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Green-adjusted share prices: A comparison between standard investors and investors with green preferences

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A B S T R A C T

We employ the green revenue factors of firms, used in the computation of the FTSE Russell 1000 Green Revenues index to create corresponding green-adjusted share prices. We compute the firm betas, under both the standard and the green-adjusted share pricing. Our findings suggest that tilting of firm stock returns towards green finance could change temporarily asset pricing views. The Fama-French risk factors display very high correlations between the two settings. Nevertheless, there are some significant differences between standard and green-adjusted betas during periods associated with green activism and positive political decisions of financially supporting the global climate action.

1. Introduction

The recent environmental concerns and societal changes leading to the global commitment towards a green economy have refocused the analysis on financial markets through various "lenses of sustainability" towards the degree of green activities reflected in the prices and in the returns of market securities (e.g. Matsumura et al., 2014; Pastor et al., 2022; Zerbib, 2022). In this context, the future of finance is directly determined by how well the social, environmental and economic systems are organized (Shiller, 2013).

In this paper, we take advantage of a novel methodology developed by FTSE Russell of dynamically capturing the green revenues exposure of individual firms by evaluating each business activity according to a robust Green Revenues Classification System (GRCS). Based on a bottom-up view of the green economy, the GRCS aligns with the environmental EU taxonomy, as it considers products and services according to their impact on climate change mitigation, climate change adaptation, pollution prevention and control, protection of healthy ecosystems, sustainable use and protection of water and marine resources, transition to a circular economy, waste prevention and recycling, sustainable and efficient agriculture.[1] Mapping revenues from the balance sheet with a comprehensive range of activities across 10 sectors, 64 sub-sectors and 133 micro sub-sectors, the Green Revenues 2.0 data model proposed by FTSE Russell provides the green revenues estimates for each company. Based on these estimates, FTSE Russell computes a unique metric for each company – the green revenues factor (GRF). Exploring in more detail the GRF metric, we found it possesses some desirable characteristics. First, it is a dynamic measure, therefore facilitating the process of monitoring the trend in the green activities of a firm, as it captures both the speed and level of a firm's transition to the green economy. Second, the GRF metric allows for the direct ranking of companies by reflecting the level of net environmental impact of companies' business activities.

Through the lens of green revenues, which is a financial dimension compared to the traditional physical dimensions such as carbon emissions and fossil fuel reserves, the GRF measure enables investors to compare companies based on various levels of "greenness". We employ the GRF green metric to distinguish between green, neutral and brown companies. Within our simplified categorisation, a green/brown company has a positive/negative green exposure (net positive/negative environmental impact), while a company with an insignificant green exposure (similar levels of negative and positive environmental impact) is considered neutral. Matsumura et al. (2014) argue that equity values should be lower for firms with higher emissions if investors are considering the likelihood of future regulatory actions arising from high

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[1] For more details see https://www.lseg.com/content/dam/ftse-russell/en_us/documents/other/ftse-russell-green-revenues-classification-system.pdf

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carbon emission. The GRF measure has an amplifying effect towards green companies and a deflationary effect for brown companies, which is also in line with the ESG integration investment practice of overweighting assets with high ESG ratings and underweighting those with low ESG ratings (Zerbib, 2022).

The novelty of our research consists in exploiting these properties of the GRF metric to construct daily pseudo green share prices (green-adjusted share prices). Using the FTSE 1000 Green Revenues Index as a proxy for the "green" U.S. market and our green-adjusted share prices of the index constituent firms, we estimate the green-adjusted analogues to the CAPM beta and conduct a comprehensive comparative analysis by reapplying the classic modelling frameworks such as the dynamic conditional correlation (DCC) model of Engle (2002) and Fama-MacBeth (1973) regression analysis.

We compare the views of a standard investor with that of a "twin" green investor who has the same risk preferences, but also holds high views on the necessity of green finance. For the latter, the "value" of firms' share prices is determined by a tilting factor towards green finance. In other words, "green" investors operate in a green-adjusted investment world where all the share prices are green-adjusted based on the value of its green revenues factor. Compared to a standard investor, a green investor manifests his green preferences by differentiating between green, neutral and brown companies when selecting his/her equity portfolio in order to hedge against climate change risks. Our main aim is to examine whether the standard and the green investors reach the same asset pricing calculations. More specifically, we investigate if there is a statistically significant difference between their betas, risk factors and the estimation of the dynamic CAPM.

For the purposes of this study, we analyse 1555 U.S. stocks which constitute the FTSE Russell 1000 Index during the period from May 26, 2016 to December 31, 2021. We estimate the "green" betas corresponding to share prices adjusted for the level of green revenues in each company and we test whether there are significant cross-sectional and time series differences between these green betas and the standard betas. Based on daily returns, we find that, overall, there is no statistically significant difference between the standard and the green-adjusted betas. Moreover, we find that the four Fama-French and Carhart risk factors are all significant in explaining stock returns and green-adjusted stock returns respectively, and the correlations between the respective factors are very high. In other words, operating in a green-adjusted world is not very different from operating in the standard world. However, the two investment worlds seem to distance from each other during periods of intensified green activism and heightened level of climate-related finance commitments.

Numerous previous empirical studies investigate the link between firms' level of engagement with the green economy and their financial performance through multidimensional sustainable metrics such as the ESG scores (e.g. Avramov et al., 2022; Pastor et al., 2021; Cao et al., 2022). By comparing FTSE USA 4 Good index with the FTSE USA index, Berk and van Binsbergen (2021) conclude that there is no significant effect on expected returns that can be attributed to screening for green stocks during the period 2015–20. The FTSE 4 Good index measures the performance of firms that have evidenced strong Environmental, Social and Governance (ESG) practices. Our approach is different in that we focus only on the environmental pillar, as the green revenues point estimate quantifies a company's exposure to environmental impact. To our knowledge, no previous study has used this type of information, namely dollar adjusted values of share prices, where the adjustment is applied in accordance with the green revenue factor. The unique data set underpinning our study comprises the daily FTSE Russell 1000 index, the daily Green Revenue Factor for all constituents of the index and the daily FTSE Russell 1000 Green Revenues index.

Examining the impact of ESG on firm values, Heinkel et al. (2001) show that firms with superior ESG performance are a good hedge for investors concerned about climate change policy. Chava (2014) considers the implied costs of capital for green companies versus non-green (brown) and finds evidence of lower ex ante returns on green assets. Focusing on European individual stock returns, Alessi et al. (2021) introduce a pricing factor as the combination of greenhouse gas emissions and the quality of the environmental disclosure and find evidence of negative greenium. Asimakopoulos et al. (2023) look at the impact of ESG rating on a firm's debt structure and find that market and book leverage ratios, and information asymmetry are reduced for ESG rated firms which also switch their financing from public debt to private debt. Focusing on systemic risk, Curcio et al. (2023) establish that the riskiness in green indexes is higher than in brown indexes.

Another strand of this literature (see In et al., 2019; Bolton and Kacperczyk, 2021, 2023; Aswani et al., 2024) examines realized returns for green and for brown stocks and their linkages to carbon risk. Following on new regulations regarding compliance with the climate change agenda, firms look to internalize the cost of carbon emissions and to report them. This process becomes more prominent when the market is apprehensive about climate change risk. Pastor et al. (2022) argue that high green returns reported in recent years should not be taken as indicative predictors of the future returns. Similarly, Pedersen et al. (2021) implement an ESG adapted CAPM and find that following a strategy based on a new efficient environment frontier does not necessarily lead to a considerable improvement of the Sharpe ratio. Avramov et al. (2022) highlight the impact of ESG uncertainty on asset pricing and portfolio management by proposing an ESG-augmented equilibrium asset pricing model. In line with Pastor et al. (2021), their results indicate a negative relationship between the ESG rating and future performance for stocks with low ESG uncertainty, while there is evidence of an insignificant or positive association when ESG uncertainty elevates. Pastor et al. (2022) suggest that a temporary surge in the prices of "green" stocks is just a simple reflection of the climate concerns and of the liquidity of green assets that are suddenly in demand, without leading to long-lasting high monetary returns. Ardia et al. (2022) confirm that an unexpected surge in concerns about climate change is associated with a rise in green firms' stock prices and a drop in brown firms' stock prices. On the other hand, Cao et al. (2022) argue that the ESG agenda brings changes in stock return patterns, with abnormal returns linked to quantitative mispricing signals and larger returns for stocks owned by socially responsible institutions.

This paper is organised as follows. In Section 2, we define the green-adjusted share price by following the green revenues model of FTSE Russell. In Section 3, we present the methods of estimating unconditional and conditional betas, that we will apply to both standard and green-adjusted market prices/returns. In Section 4, we describe and analyse the unique database containing green revenue adjustments based on individual companies' cash-flows. The main empirical results are presented and discussed in Sections 5 and 6. Section 7 concludes.

2. Green-adjusted equity valuation

2.1. Green revenues

While the green economy opportunities are increasing continuously and several green taxonomies have been developed both globally and nationally, there are still important challenges in the implementation of these green frameworks due to a lack of diverse and in-depth data on green activities. According to Kooroshy et al. (2020), less than 30 % of companies with green revenues provide granular enough disclosures that permit investors to systematically identify and quantify companies' green business activities.

In this paper, we focus on the FTSE Green Revenue Index family which reflects contemporaneous performance of 98.5 % of listed companies, including those without an open green finance agenda. The FTSE Russell's Green Revenues data model estimates the green revenue exposure of more than 16,000 securities across 48 developed and emerging markets based on FTSE Russell's Green Revenues Classification System. Based on a unique industrial taxonomy, where the green

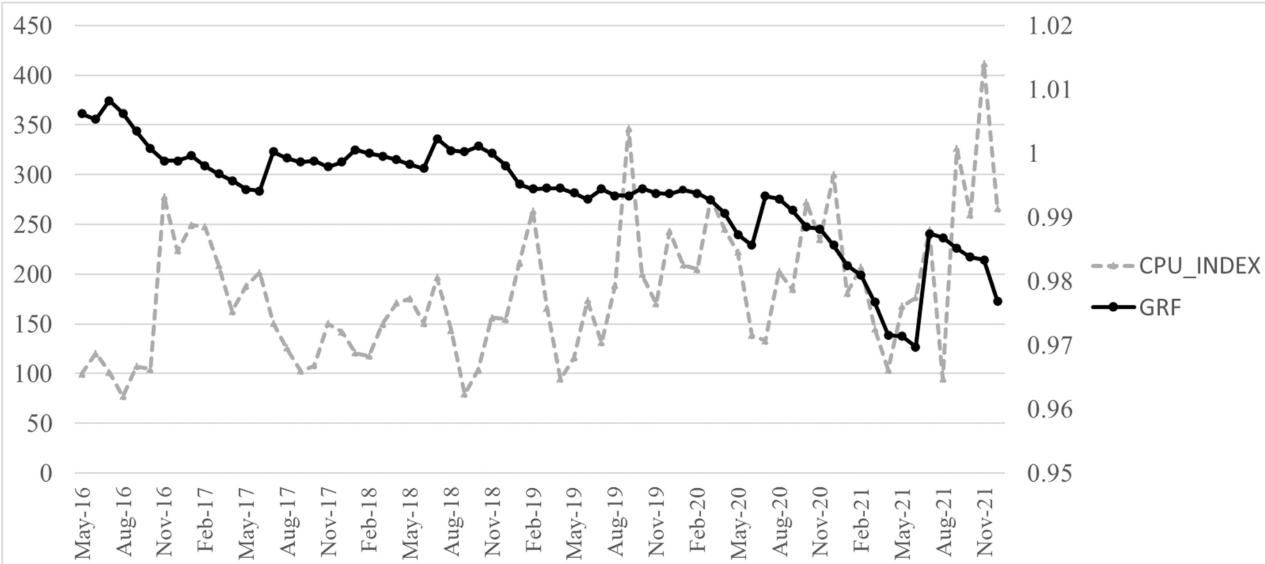

Fig. 1. The Evolution of Climate Policy Uncertainty Index versus average Green Revenues Factor. *Notes*: This plot shows the climate policy uncertainty index (https://www.policyuncertainty.com/climate_uncertainty.html) on the scale on the left versus the average green revenue factor from FTSE Russell, on the scale on the right.

economy covers 133 micro-sectors, only 2951 listed companies were found to generate green revenues from green products and services. For each company, green revenues are then filtered from the cash-flow statements based on their exposure to these green sectors. If a company has green exposure to multiple sub-sectors, then a total percentage (s) of revenue from green products is calculated. Total return indices include income based on ex-dividend adjustment with all dividends applied as declared, and the indices are calculated in several currencies on an end of day basis.[2] For each company, the FTSE Green Revenues ratio (*GRR*) is calculated as the ratio of the green revenues as classified by the FTSE Russell GRCS to the total company revenues.

2.2. The green-adjusted equity price

To help investors identify companies with high green exposure, the FTSE Russell GRCS is based on a tiering system that measures the net environmental impact of each business activity.[3] According to this classification of activities, a company may have activities across all three tiers, however on aggregate level its net environmental impact is still negative. Hence, as investors do not have access to this type of granular data, it will be very useful for investors to have a similar classification of greenness at company level. In the computation of the Russell 1000 Green Revenues Index, the investable market capitalisation weights are adjusted using the GRF, where $GRF_i = 1 + GRR_i$ for each company.

The GRF measure plays a vital role in our study and has several attributes. More specifically, GRF is a number between 0 and 2 and it can be seen as a measure of a company's greenness. Based on the GRF value, we introduce three types of companies: green companies with $1 < \mathrm{GRF_i} \leq 2$, neutral companies with $\mathrm{GRF_i} \cong 1$ and brown companies with $0 \leq \mathrm{GRF_i} < 1$. A GRF value under one applies to companies in the FTSE 1000 Index but not in the FTSE1000 Green Revenues Index. Hence, brown companies have an implied negative green revenue ratio. This reflects that it is possible for a company to have a net negative environmental impact, despite recording some exposure to green products and services. We can observe that the GRF metric has an inflationary effect on green companies, with almost no effect for neutral companies and a contraction/deflationary effect for brown companies. GRF can be interpreted as a green performance indicator,[4] which awards "green" companies and applies a penalty for "brown" companies, a mechanism in line with the suggestion that the prices of shares for firms with higher emissions should be lower (Matsumura et al., 2014). Hence, it can provide investors with a crucial tool in tracking and assessing the engagement of public companies in the transition to a global green economy, and in monitoring the green revenue exposure of their portfolios. In addition, it can be used as a signal to regulators, corporate managers and also consumers when companies become more lenient toward intensifying their green efforts. That is, disengagement from the green agenda is reflected in a decreasing GRF value over time, as their current green revenue assessment is inferior compared to a previous measurement.

We explore the link between this novel GRF metric and the climate change policy uncertainty (CPU) index. Fig. 1 illustrates the monthly evolution of the average GRF versus the CPU index.[5] Over the entire study period (May 26, 2016 to December 31, 2021), the correlation coefficient is −0.3586.[6] This negative relationship between GRF and CPU index confirms the intuition that when climate policy becomes more certain, companies will increase their presence in green activities, whereas higher climate policy uncertainty is associated with a lower GRF value.

[Fig. 1 about here]

[2] For more detailed information on the FTSE Green Revenues Classification System visit: https://www.lseg.com/content/dam/ftse-russell/en_us/documents/other/green-revenues.pdf

[3] The three tiers are defined as following: tier 1 covers activities (micro-sectors) with significant environmental benefits (e.g. solar); tier 2 covers activities with more limited, but net positive environmental benefits (e.g. water utilities); and tier 3 covers activities which have some environmental benefits but are overall net neutral or negative (e.g. nuclear).

[4] The closer GRF is to two, the greener the company is considered, whereas the closer the GRF is to zero the browner that company is. Investors may refine this classification to allow for various levels of both, greenness and brownness, helping them in a more efficient way to reflect the strengths of their green preferences in their portfolio selection.

[5] The average GRF is calculated cross sectionally and across all days in one month, to allow like for like comparison.

[6] The negative correlation coefficient is even stronger in the first half of the period (-0.5217), while almost zero (0.0221) in the second half of the study period, which includes the Covid-19 period.

To create the framework for a green-adjusted CAPM, we introduce *for the first time in the literature* a proxy for the green share price using the daily GRF data provided by FTSE Russell. For each company we compute the daily *pseudo* green-adjusted share price S^*as follows:

$$S^* = (\text{Market Share Price}) \times (\text{Green Revenues Factor}) = S \times GRF \tag{1}$$

It is important to note that depending on the value of the green revenues factor, the green share price of a company can be smaller, equal or larger than the standard market share price of that company.[7] For a green company the green share price is at least its standard market price, while for a brown company the green factor works as a penalty yielding a green share price smaller than the standard market price. For each company, we compute the daily green-adjusted returns based on the green-adjusted share prices as following:

$$R^*_{i,t} = \ln \frac{S^*_{i,t}}{S^*_{i,t-1}} = \ln \frac{S_{i,t}}{S_{i,t-1}} + \ln \frac{GRF_{i,t}}{GRF_{i,t-1}} = R_{i,t} + \ln \frac{GRF_{i,t}}{GRF_{i,t-1}} \tag{2}$$

The difference between the green-adjusted and the standard returns is driven by the logarithmic ratio of two consecutive values of the green revenues factor. From (2), we can infer that $R^* > R$ if and only if there is an improvement in the green revenues factor; and vice versa, that $R^* < R$ if and only if there is a deterioration in green revenues factors. Once a company reaches a high level of GRF and then GRF stabilizes, its adjusted return will be equal to be original return, so its adjusted beta, as implied by Eq. (2), will be the same as the original beta of the company. Therefore, one can argue that investors can expect benefits in terms of a higher green adjusted beta only during periods when the GRF of the company is improving. This resonates with Pastor et al. (2021),(2022) who argue that any asset pricing gains in green stocks are only temporarily and in the long-run in equilibrium investors should not expect higher returns from green stocks.

3. Research questions and methodology

3.1. Testing hypotheses

With this new set of green-adjusted variables (the green-adjusted share prices and the green-adjusted market returns represented by the FTSE Green Revenues Index), we can compare the asset pricing for an investor having additional green preferences with the asset pricing for a standard investor with no such preferences. Under the assumption that a green investor will care only about the green-adjusted returns R^*, tilted by the operator of green revenue factor $\ln \frac{GRF_{i,t}}{GRF_{i,t-1}}$, we investigate the relationship between the new pseudo-market green share prices and the FTSE Russell Green Revenues stock index through the lenses of equity beta. Our aim is to determine whether the new "green-adjusted" betas (β^*) estimates are different from the corresponding standard betas for the same universe of stocks; in other words, if green investors have the same systematic risk exposure as their twin standard investors.

We explore the possibility and the magnitude of such difference by trying to answer the following research questions: Is the distribution of green-adjusted returns R^*_{it} different from the distribution of the standard returns R_{it}? Are there any significant differences between the green-adjusted and the standard betas of the stocks in the FTSE Russell 1000 Index? To answer these questions, we state and test several hypotheses. First, we test if the distribution of beta measures derived from green-adjusted share prices is statistically different from the distribution of the betas for the corresponding standard share prices. Thus, we will test the following hypothesis:

H1. Green investors have the same asset pricing views on stock prices as standard investors.

This general research question is refined by testing the more specific hypothesis referring to the equality between green adjusted betas and standard betas.

H1: $\beta^*_{it} = \beta_{it}$ against the alternative that they are not equal.

We use the Kolmogorov-Smirnov test for testing this equality within each decile of the distribution of betas, monthly across time for several years.

In our analysis, we calculate the market factor (MKT), the book-to-market value (HML), the size of the firm factor (SMB) and momentum (MOM) on both, green-adjusted and standard returns. We find that the correlation coefficients between MKT, HML, SMB and MOM under green-adjusted share prices and the same market factors under the standard share prices are high. These high correlations indicate that the market structure is very much the same, irrespective whether the investor has additional green risk preferences or not.

Another research question is whether under the Fama-MacBeth (1973) regression methodology, the new risk-adjusted four factors mentioned above *are significant*. To do that, we apply an updated methodology for testing the following general hypothesis:

H2. The conditional CAPM explains the share price returns dynamics.

This general hypothesis can be refined by formulating a set of specific hypotheses for each type of investor looking at the universe of respective share prices, green revenues adjusted or standard.

H2a. For the green investor each of the four risk factors (MKT, HML, SMB, MOM) is significant in explaining green-adjusted share price returns.

H2b. For the standard investor each of the four risk factors (MKT, HML, SMB, MOM) is significant in explaining standard share price returns.

H2c. For the green investor the conditional green-adjusted CAPM cannot be rejected by the green-adjusted data.

H2d. For the standard investor the conditional standard CAPM cannot be rejected by the data.

It should be remarked that the Fama-French factors for the green-adjusted category had to be calculated from first principles, which is a first in the literature as well as far as we know. Thus, it is first and foremost important to know whether the respective four factors are significant in explaining not only the standard market share prices but also the green adjusted share prices. These are framed under H2a and H2b. Furthermore, we also test the significance of the conditional CAPM model using the latest methodology developed by Hasler and Martineau (2023). These are captured by hypotheses H2c and H2d. We consider both unconditional and conditional measures for beta as described in Bali et al. (2016). Once we have estimated the two sets of betas, the standard betas (using the standard share prices) and the green-adjusted betas (using the green-adjusted share prices), we compare them both, cross-sectionally and over time.

3.2. Estimation of unconditional beta

The unconditional beta is defined directly from the capital asset pricing model (CAPM) as

$$\beta_i = \frac{\text{cov}(R_i, R_m)}{\text{var}(R_m)} \tag{3}$$

where R_i, R_m are the share price return of company i and the return of market portfolio, respectively. The *historical CAPM beta* is estimated using the historical series of returns with the regression:

[7] For example, from a total of 1555 constituent companies in the FTSE Russell index during the 2016–2021 period, the "greenest" company is Apta Group with the highest green revenue factor of GRF = 2, while the brownest company is Sealed Air with the lowest green revenue factor GRF=0.345532.

$$r_{i,t} = \alpha_i + \beta_i r_{m,t} + \varepsilon_{i,t} \tag{4}$$

where $r_{i,t}, r_{m,t}$ are the excess return of company i and of the market portfolio over the risk-free rate, respectively, at time t. This leads to the most common beta estimate $\beta_i^{HIST} = \widehat{\beta}_i$. Typically, the regression model (4) is estimated based on a one-year rolling window of daily excess return data.[8] That is, at the end of each month t, the regression model (4) is estimated based on the previous 12-month period of daily return data, covering months $t-11$ through t, inclusively.[9]

Andersen et al. (2006) define the *realized beta* as

$$\beta_{i,\tau}^{R} = \frac{\sum_{t=1}^{t=N} r_{i,t} r_{m,t}}{\sum_{t=1}^{t=N} r_{m,t}^2} \tag{5}$$

where N is the number of observations during the estimation window τ.[10]

Fama and French (1992) employ monthly returns to estimate market beta by including the one-month lagged market return to cover for possible first-order autocorrelation in returns. Following Bali et al. (2017), we use daily returns to estimate the following model:

$$r_{i,t} = \alpha_i + \beta_{1,i} r_{m,t} + \beta_{2,i} r_{m,t-1} + \varepsilon_{i,t} \tag{6}$$

The *Fama-French beta* is defined as:

$$\beta_i^{FF} = \widehat{\beta}_{1,i} + \widehat{\beta}_{2,i} \tag{7}$$

Using daily data allows us to compute the Scholes and Williams (1977) estimator of beta that accounts for non-synchronous trading. To obtain the SW beta estimator, we need to estimate first the following three linear regression models:

$$r_{i,t} = a_i + \beta_{1,i} r_{m,t-1} + \epsilon_{i,t}$$
$$r_{i,t} = a_i + \beta_{2,i} r_{m,t} + \varepsilon_{i,t} \tag{8}$$
$$r_{i,t} = a_i + \beta_{3,i} r_{m,t+1} + u_{i,t}$$

Then, the *Scholes-Williams beta* is calculated as

$$\beta_i^{SW} = \frac{\widehat{\beta}_{1,i} + \widehat{\beta}_{2,i} + \widehat{\beta}_{3,i}}{1 + 2\rho} \tag{9}$$

where ρ is the first-order autocorrelation coefficient of the market portfolio's excess return. For this estimator we perform computations for stock i at the end of each month τ using daily data covering the one-year period.

When a stock is infrequently traded, the estimations of beta using the standard CAPM, might be severely biased (Dimson, 1979). To circumvent this problem, Dimson (1979) adds more betas to lagged market results. We use one lead and four $(L = 4)$ lags for daily returns data Then, the new equation of the linear regression model is:

$$r_{i,t} = \alpha_{i,t} + \beta_i^{(0)}(r_{m,t}) + \beta_i^{(+1)}(r_{m,t+1}) + \beta_i^{(-1)}(r_{m,t-1}) + \beta_i^{(-2)}\left(\sum\nolimits_{n=2}^{L} r_{m,t-n}\right) + \varepsilon_{i,t} \tag{10}$$

[8] Recent evidence (see Liu et al., 2018) suggests that using daily data may circumvent many of the estimation problems encountered with testing CAPM.

[9] Baker et al. (2010) calculate beta using a window size of one year of daily returns. Other window sizes may be used but the window size may have an impact on the calculation of beta. In the online appendix of this paper, we consider windows of one, three, six, 12, and 24 months that would require a minimum of 15, 50, 100, 200, and 450 days of valid return daily data, respectively, to compute the beta. The estimation windows are applied in all the estimation methods for the unconditional beta.

[10] Andersen et al. (2006) prove that under weak regularity conditions this is the only consistent measure for the true beta.

The *Dimson beta* estimator β_i^D is then calculated as:

$$\beta_i^D = \widehat{\beta}_i^{(+1)} + \sum\nolimits_{j=0}^{\min\{2,L\}} \widehat{\beta}_i^{(-j)} \tag{11}$$

3.3. Estimation of the dynamic conditional beta

The unconditional CAPM is a single period model and is subject to mean-variance optimization assumptions. Fixing the investment opportunity is a significant shortcoming. Merton (1973) offered a solution to this problem by allowing agents to trade continuously under separable von Neumann-Morgenstern utility functions. In this dynamic environment the conditional CAPM holds only if the cost of hedging is nil. Then, the equation of the model can be written as

$$E_t(r_{i,t+\Delta t}) = \beta_{it} E_t(r_{m,t+\Delta t}) \tag{12}$$

In this context, the conditional beta of firm i, at time t, is

$$\beta_{it} = \frac{cov_t(r_{i,t+\Delta t}, r_{m,t+\Delta t})}{\mathrm{var}(r_{m,t+\Delta t})} \tag{13}$$

To obtain the conditional beta (time varying beta), we must estimate the conditional covariance between the excess returns on stock i and on the market portfolio m. We employ the mean-reverting DCC model of Engle (2002). As in Bali et al. (2017) and Engle and Kelly (2012), to improve the parameter convergence, we use correlation targeting assuming that the time-varying correlations mean revert to the sample correlations. Assuming $\Delta t = 1$, the DCC model is represented by the following equations:

$$r_{i,t+1} = \alpha_0^i + \sigma_{i,t+1} u_{i,t+1}$$
$$r_{m,t+1} = \alpha_0^m + \sigma_{m,t+1} u_{m,t+1}$$
$$\sigma_{i,t+1}^2 = \beta_0^i + \beta_1^i \sigma_{i,t}^2 u_{i,t}^2 + \beta_2^i \sigma_{i,t}^2 \tag{14}$$
$$\sigma_{m,t+1}^2 = \beta_0^m + \beta_1^m \sigma_{m,t}^2 u_{m,t}^2 + \beta_2^m \sigma_{m,t}^2$$
$$\sigma_{im,t+1} = \rho_{im,t+1} \sigma_{i,t+1} \sigma_{m,t+1}$$
$$\rho_{im,t+1} = \frac{q_{im,t+1}}{\sqrt{q_{ii,t+1} q_{mm,t+1}}}$$
$$q_{im,t+1} = \overline{\rho}_{im} + a_1(u_{i,t} u_{m,t} - \overline{\rho}_{im}) + a_2(q_{im,t} - \overline{\rho}_{im})$$

where $\sigma_{i,t+1}^2$ is the day-t expected conditional variance of stock i, $\sigma_{m,t+1}^2$ is the day-t expected conditional variance of the market, $u_{i,t+1}$ and $u_{m,t+1}$ are the standardized residuals for stock i and the market portfolio, respectively; whilst $\rho_{im,t+1}$ is the day-t expected conditional correlation between the excess returns of the stock and excess returns of the market, and $\overline{\rho_{im}}$ is the unconditional correlation.

Then the *DCC beta* at time t for firm i is computed as

$$\beta_{i,t}^{DCC} = \frac{\widehat{\sigma}_{im,t+1}}{\widehat{\sigma}_{m,t+1}^2} \tag{15}$$

The same six estimation procedures above (five static and one dynamic) are applied to the green-adjusted variables (green-adjusted returns and the Russell 1000 Green Revenues Index) to measure the corresponding green-adjusted betas.

4. Data description

For our analysis, we distinguish between two sets of data. For the first set, we collect the standard data which include the daily values of the Russell 1000 Index from FTSE Russell, and the daily share prices for all constituent companies of the Russell 1000 stock index from Bloomberg. For the second set, we collect the green-adjusted data containing

Table 1
Descriptive statistics of the green-adjusted factors, returns and risk-free rate.

	Green Revenue Factor	Green Adj. Price Returns	Standard Price Returns	Risk-Free Rate
Mean	0.99	0.0003	0.0004	0.00003
SD	0.12	0.0168	0.0163	0.00002
Min	0.40	− 0.0994	− 0.0918	0.0000004
q_5	0.94	− 0.0253	− 0.0248	0.000001
q_{50}	0.97	0.0005	0.0005	0.00003
q_{95}	1.06	0.0255	0.0250	0.00006
Max	2.00	0.0914	0.0874	0.00007

Notes: This table reports the summary statistics for the Green Revenue Factor, the daily log-returns for green-adjusted and standard equity prices and for the daily OIS risk-free interest rate. We report the time series average of the cross-sectional Mean, Standard deviation (SD), Minimum (Min), 5th quantile (q_5), 50th quantile (q_{50}), 95th quantile (q_{95}) and Maximum (Max) calculated over the sample period starting from May 26, 2016 to December 31, 2021.

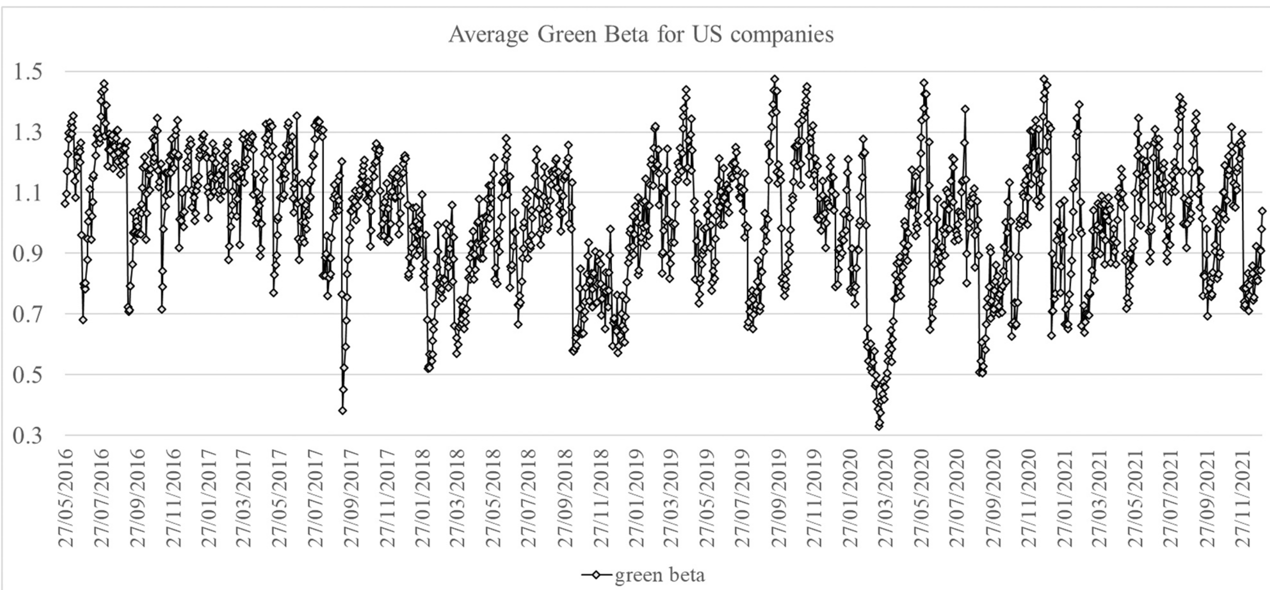

Fig. 2. Evolution of average green DCC betas for all companies in the US. *Notes:* Daily averages of conditional green DCC betas for all constituents of Russell 1000 index starting from 27 May 2016–31 December 2021.

the daily values of the Russell 1000 Green Revenues Index and the daily GRF values from FTSE Russell. All the data samples span the period from May 26, 2016 to December 31, 2021 for a total of 1462 trading days.[11]

We take the perspective of an international investor that is unhedged in exchange rates and employ all calculations in USD. We exclude days when Green Revenue Factor is zero, otherwise the green share price would be zero. Following, Hou et al. (2011), we exclude both R_t and R_{t-1} if they are higher than 100 % and if $(1+R_t)(1+R_{t-1})-1<20\%$. Any daily returns greater than 200 % are also eliminated (see Griffin et al., 2010). The daily return observations are winsorized at the 1 % and 99 % levels to further limit the effect of outliers. In the case of delisted companies, we consider all available observations as in Ince and Porter (2006). Furthermore, to remove the effect of illiquidity when stocks are traded less frequently, we discard from the sample the stocks with a price lower than $1 or higher than $1000. The cleaned data over the analysis period include a total of 1555 companies, with a minimum of 930 constituents on 25th of June 2018, and a maximum of 1031 constituents on 21st of December 2021. For the risk-free interest rate, we use the overnight index swap (OIS) curve with maturities matching each estimation window, a commonly used approach in testing the CAPM (see, Bali et al., 2016; Hendershott et al., 2020).

In Table 1, we present the summary statistics of all the variables necessary for estimating the standard and the green-adjusted beta.

For our sample period, the results in Table 1 show that the green revenue factors across all 1555 companies take values between 0.4 and 2, with 90 % of the firms having GRF values between 0.938 and 1.06. This indicates that during the study period, based on our green/yellow/brown colour system, most companies are relatively neutral (yellow). We observe that the distributions of the green-adjusted and standard returns are different with a lower mean and slightly higher standard deviation for the green-adjusted returns. This can be the result of a tilting effect that the GRF has on the standard return distribution. Given the period we cover in this research, not surprisingly the risk-free rates were close to zero.

5. Comparison between the green-adjusted and standard betas

In our analysis, we estimate the two sets of betas for all FTSE Russell constituents using the methodologies presented in Section 3. They are the unconditional measures of market beta which include the historical (CAPM) slope coefficient beta (β^{HIST}), Andersen et al. (2006) realized beta (β^{R}), Fama and French (1992) beta (β^{FF}), Scholes and Williams (1977) beta (β^{SW}) and the Dimson (1979) beta (β^{D}) and the conditional

[11] When the number of time series observations T is much smaller compared to the number of cross-section observations N asset pricing inference on betas can be impaired because of the large estimation error of the covariance matrix of the test assets, as discussed by Kleibergen and Zhan (2020). Using daily data improves the size of T.

Table 2
Univariate decile portfolios of stocks sorted by the green-adjusted betas.

Portfolio (j)	1(Low)	2	3	4	5	6	7	8	9	10(High)
Panel A: CAPM Beta Estimator										
Avg. $\bar{r}_j$	0.0069	0.0081	0.0071	0.0083	0.0090	0.0070	0.0074	0.0092	0.0132	0.0138
Avg. $\overline{\ln(MktCap)}$	9.5978	9.4919	9.3914	9.5327	9.4256	9.4548	9.4088	9.3729	9.2145	9.1647
Avg. $\overline{\beta}^{CAPM}$	0.3360	0.5613	0.6849	0.7748	0.8542	0.9308	1.0143	1.1098	1.2298	1.4883
Panel B: Scholes-Williams Beta Estimator										
Avg. $\bar{r}_j$	0.0095	0.0082	0.0109	0.0085	0.0074	0.0081	0.0066	0.0102	0.0093	0.0102
Avg. $\overline{\ln(MktCap)}$	9.6634	9.5864	9.5555	9.4594	9.5133	9.4590	9.4126	9.3564	9.1408	8.9086
Avg. $\overline{\beta}^{SW}$	0.3043	0.5931	0.7507	0.8821	0.9989	1.1115	1.2317	1.3771	1.5678	2.0234
Panel C: Dimson Beta Estimator										
Avg. $\bar{r}_j$	0.0090	0.0081	0.0104	0.0072	0.0067	0.0052	0.0100	0.0109	0.0086	0.0130
Avg. $\overline{\ln(MktCap)}$	9.5556	9.4837	9.5360	9.5153	9.4585	9.5012	9.4393	9.3845	9.2242	8.9570
Avg. $\overline{\beta}^{DIM}$	0.2136	0.5101	0.6737	0.7995	0.9143	1.0269	1.1452	1.2834	1.4752	1.9411
Panel D: Realised Beta										
Avg. $\bar{r}_j$	0.0072	0.0080	0.0068	0.0078	0.0096	0.0072	0.0064	0.0098	0.0134	0.0143
Avg. $\overline{\ln(MktCap)}$	9.5949	9.4886	9.3848	9.5334	9.4230	9.4415	9.4206	9.3737	9.2175	9.1770
Avg. $\overline{\beta}^{Realised}$	0.3361	0.5606	0.6846	0.7746	0.8543	0.9307	1.0140	1.1092	1.2281	1.4852
Panel E: Fama-French Beta Estimator										
Avg. $\bar{r}_j$	0.0113	0.0060	0.0098	0.0105	0.0089	0.0058	0.0069	0.0089	0.0085	0.0157
Avg. $\overline{\ln(MktCap)}$	9.6226	9.5013	9.5039	9.5231	9.4830	9.4520	9.3761	9.3496	9.2509	8.9928
Avg. $\overline{\beta}^{FF}$	0.3377	0.5859	0.7202	0.8222	0.9117	0.9989	1.0942	1.2069	1.3473	1.6700
Panel F: DCC Beta Estimator										
Avg. $\bar{r}_j$	0.0064	0.0090	0.0072	0.0068	0.0067	0.0063	0.0099	0.0093	0.0099	0.0068
Avg. $\overline{\ln(MktCap)}$	9.5468	9.5102	9.4294	9.4150	9.4469	9.4121	9.3910	9.3828	9.2912	9.2297
Avg. $\overline{\beta}^{DCC}$	0.2205	0.5112	0.6645	0.7857	0.8937	0.9994	1.1119	1.2435	1.4242	1.8471

Notes: The FTSE Russell index's individual stocks are sorted into 10 decile portfolios at the end of each month (t), using the CAPM beta estimator (Panel A), Scholes-Williams beta estimator (Panel B), Dimson beta estimator (Panel C), Realised beta estimator (Panel D), Fama-French beta estimator (Panel E), and the unconditional DCC beta estimator (Panel E). Each portfolio is held for a full month. The daily returns for the previous one year with at least 200 observations are used to calculate both conditional DCC and unconditional beta estimates. For each portfolio sort, we report the value-weighted average excess return ($\bar{r}_j$), average log market capitalisation $\overline{\ln(MktCap)}$, and average green-adjusted beta $\overline{\beta}^{Estimator}$. The sample covers the period from May 26, 2016 to December 31, 2021.

betas (β^{DCC}) using the dynamic conditional correlation (DCC) model of Engle (2002). To be consistent across these estimation procedures, we estimated at the end of each month the conditional and unconditional betas, using daily returns over the past 252 trading days with at least 200 observations available. Compared to the unconditional betas where a constant market exposure over a 1-year period is assumed (see Bali et al., 2017), the DCC beta has the advantage of applying high weights on more recent observations and of providing us with a 1-year set of daily beta estimates. In Fig. 2 we illustrate the daily time series evolution of the cross-sectional average of green DCC betas between mid-2016 and the end of 2021. There are two significant dips in green betas towards the end of 2017, in the aftermath of the U.S. withdrawal from the Paris Accord and in the spring of 2020, when the Trump administration rejected the new emissions rules.

5.1. Green-adjusted and standard betas comparison: decile portfolios analysis

We conduct our comparative analysis by constructing a set of ten portfolios for each green-adjusted and standard share price contexts, based on the ranking of green-adjusted and standard beta estimates, respectively. On the last day of each month, we sort the individual equities into decile portfolios based on their betas. Decile 1 portfolio contains stocks with lowest market beta, while decile 10 portfolio contains stocks with the highest market beta. Each portfolio is held for one month. Once the beta-sorted portfolios are constructed, we estimate the portfolio average betas using both unconditional and conditional estimators. We report the results for the green-adjusted share prices in Table 2, while the results for the standard prices are presented in Appendix. Panels A to E in Table 2 report the portfolio results for the unconditional market green-adjusted beta estimators and Panel F those for the dynamic conditional green-adjusted betas. The first row in each panel shows the value-weighted average excess returns. The second row of each panel reports the average log market capitalisation across all stocks in each decile portfolio. The last row in each panel presents the average market beta of the stocks in each decile portfolio.

The results presented in Table 2 show that unconditional estimates of the average green-adjusted beta vary across different methods of estimation. The largest difference between the average betas for the two extreme decile portfolios is 1.7275 and it is associated with the Dimson beta estimator, while the narrowest difference is 1.1491 and occurs for the realized beta. The average returns across different portfolio deciles vary as well, and for the unconditional betas the extreme decile portfolios seem to produce larger average returns. These findings suggest a non-linear relationship between the static betas and the expected rates of return, hence the green-adjusted CAPM does not hold for any of the static estimation methods.

A similar result regarding the standard unconditional betas was provided by Hasler and Martineau (2023), who show that the unconditional CAPM fails to explain the cross section of average asset returns. For all methods of calculating beta, the values of average beta for the respective decile portfolios are less than 1 for the first five decile portfolios and then gradually increase above 1 for the last five decile portfolios. We present the analogue of this table containing the same calculations for the standard betas in the table in Appendix A of the Online Appendix. Comparing the empirical results from Table 2 with the results from its analogue table in Appendix suggests that there are no significant discrepancies between the green-adjusted and standard betas across the estimation methods.

However, a more informed conclusion requires formal statistical testing. To test whether the green-adjusted betas are statistically different from the standard betas, we use the Kolmogorov-Smirnov (KS) test with the Abadie (2002) correction based on 10,000 bootstraps to create a heat map (see Fig. 3). We apply the KS test for each decile

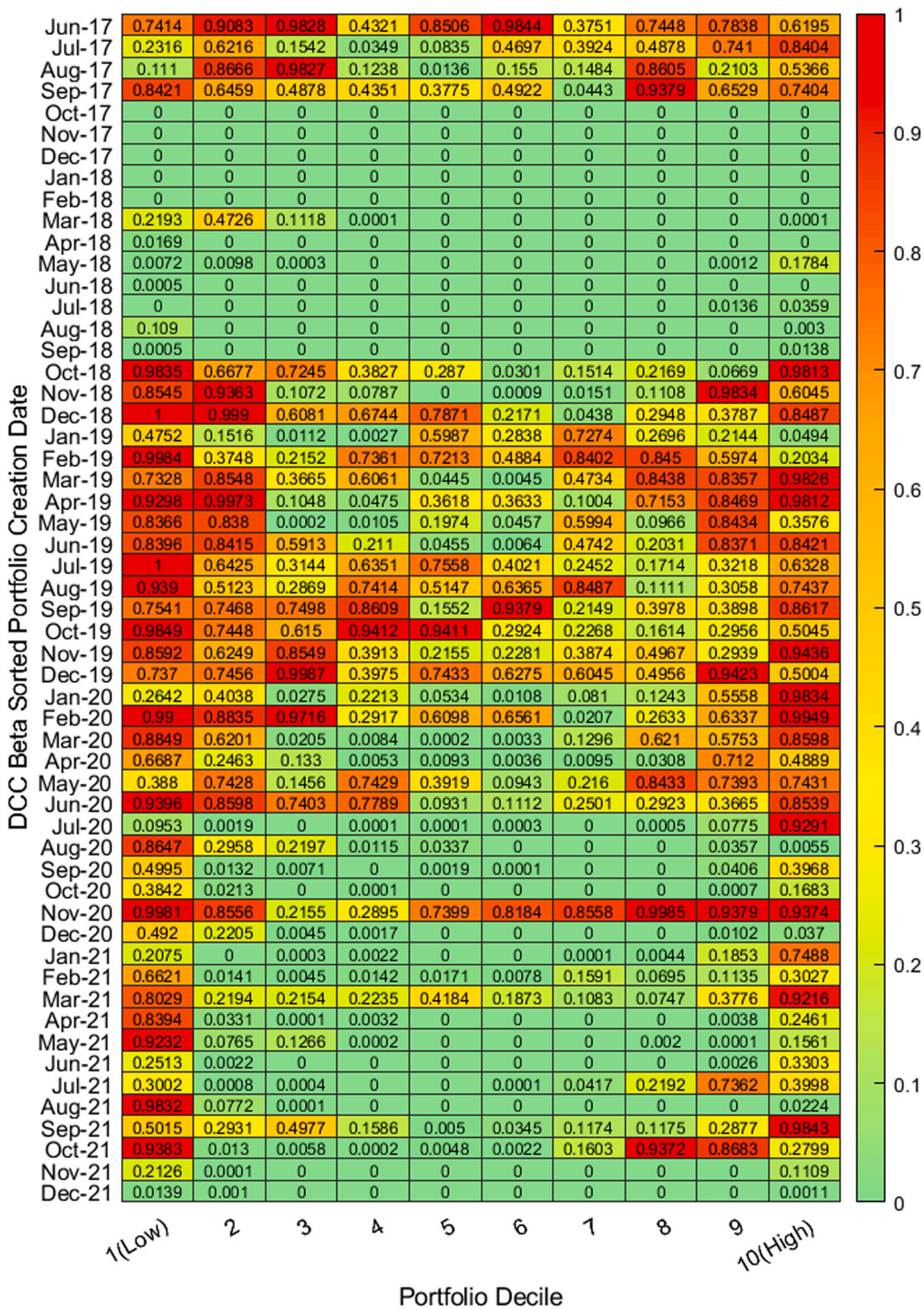

Fig. 3. A heat map of *p*-values obtained from the bootstrap Kolmogorov-Smirnov test comparing betas for all decile portfolios. *Notes:* At the end of each month, starting from June 2017 to December 2021, we create the DCC beta sorted decile portfolios and test the null hypothesis that the green-adjusted and standard DCC betas of companies within each decile portfolio are from the same distribution against the alternative that the two distributions are equal. We use the Kolmogorov-Smirnov test with Abadie (2002) correction based on 10,000 bootstraps.

portfolio based on the DCC betas. At the end of each month, starting from June 2017 to December 2021, we create the DCC beta sorted decile portfolios and test the null hypothesis that the green-adjusted and standard DCC betas of companies within each decile portfolio are from the same distribution against the alternative that the two distributions are different.

In the heat map presented in Fig. 3, the green cells are associated with very low p-values for the KS test, indicating that the green betas are different from the standard betas, hence the risk preferences of green investors are different from the risk preferences of standard investors. There are some periods for which the hypothesis H1a is rejected across all decile portfolios. For example, between October 2017 and September 2018, most cells in the heat map are green. One explanation for this could be the surge in climate finance flows as reported by various organisations, and summarised in Table 3.

This was followed by a period of failing to reject the KS tests from 2019 until early 2021, including the Covid-19 period, suggesting that there were no significant differences for beta calculations between a green investor and a standard investor. During this period, the only green cells appear mainly around the central deciles (the 5th and 6th deciles), a region where investors are neither too risk-averse nor too risk seekers. Our empirical findings support only a temporary "Greta

Table 3
Climate finance evolution between 2013 and 2019.

Year	2013	2014	2015	2016	2017	2018	2019
Climate finance flows (in $bn)	342	388	472	455	608	540	615*
Climate Finance for Developing Countries	52.2	61.8	na	58.6	71.2	78.9	na
Mobilised private finance	12.8	16.7	na	10.1	14.5	14.6	14.0

Notes: Second row values show annual climate finance flows climate finance flows from the Climate Policy Initiative (www.climatepolicyinitiative.org), see Macquarie et al. (2020). Third row values are from the OECD report "Climate finance for developing countries rose to USD 78.9 billion in 2018", see Bremer (2020). Fourth row data is from Ares and Loft (2021) and it shows the mobilised private finance that is captured only from individuals and corporations.

Thunberg effect" (Ramelli et al., 2021), as the effect of the success of the first Global Climate Strike (March 15, 2019) seems to have lasted approximately three months. We observe that Covid-19 had a negative impact on the transition to the green economy in the context of the U.S. equity markets. The heat map in Fig. 3, also correctly captures the hostility of Trump administration towards green economy, which culminates in November 2020, when the U.S. officially pulled out of the Paris Agreement. During late 2021, we can see a return to the rejection of KS tests and hence, to a differentiation between assets perceived as carrying green values and the other assets. This is not surprising, as this point in time corresponds to the joint occurrence of the Glasgow climate conference COP26 and the start of recovery from the pandemic Covid-19 as a result of successful vaccines.

The calculation of the GRF measure for all constituent companies of the Russell 1000 index allows a direct classification of companies into green companies (with net positive environmental impact) and brown (with net negative environmental impact). Moreover, this classification can be refined further to include various shades of green and brown. For simplicity, we divide the companies into green companies (with GRF $>$ 1.05), neutral companies (with very small close to zero, positive or negative net Green revenues; $0.95 < \text{GRF} < 1.05$), and brown companies (with GRF $<$ 0.95). In Fig. 4, we illustrate the scatterplot of the green-adjusted betas and standard betas for each company that was part of the Russell 1000 index across these three company categories. Most green companies are in the lower betas range, while there are more brown companies than green in the higher beta range. Furthermore, for all categories there is a very close fit between the two vectors of betas, suggesting that the betas for the green investor are statistically the same with the betas of the standard investor. This is evidence suggesting that the hypothesis H1a cannot be rejected and hence the betas for green adjusted share prices and the betas for the market share prices are not statistically different.

5.2. Green-adjusted Fama-French factors

In this section, we analyse the MKT, HML, SMB and MOM factors on both, green-adjusted and standard returns. Table 4 reports the summary statistics of these four equity market factors for all the companies in the Russell 1000 index, under both standard and green-adjusted share prices. We conclude that the four factors driving asset pricing have the same stylised features for the green investor as it has for the standard investor.

To further investigate this issue we calculate, for each decile portfolio, the correlations between the beta loadings for each market factor in that decile portfolio under standard asset pricing calculation and the beta loadings for the same factor and the same decile portfolio under green-adjusted calculations. The results presented in Table 5 show that these correlations are very high, in excess of 90 % for the SMB and MOM. For the HML, the lowest correlation is at 88.96 % for the sixth decile portfolio, while for the MKT factor the lowest correlation is 78.04 % for the second decile portfolio. This is clear evidence that we fail to reject the hypothesis H1b and therefore we infer that the driving factors for equity asset pricing in the U.S. are the same for both green

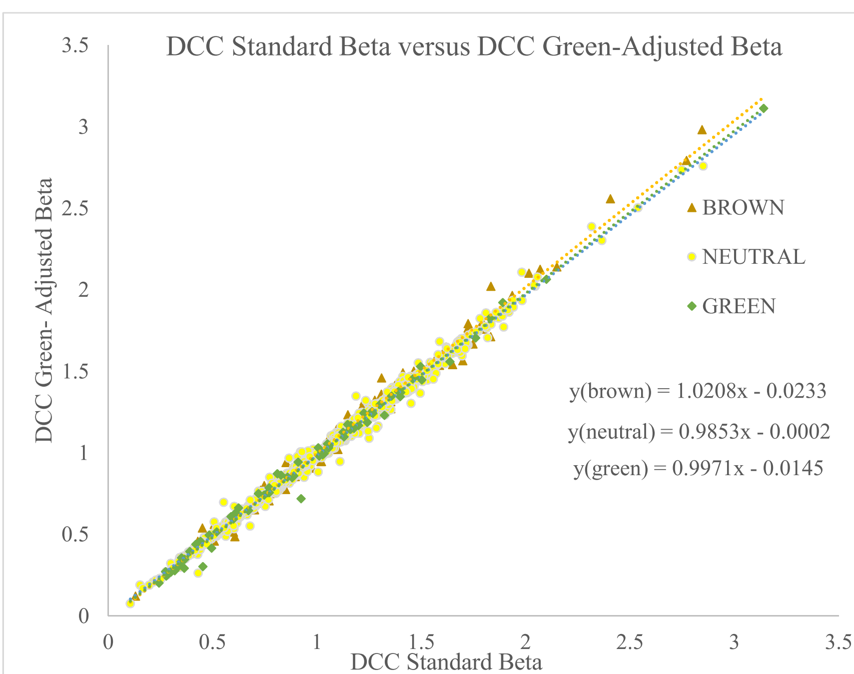

Fig. 4. Green-adjusted betas versus standard betas. *Notes*: This scatterplot diagram shows the time series average of the daily green-adjusted DCC betas against those of standard DCC betas, respectively. It is based on the clean data set of 1301 companies used to estimate the DCC models over the period 2016–2021. We classify companies as green if their GRF is greater than 1.05, neutral (yellow) if the GRF is between 0.95 and 1.05 and brown if their GRF is below 0.95. By applying these arbitrary criteria, we identify 156 brown companies, 1065 yellow and 80 green companies. We observe that for all three sub-sets of companies the relationship between standard and green-adjusted betas are very similar, with very close lines-of-best-fit.

Table 4
Summary statistics on market factors.

	MKT	HML	SMB	MOM
Panel A: Standard equity market				
Mean	0.0005	− 0.0002	− 0.0004	0.0001
SD	0.0116	0.0045	0.0045	0.0078
Min	− 0.130	− 0.0198	− 0.0233	− 0.0422
q5	− 0.0163	− 0.0068	− 0.0072	− 0.0126
q50	0.0006	− 0.0001	− 0.0004	0.00
q95	0.0145	0.0065	0.0069	0.0116
Max	0.0904	0.0217	0.0234	0.0454
Panel B: Green-adjusted equity market				
Mean	0.0005	− 0.0002	− 0.0004	0.00005
SD	0.0116	0.0046	0.0045	0.0077
Min	− 0.130	− 0.0222	− 0.0233	− 0.0426
q5	− 0.0164	− 0.0069	− 0.0077	− 0.0123
q50	0.0005	− 0.0002	− 0.0003	0.00
q95	0.0146	0.0066	0.0069	0.0111
Max	0.0904	0.0226	0.0270	0.0434

Notes: This table reports the Mean, Standard deviation (SD), Minimum (Min), 5th quantile (q_5), 50th quantile (q_{50}), 95th quantile (q_{95}) and the Maximum (max) of each of the four factors we constructed using the FTSE Russell 1000 dataset. The sample period is from May 26, 2016 to December 31, 2021. the MKT, HML, SMB, and MOM factors are respectively described in test.

Table 5
Correlations between the cross-sectional average DCC green-adjusted and standard betas, respectively.

	$Cor(\beta_{g-adj}^{DCC,MKT}, \beta_s^{DCC,MKT})$	$Cor(\beta_{g-adj}^{DCC,SMB}, \beta_s^{DCC,SMB})$	$Cor(\beta_{g-adj}^{DCC,HML}, \beta_s^{DCC,HML})$	$Cor(\beta_{g-adj}^{DCC,MOM}, \beta_s^{DCC,MOM})$
1	0.9513	0.9624	0.9245	0.9622
2	0.7804	0.9380	0.9049	0.9068
3	0.7952	0.9404	0.9391	0.9557
4	0.8926	0.9420	0.9193	0.9777
5	0.8825	0.9178	0.9171	0.9801
6	0.9144	0.9012	0.8896	0.9650
7	0.9460	0.9097	0.8955	0.9741
8	0.9439	0.9318	0.9544	0.9821
9	0.9687	0.9705	0.9801	0.9921
10	0.9716	0.9791	0.9872	0.9938

Notes: For each of the four factors i.e. $MKT, SMB, HML,$ and MOM, this table reports the correlation between average cross-sectional green-adjusted DCC betas and standard DCC-betas for each portfolio. Column (2) reports the correlation between the green-adjusted DCC betas and the standard DCC betas for the market factor, i.e. $Cor\left(\beta_{g-adj}^{DCC,MKT}, \beta_s^{DCC,MKT}\right)$. The respective correlations for SMB, HML, and MOM are reported in columns 3, 4, 5 for each of the 10 portfolios, with 1 low and 10 high. If F is the notation for a generic factor, then $\beta_{it}^{DCC,F}$ is the corresponding beta obtained by regressing excess returns for portfolio i on factor F using all returns in the estimation window (one year) prior to time t. The sample size is 56 as a result of creating the decile portfolio sorts at the end of each month over the sample period from May 26, 2016 to December 31, 2021.

and standard investors.

6. Empirical testing under conditional betas

6.1. Empirical testing for conditional standard betas

In order to test whether various estimators for CAPM, unconditional or not, work with real data we need a testing framework based on the realized stock and market returns. For the conditional betas, we employ the testing methodology presented in Hasler and Martineau (2022), adapted for the dynamic conditional betas in (17) and for a day-to-day inference ($\Delta t = 1$), by estimating the following equations:

$$r_{i,t+1} = a_i + b\left[\beta_{it}^{DCC} r_{m,t+1}\right] + \sigma_{it}\epsilon_{i,t+1} \quad (16)$$

and

$$r_{m,t+1} = E_t\left(r_{m,t+1}\right) + \sigma_{mt}\epsilon_{m,t+1} \quad (17)$$

where σ_{it} is the firm specific volatility of the company i's returns, and $\epsilon_{i,t+1}$ and $\epsilon_{m,t+1}$ are independent error terms with mean zero and variance one. Recalling the definition of conditional beta in (15) the true conditional beta satisfies the relationship $\beta_{it} = b\beta_{it}^{DCC}$.

Combining the equations in (16) and (17) leads to

$$r_{i,t+1} = a_i + b\beta_{it}^{DCC} E_t\left[r_{m,t+1}\right] + b\beta_{it}^{DCC}\sigma_{m,t}\epsilon_{m,t+1} + \sigma_{it}\epsilon_{i,t+1} \quad (18)$$

Hasler and Martineau (2022) show that if the intercept term a_i is not statistically significant and the slope b is statistically significant then the conditional CAPM holds. Moreover, if the slope $b = 1$, then the empirical beta (irrespective of the model used to estimate the conditional beta) is the true beta. However, if the coefficient b is not statistically significant, then it follows that $E_t\left(r_{i,t+1}\right) = a_i$ and in that case the market is not a priced risk factor.

Eq. (16) is the main vehicle for testing CAPM models based only on the market factor, but it can be expanded to multiple factors, under a Fama-MacBeth methodology for the 10- beta sorted portfolios. We improve the testing in two directions. First, panel regression models can be employed to test (16), see Pukthuanthong et al. (2018) and Martin and Wagner (2019) for a motivation why this is highly relevant in an asset pricing context. Second, we expand the testing to include multiple factors.

For clarity we index the sorted decile portfolios with $j \in \{1, 2, \ldots, 10\}$. Then, the regression specification for testing the dynamic beta is

$$\begin{aligned} r_{j,t+1} = a_j + b_M\left[\beta_{jt}^{DCC,M} r_{m,t+1}\right] + b_{HML}\left[\beta_{jt}^{DCC,HML} HML_{t+1}\right] \\ + b_{SMB}\left[\beta_{jt}^{DCC,SMB} SMB_{t+1}\right] + \quad b_{MOM}\left[\beta_{jt}^{DCC,MOM} MOM_{t+1}\right] + \sigma_{jt}\epsilon_{j,t+1} \end{aligned} \quad (19)$$

If F is the notation for a generic factor, then $\beta_{jt}^{DCC,F}$ is the corresponding beta loading obtained by regressing excess returns for portfolio j on factor F using all returns in the estimation window (one year) prior to time t.

In Table 6, we present the results for pooled regression (with $\alpha_i = \alpha$ for all i = 1, …, 10) and also for panel regressions with fixed effects α_i, for value weighted portfolios and Newey-West corrected standard errors. For both types of calculations, using standard and green-adjusted share prices, we find that the slope coefficients of the market risk factor alone are statistically not different from 1, while the intercepts are significant. In addition, when all four factors are included, we find that all their coefficients are statistically significant. This is evidence supporting hypotheses H2a and H2b.

The R^2 slightly increases when we add more risk factors (Fama-French and Carhart), for both green-adjusted and standard share prices calculations. Regarding the Wald tests, the conditional CAPM is valid, as we fail to reject the null hypothesis.

Table 8 shows that there is very little difference between the slopes of the four market risk factors for the green investor calculation versus the standard investor calculations. This suggests that, whatever the outcomes regarding the relevance of market factors or of the conditional CAPM itself, the results are very likely to be the same.

In the next section we apply the Fama-MacBeth regression framework, as extended in Hasler and Martineau (2022) with the assumption that the realized market returns and market return variance follow an ARMAX model, to test if the conditional CAPM holds.

6.2. Empirical testing of conditional CAPM for green-adjusted share prices

The Fama-MacBeth testing framework has been expanded by Hasler

Table 6
Pooled and Panel Regressions with value weighted portfolios (with Newey West SE).

	Pooled OLS b coefficient			Panel with Fixed Effects b coefficient		
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
PANEL A: Standard share prices						
MKT	0.9984**	1.0218***	1.0597***	0.9957***	1.0208***	1.0587***
	(0.0402)	(0.0384)	(0.0417)	(0.0403)	(0.0382)	(0.0414)
SMB		0.2937**	0.2260*		0.2748**	0.2092*
		(0.1459)	(0.1306)		(0.1380)	(0.1239)
HML		0.2202**	0.2281**		0.2320**	0.2390**
		(0.1008)	(0.1060)		(0.0994)	(0.1056)
MOM			0.3786**			0.3780**
			(0.1657)			(0.1630)
Constant	−0.000606***	−0.000222	−0.000254			
	(0.000256)	(0.000231)	(0.000229)			
Observations	550	550	550	550	550	550
R^2	0.600	0.633	0.641	0.593	0.626	0.634
$\sum_i \frac{1}{n} a_i$				−0.00061 (0.000265)	−0.00023 (0.000260)	−0.00025 (0.000257)
p-values for Wald statistics						
$H_0 : \sum_i \frac{1}{n} a_i = 0$				0.943	0.808	0.839
$H_0 : \sum_i \frac{1}{n} a_i = 0, \sum_i \frac{1}{n} a_i^2 = 0$				0.993	0.852	0.903
PANEL B: Green-adjusted share prices						
MKT	1.0069***	1.0310***	1.0665***	1.0044***	1.0297***	1.0651***
	(0.0381)	(0.0374)	(0.0406)	(0.0383)	(0.0374)	(0.0406)
SMB		0.2997**	0.2458**		0.2817**	0.2281**
		(0.1233)	(0.1088)		(0.1185)	(0.1048)
HML		0.1657*	0.1698*		0.1770**	0.1806*
		(0.0873)	(0.0903)		(0.0886)	(0.0926)
MOM			0.3403*			0.3387*
			(0.1876)			(0.1571)
Constant	−0.000751***	−0.000374	−0.000405*			
	(0.000256)	(0.000235)	(0.000233)			
Observations	550	550	550	550	550	550
R^2	0.598	0.624	0.630	0.591	0.617	0.623
$\sum_i \frac{1}{n} a_i$				−0.00075 (0.000264)	−0.00038 (0.000264)	−0.00041 (0.000262)
p-values for Wald statistics						
$H_0 : \sum_i \frac{1}{n} a_i = 0$				0.868	0.707	0.738
$H_0 : \sum_i \frac{1}{n} a_i = 0, \sum_i \frac{1}{n} a_i^2 = 0$				0.999	0.960	0.981

Notes: The table presents results from a regression of portfolio excess returns on the market, Fama and French (1993), (2015), and Carhart (1997) risk components for the ten beta-sorted portfolios. For the momentum (MOM) factor, at the end of each month all stocks are ranked based on previous year performance, the stocks in the bottom decile (lowest previous performance) are assigned to the loser portfolio, those in the top decile to the Winner portfolio. The portfolio returns are values weighted and held till the end of the next month. We estimate: $R_{i,t+1} = \alpha_i + b\left[\widehat{\beta}_{i,t}^{MKT} MKT_{t+1}\right] + h\left[\widehat{\beta}_{i,t}^{HML} HML_{t+1}\right] + s\left[\widehat{\beta}_{i,t}^{SMB} SMB_{t+1}\right] + m\left[\widehat{\beta}_{i,t}^{MOM} MOM_{t+1}\right] + \varepsilon_{i,t+1}$. Each factor loading $\widehat{\beta}_i^F \equiv \frac{Cov(R_i, F)}{Var(F)}$ is estimated using the 1-year (daily frequency) data strictly prior to the day of portfolio creation for each of the respective factors F. Panel A reports results using a pooled regression and Panel B presents results using a panel regression with fixed effects. The table also reports the adjusted R^2, the number of observations, and the p-values. Standard errors in parentheses with *** p<0.01, ** p<0.05, * p<0.1. The sample period is from May 26, 2016 to December 31, 2021. The table also reports the p-values of the Wald statistics testing the joint Hypothesis $H_0 : \sum_i \frac{1}{n} a_i = 0$, and $H_0 : \sum_i \frac{1}{n} a_i = 0$ and $\sum_i \frac{1}{n} a_i^2 = 0$ for green-adjusted and standard equity fixed effects regression models. n is the number of portfolios in the cross section.

and Martineau (2022) to investigate the relationship between unconditional and conditional CAPM. Based on the following equation

$$E(r_{i,t+1}) - \alpha_i = \beta_i E(r_{m,t+1}) \tag{20}$$

they derive the intercepts as

$$\begin{aligned}\alpha_i = &\left[1 + \frac{E(r_{m,t+1})^2}{\mathrm{var}(r_{m,t+1})}\right] \mathrm{cov}\left(\beta_{it}^{DCC}, E(r_{m,t+1})\right) \\ &- \frac{E(r_{m,t+1})}{\mathrm{var}(r_{m,t+1})}\left[\mathrm{cov}\left(\beta_{it}^{DCC}, E(r_{m,t+1})^2\right) + \mathrm{cov}\left(\beta_{it}^{DCC}, \sigma_{m,t}{}^2\right)\right]\end{aligned} \tag{21}$$

We apply Eq. (21) at portfolio level and we obtain the estimate $\widehat{\alpha}_j$ for all decile portfolios (j=1,10) presented in Table 9, Panel A. The improved testing for the unconditional beta is then performed by estimating the regression

$$r_{i,t+\Delta t} - \widehat{\alpha}_i = a + b\widehat{\beta}_i + e_{i,t+\Delta t} \tag{22}$$

We work with month-on-month Fama-MacBeth regressions of stock returns on unconditional betas with data provided by the DCC CAPM and at portfolio level, using the portfolio intercepts from Panel A. In Table 9, Panel B we present the estimates of Eq. (22) where the dependent variable is the portfolio excess returns adjusted by the alpha estimates reported in Panel A. We find that the intercepts and the slopes are statistically significant. In addition, we consider the dependent variable as the portfolio excess return without any adjustment (see Panel C) and the results indicate that both the intercepts and the slopes are insignificant. The results, in Panel B and C bring evidence that the unconditional CAPM does not explain the market, in contrast with the

Table 7
Individual portfolio fixed effects $\alpha_j$estimated for Panel Regression with Fixed Effects.

	Model : (4)		*Model* : (5)		*Model* : (6)	
Portfolio Decile Panel A: Green-adjusted beta-sorted portfolio						
1(Low)	− 0.0002	(0.0008)	− 0.00009	(0.0008)	− 0.0001	(0.0007)
2	− 0.0006	(0.0008)	− 0.0004	(0.0008)	− 0.0004	(0.0007)
3	− 0.0001	(0.0008)	0.00009	(0.0008)	0.00006	(0.0007)
4	− 0.0007	(0.0008)	− 0.0003	(0.0008)	− 0.0003	(0.0007)
5	− 0.0004	(0.0008)	− 0.00005	(0.0008)	− 0.00009	(0.0007)
6	− 0.0004	(0.0008)	− 0.00004	(0.0008)	− 0.0001	(0.0007)
7	− 0.0015 *	(0.0008)	− 0.0011	(0.0008)	− 0.0011	(0.0007)
8	− 0.0006	(0.0008)	− 0.0002	(0.0008)	− 0.0002	(0.0007)
9	− 0.0001	(0.0008)	− 0.0006	(0.0008)	− 0.0006	(0.0008)
10(High)	− 0.0016 **	(0.0008)	− 0.0009	(0.0008)	− 0.0009	(0.0008)
$H_0 : \forall_i a_i = 0$,*p*-values		0.329		0.926		0.908
Panel B: Standard beta-sorted portfolio						
1(Low)	− 0.00002	(0.0008)	0.0001	(0.0007)	0.00004	(0.0007)
2	− 0.0003	(0.0008)	− 0.0002	(0.0008)	− 0.0002	(0.0007)
3	− 0.0003	(0.0008)	− 0.0001	(0.0008)	− 0.0001	(0.0007)
4	− 0.0005	(0.0008)	− 0.0001	(0.0008)	− 0.0001	(0.0008)
5	− 0.0004	(0.0008)	0.00001	(0.0008)	− 0.00003	(0.0008)
6	− 0.0002	(0.0008)	0.0001	(0.0008)	0.00008	(0.0008)
7	− 0.0012	(0.0008)	− 0.0009	(0.0007)	− 0.0010	(0.0008)
8	− 0.00005	(0.0008)	0.0004	(0.0007)	0.0005	(0.0008)
9	− 0.0015 *	(0.0008)	− 0.0009	(0.0007)	− 0.0009	(0.0008)
10(High)	− 0.0014 *	(0.0008)	− 0.0007	(0.0008)	− 0.0006	(0.0008)
$H_0 : \forall_i a_i = 0$,*p*-values		0.524		0.949		0.936

Notes: This Table reports the output of panel regression with fixed effects a_i, with Newey-West adjusted standard errors. The *p*-values of the Wald statistics testing the hypothesis $H_0 : \forall_i a_i = 0$, where $i = 1,\ldots,10$ denote the respective portfolio deciles in the cross section. The sample period is from May 26, 2016 to December 31, 2021.

Table 8
Summary statistics on both green-adjusted and standard DCC full loadings for all four market factors for all ten decile portfolios.

	1	2	3	4	5	6	7	8	9	10
	Panel A: b×$\beta_{j,t}^{DCC,MKT}$ for green-adjusted equity market									
Mean	0.4540	0.6432	0.7646	0.8486	0.9275	1.0056	1.0794	1.1481	1.2373	1.4141
SD	0.1222	0.0815	0.0720	0.0910	0.1077	0.1467	0.1636	0.1910	0.2025	0.2888
	Panel B: s×$\beta_{j,t}^{DCC,SMB}$ for green-adjusted equity market									
Mean	−0.0104	−0.0124	0.0118	0.0285	0.0371	0.0214	0.0165	0.0184	0.0155	0.0447
SD	0.0573	0.0850	0.1080	0.1294	0.1469	0.1623	0.1691	0.1902	0.2113	0.2568
	Panel C: h ×$\beta_{j,t}^{DCC,HML}$ for green-adjusted equity market									
Mean	0.0269	0.0284	0.0394	0.0442	0.0458	0.0159	0.0113	−0.0032	−0.0162	−0.0363
SD	0.0417	0.0529	0.0722	0.0906	0.1107	0.1378	0.1549	0.1931	0.2064	0.2723
	Panel D: m×$\beta_{j,t}^{DCC,MOM}$ for green-adjusted equity market									
Mean	0.0114	0.0022	−0.0155	−0.0240	−0.0269	−0.0127	−0.0172	−0.0223	−0.0023	−0.0034
SD	0.0501	0.0582	0.0883	0.1196	0.1411	0.1596	0.1814	0.1956	0.2289	0.2991
	Panel E: b×$\beta_{j,t}^{DCC,MKT}$ for standard equity market									
Mean	0.4538	0.6399	0.7703	0.8609	0.9516	1.0125	1.0928	1.1686	1.2476	1.4373
SD	0.1097	0.0697	0.0749	0.0960	0.1309	0.1503	0.1835	0.2030	0.2191	0.2942
	Panel F: s×$\beta_{j,t}^{DCC,SMB}$ for standard equity market									
Mean	−0.0251	−0.0111	0.0091	0.0359	0.0250	0.0314	0.0064	0.0344	0.0234	0.0438
SD	0.0611	0.0802	0.0966	0.1166	0.1397	0.1467	0.1474	0.1799	0.1948	0.2495
	Panel G: h×$\beta_{j,t}^{DCC,HML}$ for standard equity market									
Mean	0.0330	0.0520	0.0596	0.0717	0.0436	0.0473	−0.0059	0.0270	−0.0095	−0.0396
SD	0.0561	0.0604	0.0836	0.1125	0.1620	0.1735	0.2017	0.2592	0.2685	0.3747
	Panel H: m×$\beta_{j,t}^{DCC,MOM}$ for standard equity market									
Mean	0.0130	−0.0062	−0.0153	−0.0269	−0.0261	−0.0147	−0.0098	−0.0282	−0.0007	−0.0040
SD	0.0501	0.0545	0.0912	0.1203	0.1490	0.1653	0.1893	0.2043	0.2334	0.3141

Notes: This table reports the mean and standard deviation (SD) of the DCC beta adjusted factor loadings in:
$$R_{i,t+1} = \alpha_i + b\left[\widehat{\beta}_{i,t}^{DCC,MKT} MKT_{t+1}\right] + h\left[\widehat{\beta}_{i,t}^{DCC,HML} HML_{t+1},\right] + s\left[\widehat{\beta}_{i,t}^{DCC,SMB} SMB_{t+1}\right] + m\left[\widehat{\beta}_{i,t}^{DCC,MOM} MOM_{t+1}\right] + \varepsilon_{i,t+1}$$
Panels A – D present the summary statistics for each of the 10 green-adjusted beta sorted portfolio. The summaries for the standard equity market are reported in panels E - H. b_M, b_{HML}, b_{SMB}, and b_{MOM} are estimated from the Eq. 19 and respectively multiplied to $\beta_{jt}^{DCC,MKT}$, $\beta_{j,t}^{DCC,HML}$, $\beta_{j,t}^{DCC,SMB}$, and $\beta_{j,t}^{DCC,MOM}$.

results for the DCC CAPM where the market factor is relevant. In the Appendix we provide further evidence for the other three factors. These results are the same qualitatively for both green-adjusted stock prices and standard stock prices.

7. Robustness checks

The overall conclusion so far is that there are no significant differences between betas calculated under standard share prices and the

Table 9
Fama-MacBeth regressions using value-weighted portfolio returns.

Panel A: Estimated value for $\widehat{\alpha}_j$		
Beta-sorted portfolios	Green-adjusted $\widehat{\alpha}_{j,greenAdjusted}$	Standard $\widehat{\alpha}_j$
1(Low)	0.00187	0.00165
2	−0.00034	−0.00048
3	−0.00131	−0.00038
4	−0.00226	−0.00043
5	−0.00405	−0.00297
6	−0.00501	−0.00451
7	−0.00517	−0.00432
8	−0.00704	−0.00508
9	−0.00708	−0.00509
10(High)	−0.00975	−0.00830
Panel B: Fama-MacBeth regressions with portfolio excess returns adjusted by alpha estimates in panel A.		
	Dependent variable	
	$R^{greenAdjusted}_{j,t+1} - \widehat{\alpha}_{j,greenAdjusted}$	$R^{standard}_{j,t+1} - \widehat{\alpha}_j$
Intercept (a)	−0.00776*** (0.00249)	−0.00725*** (0.00247)
$\widehat{\beta}_j^{DCC,M}$	0.01111***	0.01083***
	(0.00333)	(0.00338)
R-squared	0.492	0.491
N	550	550
Panel C: Fama-MacBeth regressions without alpha adjustment to portfolio excess returns		
	Dependent Variable	
	$R^{greenAdjusted}_{j,t+1}$	$R^{standard}_{j,t+1}$
Intercept (a)	0.00103	0.00111
	(0.00246)	(0.00237)
$\widehat{\beta}_j^{M}$	−0.00396 (0.00339)	−0.00391 (0.00339)
R-squared	0.396	0.401
N	550	550

Notes: The table reports $\widehat{\alpha}_j$ from Eq. (21) in Panel A and estimates from the Fama-MacBeth regressions for the 10 beta-sorted portfolios in Panel B for both green-adjusted and standard equity prices. Panel B estimates $R_{j,t+1} - \widehat{\alpha}_j = a + \gamma \widehat{\beta}_j^{DCC,M} + e_{j,t+1}$ where the dependent variable is the portfolio excess returns adjusted by the alpha estimates reported in Panel A. We also report the case where the dependent variable is simply the portfolio excess return in Panel C where $R_{j,t+1} = a + \gamma \widehat{\beta}_j^{M,DCC} + e_{j,t+1}$ for both green-adjusted and standard equities. The standard errors are presented in brackets and are calculated using the Newey-West method. In estimating Eq. (21), the estimated green-adjusted conditional beta of the 8th decile portfolio ($\beta_{8,t}^{DCC,M}$) is selected for the variable X and the lag is set to $L = 5$, as these choices minimize the AIC criterion. The estimated standard conditional beta of the lowest decile portfolio $\left(\beta_{1,t}^{DCC,M}\right)$ is selected for the variable X and the lag is set to $L = 4$. The sample period is from May 2016 to December 2021. ***, **, and * respectively denote two-tailed test significance level for less than 1 %, 5 %, and 10 %.

Table 10
Second-order stochastic dominance test for portfolio returns.

Panel A: Stochastic dominance test in each decile portfolio: $H_0 : r_{j,standard} SSD r_{j,green}$										
Portfolio	1 (Low)	2	3	4	5	6	7	8	9	10 (High)
Value-weighted	0.398	0.418	0.676	0.480	0.599	0.397	0.624	0.438	0.418	0.4915
Equally-weighted	0.526	0.560	0.284	0.791	0.559	0.209	0.270	0.347	0.526	0.4915
	Panel B: Stochastic dominance test for returns in a High minus Low strategy (monthly rebalancing)									
$H_0 : \widetilde{r}_{standard} SSD \widetilde{r}_{green}$ (using value-weighted return)	p-value: 0.4875									
$H_0 : \widetilde{r}_{standard} SSD \widetilde{r}_{green}$ (using value-weighted return)	p-value: 0.4765									
	Panel C: Stochastic dominance test for returns in a High minus Low strategy (daily rebalancing)									
$H_0 : \widetilde{r}_{standard} SSD \widetilde{r}_{green}$(using equally weighted return)	p-value: 0.1329									
$H_0 : \widetilde{r}_{standard} SSD \widetilde{r}_{green}$(using value-weighted return)	p-value: 0.6204									

Notes: This Table presents the p-values of the second order stochastic dominance (SSD) test of Linton et al. (2005). The p-values reported for each decile portfolio in Panel A conform to the null hypothesis that $r_{j,standard}$ SSD $r_{j,green}$ for the j-th decile beta portfolio sort. The corresponding alternative hypothesis states that $r_{j,standard}$ does not SSD $r_{j,green}$. In Panel B, $\widetilde{r}$ denotes, measures the difference between returns of a strategy that simultaneously longs the 10(High) portfolio and shorts the 1(Low) i.e. $\widetilde{r}_t = r_t^{High} - r_t^{Low}$ which is calculated for both green and standard portfolios. Panel B present results for equally-weighted and value-weighted returns. The null hypothesis states that the strategy returns based using standard equities second-order stochastic dominates strategy returns using green equities. The Linton et al. (2005) SSD test is based on 1000 bootstraps, using HAC standard errors. Each portfolio in Panel A and B is rebalanced at the end of each month starting from May 2016 to December 2021. Portfolios in Panel C are balanced daily over the same sample period.

Table 11
Fama-MacBeth regressions using value-weighted portfolio returns for the Covid-19 period.

Panel A: Estimated value for $\hat{\alpha}_j$		
Beta-sorted portfolios	Green-adjusted $\hat{\alpha}_{j,greenAdjusted}$	Standard $\hat{\alpha}_j$
1(Low)	−0.00038	−0.00053
2	−0.00207	−0.00228
3	−0.00274	−0.00353
4	−0.00395	−0.00528
5	−0.00503	−0.00705
6	−0.00614	−0.00702
7	−0.00659	−0.00885
8	−0.00762	−0.00977
9	−0.00902	−0.01113
10(High)	−0.01218	−0.01196
Panel B: Fama-MacBeth regressions with portfolio excess returns adjusted by alpha estimates in panel A.		
	Dependent variable	
	$R^{greenAdjusted}_{j,t+1} - \hat{\alpha}_{j,greenAdjusted}$	$R^{standard}_{j,t+1} - \hat{\alpha}_j$
Intercept (a)	−0.00735 (0.00624)	−0.00712 (0.00632)
$\hat{\beta}^{M,DCC}_j$	0.01203	0.01337
	(0.00819)	(0.00848)
R-squared	0.419	0.453
N	210	210
Panel C: Fama-MacBeth regressions without alpha adjustment to portfolio excess returns		
	Dependent Variable	
	$R^{greenAdjusted}_{j,t+1}$	$R^{standard}_{j,t+1}$
Intercept (a)	0.00277	0.00261
	(0.00664)	(0.00656)
$\hat{\beta}^{M}_j$	−0.00837 (0.00664)	−0.00809 (0.00876)
R-squared	0.379	0.387
N	210	550

Notes: The table reports $\hat{\alpha}_j$ from Eq. (22) in Panel A and estimates from the Fama-MacBeth regressions for the 10 beta-sorted portfolios in Panel B for both green-adjusted and standard equity prices. Panel B estimates $R_{j,t+1} - \hat{\alpha}_j = a + \gamma\hat{\beta}^{M,DCC}_j + e_{j,t+1}$ where the dependent variable is the portfolio excess returns adjusted by the alpha estimates reported in Panel A. We also report the case where the dependent variable is simply the portfolio excess return in Panel C where $R_{j,t+1} = a + \gamma\hat{\beta}^{M,DCC}_j + e_{j,t+1}$ for both green-adjusted and standard equities. The standard errors are presented in brackets and are calculated using the Newey-West method. In estimating Eq. (22), the estimated green-adjusted conditional beta of the lowest decile portfolio ($\beta^{M,DCC}_{1,t}$) is selected for the variable X and the lag is set to $L = 5$, as these choices minimize the AIC criterion. The estimated standard conditional beta of the 8th decile portfolio $\left(\beta^{M,DCC}_{8,t}\right)$ is selected for the variable X and the lag is set to $L = 5$. The sample period is from May 2016 to December 2021. ***, **, and * respectively denote two-tailed test significance level for less than 1 %, 5 %, and 10 %.

betas recalculated using green-adjusted share prices. In this section, we will verify if this conclusion still holds under a second-order stochastic dominance test and when the analysis is restricted to the Covid period only.[12]

We apply the second order stochastic dominance (SSD) test of Linton et al. (2005) on a like for like basis for all ten decile portfolios under both value weighted and equally weighted schemes (see Table 10, Panel A). We also compare the long high short low portfolios, green versus standard under both calculation schemes (equal and value weighted) in Panel B. The results from these tests indicate that the compared portfolios have similar performance in terms of returns. Since these tests were applied with monthly rebalancing of portfolios, one may question whether the SSD test may change when daily rebalancing occurs. Panel C of the same Table 10 reports the results of the SSD test with daily rebalancing and again we find that there is no difference between the results that a green investor would observe in his green-adjusted world and the results observed by a standard investor.

The Covid-19 pandemic period between 2020 and 2022 triggered a huge exogenous shock to the real-economies world-wide, including the US. During this period financial assets were impacted by various problems associated with very high uncertainty. In this section we would like to revisit our analysis in terms of green-adjusted share prices versus standard share prices and explore whether the Covid-19 pandemic widened the difference between green betas and standard betas or contracted this difference.

We repeat our previous calculations based on DCC beta within this latter period. The results are presented in Table 10. Over this period neither the intercepts nor the slopes are significant, showing that the CAPM models are not representative for the stock market. Switching from unconditional to conditional CAPM, the R^2 does increase substantially. Once again, these findings apply for both the green investor and for the standard investor.

8. Summary conclusions

In this paper, we reconstruct the associated betas for green-adjusted share prices. The adjustments are based on the quantitative adjustments allocated to green revenues of all companies that are the constituents of the Russell 1000 index. Using company green revenues opens a new area of research related to equity prices and investors with green preferences. One possible limitation is that the green revenues calculations are done by one company and not by the market itself. This shortcoming may be overcome with time if the methodology employed by FTSE Russell will be adopted more widely and if more companies decide to become greener.

Our comparative discussions concentrate on how the concept of the market beta of a stock will translate into a green-adjusted investment environment. Our empirical results indicate in several ways that the risk preferences of a green investor are only temporarily different than their analogues under the risk preferences of a standard market agent. Significant differences are associated with periods of high levels of uncertainty about climate change policies reflected in the CPU index.

Operating in green-adjusted equity markets will not create disadvantages to investors who are not necessarily preoccupied with climate change risk. In other words, if on a monetary utility basis there are no significant differences between the green investor and the standard investor, there are no reasons why we should not transit towards operating under the green investor world. This transition will require independent calculations of green revenues and other accounting reporting focused on climate finance criteria and measurables.

Further research may consider other aspects related to portfolio construction involving firms' measurements of green revenues beyond CAPM style models. For example, portfolio construction embedding green-revenue measures together with other strategies known to lead to performing portfolios could be investigated. Textual analysis combined with market sentiment analysis may provide useful tools that combined with green revenues classification may help identify portfolio that are admissible for the style of investment required in some countries.

In addition, further research may delve into a comparative analysis of an international stage, for which data is available for some other developed economies. We hope to report on such research in the near future.

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[12] Considering the recent pandemic as an exogenous economic shock, Dottling and Kim (2022) present evidence that funds with higher sustainability ratings were exposed to abrupt falls in retail flows during the Covid-19 period, after controlling for fund characteristics. This shows that the retail mutual fund investors' demand for socially responsible type of funds may change suddenly when faced with immediate economic distress.

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CRediT authorship contribution statement

Radu Sebastian Tunaru: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Diana Tunaru:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Project administration, Methodology, Investigation. **Enoch Quaye:** Software, Project administration, Investigation, Formal analysis, Data curation, Writing – review & editing.

Declaration of Competing Interest

None

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.jfs.2024.101314.

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