# Towards Green Adjusted Share Prices

Enoch Quaye*, Diana Tunaru† and Radu Tunaru‡

**Abstract**

Green activities are measured with a green revenue adjustment factor that can be used to adjust observed market stock prices. We examine the green revenues factors for all companies that are part of the stock indexes representing the main five economies. Overall, firms from UK, Europe and China are greener than firms from US or Japan. The standard market CAPM betas are on average lower than the standard realised betas, but the green-adjusted market CAPM betas are on average higher than the green-adjusted realised betas, indicating that the green tilting affects asset pricing relationships. The high minus low green revenue adjustment factor portfolio for US stochastically dominates the corresponding portfolios for the other economies, while the similar portfolio for Japan is stochastically dominated by the portfolios of all the other economies.

*Keywords*: Green Adjusted Share Prices; Beta; Investment Strategies; Stochastic Dominance Test

*JEL Classifications*: G12; G14; G17

*School of Accounting and Finance, University of Bristol. E-mail: Enoch.Quaye@bristol.ac.uk; Address: University of Bristol, Bristol BS8 1TU, UK

†Kent Business School, University of Kent. E-mail: D.Tunaru@kent.ac.uk; Canterbury CT2 7FS, UK

‡Corresponding Author, University of Sussex. E-mail: R.Tunaru@sussex.ac.uk; Tel:+44 (0)1273 876920; Address: Room 206, Jubillee Building, University of Sussex, Brighton BN1 9RH, UK

# 1 Introduction

Financial markets play an important role in facilitating the climate change agenda through significant financial innovation aiming to capture the firms' degree of green activities in the prices and the returns of market securities, see Matsumura et al. (2014); Pastor and Taylor (2021); Pedersen et al. (2021); Pastor and Taylor (2022); Bolton and Kacperczyk (2022); Zerbib (2019); Zerbib (2022). Shiller (2013) argued early on that the evolution of finance is shaped by the way the social, environmental and economic systems are organized.

A successful transition to a net-zero global economy calls for financial markets and economies more broadly to consider a major asset reallocation. However, the lack of standardised framework of sustainability reporting by firms and of a robust set of green metrics informing investors' sustainable investment decisions may have an adverse impact on the progress of achieving the goals of the climate change agenda (Avramov et al., 2022). Edmans (2023) points out that by the end of 2021 the assets under management by investors who signed the Principles for Responsible Investment reached 121 trillion dollars, an increase by 50% since 2019 (Matos, 2020) and of almost 20 fold since 2006. A report on Bloomberg on February 8, 2019, stated that Europe committed about 12 trillion dollars to sustainable investing. Temple-West (2023) cites a report from Bank of America stating that the ratio of ESG versus non-ESG bond funds for Western Europe is almost 10% ( $2.6 billion inflows in ESG bond funds compared with $29 billion non-ESG bond funds), while for US the respective ratio is only 0.5% ($0.82 billion in ESG bond funds compared with $150 billion in non-ESG funds). Japan experiences a new impetus in the ESG area, with a package of $144 billion in decarbonisation bonds being announced over the next ten years (Temple-West, 2023).

There is an intensive debate in the literature on the existence of a ESG risk premium that is directly associated with risks emerging from climate change. From a theoretical perspective, Pastor and Taylor (2022) provide compelling reasons to indicate that high green returns reported in recent years should not be taken as indicative predictors of the future green returns. They show that when investors take more green companies in their portfolios, the risk-adjusted expected returns on those firms will be lower in equilibrium. A similar conclusion is reached by Pedersen et al. (2021) who construct an ESG adapted CAPM and show that employing a strategy based on the new efficient environment frontier does not necessarily lead to a considerable improvement in the Sharpe ratio. A single-period equilibrium model, built with partial segmentation and heterogeneous preferences focusing on regular investors and sustainable investors, has been developed by Zerbib (2022). This new model is a sustainable factor expanded CAPM model, which implies that sustainable investors may frequently influence the costs of capital for many firms through exclusionary screening and ESG integration.

Cornell (2021) points out that ESG investments may be popular because of their social preferences but investors choosing this investment style should not expect high returns. Chava (2014) studies the implied costs of capital for green companies versus non-green (brown) and indicate that there is some evidence of lower ex ante returns on green equities. Importantly, Matsumura et al. (2014) show that equity prices should decrease for firms with higher emissions when investors are considering the likelihood of future regulatory actions arising from high carbon emission. More evidence is provided by In et al. (2019); Bolton and Kacperczyk (2022); Aswani et al. (2023) who analyze realized returns for green and for brown stocks and their linkages to carbon risk. Subsequently to introduction of new regulations to comply with the climate change agenda, companies try to internalize the cost of carbon emissions and to report them. Bolton and Kacperczyk (2022) find evidence of larger carbon premia in less developed countries that rely on large energy sectors and that have less inclusive political systems, as well as in countries with stricter domestic climate policies. The empirical evidence in favor of an ESG factor is mixed. A highly pertinent review debunking several misconceptions about ESG investing is provided by Larcker et al. (2022). A thorough bird eye view on the ESG can be found in Edmans (2023), who presents compelling arguments that ESG is important ***beyond*** pecuniary motives and it influences a firm's long-term shareholder value and its interaction more widely with society. Cornell (2021) makes a similar point that even when ESG investments may bring social benefits, investors should not expect higher future returns. Following a global survey of institutional investors on their beliefs about climate risk, Krueger et al. (2020) conclude that institutional investors still consider climate risk important although currently not as important as financial and operational risk.

We believe that many of the criticisms of ESG empirical results have roots in methodological aspects. The different conclusions in the literature regarding the significance of carbon risk premia have been explained and reconciled in Lioui (2022) by employing an improved methodology that bypasses the problem of carbon measurement scaling. Many empirical studies rely on various ESG ratings but, as discussed in Larcker et al. (2022), there is a distinct lack of agreement of ESG ratings from different ESG ratings provides, see also Chatterji et al. (2016); Dimson et al. (2020); Berg et al. (2022).

In our study, we employ for the first time in the literature, a novel granular dataset consisting of FTSE Russell Green Revenues Indexes for major economies and the daily green revenues factor values (GRF) for each constituent company of these indexes. The central element of the unique data we use is the GRF measure, which is calculated by FTSE Russell and employed in the computation of Green Revenue indices. The time-series of the GRF can be conceptualised as a dynamic green metric allowing investors to determine the trend in the green activities of firms, by simultaneously indicating the speed and level of a firm's transition to the green economy. Given its properties (which we present later in the paper), the GRF metric represents an intuitive tool that allows us to construct quasi green stock prices, called the green-adjusted stock prices.

The main aim of this paper is to compare the degree of green revenues within the major economies of the US, the UK, Europe, China and Japan, as well as of a general All-World. Furthermore, we compare the betas obtained for the green revenues adjusted share prices and show that the tilting towards green valuations impacts the distribution of the stock returns, the first two moments in particular. Our green CAPM models employ also the green revenues adjusted stock indices, as calculated independently by the FTSE Russell (LSEG). This is the first time in the literature when a green CAPM model uses green adjusted stock prices and green adjusted stock indexes. We show that the tilting towards quasi green share prices reverts the relationship between the respective estimated betas and their corresponding counterparts.

We use the GRF adjustment factors to design investment strategies that may appeal to investors with green finance preferences. We compare the performance of these investment strategies across five major economies and we use recent statistical test to conclude if the green related investment were superior or not. Our results show a superior dollar return performance for portfolios using stocks from the US. This indicates that more profits can be extracted in those economies having firms that are more heterogeneous regarding ESG principles, than in those economies where perhaps due to tighter regulation firms are more homogeneous in their behaviour towards ESG.

Green indexes have been analysed in very few previous studies. Berk and van Binsbergen (2021) compare the FTSE USA 4 Good index and the FTSE USA index and suggest that empirically there is no link between expected returns and screening of 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. Compared to their general ESG approach, our research relates only to the environmental pillar, based on the proportion of revenues of companies related to climate change. Another study of green revenue indices is Fabozzi et al. (2022), where the authors investigated the connections between green revenue indices and other financial markets variables. They also highlight that the US and Europe play a central role in green markets.

The paper is organised as follows. In section 2, we describe the process of green revenues measurement as it is independently computed by FTSE Russell and show how we use the GRF measure to construct the green-adjusted share prices and returns. In section 3, we describe and analyse the data for the main variables behind our analysis. Section 4 contains the main empirical results regarding beta estimation for the five major economies and the overall All-World as well. In section 5 we consider the trading strategy based on high minus low GRF companies and we compare the resulting portfolios for all five major economies. To this end, we apply state of the art stochastic dominance tests for all possible pairings of these economies. Last section summarizes the main findings.

# 2 Green Revenues Quantification

According to FTSE Russel (2022) the green economy is globally the fifth largest industry, similar in size to the fossil fuel sector. While its diversity is significant, the green economy seems to be concentrated in countries like the United States (54%) and China (12%). Nevertheless, countries such as Japan, France and Germany have a higher exposure despite having a smaller size green economy. In this study, we take advantage of a unique international green data set from the FTSE Russell Green Revenues Indexes series. By measuring a company's green revenue exposure, FTSE Russell have developed a range of Green Revenues Indexes based on the FTSE Russell Green Revenues 2.0 Data Model (hereafter, GRDM). Using a comprehensive taxonomy which is very similar to the EU Taxonomy, the GRDM estimates the net contribution of a company to the transition to a green economy by measuring the exposure to environmental (green) impact recorded on a company's balance sheet. FTSE Russell has applied the GRDM to an extended global dataset covering almost 99% of total global market capitalization, to estimate the net environmental impact of over 16,000 public companies across 48 developed and emerging markets. The FTSE Russell green revenues assessment provides also a granular perspective at a company activity level using a classification system covering 10 sectors, 64 sub-sectors and 133 micro sectors. This green activity classification facilitates a better estimation of the size of the green economy, by identifying hidden activities that other traditional measures of industrial sectors cannot capture. The green economy is measured using both direct disclosure data and estimates for companies where disclosure is insufficient or unavailable. In terms of data disclosure, only 28% percentage of the green economy is measured based on data directly disclosed by the companies. For a given company, any activity generating green revenues is mapped to one or more micro sectors and then an aggregate green revenue measure is computed. The GRDM relies on a three-tiers green system by dividing the activities of a company, over the 133 micro-sectors as following: Tier 1 includes activities with significant and clear environmental benefits( such as Solar); Tier 2 covers activities with limited but net positive environmental benefits (such as Water Utilities); Tier 3 includes activities with net neutral or negative environmental benefits (such as Nuclear).

The FTSE 1000 Green Revenues Indexes reflect the green exposure that investors get by holding investments in the stock of those respective companies. Our data includes, in addition to indexes, the green revenues factors for all constituents of a given index.

This is a rich database comprising cross-sectional and time series information of the Green Revenue Factors (GRF). Thus, the GRF becomes an essential yardstick that measures the level of engagement of a company over time vis-a-vis the climate change environmental agenda. The GRFs are interpreted in this paper as green/brown indicator of the net percentage of green activities. The main activities monitored by the FTSE Russsell (LSEG now) are climate change mitigation and adaptation, water, resource use, pollution, and agricultural efficiency.

The GRF takes values between 0 and 2, with 2 representing a 100% green company (the ratio of green revenues to the total revenues is +1) and 0 representing the opposite, a totally brown company activities (the net ratio of green revenues to the total revenues is -1, i.e. there are no environmental benefits, but 100% damages). The mid-value of 1 is associated with a neutral level. The majority of companies in our study have GRFs close to neutral levels, indicating that the net position (green versus brown activities) of a company is close to zero. The novelty of our study is the construction of a pseudo share price (the "green-adjusted", hereafter) by multiplying the standard market share price with the corresponding GRF ( see equation (1) below).

$$S^* = \ (MarketSharePrice) \times (GreenRevenuesFactor) = S \times GRF \tag{1}$$

Hence, for greener firms, with the GRF greater than 1, the green-adjusted price is an inflation of the standard share price, while for less green firms with a GRF value lower than 1, the green-adjusted share price is a deflation of the standard share price. For firms with GRF equal to 1 , i.e. the net environmental benefits from the green activities of the company are insignificant, the green-adjusted share price is unchanged, equal to the standard share price.

The implied daily green-adjusted returns based on the green-adjusted share prices are computed as:

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

The green-adjustment translates into an additive tilting factor applied to the standard returns which correctly captures the level of engagement with the green agenda of a company over time. More specifically, an increase in the GRF factor over a period of time (more positive environmental impact), results in a reward in term of returns, while a decrease in the GRF (more negative environmental impact) leads to a penalty, with a green-adjusted return lower than the standard return. The green-adjusted prices and returns defined above together with the Green Revenues Indexes provide the basis for a new green-adjusted investment universe that investors and policy makers could explore further to better understand how the green efforts made by companies around the world are reflected in the financial markets.

# 3 Data and Methodology

## 3.1 Data Description

The indexes we study are: All-World index, UK All Share index, China, Europe, Japan, and FTSE Russell 1000. The daily time series of the green revenues indexes and the GRF time-series for the constituents of those indexes are downloaded from FTSE Russell database. The overall sample period spans from 26th May 2016 to 21st December 2022, for a total of 1711 trading days.

As dictated by data availability, the coverage in FTSE Russell database begins at different times for different indexes and hence, the number observations varies across indexes. For example, data for the FTSE Russell 1000 green index prices is available from 26th May 2016, while coverage for Japan begins later on 21st March 2017.

The evolution of the green index price levels over time is plotted in Figure 2, indicating a clear upward trend across the six indexes, with some noticeable degree of co-movement. Interestingly, the FTSE Russell 1000 index followed by the All-World index consistently lie above all the other indexes, while the Europe (green line) and Chinese (yellow line) index levels did not exceed 1500 over the entire sample period.

[INSERT FIGURE 2 HERE ]

The number of firms utilized for each index varies across different economies by design, and within the same economy because of delisted companies. Table I shows that the US and China work with about 1000 firms on average while the UK, Europe and Japan with roughly 500-600 firms. The All-World Index has on average 3600 firms.

[INSERT TABLE I HERE ]

We present few summary statistics of the number of firms that are the constituents of the equity indexes in the five main economies and also in the All-World index in Table II.

[INSERT TABLE II HERE ]

Regarding the GRF data, we compare the means of the cross-sectional averages across the six indexes and observe that there is a clear ordering, with the smallest value for the UK, followed by Japan, then the US, all lower than 1. It continues with Europe, followed by China and then All-World. Since a green revenue factor larger than 1 implies more green activities, one may infer that firms from China are on average greener than firms from Europe, for example. However, a more informed view can be obtained by looking at all quantiles listed in columns 5-7 of that table. Furthermore, the standard deviations indicate that actually Japan has the most consistent green revenue factors and, together with Europe have the largest minima. The lowest minimum GRF and the largest maximum GRF are for the US.

Looking at the worldwide distribution of GRF average values per country for the companies that are constituents of the All-World Index, we create a geo chart as illustrated in Figure 2. Geographically there is a lot more work to be done in order to achieve the targets for climate change. Companies from China, Russia and Turkey are on average more towards the darker shades of brown while companies from Portugal, Austria and Switzerland have GRF average values that would classify them as very green. Interestingly , there is very little difference between the US and Mexico, or between South Africa, India or Australia. In the light green zone we can observe Canada, Spain and Indonesia.

[INSERT FIGURE 2 HERE ]

It would be also useful to see the evolution over time of the green revenues valuations measured by GRF. This can be observed from the graphs in Figure 3 that illustrate the monthly time series of cross-sectional averages of GRFs for companies from all five economies and All-World. The confidence intervals are computed based on the cross-sectional 2.5% and 97.5% cross-sectional quantiles of GRFs from the respective economies.

The average and most of the GRF quantities for US are below 1, indicating that between 2016 and 2022 the US was not highly geared towards climate change adjustments. This is perhaps not surprising given that this period coincided with the Trump administration, which formally withdraw from the Paris climate agreement in June 2017. Although there seems to have been a short lived recovery towards positive green adjustments in early 2020, the covid-period pushed back the GRFs below 1 in the US. Interestingly, the

GRF for Japan are not as high as expected perhaps with values in the neutral territory until covid erruption when there is a clear downward shift. By contrast, for the Chinese companies that are the constituents of the FTSE Russell China Green Revenues the GRFs are quite positive, with almost the entire distribution above 1. The average GRF scores for the UK have been consistently been above 1, with a quite tight confidence interval for GRF values roughly between 0.98 and 1.04. The GRF evolution for companies in Europe is very similar to the UK, with a cross-sectional average above 1 and the lower confidence boundary roughly at 0.98.

It is worth pointing out that the Covid-19 pandemic period impacted the green revenues assessments for companies in the US and Japan, increasing in those economies the uncertainty about green activities. China experienced a positive shock in the GRF factor in 2020 followed by a more downward trend afterwards. Perhaps surprisingly, UK and Europe were almost undeterred by the Covid shock, although for UK a slight downward trend for GRFs can also be noticed over the entire study period.

[INSERT FIGURE 3 HERE ]

We calculate the daily logarithmic returns for the green market time series, denoted $R_{i,t+1} = \ln X_{i,t+1} - \ln X_{i,t}$ for each $i$-th index $X$. The summary statistics of the green index return series reported in Table III indicate a predominantly positive mean daily return for the sampled indices, with the only exception of UK and China. The distribution of returns as depicted by the 25th-, 50th-, and 75th-quantiles does not vary substantially across different indexes, generally being within the same order of magnitude. China reported the highest standard deviation, which is not surprising given the sever adverse impact of the pandemic.

The results in Panel B of the Table III suggest that the revenues from the green revenues adjusted equity indexes in some economies are much more interdependent than other pairings. Despite its universally positive sign, unconditional sample correlation $\rho(\cdot,\cdot)$ varies substantially across the different pairs of green index returns, ranging from a minimum of 19.7% for $\rho(Japan, US)$, to a maximum of 94.9% $\rho(All\ World, US)$. Respectively, the correlation coefficient between Japan and other indexes is consistently below 39% and that between China and other indexes is 50%. The largest pairwise Pearson correlation coefficients are for US and All-World, at almost 95% and between UK and Europe, at 94%. The former relationship is perhaps not surprising given the economic dominance of the UK economy on economies in other parts of the world.

However, the latter strong connection upon green tilting of firms' in the UK and Europe was perhaps expected in sign but not so much in magnitude. It should also be noted the relative low correlation coefficients for Japan with all the other economies and also for China with all other economies. These results point out to different roles played worldwide by different economies, after adjusting firms' share prices for green activities.

[INSERT TABLE III HERE ]

## 3.2 Methodological Considerations

### 3.2.1 Beta Estimation

For a better understanding of the impact caused by the green revenues adjustment or tilting of the market share price for companies in main economies, we also consider any changes that may appear in conventional asset pricing exercises. The unconditional beta is defined directly from the capital asset pricing model (CAPM) as

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

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

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

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 is estimated based on a one-year rolling window of daily excess return data. That is, at the end of each month $t$, the regression model is estimated based on the previous 12-month period of daily return data, covering months $t - 11$ through $t$, inclusively. Andersen et al. (2006) define the realised 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 $\tau$. It is known, see Andersen et al. (2006), that under weak regularity conditions this is the only consistent measure for the true beta.

The green revenue factor allows a direct transformation of the market share price of a firm into a green-revenue adjusted dollar price. Thus, we take advantage of being able to generate the tilted green revenues adjusted share prices and compute the corresponding CAPM green beta and the realised green beta for all firms that are the constituents of our green revenues indexes.

### 3.3 Time stochastic dominance test for high minus low strategy

The GRFs permit us a quintile tranching based on time series average GRFs for the respective countries. Those portfolios can be compared using static measures such as mean returns or betas. It is of great academic and practical interest to compare also the high minus low portfolios for each economy. If these strategies pass the statistical test then we can conjecture that there is a possible green revenues adjustment factor that can be computed and utilized based on the GRF.

We use the time stochastic dominance (TSD) test discussed in Lee et al. (2023) to evaluate the dynamic performance of the high minus low strategy in country pairs. This leads to a comparison of data from UK, US, Japan, Europe, and China. The TSD test naturally allows for a pairwise comparison of dynamic utility of investors in the respective countries. We let $\mathcal{Y}_i := \{Y_{i,t} : t \in \tau\}$ and $\mathcal{Y}_j := \{Y_{j,t} : t \in \tau\}$ respectively denote the time-path of value-weighted realised return resulting from a high minus low quintile strategy simultaneously implemented in country pairs $i$ and $j$ where $(i, j) \in$ {UK, US, Japan, Europe, and China}. We work with a discrete time framework where $\tau = \{0, 1, \ldots, T\}$. The null hypothesis states that the expected discounted utility of the strategy in country $i$, $\text{NPV}_{u,v}(\mathcal{Y}_i)$, $n$-the order time and $m$-th order stochastic dominates that of $j$, $\text{NPV}_{u,v}(\mathcal{Y}_j)$. This is written as

$$H_0^{(n,m)} : \text{NPV}_{u,v}(\mathcal{Y}_i) \succeq \text{NPV}_{u,v}(\mathcal{Y}_j) \tag{6}$$

where $n, m = 1, 2$ and $u$ and $v$ respectively denote the utility and time-discount functions both assumed to be continuously differentiable. $i \neq j$. The alternative hypothesis $H_1^{(n,m)}$ is a negation of the null, and it states that there exists at least one investor who ranks prospects of a green-oriented strategy differently.[1]

### 3.4 Control variables

We test the robustness of our empirical results by applying the well-known procedures documented in relevant literature with regards to the relationship between the returns and various important variables. In addition to beta we consider the following control variables: firm size (market capitalisation), book-to-market ratio (BM), maximum daily return (MAX), downside beta (DRISK), tail beta (TRISK), Momentum (MOM), co-skewness (CoSkew), and co-kurtosis (CoKurtosis). We follow the conventional methods to construct both, the standard and the green-adjusted control variables.

We employ the market capitalisation of a particular stock at the end of month $t$ as a proxy for the firm size (SIZE). We take natural log of size in the regression analysis as the cross-sectional distribution is highly skewed. Similar to Hollstein et al. (2020), we take the natural log to remove the extreme skewness in this variable. The Book-to-Market (BM) value is the current book equity dividend divided by the market capitalisation at the end of the previous fiscal year. The MOM is defined as the cumulative stock return over the period from $t-12$ until $t-1$ (see Jegadeesh and Titman, 1993; Bali et al., 2011; Hollstein et al., 2020). The maximum return is the average of the five highest daily returns in a given month as in Bali et al. (2011). This is denoted MAX with a calculation that requires a minimum of 15 daily return observations in the given month.

[1]According to Lee et al. (2023), the test statistic is a one-sided $L-p$-type test statistic written as

$$T_N = r_N^p \int_{\mathcal{X}} \Lambda_p \left(\hat{v}_1(x), \ldots, \hat{v}_L(x)\right) \tag{7}$$

where $r_N := \sqrt{\frac{N_1 \cdot N_2}{N_1 + N_2}}$. Lee et al. (2023) suggests two different methods for critical value calculations - the contact-set approach and the numerical delta method. This is in addition to the conventional least favourable case (LFC) approach.

Harvey and Siddique (2000) CoSkew $\beta_{i,t}^{CS}$ and Dittmar (2002) CoKurtosis $\beta_{i,t}^{CK}$ are coefficients in the regression

$$r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{M} \cdot r_{M,t} + \beta_{i,t}^{CS} \cdot r_{M,t}^{2} + \beta_{i,t}^{CK} \cdot r_{M,t}^{3} + \varepsilon_{it} \tag{8}$$

where $r_{i,t} = R_{i,t} - r_{f,t}$ is expected excess return. We estimate this regression with previous 1-year daily returns. The downside beta (DRISK) from Bawa and Lindenberg (1977) is the slope coefficient from a regression of excess stock returns on the excess market returns using only days for which the market returns was below the average daily market return during the past year. This is the same as the downside beta $\beta^{-}$ in Ang et al. (2006).

Tail beta (TRISK) is the slope coefficient from a regression of excess stock returns on excess market returns using only daily observations in the bottom 10% of market excess returns over the past year (see Chabi-Yo et al., 2018).

[INSERT TABLE IV HERE ]

The summary statistics of all control variables used in this study are presented in Tables IV and V. Panel A reports the values for CoSkew and it can be noticed that this coefficient is on average negative for all economies except Europe and All-World. Panel B covers CoKurt and on average this coefficient is negative for all economies. The MAX control variable is reported in Panel C and the values are very similar for all economies, except China that in general has much lower Max values than all the other economies. In Panel D we report the values for ln(SIZE); these are very close across all economies, on a cross-sectional average and on a cross-sectional quantile basis.

[INSERT TABLE V HERE ]

The MOM is illustrated in Panel E of Table V. For this control variable the average is negative for Japan and China, and positive for all other economies. Panel F shows the summary statistics for the BM factor. The average value vary between 0.065 for the US to 1.632 for China. The DRISK and TRISK control variables are described in the Panels G and H, respectively. They are relatively similar in level of values and order among the compared economies. For these types of controls, US is the highest on average, followed by Japan and UK, and then Europe and China. The lowest values, for both controls, is achieved for All-World, perhaps not surprising given the more diversification of the constituents of that index.

# 4 Empirical Results

Returns on individual equities are winsorised at 1% and 99%. We require equities to have at least 200 non-missing returns when estimating the 1-year horizon beta and at least 15 non-missing returns in the 1-month horizon beta.

## 4.1 Beta Estimation

In Table VI we depict the summary statistics for the standard estimates of the CAPM Beta (FF) and Realised Beta (RB) for all five major economies and the world-wide economy as well. The computations are done on firms market beta estimated at the end of each month using a 1-year horizon i.e. 12-month horizon with daily data. The sample period is from May 2016 and ending December 2022. We show the time series average of cross-sectional summary statistics, that is mean (Mean), standard deviation (SD), 25% quantile ($q_{25}$), median 50% quantile ($q_{50}$), and 75% quantile ($q_{75}$), for each index.

For all countries, and for both short and longer horizon, overall, the mean realised mean beta is larger than the mean CAPM beta whilst the standard deviation of realised betas is smaller then the standard deviation of CAPM beta. The distribution of standard market betas is wider for US and Japan and it is the narrowest for China.

Table VI reports the summary statistics for the two sets of beta estimates, CAPM and realised, for firms from each of the top five economies and also the constituents of the All-World index. The Calculations are done at one-year horizon (the one month are also available from authors upon requests). The distribution of green betas is again the largest for US and Japan and the narrowest for China. For the green betas, however, it is not true that the mean of realised estimates are higher than the CAPM beta estimates like for like for all economies, whilst the standard deviation still maintain the same order relationship or becoming equal. This shows that the tilting of returns induced by the green-revenues adjustments does change the distribution of returns such that there is a significant cross-sectional and temporal change.

[INSERT TABLE VI HERE ]

The summary statistics for the beta estimates for the green-adjusted stock prices in Table VII show that the distribution of betas after the tilting for green revenues adjustment calculations are impacted. The green realised betas are lower on average country for country than the green CAPM betas. The standard deviation of green betas, under either of the estimation method, are larger than their corresponding standard deviation for standard betas for the same country. By comparing the quantiles we note that the green betas reach lower values than the corresponding 25% quantiles in Table VI. Therefore, one may conjecture that adjusting for green revenues lowers the beta in general and hence it is inducing a risk lowering effect on the stock markets worldwide.

[INSERT TABLE VII HERE ]

## 4.2 Cross-Sectional Regressions for GRF

Here we test whether the standard market beta, size, BM, as well as the risk measures (MAX, DRISK, TRISK, MOM, CoSkew, and CoKurtosis) contain information about the green revenue factor. We run the regressions at firm-level instead of stock portfolios in order to avoid the potential influence of portfolio formation method on the results (see Lo and MacKinlay, 1990; Lewellen et al., 2010; Hsu et al., 2018; Hollstein et al., 2020). This approach furthermore captures important information on individual factor loadings (as noted in Ang et al., 2020). Each month, we run the following cross-sectional regressions of green revenue factors on a constant, the stock's beta, and control variables:

$$GRF_{i,t} = \lambda_t^0 + \lambda_t^{(m)} \beta_{i,t} + \lambda_t^C \text{Controls}_{i,t} + \varepsilon_{i,t} \tag{9}$$

where $GRF_{i,t}$ is the green revenue factor of firm $i$ in month $t$. The standard stock market betas are denoted by $\beta_{i,t}$ and the vector of control variables denoted generically above with $\text{Controls}_{i,t}$ observed at the end of the previous month. The regression coefficients of interest to be estimated are $\lambda_t^0, \lambda_t^{(m)}$ and $\lambda_t^C$ whilst the error term is denoted $\varepsilon_{i,t}$ for each stock $i$ at time $t$. Based on the time-series of estimated regression coefficients, we compute robust Newey and West (1986) adjusted standard errors using 6 lags.

[INSERT TABLE VIII HERE ]

The empirical results for the first regression in equation (9) vary across the countries under study. From Panel A in Table VIII, for the first simpler regression, we observe that the relationship between the standard beta of the companies and the GRF can be characterised as negative and weak on average for most countries, apart from Japan. This is in line with the intuition that potentially more aggressive companies (with higher beta) would have a lower GRF, with the implication that greener companies (higher GRF) would more risk averse. When the firm-specific variables are considered (see Panel B) the sign of this relationship changes to positive, apart from China. For Europe and the US the coefficient for the SIZE variable is negative, suggesting that smaller companies on average have a greener agenda. The average of the effect of the BM variable on the GRF is rather significant in magnitude only for the UK with an average value of 0.192, while for the other countries the magnitude of this average value is very small. In the second panel of Table VIII, some effects are stronger than others, as the firm-specific risk variable CoKurt seems not to impact on average the GRF values, while variables like MOM and MAX would slightly have some influence on the GRF green revenues measure.

# 5 Trading Strategies with Green Revenues Classification

Table IX reports several panels of information. The first panels present the one-year horizon betas for the decile portfolios for each of the five major economies and the global All-World. The two sets of green beta estimates are very similar to the first two decimals for all economies. For the lowest decile portfolios, the All-World has the lowest average green beta, followed by the UK, whilst Japan has the highest average beta, followed by the US. For the highest decile portfolio, China has the lowest average green beta, followed by Europe, whilst All-World has the largest average green beta followed by the UK.

[INSERT TABLE IX HERE ]

## 5.1 Portfolio sorts

We test whether GRF has an effect on realised stock returns. At the end of each month, sort stocks in ascending order using their GRFs. We form quintile portfolios so that stocks with the lowest GRFs are assigned to quintile 1 and those with the highest GRFs are assigned to quintile 5. Based on the sorting outcome, we implement a trading strategy that takes a goes long on stocks with the highest GRF (quintile 5) and shorts stocks with the lowest GRFs (quintle 1). On this basis, we can attribute differences in average returns to differences inherited from the spread in the GRF variable.

In Table IX we report the results for the quintiles portfolios formed on the basis of the GRF for each economy. The first two panels present the time series average of each quintile portfolio. Upon the sorting, Japan has the largest betas compared like for like with the other economies (except for the lowest quintile for which US is the highest), whilst China has the lowest betas. One can also note the the quintiles portfolios for the US and UK give similar betas.

Panel C of the same Table shows the average values of the GRF for the respective quintile portfolios and economies. For the lowest quintile, the lowest average GRF is for Japan and the highest is for UK, followed closely by Europe. For the highest quintile portfolios, the lowest average GRF is for US at 1.083 while the largest is for China at 1.280. Europe is second largest at 1.174, followed by UK with 1.139 and Japan with 1.126. Therefore, the greenest portfolio can be constructed with companies from China while the less green would be for Japan. US quintile portfolios have average GRFs varying between 0.948 and 1.083, indicating that most companies from the US basked are classified more or less as less green or net green neutral. Japan is the only economy with two quintiles (4th and 5th) with average GRF larger than 1.

Based on the above it is very interesting to see the realised returns performance for those quintiles portfolios. For Japan and Europe, all quintiles have negative average returns but a high minus low strategy would generate a positive performance for Europe and negative performance for Japan. China has negative average returns for both low and high quintiles and positive average returns for all the other three middle quintiles. A high minus low strategy will also give positive returns for China. UK has negative average returns fro all quintiles except the 4th and a high minus low strategy would also generate positive returns. US is perhaps the best structured tranches of quintiles portfolios, with negative average returns for the first two quintiles and positive average returns for the last three quintiles. A high minus low strategy would give the largest positive returns out of all economies.

## 5.2 Time Stochastic Dominance Test Results

Table X shows the results for time stochastic dominance for all possible economies pairing. The All-World economy was left out of this analysis, since there is no clear regulatory, legal and economic jurisdiction. For robustness we present three different methods of calculation of p-values. Out of all 20 tests there are only two instances when different methods of calculating the p-values do not give qualitatively the same result, the test for UK dominating US for second order stochastic dominance and the test for China dominating UK for the first order stochastic dominance. For all the other ones the three methods give the same conclusions.

[INSERT TABLE X HERE ]

For the first order dominance we notice that a high minus low GRF portfolio for UK dominates the corresponding portfolio strategy for Japan and Europe. The US is the only economy for which the high minus low GRF portfolio dominates the corresponding portfolios for all the other economies. Japan is the only economy for which the GRF high minus low portfolio seems to be dominated by the corresponding portfolios of all the other economies. The strongest first stochastic dominance test results are observed for US versus Japan and Europe versus Japan.

The second order stochastic dominance tests portray a similar picture. If anything, the p-values for rejecting the null hypothesis of dominance are even larger than for the first test, indicating that there is even stronger dominance of second order. The US high minus low GRF strategy dominates again all the other corresponding portfolio, while Japan now only dominates China. The largest values of the p-values are observed for UK versus Japan, US versus China and Europe versus Japan.

The dominance tests refer to the dollar realised returns. At a first glance it may look surprising that US and UK somehow dominates Europe and Japan, and that in general the portfolio strategy for US dominates all the other corresponding portfolio strategies based on high minus low on GRF selection. However, one possible reason for the outcome results may be the fact that the constituents of the Green Revenues Index for US (Russell 1000) are more dispersed in terms of GRF whereas the constituents for Europe and Japan may be closer together in terms of GRF.

# 6 Conclusion

In order to move towards a fully green economy investors in the financial markets should be able to operate in a world where stock prices reflect the level of green activities of the companies they invest in. We propose a daily green-adjustment to the standard share prices observed in the equity markets to create green-adjusted share prices by using the green revenues factor GRF, which indicates not only the financial economics gains of the company but also how green are the activities leading to those gains.

We employ a granular green revenues database to follow the green activity on the stock prices around the world, comparing five main economies in the world. The green revenues tilting of stock prices imply a reversal of the order between CAPM betas estimates and the realised betas estimates. The realised betas of green revenues adjusted stock prices are smaller than the CAPM betas computed from the same stock prices. Thus, we provide evidence that green tilting may impact asset pricing views, but the direction of change depends also on the type of the estimators being used.

The firms in the UK and Europe are on average greener than the firms from the US and Japan. The economies that put more emphasis on supporting green activities, such as the UK and Europe, were also more resilient regarding climate change actions during the Covid pandemic period.

We comparatively analyse the dynamics of the GRF over the entire period of our study. We conclude overall that companies in the UK, Europe and China have more green exposure than the companies in the US and Japan. By monitoring dollar realised returns portfolio strategies, we observed that a high minus low portfolio based on the GRF measure leads to US being the dominating force in terms of dollar generation. Thus, investors can use the GRF database to design strategies that still produce significant returns while taking into consideration the green revenues levels of the companies representing the major economies.

Figure 1: Historical evolution of green index level

*Notes*: The index levels are calculated using index constituent prices in USD. The overall sample period runs from 26/05/2016 to 21/12/2022, for a total of 1711 trading days. As dictated by data availability, the coverage in FTSE Russell database begins at different times for different indexes. For example, data for the Russell 1000 US green index prices is available from 26th May 2016 while, coverage for Japan only begins in 21/03/2017.

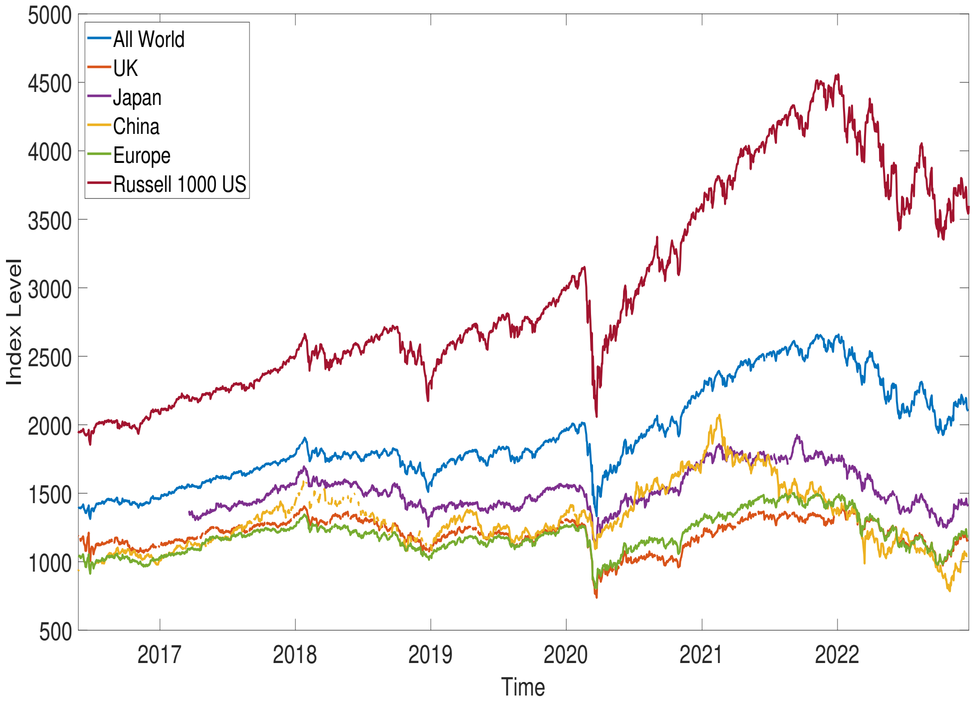


Figure 2: Distribution of GRF in the All-World Index

*Notes*: For each world country index included in the FTSE All-World Index over the sample period starting from 26/05/2016 to 21/12/2022, we report the time series average of cross-sectional green revenue factor (GRF) in a geo chart. The colour scale in the legend depicts low and high GRF factor in brown and green respectively. Regions in white were not included in the analysis period. The All-World Index consists of indices from a total of 51 countries.

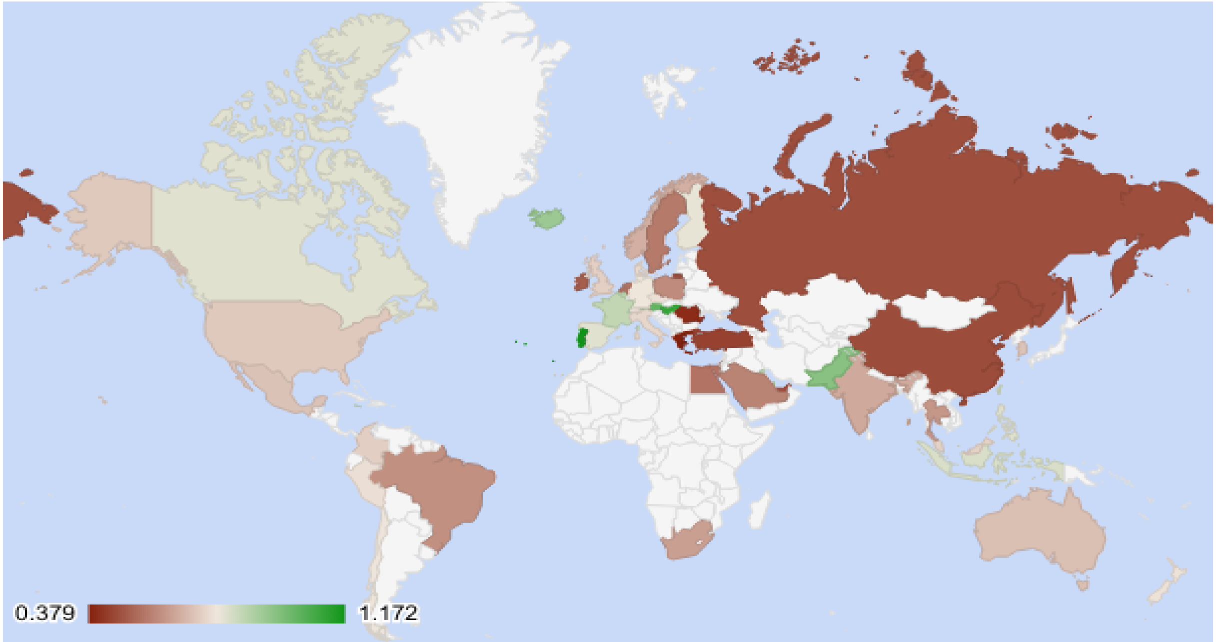
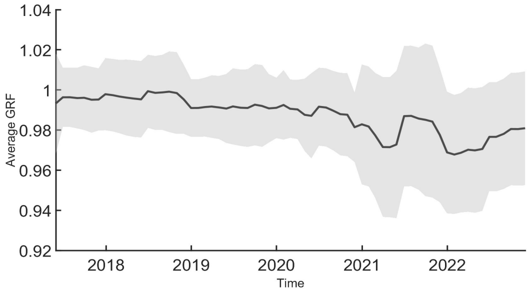
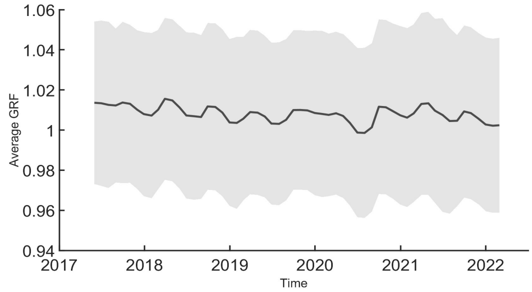


Figure 3: Time series of Cross-sectional Average GRF

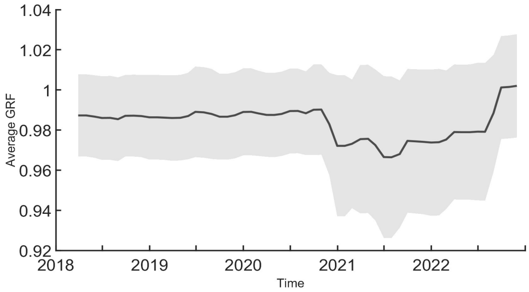
*Notes*: For each index, at the end of each month, we first calculate the time series average of GRF for each constituent stock using daily data from the past 1-year including the date of calculation. We then compute the cross-sectional average of the values obtained in the first step and plot them as monthly time series along with its 95% confidence interval depicted by the shaded area.



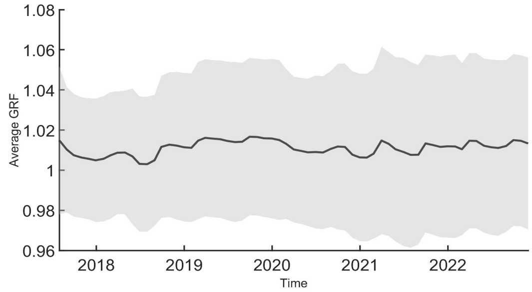

(a) Russell 1000 (US)



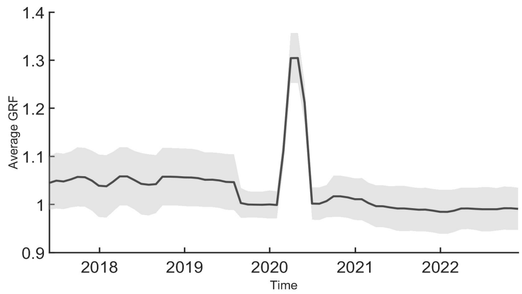

(b) UK



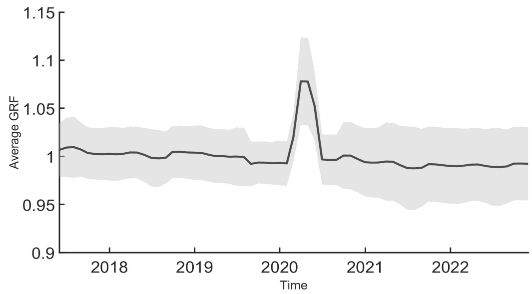

(c) Japan




(d) Europe




(e) China




(f) All-World

TABLE I: Summary Statistics for Constituents Counts

*Notes*: This table presents summary statistics for the number of constituents in each index over the entire sample period, from 26/05/2016 to 21/12/2022. We denote by Avg $\#^{\text{firms}}$, Min $\#^{\text{firms}}$, and Max $\#^{\text{firms}}$ the average, minimum, and maximum number of firms in each index. These summaries are calculated from daily time series data on the number of listed companies in each index over the sample period.

| Index | Avg $\#^{\text{firms}}$ | Min $\#^{\text{firms}}$ | Max $\#^{\text{firms}}$ |
|---|---|---|---|
| UK | 626 | 599 | 645 |
| Russell 1000 (US) | 1001 | 972 | 1031 |
| Japan | 508 | 493 | 520 |
| Europe | 663 | 634 | 689 |
| China | 1064 | 420 | 1774 |
| All-World | 3614 | 3060 | 4177 |

TABLE II: Summary Statistics for Green Revenue Factor Around the World

*Notes:* This table reports the time series averages per index of cross-sectional summary statistics for the green revenue factor of all index constituents. The cross-sectional summary statistics include Mean (Mean), Standard Deviation (SD), Minimum (Min), Maximum (Max), 25th quantile ($q_{25}$), 50th quantile ($q_{25}$), and 75th quantile ($q_{75}$) index constituents.

| Index | Mean | SD | Min | q25 | q50 | q75 | Max |
|---|---|---|---|---|---|---|---|
| UK | 0.951 | 0.153 | 0.519 | 0.925 | 0.925 | 0.927 | 1.957 |
| Russell 1000 (US) | 0.991 | 0.125 | 0.395 | 0.965 | 0.968 | 0.997 | 2.000 |
| Japan | 0.986 | 0.111 | 0.616 | 0.936 | 0.939 | 1.000 | 1.909 |
| Europe | 1.025 | 0.159 | 0.620 | 0.982 | 0.983 | 1.013 | 1.999 |
| China | 1.038 | 0.211 | 0.513 | 0.973 | 0.988 | 0.989 | 1.993 |
| All-World | 1.077 | 0.134 | 0.439 | 1.043 | 1.043 | 1.074 | 1.999 |

TABLE III: Summary Statistics of Green Revenues Adjusted Equity Index Returns

*Notes:* This Table reports the averages of cross-sectional summary statistics for the green index return from 26th May 2016 to 21st December 2022 in Panel A. The cross-sectional summary statistics include Mean (Mean), Standard Deviation (SD), Minimum (Min), Maximum (Max), Median (Median), 25th quantile ($q_{25}$), 75th quantile ($q_{75}$), and the available number of sample points ($N$) for each index return time series. The unconditional sample correlation of index returns between the All-World Index, UK All Share Index, China Index, Europe Index, Japan Index, and FTSE Russell1000 indexes are reported in Panel B.

| | All-World | UK All Share | China | Europe | Japan | Russell 1000 (US) |
|---|---|---|---|---|---|---|
| | Panel A: Descriptive statistics | | | | | |
| N (days) | 1700 | 1625 | 1492 | 1702 | 1468 | 1710 |
| Mean(%) | 0.023 | -0.001 | -0.007 | 0.006 | 0.003 | 0.036 |
| SD(%) | 1.080 | 1.329 | 1.589 | 1.266 | 1.125 | 1.355 |
| Min(%) | -9.963 | -13.707 | -7.956 | -14.056 | -6.539 | -12.985 |
| Max(%) | 7.950 | 10.885 | 12.641 | 8.499 | 6.937 | 9.039 |
| $q_{25}$(%) | -0.371 | -0.561 | -0.818 | -0.500 | -0.584 | -0.433 |
| $q_{50}$(%) | 0.072 | 0.080 | 0.038 | 0.074 | 0.031 | 0.057 |
| $q_{75}$(%) | 0.507 | 0.595 | 0.833 | 0.595 | 0.622 | 0.672 |
| | Panel B: Unconditional correlation | | | | | |
| All-World | 1.000 | 0.767 | 0.497 | 0.793 | 0.383 | 0.949 |
| UK All Share | 0.767 | 1.000 | 0.419 | 0.941 | 0.359 | 0.594 |
| China | 0.497 | 0.419 | 1.000 | 0.431 | 0.342 | 0.345 |
| Europe | 0.793 | 0.941 | 0.431 | 1.000 | 0.367 | 0.612 |
| Japan | 0.383 | 0.359 | 0.342 | 0.367 | 1.000 | 0.197 |
| Russell 1000 (US) | 0.949 | 0.594 | 0.345 | 0.612 | 0.197 | 1.000 |

TABLE IV: Summary Statistics of Important Asset Pricing Variables

*Notes*: This table presents summary statistics for the estimates control variables used for robustness test. We present the time series average of cross-sectional summary statistics i.e. mean (Mean), standard deviation (SD), 25% quantile ($q_{25}$), median 50% quantile ($q_{50}$), and 75% quantile ($q_{75}$) separately for each index. Panels A to E presents results for each index. Each control variable is constructed at the end of each month using a daily data from the past 1-year including the day of construction 1-year horizon. The sample period is from May 2016 and ending December 2022.

| Index | Mean | SD | $q_{25}$ | $q_{50}$ | $q_{75}$ |
|---|---|---|---|---|---|
| | | Panel A: CoSkew | | | |
| UK | -1.415 | 9.235 | -6.419 | -1.284 | 3.549 |
| Russell 1000 (US) | -1.351 | 6.929 | -5.191 | -1.192 | 2.604 |
| Japan | -0.606 | 4.834 | -3.474 | -0.412 | 2.467 |
| Europe | -0.386 | 8.649 | -5.463 | -0.159 | 4.914 |
| China | -2.388 | 5.625 | -5.661 | -2.038 | 1.086 |
| All-World | -0.443 | 14.941 | -9.371 | -0.697 | 8.228 |
| | | Panel B: CoKurt | | | |
| UK | -58.09 | 540.42 | -357.23 | -58.02 | 237.96 |
| Russell 1000 (US) | -173.19 | 382.19 | -383.38 | -151.74 | 63.19 |
| Japan | -126.48 | 213.51 | -262.00 | -118.94 | 13.46 |
| Europe | 19.90 | 386.03 | -205.10 | 42.65 | 269.89 |
| China | -37.82 | 193.49 | -150.83 | -32.59 | 79.41 |
| All-World | -126.12 | 1153.19 | -781.01 | -88.29 | 590.56 |
| | | Panel C: MAX | | | |
| UK | 0.157 | 0.139 | 0.000 | 0.161 | 0.257 |
| Russell 1000 (US) | 0.137 | 0.134 | 0.000 | 0.160 | 0.234 |
| Japan | 0.106 | 0.058 | 0.094 | 0.120 | 0.141 |
| Europe | 0.111 | 0.106 | 0.000 | 0.134 | 0.197 |
| China | 0.054 | 0.052 | 0.000 | 0.062 | 0.095 |
| All-World | 0.119 | 0.117 | 0.000 | 0.118 | 0.207 |
| | | Panel D: ln(SIZE) | | | |
| UK | 7.025 | 1.496 | 6.802 | 7.915 | 12.006 |
| Russell 1000 (US) | 9.323 | 1.243 | 9.169 | 10.061 | 14.038 |
| Japan | 8.232 | 1.093 | 8.057 | 8.879 | 12.059 |
| Europe | 8.758 | 1.283 | 8.732 | 9.533 | 12.586 |
| China | 6.320 | 1.373 | 6.070 | 7.127 | 12.654 |
| All-World | 8.198 | 1.614 | 8.161 | 9.299 | 14.039 |

TABLE V: Summary Statistics for Market Control Variables

*Notes*: This table presents summary statistics for the estimates control variables used for robustness test. We present the time series average of cross-sectional summary statistics i.e. mean (Mean), standard deviation (SD), 25% quantile ($q_{25}$), median 50% quantile ($q_{50}$), and 75% quantile ($q_{75}$) separately for each index. Panels A to E presents results for each index. Each control variable is constructed at the end of each month using a daily data from the past 1-year including the day of construction 1-year horizon. The sample period is from May 2016 and ending December 2022.

| Index | Mean | SD | $q_{25}$ | $q_{50}$ | $q_{75}$ |
|---|---|---|---|---|---|
| | | Panel E: MOM | | | |
| UK | 0.016 | 0.245 | -0.101 | 0.010 | 0.130 |
| Russell 1000 (US) | 0.025 | 0.242 | -0.080 | 0.008 | 0.118 |
| Japan | -0.052 | 0.207 | -0.183 | -0.072 | 0.061 |
| Europe | 0.003 | 0.222 | -0.101 | -0.004 | 0.075 |
| China | -0.008 | 0.260 | -0.099 | -0.024 | 0.043 |
| All-World | 0.000 | 0.248 | -0.109 | -0.007 | 0.067 |
| | | Panel F: BM | | | |
| UK | 0.131 | 2.036 | 0.002 | 0.006 | 0.010 |
| Russell 1000 (US) | 0.065 | 0.102 | 0.012 | 0.032 | 0.070 |
| Japan | 0.170 | 0.220 | 0.039 | 0.071 | 0.248 |
| Europe | 1.298 | 6.352 | 0.005 | 0.020 | 0.143 |
| China | 1.632 | 13.903 | 0.356 | 0.673 | 1.164 |
| All-World | 0.243 | 3.395 | 0.011 | 0.042 | 0.128 |
| | | Panel G: DRISK | | | |
| UK | 0.840 | 0.367 | 0.596 | 0.813 | 1.051 |
| Russell 1000 (US) | 0.886 | 0.366 | 0.646 | 0.865 | 1.107 |
| Japan | 0.885 | 0.285 | 0.693 | 0.881 | 1.072 |
| Europe | 0.718 | 0.334 | 0.490 | 0.715 | 0.936 |
| China | 0.694 | 0.346 | 0.450 | 0.659 | 0.902 |
| All-World | 0.607 | 0.473 | 0.280 | 0.552 | 0.886 |
| | | Panel H: TRISK | | | |
| UK | 0.795 | 0.644 | 0.404 | 0.754 | 1.141 |
| Russell 1000 (US) | 0.822 | 0.505 | 0.510 | 0.808 | 1.116 |
| Japan | 0.729 | 0.422 | 0.462 | 0.742 | 0.995 |
| Europe | 0.629 | 0.652 | 0.219 | 0.633 | 1.039 |
| China | 0.629 | 0.549 | 0.281 | 0.596 | 0.958 |
| All-World | 0.531 | 0.827 | 0.020 | 0.508 | 1.044 |

TABLE VI: Summary Statistics for Standard Market Betas Around the World

*Notes*: This table presents summary statistics for the CAPM and Realised Beta estimators. We present the time series average of cross-sectional summary statistics i.e. mean (Mean), standard deviation (SD), 25% quantile ($q_{25}$), median 50% quantile ($q_{50}$), and 75% quantile ($q_{75}$) separately for each index. We estimate the standard market beta at the end of each month using daily time series data for the past 1-year including the day of estimation. The sample period is from May 2016 and ending December 2022.

| Index | Mean | SD | $q_{25}$ | $q_{50}$ | $q_{75}$ |
|---|---|---|---|---|---|
| Panel A: CAPM Beta | | | | | |
| UK | 0.740 | 0.343 | 0.497 | 0.719 | 0.947 |
| Russell 1000 (US) | 0.930 | 0.305 | 0.730 | 0.918 | 1.119 |
| Japan | 0.946 | 0.233 | 0.786 | 0.948 | 1.105 |
| Europe | 0.759 | 0.259 | 0.574 | 0.750 | 0.933 |
| China | 0.645 | 0.278 | 0.445 | 0.608 | 0.802 |
| All-World | 0.705 | 0.330 | 0.467 | 0.650 | 0.892 |
| Realised Beta | | | | | |
| UK | 0.887 | 0.175 | 0.766 | 0.868 | 0.990 |
| Russell 1000 (US) | 0.958 | 0.155 | 0.857 | 0.947 | 1.047 |
| Japan | 0.964 | 0.128 | 0.880 | 0.968 | 1.051 |
| Europe | 0.882 | 0.141 | 0.784 | 0.881 | 0.976 |
| China | 0.773 | 0.159 | 0.666 | 0.748 | 0.850 |
| All-World | 0.847 | 0.156 | 0.740 | 0.825 | 0.934 |

TABLE VII: Summary Statistics for Green Adjusted Betas

*Notes*: This table presents summary statistics for the estimates of green adjusted beta. Panel A reports the summaries based on the CAPM and Panel B reports those from the realised beta model. We report the time series average of cross-sectional summary statistics; mean (Mean), standard deviation (SD), 25% quantile ($q_{25}$), median 50% quantile ($q_{50}$), and 75% quantile ($q_{75}$) separately for each index. The green adjusted beta is estimated at the end of each month using daily data from the past 1-year including the day of calculation. The sample period is from May 2016 and ending December 2022.

| Index | Mean | SD | $q_{25}$ | $q_{50}$ | $q_{75}$ |
|---|---|---|---|---|---|
| Panel A: CAPM Green Adjusted Beta | | | | | |
| UK | 0.833 | 0.313 | 0.612 | 0.798 | 1.015 |
| Russell 1000 (US) | 0.923 | 0.357 | 0.690 | 0.906 | 1.141 |
| Japan | 0.927 | 0.258 | 0.751 | 0.926 | 1.105 |
| Europe | 0.723 | 0.301 | 0.506 | 0.713 | 0.924 |
| China | 0.655 | 0.302 | 0.439 | 0.614 | 0.824 |
| All-World | 0.634 | 0.408 | 0.341 | 0.561 | 0.861 |
| Panel B: Realised Green Adjusted Beta | | | | | |
| UK | 0.830 | 0.312 | 0.610 | 0.796 | 1.012 |
| Russell 1000 (US) | 0.917 | 0.353 | 0.686 | 0.904 | 1.136 |
| Japan | 0.925 | 0.258 | 0.749 | 0.924 | 1.104 |
| Europe | 0.719 | 0.300 | 0.503 | 0.709 | 0.921 |
| China | 0.650 | 0.302 | 0.434 | 0.609 | 0.819 |
| All-World | 0.630 | 0.405 | 0.338 | 0.558 | 0.856 |

TABLE VIII: Cross-Sectional Regressions for GRF

*Notes*: This table reports the average coefficients from monthly Fama and MacBeth (1973) regressions. At the end of each month, we regress the green revenue factor (GRF) during that month on the market betas and a series of controls measured at the end of the previous month. Panel A presents results for regressing GRF on a constant, the market beta with firm-specific fundamentals i.e. ln(Size), and Book-to-Market (BM) as control variables. In Panel (B) we regress GRF on the firm-specific risk measures i.e. MAX, MOM, CoKurt, CoSkew, Drisk, and Trisk as controls. We report robust Newey and West (1986) standard errors using 6 lags.

| | Russell 1000 (US) | UK | Japan | Europe | China | All-World |
|---|---|---|---|---|---|---|
| | Panel A: Cross-sectional regression with firm-specific fundamentals | | | | | |
| Constant | 0.95429 | 1.00787 | 0.86063 | 1.02462 | 0.93279 | 1.00387 |
| | (0.014380) | (0.003105) | (0.021445) | (0.008658) | (0.073928) | (0.004118) |
| Beta | -0.00301 | -0.03778 | 0.04671 | -0.01143 | -0.05375 | -0.00674 |
| | (0.002146) | (0.003658) | (0.018624) | (0.003604) | (0.010849) | (0.002608) |
| SIZE | 0.00394 | 0.00435 | 0.01031 | -0.00104 | 0.00404 | -0.00020 |
| | (0.000883) | (0.000377) | (0.000621) | (0.000682) | (0.003240) | (0.000366) |
| BM | 0.00001 | 0.19221 | 0.00109 | -0.00057 | -0.00102 | 0.00002 |
| | (0.000011) | (0.057498) | (0.000611) | (0.001890) | (0.000926) | (0.000012) |
| | Panel B: Cross-sectional regressions with firm-specific risk measures | | | | | |
| Constant | 0.988006 | 1.04208 | 0.97119 | 1.02362 | 0.93147 | 1.00533 |
| | (0.004833) | (0.005617) | (0.018166) | (0.002908) | (0.081117) | (0.003392) |
| Beta | 0.048246 | 0.02050 | 0.07513 | 0.01957 | -0.09637 | 0.02091 |
| | (0.026444) | (0.020322) | (0.024982) | (0.019739) | (0.06156) | (0.006547) |
| MAX | -0.002536 | -0.05140 | -0.21336 | -0.02121 | 0.05654 | -0.01057 |
| | (0.029285) | (0.013871) | (0.06369) | (0.017749) | (0.043749) | (0.009346) |
| MOM | 0.019759 | -0.00015 | 0.01915 | 0.01214 | -0.00598 | 0.01500 |
| | (0.006554) | (0.010275) | (0.008673) | (0.005925) | (0.019542) | (0.005024) |
| CoKurt | -0.000039 | 0.00024 | -0.00002 | 0.00027 | 0.00008 | 0.00003 |
| | (0.000043) | (0.000145) | (0.000022) | (0.000172) | (0.000073) | (0.000019) |
| CoSkew | -0.002257 | -0.00275 | -0.00043 | -0.00505 | -0.00101 | -0.00091 |
| | (0.000906) | (0.001712) | (0.000709) | (0.002107) | (0.002514) | (0.000516) |
| Drisk | -0.045196 | -0.03572 | -0.01516 | -0.01333 | 0.07465 | -0.02503 |
| | (0.020184) | (0.016228) | (0.014199) | (0.012745) | (0.040088) | (0.004669) |
| Trisk | -0.001311 | -0.00479 | 0.00116 | -0.02831 | -0.02060 | -0.00465 |
| | (0.00742) | (0.006640) | (0.007004) | (0.011310) | (0.015029) | (0.003553) |

TABLE IX: Quintiles Portfolios Sorted on the Green Revenue Factor

*Notes*: At the end of each month, we sort stocks in each index into 5 annualized value-weighted portfolios according to their green revenue factor (GRF). We report the time series average of each quintile portfolio's value-weighted average CAPM beta, Realised beta, and the GRF used for sorting. Mean return denotes the annualized average portfolio excess return. The period of analysis starts from May 2016 and ends December 2022.

| Portfolio | UK | Russell 1000 (US) | Japan | Europe | China | All-World |
|---|---|---|---|---|---|---|
| | | | Panel A: CAPM Beta | | | |
| 1(Low) | 0.746 | 0.856 | 0.797 | 0.613 | 0.536 | 0.628 |
| 2 | 0.821 | 0.868 | 0.879 | 0.698 | 0.478 | 0.532 |
| 3 | 0.853 | 0.821 | 0.889 | 0.646 | 0.441 | 0.570 |
| 4 | 0.783 | 0.894 | 0.986 | 0.735 | 0.396 | 0.707 |
| 5(High) | 0.851 | 0.866 | 0.942 | 0.717 | 0.439 | 0.610 |
| | | | Panel B: Realised Beta | | | |
| 1(Low) | 0.743 | 0.851 | 0.795 | 0.610 | 0.533 | 0.623 |
| 2 | 0.819 | 0.865 | 0.878 | 0.697 | 0.475 | 0.529 |
| 3 | 0.853 | 0.819 | 0.888 | 0.645 | 0.439 | 0.569 |
| 4 | 0.782 | 0.893 | 0.985 | 0.733 | 0.393 | 0.705 |
| 5(High) | 0.849 | 0.864 | 0.941 | 0.715 | 0.437 | 0.607 |
| | | | Panel C: GRF | | | |
| 1(Low) | 0.955 | 0.948 | 0.919 | 0.953 | 0.946 | 0.947 |
| 2 | 0.977 | 0.965 | 0.930 | 0.966 | 0.977 | 0.962 |
| 3 | 0.978 | 0.967 | 0.948 | 0.967 | 0.986 | 0.966 |
| 4 | 0.981 | 0.981 | 1.001 | 0.991 | 0.990 | 0.993 |
| 5(High) | 1.139 | 1.083 | 1.126 | 1.174 | 1.280 | 1.138 |
| | | | Panel D: Mean Return | | | |
| 1(Low) | -0.018 | -0.049 | -0.099 | -0.048 | -0.064 | -0.057 |
| 2 | -0.032 | -0.007 | -0.130 | -0.025 | 0.007 | -0.026 |
| 3 | -0.019 | 0.014 | -0.089 | -0.005 | 0.019 | 0.008 |
| 4 | 0.014 | 0.014 | -0.108 | -0.043 | 0.034 | -0.018 |
| 5(High) | -0.013 | 0.033 | -0.127 | -0.033 | -0.010 | -0.029 |

TABLE X: Time stochastic dominance test for high minus low strategy

*Notes*: This Table reports the $p$-values of the Lee et al. (2023) time stochastic dominance (TSD) test using the null hypothesis specified in Equation (6). The null hypothesis states that the expected discounted utility of the strategy in $i$, $\text{NPV}_{u,v}(\mathcal{Y}_i)$, $n$-the order time and $m$-th order stochastic dominates that of $j$, $\text{NPV}_{u,v}(\mathcal{Y}_j)$. We separately test instances where $n = m = 1$ and $n = m = 2$. The reported $p$-values are those obtained from the LFC algorithm, Contact-set approach, and numerical delta method (NDM).

| | $H_0^{(1,1)}$ | | | $H_0^{(2,2)}$ | | |
|---|---|---|---|---|---|---|
| Test | LFC | Contact | NDM | LFC | Contact | NDM |
| $\text{NPV}_{u,v}(\mathcal{Y}_{UK}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{US})$ | 0.010 | 0.000 | 0.005 | 0.135 | 0.030 | 0.130 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{UK}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{JPN})$ | 0.575 | 0.575 | 0.465 | 1.000 | 1.000 | 1.000 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{UK}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{EUR})$ | 0.360 | 0.360 | 0.330 | 0.405 | 0.405 | 0.395 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{UK}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{CHN})$ | 0.010 | 0.000 | 0.005 | 0.285 | 0.280 | 0.270 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{US}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{UK})$ | 0.350 | 0.265 | 0.220 | 0.400 | 0.330 | 0.345 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{US}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{JPN})$ | 0.835 | 0.825 | 0.775 | 0.625 | 0.560 | 0.555 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{US}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{EUR})$ | 0.295 | 0.285 | 0.195 | 0.360 | 0.360 | 0.335 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{US}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{CHN})$ | 0.680 | 0.680 | 0.625 | 1.000 | 1.000 | 1.000 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{JPN}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{UK})$ | 0.120 | 0.120 | 0.105 | 0.095 | 0.095 | 0.095 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{JPN}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{US})$ | 0.030 | 0.010 | 0.030 | 0.050 | 0.000 | 0.050 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{JPN}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{EUR})$ | 0.155 | 0.155 | 0.140 | 0.085 | 0.085 | 0.085 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{JPN}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{CHN})$ | 0.030 | 0.020 | 0.030 | 0.175 | 0.175 | 0.175 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{EUR}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{UK})$ | 0.64 | 0.640 | 0.59 | 0.660 | 0.660 | 0.645 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{EUR}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{US})$ | 0.010 | 0.010 | 0.010 | 0.195 | 0.110 | 0.185 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{EUR}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{JPN})$ | 0.840 | 0.840 | 0.795 | 1.000 | 1.000 | 1.000 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{EUR}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{CHN})$ | 0.015 | 0.015 | 0.015 | 0.355 | 0.340 | 0.310 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{CHN}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{UK})$ | 0.115 | 0.045 | 0.065 | 0.355 | 0.355 | 0.340 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{CHN}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{US})$ | 0.340 | 0.340 | 0.315 | 0.235 | 0.235 | 0.230 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{CHN}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{JPN})$ | 0.375 | 0.365 | 0.280 | 0.425 | 0.415 | 0.375 |
| $\text{NPV}_{u,v}(\mathcal{Y}_{CHN}) \succeq \text{NPV}_{u,v}(\mathcal{Y}_{EUR})$ | 0.075 | 0.045 | 0.040 | 0.315 | 0.315 | 0.29 |

# References


Ang, A., Chen, J., and Xing, Y. (2006). Downside risk. *Review of Financial Studies*, 19(4):1191–1239.

Ang, A., Liu, J., and Schwarz, K. (2020). Using stocks or portfolios in tests of factor models. *Journal of Financial and Quantitative Analysis*, 55(3):709–750.

Aswani, J., Raghunandan, A., and Rajgopal, S. (2023). Are carbon emissions as-sociated with stock returns? *Review of Finance*.

Avramov, D., Cheng, S., Lioui, A., and Tarelli, A. (2022). Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics*, 145:642–664.

Bali, T. G., Cakici, N., and Whitelaw, R. F. (2011). Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, 99(2):427–446.

Bawa, V. S. and Lindenberg, E. B. (1977). Capital market equilibrium in a mean-lower partial moment framework. *Journal of Financial Economics*, 5(2):189–200.

Berg, F., Koelbel, J., and Rigobon, R. (2022). Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, 26(6):1315–1344.

Berk, J. and van Binsbergen, J. (2021). The impact of impact investing. Research Paper, Law  Economics Center at 22-008, Stanford University Graduate School of Business, George Mason University Scalia Law School.

Bolton, P. and Kacperczyk, M. (2022). Global pricing of carbon-transition risk. *Journal of Finance*, forthcoming.

Chabi-Yo, F., Ruenzi, S., and Weigert, F. (2018). Crash sensitivity and the cross section of expected stock returns. *Journal of Financial and Quantitative Analysis*, 53(3):1059–1100.

Chatterji, A., Durand, R., Levine, D., and Touboul, S. (2016). Do ratings of firms converge? implications for managers, investors and strategy researchers. *Strategic Management Journal*, 37:1597–1614.

Chava, S. (2014). Environmental externalities and cost of capital. *Management Science*, 60(3):2223–2247.

Cornell, B. (2021). ESG preferences, risk and return. *European Financial Management*, 27(1):12–19.

Dimson, E., Marsh, P., and Staunton, M. (2020). Divergent ESG ratings. *Journal of Portfolio Management*, 47:75–87.

Dittmar, R. F. (2002). Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns. *Journal of Finance*, 57(1):369–403.

Edmans, A. (2023). The end of ESG. *Financial Management*, 52:3–17.

Fabozzi, F. J., Tunaru, D., and Tunaru, R. (2022). The interconnectedness between green finance indexes and other important financial variables. *Journal of Portfolio Management*, 48(10):60–77.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, 81(3):607–636.

Harvey, C. R. and Siddique, A. (2000). Conditional skewness in asset pricing tests. *Journal of nance*, 55(3):1263–1295.

Hollstein, F., Prokopczuk, M., and Simen, C. W. (2020). Beta uncertainty. *Journal of Banking & Finance*, 116:105834.

Hsu, P.-H., Han, Q., Wu, W., and Cao, Z. (2018). Asset allocation strategies, data snooping, and the 1/n rule. *Journal of Banking & Finance*, 97:257–269.

In, S., Park, K., and Monk, A. (2019). Is 'being green' rewarded in the market? an empirical investigation of decarbonization and stock returns. Unpublished working paper, Stanford University.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of nance*, 48(1):65–91.

Krueger, P., Sautner, Z., and Starks, L. (2020). The importance of climate risks for institutional investors. *Review of Financial Studies*, 33(3):1067–1111.

Larcker, D. F., Tayan, B., and Watts, E. M. (2022). Seven myths of ESG. *European Financial Management*, 28(2):869–882.

Lee, K., Linton, O., and Whang, Y.-J. (2023). Testing for time stochastic dominance. *Journal of Econometrics*, 235(2):352–371.

Lewellen, J., Nagel, S., and Shanken, J. (2010). A skeptical appraisal of asset pricing tests. *Journal of Financial Economics*, 96(2):175–194.

Lioui, A. (2022). Understanding the carbon price(s) of risk. Technical report, SSRN:, http://dx.doi.org/10.2139/ssrn.4174385.

Lo, A. W. and MacKinlay, A. C. (1990). Data-snooping biases in tests of financial asset pricing models. *Review of Financial Studies*, 3(3):431–467.

Matos, P. (2020). Esg and responsible institutional investing around the world: A critical review. CFA Institute Research Foundations.

Matsumura, E., Prakash, R., and Vera-Munoz, S. (2014). Firm-value effects of carbon emissions and carbon disclosures. *Accounting Review*, 89:695–724.

Newey, W. K. and West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix.

Pastor, L., S. R. and Taylor, L. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, 142:550–571.

Pastor, L., S. R. and Taylor, L. (2022). Dissecting green returns. *Journal of Financial Economics*, 146:403–424.

Pedersen, L. H., Fitzgibbons, S., and Pomorski, L. (2021). Responsible investing: The ESG efficient frontier. *Journal of Financial Economics*, 142:572–597.

Shiller, R. J. (2013). Reflections on finance and the good society. *American Economic Review*, 103(3):402–405.

Temple-West, P. (2023). Us retreats from ESG investing as green bonds grow elsewhere. Financial Times.

Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: evidence from green bonds. *Journal of Banking and Finance*, 98:39–60.

Zerbib, O. D. (2022). A sustainable capital asset pricing model (S-CAPM): Evidence from environmental integration and sin stock exclusion. *Review of Finance*, 26(6):1345–1388.