The Greenium matters: evidence on the pricing of climate risk*

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Abstract

This study provides evidence on the existence of a negative Greenium, i.e. a green risk premium, based on European individual stock returns. By defining a green factor which is priced by the market, we offer a tool to assess the exposure of a portfolio to climate risk and hedge against it. We estimate that in a stressed scenario where green stocks very much outperform brown stocks, there would be losses at the global level, including for European large banks, should they fail to price the Greenium. These results call for the introduction of carbon stress tests for systemically important institutions.

Keywords: Climate risk, environmental disclosure, factor models, asset pricing, stress test.

J.E.L. classification: G01; G11; G12; Q01.

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1 Introduction

Climate change is a fact, but we are not sure what the economic costs associated with this change will be.[1] By the same token, it is difficult to estimate what the economic benefits of doing something about it would be. In particular, it would be hard to pin down the net present value of activities aimed at climate change adaptation and mitigation, as well as those directed to broader environmental objectives such as the sustainable use and protection of water and marine resources, the transition to a circular economy, waste prevention and recycling, pollution prevention and control, and the protection of healthy ecosystems.[2] At the same time, the consequences of a transition to a low-carbon, resource-efficient and circular economy, or lack thereof, are also largely uncertain. Hence, these issues have to be addressed as aspects of long-run risk. The contribution of this paper is to measure the added value of green economic activities in terms of market excess returns. To do so, we first show that indeed, the European market prices climate risk in the form of a green factor, in the context of a standard asset pricing model. Second, we estimate that the market associates a negative risk premium, which we label Greenium, to more environmentally friendly activities.

We identify the green factor based on a precise definition of green. In particular, we first construct portfolios characterized by different shades of green. This is done based on a careful assessment of the environmental impact of individual companies. In particular, we use firm-level information on greenhouse gas (GHG) or CO2 emissions, combined with a measure of the completeness of such information, to yield a synthetic greenness index for each stock. Companies which disclose comparably low levels of emissions, and are very transparent, attain the highest scores and are included in a green portfolio. The most straightforward example of green companies would be those with a large share of their turnover in green economic sectors, e.g. renewable energy. Conversely, companies which do not disclose information on their environmental performance are labeled as non-transparent. Among these nontransparent companies, those active in carbon-intensive sectors, e.g. companies operating coal power plants, are included in a brown portfolio. The green factor is constructed based on 942 companies listed on the STOXX Europe Total Market Index.

By relying on company-level disclosures and factoring-in their transparency, we try to tackle the issue of green-washing, which is likely to be the reason why the literature has so far failed to find a consensus on the existence of a priced green factor. Indeed, looking at the actual composition of the portfolios of publicly traded investment funds which label themselves as 'green' or 'sustainable', it turns out that many funds are clearly less environmentally friendly than their name would suggest. For example, a fund might indeed limit its exposure to carbon-intensive sectors, but at the same time mainly invest in e.g. financial stocks. Banks, insurers and other financial institutions are admittedly directly responsible for a very small fraction of greenhouse gas (GHG) emissions, but HSBC or

[1]On the uncertainty on the rate of increase in average temperatures in the long-medium horizon, and on the effects of climate change, see Pindyck (2013).

[2]These objectives are listed in the European Commission Action plan on financing sustainable growth, which sets out an EU strategy for sustainable finance.

Allianz is probably not what comes to mind when thinking of a company that is at the forefront of efforts to reduce emissions. At the level of the individual company, there could be a tendency to disclose only partial information, emphasizing the environmental dimensions where the firm performs best and neglecting those where the firm does not as well. For example, a car manufacturer may report its scope 1 GHG emissions, i.e. emissions from sources that it owns or controls, but could have an incentive not to disclose its scope 3 emissions, which include emissions resulting from the use of the vehicles it produces and sells. By considering the completeness of the relevant information that firms disclose, we deal with this type of greenwashing.

At the same time, however, one should be careful not to take extreme views when defining 'green' stocks. As a matter of fact, portfolio diversification is crucial for asset managers, and concentrating the exposure on a small set of pure green players is not a viable option. Our society will still need e.g. steel and cement for quite a while, and companies' low-carbon transition is a much needed but gradual process. For all these reasons, a sensible approach would be to broaden the scope of the definition of 'green' beyond pure players to also include firms that meet the highest level of energy efficiency and the lowest CO2 emissions within the relevant sector. By taking this approach, a steel manufacturer which also uses scrap steel would be greener than one that does not. By the same token, an energy company that reduces its reliance on fossil fuels though not having an entirely renewable energy mix would be greener than one that is not reducing its carbon footprint. This is the approach taken by several providers of environmental ratings, which assess the sustainability of firms relative to their peers, and also the one we take in this paper.

We show that in the context of a standard asset pricing model, the green and brown portfolios are associated with a positive intercept, suggesting the existence of an omitted factor. Based on this evidence, we propose to include a green factor, which we construct based on a long-short strategy involving the green portfolio and the brown portfolio. We find that the Greenium, i.e. the risk premium associated with this green factor, is negative and significant. This means that investors accept a lower remuneration for their investments, *ceteris paribus*, in so far as these investments are linked to greener economic activities. We interpret this as evidence of climate risk being viewed as significant, with the market seeing value in investing in green assets as a hedging strategy towards worse environmental outcomes. Indeed, in a scenario of heightened risks resulting from climate change, there would be a stronger push towards more environmentally friendly activities, with more decisive political action likely to be taken to promote sustainable growth. Hence, companies active in green sectors would operate in a more favorable environment, possibly supported by incentives, e.g. fiscal or of other nature. At the same time, the likelihood would increase that some assets, e.g. coal, would become stranded. In this context, forward-looking investors who base their portfolio allocation on a broader information set than past returns, invest in green assets already today.

The evidence we provide on the existence of a Greenium has clear financial stability implications. Indeed, we show that the European market as a whole does price climate risk. In this context, if an investor does not factor in climate risk in the construction of her portfolio, she is in fact pricing her holdings based on a misspecified model, where the green factor is omitted. Should this mispricing affect the assets held by systemically important financial institutions (SIFIs) such as large banks, insurers and pension funds, there could be consequences in terms of systemic risk. In particular, asset returns on their holdings could be negatively affected by climate change via two main channels. First, in a longer horizon perspective, more frequent and severe natural catastrophes stemming from climate change (e.g. typhoons and floods) could negatively affect returns on assets linked to particularly vulnerable economic activities.[3] These are so-called *physical risks* related to climate change, that we do not tackle in this paper directly. However, it has been shown that rising temperatures have strong adverse effects on asset valuations, as well as on key macroeconomic aggregates and productivity (see Donadelli et al., 2017). Second, in a medium-term perspective, the implementation of sustainable finance policies will imply higher costs for firms with higher emissions, causing a generalized drop in the dividend that brown firms will be able to pay to their shareholders. In parallel, carbon-intensive assets will increasingly become 'stranded' (see Campiglio et al., 2017). This is the so-called *transition risk*. These two channels characterize an environmental risk factor that investors should price. Given the lack of data on the exposure of individual companies to physical risks related to climate change, in this analysis we will focus on transition risks, i.e. the potential impacts of a shift to a lower carbon-footprint economy on firms active in climate-policy-relevant sectors.

Based on our model, we estimate that in an extreme but plausible scenario where green assets outperform brown assets, all institutional sectors at the global level, including e.g. governments, non-financial institutions and financial corporations, as well as all European SIFIs, would be hit by losses. By halving their exposure to carbon-intensive sectors and reallocating their investments towards greener assets, they could somewhat reduce the loss. However, investors could only avoid losing money if they would reallocate their investments towards greener sectors. The magnitude of the expected losses we estimate is admittedly not breathtaking. Still, we show that no one is in a safe place when it comes to climate risk, as the consequences of brown asset mispricing would be widespread. Moreover, our analysis is limited to equity holdings, that for some investors are not as relevant as other types of exposures. In a stressed scenario, however, losses would almost certainly be recorded also on the bond portfolio and notably, on banks' loan exposure. Finally, we use a simple model to compute losses, based on the marginal expected shortfall. This approach does not factor in losses resulting from second-round effects, like fire sales, which could magnify first-round losses. Taking all this into account, we conclude that a climate or climate-policy shock could have serious implications in terms of financial stability, especially if coupled with shocks of other nature. Hence, we argue that a carbon stress test is warranted for systemically important institutions to monitor their resilience to climate change. The green factor we construct could indeed be used by investors, to hedge against climate risk, and by supervisors, to measure SIFIs exposure to this risk. Notice that looking forward, we can only expect greater policy pressure to reducing carbon emissions and moving to a sustainable development path.[4]

[3] Daniel et al. (2016).

[4] Andersson et al. (2016) shows that divestment in higher emission stocks entails a cost, which investors are more likely to bear the stronger the perception of a serious commitment on the side of policymakers towards fighting climate change.

The paper is structured as follows. In the next section, we provide an overview of the relevant literature. In Section 3, we present our synthetic greenness indicator at the level of the individual company. Section 4 outlines the asset pricing theoretical framework. In Section 5, we present the results of the empirical application. First, we focus on portfolios by estimating the standard asset pricing models and defining the green factor. Then, we estimate our proposed model on individual stocks. In Section 6 we carry out a battery of robustness checks. Section 7 tests the performance of the equity portfolios of global institutional sectors and European SIFIs in a carbon-stressed scenario. Section 8 concludes.

2 Related literature

This paper stands at the crossroad of sustainable finance, asset pricing and financial stability. The sustainable finance literature has so far mostly focused on corporate performance, starting from the seminal work by Bragdon and Marlin (1972). They asked the fundamental question, whether there would be a reward for a company's virtue. Trying to answer this question, Margolis et al. (2009) finds a small and positive relationship between corporate social performances and financial performance. Along these lines, Porter (1991), Gore (1993), and Porter and van der Linde (1995) argue that improving a company environmental performance can lead to a better economic or financial performance, not necessarily accompanied by an increase in costs. Ambec and Lanoie (2008) review several empirical works showing that improvements in the environmental performance of a firm tend to be associated with improvements in the economic or financial performance, owing to potential revenue increases and/or cost cuts. More recently, Hoepner et al. (2018) show that engagement on sustainability issues can benefit shareholders' by reducing firms' downside risks.

Despite increasingly available evidence on the performance of green or sustainable corporates, however, no consensus has yet been reached in the asset pricing literature about the performance of green assets, or on environmental risk being a priced macro factor. Evidence based on a large number of studies on the performance of sustainable investment funds compared with conventional peers (e.g., Statman, 2000; Renneboog et al., 2007; Seitz, 2010) is mixed. For example, Hartzmark and Sussman (2018) find that sustainability is viewed as positively predicting future performance; however, they do not find evidence of outperformance of 'high sustainability' investment funds vs 'low sustainability' ones. Trinks et al. (2018) show that divesting in carbon fossil stocks does not impair portfolio performance. Derwall et al. (2005) find that more socially responsible portfolios provide higher average returns. On the contrary, Bolton and Kacperczyk (2019) find that stocks of companies with higher CO2 emission intensity earn higher returns. Other analyses based on publicly traded environmental portfolios find that green stocks are, on average, underperforming the market. This finding would indicate that investors are willing to earn comparatively less on these assets because they are hedging an environmental long-run risk. Finally, recent papers attempt to build climate risk hedging portfolios (see Engle et al., 2019, Choi et al., 2018, Hong et al., 2019, Kumar et al., 2018 and Goergen et al., 2019, Monasterolo and De Angelis, 2019); however, none of these works goes all the way to quantifying the associated risk premium.

Finally, the financial stability literature has started to put forward the idea of 'carbon stress tests' on the exposures of financial institutions (see Battiston et al., 2017 and Battiston and Monasterolo, 2018), as well as to develop climate stress-test methodologies for e.g. loan portfolios (see Monasterolo et al., 2018). Central Banks and international institutions, starting with the seminal speech by Carney (2015), have also emphasized on different occasions that climate change could affect systemic risk. In particular, Gros et al. (2016) distinguishes between a benign scenario, with a gradual transition to a low-carbon economy, and an adverse scenario, where the transition occurs more abruptly. In both cases, there could be financial stability consequences: with a too slow transition, the Paris Agreement goal would be missed and the catastrophic consequences of climate change would become unavoidable.[5] A too quick transition, on the other hand, would imply a sudden repricing of brown assets. We provide evidence that these concerns are shared by the market.

3 Synthetic greenness indicator

Different indicators are available to assess a company's commitment to the environment. Investors could in principle use this information to distinguish companies that are really doing green business from firms that are not transparent in this respect. However, a single indicator might not be sufficient to ensure a careful assessment of a company's environmental performance, in particular with respect to its greenhouse gas (GHG) emissions.

We focus on the Bloomberg Environmental disclosure score, which we will refer to as E score. This is an index quantifying the completeness of a firm's disclosure in terms of its impact on the environment. The E score embraces several environmental aspects of a firm's business. In particular, it looks at how transparent a company is with respect to its impact on carbon emissions, air and water pollution, protection of biodiversity, and waste, among others. The weighted E score is normalized to range from zero for companies that do not disclose environmental data to 100 for those which disclose detailed information for each pillar. The score is also tailored for industry sectors, and each component is weighted based on its importance. In particular, GHG emission disclosure is attached the highest weight.

We use the E score as a measure of the transparency of a firm with respect to its environmental sustainability commitment, and assume that higher commitment is associated with higher transparency. In other words, based on the E score, we make a first selection among firms that are transparent, at least to some extent, about their environmental performance, and firms that are not. We do not claim that firms that do not disclose information on environmental issues are necessarily ecologically destructive. However, we find it legitimate to label them as non-green, as their environmental commitment appears weaker compared to firms that do disclose (quantitative)

[5]The objective of the Paris Agreement, signed in 2015, is to keep a global temperature rise this century well below 2 degrees Celsius above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5 degrees Celsius.

information on this pillar. Among non-transparent firms, we further select a subsample that we label 'brown'. These are companies which are mainly active in sectors characterized by a comparatively higher level of carbon emissions, at the NACE-2 digit level. Based on Eurostat data, these sectors account for 85% of total greenhouse gas emissions in the EU from 2008 to 2017.[6]

To build a comprehensive index of a company's environmental performance, we combine this transparency measure with quantitative disclosure on emissions. In particular, we consider the total GHG emission intensity, i.e. the total amount on GHG emissions normalized by revenues. If this is not available, we take the total carbon dioxide (CO2) emitted, weighted by revenues. The synthetic greenness indicator $G_{i,y}$ of company i at year y is defined as the weighted average of the two components, follows:

$$G_{i,y} = \gamma K_{i,y} + (1-\gamma) E_{i,y}, \text{ with } \gamma \in [0,1], \tag{1}$$

where $K_{i,y}$ and $E_{i,y}$ are the rankings of firm i in terms of emission intensity and E score, respectively. The parameter γ controls for the relative importance of the two components of the index. We set $\gamma = 0.5$ as benchmark case, and show results for $\gamma = 0.2$ and $\gamma = 0.8$ as robustness checks in Section 6.[7] More transparent companies, for a given level of intensity of GHG or CO2 emissions, are associated with larger values of the indicator $G_{i,y}$. Firms that attain a lower emission intensity, for a given level of transparency, are also associated with larger values of $G_{i,y}$.

Figure 1 shows the number of companies in our sample which did some environmental disclosure, from 2005 to 2017 (yellow bar). The figure also reports the number of firms that disclosed their emission intensity in a given year (gray bar). The number of companies reporting on their environmental performance has exhibited an upward trend in the last ten years, reaching around 700 EUROSTOXX companies in 2017, i.e. more than half of the sample.

4 Linear factor model

We assume an approximate factor structure for excess returns combined with the absence of arbitrage opportunities to obtain asset pricing restrictions. As the greenness indicators defined in Equations (9)-(1) are only available for a relatively short sample, we opt for a time-invariant model, which assumes that the exposition of an asset i to each observable factor does not evolve over time. We acknowledge that a model that accounts for time variation in parameters and hence in risk premia would be best suited in this context, owing to the fact that awareness on climate issues has increased over time. However, a time-varying model for the excess returns could only be estimated on a much longer time series and a much larger cross-section than ours. Indeed, it would imply introducing functional specifications for the coefficients, which would result in an incidental parameter problem.

Let us define the excess return on asset $i = 1, ..., n$ at time $t = 1, 2, ...T$ as $R_{i,t} = r_{i,t} - r_{f,t}$, where $r_{i,t}$ is the

[6]Table 11 in the appendix lists the companies that are included in the brown portfolio in 2017.

[7]Figures 2 and 3 in the appendix plots the greenness indicator in its two specifications, as well as its components, for two representative companies.

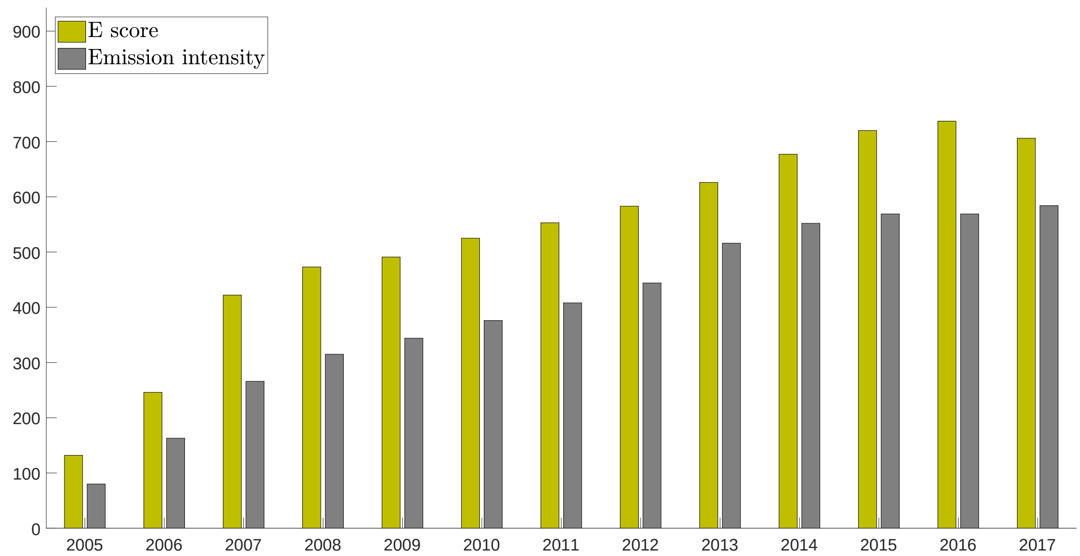

Figure 1: Total number of companies for which E score (yellow bar) and emission intensity (gray bar) are available.

log-return and $r_{f,t}$ is the risk-free return. We assume that the excess return $R_{i,t}$ satisfies the following linear factor model:

$$R_{i,t} = a_i + \sum_{k=1}^{K} b_{i,k} f_{t,k} + \varepsilon_{i,t}, \tag{2}$$

where $f_{t,k}$ is the k-th observable factor, with $k = 1, ..., K$. The error term $\varepsilon_{i,t}$ is s.t. $E[\varepsilon_{i,t}|\mathcal{F}_{t-1}] = 0$, and $Cov[\varepsilon_{i,t}, f_t|\mathcal{F}_{t-1}] = 0$, where $\mathcal{F}_{t-1}$ is the lagged information set. The approximate factor structure holds for the variance-covariance of the error terms, i.e., $\Sigma_{\varepsilon,t,n} = [Cov[\varepsilon_{i,t}, \varepsilon_{j,t}|\mathcal{F}_{t-1}]]_{i,j=1,...,n}$ with bounded largest eigenvalue (see, e.g., Chamberlain and Rothschild, 1983). The following parameter restriction holds:[8]

$$a_i = \sum_{k=1}^{K} b_{i,k} \nu_k, \tag{3}$$

where ν_k is a parameter defined for each k-th factor. The asset pricing restriction in Equation (3) can be rewritten as the usual linear relation between expected excess returns and risk premia:

$$E[R_{i,t}] = \sum_{k=1}^{K} b_{i,k} \lambda_k. \tag{4}$$

Based on Equations (3) and (4), the time-invariant risk premium associated to each k-th factor is the following:

$$\lambda_k = E[f_{t,k}] + \nu_k. \tag{5}$$

[8]We refer to Gagliardini et al. (2016) for theoretical results and proofs.

The risk premium λ_k is the sum of the expected return on the factor, which can be estimated as its first moment, plus the parameter ν_k, defined in the asset pricing restriction (3). Risk premia measure how much investors are willing to pay to hedge the systematic risk captured by the observable factors. When the factors are asset returns themselves (i.e., factors are tradable) and are assumed to be priced by the same model in (2), the risk premia are equal to the factor means (see, e.g., Jagannathan and Wang, 2002). However, if factors are non tradable, the parameter ν_k is non zero. Following Gagliardini et al. (2016), we do not assume a priori that the factors $f_{t,k}$ are tradable. Hence, we allow for the existence of market imperfections, such as transactions costs due to rebalancing and short selling, which are captured by ν (see e.g., Cremers et al., 2012).

Our baseline factor models are summarized in the table below.

Model	Reference	Abbreviation	Factors	K
Four-factor model	Carhart (1997)	CAR	$f_{m,t}, f_{smb,t}, f_{hml,t}, f_{mom,t}$	4
Three-factor model	Fama and French (1993)	3FF	$f_{m,t}, f_{smb,t}, f_{hml,t}$	3
Capital Asset Pricing Model	Sharpe (1964); Lintner (1965)	CAPM	$f_{m,t}$	1

The factors that are included in the models are the following: 1) $f_{m,t}$ is the market factor, defined as the excess return on the European value-weighted market portfolio over the risk free rate; 2) $f_{smb,t}$ is the size factor, defined as the average return on small caps minus the average return on big caps; 3) $f_{hml,t}$ is the book-to-market factor, defined as the average return on the value portfolio (i.e. stocks that have market value that is small relative to the book value) minus the average return on the growth portfolio; 4) $f_{mom,t}$ is the momentum factor, defined as the average of the returns for the winner portfolio, based on past returns, minus the average of the returns for the loser portfolio. Fama and French (2015) propose a five-factor model including the three Fama-French factors plus profitability and investment factors. However, we do not consider the five-factor model as four factors are enough to explain excess returns in a time-invariant specification, as shown by Gagliardini et al. (2019). By analogy with the $f_{m,t}$ factor, which is constructed based on the T-bill, we proxy the risk free rate with the 30-day T-bill beginning-of-month yield. The time series of European factors and the risk free rate are available on Kenneth French's website.

5 Empirical analysis

In this section, we first compare green and brown portfolios based on the models introduced in the previous section. Then, we propose an observable green factor defined as the difference between the returns on the green and the brown portfolios. Finally, we estimate the Greenium, i.e. the risk premium associated to the green factor, using a set of European individual stocks. Our sample spans from January 2006 to August 2018, covering all individual stocks included in the STOXX Europe Total Market Index (TMI) on August 2018. The STOXX Europe TMI covers approximately 95% of the free float market capitalization across 17 European countries.[9] In principle, we could estimate our model on all 20K European listed firms. However, enlarging the sample would only marginally increase its coverage in terms of market capitalization, while it may jeopardize the results owing to the quality of the information that we would feed into the model. Indeed, the reliability of the data we use for our application crucially depends on the quality of environmental disclosures of European firms. On this matter, the Non-Financial Reporting Directive imposes mandatory disclosures only on larger firms (with more than 500 employees).[10] To be on the safe side, we construct our green factor based on a sample which is more reliable in terms of data quality, in so far as it is based on an index, and still representative of the market as a whole. We present an application on a much larger sample in Section 6.

As in Fama and French (2008), we exclude financial firms (i.e., companies classified in sectors with NACE code K or L). The final dataset comprises $n = 942$ stocks. Stock returns and stock market capitalization data are sourced from Bloomberg. The panel is unbalanced, i.e., asset returns are not available for all firms at all dates.

5.1 Portfolio analysis and the Green Factor

As described in Section 3, we distinguish between transparent and non-transparent companies. The former belong to set $\mathcal{T}$ while the latter belong to set $\mathcal{T}^c$. At each month t, we define the returns on the transparent and non-transparent portfolios, i.e. $\tilde{r}_t$ and $\tilde{r}_t^c$, respectively, as follows:

$$\tilde{r}_t = \sum_{i \in \mathcal{T}} w_i r_{i,t}, \quad \text{and} \quad \tilde{r}_t^c = \sum_{i \in \mathcal{T}^c} w_i r_{i,t}, \tag{6}$$

where the weight is defined as $w_i = MC_{i,t} / \sum_t MC_{i,t}$, with $MC_{i,t}$ being the market capitalization of stock i at month t. Focussing on transparent firms, we study the returns on different portfolios characterized by different shades of green. In particular, we build portfolios of returns $\tilde{r}_t^q$ corresponding to the quintiles $q = 1, ..., 5$ of the distribution of the greenness indicator considering only firms belonging to $\mathcal{T}$.

The portfolio built on the the fifth quintile includes top-ranked firms in terms of environmental performance and is labeled 'green' portfolio. The returns on the green portfolio are indicated as $\tilde{r}_t^g$.

Focussing on non-transparent firms, we build the brown portfolio by including companies in $\mathcal{T}^c$ which are active in one or more of the industries characterized by the highest emissions, as described in Section 3. The returns on this portfolio are indicated as $\tilde{r}_t^b$. Table 12 in the appendix reports descriptive statistics for portfolios characterized by various shades of green, as well as for the transparent, non-transparent and brown portfolios. It shows that the portfolios are comparable in terms of average size of the companies and firms' leverage, while firms in the non-transparent and brown portfolio tend to have a slightly better RoA compared to greener firms.

[9] These are Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

[10] See Directive 2014/95/EU.

Table 1 reports descriptive statistics for the returns on various portfolios, namely the one including all transparent firms $\tilde{R}$, the green portfolio $\tilde{R}^g$, the portfolio including all non-transparent firms $\tilde{R}^c$, and the brown portfolio $\tilde{R}^b$.[11] With respect to the mean return, all the considered portfolios have outperformed the market, both with reference to the STOXX Europe and the Fama-French market factor, over the considered time span. With respect to the relative performance of transparent, green, non-transparent and brown firms, and looking at the mean return, the non-transparent portfolio has outperformed the others, followed by the brown and the transparent. A sounder way to assess the performance of a portfolio is the Sharpe ratio, which relates the mean performance to the standard deviation of the returns on a portfolio. In terms of Sharpe ratio, the non-transparent portfolio is still outperforming the others, which have a similarly better performance than the market. Neither the mean return nor the Sharpe ratio are monotone in the green shade, which is explained by the fact that the greenness of a portfolio is only one of the determinants of its performance (see below). Finally, the distribution of returns for all the portfolios is characterized by excess kurtosis and negative skewness.

Table 1: Descriptive statistics for the returns from January 2017 to August 2018 on various portfolios, namely the transparent $\tilde{R}$, green $\tilde{R}^g$, non-transparent $\tilde{R}^c$ and brown $\tilde{R}^b$. The table reports the monthly mean and standard deviation (Std), kurtosis (Kurt) and skewness (Skew), the Sharpe ratio, and the t-stat for the null hypothesis that the mean return is zero.

Portfolio	Mean	Std	Kurt	Skew	Sharpe	t-stat
$\tilde{R}$	1.102	0.497	3.744	-0.391	0.204	2.522
$\tilde{R}^g$	0.943	0.502	4.097	-0.593	0.188	2.315
$\tilde{R}^c$	1.732	0.586	5.210	-0.632	0.296	3.643
$\tilde{R}^b$	1.425	0.638	6.985	-0.909	0.224	2.754

We investigate the drivers of the excess returns for the portfolios described above by considering the reference models described in Section 4. In particular, Table 2 reports the estimated factor loadings for the Cahart model (CAR), the three-factor Fama-French model (3FF), and the CAPM. Results are reported for the various portfolios. Overall, results are in line with the literature with respect to the market, size, value, and momentum factors, indicating that the portfolios we analyze are rather standard with respect to these dimensions. In particular, the estimated factor loading for the market factor $\hat{b}_m$ is positive and significant across all models and portfolios. However, for the transparent and the green portfolios, the exposition to the market factor is lower compared to the non-transparent and brown portfolios. This means that more transparent and greener firms tend to be less correlated with the market compared to more opaque and browner firms. The performance of the various portfolios can also be explained by the different factor loadings on the other factors. In particular, the exposition with respect to the size factor, $\hat{b}_{smb}$, enters with a negative sign for the transparent and green portfolios, on the one hand, and a positive sign for the non-transparent and brown portfolios, on the other hand. This suggests that green and transparent firms correlate more with bigger firms, while non-transparent and brown firms correlate more with smaller firms. Indeed, based on Table 12, firms in the green and transparent portfolio exhibit a slightly larger

[11] Table 13 in the appendix reports descriptive statistics for quintile portfolios 1-4.

mean size as measured by total assets. As for the value factor $\hat{b}_{hml}$, the estimated loading is always negative and significant, except for the brown portfolio for which it is negative but non significant. Negative loadings on the value factor might mean that the portfolios include a comparatively larger share of firms with a lower book-to-market value. Considering the Carhart model, the coefficient on the momentum factor is not significant, except for the transparent portfolio. Looking at the explanatory power of the various models with respect to the different portfolios, the adjusted R-squared is lower for the brown portfolio based on all the models. Finally, the intercept is positive and significant for all portfolios and models, suggesting the existence of an omitted factor.

Table 2: Estimates of linear factor models on portfolio excess returns. The table gathers results for transparent, green, non-transparent and brown portfolios considering the following linear models: four-factor Carhart model (CAR), three-factor Fama-French model (3FF) and the CAPM. Statistical significance at the 5% (**) and 10% (*) levels , and the adjusted R-squared (R^2_{adj}).

Portfolio	$\tilde{R}$	Green	$\tilde{R}^c$	Brown
		CAR model		
$\hat{a}$	0.005**	0.004**	0.011**	0.007**
$\hat{b}_m$	0.953**	0.945**	1.061**	1.112**
$\hat{b}_{smb}$	-0.208**	-0.261**	0.476**	0.702**
$\hat{b}_{hml}$	-0.176**	-0.194**	-0.144**	-0.141
$\hat{b}_{mom}$	0.056**	0.046	-0.028	0.029
R^2_{adj}	0.979	0.947	0.940	0.864
		3FF model		
$\hat{a}$	0.005**	0.005**	0.011**	0.008**
$\hat{b}_m$	0.944**	0.938**	1.065**	1.107**
$\hat{b}_{smb}$	-0.213**	-0.264**	0.478**	0.7**
$\hat{b}_{hml}$	-0.212**	-0.224**	-0.126**	-0.159
R^2_{adj}	0.978	0.947	0.940	0.865
		CAPM		
$\hat{a}$	0.006**	0.005**	0.012**	0.009**
$\hat{b}_m$	0.899**	0.891**	1.032**	1.063**
R^2_{adj}	0.966	0.931	0.916	0.822

Finally, we define the green factor as the difference between the monthly returns on the green portfolio and those of the brown portfolio. Formally:

$$f_{g,t} = \tilde{r}_t^g - \tilde{r}_t^b. \tag{7}$$

Table 3 reports the descriptive statistics of the Fama-French observable factors, the momentum and the green factor. The table includes also the cross-correlation structure among the factors. The green factor is comparable to the other observable factors in terms of mean, standard deviation, kurtosis and skewness. It is also generally only mildly correlated with the other factors.

Table 3: Descriptive statistics of the three Fama-French factors, momentum and green factors. The table reports annualized mean return, standard deviation, kurtosis and skewness, as well as the factor correlation matrix.

Factor	Mean	Std	Kurt	Skewn	f_m	f_{smb}	f_{hml}	f_{mom}
f_m	6.035	1.885	4.690	-0.642	1			
f_{smb}	1.671	0.641	3.195	-0.129	-0.034	1		
f_{hml}	-1.378	0.788	3.582	0.519	0.533	-0.062	1	
f_{mom}	9.398	1.313	19.610	-2.546	-0.439	-0.009	-0.506	1
f_g	-4.350	1.291	4.563	0.103	-0.224	-0.483	-0.206	0.268

5.2 Asset pricing analysis

In this section we investigate if the green factor defined in Equation (7) affects the cross-section of European stock returns. In other words, we test whether investors accept lower compensation for holding environmentally friendly stocks by searching for a negative risk premium, i.e. a Greenium. The excess return $R_{i,t}$ follows the model in Equations (2)-(3). In particular, we consider the same linear factor models used in the previous section, adding the green factor f_g among the observable factors as follows:

Model	Factors	K
CAR + G	$f_{m,t}, f_{smb,t}, f_{hml,t}, f_{mom,t}, f_{g,t}$	5
3FF + G	$f_{m,t}, f_{smb,t}, f_{hml,t}, f_{g,t}$	4
CAPM + G	$f_{m,t}, f_{g,t}$	2

The risk premium of the green factor is defined as follows:

$$\lambda_g = E[f_{g,t}] + \nu_g. \tag{8}$$

In order to estimate the risk premia for the observable factors using individual stocks, we follow the estimation procedure proposed in Gagliardini et al. (2016). This procedure allows to deal with unbalanced panels, hence allowing to estimate the model on individual stocks rather than portfolios, and involves the following steps. First, we estimate the linear factor model by using the Ordinary Least Square (OLS) estimator. Second, we use the fitted residuals to test whether the model is correctly specified. In particular, we compute the diagnostic criterion proposed in Gagliardini et al. (2019), which checks whether the error terms share at least one unobserved common factor. Based on our sample, the criterion does not detect any common factor for the residuals, suggesting the validity of the factor structure.[12] Third, we compute the cross-sectional estimator ν_k from (3) by Weighted Least Squares (WLS). Finally, the estimate of the risk premium $\hat{\lambda}_k$ for each factor is given by the sum of the expected return on the factor $E[f_{k,t}]$ and the estimate of $\hat{\nu}_k$.

Table 4 shows the estimated risk premia attached to the factors, including the Greenium, as well as the estimates for ν_k. Looking at the first two columns of the table, almost all risk premia are significant across the board, and

[12] For example, for the Carhart model plus the green factor, the difference between the largest eigenvalue of the empirical cross-sectional covariance matrix of the residuals $\hat{\varepsilon}_{i,t}$ and the penalization term is negative, pointing to the absence of omitted factors.

have the expected signs. In particular, the estimated risk premia for the market, size, value and momentum factors are comparable with the results in Gagliardini et al. (2016) and Chaieb et al. (2018). The estimated Greenium is negative and significant at the 5% level in all cases. A negative Greenium indicates that investors accept lower compensation, *ceteris paribus*, to hold assets that correlate positively with the green factor, i.e. greener assets.

The last two columns of Table 4 refer to $\hat{\nu}_k$. Focussing on the green factor, $\hat{\nu}_g$ is always negative and significant at the 5% level. For this component of the risk premium, the literature has so far proposed an interpretation linked to market imperfections (see, e.g. Daniel and Titman, 1997; Haugen and Baker, 1996). With reference to the Greenium, our hypothesis is that ν_g could capture alternative preferences of market participants, for example reflecting alternative expectations on future states of the economy (see Black and McMillan, 2006). In other words, some of the information that market participants have may not be fully captured based only on past returns. In this context, the difference between the investors' larger information set and the smaller, backward-looking information set on which the model is estimated could be reflected in ν_k. This may be true in particular in the case of green and brown assets, in which case future perspectives may play a comparatively more important role than for other categories of assets.

Table 4: The table reports the estimated annualized premia for the factors in the Carhart model and for the green factor. The confidence intervals are reported at the 90% level. * and ** denote significance at 10% and 5%, respectively.

CAR + G model			
$\hat{\lambda}_m$	10.659**	$\hat{\nu}_m$	4.625**
	(0.662, 20.657)		(4.144, 5.105)
$\hat{\lambda}_{smb}$	3.326**	$\hat{\nu}_{smb}$	1.655**
	(0.321, 6.331)		(1.030, 2.279)
$\hat{\lambda}_{hml}$	-4.582*	$\hat{\nu}_{hml}$	-3.203**
	(-8.525, -0.639)		(-4.042, -2.364)
$\hat{\lambda}_{mom}$	8.986**	$\hat{\nu}_{mom}$	-0.412
	(2.277, 15.695)		(-2.148, 1.325)
$\hat{\lambda}_g$	-9.860**	$\hat{\nu}_g$	-4.076**
	(-14.455, -5.265)		(-5.453, -2.699)
3FF + G model			
$\hat{\lambda}_m$	10.534*	$\hat{\nu}_m$	4.499**
	(0.536, 20.531)		(4.028, 4.969)
$\hat{\lambda}_{smb}$	2.634	$\hat{\nu}_{smb}$	0.963**
	(-0.371, 5.639)		(0.349, 1.576)
$\hat{\lambda}_{hml}$	-5.903**	$\hat{\nu}_{hml}$	-4.525**
	(-9.846, -1.961)		(-5.351, -3.700)
$\hat{\lambda}_g$	-7.545**	$\hat{\nu}_g$	-1.781**
	(-12.160, -2.969)		(-3.132, -0.429)
CAPM + G			
$\hat{\lambda}_m$	11.137*	$\hat{\nu}_m$	5.102**
	(1.139, 21.134)		(4.649, 5.554)
$\hat{\lambda}_g$	-7.282**	$\hat{\nu}_g$	-1.498**
	(-11.877, -2.687)		(-2.693, -0.303)

6 Robustness checks

In this section we provide a battery of robustness checks. The first ones relate to the greenness indicator as defined in Equation (1), i.e. the version of the indicator based on rankings. In the benchmark specification we assign equal weight to the two components of the greenness indicator, namely the transparency and the emission intensity of a firm. This implies imposing $\gamma = 0.5$. By tuning the parameter γ, we investigate whether attaching more or less weight to one of the components of the indicator has an impact on the results. In particular, by imposing $\gamma < 0.5$, we construct an indicator where a firm's environmental score has a lower weight compared to its emission intensity. This version of the indicator attaches a larger weight to hard data and quantitative information, and a smaller weight to a transparency score which may also rely on descriptive statements and high level disclosures.

Table 5 shows estimated risk premia and $\hat{\nu}_k$ considering the Carhart model, for the cases where $\gamma = 0.2$ and $\gamma = 0.8$. The first two columns report estimates for the risk premia, which both for $\gamma = 0.2$ and $\gamma = 0.8$, and in line with the evidence presented in the previous section, have the expected signs and are significantly different from zero. The Greenium, in particular, remains negative and significant at the 5% level. The last two columns report estimates for $\hat{\nu}_k$. Also in this case, signs and significance of the estimates are in line with the benchmark case.

Table 5: The table reports the estimated annualized premia for the factors in the Carhart model and for the green factor. The green factor is computed based the greenness indicator $G_{i,y}$, with $\gamma = 0.2, 0.8$. The confidence intervals are reported at the 90% level. * and ** denote significance at 10% and 5%, respectively.

	$\gamma = 0.2$	$\gamma = 0.8$		$\gamma = 0.2$	$\gamma = 0.8$
$\hat{\lambda}_m$	10.671**	10.774*	$\hat{\nu}_m$	4.636**	4.739**
	(0.673, 20.668)	(0.777, 20.772)		(4.155, 5.117)	(4.257, 5.222)
$\hat{\lambda}_{smb}$	3.567**	3.364*	$\hat{\nu}_{smb}$	1.896**	1.693**
	(0.562, 6.572)	(0.360, 6.369)		(1.275, 2.516)	(1.066, 2.321)
$\hat{\lambda}_{hml}$	-4.733*	-4.589*	$\hat{\nu}_{hml}$	-3.355**	-3.210**
	(-8.677, -0.790)	(-8.532, -0.646)		(-4.194, -2.515)	(-4.054, -2.366)
$\hat{\lambda}_{mom}$	8.178**	8.473**	$\hat{\nu}_{mom}$	-1.220	-0.925
	(1.469, 14.887)	(1.764, 15.182)		(-3.062, 0.622)	(-2.742, 0.891)
$\hat{\lambda}_g$	-8.290**	-9.853**	$\hat{\nu}_g$	-2.860**	-5.554**
	(-12.763, -3.817)	(-14.627, -5.078)		(-4.205, -1.515)	(-7.047, -4.061)

The second robustness check involves the functional form adopted to build the greenness indicator. We propose an alternative specification where the two components of the indicator are related to each other in the form of a ratio, as follows:

$$G^*_{i,y} = \frac{E^*_{i,y}}{K^*_{i,y}} = E^*_{i,y} \left(\frac{Sales}{Emissions} \right)_{i,y}, \tag{9}$$

where $E^*_{i,y}$ is the E score and $K^*_{i,y}$ is the ratio of total GHG or CO2 emissions over sales. The higher nonlinearity of this version of the greenness indicator does not affect the results, as shown in Table 6. In particular, the Greenium and $\hat{\nu}_k$ remain negative and significant at the 5% level.

Table 6: The table reports the estimated annualized premia for the factors in the Carhart model and for the green factor. The green factor is computed based on the greenness indicator $G^*_{i,y}$. The confidence intervals are reported at the 90% level. * and ** denote significance at 10% and 5%, respectively.

Green factor based on $G^*_{i,t}$			
$\hat{\lambda}_m$	10.746*	$\hat{\nu}_m$	4.711**
	(0.748, 20.744)		(4.229, 5.193)
$\hat{\lambda}_{smb}$	3.459*	$\hat{\nu}_{smb}$	1.788**
	(0.454, 6.464)		(1.159, 2.416)
$\hat{\lambda}_{hml}$	-4.564*	$\hat{\nu}_{hml}$	-3.186**
	(-8.5070, -0.622)		(-4.029, -2.343)
$\hat{\lambda}_{mom}$	8.278**	$\hat{\nu}_{mom}$	-1.120
	(1.570, 14.987)		(-2.944, 0.7051)
$\hat{\lambda}_g$	-8.873**	$\hat{\nu}_g$	-4.313**
	(-13.660, -4.085)		(-5.812,-2.815)

As a further robustness check, we expand our sample to include all listed European companies which do some environmental disclosure, i.e. have an E score larger than zero, and those that do no disclosure and belong to brown sectors, as defined in Section 3. By doing so, we more than double the size of the sample, bringing it to 2,154 stocks. However, as discussed in Section 5, enlarging the sample to include mid and small caps may affect the quality of the environmental information used to construct the greenness indicator. For this reason, in this exercise we still use the green factor as constructed on the smaller, more reliable sample. Table 7 reports estimates for the risk premia and $\hat{\nu}_k$ based on the Carhart model and the larger sample of European stocks. As shown in the first column, the market risk premium and the premium attached to the value factor remain significantly positive and negative, respectively. The sign of the risk premium on the size factor changes, while the premium associated with the momentum factor remains positive but loses significance. As for the Greenium, it remains negative and significant at the 5% level. At the same time, $\hat{\nu}_g$ is estimated to be non significantly different from zero in this exercise.

Table 7: Results on a larger sample comprising 2,154 European stocks. The table reports the estimated annualized premia for the factors in the Carhart model and for the green factor. The green factor is computed based the greenness indicator $G_{i,y}$ with $\gamma = 0.5$ as in the baseline specification. The confidence intervals are reported at the 90% level. * and ** denote significance at 10% and 5%, respectively.

Larger sample			
$\hat{\lambda}_m$	13.462*	$\hat{\nu}_m$	7.427**
	(3.464, 23.460)		(6.876, 7.979)
$\hat{\lambda}_{smb}$	-0.545	$\hat{\nu}_{smb}$	-2.215**
	(-3.548, 2.461)		(-2.837, -1.593)
$\hat{\lambda}_{hml}$	-5.331**	$\hat{\nu}_{hml}$	-3.953**
	(-9.274, -1.388)		(-4.610, -3.295)
$\hat{\lambda}_{mom}$	4.913	$\hat{\nu}_{mom}$	-4.485**
	(-1.796, 11.622)		(-6.338, -2.632)
$\hat{\lambda}_g$	-5.156**	$\hat{\nu}_g$	0.628
	(-9.751, -0.561)		(-0.692, 1.949)

Finally, we check the robustness of the results with respect to the set of firms we oppose to ‘green’ firms. In the benchmark application, we build a portfolio of brown firms selecting the ones belonging to the highest emitting NACE economic sectors, among those that do no environmental disclosure. However, one could argue that the NACE classification is in some cases unsuitable for sustainability analysis. Hence, we build an alternative green factor based on the returns on the green portfolio $\tilde{r}_t^g$, on the one hand, and those of the portfolio including all non-transparent firms $\tilde{r}_t^c$, on the other. Formally:

$$f_{g,t} = \tilde{r}_t^g - \tilde{r}_t^c$$

The upper part of Table 8 shows results for the case where the green factor is constructed based on all non-transparent firms. Looking at the first column of the table, the results hold for all the risk premia, which keep their sign and significance. The Greenium, in particular, remains negative and significant at the 5% level. Looking at the second column, $\hat{\nu}_g$ is estimated to be positive and significant in this case.

Finally, we test yet another specification for the green factor, only based on transparent firms. In particular, we construct the green factor as the difference between the returns on green firms and firms that do some environmental disclosure, but only attain lower levels of greenness. The former correspond to the green portfolio as defined in Section 5, i.e. the one including firms in the top quintile of the distribution of the greenness indicator. The latter firms correspond to those in the lower quintile of the distribution of the greenness indicator. Also in this case, we test both specifications of the greenness indicator. Formally, the green factor is constructed as follows:

$$f_{g,t} = \tilde{r}_t^g - \tilde{r}_t^1$$

The lower part of Table 8 shows that with respect to risk premia, all the signs are unchanged with respect to the benchmark specification, including for the Greenium which remains negative. However, in the baseline specification reported in the table the Greenium is non significantly different from zero. It remains significant only in the specification where the greenness indicator is constructed as a ratio of its two components (see above). Looking at the right part of the table, $\hat{\nu}_g$ is estimated to be negative but non significant in this case. Non-significant results are not surprising, as the factor is constructed starting from two classes of firms which are more similar to each other compared to the other specifications.

Table 8: The table reports the estimated annualized risk premia for the factors in the Carhart model and for the green factor. The confidence intervals are reported at the 90% probability level. * and ** denote significance at 10% and 5%, respectively. The results are reported for the European individual stocks.

Green factor based on green and non-transparent firms			
$\hat{\lambda}_m$	10.337*	$\hat{\nu}_m$	4.302**
	(0.339, 20.334)		(3.817, 4.787)
$\hat{\lambda}_{smb}$	3.533*	$\hat{\nu}_{smb}$	1.861**
	(0.528, 6.537)		(1.234, 2.486)
$\hat{\lambda}_{hml}$	-4.728**	$\hat{\nu}_{hml}$	-3.349**
	(-8.671, -0.785)		(-4.188, -2.511)
$\hat{\lambda}_{mom}$	7.347*	$\hat{\nu}_{mom}$	-2.051*
	(0.638, 14.056)		(-3.886, -0.216)
$\hat{\lambda}_g$	-5.500**	$\hat{\nu}_g$	3.415**
	(-10.101, -0.899)		(2.282, 4.549)
Green factor based on greenest and less-green firms			
$\hat{\lambda}_m$	10.951*	$\hat{\nu}_m$	4.917**
	(0.954, 20.949)		(4.447, 5.386)
$\hat{\lambda}_{smb}$	2.628	$\hat{\nu}_{smb}$	0.957**
	(-0.376, 5.633)		(0.370,1.545)
$\hat{\lambda}_{hml}$	-4.907**	$\hat{\nu}_{hml}$	-3.529**
	(-8.850, -0.964)		(-4.365,-2.692)
$\hat{\lambda}_{mom}$	5.071	$\hat{\nu}_{mom}$	-4.327**
	(-1.638, 11.780)		(-5.899, -2.756)
$\hat{\lambda}_g$	-3.228	$\hat{\nu}_g$	-0.393
	(-6.481, 0.025)		(-1.379, 0.594)

7 Carbon stress test on actual holdings

Based on the estimates derived in the previous section, we carry out a carbon stress test on actual investors' equity holdings. We consider the various institutional sectors at the global level, as well as European SIFIs in particular. The aim of a carbon stress test is to measure the exposure of investors to climate risk, in a scenario where more stringent sustainability-oriented policies are progressively implemented, with increasing pressure on comparatively more carbon-intensive firms and sectors. In such a scenario, the expected returns on greener stocks increase, as more sustainable firms are able to distribute higher dividends, while the price of brown stocks drops for the same reason. In other words, the expected return on stocks of more environmentally sustainable firms conditional to the implementation of sustainability policies increases. Formally, this implies that the return on the green factor in Equation (7), which is positively correlated with returns on greener stocks, increases.

We test the resilience of investors to climate risk by borrowing data on equity exposures and the classification of economic sectors into climate-policy-relevant sectors from Battiston et al. (2017). Following the indication provided by the authors as supplementary information in Table 3, we group individual stocks (see Section 5) according to their associated NACE code. In particular, we classify stocks in the following economic sectors: fossil fuels, energy intensive activities, housing, utilities, transport, finance and other. Table 1 in Battiston et al. (2017) provides aggregate holdings into climate-policy-relevant sectors, as of 2015, for the following institutional sectors: Individuals, Governments (GOV), Non-Financial Companies (NFCs), Other Credit Institutions (OCIs), Other Financial Services (OFSs), as well as the institutional financial sectors as defined in the ESA classification, i.e. Banks, Investment Funds (IFs), and Insurance and Pension Funds (IPFs). Battiston et al. (2017) also classify equity holdings of individual financial institutions by climate-policy-relevant sectors, obtaining the share of their portfolio invested into each of these sectors. Based on their data, we focus on European SIFIs, as identified by the Financial Stability Board.

The equity portfolio of an investor j at time t is defined as follows:

$$r_{j,t} = \sum_{\kappa=1}^{7} \omega_\kappa r_{\kappa,t}, \tag{10}$$

where ω_κ corresponds to the equity exposure to the climate-policy-relevant sector κ and $r_{\kappa,t}$ is the monthly average value weighted portfolio return of sector κ.

For each institutional sector and individual bank j, we compute the marginal expected shortfall (MES) introduced by Acharya et al. (2010). The MES is defined as the expected equity loss conditional on a particular factor return taking a loss greater than Γ. Based on the definition of our green factor, in this application we estimate the expected equity loss conditional on the green factor return defined in Equation (7) realizing a gain greater than Γ, i.e. a scenario where greener stocks outperform brown stocks by more than a particular threshold. Hence, we can write the MES as follows:

$$\begin{aligned} MES_{j,t} &= -E[r_{j,t} | -f_{g,t} < -\Gamma], & (11)\\ &= -E[r_{j,t} | f_{g,t} > \Gamma]. & (12) \end{aligned}$$

We compute the MES considering the following three cases, which are defined in terms of portfolio allocation:

- *Baseline Case*: the investors' portfolio allocation is defined as in Equation (10) and reflects the actual allocation of institutional sectors and financial institutions as in Battiston et al. (2017). The portfolio share invested in each of the stocks included in on our sample is derived accordingly.

- *Case 1*: the investors' portfolio allocation is defined as $r_{j,t} = \frac{1}{2}\omega_{j,1} r_{1,t} + \frac{1}{2}\omega_{j,1} r_t^+ + \sum_{\kappa=2}^{7} \omega_{j,\kappa} r_{\kappa,t}$, where the exposure to the fossil fuel sector is reduced by 50% compared to the baseline and investments. We assume that investors would shorten companies in the fossil fuel sectors because this sectors is characterized by the highest emissions. At the same time, we assume that investments are reallocated to greener stocks, defined as the stocks with a positive exposition to the green factor.

- *Case 2*: the investors' portfolio allocation is defined as $r_{j,t} = \sum_{\kappa=1}^{7} \omega_{j,\kappa} r_{\kappa,t}^+$, i.e. only green stocks, as defined above, are included in the portfolio.

In all three cases, the $MES_{j,t}$ is computed w.r.t. the event $f_{g,t} > q_{0.95}$, where $q_{0.95}$ indicates the 95^{th} percentile of the distribution of the green factor. This corresponds to an extreme, but still plausible scenario.

Tables 9 and 10 report MES results for the institutional sectors at the global level and European SIFIs, respectively. The MES is expressed both as percentage loss and in billions of US dollars. Looking at Table 9, the average MES at the global level in the baseline scenario, i.e. given the actual portfolio allocation in 2015, is estimated to be -1.5% and the very limited variation across institutional sectors and institutions indicates that no one would be immune. A loss of -1.5% on equity portfolios globally corresponds to USD 387 bn. For comparison, this figure is close to the total disbursements under the Troubled Asset Relief Program (TARP), through which the US Government purchased or insured troubled assets between 2008 and 2014. Table 9 also shows what would happen should a global portfolio reallocation take place. The figures obtained under Scenario 1 indicate that halving the exposure to carbon-intensive sectors would reduce the MES only marginally. Losses would be avoided only under Scenario 2, characterized by a radical portfolio reallocation.

Turning to Table 10, we estimate a loss of -1.6%, with individual banks recording losses of up to -2.2% on their equity portfolio. An average loss of -1.6% for European SIFIs corresponds to almost USD 7 bn. These figures are admittedly not breathtaking, and one might argue that losses of this magnitude would be unlike to trigger a financial crisis. However, this exercise only focuses on equity exposures, and only on first-round losses. Actually, one should consider that a scenario where green assets very much outperform brown ones would be rooted into a deep transformation of the economy as a whole. The low-carbon transition, if implemented in a sudden and disorderly manner, would be associated with stranded assets and non-performing loans, on top of losses on the stock market, which would also very much weigh on bank's profits. In fact, only a comparatively small fraction of the overall exposure of banks to carbon-intensive economic sectors is due to banks' equity holdings. Moreover, the stress-testing literature has shown that second-round effects, such as contagion dynamics, the devaluation of counterparties' debt obligations, as well as the price impact of fire sales, may considerably amplify first-round losses. In particular, according to the bank stress-testing literature based on network models, second-round losses are comparable in magnitude to first round losses (see Battiston et al. (2017) and references therein). Having said that, our data is not granular enough to estimate the amount of losses that could add up to first-round impacts in a scenario like the one we are considering. Moreover, the MES-based stress-testing tool we propose is specifically targeted to assess climate risk in the equity portfolio. However, it's worth recalling that the global financial crisis, culminating in trillions of losses in world GDP, was triggered by writedowns on the value of loans and securitized assets due to the US subprime crisis, which for many banks amounted to just few billions.

Table 9: The table reports the MES in percentage terms and in billions of dollars, for the three scenarios, for global institutional sectors. The MES is computed conditional to the event $f_{g,t} > q_{0.95}$.

	MES (%)			MES (Bn $)		
	Baseline	Scenario 1	Scenario 2	Baseline	Scenario 1	Scenario 2
OCIs	-1.592	-1.511	0.113	-8.236	-7.821	0.584
Governments	-1.411	-1.259	-0.085	-8.169	-7.286	-0.493
Individuals	-1.433	-1.383	0.245	-37.270	-35.964	6.375
Banks	-1.495	-1.411	0.062	-40.864	-38.553	1.686
IPFs	-1.434	-1.339	0.096	-46.529	-43.460	3.119
OFSs	-1.447	-1.376	0.200	-50.261	-47.791	6.931
Non-Financial Companies	-1.462	-1.355	0.095	-68.476	-63.444	4.469
Investment Funds	-1.404	-1.323	0.211	-127.646	-120.310	19.194
Average and Total	-1.460	-1.370	0.117	-387.451	-364.630	41.866

Table 10: The table reports the MES in percentage terms and in billions of dollars, for the three scenarios, for European SIFIs. The MES is computed conditional to the event $f_{g,t} > q_{0.95}$.

	MES (%)			MES (Bn $)		
	Baseline	Scenario 1	Scenario 2	Baseline	Scenario 1	Scenario 2
DEUTSCHE BANK AG via its funds	-1.455	-1.321	-0.032	-2.348	-2.131	-0.052
BPCE SA via its funds	-1.590	-1.539	0.112	-2.325	-2.251	0.164
BNP PARIBAS via its funds	-1.621	-1.518	-0.141	-1.090	-1.021	-0.095
UNICREDIT SPA via its funds	-1.482	-1.415	0.145	-0.438	-0.418	0.043
BARCLAYS PLC via its funds	-1.512	-1.394	-0.079	-0.572	-0.528	-0.030
CREDIT SUISSE GROUP AG via its funds	-1.420	-1.325	0.158	-1.300	-1.212	0.145
BANCO SANTANDER SA	-1.912	-1.904	-0.486	-0.155	-0.154	-0.039
UBS GROUP AG via its funds	-1.432	-1.314	0.097	-2.604	-2.390	0.176
ING BANK NV	-2.225	-2.049	-1.120	-0.042	-0.039	-0.021
SOCIETE GENERALE GESTION	-1.571	-1.496	0.088	-0.771	-0.734	0.043
Average and Total	-1.647	-1.552	-0.167	-6.971	-6.496	0.222

8 Conclusions and further research

Based on European stocks, we provide evidence of the existence of a pricing factor linked to climate risk and find that the Greenium, i.e. the associated risk premium, is negative and significant. So far, no consistent evidence was available in the literature based on stock returns, and an estimate of the risk premium associated to climate risk was the Holy Grail of asset pricing research in relation to climate finance. We obtain this result because we take green seriously, unlike studies based on publicly traded funds or indices, which often market themselves as greener than they actually are. To attenuate the problem of greenwashing, we construct an index of greenness at the individual company level, which takes into account both the GHG emission intensity of a company and the quality of its environmental disclosure. Based on this index we identify the greenest companies, while we select brown companies among those that do no disclosure, and operate in brown sectors. These two portfolios are used to define the green factor. The negative sign attached to the Greenium indicates that investors buy greener assets accepting a *ceteris paribus* lower return, as a hedging strategy to reduce their exposure to climate risk.

In the last part of the paper we use our model to price investors' equity holdings. We find that the current allocation in terms of green vs brown sectors exposes them to non-negligible losses in a severe but plausible scenario where green assets outperform brown assets. We estimate that direct losses could amount to 1.5% of the global equity exposure, and to USD 7 bn for European SIFIs overall. By adding up second-round effects and losses on loans and other assets, this figure could rapidly increase. We calculate that halving investors' exposure to carbon-intensive sectors would decrease losses only marginally, while only a radical portfolio reallocation towards greener assets would ensure resilience. Based on our results, and considering that we only focus on equity exposures, we argue in favor of introducing carbon stress tests for systemic financial institutions to make sure that climate risk is suitably priced. The methodology we propose to assess climate risk in equity portfolios is based on a comparatively simple and well-known methodology, the marginal expected shortfall, and could easily become part of a broader stress-testing exercise.

Given that the awareness of investors towards climate-related issues has clearly increased in recent years, it would make sense to estimate a model with a time-varying risk premium. As discussed, this presents challenges in terms of estimation, and will be the object of future research. Another interesting avenue relates to the drivers of the Greenium, and in particular to our hypothesis that its negative sign could be driven by the component which is not related to past returns. The issue of the smaller information set on which model estimation is based, compared to the larger information set available to economic agents, has been studied in the macroeconometric literature and could be relevant also in the asset pricing context.

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Appendix: Additional tables and figures

Figures 2 and 3 show the time-series of the greenness indicator $G_{i,y}$ (top panels) for two representative companies, as well as the ranking of the relevant firm in terms of E score and emission intensity over time. The bottom panels plot the firms' E and ESG scores over time, as well as their emission intensity. NIBE Industrier AB develops solutions for smart heating and intelligent control in industry and infrastructure. International Airlines Group is the largest airline group globally. The greenness indicator for the two companies differs by three orders of magnitude. For NIBE Industrier AB, the quality and quantity of disclosures have improved over time, together with a slightly decreasing emission intensity, both resulting in an increasing value for the greenness indicator over time. International Airlines Group attained an E score in 2011 which was comparable to that of NIBE Industrier AB in 2009. However, International Airlines Group's disclosures only marginally improved over time, if at all. With respect to emissions, they are obviously incomparably larger for airlines than for many other companies.

NIBE Industrier AB

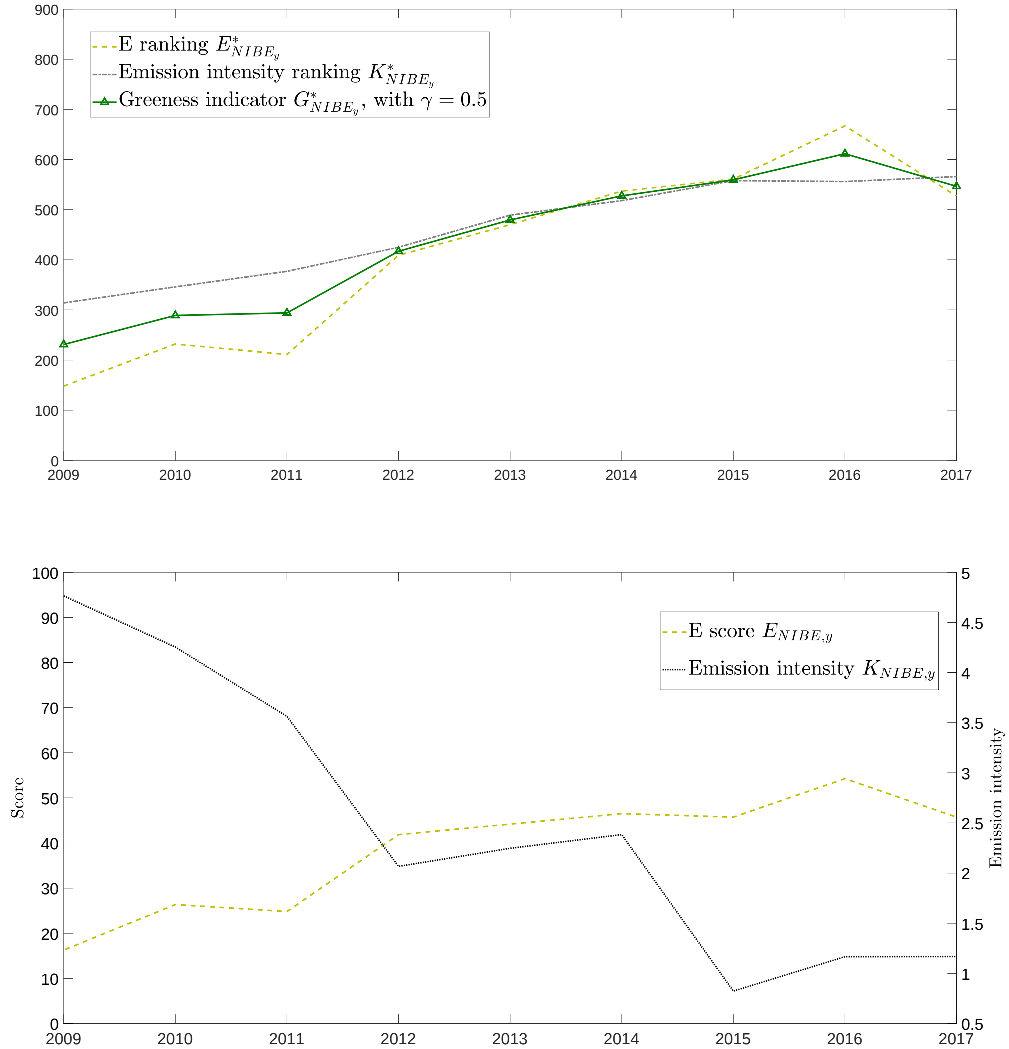

Figure 2: Greenness indicators $G_{NIBE,y}$ and $G^*_{NIBE,y}$, E score and emissions intensity in raw and ranked values, of the NIBE Industrier AB.

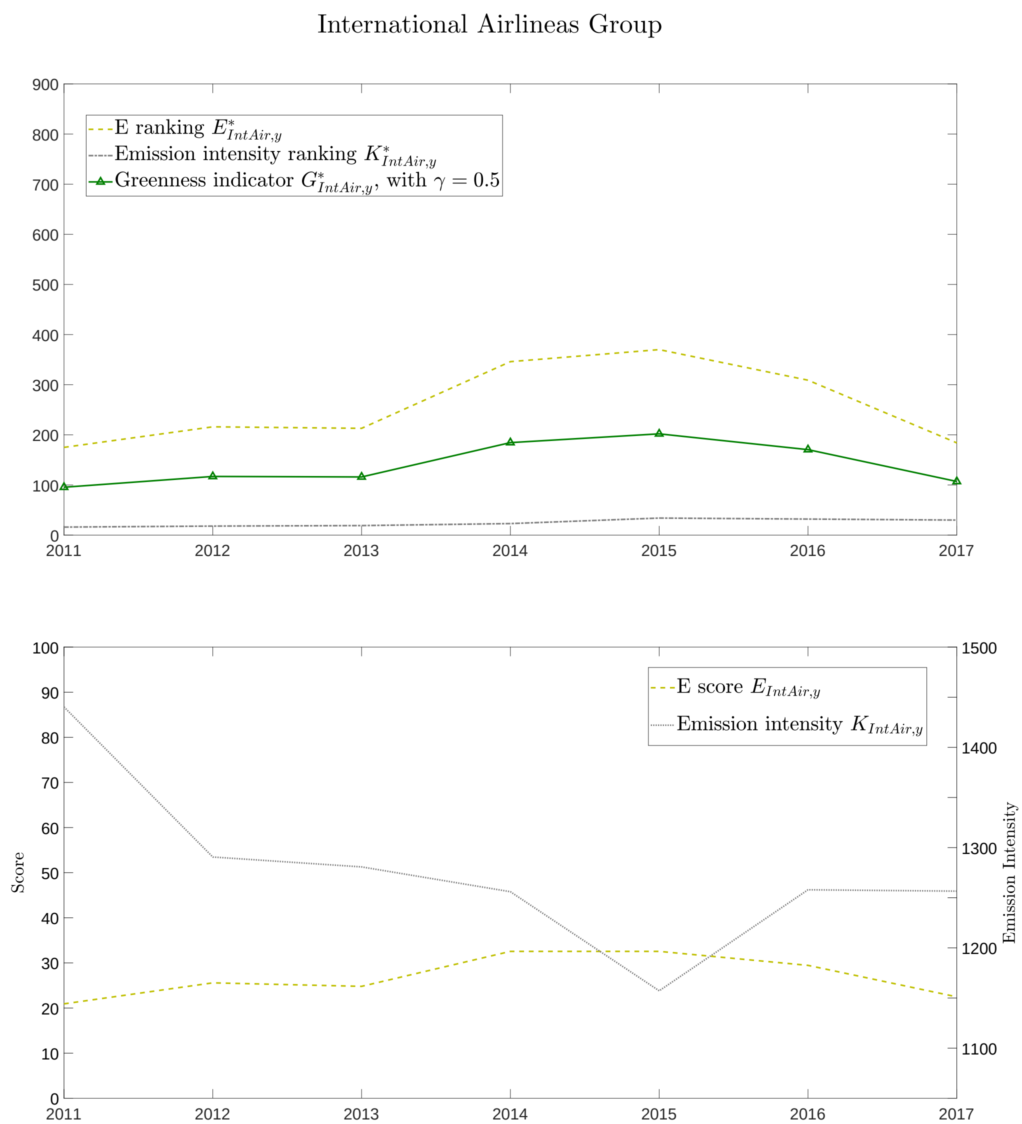

Figure 3: Greenness indicators $G_{IntAir,y}$ and $G^*_{IntAir,y}$, E score and emissions intensity in raw and ranked values, of the International Airlines Group.

Table 11: List of brown companies in 2017. The brown companies are non-transparent companies and belonging in the industries account for 85% of total greenhouse gas emissions in the EU from 2008 to 2017: Mining of coal and lignite (B05), Extraction of crude petroleum and natural gas (B06), Mining of metal ores (B07), Mining support service activities (B09), Manufacture of chemicals and chemical products(C20),Manufacture of rubber and plastic products (C22), Manufacture of other non-metallic mineral products (C23), Manufacture of fabricated metal products, except machinery and equipment(C25), Electricity, gas, steam and air conditioning supply (D35), Land transport and transport via pipelines (H49), Water transport (H50), Air transport (H51).

Company Name	NACE code	Company Name	NACE code
Lubelski Wegiel Bogdanka SA	B05	Ibstock PLC	C23
Genel Energy Plc	B06	Rhi Magnesita NV	C23
Norwegian Energy Co ASA	B06	Bossard Holding AG	C25
BHP Billiton PLC	B07	Beijer Alma AB	C25
Grupa Kety SA	B07	Indus Holding AG	C25
Stalprodukt SA	B07	Boryszew SA	C25
Alumetal SA	B07	Mennica Polska SA	C25
Elkem ASA	B07	SFS Group AG	C25
Northern Drilling Ltd	B09	Fiskars OYJ Abp	C25
Bonheur ASA	B09	Elektrobudowa SA	D35
Borr Drilling Ltd	B09	Kogeneracja	D35
Shelf Drilling Ltd	B09	BKW AG	D35
Odfjell Drilling Ltd	B09	Arendals Fossekompani A/S	D35
EMS-Chemie Holding AG	C20	Nobina AB	H49
Ciech SA	C20	PKP Cargo SA	H49
Tikkurila Oyj	C20	Dfds A/S	H50
Tessenderlo Group SA	C20	Fjord1 ASA	H50
Recticel SA	C22	Ocean Yield ASA	H50
Sanok Rubber Co SA	C22	Frontline Ltd/Bermuda	H50
Forbo Holding AG	C22	Wizz Air Holdings Plc	H51
Vidrala SA	C23		

Table 12: Companies' fundamentals (year 2017). The table reports descriptive statistics for size (measured by the log of total assets), leverage and RoA, considering companies included in the various portfolios.

Portfolio	Size		Leverage		RoA	
	Mean	Std	Mean	Std	Mean	Std
$\tilde{R}^1$	9.683	1.013	25.933	16.168	6.619	5.790
$\tilde{R}^2$	9.368	1.099	23.027	15.349	6.474	6.825
$\tilde{R}^3$	9.440	1.258	22.208	16.330	6.685	6.741
$\tilde{R}^4$	9.496	1.201	22.019	14.405	6.977	7.577
$\tilde{R}^g$	9.513	1.184	23.466	15.666	5.526	6.585
$\tilde{R}$	9.473	1.158	23.196	15.365	6.627	6.922
$\tilde{R}^c$	9.368	1.201	24.018	16.372	7.187	8.208
$\tilde{R}^b$	9.433	1.164	24.888	17.461	7.163	8.077

Table 13: Descriptive statistics of 1-4 transparent portfolios. The table reports the mean and standard deviation (Std), kurtosis (Kurt) and skewness (Skew), the Sharpe ratio, t-stat for the null hypothesis that the mean return is zero.

Portfolio	Mean	Std	Kurt	Skew	Sharpe	t-stat
$\tilde{R}_1$	1.065	0.503	3.579	-0.099	0.212	2.611
$\tilde{R}_2$	1.160	0.547	5.257	-0.684	0.212	2.617
$\tilde{R}_3$	0.786	0.530	4.175	-0.391	0.148	1.827
$\tilde{R}_4$	0.920	0.489	3.445	-0.232	0.188	2.317

Table 14: Estimates of linear factor models on the excess returns on portfolios built based on the indicator $G_{i,y}$. The table gathers results for 1-4 transparent portfolios considering the following linear models: four-factor Carhart model (CAR), three-factor Fama-French model (3FF) and the CAPM. Statistical significance at the 5% (**) and 10% (*) levels , and the adjusted R-squared (R^2_{adj}).

Portfolio	$\tilde{R}^1$	$\tilde{R}^2$	$\tilde{R}^3$	$\tilde{R}^4$
		CAR model		
$\hat{a}$	0.005**	0.007**	0.003**	0.004**
$\hat{b}_m$	0.925**	1.004**	0.991**	0.931**
$\hat{b}_{smb}$	-0.119	-0.052	-0.202**	-0.255**
$\hat{b}_{hml}$	-0.103	-0.289**	-0.317**	-0.205**
$\hat{b}_{mom}$	0.144**	-0.057	-0.05	0.086**
R^2_{adj}	0.878	0.916	0.941	0.938
		3FF model		
$\hat{a}$	0.006**	0.006**	0.003**	0.005**
$\hat{b}_m$	0.902**	1.014**	0.999**	0.916**
$\hat{b}_{smb}$	-0.131	-0.048	-0.198**	-0.262**
$\hat{b}_{hml}$	-0.194**	-0.252**	-0.285**	-0.26**
R^2_{adj}	0.87	0.915	0.940	0.935
		CAPM		
$\hat{a}$	0.006**	0.007**	0.003**	0.005**
$\hat{b}_m$	0.860**	0.958**	0.938**	0.861**
R^2_{adj}	0.864	0.908	0.926	0.917