Navigating Climate Uncertainty: Clean Tech vs Fossil Fuel ETFs*

Minh Nhat Nguyen

Department of Finance
Deakin Business School, Deakin University
221 Burwood Highway, Melbourne,
VIC 3125 Australia
Email: mnn@deakin.edu.au

Ruipeng Liu

Department of Finance
Deakin Business School, Deakin University
221 Burwood Highway, Melbourne,
VIC 3125 Australia
Email: ruipeng.liu@deakin.edu.au

Abstract

Using non-parametric estimates with imposing inequality restrictions, we compare unconditional to conditional tests on green and brown portfolios constructed from fossil fuel and clean energy ETFs. While unconditional tests could not indicate that green portfolio outperform brown one, the outperformance of green portfolio is statistically significant in conditional tests when incorporating climate-related information such as natural disasters and Climate policy uncertainty (CPU). The conditional tests also show that brown portfolio is riskier than green one that is hidden under unconditional tests. Furthermore, we document that non-fundamental demands proxied by fund flows for green assets are higher than that for the brown only when incorporating the climate information in the inequality test. Our findings are robust to alternative specifications.

JEL classifications: G11; G12; C58, Q54.

Keywords: Climate change uncertainty; clean energy ETFs; fossil fuel ETFs; inequality tests; portfolio returns; idiosyncratic risks.

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1 Introduction

Climate risks are of increasing concern to investors. According to the survey by Krueger et al., (2020), institutional investors believe that climate risks have considerable impacts on their portfolios and the risks related to climate regulations have begun to materialize already. Especially, climate risks put particular pressure on the operation of fossil fuel and high-emission firms, such as oil and coal firms, which are major drivers of climate change. For example, the European Investment Bank planned to stop providing loans for fossil fuel energy projects after 2021, and Chubb insurance company, a US insurer, has announced a plan to rule out investment in coal.[1] In contrast, clean energy is encouraged to motivate the transition to a low-carbon economy.

Therefore, green and brown assets attract much attention from researchers due to concerns about climate risks. Theoretically, green assets are assets hedging against climate risks because their values are expected to increase when climate risks are realized, while brown assets are supposed to depreciate (Pástor et al., 2021). There is a vast empirical literature on green and brown stocks performances (Chava, 2014; Baker et al., 2022; Choi et al., 2020; Ardia et al., 2020; Hsu et al., 2022; Pástor et al., 2022), and the empirical evidence is mixed. To shed light on the puzzle about the performances of green and brown investments, we present a rigorous study on performances green and brown assets proxied by clean energy and fossil fuel ETFs. Specifically, we compare unconditional and conditional performances of both green and brown portfolios returns. Apart from studies on portfolio returns, there is a lack of formal tests on risks of green and brown assets. It is quite surprising because both systematic and idiosyncratic risks play important roles in investor’s decision on asset allocations. Thus, our paper also presents formal tests on risk of green and brown portfolios under conditional settings, especially conditional settings that incorporate climate-related information. Our findings provide implications optimal portfolios allocations and hedging.

The paper focuses on clean energy and fossil fuel ETFs as proxies for green and brown assets because the energy sector experiences a variety of exposures to climate risks (van Benthem et al., 2022). While fossil fuels face pressure under the transition to a net-zero economy, clean energy benefits from the transition. Importantly, energy firms provide a great setting to examine the effects of climate policies and better understand the interaction of finance and climate science (van Benthem et al., 2022). In addition, while most empirical

[1] https://www.washingtonpost.com/climate-environment/2021/10/26/climate-change-insurance-coal/

studies rely on ESG rankings to identify "green" and "brown" assets, Avramov et al. (2021) find that uncertainty in rankings could affect the expected return of assets. In addition, ETFs are used by a broad cross-section of market participants such as retail traders, large institutions, and hedge funds; and ETF flows provide unique information about non-fundamental demand for assets (Brown et al., 2021). Therefore, we form green and brown portfolios by using clean energy and fossil fuel ETFs.

We investigate whether green portfolio outperforms brown one in a conditional setting that climate-related information including natural disasters and climate policy uncertainty (CPU) is incorporated. The hypothesis is motivated by the theoretical model of Pástor et al. (2021) that predicts that green assets outperform brown ones in times when there are unexpected shifts in customers' tastes for green products and investors' tastes for green assets. The model indicates that values of green assets are expected to increase when climate risks materialize. Besides returns, we test on volatilities of green and brown portfolios such as market beta, semibetas and idiosyncratic risk. From that, we provide insights about the impact of climate-related information on returns and risks of green and brown assets.

To test hypotheses, this paper employs the conditional inequality test proposed by Wolak (1987, 1989) and Boudoukh et al. (1993). Specifically, we jointly test inequality restrictions on return (risk) differences between green and brown portfolios by using nonparametric approaches that do not require structural models for conditional expected returns. To facilitate the hypothesis testing, we construct instruments related to natural disasters and the Climate Policy Uncertainty index (CPU). Specifically, we generate dummy and magnitude-based instruments. These instruments are motivated by literature and economically intuitive to capture information affecting moments of green and brown portfolios. We jointly test inequality restrictions on returns and risks conditional on the high number of natural disasters and high CPU.

We find that while unconditional returns do not provide rigorous evidence on the outperformance of green portfolios, conditional studies show statistical significances of green portfolio outperforming brown ones. Specifically, brown-minus-green mean CAPM-adjusted returns conditional on natural disasters and CPU are -1.433% and -3.74%, which is far lower than the unconditional mean return (-0.68%). Indeed, brown portfolios have unconditionally negative mean returns, and the mean returns are more negative when information related to natural disasters and CPU incorporated. Unconditionally, green returns are significantly negative, but the conditional tests do not lead to rejections of green portfolios mean returns being nonnegative. For example, while the unconditional mean return is -0.877%, the mean return conditional on CPU is 1.261%. Therefore, conditional inequality tests indicate green portfolios have nonnegative mean returns, which verifies the predictions by the theoretical model of Pástor et al. (2021).

Although green-minus-brown market beta is unconditionally positive, conditional tests lead to rejections of green-minus-brown market beta being nonnegative. In other words, after taking climate-related information into account, it is also evident that brown portfolios have much higher market beta than green ones. For example, while the green-minus-brown market beta is unconditionally 0.019, it is -0.245 associated with CPU. We also find that the brown portfolio has a higher semi-beta, for instance $\hat{\beta}_{t,i}^{N}$, the covariation between negative returns and negative market returns, than the green portfolio in conditional setting. The joint test statistic is significant at the 1% level. Specifically, green-minus-brown $\hat{\beta}_{t,i}^{N}$ associated with CPU is -0.104 which is far higher than the unconditional value of -0.015 which is statistically insignificant (p-value = 0.226). In addition, brown portfolios have higher idiosyncratic risks than green ones. In general, after considering climate-related information, we find that brown portfolios are riskier than green ones, which is hardly found in unconditional tests.

Furthermore, we investigate the non-fundamental demand for green and brown assets. Following Brown et al. (2021) and Davies (2022), we use fund flow as a proxy for the non-fundamental demand. While there is no unconditional difference in non-fundamental demand between green and brown portfolios, we find strong evidence that the non-fundamental demand for green is higher than that for brown when conditioning information related to high natural disasters and CPU incorporated. For example, brown-minus-green fund flow is unconditionally -0.038 with one-side p-value of 0.08 but brown-minus-green fund flow conditional on instruments is -0.032 and -0.114 and multivariate inequality test is significant at 1% level. Since the non-fundamental demand signals investor sentiment, our results imply investor sentiment in green and brown assets.

To test whether our results are driven by particular economic conditions, we use cyclicality-adjusted real P/E (CAPE) ratios and NBER-designated recession periods. The results do not indicate that green portfolios outperform brown portfolios during economic recession periods. In other words, climate-related instruments are more informative about outperformance of green portfolios relative to brown ones than economic instruments. Indeed, we still find evidence about the outperformance of green portfolios when climate-related instruments are incorporated during recession periods. We have conducted further robustness checks and find the outperformance of green portfolios still hold when four Carhart (1997) factors and oil returns employed. In addition, the results are more statistically and economically significant when we reconstruct instruments based on the 75% quantile of the instruments instead of the median. Brown-minus-green return is more negative when we condition values above the 75% quantile of the instruments.

This study makes two major contributions. First, it provides rigorous testing of inequality constraints on green and brown assets with validating predictions of Pástor et al. (2021). Our paper relates to a large empirical literature documenting the performances of green and brown assets. A set of studies show that brown assets have higher expected returns than green assets because they are riskier (Chava, 2014; Bolton & Kacperczyk, 2021; Hsu et al., 2022). Other studies find that green assets outperform brown assets at certain time periods. For example, Choi et al. (2020) find green assets have higher returns than brown ones during months with high abnormal temperatures. Ardia et al. (2020) and Pástor et al. (2022) show that green assets outperform brown assets when media news about climate change is high. Our paper differs from theirs in various ways. Specifically, we use conditional tests with imposing restrictions on assets returns and risks, and we use the nonparametric approach that does not require a structural model for conditional expected returns, which is novel relative to the existing empirical literature. In addition, we emphasize the difference in results between unconditional and conditional tests. Using instruments, our paper emphasizes the state dependence of green and brown assets in terms of return and risk, which contributes to emerging literature in climate finance. From that, we shed light on the performances of green and brown assets.

The second contribution of this paper is that it explores the difference in risk sensitivities between green and brown assets. Specifically, we conduct formal testing of the restrictions on the market beta and realized semibetas of green and brown portfolios. We also examine the difference in idiosyncratic risk between green and brown portfolios. To the best of our knowledge, existing studies have not performed such tests. Therefore, our paper helps to answer not only the controversial question of whether green assets outperform brown assets, but also the question of whether brown assets are riskier than green assets.

Most existing papers use environmental scores from ESG rankings or carbon emissions to define green and brown assets. We focus on energy-related industries that provides a great setting to understand the impact of climate change on financial markets (van Benthem et al., 2022). Additionally, using clean energy and fossil fuel ETFs allows us to study non-fundamental demand through ETF fund flows proposed in ETF literature (Brown et al., 2021; Briere & Ramelli, 2021; Davies, 2022). Therefore, we show how different non-fundamental demand for brown and green assets is when incorporating climate-related information.

Our results have important implications for investors who care about hedging against climate risks. If investors solely consider unconditionally tests, they could conclude that there is no difference in return and risk between green and brown assets. Our findings show that accounting for climate-related information makes green and brown assets different in terms of return and risk. Therefore, the results affect investors in making investment decisions.

The remainder of this study proceeds as follows. Section 2 reviews the relevant literature and hypotheses. Section 3 describes our data and method for testing the hypotheses. Sections 4 and 5 presents empirical results and robustness checks. Finally, Section 6 presents the conclusions.

2 Literature review and hypotheses

Pástor et al. (2021) derive a theoretical equilibrium model of investing based on environmental, social, and governance (ESG) criteria. The model predicts that green stocks have lower expected returns than brown stocks in the long run. However, green assets outperform brown assets when there are unexpected increases in customers' tastes for green products and investors' tastes for sustainable investing. For example, negative climate shocks not only motivate customers to tilt toward green products, but also lead the government to impose climate regulations which favour green firms over brown firms.

Particularly, the unexpected returns are given by

$$\tilde{r} = \beta_m \tilde{r}_m + g \tilde{f}_g^e + \tilde{\xi} \tag{1}$$

with an ESG factor of

$$\tilde{f}_g^e = \tilde{z}_g + \frac{1}{a}[\bar{d}_1 - E_0\{\bar{d}_1\} \tag{2}$$

Here, $\bar{d}_1$ denotes the average investor's ESG taste at time 0, and $E_0\{\,\}$ denotes the expectation of time 0. Eq (1) and (2) predict that green stocks (g > 0) outperform brown stocks (g < 0) when ESG concerns strengthen unexpectedly, $\tilde{f}_g^e > 0$, through the customer channel ($\tilde{z}_g$) or the investor channel ($\frac{1}{a}[\bar{d}_1 - E_0\{\bar{d}_1\}$). Particularly, unexpected worsening of the climate could strengthen not only customers' demands for green products but also investors' preference for green holdings.

Therefore, our study aims to provide a formal hypothesis testing if green assets outperform brown assets conditional on instruments reflecting investors' preferences for sustainability and hedging against climate risks. Specifically, we jointly test the null that the returns of the brown (fossil) portfolios are greater than or equal to that of the green (clean energy) ETFs.

H1: The Green (Clean energy) portfolio outperforms brown (fossil) portfolio conditional on information set about unexpected shifts in investor's preferences toward sustainability.

The market beta of green assets could be lower than that of brown assets when there are unexpected shifts in customers' and investors' preferences toward sustainability. For example, adverse climate shocks could strengthen agents' preferences for sustainability, but the shocks could negatively affect the aggregate output. Indeed, Giglio et al. (2021) suggest that climate shocks reduce consumption but favour green assets because of their ability to hedge against climate risks.

In addition, environmentally friendly firms have lower systematic risks (market betas) than environmentally unfriendly firms (Sharfman & Fernando, 2008; Albuquerque et al., 2019). Therefore, we hypothesize that brown assets have higher market betas than green assets, conditional on instruments for agent preferences. We propose formal conditional testing of the inequality restriction on market betas which jointly tests the null that the market beta of the green (clean energy) portfolio is greater than or equal to that of the brown (fossil) portfolio.

H2a: The market beta of the brown (fossil) portfolio is higher than that of green (clean energy) portfolio conditional on information set about unexpected shifts in investors' preferences toward sustainability.

We study the covariation between green (brown) portfolio returns and market returns further by following Bollerslev et al. (2021) and decomposing the market beta into four realized semibetas that depend on the signed covariation between the market and asset returns. Bollerslev et al. (2021) show that the semibetas that result from the negative market and negative asset return covariation predict significantly higher future returns. Specifically, we test the null that the semibetas of the green (clean energy) portfolio are greater than or equal to those of the brown (fossil) portfolio, conditional on instruments.

H2b: The brown (fossil) portfolio has higher semibetas than the green (clean energy) portfolio conditional on information set about unexpected shifts in investors' preferences toward sustainability.

Idiosyncratic risk is related to firm-specific risks that stem from adverse events such as lawsuits, strikes, brand and reputation erosion, and boycotts, which could affect a firm's profitability and overall risk profile considerably. Lee & Faff (2009)find that firms with strong corporate social performances (CSPs) have lower idiosyncratic risks than firms with weak CSPs. Due to the increasing concern about climate change, fossil fuel firms are not only under the pressure of divestment campaigns, but also face potential lawsuits related to the damage caused by global warming. Therefore, we hypothesize that the brown portfolio has a higher idiosyncratic risk than the green portfolio. Specifically, we jointly test the null that the idiosyncratic risk of the green (clean energy) portfolio is greater than or equal to that of the brown (fossil) portfolio, conditional on instruments for investors' preferences.

H3: The brown (fossil energy) portfolio has a higher idiosyncratic risk (volatility) than the green (clean energy) portfolio conditional on unexpected shifts in investors' preferences toward sustainability.

3 Data and methodology:

3.1 Instrumental variables

We have collected the following instrumental variables data in our study:

1. Natural disasters data are obtained from the National Oceanic and Atmospheric Administration (NOAA) from 2008 to 2020.[2] These data contain the number of U.S. billion-dollar disaster events, the financial cost of each disaster and the number of deaths caused by each disaster. Theoretically, natural disasters induced by climate change affect aggregate wealth and asset valuations (Bansal et al., 2016). Some existing papers find the effect of natural disasters on market anomalies (Tsai & Wachter, 2016; Bai et al., 2019; Lanfear et al., 2019) and return comovement (Ma et al., 2022).

[2] ncdc.noaa.gov/billions/events

2. Climate Policy Uncertainty (CPU) index proposed by Gavriilidis (2021). CPU captures the uncertainty related to climate policy which is likely to affect investors' decisions.3 The index is constructed by extracting news about climate policy from major US newspapers, including the Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and the Wall Street Journal. This follows the methodology by which Baker et al. (2016) constructed the Economic Policy Uncertainty (EPU) index. CPU contains information that could affect the expected returns of green and brown assets. In fact, the index reaches a peak when there are important climate events such as new emissions legislation, global strikes about climate change and Presidents' statements about climate policy, among other developments.

Overall, natural disasters and CPU could proxy for physical risk and transition risk due to climate change. These instruments are economically motivated and intuitive. We also economic-related instruments including cyclicality-adjusted real P/E (CAPE) ratio from Shiller's website[4] and NBER-based recession periods from the Federal Reserve Bank of St. Louis in robustness checks. We obtain four Carhart factors from Kenneth R. French website[5] and oil prices from the Federal Reserve Bank of St. Louis.

3.2 Green and brown portfolios

We use fossil fuel ETFs and clean energy ETFs as proxies for brown and green assets. Specifically, our study uses four clean energy ETFs including iShares Global Clean Energy ETF (ICLN), Invesco WilderHill Clean Energy ETF (PBW), Invesco Global Clean Energy ETF (PBD) and First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN). In addition, the study uses four fossil fuel energy ETFs including Energy Select Sector SPDR Fund (XLE), Vanguard Energy ETF (VDE), SPDR S&P Oil & Gas Exploration & Production ETF (XOP) and VanEck Vectors Coal ETF (KOL). They are top ETFs based on assets under management.

Since ICLN return data is available from June 2008, our sample covers from June 2008 to December 2020. ETFs data are obtained from the Center for Research in Security Prices (CRSP). we form an equally-weighted green portfolio consisting of four clean energy ETFs and an equally-weighted brown portfolio consisting of four fossil fuel ETFs.

[3] https://policyuncertainty.com/climate_uncertainty.html
[4] http://www.econ.yale.edu/~shiller/
[5] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Panel A of Table 1 provides the correlation estimates between ETFs. We observe that three of the clean energy ETFs (ICLN, PBW, QCLN) are highly correlated, with estimates from 0.873 to 0.955. Three of the fossil fuel energy ETFs (XLE, VDE and XOP) are also highly correlated, at well above 90%, though the correlations of these ETFs with KOL are from 61.3% to 71.6%. The correlation estimates between the fossil fuel ETFs and clean energy ETFs are also moderate.

Panel B of Table 1 reports summary statistics of ETF returns, and the variables used to construct instruments from 2008 to 2020. As can be seen, all clean energy ETFs have positive mean returns, whereas the fossil fuel ETFs have negative mean returns except XLE (0.008). Also, the mean excess return of the green (clean) portfolio is 0.583%, while that of the brown (fossil) portfolio is −0.193%. While the standard deviations of the green and brown portfolios are not very different, the green portfolio is much more negatively skewed than the brown portfolio. In addition, we have 165 natural disasters during the sample and monthly mean and median numbers of natural disasters are two and one. The mean and median of the Climate Policy Uncertainty (CPU) index are 125 and 104.32.

[Table 1 about here]

3.3 Conditional testing procedures

We validate Pástor et al. (2021)'s assertions by adopting the multivariate inequality constraints approach proposed by Wolak (1987, 1989), which provides a rigorous test of the validity of the priori signs of the parameters, where such a priori beliefs point to an inequality restriction rather than an equality restriction. This approach allows moments to be conditioned on observable information and takes the unobservability of expected returns into account by employing instrumental variables.

The conditional test with multivariate inequality constraints has several attractive features, which have been demonstrated by Boudoukh et al. (1993). First, the test does not require a model for conditional expectations. This is especially important because conditional expectations are not modelled explicitly for many asset pricing theories. As it turns out, all that needs to be satisfied are the stationarity and ergodicity assumptions on the observable variables. Second, econometricians tend to include instrumental variables but may not know how they enter the model. Therefore, this approach is advantageous because it does not require an assumed functional form. Third, the restrictions can be tested jointly, meaning that the test will consider any correlations across the mean estimators.

We consider a model that implies the following restriction:

$$E_t\left[R_{\text{brown},t+1} - R_{\text{green},t+1}\right] = D_t \geq 0\,, \tag{3}$$

under the null model, where $R_{\text{brown},t+1}$ is brown (fossil) portfolio returns at time t + 1, $R_{\text{green},t+1}$ is green (clean energy) portfolio returns at time t + 1 and D_t is defined as the difference. Eq. (3) states that the ex-ante return difference between the brown and green portfolios is nonnegative.

Following Pástor et al. (2021), portfolio returns may depend on a variety of instruments related to either the customer channel or the investor channel in the agent's information sets. Specifically, we use information about natural disasters and climate policy uncertainty. The sign of the equation does not change when both sides of Eq. (3) are multiplied by nonnegative instruments z_t^+. Therefore, we obtain:

$$E\left[\left(R_{\text{brown},t+1} - R_{\text{green},t+1}\right) \otimes\ z_t^+ -\ \theta_{Dz^+}\right] = 0\,, \tag{4}$$

where

$$\theta_{Dz^+} = E[D_t \otimes\ z_t^+] \geq 0\,. \tag{5}$$

Since we have two instruments, we expand the restrictions given in Eqs. (4) and (5) as a system of 2-moment conditions:

$$\begin{aligned} E\left[\left(R_{\text{brown},t+1} - R_{\text{green},t+1}\right)z_{1t}^+\right] &= \theta_{Dz_1^+} \\ E\left[\left(R_{\text{brown},t+1} - R_{\text{green},t+1}\right)z_{2t}^+\right] &= \theta_{Dz_2^+} \end{aligned} \tag{6}$$

$$H_0\colon \theta_{Dz_i^+} \geq 0 \qquad \forall_i = 1, 2$$

$$H_A\colon \theta_{Dz_i^+} \in R^N$$

We calculate the unrestricted estimate (sample mean) and the restricted estimate nonnegative under the null by using non-parametric approach. Then, we test the difference between unrestricted and restricted estimators that under the null, the difference should be small. The test statistic is calculated as the Wald statistic, and the statistic is distributed as a weighted sum of chi-squared variables with different degrees of freedom (Wolak, 1989). The *p*-value is calculated based on 1000 draws from Monte Carlo simulations. The detailed procedure for conducting the multivariate inequality testing is described in the Appendix.

Following Boudoukh et al. (1993), we construct dummy and magnitude-based instruments. Specifically, we use their median as a threshold to construct nonnegative instruments. For dummy instruments, we define as following

$$z_{it}^{*} = \begin{cases} 1 & if\ x_{it} > x_{it}^{med} \\ 0 & otherwise \end{cases} \tag{7}$$

where x_{it} are number of natural disasters and CPU index in each month, whose median is denoted as x_{it}^{med}.

Since the dummy instruments may not utilize all available information up to month t, we also generate magnitude-based instruments to consider their magnitude. For magnitude-based instruments, we define as following

$$z_{it}^{*} = \max\left(0, x_{it} - x_{it}^{med}\right) \tag{8}$$

The instruments are normalized as $z_{it}^{+} = 1/E[z_{it}^{*}]$ if $z_{it}^{*} \neq 0$, and $z_{it}^{+} = 0$ otherwise. This normalization ensures that these instruments have a clear economic interpretation. For example, $\hat{\theta}_{Dz_2^+}$ is the sample mean of brown-minus-green returns conditional on a high CPU.

We also apply the inequality tests for market beta, semibetas and idiosyncratic risk. However, regarding risk metrics, we test the null that green-minus-brown risk metrics are greater than or equal to zero instead of brown-minus-green as returns. We would like to examine whether we reject the null that green-minus-brown risk metrics being nonnegative. If we reject the null, we could conclude that brown portfolio is riskier than green portfolio conditional on instruments.

4 Empirical findings

4.1 Preliminary results

We first examine the unconditional tests of portfolios returns including risk-adjusted returns estimated from CAPM and four Carhart factors with oil returns, the results of which are reported in Table 2. At first glance, we observe the insignificant of nonnegative returns of green and brown portfolios returns, although we can reject the null that green and brown portfolios returns are nonnegative for both risk-adjusted returns, namely p-values are 0.016 and 0.000 for “green” and “brown” portfolios, respectively. We are more interested in the brown-minus-green portfolios, as can be seen, apart from the marginal rejection of the null that brown-minus-green mean return is nonnegative for raw returns (p-values = 0.083), we cannot reject the null that brown-minus-green mean return is nonnegative for both risk-adjusted returns (p-values =

0.113 and 0.259). These preliminary results of unconditional tests indicate that green portfolios do not outperform brown ones.

Table 2 also reports the differences of the “green” and “brown” for their market beta, realized semibetas and idiosyncratic risk, respectively. In particular, we cannot reject the null that market beta of “green” portfolio is greater than or equal to that of “brown” portfolio. Regarding realized semibetas, especially $\hat{\beta}^{N}$, the covariance between negative portfolios returns and negative market returns, we cannot reject the null the $\hat{\beta}^{N}_{green}$ is greater than or equal to $\hat{\beta}^{N}_{brown}$. This is similar to $\widehat{\beta}^{P}$, the covariance between positive portfolios returns and positive market returns. However, we reject the null that “green” portfolio has a higher $\hat{\beta}^{M^-}$, the covariance between positive portfolios returns and negative market returns, and $\hat{\beta}^{M^+}$, the covariance between negative portfolio returns and positive market return, than the “brown” portfolio. In addition, there is a rejection of the null that idiosyncratic risk of the “green” portfolio is higher than or equal to that of the “brown” portfolio with p-value of 0.003. We also find weak evidence that fund flow to green ETFs is greater than that to brown ETFs. In general, unconditional tests indicate that brown portfolio is not riskier than green portfolio.

[Insert Table 2 Here]

4.2 Testing on CAPM-adjusted returns:

We use CAPM-adjusted returns to test the first hypothesis. Table 3 reports conditional mean returns and test statistics. The multiple inequality restriction statistics are 1.879 (p-value = 0.086) and 4.757 (p-value=0.014) for dummy and magnitude-based instruments. We jointly reject the null that brown-minus-green return is greater than or equal to zero in conditional tests using magnitude-based instruments at 5% level of significance. Indeed, when we change from dummy instruments to magnitude-based instruments, brown-minus-green mean returns are more negative. For example, conditional on Climate Policy Uncertainty (CPU), mean returns decreases from -1.562 to -3.738%. Compared to unconditional mean return of -0.675% (p-value=0.113), we find strong evidence about outperformance of green portfolio relative to brown portfolio by taking magnitude of instruments into account. The result supports prediction from Pástor et al. (2021)’s model.

Furthermore, we test whether that brown (green) portfolio return is nonnegative conditional on instruments. The results are reported in columns 3, 4, 6 and 7. Regarding brown portfolio return, we reject the null that brown portfolio mean return is nonnegative, which is consistent with unconditional test. The multiple statistics are significant at 1% level. Compared to unconditional mean returns which is-1.552%, incorporating instruments make the brown portfolio returns more negative, i.e., conditional mean returns are -2.371% and -2.477% associated with natural disasters and CPU, respectively. In particular, the results of green portfolio returns based on our conditional tests are more persuasive. Recalling the significant negative green portfolio risk-adjusted returns in Table 2, our conditional tests reveal that we cannot reject the green portfolio returns are nonnegative, whose p-values are0.218and 0.210 for dummy and magnitude-based instruments, respectively. For a better illustration, the mean returns of brown and green portfolios are graphed in Figure 1. Compared to unconditional mean return, the brown portfolio returns are more negative when conditional on instruments of natural disasters and CPU. The differences are much more substantial for green returns, compared to the unconditional return of -0.88%, the mean return conditional on CPU is 1.261%.

In general, conditional tests on CAPM-adjusted returns support hypothesis 1 that the green portfolio return is higher than the brown portfolio one conditional on climate-related instruments. Our results also are consistent with predictions of Pástor et al. (2021)'s model. In addition, the results show the significant impact of Climate Policy Uncertainty (CPU) on green and brown portfolios returns. According to Krueger et al. (2020), institutional investors believe that regulatory risks due to climate change have begun to materialize already. Our conditional tests show not only the outperformance of green portfolio relative to brown one but also nonnegative mean return during high CPU. In addition to provide formal tests on the impact of climate related policies and events on the energy industry motivated by van Benthem et al. (2022), our findings have explicit hedge implications of green (clean energy) assets against climate risks, including regulatory risks.

[Insert Table 3 Here]

[Insert Figure 1 Here]

4.3 Testing on market beta and semibteas

For the second hypothesis, we begin with testing the null that the market beta of the "green" (clean) portfolio is greater than or equal to that of the "brown" (fossil) portfolio, whose results are reported in Table 4. Specifically, market betas are estimated based on CAPM with 36-month rolling window regressions. As is shown that the multiple inequality restrictions statistic is 2.259 (p-value = 0.067) and 2.962 (p-value = 0.043) for dummy and magnitude-based instruments, respectively. Therefore, we reject the null that the green-minus-brown market beta is nonnegative. While the unconditional green-minus-brown market beta is significantly nonnegative (0.019 from Table 2), conditional tests indicate that green-minus-brown market beta is negative. Similar to comparisons of return performances, the magnitude-based instruments conditional tests present more significant results than that of the dummy-based ones, and the difference of (green-minus-brown) market beta is wider when changing from dummy to magnitude-based instruments. For example, it decreases from 0.004 to -0.027 for natural disaster instrument and from -0.118 to -0.245 for CPU instrument.

Specifically, Figure 2 shows changes in market betas when we consider instruments. Unconditionally, green portfolio has a slightly higher market beta than brown portfolio, namely 1.37 and 1.35. However, when conditioning instruments related to natural disasters and especially CPU, the increase in market beta of brown portfolio is higher than that of green portfolio. For example, market beta of brown portfolio is 1.59 and market beta of green portfolio is 1.34 conditional on CPU.

Overall, our results support hypothesis 2a that the brown portfolio has higher market betas than the green portfolio under the conditional setting. The results provide explicit implications on market beta hedging and reducing the overall beta of a portfolio by longing assets with offsetting betas. In addition, our results complement results of Ma et al. (2022) by showing the difference in comovement between brown and green assets under the impact of climate risks.

[Insert Table 4 Here]

[Insert Figure 2 Here]

4.4 Testing on Semibetas

Due to an extensive literature questioning the ability of the standard market beta explaining the cross-sectional variation in asset returns, we decompose market beta into four realized semibetas as proposed by Bollerslev et al. (2021):

$$\hat{\beta}_{t,i} \equiv \frac{\sum_{k=1}^{m} r_{t,k,i} f_{t,k}}{\sum_{k=1}^{m} f_{t,k}^2} = \hat{\beta}_{t,i}^{N} + \hat{\beta}_{t,i}^{P} - \hat{\beta}_{t,i}^{M^+} - \hat{\beta}_{t,i}^{M^-} \tag{9}$$

Let $r_{t,k,i}$ denote returns on asset i over the k^{th} time interval within some fixed period t, with the concurrent returns for the aggregate market denoted by $f_{t,k}$, namely k is a day and t is a month in the study. The decomposition is based on semicovariance concept of Bollerslev et al. (2020). Let r and f denote returns on some risky assets and aggregate market portfolio, respectively. Specifically, $N, P, M^{+}, and\ M^{-}$ semicovariance components refer to respective portions of total covariance $Cov(r, f)$ defined by both returns being positive (P state), both returns being negative (N), mixed sign with positive market return (M^{+}), and mixed sign with negative market return ("M^{-}"). Defined the signed intra-period asset returns by $r_{t,k,i}^{+} \equiv$ max $(r_{t,k,i}, 0)$ and $r_{t,k,i}^{-} \equiv$ min $(r_{t,k,i}, 0)$, with the signed intra-period market returns defined analogously. The realized semibetas are then defined by:

$$\begin{aligned} \hat{\beta}_{t,i}^{N} &\equiv \frac{\sum_{k=1}^{m} r_{t,k,i}^{-} f_{t,k}^{-}}{\sum_{k=1}^{m} f_{t,k}^{2}}, \quad \hat{\beta}_{t,i}^{P} \equiv \frac{\sum_{k=1}^{m} r_{t,k,i}^{+} f_{t,k}^{+}}{\sum_{k=1}^{m} f_{t,k}^{2}} \\ \hat{\beta}_{t,i}^{M^{-}} &\equiv \frac{-\sum_{k=1}^{m} r_{t,k,i}^{+} f_{t,k}^{-}}{\sum_{k=1}^{m} f_{t,k}^{2}}, \quad \hat{\beta}_{t,i}^{M^{+}} \equiv \frac{-\sum_{k=1}^{m} r_{t,k,i}^{-} f_{t,k}^{+}}{\sum_{k=1}^{m} f_{t,k}^{2}} \end{aligned} \qquad (10)$$

where m denotes the number of higher-frequency return intervals within each time period.

Table 5 reports the results of inequality tests on the null that green-minus-brown semibetas are nonnegative. We focus on $\hat{\beta}^{N}$ (covariance between negative portfolio returns and negative market returns), since investors care more about downside variations, then the covariation associated with positive aggregate market returns should not be priced in equilibrium. Subsequently, the downside beta can better explain the cross-sectional variation in equity returns and provides superior predictions, see relevant findings in Ang et al., (2006) and Bollerslev et al. (2021). As reported, the multiple inequality restrictions statistics are 6.252 (p-value=0.006) for dummy instruments and 5.770 (p-value=0.008) for magnitude-based instruments. Therefore, brown portfolio has higher $\hat{\beta}^{N}$ than green portfolio. In other words, when market returns go down, brown portfolio returns go down more than green ones.

Interestingly, this has not be found in the unconditional study which does not reject green-minus-brown $\hat{\beta}^{N}$ is nonnegative (Table 2). When conditioning instruments, green-minus-brown $\hat{\beta}^{N}$ are -0.032 and -0.104 associated with natural disasters and CPU. They are higher than the unconditional estimate, -0.015. Specifically, Figure 3 shows during period of high CPU, while brown portfolios $\hat{\beta}^{N}$ appears to go down slightly compared to its unconditional $\hat{\beta}^{N}$ from 0.65 to 0.63, brown portfolios $\hat{\beta}^{N}$ decreases significantly from 0.63 to 0.53.

The results are supported by Giglio et al. (2021). Their argument is that climate shocks could negatively affect the market but favour green assets because of their ability to hedge climate risks. Pástor et al.(2021) also suggest that while climate shocks negatively affect the economy, they favour the "green" assets because of their hedging ability and shifts in investor preferences for sustainability. Therefore, it is plausible that conditional means of $\hat{\beta}_{t,i}^{N}$, the covariance between negative portfolio and market returns, of the "green" portfolio tend to be lower compared to the unconditional mean in the states of high investor's preferences for "green" holding.

Furthermore, conditional tests show that brown portfolio has higher $\hat{\beta}^{N}$ and $\hat{\beta}^{M^{+}}$ than green portfolio. However, brown portfolio does not have higher $\hat{\beta}^{M^{-}}$ and $\hat{\beta}^{P}$ than green portfolio. This implies that brown portfolio appears riskier than green portfolio during periods of high natural disasters and especially CPU. For example, during periods of high CPU, when market return goes down, brown portfolios return tends to go down more than green portfolios. In general, our results support conjecture that brown (fossil fuel) portfolio is riskier than green (clean energy) portfolio during high climate risks and particularly in the market downside periods.

[Insert Table 5 Here]

[Insert Figure 3 Here]

4.5 Testing on Idiosyncratic volatility

There is a plethora of literature linking idiosyncratic volatility to cross-sectional returns (Campbell, et al., 2001; Ang, et al., 2006). Next, we move our attention to idiosyncratic volatilities of green and brown portfolios, which are conventionally calculated as the standard deviation of residuals from the CAPM model. Table 6 reports the multiple inequality testing on the null that the idiosyncratic volatility of the "green" (clean) portfolio is higher than or equal to that of the "brown" (fossil) portfolio.

Specifically, we reject the null at 1% level for dummy and magnitude-based instruments. Table 6 shows that the multiple inequality restriction statistics are 13.881 (p-value = 0.000) and 12.232 (p-value = 0.000). Compared to the unconditional volatility of -0.933, the conditional volatilities associated with natural disasters and CPU are -1.329 and -1.346 for dummy instruments and -1.591 and -1.819 for magnitude-based instruments. This indicates that these instruments are informative about the volatility of clean and fossil portfolios.

Figure 4 shows how instruments affect idiosyncratic risks of green and brown portfolios. Specifically, the green-minus-brown idiosyncratic risk is more negative because, after conditioning instruments, the brown portfolio is more volatile than the green one. For example, compared to the unconditional idiosyncratic risk of 4.86 %, conditional estimates are 5.22% and 6.17% associated with natural disasters and Climate Uncertainty Policy (CPU). In contrast, the green portfolios volatility is less affected by instruments. Compared to unconditional mean volatility of 3.93%, conditional estimates are 3.63% and 4.35% associated with natural disasters and CPU, respectively.

Therefore, our results support the hypothesis that the brown portfolio has a higher idiosyncratic risk than the green portfolio conditional on climate-related information. The high idiosyncratic risk of the brown portfolio is plausible because fossil fuel firms increasingly face lawsuits related to climate change and the effects of climate activism actions such as the Global Climate Strike on March 15, 2019 (Ramelli, et al., 2021).

[Insert Table 6 Here]

[Insert Figure 4 Here]

5 Further Analysis and Robustness checks

5.1 Non-fundamental demands for brown and green ETFs

Brown et al. (2021) and Davies (2022) find that ETF fund flows signal about non-fundamental demand for assets. Following them, we define ETF fund flows as percentage change in ETF shares outstanding for fund i at time $t$denoted by $SO_{i,t}$

$$ETF\ Flow_{i,t} = \frac{SO_{i,t}}{SO_{i,t-1}} - 1 \tag{11}$$

We adjust fund flows to control for factors affecting ETF fund flows. Specifically, for each ETF, we run time-series regression as follows

$$ETF\ Flow_{i,t} = a_t + \gamma_t C_{t-1} + \epsilon_{i,t} \tag{11}$$

where C denotes control variables including fund returns, fund volatilities and oil returns. We measure adjusted fund flows for each ETF fund as follows

$$Adjusted\_ETF\ Flow_{i,t} = ETF\ Flow_{i,t} - \gamma_t C_{t-1} \tag{12}$$

We take the average of green and brown ETFs adjusted flows as measures for greens and brown flows. We hypothesize that the green flow is higher than brown flow conditional on climate-related instruments. Specifically, we test the null that brown-minus-green flow is nonnegative. As reported in Table 2, the brown-minus-green flow is unconditionally -0.038 and it is significant at the 10% level. For a comparison, our conditional results reported in Table 7 provide statistically strong evidence that the green flow is higher than the brown flow, i.e., the multiple test statistics are 4.753 (p-value=0.014) and 6.355 (p-value=0.006) for dummy and magnitude-based instruments.

We observe that the difference of brown and green is broader when changing from dummy to magnitude-based instruments, i.e., the brown-minus-green flow is more negative. For example, it decreases from -0.026 to -0.032 conditional on natural disasters and from -0.063 to -0.114 conditional on CPU. Therefore, using magnitude-based instruments result in a strong rejection of brown-minus-green flow being nonnegative. Figure 5 shows during periods of a high number of natural disasters, the brown flow is negative (-0.01). Also, during periods of high CPU, we have a high green flow, while brown flow appears unchanged. For example, compared to unconditional green flow (0.05), the green flow conditional on CPU is 0.13.

The result of higher green flow implies that climate-related information affects non-fundamental demand for green and brown assets, . and the non-fundamental demand based on ETF flow can be used to measure investor sentiment as indicated in Davies (2022). Our findings provide evidence about the impact of climate-related information on investor sentiment for green and brown assets because the non-fundamental shocks to ETFs can be transmitted to the underlying assets and can propagate into underlying asset prices. In addition, ETF flows also provide informative signals of non-fundamental demand shocks and that conditioning on these signals yields return predictability.

[Insert Table 7 Here]

[Insert Figure 5 Here]

5.2 Conditioning bad economic periods

In this section, we use economic instruments to examine whether our results are driven by certain economic conditions instead of climate-related information. An argument is that the underperformance of brown portfolio may be due to low demand for fossil fuel energy during bad economic periods. Following Bansal et al. (2022), we use cyclically-adjusted real P/E

(CAPE) ratios and NBER-based recessions to construct nonnegative instruments related to bad economic periods as follows

$$z^*_{CAPEt} = \begin{cases} 1 & if\ x_{it} < \ median\ (10\ year\ rolling) \\ 0 & otherwise \end{cases} \tag{13}$$

$$z^*_{NBERt} = \begin{cases} 1 & if\ NBER\ recession \\ 0 & otherwise \end{cases} \tag{14}$$

Similar to climate instruments, we normalize economic instruments. Also, we construct a magnitude-based instrument for CAPE as max $[0, -(CAPE_t - median)]$. Panel A of Table 8 provides conditional tests based on economic cycle instruments. The multiple inequality statistics are 1.503 (p-value=0.109) and 1.445 (p-value=0.115) for dummy and magnitude-based instruments. Therefore, we fail to reject the null that the brown-minus-green return is nonnegative in recession economic periods. In other words, there is no evidence that the green portfolio outperforms the brown one conditional on bad economic instruments. Although the brown-minus-green return is negative conditional on NBER, its standard error is high, and the joint test does not indicate a rejection. In contrast to results using climate instruments, we can not reject that null that the brown mean return is nonnegative during bad economic periods. Therefore, climate-related instruments are more informative about outperformance of the green portfolio relative to the brown one.

Panel B of Table 8 provides conditional tests using climate-related instruments during NBER-based economic recessions. For example, for dummy instruments, they will take a value of 1 if both natural disasters (CPU) > its median and NBER-based recession = 1, and zero otherwise. In the same measure, we also construct magnitude-based instruments. While the test statistic is 1.556 (p-value=0.106) for dummy instruments, it is 3.011 (p-value=0.042) for magnitude-based instruments. Therefore, we find that the green portfolio outperforms the brown one in conditional test with magnitude-based instruments. Indeed, brown-minus-green returns are more negative when switching from dummy to magnitude-based instruments. For example, while brown-minus-green returns are -3.167% and -3.584% for dummy instruments, they are -6.425% and -5.689% for magnitude-based instruments. In addition, when conditioning instruments, green (brown) returns are positive (negative). Compared to results in Table 3, brown-minus-green returns are much lower. This indicates that the outperformance of the green portfolio relative to the brown one is more pronounced when climate risks are high during economic recession periods.

[Insert Table 8 Here]

5.3 Controlling for Carhart four factors and oil returns

For a further robustness check, we use returns adjusted by four Carhart factors and oil returns. The results reported in Table 9 are consistent with those in Table 3. Specifically, we find evidence that green portfolios return is higher than brown portfolios in conditional test with magnitude-based instruments. For example, the test statistic is 3.050 (p-value=0.039). Conditional brown-minus-green returns are -0.797% and -2.801% associated with natural disasters and CPU. We reject the null that brown portfolio has a nonnegative mean return conditional on instruments. Also, conditional tests show that green portfolio has a nonnegative mean return. The test statistics are 0.849 (p-value=0.179) and 1.069 (p-value=0.145) for dummy and magnitude-based instruments.

Similar to CAPM-adjusted returns, green and brown portfolios have unconditionally negative mean returns and we cannot reject the null that brown-minus-green return is unconditional nonnegative, which is reported in Table 2. However, when incorporating instruments into tests, we find evidence about outperformance of green portfolio relative to brown portfolio and evidence about nonnegative mean return of green portfolio. Overall, our main findings are still robust when we control for more factors.[6]

[Insert Table 9 Here]

5.4 Alternative instruments

We use the cost of natural disasters to reconstruct an instrument instead of using the number of natural disasters each month. Specifically, we define the natural disaster instrument by comparing the cost caused by natural disasters in each month to median cost in the sample. We replicate results in Table 3 using the new instruments, which are reported in Table 10. The results are qualitatively similar to the main findings in Table 3. For example, we reject the null that brown-minus-green returns are nonnegative. The multiple statistics are 1.932 (p-value=0.084) and 4.727 (p-value=0.014) for dummy and magnitude-based instruments. In addition, the magnitudes of brown-minus-green returns conditional on natural disasters and CPU are close to results in Table 3. Using the new instrument, we still reject the null that brown portfolios returns are nonnegative, i.e., p-value = 0.001, and fail to reject the null that green portfolio has nonnegative mean return, i.e., p-value = 0.180 and 0.416.

Furthermore, we reconstruct instruments by using the 75% quantile as a threshold instead of the median. In other words, instruments capture extreme values of the number of

[6] Results with the raw returns are qualitatively the same, as reported in Appendix A2 (Table A2.2)

natural disasters and CPU. Panel B of Table 10 reports the conditional tests with the 75%-quantile instruments. The results are more statistically significant. The test statistics are 3.979 (p-value=0.024) and 4.994 (0.012) for dummy and magnitude-based instruments. The results are also more economically significant compared to those using median-based instruments. Regarding dummy instruments, brown-minus-green returns are -1.8 % and 4.236% associated with natural disasters and CPU. Regarding magnitude-based instruments, brown-minus-green returns are -2.089 % and 4.335% associated with natural disasters and CPU. Overall, our results are still robust. [7]

[Insert Table 10 Here]

6 Conclusions

The evidence of green and brown assets performances is becoming intriguing in empirical finance in particular with debatable findings. This paper provides rigorous comparisons of green and brown portfolios constructed from clean and fossil energy ETFs. Our paper studies their returns performances differences and also the associated risk measurements by using multiple inequality tests. While most papers focus on unconditional studies, we present novel evidence under conditional settings. Our conditional study uses variables of natural disasters and the Climate Policy Uncertainty (CPU) index, which are the most climate-related instruments.

We find that adjusted green portfolios outperform brown ones when including climate-related information, and this outperformance is not found in unconditional tests. Our results also show that the brown portfolio has a higher market beta, and we further report that the brown portfolio's high systematic risk is mainly due to downside covariations. We provide new evidence that green fund flow is higher than the brown one. For the robustness check, we have examined if our findings are driven by economic cycles instead of climate-related information, we have also demonstrated that our results are robust to Carhart's four-factor models and alternative specifications of climate-related instruments. Our study contributes to the understanding of the difference in performances of green and brown portfolios and the associated risks. The results emphasize the impact of climate-related information on investment decisions and have important implications for investors constructing portfolio allocations hedging climate change risks.

[7] Similarly, results are more statistically and economically significant for 4FF-oil returns, market beta, semibetas, idiosyncratic risk and fund flows. Those are reported in Appendix A2 (Table A2.3-A2.7)

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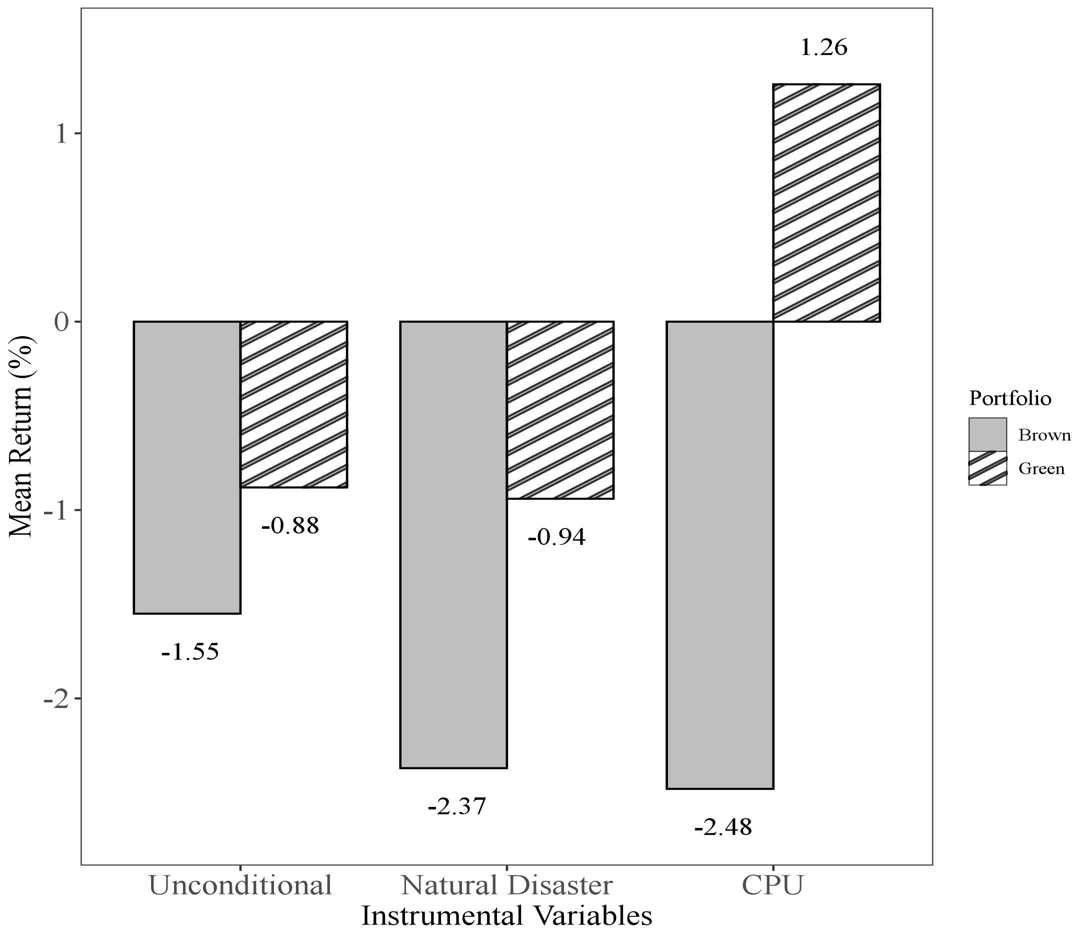

Figure 1. Unconditional mean and conditional portfolios mean returns in the period 2008-2020.
Figure plots brown and green portfolios mean returns. These portfolios are formed from fossil fuel and clean energy ETFs. Specifically, this figure includes unconditional mean and conditional means weighted by the magnitude of number of natural disasters and Climate Policy Uncertainty (CPU).

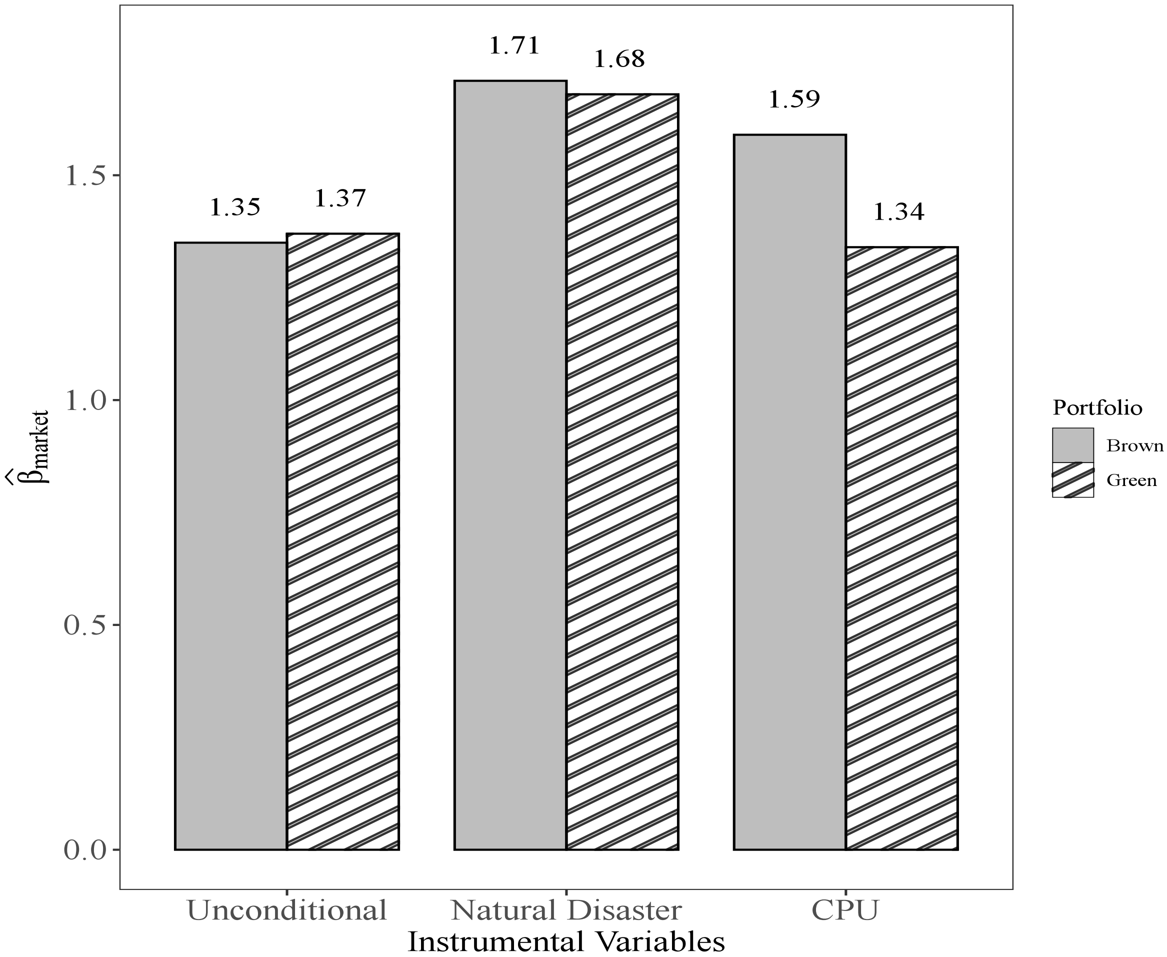

Figure 2. Unconditional mean and conditional portfolios $\widehat{\boldsymbol{\beta}}_{market}$ in the period 2008-2020.
Figure plots brown and green portfolios mean $\widehat{\boldsymbol{\beta}}_{market}$. These portfolios are formed from fossil fuel and clean energy ETFs. Specifically, this figure includes unconditional mean and conditional mean $\widehat{\boldsymbol{\beta}}_{market}$ weighted by the magnitude of number of natural disasters and Climate Policy Uncertainty (CPU).

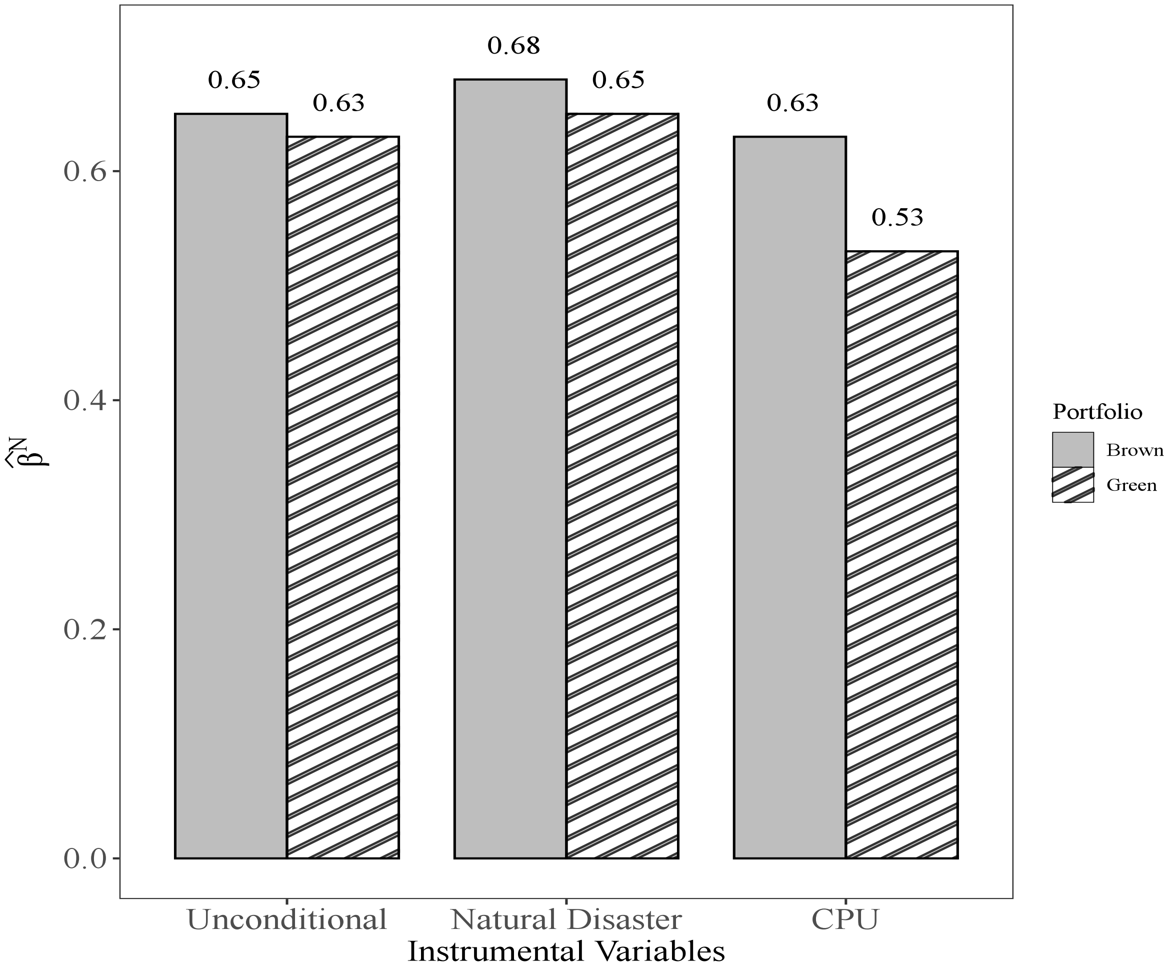

Figure 3. Unconditional mean and conditional portfolios $\widehat{\boldsymbol{\beta}}^{\boldsymbol{N}}$ in the period 2008-2020.
Figure plots brown and green portfolios mean $\widehat{\boldsymbol{\beta}}^{\boldsymbol{N}}$. These portfolios are formed from fossil fuel and clean energy ETFs. Specifically, this figure includes unconditional mean and conditional mean $\widehat{\boldsymbol{\beta}}^{\boldsymbol{N}}$ weighted by the magnitude of number of natural disasters and Climate Policy Uncertainty (CPU).

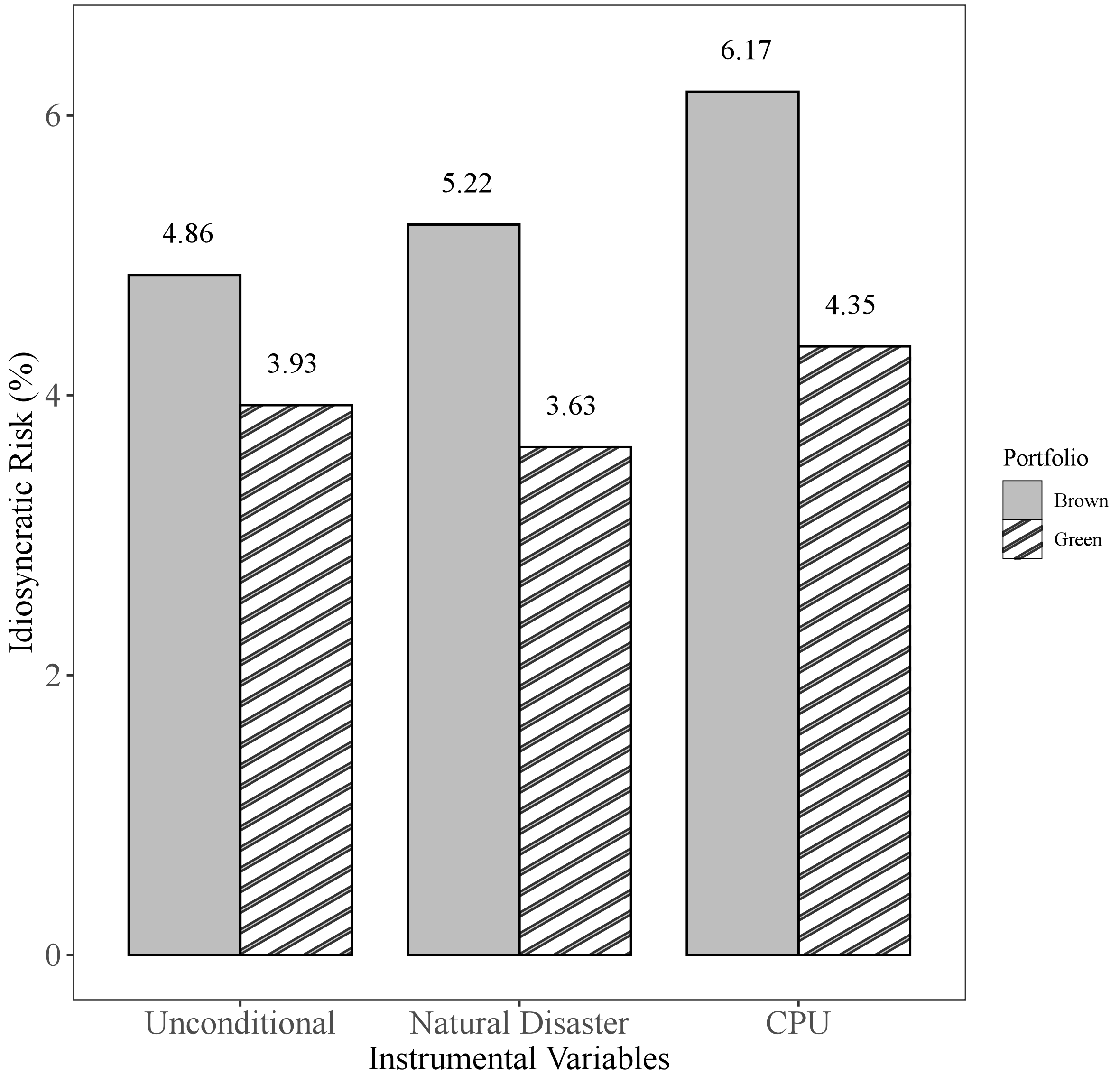

Figure 4. Unconditional mean and conditional portfolios idiosyncratic risk in the period 2008-2020. Figure plots brown and green portfolios idiosyncratic risk. These portfolios are formed from fossil fuel and clean energy ETFs. The figure plots the unconditional and conditional idiosyncratic risk associated with magnitude-based instruments. The idiosyncratic risk is standard deviation of residuals estimated from CAPM. The instruments include number of natural disasters and Climate Policy Uncertainty (CPU).

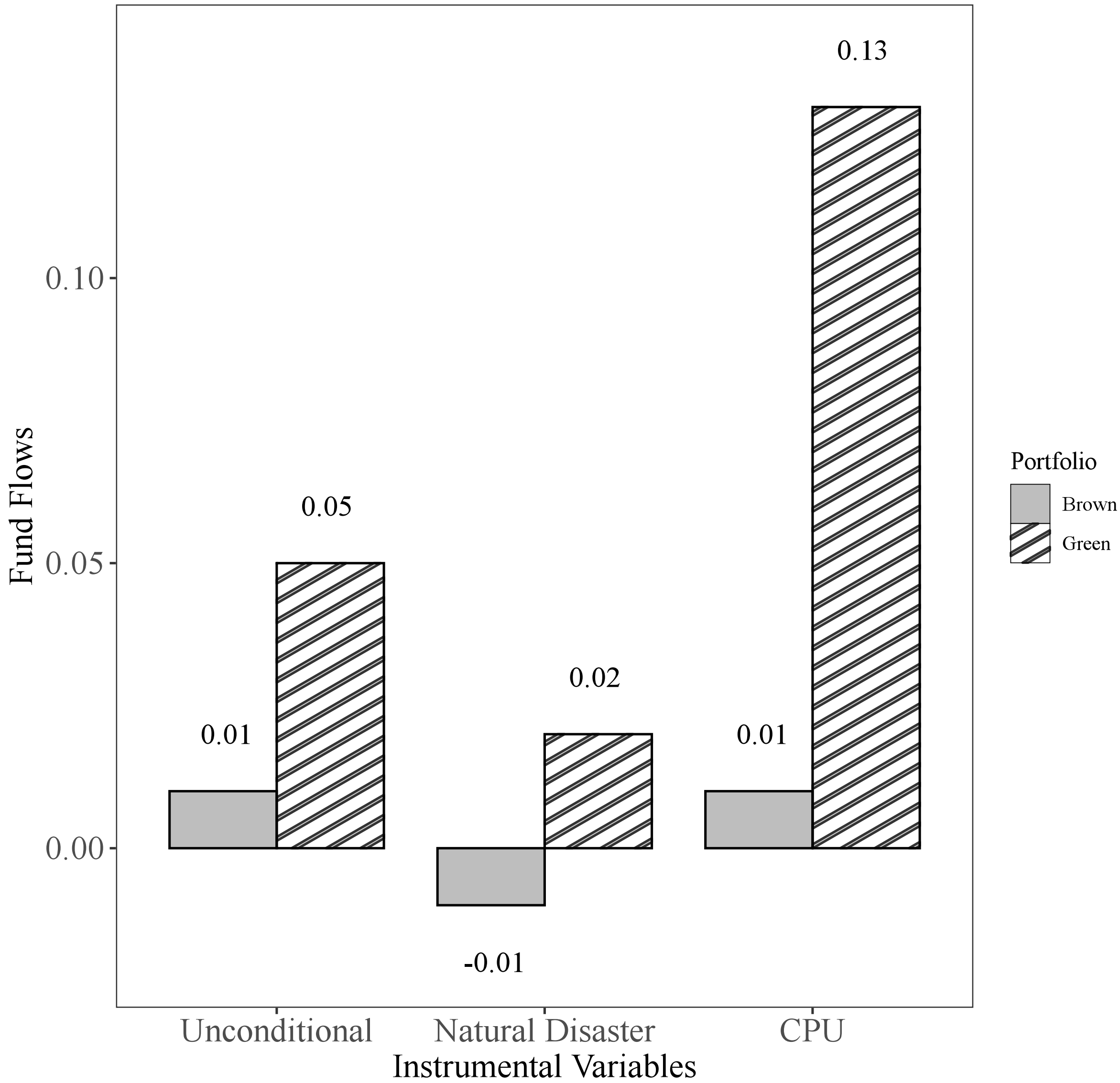

Figure 5. Unconditional mean and conditional portfolios fund flows in the period 2008-2020.
Figure plots brown and green portfolios fund flows. Brown flow is average of brown ETFs fund flows and green flow is average of green ETFs fund flows. The figure plots the unconditional and conditional fund flows associated with magnitude-based instruments. Fund flows are adjusted by past fund return, fund volatility and oil return. The instruments include number of natural disasters and Climate Policy Uncertainty (CPU).

Table 1

Descriptive statistics

Panel A reports correlation estimates between energy ETFs, including four clean energy ETFs, i.e., iShares Global Clean Energy ETF (ICLN), Invesco WilderHill Clean Energy ETF (PBW), Invesco Global Clean Energy ETF (PBD) and First Trust NASDAQ Clean Edge Green Energy Index Fund (QCLN), and four fossil fuel energy ETFs, i.e., Energy Select Sector SPDR Fund (XLE), Vanguard Energy ETF (VDE), SPDR S&P Oil & Gas Exploration & Production ETF (XOP) and VanEck Vectors Coal ETF (KOL). Panel B reports summary statistics for ETFs returns, natural disasters and Climate Policy Uncertainty (CPU) over the sample period from June 2008 to December 2020.

Panel A: Correlation

	ICLN	PBW	QCLN	PBD	XLE	VDE	XOP	KOL
ICLN	1							
PBW	0.886	1						
QCLN	0.873	0.955	1					
PBD	0.935	0.933	0.932	1				
XLE	0.566	0.64	0.646	0.666	1			
VDE	0.569	0.645	0.649	0.669	0.998	1		
XOP	0.515	0.589	0.605	0.614	0.943	0.951	1	
KOL	0.648	0.622	0.635	0.716	0.664	0.666	0.613	1

Panel B: Descriptive statistics

Variable	N	Mean	25th	Median	75th	Std.Dev	Skewness	Kurtosis
ICLN	151	0.237	-4.340	0.846	5.483	9.240	-0.906	2.687
PBW	151	0.568	-5.106	0.733	6.273	9.858	0.147	2.974
QCLN	151	1.099	-3.936	1.561	6.324	9.111	-0.204	1.964
PBD	151	0.596	-4.443	1.014	5.161	8.558	-0.356	2.561
XLE	151	0.008	-3.515	0.870	3.875	7.759	-0.118	4.042
VDE	151	-0.043	-3.721	1.079	3.881	7.993	-0.135	4.190
XOP	151	-0.208	-5.479	-0.104	5.813	11.696	0.787	6.889
KOL	151	-0.362	-5.937	-0.435	5.437	10.348	-0.135	2.237
Green portfolio	151	0.583	-4.344	0.860	5.624	8.912	-0.424	2.469
Brown portfolio	151	-0.193	-4.635	0.310	4.737	8.694	-0.023	2.819
Natural disaster (number)	165	1.618	1.000	1.000	2.000	1.005	1.937	6.849
CPU	151	125.009	72.435	104.32	159.90	84.153	2.242	8.340

Table 2

Unconditional tests for “Brown” and “Green” portfolios

This table reports mean values and one-side (left-tailed) p-values of t-tests over the sample period. Specifically, we conduct the unconditional test on raw returns, risk-adjusted returns estimated from CAPM, and four factor Carhart model with oil return, fund flows, market beta, realized semibetas proposed by Bollerslev et al. (2021) and idiosyncratic risks estimated from CAPM. $Fund\ Flow_{Brown}$ is the average of brown ETFs fund flows and $Fund\ Flow_{green}$ is the average of green ETFs fund flows. Fund flows are adjusted by past fund returns, fund volatilities and oil returns. Regarding realized semibetas, $N, P, M^{+}, and\ M^{-}$ semicovariance components refer to respective portions of total covariance $Cov(r, f)$ defined by both returns being positive (P state), both returns being negative (N), mixed sign with positive market return (M^{+}), and mixed sign with negative market return (“M^{-}”). The green portfolio constructed by equal-weighted four clean energy ETFs (ICLN, PBW, QCLN and PBD). The brown one is the equal-weighted portfolio of four fossil fuel energy ETFs (XLE, VDE, XOP and KOL).

Variables	**Mean**	***P*-value**
“Green” return	0.583	0.789
“Brown” return	-0.193	0.393
“Brown” – “Green”	-0.776	0.083
Risk-adjusted “Green” return (CAPM)	-0.877	0.016
Risk-adjusted “Brown” return (CAPM)	-1.552	0.000
Risk-adjusted “Brown” – “Green” (CAPM)	-0.675	0.113
Risk-adjusted “Green” return (4FF + oil return)	-1.014	0.004
Risk-adjusted “Brown” return (4FF + oil return)	-1.363	0.001
Risk-adjusted “Brown” – “Green” (4FF + oil return)	-0.349	0.259
$Fund\ Flow_{Brown} - Fund\ Flow_{Green}$	-0.038	0.079
$\hat{\beta}_{market,green} - \hat{\beta}_{market,brown}$	0.019	0.757
$\hat{\beta}^{N}_{green} - \hat{\beta}^{N}_{brown}$	-0.015	0.226
$\hat{\beta}^{M^{-}}_{green} - \hat{\beta}^{M^{-}}_{brown}$	-0.006	0.050
$\hat{\beta}^{P}_{green} - \hat{\beta}^{P}_{brown}$	-0.023	0.140
$\hat{\beta}^{M^{+}}_{green} - \hat{\beta}^{M^{+}}_{brown}$	-0.017	0.003
$Idio\_risk_{green} - Idio\_risk_{brown}$	-0.933	0.000

Table 3
Conditional test of $ret_{brown} - ret_{green} \geq 0$ (CAPM-adjusted return).

The table reports multiple inequality tests for CAPM-adjusted returns of brown and green portfolios conditional on Natural disasters and the Climate Policy Uncertainty index over the time period 2008-2020. The green portfolio includes clean energy ETFs and the brown portfolio includes fossil fuel ETFs. We test the null that brown-minus-green return ≥ 0 with restrictions corresponding to a large number of Natural disasters and high Climate Policy uncertainty (CPU). Besides dummy instruments, the test uses magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the conditional mean of brown-minus-green returns in these two climate-related instruments. In addition, we test whether brown (green) portfolios returns are nonnegative conditional on the instruments. Also given are the standard errors of the conditional means. Note that high (low) is defined as being above (below) the median of the instrumental variables. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using Monte Carlo simulations.

Statistics	Dummy instruments			Magnitude-based instruments		
	Brown-Green	Brown	Green	Brown-Green	Brown	Green
Natural Disaster						
Mean $\hat{\theta}_{Dz_1^+}$	-1.002	-1.930	-0.928	-1.433	-2.371	-0.938
(Standard error)	(1.585)	(0.974)	(1.191)	(1.582)	(0.887)	(1.171)
Climate Policy Uncertainty (CPU)						
Mean $\hat{\theta}_{Dz_2^+}$	-1.562	-1.652	-0.090	-3.738	-2.477	1.261
(Standard error)	(1.140)	(0.583)	(0.868)	(1.714)	(1.038)	(1.669)
Multiple inequality restriction statistic W	1.879	10.009	0.607	4.757	10.581	0.641
(p-value)	(0.086)	(0.001)	(0.218)	(0.014)	(0.001)	(0.210)

Table 4
Conditional tests of $\widehat{\boldsymbol{\beta}}_{\boldsymbol{market,green}} - \widehat{\boldsymbol{\beta}}_{\boldsymbol{market,brown}} \geq \mathbf{0}$.

The table reports multiple inequality test for $\widehat{\boldsymbol{\beta}}_{\boldsymbol{market}}$ of brown and green portfolios conditional on Natural disasters and the Climate Policy Uncertainty index over the time period 2008-2020. The green portfolio includes clean energy ETFs and the brown portfolio includes fossil fuel ETFs. We test the null that the green-minus-brown $\widehat{\boldsymbol{\beta}}_{\boldsymbol{market}} \geq 0$ with restrictions corresponding to a large number of Natural disasters and high Climate Policy uncertainty (CPU). Besides dummy instruments, the test uses the magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the conditional mean of green-minus-brown $\widehat{\boldsymbol{\beta}}_{\boldsymbol{market}}$ in these states. Also given are the standard errors of the conditional means. Note that high (low) is defined as being above (below) the median of the instrumental variables. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using Monte Carlo simulations.

Statistics	Dummy	Magnitude-based
Natural Disaster		
Mean $\hat{\theta}_{Dz_1^+}$	0.004	-0.027
(Standard error)	(0.123)	(0.116)
Climate Policy Uncertainty (CPU)		
Mean $\hat{\theta}_{Dz_2^+}$	-0.118	-0.245
(Standard error)	(0.078)	(0.143)
Multiple inequality restriction statistic W	2.259	2.962
(p-value)	(0.067)	(0.043)

Table 5

Conditional test of $\boldsymbol{semibeta_{green} - semibeta_{brown} \geq 0}$.

This table provides the multiple inequality tests on the null that green-minus-brown semibetas $\geq \mathbf{0}$ conditional on large number of Natural disasters and high Climate Policy uncertainty (CPU). The tests use dummy and magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the estimate of the conditional green-minus-brown semibeta . All standard errors are calculated via the Newey & West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator. Note that high (low) is defined as being above (below) the median of the instrumental variables. The statistic's p-value is calculated using Monte Carlo simulations.

	Dummy Instruments				**Magnitude-based Instruments**			
Statistic	$\hat{\boldsymbol{\beta}}^{N}$	$\hat{\boldsymbol{\beta}}^{M-}$	$\hat{\boldsymbol{\beta}}^{P}$	$\hat{\boldsymbol{\beta}}^{M+}$	$\hat{\boldsymbol{\beta}}^{N}$	$\hat{\boldsymbol{\beta}}^{M-}$	$\hat{\boldsymbol{\beta}}^{P}$	$\hat{\boldsymbol{\beta}}^{M+}$
Natural Disasters								
Mean $\hat{\theta}_{Dz_1^+}$	-0.005	-0.008	0.009	-0.029	-0.032	-0.010	0.009	-0.031
(Standard error)	(0.030)	(0.007)	(0.064)	(0.017)	(0.036)	(0.009)	(0.070)	(0.015)
Climate Policy Uncertainty								
Mean $\hat{\theta}_{Dz_2^+}$	-0.061	-0.009	-0.012	-0.034	-0.104	-0.004	0.053	-0.035
(Standard error)	(0.024)	(0.006)	(0.035)	(0.013)	(0.044)	(0.010)	(0.055)	(0.022)
Multiple inequality restriction statistic W	6.252	3.205	0.116	7.007	5.770	1.404	0.000	4.527
(p-value)	(0.006)	(0.036)	(0.365)	(0.004)	(0.008)	(0.116)	(0.500)	(0.017)

Table 6
Conditional test of $\boldsymbol{idio\_risk_{green} - idio\_risk_{brown} \geq 0}$.

This table provides the multiple inequality tests on whether green-minus-brown idiosyncratic risk ≥ 0 conditional on a large number of Natural Disasters and high Climate Policy uncertainty. The idiosyncratic risk is the standard deviation of residuals estimated from CAPM. The tests use dummy and magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the estimate of conditional green-minus-brown idiosyncratic risk in these states. Also, the table reports the standard errors of the conditional means. Note that high (low) is defined as being above (below) the median of the instrumental variables. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using Monte Carlo simulations.

Statistics	Dummy	Magnitude-based
Natural Disaster		
Mean $\hat{\theta}_{Dz_1^+}$	-1.329	-1.591
(Standard error)	(0.469)	(0.483)
Climate Policy Uncertainty (CPU)		
Mean $\hat{\theta}_{Dz_2^+}$	-1.346	-1.819
(Standard error)	(0.366)	(0.651)
Multiple inequality restriction statistic W	13.881	12.232
(p-value)	(0.000)	(0.000)

Table 7
Conditional test of $\boldsymbol{fund\_flows_{brown} - fund\_flows_{green} \geq 0}$.

This table provides the multiple inequality tests on the null that brown-minus-green fund flows ≥ 0 conditional on **a** large number of Natural Disasters and high Climate Policy uncertainty. Fund flows are adjusted by the past month oil return, fund return and fund volatility. The tests use a dummy and magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the estimate of conditional brown-minus-green fund flows in these states. Also, the table reports the standard errors of the conditional means. Note that high (low) is defined as being above (below) the median of the instrumental variables. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using Monte Carlo simulations.

Statistics	Dummy	Magnitude-based
Natural Disaster		
Mean $\hat{\theta}_{Dz_1^+}$	-0.026	-0.032
(Standard error)	(0.014)	(0.014)
Climate Policy Uncertainty (CPU)		
Mean $\hat{\theta}_{Dz_2^+}$	-0.063	-0.114
(Standard error)	(0.053)	(0.094)
Multiple inequality restriction statistic W	4.753	6.355
(p-value)	(0.014)	(0.006)

Table 8

Conditional test of $CAPM\_ret_{brown} - CAPM\_ret_{green} \geq 0$ with economic instruments

The table reports multiple inequality tests for CAPM-adjusted returns of green and brown portfolios over the period 2008-2020. We test the null that the brown-minus-green returns with restrictions corresponding to bad economic periods proxied by low CAPE and NBER recession. Besides dummy instruments, the test uses magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the estimate of the conditional mean of brown-minus-green returns in these states. In addition, we test whether brown (green) portfolios returns are nonnegative conditional on these states. Also given are the standard errors of the conditional means. Note that low CAPE is defined as being below the median of 10-year rolling window. Panel A reports the results conditional on instruments indicating bad economic periods, and Panel B reports the results conditional on high number of Natural disasters and high CPU during NBER-based recession periods. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using Monte Carlo simulations.

Panel A Tests conditional on instruments indicating bad economic periods

Statistics	Dummy instruments			Magnitude-based instruments		
	Brown – Green	Brown	Green	Brown – Green	Brown	Green
CAPE						
Mean	1.627	-0.631	-2.258	1.490	0.839	-0.651
(Standard error)	(0.885)	(0.571)	(0.952)	(0.867)	(2.099)	(2.561)
NBER						
Mean	-3.340	-1.408	1.932	-3.372	-0.985	2.387
(Standard error)	(2.724)	(1.430)	(3.210)	(2.805)	(3.311)	(5.362)
Multiple inequality restriction statistic W	1.503	1.718	5.626	1.445	0.088	0.065
(p-value)	(0.109)	(0.096)	(0.009)	(0.115)	(0.379)	(0.391)

Panel B Tests conditional on high number of Natural disasters and high CPU during recession.

Statistics	Dummy instruments			Magnitude-based instruments		
	Brown – Green	Brown	Green	Brown – Green	Brown	Green
Natural Disaster						
Mean	-3.167	-0.485	2.682	-6.425	-2.389	4.037
(Standard error)	(5.641)	(2.696)	(5.171)	(6.266)	(2.572)	(7.297)
Climate Policy Uncertainty (CPU)						
Mean	-3.584	-0.825	2.759	-5.689	-1.292	4.398
(Standard error)	(2.873)	(1.467)	(3.067)	(3.279)	(1.916)	(10.121)
Multiple inequality restriction statistic W	1.556	0.316	0.000	3.011	0.862	0.000
(p-value)	(0.106)	(0.287)	(0.502)	(0.042)	(0.177)	(0.684)

Table 9

Conditional test of $\boldsymbol{return_{brown} - return_{green}} \geq \mathbf{0}$ (Carhart **+ oil returns).**

The table reports multiple inequality test for 4FF and oil-adjusted returns of brown and green portfolios conditional on Natural disasters and the Climate Policy Uncertainty index over the period 2008-2020. The green portfolio includes clean energy ETFs and the brown portfolio includes fossil fuel ETFs. Portfolio returns are adjusted by the Carhart four factors and oil returns. We test the null that brown-minus-green return ≥ 0 with restrictions corresponding to large number of Natural disasters and high Climate Policy uncertainty (CPU). Besides dummy instruments, the test uses magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the conditional mean of brown-minus-green returns in these states. In addition, we test whether brown (green) portfolios returns are nonnegative conditional on these states. Also given are the standard errors of the conditional means. Note that high (low) is defined as being above (below) the median of the instrumental variables. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using Monte Carlo simulations.

Statistics	Dummy instruments			Magnitude-based instruments		
	Brown – Green	Brown	Green	Brown – Green	Brown	Green
Natural Disaster						
Mean $\hat{\theta}_{Dz_1^+}$	-0.447	-1.500	-1.054	-0.797	-1.933	-1.136
(Standard error)	(1.541)	(0.876)	(1.144)	(1.460)	(0.831)	(1.099)
Climate Policy Uncertainty (CPU)						
Mean $\hat{\theta}_{Dz_2^+}$	-1.077	-1.532	-0.455	-2.801	-2.325	0.476
(Standard error)	(1.088)	(0.542)	(0.754)	(1.604)	(0.890)	(1.298)
Multiple inequality restriction						
statistic W	0.980	9.707	0.849	3.050	9.872	1.069
(p-value)	(0.163)	(0.001)	(0.179)	(0.039)	(0.001)	(0.145)

Table 10

Conditional test of $\boldsymbol{return_{brown} - return_{green} \geq 0}$ (with alternative instruments)

Table reports multiple inequality tests for CAPM-adjusted returns of brown and green portfolio conditional on Natural disasters and Climate Policy Uncertainty index over period 2008-2020. Panel A represents tests conditional on Natural disasters with high cost and high Climate Uncertainty Policy. Besides dummy instruments, the test conditions on the magnitude of cost caused by Natural disasters and Climate Policy Uncertainty. Note that high (low) is defined as being above (below) the median of the instrumental variables. Panel B represents tests with instruments based on 75%-quantile value. Instruments captures number of natural disasters and CPU above their 75%-quantile values. Panels report tests on the null that brown-minus-green return ≥ 0 conditional on dummy and magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ are brown-minus-green returns in these states. We also test whether brown (green) portfolios returns are nonnegative conditional on these states. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using a Monte Carlo simulation.

Panel A: Inequality tests conditional on cost caused by natural disasters and high Climate Uncertainty Policy						
Statistics	Dummy instruments			Magnitude-based instruments		
	Brown – Green	Brown	Green	Brown – Green	Brown	Green
Natural Disaster (Cost-based)						
Mean $\hat{\theta}_{Dz_1^+}$	-0.217	-1.220	-1.003	-1.427	-1.678	-0.251
(Standard error)	(1.201)	(0.773)	(1.089)	(1.575)	(0.771)	(1.214)
Climate Policy Uncertainty (CPU)						
Mean $\hat{\theta}_{Dz_2^+}$	-1.562	-1.652	-0.090	-3.738	-2.477	1.261
(Standard error)	(1.124)	(0.585)	(0.879)	(1.719)	(1.026)	(1.690)
Multiple inequality restriction statistic W	1.932	8.917	0.848	4.727	9.848	0.043
(p-value)	(0.084)	(0.001)	(0.180)	(0.014)	(0.001)	(0.416)

Panel B: Inequality tests conditional on number of natural disasters and CPU above their 75%-quantile values						
Statistics	Dummy instruments			Magnitude-based instruments		
	Brown – Green	Brown	Green	Brown – Green	Brown	Green
Natural Disaster						
Mean $\hat{\theta}_{Dz_1^+}$	-1.800	-2.930	-1.130	-2.088	-3.041	-0.953
(Standard error)	(2.183)	(1.246)	(1.446)	(1.913)	(1.142)	(1.416)
Climate Policy Uncertainty (CPU)						
Mean $\hat{\theta}_{Dz_2^+}$	-4.236	-2.782	1.454	-4.335	-2.756	1.580
(Standard error)	(2.124)	(1.026)	(1.554)	(1.964)	(1.454)	(2.237)
Multiple inequality restriction statistic W	3.979	11.098	0.611	4.994	9.995	0.453
(p-value)	(0.024)	(0.000)	(0.211)	(0.012)	(0.001)	(0.253)

Appendix A1:

The detailed procedure for conducting the multivariate inequality testing is as follows.

Step 1: We estimate the sample means of the product of the observable variables. In particular,

$$\hat{\theta}_{Dz_i^+} = \frac{1}{T}\sum_{t=1}^{T}[\left(R_{\mathrm{brown},t+1} - R_{\mathrm{green},t+1}\right)z_{it}^{+}], \qquad \forall_i = 1, 2, \mathrm{I}\ldots, N\ . \text{(A1)}$$

There is no restriction on the sign of the difference returns. In other words, they may be negative due to sampling error or the possible rejection of the null hypothesis. The vector $\hat{\theta}_{Dz^+}$ is asymptotically normal with mean θ_{Dz^+} and variance-covariance matrix Ω, which is estimated using the Newey & West (1987) approach.

Step 2: Under the null hypothesis restriction, the parameter estimates must be nonnegative. Estimates are derived under the null restriction by minimizing deviations from the unrestricted model:

$$\min_{\theta_{Dz^+}} \ (\hat{\theta}_{Dz^+} - \theta_{Dz^+})' \, \hat{\Omega}^{-1}(\hat{\theta}_{Dz^+} - \theta_{Dz^+}), \qquad \text{(A2)}$$

$$\text{subject to } \theta_{Dz^+} \geq 0\ .$$

Let $\hat{\theta}_{Dz^+}^{R}$ be the solution to this quadratic program.

Step 3: The statistic for testing the null hypothesis is generated. The purpose is to test how close the restricted estimates $\hat{\theta}_{Dz^+}^{R}$ are to the unrestricted estimates $\hat{\theta}_{Dz^+}$. Under the null, the difference should be small. The test statistic is then computed as:

$$W \equiv T\left(\hat{\theta}_{Dz^+}^{R} - \hat{\theta}_{Dz^+}\right)' \, \hat{\Omega}^{-1}\left(\hat{\theta}_{Dz^+}^{R} - \hat{\theta}_{Dz^+}\right). \qquad (A3)$$

Wolak (1989) showed that the W statistic no longer has an asymptotic chi-squared distribution in the presence of inequality restrictions. Instead, the statistic is distributed as a weighted sum of chi-squared variables with different degrees of freedom. The asymptotic distribution of W is given by:

$$\sum_{k=0}^{N} P_r[\chi_k^2 \geq c]w\left(N, N-k, \frac{\hat{\Omega}}{T}\right), \qquad (A4)$$

where $c \in R^+$ is the critical value for a given size, and the weight $w\left(N, N-k, \frac{\hat{\Omega}}{T}\right)$ is the probability that θ_{Dz^+} has exactly $N-k$ positive elements.

Wolak (1989) indicates that calculating the weights $w\left(N, N-k, \frac{\hat{\Omega}}{T}\right)$ can be nontrivial because the weights require the evaluation of N-multiple integrals, and closed forms have been calculated for only a small number of restrictions ($N \leq 4$). As an alternative, Kodde & Palm (1986) provide upper- and lower-bound critical values which do not require the calculation of the weights. These bounds are given by:

$$\alpha_l = \frac{1}{2} Pr(\chi_1^2 \geq c_l) \tag{A5}$$

$$\alpha_u = \frac{1}{2} Pr(\chi_{N-1}^2 \geq c_u) + \frac{1}{2} Pr(\chi_N^2 \geq c_u) \tag{A6}$$

where c_l and c_u are the critical values of the lower and upper bounds, respectively.

The weights need only be calculated when the test statistic value lies within these bounds. Wolak (1989) proposes a procedure for calculating the weights based on Monte Carlo simulations. Specifically, a multivariate normal distribution with mean zero and covariance matrix $\left(\frac{\Omega}{T}\right)$ is simulated. Given the realizations $\theta_{Dz^+}^*$ which denote the vector of realizations from each replication, we then search for the $\hat{\theta}_{Dz^+}$ which solves the minimization problem

$$min\left(\theta_{Dz^+}^* - \tilde{\theta}_{Dz^+}\right)\left(\frac{\hat{\Omega}}{T}\right)^{-1}\left(\theta_{Dz^+}^* - \tilde{\theta}_{Dz^+}\right), \qquad \text{(A7)}$$

$$\text{subject to } \tilde{\theta}_{Dz^+} \geq 0 .$$

As advocated by Wolak (1989), the approximate weight $\hat{w}\left(N, N-k, \frac{\hat{\Omega}}{T}\right)$ is the fraction of replications in which the estimated $\tilde{\theta}_{Dz^+}$ has exactly $N-k$ elements exceeding zero.

Appendix A2:

Table A2.1
Variable definitions

Variable	Definition	Source
ICLN	iShares Global Clean Energy ETF	CRSP
PBW	Invesco WilderHill Clean Energy ETF	CRSP
PBD	Invesco Global Clean Energy ETF	CRSP
QCLN	First Trust NASDAQ Clean Edge Green Energy Index Fund	CRSP
XLE	Energy Select Sector SPDR Fund	CRSP
VDE	Vanguard Energy ETF	CRSP
XOP	SPDR S&P Oil & Gas Exploration & Production ETF	CRSP
KOL	VanEck Vectors Coal ETF	CRSP
Natural disasters	U.S. billion-dollar disaster events	NOAA
CPU	Climate Policy Uncertainty Index	Gavriilidis, K. (2021)
SO	Shares Outstanding	CRSP
Oil price	Crude Oil Prices: West Texas Intermediate (WTI)	St. Louis Fed
CAPE	Cyclicality-adjusted real P/E (CAPE) ratio	Shiller's website
NBER-based recession	NBER-based recession	St. Louis Fed
SMB	Size factor	Kenneth French data library
HML	Value factor	Kenneth French data library
MOM	Momentum factor	Kenneth French data library
MKT	Market return	Kenneth French data library

Table A2.2
Conditional test of $ret_{brown} - ret_{green} \geq 0$ (raw returns).

The table reports multiple inequality tests for raw returns of brown and green portfolios conditional on Natural disasters and the Climate Policy Uncertainty index over the time period 2008-2020. The green portfolio includes clean energy ETFs and the brown portfolio includes fossil fuel ETFs. We test the null that brown-minus-green return ≥ 0 with restrictions corresponding to a large number of Natural disasters and high Climate Policy uncertainty (CPU). Besides dummy instruments, the test uses magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the conditional mean of brown-minus-green returns in these states. In addition, we test whether brown (green) portfolios returns are nonnegative conditional on these states. Also given are the standard errors of the conditional means. Panel A uses instruments that is defined as being above the median of the instrumental variables, and Panel B uses instruments that is defined as being above the 75%-quantile of the instrumental variables. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using Monte Carlo simulations.

Panel A: Inequality tests conditional on instruments based on median values						
Statistics	Dummy instruments			Magnitude-based instruments		
	Brown-Green	Brown	Green	Brown-Green	Brown	Green
Natural Disaster						
Mean $\hat{\theta}_{Dz_1^+}$	-1.126	-0.261	0.865	-1.568	-0.560	1.008
(Standard error)	(1.619)	(1.864)	(2.235)	(1.610)	(1.456)	(1.944)
Climate Policy Uncertainty (CPU)						
Mean $\hat{\theta}_{Dz_2^+}$	-1.681	-0.057	1.624	-3.986	0.848	4.834
(Standard error)	(1.153)	(1.199)	(1.435)	(1.749)	(1.991)	(2.754)
Multiple inequality restriction statistic W	2.127	0.020	0.000	5.194	0.148	0.000
(p-value)	(0.073)	(0.442)	(0.500)	(0.011)	(0.354)	(0.497)

Panel B: Inequality tests conditional on instruments based on 75%-quantile values						
Statistics	Dummy instruments			Magnitude-based instruments		
	Brown-Green	Brown	Green	Brown-Green	Brown	Green
Natural Disaster						
Mean $\hat{\theta}_{Dz_1^+}$	-1.949	-0.931	1.018	-2.239	-1.015	1.224
(Standard error)	(2.210)	(1.626)	(2.065)	(1.934)	(1.529)	(2.045)
Climate Policy Uncertainty (CPU)						
Mean $\hat{\theta}_{Dz_2^+}$	-4.411	-0.435	3.976	-4.663	1.638	6.301
(Standard error)	(2.138)	(1.725)	(2.129)	(2.017)	(2.876)	(4.038)
Multiple inequality restriction statistic W	4.256	0.359	0.000	5.461	0.440	0.000
(p-value)	(0.020)	(0.268)	(0.479)	(0.009)	(0.255)	(0.506)

Table A2.3
Conditional test of $\boldsymbol{return_{brown} - return_{green}} \geq \mathbf{0}$ (4FF + oil returns)
(Using instruments based on 75% quantile)

The table reports multiple inequality tests for 4FF_oil-adjusted returns of brown and green portfolios conditional on Natural disasters and the Climate Policy Uncertainty index over the period 2008-2020. The green portfolio includes clean energy ETFs and brown portfolio includes fossil fuel ETFs. Portfolio returns are adjusted by four Carhart factors and oil returns. We test the null that brown-minus-green return ≥ 0 with restrictions corresponding to large number of Natural disasters and high Climate Policy uncertainty (CPU). Besides dummy instruments, the test uses magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the conditional mean of brown-minus-green returns in these states. In addition, we test whether brown (green) portfolio returns are nonnegative conditional on these states. Also given are the standard errors of the conditional means. Note that high (low) is defined as being above (below) the 75% quantile of the instrumental variables. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using Monte Carlo simulations.

Statistics	Dummy instruments			Magnitude-based instruments		
	Brown-Green	Brown	Green	Brown-Green	Brown	Green
Natural Disaster						
Mean $\hat{\theta}_{Dz_1^+}$	-1.184	-2.545	-1.361	-1.328	-2.590	-1.261
(Standard error)	(1.905)	(1.231)	(1.235)	(1.701)	(1.161)	(1.346)
Climate Policy Uncertainty (CPU)						
Mean $\hat{\theta}_{Dz_2^+}$	-3.417	-2.490	0.927	-3.113	-2.562	0.550
(Standard error)	(1.972)	(0.863)	(1.387)	(1.844)	(1.201)	(1.663)
Multiple inequality restriction statistic W	3.004	10.422	1.214	2.906	8.441	0.878
(p-value)	(0.040)	(0.001)	(0.129)	(0.042)	(0.002)	(0.175)

Table A2.4
Conditional tests of $\boldsymbol{\hat{\beta}_{market,green} - \hat{\beta}_{market,brown}} \geq \mathbf{0}$.
(Using instruments based on 75% quantile)

The table reports multiple inequality tests for $\boldsymbol{\hat{\beta}_{market}}$ of brown and green portfolios conditional on Natural disasters and Climate Policy Uncertainty index over the period 2008-2020. Green portfolio includes clean energy ETFs and brown portfolio includes fossil fuel ETFs. We test the null that green-minus-brown $\boldsymbol{\hat{\beta}_{market}} \geq 0$ with restrictions corresponding to large number of Natural disasters and high Climate Policy uncertainty (CPU). Besides dummy instruments, the test uses magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the conditional mean of green-minus-brown $\boldsymbol{\hat{\beta}_{market}}$ in these states. Also given are the standard errors of the conditional means. Note that high (low) is defined as being above (below) the 75% quantile of the instrumental variables. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using Monte Carlo simulations.

Statistics	Dummy	Magnitude-based
Natural Disaster		
Mean $\hat{\theta}_{Dz_1^+}$	-0.068	-0.075
(Standard error)	(0.167)	(0.122)
Climate Policy Uncertainty (CPU)		
Mean $\hat{\theta}_{Dz_2^+}$	-0.200	-0.322
(Standard error)	(0.160)	(0.165)
Multiple inequality restriction statistic W	1.566	3.800
(p-value)	(0.106)	(0.025)

Table A2.5
Conditional test of $\boldsymbol{semibeta_{green}} - \boldsymbol{semibeta_{brown}} \geq \mathbf{0}$.
(Using instruments based on 75% quantile)

This table provides the multiple inequality tests on the null that green-minus-brown semibetas $\geq \mathbf{0}$ conditional on large number of Natural disasters and high Climate Policy uncertainty (CPU). The tests use dummy and magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ are the estimate of the conditional green-minus-brown semibetas. All standard errors are calculated via the Newey & West (1987) heteroscedasticity and autocorrelation consistent (HAC) covariance matrix estimator. Note that high (low) is defined as being above (below) 75% quantile of the instrumental variables. The statistic's p-value is calculated using Monte Carlo simulations.

	Dummy Instruments				**Magnitude-based Instruments**			
Statistic	$\hat{\boldsymbol{\beta}}^{N}$	$\hat{\boldsymbol{\beta}}^{M-}$	$\hat{\boldsymbol{\beta}}^{P}$	$\hat{\boldsymbol{\beta}}^{M+}$	$\hat{\boldsymbol{\beta}}^{N}$	$\hat{\boldsymbol{\beta}}^{M-}$	$\hat{\boldsymbol{\beta}}^{P}$	$\hat{\boldsymbol{\beta}}^{M+}$
Natural Disasters								
Mean $\hat{\theta}_{Dz_1^+}$	-0.058	-0.007	-0.025	-0.033	-0.074	-0.014	0.010	-0.035
(Standard error)	(0.064)	(0.008)	(0.116)	(0.020)	(0.056)	(0.013)	(0.082)	(0.017)
Climate Policy Uncertainty								
Mean $\hat{\theta}_{Dz_2^+}$	-0.096	-0.011	0.057	-0.046	-0.129	0.002	0.079	-0.028
(Standard error)	(0.042)	(0.007)	(0.062)	(0.023)	(0.065)	(0.015)	(0.066)	(0.026)
Multiple inequality restriction statistic W	5.463	3.116	0.047	5.539	4.870	1.080	0.000	4.981
(p-value)	(0.010)	(0.038)	(0.413)	(0.009)	(0.013)	(0.150)	(0.504)	(0.013)

Table A2.6
Conditional test of $\boldsymbol{idio\_risk_{green} - idio\_risk_{brown} \geq 0}$.
(Using instruments based on 75% quantile)

This table provides the multiple inequality tests on whether green-minus-brown idiosyncratic risk ≥ 0 conditional on a large number of Natural Disasters and high Climate Policy uncertainty. The idiosyncratic risk is standard deviation of residuals estimated from CAPM. The tests use dummy and magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the estimate of conditional green-minus-brown idiosyncratic risk in these states. Also, the table reports the standard errors of the conditional means. Note that high (low) is defined as being above (below) the 75% quantile of the instrumental variables. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using Monte Carlo simulations.

Statistics	Dummy	Magnitude-based
Natural Disaster		
Mean $\hat{\theta}_{Dz_1^+}$	-1.949	-1.989
(Standard error)	(0.717)	(0.628)
Climate Policy Uncertainty (CPU)		
Mean $\hat{\theta}_{Dz_2^+}$	-2.029	-1.924
(Standard error)	(0.640)	(0.822)
Multiple inequality restriction statistic W	12.457	12.637
(p-value)	(0.000)	(0.000)

Table A2.7
Conditional test of $\boldsymbol{fund\_flows_{brown} - fund\_flows_{green} \geq 0}$.
(Using instruments based on 75% quantile)

This table provides the multiple inequality tests on the null that brown-minus-green fund flows ≥ 0 conditional on a large number of Natural Disasters and high Climate Policy uncertainty. Fund flows are adjusted by the past month oil return, fund return and fund volatility. The tests use dummy and magnitude-based instruments. $\hat{\theta}_{Dz_i^+}$ is the estimate of conditional brown-minus-green fund flows in these states. Also, the table reports the standard errors of the conditional means. Note that high (low) is defined as being above (below) the median of the instrumental variables. All estimates are adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987). The statistic's p-value is calculated using Monte Carlo simulations.

Statistics	Dummy	Magnitude-based
Natural Disaster		
Mean $\hat{\theta}_{Dz_1^+}$	-0.044	-0.040
(Standard error)	(0.020)	(0.018)
Climate Policy Uncertainty (CPU)		
Mean $\hat{\theta}_{Dz_2^+}$	-0.120	-0.140
(Standard error)	(0.104)	(0.110)
Multiple inequality restriction statistic W	6.146	6.337
(p-value)	(0.006)	(0.006)