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Transition versus physical climate risk pricing in euro area financial markets: A text-based approach[1]

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Transition versus physical climate risk pricing in European financial markets: A text-based approach

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Abstract

We examine the existence of physical and transition climate risk premia in euro area equity markets. To do so, we develop two novel physical and transition risk indicators, based on text analysis, which are then used to gauge the presence of climate risk premia. Results suggest that climate risk premia for both, transition and physical climate risk, have increased since the time of the Paris Agreement. In addition, we investigate which metrics may be used by investors to proxy a firm's exposure to either physical or transition risk. To this end, we construct portfolios according to the most common firm-specific climate metrics and estimate the sensitivity of these portfolios to our risk indicators. We compare results from these firm-level proxies to much simpler sectoral classifications to see if investors may simply pigeonhole firms into the industry they operate in. We find that firm level information appears to be used as a gauge for transition risk, in particular since 2015, whereas sectoral classifications appear insufficient. However, sectoral classification may be employed to broadly gauge firms' exposures to physical risk.

Keywords: Climate risk premia, Transition risk, Physical risk, Text analysis

JEL Classification: C58, G12, G14, G28, Q51

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Introduction

As climate change progresses, investors are increasingly reported to reflect climate-related risks in firms' valuations. While this observation may seem obvious in light of the overarching evidence which shows that climate change and the measures taken to combat it represent a source of financial risk, documenting climate risk pricing or the presence of climate risk premia is not trivial - as demonstrated by conflicting results throughout the green finance literature (Bolton & Kacperczyk, 2021a; In et al., 2019; Alessi et al., 2019; Hsu et al., 2020; Pastor et al., 2021b). Several factors might impede investors from allocating capital to firms which serve as a hedge from climate change; for example the lack of agreed-upon metrics for firms' exposure to climate-related risks, alongside the difficulty of identifying and measuring climate risk events over time (Engle et al., 2020). It follows that investors might not be able to easily screen exposed firms, failing to detect climate risky investments (Bolton & Kacperczyk, 2021b). In contrast, there is the possibility that market participants are insensitive to shocks in climate change, which would suggest that they do not perceive these risks as a major source of financial risk. Both scenarios could lead to a mispricing of climate change risks with important consequences for the functioning of the financial sector as such and as a vehicle to transmit climate mitigation policies.

To investigate the pricing of climate risk, we first build two novel physical and transition risk indices exploiting text analysis and then use these to gauge the presence of physical and transition climate risk premia in euro area equity markets over the period from January 2005 to October 2021. We then investigate the impact of these climate risk factors on portfolios constructed according to common firm-specific climate metrics in order to identify which metrics are likely used by investors to proxy for a firm's exposure to either physical or transition risk. As an alternative exposure metric we also use sector classifications and investigate if investors simply pigeonhole firms into the industry they operate in – rather than using firm-level information, as hypothesized by Bolton & Kacperczyk (2021b).

Considering that climate change can affect asset prices through changes in physical risk or transition risk[2] we propose to distinguish between physical and transition risk using a text analysis approach proposed by Engle et al. (2020). To this end, we examine scientific texts on climate change to build two novel vocabularies on physical and transition risk which are able to capture the multifaceted characteristics of these two risk types. We compare the vocabularies with a corpus of news sourced from Reuters News, from which we obtain a Physical Risk Index (PRI) and a Transition Risk Index (TRI). The approach is based on the idea that investors use newspapers as a source of information to update beliefs about gyrations in climate

[2] Physical risk materialises in the form of financial losses/increased costs from the impact of chronic (gradual shifts in, e.g., wind and precipitation, and longer-term, e.g., sea levels, desertification, and ocean temperatures changes) and acute (extreme weather such as floods, droughts, and wildfires) physical events. Exposed companies can be affected through damaged assets and disruption of business operations. Transition risk arises from the costly adjustment towards a low-carbon economy and it is typically prompted by changes in climate and/or environmental policy, technological advances, and/or shifts in public preferences (ECB, 2019; NGFS, 2020). Transition risk is usually of most concern for companies with large dependencies on energy and fossil fuels and, depending on how fast and orderly the process of decarbonization occurs, its impact may worsen over time with the potential to cause large swings in asset prices and "stranded" assets.

change risks and supposes that news coverage on climate change intensifies if as climate risks rise (Engle et al., 2020).

We find that PRI and TRI spike during days where the discussion on either risk type increases substantially. Results show that PRI captures multiple aspects of physical risk, allowing for instance to detect unexpected news concerning rising sea levels, heat waves, permafrost thawing, floods, adaptation measures. The TRI is able to detect news regarding the introduction of new regulation to curb greenhouse gas (GHG) emissions as well as news discussing the importance of technological advances to a climate-neutral economy, among others.

To assess the presence of climate risk premia for physical and transition risk in the crosssection of European stock returns we adopt a standard portfolio sorting approach covering the period January 2005 to October 2021, which we further divide in two sub-periods, before and after 2015. This is in line with recent studies that document an increase in the importance of climate risks since the time of the Paris Agreement (Bolton & Kacperczyk, 2021a; Goldsmith- Pinkham et al., 2021; Krueger et al., 2020; Painter, 2020). We perform time series regressions of equity returns on climate risks, controlling for Fama French factors known to drive returns, and gauge equity market sensitivities to carbon risk. The resulting loading on the risk factors, i.e. the transition and physical risk betas, are our firm-level indicators of climate risk exposure. Stocks which depict a positive climate risk beta tend to appreciate when investors are concerned about climate risk. Since investors can be expected to want to hedge against climate risk, they should be willing to accept lower expected returns for equities that appreciate when climate risk increases (high beta portfolios). In turn, this means that 'climate risky' stocks should trade at a discount and offer higher expected returns. A low-minus-high transition (physical) climate beta portfolio should therefore earn positive excess returns in case a climate risk premium existed. Results indicate the emergence of both, a physical and transition climate risk premium since 2015.

To test which exposure metrics may be used by investors to proxy firms' exposure to physical or transition risk, we then include the constructed climate risk series into a Fama & French (2015) five factors asset pricing model. Firms are sorted according to their GHG emissions levels, GHG emissions intensity, Environmental (E) scores, and Environmental, Social, and Governance (ESG) scores, with returns being aggregated into green and brown portfolios. Second, we conduct a sectoral analysis by aggregating returns of firms belonging to the same sector (NACE Rev. 2 classification). Overall, we find that firm level information appears to be used as a gauge for transition risk exposure, in particular since 2015. In contrast, sectoral classifications, in the light of many investors, appears to be sufficient to identify exposures to physical risk.

This paper contributes and relates to a growing strand of literature which focuses on understanding the impact of physical and transition climate risks on asset prices[3]. Pástor et al. (2021a) recently developed an equilibrium model which predicts that, in a crosssectional setting, green assets generate negative alpha (lower expected returns) compared to brown assets, but green assets can outperform brown assets (higher realized returns) when agents are surprised by climate change concerns. While this conjecture appears convincing, empirical evidence on the presence of carbon risk premia is not yet conclusive. Whereas some authors find that investors do require additional compensation for holding brown assets, especially following the Paris

[3] for a more complete review see Hong et al. (2020) and Giglio et al. (2021)

Agreement, others provide no evidence of price differentials (see Bolton & Kacperczyk (2021a); In et al. (2019); Alessi et al. (2019); Hsu et al. (2020); Pastor et al. (2021b)). As such, the literature on the consequences of changes in physical risk is less developed and has so far mainly focused on specific risk events. For example, Addoum et al. (2020) analyse high temperature events, finding only limited impact on companies' sales, productivity, and earnings. Hong et al. (2019) focus on the occurrence of droughts, documenting an impact on food companies' stock returns. Kruttli et al. (2019) explore how the uncertainty resulting from hurricanes impact financial markets.

This paper also relates to the strand of the climate finance literature which uses text analysis to measure climate risks (Batten et al., 2016; Engle et al., 2020; Meinerding et al., 2020; Faccini et al., 2021). While these studies all improve upon risk identification in their own rights, they either consider climate change as a single risk factor (Engle et al., 2020), focus only transition risks (Batten et al., 2016; Meinerding et al., 2020), or focus on specific sub-categories of physical and transition risks (Ardia et al., 2020; Faccini et al., 2021)[4].

This study differs from previous ones as it separates climate change risks into physical and transition risk, capturing the entire multifaceted characteristics and multiple dimensions of the two climate risks without discarding relevant categories. Our vocabularies are able to capture both, extreme and chronical physical hazards directly caused by climate change, including natural disasters attributable to other sources. This sets our physical risk index apart from many other physical risk databases. Another advantage of the proposed methodology is that the phraseology associated is extracted from authoritative texts rather than being defined ex-ante by the authors. Finally, the estimation of physical- and transition specific betas allows us to investigate the information content of specific exposure metrics and to understand how they are used by investors.

The remainder of this paper is organised as follows: Section 2 describes the text analysis methodology and provide a discussion of the resulting physical and transition risk indices. Section 3 provides estimates of transition and physical risk pricing in euro area equity markets. Section 4 describes the data and section 5 lays out the main results. Section 6 concludes.

Measuring climate risk through text analysis

To test whether financial markets are sensitive to shocks in physical and transition climate risks we need proxies to measure these risks. We exploit newspaper content to identify shocks in physical and transition risk. We do so following and expanding upon the text analysis approach used by Engle et al. (2020) - who proxy innovations to climate change news, but without distinguishing between physical and transition risk. More precisely, we first compare authoritative texts on climate risk with a large

[4] Using a textual analysis approach, Ardia et al. (2020) identify eight climate change sub-categories, labelled by the authors as "Financial and Regulation", "Agreement and Summit", "Public Impact", "Research", "Disaster", "Environmental Impact", "Agricultural Impact", and "Other". Faccini et al. (2021) filter news by "climate change" and "global warming" to then employ a Latent Dirichlet Allocation approach to cluster news topics. The authors label the resulting topics into a "Natural Disasters", "Global Warming", "International Summit", and "U.S. Climate Policy" factors

amount of news with a European regional focus from Reuters News[5] based on the assumption that events covered in newspapers can carry relevant and genuinely new information on climate change. We create two separate vocabularies, i.e. lists of words associated with the topic of interest, and use these to construct two risk indices, one containing physical and one containing transition risk shocks. The main innovation here lies in the fact that our indices relate to both risk types *separately* and embody the multifaceted characteristics of each one.

Physical risk and transition risk vocabulary

We create two separate vocabularies for physical risk and transition risk. These are context-scaled, i.e. capture risk-specific characteristics and their interconnections. A key feature of our vocabularies is the ability to rank terms by relevance. This allows for a deeper understanding of each risk nature and to examine which risk aspects turn out to be most important in the overall risk description.

To construct the climate risk vocabularies, we follow three main steps. First, we select a large number of scientific and authoritative texts on the topic of climate change published by governmental authorities and other institutions, starting with the collection already adapted by Engle et al. (2020). We screen these texts' content and retain those whose content can be associated to either physical risk or transition risk topics. We further add financial texts describing both risk types as a genuine attempt to construct risk measures which incorporate multiple perspectives. The complete list of texts is summarised in Table A2 in the Appendix. We aggregate the 13 (10) texts covering physical (transition) risk to create a single document on physical (transition) risk.

Second, we create two lists of unique stemmed unigrams and bigrams, jointly referred to as terms, with the associated term frequency scores (*tf*) from these physical risk and transition risk documents. Then, we create an analogous list of terms and frequencies from Reuters News, where real-time news are aggregated into daily documents. To do so, we retrieve a total of over 2.5 million real time news from the Factiva database over the period Jan 2005-Oct 2021. Thereafter, we apply a one-day novelty filter to the sample to eliminate redundancy among the data. Specifically, only the first news of the day is kept from a series of similar news published on the same day (see Dang et al. (2015), Rognone et al. (2020), and Faccini et al. (2021)) and only news published during days in which European equity markets are open for trading are retained[6]. The final sample contains 1,096,392 news. We then convert the physical transition) risk document and each daily news document into term frequency-inverse document frequency (*tf-idf*). Terms earn high *tf-idf* if they are representative for the individual text. This means that they are frequent within the document (high *tf*) and infrequent among other documents (high *idf*). Low *tf-idf* score terms are common to many documents (low *idf*) or very infrequent within the document (low *tf*) and

[5] Reuters provides business, financial, national and international news to professionals via desktop terminals, the world's media organizations, industry events and directly to consumers. Reuters News also includes the Breakingviews.com content and provides news delivered instantly in multiple languages (Source reuters.com and reutersagency.com, accessed on 16/06/2021). We use English language news.

[6] News which corpus length exceeds 5,000 words are not included in our analysis for both computational reasons and because they can be considered as outliers due to their great length and very marginal occurrence.

therefore have poor ability in representing the content of the individual text (Engle et al., 2020; Gentzkow et al., 2019).

Third, by multiplying the tf scores of the physical risk and transition risk documents by their relative idf scores from the collection of news[7], we are able to obtain vocabularies ranked by term relevance.

The advantage of our methodology, which combines the *tf-idf* with the screening of texts on the topic of physical and transition risks, is that the phraseology associated with the two types of risks is extracted from the authoritative texts rather than being defined ex-ante by the authors. Each vocabulary is also found to capture the multifaceted characteristics of each climate risk type, rather than single aspects. This can be seen in Figure 1, which shows the most relevant terms of the transition risk vocabulary (right panel) and the physical risk vocabulary (left panel) as word clouds, where each term size is proportional to its *tfidf* score. For instance, the physical risk vocabulary includes both extreme and chronical hazards directly caused by climate change, excluding natural disasters attributable to other sources. Accordingly, the transition risk vocabulary includes various aspects of this climate risk such as technological advances and environmental policies. Terms such as "*ecosystems*", "*sea level*", and "*precipitation*" are representative of the physical risk topic, while terms such as "*hydrofluorocarbon*" (HFC), "*bioenergy*", and "*greenhouse gas*" (GHG) are representative of the transition risk topic.

In addition, the estimation technique allows to distinguish between physical and transition risk while acknowledging that these are overlapping concepts to some extent. For instance, the term "*GHG*" appears in both vocabularies, but to a different extent. It plays a primary role in explaining transition risk and a minor one for physical risk. The term "adaptation", on the other hand, represents a common concept for physical and transition risk and therefore appears in both vocabularies. However, its semantic differs depending on it being considered within the context of physical or transition risk and thus depends on the other terms in the vocabulary. These examples suggest that the constructed vocabularies are also likely to capture interconnections between the two complex concepts of physical and transition risks, and to contextualise common terms. Nevertheless, for the exercises to be carried out later on, it has to be assured that dictionaries are sufficiently different in terms of the content they describe. To confirm that this is the case, we apply a test proposed by Dang et al. (2015)[8]. Results show that the transition risk vocabulary is able to explain less than the 5% of the physical risk vocabulary, which in turns carries about 95% of individual information, and vice-versa.

[7] The final collection documents is then composed by T documents, as a total of T-1 daily news documents and 1 physical (transition) risk document, which enables us to calculate the idf scores. At this stage, to lighten the computational load and avoid the so-called machine learning overfitting issue, we consider a subsample of the Reuters News (2015-2019).

[8] We evaluate the actual degree of commonality between the two vocabularies as the R squared from regressing the physical risk vocabulary on the transition risk one, and vice-versa. Despite there not being a clear threshold level (Rognone et al., 2020), the resulting R square of less than 5 percent is considered sufficiently small to support a reliable separation of the two risks.

Word clouds summary for physical and transition risk vocabularies

Figure 1

(a) Physical risk vocabulary (b) Transition risk vocabulary

Word cloud summaries for the physical risk (a) and transition risk (b) vocabularies. Term sizes depend on the relative importance of the term according to the individual *tf -idf* score. Reported terms are the reconstructed stemmed terms. Major acronyms: Representative Concentration Pathways (RCP), hydrofluorocarbon (HFC), hydrochlorofluorocarbon (HCFC). Table A1 reports the full list of acronyms.

Physical risk and transition risk indices

In order to calculate our two risk indices we first compute two "concern" series. These news media concern series for physical/transition risk, on any given day t, are defined as the cosine similarity between the tf-idf vector of the news document and the physical (transition) risk document. Cosine-similarity is a technique used in text-analysis to evaluate similarity between pairs of texts. It expresses the angular distance between two pairs of text such that the closer these are to each other, the smaller their angular distance, the higher the cosine, and the higher their similarity. In other words, we consider our physical (transition) risk dictionary as a vector, the direction of which depends on the intensity of each element, given by the tf-idf of vocabulary terms. This means that daily news which point in the same direction as the physical (transition) risk vector are assessed to discuss the physical (transition) risk topic.

We then, in order to gauge the unexpected change in physical/transition risk, construct the Physical Risk Index (PRI) and the Transition Risk Index (TRI) as residuals from autoregressive processes of order 1 (AR1), as follows

$$\text{Concern}_{t,PR} = c_{PR} + \phi_{PR}\text{Concern}_{t-1,PR} + PRI_{t,PR} \quad (1a)$$

$$\text{Concern}_{t,TR} = c_{TR} + \phi_{TR}\text{Concern}_{t-1,TR} + TRI_{t,TR} \quad (1b)$$

Table 3 reports the dates with the highest physical and transition risk shocks together with the topic of the most relevant news. For instance, the peak for PRI is registered on 19/09/2018, on account of a large discussion revolving around a natural hazard, which on this occasion was a loss of arctic sea. High shock days might cover a multiplicity of physical risk topics. For example, the PRI peak is related not only to the physical chronic risk of permafrost thawing, but also to a rise of sea levels and changes in the salinity of oceans. As such, the table shows that our PRI shocks capture not only acute risks such as floods, or extreme weather events, but also a plurality of chronic risks such as permafrost thawing, droughts, sea level rise, and the adverse impacts on the ecosystem from e.g. a loss of biodiversity. This sets the PRI apart from many other physical risk databases, which mainly identify extreme weather events only. The largest shock for TRI concurs with news published on 24/08/2011, which covered the worryingly high levels of EU GHG emissions, which would need to be reduced. In addition, the table also lists many news on regulation and measures to curb GHG emissions - all of which generate large spikes in TRI (e.g. news regarding the EU carbon reform deal or the Kyoto Protocol, as well as news concerning the costs associated to the transition and the advances of technological innovation and renewable energies).

AR1 estimates of physical risk and transition risk concern — Table 1

	$\text{Concern}_{t,PR}\ x\ 100$	$\text{Concern}_{t,TR}\ x\ 100$
Drift c	7.863	8.462
	(0.047)	(0.061)
ϕ	0.326	0.413
	(0.014)	(0.014)

Note: Estimates of autoregressive process of order 1 (AR1) concern time series on physical risk, as in equation (1a), and transition risk as in equation (1b). Standard error in parenthesis.

Figure 2 shows the scatter plots of daily physical and transition media concerns (panels a and b), together with their monthly average (panels c and d). Table 1 summarises the AR1 estimates from Equations (1a) and (1b). Both physical risk and transition risk concern time series depict positive drifts (c_{TR} = 8.462% and c_{PR} = 7.862%), showing that the news coverage toward these climate risks tends to increase over time. The media concern for transition risk seems to be more persistent than that for physical risk with ϕ_{PR} = 0.326 and ϕ_{TR} = 0.413.

Transition and physical risk pricing in euro are equity markets

In the following, we examine the existence of physical and transition climate risk premia in equity markets using our physical and transition risk indicators. Thereafter, we investigate which metrics may be used by investors to proxy for a firm's exposure to either physical or transition risk.

A. Transition and physical risk premia

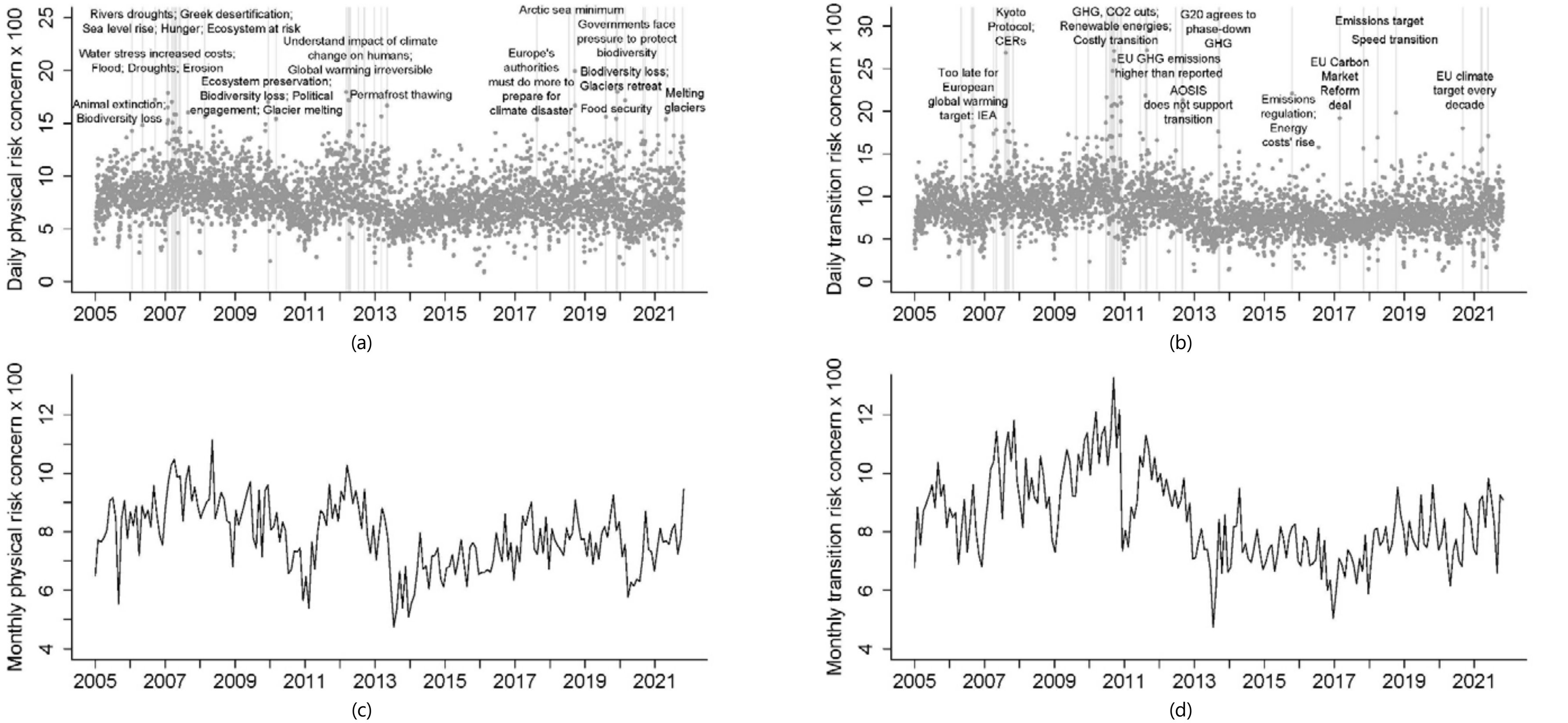
To assess the presence of climate risk premia for physical and transition risk in the cross-section of European stock returns we adopt a standard portfolio sorting approach. We perform time-series regressions of equity returns on our climate risk factors, controlling for Fama French factors which are known to drive returns, to gauge stock return sensitivities to carbon risk. The resulting loading on the risk factors, i.e. the transition and physical risk betas, are our firm-level indicators of climate risk exposure. Stocks which depict a positive climate risk beta tend to appreciate when investors are concerned about climate risk. These stocks can thus be thought of as a hedge against climate risk as they deliver high returns when climate change concerns increase. We sort these companies from low to high according to their climate exposure and group them into portfolios.

Since investors can be expected to want to hedge against climate risk, they should be willing to accept lower expected returns for equities that appreciate when climate risk increases (high beta portfolios). In turn, this means that 'climate risky' stocks should trade at a discount and offer higher expected returns. A low-minus-high transition (physical) climate beta portfolio should therefore earn positive excess returns in case a climate risk premium existed.

Specifically, we recursively estimate the sensitivity of each stock to both transition and physical climate risk, which yields the so-called climate-risk beta. We do so in a three-months rolling window regression with daily observations and control for the standard Fama & French (2015) five factors. We then sort stocks according to their estimated betas and group them into 25 portfolios for which we compute the post-ranking equal-weighted monthly returns. To examine the TRI-return relation (PRI-return relation), we also form a low-minus-high (LMH) portfolio that takes a long position in the negative-beta TRI (PRI) portfolio and a short position in the positive-beta TRI (PRI) portfolio, and we calculate the returns on this portfolio. We evaluate the transition (physical) risk premium, estimating each LMH climate portfolio's alpha while considering the Fama & French (2015) five factors asset pricing model specification.

Physical and transition risk concern timeseries 2005-2021

Figure 2



Note: Daily physical risk concern (a) and daily transition risk concern (b) with the major risk shock topics (vertical bars) for the period Jan 2005-Oct2021. Monthly average physical (c) and transition (d) risk concern.

B. The use of risk exposure metrics by investors

B.a. Indicators for firms' climate risk exposure

In the following we discuss the most relevant metrics to identify exposure to climate risks. We reckon that while most of the metrics have been used to capture exposure to transition, rather than physical risk, this distinction is not always clear and their potential to capture physical exposure has been largely unexplored. For this reason, in this study we decided to test a wide range of exposure metrics in light of their potential use for investors to hedge against physical and/or transition risks.

Academics, practitioners, and supervisors typically use GHG emissions or GHG emissions intensity (GHG emissions scaled by some organization-specific metric) to proxy a firm's exposure to transition risk, motivated by the fact that carbon-intensive activities are likely affected by GHG emissions reduction policies (Ardia et al., 2020; Bolton & Kacperczyk, 2021a; In et al., 2019; NGFS, 2020). However, empirical findings based on these measures are not conclusive. Bolton & Kacperczyk (2021a) provide evidence of the existence of a carbon premium while considering both emissions levels and changes, but no relation with carbon intensity exists. Also Barnett (2019), Bolton & Kacperczyk (2021b) and Ramelli et al. (2021) find that transition risks related to carbon emissions are priced. In contrast, In et al. (2019) find that green firms outperform brown firms when considering carbon intensity and Hsu et al. (2020) show that a long-short portfolio constructed from firms with high versus low emission intensity generates positive excess return.

Other potential measures of climate exposure are E and ESG scores, which aim to measure the environmental, or environmental, social and governance-related performance of a company[9]. A number of academic studies rely on E/ESG scores (possibly in combination with other company-specific metrics) to identify climate sensitive companies. Görgen et al. (2020), for example, build a "grenness" score based on carbon intensity, ESG scores and an adaptability score. Alessi et al. (2019) combines ESG disclosure scores with quantitative measures on emissions, while Engle et al. (2020) focus exclusively on the E score.

Other studies consider sectoral classifications and define climate sensitive companies as those belonging to high GHG emissions sectors. This approach is particularly relevant in contexts where the lack of transparent indicators (e.g. ESG ratings) may limit the ability of investors to understand to steer their investment toward climate-hedged portfolios (Bolton & Kacperczyk, 2021b). As such, Choi et al. (2020) finds that the sectors identified as major emitters by the Intergovernmental Panel on Climate Change (IPCC) earn lower stock returns than other firms. Bolton & Kacperczyk (2021a) argue that relying on a sectoral analysis may facilitate the detection of climate-risky investments, whereas such approach may ignore relevant intra-sectoral differences. Batten et al. (2016) document the impact of transition risk on the energy sector and concludes that only renewable energy companies generate abnormal returns.

Measuring firms' exposure to physical risk is challenging as physical risk arises from the interaction of hazard (occurrence, or probability of occurrence, of a physical

[9] The exact information contained in any ESG score depends on the methodology used to calculate it, which, in turn, differs across credit/rating providers. Existing research documents large differences between ESG ratings (Chatterji et al., 2016; Gibson Brandon et al., 2021) and elaborates on the possible reasons for these Berg et al. (2019).

event), exposure (presence of elements in areas and settings that could be adversely affected), and vulnerability (predisposition of exposed elements to suffer damages due to the hazardous event). Such dimensions typically depend on both local/specific and macro factors. Currently, most of the information on physical risk exposure is provided by some public sources (e.g. EC JRC Risk Data Hub) and private data providers. These databases, however, are not fully comparable as they focus on different risk aspects, types of hazard and types of entities. Due to data limitations, studies that explore the consequences of physical risks on asset prices mainly focus on specific physical events and/or consider only some dimensions of physical risk (see Addoum et al. (2020); Hong et al. (2019); Kruttli et al. (2019)). Alternatively, as is the the case for transition risk, sectors can be used to proxy physical risk exposure. While all sectors can suffer from natural disasters, some sectors, including energy, transportation, and telecommunications, are expected to be more exposed to climate hazards through their infrastructure assets (ECB, 2021). Primary economic activities, including agriculture, forestry, fishing, mining and quarrying, are exposed through the natural and/or food systems on which they depend. Among services, the insurance sector, tourism and health care might be particularly sensitive to physical risk (IPCC, 2014).

While E, ESG, and GHG emissions have mainly been used to capture exposure to transition, rather than physical risk, this distinction is not always clear and these metrics' potential to capture physical exposure has been largely unexplored. In this study we decided to test all of the above-mentioned exposure metrics in light of their potential use for investors to hedge against physical and/or transition risks.

B.b Information content of risk exposure metrics for investors

To test which exposure metrics may be used by investors to proxy firm's exposure to transition and physical risk, we add the Physical Risk Index (PRI) and Transition Risk Index (TRI) to a Fama & French (2015) five factors (FF5) asset pricing model. We consider the E score, ESG score, GHG emissions level, and GHG emissions intensity as exposure metrics to sort firms and create green and brown portfolios, as follows:

- *E score and ESG score metrics.* Firms whose E score is above (below) the 75th (25th) percentile are defined as green (brown). The green (brown) portfolio is then created as an equally weighted portfolio composed of green (brown) firms. The same approach is applied to the ESG score metric. Portfolios are rebalanced annually;
- *GHG emissions level and GHG emissions intensity metrics.* The GHG emissions level ($\mathrm{GHG_E}$) is calculated as the sum of Scope 1 and 2, while the GHG emissions intensity ($\mathrm{GHG_{EI}}$) is calculated as GHG emissions level scaled by firms' net revenue. As before, firms whose emissions level is below (above) the 25th (75th) percentile are defined as green (brown) firms. Portfolios are again rebalanced annually.

We then include our TRI and PRI into a model to gauge equity excess returns

$$r_{p_i,t}^{exc} = c_{p_i} + \beta_{p_i}^{TRI} TRI_t + \gamma_{p_i}^{TRI} X_t + \epsilon_t \tag{2a}$$

to price transition risk, and

$$r_{p_i,t}^{exc} = c_{p_i} + \beta_{p_i}^{PRI} PRI_t + \gamma_{p_i}^{PRI} X_t + \epsilon_t \quad (2b)$$

to price physical risk. $r_{p_i,t}^{exc}$ denotes the excess return at time t for green or brown portfolios where p = {green portfolio, brown portfolio} and i = {$\mathrm{GHG_E}$, $\mathrm{GHG_{EI}}$, E, ESG}. c_{p_i} is the constant term and the vector X_t controls for the market factor, the size factor, the book-to-market factor, as well as the profitability and investment factors[10]. The coefficients β^{PRI} and β^{TRI} measure the contemporaneous relationship between an unexpected change in physical and transition risk, and the excess returns of portfolios constructed according to different exposure metrics. The results from this exercise could inform us about the exposure metric used by investors to proxy firms' exposure to physical or transition risk.

Data

The augmented FF5 model (Equations 2a and 2b) uses the 1-month Overnight Index Swap (OIS) rate as the risk-free rate, and returns of the EuroStoxx 600 Index as the proxy for the market return. All data is used at daily frequency. We collect price time series for the historical constituents of the Eurostoxx 600 Index from Datastream over the period Jan 2005-Oct 2021, resulting in a total of 1,198 companies.

Data on firms' GHG emissions level, GHG emissions intensity, E score, and ESG core are sourced from Refinitiv. The level of GHG emissions indicates (in thousands) the metric tonnes of carbon dioxide equivalent a company produces[11]. We compute the GHG emissions intensity as GHG emissions scaled by the firm's net-revenue. In contrast, the E score reflects the environmental performance of a company in terms of its commitment and effectiveness to tackle issues related to the use of resources, emissions, and innovation, while the ESG score is also argued to be informative about a firm's performance concerning social and governance issues. E and ESG scores are industry-based relative performances and scores range between 0 and 100, with higher values indicating better firm' performances, relative to sector peers[12].

We define sectors using the Statistical Classification of Economic Activities in the European Community (NACE Rev. 2)[13].

[10] The Fama & French (2015) five factors are constructed considering the EuroStoxx 600 Index constituents over the period Jan 2005-Oct 2021 for which we calculate the 6 value-weight portfolios formed on size (market capitalisation) and book-to-market, the 6 value-weight portfolios formed on size and operating profitability, and the 6 value-weight portfolios formed on size and investment (change in total assets). Data are collected from Eikon. More details on the methodology can be found in the Fama-French data library.

[11] The GHG Protocol Accounting and Reporting Standard classifies (WBCSD & WRI, 2004) a company's GHG emissions into three scopes: direct emissions from company-owned and controlled resources, scope 1; indirect emissions from purchased electricity by the owned or controlled equipment or operations of the firm, scope 2; and other supply chain emissions, scope 3. We measure GHG emissions as the sum of scope 1 and 2 because including scope 3 reduces the data coverage. We consider only data reported by the company.

[12] Environmental and Social pillars are constructed according to categories which weights vary with the industry, while the Governance pillar category weights remain fixed across industries. Scores also consider firms' data transparency penalising firms which do not disclose data.

[13] Eurostat (2008). Dafermos et al. (2020) for example identifies high-carbon intensive activities taking NACE 1-digit sectors that mostly contribute to EU emissions.

Descriptive analysis

Table 2 shows the exposure metrics used. The table nicely illustrates a general increase in data coverage over time. In addition, it reports the thresholds used (25th and 75th percentiles) to construct brown and green portfolios.

In order to give a better overview of the composition and characteristics of the EuroStoxx 600 Index at the sectoral level, table 2 reports the number of firms in our sample (No.), the average of the exposure metrics(E, ESG, log-$\mathrm{GHG}_{\mathrm{EI}}$,log-$\mathrm{GHG}_{\mathrm{E}}$*)* and the yearly average contribution of each sector to EuroStoxx 600 Index GHG emissions. In the last column, we also add the overall sector contribution to EU GHG emissions (EU contribution)[14]. The table is sorted by GHG emissions in descending order, with a light (dark) colour being associated with green (brown) sectors.

As expected, D-Electricity, gas, steam and air conditioning supply (D- Electricity), CManufacturing, and H-Transportation and storage (H-Transportation) are among the most carbon-emitting sectors, contributing around 70% of total EU emissions and 55% of total EuroStoxx 600 Index emissions, respectively.In comparison, the A-Agriculture, forestry and fishing (A-Agriculture) is a high emissions contributor at the European level (16%), but not in our sample (0%), due to low representation of companies from this sector in the EuroStoxx 600 Index (one company). B-Mining and quarrying (B-Mining) and M-Professional, scientific and technical activities (M-Professional)[15] are small contributors at European level but show high level of GHG emissions in our sample.

Table 4 also shows that sectors with good average E (and ESG) ratings also have, on average, high GHG emissions levels (and intensity). This observation suggests that companies with high GHG emissions can receive positive environmental and ESG scores, and vice versa (Boffo et al., 2020). In other words, positive environmental, or ESG, ratings are not necessarily associated with low carbon emissions, aligned with the assumption that E, and ESG, can capture aspects of climate risk further to GHG production (Faccini et al., 2021).

Figure 3 presents the distribution of the four metrics used. E and ESG scores are quite homogeneous across sectors, while GHG emissions differ largely within and across sectors. This is in line with the fact that Refinitiv ESG scoring methodology is aimed at reducing portfolio concentration by sectors and thus recalibrates upwards the rating of high pollution companies if they are in highly polluting sectors, i.e. a company is largely evaluated relative to its sector peers. The distribution of GHG emissions by sectors also shows that the NACE classification does not take into account important emissions-related intra-sectoral differences.

[14] EU27, Data source: Eurostat.

[15] The broad characterisation of this sector makes its interpretation challenging. In our sample 70 percent are activities carried on by head offices.

Exposure data

Table 2

Panel a) % of firms with data

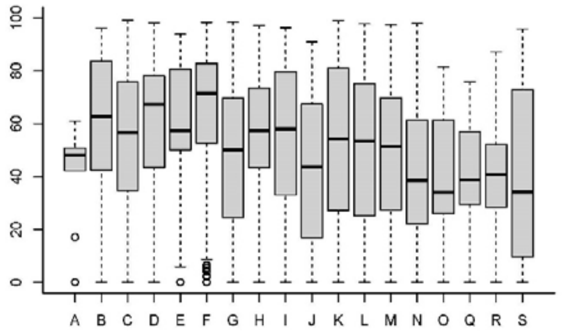
Year	GHG_E	GHG_{EI}	E Score	ESG Score
2005	259	254	537	686
2006	341	336	584	717
2007	423	413	706	777
2008	463	445	756	805
2009	547	518	776	823
2010	587	548	817	852
2011	626	583	833	874
2012	659	608	859	897
2013	689	634	880	913
2014	734	670	900	939
2015	773	707	945	978
2016	811	732	962	994
2017	857	767	1,011	1,044
2018	907	797	1,056	1,089
2019	944	818	1,074	1,105
2020	953	811	1,087	1,115
2021	949	793	1,081	1,116
Panel b) Threshold				
25^{th} Percentile	4.45	0.97	34.55	38.15
75^{th} Percentile	6.00	2.14	76.46	69.56

Note: exposure data % coverage over time (from 2015 to 2021) for the EuroStoxx 600 Index constituents (panel a) and the threshold levels to construct green and brown portfolios (panel b) for log-GHG emissions levels (GHG_E), log-GHG emissions intensity (GHG_{EI}), Environmental score (E-Score), and Environmental, Social, and Governance score (ESG-Score).

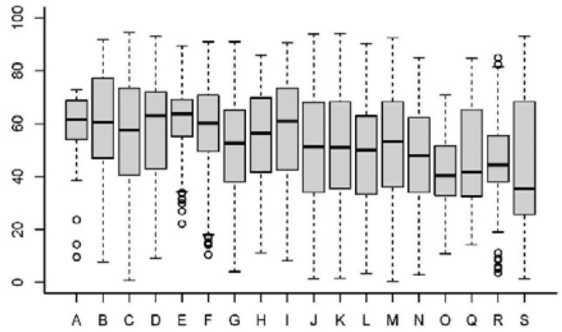
Finally, Table 5 shows the sectoral composition of brown and green portfolios according to the different exposure metrics used. The composition of brown (green) E and ESG portfolios is very similar, and so is the composition of brown (green) portfolios constructed according to GHG and GHG emission intensity. However, the portfolios constructed according to E or ESG criteria differ significantly from the ones based on GHG emissions. This is in line with the observation that high GHG emitting companies can receive high ESH and E scores.

Distribution of exposure metrics

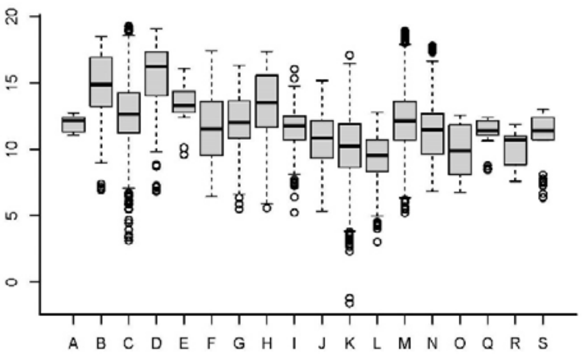
Figure 3



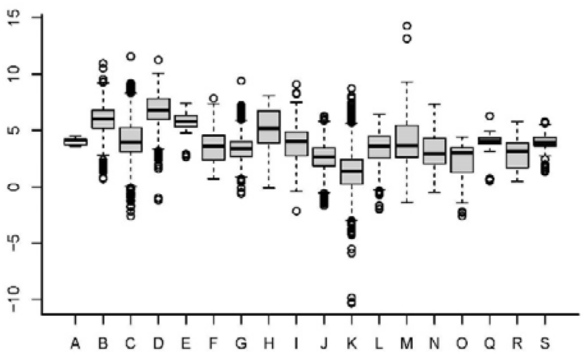
(a) Environmental score



(b) ESG score



(c) GHG emissions level



(d) GHG emission intensity

Note: Environmental score (a), ESG score (b), GHG emissions levels (c), and GHG emissions intensity (d) NACE Rev. 2 sectors boxplots.

Results

A. Transition and Physical Climate Risk Premia

Results indicate the emergence of both, a physical and transition climate risk premium since 2015. First, table 6 presents the annualized average excess stock returns in percent (E[R]-Rf, in excess of the risk free-rate), and Sharpe ratios of the 26 portfolios we form for transition risk (Panel a) and physical risk (Panel b), over the three periods studied (full sample, before 2015 and after 2015). The LMH transition (physical) generates an average annualized return of about -3.08% (-3.75%) in the period before 2015 and 9.61% (6.71%) after 2015. In addition, Figure 4 (a-b) shows a strong increase in the cumulative return of the LMH transition and physical portfolios after 2015 - depicting a decline in the performance of the high beta portfolio (Figure 4 (c-d)).

Second, table 7 shows the estimated physical and transition risk premia (alpha for the LMH portfolio). These estimates document the emergence of a positive risk premium for the low beta portfolio since 2015, i.e. a relatively higher required return for stocks which provide a bad hedge against climate risk. More specifically, the long-short PRI and TRI portfolios generate an average abnormal return of about -4.09% and -3.01% per year before 2015, and of about 6.14% and 7.05% after 2015, respectively.

B. The use of risk exposure metrics by investors

Overall, we find that firm level information appears to be used as a gauge for transition risk, in particular since 2015. In contrast, sectoral classifications appears to be sufficient to be employed to identify exposures to physical risk - but this information may not be granular enough to capture transition risk exposure. More specifically, table 8 reports the results for the estimated factor sensitivities of green and brown portfolios constructed according to E scores, columns (1-4); ESG scores, columns (5-8); $\mathrm{GHG_{EI}}$ columns (9-12); and $\mathrm{GHG_{E}}$, columns (13-16); from the daily augmented FF5 model as presented in Equations (2a) and (2b) over three periods (full sample, before 2015, and after 2015) reported together with t-statistics and considering Newey & West (1987) robust standard errors[16].

The table shows that since 2015 both E/ESG and GHG emissions appear to be a useful gauge for investors to identify companies less effected by climate risk. This is evident from positive and statistically significant TRI coefficients in the bottom panel of the table. In contrast, these measures do not appear to be used by investors to gauge exposures to physical risk. Our findings are in line with with Ardia et al. (2020) and Pastor et al. (2021b) who find that green assets earn positive return when they are surprised by climate risk. Additionally, Ardia et al. (2020) document that unexpected increases in climate change concerns decrease the returns of US brown firms, a finding which we cannot confirm.

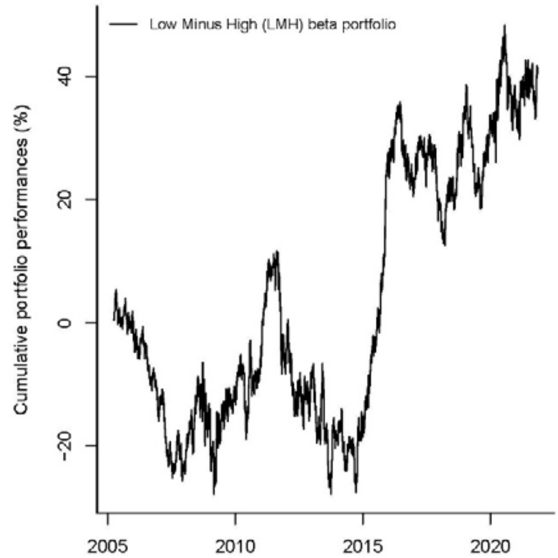
Turning to sector classification as a gauge for climate risk exposures, table 9 shows regression results for the three sample periods (full sample, before 2015, and after 2015), using the NACE sectoral classification to group excess returns of EU companies. Coefficients for TRI are largely insignificant post 2015. This suggests that sectoral information may not or no longer be granular enough to capture transition risk exposure. Rather investors may use more sophisiticated firm-level information, such as ESG or E ratings. This finding also speaks to the discussion raised by Bolton & Kacperczyk (2021a), who question whether investors consider the industry where firms operate as material information on firm' climate exposure, or use firms level information.

Table 10 provides the same information as 9, but for physical risk. We find that, after 2015, coefficients for sectors which are expected to be exposed to physical risk events (mining and quarrying, transportation and storage, and telecommunications) are negative and significant. These sectors are exposed to physical risk through their infrastructure assets or natural system such that these activities suffer losses from, e.g. interruptions of operational activities due physical hazards. This suggests that sectoral classifications may be used by investors to identify exposures to physical risk.

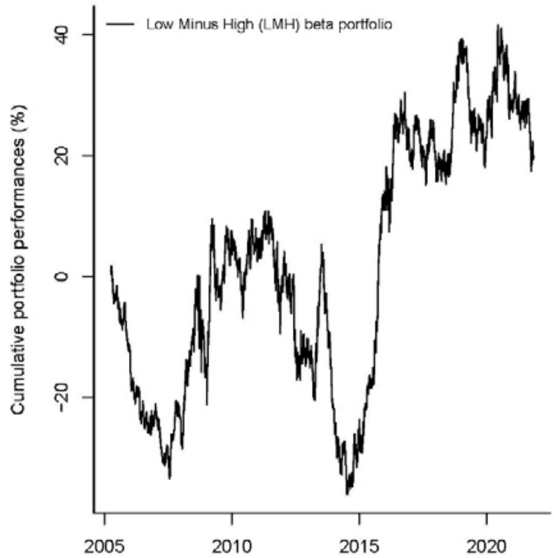
[16] We use Newey-West standard errors throughout.

Cumulative performances of portfolios sorted on TRI and PRI

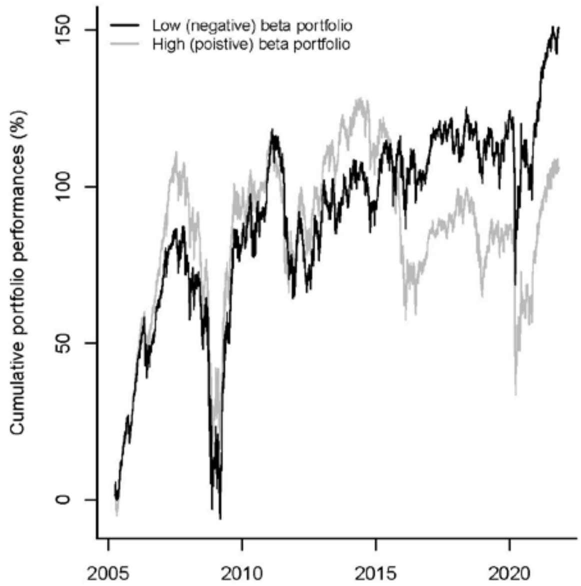
Figure 4



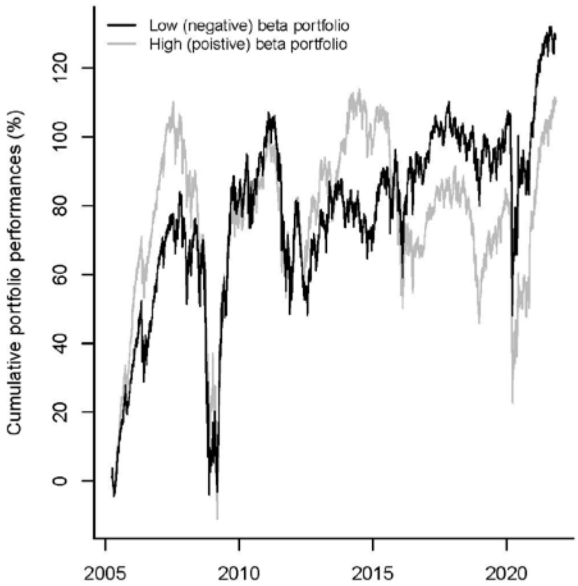
(a) Transition LMH beta portfolio



(b) Physical LMH beta portfolio



(c) Transition low and high beta portfolios



(d) Physical low and high beta portfolios

Note: Cumulative performances of the low-minus-high beta transition (a) and physical (b) beta portfolios; and of the low and high transition and physical beta portfolios separately (c) and (d) considering EuroStoxx 600 Index historical constituents stocks.

Conclusion

This study has examined the existence of physical and transition climate risk premia in euro area equity markets. It laid out two novel physical and transition risk indicators based on text analysis, which were then used to gauge the presence of climate risk premia. Results showed that climate risk premia for both, transition and physical climate risk, have increased since the time of the Paris Agreement. Portfolios, constructed according to the most common firm-specific climate metrics, were used to estimate the sensitivity of these portfolios to our risk indicators. We compared these to sectoral classifications to see if investors may simply pigeonhole firms into the industry they operate in - rather than to use more elaborate firm-level information. Findings showed that firm level information indeed appears to be used as a gauge for transition risk, in particular since 2015, whereas sectoral classifications appear insufficient. However, sectoral classification may be employed to broadly gauge firms' exposures to physical risk.

The findings presented in this study, with the most important contribution being the transition and physical risk indices, can be used to inform investors, policy makers, and financial institutions alike about the extent to which financial markets price climate risks. They can and are already be used by others for applications to other asset classes, risk management and portfolio management issues, or the investigation of climate hedging investment strategies. We deem that future research which more extensively investigates the link between climate risks and granular firm characteristics can yield many interesting results.

References

Addoum, J. M., Ng, D. T., & Ortiz-Bobea, A. (2020). Temperature Shocks and Earnings News. Review of Financial Studies, 33, 1331–1366.

Alessi, L., Ossola, E., & Panzica, R. (2019). The Greenium Matters: Evidence on the Pricing of Climate Risk. SSRN Electronic Journal, . URL: https://www.ssrn.com/abstract=3452649. doi:10.2139/ssrn.3452649.

Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2020). Climate Change Concerns and the Performance of Green Versus Brown Stocks. SSRN Electronic Journal, . URL: https://www.ssrn.com/abstract=3717722. doi:10.2139/ssrn.3717722.

Barnett, M. (2019). A Run on Oil: Climate Policy, Stranded Assets, and Asset Prices. Working Paper, .

Batten, S., Sowerbutts, R., & Tanaka, M. (2016). Let’s Talk About the Weather: The Impact of Climate Change on Central Banks. SSRN Electronic Journal, . URL: https://www.ssrn.com/abstract=2783753. doi:10.2139/ssrn.2783753.

Berg, F., Kölbel, J., & Rigobon, R. (2019). Aggregate Confusion: The Divergence of ESG Ratings. SSRN Electronic Journal, . URL: https://www.ssrn.com/abstract=3438533. doi:10.2139/ssrn.3438533.

Boffo, R., Marshall, C., & Palatano, R. (2020). ESG Investing: Environmental Pillar Scoring and Reporting. Technical Report. URL: www.oecd.org/finance/esg-investing-environmental-pillar-scoring-and-reporting.pdf.

Bolton, P., & Kacperczyk, M. T. (2021a). Do Investors Care about Carbon Risk? Journal of Economics, forthcoming, .

Bolton, P., & Kacperczyk, M. T. (2021b). Global Pricing of Carbon-Transition Risk. SSRN Electronic Journal, . URL: https://www.ssrn.com/abstract=3795029. doi:10.2139/ssrn.3795029.

Chatterji, A. K., Durand, R., Levine, D. I., & Touboul, S. (2016). Do ratings of firms converge? Implications for managers, investors and strategy researchers. Strategic Management Journal, 37, 1597–1614. URL: https://onlinelibrary.wiley.com/doi/10.1002/ smj.2407. doi:10.1002/smj.2407.

Choi, D., Gao, Z., & Jiang, W. (2020). Attention to Global Warming. The Review of Financial Studies, 33, 1112–1145. URL: https://academic.oup.com/rfs/article/33/3/1112/5735304. doi:10.1093/rfs/hhz086.

Dafermos, Y., Gabor, D., Nikolaidi, M., Pawloff, A., & Van Lerven, F. (2020). Decarbonising is easy. Beyond market neutrality in the ECB’s corporate QE. The New Economics Foundation, .

Dang, T. L., Moshirian, F., & Zhang, B. (2015). Commonality in news around the world. Journal of Financial Economics, 116, 82–110. URL: https://linkinghub.elsevier.com/retrieve/pii/S0304405X14002530. doi:10.1016/j.jfineco.2014.11.007.

ECB (2019). European Central Bank, Financial Stability Review, . May 2019.

ECB (2021). European Central Bank, Shining a light on climate risks: the ECB's economywide climate stress test, .

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging Climate Change News. The Review of Financial Studies, 33, 1184–1216. URL: https://academic.oup.com/rfs/article/33/3/1184/5735305. doi:10.1093/rfs/hhz072.

Eurostat (2008). NACE Rev. 2 – Statistical classification of economic activities in the European Community.

Faccini, R., Matin, R., & Skiadopoulos, G. (2021). Dissecting Climate Risks: Are they Reflected in Stock Prices? SSRN Electronic Journal, . doi:10.2139/ssrn.3795964.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116, 1–22. URL: https://linkinghub.elsevier.com/retrieve/pii/S0304405X14002323. doi:10.1016/j.jfineco.2014.10.010.

Gentzkow, M., Kelly, B., & Taddy, M. (2019). Text as Data. Journal of Economic Literature, 57, 535–574. URL: https://pubs.aeaweb.org/doi/10.1257/jel.20181020. doi:10.1257/jel.20181020.

Gibson Brandon, R., Krueger, P., & Schmidt, P. S. (2021). ESG Rating Disagreement and Stock Returns. Financial Analysts Journal, 77, 104–127. URL: https://www.tandfonline.com/doi/full/10.1080/0015198X.2021.1963186. doi:10.1080/0015198X.2021.1963186.

Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate Finance. Annual Review of Financial Economics, 13. URL: https://www.annualreviews. org/doi/10.1146/annurev-financial-102620-103311. doi:10.1146/annurev-financial-102620-103311.

Goldsmith-Pinkham, P., Gustafson, M. T., Lewis, R., & Schwert, M. (2021). Sea Level Rise Exposure and Municipal Bond Yields. Working Paper, .

Görgen, M., Nerlinger, M., & Wilkens, M. (2020). Carbon Risk. SSRN Electronic Journal, . URL: http://www.ssrn.com/abstract=2930897.

Hong, H., Karolyi, G. A., & Scheinkman, J. A. (2020). Climate Finance. The Review of Financial Studies, 33, 1011–1023. URL: https://academic.oup.com/rfs/article/33/3/1011/5735309. doi:10.1093/rfs/hhz146.

Hong, H., Li, F. W., & Xu, J. (2019). Climate risks and market efficiency. Journal of Econometrics, 208, 265–281. URL: https://linkinghub.elsevier.com/retrieve/pii/S0304407618301817. doi:10.1016/j.jeconom.2018.09.015.

Hsu, P.-H., Li, K., & Tsou, C.-Y. (2020). The Pollution Premium. SSRN Electronic Journal, . URL: https://www.ssrn.com/abstract=3578215. doi:10.2139/ssrn.3578215.

In, S., Park, K., & Monk, A. (2019). Is "Being Green" Rewarded in the Market? An Empirical Investigation of Decarbonization Risk and Stock Returns. Stanford Global Projects Center Working Paper, (p. 46). IPCC (2014). Intergovernmental Panel on Climate Change, AR5 Climate Change 2014: Impacts, Adaptation, and Vulnerability, . Fifth Assesment Report.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The Importance of Climate Risks for Institutional Investors. The Review of Financial Studies, 33, 1067–1111. URL: https://academic.oup.com/rfs/article/33/3/1067/5735302. doi:10.1093/rfs/hhz137.

Kruttli, M. S., Tran, B. R., & Watugala, S. W. (2019). Pricing Poseidon: Extreme Weather Uncertainty and Firm Return Dynamics. Finance and Economics Discussion Series, 2019. URL: http://www.federalreserve.gov/econres/feds/files/2019054pap.pdf. doi:10.17016/FEDS.2019.054.

Meinerding, C., Sch¨uler, Y. S., & Zhang, P. (2020). Shocks to Transition Risk. SSRN Electronic Journal, . doi:10.2139/ssrn.3654155.

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Author(s): Whitney K. Newey and Kenneth D. West Source:. Econometrica, 55, 703–708. URL: https://teach.business.uq.edu.au/courses/FINM6905/files/module-1/readings/NeweyWest.pdf.

NGFS (2020). Guide for supervisors. Integrating climate-related and environmental risks into prudential supervision, . May 2020.

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. Journal of Financial Economics, 135, 468–482. URL: https://linkinghub.elsevier.com/retrieve/pii/S0304405X19301631. doi:10.1016/j.jfineco.2019.06.006.

Pastor, L., Stambaugh, R. F., & Taylor, L. A. (2021b). Dissecting Green Returns. SSRN Electronic Journal, . URL: https://www.ssrn.com/abstract=3870942. doi:10.2139/ssrn.3870942.

Pástor, , Stambaugh, R. F., & Taylor, L. A. (2021a). Sustainable investing in equilibrium. Journal of Financial Economics, 142, 550–571. URL: https://linkinghub.elsevier.com/retrieve/pii/S0304405X20303512. doi:10.1016/j.jfineco.2020.12.011.

Ramelli, S., Wagner, A. F., Zeckhauser, R. J., & Ziegler, A. (2021). Investor Rewards to Climate Responsibility: Stock-Price Responses to the Opposite Shocks of the 2016 and 2020 U.S. Elections. The Review of Corporate Finance Studies, 10, 748–787. URL: https://academic.oup.com/rcfs/article/10/4/748/6303621. doi:10.1093/rcfs/cfab010.

Rognone, L., Hyde, S., & Zhang, S. S. (2020). News sentiment in the cryptocurrency market: An empirical comparison with Forex. International Review of Financial Analysis, 69, 101462. URL: https://linkinghub.elsevier.com/retrieve/pii/S105752192030106X. doi:10.1016/j.irfa.2020.101462.

WBCSD & WRI (2004). World Business Council for Sustainable Development and World Resources Institute, The Greenhouse Gas Protocol, . URL: http://76.227.223.196/uploads/committee-documents/lV5aXV9d20091030152146.pdf.arXiv:1-56973-568-9.

Physical and transition risk top news articles

Table 3

Date	PRI	Physical risk news topics	Physical risk relevant news titles
19/09/2018	12.3%	Artic Sea Minimum; Melting glaciers; Permafrost thawing Ocean acidification	Greenland and the hunt for better climate science; In Greenland a glacier's collapse shows climate impact; Coceral cuts sharply EU cereal rapeseed crop estimates
01/02/2007	9.8%	IPCC draft report by the U.N. climate panel in Paris; Climate Sea Level Rise; change affects fishery	Global warming impacts of temperature rises; Draft findings by U.N. climate panel; Seas rising faster than U.N. predicts study; U.N. panel to link warming to humans project more; Cool water surges could affect fish stocks report; U.N. panel says "very likely" humans cause warming
06/12/2019	9.6%	Biodiversity Loss; Europe must protect rivers and lakes; Fishing, reef, tourism at risk; Increased costs due to climate stress	Europe must do more to protect its rivers and lakes: scientists; Runaway warming could sink fishing and reef tourism researchers warn; Forward prices slip on wetter weather view lower German rates
27/03/2012	9.1%	Global warming irreversible; Spain droughts, water stress; Frost impact on agriculture	Global warming close to becoming irreversible scientists; Spain drought hits hydro, irrigation stocks again; EU wheat too expensive for export – Toepfer Clouds a puzzle for U.N. global warming panel; Millions to go hungry, waterless; Bird ranges move, but is it climate change?; Europe's wheat crop on track, frost fears ease; Compulsory water metering takes step closer
30/01/2007	8.9%	Hunger due to water scarcity; Adaptation measure for companies; Animal migration	
27/02/2020	8.7%	Governments face pressure to protect biodiversity	Governments face pressure to protect nature in biodiversity
18/09/2006	8.7%	Raising temperatures causes floods, droughts, erosion; Hungary risk sand dunes, floods; Rising water costs; Water scarcity	Eco-paradises in crossfire of water scarcity fight; Hungary region battles advancing sand dunes, floods; Water everywhere but not clean enough to drink; Investors bet on rising costs for scarce water; Spanish wetland struggles as water levels drop
05/04/2012	8.6%	People cause climate change, need to understand impact on humans	Climate contrarian case wilts: Gerard Wynn
14/12/2009	8.5%	Forests to climate fight; Coral climate crisis costs; Biodiversity loss; Politic engagement in climate fight	Climate change makes finding Nemo even harder report; Coral climate crisis puts 250 million at risk: U.N.; Forest communities said key to climate fight; Natural disasters at decade low in 2009-UN report; Antarctic researcher commutes across continents for work
08/08/2019	8.4%	Food security	Farming and eating need to change to curb global warming: UN report
Date	**TRI**	**Transition risk news topics**	**Transition risk relevant news titles**
24/08/2011	19.1%	EU GHG emissions higher than reported	EU HFC emissions higher than reported; New research links cosmic rays to cloud formation
13/08/2007	17.5%	Kyoto Protocol; Certified Emission Reduction (CER)	Kyoto projects harm ozone layer: U.N. official; Daily secondary CER market report
01/09/2010	16.3%	Kyoto CO2 scheme probed; CER	HFC cutting plants under Kyoto CO2 scheme probed; EU carbon permit volumes fall in Aug, CERs rise
15/09/2010	15.0%	Review of carbon offsets; Low-carbon heating sources raises industry costs	UN to review CO2 offset request from 9th plant; UK business group warns on new low-carbon support
15/10/2015	13.8%	Emissions regulation; Increase in energy costs	U.S. announces new moves to limit super greenhouse gases; German 2016 green power surcharge at 6.354 cents/kWh - grid firms
09/08/2011	13.8%	Costly transition	Money spinning China carbon scheme may end with loss; Sberbank CO2 role questioned after huge issuance; Kyoto CO2 offset issuances grind to crawl in June; UK needs step change to meet climate target report; India, China seen partly out of carbon mkt post 2012; EU climate policy said costly with tiny benefits; EU carbon hits fresh 3-wk low on weak German power
30/06/2010	12.5%	CER issuances at lowest; Costly transition; International carbon market	
24/08/2012	11.8%	CERs request	Developers seek 4.7 mln CERs, incl. 1.5 mln HFC units
28/02/2017	11.4%	Carbon Reform Deal; Renewable energies; Emissions targets	Nineteen EU nations back common position on carbon market reform; France's EDF hydropower availability down 1.3 GW due to strike; Marshall Islands first to ratify global HFC greenhouse gas pact; Austria's EVN puts Bulgarian hydropower project on hold
16/09/2010	11.4%	Green incentive for coal; Clean energy projects; Carbon Capture and Storage technologies	UN panel to rule on green incentives for coal; Ozone recovering but will take longer over poles; UN gives CO2 auditors time to study liability plan; Carbon capturing technology doomed in Europe - study; Mexico says world should trust U.S. on emissions

Note: This table reports the dates, the Physical Risk Index (PRI) and Transition Risk Index (TRI), the main news topics, and lists of relevant article's title for the ten days with highest physical and transition risk.

EuroStoxx 600 Index historical constituents' sectoral composition

Table 4

	NACE code - sector	No.	log-GHG_E	log-GHG_{EI}	ESG	E	GHG_E contribution Index	GHG_E contribution EU
D	Electricity, gas, steam and air conditioning supply	37	17.09	7.77	56.73	60.4	41%	28%
B	Mining and quarrying	48	16.52	6.95	59.27	59.29	23%	2%
M	Professional, scientific and technical activities	150	15.62	7.64	51.74	48.04	9%	1%
H	Transportation and storage	37	15.36	6.16	55.75	55.93	7%	14%
C	Manufacturing	309	15.36	6.09	56.15	53.57	7%	26%
N	Administrative and support service activities	36	14.87	4.86	47.65	40.75	4%	1%
E	Water supply; sewerage, waste management and remediation activities	9	14.43	6.08	61.2	61.19	3%	5%
F	Construction	35	13.84	4.76	58.88	65.16	2%	2%
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	81	13.66	4.83	51.48	47.81	1%	3%
I	Accommodation and food service activities	16	13.18	5.71	57.7	55.2	1%	1%
K	Financial and insurance activities	252	12.67	3.84	50.67	53.52	0%	0%
J	Information and communication	109	12.53	3.36	50.74	41.76	0%	0%
A	Agriculture, forestry and fishing	1	12.12	4.07	54.92	39.16	0%	16%
S	Other service activities	6	11.81	4.42	45.04	42.05	0%	0%
Q	Human health and social work activities	9	11.67	4.21	47.1	39.97	0%	1%
O	Public administration and defence; compulsory social security	4	11.19	3.08	41.36	41.53	0%	1%
R	Arts, entertainment and recreation	12	10.67	3.55	47.08	39.91	0%	0%
L	Real estate activities	47	10.38	4.3	48.02	49.79	0%	0%

EuroStoxx 600 Index historical constituents sectoral (NACE code - sector) composition over the period Jan 2015-Oct 2021, number of companies per sector (No.), average environmental score (E score), environmental, social, and governance score (ESG score), log-GHG emissions levels (log GHG_E), log-GHG emissions intensity (log GHG_{EI}). Per year average GHG emission contribution of each EuroStoxx 600 Index NACE sector to the total EuroStoxx 600 Index emissions (GHG_E contribution Index), and the per year average GHG emissions of the full NACE sector to the total European Union GHG emission (GHG_E contribution EU) as from EU27 sourced from Eurostat. The table is sorted according to descending greenhouse gas emissions. The lighter the colour the 'greener' the sector, the darker the colour, the 'browner' the sector according to each metric (E score, ESG score, GHG_{EI}, or GHG_E).

Green and brown E, ESG, GHG_{EI}, GHG_E portfolios composition

Table 5

Panel a)	E score		ESG score		log-GHG_{EI}		log-GHG_E	
	Green	Brown	Green	Brown	Green	Brown	Green	Brown
Metric average	85.64	19.89	78.77	25.42	0.92	6.47	8.69	15.67
Number of assets	456	708	524	696	396	285	409	241
Panel b) Sectoral composition (%)								
NACE code - sector								
A Agriculture, forestry and fishing	0.00	0.14	0.19	0.14	0.00	0.00	0.00	0.00
B Mining and quarrying	4.82	3.95	4.58	3.45	1.01	12.63	1.47	11.62
C Manufacturing	28.73	26.55	30.73	27.16	14.65	33.68	16.87	34.44
D Electricity, gas, steam and air conditioning supply	4.17	2.97	3.82	2.59	0.51	9.82	0.98	11.62
E Water supply; sewerage; waste management and remediation activities	0.88	0.56	0.95	0.29	0.00	2.11	0.24	2.07
F Construction	5.48	2.97	3.82	2.73	3.28	3.51	3.42	4.15
G Wholesale and retail trade; repair of motor vehicles and motorcycles	5.26	7.91	5.53	6.61	5.05	2.81	5.87	6.64
H Transporting and storage	3.51	2.40	3.44	2.87	1.26	7.02	1.71	7.05
I Accommodation and food service activities	1.75	1.69	1.53	1.29	1.26	1.40	0.98	0.83
J Information and communication	5.48	9.75	7.82	8.91	13.89	2.11	12.71	2.90
K Financial and insurance activities	24.12	19.63	18.32	20.98	39.65	4.56	33.50	5.39
L Real estate activities	3.29	3.25	3.24	4.17	3.79	3.51	7.33	0.00
M Professional, scientific and technical activities	9.87	12.15	12.98	11.78	10.10	13.68	9.54	11.62
N Administrative and support service activities	1.75	2.82	1.53	3.30	3.28	1.75	2.93	1.66
O Public administration and defence; compulsory social security	0.22	0.56	0.19	0.57	0.51	0.00	0.49	0.00
Q Human health and social work activities	0.00	0.56	0.38	0.72	0.25	0.35	0.24	0.00
R Arts, entertainment and recreation	0.22	1.41	0.57	1.58	1.26	0.35	1.47	0.00
S Other services activities	0.44	0.71	0.38	0.86	0.25	0.70	0.24	0.00

Note: We sort the EuroStoxx 600 Index historical constituents on environmental score (E score), environmental, social and governance score (ESG score), greenhouse gas emissions intensity (GHG_{EI}), greenhouse gas emissions (GHG_E) and we create individual green and brown portfolios. This table reports each portfolio metric average (E, ESG, GHG_{EI}, or GHG_E), the number of assets, and the relative NACE sectoral (%) composition over the period Jan 2005-Oct 2021. Environmental, ESG, and GHG emissions data are sourced from Refinitiv.

Portfolios sorted on transition and physical climate betas			Table 6
Panel a) Transition risk beta portfolios			
Full sample TRI	L	H	LMH
E(R)-Rf (%)	8.46	5.71	1.96
σ (%)	22.35	22.47	13.05
SR	0.38	0.25	0.15
Before 2015 TRI	L	H	LMH
E(R)-Rf (%)	8.32	10.21	-3.08
σ (%)	23.53	23.16	12.76
SR	0.35	0.44	-0.24
After 2015 TRI	L	H	LMH
E(R)-Rf (%)	8.68	-0.41	9.61
σ (%)	20.57	21.46	13.44
SR	0.42	-0.02	0.71
Panel b) Physical risk beta portfolios			
Full sample PRI	L	H	LMH
E(R)-Rf (%)	7.08	5.94	0.43
σ (%)	22.83	23.07	13.29
SR	0.31	0.26	0.03
Before 2015 PRI	L	H	LMH
E(R)-Rf (%)	6.11	8.71	-3.75
σ (%)	23.71	23.62	12.91
SR	0.26	0.37	-0.29
After 2015 PRI	L	H	LMH
E(R)-Rf (%)	8.47	2.1	6.71
σ (%)	21.51	22.26	13.8
SR	0.39	0.09	0.49

Note: This table shows the performances of the low (L), high (H), and low-minus-high (LMH) 25 portfolios sorted according to their sensitivity to the Transition Risk Index (TRI) and to the Physical Risk Index (PRI), alongside the low-minus-high (LMH) transition and physical risk spread returns portfolios. The table reports the portfolios percentage annualised excess returns(E(R)-Rf) and standard deviations (σ), as well as the Sharpe ratios (SR), for three periods (full sample, Jan 2005-Oct 2021; before 2015, Jan 2005-Dec 2014; and after 2015, Jan 2015-Oct 2021). The EU stocks return universe is composed by the EuroStoxx 600 Index constituents.

Transition and physical risk premium — Table 7

Physical risk premium				Transition risk premium			
Full sample	25 Percentiles			Full sample	25 Percentiles		
	L	H	LMH		L	H	LMH
αFF5	5.14	4.54	-0.07	αFF5	6.1	3.94	1.42
[t]	1.69	1.65	-0.02	[t]	2.19	1.51	0.46
MKT_t	1.08	1.09	0	MKT_t	1.06	1.07	-0.02
[t]	48.6	62.6	-0.18	[t]	63.7	44.2	-0.73
SMB_t	0.63	0.66	-0.03	SMB_t	0.54	0.58	-0.04
[t]	12.7	16.9	-0.68	[t]	13.9	12	-0.71
HML_t	0.23	0.25	-0.02	HML_t	0.21	0.21	0
[t]	5.5	5.5	-0.49	[t]	6.91	5.54	-0.06
CMA_t	0.11	0.09	0.02	CMA_t	0.12	0.08	0.04
[t]	2.4	2.32	0.39	[t]	3.05	1.99	0.72
RMW_t	-0.19	-0.23	0.04	RMW_t	-0.2	-0.2	0
[t]	-6.33	-7.01	1.16	[t]	-7.5	-6.03	-0.08
Before 2015	25 Percentiles			Full sample	25 Percentiles		
	L	H	LMH		L	H	LMH
αFF5	3.15	6.06	-4.09	αFF5	5.22	6.98	-3.01
[t]	0.85	1.64	-0.98	[t]	1.36	2.06	0.77
MKT_t	1.11	1.09	0.01	MKT_t	1.1	1.09	0
[t]	47.6	57	0.51	[t]	49.7	52.1	0.06
SMB_t	0.57	0.57	0	SMB_t	0.51	0.51	0
[t]	10.9	12	0.02	[t]	7.19	11.8	0.02
HML_t	0.19	0.25	-0.06	HML_t	0.16	0.17	-0.01
[t]	3.57	3.9	-0.88	[t]	3.24	3.81	-0.12
CMA_t	0.13	0.13	0.01	CMA_t	0.12	0.15	-0.04
[t]	2.54	2.74	0.11	[t]	2.13	3.42	-0.51
RMW_t	-0.25	-0.25	0	RMW_t	-0.23	-0.24	-0.24
[t]	-6.95	-5.55	-0.07	[t]	-6.37	-6.38	0.04
After 2015	25 Percentiles			Full sample	25 Percentiles		
	L	H	LMH		L	H	LMH
αFF5	9.85	3.95	6.14	αFF5	8.63	1.92	7.05
[t]	2.15	0.97	1.15	[t]	2.1	0.49	1.41
MKT_t	1.02	1.05	-0.03	MKT_t	0.98	1.01	-0.04
[t]	35.9	41	-1.19	[t]	47.8	27.2	-1.15
SMB_t	0.76	0.82	-0.06	SMB_t	0.64	0.7	-0.06
[t]	14.9	21.8	-1.08	[t]	17.6	11.2	-0.85
HML_t	0.24	0.21	0.03	HML_t	0.25	0.22	0.03
[t]	5.89	5.27	0.59	[t]	5.69	5.08	0.5
CMA_t	0.11	0.06	0.05	CMA_t	0.16	0.02	0.14
[t]	2	0.99	0.64	[t]	2.66	0.27	1.99
RMW_t	-0.09	-0.22	0.13	RMW_t	-0.14	-0.15	0.01
[t]	-2.45	-4.99	2.53	[t]	-3.66	-3.2	0.15

Note: This table shows the estimated abnormal returns (αFF5) and coefficients to the market factor (MKT), size factor (SMB), value factor (HML), the investment factor (CMA) and the profitability factor (RMW) of the 25 portfolios sorted according to their sensitivity to the Transition Risk Index (TRI), alongside the low-minus-high (LMH) transition and physical risk spread returns portfolios, considering a Fama & French (2015) five factor (FF5) asset pricing model specification. Eurostoxx 600 Index historical constituents are used and results are reported for three periods (full sample, Jan 2005-Oct 2021; before 2015, Jan 2005-Dec 2014; and after 2015, Jan 2015-Oct 2021).

Sensitivity of green and brown E, ESG, GHG_EI, GHG_E portfolios to PRI and TRI

Table 8

Full sample	E score				ESG score				GHG_{EI}				GHG_E			
	Brown		Green		Brown		Green		Brown		Green		Brown		Green	
Intercept	0.038***	0.038***	0.022***	0.022***	0.040***	0.040***	0.021***	0.021***	0.029***	0.029***	0.044***	0.044***	0.029***	0.029***	0.046***	0.046***
[t]	7.285	7.349	6.789	6.838	6.357	6.431	7.381	7.329	4.994	4.991	7.211	7.212	5.915	5.920	8.244	8.204
MKT	0.960***	0.960***	1.029***	1.029***	0.922***	0.922***	1.016***	1.016***	1.024***	1.024***	1.047***	1.047***	1.018***	1.017***	1.008***	1.008***
[t]	104.020	103.918	125.059	125.438	89.915	90.097	145.915	148.181	95.980	96.076	74.323	74.183	119.278	119.423	80.639	80.872
SMB	0.451***	0.451***	0.101***	0.101***	0.398***	0.398***	0.082***	0.082***	0.230***	0.229***	0.264***	0.264***	0.151***	0.150***	0.467***	0.467***
[t]	22.770	22.987	5.242	5.330	18.266	18.441	5.161	5.431	8.227	8.237	8.921	8.935	6.295	6.303	20.994	20.907
HML	-0.010	-0.010	0.253***	0.253***	-0.001	-0.001	0.161***	0.161***	0.105***	0.105***	0.372***	0.372***	0.127***	0.128***	0.173***	0.173***
[t]	-0.568	-0.567	17.833	18.073	-0.048	-0.043	16.861	17.002	3.459	3.465	10.436	10.447	5.306	5.317	5.839	5.790
RMW	-0.059***	-0.059***	-0.067***	-0.067***	-0.111***	-0.111***	-0.043***	-0.043***	-0.139***	-0.139***	-0.041*	-0.041*	-0.085***	-0.085***	-0.001	-0.001
[t]	-4.208	-4.225	-5.486	-5.535	-7.209	-7.268	-4.562	-4.604	-7.103	-7.100	-1.649	-1.647	-4.999	-4.991	-0.047	-0.043
CMA	0.183***	0.183***	-0.008	-0.009	0.192***	0.192***	-0.025**	-0.025**	0.049	0.049	0.092***	0.092***	-0.033	-0.033	0.199***	0.199***
[t]	9.498	9.543	-0.629	-0.644	9.227	9.305	-1.969	-1.997	1.607	1.610	3.442	3.446	-1.323	-1.326	9.005	8.970
TRI	0.095		0.145		0.170		0.276**		-0.031		0.005		0.040		0.055	
[t]	0.529		1.202		0.866		2.488		-0.145		0.023		0.215		0.268	
PRI		-0.269		0.010		-0.087		-0.072		-0.249		-0.019		-0.312		-0.123
[t]		-1.353		0.068		-0.381		-0.548		-0.985		-0.075		-1.468		-0.535
Before 2015	E score				ESG score				GHG_{EI}				GHG_E			
	Brown		Green		Brown		Green		Brown		Green		Brown		Green	
Intercept	0.028***	0.029***	0.021***	0.021***	0.029***	0.030***	0.017***	0.018***	0.033***	0.033***	0.036***	0.035***	0.030***	0.030***	0.038***	0.038***
[t]	4.594	4.744	4.711	4.832	4.430	4.617	4.584	4.916	4.486	4.519	4.872	4.873	5.090	5.259	5.469	5.570
MKT	0.978***	0.978***	1.038***	1.038***	0.958***	0.958***	1.015***	1.015***	1.039***	1.039***	1.056***	1.056***	1.007***	1.007***	1.029***	1.030***
[t]	93.189	93.319	111.193	111.521	100.705	100.708	113.891	113.882	78.573	78.984	62.179	62.370	94.196	93.987	59.989	59.455
SMB	0.453***	0.453***	0.045**	0.045**	0.450***	0.450***	0.009	0.009	0.137***	0.137***	0.252***	0.252***	0.046**	0.046**	0.511***	0.511***
[t]	18.773	18.789	2.415	2.418	17.683	17.686	0.550	0.564	4.341	4.373	8.436	8.444	2.039	2.041	20.194	20.274
HML	0.051**	0.051**	0.266***	0.266***	0.063***	0.062***	0.160***	0.160***	0.005	0.005	0.533***	0.534***	0.011	0.011	0.293***	0.293***
[t]	2.376	2.376	15.096	15.110	2.762	2.761	13.576	13.567	0.144	0.148	16.091	16.141	0.480	0.477	9.501	9.575
RMW	-0.052***	-0.052***	-0.087***	-0.087***	-0.085***	-0.085***	-0.053***	-0.054***	-0.164***	-0.164***	-0.028	-0.027	-0.124***	-0.125***	0.042	0.042
[t]	-3.006	-3.018	-5.943	-5.944	-4.825	-4.847	-4.257	-4.284	-6.820	-6.886	-0.899	-0.892	-7.358	-7.373	1.613	1.621
CMA	0.151***	0.151***	0.003	0.003	0.155***	0.155***	-0.023	-0.023	0.114***	0.114***	0.043	0.044	0.028	0.028	0.154***	0.154***
[t]	6.335	6.322	0.155	0.156	6.399	6.381	-1.490	-1.496	3.216	3.253	1.359	1.373	1.135	1.131	5.768	5.823
TRI	0.148		0.047		0.307		0.308**		-0.050		-0.138		0.108		0.040	
[t]	0.657		0.302		1.375		2.245		-0.196		-0.517		0.518		0.143	
PRI		-0.022		0.171		0.178		0.137		0.112		0.376		-0.076		0.172
[t]		-0.087		0.863		0.680		0.815		0.387		1.130		-0.334		0.568
After 2015	E score				ESG score				GHG_{EI}				GHG_E			
	Brown		Green		Brown		Green		Brown		Green		Brown		Green	
Intercept	0.049***	0.047***	0.029***	0.027***	0.052***	0.051***	0.031***	0.029***	0.033***	0.032***	0.056***	0.053***	0.038***	0.036***	0.053***	0.051***
[t]	6.237	6.514	5.863	5.623	5.420	5.413	6.576	6.258	3.784	3.821	7.895	8.051	4.735	4.742	7.861	8.141
MKT	0.926***	0.926***	0.996***	0.996***	0.873***	0.873***	0.995***	0.995***	0.975***	0.975***	1.020***	1.020***	1.010***	1.009***	0.981***	0.980***
[t]	70.400	71.267	100.968	102.227	67.682	67.457	103.725	110.242	86.887	85.273	64.946	65.476	86.060	85.419	82.930	83.117
SMB	0.528***	0.527***	0.231***	0.230***	0.411***	0.410***	0.219***	0.218***	0.352***	0.351***	0.417***	0.416***	0.244***	0.243***	0.504***	0.503***
[t]	23.411	23.372	13.456	13.554	15.574	15.649	13.882	14.417	14.119	14.212	15.100	15.135	9.711	9.727	19.735	19.479
HML	-0.113***	-0.112***	0.205***	0.206***	-0.099***	-0.099***	0.144***	0.145***	0.222***	0.224***	0.105***	0.106***	0.283***	0.285***	-0.013	-0.012
[t]	-6.452	-6.441	15.675	15.814	-4.894	-4.897	11.520	12.126	11.838	11.932	5.869	5.979	15.624	16.018	-0.830	-0.760
RMW	-0.047**	-0.046**	-0.035***	-0.034**	-0.122***	-0.121***	-0.031***	-0.029***	-0.132***	-0.131***	-0.016	-0.014	-0.064***	-0.063***	-0.031	-0.029
[t]	-2.471	-2.427	-2.605	-2.531	-5.899	-5.822	-2.744	-2.660	-6.576	-6.641	-0.916	-0.805	-3.314	-3.322	-1.574	-1.500
CMA	0.191***	0.192***	-0.017	-0.017	0.187***	0.187***	-0.002***	-0.002	0.039	0.040*	0.069***	0.069***	-0.022	-0.021	0.176***	0.177***
[t]	7.532	7.631	-1.121	-1.104	6.502	6.405	-0.149	-0.118	1.567	1.649	3.515	3.541	-0.927	-0.876	7.744	7.745
TRI	0.156		0.330*		0.059		0.345*		-0.166		0.521*		-0.095		0.284	
[t]	0.484		1.716		0.150		1.931		-0.456		1.902		-0.283		1.014	
PRI		-0.463		-0.160		-0.313		-0.298		-0.921***		-0.260		-0.765**		-0.330
[t]		-1.475		-0.789		-0.791		-1.595		-2.642		-1.010		-2.376		-1.109

Note: We group the EuroStoxx 600 Index historical constituents into brown and green portfolios according to firms' environmental score (E), environmental, social and governance score (ESG), greenhouse gas emissions intensity (GHGEI) calculated as the sum of scope 1 and 2 divided by net revenue, and greenhouse gas emissions (GHGE) calculated as the sum of scope 1 and 2. We perform time-series regressions of the brown and green portfolios excess returns on the Fama-French five factors (the market factor, MKT; the size factor, SMB; the value factor, HML; the profitability factor, RMW; and the investment factor, CMA) plus Physical Risk Index (PRI) or Transition Risk Index (TRI) over the period Jan 2005-Oct 2021 (Full sample), Jan 2005-Dec 2014 (Before 2015), and Jan 2015-Oct 2021 (After 2015). t-statistics ([t]), and Newey-West standard are adopted. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Sensitivity of NACE to TRI

Table 9

Full sample	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Q	R	S
Intercept	0.061	0.034**	0.033***	0.044***	0.037***	0.013	0.040***	0.032***	0.018*	0.037***	0.041***	0.022**	0.041***	0.041***	0.022*	0.068***	0.023*	-0.006
[t]	1.465	1.994	6.606	4.778	3.008	1.552	5.951	4.238	1.745	7.120	8.271	2.264	7.284	5.356	1.946	4.856	1.731	-0.450
MKT	0.919***	1.156***	0.933***	0.780***	0.696***	1.084***	0.908***	0.951***	1.068***	0.866***	0.950***	0.747***	0.915***	1.055***	0.986***	0.663***	0.824***	0.827***
[t]	15.604	39.596	60.647	35.638	35.224	47.997	78.261	55.310	45.394	124.048	74.829	33.050	76.782	55.300	26.580	40.358	43.674	32.875
SMB	-0.070	0.523***	0.403***	0.015	0.235***	1.055***	0.813***	0.998***	1.365***	0.514***	0.393***	0.646***	0.383***	0.919***	1.141***	0.408***	1.115***	0.893***
[t]	-0.423	5.990	17.580	0.379	4.859	23.723	28.388	22.929	15.660	22.307	13.224	11.394	13.044	21.943	20.960	7.667	17.154	14.510
HML	-0.051	0.359***	-0.043	-0.125***	-0.194***	0.444***	-0.046	0.195***	0.349***	-0.101***	0.462***	0.171***	-0.027	-0.021	-0.038	-0.239***	-0.086**	0.321***
[t]	-0.396	4.915	-1.643	-3.296	-5.691	10.271	-1.462	5.758	6.058	-5.764	18.719	4.762	-0.989	-0.457	-0.625	-6.789	-2.266	5.779
RMW	-0.658***	-0.170**	-0.111***	-0.226***	0.166***	0.174***	0.106***	0.070**	0.431***	-0.080***	-0.105***	-0.126***	-0.184***	0.141***	0.399***	-0.221***	0.117***	0.205***
[t]	-4.802	-2.456	-6.958	-7.617	3.746	5.256	4.574	2.237	8.379	-4.373	-5.358	-3.781	-10.523	4.148	8.556	-5.352	2.711	4.144
CMA	0.493***	0.367***	0.138***	-0.067*	-0.094*	0.290***	0.113***	0.013	0.101*	0.047**	0.006	0.289***	0.177***	0.147***	0.016	0.238***	0.197***	0.115*
[t]	3.097	3.870	6.493	-1.740	-1.860	8.617	4.459	0.341	1.719	2.055	0.211	6.836	6.035	4.686	0.282	5.434	4.568	1.792
TRI	-3.045*	0.004	0.474**	-0.589	-0.121	0.424	0.207	0.561*	0.127	0.024	0.063	0.624	0.268	0.391	0.422	0.665	-0.369	0.119
[t]	-1.847	0.008	2.380	-1.532	-0.233	1.262	0.853	1.734	0.292	0.111	0.338	1.482	1.252	1.252	0.712	1.113	-0.643	0.207
Before 2015	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Q	R	S
Intercept	0.108*	0.060***	0.033***	0.056***	0.045***	0.015	0.019**	0.025***	0.008	0.037***	0.039***	0.015	0.045***	0.037***	0.029**	0.072***	0.002	0.006
[t]	1.728	3.153	4.823	5.081	2.915	1.324	2.304	2.625	0.536	5.628	6.767	1.299	5.598	3.857	2.007	3.807	0.122	0.326
MKT	1.030***	1.156***	0.915***	0.732***	0.673***	1.090***	0.887***	0.899***	1.036***	0.863***	0.912***	0.724***	0.909***	1.040***	0.920***	0.670***	0.760***	0.814***
[t]	12.510	36.493	45.507	29.713	27.602	30.652	74.889	55.238	39.407	104.128	63.404	42.851	54.799	60.177	18.917	31.210	34.319	22.558
SMB	-0.058	0.117	0.443***	-0.009	0.338***	1.035***	0.852***	0.835***	1.179***	0.596***	0.360***	0.677***	0.389***	0.970***	1.127***	0.440***	0.930***	0.814***
[t]	-0.234	1.325	15.736	-0.196	6.523	21.279	27.204	20.551	16.535	19.150	12.881	15.178	10.298	23.818	14.585	6.103	12.829	11.308
HML	-0.219	0.014	0.022	-0.093*	-0.154***	0.557***	0.082***	0.220***	0.445***	-0.039*	0.517***	0.252***	0.023	0.090*	-0.052	-0.175***	-0.025	0.372***
[t]	-1.142	0.166	0.606	-1.781	-3.176	8.783	2.578	6.245	6.452	-1.822	17.021	6.618	0.645	1.867	-0.558	-3.514	-0.523	4.492
RMW	-1.037***	-0.161**	-0.107***	-0.203***	0.131**	0.170***	0.146***	0.074**	0.473***	-0.122***	-0.158***	-0.197***	-0.186***	0.173***	0.397***	-0.218***	0.08	0.218***
[t]	-5.256	-2.443	-4.702	-5.752	2.196	3.526	4.912	2.054	8.670	-5.003	-6.321	-4.710	-7.786	4.227	6.243	-3.917	1.429	2.994
CMA	0.563***	0.727***	0.132***	-0.092*	-0.144**	0.259***	0.073**	0.057	0.110*	-0.022	0.043	0.226***	0.181***	0.164***	0.174***	0.173***	0.248***	0.175**
[t]	2.615	8.265	4.663	-1.942	-2.156	6.303	2.237	1.509	1.766	-0.738	1.326	4.922	4.608	5.397	2.842	3.047	4.821	2.111
TRI	-4.337*	-0.056	0.841***	-0.900*	-0.405	0.341	0.468	0.827**	0.484	0.029	-0.099	0.760	0.298	0.498	0.993	1.017	-0.223	-0.129
[t]	-1.951	-0.091	3.121	-2.032	-0.657	0.793	1.567	2.256	0.883	0.116	-0.427	1.516	0.990	1.281	1.260	1.288	-0.312	-0.172
After 2015	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Q	R	S
Intercept	0.018	0.017	0.023***	0.027*	0.024	0.007	0.064***	0.041***	0.028	0.032***	0.039***	0.027*	0.032***	0.042***	0.004	0.051***	0.055**	-0.020
[t]	0.510	0.662	3.691	1.659	1.319	0.547	6.961	2.866	1.603	4.026	6.767	1.831	4.543	3.260	0.205	2.750	2.562	-0.992
MKT	0.754***	1.136***	0.958***	0.853***	0.739***	1.063***	0.934***	1.016***	1.094***	0.873***	0.912***	0.779***	0.920***	1.069***	1.079***	0.652***	0.899***	0.833***
[t]	13.133	33.200	73.758	29.179	21.313	49.199	64.873	42.316	28.970	69.284	63.404	19.525	66.340	31.827	35.161	28.689	33.336	29.325
SMB	0.044	0.753***	0.379***	-0.001	0.080	1.246***	0.858***	1.211***	1.737***	0.469***	0.360***	0.687***	0.423***	0.926***	1.004***	0.451***	1.408***	1.055***
[t]	0.278	7.908	12.589	-0.013	0.780	19.967	22.017	20.215	12.750	15.722	12.881	6.550	11.930	11.638	14.552	5.597	14.069	13.782
HML	-0.049	0.714***	-0.134***	-0.085*	-0.160***	0.171***	-0.245***	0.143***	0.101	-0.163***	0.517***	0.075	-0.135***	-0.236***	0.018	-0.344***	-0.222***	0.143**
[t]	-0.308	10.171	-5.915	-1.689	-3.031	3.719	-10.107	2.885	1.538	-6.900	17.021	1.579	-5.071	-5.315	0.296	-6.672	-3.492	2.451
RMW	-0.200	-0.336***	-0.103***	-0.232***	0.260***	0.164***	0.071**	0.053	0.344***	0.012	-0.158	0.010	-0.185***	0.093*	0.396***	-0.213***	0.159**	0.150***
[t]	-1.494	-4.639	-4.540	-4.845	4.359	4.183	2.527	1.084	4.087	0.449	-6.321	0.190	-7.080	1.941	6.529	-3.557	2.502	2.610
CMA	0.223	0.129	0.097***	0.064	0.005	0.156***	0.058*	0.004	0.006	0.096***	0.043***	0.335***	0.104***	-0.021	-0.129	0.258***	0.130*	-0.062
[t]	1.478	1.489	3.633	0.967	0.070	3.139	1.799	0.070	0.064	2.946	1.326	4.903	3.937	-0.432	-1.528	3.760	1.742	-0.777
TRI	-2.601	-0.553	-0.308	0.006	0.384	0.284	0.236	0.292	-0.449	-0.038	-0.099	0.464	0.014	0.227	-0.753	-0.311	-0.084	0.210
[t]	-1.503	-0.499	-1.110	0.008	0.422	0.530	0.577	0.421	-0.575	-0.101	-0.427	0.672	0.050	0.422	-0.915	-0.396	-0.086	0.242

Note: We group the EuroStoxx 600 Index historical constituents into NACE sectors: Agriculture, forestry and fishing (A), Mining and quarrying (B), Manufacturing (C), Electricity, gas, steam and air conditioning supply (D), Water supply; sewerage, waste management and remediation activities (E), Construction (F), Wholesale and retail trade; repair of motor vehicles and motorcycles (G), Transportation and storage (H), Accommodation and food service activities (I), Information and communication (J), Financial and insurance activities (K), Real estate activities (L), Professional, scientific and technical activities (M), Administrative and support service activities (N), Public administration and defence; compulsory social security (O), Human health and social work activities (Q), Arts, entertainment and recreation (R), Other service activities (S). We perform time-series regressions of the NACE sectors excess returns on the Fama-French five factors (the market factor, MKT; the size factor, SMB; the value factor,HML; the profitability factor, RMW; and the investment factor, CMA) plus Transition Risk Index (TRI) over the period Jan 2005-Oct 2021 (Full sample), Jan 2005-Dec 2014 (Before 2015), and Jan 2015-Oct 2021 (After 2015). t-statistics ([t]), and Newey-West standard are adopted. * p < 0.1; ** p < 0.05; *** p < 0.01.

Sensitivity of NACE to PRI

Table 10

Full sample	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Q	R	S
Intercept	0.061	0.034**	0.033***	0.044***	0.037***	0.013	0.040***	0.032***	0.018*	0.037***	0.041***	0.022**	0.041***	0.041***	0.022*	0.068***	0.023*	-0.006
[t]	1.466	1.992	6.581	4.750	3.037	1.554	5.976	4.242	1.746	7.132	8.319	2.270	7.289	5.369	1.947	4.876	1.728	-0.450
MKT	0.920***	1.155***	0.933***	0.780***	0.697***	1.083***	0.908***	0.951***	1.068***	0.865***	0.950***	0.746***	0.915***	1.054***	0.987***	0.663***	0.824***	0.826***
[t]	15.741	39.588	60.500	35.631	34.818	47.971	77.954	55.223	45.335	123.484	75.016	33.020	76.784	55.286	26.585	40.543	43.658	32.995
SMB	-0.068	0.522***	0.402***	0.014	0.235***	1.054***	0.813***	0.997***	1.365***	0.513***	0.394***	0.645***	0.383***	0.918***	1.142***	0.407***	1.116***	0.891***
[t]	-0.410	5.994	17.480	0.353	4.825	23.717	28.412	22.885	15.640	22.288	13.346	11.357	13.034	21.867	20.967	7.588	17.115	14.580
HML	-0.051	0.359***	-0.043	-0.125***	-0.194***	0.444***	-0.046	0.195***	0.349***	-0.101***	0.462***	0.171***	-0.027	-0.021	-0.038	-0.239***	-0.086**	0.321***
[t]	-0.392	4.918	-1.640	-3.285	-5.621	10.263	-1.459	5.749	6.059	-5.748	18.915	4.755	-0.991	-0.457	-0.628	-6.837	-2.267	5.815
RMW	-0.659***	-0.170**	-0.111***	-0.226***	0.166***	0.174***	0.106***	0.070**	0.431***	-0.079***	-0.105***	-0.126***	-0.184***	0.141***	0.399***	-0.221***	0.117***	0.206***
[t]	-4.825	-2.454	-6.973	-7.621	3.721	5.254	4.580	2.245	8.373	-4.372	-5.390	-3.769	-10.512	4.153	8.548	-5.399	2.698	4.149
CMA	0.497***	0.367***	0.137***	-0.066*	-0.094*	0.290***	0.113***	0.012	0.100*	0.047**	0.005	0.288***	0.177***	0.146***	0.016	0.237***	0.198***	0.115*
[t]	3.148	3.871	6.443	-1.708	-1.859	8.584	4.445	0.321	1.717	2.063	0.208	6.798	6.032	4.671	0.270	5.399	4.586	1.802
PRI	-0.981	-0.248	-0.107	-0.935**	0.217	0.181	-0.164	-0.184	0.081	-0.559**	0.326*	0.102	0.145	0.071	0.483	0.173	0.1	-0.633
[t]	-0.564	-0.366	-0.506	-2.260	0.400	0.482	-0.585	-0.525	0.152	-2.421	1.708	0.244	0.596	0.198	0.846	0.280	0.165	-0.954
Before 2015	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Q	R	S
Intercept	0.094	0.059***	0.036***	0.055***	0.044***	0.016	0.021**	0.027***	0.010	0.038***	0.038***	0.017	0.045***	0.038***	0.031**	0.074***	0.001	0.006
[t]	1.525	3.109	5.297	4.848	2.791	1.399	2.509	2.895	0.695	5.766	6.681	1.421	5.712	3.999	2.185	3.899	0.057	0.363
MKT	1.030***	1.157***	0.915***	0.732***	0.673***	1.090***	0.887***	0.900***	1.036***	0.863***	0.912***	0.725***	0.909***	1.041***	0.920***	0.671***	0.760***	0.813***
[t]	12.599	36.547	45.192	29.763	27.119	30.676	74.532	54.994	39.334	104.057	63.883	42.482	54.786	60.116	18.928	30.981	34.362	22.520
SMB	-0.051	0.119	0.441***	-0.010	0.339***	1.035***	0.851***	0.835***	1.177***	0.595***	0.362***	0.678***	0.389***	0.970***	1.128***	0.441***	0.930***	0.813***
[t]	-0.208	1.336	15.511	-0.208	6.469	21.259	27.032	20.246	16.577	19.123	12.892	14.957	10.301	24.065	14.610	6.139	12.808	11.268
HML	-0.215	0.014	0.021	-0.092*	-0.153***	0.556***	0.082**	0.219***	0.445***	-0.039*	0.517***	0.252***	0.022	0.089*	-0.053	-0.177***	-0.025	0.373***
[t]	-1.134	0.165	0.582	-1.762	-3.115	8.784	2.523	6.138	6.438	-1.821	17.163	6.547	0.635	1.822	-0.572	-3.508	-0.521	4.493
RMW	-1.032***	-0.161**	-0.108***	-0.201***	0.131**	0.169***	0.145***	0.073**	0.472***	-0.121***	-0.158***	-0.198***	-0.187***	0.172***	0.396***	-0.219***	0.08	0.218***
[t]	-5.231	-2.449	-4.758	-5.712	2.177	3.521	4.890	2.021	8.668	-5.029	-6.336	-4.754	-7.807	4.196	6.224	-3.914	1.436	2.999
CMA	0.567***	0.727***	0.131***	-0.090*	-0.143**	0.259***	0.073**	0.055	0.109*	-0.022	0.043	0.224***	0.181***	0.164***	0.173***	0.171***	0.248***	0.176**
[t]	2.665	8.283	4.601	-1.891	-2.129	6.276	2.208	1.455	1.764	-0.733	1.330	4.847	4.616	5.347	2.812	3.040	4.824	2.121
PRI	-0.452	0.711	0.010	-0.946*	0.064	0.241	0.010	0.442	-0.345	-0.408	0.475**	0.686	0.441	0.511	1.094	0.994	0.161	-0.623
[t]	-0.176	0.968	0.036	-1.882	0.096	0.489	0.028	0.981	-0.500	-1.453	2.071	1.355	1.343	1.124	1.416	1.163	0.223	-0.735
After 2015	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	Q	R	S
Intercept	0.026	0.014	0.024***	0.024	0.023	0.006	0.062***	0.037***	0.032*	0.031***	0.046***	0.024	0.031***	0.039***	0.006	0.050***	0.057***	-0.024
[t]	0.722	0.571	4.023	1.539	1.309	0.479	7.075	2.709	1.954	4.021	5.724	1.625	4.620	3.288	0.334	2.704	2.783	-1.187
MKT	0.755***	1.136***	0.958***	0.852***	0.739***	1.063***	0.933***	1.015***	1.095***	0.873***	0.999***	0.778***	0.920***	1.068***	1.080***	0.651***	0.899***	0.833***
[t]	13.344	33.262	74.030	28.942	21.414	49.206	64.928	42.411	28.881	68.577	79.506	19.546	66.847	31.856	35.489	28.781	33.132	29.225
SMB	0.042	0.749***	0.379***	-0.002	0.081	1.246***	0.857***	1.209***	1.738***	0.468***	0.464***	0.686***	0.422***	0.925***	1.003***	0.449***	1.408***	1.053***
[t]	0.262	7.902	12.527	-0.039	0.782	19.910	22.024	20.210	12.794	15.726	12.040	6.474	11.840	11.528	14.835	5.550	14.059	13.529
HML	-0.047	0.714***	-0.133***	-0.085*	-0.160***	0.171***	-0.245***	0.142***	0.101	-0.163***	0.360***	0.075	-0.135***	-0.236***	0.018	-0.344***	-0.222***	0.143**
[t]	-0.305	10.233	-5.927	-1.681	-3.033	3.716	-10.127	2.886	1.547	-6.903	13.536	1.565	-5.089	-5.341	0.303	-6.732	-3.494	2.409
RMW	-0.205	-0.338***	-0.104***	-0.233***	0.261***	0.164***	0.072**	0.053	0.344***	0.012	-0.028	0.010	-0.185***	0.093*=	0.394***	-0.214***	0.159**	0.150***
[t]	-1.540	-4.669	-4.566	-4.857	4.367	4.185	2.529	1.083	4.079	0.428	-1.126	0.195	-7.105	1.945	6.454	-3.572	2.497	2.598
CMA	0.228	0.130	0.098***	0.064	0.005	0.155***	0.057*	0.003	0.007	0.096***	-0.081***	0.334***	0.104***	-0.022	-0.128	0.259***	0.130*	-0.063
[t]	1.497	1.495	3.657	0.958	0.061	3.120	1.786	0.057	0.076	2.928	-2.597	4.861	3.929	-0.446	-1.499	3.769	1.743	-0.766
PRI	-2.184	-2.420**	-0.299	-1.006	0.464	0.065	-0.122	-1.058*	0.826	-0.697**	0.452	-0.574	-0.364	-0.564	-0.615	-1.124	0.361	-0.868
[t]	-1.151	-2.392	-0.963	-1.438	0.574	0.123	-0.289	-1.828	0.990	-2.012	1.345	-0.841	-1.090	-1.008	-0.698	-1.308	0.358	-0.840

Note: We group the EuroStoxx 600 Index historical constituents into NACE sectors: Agriculture, forestry and fishing (A), Mining and quarrying (B), Manufacturing (C), Electricity, gas, steam and air conditioning supply (D), Water supply; sewerage, waste management and remediation activities (E), Construction (F), Wholesale and retail trade; repair of motor vehicles and motorcycles (G), Transportation and storage (H), Accommodation and food service activities (I), Information and communication (J), Financial and insurance activities (K), Real estate activities (L), Professional, scientific and technical activities (M), Administrative and support service activities (N), Public administration and defence; compulsory social security (O), Human health and social work activities (Q), Arts, entertainment and recreation (R), Other service activities (S). We perform time-series regressions of the NACE sectors excess returns on the Fama-French five factors (the market factor, MKT; the size factor, SMB; the value factor,HML; the profitability factor, RMW; and the investment factor, CMA) plus Physical Risk Index (PRI) over the period Jan 2005-Oct 2021 (Full sample), Jan 2005-Dec 2014 (Before 2015), and Jan 2015-Oct 2021 (After 2015). t-statistics ([t]), and Newey-West standard are adopted. * p < 0.1; ** p < 0.05; *** p < 0.01.

Appendix 1

Physical risk and transition risk vocabularies list of acronyms

Table A1

Physical risk vocabulary acronyms			
GHG	Greenhouse gas	RCP	Representative Concentration
IPCC	Intergovernmental Panel on Climate change		
Transition risk vocabulary acronyms			
EJ/yr	Exajoules per year	MtCO2	Megatonne of carbon
eq/yr	Equivalent per year	MtCO2 eq	Megatonne of carbon equivalent
GHG	Greenhouse gas	TCO2	Tonne of carbon
GtCO2	Gigatonne of carbon	TEAP	Technology and Economic Assessment Panel
HCF	Hydrofluorocarbon	TWh/yr	Terawatt hours/year
HCFC	Hydrochlorofluorocarbon	UNEP	United Nations Environment Programme
IPCC	Intergovernmental Panel on Climate change	UNFCCC	United Nations Framework Convention on Climate Change
IEA	International Energy Agency	USD/kWh	United States Dollar/Kilowatt hour

Note: Physical risk and transition risk summary vocabularies as in figure 1 list of acronyms.

List of climate change white papers for transition and physical risk

Table A2

Year	Source	Title	Transition	Physical
1990	IPCC	IPCC Synthesis Report 1990	115-148p	
1990	IPCC	Climate change: The IPCC Impacts Assessment		Entire
1992	IPCC	Climate change: The IPCC 1990 and 1992 Assessments		87-113p
1999	IPCC	IPCC Special Report: Aviation and the global atmosphere	Entire	
2000	IPCC	IPCC Special Report: Methodological and technological issues in technology transfer	Entire	
2001	IPCC	IPCC Synthesis Report 2001	302-354p	
2001	IPCC	Climate change 2001: Impacts, adaptation and vulnerability		Entire
2005	IPCC	IPCC Special Report: Carbon dioxide capture and storage	Entire	
2005	IPCC	IPCC Special Report: Safeguarding the ozone layer and the global climate system: Issues related to hydrofluorocarbons and perfluorocarbons	Entire	
2007	IPCC	IPCC Synthesis Report 2007	55-70p	
2007	IPCC	Climate change 2007: Impacts, Adaptation and Vulnerability		Entire
2011	IPCC	IPCC Special Report: Renewable energy sources and climate change mitigation	Entire	
2012	IPCC	IPCC Special Report: Managing the risks of extreme events and disasters to advance climate change adaptation		Ch. 2 & 4
2014	IPCC	IPCC Synthesis Report 2014	75-112p	
2014	IPCC	Climate change 2014: Impacts, adaptation and vulnerability		Part A & B
2018	UNEP FI - Acclimatise	Navigating a new climate. Part 2: Physical risks and opportunities		Entire
2019	IPCC	IPCC Special Report: Global warming of 1.5C	Ch. 2 & 4	Ch. 3
2019	IPCC	IPCC Special Report: Climate change and land		Ch. 1-5
2019	IPCC	IPCC Special Report: The ocean and cryosphere in a changing climate		Entire
2020	IMF – Journal of Macroeconomics	The effects of weather shocks on economic activity: What are the channels of impact?		Entire
2020	McKinsey Global Institute	Climate risk and response: Physical hazards and socioeconomic impacts		Entire
2020	Swiss Re Institute	Natural catastrophes in times of economic accumulation and climate change		Entire

Note: This table reports the year of publication, source, title of the list of texts used to construct the physical and transition risk vocabularies.
List of acronyms: IPCC, Intergovernmental Panel on Climate Change; IMF, International Monetary Fund; UNEP FI, United Nations Environment Programme Finance Initiative.