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When do investors go green?
Evidence from a time-varying asset-pricing model *

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Abstract

This paper studies the evolution of the greenium, i.e. a risk premium linked to firms' greenness and environmental transparency, based on individual stock returns. We estimate an asset pricing model with time-varying risk premia, where the greenium is associated to a priced 'greenness and transparency' factor, which considers both companies' greenhouse gas emissions and the quality of their environmental disclosures. We show that investors in the European equity market tend to accept lower returns, ceteris paribus, to hold greener and more transparent assets when the shift of the economy towards low-carbon becomes more credible. This happened after the Paris Agreement, the first Global Climate Strike and the announcement of the EU Green Deal. Signals going in the opposite direction, such as the US withdrawal from the Paris Agreement, increasing fossil fuel prices and more bad news about climate change, are associated with increases in the greenium.

Keywords: Climate risk, environmental disclosure, conditional factor models, asset pricing.
J.E.L. classification: G01; G11; G12; Q01.

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1 Introduction

There is no consensus in the literature on how to measure whether financial markets price climate risk; hence, evidence is mixed on whether in fact a "greenium", i.e. a green risk premium, exists.[1] However, recent works increasingly find evidence of a greenium, at least in some markets and/or under some conditions and/or at a specific point in time. For example, based on green bond yields, Fatica et al. (2021) show that companies financing themselves on the green bond market do enjoy a lower cost of funding, but only if their environmental commitment is perceived as credible, e.g. owing to external verification. Still on green bonds, Zerbib (2019) also find a small negative premium, while Ma et al. (2020) show that over the recent years, the greenium turned from slightly positive to negative. Looking at the stock market, Monasterolo and de Angelis (2020) estimate a standard asset pricing model and compare the assets' betas before and after the Paris Agreement, finding that after the announcement the market considered most low-carbon portfolios as less risky. Ramelli et al. (2021) study the impact of Trump's election and find that, contrary to what one may think, investors rewarded companies demonstrating more responsible climate strategies. Similarly, Ramelli et al. (2021) show that the wave of environmental activism by young people is penalizing firms operating in high-polluting sectors. Alessi et al. (2021b), focusing on European stocks, find a negative and highly significant greenium, defined as the risk premium attached to a systematic 'greenness and transparency' factor. Indeed, another element that seems to emerge in the literature is that the environmental performance of a firm, as measured e.g. by CO_2 emissions, is not the only element investors look at. As mentioned, transparency and credibility also play a role (see Fatica et al., 2021), as well as climate responsibility, which is related to a company's strategy (see Ramelli et al., 2021).

With respect to equity markets, evidence based on the analysis of particular events clearly points towards changing investors' attitudes towards green or carbon-intensive assets around the time of such events. Based on these findings, and on a strand of theoretical literature explaining investors' 'taste for sustainability' (see e.g. Baker et al., 2018; Zerbib, 2020; Avramov et al., 2021; Pastor et al., 2021b; Pedersen et al., 2021), in this paper we relax the assumption of a constant

[1] See Giglio et al. (2020) for a survey of the climate finance literature.

greenium introducing a conditional model with a factor structure similar to that in Alessi et al. (2021b), i.e. a standard asset pricing model for the excess returns of stocks, including a 'greenness and transparency' factor. This is constructed based on a synthetic index considering both the CO2 emission intensity of a company and the completeness of its environmental disclosures. Our framework follows Gagliardini et al. (2016, 2019), which provide a theoretical conditional asset pricing setting that accommodates for time-varying risk premia and large unbalanced panels of individual stock returns.

Considering the whole European stock market from January 2006 to August 2020, we estimate the time-varying greenium at a monthly frequency. Our first result is that the greenium is indeed time varying, and changes sign. A negative greenium indicates that investors are willing to earn lower expected returns, ceteris paribus, to hold greener and more transparent stocks. Indeed, we find that the greenium started to decrease after mid-2014 and decreased further after the Paris Agreement was reached in December 2015, becoming stably negative. The greenium also dropped after the First Global Climate Strike and the launch of the European Green Deal. This indicates that in those periods, investors became increasingly willing to buy or not sell greener and more transparent stocks at the cost of earning a lower compensation, ceteris paribus. We also find that the greenium started to increase when the US announced its withdrawal from the Paris Agreement. Once established that the greenium changes over time, we investigate the drivers of the greenium by testing a set of candidate explanatory variables, including sentiment and volatility indicators as well as relevant commodity prices. We find that increasing fossil fuel prices and a better economic outlook are associated with a larger greenium, which also means that when economic expectations worsen investors tend to invest in greener assets. The same happens in times of market turmoil. Rising prices for essential raw materials for the low carbon transition are associated with higher greenium levels, as higher prices signal scarcity and hence, increased difficulties in the implementation and scaling up of low-carbon technologies. Looking at the tail of the distribution, we find that more negative climate news, stressing e.g. how much CO2 we are still emitting to the atmosphere, are also associated with a larger greenium.

Our findings are compatible with the existence of a hedging strategy, whereby political events, as well as market- and sentiment-based signals, steer investors' preferences towards green firms. In particular, whenever investors expect that companies active in greener sectors, and more transparent on their environmental performance, will operate in a more favorable environment, they tend to see them as less risky and demand a lower compensation to hold these stocks (lower greenium). In these periods, when the push towards a green economy is stronger, e.g. because of increased public attention or more decisive political action, investors become more sensitive to climate-transition risks, i.e. the likelihood that some assets, e.g. coal-related, will become stranded (see, e.g. Atanasova and Schwartz, 2019). However, whenever investors are reminded of the challenges of the low-carbon transition, or receive political signals pointing to the opposite direction, they tend to see high-carbon firms are less risky, thereby asking for a lower compensation to hold these stocks (larger greenium).

The paper is structured as follows. In Section 2, we outline the theoretical setting, including the definition of 'green and transparent' as well as 'high-carbon' companies, and the pricing model for equity returns. In Section 3, we describe the dataset and construct the greenness and transparency indicator. In Section 4, we build the greenness and transparency factor based on portfolios characterized by different shades of green. In Section 5, we gather empirical results on the estimates of the greenium. In Section 6, we provide robustness checks based on a different dataset. Finally, in Section 7, we investigate the drivers of the greenium. In Section 8, we conclude.

2 Theoretical setting

In this section, we provide details on the theoretical setting introduced to estimate the time-varying greenium. First, we identify greener and more transparent companies based on the indicator proposed in Alessi et al. (2021b), as well as high-carbon companies. Based on this identification we build six portfolios formed on size and greenness, and we define the greenness and transparency factor. Next, we estimate the time-varying greenium assuming a conditional factor model for excess returns under no-arbitrage opportunities (see Gagliardini et al., 2020 for a review on the estimation of large dimensional conditional factor models).

2.1 High-carbon, green and transparent companies

Our analysis exploits the 'greenness and transparency' indicator proposed in Alessi et al. (2021b), which we refer to for details. The indicator is constructed as a weighted average of two company's characteristics, namely its emission intensity and its environmental score (E-score). The former is defined as the total greeenhouse gas (GHG) emissions, or the total carbon dioxide (CO2) emitted, normalized by revenues. The E-score is a rating of a company reflecting the completeness of the reported environmental information. Formally, at each year y, the indicator is defined as follows:

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

where $K_{i,y}$ is the inverse of the ranking of firm i in terms of emission intensity, and $E_{i,y}$ is the ranking of firm i in terms of E-score. Parameter γ controls for the relative importance of the two components. We set $\gamma = 0.5$. Indeed, Alessi et al. (2021b) show that only by including both emissions and disclosures' quality the identified greenium is different from zero. The greenness indicator can be computed only for companies that disclose environmental information, which are a minority of listed firms.

Based on the distribution of the greenness and transparency indicator $G_{i,y}$, one can distinguish different shades of greenness and transparency. By considering both a qualitative and a quantitative assessment of a firm environmental performance, we broaden the approach commonly used in other papers, such as Pastor et al. (2021a,b), which measure the greenness of individual stocks based only environmental ratings, or Bolton and Kacperczyk (2021), who only consider CO2 emissions. Focusing on the tails of the distribution, we select the top 20% firms ranked in terms of greenness and transparency, i.e. the 'greener and more transparent' companies. However, given the observed correlation between firm size and the availability of environmental information - disclosed mainly by large companies - instead of building just one 'greener and more transparent' portfolio as in Alessi et al. (2021b), we follow Fama and French (1993) and control for market capitalization. In particular, we build three value-weighted portfolios formed on size, namely, a green portfolio including smaller firms $\tilde{r}_{g,s}$, a green portfolio including medium-size firms $\tilde{r}_{g,m}$, and a green portfolio including larger firms $\tilde{r}_{g,b}$.[2] We then consider the average return of these three portfolios. With respect to highly polluting firms, we label as 'high carbon' those firms that do no environmental disclosures (hence, their E-score and their emission intensity are missing) and are active in high-carbon sectors (see details in Section 3). Also for high-carbon firms we build three value-weighted portfolios formed on size, i.e. a high-carbon portfolio including smaller firms $\tilde{r}_{hc,s}$, one including medium-size firms $\tilde{r}_{hc,m}$, and one including larger firms $\tilde{r}_{hc,b}$, and consider the average return on these three high-carbon portfolios. The greenness and transparency factor is defined as follows:

$$f_{g,t} = \frac{1}{3}(\tilde{r}_{g,s} + \tilde{r}_{g,m} + \tilde{r}_{g,b}) - \frac{1}{3}(\tilde{r}_{hc,s} + \tilde{r}_{hc,m} + \tilde{r}_{hc,b}), \tag{2}$$

i.e. a portfolio, that hedges against climate risk, goes long on greener and more transparent stocks, and short on high-carbon assets.

2.2 Conditional factor model for equity returns

In order to estimate time-varying equity premia, we assume a conditional linear factor model for excess returns. We follow the theoretical framework in Gagliardini et al. (2016).[3] In particular, the excess return $R_{i,t}$ satisfies the following linear model:

$$R_{i,t} = a_{i,t} + b'_{i,t} f_t + \varepsilon_{i,t}, \tag{3}$$

where f_t is a vector of K observable systematic factors, and the constant $a_{i,t}$ and the factor loadings $b_{i,t}$ vary over time. The set of observable factors includes also the greenness and transparency factor defined in Eq. (2). Indeed, climate risk can affect almost all assets, hence $f_{g,t}$ can be defined as a pervasive factor (see e.g. Pastor et al., 2021b; Engle et al., 2020). 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. $\Sigma_{\varepsilon,t,n} = [Cov[\varepsilon_{i,t}, \varepsilon_{j,t}|\mathcal{F}_{t-1}]]_{i,j=1,\ldots,n}$ with bounded largest eigenvalue (see, e.g. Chamberlain and Rothschild,

[2] The size breakpoints correspond to the terciles of the yearly aggregate market capitalization distribution.

[3] Gagliardini et al. (2016) describes the generating process for the excess returns assuming a multi-period economy with a continuum number of assets. For a simpler exposition, we provide the specification of excess returns in a finite setting, after applying the sampling scheme as described in Section 2.3 in Gagliardini et al. (2016).

1983). Under no-arbitrage opportunities, the following parameter restriction holds:

$$a_{i,t} = b'_{i,t}\nu_t, \tag{4}$$

where ν_t is a vector of K parameter.[4] The parameter restriction in Eq. (4) can also be written as

$$E[R_{i,t}|\mathcal{F}_{t-1}] = b'_{i,t}\lambda_t, \text{with } \lambda_t = E[f_t|\mathcal{F}_{t-1}] + \nu_t. \tag{5}$$

The conditioning information $\mathcal{F}_{t-1}$ contains the vector Z_{t-1} of p lagged instruments common to all stocks, and the vector $Z_{i,t-1}$ of q lagged characteristics specific to stock i. Vector Z_{t-1} may include the constant, past observations of the factors and some additional variables such as macroeconomic variables. Vector $Z_{i,t-1}$ may include past observations of firm characteristics and stock returns.

Eq. (5) shows that expected excess returns are driven by the risk premia λ_t. We call *greenium* the risk premium associated to the greenness and transparency factor $f_{g,t}$. Risk premia result from the sum of two components, namely the conditional expectation on the factor, and the process ν_t, which captures market imperfections (see e.g. Cremers et al., 2012).

In order to get a workable version of the model (3)-(4), we define the dynamics of the factor loadings $b_{i,t}$ as a linear function of Z_{t-1} (Shanken, 1990, Ferson and Harvey, 1991) and $Z_{i,t-1}$ (Avramov and Chordia, 2006). In particular, the vector of factor loadings $b_{i,t}$ is linear in the lagged common and asset-specific instruments, i.e. $b_{i,t} = B_i Z_{t-1} + C_i Z_{i,t-1}$. Moreover, we define the vector of risk premia λ_t as a linear function of lagged common variables, i.e. $\lambda_t = \Lambda Z_{t-1}$ (Dumas and Solnik, 1995, Cochrane, 1996, Jagannathan and Wang, 1996 and Lettau and Ludvigson, 2001), and we specify the conditional expectation of the factor as follows: $E[f_t|\mathcal{F}_{t-1}] = F Z_{t-1}$. From these specifications and using the asset pricing restriction in Eq. (4), Eq. (3) can be expressed as:

$$R_{i,t} = x'_{i,t}\beta_i + \varepsilon_{i,t}, \tag{6}$$

where $x_{i,t} = \left(x'_{1,i,t}, x'_{2,i,t}\right)'$ involves cross-terms of common and asset specific instruments, and ob-

[4] Gagliardini et al. (2016) exclude asymptotic arbitrage opportunity, such that there is no portfolio sequence with zero cost and positive payoff. We refer to Gagliardini et al. (2016) for theoretical results and proofs.

servable factors, and has dimension $d = d_1 + d_2$, with $d_1 = p(p+1)/2 + pq$ and $d_2 = K(p+q)$. The regressors include d_1 predetermined variables $x_{1,i,t} = \left(vech\,[X_t]', Z'_{t-1} \otimes Z'_{i,t-1}\right)'$, where the $p \times p$ symmetric matrix $X_t = [X_{t,k,l}]$ is such that $X_{t,k,l} = Z^2_{t-1,k}$, if $k = l$, and $X_{t,k,l} = 2Z_{t-1,k}Z_{t-1,l}$, otherwise, $k, l = 1, \dots, p$.[5] Furthermore, the regressors also include the vector $x_{2,i,t} = \left(f'_t \otimes Z'_{t-1}, f'_t \otimes Z'_{i,t-1}\right)'$ of dimension d_2. The time-invariant parameters $\beta_i = (\beta'_{1,i}\beta'_{2,i})'$ are unconditional transformations of matrices B_i, C_i, Λ and F. In particular,

$$\beta_{1,i} = \left(\left(N_p\left[(\Lambda - F)' \otimes I_p\right] vec\,[B'_i]\right)', \left(\left[(\Lambda - F)' \otimes I_q\right] vec\,[C'_i]\right)'\right)', \qquad N_p = \frac{1}{2}D_p^+(W_p + I_{p^2}),$$
$$\beta_{2,i} = \left(vec\,[B'_i]', vec\,[C'_i]'\right)'.$$

The vector operator $vec\,[\cdot]$ stacks the elements of an $m \times n$ matrix as a $mn \times 1$ vector. The matrix D_p^+ is the $p(p+1)/2 \times p^2$ Moore-Penrose inverse of the duplication matrix D_p, such that $vech\,[A] = D_p^+ vec\,[A]$ for any matrix $A \in \mathbb{R}^{p \times p}$. The commutation matrix $W_{p,q}$ is such that $vec[A'] = W_{p,q} vec[A]$, for any matrix $A \in \mathbb{R}^{p \times q}$, and $W_p := W_{p,p}$.

The asset pricing restriction (4) implies

$$\beta_{1,i} = \beta_{3,i}\nu, \text{with } \nu = vec[\Lambda' - F'], \tag{7}$$

where $\beta_{3,i} = \left([N_p\,(B'_i \otimes I_p)]', [W_{p,q}\,(C'_i \otimes I_p)]'\right)'$ is a transformation of matrices B_i and C_i.[6]

3 Data

Our empirical analysis covers 4,163 European stocks traded in the main European stock market exchanges. Table A1 in Appendix B reports the list of stock exchanges included in the sample.[7] The sample begins in January 2006 and ends in August 2020. Together with stock returns and market capitalization, we also use information on firms' characteristics, namely their economic

[5]The vector-half operator $vech\,[\cdot]$ stacks the elements of the lower triangular part of a $p \times p$ matrix as a $p\,(p+1)\,/2 \times 1$ vector.

[6]See Gagliardini et al. (2016).

[7]In case of dual listings, we keep the asset traded in the major market, i.e. the one with the highest number of listed stocks.

sector as based on the NACE classification, as well as their E-score and emission intensity.[8] The data source is Bloomberg. We remove financial firms (i.e. companies belonging to the NACE divisions 64, 65, 66 and 68, see Fama and French, 2008) and exclude 'penny stocks', i.e. assets trading at below 5 USD, which are mostly illiquid and highly volatile (see, e.g. Chen and Petkova, 2012, Stambaugh et al., 2015 and Engle et al., 2020). The final dataset includes $T = 176$ monthly observations for $n = 3,486$ stocks. The European market, size, value, and momentum factors are downloaded from Kenneth French's website. Finally, we proxy the risk-free rate with the 1-month T-bill rate.

For companies that disclose on their environmental performance, we compute the greenness and transparency indicator defined in Eq. (1). The indicator is available at a yearly frequency and for about 25% of the firms in 2019, against 4% in 2005. Figure 1 displays the evolution of the indicator for greener firms (upper panel) and less green firms (lower panel). For both groups, the median level of the indicator increases over time, indicating a generalized improvement in greenness and transparency. While greener and more transparent firms have recorded a marked improvement over time, for firms belonging to the first quintile the improvement has been only marginal in absolute terms. However, in relative terms this latter set of firms perform much better in 2019 compared to 2005, as they started much closer to zero, compared to firms in the top quintile. The variance is also much larger and increasing for bottom-quintile firms. The increase in the overall indicator is essentially driven by both a progressive reduction in the average emission intensity, which more than halves from 2005 to 2019, and an increase of the mean E-score by more than 50% over the same time-span.

Considering companies that does not disclose any environmental information, we construct a high-carbon portfolio by selecting firms that are active in the following climate-policy-relevant sectors (CPRS): fossil-fuel, utilities, energy-intensive, and transport.[9] In doing so, we improve over Alessi et al. (2021b), where high-carbon companies are identified based on high-carbon NACE 2-digit sectors based on Eurostat data. Indeed, using CPRS allows a more accurate selection

[8] In detail, the emission intensity corresponds to as Total GHG or Total CO2 scope 1 and scope 2 emissions, expressed in CO2 equivalents, over net sales.

[9] The CPRS classification, defined in Battiston et al. (2017) maps NACE sections and divisions into broader sectors suitable for sustainability analysis.

procedure, as CPRS rely on NACE codes at the 4-digit level. In particular, not all the companies that belong to high-carbon NACE divisions (2-digit) ultimately also belong to the considered CPRS sectors. At the same time, some of the companies belonging to the considered CPRS do not belong to the high-carbon NACE 2-digit sectors considered in Alessi et al. (2021b). Overall, the high-carbon portfolio comprises 219 firms in 2019.

4 The greenness and transparency factor

Following the definition in Eq. (2), at each month t, we define the returns of the various portfolios as a weighted average of the monthly returns of the assets included in each portfolio.[10]

The first four columns in Table 1 show descriptive statistics for the distribution of total excess returns for all portfolios. The green portfolios $\tilde{R}_{g,s}$, $\tilde{R}_{g,m}$ and $\tilde{R}_{g,s}$ have lower average excess returns than the high-carbon portfolios $\tilde{R}_{hc,s}$, $\tilde{R}_{hc,m}$ and $\tilde{R}_{hc,s}$. In line with the literature, the average returns on smaller firms are higher than on bigger firms (see e.g. Cochrane, 1996). The distributions of returns are leptokurtic and generally left-skewed. The last three columns in Table 1 report the the estimated intercept $\hat{\alpha}$ from various models, where the returns of the relevant portfolio are explained by the market factor alone (Sharpe, 1964 and Lintner, 1965), or by the three Fama and French factors (Fama and French, 1993), or the four factors in the Carhart model (Carhart, 1997). Looking at the green and the high-carbon portfolios, the estimated $\hat{\alpha}$ are significantly different from zero in all cases, pointing to a misspecification of the various models and justifying the inclusion of an additional or a different factor. With respect to the long-short strategy portfolio defined by the difference in Eq. (2), $\hat{\alpha}$ is negative and significant in all models meaning that investors, who neglect the greenness and transparency factor, misprice their investments. This result is in line with Engle et al. (2020) and Pastor et al. (2021b) showing that the alpha of a climate hedge portfolio would generally be negative.

Finally, Table A2 in Appendix B provides the correlation matrix for the observable factors. No factor pair shows a high correlation. At the same time, the market factor f_{mkt} mildly correlates

[10]Portfolios are re-balanced each year based on the value of the greenness and transparency indicator, the market capitalization, and the NACE code associated to each firm.

with the value and the momentum factors, while the greenness and transparency factor f_g is mildly correlated with the size factor.

5 The time-varying greenium

We estimate the risk premia based on a baseline specification for Eq. (3) that includes two observable factors, namely the market factor f_{mkt} and the greenness and transparency factor f_g defined in Eq. (2). The inclusion of two factors is justified both from a theoretical and an empirical point of view. Indeed, Pastor et al. (2021b) show that a two factor model, involving the market portfolio and an ESG factor, is able to price assets. Furthermore, the diagnostic tool proposed by Gagliardini et al. (2019) indicates that the factor structure is correctly specified.[11] The estimation methodology consists in the two-pass approach presented in Gagliardini et al. (2019).

Figure 2 plots the path of the estimated annualized risk premia and their pointwise confidence intervals at the 95% probability level. For the greenium (lower panel), the chart indicates historical events related to the low-carbon transition, i.e. the adoption of the Paris Agreement in December 2015 (Monasterolo and de Angelis, 2020), the announcement of the US withdrawal from the Paris Agreement in June 2017 (Zhang et al., 2017; Nong and Siriwardana, 2018; Alessi et al., 2021a), the first Global Climate Strike in March 2019 (Ramelli et al., 2021), and the launch of European Green Deal in December 2019.[12]

The European market premium $\tilde{\lambda}_{m,t}$, in Panel A of Figure 2, exhibits a similar pattern as, for example, the market premium estimated in Chaieb et al., 2021.[13] At the beginning of the global financial crisis the market premium is largely negative and significant, then, in 2009, it becomes positive and significant. Looking through the volatility characterizing the following decade, it is possible to identify different phases of a length between one and three years, when the market risk premium hovered stably either above or below zero. Looking at the final part of the sample, the volatility of the market risk premium seems to increase, possibly also owing to the Covid crisis.

[11] See Appendix A for details on the empirical methodology applied.

[12] The European Green Deal is the policy plan to make the EU's economy sustainable. See `https://ec.europa.eu/info/strategy/priorities-2019-2024/european-green-deal_en`.

[13] In an international asset pricing setting, Chaieb et al. (2021) estimate risk premia for developed and emerging markets.

Its correlation with the greenium is -0.55.

Focusing on the greenium $\tilde{\lambda}_{g,t}$, shown in Panel B of Figure 2, its evolution is more volatile in the first part of the sample. When considering specific dates that are relevant for the green discussion, some of the peaks and throughs of the greenium over the last six years become more easily interpretable. The estimated greenium started to decline since mid-2014 and entered negative territory at the beginning of 2015, when governments started planning in view of the Paris Agreement,[14] never getting back to positive territory until the end of the sample. A negative greenium indicates that investors are, ceteris paribus, willing to receive a lower compensation for holding greener and more transparent stocks, compared to periods when the greenium is zero or positive. While the market has been stably characterized by this 'taste for green' in the last six years, when Donald Trump announced the US withdrawal from the Paris Agreement the European greenium started to increase, indicating that climate-transition risks were perceived as less and less relevant by European investors as well. The next turning point is July-August 2018, some months after the launch of the European Commission Action Plan on Sustainable Finance in March 2018. Also, in August 2018 the news spread of a Swedish girl going on strike every Friday to protest against the lack of political will to fight climate change. The market possibly understood what impact Greta Thunberg would have had, as reflected in the greenium starting again to trend downwards. The trend steepened after the first Global Climate Strike. Finally, after the announcement of European Green Deal in December 2019, the greenium sharply decreased. Arguably, the expected introduction of stricter environmental policies increased the perceived riskiness of high-carbon companies, hence leading investors to demand higher returns to hold such stocks - and lower returns to hold greener stocks (negative greenium).

Next, we investigate the dynamics of the time-varying risk premia, as defined in Eq. (5), through their two components, namely the conditional expectation of the factors $E[f_t|\mathcal{F}_{t-1}]$ and the process ν_t. Table 2 reports the estimated coefficients $vec[\hat{F}']$ resulting from a seemingly unrelated regression (SUR) of the factors f_t on the set of common instruments (Column 1), as well as the estimated coefficients $\hat{\nu}$ from the cross-sectional regression in Eq. (7) (Column 2).[15] The

[14]We refer, for example, to the COP20 that took place in Lima in December 2014, and to the negotiations in Geneve in February 2015.

[15]See Appendix A for details.

factors' conditional mean, i.e. the constant, is positive but not significant for the market, while it is negative and highly significant for the greenness and transparency factor. These results are comparable with the annualized averages of these two factors, i.e. 5.504 for the market factor and -8.657 for the greenness and transparency factor. The effect of the term spread on the factor conditional mean is not significant for either of the two factors. Instead, the coefficients attached to the smoothed market factor are large and highly significant for both factors, though with opposite signs. Furthermore, the coefficient attached to the default spread is only significant, and positive, for the market premium. Looking at the ν_t component, while the term spread and the default spread have a significant impact only on the market premium, the smoothed market factor has a significant impact only on the greenium.

Finally, as robustness check, we estimate the time-varying risk premia by adding the greenness and transparency factor to the Carhart model. In this case, the greenium is mildly negatively correlated with the market (-0.60), the size (-0.39) and value (-0.56) premia, and mildly positive correlated with the momentum (0.57) premium. As further robustness checks, we assume different functional specifications for the factor loadings $b_{i,t}$ and the risk premia λ_t. The estimated patterns are similar to the ones in Figure 2.

6 The relevance of disagreement on non-financial information

The greenness and transparency indicator in Eq. (1) relies on environmental information, which may vary across data providers. Disagreement on the quality of a company environmental disclosures is due to the fact that sustainability rating agencies use different methodologies to score companies on various sustainability-related aspects, and the E-score is one of those measures that can vary based on the underlying approach and the judgment calls that each provider makes.[16] It is somewhat more surprising that also emission data may vary depending on providers. However,

[16]For example, Dorfleitner et al. (2015) suggest an evident lack in the convergence of ESG measurement concepts. Berg et al. (2020) provide an analysis of the divergence of broader ESG ratings across providers, including for each of the E, S and G components. Moreover, Berg et al. (2021) document widespread changes to the historical ratings.

how to report firms' GHG emissions also involves choices on the part of data providers, particularly in those cases when firms themselves only report emissions on a fraction of their activities (e.g. only EU-based). Some providers may choose to estimate the remaining part, while others may only report emissions if representing at least some large portion of the overall company's activity. Finally, also the NACE codes associated to individual firms may vary across data providers. For example, a provider may use the NACE code declared when the firm was established (e.g. the one for bookstores in the case of Amazon) while another may use the NACE code associated to the current main activity of the company. In some cases, it is more difficult to understand the rationale behind the association of a particular NACE code to a particular firm. Given the relatively large variability of firm-level non-financial indicators across various providers compared to financial information, it is warranted investigating whether the results presented in the previous section are driven by the choice of a particular data source. To test whether this is the case, in this section we consider an alternative data source to Bloomberg, namely Refinitiv. We first analyze to what extent the environmental information actually differs across the two providers. Then, we build the greenness and transparency factor based on Refinitiv non-financial information and compare the associated greenium with the one obtained in the baseline case.

6.1 Disagreement on non-financial information

Discrepancy between Refinitiv and Bloomberg with respect to NACE sectors affects the effective sample size. Indeed, owing to some companies being defined as financials in Refinitiv but as non-financials in Bloomberg, and viceversa, the effective sample based on Refinitiv includes 3,476 stocks against 3,486 in the baseline analysis.[17]

Looking at environmental disclosures, the number of firms for which an E-score is provided is larger using Refinitiv than Bloomberg. With reference to 2005, Refinitiv provides a score for more than twice as many firms (321) compared to Bloomberg (147), while at the end of the sample

[17] For example, the oil and gas company Longboat Energy, the wine producer Gusbourne, and the infrastructure developer John Laing, are classified under financials by Refinitiv. The private equity provider CEPS and the investment holding company Airesis are classified under manufacturing by Bloomberg. Poste Italiane, the Italian postal service provider which also offers financial products, is classified under financials by Refinitiv, while Bloomberg classifies it under transport.

the gap is smaller (1094 firms vs 888). Looking at the scale of the E-score, the average value of the E-score from Bloomberg over the whole time-span is roughly 25% lower than the E-score provided by Refinitiv. The correlation between Bloomberg E-scores and Refinitiv E-scores steadily increases over time, going from 37% at the beginning of the sample to around 70% at the end of the sample, considering only firms present in both datasets. Notice that 23% of the firms having the environmental score in Bloomberg are not present in Refinitiv.

Considering data on emissions, the number of firms for which the emission intensity is available is comparable, though not identical, across the two providers (e.g. in 2019, 855 for Refinitiv vs 783 for Bloomberg). The average emission intensity, measured as tonnes/ millions of sales, halves from 2005 to 2019, going from 590 to 241 based on Bloomberg and from 496 to 225 based on Refinitiv. Bloomberg reported average emissions are generally higher than those reported by Refinitiv, possibly due to Bloomberg reporting emissions for a company only if they cover at least 80% of its overall activity. The correlation of emission data across the two data provided is anyway high, at 90% considering the whole sample and only firms present in both datasets.

As a consequence of both the E-score being generally lower and emissions being generally higher based on Bloomberg, the greenness and transparency indicator is on average lower based on Bloomberg (239) compared to Refinitiv (254) over the whole sample and across years. However, what ultimately matters for the construction of the green and transparent portfolio is the ranking of firms based on the indicator. Based on the Spearman's rank correlation coefficient, the correlation of the two rankings is 0.84 in 2019 computed on the common set of company.

Lastly, following Berg et al. (2020), we compute the Mean Absolute Distance (MAD) of standardized environmental variables for each firm that is present in both datasets. The MAD essentially measures the disagreement with respect to a particular variable at firm level.[18] High values of the MAD reflect a strong disagreement between providers. With respect to the E-score, the disagreement between Bloomberg and Refinitiv is on average mild, around 0.32 across years, while it is very close to zero (0.09) with respect to emissions. Disagreement between the two providers has decreased over time for both variables. Table A3 in Appendix B reports the MAD distribution

[18] In particular, it measures the absolute deviation from the average of the two values. Since the E-score and the emission intensity have been normalized to have mean zero and unit variance, the MAD can be interpreted in terms of standard deviations.

over the years.

6.2 Time-varying greenium based on Refinitiv data

The greenness and transparency factor obtained by replicating the empirical application in Sections 4 and 5 on Refinitiv data has a 60% correlation with the factor based on Bloomberg data. The risk premia are then estimated following the same approach as in Section 5, i.e. based on a CAPM with the inclusion of the greenness and transparency factor as additional observed factor. Figure 3 compares the time-varying risk premia obtained by using data from Refinitiv (blue line) and from Bloomberg (red dashed line). The market premia (upper panel) estimated based on the two datasets are virtually identical. This results is not surprising since the estimates for market premium are based only on financial information and on the same market factor. The lines denoting the two greenia (lower panel) are in general very close, exhibiting very similar dynamics. When there is a discrepancy between the two greenia, the one based on Refinitiv data is slightly larger than the one based on Bloomberg data.

Table 3 looks at the two components of the risk premia, namely the conditional expectation on the factors and the process ν_t. Analogously to Table 2, Table 3 reports the estimated coefficients $vec[\hat{F}']$ and $\hat{\nu}$. The vector $vec[\hat{F}']$ is obtained by projecting factors on the instruments (see Appendix A), while $\hat{\nu}$ results from the cross-sectional regression in Eq. (7). Focusing on the market premium, the slight difference in the exposure of process ν_t to the instruments explains the small differences between the two market premia estimated in the baseline exercise and in this robustness check. With respect to the greenium, also in this case the conditional mean of the greenness and transparency factor, i.e. the constant term, is negative and significantly different from zero. However, its value is smaller, in absolute value, than the corresponding constant in the baseline case, explaining the upward level shift in the greenium as estimated based on Refinitiv data.

7 Greenium drivers

As discussed in Section 5, some of the turning points of the estimated time-varying greenium correspond to particular events related to the low-carbon transition, in particular over the last part of the sample. For some of these events, the literature has indeed identified an impact on the stock market. In this section, we make a step further by investigating possible drivers of the greenium based on a time-series analysis, i.e. by looking at the greenium dynamics as a whole and not only in relation to particular occurrences (see Section 5). We estimate the following linear model:

$$\lambda_{g,t} = \phi_1 + \phi_2 \lambda_{g,t-1} + \phi_3 X_{t-1} + e_t, \tag{8}$$

where $\lambda_{g,t-1}$ captures the persistence of the time series of the greenium, and X_{t-1} is a vector of explanatory variables. In order to account for different channels, we test a wide range of variables including fossil fuels, namely coal and oil; all critical minerals for clean energy technologies listed by the World Bank (2020) and the International Energy Agency (2021); market volatility; a market-based economic sentiment index for the European Union; and the negative climate sentiment index defined in Engle et al. (2020), which captures public attention and sentiment towards climate change based on news.[19]

Together with a standard OLS regression we also run quantile regressions (Koenker and Hallock, 2001), investigating to which extent the explanatory variable has an impact on a given τth quantile of the dependent variable. By doing so, we look at higher distribution moments of the response variable, beyond the mean, which may also carry relevant information (see e.g. Bonaccolto et al., 2019). In particular, we focus on the right tail of the greenium distribution, corresponding to periods where the investors' 'taste for green' was lowest. This is the part of the distribution that is more interesting from a policy perspective, as it corresponds to those periods where the credibility of the low-carbon transition was also lowest, and hence, there is arguably more room for policy action. By focusing on this tail, we identify the drivers of the perceived riskiness of green assets

[19]All market variables used in this section are sourced from Refinitiv. Commodity prices are taken in the form of returns, as well as the economic sentiment index which is taken in differences. The negative climate sentiment index is available at monthly frequency from July 2008 to May 2018 at `https://drive.google.com/file/d/1pCHmcebmOwrVCFim78ALhB51c3h1qt2T/view.`. Table A4 reports descriptive statistics for the variables shown in Tables 4-6 and the results of the Dickey-Fuller test.

when they are perceived as particularly risky.

Table 4 reports results from standard OLS regressions, assuming Gaussian innovations and accounting for heteroscedasticity, where we include candidate explanatory variables one at a time.[20] The coefficients attached to coal and oil (see Columns I and II) are both positive and strongly significant. This means that when fossil fuel prices increase, stressing the still high dependency of the global economy on fossil fuels, investors tend to see high-carbon firms as comparatively less risky.

Several critical minerals for clean energy technologies, namely nickel, silicon, aluminium, copper, lead and zinc, are attached a positive and strongly significant coefficient (see Columns III-VIII). This means that when the price of these energy transition minerals increases, green firms are seen as more risky. This result is not obvious a priori: indeed, increased prices on the one hand reflect stronger demand, which points towards a low-carbon transition being already on the move, and would then lead to green firms being perceived as less risky. However, higher prices also reflect low supply, which seems to be the aspect investors focus their attention on. Indeed, the scarce supply of these critical minerals compared to expected needs may raise concerns about the large-scale deployment of clean energy technologies, thus increasing the perceived risk associated to greener firms.

The coefficient attached to the Euro Stoxx 50 Volatility Index is negative and strongly significant (see Column IX), indicating that investors tend to go green in times of higher market volatility. This finding is consistent with the result on the economic sentiment index (see Column X), showing that investors' 'taste for green' tends to increase also when the economic outlook worsens.

Tables 5 and 6 report estimation results from Eq.(8) using quantile regressions with τ equal to 75% and 90%, respectively. The results on commodity prices are broadly similar when looking at the tail of the distribution. Moreover, we uncover another relevant relationship, notably a positive coefficient attached to the negative climate sentiment index, significant at the 5% level

[20]Given the inclusion of the lagged dependent variable $\lambda_{g,t-1}$ on the right-hand-side, OLS estimates might be biased. However, the focus of these regressions is not on the value of the coefficients, rather on the identification of relevant explanatory variables. Furthermore, in Table A5 we show that the results are stable also when accounting for hetereschedacity and autocorrelation in the estimation of the standard errors through the Newey-West estimator.

when looking at the 75^{th} quantile (see Column XI in Table 5) and at the 1% level when looking at the very tail (see Column XI in Table 6). Higher values of the climate change sentiment news index indicate a larger number of negative news on climate change, e.g. reporting the materialization of the adverse effects of global warming, such as climate-related natural disasters. A positive coefficient indicates that when negative news on climate change become more frequent, or news become more negative, investors tend to ask for higher compensation, ceteris paribus, to hold greener stocks. Higher compensation is due to greener firms being perceived as more risky, and high-carbon firms being perceived as less risky, in a context where the level of carbon emissions is still far above net-zero and the economy may at times seem not to be able or willing to decisively shift to sustainable products and processes.[21] This result is in line with the similar findings in Huynh and Xia (2021), who study the effect of climate related news, and in Choi et al. (2020), who show that stocks of carbon-intensive firms underperform in case of abnormally warm weather.

8 Conclusions

In this paper, we contribute to the empirical asset pricing literature, on the one hand, and to the sustainable finance literature, on the other, by estimating a time-varying greenium, which we define as a risk premium associated to greener and more transparent stocks. The time-varying greenium is estimated for the European market using a conditional factor model under no-arbitrage restrictions. We show that the greenium changes indeed over time, with turning points corresponding to events such as the Paris Agreement and the US withdrawal from it. By analyzing potential drivers of the greenium, we find that when the economy seems to be struggling to shift towards low-carbon - as signalled by e.g. increases in relevant commodity prices - investors' taste becomes less green as high-carbon assets are perceived as less risky. On the contrary, in periods of market turmoil and worsening economic outlook investors tend to go green.

[21] Engle et al. (2020) do not distinguish the different types of climate change news accounted for in the sentiment index. Consequently, we are not able to disentangle the relative weight of news related to the low-carbon transition, on the one hand, versus those related to natural disasters, on the other hand. However, the authors show that their index is sensitive to the most crucial transition-related announcements, such as the US withdrawal from the Paris agreement in 2017.

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Tables and Figures

Table 1: **Descriptive statistics of the green and transparent and the high-carbon portfolios and the greenness and transparency factor.** The statistics (i.e. mean, standard deviation, kurtosis and skewness) are computed on the annualized excess returns $\tilde{R}$ of portfolios in percentage. The last three columns report for each portfolios the alphas with respect to the CAPM, the three Fama and French factor model (FF) and the Carhart model (CAR). ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Mean	Std	Kurtosis	Skewness	α_{CAPM}	α_{3FF}	$\alpha_{Carhart}$
$\tilde{R}_{g,s}$	12.961	24.849	5.829	-0.787	0.0053**	0.0052***	0.006***
$\tilde{R}_{g,m}$	11.421	21.503	6.133	-0.823	0.0045***	0.0038***	0.0044***
$\tilde{R}_{g,b}$	8.573	16.647	3.442	-0.504	0.0034***	0.0025**	0.0015
$\tilde{R}_{hc,s}$	31.887	22.805	5.802	0.233	0.0224***	0.0202***	0.0207***
$\tilde{R}_{hc,m}$	15.968	21.406	6.261	-1.027	0.0086***	0.0076***	0.0072***
$\tilde{R}_{hc,b}$	11.070	22.021	7.633	-1.174	0.0042***	0.0027**	0.0028**
f_g	-8.657	8.359	4.107	-0.072	-0.0073***	-0.0063***	-0.0063***

Table 2: **Estimated annualized components of risk premia.** The table reports the estimated vectors of parameters $vec[F']$ and ν, defined in Eq. (7). The term spread ts_{t-1}, the default spread ds_{t-1}, and the smoothed market factor $\tilde{f}_{m,t-1}$ are centered and standardized. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

parameters	$vec[F']$	ν
	market premium	
constant	5.071	-3.849***
ts_{t-1}	-3.574	1.468***
ds_{t-1}	15.576**	-7.011***
$\tilde{f}_{m,t-1}$	30.484***	-0.945
	greenium	
constant	-8.956***	4.456***
ts_{t-1}	3.514	0.437
ds_{t-1}	-4.165	0.730
$\tilde{f}_{m,t-1}$	-5.800**	2.566***

Table 3: **Estimated annualized components of risk premia based on Refinitiv data.** The table reports the estimated vectors of parameters $vec[F']$ and ν, defined in Eq. (7). The term spread ts_{t-1}, the default spread ds_{t-1}, and the smoothed market factor $\tilde{f}_{m,t-1}$ are centered and standardized. ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

	$vec[F']$	ν
	market premium	
constant	5.071	-2.863***
ts_{t-1}	-3.574	2.207***
ds_{t-1}	15.576**	-8.559***
$\tilde{f}_{m,t-1}$	30.484***	-1.271
	greenium	
constant	-6.577***	5.926***
ts_{t-1}	-0.028	4.611***
ds_{t-1}	0.391	-2.276**
$\tilde{f}_{m,t-1}$	-2.178	1.030

Table 4: **Greenium drivers.** The table reports estimates of Eq. (8) from stand alone OLS regressions (Columns I-XI). Standard errors are in parenthesis and robust for heteroskedasticity (Huber-White standard errors). ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dependent variable: $\lambda_{g,t}$	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
$\lambda_{g,t-1}$	0.9224***	0.9501***	0.9533***	0.9349***	0.9343***	0.9552***	0.9607***	0.9396***	0.9335***	0.8796***	0.9305***
	(0.028)	(0.026)	(0.027)	(0.027)	(0.028)	(0.027)	(0.027)	(0.027)	(0.026)	(0.047)	(0.027)
$COAL_{t-1}$	0.0043***										
	(0.002)										
OIL_{t-1}		0.0057***									
		(0.001)									
$NICK_{t-1}$			0.0039***								
			(0.001)								
SIL_{t-1}				0.0068***							
				(0.002)							
ALU_{t-1}					0.0077***						
					(0.002)						
COP_{t-1}						0.0074***					
						(0.001)					
$LEAD_{t-1}$							0.0052***				
							(0.002)				
$ZINC_{t-1}$								0.0036**			
								(0.002)			
VIX_{t-1}									-0.0046***		
									(0.002)		
$EconSent_{t-1}$										0.0164**	
										(0.006)	
$NegClSent_{t-1}$											0.0004
											(0.001)
Constant	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0001	-0.0002	0.0008**	-0.0004	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	167	173	173	173	173	173	173	173	174	120	173
R-squared	0.8700	0.8932	0.8786	0.8778	0.8822	0.8872	0.8825	0.8751	0.8803	0.8112	0.8777
Adjusted R-squared	0.868	0.892	0.877	0.876	0.881	0.886	0.881	0.874	0.879	0.808	0.876

Table 5: **Greenium drivers for the 75^{th} quantile.** The table reports estimates of Eq. (8) from quantile regressions focusing on the 75^{th} quantile. Columns I-XI refer to stand alone regressions. Standard errors are in parenthesis and robust for heteroskedasticity (Huber-White standard errors). ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dependent variable: $\lambda_{g,t}$	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
$\lambda_{g,t-1}$	0.8971***	0.9317***	0.9386***	0.8978***	0.9485***	0.9421***	0.9697***	0.9204***	0.9006***	0.8357***	0.8959***
	(0.030)	(0.029)	(0.027)	(0.033)	(0.026)	(0.030)	(0.026)	(0.025)	(0.029)	(0.056)	(0.033)
$COAL_{t-1}$	0.0020										
	(0.001)										
OIL_{t-1}		0.0028*									
		(0.001)									
$NICK_{t-1}$			0.0026**								
			(0.001)								
SIL_{t-1}				0.0042*							
				(0.002)							
ALU_{t-1}					0.0064***						
					(0.002)						
COP_{t-1}						0.0065***					
						(0.002)					
$LEAD_{t-1}$							0.0057***				
							(0.001)				
$ZINC_{t-1}$								0.0043***			
								(0.001)			
VIX_{t-1}									0.0016		
									(0.002)		
$EconSent_{t-1}$										-0.0003	
										(0.006)	
$NegClSent_{t-1}$											0.0036**
											(0.002)
Constant	0.0005***	0.0006***	0.0006***	0.0004**	0.0007***	0.0006***	0.0007***	0.0006***	0.0001	-0.0003	0.0005**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	167	173	173	173	173	173	173	173	174	120	173

Table 6: **Greenium drivers for the 90^{th} quantile.** The table reports estimates of Eq. (8) from quantile regressions focusing on the 90^{th} quantile. Columns I-XI refer to stand alone regressions. Standard errors are in parenthesis and robust for heteroskedasticity (Huber-White standard errors). ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dependent variable: $\lambda_{g,t}$	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
$\lambda_{g,t-1}$	0.9611***	0.9748***	0.9920***	0.9848***	0.7941***	0.9918***	0.9922***	0.9692***	0.9700***	1.0083***	0.9550***
	(0.067)	(0.069)	(0.072)	(0.067)	(0.058)	(0.076)	(0.059)	(0.049)	(0.068)	(0.078)	(0.069)
$COAL_{t-1}$	0.0053*										
	(0.003)										
OIL_{t-1}		0.0021*									
		(0.001)									
$NICK_{t-1}$			0.0038								
			(0.003)								
SIL_{t-1}				0.0084**							
				(0.003)							
ALU_{t-1}					0.0072*						
					(0.004)						
COP_{t-1}						0.0104***					
						(0.003)					
$LEAD_{t-1}$							0.0051				
							(0.004)				
$ZINC_{t-1}$								0.0055**			
								(0.003)			
VIX_{t-1}									0.0062		
									(0.005)		
$EconSent_{t-1}$										-0.0000	
										(0.021)	
$NegClSent_{t-1}$											0.0041***
											(0.001)
Constant	0.0017***	0.0018***	0.0016***	0.0005	0.0004	0.0018***	0.0020***	0.0016***	0.0015***	0.0016***	0.0017***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	167	173	173	173	173	173	173	173	174	120	173

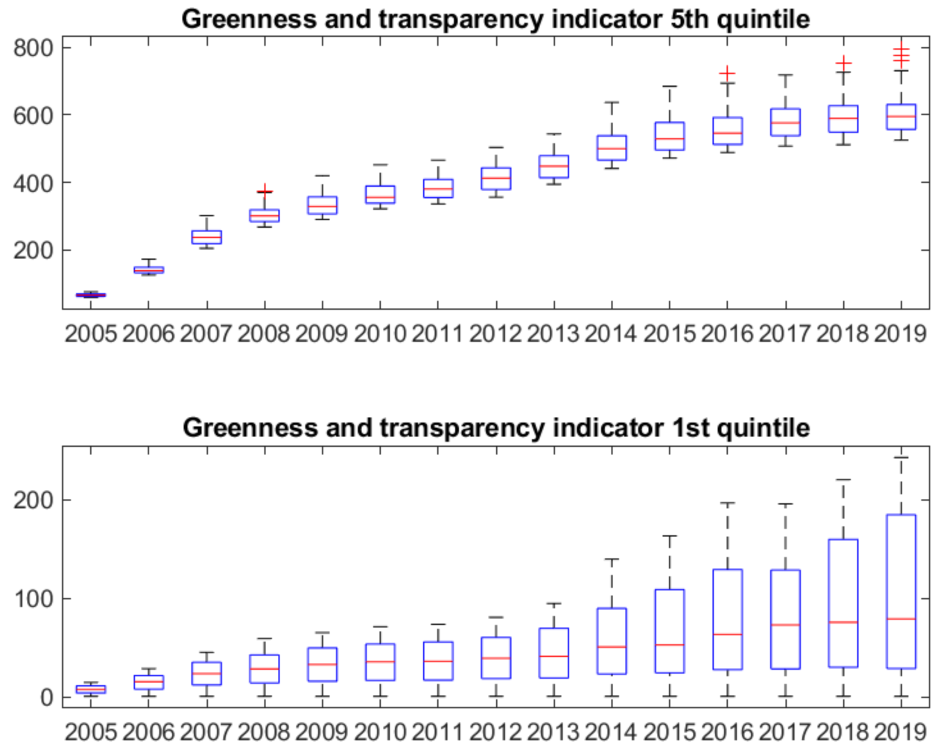
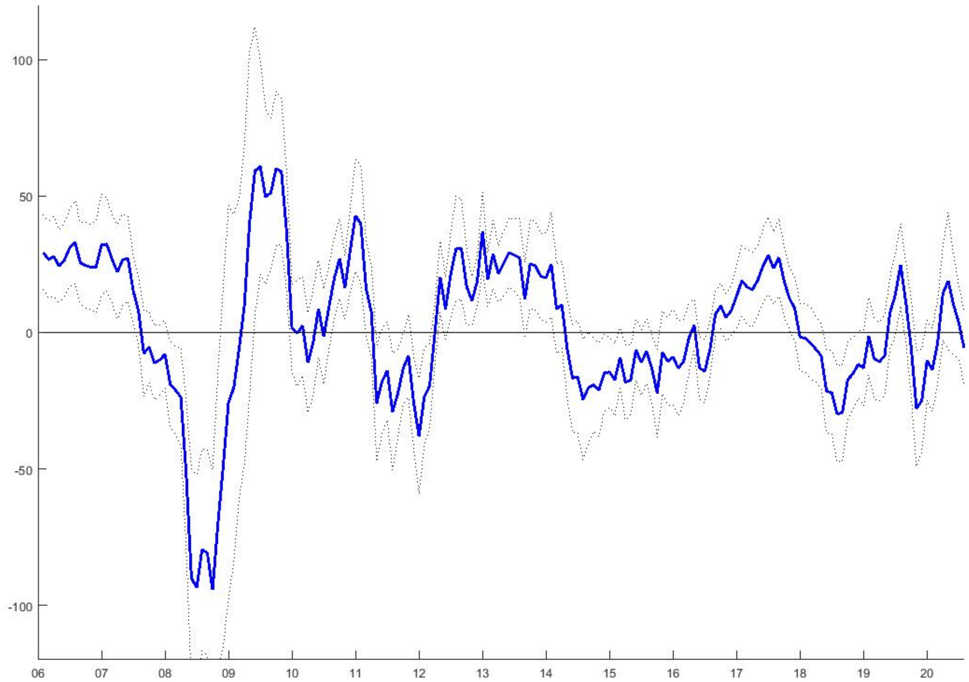


Figure 1: **Distribution over time of the greenness and transparency indicator.** The box-plot in the top panel reports the evolution of the greenness and transparency indicator for stocks belonging to the 5^{th} quintile, i.e. greener and more transparent stocks. The bottom panel refers to stocks belonging to the 1^{st} quintile.

Panel A: market premium $\hat{\lambda}_{m,t}$



Panel B: greenium $\hat{\lambda}_{g,t}$

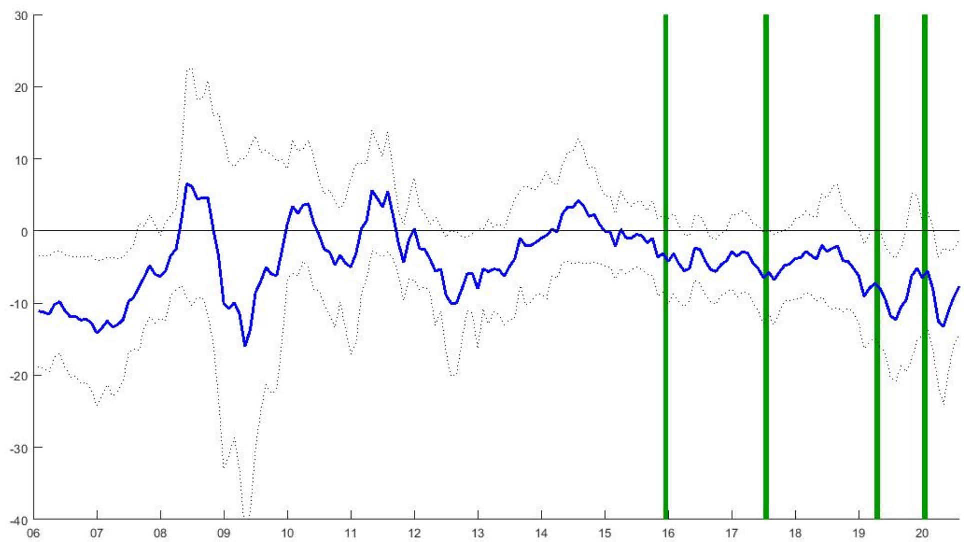
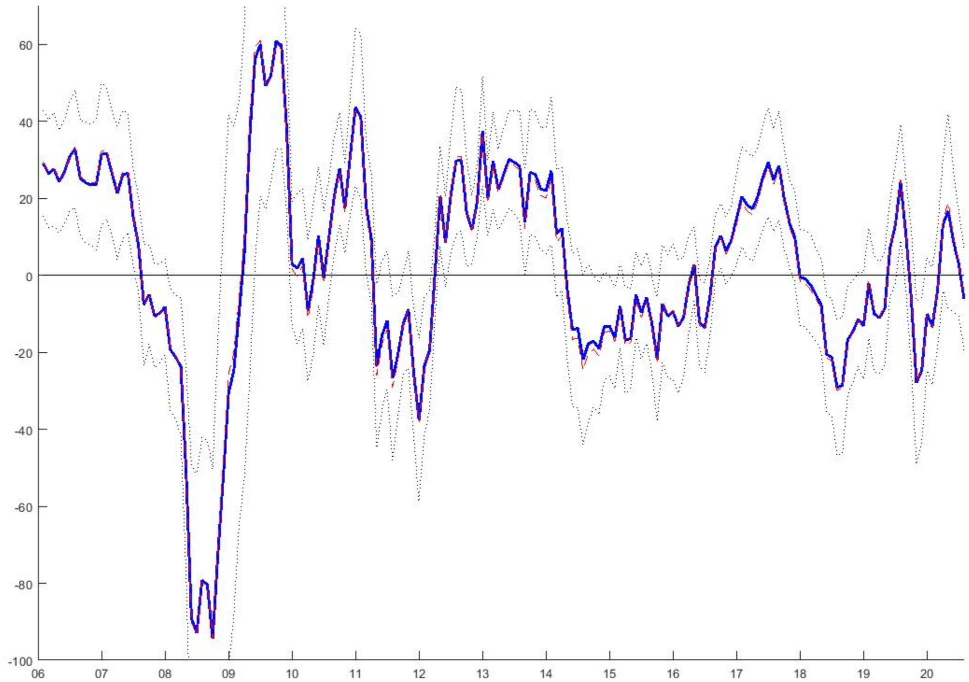


Figure 2: **Time-varying estimates of risk premia.** Evolution over time of the annualized risk premia estimated from a CAPM including the greenness and transparency factor. Dotted lines correspond to the pointwise confidence intervals at the 95% level. The green vertical lines denote, in chronological order, the Paris Agreement, the US withdrawal from the Paris Agreement, the Global Climate Strike, and the launch of the European Green Deal.

Panel A: market premium $\hat{\lambda}_{m,t}$



Panel B: greenium $\hat{\lambda}_{g,t}$

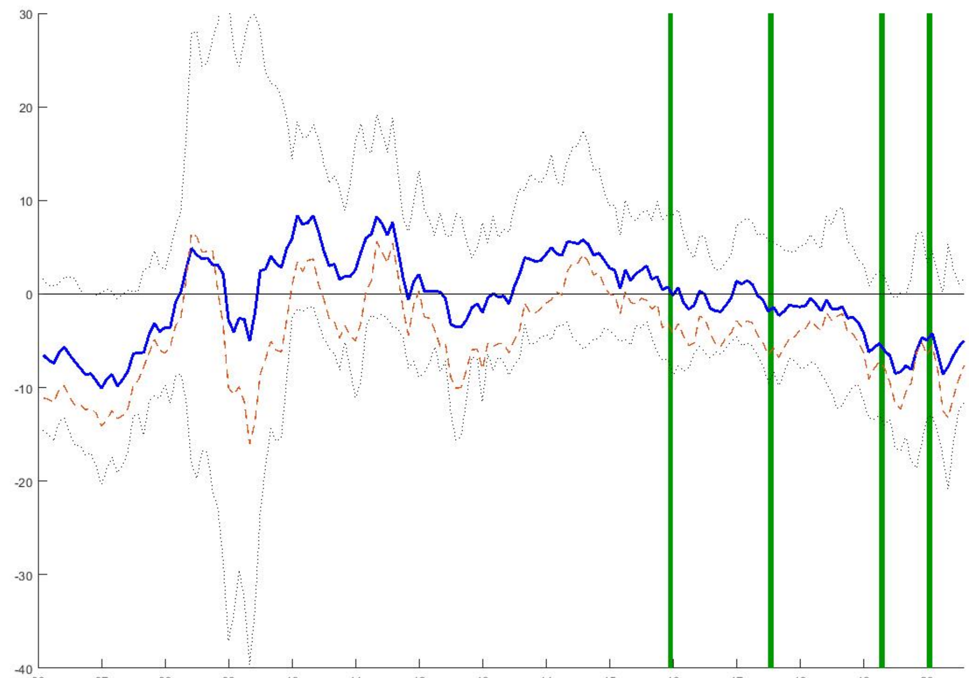


Figure 3: **Time-varying estimates of risk premia based on Refinitiv data.** Evolution over time of the annualized risk premia estimated from a CAPM including the greenness and transparency factor based on Refinitiv data (blue line). Dotted lines correspond to the pointwise confidence intervals at the 95% level. The dashed red lines indicate the risk premia based on Bloomberg data. The green vertical lines denote, in chronological order, the Paris Agreement, the US withdrawal from the Paris Agreement, the Global Climate Strike, and the launch of the European Green Deal.

A Empirical methodology to estimate risk premia

This section describes the empirical methodology applied for the estimation of risk premia. To model the dynamics of risk premia as described in Subsection 2.2, we include the following common instruments Z_t: the constant; the term spread, proxied by the difference between yields on the 10-year Treasury and the 3-month T-bill; and the default spread, proxied by the yield difference between BAA- and AAA-rated companies.[22] In order to capture the business cycle, we also include as common instrument the lagged smoothed market factor. All instruments are centered and standardized.

Furthermore, owing to the relatively short time dimension, and to avoid overparametrization issues when modelling the dynamics of factor loadings, we assume that the coefficients $b_{i,t}$ are only function of asset-specific characteristics, i.e. $b_{i,t} = C_i Z_{i,t}$.[23] In particular, we include the constant and the market capitalization as asset-specific instruments (see, e.g. Stock and Watson, 1989; Bernanke, 1990; Avramov and Chordia, 2006).

In order to estimate the vector of risk premia λ_t, we apply the estimation approach proposed in Gagliardini et al. (2016). We use two-pass regressions for individual stock returns, given the unbalanced dataset. The first pass consists in computing time-series OLS estimators $\hat{\beta}_i$ from Eq. (6). The second pass consists in computing a cross-sectional estimate of ν by regressing the $\hat{\beta}_{1,i}$ on the $\hat{\beta}_{3,i}$ from Eq. (7). We implement the bias correction in Gagliardini et al. (2016) to correct for the Error-in-Variable problem coming from the estimation of the betas in the first pass regressions. The final estimator of the risk premia is $\hat{\lambda}_t = \hat{\Lambda} Z_{t-1}$, where we $\hat{\Lambda}$ is obtained from the relationship $vec[\hat{\Lambda}'] = \hat{\nu} + vec[\hat{F}']$ with the estimator $\hat{F}$ based on a SUR regression of the factors f_t on the lagged instruments Z_{t-1}.

To empirically assess if the factor structure in Eq. (3) is correctly specified, i.e. it captures systematic risk, we use the diagnostic tool by Gagliardini et al. (2019), which checks for common factors in idiosyncratic shocks. The idea behind the diagnostic is that if there are no factors in the

[22]US MOODCBAA and MOODCAAA Indexes are used, consistently with the use of the T-bill as risk-free asset. The correlation between US and European series is larger than 0.9, and results are robust to using European series. All series are sourced from Bloomberg. Note that we do not include the dividend yield as common instrument, because the use of the dividend yield is motivated by Ferson and Harvey (1991, 1999) only in an international equity setting.

[23]This assumption corresponds to a particular case in the general setting provided in Subsection 2.2.

residuals, the maximum eigenvalues of the scaled matrix of the residuals goes to zero at a faster rate than a penalty term as n and T increase. On the contrary, if there remains at least one factor in the residuals, then the maximum eigenvalue stays large and positive. This procedure extend the methodology by Bai and Ng (2002) and Bai and Ng (2006) to unbalanced panels and uses estimated errors, instead of assuming true ones (see also Onatski, 2010 and Ahn and Horenstein, 2013).

B Additional tables and figures

Table A1: **List of stock market exchanges.** The table provides the list of Stock Exchanges in which the stocks in our samples are listed. The table reports the percentage number of stocks available for each stock market exchange.

Stock Exchange	Country	Frequency
London	United Kingdom	24.77%
Euronext.liffe Paris	France	16.26%
Stockholm	Sweden	14.1%
Deutsche Boerse AG	Germany	11.05%
Milan	Italy	7.21%
Oslo Bors	Norway	4.49%
Six Swiss	Switzerland	3.7%
Mercado Continuo Espanol	Spain	3.53%
Euronext.liffe Brussels	Belgium	3.27%
Helsinki	Finland	3.24%
OMX Nordic Exchange Copenhagen	Denmark	2.57%
Euronext.liffe Amsterdam	Netherlands	2.04%
Vienna Stock Exchange	Austria	1.32%
Euronext.liffe Lisbon	Portugal	0.98%
Xetra	Germany	0.96%
Dublin	Ireland	0.5%
European Market	4,163 stocks	100%

Table A2: **Correlation matrix of observable factors.** The table shows the correlation matrix between the observable factors: the market factor $f_{m,t}$, defined as the excess return on the European value-weighted market portfolio over the risk free rate; the size factor $f_{smb,t}$, defined as small caps minus big caps; the book-to-market factor $f_{hml,t}$, defined as the value portfolio minus the growth portfolio; the momentum factor $f_{mom,t}$, defined as the winner portfolio minus the loser portfolio; and greenness and transparency factor f_g.

	f_{mkt}	f_{smb}	f_{hml}	f_{mom}	f_g
f_{mkt}	1.000	0.046	0.484	-0.437	0.063
f_{smb}	0.046	1.000	-0.054	0.000	-0.561
f_{hml}	0.484	-0.054	1.000	-0.520	0.110
f_{mom}	-0.437	0.000	-0.520	1.000	-0.059
f_g	0.063	-0.561	0.110	-0.059	1.000

Table A3: **MAD for the E-score and the emission intensity.** The table shows the distribution, across years, of the MAD computed for each firm w.r.t. the E-score (Panel A) and the emission intensity (Panel B). Column *Corr* reports the correlation coefficient between Bloomberg and Refinitiv for a given variable. The computation of MAD and the correlation are performed on the common sample of reporting firms. The number of firms $N^{(Bl \cap Rfn)}$ included both in Bloomberg (Bl) and Refinitiv (Rfn) are also reported.

year	Mean	Std	min	p25	p75	max	$Corr$	$N^{(Bl \cap Rfn)}$
Panel A: MAD E score								
2005	0.43	0.34	0.00	0.15	0.63	1.45	0.37	120
2006	0.36	0.32	0.00	0.12	0.55	1.79	0.48	237
2007	0.33	0.27	0.00	0.13	0.45	1.42	0.63	359
2008	0.33	0.24	0.00	0.14	0.46	1.23	0.66	400
2009	0.31	0.24	0.00	0.13	0.43	1.10	0.69	431
2010	0.32	0.25	0.00	0.12	0.46	1.47	0.67	447
2011	0.32	0.23	0.00	0.15	0.44	1.19	0.68	470
2012	0.30	0.23	0.00	0.12	0.46	1.49	0.70	490
2013	0.30	0.23	0.00	0.11	0.45	1.40	0.71	516
2014	0.31	0.24	0.00	0.13	0.43	1.44	0.70	541
2015	0.29	0.22	0.00	0.11	0.43	1.34	0.73	594
2016	0.30	0.24	0.00	0.12	0.42	1.60	0.70	607
2017	0.30	0.24	0.00	0.12	0.43	1.31	0.71	656
2018	0.30	0.24	0.00	0.12	0.42	1.37	0.70	755
2019	0.32	0.25	0.00	0.13	0.45	1.40	0.66	765
Panel B: MAD Emissions intensity								
2005	0.14	0.23	0.00	0.02	0.24	0.55	0.85	8
2006	0.03	0.05	0.00	0.01	0.02	0.31	0.99	67
2007	0.04	0.09	0.00	0.01	0.02	0.65	0.98	145
2008	0.04	0.10	0.00	0.01	0.02	0.88	0.97	220
2009	0.04	0.11	0.00	0.00	0.02	1.30	0.97	267
2010	0.08	0.34	0.00	0.02	0.03	4.90	0.76	298
2011	0.03	0.14	0.00	0.00	0.01	2.01	0.96	330
2012	0.03	0.12	0.00	0.01	0.02	1.55	0.97	356
2013	0.03	0.11	0.00	0.00	0.01	1.19	0.97	386
2014	0.08	0.32	0.00	0.02	0.03	5.75	0.78	445
2015	0.04	0.15	0.00	0.00	0.01	2.07	0.95	491
2016	0.11	0.38	0.00	0.04	0.05	7.53	0.69	522
2017	0.06	0.28	0.00	0.01	0.02	5.55	0.84	562
2018	0.05	0.23	0.00	0.00	0.01	3.18	0.89	650
2019	0.04	0.19	0.00	0.01	0.01	2.97	0.93	689

Table A4: **Descriptive statistics for the greenium drivers.** The table reports the following descriptive statistics: number of observations (N), mean, standard deviation (Std), kurtosis, skewness, minimum, median and maximum, for the greenium and the set of greenium drivers. The values expressed in returns are annualized and in percentage. The last column reports the statistic and p-value (in parenthesis) for the Dickey Fuller (DF) test.

Variable	Description	N	Mean	Std	Kurtosis	Skewness	Min	Median	Max	DF test
$\hat{\lambda}_g$	Greenium	175	-4.48	1.41	0.04	2.46	-4.49	-14.16	6.13	-2.58 (0.01)
$COAL$	Coal Intercontinental Exchange	168	-2.06	27.92	0.15	5.27	1.56	-315.60	331.20	-9.82 (0.00)
OIL	Europe Brent Spot Price Free on Board (Dollars Per Barrel) Daily	174	0.30	37.41	-0.78	5.80	10.93	-532.80	316.80	-10.21 (0.00)
$NICK$	London Metal Exchange (LME)-Nickel 3 Months US Dollar Per Metric Tonne	174	-0.75	33.91	-0.25	2.81	-5.16	-307.20	253.20	-11.81 (0.00)
SIL	Silicon Lumps Cost, Insurance and Freight North West Europe US Dollar Per Metric Tonne	174	0.71	17.91	-0.41	5.75	0.00	-204.00	175.20	-11.23 (0.00)
ALU	LME-Aluminium 99.7% 3 Months United States Dollar Per Metric Tonne	174	-2.51	19.81	0.09	3.15	-3.61	-169.20	163.20	-12.01 (0.00)
COP	LME-Copper, Grade A 3 Months US Dollar Per Metric Tonne	174	2.52	25.22	-0.47	4.70	5.42	-334.80	219.60	-10.99 (0.00)
$LEAD$	LME-Lead 3 Months	174	2.35	30.66	-0.59	4.29	11.46	-375.60	232.80	-12.26 (0.00)
$ZINC$	LME-Special High Grade Zinc 99.995% Cash US Dollar Per Metric Tonne	174	1.07	27.61	-0.16	2.88	3.56	-250.80	226.80	-12.87 (0.00)
VIX	Euro Stoxx 50 volatility index	175	273.60	28.23	1.33	4.71	250.80	145.20	616.80	-4.28 (0.00)
$EconSent$	Economic Sentiment Index in European Union	174	0.22	7.66	-0.87	9.44	1.17	-113.04	100.20	-6.30 (0.00)
$NegClSent$	Crimson Hexagon's negative sentiment climate change news index	120	258.00	42.61	1.89	7.07	204.00	96.84	843.60	-4.84 (0.00)

Table A5: **Greenium drivers.** The table reports estimates of Eq. (8) from stand alone OLS regressions (Columns I-XI). Standard errors are in parenthesis and robust for heteroskedasticity and autocorrelation (Newey-West standard errors). ***, **, and * indicate that the parameter estimate is significantly different from zero at the 1%, 5%, and 10% level, respectively.

Dependent variable: $\lambda_{g,t}$	I	II	III	IV	V	VI	VII	VIII	IX	X	XI
$\lambda_{g,t-1}$	0.9224***	0.9501***	0.9533***	0.9349***	0.9343***	0.9552***	0.9607***	0.9396***	0.9335***	0.8796***	0.9305***
	(0.030)	(0.027)	(0.029)	(0.029)	(0.028)	(0.028)	(0.029)	(0.028)	(0.029)	(0.051)	(0.029)
$COAL_{t-1}$	0.0043**										
	(0.002)										
OIL_{t-1}		0.0057***									
		(0.001)									
$NICK_{t-1}$			0.0039***								
			(0.001)								
SIL_{t-1}				0.0068**							
				(0.003)							
ALU_{t-1}					0.0077***						
					(0.002)						
COP_{t-1}						0.0074***					
						(0.002)					
$LEAD_{t-1}$							0.0052***				
							(0.002)				
$ZINC_{t-1}$								0.0036**			
								(0.002)			
VIX_t-1									-0.0046**		
									(0.002)		
$EconSent_{t-1}$										0.0164**	
										(0.007)	
$NegClSent_{t-1}$											0.0004
											(0.002)
Constant	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0002	-0.0001	-0.0002	0.0008**	-0.0004	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	167	173	173	173	173	173	173	173	174	120	173

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