_equal	1.00									
ESG_value	0.67***	1.00								
ESG_LT	0.43***	0.40***	1.00							
CARBON_equal	0.46***	0.22**	0.40***	1.00						
CARBON_value	0.31***	0.10	0.08	0.69***	1.00					
PMC	−0.13	0.04	0.38***	−0.37***	−0.55***	1.00				
BMG	−0.01	0.12	0.57***	−0.22**	−0.52***	0.64***	1.00			
BMG_IN	−0.12	−0.02	0.20**	−0.40***	−0.82***	0.58***	0.69***	1.00		
ESG value (Long Leg)	−0.19**	−0.14	−0.39***	−0.13	0.13	−0.14	−0.45***	−0.41***	1.00	
CARBON value (Long Leg)	−0.28***	−0.31***	−0.44***	−0.07	0.26***	−0.21**	−0.54***	−0.53***	0.96***	1.00
MKT	−0.32***	−0.34***	−0.47***	−0.17*	0.08	−0.14	−0.47***	−0.38***	0.97***	0.97***
SMB	−0.53***	−0.45***	−0.62***	−0.44***	−0.21**	−0.29***	−0.27***	−0.01	0.28***	0.31***
HML	−0.48***	−0.39***	0.03	−0.24***	−0.15	0.26***	0.18*	0.06	0.09	0.20**
RMW	0.38***	0.52***	0.48***	0.11	−0.10	0.41***	0.44***	0.23**	−0.23**	−0.36***
CMA	−0.33***	−0.32***	0.27***	−0.22**	−0.33***	0.46***	0.52***	0.38***	−0.05	−0.03
BAB	0.23**	0.02	0.31***	0.33***	0.25***	−0.01	0.19**	0.03	−0.27***	−0.27***
MOM	0.23**	0.20**	0.13	0.28***	0.11	−0.10	0.05	−0.01	−0.22**	−0.24***
QMJ_GROWTH	0.49***	0.48***	0.21**	0.38***	0.30***	−0.22**	−0.16*	−0.20**	−0.21**	−0.25***
QMJ_SAFETY	0.54***	0.49***	0.63***	0.55***	0.26***	−0.03	0.25***	0.05	−0.59***	−0.62***

This table presents the correlations of the monthly returns of the factors described in Table 1 with the ESG and Carbon factors. The equal-weighted and value-weighted versions of the *CARBON* and *ESG* factors are both used (*CARBON_equal, CARBON_value, ESG_equal* and *ESG_value*, respectively) as well as the value-weighted versions of their long legs. The sample period is June 2009 to March 2019. Coefficients with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively.

$$Y_t = \alpha + \sum_{k=1}^{K} \beta_k X_{k,t} + \varepsilon_t, \tag{1}$$

where $Y_t = CARBON_t$ or ESG_t is the value of the respective factor in month t, α is a constant, β_k is the slope coefficient of the kth factor, $X_{k,t}$ is the value of the kth factor in month t and ε_t is the value of the idiosyncratic error term in month t. The following 9 explanatory factors are used (K = 9): *MKT, SMB, HML, RMW, CMA, MOM, BAB, QMJ_GROWTH* and *QMJ_SAFETY*. All explanatory factors are time-series of zero-cost portfolio returns. The equal-weighted and value-weighted versions of the *CARBON* and ESG factors are both used (*CARBON_equal, CARBON_value, ESG_equal* and *ESG_value*, respectively). The equal weighting scheme ensures meaningful representation of stocks with very low market capitalization values in the factor portfolios, whereas value weighting ensures representation that is proportional to the significance of each stock in the whole economy. In addition, we have included the *PMC, BMG* and *BMG_IN* factors and the *ESG_LT* factor, described in Section 3.2, Table 1, as the dependent variable in equation (1) for comparison. We reverse the sign of the values of the *PMC, BMG* and *BMG_IN* factors before conducting the analysis below in order to have consistency with the Pedersen carbon factors, which are long the "clean" companies and short the polluters.

Our primary analysis aims at analyzing whether carbon and ESG factors are explained by other well-known factors. The results of the OLS regressions are presented in Table 4. Columns (1)-(5) show the estimates for the different carbon factors, and (6)-(8) for the ESG factors.[11] The market factor (*MKT*) has a strong positive relation to the carbon factors but not to the ESG factors. This suggests that high beta companies are more environmentally friendly on average. In contrast, the size factor (*SMB*) is strongly negatively related to both types of factors, with the notable exceptions of *PMC*[12] and *BMG*, which are carbon-based factors. The results for *BMG_IN* are more consistent than those for *BMG* with the Pedersen carbon factors results in columns (1) and (2), since only *BMG* of the above is based on total carbon emissions without any adjustments for firm size. It appears that, overall, low carbon emissions and low ESG risk companies have a tendency to be large. The profitability factor (*RMW*) exhibits a strong negative relation to the carbon factors and a strong positive relation to the value-weighted ESG factors. Therefore, both ESG scores and carbon levels and intensity are positively associated with profitability, since the carbon factors are based on negated carbon metrics. In addition, the investment factor (*CMA*) has a strong negative association with the value-weighted carbon factors, implying that companies with more aggressive corporate investment policies tend to have superior environmental performance, which may be due to the fact that these companies engage in more "green" investments.

Furthermore, the *BAB* factor has a strong negative relation to the Pedersen ESG factors, indicating that investing in these factors is an implicit bet on companies with high market betas. The growth component of the quality factor is negatively related to the value-weighted ESG factors. In contrast, there is a strong positive relation between the safety component of the quality factor and both the carbon and the ESG factors, with the exceptions of *BMG* and *BMG_IN*. Thus, financially safe companies are overall more likely to manage environmental risks well or be less exposed to them and adopt good ESG risk management practices. Furthermore, the value (*HML*) and momentum (*MOM*) factors do not have a consistently significant effect on the carbon and ESG factors. Finally, the constants representing the carbon and ESG factors alphas are not statistically significant, with the exception of the *PMC* factor, which exhibits a statistically significant at the 10 % level 21 basis-points alpha. This leads us to conclude that the carbon and ESG factors are subsumed by the conventional risk factors.

4.2. ESG indexes exposures

Investing in ESG strategies is often done through indexes. In this section, we analyze the exposure of US MSCI ESG indexes to the ESG factor, the carbon factor, and other common factors. For consistency with other common risk factors and to avoid multicollinearity issues, we only use value-weighted carbon and ESG factors.

Panel A of Table 5 reports the regression results. The adjusted R-squared of all regressions are very close to 1, implying that the risk factors explain almost entirely the variation of the ESG indexes. Thus, an investor can almost perfectly replicate these indexes by investing in the risk factors. Only *ESG_LEADERS* has a significantly negative loading on the *CARBON* factor at the 5 % level. In contrast, *ESG_FOCUS* and *ESG_UNIVERSAL* have significantly positive exposures to the ESG factor at the 5 % level. Furthermore, all indexes have market betas that are indistinguishable from one. Thus, investors fully bear market risk. In addition, all indexes have significantly negative loadings on the size factor, implying a style tilt towards large companies. Only *ESG_SELECT* exhibits contrarian investing properties through a significantly negative exposure at the 5 % level to the momentum factor. Conversely, only *ESG_UNIVERSAL* is positively exposed to the *BAB* factor at the 10 % level. Finally, all indexes show significantly negative loadings on the growth component of the quality factor.

So far, we have only considered factors that are built from long and short portfolios. However, the ESG indexes are long-only portfolios. Therefore, it is worth verifying whether the ESG indexes are sufficiently well-explained by the long legs of the *CARBON* and *ESG* factors. To do this, we regress the ESG indexes on the long-leg portfolios of the carbon and ESG factors, which consist of the companies with the best environmental and ESG performance, respectively. The results are presented in Panel B of Table 5. Again, the

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[11] Additional robustness analyses are presented in the appendices like stability of results over time (Appendix A) and LASSO regression (Appendix B) and Vector Autoregression (Appendix C).

[12] The positive sign of the *PMC* coefficient is not driven by the inclusion of data back to January 2004. If the data is restricted to start in June 2009, as in columns (1) and (2), the coefficient value is 0.2021, and its p-value is 0.003.

Table 4

The relationship between common risk factors and CARBON and ESG factors.

	Carbon factors					ESG Factors		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CARBON_ equal	CARBON_ value	PMC	BMG	BMG_IN	ESG_equal	ESG_value	ESG_LT
MKT	0.2757***	0.2427***	0.0858**	0.2820***	0.4256***	0.0404	0.0699	0.0474
	(0.001)	(0.001)	(0.050)	(0.000)	(0.000)	(0.222)	(0.142)	(0.216)
SMB	−0.4132***	−0.2292**	0.2160***	0.0409	−0.2425*	−0.1338***	−0.1542**	−0.3063***
	(0.000)	(0.014)	(0.000)	(0.687)	(0.062)	(0.004)	(0.020)	(0.000)
HML	0.0801	0.2243*	−0.0964	0.0962	0.3708**	−0.0340	−0.0264	0.1075**
	(0.549)	(0.059)	(0.119)	(0.434)	(0.019)	(0.513)	(0.723)	(0.048)
RMW	−0.4683***	−0.3992***	−0.5974***	−0.6209***	−0.4341**	0.0603	0.2516**	0.1424**
	(0.004)	(0.006)	(0.000)	(0.000)	(0.028)	(0.391)	(0.014)	(0.043)
CMA	0.0051	−0.4598**	−0.4003***	−0.9665***	−0.8444***	−0.0643	−0.1934	0.5063***
	(0.981)	(0.015)	(0.000)	(0.000)	(0.001)	(0.461)	(0.124)	(0.000)
MOM	0.1037	−0.0000	−0.1290***	0.0355	0.0795	0.0347	0.0267	−0.0348
	(0.218)	(1.000)	(0.000)	(0.650)	(0.425)	(0.188)	(0.480)	(0.235)
BAB	0.0282	0.1978*	−0.0693	−0.1285	−0.0519	−0.1117***	−0.1920***	−0.0466
	(0.829)	(0.088)	(0.167)	(0.329)	(0.757)	(0.006)	(0.001)	(0.282)
QMJ_GROWTH	0.1721	0.2183	−0.1988**	0.5028**	0.4572	−0.0500	−0.2502**	−0.2649***
	(0.460)	(0.288)	(0.032)	(0.023)	(0.102)	(0.475)	(0.014)	(0.001)
QMJ_SAFETY	0.8282***	0.3858**	0.4432***	−0.0403	0.2497	0.2290***	0.3755***	0.6495***
	(0.000)	(0.021)	(0.000)	(0.815)	(0.257)	(0.001)	(0.000)	(0.000)
CONSTANT	0.0011	0.0004	0.0021*	0.0030	0.0000	−0.0002	−0.0010	−0.0012
	(0.656)	(0.837)	(0.091)	(0.188)	(0.997)	(0.872)	(0.500)	(0.290)
N	118	118	183	111	111	146	146	195
adj. R^2	0.4207	0.2936	0.4262	0.5554	0.3426	0.3410	0.3800	0.6573

This table shows the equation (1) parameter estimates. Factors descriptions are available in Table 1. P-values are presented in parentheses. Co-efficients with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively. Sample period: June 2009 to March 2019 for models (1) and (2), January 2004 to March 2019 for model (3), January 2010 to March 2019 for models (4) and (5), February 2007 to March 2019 for models (6) and (7), and January 2003 to March 2019 for model (8).

adjusted R-squared of the regressions are close to 1.[13] Furthermore, all ESG indexes have significantly positive ESG long leg slope coefficients at the 5 % and 1 % levels. It follows that the indexes follow the long legs of the ESG factor. Conversely, only *ESG_LEADER* has a statistically significant negative exposure to the long leg of the *CARBON* factor.

To assess the robustness of our findings, we conduct further analysis using additional indexes, specifically the S&P 500 ESG index and the RAFI ESG index for the US. Our findings reported in Panel A of Table D1 of Appendix D corroborate the primary conclusion that the market betas of all examined indexes are effectively equal to one, indicating that investors are fully exposed to market risk. Furthermore, all indexes exhibit significantly negative loadings on the size factor, which suggests the inclusion of larger companies. However, the indexes demonstrate inconsistent exposures to both the ESG and carbon factors with RAFI ESG showing exposure to the carbon factor and the S&P 500 ESG index showing exposure to the ESG factor, which does not change when we only use the "long legs" in Panel B.

While indexes serve as benchmarks, Exchange Traded Funds (ETFs) are tradable products that seek to replicate the performance of indexes by holding the same securities or a representative selection. The iShares MSCI USA ESG Select ETF tracks the MSCI USA ESG Select Index, offering investors an efficient way to gain exposure to this index. The ETF's investability feature, combined with its return's near 100 % correlation with the index's return, strongly motivates us to repeat the analysis above using this ETF as a representative vehicle for further evaluation.

Column (1) of Table D2 shows that the ETF has an exposure to the ESG factor, a market beta of one and negative exposure to the size factor, and the coefficients resemble those in Panel A of Table 5. In columns (2) and (3), ETF returns are regressed on the long legs of the carbon and ESG factors. Again, coefficients are practicable indistinguishable from those in columns (5) and (6) of Panel B of Table 5. Thus, we conclude that our results for the factor exposures of ESG indexes in Table 5 are generally robust to using alternative ESG indexes and investible ESG ETFs tracking those indexes.[14]

4.3. Additional robustness checks

In this section, we repeat the main empirical analysis presented in Section 4.1 with more recent data for some of the carbon and ESG factors and the common risk factors used in this study.[15] We use the long-minus-short Pollutive-Minus-Clean (PMC) portfolios

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[13] Further analysis shows that the market factor alone explains more than 95% of the variation of each index.

[14] In untabulated results, we have used ETFs focused on equity factors such as large-cap, small-cap, value and growth. However, they exhibit high correlations with each other. As a result, using all ETFs as regressors would be redundant.

[15] The Pedersen carbon and ESG factors are not available after March 2019 to the best of our knowledge.

Table 5

The factor exposures of ESG indexes.

Panel A: Exposures of ESG Indexes to the *CARBON* and *ESG* factors (Long-short)				
	(1) *ESG*_FOCUS	(2) *ESG*_LEADERS	(3) *ESG*_SELECT	(4) *ESG*_UNIVERSAL
CARBON_value	−0.0181*	−0.0507**	−0.0295	−0.0027
	(0.086)	(0.034)	(0.285)	(0.819)
ESG_value	0.0543***	0.0577	0.0799*	0.1325***
	(0.001)	(0.107)	(0.056)	(0.000)
MKT	1.0090***	0.9832***	1.0120***	1.0036***
	(0.000)	(0.000)	(0.000)	(0.000)
SMB	−0.1121***	−0.0509**	−0.0732***	−0.1088***
	(0.000)	(0.034)	(0.009)	(0.000)
HML	−0.0057	−0.0262	−0.0545	−0.0296**
	(0.659)	(0.373)	(0.114)	(0.038)
RMW	0.0018	0.0310	0.0115	0.0075
	(0.916)	(0.415)	(0.796)	(0.684)
CMA	−0.0066	0.0300	−0.0623	0.0003
	(0.751)	(0.525)	(0.259)	(0.990)
MOM	−0.0088	−0.0192	−0.0542**	−0.0153*
	(0.278)	(0.291)	(0.012)	(0.089)
BAB	0.0098	0.0480	−0.0065	0.0264*
	(0.460)	(0.111)	(0.853)	(0.099)
QMJ_GROWTH	−0.0382*	−0.1235**	−0.1101*	−0.0641**
	(0.094)	(0.017)	(0.067)	(0.013)
QMJ_SAFETY	0.0132	0.0386	0.0617	0.0151
	(0.474)	(0.355)	(0.206)	(0.450)
CONSTANT	0.0001	−0.0002	−0.0002	−0.0002
	(0.631)	(0.761)	(0.765)	(0.369)
N	118	118	118	112
Adj R2	1.00	0.98	0.98	1.00

Panel B: Exposures of ESG indexes to CARBON and ESG factors (Long only)								
	(1) *ESG_FOCUS*	(2) *ESG_FOCUS*	(3) *ESG_LEADERS*	(4) *ESG_LEADERS*	(5) *ESG_SELECT*	(6) *ESG_SELECT*	(7) *ESG_UNIVERSAL*	(8) *ESG_UNIVERSAL*
CARBON_value (Long Leg)	−0.0199		−0.2178***		−0.1061		0.0405	
	(0.499)		(0.000)		(0.151)		(0.288)	
ESG_value (Long Leg)		0.1252***		0.1206**		0.2753***		0.2576***
		(0.000)		(0.045)		(0.000)		(0.000)
MKT	1.0249***	0.8828***	1.2096***	0.8656***	1.1196***	0.7228***	0.9548***	0.7468***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SMB	−0.1197***	−0.1059***	−0.0861***	−0.0218	−0.0971***	−0.0401	−0.1246***	−0.1011***
	(0.000)	(0.000)	(0.001)	(0.352)	(0.001)	(0.112)	(0.000)	(0.000)
HML	−0.0083	−0.0040	0.0063	−0.0165	−0.0423	−0.0144	−0.0434**	−0.0275**
	(0.580)	(0.718)	(0.838)	(0.515)	(0.259)	(0.598)	(0.024)	(0.042)
RMW	0.0245	0.0284*	0.0391	0.0546	0.0350	0.0265	0.0567**	0.0142
	(0.148)	(0.063)	(0.264)	(0.115)	(0.409)	(0.476)	(0.010)	(0.404)
CMA	−0.0120	0.0044	−0.0199	0.0177	−0.0918	−0.0690	−0.0044	0.0134
	(0.604)	(0.816)	(0.677)	(0.680)	(0.115)	(0.135)	(0.882)	(0.529)
MOM	−0.0062	0.0029	−0.0212	−0.0338***	−0.0522**	−0.0274**	−0.0058	0.0008
	(0.466)	(0.605)	(0.230)	(0.009)	(0.016)	(0.049)	(0.599)	(0.926)
BAB	−0.0073	−0.0139	0.0253	0.0388*	−0.0316	−0.0041	−0.0141	0.0105
	(0.583)	(0.114)	(0.357)	(0.053)	(0.341)	(0.847)	(0.445)	(0.471)
QMJ_GROWTH	−0.0266	−0.0052	−0.1023**	−0.0671*	−0.0876	−0.0923**	−0.0349	−0.0503**
	(0.261)	(0.728)	(0.038)	(0.051)	(0.141)	(0.013)	(0.261)	(0.037)
QMJ_SAFETY	0.0124	−0.0142	0.0335	0.0092	0.0625	0.0317	0.0255	0.0169
	(0.514)	(0.344)	(0.396)	(0.787)	(0.192)	(0.387)	(0.293)	(0.369)
CONSTANT	0.0002	0.0005**	−0.0001	−0.0000	−0.0000	0.0003	0.0001	0.0001
	(0.325)	(0.028)	(0.918)	(0.928)	(0.997)	(0.579)	(0.702)	(0.775)
N	118	146	118	146	118	146	112	112
Adj R2	0.9961	0.9969	0.9828	0.9842	0.9762	0.9816	0.9937	0.9962

This table presents the results of regressions, in which the MSCI ESG indexes indicated on top of columns are regressed on the *CARBON* and *ESG* factors in Panel A and on their long legs (in separate model specifications to avoid multicollinearity issues) in Panel B. Only value-weighted carbon and ESG factors are included in the regressions to avoid multicollinearity issues. Conventional risk factors are added as controls. Factors descriptions are available in Table 1. Coefficients with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively. P-values are presented in parentheses. Sample period: June 2009 to March 2019 for models (1)-(3) in Panel A and models (1), (3) and (5) in Panel B, December 2009 to March 2019 for model (4) in Panel A and models (7) and (8) in Panel B, and February 2007 to March 2019 for models (2), (4) and (6) in Panel B.

Table 6

The relationship between common risk factors and CARBON and ESG factors (extended sample analysis).

	(1) PMC	(2) BMG	(3) BMG_IN	(4) ESG_LT
MKT	0.0400	0.2758***	0.3942***	0.0414
	(0.304)	(0.000)	(0.000)	(0.246)
SMB	0.1915***	0.1476	−0.2060*	−0.3034***
	(0.001)	(0.105)	(0.097)	(0.000)
HML	−0.1489***	0.0358	−0.1173	0.0518
	(0.006)	(0.673)	(0.311)	(0.280)
RMW	−0.7340***	−0.5952***	−0.4130***	0.1839***
	(0.000)	(0.000)	(0.006)	(0.004)
CMA	−0.4550***	−0.7500***	−0.2560	0.4764***
	(0.000)	(0.000)	(0.162)	(0.000)
MOM	−0.1230***	−0.0586	0.0220	−0.0410
	(0.000)	(0.375)	(0.807)	(0.153)
BAB	−0.0210	−0.0152	−0.1436	−0.0589
	(0.637)	(0.850)	(0.192)	(0.130)
QMJ_GROWTH	−0.1964**	0.1933	0.4977**	−0.2855***
	(0.027)	(0.278)	(0.042)	(0.000)
QMJ_SAFETY	0.4010***	0.1447	0.1986	0.6037***
	(0.000)	(0.291)	(0.288)	(0.000)
CONSTANT	0.0027**	0.0027	0.0029	−0.0005
	(0.030)	(0.159)	(0.276)	(0.609)
N	216	144	144	216
adj. R^2	0.4987	0.5059	0.2926	0.6652

This table shows the equation (1) parameter estimates with an extended sample based on the availability of carbon and ESG factors as of May 2024. Factors descriptions are available in Table 1. P-values are presented in parentheses. Coefficients with "*", "**", and "***" are significant at the 10%, 5%, and 1% levels, respectively. Sample period: January 2004 to December 2021 for model (1), January 2010 to December 2021 for models (2) and (3), and January 2003 to December 2020 for model (4).

developed by Huij et al. (2021) as proxies for carbon risk, focusing specifically on the long-minus-short portfolio based on total carbon emission (Scope 1 & 2) intensity. Additionally, we incorporate the factors for carbon risk proposed by Bauer et al. (2022); specifically the BMG factor based on total carbon emissions and a factor based on carbon intensity, which is carbon emissions adjusted for firm size, referred to as BMG_IN. To ensure consistency with the Pedersen carbon factor, we reverse the signs of the BMG and BMG_IN factors. Furthermore, we include the ESG factor introduced by Lioui and Tarelli (2022) in our analysis. Summary statistics for all factors are presented in Table 1. The sample period extends to December 2021 for the PMC and BMG_IN portfolios and to December 2020 for the ESG factor.

The results are presented in Table 6. The findings are broadly consistent with the main results for all factors and the intercept with a few notable exceptions. First, the *PMC* factor does not have a significantly positive exposure to the market factor. Second, the coefficients on the *HML* factor exhibit instability, consistent with Figs. A1-A4 in Appendix A. Third, the loading of *BMG_IN* on the investment factor (*CMA*) is not significantly negative. Finally, the alpha (*CONSTANT*) of the *PMC* factor is statistically significant at the 5 % level, suggesting that this factor may exhibit some uniqueness. Nevertheless, the adjusted R^2 values suggest that common factors still have explanatory power during the period.

5. Conclusion

ESG investing has become increasingly mainstream in portfolio management, driven by increasing investor demand for sustainability-focused assets. However, the finance literature continues to debate whether ESG and carbon factors represent unique systematic risk sources or are fully absorbed by traditional risk factors. This study addresses this gap by empirically testing whether incorporating ESG and carbon factors into asset pricing models enhances explanatory power. The main findings reveal that the size factor, profitability factor and the safety component of the quality factor are strongly contemporaneously related to both types of factors of interest, whereas the market factor is strongly related only to the carbon factors. This suggests that the two factor categories have their own identities. Most importantly, the carbon and ESG risk factors can be replicated as linear combinations of risk factors based on stock characteristics that are not directly related to environmental or ESG policies. Notably, the main inputs for building ESG factors are ESG ratings, which have a documented link with firm size. Larger firms tend to have greater resources for gathering and disclosing ESG information.

We also examine the risk exposures of popular ESG indexes, which provide a convenient means to invest in ESG-focused companies. Our findings indicate that the indexes examined are all exposed to the market and size factors. Moreover, investors who invest in ESG indexes gain exposure to the long leg of the ESG factor.

Systematic risks related to carbon and ESG can be quantified through exposures to traditional risk factors, underscoring the need for investors to evaluate ESG exposures within the context of existing risk frameworks.

CRediT authorship contribution statement

Svetoslav Covachev: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jocelyn Martel:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Sofia Brito-Ramos:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

Appendix A:. Time-varying factor loadings

In this appendix, we analyze the stability of the results of Section 4.1 over time. More precisely, we show graphically the evolution of the slope coefficients of Table 4 over time in Figs. A1-A4 to detect major structural changes. The coefficients are estimated over a 5-year rolling window, and only coefficients that exceed 0.20 in magnitude at least once during the estimation period are plotted for brevity. Overall, the coefficients are stable over time for the carbon factor (Figs. A1 and A2). A notable exception is the slope coefficient of the growth component of the quality factor (*QMJ_GROWTH*), which went up abruptly in 2016. The coefficients for the *ESG* factor are less stable (Figs. A3 and A4). The slope coefficients of the value and profitability factors and the safety component of the quality factor (*QMJ_SAFETY*) for the equal-weighted ESG factor trend downwards, whereas the *QMJ_GROWTH* coefficient trends upwards. In contrast, the *BAB* and *QMJ_SAFETY* slope coefficients trend downwards for the value-weighted ESG factor, while the coefficient of *QMJ_GROWTH* trends upwards.

Fig. A1. The time-varying slope coefficients of common risk factors for the equal-weighted carbon factor. Description: This figure depicts the time-varying slope coefficients of regressions of the equal-weighted carbon factor on common risk factors. We use 5-year rolling windows and only plot coefficients that exceed 0.20 in absolute value at least once.
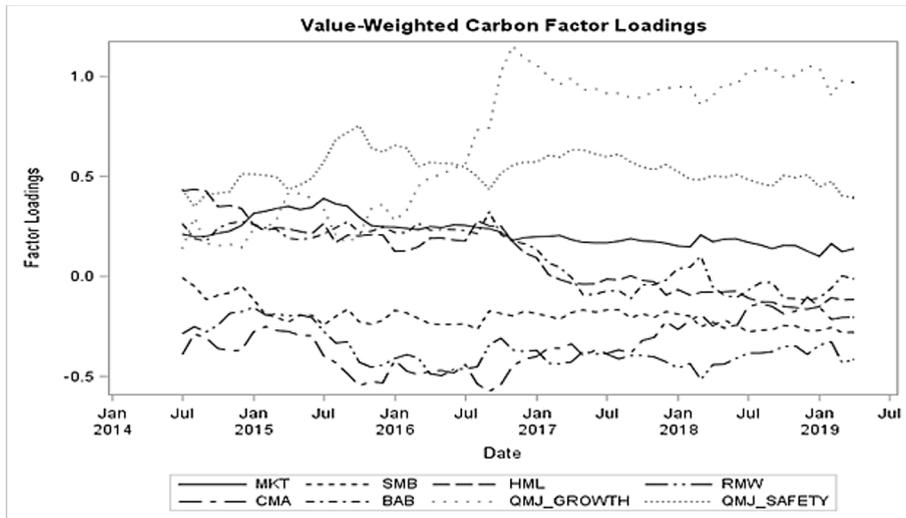
Fig. A2. The time-varying slope coefficients of common risk factors for the value-weighted carbon factor. Description: This figure depicts the time-varying slope coefficients of regressions of the value-weighted carbon factor on common risk factors. We use 5-year rolling windows and only plot coefficients that exceed 0.20 in absolute value at least once.
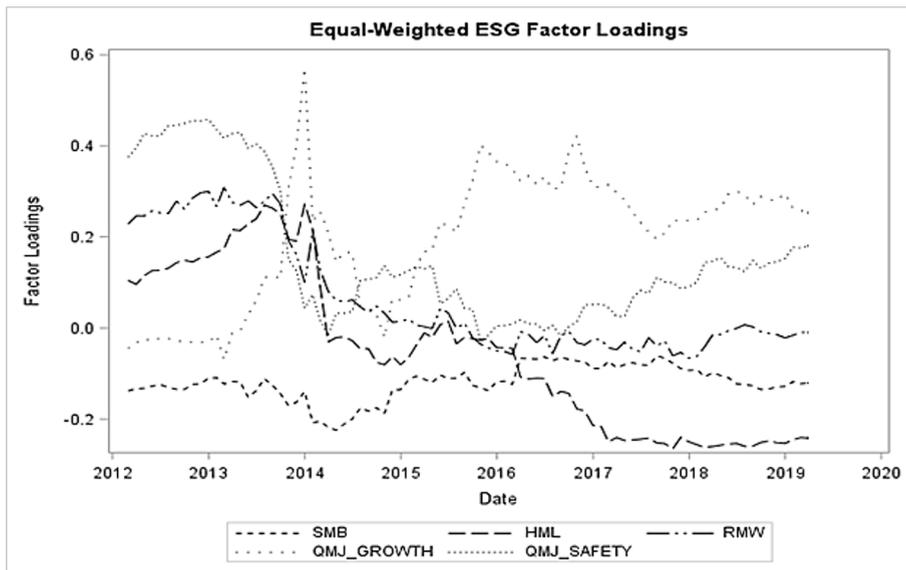
Fig. A3. The time-varying slope coefficients of common risk factors for the equal-weighted ESG factor. Description: This figure depicts the time-varying slope coefficients of regressions of the equal-weighted ESG factor on common risk factors. We use 5-year rolling windows and only plot coefficients that exceed 0.20 in absolute value at least once.
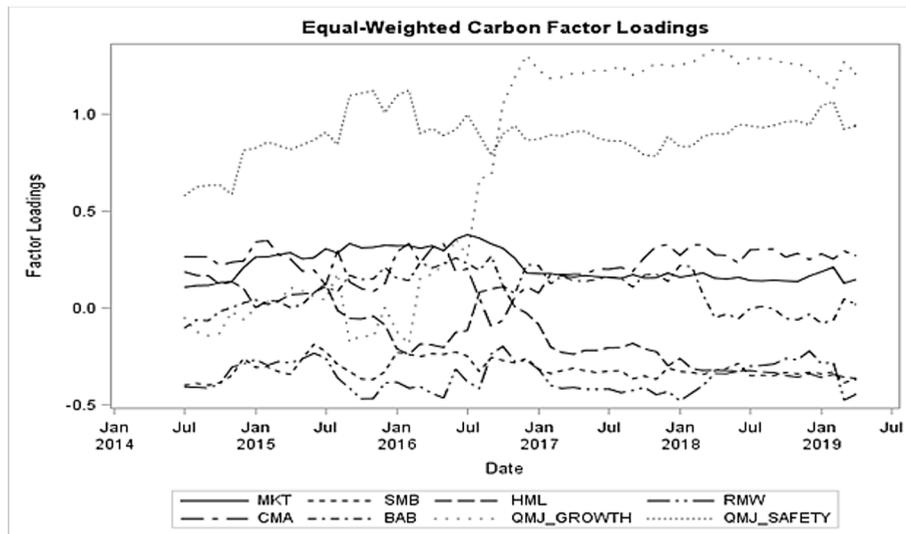
Fig. A4. The time-varying slope coefficients of common risk factors for the value-weighted ESG factor. Description: This figure depicts the time-varying slope coefficients of regressions of the value-weighted ESG factor on common risk factors. We use 5-year rolling windows and only plot coefficients that exceed 0.20 in absolute value at least once.
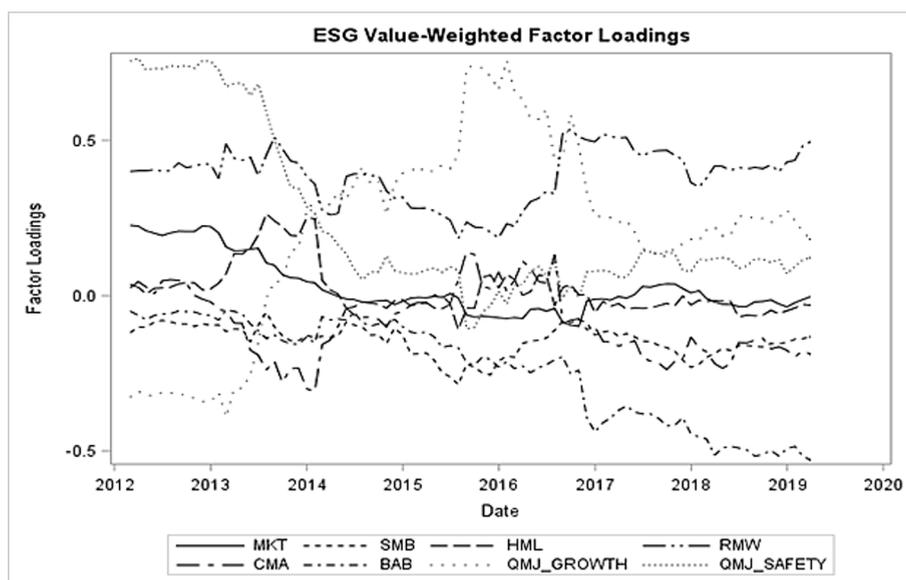
Appendix B:. LASSO regressions

LASSO regressions are utilized as a robustness test for the contemporaneous relationships between the carbon and ESG factors and common risk factors presented in Section 4.1. The equal-weighted carbon factor is positively related to the safety component of the quality factor and the market factor and negatively related to the profitability and size factors. This is consistent with the OLS regression results presented in Table 4. Conversely, the LASSO fails to select any explanatory factors for the value-weighted carbon factor. The ESG factor is positively related to the safety component of the quality factor and negatively related to the value factor, regardless of which weighting scheme is used. Furthermore, the value-weighted version of the ESG factor is positively related to the profitability factor. These results are broadly consistent with the ones in Table 4. However, it stands out that the size factor, the *BAB* factor and the growth component of the quality factor are not included in the LASSO models for the ESG factor, despite their significance in the OLS regressions results. On the other hand, the value factor is not significant in the OLS setting but is chosen by LASSO for the ESG factor. Overall, the LASSO results need to be interpreted with caution due to the relatively small subsamples used for model selection.

Table B1
The relationship between common risk factors and carbon and ESG factors according to LASSO regressions over the period from February 2007 to March 2019.

	(1)	(2)	(3)	(4)
	CARBON_equal	CARBON_value	ESG_equal	ESG_value
MKT	0.0097			
SMB	−0.0041			
HML			−0.0025	−0.0035
RMW	−0.0083			0.0012
CMA				
MOM				
BAB				
QMJ_GROWTH				
QMJ_SAFETY	0.0237		0.0013	0.0020
CONSTANT	0.0000	0.0000	0.0000	0.0000
Method	Adaptive	CV, BIC, Adaptive	CV, BIC, Adaptive	CV, Adaptive
R^2	0.2291	−0.0043	0.1816	0.1411

This table presents the results of LASSO regressions. The LASSO selects the optimal model from all potential models. Three different model selection methods are used: cross-validation (CV), Bayesian information criterion minimization (BIC) and Adaptive. The results of the selection methods that produce the highest out-of-sample R-squared are reported with priority given to the CV coefficients in case of a tie. The monthly returns are from February 2007 to March 2019. Factors descriptions are available in Table 1.

Appendix C:. VAR analysis

To infer predictability and spillover effects, we use a VAR model framework that allows for lagged effects. The regression equation of primary interest is:

$$Y_t = \alpha + \sum_{k=1}^{K+1} \sum_{j=1}^{J} \beta_{k,j} X_{k,t-j} + \varepsilon_t, \tag{C1}$$

where the terms are similar to those of eq. (1), but *CARBON* and *ESG* are added as the K + 1st explanatory factor and J lags of all K + 1 explanatory variables replace the contemporaneous values. The lag length of each VAR is determined by the likelihood ratio test and Akaike's information criterion. Additionally, Granger causality tests are applied to eq. (C1) to test the joint significance of the *J* lags of each variable separately, while controlling for the lags of the remaining variables. Finally, shocks to the explanatory variables that are uncorrelated across the VAR equations are introduced to examine their impacts on *CARBON* and *ESG* over the subsequent months. The resulting impulse-response functions are presented graphically.

The results of the VAR are in Table C1. While all VAR equations are estimated simultaneously, only the results for the equation of primary interest, eq. (C1), are tabulated for brevity. None of the equation F-statistics are statistically significant at the 10 % level. Therefore, the lags of the explanatory factors do not jointly have satisfactory explanatory power. While some individual lags are statistically significant at the 5 % level, we focus on the Granger causality test results to potentially identify reliable predictors of the carbon and ESG factors.

Table C1
The lagged relationship between common risk factors and carbon and ESG factors over the period from February 2008 to March 2019.

	(1) CARBON_equal	(2) CARBON_value	(3) ESG_equal	(4) ESG_value
Equation F-statistic	1.8433	2.2872	1.0647	1.2384
	(0.200)	(0.123)	(0.485)	(0.349)
L1.DEPVAR	−0.0721	−0.2767	0.0772	−0.0808
	(0.830)	(0.279)	(0.841)	(0.776)
L2.DEPVAR	−0.0392	0.2537	−0.0713	−0.0834
	(0.904)	(0.304)	(0.868)	(0.828)
L3.DEPVAR	0.2322	0.7466**	0.3487	0.6653*
	(0.676)	(0.034)	(0.360)	(0.078)
L4.DEPVAR	0.9966*	0.4823	−0.3496	0.3323
	(0.067)	(0.104)	(0.526)	(0.398)
L5.DEPVAR	0.6068	−0.2150	−0.2518	0.3123
	(0.418)	(0.407)	(0.590)	(0.507)
L6.DEPVAR	−0.5266	0.1139	−0.0836	0.3888
	(0.521)	(0.776)	(0.848)	(0.426)
L7.DEPVAR	0.0912	0.7822**	0.2661	0.7927*
	(0.785)	(0.039)	(0.511)	(0.075)
L8.DEPVAR	−0.1106	0.5340	0.3717	−0.8769*
	(0.774)	(0.203)	(0.487)	(0.050)
L9.DEPVAR	0.5315	0.3475	0.1187	−0.0595
	(0.213)	(0.291)	(0.812)	(0.880)
L10.DEPVAR	−0.8121*	−0.8465**	0.1664	0.1458
	(0.060)	(0.021)	(0.752)	(0.688)
L11.DEPVAR			0.3339	0.5255*
			(0.470)	(0.058)
L12.DEPVAR			0.1319	0.2506
			(0.711)	(0.434)
L1.MKT	0.3868	0.3003	−0.0371	−0.2061
	(0.369)	(0.210)	(0.761)	(0.235)
L2.MKT	0.4559	0.1246	0.1147	−0.1560
	(0.532)	(0.617)	(0.311)	(0.387)
L3.MKT	0.8868	0.2557	0.0432	−0.1314
	(0.161)	(0.273)	(0.793)	(0.581)
L4.MKT	0.0205	−0.2112	0.0720	−0.5989
	(0.976)	(0.363)	(0.710)	(0.146)
L5.MKT	0.0497	0.2292	0.0250	−0.3761
	(0.868)	(0.280)	(0.888)	(0.249)
L6.MKT	−0.3105	−0.1876	0.0626	0.1530
	(0.481)	(0.401)	(0.613)	(0.399)
L7.MKT	0.1183	−0.6034**	0.1666	0.0965
	(0.770)	(0.021)	(0.234)	(0.697)
L8.MKT	−0.1630	−0.4065*	0.2080	−0.2632

(continued on next page)

Table C1 (*continued*)

	(1)	(2)	(3)	(4)
	CARBON_equal	*CARBON_value*	*ESG_equal*	*ESG_value*
	(0.593)	(0.061)	(0.206)	(0.295)
L9.MKT	0.1449	0.0879	0.1395	−0.2123
	(0.698)	(0.647)	(0.515)	(0.426)
L10.MKT	0.5176	0.1554	−0.0564	−0.5582*
	(0.128)	(0.774)	(0.375)	(0.071)
L11.MKT			0.1657	−0.1716
			(0.346)	(0.520)
L12.MKT			0.1478	−0.1448
			(0.365)	(0.589)
L1.SMB	−0.4593	0.1963	0.1657	0.3374
	(0.556)	(0.577)	(0.440)	(0.246)
L2.SMB	−0.4445	0.0396	−0.0663	−0.5770
	(0.439)	(0.917)	(0.801)	(0.182)
L3.SMB	−1.0922*	−0.3976	−0.0121	−0.1590
	(0.061)	(0.201)	(0.963)	(0.635)
L4.SMB	0.7837	0.3468	0.1968	0.7268**
	(0.298)	(0.246)	(0.426)	(0.013)
L5.SMB	0.3932	−0.7642**	0.1080	0.1924
	(0.429)	(0.037)	(0.548)	(0.415)
L6.SMB	−0.2559	−0.4740*	−0.0368	−0.1624
	(0.418)	(0.088)	(0.854)	(0.560)
L7.SMB	−0.3590	−0.6563*	−0.0295	0.2265
	(0.467)	(0.076)	(0.853)	(0.332)
L8.SMB	−0.4246	0.2849	0.0419	−0.1399
	(0.440)	(0.311)	(0.786)	(0.553)
L9.SMB	0.3345	0.1291	−0.1254	−0.4540*
	(0.653)	(0.577)	(0.517)	(0.083)
L10.SMB	−0.7372	−1.1315***	0.1413	−0.1216
	(0.166)	(0.009)	(0.510)	(0.627)
L11.SMB			0.1780	0.6151**
			(0.483)	(0.029)
L12.SMB			0.0745	0.7155**
			(0.755)	(0.038)
L1.HML	−0.4717	−0.3693	−0.1367	−0.6084*
	(0.252)	(0.209)	(0.628)	(0.070)
L2.HML	−0.3057	−0.9453**	−0.1634	−0.2982
	(0.459)	(0.023)	(0.506)	(0.342)
L3.HML	−0.0580	0.7033**	0.3910*	0.8889**
	(0.891)	(0.050)	(0.097)	(0.024)
L4.HML	0.1970	0.1253	0.4017	0.6869**
	(0.655)	(0.682)	(0.110)	(0.040)
L5.HML	0.2122	−0.8925**	−0.2671	−0.3610
	(0.793)	(0.048)	(0.310)	(0.376)
L6.HML	0.2820	0.1848	−0.2099	−0.1567
	(0.587)	(0.634)	(0.349)	(0.641)
L7.HML	−0.9135	−0.2923	−0.0586	0.1069
	(0.192)	(0.349)	(0.843)	(0.751)
L8.HML	−0.8216	−0.0467	0.0208	−0.6830
	(0.344)	(0.910)	(0.957)	(0.108)
L9.HML	−0.4304	−0.1664	−0.0520	−0.0025
	(0.635)	(0.643)	(0.871)	(0.994)
L10.HML	0.2078	−0.3911	0.4325	0.5718
	(0.766)	(0.229)	(0.109)	(0.156)
L11.HML			−0.0741	−0.0053
			(0.848)	(0.991)
L12.HML			−0.0288	−0.6781
			(0.908)	(0.127)
L1.RMW	−1.2169	1.3484*	0.0329	0.6939
	(0.173)	(0.057)	(0.921)	(0.140)
L2.RMW	1.0313	−0.1003	−0.0873	−0.5508
	(0.134)	(0.812)	(0.792)	(0.392)
L3.RMW	−0.5933	−0.2275	−0.4049	−0.2775
	(0.443)	(0.629)	(0.335)	(0.549)
L4.RMW	0.4441	1.0060	0.1160	0.5409
	(0.830)	(0.203)	(0.810)	(0.342)
L5.RMW	0.3546	−1.2562*	0.1820	−0.0934
	(0.724)	(0.054)	(0.687)	(0.874)
L6.RMW	−0.2360	0.8774	−0.1261	−0.7882

Table C1 (*continued*)

	(1)	(2)	(3)	(4)
	CARBON_equal	*CARBON_value*	*ESG_equal*	*ESG_value*
	(0.850)	(0.129)	(0.772)	(0.217)
L7.RMW	1.3426	0.3973	−0.2059	0.2408
	(0.470)	(0.448)	(0.608)	(0.690)
L8.RMW	−0.5139	−1.6518**	0.1302	−0.2240
	(0.508)	(0.026)	(0.643)	(0.658)
L9.RMW	0.3001	0.6582	−0.1719	−0.5249
	(0.813)	(0.197)	(0.683)	(0.357)
L10.RMW	−0.7070	−0.4117	0.2880	0.6504
	(0.551)	(0.461)	(0.548)	(0.400)
L11.RMW			0.2258	−0.3158
			(0.460)	(0.497)
L12.RMW			−0.1165	−1.3220*
			(0.773)	(0.059)
L1.CMA	0.7468	−0.1604	0.1626	0.6612
	(0.478)	(0.738)	(0.685)	(0.261)
L2.CMA	−0.9895	0.6308	0.4030	0.0940
	(0.199)	(0.216)	(0.372)	(0.862)
L3.CMA	−0.3060	−0.3238	−0.0841	−0.7665
	(0.603)	(0.475)	(0.852)	(0.255)
L4.CMA	−1.5070	−1.4010**	−0.6039	−1.3419**
	(0.245)	(0.024)	(0.137)	(0.026)
L5.CMA	−0.3700	0.3435	0.4548	1.1826
	(0.593)	(0.502)	(0.307)	(0.118)
L6.CMA	−0.3642	−0.9810	0.5666	0.5383
	(0.709)	(0.135)	(0.106)	(0.301)
L7.CMA	0.1862	0.2293	0.1945	−0.3350
	(0.837)	(0.629)	(0.651)	(0.553)
L8.CMA	1.5403	0.9556	0.2458	1.1344
	(0.170)	(0.198)	(0.625)	(0.139)
L9.CMA	0.9240	−0.2627	0.3895	0.4782
	(0.416)	(0.608)	(0.435)	(0.470)
L10.CMA	−0.2482	0.4794	−1.0849*	−2.0105**
	(0.786)	(0.249)	(0.087)	(0.042)
L11.CMA			−0.3132	0.0491
			(0.600)	(0.939)
L12.CMA			0.2282	0.9429
			(0.634)	(0.284)
L1.MOM	−1.0554	−0.9140**	−0.1821	−0.1928
	(0.107)	(0.018)	(0.265)	(0.482)
L2.MOM	−0.3366	−0.5120**	−0.0432	0.4902
	(0.613)	(0.044)	(0.876)	(0.256)
L3.MOM	−0.6080	0.0603	0.1963	0.7681*
	(0.211)	(0.802)	(0.368)	(0.055)
L4.MOM	0.0411	−0.2521	0.0591	0.0942
	(0.934)	(0.220)	(0.679)	(0.570)
L5.MOM	−0.1973	−0.3089	−0.1596	−0.2292
	(0.672)	(0.219)	(0.224)	(0.193)
L6.MOM	0.4582	0.0283	−0.0692	−0.0959
	(0.233)	(0.919)	(0.563)	(0.531)
L7.MOM	−0.1339	−0.1787	−0.1154	−0.1459
	(0.754)	(0.380)	(0.357)	(0.408)
L8.MOM	0.8210*	0.1341	−0.0872	−0.0251
	(0.079)	(0.501)	(0.500)	(0.886)
L9.MOM	−0.1319	−0.1608	0.1502	0.2267
	(0.808)	(0.474)	(0.314)	(0.184)
L10.MOM	0.1274	0.0638	0.0735	−0.0297
	(0.689)	(0.788)	(0.629)	(0.837)
L11.MOM			−0.0094	0.0092
			(0.944)	(0.962)
L12.MOM			0.0090	−0.1798
			(0.941)	(0.210)
L1.BAB	0.7834	−0.5158	0.0500	0.1742
	(0.411)	(0.244)	(0.804)	(0.521)
L2.BAB	0.3121	−0.2687	−0.2149	−0.3123
	(0.525)	(0.496)	(0.242)	(0.320)
L3.BAB	0.2276	−0.1846	−0.1235	0.2579
	(0.727)	(0.595)	(0.480)	(0.393)
L4.BAB	0.0884	−0.4274	0.2067	0.3364

(*continued on next page*)

Table C1 (*continued*)

	(1)	(2)	(3)	(4)
	CARBON_equal	*CARBON_value*	*ESG_equal*	*ESG_value*
	(0.924)	(0.342)	(0.362)	(0.287)
L5.BAB	−0.8848	−0.6515	−0.0846	0.0865
	(0.245)	(0.192)	(0.791)	(0.848)
L6.BAB	1.0948	0.5677	−0.0188	0.0456
	(0.111)	(0.238)	(0.947)	(0.912)
L7.BAB	−0.2259	−0.1343	0.0360	0.5541
	(0.722)	(0.739)	(0.881)	(0.135)
L8.BAB	0.4201	0.0956	−0.1296	−1.0205*
	(0.642)	(0.836)	(0.649)	(0.059)
L9.BAB	−1.5496**	−0.7740*	−0.3495	−0.3870
	(0.050)	(0.093)	(0.163)	(0.388)
L10.BAB	−0.8475	−0.6812*	0.2579	0.6532*
	(0.179)	(0.090)	(0.322)	(0.072)
L11.BAB			0.0270	0.4906
			(0.891)	(0.250)
L12.BAB			−0.1581	0.1990
			(0.443)	(0.573)
L1.QMJ_GROWTH	−0.6045	−0.1983	−0.1672	−0.4096
	(0.486)	(0.788)	(0.497)	(0.280)
L2.QMJ_GROWTH	−1.0100	0.4091	−0.1704	−0.1773
	(0.346)	(0.514)	(0.537)	(0.610)
L3.QMJ_GROWTH	0.5462	−0.2707	0.4345*	0.7254**
	(0.678)	(0.622)	(0.061)	(0.023)
L4.QMJ_GROWTH	−1.5831	−1.9629**	−0.0871	0.3537
	(0.367)	(0.024)	(0.758)	(0.532)
L5.QMJ_GROWTH	−0.3324	−0.0317	0.0732	0.6951
	(0.772)	(0.965)	(0.794)	(0.202)
L6.QMJ_GROWTH	−0.8879	−0.3999	0.2238	−0.0495
	(0.278)	(0.474)	(0.492)	(0.894)
L7.QMJ_GROWTH	0.6782	1.7257**	0.0702	−0.2321
	(0.488)	(0.034)	(0.820)	(0.558)
L8.QMJ_GROWTH	1.4181	1.1942**	0.1002	−0.1463
	(0.157)	(0.049)	(0.769)	(0.770)
L9.QMJ_GROWTH	−0.0512	−1.6558**	0.2847	−0.3974
	(0.974)	(0.048)	(0.480)	(0.469)
L10.QMJ_GROWTH	−0.4409	1.8671**	0.0269	0.3144
	(0.623)	(0.041)	(0.940)	(0.522)
L11.QMJ_GROWTH			−0.2299	0.2091
			(0.534)	(0.610)
L12.QMJ_GROWTH			−0.0294	−0.8750
			(0.934)	(0.125)
L1.QMJ_SAFETY	0.7038	0.4486	0.1384	−0.1036
	(0.548)	(0.354)	(0.623)	(0.788)
L2.QMJ_SAFETY	−0.3118	−0.8375	0.2424	−0.6207
	(0.744)	(0.176)	(0.434)	(0.168)
L3.QMJ_SAFETY	0.6006	−0.8340	0.1181	−0.5896
	(0.458)	(0.159)	(0.771)	(0.301)
L4.QMJ_SAFETY	−0.3029	0.2024	0.4635	−0.3102
	(0.697)	(0.676)	(0.195)	(0.622)
L5.QMJ_SAFETY	0.2498	0.3734	0.0777	−0.3072
	(0.749)	(0.489)	(0.852)	(0.517)
L6.QMJ_SAFETY	−0.5776	−1.3848**	−0.2598	0.2039
	(0.628)	(0.021)	(0.447)	(0.623)
L7.QMJ_SAFETY	−0.7501	−2.1021**	0.2226	−0.3621
	(0.449)	(0.013)	(0.539)	(0.440)
L8.QMJ_SAFETY	−1.7206*	−0.2727	0.0780	0.6188
	(0.098)	(0.659)	(0.801)	(0.171)
L9.QMJ_SAFETY	0.5888	0.7834*	0.0070	0.1273
	(0.375)	(0.073)	(0.987)	(0.813)
L10.QMJ_SAFETY	1.1217	−0.7823	−0.3602	−0.9831**
	(0.205)	(0.151)	(0.214)	(0.028)
L11.QMJ_SAFETY			0.3138	0.0761
			(0.262)	(0.833)
L12.QMJ_SAFETY			0.2261	0.8342*
			(0.493)	(0.070)
CONSTANT	−0.0152	0.0336**	−0.0087	0.0234
	(0.818)	(0.045)	(0.408)	(0.240)
N lags	10	10	12	12
N obs	108	108	134	134

This table presents the equation (C1) parameter estimates. L. stands for the Lag operator. Factors descriptions are available in Table 1. Coefficients with "*", "**", and "***" are significant at the 10 %, 5 %, and 1 % levels, respectively.

We use the Granger causality tests to detect whether our explanatory factors have predictive power for the *CARBON* and *ESG* factors. The lags of all explanatory factors are jointly tested for significance and the lags of each separate explanatory factor are also jointly tested for significance, while controlling for the lags of the remaining explanatory factors. The Granger causality tests' F-statistics are presented in Table C2. The F-statistics for all explanatory variables in the first row of Table C2 are very similar to the equation F-statistics in the first row of Table C1. The difference is that the lags of the dependent variables are excluded from the joint test for significance but remain as controls in the estimation equation. The lags of all explanatory factors are not jointly statistically significant at the 5 % level in the equations for the *CARBON* and *ESG* factors after controlling for their own lags. Nonetheless, column (2) of Table C2 shows that two factors have jointly significant lags at the 5 % level—*SMB* and *QMJ_SAFETY*, and the market factor has jointly significant lags at the 10 % level. There is some evidence that these factors Granger-cause the value-weighted carbon factor, or equivalently, they have predictive power. However, given the general lack of statistical significance and consistency across equations, the results in column (2) should be interpreted with caution. In particular, the results vary considerably across the equal-weighted and value-weighted carbon factor equations in columns (1) and (2), respectively. Only the size factor is significant at the 10 % level in the former. Such large inconsistencies are not present in Table 4 which focuses on contemporaneous relations.

Table C2
Granger causality of common risk factors on carbon and ESG factors over the period from February 2008 to March 2019.

	(1)	(2)	(3)	(4)
	CARBON_equal	CARBON_value	ESG_equal	ESG_value
ALL	1.9005	2.4057	0.8911	1.1498
	(0.187)	(0.110)	(0.651)	(0.414)
MKT	2.1226	3.0541*	0.7341	0.8643
	(0.165)	(0.076)	(0.700)	(0.597)
SMB	3.3026*	3.7358**	0.5693	1.8729
	(0.063)	(0.047)	(0.831)	(0.138)
HML	1.7819	2.0639	1.2877	1.8749
	(0.228)	(0.174)	(0.328)	(0.138)
RMW	1.5441	1.2783	0.5475	1.0004
	(0.290)	(0.383)	(0.847)	(0.497)
CMA	1.5562	1.6243	0.9456	1.1481
	(0.286)	(0.267)	(0.536)	(0.403)
MOM	1.9059	1.8906	0.5398	0.8444
	(0.202)	(0.205)	(0.853)	(0.612)
BAB	1.9512	1.4295	1.0214	1.2822
	(0.194)	(0.326)	(0.482)	(0.331)
QMJ_GROWTH	2.2965	2.6483	0.7073	2.0496
	(0.141)	(0.105)	(0.722)	(0.107)
QMJ_SAFETY	1.5293	3.9884**	0.8569	1.0134
	(0.294)	(0.040)	(0.602)	(0.488)

This table presents the F-statistics of Granger causality tests based on equation (C1) parameter estimates. Factors descriptions are available in Table 1. Coefficients with "*", "**", and "***" are significant at the 10 %, 5 %, and 1 % levels, respectively.

We also attempt to trace how shocks to each explanatory factor impact the carbon and ESG factors over time by computing impulse-response functions based on our estimated VAR model. The visualization of these functions shows how the numerous delayed impacts captured by the VAR interact with each other over time. The impulse-response functions for *ESG_equal* and *ESG_value* are graphed in Fig. C1 and Fig. C2, respectively.[16] The 95 % confidence intervals in Fig. C1 and Fig. C2 are very wide and contain the value zero over the entire subsequent 24-month period, indicating that impacts of shocks to the explanatory factors on the ESG factor cannot be identified with any reasonable degree of confidence.

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[16] The impulse-response functions for *CARBON_equal* and *CARBON_value* could not be computed, because the relevant matrices are not positive definitive.
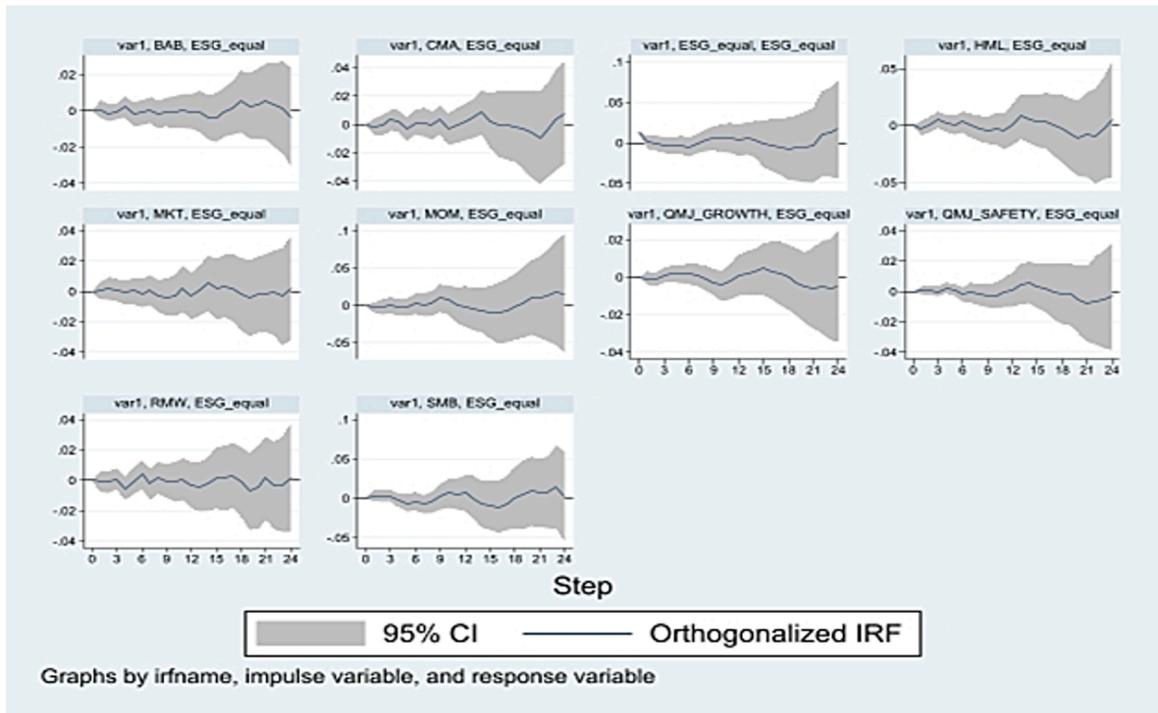
Fig. C1. Impulse-response functions of common risk factors on the equal-weighted ESG factor over the period from February 2008 to March 2019. Description: The impulse-response functions depict how shocks in common risk factors impact the equal-weighted ESG factor and are computed using the VAR model. A separate panel is used for each common risk factor. The relevant factor names are provided above the corresponding panels. The grey areas represent the 95 % confidence intervals.

Fig. C2. Impulse-response functions of common risk factors on the value-weighted ESG factor over the period from February 2008 to March 2019. Description: The impulse-response functions depict how shocks in common risk factors impact the value-weighted ESG factor and are computed using the VAR model. A separate panel is used for each common risk factor. The relevant factor names are provided above the corresponding panels. The grey areas represent the 95 % confidence intervals.
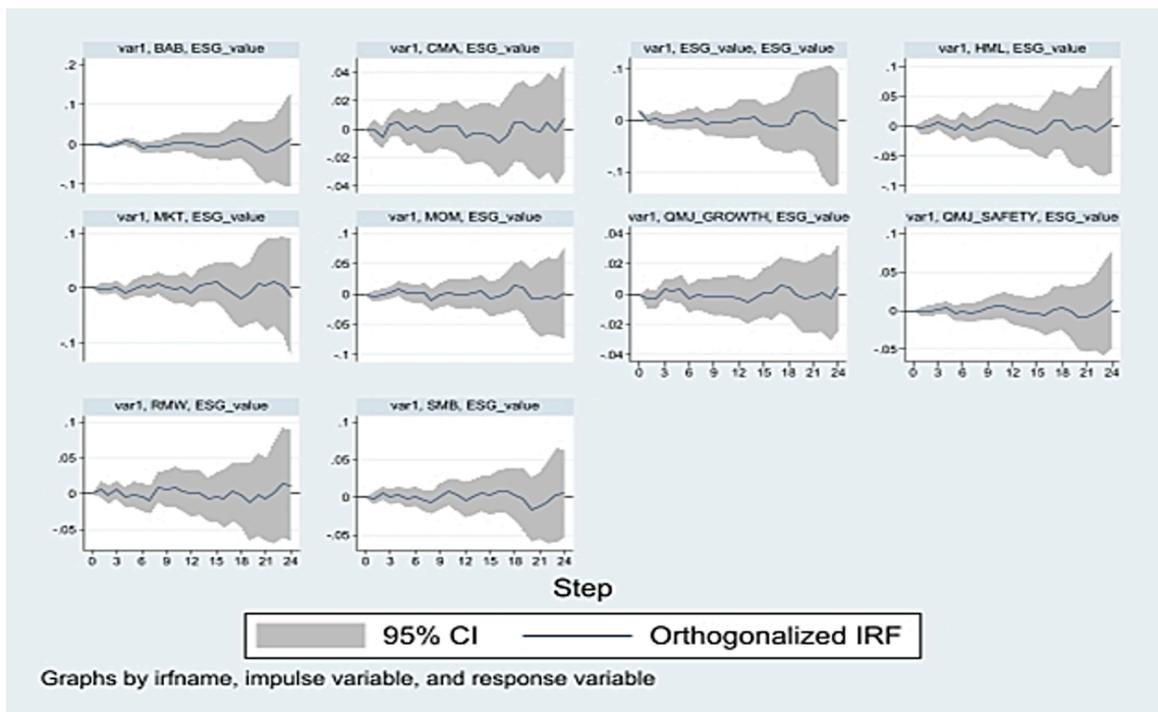
Appendix D:. ESG indexes regressions—additional regressions

Table D1
The factor exposures of RAFI ESG and S&P 500 ESG.

Panel A: Exposures of RAFI ESG and S&P 500 ESG to the *CARBON* and *ESG* factors (Long-short)

	(1) RAFI ESG	(2) S&P 500 ESG
CARBON_value	0.1841***	−0.0102
	(0.000)	(0.573)
ESG_value	−0.0280	0.0652**
	(0.565)	(0.014)
MKT	0.9852***	0.9897***
	(0.000)	(0.000)
SMB	−0.1156***	−0.1216***
	(0.001)	(0.000)
HML	0.1100***	0.0200
	(0.007)	(0.351)
RMW	−0.0198	0.0213
	(0.703)	(0.454)
CMA	0.3008***	0.0833**
	(0.000)	(0.015)
MOM	−0.1242***	0.0079
	(0.000)	(0.584)
BAB	−0.0229	−0.0079
	(0.602)	(0.742)
QMJ_GROWTH	−0.0548	0.0299
	(0.435)	(0.440)
QMJ_SAFETY	0.1099*	0.0312
	(0.053)	(0.316)
CONSTANT	0.0006	0.0002
	(0.439)	(0.568)
N	117	107
Adj R²	0.971	0.991

Panel B: Exposures of RAFI ESG and S&P 500 ESG to the *CARBON* and *ESG* factors (Long only)

	(1) RAFI ESG	(2) RAFI ESG	(3) S&P 500 ESG	(4) S&P 500 ESG
CARBON_value (Long Leg)	0.2138**		0.0609	
	(0.025)		(0.202)	
ESG_value (Long Leg)		0.0846		0.1642***
		(0.412)		(0.001)
MKT	0.7946***	0.9471***	0.9186***	0.8248***
	(0.000)	(0.000)	(0.000)	(0.000)
SMB	−0.1174***	−0.1444***	−0.1210***	−0.1118***
	(0.003)	(0.000)	(0.000)	(0.000)
HML	0.1077**	0.1558***	0.0035	0.0219
	(0.027)	(0.001)	(0.881)	(0.288)
RMW	−0.0703	−0.1142**	0.0528*	0.0221
	(0.199)	(0.044)	(0.060)	(0.405)
CMA	0.2837***	0.2292***	0.0976***	0.0983***
	(0.000)	(0.002)	(0.008)	(0.003)
MOM	−0.1205***	−0.1226***	0.0135	0.0180
	(0.000)	(0.000)	(0.355)	(0.197)
BAB	0.0144	0.0245	−0.0295	−0.0134
	(0.753)	(0.611)	(0.201)	(0.550)
QMJ_GROWTH	−0.0367	−0.0256	0.0368	0.0304
	(0.632)	(0.744)	(0.337)	(0.401)
QMJ_SAFETY	0.1688***	0.1736***	0.0321	0.0265
	(0.007)	(0.007)	(0.297)	(0.364)
CONSTANT	0.0006	0.0006	0.0004	0.0004
	(0.446)	(0.495)	(0.320)	(0.316)
N	117	117	107	107
Adj R²	0.963	0.962	0.990	0.991

This table presents the results of regressions, in which the ESG indexes indicated on top of columns are regressed on the Pedersen *CARBON* and *ESG* factors in Panel A and on their long legs (in separate model specifications to avoid multi-collinearity issues) in Panel B. Only value-weighted carbon and ESG factors are included in the regressions to avoid multi-collinearity issues. Conventional risk factors are added as controls. Factors descriptions are available in Table 1. Coefficients with "*", "***", and "***" are significant at the 10 %, 5 %, and 1 % levels, respectively. P-values are presented in parentheses.

Sample period: July 2009 to March 2019 for the RAFI ESG index in column (1) in Panel A and columns (1) and (2) in Panel B and May 2010 to March 2019 for the S&P 500 ESG index in column (2) in Panel A and columns (3) and (4) in Panel B due to the limited availability of index data.

Table D2
The factor exposures of the iShares MSCI USA ESG Select ETF.

	(1) ESG Select ETF	(2) ESG Select ETF	(3) ESG Select ETF
CARBON_value	−0.0294		
	(0.288)		
CARBON_value (Long Leg)		−0.1071	
		(0.148)	
ESG_value	0.0789*		
	(0.060)		
ESG_value (Long Leg)			0.2727***
			(0.000)
MKT	1.0100***	1.1187***	0.7233***
	(0.000)	(0.000)	(0.000)
SMB	−0.0737***	−0.0976***	−0.0411
	(0.009)	(0.001)	(0.104)
HML	−0.0553	−0.0429	−0.0150
	(0.110)	(0.254)	(0.581)
RMW	0.0120	0.0350	0.0270
	(0.787)	(0.410)	(0.467)
CMA	−0.0611	−0.0908	−0.0687
	(0.269)	(0.120)	(0.137)
MOM	−0.0539**	−0.0521**	−0.0270*
	(0.012)	(0.016)	(0.053)
BAB	−0.0067	−0.0315	−0.0042
	(0.849)	(0.344)	(0.843)
QMJ_GROWTH	−0.1079*	−0.0855	−0.0907**
	(0.074)	(0.152)	(0.014)
QMJ_SAFETY	0.0608	0.0616	0.0307
	(0.213)	(0.199)	(0.402)
CONSTANT	−0.0002	0.0000	0.0003
	(0.783)	(0.987)	(0.561)
N	118	118	146
Adj R2	0.9763	0.9760	0.9816

This table presents the results of regressions, in which the iShares MSCI USA ESG Select ETF indicated on top of the columns is regressed on the Pedersen *CARBON* and *ESG* factors in column (1) and on their long legs in columns (2) and (3). Only value-weighted carbon and ESG factors are included in the regressions to avoid multicollinearity issues. Conventional risk factors are added as controls. Factors descriptions are available in Table 1. Coefficients with "*", "**", and "***" are significant at the 10 %, 5 %, and 1 % levels, respectively. P-values are presented in parentheses. Sample period: June 2009 to March 2019 in columns (1) and (2) and February 2007 to March 2019 in column (3).

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