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Climate Finance PhD Workshop
National Bureau of Economic Research
Cambridge, Massachusetts

To Whom It May Concern,

I am writing to express my interest in the Climate Finance PhD Workshop hosted by NBER. I am currently a 4th year PhD Candidate in Finance at New York University Stern School of Business. My expected completion date is May 2027. I believe my research interests and past experience will allow me to meaningfully contribute to the workshop and greatly improve my research ability to aid in my dissertation writing and impact on the broader research community.

My current research projects directly concern climate sustainability and real estate resiliency. One project, co-authored with Robert Engle, investigates how we can identify sustainable companies through public stock returns. We construct hedge portfolios for specific climate-related regulation risks, including subsidies, emissions, and production regulation, and then determine which stocks co-vary positively with these portfolios. The results point to the fact that firms best poised to act as hedges and handle future climate risks are those in good financial shape in industries isolated from cyclic moves, such as healthcare. Another project in collaboration with Shan Ge examines how payments in the aftermath of flood events can affect future climate-proofing of residential homes from a moral hazard standpoint. We examine how news heard through friend networks regarding FEMA aid distributions reduces the likelihood of future climate-proofing projects at a household level, especially for homes in at-risk areas. Further, these payments buoy home prices, preventing the climate risk from fully being incorporated into real estate returns. The results speak to the unintended consequences of disaster aid.

I hope to continue to expand upon moral hazard in examining conflicts of interest in publicly listed private equity firms for my dissertation. Simply, when these asset management firms become publicly traded, they are adding additional, conflicting incentives to their business model that are in conflict with existing investors in their private funds. This is more salient recently, as there is increased discussion regarding retail investor access to the private funds. Further, the precise incentives that public listing imparts may affect their investment choices for portfolio companies, especially regarding the climate sustainability of the investments. There is significant room for development of these ideas.

Both Robert Engle and Shan Ge are willing to be references in support of this application.

I appreciate your consideration and look forward to hearing from you soon.

Best Regards,

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Education

New York University, Stern School of Business August 2022 – Present
Ph.D. Candidate in Finance

Columbia University May 2020
B.S. in Operations Research: Financial Engineering, Minor in Applied Mathematics
Cum Laude, Tau Beta Pi, GPA: 3.86

Publications

Monetary Policy, Business Liquidity and Survival: Evidence from the Refinancing Channel 2023
With Rodney Ramcharan and Haoyang Liu Review of Financial Studies

Policy Reports

VC Funds and Regulation D's Rule 506(c): Did Permitting General Solicitation Open the Door for Emerging and Underrepresented Managers? 2024
With Sabrina Howell SEC

Working Papers

Tyranny of the Personal Network: The Limits of Arm's Length Fundraising in Venture Capital 2025
With Sabrina Howell and Ting Xu R&R Journal of Finance, SSRN

Mirror, Mirror, on The Wall, Who's the Greenest of Us All? 2025
With Robert Engle Bloomberg Quant, SSRN

Does Disaster Aid Cause Moral Hazard in the Housing Market? Evidence from Climate Adaptation and Transaction Prices 2025
With Shan Ge In Progress

Code

STATA Package: twoway_pbar Github

- Patterned bar charts for STATA twoway framework

Blog Posts

The Term Spread as a Predictor of Financial Instability 2021
With Moritz Schularick FRBNY Blog Post

The Housing Boom and the Decline in Mortgage Rates 2021
With Haoyang Liu, David Lucca, and Gabriela Rays-Wahba FRBNY Blog Post, WSJ

Do People View Housing as a Good Investment and Why? 2021
With Andrew Haughwout, Haoyang Liu, and Xiaohan Zhang FRBNY Blog Post, Reuters

Research Analyst Contributions

Bhardwaj, Abhishek, Abhinav Gupta, and Sabrina T. Howell. Capital Structure & Firm Outcomes: Evidence From Dividend Recapitalizations in Private Equity (2025). *NBER Working Paper No. 33435.*

Parlatore, Cecilia, and Thomas Phillipon. Designing Stress Scenarios (2025). *Journal of Finance.*

Dávila, Eduardo, and Cecilia Parlatore. Identifying Price Informativeness (2025). *Review of Financial Studies.*

Fleming, Michael, Haoyang Liu, Rich Podjasek, and Jake Schurmeier. The Federal Reserve's Market Functioning Purchases (2021). *Federal Reserve Bank of New York Staff Report No. 998.*

Volker, Desi. The Paycheck Protection Program Liquidity Facility (2021). *Federal Reserve Bank of New York Staff Report No. 978.*

Liu, Haoyang, Zhaogang Song, and James Vickery. Defragmenting Markets: Evidence from Agency MBS (2021). *Federal Reserve Bank of New York Staff Report No. 965.*

Liu, Haoyang, and Christopher Palmer. Are Stated Expectations Actual Beliefs? New Evidence for the Beliefs Channel of Investment Demand (2021). *NBER Working Paper No. 28926.*

Bartscher, Alina K., Moritz Kuhn, Moritz Schularick, and Paul Wachtel. Monetary Policy and Racial Inequality (2021). *Federal Reserve Bank of New York Staff Report No. 959.*

Jordà, Òscar, Martin Kornejew, Moritz Schularick, and Alan M. Taylor. Zombies at Large? Corporate Debt Overhang and the Macroeconomy. *Federal Reserve Bank of New York Staff Report No. 951.*

Professional Experience

Federal Reserve Bank of New York June 2020 – August 2022
Senior Research Analyst, Capital Markets Function

- Performed research with economists Haoyang Liu, Moritz Schularick, and David Lucca for monetary policy reports and publication in academic journals and Liberty Street Economics blog.
- Maintained and improved the FRBNY MBS prepayment model in Stata and Python.
- Contributed regression and event study ideas to projects involving TRACE and eMBS data.
- Processed raw data from sources including TRACE, eMBS, and McDash.
- Conducted exploratory data analysis and visualization with techniques such as local projections.

AlphaQuest, f.k.a. Quest Partners LLC November 2019 – June 2020
Quantitative Research Intern

- Developed decision tree and gradient boosting machine learning algorithms with custom selection criteria from scratch in Python/Cython.

JP Morgan Chase & Co. June 2019 – August 2019
Summer Analyst, Market Risk, Foreign Exchange Options

- Monitored market movements in currency levels and risk reversal and butterfly option spreads to ensure awareness of market risk factors.

Mirror, Mirror, on The Wall, Who's the Greenest of Us All?[1]

Dean Parker[2] and Robert Engle[3]

Draft: July 22, 2025

Abstract

Financial assets are often exposed to long-run risks, such as physical risk or transition risk, associated with climate change. We define brown assets as those most exposed to transition risk and green assets as those for whom transition risk is an opportunity (that is, a negative risk). We develop hedge portfolios for different forms of transition risk and use them to evaluate the exposure of US stocks to these risks. The firm characteristics that explain the exposure of stocks can be based upon sector, accounting data, and ESG data. In this analysis, the most important data explaining how the market prices these risks, is sector data. ESG data on emissions is useful but most other ESG measures appear to be irrelevant.

[1] We thank Richard Berner, Ľuboš Pástor, Sujit Kapadia, and Tiffany Yong for helpful discussions and comments. We thank Brian Reis and Robert Capellini for help in sourcing data from the Volatility and Risk Institute at NYU Stern. We thank participants at the Bloomberg Quant Seminar, the European Central Bank, the Rimini Centre for Economic Analysis, the 17th annual SoFIE conference in Paris, and the 2025 QFFE conference in Marseille for helpful comments and questions.

[2] NYU Stern

[3] NYU Stern and NBER

I. Introduction

A risk is an adverse event that might occur, and if it is far in the future, it is called a long-term risk. Assets exposed to long-term risk are less desirable than other equivalent assets and consequently are less expensive and have higher expected returns. This elevation of expected returns is a risk premium that investors receive for bearing long run risk. Climate change is best thought of as a long-term risk and can be described in terms of both physical risk and transition risk. Physical risks are the risks associated with heat waves, drought, extreme storms, floods, wildfires, and the associated damages from these events. Transition risks on the other hand are the risks that develop during transition to a low carbon emission economy. These are primarily human and political risks and therefore are best understood from a financial perspective rather than earth science. These risks include, among others: potential taxes on greenhouse gas emissions, exclusion from subsidies targeting green industries, and regulations directly impacting various business operations. Of course, all of these risks are fluid and do not have sharply defined boundaries for which firms they affect, when they affect them, and to what extent the firm is able to adjust and account for the materialization of the risks.

In this paper, we construct and investigate a numerical measure for whether an asset, in our case publicly traded US equities, is "green" or "brown." We define an asset as "brown" if it is highly exposed to transition risk and as "green" if it is negatively exposed. In other words, green firms can be viewed as good hedges against transition risk, while brown firms are those more exposed to transition risk. Green firms find transition to be an opportunity rather than a risk and the green representation matches the green of chlorophyll that is a nature-based solution to climate change mitigation.

The asset pricing response to transition risk is extremely important as these prices guide investment decisions today even though the risk is in the future. To finance the green transition, it is only necessary to make it a profitable investment opportunity to get a massive flow of capital into the transition. Hence, policy decisions designed to mitigate climate change may have various effects on stocks with different characteristics and based upon these results, policies and portfolios can be optimized.

The main contribution of this paper is to consider various forms of transition risk and evaluate the impact on US equity prices. This gives a purely market-based estimate of the greenness of each stock. By letting this be a yearly regression, we get a time varying estimate of the greenness in

terms of a t-statistic for a given firm-year observation. In order to better understand why the market considers some stocks as greener than others and how this changes, we run a panel regression of the estimated t-statistic on firm characteristics. We find a strong effect of balance sheet data and sector membership on the greenness measure, but only minimal effects of ESG data. We also document that it is generally easier to identify a brown firm (high emissions, low profitability) as opposed to a less well-defined sustainably green firm. The brownest firms over our sample period are oil producers and heavy manufacturing, while the greenest are a combination of semiconductor, technology, and healthcare firms. There are significant non-linearities in which traditional balance sheet factors predict whether a firm is brown versus whether it is green.

This paper contributes to a large and growing strand of literature concerning climate and transition risks, especially related to measuring firm specific exposure to these risks. A number of studies use ESG ratings or government taxonomies to identify green stocks, assuming that these entities are able to correctly identify the appropriate companies. (Pástor, Stambaugh and Taylor 2022, De Angelis and Monasterolo 2024, Xu, et al. 2024, Cenedese, Han and Kacperczyk 2023) Others use emissions, emissions intensity, or toxic emissions intensity. (Bolton and Kacperczyk 2021, Bolton and Kacperczyk 2023, Hsu, Li and Tsou 2023) Others still also look directly at what firms say about the risks they face, both in earnings calls and SEC filings (Li, et al. 2024, Lu, et al. 2024). Van der Beck (2024) uses the revealed preferences of sustainability focused mutual funds to indicate a stock's relative greenness. Archarya et al. (2025) limit their analysis to the energy sector and identify firms that are better able to adapt (new entrants) and those that are already invested in brown energy production methods (incumbents) based on their asset development level.

There is also the existing literature on disagreement in the multitude of ESG ratings that are available to investors. Ratings produced by different providers can differ greatly from each other, and this impacts both the investors' evaluation of the firm's status and management's evaluation of the firm's progress relative to peers (Chatterji, et al. 2015, Billio, et al. 2021, Berg, Kölbel and Rigobon 2022). This study contributes by providing a methodology to evaluate firms that is separated from reported criteria and relies on the market's evaluation of the situation.

This paper also contributes to the broader literature on asset allocation and portfolio optimization and construction. Similar to "sin" stocks, as showcased in Hong and Kacperczyk (2009), "green"/sustainable investing can represent a non-pecuniary, or at least hard to quantitatively measure, constraint on portfolio choice. Pedersen et al. (2021) use ESG scores to

construct an efficient frontier that trades off Sharpe ratio and greenness of investments. The European Union maintains a taxonomy for sustainable investments as part of Article 8 to guide fund allocation decisions (EU 2020). As the stock market is forward looking, the measure we derive to measure greenness will also be forward looking. This is important for evaluation of risks which have not yet manifested. Just as accurately estimating expected excess returns and variances improves the reliability of the claimed Sharpe ratio, the more accurately the future transition risk of a given firm can be measured directly impacts the extent to which the benefit of this trade-off is understood.

Our paper follows a methodology very close to Jung, Engle, and Berner (2023). Like their study, we construct hedge portfolios, verify them against the same climate events identified by them, and estimate firm specific exposures to these hedge portfolios. They focus on quantifying the dollar value of climate risk that financial institutions face. This paper only considers the statistical relation to obtain a measurement of risk exposure and takes no stance on the true quantity of potential downside risk that firms face. While they limit their analysis to financial firms, we extend this to all non-financial US public equities that fit minimal inclusion criteria. In this way, our study in complementary as we examine the correlates of climate and transition risk exposure for non-financial US firms.

II. Data and Measurement Methodology

i. Data Sources

We use the CRSP-Compustat merge provided by WRDS with standard filters applied for share codes and exchanges.[4] This provides us with yearly balance sheet information for each firm as well as daily total returns for each firm's stock. Additionally, from Compustat we obtain the MSCI Global Industry Classification Standard (GICS) to identify the firm's industry. Likewise, Compustat in WRDS provides daily return indices for each GICS Sector as tracked by Standard & Poor's.[5]

We augment this data with environmental data from Refinitiv/LSEG, also provided through WRDS. Refinitiv tracks a number of ESG variables at the yearly frequency, including CO2

[4] Specifically, we limit to CRSP share codes 10 and 11, and stocks listed on NYSE, AMEX, and Nasdaq (exchange codes 1, 2, and 3, respectively).

[5] We use the S&P1500 versions of these portfolios.

emissions, for each firm and computes an associated score ranging from 0 to 1 for the firm based on these values. We are most concerned with the environmental score or "E-Score." The Refinitiv data is matched to the CRSP-Compustat data through both stock ticker and CUSIP. As this is not necessarily a one-to-one or stable matching, manual review was undertaken to ensure each firm is matched to the correct Refinitiv observation. In total, Refinitiv tracks 185 factors related to a firm's E-Score; however, very few of these have full coverage across all firms. As a result, we focus on the headline summary number for E-Score, the sub-scores for "Resource Use", "Innovation", and "Emissions", and total scope 1 and scope 2 CO2 emissions.

Outside of WRDS, we take a number of precomputed indices from NYU Stern's Volatility and Risk Institute and other sources. Oil returns are derived from the daily WTI price sourced from FRED (DCOILWTICO). For the risk-free rate, we use the daily rate implied by the 3-month constant maturity yield from FRED (DGS3MO). For total market return, we use the Vanguard total stock market ETF (VTI).

ii. Hedge Portfolio Construction

This section describes the process used to create three hedge portfolios and construct a final principal component portfolio.

First, we construct the emissions hedge portfolio, from now on referred to as "EMIT". The short leg of the EMIT portfolio consists of a CO2 emissions weighted portfolio. On the first day of each year, we take the median emissions of each firm's three digit SIC industry from two years ago and construct portfolio weights based on them for stocks that are available to trade on that day. These stocks are then tracked throughout the year with dividends and delisting returns reinvested in the portfolio.[6] The long leg of the EMIT portfolio consists simply of the total market return portfolio. Intuitively, this portfolio consists of going short emissions-heavy stocks and long low-emissions stocks, and as a result should perform well if emissions are taxed higher. For this and subsequent portfolios, we normalize the dollar amount invested by the unnormalized standard deviation of the portfolio up until that point. This results in the three hedge portfolios having a similar volatility, while having minimal impact on their interpretability.[7]

[6] Delisting returns are the returns between delisting and when the stock is deemed worthless, e.g., on other exchanges. This includes both prices returns and distributions for up to 10 days after the delisting event.

[7] Similarly, we could normalize by the overall standard deviation from the entire sample; however, we choose this method to preserve investibility.

Second, we construct the subsidy hedge portfolio, which we refer to as "SUB". The long leg of the SUB portfolio is the iShares Global Clean Energy ETF (ICLN), which tracks stocks that produce energy from renewable sources. The short leg of the SUB portfolio is the Stranded Assets portfolio as constructed by Litterman (n.d.) and implemented by Jung et al. (2023). As a result, this portfolio is generally long green energy and short fossil fuel energy, which should perform well if the former is increasingly subsidized more relative to the latter.

Third, we construct the regulation hedge portfolio, which will be referred to as "REG". Regulation can either represent regulation on the production of fossil fuels or the consumption of fossil fuels. Regulation on production will increase prices, which leads to an ambiguous effect on production companies based on the elasticity of demand but a clear effect on firms that use fossil energy. Therefore, we focus on regulation on the consumption side. For example, imposing stricter emissions standards on manufactured cars will lead to forced investment in retooling production lines to the (short-term) detriment of car producers. The long leg of this portfolio, like the EMIT portfolio, consists of the total market return. The short leg has two components. The first is the Vanguard industrials sector ETF (VIS). The second is a portfolio based on stock oil betas. We run a 60-month rolling regression of daily excess stock returns against oil price returns in excess of the risk-free rate, controlling for the market risk factor, and recover the resulting beta for each firm-month. Each month, we select the bottom quartile of stocks based on these betas and construct an equal-weighted portfolio with them. With both the oil portfolio and VIS, we take a 50-50 combination to construct the short leg of REG. This portfolio should perform well if increasing regulations are put in place to curtail either fossil fuel demand or supply.

Finally, with the previous three portfolios (EMIT, SUB, and REG), we construct an investible version based on the first principal component, which we call "PC1". As the name implies, this portfolio is constructed by performing principal components analysis (PCA) on the three portfolios constructed above. To ensure the portfolio is investible, we run an expanding window PCA on the daily returns starting on the first day of 2010, and use the weights from the first principal component to weight the portfolios for the following month. For the first month (January 2010), we equally weight the three portfolios. As of the final month (December 2023), the weights are 49% on EMIT, 7% on SUB, and 44% on REG. This portfolio should broadly reflect the many types of transition risks faced by firms, either by emissions standards, competitive subsidies, or regulations.

A plot of the additively cumulated returns for each of the four portfolios is shown in Figure 1 with associated annualized moments and correlations in Table 1. As we can see, while SUB has moderate volatility and averages an annual return of around 7%, EMIT has an annual loss around 1%, REG is nearly flat over the sample period, and PC1 is has an average return of -0.43%. In terms of correlations, PC1 has at least 20% correlation with the three sub portfolios and reaches 91% correlation with the EMIT portfolio. In addition, it is negatively correlated with both the overall market (-9%) and oil prices (-17%).

In Table 2, we present an analysis of the hedge portfolio returns against common risk factors. Panel A shows specifications that regress the returns against the Fama-French (1993) three factors. For the EMIT, REG, and PC1 portfolios, the three factors account for a relatively large share of variation (51%, 57%, and 65%, respectively). The SUB portfolio faces low explanatory power from the three factors at only 14%. The EMIT portfolio has significantly negative loadings on the market, value, and size factors. The SUB portfolio has slightly negative loading on the market factor, a negative coefficient on the HML factor, and a slightly positive loading on the SMB factor. The REG portfolio has a significantly positive coefficient on the market factor (by construction), and like the EMIT portfolio, has significantly negative loadings on the other two factors. The PC1 portfolio has a slightly positive coefficient on the market factor and negative coefficients on the size and value factors. This is because PC1 is generally short large firms with high book values (high emitters from EMIT and/or manufacturing from REG). Generally, the portfolios have insignificant or negative alpha. This is expected since these are hedge portfolios.

In Panel B of Table 2, we expand the explanatory factors to include 10 sector returns. These sector returns are constructed as the relevant S&P1500 portfolio minus the market portfolio. Our hedge portfolios still have a sizeable amount of unexplained variation, with the highest explained variation coming from the REG and PC1 portfolios at 57%. Therefore, our portfolios capture variation that comes from outside sector or industry returns alone. As the PC1 portfolio summarizes the other 3, we will focus on the loadings that it has relative to the sector risk factors. It has positive coefficients on consumer staples, healthcare, and information technology, and significantly negative coefficients on all other factors apart from financials, communications, and utilities.

iii. Hedge Portfolio Validation

This section details two exercises to validate the hedge portfolios and show that they respond to high-frequency, climate-related shocks.

First, we examine the response of each hedge portfolio to climate news shocks as listed in Jung, Engle, and Berner (2025) (JEB). These JEB shocks are zero if there is no event during the day, positive one if there is an event that is interpreted as a strengthening of climate risk or regulation, and negative one if there is an event that is a weakening of climate risk or policy. As a result, the hedge portfolios we have constructed should have a positive relation with these shocks, as they are meant to offset risks associated with transition. Over the period between January 2010 and December 2021 (the last month of listed shocks), we run the following specification for each portfolio p and date τ:

Equation 1. $$r_{p,\tau} = \alpha_p + \sum_{k=0}^{5} \beta_{p,k} JEB_{\tau-k} + \gamma_p MKT_\tau + \epsilon_{p,\tau}$$

The coefficients $\beta_{p,k}$ are then summed cumulatively and plotted in Figure 2. Each portfolio shows a positive response to the shocks, with all responses also being statistically significant at the 90% level at time $t+1$. Since each event takes place at different times of the day, it might take the market until the next day to fully incorporate all new information contained in the news. Apart from the REG portfolio, all statistical significance persists out to $t+5$.

Second, we look at the relation of the hedge portfolio performance to a lower frequency, but continuous measure of climate news. Namely, we use the weekly New York Times climate index as constructed by De Nard et al. (2024). Since this is a weekly measure, we aggregate the total returns of each hedge portfolio by week to match the frequency.

In Table 3, we regress an indicator of whether the hedge portfolio experienced a top-decile return week against the continuous news measure and other portfolios. In both Panel A, which only controls for the market risk premium, and Panel B, which includes all GICS Sector portfolios, the NYT index is highly significant in predicting high return weeks of the hedge portfolios. This supports that these hedge portfolios capture variation in climate news events and provide positive returns to compensate heightened risks.

iv. Measurement of Greenness

Once the hedge portfolios are calculated for our sample period, we then use the daily returns of the hedge portfolios and individual stocks to obtain the greenness measure for each firm. Specifically, we run the following specification in Equation 2, with firms indexed by f and days by τ:

Equation 2. $$r_{f,\tau} = \alpha_f + \beta_f PC1_\tau + \Gamma_f' X_\tau + \epsilon_{f,\tau}$$

PC1 is the hedge portfolio with β_f being the associated coefficient of interest. In order to ensure the β_f coefficient is not picking up other systemic risk factors embedded in the hedge portfolio, we include four other common factors in X_τ, namely the Fama-French 3 factors (market, size, and value) and the daily price return on oil. From the specification, we recover the estimate of β_f and the relevant standard error for each stock and compute the t-statistic for the firm. This will be called t_{PC1}, or "PC1 T-Statistic" and is the central measure of greenness for firms that we will use throughout the rest of the analysis. If t_{PC1} is high/positive, the stock varies positively with the hedge portfolio, and thus can be considered a good hedge (or "green"). If t_{PC1} is low/negative, the stock varies negatively with the hedge portfolio, and thus is a risk stock (or "brown").

The specification above makes no reference for the period over which it is run. For the scope of this analysis, we run the specification for each stock-year individually, ensuring that each stock has at least 200 daily returns available within the year. This results in a panel of measured t-statistics for each firm-year. However, this can easily be extended to be a rolling regression that provides up-to-date estimates at the quarterly, monthly, or daily frequency. It can also be relaxed to instead use all available returns of a stock at one, giving a single t-statistic measurement for each firm.

A histogram of the resulting panel of t-statistics is shown in Figure 3. The distribution is negatively biased with slight negative skew. There is considerable variation in the estimated t-statistics, with 10% of the sample having a statistic lesser than -2.7 and 10% having a statistic greater than 1.2. The downward bias is likely because there tend to be more firms that are significantly brown than significantly green, i.e., it is easier to identify brown firms.

v. Verification Checks

As a basic check to see if these t-statistics are reasonably identifying "green" versus "brown" firms, we list the top 10 and bottom 10 firms when ordered by their average t-statistic over the sample period in Table 4. On the right are the brownest firms, which consist of either heavy industrial producers (such as Caterpillar) or oil production and refinery companies (such as Phillips 66). On the left are the greenest firms, which consist of healthcare sector companies, information technology firms, and large consumer product conglomerates. These may not be what comes to mind when one thinks about a "green" firm; instead, these firms seem to be poised to benefit from the increased digitalization of the economy and evergreen need for health services and general life products. This points to two facts. First, "brown" firms are easy to identify, but "green" firms can be much more ambiguous. Second, "green" in this context can mean both currently environmentally friendly and the capability to become environmentally friendly in the future, i.e. able to handle transition risk. The ranking seems to imply that the latter are generally what we identify here.

An additional check is to compare our measure of greenness against other previously used measures. Specifically, we will use van der Beck's (2024) measure which uses sustainability targeted mutual fund holdings to construct a revealed preference-based metric for each stock. This measure is closely related to our own as it is measured based on what market participants believe about individual stocks. We follow van der Beck's construction process using quarterly mutual fund holdings from CRSP, thereafter taking the observation of the last quarter each year to match our annual frequency. We use the magnitude of the difference between the market and representative sustainable fund scaled by the sum of the representative portfolio weights instead of an indicator to include a sense of how big the divergence is in the measure. This allows us to capture variation in the magnitude without distortion due to the scale of holdings (for example, a tilt in holdings of 1pp is different for a 1% weight stock than for a 0.01% weight stock). The results are presented in Table A.1. In all specifications, the positive coefficient on van der Beck's measure is significantly related to our own. However, it captures very little of the observed variation in our measure ($R^2 < 0.001$ in column 1).

These above results imply that while our measure captures some of the same firms as our intuition and previously documented metrics imply, there is still much unexplained variation. The next section will investigate this variation using firm fundamentals.

III. Drivers of Greenness

i. Linear Models

With the firm-year panel of t-statistics with respect to the PC1 hedge portfolio constructed in the previous section, we then proceed to investigate the correlates of these measurements. For this section, we ensure firms have at least 5 years of non-missing t-statistic measurements, at least 10m USD in assets, book equity, and market equity, and non-missing observations of market beta and idiosyncratic volatility. In addition, we exclude financial institutions and real estate firms (GICS Sector codes 40 and 60). This leaves an unbalanced panel with 2,926 stocks.

First, we start by considering only Compustat-derived variables. Table 5 shows the specifications which do not include fixed effects. Table 6 includes both year and industry fixed effects. The first twelve columns show independent univariate regression results in which each dependent variable enters one at a time. The last column shows the multivariate specification in which all measures are combined into a single model. In total, we examine 12 measures: the log of total assets, the ratio of the current year's CAPX to total assets, the share of intangible assets out of total assets, the current year's research spending over sales, the gross profit margin, long-term debt over total capital, total interest expense scaled by total liabilities, Altman's Z-Score, the book equity to market equity ratio, the within-year CAPM market beta, and the within-year idiosyncratic volatility with respect to the market portfolio. A negative (positive) coefficient indicates that increasing that variable is associated with a "browner" ("greener") firm measurement.

A number of variables are consistently significant with a consistent sign across all specifications they appear in. The log of total assets has a negative coefficient, indicating larger firms are generally browner, perhaps simply due to scale of operations. Share of intangible assets has a positive coefficient, as the firms with more intangible assets are likely technology or biotechnology firms with less reliance on industrial, capital-intensive production. Advertising-sales ratio has a positive coefficient, possibly related to consumer facing firms being greener, while browner firms tend to be business-to-business. Gross profit margin, interest coverage ratio, and z-score are all positive, indicating that more profitable and secure firms are greener, although interest coverage is insignificant in the multivariate column. Long-term debt to capital is significantly negative in all but the multivariate columns, indicating that brown firms have a greater dependence on long-term debt. Interest expense ratio is significantly negative, indicating that brown firms pay

higher interest rates on average. A contributing factor to this relation is that oil exploration firms face additional risks in developing production fields and pay higher interest spreads to compensate. Book-to-market is also significantly negative, indicating that brown firms are undervalued by the market relative to their book value. This relation has previously been documented by Pederson et al. (2021). This can also represent firms with a large balance sheet made up of stranded assets, such as coal companies, being evaluated as brown. Z-Score is significantly positive. Since Z-Score is interpreted as distance to default, firms farther from default are greener, which agrees with interpretations above. Finally, both market beta and idiosyncratic volatility has a negative coefficient. This implies brown firms are both more exposed to market factors and have greater idiosyncratic risks affecting their returns compared to green firms, which are relatively isolated both from market and idiosyncratic factors.

Transition risk for some companies can be easily accommodated but for others it may dramatically reduce their ability to produce and sell products. In this case, transition risk can be interpreted as termination risk as introduced by Engle (2025). The implication of this is that such firms should face a higher cost of capital through increased credit spreads and equity risk premia, as documented in Gormsen et al. (2024). They should reduce capital expenditures and may have stranded assets on their books leading to high book to market ratios. Reductions in R&D or CAPX may also be expected. Many of these features show up as significant determinants of exposure to transition risk.

Other variables of interest have mixed signs across models. The CAPX ratio is significantly negative in the OLS specifications and changes to significantly positive in the fixed effects regressions. This is most likely due to CAPX being indicative of each sector (similar to intangible assets); however, within sector, firms with higher capital expenditures are most likely more secure firms investing in their future business. Equivalently, firms with low CAPX may be firms that are facing termination risk, and thus reducing investment in existing capital. Thus, within industry, firms that are investing are those that view themselves as non-exposed to transition risk. Similarly, research and development to sales ratio is positive in the OLS specifications and changes to negative in the fixed effects specifications. High R&D is correlated with specific green industries (pharmaceuticals, information technology); however, within these industries it is likely of little use and firms with exceptionally high R&D relative to revenue are likely riskier.

Next, we consider the environmental variables sourced from Refinitiv/LSEG. As mentioned in the data sources section above, we restrict our analysis to the most populated environmental factors tracked by Refinitiv. These are also the factors most likely to be referenced by the market participants, as they are easily digestible numerical datapoints that summarize many other factors. Like the Compustat specifications, Table 7 shows both OLS specifications (Panel A) and specifications including sector and year fixed effects (Panel B). Columns 1 through 4 show the relation between the headline E-Score and sub-environmental scores. Surprisingly, in all of these univariate columns, the coefficient is significantly negative. In column 5, the coefficient on the log of CO2 emissions is negative and significant in all cases. This is consistent with our measurement as higher polluting firms are considered browner. Columns 6 and 7 include both the summary numbers and CO2 emissions, though not all at the same time as the headline number would be highly correlated with the three sub-numbers. After adding emissions, the headline environmental score coefficient now has a positive sign, as well as the resource use score. After adding fixed effects, however, only the resource use score remains significantly positive, with emissions score, innovation score, and log emissions being significantly negative.

Finally, we combine the Compustat and Refinitiv variables into a single specification in Table 8. In Column 1, we include the 14 factors with no fixed effects, and are able to explain only 8% of the variation of the t-statistic measure. All factors, except log assets, interest coverage ratio, and environmental score, enter significantly with the same signs as we interpreted previously. In column 2, we add sector fixed effects, and column 3 adds year fixed effects. Columns 4 reports the most stringent specification where we have both firm and year fixed effects. In this regression, the only six variables to maintain significance are log assets, CAPX asset ratio, gross profit margin, long-term debt to capital, interest expense to liabilities, market beta, and idiosyncratic volatility. Even with firm fixed effects, we are only able to account for 54% of the variation in the measured t-statistic. In summary, these results point to a number of factors that contribute to our measure of greenness. These "green" firms tend to be those that are well-capitalized, financially healthy, investing in growth with low emissions and few idiosyncratic events affecting their returns. The former factors especially make those firms good hedges for many risks in addition to climate risk.

There is the additional test related to firms' reporting of emissions we can conduct with our greenness measure. Refinitiv reports CO2 emissions regardless if the firm itself has disclosed their own measurements by imputing an estimate through either industry median or energy use. They

preserve whether the reported number was sourced from the company or through an imputed estimation method. As a result, we can check whether the market considers the imputed numbers or the reported numbers when determining the greenness of a firm. We run specifications of our t-statistic measure against standardized log CO2 emissions and an indicator for whether the firm-year observation had self-reported emissions quantities. The results are shown in Table 9. The first column shows the t-statistic against a single indicator for reporting emissions. This coefficient is significantly negative, indicating that firms that choose to report emissions are deemed bronwer by the market. Column 2 adds an interaction with the quantity of emissions. The quantity is significantly positive, while the interaction term is significantly negative. This implies that the market only correctly accounts for emissions when they are self-reported by the company. Finally, column 3 adds industry-by-year fixed effects. This specification agrees with Column 2 in that the market only prices reported emissions, but the magnitude of the effect is smaller. In summary, self-reported emissions are more trusted than non-self-reported; this may provide a disincentive for firms to report their own emissions, lest they be priced more in line with their own risks.

ii. Logistic and Non-Parametric Models

We expand on the above analysis by examining possible non-linearities in predicting the greenness of a firm.

First, we fit a logistic model using the same variables as the linear model in that was presented in Table 8. The dependent variables will be an indicator for whether a particular stock is in the top or bottom quintile among stocks within a year in terms of its t-statistic. In other words, we aim to predict if a stock is relatively one of the greenest or brownest within the year, as opposed to previous specifications which predicted the sign and magnitude of the t-statistic. The results are shown in Table 10. Many coefficients enter significantly and with the same sign as models in Table 7. We draw attention to the R^2 of these specifications, especially comparing the top quintile models to the bottom quintile models. The models predicting whether a firm is brown have 50% greater predictive power compared to the equivalent green prediction model.

To show this another way, we show the receiver operating characteristic (ROC) curves for columns 2 and 4 of Table 9 in Figure 4. The ROC plots the true positive rate (sensitivity) against the false positive rate (one minus specificity), and a perfect model will have an area of one. In green is the ROC curve for column 2 and in orange is the ROC curve for column 4. The brown

model dominates the green model by 0.04, a significantly higher value for predictive ability. In total, these results point to the fact that it is easier to conclude a firm is “brown” as opposed to concluding a firm is “green”.

Second, we fit a regression tree model, as described by Breiman et al. (2017), on our data. Regression trees are machine learning models that use a number of independent variables to predict a single dependent variable. They accomplish this by choosing the best splits of the data to minimize the mean square error (MSE) of the predicted values relative to the true values. At each split, the sample is divided into two, not necessarily equal sized parts and the process continues until either a maximum depth (the number of splits) or minimum sample size is reached. The predicted value of a datapoint is the mean of the in-sample data at the terminal node. This process is informative in two ways. One: at each point, the variable which incrementally decreases the MSE the most is chosen for the split, so variables are indirectly ranked based on where they are included in the tree. Two: as each split is based on splits done previously, the model is able to pick-up non-linearities in the data. This also means that, like stepwise regression, multicollinearity is a serious problem which is dealt with sequentially rather than jointly.

Regression trees have a readily interpretable and viewable output based on the splits they generate, unlike other “black-box” models. The fitted result of this model is shown in Figure 5. As displayed, the tree follows a top-down structure tracing paths from the root down to the terminal nodes or leaves at the bottom. A left branch is followed if a data point satisfies the inequality within the node, else a right branch is taken. In our visualization, we have constructed the inequalities such that the browner child nodes are on the left and the greener are on the right after each split.

In terms of input, we provide the model with all data used in Table 8 including all the years and firms. In terms of hyperparameters, we only set the maximum depth to three in order to allow reasonable output to view and interpret; all other parameters are left as “out-of-the-box” from Python’s scikit-learn package.

There are a number of things to note from this figure. First, the initial node uses the market beta coefficient to split the data. This implies that it is the strongest predictor out of many potential options from Compustat, V-LAB and Refinitiv. The full path taken to the brownest node (left, left, left) states that high beta, low R&D and high emissions characterize the brownest

firms. The greenest node (right, right, right) states that especially low beta and low idiosyncratic vol characterize the greenest firms. Notice that the only ESG related variable appearing in the figure is Emissions and it is only relevant for one split.

This model achieves an R-squared of 20.2% which is measured as usual as the sum of squared residuals divided by the sum of squares of the dependent variable around the mean. This can therefore be compared with the linear model without fixed effects from Table 8 which has R2 of 14.8%. This suggests the importance of non-linearities although there may be other explanations including those discussed above. For example, if the tree is continued beyond 3 levels, the R2 will approach 1.

In Figure 6 another regression tree is presented. This uses a much wider set of variables including all the variables from Compustat's financial ratios database that have less than 5% of their permno-year observations missing, and then union with the variables used in Table 8. In this table, the brown nodes are quite similar to the previous tree with decisions (left,left,left) reflecting high market beta, low R&D and high emissions. However, there is an even browner terminal node following (right, right, left) which selects firms with low market beta, high operating margin after depreciation and a low enterprise value multiple. This node has only 43 firm-year observations but has a mean t-statistic of -2.2. All the other nodes have more than 1000 observations. The R^2 is similar to that in Figure 5 although slightly lower.[8] Again, the trees emphasize the value of non-linearities and expanded data sets.

IV. Changes Over Time

In this section, we investigate the movement of firms between "green" and "brown" across time and the return performance of stocks binned by our greenness measure.

First, we consider the changes of each firm's measure of greenness over time. Our measure is constructed such that each year is measured in isolation for a given firm. While each firm-year observation is measured independently, it should be unlikely that a firm switches from being one of the "brownest" to one of the "greenest" one year to the next. Table 11 investigates this in two ways. In Panel A, we bin stocks into three terciles based on fixed cutoffs for the measured t-statistic. Since we use t-statistic, as opposed to betas, the first tercile represents being

[8] The sample is slightly different across models due to missing values, so the R-squared may not strictly decrease by adding more independent variables.

(statistically) significantly "brown", the middle tercile represents being neither "green" nor "brown", and the third tercile represents being significantly "green." The table shows the transition matrix between these terciles year-to-year, with each row summing to 100%. For the bottom tercile, these firms stay in that bin 44% of the time and jump to the top tercile only 1% of the time. Similarly, firms in the top tercile stay there 18% of the time, and transition to the bottom tercile 3% of the time. In total, Panel A suggests firms become and stay significantly "brown" more often than significantly "green."

Panel B provides an alternate framing. Instead of setting fixed bounds for the bins, we allow them to vary over time to reflect relative greenness. These are set at the quintiles for each year. An additional benefit is that the flexible quintiles provide a natural baseline for comparing the transition probabilities: if the firm rankings were assigned randomly, then the year-to-year transition probabilities between all quintiles would be 20%. Therefore, any probability above 20% reflects higher than random chance. The top left cell of the matrix shows that the relatively brownest firms are more than twice as likely than random (44%) to stay the brownest. In contrast, and in agreement with Panel A, the bottom left cell states that the greenest firms are only 37% likely to stay the greenest. The firms in the middle three quintiles have only marginally higher probabilities compared to the baseline of staying within their original quintile year-to-year. These results again point to the theme that brown firms are easier to identify than the more nebulous green firms, although both are somewhat stable in their relation to other firms over time.

Instead of looking at year-to-year changes within our panel, we can also address longer term changes in how the market views firms. To do this, we first limit to firms which exist for the entire sample of 2010 to 2023. This leaves us with 1,180 firms. Then, we take a three-year average of the first three t-statistics for a firm (from 2010, 2011, and 2012) and the last three t-statistics (from 2021, 2022, 2023). We use a three-year average to reduce noise in the longer-term measurement. The difference between the latter and former represents long-term movement in how green or brown a firm is, with a positive difference indicating the firm becoming greener. Table 12 shows two different summaries based on this difference. In Panel A, we list the top and bottom five firms based on this difference, similar to Table 4. On the left are the firms that have improved their t-statistic the most to become greener. These firms are mixed and seem to be those that started as substantially brown, and thus had large room to improve. On the right are

the firms that worsened their t-statistic. These are dominated by energy firms. This makes sense, as environmental concerns and termination risk have increased over time. Panel B shows the differences aggregated by GICS sector. This shows that many of the broad moves are shared by the industry of a firm rather than the firm itself. The greatest decrease is found the energy sector, as expected, while the greatest increase is from communications. Overall, these results point to transition risk becoming a significantly greater concern for energy firms over the time of our sample.

V. Portfolio Construction

We next examine portfolios constructed based on bins of our t-statistic measure. This allows us to compare portfolios of stocks selected based on our measure to those previously identified in the literature. In addition, we speak to the tension between the growing market capitalization of green firms and how this impacts the performance of the portfolio depending on the construction choices. For this exercise, we assign stocks to portfolios based on their rolling average t-statistic based on prior years' measurement. For example, for the 2011 assignment, we use the t-statistic from 2010; for the 2012 assignment, we use the average of the 2010 and 2011 t-statistic. This smooths inclusion in the portfolio to prevent large swings in both constituents and total market capitalization. We assign a firm to the long (short) leg of the portfolio if it has a positive (negative) average t-statistic. This essentially tries to recreate the "green-minus-brown" portfolio found in prior literature (Bauer, et al. 2022, Bolton and Kacperczyk 2023, El Ghoul, et al. 2023, Pástor, Stambaugh and Taylor 2022, Ardia, et al. 2023). We construct two versions: the first is equal weighted, while the second is market capitalization weighted. The cumulative performance from 2011 to the end of 2024 is shown in Panel A of Figure 7. We can see that the equal weighted portfolio initially outperforms the market weighted portfolio until it is surpassed in cumulative performance in 2020. At that point, the market weighted portfolio continues to grow, while the equal weighted portfolio drops and stagnates. The general decline in market cap of brown firms is consistent with the idea that they are exposed to termination risk. In order to pay the equity risk premia, firms pay outsized dividends and stock buybacks, thus shrinking their market cap which is consistent with the shrinking remaining years of the business.

Panel B of Figure 7 shows the share of the overall portfolio market capitalization made of the long (green) end. This share has steadily increased from 47% to 70% over the sample period,

reaching as high as 71% in early 2020 during the COVID-19 period. From an unreported regression, the outperformance of the market weighted portfolio relative to the equal weighted portfolio is significantly associated with the capitalization share of green firms.

As a result, Figure 7 presents a potential reconciliation of prior results in the literature. In Bolton and Kacperczyk (2021), they find that high emitting stocks outperform low emitting stocks, while Pástor et al. (2022) find that green stocks outperform brown stocks. In terms of equations, these frameworks state the following:

Equation 3. (BK) $$E_{t-1}[\pi_t] = E_{t-1}[r_{g,t}] - E_{t-1}[r_{b,t}]$$

Equation 4. (PST) $$E_{t-1}[\pi_t] = \frac{V_{g,t-1}}{V_{b,t-1}+V_{g,t-1}} E_{t-1}[r_{g,t}] - \frac{V_{b,t-1}}{V_{b,t-1}+V_{g,t-1}} E_{t-1}[r_{b,t}]$$

In the above equations, π is the return on a "green minus brown" portfolio, and r_b and r_g are the returns on brown and green stocks, respectively. If we assume that $E[r_b] > E[r_g]$, as brown firms earn a risk premium associated with transition risk, then the expected performance of the BK vs PST constructions is dependent on the relative market share of brown and green stocks. Unless the market share of green stocks is sufficiently high, the equal weighted BK portfolio will dominate. This is precisely what we observe in the previously discussed Figure 7. We stress that this is far from identified, as there are a number of endogenous factors that drive both the relative market share and returns for green stocks.

VI. Conclusion

In this paper, we have presented a method of identifying green and brown assets through their correlations with hedge portfolios representing various transition risks. We show that this numeric score reasonably separates green and brown companies, although the former are not necessarily companies directly committed to the green transition itself; rather, they are often companies that are better positioned to grow and weather the future uncertainty climate risks pose. We find that our measure is somewhat stable over time; this could reflect measurement noise or changing market perception of which firms are truly green or brown year-to-year. Finally, we provide commentary on the differences between realized returns between equal weighted and market capitalization weighted indices and how this impacts the existence (or absence) of a "greenium".

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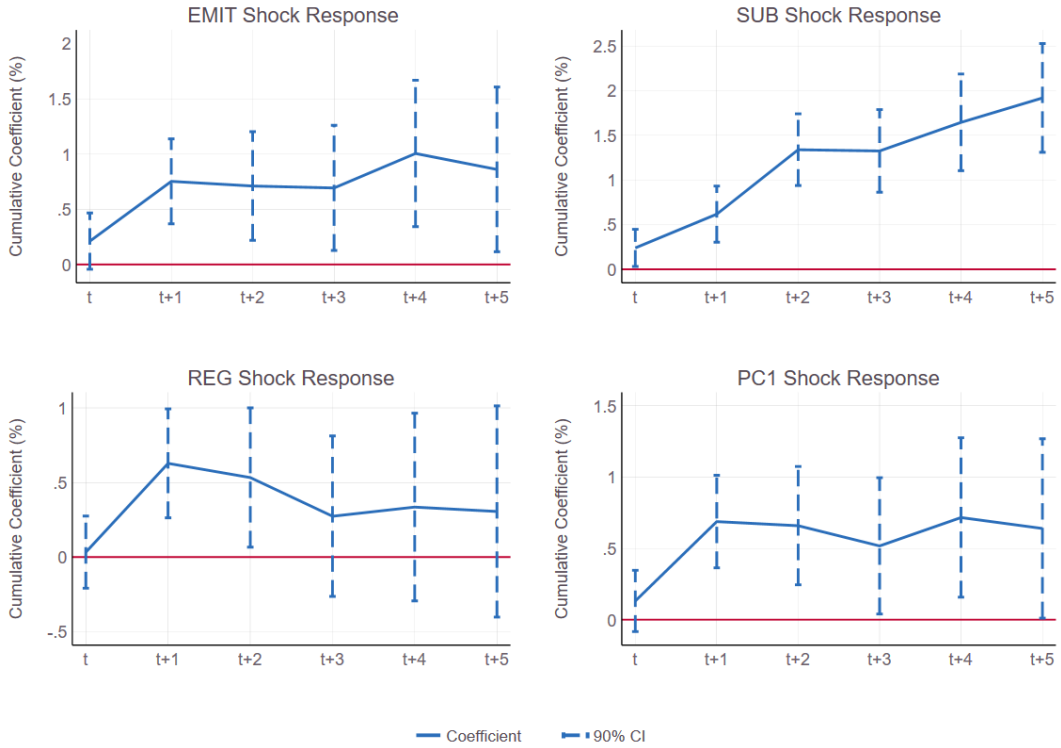
Figures and Tables

Figure 1. Time Series of Hedge Portfolios



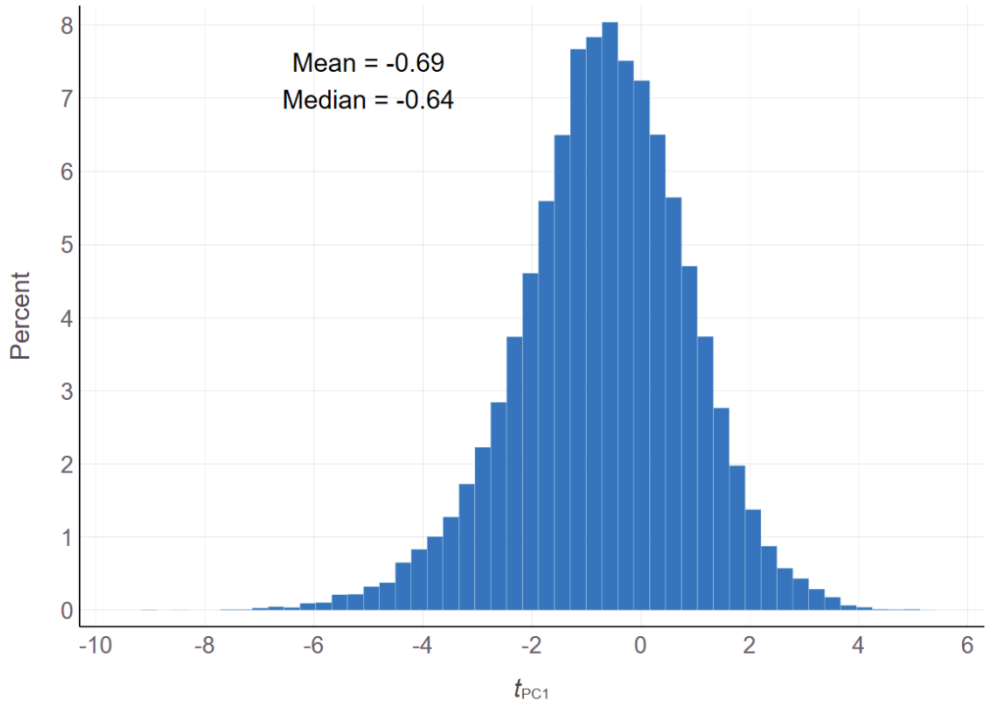
Note: This figure shows the cumulative performance of the three constructed hedge portfolios and the first principal component over the period from January 1, 2010 to December 31, 2023. The cumulative performance is shown in terms of additive returns so that variation appears constant across the sample and between portfolios.

Figure 2. Response of Hedge Portfolios to Climate Event Shocks



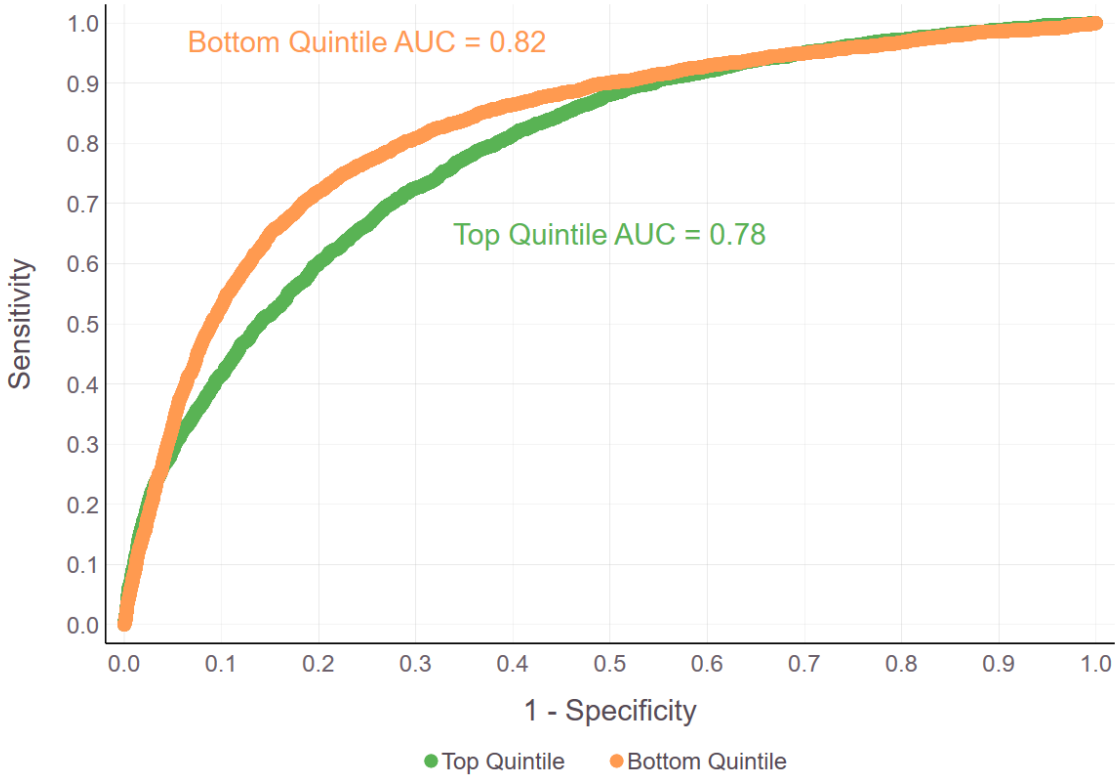
Note: This figure shows the cumulative daily return response of the three constructed hedge portfolios and their first principal component. The events are climate news shocks taken from Jung, Engle, and Berner (2023). For events taking place on a non-trading day, they will only impact returns on the following trading days (from $t+1$ or $t+2$ onward). The specific model is estimated is $r_{p,\tau} = \alpha_p + \sum_{k=0}^{5} \beta_{p,k} JEB_{\tau-k} + \gamma_p MKT_\tau + \epsilon_{p,\tau}$ with the resulting summed β coefficients and associated 90% confidence intervals being shown in the plots. The sample is limited by the shock availability from January 1, 2010 to December 31, 2021.

Figure 3. T-Statistic Histogram



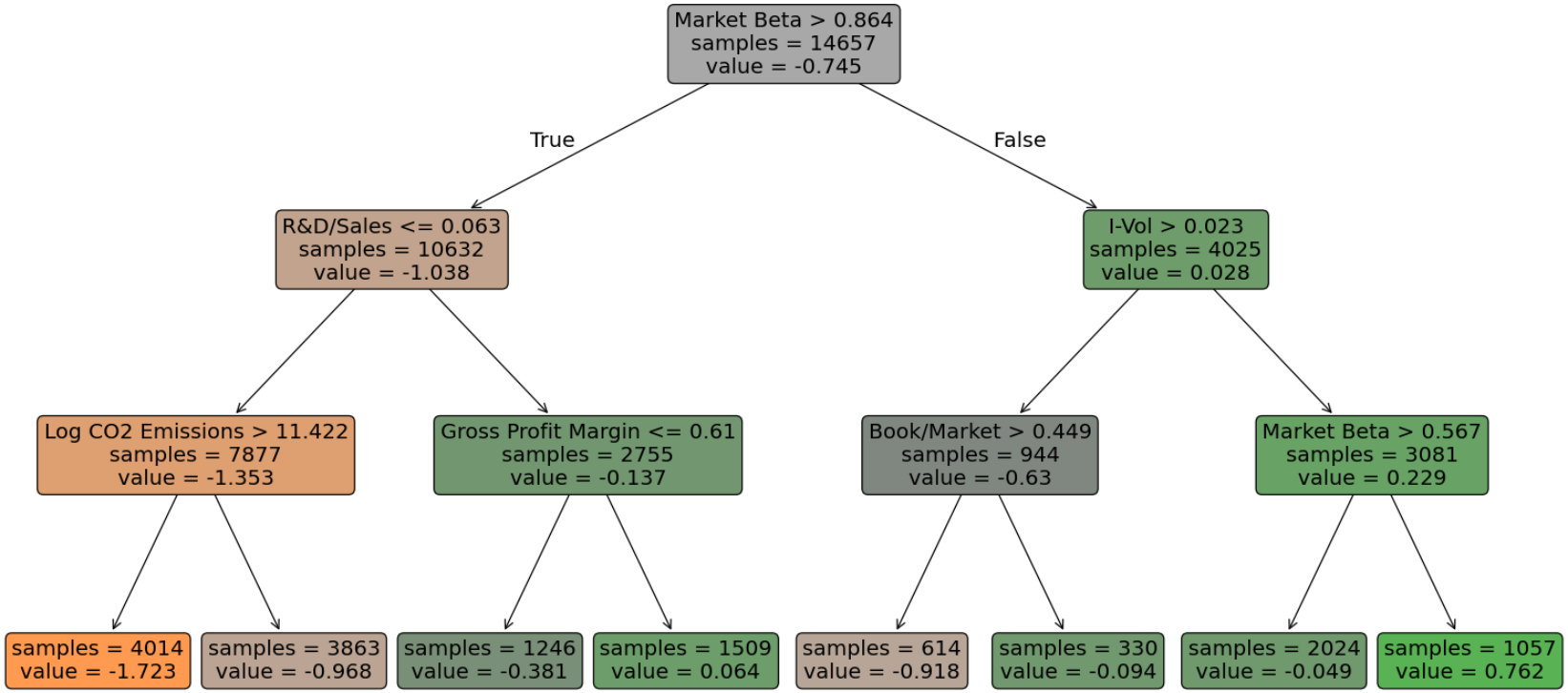
Note: This figure shows the distribution of firm-year measurements of the t-statistic with respect to the PC1 portfolio. The sample contains firms with at least five years of measured t-statistics and at least $10m in both book equity and market equity over the period 2010 to 2023.

Figure 4. Receiver Operating Characteristic (ROC) Curves



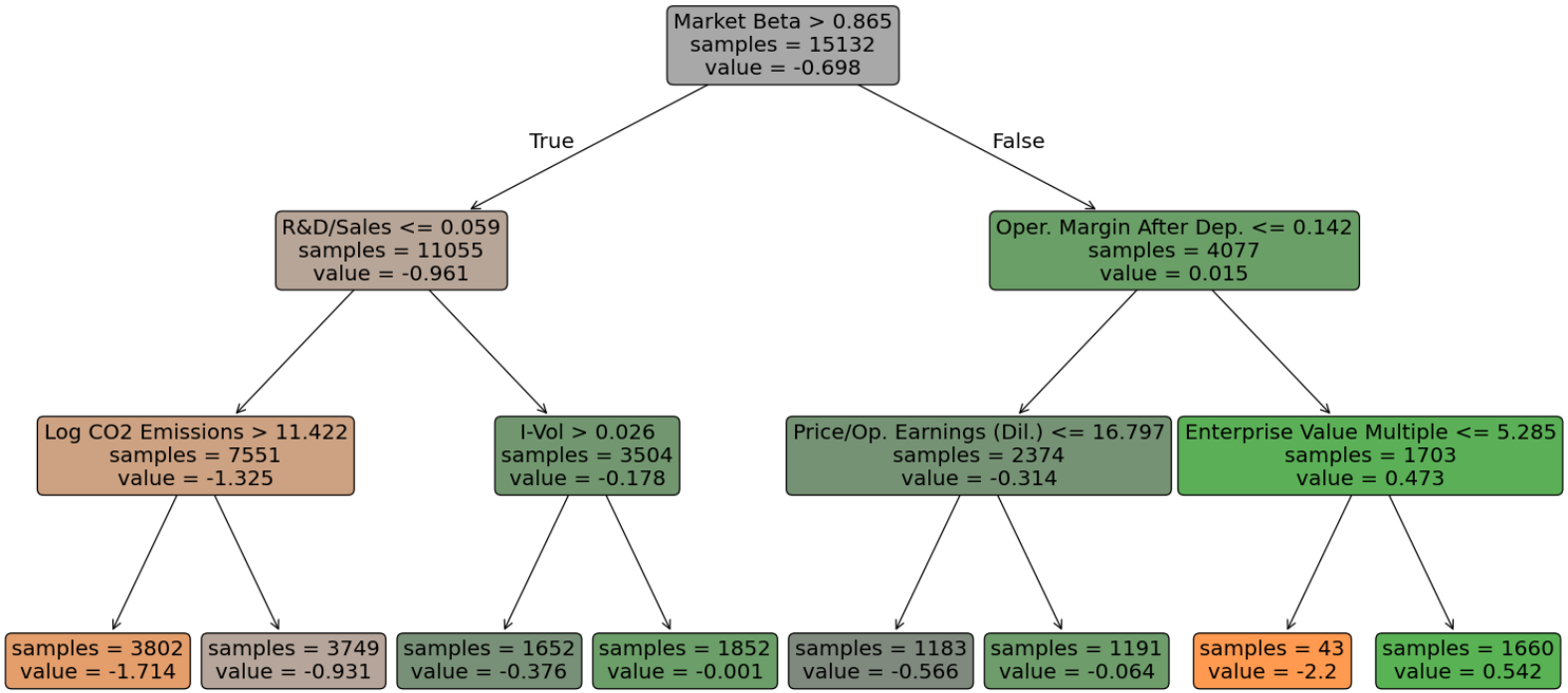
Note: This figure shows the ROC curves for logistic models predicting whether a firm is in the top or bottom quintile of PC1 t-statistics within a given year. These logistic models use the same covariates as shown in columns 2 and 4 of Table 9. The green line represents the ROC for predicting the top quintile and the brown line represents the ROC for predicting the bottom quintile. The labels list the "area-under-the-curve" (AUC) of each model, where a value of one would be a perfect prediction model.

Figure 5. Regression Tree Specification, Limited Variables



Note: This figure shows the resulting tree from fitting a regression tree on the balance sheet and ESG variables used in Table 8. The first line in each cell shows the decision criterion for moving to the next cell. If the criterion is satisfied, the left path is taken; otherwise, the rig ht path is taken. The second line in each cell shows the remaining number of observations. The third line shows the average PC1 t-statistic of the observations remaining for that cell. The colors of the cells reflect the average t-statistic ranging from highest (green) to lowest (brown). The sample are firm-year observations between 2010 and 2023.

Figure 6. Regression Tree Specification, Expanded Variables



Note: This figure repeats the fitting process in Figure 5, but expands the variables available to 70 ratios available from Compustat and Refinitiv. The first line in each cell shows the decision criterion for moving to the next cell. If the criterion is satisfied, the left path is taken; otherwise, the right path is taken. The second line in each cell shows the remaining number of observations. The third line shows the average PC1 t-statistic of the observations remaining for that cell. The colors of the cells reflect the average t-statistic ranging from highest (green) to lowest (brown). The sample are firm-year observations between 2010 and 2023.

Figure 7. Portfolios Based on T-Statistic

Panel A. Cumulative Performance



Panel B. Market Capitalization Share



Note: Panel A shows the additively cumulated returns for two long-short portfolios constructed by assigning stocks based on their PC1 t-statistic. Stocks are assigned to the long leg of the portfolio if they have a rolling average positive t-statistic over previous years, and to the short end if they have a rolling average negative t-statistic. Panel B shows the share of total market capitalization made up of the "green" stocks with a positive t-statistic.

Table 1. Hedge Portfolio Summary Statistics and Correlations

Panel A. Summary Statistics

	Mean	SD	Skew
EMIT	-1.21	18.47	-0.04
SUB	6.99	15.98	0.01
REG	0.36	17.53	-0.02
PC1	-0.43	15.47	-0.03

Panel B. Correlations

	EMIT	SUB	REG	PC1	Market	Oil
EMIT	1.00					
SUB	0.22***	1.00				
REG	0.60***	0.04*	1.00			
PC1	0.91***	0.20***	0.87***	1.00		
Market	-0.17***	0.03	-0.00	-0.09***	1.00	
Oil	-0.25***	-0.21***	-0.02	-0.17***	0.24***	1.00

Note: This table shows various high level summary statistics for the hedge portfolios. Panel A shows the first three moments of each of the three hedge portfolios and the first principal component. Each moment is annualized from daily data. Panel B shows correlations for the hedge portfolios, as well as the market portfolio and the price return on WTI oil. The sample for both panels is from January 1, 2010, to December 31, 2023.

Table 2. Hedge Portfolio Explanatory Factors

Panel A. Fama-French 3 Factor Model

Dependent Variable:	EMIT (1)	SUB (2)	REG (3)	PC1 (4)
Market−RF	-0.06***	-0.05***	0.16***	0.04**
	(-2.79)	(-2.73)	(5.64)	(2.33)
HML	-0.40***	-0.34***	-0.26***	-0.33***
	(-22.42)	(-14.41)	(-13.28)	(-24.95)
SMB	-0.50***	0.09***	-0.60***	-0.51***
	(-28.12)	(4.40)	(-32.01)	(-37.90)
α	-0.02	0.02	-0.02*	-0.02*
	(-1.21)	(1.52)	(-1.75)	(-1.85)
N	3,496	3,496	3,496	3,496
R^2	0.51	0.14	0.57	0.65

Panel B. Sector Portfolio Factors

Dependent Variable:	EMIT (1)	SUB (2)	REG (3)	PC1 (4)
Energy−Market	-0.31***	-0.36***	0.01	-0.17***
	(-11.92)	(-18.43)	(0.52)	(-7.88)
Materials−Market	-0.41***	-0.17***	0.04	-0.19***
	(-9.67)	(-4.33)	(1.09)	(-6.15)
Industrials−Market	-0.38***	-0.04	-1.56***	-0.90***
	(-8.47)	(-0.80)	(-39.17)	(-25.88)
Cons. Discretionary−Market	-0.10*	-0.01	-0.30***	-0.19***
	(-1.79)	(-0.33)	(-4.37)	(-4.01)
Cons. Staples−Market	0.29***	-0.28***	0.19***	0.20***
	(8.11)	(-7.00)	(6.46)	(7.58)
Healthcare−Market	0.26***	-0.16***	-0.10**	0.07*
	(5.37)	(-3.67)	(-2.20)	(1.92)
Financials−Market	-0.01	-0.18***	-0.04	-0.04
	(-0.21)	(-4.60)	(-0.89)	(-1.07)
Info. Tech.−Market	0.35***	-0.21***	0.32***	0.30***
	(6.07)	(-4.03)	(5.37)	(6.01)
Communications−Market	0.04**	-0.12***	0.01	0.02
	(1.99)	(-5.37)	(0.57)	(0.95)
Utilities−Market	-0.08***	0.12***	-0.01	-0.03
	(-2.81)	(4.47)	(-0.39)	(-1.41)
α	-0.02*	0.01	-0.01	-0.02
	(-1.76)	(0.58)	(-0.73)	(-1.57)
N	3,522	3,522	3,522	3,522
R^2	0.51	0.25	0.57	0.57

Note: This table shows various factor models for explaining variation in returns of the hedge portfolios. Panel A shows the traditional Fama-French three factor model. Panel B shows an industry factor model, where each factor is the returns of the GICS sector S&P1500 portfolios. The abbreviation "cons." stands for "consumer" and the abbreviation "info. tech." stands for "information technology". Robust t-statistics reported in parentheses. Stars *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 3. Hedge Portfolio Response to NYT Index

Panel A. NYT Index and Market

Dependent Variable:	𝟙(Weekly Return Above 90th Percentile)			
	EMIT	SUB	REG	PC1
	(1)	(2)	(3)	(4)
Weekly NYT Index	1.572**	2.362**	2.417***	2.034***
	(2.10)	(2.46)	(3.07)	(2.71)
Market	-0.000	-0.010	0.006	0.004
	(-0.06)	(-1.54)	(1.19)	(0.80)
HML	-0.031***	-0.029***	-0.021***	-0.032***
	(-6.05)	(-5.16)	(-4.06)	(-6.19)
SMB	-0.038***	0.001	-0.049***	-0.044***
	(-8.36)	(0.25)	(-9.77)	(-9.06)
Constant	0.072***	0.065***	0.057***	0.062***
	(5.15)	(4.11)	(4.21)	(4.68)
N	728	728	728	728
R^2	0.20	0.06	0.23	0.24

Panel B. NYT Index and Sector Portfolios

Dependent Variable:	𝟙(Weekly Return Above 90th Percentile)			
	EMIT	SUB	REG	PC1
	(1)	(2)	(3)	(4)
Weekly NYT Index	1.701**	2.459**	2.291***	2.090**
	(2.01)	(2.56)	(2.63)	(2.47)
Market	-0.068	0.170**	0.060	0.011
	(-1.05)	(2.30)	(0.97)	(0.19)
Energy	-0.025***	-0.028***	0.001	-0.012**
	(-4.78)	(-4.40)	(0.20)	(-2.27)
Materials	-0.026***	-0.029**	0.006	-0.010
	(-2.78)	(-2.48)	(0.64)	(-0.99)
Industrials	-0.010	-0.009	-0.106***	-0.087***
	(-0.74)	(-0.64)	(-6.21)	(-5.51)
Cons. Discretionary	-0.000	-0.006	-0.017	-0.009
	(-0.01)	(-0.35)	(-1.32)	(-0.76)
Cons. Staples	0.024**	-0.019	0.005	0.020*
	(2.45)	(-1.64)	(0.43)	(1.95)
Healthcare	0.029**	-0.009	-0.008	0.024*
	(2.25)	(-0.63)	(-0.64)	(1.87)
Financials	0.019*	-0.019	-0.001	0.019*
	(1.72)	(-1.62)	(-0.05)	(1.68)
Info. Tech.	0.054***	-0.037*	0.043**	0.046**
	(3.00)	(-1.84)	(2.30)	(2.58)
Communications	0.022***	-0.016**	0.007	0.016**
	(3.28)	(-2.18)	(0.92)	(2.42)
Utilities	-0.012*	-0.004	0.012	-0.009
	(-1.77)	(-0.55)	(1.64)	(-1.35)
Constant	0.069***	0.057***	0.062***	0.062***
	(4.70)	(3.56)	(4.16)	(4.29)
N	728	728	728	728
R^2	0.23	0.10	0.21	0.25

Note: This table shows the relation between the weekly New York Times news index constructed by De Nard et al. (2024) and high return weeks on each of the hedge portfolios. Panel A shows the relation controlling for the market rate of return that week. Panel B shows specifications controlling for the market rate of return and individual GICS sector S&P1500 portfolios. The abbreviation "cons." stands for "consumer" and the abbreviation "info. tech." stands for "information technology". Robust t-statistics reported in parentheses. Stars *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Firm Rankings by Mean T-Statistic

Greenest		Brownest	
Rank	**Company (Sector)**	**Rank**	**Company (Sector)**
1	Procter & Gamble (Cons. Staples)	1	Caterpillar (Industrials)
2	MGE Energy (Utilities)	2	Flowserve (Industrials)
3	American States Water (Utilities)	3	Parker-Hannifin (Industrials)
4	Pepsico (Cons. Staples)	4	Eagle Materials (Materials)
5	Clorox (Cons. Staples)	5	Genesee & Wyoming (Industrials)
6	Spire (Utilities)	6	Dover Corp. (Industrials)
7	Unitil (Utilities)	7	Emerson Electric (Industrials)
8	Johnson & Johnson (Healthcare)	8	Phillips 66 (Energy)
9	California Water (Utilities)	9	Norfolk Southern (Industrials)
10	One Gas (Utilities)	10	Cummins (Industrials)

Note: This table shows the ranking of firms by their average PC1 t-statistic over the period 2010-2023. The left columns list the top 10 firms in decreasing order (the first ranked firm has the highest t-statistic), while the right columns list the bottom 10 firms in increasing order (the first ranked firm has the lowest t- statistic).

Table 5. Compustat Data Specifications, No Fixed Effects

Dependent Variable:	t_{PC1}												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Ln(Assets)	-0.05*** (-5.08)												-0.03** (-2.43)
CAPX/Assets		-0.07*** (-7.20)											-0.01 (-1.19)
Share Intangible Assets			0.12*** (11.88)										0.06*** (5.50)
R&D/Sales				0.05*** (4.80)									0.05*** (4.12)
Advertising/Sales					0.16*** (18.89)								0.08*** (8.74)
Gross Profit Margin						0.31*** (32.18)							0.23*** (22.58)
LT Debt/Capital							-0.13*** (-13.47)						-0.02* (-1.74)
Interest Expense/Liabilities								-0.19*** (-20.47)					-0.07*** (-6.89)
Z-Score									0.18*** (19.60)				0.06*** (6.04)
Book/Market										-0.20*** (-20.96)			-0.12*** (-11.65)
Market Beta											-0.31*** (-31.25)		-0.31*** (-29.66)
I-Vol												-0.13*** (-11.69)	-0.04*** (-3.22)
N	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708
R^2	0.001	0.002	0.005	0.001	0.010	0.037	0.007	0.014	0.013	0.016	0.038	0.007	0.097
GICS Sector FE	No	No	No	No	No	No	No	No	No	No	No	No	No
Year FE	No	No	No	No	No	No	No	No	No	No	No	No	No

Note: This table shows various specifications relating a firm-year PC1 t-statistic to variables constructed from Compustat information. Sample is limited to firms with at least $10M USD in book value and market value, and excludes financial and real estate firms. All independent variables have been standardized to mean 0 and variance 1. Columns 1 through 12 shows univariate results in which each of the variables enters in a separate OLS regression. Column 13 adds all variables to a single OLS specification at the same time. Robust t-statistics reported in parentheses. Stars *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 6. Compustat Data Specifications, With Fixed Effects

Dependent Variable:	t_{PC1}												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Ln(Assets)	-0.04*** (-4.13)												-0.07*** (-5.05)
CAPX/Assets		0.07*** (6.65)											0.09*** (8.29)
Share Intangible Assets			0.07*** (7.41)										0.10*** (9.87)
R&D/Sales				-0.04*** (-5.11)									-0.02** (-2.48)
Advertising/Sales					0.06*** (6.88)								0.03*** (3.09)
Gross Profit Margin						0.14*** (14.91)							0.08*** (7.57)
LT Debt/Capital							-0.10*** (-10.77)						-0.03** (-2.12)
Interest Expense/Liabilities								-0.13*** (-14.79)					-0.06*** (-6.06)
Z-Score									0.12*** (12.88)				0.06*** (6.18)
Book/Market										-0.10*** (-10.57)			-0.05*** (-5.47)
Market Beta											-0.19*** (-19.97)		-0.17*** (-16.65)
I-Vol												-0.12*** (-9.83)	-0.06*** (-4.59)
N	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708	24,708
R^2	0.240	0.240	0.241	0.240	0.240	0.245	0.242	0.245	0.244	0.242	0.251	0.243	0.271
Within Group R^2	0.001	0.002	0.002	0.001	0.002	0.008	0.004	0.008	0.007	0.004	0.016	0.006	0.042
GICS Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows various specifications relating a firm-year PC1 t-statistic to variables constructed from Compustat information. Sample is limited to firms with at least $10M USD in book value and market value, and excludes financial and real estate firms. All independent variables have been standardized to mean 0 and variance 1. All columns include industry and year fixed effects. Columns 1 through 12 shows univariate results in which each of the variables enters in a separate regression. Column 13 adds all variables to a single specification at the same time. Robust t-statistics reported in parentheses. Stars *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 7. Refinitiv Data Specifications

Panel A. OLS Specifications

Dependent Variable:	t_{PC1}						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
E-Score	-0.09***					0.04**	
	(-6.67)					(2.52)	
Emissions Score		-0.06***					0.02
		(-4.20)					(0.64)
Innovation Score			-0.14***				-0.12***
			(-9.98)				(-7.21)
Resource Use Score				-0.04***			0.13***
				(-2.86)			(5.24)
Ln(Scope 1 + 2 Emissions)					-0.22***	-0.24***	-0.25***
					(-16.28)	(-15.18)	(-15.67)
Constant	-0.71***	-0.71***	-0.71***	-0.71***	-0.71***	-0.71***	-0.71***
	(-55.03)	(-54.99)	(-55.14)	(-54.97)	(-55.45)	(-55.46)	(-55.60)
N	16,911	16,911	16,911	16,911	16,911	16,911	16,911
R^2	0.003	0.001	0.006	0.001	0.018	0.018	0.023

Panel B. Specifications with Fixed Effects

Dependent Variable:	t_{PC1}						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
E-Score	-0.03**					-0.01	
	(-2.41)					(-0.80)	
Emissions Score		-0.02*					-0.05**
		(-1.88)					(-2.31)
Innovation Score			-0.06***				-0.08***
			(-5.39)				(-5.61)
Resource Use Score				0.00			0.10***
				(0.18)			(4.58)
Ln(Scope 1 + 2 Emissions)					-0.05***	-0.04**	-0.05***
					(-3.31)	(-2.45)	(-2.89)
N	16,911	16,911	16,911	16,911	16,911	16,911	16,911
R^2	0.274	0.274	0.276	0.274	0.275	0.275	0.277
Within Group R^2	0.000	0.000	0.002	0.000	0.001	0.001	0.003
GICS Sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: This table shows various specifications relating a firm-year PC1 t-statistic to variables from Refinitiv/LSEG ESG information. In Panel A, we present OLS specifications. All independent variables have been standardized to mean 0 and variance 1. Columns 1 to 5 show univariate regressions. Columns 6 and 7 show specifications that combine headline numbers with emissions as a control. The headline E-Score and sub-scores cannot be combined in a single regression due to collinearity concerns. Panel B repeats the same specifications with sector and year fixed effects. Robust t-statistics reported in parentheses. Stars *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 8. Combined Compustat and Refinitiv Specifications

Dependent Variable:	t_{PC1}			
	(1)	(2)	(3)	(4)
Ln(Assets)	0.08***	-0.06***	-0.06***	-0.08
	(4.03)	(-3.31)	(-2.90)	(-1.15)
CAPX/Assets	-0.03**	0.08***	0.09***	0.10***
	(-2.24)	(5.27)	(6.12)	(4.25)
Share Intangible Assets	0.02	0.08***	0.08***	0.01
	(1.64)	(5.99)	(5.81)	(0.38)
R&D/Sales	0.03*	-0.04***	-0.04***	-0.02
	(1.71)	(-3.79)	(-3.10)	(-1.03)
Advertising/Sales	0.08***	0.04***	0.04***	0.04
	(6.82)	(2.97)	(3.31)	(1.09)
Gross Profit Margin	0.25***	0.06***	0.06***	0.10***
	(17.25)	(4.47)	(4.31)	(2.93)
LT Debt/Capital	-0.00	-0.02	-0.03**	-0.06**
	(-0.04)	(-1.08)	(-2.08)	(-2.35)
Interest Expense/Liabilities	-0.11***	-0.10***	-0.08***	-0.06***
	(-7.55)	(-7.57)	(-5.85)	(-2.95)
Z-Score	0.04***	0.03*	0.02*	-0.03
	(2.81)	(1.82)	(1.70)	(-1.43)
Book/Market	-0.12***	-0.07***	-0.05***	-0.02
	(-8.18)	(-4.90)	(-3.88)	(-1.18)
Market Beta	-0.48***	-0.27***	-0.30***	-0.15***
	(-32.66)	(-19.52)	(-20.32)	(-8.32)
I-Vol	0.02	-0.04***	-0.07***	-0.09***
	(1.03)	(-2.64)	(-3.76)	(-3.72)
E-Score	-0.07***	-0.01	-0.02	0.01
	(-4.20)	(-0.91)	(-1.15)	(0.38)
Ln(Scope 1 + 2 Emissions)	-0.18***	-0.09***	-0.08***	-0.02
	(-8.79)	(-4.72)	(-4.32)	(-0.63)
N	14,657	14,657	14,657	14,565
R^2	0.148	0.329	0.341	0.537
Within R^2		0.062	0.067	0.018
GICS Sector FE	No	Yes	Yes	No
Year FE	No	No	Yes	Yes
Firm FE	No	No	No	Yes

Note: This table shows various specifications relating a firm-year PC1 t-statistic to variables constructed from both Compustat and Refinitiv/LSEG ESG information. All independent variables have been standardized to mean 0 and variance 1. Column 1 shows a multivariate specification with no fixed effects. Column 2 shows a specification with only sector fixed effects. Column 3 adds year fixed effects. Column 4 has both year and firm specific fixed effects. Robust t-statistics reported in parentheses. Stars *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 9. Specifications Investigating Reporting of Emissions

Dependent Variable:	t_{PC1}		
	(1)	(2)	(3)
$\mathbb{1}$(Reported Emissions)	-0.20***	-0.11***	-0.01
	(-5.75)	(-2.89)	(-0.32)
Std. Ln(Scope 1 + 2 Emissions)		0.06**	0.06*
		(2.22)	(1.88)
$\mathbb{1}$(Reported Emissions) × Std. Ln(Scope 1 + 2 Emissions)		-0.25***	-0.10***
		(-6.25)	(-3.26)
N	18,503	18,022	17,983
R^2	0.420	0.424	0.888
Outcome Mean	-1.63	-1.64	-1.64
Year × GICS Sector FE	Yes	Yes	Yes
Firm FE	No	No	Yes

Note: This table shows specifications relating a firm-year PC1 t-statistic to emissions and whether a firm reports their emissions. Refinitiv/LSEG provides an indicator for whether the listed emissions for a firm are reported or interpolated. Column 1 only regresses the t-statistic against an indicator for if the firm has directly reported emissions in that year. Column 2 adds an interaction with the standardized log of emissions. Column 3 adds sector-year fixed effects. Robust t-statistics reported in parentheses. Stars *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 10. Specifications for Predicting Top and Bottom Quintiles

Dependent Variable:	1(Top 20%)		1(Bottom 20%)	
	(1)	(2)	(3)	(4)
Ln(Assets)	0.17***	0.10***	0.04**	0.18***
	(8.99)	(4.86)	(2.23)	(8.11)
CAPX/Assets	0.20	2.49***	1.36***	-1.93***
	(0.45)	(4.58)	(3.03)	(-4.20)
Share Intangible Assets	0.05	0.29**	-0.22*	-0.57***
	(0.41)	(2.37)	(-1.92)	(-4.20)
R&D/Sales	0.05	-0.07	-0.65	0.13**
	(1.27)	(-1.31)	(-0.94)	(2.33)
Advertising/Sales	0.04	0.70	-9.90***	-4.48***
	(0.06)	(0.87)	(-6.74)	(-3.47)
Gross Profit Margin	1.32***	0.37***	-1.33***	-0.30**
	(11.35)	(3.04)	(-10.42)	(-2.15)
LT Debt/Capital	-0.32**	-0.54***	-0.19	-0.08
	(-2.49)	(-3.87)	(-1.42)	(-0.58)
Interest Expense/Liabilities	-8.69***	-8.08***	7.03***	5.22***
	(-4.35)	(-4.26)	(4.54)	(2.88)
Z-Score	0.00	-0.00	-0.02**	-0.01*
	(0.92)	(-0.30)	(-2.37)	(-1.66)
Book/Market	-0.44***	-0.44***	0.19***	0.07
	(-6.27)	(-5.81)	(3.25)	(1.31)
Market Beta	-1.33***	-0.82***	1.19***	0.94***
	(-20.97)	(-12.44)	(22.89)	(15.08)
I-Vol	-8.76***	-16.11***	-7.93***	0.94
	(-3.23)	(-4.99)	(-3.18)	(0.35)
E-Score	-0.42***	-0.19*	0.27***	0.08
	(-4.54)	(-1.89)	(2.96)	(0.78)
Ln(Scope 1 + 2 Emissions)	-0.04***	-0.03**	0.10***	0.04***
	(-3.68)	(-2.25)	(7.89)	(3.59)
N	14,657	14,657	14,657	14,657
R^2	0.090	0.176	0.109	0.233
GICS Sector FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

Note: This table shows logistic regressions predicting whether a firm is in the top or bottom 20% of firms based on PC1 t-statistic within a year. All independent variables have been standardized to mean 0 and variance 1. The first two columns predict an indicator for if the firm is in the top 20% of firms (greenest), while the last two columns predict an indicator for if the firm is in the bottom 20% of firms (brownest). Columns 2 and 4 add sector and year fixed effects to the specifications displayed in Columns 1 and 3. Robust t-statistics reported in parentheses. Stars *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.

Table 11. Firm Transition Matrices

Panel A. Fixed Terciles

	Bins	$t_{PC1,t}$		
		$(-\infty, -1.96]$	$(-1.96, 1.96]$	$(1.96, \infty)$
$t_{PC1,t-1}$	$(-\infty, -1.96]$	44%	56%	1%
	$(-1.96, 1.96]$	14%	82%	4%
	$(1.96, \infty)$	3%	78%	18%

Panel B. Year-by-Year Quintiles, 1 Year Rolling

	Quintiles	$t_{PC1,t}$				
		1	2	3	4	5
$t_{PC1,t-1}$	1	44%	22%	16%	12%	7%
	2	22%	24%	21%	20%	14%
	3	15%	22%	22%	21%	19%
	4	12%	19%	22%	23%	24%
	5	7%	14%	19%	24%	37%

Note: This table shows transition matrices of firms across bins from year $t-1$ to year t. Firms are assigned to bins based on their PC1 t-statistic in year t. In Panel A, the bins are terciles with fixed cutoff levels that do not vary year-to-year (defined at standard 95% confidence interval cutoffs). In panel B, the bins are quintiles with variable cutoff levels dependent on the distribution of firm t-statistics each year. For a given year, the cutoffs are set at the quintiles of the measured t-statistics (0th to 20th percentile, 20th to 40th percentile, etc.). As each panel is a transition matrix, each row sums to 100%, with any discrepancy due to rounding for display purposes.

Table 12. Greatest Firm Changes in T-Statistic

Panel A. Largest Changing Firms

Greatest Increase				Greatest Decrease			
Rank	**Company (Sector)**	**Original t_{PC1}**	**Final t_{PC1}**	**Rank**	**Company (Sector)**	**Original t_{PC1}**	**Final t_{PC1}**
1	Danaher Corp (Industrials)	-3.63	0.77	1	Eagle Materials (Materials)	-3.04	-7.5
2	SPX Technologies (Industrials)	-4.58	-0.75	2	Exxon Mobil (Energy)	0.60	-3.14
3	Amicus Therapeutics (Healthcare)	-1.56	1.65	3	Vaalco (Energy)	0.93	-2.79
4	RTX (Industrials)	-4.87	-1.74	4	Kinder Morgan (Energy)	1.26	-2.42
5	Honeywell (Industrials)	-5.71	-2.73	5	Kaiser Aluminum (Materials)	-1.22	-4.76

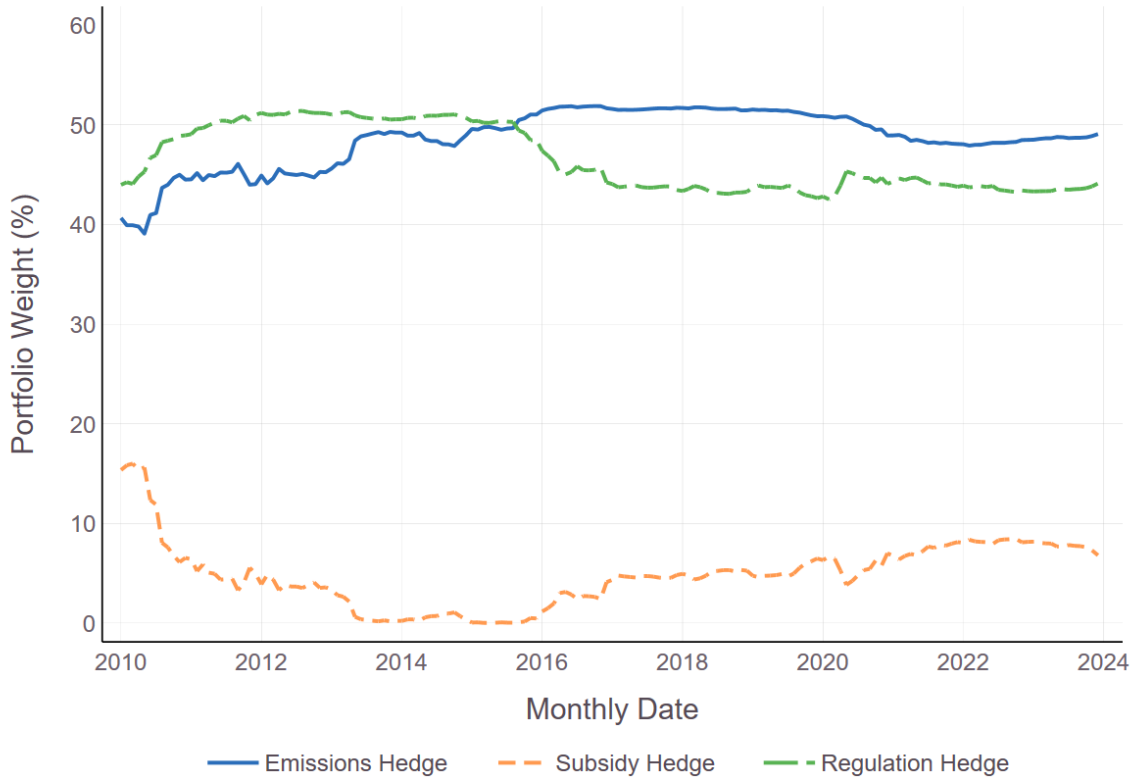
Panel B. Industry Changes

2 Digit GICS Sector	**Average Δt_{PC1}**
Energy	-1.83
Materials	-0.50
Industrials	0.14
Consumer Discretionary	-0.24
Consumer Staples	0.36
Healthcare	0.55
IT	-0.39
Communication Services	0.90
Utilities	0.85

Note: This table shows the long-run changes over time in the PC1 t-statistic measure. We take firms that exist for the entire sample (from 2010 to 2023), and calculate the difference between the average t-statistic in the first three years (2010-2012) and the last three years (2021-2023). Panel A lists the top five and bottom five firms by the difference in these two averages. Panel B shows the average difference for firms within each industry.

Appendix

Figure A.1. PC1 Portfolio Weights Time Series



Note: This figure shows the time series variation in the constituent hedge portfolios for the PC1 portfolio.

Table A.1. Mutual Fund Tilt Robustness

Dependent Variable:	t_{PC1}	
	(1)	(2)
Scaled van der Beck Mutual Fund Green Tilt	0.03***	0.03**
	(4.21)	(2.55)
N	29,585	29,594
R^2	0.293	0.442
Year × GICS Sector FE	Yes	No
Year FE	No	Yes
Firm FE	No	Yes

Note: This table shows specifications regressing the PC1 t-statistic against van der Beck (2024) mutual fund-based greenness measure. The independent variable is the scaled portfolio weight difference, i.e., $scaled_{i,t} = (w_{i,t}^{E} - w_{i,t}^{Mkt})/(w_{i,t}^{E} + w_{i,t}^{Mkt})$. Robust t-statistics reported in parentheses. Stars *, **, *** represent significance at the 10%, 5%, and 1% levels, respectively.