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The relation between environmental awareness and stock returns☆

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ABSTRACT

We analyze the green stock premium and assess if a measure of global environmental awareness can forecast the returns of stocks listed in the MSCI North America All Cap Index from 2010 to 2019. The E-pillar score of Sustainalytics' ESG rating is used as a proxy for companies' environmental risk. We find that stocks with a higher environmental risk show higher returns and alphas, on average. When environmental awareness among investors increases stock returns decrease, on average. However, stocks of more environmentally friendly companies suffer less during such periods. Therefore, stocks with lower environmental risk reduce the differences in returns and alphas or even show higher returns and alphas than stocks with higher environmental risk.

1. Introduction

Classical asset pricing models are based on the assumption that investors will build their investment decisions by relying only on risk and returns (Brodback et al., 2019). More recent works in the asset pricing literature deviate from this assumption by incorporating that some investors gain utility from investing in more sustainable assets (Barber et al., 2021; Bauer et al., 2021; Goldstein et al., 2022; Li, Watts, & Zhu, 2024; Li et al., 2022), particularly from investing in stocks of environmental-friendly companies. For instance, Ceccarelli et al. (2024) establish that investors value sustainability and the literature provides consensus on investors sustainability preferences (Bauer et al., 2021; Heeb et al., 2023). However, the literature offers mixed results on whether ESG and green investments underperform brown investments. Several authors document that green investments underperform brown ones (Baker et al., 2022; Faccini et al., 2023; Hsu et al., 2023; Seltzer et al., 2022), while others establish a positive association between a firm's ESG profile and its returns (Duan et al., 2021). Further, recent studies show that the premium that investors are willing to pay for environmentally friendly stocks oscillates with the level of climate change concerns among investors, for instance Ardia et al. (2022) and Pástor et al. (2022) find that stock returns react with a delay to climate news (see also Hong et al., 2019). Therefore, it is possible to forecast stock returns with a climate news proxy. However, climate change is not the only material challenge in the environmental dimension.

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Therefore, we widen the focus from investors' awareness regarding climate risk to investors' environmental awareness and answer the question whether a measure of global environmental awareness can forecast stock returns. Specifically, this study aims to answer three main research questions: Is there a positive relation between environmental awareness and stock returns/alphas? Are stock returns expected to be lower after periods of high environmental awareness? Can stocks with lower environmental risk outperform those with higher environmental risk after periods of abnormal increases in environmental awareness?

Our paper makes two important contributions to the literature. First, in contrast to previous studies, we do not use newspaper coverage to proxy for investors' awareness regarding environmental issues (specifically climate change topics in the cases of Ardia et al., 2022; Engle et al., 2020; Gavriilidis, 2021). The rationale is that such newspaper-based proxies are only an indirect measure, which makes the assumption that investors actually pay as much attention to environmental issues as the newspapers do (Da et al., 2011). Instead, we use aggregate Google search frequency as a direct measure of attention, meaning that we can be confident that investors are paying attention to environmental issues when they Google them. Dabbous et al. (2023) develop a measure of the environmental awareness of the population of different countries based on Google search volume, the Environmental Awareness Index (EAI). The EAI is significantly correlated with the pro-environmental behavior of the inhabitants of 18 EU countries and Great Britain. Although Google search volumes reflect the general public's search behavior, Da et al. (2015) and Gao et al. (2020) show that sentiment indices based on Google search volume are significantly related to stock returns. Da et al. (2011) provide strong evidence that Google search volume captures the attention of individuals and trading by retail investors (in particular of less sophisticated retail investors). Therefore, the EAI should serve as a valid proxy for investors' preferences for stocks of environmental-friendly companies.

Second, we widen the focus from stocks with low climate risk to stocks of environmental-friendly companies. Environmental awareness is about more than just climate change. Therefore, we do not analyze the impact of environmental awareness on the green stock premium only, but rather on an environmental stock premium that includes the green stock premium. This is an important contribution since further environmental risks, such as loss of biodiversity (Karolyi & de la Puente, 2023), are also considered material for companies' future earnings, which is why regulators of the EU oblige companies to disclose such risks in the Corporate Sustainability Reporting Directive (CSRD) starting from the financial year 2024.

We use the score associated with the E-pillar of the ESG ratings provided by Sustainalytics to proxy how environmentally friendly companies are (see, e.g., Engle et al., 2020, who also apply the scores of Sustainalytics). The stock sample considered in this study covers all stocks that have been listed in the MSCI North America All Cap Index and that received an ESG rating. We use survivorship-bias-free daily total return and market capitalization data from Thomson Reuters Datastream from the beginning of the year 2010 until the end of the year 2019. For every stock, we compute the monthly return and alpha per month in a Fama and French (2015) five-factor model. The relation between the Abnormal Changes in Environmental Awareness (*AEAI*) and individual stock returns is analyzed with correlation and panel regression analyses. We find that stock returns are lower after periods of high environmental awareness. However, not all stocks suffer equally from lower returns in these times. Stocks with lower environmental risk show relatively higher returns. The relation between *AEAI* and individual stock alphas is less pronounced or insignificant in some model specifications.

In addition to the analysis with individual stock level data, we sort stocks based on their E-pillar score and form quintile portfolios for every month (Horn & Oehler, 2024 for a similar approach with ESG ratings). The focus of this analysis is on the difference between the returns of the fifth quintile portfolio, which includes the stocks with the highest E-pillar score, and the first quintile portfolio, which covers the stocks with the lowest E-pillar score. Further, to examine the fact that environmental awareness varies over time, we run time-varying Granger causality tests (see Baum et al., 2022) on the differences between portfolio returns and alphas of the fifth quintile portfolio and first quintile portfolio and *AEAI*. In addition to the analysis that covers the entire sample period, we also provide regression analyses for the months in which *AEAI* Granger causes the return and alpha differences between the fifth quintile portfolio and the first quintile portfolio. The results indicate higher abnormal returns of stocks with low environmental risk after abnormal increases in environmental awareness.

The paper is organized as follows. Section 2 reviews the literature. Section 3 presents the data and methodology. Section 4 discloses the results while Section 5 presents the discussion. Section 6 concludes and displays the implications of this study.

2. Literature review

The literature that lays forth the theoretical underpinning of the interaction between investor preferences, ESG performance, and asset prices serves as the basis for this research. Many institutional investors as well as retail investors consider ESG aspects as a major objective when performing their portfolio asset allocation. For instance, these investors tilt their portfolios towards more sustainable stocks by avoiding investing in "sin stocks" and stocks of businesses that have a significant negative environmental impact, (Giglio et al., 2021; Oehler et al., 2018; Pedersen et al., 2021; Zerbib, 2022). Several studies model the impact of these preferences. Baker et al. (2018) construct a model in which two categories of investors have mean-variance preferences. Green investments are the preferred option for one type of investor. According to the model outcomes, green assets will have lower anticipated returns and more concentrated ownership. Similarly, asset pricing models by Pástor et al. (2021), Pedersen et al. (2021), and Zerbib (2022) show that investors with a preference for sustainable stocks are willing to pay a premium to hold more sustainable stocks, which leads to lower returns and underperformance of these stocks in the long run compared to less sustainable stocks. Empirical support for the latter is provided by Busch et al. (2022) who show that there is a negative association between environmental performance and financial performance. Bolton and Kacperczyk (2021) measure environmental performance via firms' carbon emission. Yet, the findings are similar and show that firms with higher carbon emissions tend to have higher returns although Aswani et al. (2024) find important constraints for this relation. Given the insights on the relation between sustainability and stock returns and performance by previous studies, our first hypothesis states:

There is a significant positive relation between environmental risk and stock returns/alphas (H1).

In addition to the rather stable general preferences for sustainability, a further factor explaining return differences between more and less environmental-friendly stocks is their different risk exposure. Less environmental-friendly stocks are subject to higher litigation, reputational, and transition risk. Regulation that mitigates negative environmental impact by firms reduce firms' profitability in general. However, the profitability of the least environmental-friendly firms will drop more than that of the most environmental-friendly firms. In times when the perceived probability that the government will adopt strong-regulation regime increases, the latter effect leads to a stronger negative impact on valuations of firms with high environmental risk (Hsu et al., 2023). The perceived probability of rating regime changes can be influenced through many channels. Engle et al. (2020), for example, show that stocks with lower environmental risk outperform high environmental risk stocks in periods characterized by negative news about climate change. According to Choi et al. (2020), abnormally warm weather can point investors' attention to climate risk issues, leading to an underperformance of stocks of carbon-intensive companies. When an unanticipated high number of newspaper articles indicate increasing worries about climate change, stocks of green businesses outperform those of brown enterprises (Ardia et al., 2022). Given the time-varying awareness and pricing of environment-related risks among investors, we propose the following two hypothesis.

On average, stock returns are lower after periods of high environmental awareness (H2).

Stocks with lower environmental risk outperform stocks with higher environmental risk after abnormal increases in environmental awareness (H3).

The paper probably closest related to our study is by El Ouadghiri et al. (2021). The authors show that increasing public attention to climate change and pollution has a positive influence on the weekly returns of US sustainability stock indices. In contrast to El Ouadghiri et al. (2021), we employ daily instead of weekly returns, thousands of individual stocks instead of stock indices, and search volumes of more than 300 keywords (instead of two). The latter ensures a broader measurement of environmental awareness and, therefore, a more complete picture of the different influences that might affect the environmental stock premium.

3. Data and methodology

Dabbous et al. (2023) identify 342 keywords and aggregate the individual Google search volumes of these keywords to construct their EAI. We slightly deviate from the approach of Dabbous et al. (2023) and incorporate methodologies used by Baker and Wurgler (2006) and Da et al. (2015) to compute a winsorized, deseasonalized, and standardized measure. Since we are accounting for seasonal trends, we state that our measure captures Abnormal Changes in Environmental Awareness (*AEAI*). More specifically, we download the monthly search volume index for each keyword from Google Trends for the time period starting in January 2004 and ending in July 2022. Although we focus on North-American stocks, we gather the global search volume since investors from all over the world invest in these stocks. We only use keywords in the English language as this is the dominant language in the financial domain. We then logarithmize the search volume index of each keyword and compute the monthly change as the difference between two monthly observations. This time series is winsorized at the 5 % level (2.5 % in each tail) for each keyword and regressed on month dummies to eliminate seasonal effects. We only keep the residuals of these regressions per month and standardize each of the time series by scaling it by its standard deviation. The values of all keyword time series are summed up for each month to get our *AEAI*.

The environmental performance associated with the stocks in our study is measured with the score of the E-pillar of the ESG ratings provided by Sustainalytics (*Env*) (see Engle et al., 2020, for a similar approach). We apply the ESG ratings based on the methodology before September 2018, i.e. a score of 100 of the E-pillar indicates lowest environmental risk, and a score of 0 indicates highest environmental risk (see Rzeznik et al., 2022 for a detailed description of Sustainalytics' rating approach). To analyze whether abnormal increases (decreases) in environmental awareness are related to higher (lower) returns of stocks with higher (lower) score of the E-pillar, we introduce an interacted variable which is computed as the product of *AEAI* and *Env* (*AEAI_Env*).

Our stock sample covers all stocks that have been listed in the MSCI North America All Cap Index and that received an ESG rating. Since not all stocks received an ESG rating (see Horn, 2023), the analysis covers fewer stocks than those listed in this index. We use survivorship-bias-free daily total return and market capitalization data from Thomson Reuters Datastream from the beginning of the year 2010 until the end of the year 2019. The analysis does not include stock data before the year 2010 because of the low availability of ESG ratings before that time (see Oehler & Horn, 2022). For every stock, we compute the monthly return and alpha per month in a Fama and French (2015) five-factor model. For the computation of the latter, for every month t, daily stock returns are regressed on the daily factor data provided on Kenneth French's homepage.[1] Returns and alphas are winsorized at the 1st and 99th percentiles to minimize the influence of outliers and data errors.

Included control variables are the Media Climate Change Concerns Index (*MCCCI*)[2] (Ardia et al., 2022; Pástor et al., 2022), Climate Policy Uncertainty Index (*CPU*)[3] (Gavriilidis, 2021), Global Economic Policy Uncertainty Index (*GEPU*)[4] (Baker et al., 2016), liquidity risk (*Liq*; see Pástor & Stambaugh, 2003; also referred to as the non-traded liquidity factor to capture innovations in market liquidity and to estimate an asset's liquidity risk, see Pástor & Stambaugh, 2019),[5] investor sentiment (*Sentiment*; see Baker & Wurgler, 2006;

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[2] The data is from https://sentometrics-research.com/download/mccc/. Please note that the MCCCI is only available until June 2018.

[3] The data is from https://www.policyuncertainty.com/climate_uncertainty.html.

[4] The data is from https://www.policyuncertainty.com/global_monthly.html.

[5] The factor data is from Robert Stambaugh's homepage http://finance.wharton.upenn.edu/~stambaug/.

Stambaugh et al., 2012),[6] innovations in volatility risk proxied as changes in the S&P 500 VIX (ΔVIX; see Ang et al., 2006), market capitalization (*Size;* the log market capitalization in million US Dollars), firm age (*Age*; log age defined as the number of years since the first date of trading of the stock; see Cao et al., 2008; Ferreira & Laux, 2007; Pástor & Veronesi, 2003),[7] and industry sectors (*IS*; see Moskowitz & Grinblatt, 1999).

The relation between the *AEAI* and individual stock returns is analyzed with correlation and panel regression analyses. The full regression model is as follows:

$$X_{i,t} = \beta_{1i}{*}AEAI\_Env_{i,t-1} + \beta_{2i}{*}AEAI_{t-1} + \beta_{3i}{*}Env_{i,t-1} + \beta_{4i}{*}MCCCI\_Env_{i,t} + \beta_{5i}{*}MCCCI_t + \sum_{j=6}^{10}\beta_{j,i}{*}Y_{j,t} + \beta_{11i}{*}Size_{i,t} + \beta_{12i}{*}Age_{i,t} + \gamma{*}IS_i + \beta_{0,i} + u_{i,t}, \quad (1)$$

where $X_{i,t}$ is the return of stock i in month t in percent or the five-factor alpha of stock i in month t in per mille in the period from January 2010 to December 2019. $AEAI\_Env_{i,t-1}$ is an interacted variable of the abnormal change in environmental awareness ($AEAI_{t-1}$) in month t-1 and $Env_{i,t-1}$ as the score of the E-pillar of the ESG rating that company i receives from Sustainalytics in month t-1, $MCCCI\_Env_{i,t}$ is an interacted variable of the Media Climate Change Concerns Index ($MCCCI_t$) in month t and $Env_{i,t}$ as the score of the E-pillar of the ESG rating that company i receives from Sustainalytics in month t, $Y_{6,t}$, …, $Y_{10,t}$ are the control variables CPU_t, $GEPU_t$, Liq_t, ΔVIX_t, and $Sentiment_t$. $Size_{i,t}$ is the log market capitalization in million US Dollars of stock i in month t, $Age_{i,t}$ is the log number of years since the first date of trading of stock i in month t, and IS_i is the vector of ten dummy variables to reflect firms' industrial sector.

In addition to the analysis with individual stock level data, we sort stocks based on their E-pillar score and form quintile portfolios for every month (Horn & Oehler, 2024 for a similar approach with ESG ratings). The returns of the stocks are value-weighted with their market capitalization to compute value-weighted portfolio returns. The focus of this analysis is on the difference between the returns of the fifth quintile portfolio, which includes the stocks with the highest E-pillar score, and the first quintile portfolio, which covers the stocks with the lowest E-pillar score. Due to insufficient data/number of observations, the sample period for portfolio analyses starts in March 2010. The full model for the respective OLS regressions is as follows:

$$X_{5thQuint,t} - X_{1stQuint,t} = \beta_{1i}{*}AEAI_{t-1} + \beta_{2i}{*}MCCCI_t + \sum_{j=3}^{7}\beta_{j,i}{*}Y_{j,t} + \beta_{0,i} + \varepsilon_t, \quad (2)$$

where $X_{5thQuint,t}$ is the return in percent or the five-factor alpha in per mille of the fifth quintile portfolio in month t in the period from March 2010 to December 2019, $X_{1stQuint,t}$ is the return in percent or the five-factor alpha in per mille of the first quintile portfolio in month t in the period from March 2010 to December 2019. $Y_{3,t}$, …, $Y_{7,t}$ are the control variables CPU_t, $GEPU_t$, Liq_t, ΔVIX_t, and $Sentiment_t$.

An overview of all variables used in the empirical analysis, along with variables definitions and data sources, is presented in Table 1.

Previous studies show that the perceived importance of environmental issues varies considerably over time (e.g. Ardia et al., 2022); and so does the influence of environmental issues on asset prices (e.g. Ren et al., 2023, see also Cornell, 2021). Hence, we would not exclude the possibility that environmental issues are pushed into the background by other topics in certain periods of time or that environmental issues matter more when they receive a lot of attention, e.g. in times of large climate change conferences or natural disasters. To examine this aspect, we run time-varying Granger causality tests (see Baum et al., 2022) on the differences between portfolio returns and alphas of the fifth quintile portfolio and first quintile portfolio and the *AEAI*. The Granger causality tests are run with the default settings of Baum et al. (2022) (2 lags in the VAR model, 1 lag in the lag-augmented part of the VAR model, rolling window of 20 % of the sample). In addition to the analysis that covers the entire sample period, we also provide regression analyses for the months in which *AEAI* Granger-causes the return and alpha differences between the fifth quintile portfolio and first quintile portfolio with a statistical significance at the ten percent level based on recursive evolving estimation.

Descriptive statistics of the described variables are presented in Table 2. The analyzed time period can be considered a rather bullish one. The MSCI North America All Cap Index more than doubled, the financial crises had ended, and the COVID crash does not yet fall in the period. The mean monthly return of all 94,107 stock-month observations is .89 percent. The mean monthly return of the quintile portfolio covering the stocks with the highest E-pillar scores is 1.41. Our results provide further support for a positive relation between stocks' environmental risk and returns and our first hypothesis (H1). The monthly return of the portfolio of stocks with the lowest E-pillar scores is .21 percentage points higher (1.62 percent). Although the returns of the latter portfolio show a wider distribution (indicating higher risk), the alphas of the portfolio of stocks with the lowest E-pillar scores are higher (.58) than the alphas of the portfolio of stocks with the highest E-pillar scores (.25). Please note that it has been documented in other studies that stocks that receive an ESG rating tend to show slightly positive alphas (see Horn & Oehler, 2024).

Pearson correlations between the stock and portfolio returns and alphas, $AEAI_{t-1}$, $Env_{i,t-1}$, $AEAI\_Env_{i,t-1}$, and the control variables are presented in Table 3. The correlation between individual stocks' return and alpha and $AEAI_{t-1}$, $Env_{i,t-1}$, and $AEAI\_Env_{i,t-1}$ are significant at the one-percent level, yet the coefficients do not exceed .02. Hence, the correlations seem hardly significant in

[6] The factor data is from Jeffrey Wurgler's homepage http://people.stern.nyu.edu/jwurgler/.

[7] According to Pástor and Veronesi (2003) the effect of firm age is very similar when age is measured as 1/(1+age), log(age), or even plain age.

Table 1
Variables.

Variable	Definition	Data source
AEAI	Winsorized, deseasonalized, and standardized measure of abnormal changes in environmental awareness based on the Google search volume of 342 keywords suggested by Dabbous et al. (2023)	Google Trends and own calculations
AEAI_Env	Interacted variable which is computed as the product of AEAI and Env	Google Trends, Sustainalytics, and own calculations
Age	The log of the number of years since the first date of trading of a stock	WRDS and own calculations
CPU	Climate Policy Uncertainty index by Gavriilidis (2021)	https://www.policyuncertainty.com/climate_uncertainty.html
Env	E-pillar score of the ESG ratings provided by Sustainalytics	Sustainalytics
GEPU	Global Economic Policy Uncertainty Index	https://www.policyuncertainty.com/global_monthly.html
IS	Firms' industrial sector according to the MSCI Global Industry Classification Standard (GICS). The sectors are Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities, and Real Estate.	WRDS
Liq	Liquidity risk also referred to as the non-traded liquidity factor to capture innovations in market liquidity and to estimate an asset's liquidity risk, see Pástor and Stambaugh (2019)	http://finance.wharton.upenn.edu/~stambaug/
MCCCI	Media Climate Change Concerns Index developed by Ardia et al. (2022). Please note that we used the original version of the MCCCI which was only available until June 2018.	https://sentometrics-research.com/download/mccc/
MCCCI_Env	Interacted variable which is computed as the product of MCCCI and Env	https://sentometrics-research.com/download/mccc/ , Sustainalytics, and own calculations
Sentiment	Investor sentiment by Baker and Wurgler (2006)	http://people.stern.nyu.edu/jwurgler/
Size	The log market capitalization in million US Dollars	Thomson Reuters Datastream and own calculations
ΔVIX	Monthly percentage change in the S&P 500 VIX	WRDS and own calculations

Table 2
Descriptive statistics.

	Mean	Median	Std. Dev.	Min	Max	N
Panel A: Monthly variables on stock level						
Return	.89	1.00	8.51	−30.40	43.32	94,107
Alpha (five-factor)	.01	.01	.38	−1.68	2.12	94,107
Env	51	49	13	20	100	94,107
AEAI_Env	−14	185	1965	−8930	8540	94,107
Size	8.9	8.9	1.3	3.5	13.9	94,107
Age	3.0	3.1	.8	0	3.8	94,107
Panel B: Variables on a monthly basis						
Return 5th quintile portfolio	1.41	1.89	3.39	−8.56	9.14	118
Return 1st quintile portfolio	1.62	1.99	4.02	−10.4	14.5	118
Alpha 5th quintile portfolio	.25	.26	.66	−1.89	1.72	118
Alpha 1st quintile portfolio	.58	.65	1.16	−3.39	3.20	118
Return difference 5th – 1 st quintile portfolio	−.21	−.32	1.74	−4.84	4.19	118
Alpha difference 5th – 1 st quintile portfolio	−.32	−.36	1.53	−3.83	3.31	118
AEAI	0	6	37	−93	102	118
MCCCI	1.12	1.09	.31	.63	2.10	100
CPU	121	107	53	38	346	118
GEPU	158	147	52	86	315	118
Liq	.02	.02	.04	−.08	.13	118
ΔVIX	16.8	15.5	5.2	10.1	36.5	118
Sentiment	−.08	−.08	.21	−.89	.38	106

magnitude. The correlation coefficients between the return and alpha differences of the fifth quintile portfolio and first quintile portfolio and the $AEAI_{t-1}$ have the expected positive sign and are higher in magnitude (up to .1) but lack statistical significance. However, it is important to note that the latter is based on only 118 observations. Untabulated correlations between $AEAI_{t-1}$, $MCCCI_t$, CPU_t, $GEPU_t$, Liq_t, ΔVIX_t, and $Sentiment_t$ are not significant with three exceptions. CPU_t and $GEPU_t$ are positively correlated with a statistical significance at the one-percent level and a coefficient of .60. $MCCCI_t$ and CPU_t are positively correlated with a statistical significance at the one-percent level and a coefficient of .26. $MCCCI_t$ and ΔVIX_t are negatively correlated with a statistical significance at the one-percent level and a coefficient of −.45.

4. Results

The results of stepwise panel regression analyses based on equation (1) with individual monthly stock returns as the dependent variable are provided in Table 4. The negative coefficient of $AEAI_{t-1}$ in model specifications (1), (3), and (4) shows that stock returns

Table 3
Pearson correlations.

	Individual stocks		Differences between 5th and 1st quintile portfolio	
	Return	Alpha	Return	Alpha
$AEAI\_Env_{i,t-1}$	−.02***	−.01***		
$AEAI_{t-1}$	−.02***	−.02***	.07	.10
$Env_{i,t-1}$	.00	−.01***		
$MCCCI\_Env_{i,t}$	−.01***	−.01**		
$MCCCI_t$	−.02***	−.00	.05	.01
CPU_t	.02***	.01***	.09	.13
$GEPU_t$	−.05***	.01**	.18*	.16
Liq_t	.10***	−.00	−.11	−.01
ΔVIX_t	−.15***	.01*	.09	−.03
$Sentiment_t$	−.03***	−.01*	−.03	−.04
$Size_{i,t}$	.06***	.02***		
$Age_{i,m}$	.00	−.01***		

Notes: We provide Pearson correlation coefficients. The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % level, respectively.

are lower after periods of high environmental awareness. This is support for H2. However, not all stocks suffer equally from lower returns in these times. Stocks with higher E-pillar scores, i.e. lower environmental risk, show relatively higher returns compared to stocks with lower E-pillar scores. The positive coefficient of the respective interacted variable $AEAI\_Env_{i,t-1}$ is significant at the one-percent level in model specifications (1), (3), and (4), providing support for H3. Hence, abnormal changes in environmental awareness have a similar effect to changes in climate change concerns measured by the MCCCI. $MCCCI_t$ also is significantly negatively related to stock returns. However, lower environmental risk mitigates the negative impact on stocks' returns in times of higher climate change concerns and higher environmental awareness. Our results also show that the employed measures of environmental awareness and climate change concerns do not cannibalize each other when employed in the same regression model, i.e., also related, both measures proxy different constructs.

Table 4
Regression results for individual stock returns.

	(1)	(2)	(3)	(4)
$AEAI\_Env_{i,t-1}*10^{-2}$	.017*** (.005)		.018*** (.005)	.015*** (.005)
$AEAI_{t-1}$	−.013*** (.003)		−.021*** (.003)	−.019*** (.003)
$Env_{i,t-1}$	−.016*** (.004)	−.004 (.008)	−.072*** (.009)	−.068*** (.008)
$MCCCI\_Env_{i,t}$		.008 (007)	.031*** (.006)	.036*** (.007)
$MCCCI_t$		−1.01*** (.364)	−4.55*** (.376)	−5.00*** (.381)
CPU_t*10^{-2}			.047 (.069)	.029 (.070)
$GEPU_t$			.012*** (.001)	.009*** (.001)
Liq_t			10.3*** (.72)	7.96*** (.70)
ΔVIX_t			−.308*** (.008)	−.309*** (.008)
$Sentiment_t$			−3.55*** (.145)	−3.03*** (.145)
$Size_{i,t}$			1.93*** (.117)	.508*** (.033)
$Age_{i,t}$			−2.72*** (.243)	−.157*** (.041)
IS_i	No	No	No	Yes
$\beta_{0,i}$	1.72*** (.216)	2.04*** (.425)	1.95* (1.16)	7.41*** (.529)
Effects	Company-Fixed	Company-Fixed	Company-Fixed	Random
N	94,107	87,252	85,289	85,289

Notes: We provide coefficients and robust standard errors (in parentheses) clustered by company for panel regression analysis with the model.

$$X_{i,t} = \beta_{1i}*AEAI_{Env\,i,t-1} + \beta_{2i}*AEAI_{t-1} + \beta_{3i}*Env_{i,t-1} + \beta_{4i}*MCCCI\_ENV_{i,t} + \beta_{5i}*MCCCI_t + \sum_{j=6}^{10}\beta_{j,i}*Y_{j,t} + \beta_{11i}*Size_{i,t} + \beta_{12i}*Age_{i,t} + \gamma*IS_i + \beta_{0,i} + u_{i,t},$$

where $X_{i,t}$ is the return of stock i in month t in percent in the period from January 2010 to December 2019. $AEAI\_Env_{i,t-1}$ is an interacted variable of the abnormal change in environmental awareness ($AEAI_{t-1}$) in month t-1 and $Env_{i,t-1}$ as the score of the E-pillar of the ESG rating that company i receives from Sustainalytics in month t-1, $MCCCI\_Env_{i,t}$ is an interacted variable of the Media Climate Change Concerns Index ($MCCCI_t$) in month t and $Env_{i,t}$ as the score of the E-pillar of the ESG rating that company i receives from Sustainalytics in month t, $Y_{6,t}$, …, $Y_{10,t}$ are the control variables CPU_t, $GEPU_t$, Liq_t, ΔVIX_t, and $Sentiment_t$. $Size_{i,t}$ is the log market capitalization in million US Dollars of stock i in month t, $Age_{i,t}$ is the log number of years since the first date of trading of stock i in month t, and IS_i is vector of ten dummy variables to reflect firms' industrial sector. N is the number of stock-month observations. The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % level, respectively. Coefficients with p-values $\geq$ .10 are not labeled as significant. Example: Regressing the return of stock i in month t on the abnormal change in environmental awareness in month t-1 ($AEAI_{t-1}$) (model (1)) yields a coefficient of −.013 with a p-value of $<$ .01 for this variable.

Table 5
Regression results for individual stock alphas.

	(1)	(2)	(3)	(4)
$AEAI\_Env_{i,t-1}*10^{-2}$	.004* (.002)		.003 (.003)	.003 (.003)
$AEAI_{t-1}$	−.004*** (.001)		−.003** (.001)	−.002 (.001)
$Env_{i,t-1}$	−.005** (.002)	−.014*** (.004)	−.016*** (.004)	−.014*** (.003)
$MCCCI\_Env_{i,t}$		.009*** (003)	.009*** (.003)	.007** (.003)
$MCCCI_t$		−.523*** (.150)	−.630*** (.155)	−.412*** (.149)
CPU_t*10^{-2}			.025 (.038)	−.006 (.046)
$GEPU_t$			.001*** (.000)	.001 (.000)
Liq_t			−.213 (.321)	−.329 (.325)
ΔVIX_t			.006* (.003)	.002 (.003)
$Sentiment_t$			−.265*** (.061)	−.023 (.063)
$Size_{i,t}$			.078*** (.057)	.173*** (.017)
$Age_{i,t}$			−.380*** (.100)	−.072*** (.021)
IS_i	No	No	No	Yes
$\beta_{0,i}$	.357*** (.106)	.892*** (.192)	−5.01*** (.517)	−.446* (.238)
Effects	Company-Fixed	Company-Fixed	Company-Fixed	Random
N	94,104	87,249	85,289	85,289

Notes: We provide coefficients and robust standard errors (in parentheses) clustered by company for panel regression analysis with the model.

$$X_{i,t} = \beta_{1i}*AEAI_{Env\,i,t-1} + \beta_{2i}*AEAI_{t-1} + \beta_{3i}*Env_{i,t-1} + \beta_{4i}*MCCCI\_ENV_{i,t} + \beta_{5i}*MCCCI_t + \sum_{j=6}^{10}\beta_{j,i}*Y_{j,t} + \beta_{11i}*Size_{i,t} + \beta_{12i}*Age_{i,t} + \gamma*IS_i + \beta_{0,i} + u_{i,t},$$

where $X_{i,t}$ is the five-factor alpha of stock i in month t in per mille in the period from January 2010 to December 2019. $AEAI\_Env_{i,t-1}$ is an interacted variable of the abnormal change in environmental awareness ($AEAI_{t-1}$) in month t-1 and $Env_{i,t-1}$ as the score of the E-pillar of the ESG rating that company i receives from Sustainalytics in month t-1, $MCCCI\_Env_{i,t}$ is an interacted variable of the Media Climate Change Concerns Index ($MCCCI_t$) in month t and $Env_{i,t}$ as the score of the E-pillar of the ESG rating that company i receives from Sustainalytics in month t, $Y_{6,t}$, …, $Y_{10,t}$ are the control variables CPU_t, $GEPU_t$, Liq_t, ΔVIX_t, and $Sentiment_t$. $Size_{i,t}$ is the log market capitalization in million US Dollars of stock i in month t, $Age_{i,t}$ is the log number of years since the first date of trading of stock i in month t, and IS_i is a vector of ten dummy variables to reflect firms' industrial sector. N is the number of stock-month observations. The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % level, respectively. Coefficients with p-values ≥ .10 are not labeled as significant. Example: Regressing the alpha of stock i in month t on the abnormal change in environmental awareness in month t-1 ($AEAI_{t-1}$) (model (1)) yields a coefficient of −.004 with a p-value of < .01 for this variable.

Regressions with stock alphas as dependent variable provide further support for H1, since the coefficient of $Env_{i,t-1}$ is negative and significant at the one percent level, i.e. stocks with higher environmental risk (a lower E-pillar score) have higher alphas. The relation between abnormal changes in environmental awareness and individual stock alphas is less pronounced. Respective stepwise panel regression analyses based on equation (1) are provided in Table 5. Without control variables, abnormal changes in environmental awareness are negatively related to alphas with a statistical significance at the one-percent level. With control variables and depending on fixed or random effects model specifications, the coefficient of $AEAI_{t-1}$ stays negative but is only significant at the five-percent level or insignificant. The positive coefficient of the interacted variable $AEAI\_Env_{i,t-1}$ indicates that the alphas of stocks with lower environmental risk decrease less or even increase after periods of rising environmental awareness. Yet, the coefficient is only significant at the ten-percent level when no control variables are employed. With control variables, the statistical significance disappears. Again, the pattern for changes in climate change concerns is similar to the pattern observed for changes in environmental awareness, however, the relation between changes in climate change concerns and stock alphas shows higher levels of statistical significance.

Table 6 displays the results of OLS regression analyses based on equation (2) with the return difference of the portfolio of stocks with the highest E-pillar scores (5th quintile portfolio) and the portfolio of stocks with the lowest E-pillar scores (1st quintile portfolio) as the dependent variable. We do not find a significant relation between abnormal changes in environmental awareness or climate change concerns and the return differences for the entire observation period (see model specifications (1) to (3)).

However, Ardia et al. (2022) and Ren et al. (2023) show that the perceived importance of environmental issues varies considerably over time. Moreover, we are not aware of an asset pricing factor that covers environmental risks entirely and that has a significant systemic influence on asset prices comparable to the Fama and French (2015) factors (see also Cornell, 2021, on this issue). Hence, we follow Ren et al. (2023) and use time-varying Granger causality tests to check when abnormal changes in environmental awareness Granger cause the return difference of the 5th and 1st quintile portfolios. This is the case in the period from June 2015 to September 2016. This period can be linked to an event that is associated with a severe peak in public climate change concerns: the 2015 Paris climate change conference COP 21, which took place from November 30th to December 12th (see Ardia et al., 2022). The key achievement of the conference was an agreement to reduce emissions to limit the global temperature increase to 1.5 °C compared to pre-industrial levels. According to Ardia et al. (2022) the 2009 Copenhagen climate change conference COP 15 (December 7th to December 18th) created a similar shock in climate change concerns than the COP 21. Furthermore, we find large increases in environmental awareness that are triggered by two catastrophes. The explosion of Deepwater Horizon in April 2010 and the nuclear

Table 6
Regression results for quintile portfolio return differences.

	All monthly observations			Monthly observations with significant Granger causality		
	(1)	(2)	(3)	(4)	(5)	(6)
$AEAI_{t-1}$	.003 (.004)		.007 (.005)	.017** (.007)		.018** (.007)
$MCCCI_t$		.243 (.533)	.583 (.629)		.574 (.931)	1.14 (1.00)
CPU_t*10^{-2}			.056 (.514)			1.53 (1.15)
$GEPU_t$			.001 (.000)			.007 (.009)
Liq_t			−2.04 (4.26)			6.78 (7.76)
ΔVIX_t			.049 (.036)			.039 (.057)
$Sentiment_t$			.298 (.885)			.822 (1.10)
$\beta_{0,i}$	−.250 (.167)	−.631 (.624)	−2.02* (1.20)	−.178 (.285)	−.850 (1.06)	−4.77** (2.24)
N	118	100	100	41	41	41

Notes: We provide coefficients and standard errors (in parentheses) for OLS regression analysis with the model.

$$X_{5thQuint,t} - X_{1stQuint,t} = \beta_{1i}{*}AEAI_{t-1} + \beta_{2i}{*}MCCCI_t + \sum_{j=3}^{7}\beta_{j,i}{*}Y_{j,t} + \beta_{0,i} + \varepsilon_t,$$

where $X_{5thQuint,t}$ is the return in percent of the fifth quintile portfolio (containing the stocks with the highest score of the E-pillar) in month t in the period from March 2010 to December 2019, $X_{1stQuint,t}$ is the return in percent of the first quintile portfolio (containing the stocks with the lowest score of the E-pillar) in month t in the period from March 2010 to December 2019. $AEAI_{t-1}$ is the abnormal change in environmental awareness in month t-1, $MCCCI_t$ is the Media Climate Change Concerns Index ($MCCCI_t$) in month t. $Y_{3,t}$, …, $Y_{7,t}$ are the control variables CPU_t, $GEPU_t$, Liq_t, ΔVIX_t, and $Sentiment_t$. N is the number of monthly observations. The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % level, respectively. Coefficients with p-values $\geq$ .10 are not labeled as significant. Example: Regressing the difference between the monthly return of the fifth quintile portfolio and the first quintile portfolio on the abnormal change in environmental awareness in month t-1 ($AEAI_{t-1}$) (model (1)) yields a coefficient of .003 with a p-value of $>$ .10 for this variable.

disaster of Fukushima in March 2011. Due to the rolling windows of the Granger causality tests, however, we do not have test statistics until January 2012. We, therefore, assume that the *AEAI* also Granger causes the return difference of the 5th and 1st quintile portfolios until January 2012. The respective results are presented in Fig. 1, times of significant or assumed Granger causality are represented by

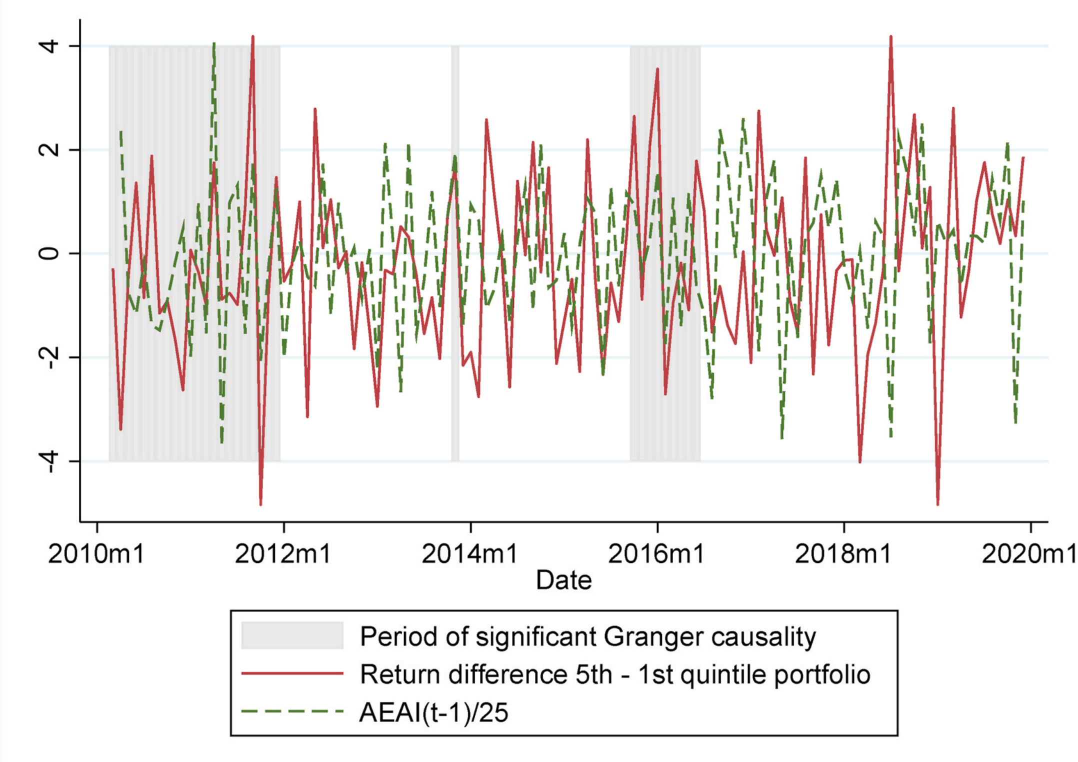

Fig. 1. Time-varying Granger causality $AEAI_{t-1}$ and quintile portfolio return difference.

Table 7
Regression results for quintile portfolio alpha differences.

	All monthly observations			Monthly observations with significant Granger causality		
	(1)	(2)	(3)	(4)	(5)	(6)
$AEAI_{t-1}$	.040 (.040)		.052 (.045)	.104** (.051)		.127** (.048)
$MCCCI_t$		.342 (5.08)	−1.70 (6.00)		2.61 (6.32)	3.33 (5.95)
CPU_t*10^{-2}			2.38 (4.91)			17.8** (6.93)
$GEPU_t$			.051 (.056)			.170*** (.059)
Liq_t			−5.65 (40.6)			78.2* (45.5)
ΔVIX_t			−.079 (.347)			−.723* (.374)
$Sentiment_t$			1.18 (8.44)			2.65 (7.68)
$\beta_{0,i}$	−3.34** (1.52)	−4.06 (5.92)	−10.2 (11.4)	−3.62* (1.81)	−6.40 (6.75)	−35.9*** (11.6)
N	118	100	100	69	69	69

Notes: We provide coefficients and standard errors (in parentheses) for OLS regression analysis with the model.

$$X_{5thQuint,t} - X_{1stQuint,t} = \beta_{1i}{*}AEAI_{t-1} + \beta_{2i}{*}MCCCI_t + \sum_{j=3}^{7}\beta_{j,i}{*}Y_{j,t} + \beta_{0,i} + \varepsilon_t,$$

where $X_{5thQuint,t}$ is the five-factor alpha in per mille of the fifth quintile portfolio (containing the stocks with the highest score of the E-pillar) in month t in the period from March 2010 to December 2019, $X_{1stQuint,t}$ is the five-factor alpha in per mille of the first quintile portfolio (containing the stocks with the lowest score of the E-pillar) in month t in the period from March 2010 to December 2019. $AEAI_{t-1}$ is the abnormal change in environmental awareness in month t-1, $MCCCI_t$ is the Media Climate Change Concerns Index ($MCCCI_t$) in month t. $Y_{3,t}$, …, $Y_{7,t}$ are the control variables CPU_t, $GEPU_t$, Liq_t, ΔVIX_t, and $Sentiment_t$. N is the number of monthly observations. The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % level, respectively. Coefficients with p-values $\geq$ .10 are not labeled as significant. Example: Regressing the difference between the alpha of the fifth quintile portfolio and the first quintile portfolio on the abnormal change in environmental awareness in month t-1 ($AEAI_{t-1}$) (model (1)) yields a coefficient of .040 with a p-value of $>$ .10 for this variable.

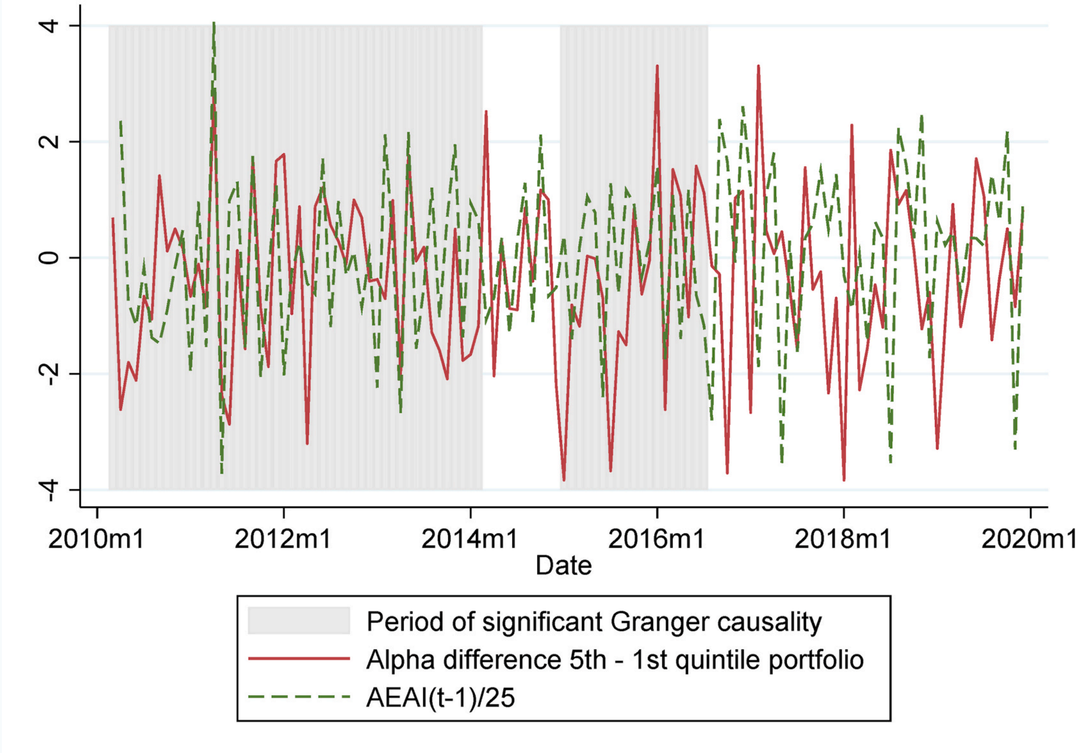

Fig. 2. Time-varying Granger causality $AEAI_{t-1}$ and quintile portfolio alpha difference.

Table 8
Regression results for alpha of 5th and 1st quintile portfolios from March 2010 to February 2014 and from October 2014 to August 2016.

	Alpha of 5th quintile portfolio			Alpha of 1st quintile portfolio		
	(1)	(2)	(3)	(4)	(5)	(6)
$AEAI_{t-1}$	.038 (.024)		.047** (.023)	−.065* (.039)		−.078** (.038)
$MCCCI_t$		−.948 (2.97)	−.041 (2.88)		−3.56 (4.71)	−3.35 (4.65)
CPU_t*10^{-2}			3.13 (3.36)			−14.5*** (5.41)
$GEPU_t$			.101*** (.028)			−.070 (.046)
Liq_t			13.7 (22.0)			−63.4* (35.5)
ΔVIX_t			−.245 (.181)			.483 (.292)
$Sentiment_t$			−1.30 (3.72)			−3.64 (6.00)
$\beta_{0,i}$	2.10** (.861)	3.04 (3.17)	−10.5* (5.95)	5.82*** (1.37)	9.54 (5.03)	24.9** (9.60)
N	69	69	69	69	69	69

Notes: We provide coefficients and standard errors (in parentheses) for OLS regression analysis with the model.

$$\alpha_{Quint,t} = \beta_{1i}*AEAI_{t-1} + \beta_{2i}*MCCCI_t + \sum_{j=3}^{7}\beta_{j,i}*Y_{j,t} + \beta_{0,i} + \varepsilon_t.$$

where $\alpha_{5Quint,t}$ is the five-factor alpha in per mille of the fifth quintile portfolio (containing the stocks with the highest score of the E-pillar) or the five-factor alpha in per mille of the first quintile portfolio (containing the stocks with the lowest score of the E-pillar) in month t in the periods from March 2010 to February 2014 and from October 2014 to August 2016. $AEAI_{t-1}$ is the abnormal change in environmental awareness in month t-1, $MCCCI_t$ is the Media Climate Change Concerns Index ($MCCCI_t$) in month t. $Y_{3,t}, \ldots, Y_{7,t}$ are the control variables CPU_t, $GEPU_t$, Liq_t, ΔVIX_t, and $Sentiment_t$. N is the number of monthly observations. The symbols ***, **, and * denote significance at the 1 %, 5 %, and 10 % level, respectively. Coefficients with p-values $\geq$ .10 are not labeled as significant. Example: Regressing the five-factor alpha in per mille of the fifth quintile portfolio on the abnormal change in environmental awareness in month t-1 ($AEAI_{t-1}$) (model (3)) yields a coefficient of .047 with a p-value of < .05 for this variable.

the grey-shaded areas of the graph.

We re-run the regression analyses based on equation (2) for the 41 months in which we found or assume a Granger causality. In line with H3, regression results presented in Table 6, model specifications (4) and (6), show a positive relation between $AEAI_{t-1}$ and the return difference of the 5th and 1st quintile portfolios with a statistical significance at the five-percent level. I.e., in times surrounding major climate change conferences and natural disasters, abnormal changes in environmental awareness are more positive for returns of stocks with higher E-pillar scores. Interestingly, we do not observe a similar statistically significant relation between abnormal changes in climate change concerns and the return difference of the 5th and 1st quintile portfolios in these time periods.

Similar to the return differences, differences in alphas between the 5th and 1st quintile portfolios are not significantly related to abnormal changes in environmental awareness or climate change concerns over the full sample period (see Table 7, model specifications (1) to (3)). However, *AEAI* Granger causes the alpha differences around the Paris Agreement from June 2015 to September 2016. Furthermore, we find a significant Granger causality from January 2012 to February 2014. The latter time period surrounds the 2012 United Nations Climate Change Conference COP 18 (November 26th to December 8th), at which the Kyoto Protocol has been extended until 2020. We, again, assume that alpha differences between the 5th and 1st quintile portfolios are also Granger caused by *AEAI* until January 2012 – although we cannot test this assumption. Fig. 2 indicates the 69 months with significant or assumed Granger causality as grey-shaded areas.

According to regression results presented in Table 7, model specifications (4) and (6), there is a positive relation between $AEAI_{t-1}$ and the alpha difference of the 5th and 1st quintile portfolios with a statistical significance at the five-percent level. This further supports H3. In addition, we find a positive relation between the alpha difference and climate policy uncertainty (*CPU*) as well as global economic policy uncertainty (*GEPU*). These results indicate that when environmental awareness, climate policy uncertainty, and global economic policy uncertainty increase, the alphas of stocks of companies with higher E-pillar scores, i.e. lower environmental risk, decrease less or increase more than the alphas of stocks of companies with lower E-pillar scores – however only in times of major climate change conferences or natural disasters.

To better understand whether the positive relation between $AEAI_{t-1}$ and the alpha difference of the 5th and 1st quintile portfolios is caused by an appreciation of the rather environmental-friendly stocks in the 5th quintile portfolio and/or a depreciation of the stocks with high environmental risk in the 1st quintile portfolio, we run further OLS regression analyses with the alphas of the two portfolios as dependent variables. These OLS regressions only cover the 69 months with significant or assumed Granger causality as highlighted in Fig. 2. During these months, the 5th quintile portfolio has a mean alpha of .23 percent while the 1st quintile portfolio has a mean alpha of .55 percent. Hence, the mean alphas in these 69 months are almost equal to the mean alphas during the entire observation period. The results of the respective OLS regressions are presented in Table 8.

Results for the full regression models, i.e. model specifications (3) and (6) in Table 8, show a positive relation between $AEAI_{t-1}$ and the alpha of the 5th quintile portfolio and a negative relation between $AEAI_{t-1}$ and the alpha of the 1st quintile portfolio. Hence, after abnormal increases in environmental awareness, stocks with low environmental risk show higher abnormal returns than in times after decreases in environmental awareness. The relation goes in the opposite direction for stocks with high environmental risk. The latter stocks suffer from lower alphas after abnormal increases in environmental awareness compared to times after decreases in environmental awareness. Furthermore, policy uncertainty is significantly related to stock alphas. We find a positive relation between global economic policy uncertainty and the alphas of the 5th quintile portfolio. Moreover, we find a negative relation between climate policy uncertainty and the alpha of the 1st quintile portfolio, i.e. stocks with higher environmental risk suffer in times of higher climate policy uncertainty due to the risk of negative impacts by new (stricter) climate-related laws.

5. Discussion, limitations, and future research venues

We find a statistically significant relation between $AEAI_{t-1}$ and individual stock returns. Stocks with higher E-pillar score reduce the return difference or show even higher returns than stocks with lower E-pillar score after environmental awareness spikes. A statistically significant relation between the returns and alphas of portfolios containing stocks with the highest or lowest E-pillar scores and $AEAI_{t-1}$ is only found for times surrounding major climate change conferences and natural disasters. During these times and when environmental awareness spikes, the portfolio of stocks with the highest E-pillar scores reduces the return and alpha difference or shows even higher returns and alphas than the portfolio of stocks with the lowest E-pillar score. However, it has to be considered that these results are based on less than 100 months of data. Hence, further studies should try to replicate the results when more data points are available.

Our results support several previous findings. First, in line with Pástor et al. (2021, 2022), Pedersen et al. (2021), and Zerbib (2022) we find that, on average, individual stocks with a higher E-pillar score show lower returns and alphas (H1). This can be explained by investors' preferences for green stocks and stocks with high ESG ratings. Second, when climate change concerns rise unexpectedly, stock returns are lower (H2) and stocks with higher E-pillar score reduce the differences in returns and alphas or show even higher returns and alphas than stocks with lower E-pillar score (H3) (see Ardia et al., 2022; Pástor et al., 2021). Third, we do not find an asset pricing factor capturing environmental risk that is consistently and permanently significant for the cross-section of stock returns (see also Cornell, 2021). Instead, we find that environmental issues matter from time to time for the cross-section of stock returns. But when environmental issues matter, then in a predictable way, i.e. stocks with higher environmental risk suffer more than stocks with lower environmental risk when climate policy uncertainty is higher and when climate change concerns increase (Ardia et al., 2022; Ren et al., 2023).

We introduce a new measure of abnormal changes in environmental awareness (*AEAI*) and apply it to stock returns. The measure is uncorrelated with existing measures of environmental issues like the MCCCI of Ardia et al. (2022) or the CPU index by Gavriilidis (2021). The *AEAI* is based on Google search traffic. We assume that, in absolute numbers, many more retail investors than institutional investors use Google search. Hence, the *AEAI* can be considered a measure of abnormal changes in retail investors' environmental awareness. Our paper only shows a statistically significant relation between the *AEAI* and stock returns and alphas. However, we cannot prove how, and if so, through which channels this relation exactly works. A reasonable explanation would be that increases in retail investors' environmental awareness drive them to rather invest in environmental-friendly stocks (see, e.g., Benuzzi et al., 2024 for the relevance of the E-pillar to retail investors). Retail investors could directly invest in these stocks or via mutual funds and ETFs. This could lead to buy pressure and hence, increase prices of stocks with high E-pillar scores. As retail investors first have to gather information on which stocks/funds to invest in, this could also explain why the stock returns are related to the *AEAI* of the previous month. However, findings by Moss et al. (2024) that traders on Robinhood do not considerably react to ESG press releases speak against this explanation. Moreover, the households with the strongest pro-environmental values, i.e. households that probably drive a considerable part of the *AEAI*, maybe not even engage in the stock market (Anderson & David, 2022). A further explanation could be that (retail) investors adopt their price targets as a consequence of raising environmental awareness and expected buy pressure and/or expected changes in the policies on environmental issues. We do not have the data to analyze these possible explanations, but our study is a starting point for further research on these issues.

We consider it a limitation of our study that we use the E-pillar score of only one rating provider. Previous studies document considerable rating disagreement (Berg et al., 2021, 2022; Billio et al., 2021; Gibson et al., 2021; Kotsantonis & Serafeim, 2019; Oehler & Horn, 2022), which could lead to different results since E-pillar scores are subject to some controversies, e.g. whether nuclear power generation is environmentally friendly or not (Edmans, 2023; Oehler et al., 2018). Moreover, Horn and Oehler (2024), Liang and Renneboog (2017), and Oehler and Horn (2022) document strong differences across countries and geographic regions in terms of ESG risk at the firm level and the relation between ESG ratings and stock returns and alphas. Hence, we call for further studies that analyze the relationships identified in this analysis in other geographic regions.

6. Conclusion and implications

Our study answers the question whether a measure of global environmental awareness can forecast stock returns. Based on previous studies, we derive three hypotheses. First, that there is a significant positive relation between environmental risk and stock returns/alphas (H1), since investors are willing to pay a premium to hold more sustainable stocks (i.e. the green stock premium). Second, on average, stock returns are lower after periods of high environmental awareness (H2), e.g., because investors expect strong-regulation regimes. Third, stocks with lower environmental risk outperform stocks with higher environmental risk after abnormal increases in environmental awareness (H3) since the latter would suffer from a stronger negative impact on their valuations of firms in strong-regulation regimes.

Our results are in line with those hypotheses. First, on average, individual stocks with a higher E-pillar score show lower returns and alphas. Second, stock returns are lower after periods of high environmental awareness. Third, when climate change concerns rise unexpectedly, stocks with higher E-pillar score reduce the differences in returns and alphas or show even higher returns and alphas than stocks with lower E-pillar score. Fourth, the analysis conducted could not depict an asset pricing factor capturing environmental risk that is consistently and permanently significant for the cross-section of stock returns. Rather the results show that environmental issues matter from time to time for the cross-section of stock returns.

This study extends the existing body of knowledge considerably. Previous studies used indirect measures such as newspaper coverage to proxy for investors' climate change concerns or the uncertainty regarding climate policies (Ardia et al., 2022; Engle et al., 2020; Gavriilidis, 2021) and then use these proxies to explain the temporary outperformance of green stocks. In contrast, we use a measure of the environmental awareness of the global population based on Google search volume. This stems from our belief that environmental awareness is about more than just climate change. The index developed by Dabbous et al. (2023) is considered a direct measure of public environmental awareness. Further, this analysis considers all aspects of the E-pillar in "ESG" to assess the stock's environmental performance.

The results of this study have important implications for researchers and practitioners. First, they demonstrate that environmental awareness and the perceived importance of environmental issues are not constant over time and their impact on stock returns also varies. This underlines the fact that using recent returns to predict future expected returns could be misleading particularly since the outperformance of assets with high environmental performance during periods of high environmental attention does not suggest that higher returns for this type of stock will continue for future periods. Further, during periods characterized by higher environmental awareness, in general occurring in times of high climate change concerns, natural disasters, or higher climate policy uncertainty, firms with the high environmental risk associated with lower E-pillar scores would expect a higher decrease in their returns relative to those with lower environmental risks and as such, they are advised to start adopting strategies that help to enhance their ESG rating score. An important message for practitioners is, therefore, that environmental awareness matters for stock returns and it becomes essential to account for it when calculating returns or environmental premiums. The results would also be of particular interest to ESG investors. The results confirm that this type of investment is considered a better hedge against environmental risks associated with periods of higher environmental awareness since it provides investors with higher returns during these periods.

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.

References

Anderson, Anders, & David, T. Robinson (2022). *Financial Literacy in the Age of Green Investment. Review of Finance, 26*(6), 1551–1584. https://doi.org/10.1093/rof/rfab031.
Ang, A., Hodrick, R. J., Xing, Y., & Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance, 61*(1), 259–299. https://doi.org/10.1111/j.1540-6261.2006.00836.x
Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2022). Climate change concerns and the performance of green vs. brown stocks. *Management Science, 69*(12), 7607–7632. https://doi.org/10.1287/mnsc.2022.4636
Aswani, J., Raghunandan, A., & Rajgopal, S. (2024). Are carbon emissions associated with stock returns? *Review of Finance, 28*(1), 75–106. https://doi.org/10.1093/rof/rfad013
Baker, M., Bergstresser, D., Serafeim, G., & Wurgler, J. (2018). *Financing the response to climate change: The pricing and ownership of US green bonds (working paper no. w25194)*. National Bureau of Economic Research. https://ssrn.com/abstract=3274420.
Baker, M., Bergstresser, D., Serafeim, G., & Wurgler, J. (2022). The pricing and ownership of US green bonds. *Annual review of financial economics, 14*(1), 415–437. https://doi.org/10.1146/annurev-financial-111620-014802
Baker, S., Bloom, N., & Davis, S. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics, 131*(4), 1593–1636. https://doi.org/10.1093/qje/qjw024
Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance, 61*(4), 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x
Barber, B. M., Morse, A., & Yasuda, A. (2021). Impact investing. *Journal of Financial Economics, 139*(1), 162–185. https://doi.org/10.1016/j.jfineco.2020.07.008
Bauer, R., Ruof, T., & Smeets, P. (2021). Get real! individuals prefer more sustainable investments. *Review of Financial Studies, 34*(8), 3976–4043. https://doi.org/10.1093/rfs/hhab037
Baum, C. F., Hurn, S., & Otero, J. (2022). Testing for time-varying granger causality. *STATA Journal, 22*(2), 355–378. https://doi.org/10.1177/1536867X221106403
Benuzzi, M., Klaser, K., & Bax, K. (2024). Which ESG+F dimension matters Most to private investors? An experimental study on financial decisions and future generations. *J. Behav. Exp. Finance, 41*, Article 100882. https://doi.org/10.1016/j.jbef.2023.100882
Berg, F., Koelbel, J., Pavlova, A., & Rigobon, R. (2021). *ESG confusion and stock returns: Tackling the problem of noise*. National Bureau of Economic Research. Working Paper No. w30562) https://www.nber.org/papers/w30562.
Berg, F., Koelbel, J., & Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. *Review of Finance, 26*(6), 1315–1344. https://doi.org/10.1093/rof/rfac033
Billio, M., Costola, M., Hristova, I., Latino, C., & Pelizzon, L. (2021). Inside the ESG ratings: (dis)agreement and performance. *Corporate Social Responsibility and Environmental Management, 28*(5), 1426–1445. https://doi.org/10.1002/csr.2177
Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics, 142*(2), 517–549. https://doi.org/10.1016/j.jfineco.2021.05.008
Brodback, D., Guenster, N., & Mezger, D. (2019). Altruism and egoism in investment decisions. *Review of Financial Economics, 37*(1), 118–148. https://doi.org/10.1002/rfe.1053
Busch, T., Bassen, A., Lewandowski, S., & Sump, F. (2022). Corporate carbon and financial performance revisited. *Organization & Environment, 35*(1), 154–171. https://doi.org/10.1177/1086026620935638
Cao, C., Simin, T., & Zhao, J. (2008). Can growth options explain the trend in idiosyncratic risk? *Review of Financial Studies, 21*(6), 2599–2633. https://doi.org/10.1093/rfs/hhl039
Ceccarelli, M., Ramelli, S., & Wagner, A. F. (2024). Low carbon mutual funds. *Review of Finance, 28*(1), 45–74. https://doi.org/10.1093/rof/rfad015
Choi, D., Gao, Z., & Jiang, W. (2020). Attention to global warming. *Review of Financial Studies, 33*(3), 1112–1145. https://doi.org/10.1093/rfs/hhz086
Cornell, B. (2021). ESG preferences, risk and return. *European Financial Management, 27*(1), 12–19. https://doi.org/10.1111/eufm.12295
Da, Z., Engelberg, J., & Gao, P. (2011). In search of attention. *The Journal of Finance, 66*(5), 1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x
Da, Z., Engelberg, J., & Gao, P. (2015). The sum of all FEARS investor sentiment and asset prices. *Review of Financial Studies, 28*(1), 1–32. https://doi.org/10.1093/rfs/hhu072

Dabbous, A., Horn, M., & Croutzet, A. (2023). Measuring environmental awareness: An analysis using google search data. *Journal of Environmental Management, 346*, Article 118984. https://doi.org/10.1016/j.jenvman.2023.118984

Duan, T., Li, F. W., & Wen, Q. (2021). Is carbon risk priced in the cross section of corporate bond returns? *Journal of Financial and Quantitative Analysis*, 1–35. https://doi.org/10.1017/S0022109023000832

Edmans, A. (2023). The end of ESG. *Financial Management, 52*(1), 3–17. https://doi.org/10.1111/fima.12413

El Ouadghiri, I., Guesmi, K., Peillex, J., & Ziegler, A. (2021). Public attention to environmental issues and stock market returns. *Ecological Economy, 180*, Article 106836. https://doi.org/10.1016/j.ecolecon.2020.106836

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *Review of Financial Studies, 33*(3), 1184–1216. https://doi.org/10.1093/rfs/hhz072

Faccini, R., Matin, R., & Skiadopoulos, G. (2023). Dissecting climate risks: Are they reflected in stock prices? *Journal of Banking & Finance, 155*, Article 106948. https://doi.org/10.1016/j.jbankfin.2023.106948

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1), 1–22. https://doi.org/10.1016/j.jfineco.2014.10.010

Ferreira, M., & Laux, P. (2007). Corporate governance, idiosyncratic risk, and information flow. *The Journal of Finance, 62*(2), 951–989. https://doi.org/10.1111/j.1540-6261.2007.01228.x

Gao, Z., Ren, H., & Zhang, B. (2020). Googling investor sentiment around the world. *Journal of Financial and Quantitative Analysis, 55*(2), 549–580. https://doi.org/10.1017/S0022109019000061

Gavriilidis, K. (2021). Measuring climate policy uncertainty (Working Paper) https://dx.doi.org/10.2139/ssrn.3847388.

Gibson, R., Krueger, P., & Schmidt, P. (2021). ESG rating disagreement and stock returns. *Financial Analysts Journal, 77*(4), 104–127. https://doi.org/10.1080/0015198X.2021.1963186

Giglio, S., Kelly, B. T., & Stroebel, J. (2021). Climate finance. *Annu. Rev. Financ. Econ., 13*, 15–36. https://doi.org/10.1146/annurev-financial-102620-103311

Goldstein, I., Kopytov, A., Shen, L., & Xiang, H. (2022). *On ESG investing: Heterogeneous preferences, information, and asset prices*. National Bureau of Economic Research. Working Paper No. w29839) http://www.nber.org/papers/w29839.

Heeb, F., Kölbel, J. F., Paetzold, F., & Zeisberger, S. (2023). Do investors care about impact? *Review of Financial Studies, 36*(5), 1737–1787. https://doi.org/10.1093/rfs/hhac066

Hong, H., Li, F., & Xu, J. (2019). Climate risks and market efficiency. *Journal of Econometrics, 208*, 265–281. https://doi.org/10.1016/j.jeconom.2018.09.015

Horn, M. (2023). The influence of ESG ratings on idiosyncratic stock risk: The unrated, the good, the bad, and the sinners. *Schmalenbach J. Bus. Res., 75*, 415–442. https://doi.org/10.1007/s41471-023-00155-1

Horn, M., & Oehler, A. (2024). Constructing stock portfolios by sorting on ESG ratings: Does the rating provider matter? Internat. *Rev. Financ. Anal., 96*, Article 103568. https://doi.org/10.1016/j.irfa.2024.103568

Hsu, P. H., Li, K., & Tsou, C. Y. (2023). The pollution premium. *The Journal of Finance, 78*(3), 1343–1392. https://doi.org/10.1111/jofi.13217

Karolyi, G. A., & de la Puente, J. T. (2023). Biodiversity finance: A call for research into financing nature. *Financial Management, 52*(2), 231–251. https://doi.org/10.1111/fima.12417

Kotsantonis, S., & Serafeim, G. (2019). Four things no one will tell you about ESG data. *J. Appl. Corp. Finance, 31*(2), 50–58. https://doi.org/10.1111/jacf.12346

Li, Q., Watts, E., & Zhu, C. (2024). Retail investors and ESG news (working paper). *Jacobs Levy Equity Management Center for Quantitative Financial Research*. https://doi.org/10.2139/ssrn.4384675

Li, S., Ruan, H., Titman, S., & Xiang, H. (2022). ESG spillovers (Working Paper) https://doi.org/10.2139/ssrn.4099947.

Liang, H., & Renneboog, L. (2017). On the foundations of corporate social responsibility. *The Journal of Finance, 72*(2), 853–910. https://doi.org/10.1111/jofi.12487

Moskowitz, T. J., & Grinblatt, M. (1999). Do industries explain momentum? *The Journal of Finance, 54*(4), 1249–1290. https://doi.org/10.1111/0022-1082.00146

Moss, A., Naughton, J., & Wang, C. (2024). The irrelevance of environmental, social, and governance disclosure to retail investors. *Management Science, 70*(4), 2023–2704. https://doi.org/10.1287/mnsc.2023.4822

Oehler, A., & Horn, M. (2022). Contemporaneous ESG ratings and idiosyncratic stock risk: Empirical evidence on measures of market consensus and dispersion (working paper). *Chair of finance*. Bamberg University.

Oehler, A., Horn, M., & Wendt, S. (2018). Why self-commitment is not enough: On a regulated minimum standard for ecologically and socially responsible financial products and services. In T. Walker, S. D. Kibsey, & R. Crichton (Eds.), *Designing a sustainable financial system: Development goals and socio-ecological responsibility* (pp. 405–421). Cham: Palgrave Macmillan. https://doi.org/10.1007/978-3-319-66387-6_15.

Pástor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111*, 642–685. https://doi.org/10.1086/374184

Pástor, L., & Stambaugh, R. F. (2019). Liquidity risk after 20 years. *Chicago Booth Research Paper No.*. https://doi.org/10.2139/ssrn.3371948, 19–13.

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics, 142*(2), 550–571. https://doi.org/10.1016/j.jfineco.2020.12.011

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics, 146*(2), 403–424. https://doi.org/10.1016/j.jfineco.2022.07.007

Pástor, L., & Veronesi, P. (2003). Stock valuation and learning about profitability. *The Journal of Finance, 58*(5), 1749–1789. https://doi.org/10.1111/1540-6261.00587

Pedersen, L. H., Fitzgibbons, S., & Pomorski, L. (2021). Responsible investing: The ESG-Efficient frontier. *Journal of Financial Economics, 142*(2), 572–597. https://doi.org/10.1016/j.jfineco.2020.11.001

Ren, X., Li, J., He, F., & Lucey, B. (2023). Impact of climate policy uncertainty on traditional energy and green markets: Evidence from time-varying granger tests. *Renewable & Sustainable Energy Reviews, 173*, Article 113058. https://doi.org/10.1016/j.rser.2022.113058

Rzeznik, A., Hanley, K., & Pelizzon, L. (2022). *Investor reliance on ESG ratings and stock price performance (working paper no. 310)*. Sustainable Architecture for Finance in Europe (SAFE). https://doi.org/10.2139/ssrn.3801703

Seltzer, L. H., Starks, L., & Zhu, Q. (2022). *Climate regulatory risk and corporate bonds (no. w29994)*. National Bureau of Economic Research. https://www.nber.org/papers/w29994.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it: Investor sentiment and anomalies. *Journal of Financial Economics, 104*, 288–302. https://doi.org/10.1016/j.jfineco.2011.12.001

Zerbib, O. (2022). A sustainable capital asset pricing model (S-CAPM): Evidence from green investing and sin stock exclusion. *Review of Finance, 26*(6), 1345–1388. https://doi.org/10.1093/rof/rfac045