Performance of Energy ETFs and Climate Risks

Minh Nhat Nguyen

Faculty of Finance
University of Economics
The University of Danang, Vietnam.
Email: nhatnm@due.edu.vn

Ruipeng Liu

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

Youwei Li

Hull University Business School
Cottingham Rd, Hull
HU6 7RX, United Kingdom
Email: Youwei.Li@hull.ac.uk

Acknowledgements: Youwei Li acknowledges financial support from the National Natural Science Foundation of China (NSFC) (Grant No. 72271184 and No. 72342022). The usual caveats apply.

Performance of Energy ETFs and Climate Risks

Abstract

We investigate whether green (brown) portfolios constructed from clean energy ETFs (fossil fuel ETFs) yield positive (negative) returns conditional on climate-related risks. While the green portfolios do not unconditionally outperform the brown ones, the outperformance of green portfolios is statistically significant under the conditional setting using non-parametric estimates with imposing inequality restrictions. Our conditional studies also show that brown portfolios are riskier than green ones with various measurements. We present the heterogeneity in the effect of climate information on the return and risk of green and brown portfolios. Furthermore, we document that fund flows for green assets are higher than those for brown ones during periods of high climate risks. Our findings are robust to alternative specifications.

JEL classifications: G11; G12; C58, Q54.

Keywords: Clean energy ETFs; fossil fuel ETFs; climate risks; inequality tests; portfolio returns; semibeta, idiosyncratic risks.

1 Introduction

Investors are becoming more concerned about climate risk. Institutional investors feel that climate change has a significant impact on their portfolios and that the risks associated with climate laws have already started to materialize, according to a poll conducted by Krueger et al. in 2020. Climate hazards, in particular, exert pressure on the operations of fossil fuel and high-emission companies, such as coal and oil companies, which are significant contributors to climate change. For instance, the US insurance Chubb has stated that it will not be making any further investments in coal, while the European Investment Bank has indicated that it would no longer be making loans for fossil fuel energy projects after 2021. The increasing issues brought about by climate change make it necessary for investment portfolios to manage climate risks. The decision between green and brown investments represents a pivotal decision that not only influences financial returns but also shapes environmental impact and resilience against climate risks.

While other studies focus on fixed-income markets (Goldsmith-Pinkham et al., 2019; Huynh & Xia, 2021), real estate markets (Giglio et al., 2021), and foreign exchange markets (Kapfhammer et al., 2020), A growing literature has explored the impact of environmental and climate-related risks on stock markets.[1] Studies (Barnett & Salomon, 2006; Sharfman & Fernando, 2008; El Ghoul et al., 2011; Guenster et al., 2011; Chava, 2014) have specifically looked at the connection between environmental or ESG scores and stock returns. According to environmental or ESG scores, several research has looked at how well long-short portfolios perform (Kempf & Osthoff, 2007; Statman & Glushkov, 2009; Trinks et al., 2018; Hsu et al., 2020). The empirical data on whether green assets perform better than brown assets is conflicting, with the majority of the results being based on unconditional and ex-post fitted estimates. Especially, the positive green (brown) asset returns have not been sufficiently explained in existing literature for two main reasons. Most existing studies focus on comparing green asset returns to brown asset returns and they use the linear model to examine the relationship between climate-related variables and asset returns (Choi et al., 2020; Bolton & Kacperzyk, 2021; Ardia et al., 2022; Pastor et al., 2022). Therefore, while the positivity of green (brown) asset returns has important implications for investors seeking to hedge against climate risks, there is a lack of investigating whether green (brown) assets generate positive (negative) returns when climate risks materialize. This requires rigorous studies on the green and brown portfolio performance conditional on various climate-related risks. Indeed, identifying which assets are likely to do well or poorly during periods of high climate risks is essential for constructing hedging portfolios.

Therefore, we aim to bridge this gap by providing robust evidence on whether green assets outperform brown assets and whether green (brown) asset returns are positive (negative)

[1] Chava (2014), Hong, et al (2019)., Bolton & Kacperczyk (2020), Faccini et al (2021), Hsu et al., 2022 (2020), Ardia et al. (2022) and Pástor et al. (2022).

in the presence of various climate risks. This contributes to clarifying the reasons behind the outperformance of green assets relative to brown assets. Furthermore, our focus extends to investigating the state dependence of green and brown asset returns and risks. We study green and brown asset returns and risks conditional on quantified climate-related information. Whereas prior studies assume a linear relationship between climate information and returns, we explore heterogeneity in the effects, and we show that the effect becomes more pronounced when the upper quantile of climate-related information is used.

The energy sector is exposed to a range of climate hazards (van Benthem et al., 2022), and these risks have a significant impact on how investors allocate money and monitor energy companies. For these reasons, our research focuses on clean energy and fossil fuel ETFs. Moreover, the underlying assets of exchange-traded funds (ETFs) aid in identifying the climate risks associated with investments, and the flows of these funds offer distinct insights into the non-fundamental demand for assets (Brown et al., 2021). The inadequacy and opacity of ESG data, coupled with nonstructured methodology, is another reason we employ exchange-traded funds (ETFs) as stand-ins for green and brown assets rather than depending solely on ESG rankings. As pointed out by Avramov et al. (2021), there is an absence of a reliable measure of the true ESG performance, which turns out that ESG investors often confront a substantial amount of uncertainty about the true ESG profile. Therefore, we form green and brown portfolios by using clean energy and fossil fuel ETFs. We investigate whether the green portfolio outperforms the brown portfolio in a conditional setting in which climate-related information including natural disasters and climate policy uncertainty (CPU) is incorporated. In addition, we also study risk metrics of green and brown portfolios such as market beta, downside beta and idiosyncratic risk. Balancing financial returns and risks with environmental instrumental variables becomes the cornerstone of responsible investing in an era defined by climate risks.

We employ the conditional inequality test, which was suggested by Boudoukh et al. (1993) and Wolak (1987, 1989). Specifically, we use the nonparametric approach, which does not require structural models for conditional anticipated returns, to jointly assess inequality limitations on the return (risk) of the green and brown portfolios. By improving the accuracy and application of statistical analysis, this conditional inequality test helps us to extract more precise and complex insights from the data. We build tools pertaining to the CPU index and natural calamities to aid in the hypothesis testing. The instruments record the times when CPU and natural calamities are higher than the median. These tools are economically straightforward and inspired by earlier research to record data impacting the moments of green and brown portfolios.

For the performances of the green and brown portfolios, we present the variations between the unconditional and conditional results. For example, we observe that the green portfolio's mean return, conditional on CPU, is 1.261%, whereas its unconditional mean return is -0.877%. Furthermore, we offer solid proof that, in conditional conditions, the green portfolio performs better than the brown portfolio. In particular, the conditional on natural catastrophes and CPU, the CAPM-adjusted return disparities (brown-minus-green) are -1.433% and -3.74%, respectively, which is much less than the unconditional mean return (-0.675%). It's interesting to note that, contrary to what unconditional tests indicate, our findings indicate that, when conditioning on climate information, the green portfolio produces positive expected returns. Furthermore, we discover that the brown portfolio produces negative returns in response to climate risks.

For risk measurements, the unconditional results report that there is no difference in market beta between green and brown portfolios, but the brown portfolio has a higher market beta than the green portfolio after incorporating climate-related information. We further provide convincing findings when turning to downside semibeta $\hat{\beta}_{t,i}^{N}$ -- the covariation between negative returns and negative market returns. We find that the brown portfolio has a significantly higher downside risk than the green one, specifically, the downside semibeta difference conditional on CPU is -0.104 which is far lower than the unconditional difference of -0.015.

Using fund flows, we examine the market for green and brown assets in the wake of Brown et al. (2021) and Davies (2022). Pástor et al. (2021) specifically contend that the outperformance of green assets is a result of the high demand for green assets brought on by climatic shocks. When conditioning on high natural disasters and CPU included, we find that the non-fundamental demand for green ETFs is higher than that for brown ETFs. These findings provide an explanation for the green portfolio's superior performance in climate-risky areas.

We use NBER-designated recession periods and cyclicality-adjusted real P/E (CAPE) ratios to investigate if our findings are driven by specific economic situations. We discover that green portfolios outperform brown portfolios when climate-related instruments are integrated during recessionary periods, even though the results do not show that green portfolios outperform brown portfolios during economic recessions. Furthermore, our findings hold up well when we account for the four Carhart (1997) components, oil returns, and recreate alternative instruments.

The paper contributes to several strands of green investment literature. Firstly, we provide rigorous comparisons of the clean energy (green) and fossil fuel (brown) ETFs performances, and their evaluations are conducted based on conditional settings. The conditional inequality test is a nonparametric approach that does not depend on a structural model for expected returns under specific conditions. This approach is novel and allows us to understand why the green assets outperform the brown assets under the impact of climate-related information, including natural disasters and uncertainties in climate policies. Importantly, our paper documents the positivity of green and brown asset returns, which contribute to emerging literature related to hedging against climate risks (Engle et al., 2020; Alekseev et al., 2022).

In contrast to most existing literature which provides green and brown asset performances with unconditional comparisons, our study reports both conditional and unconditional results and separately explores the impact of physical risk and policy transition risk. We further investigate the performances of clean energy and fossil fuel ETFs conditional on the extreme climate-related risk by using the 75th percentile risk proxy. Our results diverge from previous studies, such as those by Ardia et al. (2022) and Pástor et al. (2022), which focus on the linear relationship between long-short green and brown portfolios. We find the disparity between green and brown portfolio returns are more pronounced conditional on severe environmental catastrophes and regulatory directives.

The paper also contributes to climate finance literature by studying the risks associated with green and brown portfolios. We provide comprehensive comparisons of systematic risk (beta), and downside risk (semi-beta) and idiosyncratic risks of clean energy and fossil fuel ETFs. To the best of our knowledge, no earlier study has conducted the different risk measurements conditional on climate-related information. We find brown fossil fuel ETFs are more sensitive to market movements than clean energy ETFs, and it is mainly driven by the downside risk, which is opposite to the finding based on the unconditional comparison, i.e., the brown portfolio does not have a higher downside beta. We also report how climate-related instruments affect the idiosyncratic volatilities of green and brown ETF portfolios. In addition, the paper contributes to a strand of burgeoning literature that investigates the impact of climate risks on energy industries (He & Zhang, 2022; Pham et al., 2023; Siddique et al., 2023; Li et al., 2024).

Our results offer insights for evaluating portfolio investment performances and risk perceptions. If we solely consider unconditionally estimates, one could conclude that there are no differences in returns and risks between green and brown assets. In contrast, our findings reveal that green and brown assets are significantly different in terms of returns and risks when considering climate risk-related information. Specifically, while fossil fuel ETFs provide negative returns, clean tech ETFs provide positive returns during periods of high climate risks. Investors also need to differentiate market risks (particularly the downside market beta), of green and brown portfolios by incorporating the correlations with climate risks. Therefore, our conditional results provide important implications for portfolio allocations and hedging against climate risks, and investment decisions cannot be solely based on unconditional measurements.

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

2 Literature review and hypotheses

Numerous studies have looked at how well green and brown assets perform. The results that are currently available are mixed. For instance, the earlier studies examine whether investing strategies that are environmentally friendly or socially responsible (SRI) produce positive anomalous returns in comparison to conventional strategies that are based on traditional asset pricing models. According to some research, the average alphas of SRI and non-SRI funds do not differ statistically significantly (Hamilton et al., 1993; Statman, 2000). Nonetheless, additional research suggests that SRI tactics may have favourable outcomes (Kempf & Osthoff, 2007; Statman & Glushkov, 2009; Guenster et al., 2011). Conversely, Geczy et al. (2021) discover that diversification costs cause SRI techniques to perform worse than traditional investing strategies.

Furthermore, some research indicates that socially irresponsible or environmentally unfriendly stocks are riskier than other stocks because of investor boycotts (Luo & Balvers, 2017) and shifts in environmental regulations (Hsu et al., 2020). As a result, such stocks have to offer higher expected returns to attract investors. For example, Chava (2014) finds that firms with environmental concerns, such as hazardous chemicals, substantial emissions, or climate change concerns, have higher expected returns than firms without such environmental concerns. Choi et al. (2020) find green assets have higher returns than brown ones during months with high abnormal temperatures. Bolton and Kacperczyk (2021) find that stocks of firms with higher total CO2 emissions earn higher returns since investors demand compensation for their exposure to carbon emission risk. Ardia et al. (2022) and Pástor et al. (2022) show that green assets outperform brown assets when media news about climate change is high. In general, the existing studies find that green assets outperform brown assets only at certain periods. However, they do not directly test whether green (brown) assets offer positive (negative) returns during periods of high climate risks.

Apart of mixing empirical findings, theoretical studies attempt to shed light on the relationship between sustainability and asset returns. Heinkel et al. (2001) develop a theoretical model based on the price implications of limited risk sharing proposed by Merton (1987), to investigate the effect of exclusionary ethical investing on corporate behavior in an equilibrium setting. Pástor et al. (2021) propose 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. Specifically, negative climate shocks not only motivate customers to tilt toward green products but also lead the government to impose climate regulations that favor green firms over brown firms. In other words, the unexpected worsening of climate change could strengthen not only customers' demands for green products but also investors' preference for green holdings. While Baker et al. (2022)'s multiple-agent model asserts that polluting firms attract more investment capital than identical non-polluting firms through a hedging channel. Other theoretical work including Hsu et al. (2022) develops a general equilibrium asset pricing model in which firms' cash flows face the uncertainty of policy regime shifts in environmental regulations, therefore, high-emission firms are more exposed to the policy regime shift risk and expected to earn a higher average return than low emission firms.

Market efficiency theories suggest that asset prices reflect all available information. When new information about climate risks is released, it should be quickly incorporated into asset prices. Green portfolio is composed of companies that are environmentally friendly or have low carbon footprints. These companies are likely to benefit from climate risk-related information (e.g., new regulations favoring green technology, and consumer shifts towards sustainable products) (Pastor et al., 2021; Giglio et al., 2021). As this information is incorporated into the market, the value of green stocks increases, leading to positive returns. From the behavioural perspective, investors possess a positive sentiment towards green assets, and there is a growing positive sentiment and investor enthusiasm for green investments (Briere & Ramelli, 2022).

Our study aims to provide a formal hypothesis testing if green assets outperform brown assets conditional on climate risk instruments. In addition, we investigate whether the green (brown) portfolio generates positive (negative) returns conditional on climate risk instruments.

H1a: The green portfolio outperforms the brown portfolio conditional on climate risk-related information.

H1b: The green (brown) portfolio yields positive (negative) returns conditional on climate risk-related information.

The market beta of green assets could be lower than that of brown assets when climate risks are realized. Giglio et al. (2021) suggest that adverse climate shocks reduce consumption but favor green assets because of their ability to hedge against climate risks. Therefore, adverse climate shocks could affect the correlation of the green (brown) portfolio with the market.

Furthermore, 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 reflecting climate risk.

H2a: The market beta of the brown (fossil) portfolio is higher than that of the green (clean energy) portfolio conditional on climate risk-related information.

We further investigate the covariation between green (brown) portfolio returns and market returns 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:

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

Let $r_{t,k,i}$ denote returns on asset i over the k^{th} time interval within a 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, and *m* denotes the number of higher-frequency return intervals within each period. The decomposition is based on the semicovariance concept of Bollerslev et al. (2020). 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:

$$\begin{aligned}\hat{\beta}^N_{t,i} &\equiv \frac{\sum_{k=1}^m r^-_{t,k,i} f^-_{t,k}}{\sum_{k=1}^m f^2_{t,k}}, \qquad \hat{\beta}^P_{t,i} \equiv \frac{\sum_{k=1}^m r^+_{t,k,i} f^+_{t,k}}{\sum_{k=1}^m f^2_{t,k}} \\ \hat{\beta}^{M^-}_{t,i} &\equiv \frac{-\sum_{k=1}^m r^+_{t,k,i} f^-_{t,k}}{\sum_{k=1}^m f^2_{t,k}}, \quad \hat{\beta}^{M^+}_{t,i} \equiv \frac{-\sum_{k=1}^m r^-_{t,k,i} f^+_{t,k}}{\sum_{k=1}^m f^2_{t,k}}\end{aligned} \tag{2}$$

Bollerslev et al. (2021) show that the $\hat{\beta}^N$ and $\hat{\beta}^{M-}$ disentangle the risk premium from downside risk, and the correlation between asset returns and market downturns is the main concern of investors. Fossil fuel firms are more exposed to climate risk-related information that negatively impacts their returns. Regulatory frameworks and policies aimed at mitigating climate change disproportionately impact fossil fuel companies. Stricter regulations on fossil fuels, such as carbon taxes, emission caps, and fossil fuel divestment policies directly affect brown portfolios. In addition, Giglio et al. (2021) indicate that the materialization of climate shock lowers consumption. In other words, climate risks lead to a downturn in the stock market. So, regulatory changes, shifts in investor preferences, and potential stranded assets make brown assets more vulnerable to adverse market conditions triggered by climate-related risks, and negative climate risk-related information exacerbates investor sentiment against brown assets, leading to selloffs and higher downside risk, therefore increasing the downside risk (semibetas) of brown portfolios.

On the contrary, when an adverse climate shock occurs, the value of green (clean energy) stocks will increase because they are hedging assets (Giglio et al., 2021; Pastor et al., 2021). In other words, when a downturn in the market due to climate risks occurs, the value of green (clean energy) stocks increases, which explains why green assets have lower downside risk compared to brown ones. The supportive policies for carbon reduction and incentives for clean energy technologies reduce the downside risk (semibetas) for green portfolios. As a result, clean energy companies are less sensitive to negative climate news since they are aligned with sustainability trends and often benefit from regulatory support and positive investor sentiment.

Therefore, we focus on the correlation between green (brown) returns and the market downturns when climate risks are realized. 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 climate risk instruments.

H2b: The brown (fossil) portfolio has higher semibetas than the green (clean energy) portfolio conditional on climate risk-related information.

Idiosyncratic risk includes 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. 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 climate risk instruments.

H3: The brown (fossil energy) portfolio has a higher idiosyncratic risk (volatility) than the green (clean energy) portfolio conditional on information set about climate risks.

3 Data and methodology

3.1 Instrumental variables

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

1. U.S. natural disaster data were obtained from the National Oceanic and Atmospheric Administration (NOAA) from 2008 to 2020.[2] These data contain the number of disaster events that cause losses of more than U.S. billion dollars, the financial cost of each disaster and the number of deaths as a result of 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

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

natural disasters on market anomalies (Tsai & Wachter, 2016; Bai et al., 2019; Lanfear et al., 2019) and return comovement (Ma et al., 2022).

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 indexing method follows the methodology of Baker et al. (2016) who construct the Economic Policy Uncertainty (EPU) index. CPU contains information that could affect the expected returns of green and brown assets. 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 proxy for physical risk and transition risk due to climate change. These instruments are economically motivated and intuitive. We also obtained cyclicality-adjusted real P/E (CAPE) ratio from Shiller's website,[4] oil price, and NBER-based recession periods from the Federal Reserve Bank of St. Louis in robustness checks. We have collected four Carhart factors data 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 (AUM). ETF data are obtained from the Centre for Research in Security Prices (CRSP). We form an equally weighted green portfolio consisting of four clean energy ETFs and an equal-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 the clean energy ETFs (ICLN, PBW, QCLN, PBD) 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, their paired correlation coefficients are well above 90%. However, the correlations of these ETFs with KOL are lower, 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 June 2008 to December 2020.[6] 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. There are 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, respectively.

[Table 1 about here]

3.3 Conditional testing procedure

We examine the assertions of Pástor et al. (2021) by adopting the multivariate inequality constraints approach proposed by Wolak (1987, 1989). This approach provides a rigorous test for validating the priori signs of the parameters to be estimated, where such a priori beliefs point to an inequality restriction rather than an equality restriction. It allows moments to be conditioned on observable information and takes the unobservability of expected returns into account by employing instrumental variables. Wolak (1987) also illustrates how to compute critical values for a small sample size (refer to Lemma 4.1 and Theorem 4.4); and further details the exact distributions for the various forms of the test statistic, including the covariance matrix of errors for a small sample, and demonstrates that small sample results continue to hold (refer to Section 6 of Wolak (1987)).

The conditional test with multivariate inequality constraints has several attractive features as demonstrated by Boudoukh et al. (1993), which study the market annual risk premium. First, this approach does not require a model for conditional expectations. This is especially

[6] Our sample starts from 2008 due to most of the green energy ETFs data available from June 2008.

important because most asset pricing theories do not explicitly model conditional expectations. 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. Indeed, while the existing studies use a linear model, the relationship between climate-related variables and returns is unknown. Therefore, this non-parametric approach is advantageous because it does not require an assumed functional form nor the conditional distribution of data to be tested. Third, the restrictions can be tested jointly, meaning that the test incorporates any correlations across the mean estimators. For example, natural disasters and climate policy could be correlated. Therefore, the approach makes the results more robust.

In contrast to other commonly used approaches, such as t-test and F-test, which require strong assumptions on the data distribution, and often require a large sample size; regression methods require assumptions of linear relationship, normality of residuals, and homoscedasticity. Other alternative non-parametric methods, such as the Mann-Whitney U test and the Kruskal-Wallis test, both are unconditional approaches that generally test for equality rather than inequality; and are less powerful for detecting specific types of differences with smaller sample sizes. Other conditional tests use Bayesian approaches, which require the specification of prior distributions, and their results are typically presented in terms of posterior probabilities, which are not intuitive to communicate and interpret, especially when dealing with multiple inequality constraints. See Klugkist and Hoijtink (2007), Van West, et. al, (2011) for details. Most of the Bayesian approaches involve computational complexity and convergence issues. Of particular interest, the inequality approach by Wolak (1987, 1989) is easy to implement and results are intuitive to interpret.

We consider a model that implies the following null hypothesis:

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

where $R_{\text{brown},t+1}$ and $R_{\text{green},t+1}$ are brown (fossil) and green (clean energy) portfolio returns, respectively, 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

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

Eq. (4) provides a set of moment conditions for which the econometrician needs to estimate the vector of parameters θ_{Dz^+}. The attractiveness of this approach is that, it does not matter if D_t is observable or not, because the vector of observables ($R_{\text{brown},t+1}$, $R_{\text{green},t+1,}$, z_t^+) is enough to identify θ_{Dz^+}. Since we have two instruments, we expand the restrictions given in Eqs. (4) and (5) as a system of 2-moment conditions:

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

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

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

We calculate the unrestricted estimate (sample mean) and the restricted estimate nonnegative under the null by using a 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 outlined in Appendix A1.

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

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

where x_{it} is the number of natural disasters and the 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 magnitudes. For the magnitude-based instrument, we define it as

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

The instruments are normalized as $z_{it}^{+} = z_{it}^{*}/E[z_{it}^{*}]$ 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. The detailed procedure of conducting the inequality test is provided in Appendix A1.

We also apply the inequality tests for market betas, semibetas, and idiosyncratic risks. 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 examine whether we can reject the null that green-minus-brown risk metrics are nonnegative (if we can reject the null, we conclude that the brown portfolio is riskier than the green portfolio conditional on the climate-related instruments).

4 Empirical findings

4.1 Unconditional comparisons

We first examine the unconditional tests of portfolio returns including risk-adjusted returns estimated from the CAPM and Carhart four-factor model with oil returns, the results are presented in Table 2. At first glance, the green portfolio raw return is insignificantly positive, and the brown portfolio raw return is insignificantly negative. It appears both risk-adjusted returns of the brown portfolio are significantly negative. We are more interested in the difference between the two portfolios as it is more important to our understanding of the underlying issue. Although Table 2 implies a marginal rejection ($p = 0.083$) of nonnegativity for the mean difference between the raw returns (i.e., brown-minus-green mean return), 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 disparities between the green and brown portfolios' market betas, realized semibetas, and idiosyncratic risks, respectively. First of all, we cannot reject the null that the market beta of the green portfolio is greater than or equal to that of the brown portfolio. This implies that the brown portfolio does not have a higher systematic risk than the green portfolio under an unconditional setting. If we further look into the covariation with the market by separately considering negative and positive returns, i.e., examining the covariance between the negative (positive) returns of the portfolios and the negative (positive) returns of the market that is denoted by $\hat{\beta}^N$ ($\widehat{\beta}^P$), the unconditional test indicates that $\hat{\beta}^N_{brown}$is not higher than $\hat{\beta}^N_{green}$ (we cannot reject the null that the $\hat{\beta}^N_{green}$ is greater than or equal to $\hat{\beta}^N_{brown}$). Since $\hat{\beta}^N$measures the risk during the market downturn, this unconditional comparison implies that the brown portfolio is less volatile than the green portfolio in market downturn periods. For the idiosyncratic risk comparison, we reject the null that the idiosyncratic risk of the "green" portfolio is higher than or equal to that of the "brown" portfolio at the 1% level, which implies that the brown portfolio has unconditionally higher idiosyncratic volatility than the green portfolio. The bottom of the table reports the result for the fund flow, we find weak evidence that green ETFs attract more inflows compared to the brown portfolio at the 10% significant level.

[Insert Table 2 Here]

4.2 Conditional testing on portfolio returns

We use CAPM-adjusted returns to test the first hypothesis. Panel A of 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. Thus, we can jointly reject the null that the brown-minus-green return is greater than or equal to zero in conditional tests using magnitude-based instruments at the 5% level of significance. Indeed, when we change from dummy instruments to magnitude-based instruments, the brown-minus-green mean difference becomes more negative. For example, conditional on natural disasters, it decreases from -1.002 to -1.423%. Similarly, conditional on Climate Policy Uncertainty (CPU), it decreases from -1.562 to -3.738%. In contrast to pertinent results in Table 2, we find convincing evidence of the outperformance of the green portfolio to the brown portfolio by taking the magnitude of instruments into account.

Columns 3, 4, 6, and 7 in Panel A of Table 3 present results of testing whether the returns of brown and green portfolios are nonnegative conditional on climate-related instruments. We can reject the null that the brown portfolio's mean return is nonnegative, which is consistent with the unconditional test. The multiple statistics are significant at the 1% level. Compared to the unconditional mean returns of -1.552%, incorporating instruments makes the brown portfolio returns more negative, i.e., conditional mean returns are -2.371% and -2.477% associated with natural disasters and CPU when using magnitude-based instruments. In contrast, the result of green portfolio returns based on our conditional tests are not statistically negative. Indeed, we cannot reject the green portfolio returns are nonnegative (p-values of these tests are 0.218 and 0.210 for dummy and magnitude-based instruments, respectively). This is in sharp contrast to the green portfolio's unconditional risk-adjusted return documented in Table 2, which is significantly negative. The return differences between these two portfolios are more clearly visible in Figure 1. Conditional returns for the brown portfolio returns are more negative than its unconditional return. While we cannot reject the nonnegativity of the green portfolio's return conditional on natural disasters, its mean return conditional on CPU is positive, with a value of 1.261%.

Furthermore, we reconstruct instruments by using the 75th percentile as the threshold instead of the median. In other words, the new instruments capture a higher number of natural disasters and CPU levels. Panel B of Table 3 displays the conditional tests with these 75th percentile threshold instruments, and the results are statistically significant at the 5% level. We also observe that the results are 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. For magnitude-based instruments results, brown-minus-green returns are -2.089 % and -4.335% associated with natural disasters and CPU. Compared to the existing studies assume a linear relationship between climate change news and asset returns (Ardia et al., 2022; Pástor et al., 2022), we report the effect of climate information is not uniform and values above the 75th percentile have a more significant impact on the performances of green and brown portfolios.

In general, conditional tests on CAPM-adjusted returns support our first hypothesis that the green portfolio has a higher return than the brown one conditional on climate-related instruments. In addition, the results show the significant impact of CPU on green and brown portfolio 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 the green portfolio relative to the brown one, but also a positive mean return of the green portfolio during high CPU. The results confirm that holding a green portfolio pays off when climate risks are realized. In contrast, the brown portfolio's returns are statistically and economically negative during high climate risks. In addition to providing 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 Conditional testing on the market beta and semibetas

For the second hypothesis, we begin by testing the null that the market beta of the green portfolio is greater than or equal to that of the brown portfolio, and results are reported in Table 4. Specifically, market betas are estimated based on the CAPM with a 36-month rolling window of regressions. 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, and these results infer that the brown portfolio has higher market betas than the green portfolio after conditioning instruments. This is in contrast to the unconditional study where the brown portfolio's market beta is not higher than the green portfolio's.

Similar to the comparisons of return performances, the tests conditional on magnitude-based instruments present more significant results than those of the dummy-based tests, and the beta difference varies from 0.004 to -0.027 for the natural disaster instrument and from -0.118 to -0.245 for the CPU instrument. Figure A2.1 (Appendix) shows changes in market betas when we include climate-related instruments. As can be seen, when conditioning instruments related to natural disasters and especially CPU, the increment in the market beta of the brown portfolio is higher than that of the green portfolio.

Overall, our results support hypothesis 2a that the brown portfolio has a higher market beta 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 the 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]

Table 5 reports the results of inequality tests on the null that the green portfolio has higher semibetas than the brown portfolio. We focus on $\hat{\beta}^N$ (covariance between negative portfolio returns and negative market returns) since investors care more about downside variations, and the downside beta can better explain the cross-sectional variation in asset returns and provides superior predictions in the presence of leverage effects, as conjectured in Ang et al., (2006) and Bollerslev et al. (2021). Specifically, Bollerslev et al. (2021) find that the correlation with the market downturns appears to carry a significant risk premium. 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, which implies the brown portfolio has a higher $\hat{\beta}^N$ than the green portfolio. In other words, conditioning on climate instruments, the brown portfolio has greater correlation with market during market downturns.

Here we again find the opposite result of the unconditional comparisons in Table 2 which indicates that the brown portfolio does not have a higher $\hat{\beta}^N$ than the green one. When conditioning on magnitude-based instruments, absolute values of the difference are 0.032 and 0.104 associated with natural disasters and CPU. The $\hat{\beta}^N$ difference becomes prominent because of the decrease in $\hat{\beta}^N$ of the green portfolio during high CPU. Figure A2.2 (Appendix) also shows that the conditional mean of $\hat{\beta}^N_{t,i}$ of the green portfolio tends to be lower compared to the unconditional mean in the states of high CPU. These results are therefore supportive of the argument of Giglio et al. (2021) that climate shocks could negatively affect the market but favor green assets because of their ability to hedge climate risks.

Furthermore, the brown portfolio has a higher $\hat{\beta}^{M^+}$ (positive market returns and negative portfolio returns covariation) and does not have a higher $\hat{\beta}^P$ (positive market returns and positive portfolio returns covariation) than the green portfolio. Interestingly, using magnitude-based instruments, the brown portfolio does not have a higher $\hat{\beta}^{M^-}$(the negative market return and positive portfolios returns covariation) than the green portfolio, which contradicts the unconditional comparison in Table 2. In other words, when conditioning magnitude-based instruments, the brown portfolios' ability to hedge against market downturns is not superior to green portfolios. Overall, the results imply that the brown portfolio has higher downside risks than the green one during periods of high natural disasters and especially CPU.[7] Therefore, if investors are averse to downside risk, they will not hold brown assets when climate risks are realized.

[Insert Table 5 Here]

[7] Results are more statistically and economically significant with 75th percentile instruments. Those are reported in Appendix A2 (Table A2.2-A2.3).

4.4 Conditional testing on idiosyncratic volatilities

The empirical existence of a positive/negative relationship between idiosyncratic risk and returns has been tested and debated for more than a decade, c.f Campbell, et al., 2001; Ang, et al., 2006. To understand which portfolios might be more prone to specific asset-related risks rather than market-wide movements, we move to study our third hypothesis and focus on the comparisons of idiosyncratic volatilities of green and brown portfolios, which are conventionally calculated as the standard deviation of residuals from the CAPM model. Table 6 demonstrates that the multiple inequality testing rejects the null that the idiosyncratic volatility of the green (clean) portfolio is higher than or equal to that of the brown (fossil) portfolio at the 1% level for dummy and magnitude-based instruments. Their 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 A2.3 (Appendix) shows how instruments affect the idiosyncratic risks of green and brown portfolios, i.e., conditional on climate related 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 portfolio's 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.[8]

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 higher idiosyncratic risk of the brown portfolio is plausible, for example, 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]

[8] Results are more statistically and economically significant with 75th percentile instruments. Those are reported in Appendix A2 (Table A2.4).

5 Further results and robustness checks

5.1 Non-fundamental demands for brown and green ETFs

Pástor et al. (2021) indicate that climate shocks lead to an increase in the demand for green assets, which makes green assets outperform brown ones. Therefore, we test whether green ETFs' flows are higher than brown ETFs' flows conditional on climate instruments. In addition, Brown et al. (2021) and Davies (2022) find that ETF fund flows signal non-fundamental demand for assets. We define ETF fund flows as the percentage change in ETF shares outstanding for fund i at time t denoted by $SO_{i,t}$

$$ETF\ Flow_{i,t} = \frac{SO_{i,t}}{SO_{i,t-1}} - 1 \tag{9}$$

and run the following time-series regression

$$ETF\ Flow_{i,t} = a_t + \gamma_t C_{t-1} + \epsilon_{i,t} \tag{10}$$

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

$$Unexpected\_ETF\ Flow_{i,t} = ETF\ Flow_{i,t} - \gamma_t C_{t-1} \tag{11}$$

We take the average of green and brown ETFs' unexpected flows as measures for greens and brown flows. We hypothesize that the green flow is higher than the 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 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. [9]

We observe that the difference between the brown and green portfolios is broader when changing from dummy to magnitude-based instruments. Indeed, the absolute value of the difference increases from 0.026 to 0.032 conditional on natural disasters and from 0.063 to 0.114 conditional on CPU. Using magnitude-based instruments results in a strong rejection of the brown-minus-green flow being nonnegative. Specifically, Figure 2 shows, that during periods of a high number of natural disasters, the brown flow is negative (-0.01). Also, during

[9] Results are statistically and economically significant with 75th percentile instruments. Those are reported in Appendix A2 (Table A2.5).

periods of high CPU, we have a high green flow, while the brown flow appears unchanged. Compared to unconditional green flow (0.05), the green ETF flow conditional on CPU is 0.13.

The result of higher unexpected green flow implies that climate-related information significantly affects the demand for green and brown assets. These results support Pástor et al. (2021)'s argument. In addition, Davies (2022) finds that ETF flows provide information about the non-fundamental demand signaling investor sentiment. Therefore, the conditional tests on fund flows explain the outperformance of the green portfolio reported in Section 3.

[Insert Table 7 Here]

[Insert Figure 2 Here]

5.2 Conditioning on bad economic periods

In this section, we use economic instruments to examine whether our results are driven by particular economic conditions instead of climate-related information. One argument is that the underperformance of the brown portfolio might be due to low demands for fossil fuel energy during bad economic periods. Following Bansal et al. (2022), the good-times indicator is defined by cyclically-adjusted real P/E (CAPE), and a bad time indicator is defined by the National Bureau of Economic Research (NBER) recessions, and we use CAPE ratios and NBER-based recessions to construct nonnegative instruments related to bad economic periods as follows

$$z^*_{CAPEt} = \begin{cases} 1 & if\ CAPE_{it} < \ CAPE^{median}\ (based\ on\ 10\ year\ rolling) \\ 0 & otherwise \end{cases} \tag{12}$$

$$z^*_{NBERt} = \begin{cases} 1 & if\ NBER\ recession = 1 \\ 0 & otherwise \end{cases} \tag{13}$$

Similar to climate instruments, we normalize economic instruments. Also, we construct a magnitude-based instrument for CAPE as max $[0, -(CAPE_t - CAPE^{median})]$. Panel A of Table 8 provides results of conditional tests based on economic 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 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 cannot reject that null that the brown mean return is nonnegative during bad economic periods.

Therefore, climate-related instruments are more informative about the outperformance of the green portfolio relative to the brown one.

Panel B of Table 8 provides conditional test results by using climate-related instruments during NBER-based economic recessions. For example, for the dummy instrument, it takes the value of 1 if both natural disasters (CPU) > its median and NBER-based recession = 1, and zero otherwise. We also construct magnitude-based instruments by analogy. 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. Overall, we find that the green portfolio outperforms the brown one in the conditional test with magnitude-based instruments. Indeed, brown-minus-green returns are more negative when switching from dummy to magnitude-based instruments as they are -3.167% and -3.584% for dummy instruments and -5.689% for magnitude-based instruments. In addition, when conditioning instruments, green (brown) returns are positive (negative). Compared to the results in Table 3, the return differences are much wider. This indicates that the outperformance of the green portfolio relative to the brown one is more pronounced when climate risks are high, and also the economy is in recession.

[Insert Table 8 Here]

5.3 Controlling for Carhart four factors and oil returns

For a further robustness check, we use returns adjusted by Carhart four factors and oil returns. The results reported in Table 9 are consistent with those in Table 3. Specifically, we find persuasive evidence that the green portfolio return is higher than the brown portfolio in the conditional test with magnitude-based instruments as the test statistic is 3.050 and significant at the 5% level. Moreover, we reject the null that the brown portfolio has a nonnegative mean return conditional on instruments but cannot reject the null that the green portfolio has a nonnegative mean return.

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 climate-related instruments into our tests, we again find evidence of the outperformance of green portfolios relative to brown ones and the nonnegative mean return of green portfolios. Overall, our main findings are still robust when controlling for more factors adjusted returns.[10]

[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 the median cost in the sample. We replicate studies in Table 3 by using the new instruments, whose results are reported in Table 10. As can be seen, they are qualitatively similar to the main findings reported in Table 3, i.e., we can reject the null that brown-minus-green returns are nonnegative (the green portfolio outperforms the brown one). We also find that brown (green) portfolio returns are negative (positive) conditional on the new climate-related instruments. Overall, our results are still robust with alternative measurements in constructing the climate risk related instruments.

[Insert Table 10 Here]

6 Concluding remarks

The evidence of green and brown assets performances is becoming intriguing in empirical finance with debatable findings. This paper provides rigorous comparisons of green and brown portfolios constructed from clean and fossil energy ETFs. We study the portfolio returns performances and the associated risk measurements by using multiple inequality tests. We present novel evidence under conditional settings using natural disasters and the climate policy uncertainty (CPU) index as instrumental variables.

We find that the green portfolio outperforms the brown portfolio conditioning climate-related information, while this outperformance is not significant in unconditional tests. In addition, we find that green the (brown) portfolio yields positive (negative) returns during periods of high natural disasters and CPU. Our results also show that the brown portfolio has a higher market beta, and we further report that the brown portfolio's higher systematic risk is mainly due to downside covariations (higher downside semibeta), which is not found in unconditional comparisons. Interestingly, we show that the effects of climate information on

[10] Results with the raw returns and adjusted returns (4FF+oil returns) using instruments based on 75th percentile are qualitatively the same, as reported in Appendix A2 (Table A2.6 and A2.7)

inequality tests are not uniform, i.e., when using the instruments based on higher thresh hold values the effects are more pronounced.

We provide further evidence that unexpected fund flow into the green ETFs is higher than the brown ETFs conditional on climate instruments, this finding contributes to explaining the outperformance of the green portfolio relative to the brown one. Through the robustness checks, we have confirmed that our findings are not driven by economic cycles, alternative instruments and specifications. Our study reveals the state dependence of green and brown assets' returns and risks. The results emphasize the impact of climate-related information on investment decisions and have important implications for investors constructing portfolio allocations when hedging climate change risks. We hope to explore the hedging implication in future research.

References:

Albuquerque, R., Koskinen, Y., & Zhang, C. (2019). Corporate Social Responsibility and Firm Risk: Theory and Empirical Evidence. *Management Science*, *65*(10), 4451–4469.

Alekseev, G., Giglio, S., Maingi, Q., Selgrad, J., & Stroebel, J. (2022). A Quantity-Based Approach to Constructing Climate Risk Hedge Portfolios. Working Paper.

Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2022). Climate Change Concerns and the Performance of Green Versus Brown Stocks. *Management Science, Forthcoming*.

Avramov, D., Cheng, S., Lioui, A., & Tarelli, A. (2021). Sustainable investing with ESG rating uncertainty. *Journal of Financial Economics*.

Bai, H., Hou, K., Kung, H., Li, E. X. N., & Zhang, L. (2019). The CAPM strikes back? An equilibrium model with disasters. *Journal of Financial Economics*, *131*(2), 269–298.

Baker, S. D., Hollifield, B., & Osambela, E. (2022). Asset Prices and Portfolios with Externalities. *Working Paper*.

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593–1636.

Bansal, R., Kiku, D., & Ochoa, M. (2016). Price of Long-Run Temperature Shifts in Capital Markets. *Working Paper*.

Bansal, R., Wu, D. (Andrew), & Yaron, A. (2022). Socially Responsible Investing in Good and Bad Times. *The Review of Financial Studies*, *35*(4), 2067–2099.

Barnett, M. L., & Salomon, R. M. (2006). Beyond dichotomy: The curvilinear relationship between social responsibility and financial performance. *Strategic Management Journal, 27(11)*, 1101–1122.

Bollerslev, T., Li, J., Patton, A. J., & Quaedvlieg, R. (2020). Realized Semicovariances. *Econometrica*, *88*(4), 1515–1551.

Bollerslev, T., Patton, A. J., & Quaedvlieg, R. (2021). Realized semibetas: Disentangling "good" and "bad" downside risks. *Journal of Financial Economics*.

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517–549.

Boudoukh, J., Richardson, M., & Smith, T. (1993). Is the ex-ante risk premium always positive?: A new approach to testing conditional asset pricing models. *Journal of Financial Economics*, *34*(3), 387–408.

Briere, M., & Ramelli, S. (2022). Green Sentiment, Stock Returns, and Corporate Behavior. Working Paper.

Brown, D. C., Davies, S. W., & Ringgenberg, M. C. (2021). ETF Arbitrage, Non-Fundamental Demand, and Return Predictability. *Review of Finance*, *25*(4), 937–972.

Carhart, M. M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, *52*(1), 57–82.

Chava, S. (2014). Environmental Externalities and Cost of Capital. *Management Science*, *60*(9), 2223–2247.

Choi, D., Gao, Z., & Jiang, W. (2020). Attention to Global Warming. *The Review of Financial Studies*, *33*(3), 1112–1145.

Davies, S. W. (2022). Speculation Sentiment. *Journal of Financial and Quantitative Analysis*, 1–31.

El Ghoul, S., Guedhami, O., Kwok, C. C. Y., & Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital? *Journal of Banking & Finance, 35(9)*, 2388–2406.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging Climate Change News. *The Review of Financial Studies*, *33*(3), 1184–1216.

Gavriilidis, K. (2021). Measuring Climate Policy Uncertainty. *Working paper.*

Geczy, C. C., Stambaugh, R. F., & Levin, D. (2021). Investing in Socially Responsible Mutual Funds. *The Review of Asset Pricing Studies*, *11*(2), 309–351.

Giglio, S. Maggiori, M. Rao, K,. Stroebel, J. Weber, A. (2021). Climate change and long-run discount rates: evidence from real estate. *Review of Financial Studies*, 34(8):3527–71

Giglio, S., Kelly, B., & Stroebel, J. (2021). Climate Finance. *Annual Review of Financial* Economics, 13(1), 15–36.

Goldsmith-Pinkham, P. Gustafson, M. Lewis, R. Schwert, M. (2019). Sea level rise and municipal bond yields. SSRN Work. Pap. 3478364

Guenster, N., Bauer, R., Derwall, J., & Koedijk, K. (2011). The Economic Value of Corporate Eco-Efficiency. *European Financial Management*, *17(4)*, 679–704.

Hamilton, S., Jo, H., & Statman, M. (1993). Doing Well While Doing Good? The Investment Performance of Socially Responsible Mutual Funds. *Financial Analysts Journal*, *49(6)*, 62–66.

He, M., & Zhang, Y. (2022). Climate policy uncertainty and the stock return predictability of the oil industry. Journal of International Financial Markets, Institutions and Money, 81, 101675.

Heinkel, R., Kraus, A., & Zechner, J. (2001). The Effect of Green Investment on Corporate Behavior. *The Journal of Financial and Quantitative Analysis*, *36(4)*, 431–449.

Hong, H. Li, FW. Xu, J. (2019). Climate risks and market efficiency. *Journal of Econometrics*. 208(1):265–81

Hsu, P.-H., Li, K., & Tsou, C.-Y. (2022). The Pollution Premium. *Journal of Finance, Forthcoming*.

Huynh, T. and Xia, Y. (2021). Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis*.56(6):1985–2009

Kapfhammer, F. Larsen, V. Thorsrud, LA. (2020). Climate risk and commodity currencies. Preprint, submitted December 20, http://dx.doi.org/10.2139/ ssrn.3754679.

Kempf, A., & Osthoff, P. (2007). The Effect of Socially Responsible Investing on Portfolio Performance. *European Financial Management*, *13(5)*, 908–922.

Kodde, D. A., & Palm, F. C. (1986). Wald Criteria for Jointly Testing Equality and Inequality Restrictions. *Econometrica*, *54*(5), 1243–1248.

Klugkist, I. H. Hoijtink, (2007). The Bayes factor for inequality and about equality constrained models. Computational Statistics & Data Analysis, Vol 51, 6367-6379.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The Importance of Climate Risks for Institutional Investors. *The Review of Financial Studies*, *33*(3), 1067–1111.

Lanfear, M. G., Lioui, A., & Siebert, M. G. (2019). Market anomalies and disaster risk: Evidence from extreme weather events. *Journal of Financial Markets*, *46*, 100477.

Lee, D. D., & Faff, R. W. (2009). Corporate Sustainability Performance and Idiosyncratic Risk: A Global Perspective. *Financial Review*, *44*(2), 213–237.

Li, D., Wu, Z., & Tang, Y. (2024). Do climate risks affect dirty–clean energy stock price dynamic correlations? *Energy Economics*, *136*, 107713.

Luo, H. A., & Balvers, R. J. (2017). Social Screens and Systematic Investor Boycott Risk. *Journal of Financial and Quantitative Analysis, 52(1)*, 365–399.

Ma, R., Marshall, B. R., Nguyen, H. T., Nguyen, N. H., & Visaltanachoti, N. (2022). Climate events and return comovement. *Journal of Financial Markets,* 100731.

Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *The Journal of Finance, 42(3),* 483–510.

Newey, W. K., & West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, *55*(3), 703–708.

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, *142*(2), 550–571.

Pástor, Ľ., Stambaugh, R. F., & Taylor, L. A. (2022). Dissecting green returns. *Journal of Financial Economics*, *146*(2), 403–424.

Pedersen, L. H., Fitzgibbons, S., & Pomorski, L. (2020). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics.*

Pham, L., Hao, W., Truong, H., & Trinh, H. H. (2023). The impact of climate policy on U.S. environmentally friendly firms: A firm-level examination of stock return, volatility, volume, and connectedness. *Energy Economics, 119,* 106564.

Ramelli, S., Ossola, E., & Rancan, M. (2021). Stock price effects of climate activism: Evidence from the first Global Climate Strike. *Journal of Corporate Finance*, *69*, 102018.

Sharfman, M. P., & Fernando, C. S. (2008). Environmental risk management and the cost of capital. *Strategic Management Journal*, *29*(6), 569–592.

Siddique, Md. A., Nobanee, H., Hasan, Md. B., Uddin, G. S., Hossain, Md. N., & Park, D. (2023). How do energy markets react to climate policy uncertainty? Fossil vs. renewable and low-carbon energy assets. *Energy Economics, 128,* 107195.

Statman, M. (2000). Socially Responsible Mutual Funds. F*inancial Analysts Journal, 56(3),* 30–39.

Statman, M., & Glushkov, D. (2009). The Wages of Social Responsibility. *Financial Analysts Journal, 65(4),* 33–46.

Trinks, A., Scholtens, B., Mulder, M., & Dam, L. (2018). Fossil Fuel Divestment and Portfolio Performance. *Ecological Economics*, *146*, 740–748.

Tsai, J., & Wachter, J. A. (2016). Rare Booms and Disasters in a Multisector Endowment Economy. *The Review of Financial Studies*, *29*(5), 1113–1169.

van Benthem, A. A., Crooks, E., Giglio, S., Schwob, E., & Stroebel, J. (2022). The effect of climate risks on the interactions between financial markets and energy companies. *Nature Energy*, *7*(8), Article 8.

Van West, F., H. Hoijtink, and I. Klugkist, (2011). Choosing Priors for Constrained Analysis of Variance: Methods Based on Training Data. *Scandinavian Journal of Statistics*. 38(4), 666-690.

Wolak, F. A. (1987). An Exact Test for Multiple Inequality and Equality Constraints in the Linear Regression Model. *Journal of the American Statistical Association*, *82*(399), 782–793.

Wolak, F. A. (1989). Testing inequality constraints in linear econometric models. *Journal of Econometrics*, *41*(2), 205–235.

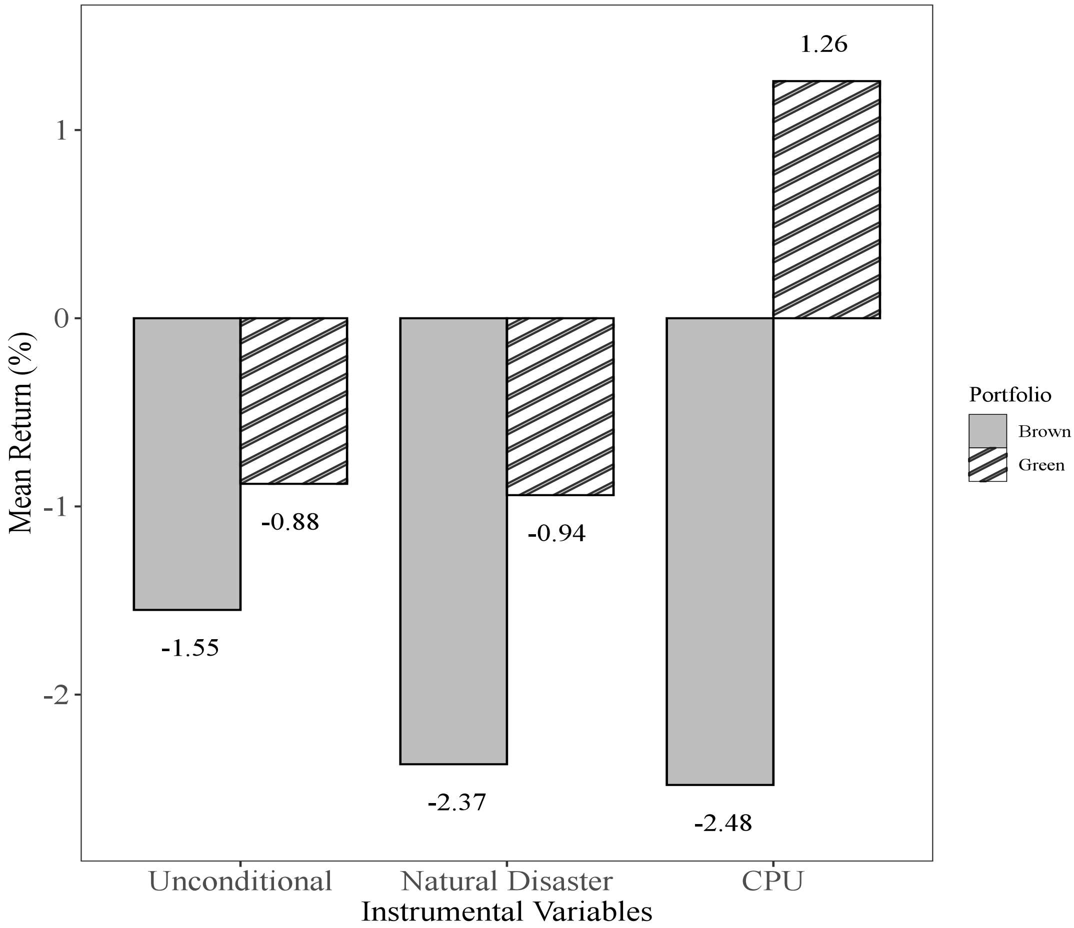

Figure 1. Unconditional mean and conditional portfolios mean returns in the period 2008-2020.
This figure plots brown and green portfolios mean returns. These portfolios are formed from fossil fuel and clean energy ETFs. Specifically, this figure includes unconditional mean and conditional means weighted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

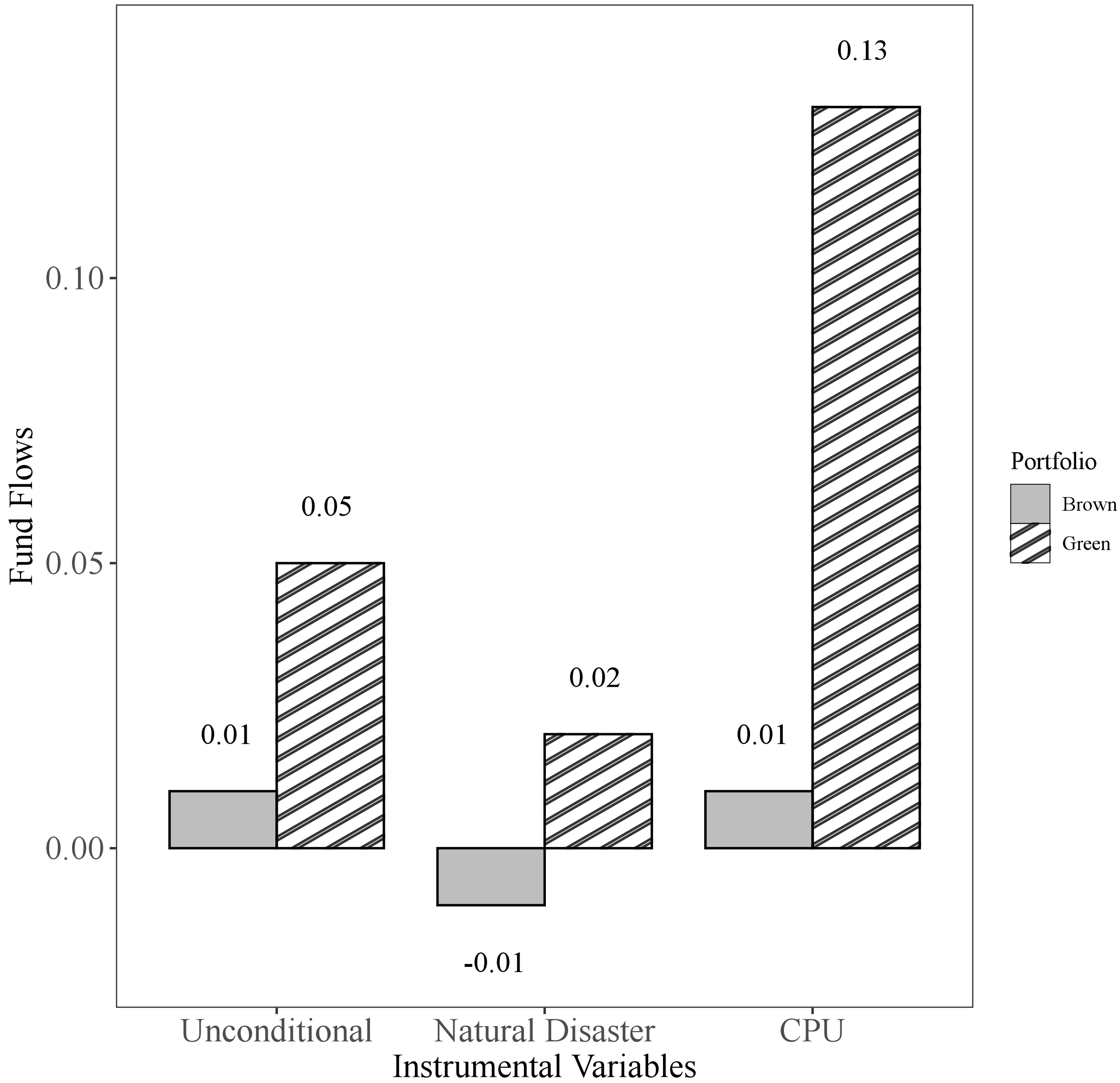

Figure 2. Unconditional mean and conditional portfolios fund flows in the period 2008-2020.
This figure plots brown and green portfolios fund flows. Brown flow is average of brown ETFs fund flows and green flow is the average of green ETFs fund flows. The figure plots the unconditional and conditional 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 ETF 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 differences between 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 the 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 was 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
$\hat{\beta}_{market,green} - \hat{\beta}_{market,brown}$	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
$Fund\ Flow_{Brown} - Fund\ Flow_{Green}$	-0.038	0.079

Table 3

Conditional difference between green and brown Returns (CAPM-adjusted return).

This 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 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) portfolio returns are nonnegative conditional on the instruments. Panel A represents tests with instruments based on median values which capture a number of natural disasters and CPU above median values. Panel B reports tests with instruments based on 75th percentile. Instruments capture the number of natural disasters and CPU above their 75th percentile. Also given are the standard errors of the conditional means. 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 number of natural disasters and CPU above their median values

Statistics	**Dummy instruments**			**Magnitude-based instruments**		
	Brown – Green	**Brown**	**Green**	**Brown – Green**	**Brown**	**Green**
Natural Disaster (Cost-based)						
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)

Panel B: Inequality tests conditional on number of natural disasters and CPU above their 75th percentile

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)

Table 4
Conditional differences of market betas

This table reports multiple inequality tests for $\widehat{\boldsymbol{\beta}}_{\boldsymbol{market}}$ 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. 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.

	Green - Brown	
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 difference in semibetas

This table provides the multiple inequality tests on the null that green-minus-brown semibetas $\geq \mathbf{0}$ conditional on a 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.

	Green - Brown							
	Dummy Instruments				**Magnitude-based Instruments**			
Statistic	$\hat{\boldsymbol{\beta}}^{\boldsymbol{N}}$	$\hat{\boldsymbol{\beta}}^{\boldsymbol{M-}}$	$\hat{\boldsymbol{\beta}}^{\boldsymbol{P}}$	$\hat{\boldsymbol{\beta}}^{\boldsymbol{M+}}$	$\hat{\boldsymbol{\beta}}^{\boldsymbol{N}}$	$\hat{\boldsymbol{\beta}}^{\boldsymbol{M-}}$	$\hat{\boldsymbol{\beta}}^{\boldsymbol{P}}$	$\hat{\boldsymbol{\beta}}^{\boldsymbol{M+}}$
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 difference in idiosyncratic risk

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.

	Green - Brown	
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 difference in unexpected fund flows

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's 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.

	Brown - Green	
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 difference in CAPM-adjusted returns with economic instruments

This 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 a 10-year rolling window. Panel A reports the results conditional on instruments indicating bad economic periods, and Panel B reports the results conditional on the 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 a high number of Natural disasters and high CPU during recessions.						
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 difference in returns Adjusted by the Carhart four factors and oil returns

This table reports multiple inequality tests 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 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) 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 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

The conditional difference in CAPM-adjusted returns (with alternative instruments)

This 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 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. 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.

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)

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,

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

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:

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

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:

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

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

Wolak (1989) indicates that calculating the weights $w\left(N, N-k, \frac{\widehat{\Omega}}{T}\right)$ 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:

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

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

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

Appendix A2:

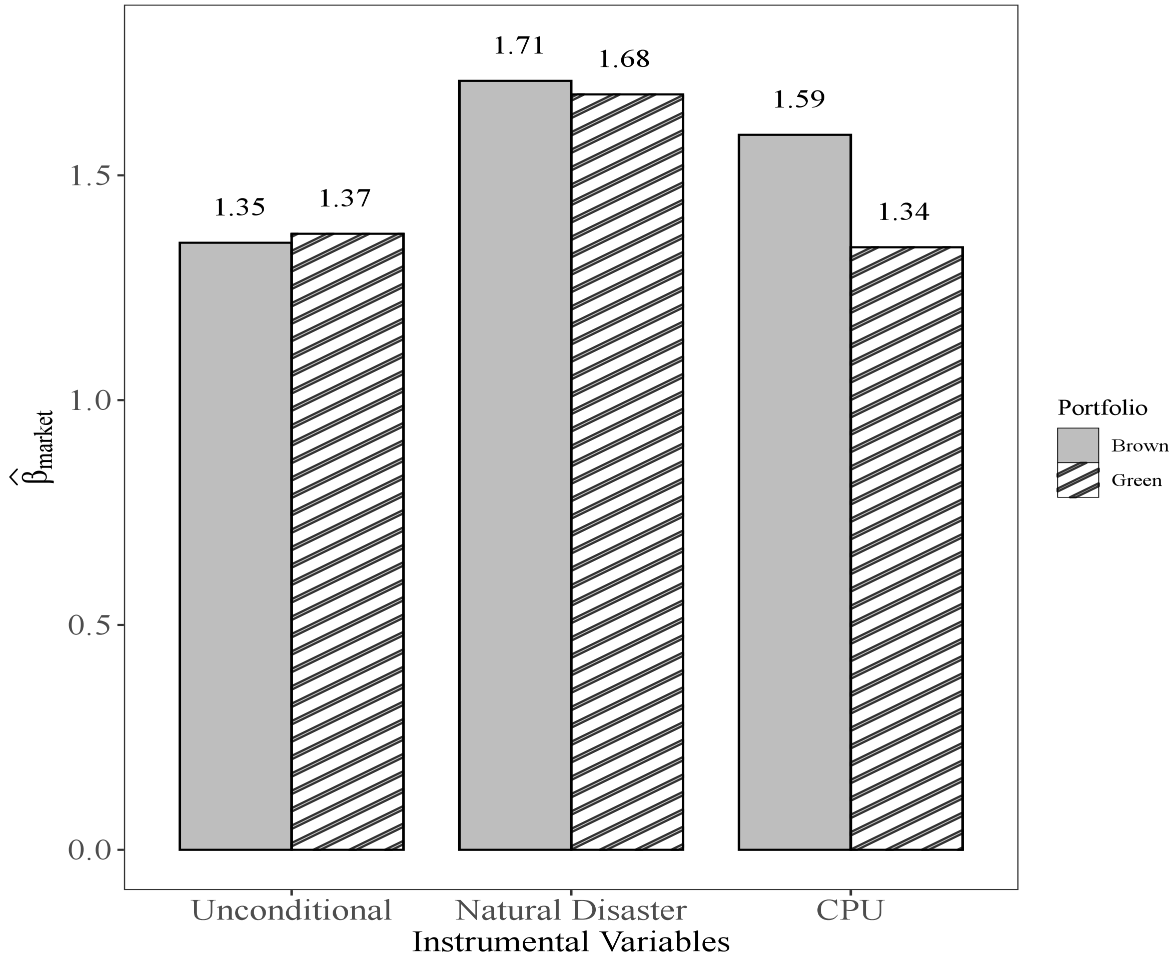

Figure A2.1. Unconditional and conditional portfolios $\widehat{\boldsymbol{\beta}}_{market}$ in the period 2008-2020.
This figure plots brown and green portfolios mean $\widehat{\boldsymbol{\beta}}_{market}$. These portfolios are formed from fossil fuel and clean energy ETFs. Specifically, this figure includes unconditional mean and conditional mean $\widehat{\boldsymbol{\beta}}_{market}$ weighted by the magnitude of number of natural disasters and Climate Policy Uncertainty (CPU).

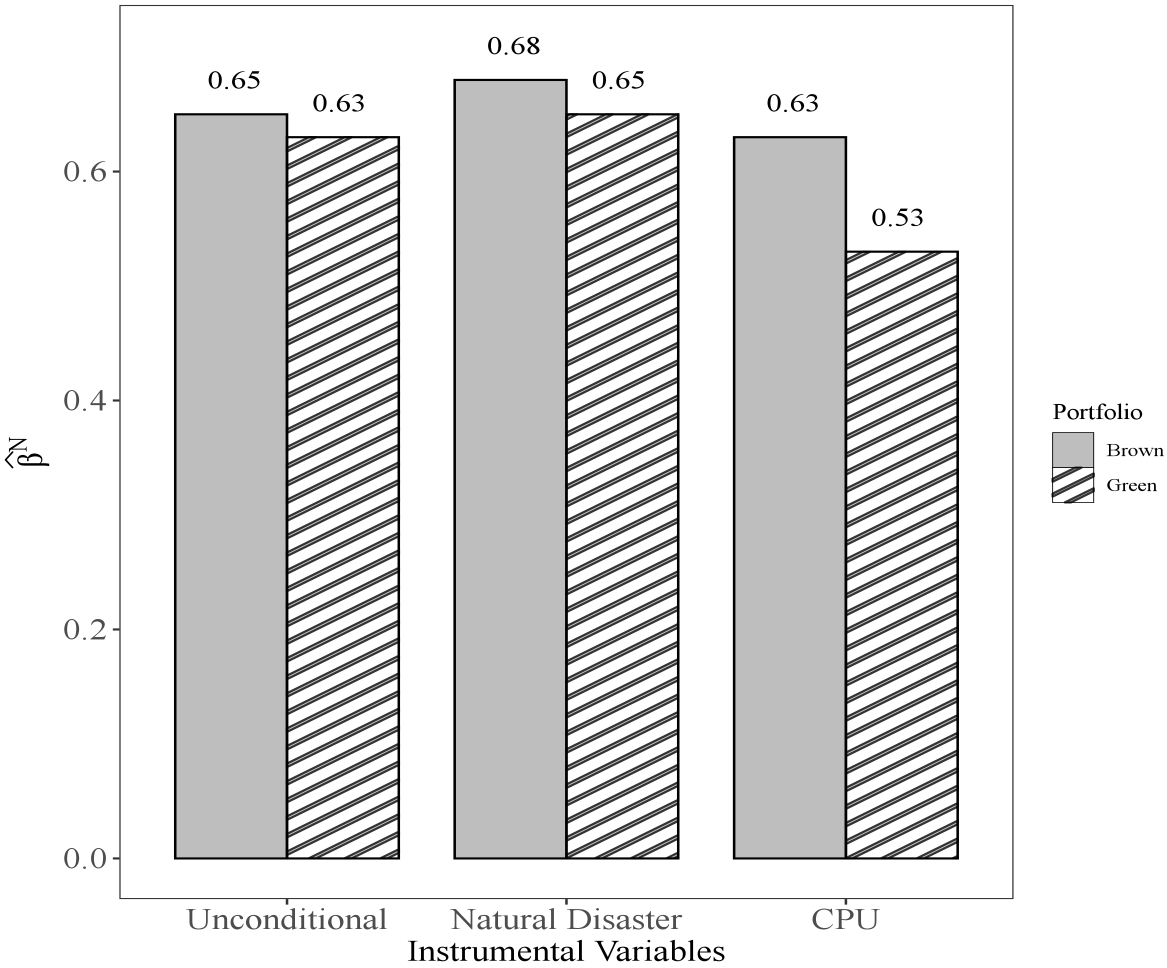

Figure A2.2. Unconditional and conditional portfolios $\widehat{\boldsymbol{\beta}}^{\boldsymbol{N}}$ in the period 2008-2020.
This figure plots brown and green portfolios mean $\widehat{\boldsymbol{\beta}}^{\boldsymbol{N}}$. These portfolios are formed from fossil fuel and clean energy ETFs. Specifically, 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).

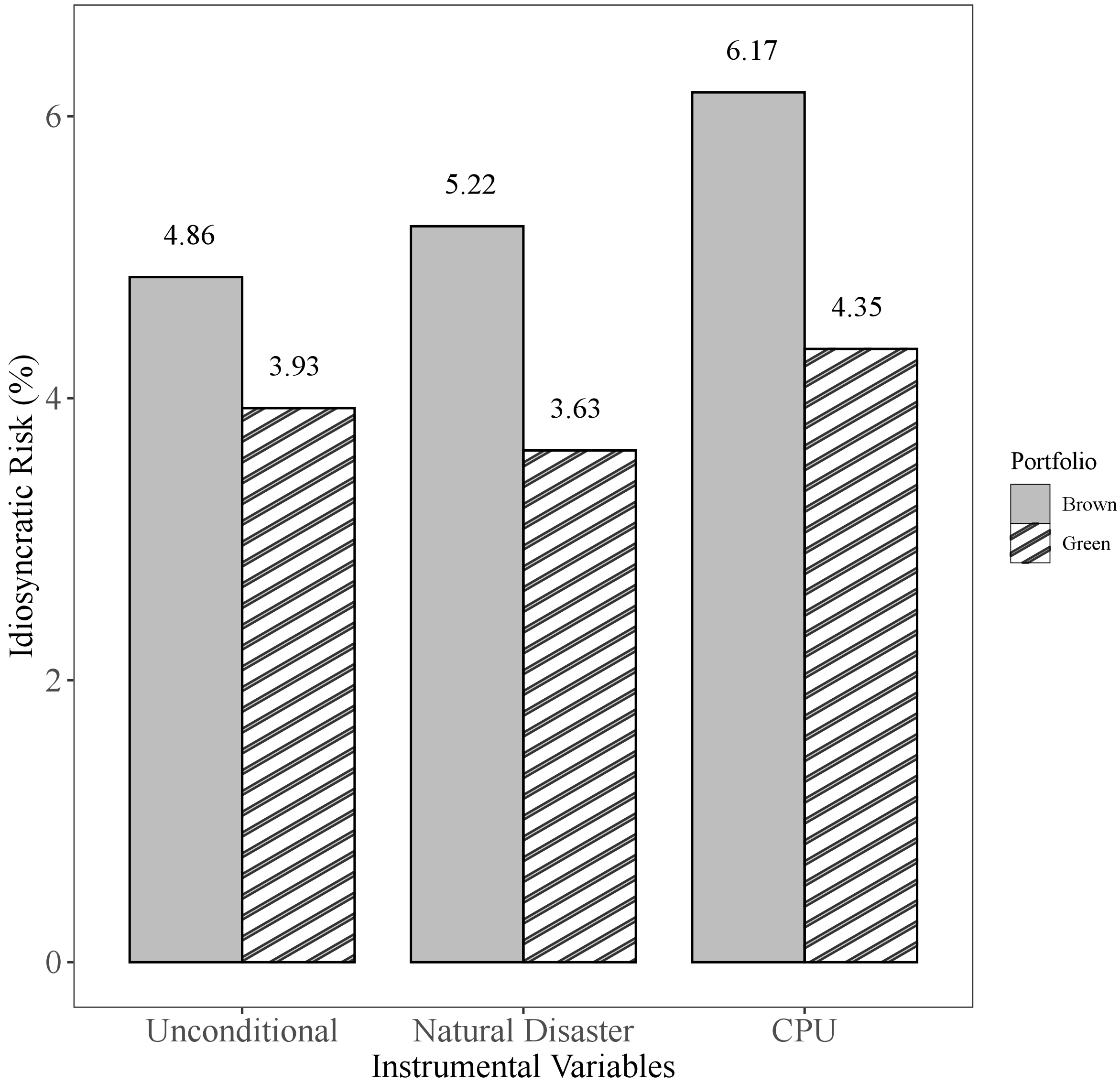

Figure A2.3. Unconditional and conditional portfolios idiosyncratic risk in the period 2008-2020.
This figure plots brown and green portfolios idiosyncratic risk. These portfolios are formed from fossil fuel and clean energy ETFs. The figure plots the unconditional and conditional idiosyncratic risk associated with magnitude-based instruments. The idiosyncratic risk is the standard deviation of residuals estimated from CAPM. The instruments include number of natural disasters and Climate Policy Uncertainty.

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)
SharesOutstanding	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