Oil-Driven Greenium

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Abstract

An influential view attributes the "greenium"—the cost-of-capital gap between carbon-intensive and greener firms—to climate risks and investor preferences. We challenge this by showing that oil shocks are pivotal: rising prices, driven by foreign supply or sector-specific demand shocks, reduce energy firms' cost of capital by enhancing their growth opportunities, creating a divergence from other brown firms. This energy-specific component explains 20% of greenium fluctuations, peaking at 50%. Reassessing events like the Paris Agreement suggests the impact of investor discipline weakens when oil's role is considered. Overall, markets price climate risks less effectively than assumed.

Keywords: climate change, ESG, green premium, oil, omitted variable

1 Introduction

One of the most pressing questions in climate finance is whether financial markets materially factor firms' environmental, social, and governance (ESG) performance into asset prices. At the heart of this issue is the concept of "greenium," which posits that, during the transition to net zero, carbon-intensive firms face a higher cost of capital due to increased climate policy risk and investor preference shifts, while less carbon-intensive firms benefit from a lower cost of capital. Such investor commitment can potentially aid efforts to combat climate change without extensive government intervention (Hong, Wang and Yang, 2023). Over the past decade, the greenium has grown in general, reflecting a higher relative cost of capital faced by carbon-intensive firms (Pástor, Stambaugh and Taylor, 2022; Sautner et al., 2023; Gormsen, Huber and Oh, 2023; Eskildsen et al., 2024). More importantly, the greenium seems to respond to climate-related events, such as the Paris Agreement (Monasterolo and De Angelis, 2020). This evidence is often interpreted as indicating that investors have begun to incorporate firms' ESG performance in asset prices. In essence, this view aligns with Milton Friedman's 1970 argument: markets should solve societal problems efficiently without relying on regulation or policy enforcement.

In this paper, we challenge this prevailing narrative that the documented greenium variation reflects genuine investor commitment to climate-aware investments. A large fraction of carbon-intensive firms are concentrated in the oil and gas industries, in which their product price are closely tied to fluctuations in the oil market. As such, the ESG investment return is exposed to oil shocks, as evidenced by the turn of ESG returns following the outbreak of the Russian-Ukraine military conflict and documented more broadly by Blitz (2022). The oil price has experienced several booms and busts over the past two decades, which coincide with various climate events. Hence, fluctuations in the greenium might have been mistakenly attributed to climate policy risk or sustainable investing when, in fact, they reflect time-varying risks that affect oil-dependent firms. Indeed, our analysis reveals that oil shocks play a significant role in explaining variations in the greenium. Oil shocks affect not only the cash flows of oil and gas producers but also their expected profit margins and investment decisions, leading to variations in discount rates. After accounting for the influence of oil shocks, we find that investor discipline surrounding key climate-related events, such as the Paris Agreement, has only modest if any, effects. Overall, financial markets may not be as responsive to climate shocks as previously assumed.

To examine the potential contribution of oil shocks to the greenium, we decompose the greenium (the spread between all brown and green firms) into the ex energy greenium—the cost of capital gap between non-energy brown and green firms—and the energy spread, the cost of capital gap between energy and other brown firms. These two components exhibit distinct dynamics and the energy spread drives an additional 20% of equity greenium variation and 15% of bond greenium variation beyond the contribution of ex energy greenium on average. Notably, since the 2014 oil price collapse, the energy spread's contribution to the bond greenium has consistently exceeded 40%, as sustained low prices amplified credit risk differentials between energy and non-energy brown sectors.

Why are oil shocks discount rate shocks that affect energy firms' cost of capital? We study a stylized model with oil demand shocks for energy companies and no productivity shocks for simplicity. In the model, energy firms produce oil, and non-energy firms produce other goods, either brown or green. A high demand for oil and gas products, driven by international supply shocks or sector-specific oil demand shocks, raises energy firms' forward-looking output price expectation and growth opportunities, lowering their cost of capital relative to other firms. This result holds generally when the energy firm is compared to a non-energy firm, either brown or green, and is different from the impact of green preference shocks in the literature (Pástor, Stambaugh and Taylor, 2021).

Our empirical analysis, spanning a half-century sample (1974–2021), robustly corroborates theoretical predictions. Consistent with our model, positive oil price shocks correlate with elevated relative product prices in the energy sector and statistically significant improvements in growth opportunities—proxied by Tobin's Q, sales growth, asset growth, and profitability. Conversely, negative oil price shocks depress these metrics. Energy firms' cost of capital exhibits pronounced sensitivity to oil shocks: rising oil prices reduce financing costs.

To further disentangle causality, we exploit various quasi-natural experiments: the OPEC announcement surprises, the COVID-19 pandemic lockdown, and the 2022 Russia-Ukraine military conflict. These exogenous demand and supply disruptions impacted global energy prices, tilted demand for U.S. hydrocarbons, and structurally changed growth prospects for domestic energy firms. For example, energy firms' equity ICCs vary up to 3% per annum and bond yield spreads vary by almost 1% following the COVID-19 outbreak. This response starkly contrasts with the ex energy greenium—defined as the cost of capital spread between other brown and green firms—which shows only marginal and small sensitivity, due to supply chain linkages. The asymmetry underscores oil shocks as a first-order determinant of energy-sector financing dynamics.

We revisit key climate events studied in the literature to assess whether oil shocks may have biased existing estimates. The Paris Agreement (PA), adopted at COP21 in December 2015, is among the most analyzed events in climate finance (Monasterolo and De Angelis, 2020). We find that while the equity greenium remains unchanged, the bond greenium significantly increases post-PA, consistent with Seltzer, Starks and Zhu (2022). However, this rise is not due to heightened climate policy risk or attention but is concentrated in the energy sector and driven by sharp oil price fluctuations. The PA coincided with the bottom of the 2014 oil price crash, and the subsequent V-shaped oil recovery explains the tent-shaped greenium dynamics observed. After excluding energy firms or controlling for oil price movements, the estimated PA effect is no longer significantly positive.

Next, we examine the election of President Trump in November 2016 (Ilhan, Sautner and Vilkov, 2021), an event that lowered perceived climate policy risk. This event coincided with the oil price recovery following the 2014 crash, driven by the Organization of the Petroleum Exporting Countries (OPEC) and Russia's decision to cut production that same month. We find no significant impact on equity greenium, while the bond greenium declines significantly after the election. However, this effect weakens once oil shocks are accounted for.

We further examine the role of climate concern shocks and sustainable investing in shaping the greenium. Prior studies suggest that climate concern shocks increase brown firms' cost of capital relative to green peers, functioning as discount rate shocks (Pástor, Stambaugh and Taylor, 2021, 2022). While we replicate these findings using the original 2011–2018 sample, extending the analysis to 2006–2022 reveals that investor preference shocks have an insignificant effect. For example, although the greenium rose sharply from 2017 to 2020, aligning with the rise of sustainable investing, it subsequently declined despite record sustainable inflows in 2021 and stable sustainable assets in 2022. In contrast, oil price shocks alone explain more than 20% of bond greenium variations across both sample periods. These results underscore the need to contextualize climate risk premia within broader commodity cycles and sectoral dynamics.

This paper contributes to three key strands of literature. First, we add to the growing research on climate-related event studies by emphasizing industry heterogeneity. Much of the existing literature examines how key climate events shape the greenium, including the Stern Review, the Paris Agreement (Monasterolo and De Angelis, 2020; Bolton and Kacperczyk, 2021; Seltzer, Starks and Zhu, 2022; Duan, Li and Wen, 2023), the 2016 U.S. presidential election (Ilhan, Sautner and Vilkov, 2021), and climate concern shocks tied to sustainable investing (Ardia et al., 2023; Van der Beck, 2021; Pástor, Stambaugh and Taylor, 2022). These studies often treat brown firms as a homogeneous group, with energy firms as the primary example. However, we show that these events coincide with distinct oil price fluctuations. Neglecting oil shocks skews estimates of climate-related effects, causing especially large distortions for energy stocks.

Second, we contribute to the literature on time-varying ex-ante greenium. Prior studies explore various drivers of greenium variation, such as environmental policy risk (Hsu, Li and Tsou, 2023), past stock returns (Hartzmark and Shue, 2022), and green preferences (Pedersen, Fitzgibbons and Pomorski, 2021; Pástor, Stambaugh and Taylor, 2021). In contrast, Berk and van Binsbergen (2025) and De Angelis, Tankov and Zerbib (2023) find negligible effects, while Chen, Garlappi and Lazrak (2023) document opposite effects driven by responsible consumption preferences. To our knowledge, this paper is the first to highlight the role of oil shocks in shaping the ex-ante greenium, especially through the energy sector. Related work by Sautner et al. (2023) and D'Amico, Klausmann and Pancost (2023) links the pricing of climate-related risks to oil prices. We propose a novel mechanism: growth opportunity variation, which persists without carbon transition shocks. This channel aligns with the investment-based literature (Liu, Whited and Zhang, 2009; Kuehn and Schmid, 2014), and we extend this framework by incorporating output heterogeneity and demand shocks.

Third, we contribute to the debate on the magnitude of the average greenium. Existing studies report varying estimates of the greenium (Bolton and Kacperczyk, 2021; Aswani, Raghunandan and Rajgopal, 2024; Zhang, 2025) and that the greenium may have increased since 2016. Our findings suggest that the idea of an "average greenium" is elusive, as its magnitude is highly sensitive to prevailing oil price levels. This underscores the need for caution when interpreting greenium estimates from any specific sample.

The remainder of the paper is as follows. Section 2 explains the data and decomposes the greenium into sectoral contributions. Section 3 presents a stylized model to characterize the relation between oil shocks and the greenium. Section 4 studies the pricing relation empirically. Section 5 revisits existing event studies in the literature. Section 6 concludes.

2 Data and Greenium Decomposition

This section presents data and conducts preliminary empirical analysis. First, we explain various data used in this study. Second, we highlight the strong industry structure in carbon intensity and then quantify the contribution of the energy sector to aggregate greenium variations.

2.1 Data and Summary Statistics

Our empirical analysis leverages firm-level climate performance data sourced from S&P Trucost, a leading provider of annual carbon emission metrics expressed in terms of carbon dioxide equivalent (tCO2e). We focus on emissions categorized under Scope 1 and 2. Scope 1 greenhouse gas (GHG) emissions encompass direct emissions originating from sources that are either owned or controlled by the firm, such as fleet vehicles or emissions attributable to manufacturing processes. Scope 2 GHG emissions refer to indirect emissions arising from the consumption of purchased electricity, steam, heating, and cooling by the reporting entity.

Our primary metric for assessing a firm's climate profile is carbon intensity, calculated as the logarithm of total emissions scaled by sales over the period of emission. We use the most recent carbon emission and accounting data based on their respective release dates, following Zhang (2025) when combining various datasets. Given that Trucost conducted a review and updated all data from 2002 to 2008 in May 2009, we assume the original release date of the data to be October of the subsequent year, coinciding with the Carbon Disclosure Project's October release cycle.

The estimation of firm-level equity implied cost of capital (ICC) is challenging due to the inherent noise associated with assumptions regarding expected future cash flows and the potential for non-unique numerical solutions. We employ the average of four published ICC estimates to measure the ex-ante cost of equity. Lee, So and Wang (2021) demonstrate that these implied cost of capital (ICC)-based estimates are most reliable in the time series analysis.[1] For corporate bond pricing, we extract month-end pricing data from the ICE Index Platform following Bekaert and De Santis (2021) and Huang, Nozawa and Shi (2024). The duration-matched corporate bond yield spreads are winsorized at the 1% level following Kaviani et al. (2020). We supplement the bond pricing information with additional issuance information from Refinitiv Eikon. Firm-level equity and accounting data come from CRSP and Compustat N.A. We focus on the primary common stocks listed on the primary exchange.

We define the firms to be in the energy sector if they are in the MSCI energy sector (sector code 10), consisting of energy equipment & services and oil, gas, and consumable energy. Before MSCI, we classify based on matching NAICS and SIC codes. We construct the real price of oil by adjusting the nominal price of oil using the U.S. Consumer Price Index

[1] These ICC measures are proposed by (1) Gebhardt, Lee, and Swaminathan (2001), (2) Claus and Thomas (2001), (3) Easton (2004), and (4) Ohlson and Juettner-Nauroth (2005).

(CPI). The nominal oil price is derived from the refiner acquisition cost of crude oil imports, as reported by the U.S. Energy Information Administration, and extended back historically using the WTI index prior to 1983. The U.S. CPI data are sourced from FRED at the St. Louis Fed.

Panel A, Table 1 presents summary statistics for cost of capital measures. The ICC measure has an annualized mean of 7.39% and a standard deviation of 11.34%. The yield spread has an annualized mean of 1.93% and a standard deviation of 2.96%, comparable to quantities reported in previous studies on the US corporate bond market.

Panel B shows that the average carbon intensities for Scope 1 and 2 emissions are 4.1 and 2.03 logarithmic tons of CO2e per million U.S. dollars, respectively. Our regression models incorporate a variety of control variables to ensure robustness. Firm and equity attributes include market beta estimated over a 60-month rolling window, log assets, (log) book-to-market ratio, momentum, ROE, investment, sales growth, leverage (debt/total assets), and idiosyncratic volatility as derived from the Fama-French three-factor model. Bond-specific characteristics include duration, bond age, and credit ratings. To mitigate the influence of outliers, carbon variables and control variables are subjected to winsorization at the 1st and 99th percentiles before their inclusion as explanatory variables in our empirical analyses.

Finally, Panel C presents summary statistics of aggregate variables. The log growth of the real price of oil (ΔRPO) has a monthly standard deviation of 8%. The climate concern measure is calculated following Pástor, Stambaugh and Taylor (2022) using data provided by Ardia et al. (2023). The equity and bond ESG shares, representing the proportion of equity and bond funds with ESG considerations among all equity and bond funds, average 0.41% and 0.39%, respectively.

2.2 Constructing the Greenium

To construct measures of green premium (greenium), we employ firm-level emission data and classify firms into brown and green based on Scope 1 and 2 carbon intensity, institutional practices for carbon-aware portfolio management (Bolton and Kacperczyk, 2021;

Hartzmark and Shue, 2022). Specifically, we first sort firms into tercile portfolios and then classify the top tercile as brown firms and the bottom tercile as green peers. The aggregate greenium $Spread^{B-G}$ is then computed as the value-weighted ICC differential between brown (top tercile) and green (bottom tercile) portfolios for equity and corresponding yield spread differential for bonds. To isolate oil shock effects from climate-related risks, we consider excluding energy firms from other brown firms and calculate the non-energy greenium $Spread^{BNE-G}$.

Prior research underscores that cross-industry heterogeneity drives the majority of carbon intensity variation (Zhang, 2025). As shown in Table IA.1 of Internet Appendix, sectoral variations explain 68% of emission disparities in our sample, with other firm characteristics adding limited explanatory power. Table 2 quantifies this heterogeneity: utilities (3,288 tCO2e/\$M), materials (686), and energy (539) emerge as the three most carbon-intensive sectors, collectively representing 16% stocks and 11% of overall market capitalization. However, energy firms are not the most carbon-intensive entities; rather, they represent the median brown stocks in the top brown tercile, with the utility sector displaying the greatest emission intensity overall.

Figure 1 presents the sector representation in sorted equity and bond portfolios. Consistent with the firm-level intensity distribution, utility, materials, and energy sectors are concentrated in the brown tercile and are barely represented in the other terciles. Within the brown tercile, the portfolio weight of the energy sector is 18% for equity and 26% for bonds. For comparison, the portfolio weight of utilities and materials, the two most carbon-intensive sectors, is 25% for brown equity tercile and 35% for brown bond tercile. Other sectors make up 57% of brown equity and 40% of brown bonds. Similarly, Financials, Information Technology, and Health Care are over-represented in low-carbon portfolios. Overall, these systematic differences in sector composition between high- and low-carbon portfolios validate sector-based measurements of firms' carbon footprint.

2.2.1 The Energy Spread and A Narrative on Oil Shocks

The energy sector is particularly vulnerable to oil shocks, given its direct involvement in the production of oil, gas, and other energy-related products. Many downstream industries that rely on energy inputs are also classified as brown industries due to their carbon intensity. However, the impact of oil shocks on these industries can be more muted for several reasons. First, energy costs typically constitute only a small fraction of total production costs for most downstream industries. Second, the extent to which firms can pass oil-related cost fluctuations to consumers depends on their market power (Katz and Rosen, 1985) and how global oil shocks affect demand for brown goods produced in the U.S. versus other regions. This creates an ambiguous net effect on profitability. Finally, some industries, particularly utilities, are subject to regulatory constraints that limit their exposure to oil price fluctuations.

Given these differences, we focus on the energy sector, which is most directly exposed to oil shocks, and compare it to other brown firms to isolate the role of oil-driven growth expectations, as oil shocks can have a stronger and more immediate impact on energy firms' expected returns. We thus decompose the brown-green spread $Spread^{B-G}$ into two components.

1) The first component is the ex energy greenium $Spread^{BNE-G}$, which represents the spread between top tercile brown firms (excluding energy) and bottom tercile green firms.

2) The second component is the energy spread $Spread^{Energy-BNE}$, which is the value-weighted cost of capital difference between energy firms and other non-energy brown firms, isolating energy commodity price effects.

This decomposition allows us to distinguish oil shock-induced return dynamics from broader climate risk channels, going beyond prior studies that treat brown firms as homogeneous.[2] Figure 2 presents the time-series evolution of the energy spread and ex energy greenium

[2] To further enable us to distinguish oil shocks from climate risk and climate-related shocks, we utilize the long sample going back to 1974 for equity and 1997 for bonds. As such, for pre-2003 periods lacking firm-level emissions data, we impute Fama-French 49-industry-level emission intensities using post-2003 firm-level data.

across the long sample. These two series display distinct dynamics over the half-century period. The two equity series exhibit a low but statistically significant correlation of -0.27 ($p<0.01$), while correlations of the bond market series remain statistically insignificant at -0.17 ($p>0.1$).

A closer examination of historical episodes reveals divergent dynamics of the series which are tied to structural shifts in energy markets. Over the 1970s energy crisis, characterized by the 1973 oil embargo and the 1979 Iranian Revolution, energy firms enjoy substantially lower equity financing costs relative to other brown firms, as input supply shocks constrained downstream industries. This gap inverted during the 1980s oil glut, as collapsing oil prices (down 70% from 1980 to 1986) eroded energy sector profits amid surging non-OPEC supply and Saudi Arabia's market-share strategy, while other brown firms gained temporary relief from cheaper inputs. The energy spreads remain subdued through the 1990s and early 2000s. However, the Global Financial Crisis (2007–2009) reignited divergence: oil demand contracted for the first time since 1983, driving sequential increases in energy firms' cost of equity and debt.

The 2010s, the sample most studied by climate finance, experienced several large oil shocks. Following the 2014 oil crash, driven by U.S. shale oversupply, OPEC's price war, and weak global demand, the energy sector ICC spread and bond yield spread noticeably increased, while non-energy brown firms partially offset demand weakness through input cost savings. Subsequently, during the COVID-19 pandemic, collapsing demand and negative oil prices pushed energy firms' cost of capital to decade highs. Most recently, following the Russia-Ukraine military conflict, sanctions on the Russian oil supply dramatically reduced the global oil supply, significantly boosting the U.S. energy firms' profitability and growth opportunities and reducing their cost of financing. In short, these dynamics underscore how macro-structural shifts—from financial crises to geopolitical conflicts—reshape the relative cost of capital.

2.2.2 Quantifying the Contribution of the Energy Spread

To quantify oil shocks' contribution to the greenium, we estimate the following time-series regressions over rolling five-year windows:

$$\begin{aligned} \Delta Spread_t^{B-G} &= a + b \cdot \Delta Spread_t^{BNE-G} + e_t, \\ \Delta Spread_t^{B-G} &= a + b \cdot \Delta Spread_t^{BNE-G} + c \cdot \Delta Spread_t^{Energy-BNE} + e_t. \end{aligned} \tag{1}$$

where $Spread^{B-G}$ is the aggregate greenium (brown vs. green firms), $Spread^{BNE-G}$ is the ex energy greenium, and $Spread^{Energy-BNE}$ is the energy spread. The marginal contribution of the energy spread—orthogonal to the ex energy greenium—is measured by the incremental R^2 from adding $Spread_t^{Energy-BNE}$ to the regression analysis.

Figure 3 plots the contribution by ex energy greenium and energy spread to aggregate greenium variations. Over the full sample, the energy spread explains 20% (15%) of equity (bond) greenium variations beyond the ex energy greenium on average.

This additional explanatory power varies over time, depending on the oil cycle. Before the 1990s, the energy spread can often explain another 50% of aggregate greenium variations driven by intense oil shocks. This effect weakened in the 1990s but saw a substantial resurgence in the energy spread's contribution to the aggregate greenium following the Global Financial Crisis. In particular, following the oil price collapse in 2014 and the prolonged downturn, the energy spread accounts for over 40% of bond greenium fluctuations, reflecting amplified credit risk differentials between energy and other brown firms.

These findings underscore that conventional greenium metrics, which aggregate all brown firms, conflate climate transition risks with energy-sector-specific commodity cycles. By separating the energy component, we provide a more nuanced understanding of how industry-specific factors influence energy firms through their operational exposure to oil price fluctuations. Understanding the sector-level heterogeneity can help better assess the true "greenium" variations driven by climate-related shocks.

3 Theoretical Model

The empirical observations highlight the tight linkage between oil shocks and the financing cost of energy firms. Economically, oil shocks not only constitute cash flow shocks to these firms but further significantly impact expected return variations and are thus discount rate shocks. This section now studies a simple theoretical model to conceptualize the economic channel.

3.1 Model Setup

Consider an economy in which agents consume oil-and-gas products E (for energy), and non-energy goods NE, including both other brown and green goods. The non-energy good is the numeraire in the economy. In the spirit of Kogan, Livdan and Yaron (2009) and Ready (2018), the demand for both goods is represented by

$$\begin{aligned} P_{Et} &= A_t \left(\frac{Y_{Et}}{Y_{NEt}} \right)^{-1/\epsilon}, \\ P_{NEt} &= 1. \end{aligned} \tag{2}$$

where P_E is the real price of oil, changes in A denote unexpected oil shocks. Examples of positive A shocks include the oil embargo of 1970s and outbreak of the Russian-Ukraine military conflict, which boosted demand for U.S. oil and gas and boosted energy firms' profitability. Examples of negative A shocks include the oil glut of 1980s and COVD-19 lockdown, which destroyed U.S. energy firms' profitability. Y_E and Y_{NE} are aggregate good production for non-energy goods, respectively, and ϵ is the elasticity of demand.

The model consists of a continuum of competitive firms in each sector,

$$Y_{it} = K_{it}^{\alpha}, \tag{3}$$

where K_i is the level of capital in each sector. The capital in each sector accumulates as follows,

$$K_{it+1} = (1-\delta)K_{it} + I_{it}, \tag{4}$$

where δ is the depreciation rate. The adjustment cost Φ equals

$$\Phi_{it} = \chi \frac{I_{it}^2}{K_{it}}. \tag{5}$$

The firm can be financed with debt b_{t+1} and equity s_{t+1}. Firms take product prices as given, produce, invest, and pay out dividends D,

$$D_{it} = (1-\tau)(P_{it}Y_{it} - \Phi_{it}) - I_{it} + \delta\tau K_{it} + b_{it+1} - r_{it}^b b_{it}, \tag{6}$$

where r^b is the gross interest on bonds. Taking the stochastic discount factor M_{t+1} as given, firm i chooses its investment I_{it}, its future capital K_{it+1}, and debt b_{it+1} to maximize its cum-dividend market value of equity,

$$V_{it} = E_t \left[\sum_{s=0}^{\infty} M_{t+s} D_{t+s} \right],$$

subject to $\lim_{T\to\infty} E_t \left[M_{t+T} b_{it+T+1} \right] = 0$ (the transversality condition), which prevents the firm from borrowing an infinite amount of debt. There is no tax shield or financial friction in the model, including issuance costs or bankruptcy costs. As such, the capital structure is indeterminate, and the Modigliani-Miller theorem holds.

3.2 Model Dynamics

The demand follows an auto-regressive process as follows,

$$A_{t+1} = (1-\rho) + \rho A_t + \sigma e_{t+1}. \tag{7}$$

where e is an i.i.d shock that follows a standard normal distribution. The stochastic discount factor is

$$\frac{M_{it+1}}{M_{it}} = \beta(1 - \gamma e_{t+1}), \tag{8}$$

where γ is risk loading.

The first-order condition of new debt implies $E_t[\frac{M_{it+1}}{M_{it}} r^b_{it+1}] = 1$. Define $P_{it} = V_{it} - D_{it}$ as the ex-dividend market value of equity, $r^s_{it+1} = (P_{it+1} + D_{it+1})/P_{it}$ as the stock return. We define $w^b_{it} = B_{it+1}/(P_{it} + B_{it+1})$ as the market leverage and $w^s_{it} = 1 - w^b_{it}$. The Euler equation for equity is $E_t[\frac{M_{it+1}}{M_{it}} r^s_{it+1}] = 1$. We define the energy spread as the expected return difference between energy and non-energy firms

$$Spread^{E-NE}_{it+1} = \left(w^b_{Et} r^b_{Et+1} + w^s_{Et} r^s_{Et+1}\right) - \left(w^b_{NEt} r^b_{NEt+1} + w^s_{NEt} r^s_{NEt+1}\right). \tag{9}$$

The bond and equity energy spread are defined as $r^b_{Bt+1} - r^b_{Gt+1}$ and $r^s_{Bt+1} - r^s_{Gt+1}$, respectively.

3.3 Equilibrium and Investment Return

The equilibrium of the economy consists of optimality investment decisions I_{Et+1}, I_{NEt+1}, K_{Et+1}, K_{NEt+1}, and product prices consistent with aggregate quantities. In particular, the first-order condition concerning the optimal investment in sector i is

$$\begin{aligned} &1 + (1-\tau)\chi\frac{I_{it}}{K_{it}} \\ =&E_t\frac{M_{t+1}}{M_t} \cdot \left((1-\tau)\left(\alpha P_{it+1}K^{\alpha-1}_{it+1} + \delta\tau + \frac{\chi}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2\right) + (1-\delta)\left(1 + (1-\tau)\chi\frac{I_{it+1}}{K_{it+1}}\right)\right). \end{aligned} \tag{10}$$

The left-hand side is the marginal Q, which equals the marginal cost of investment and also the shadow price of physical capital.

The first-order condition of physical investment also implies that $E_t\left[M_{t+1} r^K_{it+1}\right] = 1$, in which r^K_{it+1} is the physical capital investment return,

$$r^K_{it+1} = \frac{(1-\tau)\left(\alpha P_{it+1}K^{\alpha-1}_{it+1} + \delta\tau + \frac{\chi}{2}\left(\frac{I_{it+1}}{K_{it+1}}\right)^2\right) + (1-\delta)\left(1 + (1-\tau)\chi\frac{I_{it+1}}{K_{it+1}}\right)}{1 + (1-\tau)\chi\frac{I_{it}}{K_{it}}}. \tag{11}$$

The investment return can be shown to equal the average cost of capital following Liu, Whited and Zhang (2009),

$$r^K_{it+1} = w^b_{it} r^b_{it+1} + w^s_{it} r^s_{it+1}. \tag{12}$$

As such, the energy spread equals the investment return difference between energy and non-energy firms

$$Spread^{E-NE}_{t+1} = r^K_{Et+1} - r^K_{NEt+1}. \tag{13}$$

3.4 Energy Spread Analysis

In the model, the optimization problem for non-energy firms has no shocks. Non-energy firms maintain a constant level of investment, capital level, and investment return. The investment rule and investment return of energy firms vary with A. The time-series variation in the energy spread is all driven by energy firms' investment return. We can spell out the energy spread as

$$\begin{aligned} & Spread^{E-NE}_{t+1} \\ = & \frac{(1-\tau)\left(\alpha A_{t+1}K^{\alpha\left(1-\frac{1}{\epsilon}\right)-1}_{Et+1} + \delta\tau + \frac{\chi}{2}\left(\frac{I_{Et+1}}{K_{Et+1}}\right)^2\right) + (1-\delta)\left(1 + (1-\tau)\chi\frac{I_{Et+1}}{K_{Et+1}}\right)}{1 + (1-\tau)\chi\frac{I_{Et}}{K_{Et}}} - r^K_{NE}. \end{aligned} \tag{14}$$

The equation shows that current asset growth, future profitability $(1-\tau)\alpha A_{t+1}K^{\alpha\left(1-\frac{1}{\epsilon}\right)-1}_{Et+1}$, and future investment growth all play a role in determining the average spread. However, A_t jointly determines all these variables.

We now solve for the model with the first-approximation to account for the joint impact. When A is high, energy firms' marginal $Q = 1 + \chi\frac{I_{Et}}{K_{Et}}$ increases, because their investment is increasing in A,

$$\frac{\partial\left(I_{Et}-I_{NEt}\right)}{\partial A_t}\approx\frac{\alpha\beta\epsilon\rho K_0}{K_0^{\alpha-1}\alpha\beta(\alpha+(1-\alpha)\epsilon)+\epsilon\chi(1+\beta(1-\rho)(1+\delta-\tau))}>0, \tag{15}$$

which reduces the energy spread. The future marginal profit $(1-\tau)\alpha A_{t+1}K_{Et+1}^{\alpha\left(1-\frac{1}{\epsilon}\right)-1}$ is also increasing in A and can push up the greenium instead. In addition, as A reverts to the long-run mean over time, energy firms' marginal $Q=1+(1-\tau)\chi\frac{I_{Et}}{K_{Et}}$ and the energy-minus-non-energy Q spread also gradually revert over time.

Together, when τ is higher than a threshold $\tau>\bar{\tau}$, this investment and future investment effect dominate, and a negative relation between the current oil price and the ex-ante expected return arises,

$$\begin{aligned}\frac{\partial E_t Spread_{t+1}^{E-NE}}{\partial A_t}&\approx\frac{\alpha\beta\epsilon\rho\chi K_0^{\alpha-1}}{2(1+\delta\chi)^2}\\ &\cdot\frac{-2(1-\beta\delta(2-\rho))(1+\delta\chi)+\tau\left(\delta\chi\left(2-2\beta(2-\rho)(\delta+1)+\beta\delta\right)-2\beta\left((2+\delta)(1-\rho)+1\right)\right)}{\alpha\beta((1-\alpha)\epsilon+\alpha)+\epsilon\chi(1+\beta(1-\rho)(1-\delta-\tau))}\\ &<0,\end{aligned} \tag{16}$$

where $K_0^{1-\alpha}=\frac{\alpha\beta}{1+\delta\chi+\beta(1+\delta\chi-\frac{\delta^2\chi}{2})}$.[3]

The presence of physical adjustment cost is a key force that generates energy spread variations. If we assume away the adjustment cost $\chi\to 0$, energy firms' marginal Q stays constant, and the energy spread does not vary with the oil demand $\frac{\partial E_t Spread_{t+1}^{E-NE}}{\partial A_t}\to 0$.

Equation (16) also highlights the role of demand elasticity. If the oil demand is perfectly inelastic $\epsilon\to 0$, firms barely change their investment in response to oil demand and the greenium stays the same.

In addition, if the oil demand is not persistent $\rho\to 0$, the current oil price is not informative about future oil prices and does not drive greenium variations.

[3] The threshold $\bar{\tau}=\frac{2(1-\beta\delta(2-\rho))(1+\delta\chi)}{-2\beta((2+\delta)(1-\rho)+1)+\delta\chi(2-2\beta(2-\rho)(\delta+1)+\beta\delta)}$. When all parameters in $\bar{\tau}$ are between 0 and 1, the value of $\bar{\tau}$ is a small positive number. For example, under the baseline calibration, its value is 0.01.

3.5 Numerical Results

This section solves the model numerically and presents quantitative results. We calibrate the model at a quarterly frequency and present parameters in Panel A, Table 3. The discount rate β is 0.99, implying an annual risk-free rate of 4%. The return to scale α is 0.33, consistent with Kydland and Prescott (1982) and Gourio (2013). The quarterly depreciation rate δ is 0.03, implying an annual rate of 0.12 as in Cooper and Haltiwanger (2006). We follow Kuehn and Schmid (2014) to set the tax rate to 0.14.

For oil-related variables, we set the oil demand elasticity ϵ to 0.1, matching the low estimates in Kilian (2022). The persistence of aggregate oil demand ρ_A is set to 0.91, matching the empirical persistence of the real oil price. The conditional volatility of the oil demand σ is set to 0.087 to match the empirical volatility of the real oil price. The adjustment cost coefficient χ is set to 7 such that the oil supply elasticity is 0.02, within the range of estimates obtained in Kilian and Murphy (2014) and Baumeister and Hamilton (2019). We set the price of oil demand risk λ to 0.5.

We simulate the model for 20,000 times. Panel B presents the simulated moments. Target moments well match the data, and the energy spread has a quarterly standard deviation of 1.18%. The oil demand is almost perfectly correlated with the oil price, consistent with the interpretation of oil prices representing the level of oil demand. The simulation further generates a strong negative relation between the oil price and the energy spread, consistent with the analytical approximation. The correlation coefficient is as low as -0.97 between the oil price and forward-looking energy spread. The correlation is close to perfectly negative because the oil demand shock is the only shock in the economy. Second, consistent with analytical approximation, higher oil demand A is positively associated with brown-minus-green marginal Q spread and asset growth spread with correlation coefficients of 0.17.

In sum, the model predicts that oil demand is negatively associated with the energy spread. Higher oil demand is associated with higher marginal Q, asset growth, sales, and profitability for energy firms compared to other firms. In contrast, lower oil demand is associated with a lower energy-minus-non-energy Q spread, lower asset growth spread, lower profitability spread, and higher expected return spread.

4 Oil Shocks and Energy Spread

This section builds on the theoretical predictions of the model and formally examines the relationship between oil shocks and the cost of capital empirically over a long sample starting from 1974. First, we validate the theoretical link between oil prices and energy-sector output prices and growth opportunities. Then we examine various oil shock proxies, including oil price shocks, the COVID-19 pandemic lockdown, and the 2022 Russian-Ukraine military conflict, and quantify oil shocks' differential impact on energy firms and non-energy brown firms' cost of capital.

4.1 Producer Prices and Growth Opportunities

In this section, we examine the relationship between oil shocks, output prices, and growth opportunities. First, we test the model's core assumption, oil price shocks transmit to energy firms' output prices, using industry-level producer price index (PPI) data from the U.S. Bureau of Labor Statistics. Because price levels are non-stationary, our analysis studies the relationship using price changes,

$$\Delta PPI_{it} = a + b \cdot 1(Energy)_{it} \times \Delta RPO_t + \kappa_i + \iota_t + e_{it+\tau}, \tag{17}$$

where $\Delta PPI_t = \log(PPI_t/PPI_{t-1})$ measures changes in the producer product price index (PPI) of the NAICS4 level that the firm belongs to, $1(Energy)$ is an energy-sector indicator, and ΔRPO_t is the log oil price change. The regression model incorporates industry (κ_i) and time (ι_t) fixed effects, with standard errors double clustered at both the industry and month levels.

Other brown firms, particularly hydrocarbon-reliant downstream industries, face supply chain spillover effects from oil and gas input costs. We estimate the impact as follows

$$\begin{aligned}\Delta PPI_{it} &= a + b \cdot 1(Energy)_{it} \times \Delta RPO_t + c \cdot Intensity_{it} \times \Delta RPO_t + \kappa_i + \iota_t + e_{it+\tau}, \\ \Delta PPI_{it} &= a + b \cdot 1(Energy)_{it} \times \Delta RPO_t + c \cdot 1(Brown)_{it} \times \Delta RPO_t + \kappa_i + \iota_t + e_{it+\tau},\end{aligned} \tag{18}$$

where $Intensity_{it}$ is the standardized log carbon intensity and $1(Brown)$ equals one for industries in the top third of carbon intensity and zero otherwise. Table 4 presents the results. For example, a 10% oil price increase raises energy-sector output prices by 3.9% (t=15.97), but only 0.23% for average non-energy brown firms in the brown tercile, and 0.15% per-standard-deviation increase in carbon intensity for non-energy firms. Overall, our results show that oil price shocks significantly influence energy-sector output prices, while their impact on other brown industries is more limited, likely due to lower operational exposure to oil shocks and regulatory constraints.

One possible concern is that the input price for the energy industry also varies with the oil price. To address this, we build the input price index changes using the 71 industry-level input-output table from the Bureau of Economic Analysis (BEA), scaled by the cost of goods sold (COGS) share in total sales (SALE) for each industry using Compustat data. We estimate the relationship empirically as in equations (17) and (18) and results in Columns (4) to (6) show that the effect on input prices is negligible. Energy-sector input costs rise by only 0.3% per 10% oil shock, versus 3.9% output price gains. In other words, the results suggest that profit margins thus expand asymmetrically for energy firms during oil upswings.

Next, we turn to the key prediction of the theoretical framework that energy firms have greater increases in growth options than other firms when the oil price increases. We conduct the following regression,

$$\Delta Y_{it+1} = a + b \cdot 1(Energy) \times \Delta RPO_t + d \cdot X_{it} + \kappa_i + \iota_t + e_{it+\tau}, \tag{19}$$

where Y denotes firm-level measures of growth opportunities, and ΔRPO denotes log oil price changes. The annual estimation includes firm and time-fixed effects and standard errors are double clustered at the firm and yearly levels. We include the interaction between oil shocks and log carbon intensity or brown firm status to examine potential supply chain spillovers.

Panel B of Table Table 4 provides robust evidence that higher oil prices are associated with a widening disparity in growth options between energy and non-energy firms. Tobin's average Q, a proxy for marginal Q in our model, increases significantly following oil price increases. The effect for non-energy brown firms, potentially due to supply chain effects, is substantially smaller and insignificant (0.32 for energy firms and 0.03 for non-energy brown firms). The relationship is also reflected in one-year-ahead actual growth, measured as sales growth, investment rates, and ROE improvements.

Additional results in Table IA.2 of Internet Appendix show that these results remain highly significant after controlling for firm-level characteristics. As such, our findings underscore the importance of explicitly controlling for oil shocks when conducting empirical studies. Collectively, these results highlight the differential impacts of oil shocks on the growth options of energy and non-energy firms, with energy firms benefiting more from elevated oil prices.

4.2 Time Series Evidence on Oil Shocks

We now evaluate the impact of oil shocks on return differentials between energy firms and other firms. We begin by focusing on oil price shocks and estimate the following time series regression

$$\Delta Spread_t^i = \alpha + \beta \Delta RPO_t + \varepsilon_t, \tag{20}$$

where i =Energy-BNE or BNE-G, denoting energy spread or ex energy greenium, and ΔRPO is the log change in oil prices. Standard errors are adjusted for autocorrelation up to 12 lags.

Consistent with the model prediction, Panel A of Table 5 shows that oil price fluctuations negatively impact the greenium ($\beta < 0$) over the long sample, with the effect being more muted for ex energy greenium. A one-standard-deviation increase in oil prices reduces the equity and bond energy spreads by 14 and 6 basis points (bps), respectively—translating to a roughly quarter standard deviation of the corresponding energy spread's historical volatility. For R^2, the oil price shocks explain 4% energy spread variations in equity and 11% in bonds.

The effect is smaller and often insignificant significant for non-energy brown firms. Specifically, the coefficient is 0.14 for non-energy equity greenium, compared to -1.75 for equity energy spread, and -0.30 for non-energy bond greenium, compared to -0.84 for bond energy spread. Similarly, the explantory power for ex energy greenium variations is also low, with $R^2 = 0\%$ and 3% for equity and bonds, respectively.

Time-series dynamics presented in Figure 4 reveals strong negative co-movement between oil prices and greenium. First, the greenium varies substantially throughout the sample but becomes more elevated from mid-2014 onward, a trend that aligns with the below-mean oil price observed over the same interval. Second, in the past two decades, a few major boom-and-bust cycles in oil prices have closely aligned with greenium fluctuations. The first oil price bust occurred during the Global Financial Crisis, and the second occurred between 2014 and 2016, leading to prolonged downturns. The third oil bust took place in 2020 following the outbreak of COVID-19, while the outbreak of Russian-Ukraine military conflicted led to sharp rallies in oil prices. These dramatic crashes and recoveries in oil prices are mirrored by sharp rallies and reversals in the bond greenium and similar, albeit less pronounced, patterns in the equity greenium.

Alternatively, we can focus on energy and utility firms to isolate dynamics unrelated to the energy transition. The utility sector, a key brown industry and a major energy consumer, is heavily affected by decarbonizing policies and targeted by sustainable investing. While closely linked to the energy sector, utilities face strict regulatory constraints on pricing flexibility, such as rate-of-return regulations. These regulations help insulate utilities' cash flows and valuations from oil price volatility. Results in Table IA.3 of the Internet Appendix, based on the spreads between the energy and utility sectors, closely align with those of the baseline analysis, showing similar coefficient magnitudes and statistical significance. Overall, the asymmetric effects of oil shocks on energy versus non-energy firms highlight the impact of commodity price driving greenium dynamics.

4.3 Security-Level Panel Evidence

The baseline analysis employs time series analysis for clarity and ease of interpretation. This section now conducts the analysis using panel regressions, which are often adopted by event studies in the literature. The panel method also allows us to account for various security characteristics. We estimate the following panel regression:

$$\Delta ER_{it} = a + b \cdot 1(Energy)_{it} \times \Delta RPO_t + d \cdot X_{it} + \kappa_i + \iota_t + e_{it}, \tag{21}$$

where ER denotes the cost of capital measures (ICCs for equity and yield spreads for bonds), $1(Energy)$ is the energy sector indicator, ΔRPO is the log changes in the oil price, and X represents the bond- and firm-level controls. The regression is conducted at the security-month level and includes firm and time-fixed effects. Standard errors are double-clustered at the firm and month levels. We further include the interaction of oil shocks with log carbon intensity and brown firm status.

Panel B of Table 5 shows that consistent with the baseline analysis, oil price shocks negatively impact the cost of capital for energy firms in both equity and bond. The coefficients are -2.84 and -1.25, comparable to the baseline portfolio-based coefficients (-1.75 and -0.84). In contrast, we do not detect a significant impact on general carbon-intensive firms or high carbon-intensity brown firms.

4.4 Event Studies of Oil Shocks

The earlier sections show that oil price innovations significantly change production prices, growth opportunities, and cost of capital for energy firms. In particular, the effect arises absent of climate policy risk changes or climate preference shifts and does not significantly impact the ex energy greenium. However, the oil price itself can be endogenous (Kilian, 2009; Baumeister and Hamilton, 2019; Känzig, 2021). Different oil shocks that affect energy firms' growth opportunities may influence oil prices in various ways. To isolate causal effects, we adopt an instrumental variables (IV) approach following Känzig (2021), using OPEC announcement surprises as an exogenous shock to global oil supply. The instrument—the first principal component of daily WTI crude futures price changes (1- to 12-month maturities) around OPEC meetings—captures unanticipated shifts in foreign oil supply. Negative (positive) surprises raise (lower) demand for U.S. energy output, thereby affecting U.S. energy firms' cost of capital.

Specifically, we estimate a two-stage model:

$$\begin{aligned} \text{first stage: } \Delta RPO_t &= \gamma_0 + \gamma_1 Z_t + u_t, \\ \text{second stage: } \Delta Spread_t^i &= \alpha_{IV} + \beta_{IV} \widehat{\Delta RPO}_t + e_t, \end{aligned} \tag{22}$$

where Z_t denotes OPEC announcement surprises. First-stage results, as presented in Table IA.4 of Internet Appendix, confirm the instrument's strength (F-statistic>10). The second-stage results in Panel A of Table 6 reinforce the baseline results. Indeed, the IV-based estimates even reveal amplified effects relative to baseline OLS: equity greenium coefficients strengthen from -1.75 to -6.88 ($t = -2.71$), and bond greenium from -0.84 to -1.74 ($t = -2.76$). This sharp increase in magnitude suggests that endogenous oil price fluctuations in the baseline model likely attenuate the true causal effect of oil shocks on greenium dynamics. Further, the improved model fit—R^2 increases to 34% (equity) and 19% (bond) from 4% and 11% in the baseline—indicates that foreign supply shocks explain substantially more energy spread variations than generic oil price changes. These results underscore the importance of exogenous foreign oil supply shocks in driving financing cost variations of energy firms. In contrast, the estimated impacts on the ex energy greenium are economically small and statistically indistinguishable from zero.

To further address endogeneity concerns in oil price dynamics, we leverage two quasi-natural experiments—the COVID-19 pandemic lockdown and the Russia-Ukraine military conflict——to isolate the causal effects of oil shocks on energy firms' cost of capital. For each event, we estimate a difference-in-differences specification in the panel setting,

$$ER_{it} = a + b \cdot 1(Energy)_{it} \times PostEvent_t + c \cdot X_{it} + \kappa_i + \iota_t + \varepsilon_{it}, \tag{23}$$

where $PostEvent$ is a dummy for post-shock periods. We define the event window as the 12-month window around the shock. Firm and bond-level controls X are included as in the baseline regression equation (21). The regression includes firm and time-fixed effects, with standard errors double-clustered at the firm and month levels.

Unlike the OPEC supply news shocks, The COVID-19 pandemic triggered an unprecedented collapse in global oil demand, as lockdowns halted transportation and industrial activity. By April 2020, West Texas Intermediate (WTI) crude futures turned negative for the first time in history. U.S. shale firms faced unprecedented losses, idling over 2 million barrels/day of output by mid-2020 through well caps and drilling cuts. Panel B of Table 6 shows that following the pandemic lockdown, energy firms' equity cost of capital increased by 2.98% annually, and their bond yield spreads increased by 0.65% relative to non-energy peers. Notably, these effects are unique to energy firms. Other carbon-intensive sectors experienced lower equity ICCs and no statistically significant bond yield response, underscoring the distinct role of commodity price cycles (vs. broad climate risks) in energy-sector financing dynamics.

We further study the Russia-Ukraine military conflict in Panel C of Table 6. This exogenous foreign supply shock drove global oil prices higher, redirected demand toward non-Russian suppliers, and incentivized U.S. producers to increase production. Energy firms' equity cost of capital dropped by 2.15% annually, while their bond yield spreads tightened by 0.21% relative to non-energy peers following the outbreak in February 2022. On the other hand, non-energy brown firms again exhibited muted effects.

Together, these analyses show that while all carbon-intensive firms face transition risks, energy firms' financing costs remain uniquely exposed to oil price shocks, such as demand-side collapses (COVID-19) and supply-side foreign disruptions (OPEC announcements and Russian-Ukraine). The supply chain effect is considerably smaller, compared to the energy firm effect.

5 Climate Event Studies

Thus far, our analysis has established that oil shocks can significantly influence the energy spread, independent of climate-related shocks. The oil shock has a significant impact on the cost of capital and small spillovers on other carbon-intensive firms. This finding is critical because it suggests that failing to account for oil prices in climate-related event studies could introduce bias in the estimated impact of various events, which treat all brown firms homogeneously. In this section, we revisit the impact of commonly studied climate-related events to assess whether movements in oil prices have confounded prior conclusions.

5.1 The Paris Agreement

The most studied event in the climate literature is arguably the Paris Agreement. Adopted by 196 Parties at the UN Climate Change Conference (COP21) in Paris on December 12, 2015, the agreement aims to hold "the increase in the global average temperature to well below 2°C above pre-industrial levels" and to "limit the temperature increase to 1.5°C above pre-industrial levels." A typical hypothesis is that the agreement provides an exogenous positive shock to expectations of future climate regulations, thereby increasing the cost of capital for brown firms and widening the greenium (Monasterolo and De Angelis, 2020).

However, the Paris Agreement (PA) coincides closely with the oil bust and recovery from 2014 to 2016. Figure 5 shows that the oil price crash began in mid-2014, bottomed in January 2016, and rebounded strongly thereafter. The crash was driven by an oversupply of U.S. shale oil, OPEC's decision not to cut production to maintain market share, and weakened demand growth due to improved energy efficiency and a sluggish Chinese economy.[4] The rebound in 2016 was fueled by a resurgence in global demand. This V-shaped oil price pattern mirrors the tent-shaped dynamics of the greenium during the event window. The ex-energy greenium peaked in December 2015 and has declined since, while the equity and bond energy spreads peaked in September 2015 and February 2016, respectively. In short,

[4] The surprise decision of OPEC in November 2014 increases energy firms' cost of equity by 3% and cost of debt by 0.64% (Table IA.5 in Internet Appendix).

the oil price shock confounds the PA event, highlighting the need to control for oil shocks.

To start, we follow Bolton and Kacperczyk (2021) and employ a difference-in-difference specification to estimate the impact of the PA,

$$ER_{it} = a + b \cdot Carbon_{it} \times AfterPA_t + c \cdot X_{it} + \kappa_i + \iota_t + \varepsilon_{it}, \tag{24}$$

where $Carbon$ denotes the log emission intensity or the brown dummy indicating the top third of emission intensity, $AfterPA$ is a dummy variable indicating the period after the PA. We define the event window as the 12-month window around the PA, in line with Bolton and Kacperczyk (2021) and Seltzer, Starks and Zhu (2022). The regression includes firm and time-fixed effects, with standard errors double-clustered at the firm and month levels. Table 7 presents the baseline results. Following the Paris Agreement, brown firms' equity ICCs decreases, though insignificantly, while their bond yield spreads significantly increase for 6 bps per standard deviation increase in emission intensity, or 18 bps for top-third carbon-intensive brown firms. The effect translates to about 32 bps based on quartile sorting, similar to the 30 bps effect estimated in (Seltzer, Starks and Zhu, 2022).

We now address the confounding oil effect in two ways. First, we incorporate the interaction of the energy indicator with the event dummy in our DiD estimation.

$$ER_{it} = a + b \cdot Carbon_{it} \times AfterPA_t + e \cdot 1(Energy)_{it} \times AfterPA_t + c \cdot X_{it} + \kappa_i + \iota_t + \varepsilon_{it}. \tag{25}$$

Panel B shows that after accounting for energy firms' unique exposure to oil shocks, the cost of capital of non-energy brown firms remains similar to greener firms after December 2015. There is no significant cost of capital variations at any conventional significance level. In contrast, energy firms experience a 70 bps ICC increase ($p > 0.1$) and a 60 bps yield spread increase ($p < 0.05$), driven by oil price variations.

Second, we directly control oil price dynamics through the interaction of carbon performance and real oil prices,

$$ER_{it} = a + b \cdot Carbon_{it} \times AfterPA_t + e \cdot Carbon_{it} \times RPO_t + c \cdot X_{it} + \kappa_i + \iota_t + \varepsilon_{it}. \quad (26)$$

We observe in Panel B that, the oil impact $Carbon_{it} \times RPO_t$ is negative for both equity and bonds, and the effect is statistically significant for bonds (p <0.01). After controlling for the oil effect directly, the greenium appears to decrease following the PA through all specifications instead. This inconsistent response, despite heightened climate attention, undercuts the narrative that climate policy shocks dominate brown firms' financing costs in the event window. Instead, the "greenium" documented in prior studies appears largely driven by energy firms' oil-linked volatility, not systemic climate risk repricing.

It is worth noting that the extant literature acknowledges the potential contamination of oil shocks. Studies often control for the oil beta, as exemplified in Seltzer, Starks and Zhu (2022), which is derived from the sensitivity of security returns to oil price innovations. However, this method has a few key limitations. First, the oil beta for individual securities is often imprecisely estimated and inaccurately flags firms as oil-exposed due to random price co-movements instead of fundamental exposure. Second, oil beta's reliance on historical averages fails in extreme events like oil crashes, where nonlinear dynamics dominate. Additional results in Table IA.6 of the Internet Appendix show that oil beta fails to account for the oil effect and especially so for equity beta used in Seltzer, Starks and Zhu (2022). To summarize, the significant impact of the PA on the greenium, as documented in prior studies, primarily reflects concurrent oil price fluctuations, not climate policy shifts. This underscores the need to account for oil shocks in climate finance studies to disentangle policy effects from commodity-driven fluctuations.

5.2 The 2016 Election of President Trump

Another commonly studied event is the 2016 election of President Trump on November 8, 2016 (Ilhan, Sautner and Vilkov, 2021). The event is unexpected and reduces the climate policy uncertainty in the short term. We follow the literature and hypothesize that the election's surprise outcome lowered the climate policy risk, compressing the greenium.

However, concurrent oil market developments complicate this narrative. The 171st OPEC Conference (November 30, 2016) resulted in a coordinated production cut by OPEC and non-OPEC countries, including Russia, boosting oil prices and demand for U.S. energy output. This oil market recovery likely exerted independent downward pressure on the greenium, highlighting explicit controls for oil price effects.

We now assess the election's impact on the greenium without and with the oil control. First, we employ the regression model outlined in Eq. (24) and examine the 12 months surrounding the event. Table 8 details the findings. In the wake of the election, the equity greenium insignificantly decreased. The bond greenium decreases for 13 bps per standard deviation increase in emission intensity, or 36 bps for top brown firms, consistent with the hypothesis.

Next, we account for the oil effect by allowing for a differential effect on energy firms and controlling for oil price variations directly. The equity response remains positively insignificant, whereas the bond coefficients remain negative but shrink to -0.07 and -0.18 (compared to -0.13 and -0.36), depending on specification. In contrast, energy firms' cost of capital decreases by nearly one percent after November 2016, consistent with a strong response to the oil shock. Collectively, these refined estimates indicate that the 2016 presidential election may have influenced the greenium, although magnitudes are attenuated after the oil's impact is accounted for, relative to the initial estimates.

5.3 Climate Concern and Sustainable Investing

Finally, this section examines the influence of climate concern and investor flows on the greenium, which has been attributed to the strong performance of green assets and ESG-related discount rate shocks in recent years. The underlying hypothesis is that heightened climate concern leads to increased demand for green assets and higher expected returns on brown stocks, raising the greenium.

Figure 6 plots the time series of greenium, climate concern, and oil price variations. An initial look shows that the greenium rose sharply from 2017 to 2020, mirroring the rise of sustainable investing. However, the greenium declined subsequently, despite record sustainable inflows in 2021 and stable sustainable assets in 2022. In contrast, oil price movements align more closely with greenium trends, as oil prices fell to a sample low in 2020 and recovered steadily thereafter. Similarly, the positive climate concern shocks following the Stern Review released in 2006 also failed to generate greenium increases in the longer sample. This pattern underscores the need to account for oil prices when understanding greenium dynamics.

We conduct time series analysis but focus on discount rate variations directly by regressing the spreads on climate concern shocks, ESG flows, and ESG assets, instead of inferring discount rate variations from realized returns as in Pástor, Stambaugh and Taylor (2022).

$$\Delta Spread_t^i = \alpha + \beta \mathbf{CConcern_t} + \varepsilon_{\mathbf{t}}, \tag{27}$$

where $i =$Energy-NE or NE-G, denoting energy spread or ex-energy greenium, and **CConcern** is a vector containing various climate concern and sustainable investment measures. Climate concern shocks are constructed in line with Ardia et al. (2023).

We isolate the potential impact of oil shocks in two ways. First, we conduct the regression using the ex energy greenium instead of the aggregate one. Second, we include oil price innovations in the regression above. Table 9 reports the results. Replicating Pástor, Stambaugh and Taylor (2022)'s 2012–2018 sample, climate concern shocks significantly increases the aggregate greenium. Together, the model explains 8% of equity and 23% of bond greenium variation. Climate concern coefficients somewhat decrease, but largely remain robust when we focus on the ex energy greenium or control for the oil price directly. The contribution of oil price shocks to the aggregate equity greenium is small, due to the relatively small representation in the equity portfolio. However, the contribution to the aggregate bond greenium is large, adding 29% in explanatory power, consistent with the large contribution of the energy spread in the aggregate greenium during this sample period.

However, the impact of climate concern shocks is time-sensitive. Panel B extends the sample to 2006–2022, the full period for which climate concern shocks data is available, the model's explanatory power drops to below 2% for both equity and bond, with coefficients statistically insignificant. Instead, we find that oil price shocks still add 21% explanatory power to bond greenium variations with a small impact on equity greenium. In short, while climate concern shocks appear to influence discount rate variations in the 2012–2018 window, their effects do not generalize beyond this period, aligning with the visual impression in Figure 6. Our results highlight the importance of contextualizing climate risk premia within broader commodity cycles and sectoral dynamics.

In conclusion, our analysis reveals that ignoring oil price fluctuations can bias the estimated impact of targeted events. After accounting for the influence of oil prices, we find that investor discipline surrounding key climate-related events (e.g., the Paris Agreement) has only minor, if any, effects on the greenium. Instead, oil shocks—distinct from climate transition shocks—play a significant role. Our findings caution against the homogeneous "brown" classifications, advocating instead for granular frameworks that reflect oil shocks' asymmetric impacts.

6 Conclusion

Our analysis challenges the prevailing view that variations in the greenium primarily reflect investor commitment to climate-conscious investments. Instead, we demonstrate that oil shocks play a crucial role in driving these variations. When oil shocks increase growth opportunities for firms in the oil and gas sector, these firms' cost of capital decreases relative to non-energy firms. After accounting for the impact of oil shocks, climate risk shocks and concerns have a marginal, if any, effect on the greenium. This suggests that financial markets respond more to oil shocks than to climate policy risks or sustainability preferences.

The evidence highlights the challenges of relying solely on time series shocks in climate finance event studies, emphasizing the need to carefully account for oil price dynamics. Additionally, while this paper focuses on the greenium, oil prices have broader implications for carbon pricing, firms' capital budgeting, bank lending, and corporate behavior.

A few remedies can address these challenges. First, controlling for the oil shocks and characterizing the heterogeneity by separating the energy sector from other brown firms can offer a clearer analysis. Second, cross-sectional shocks across multiple entities can provide valuable complementary evidence.

These findings raise concerns about how effectively markets price the risks of the carbon transition and their potential contribution to decarbonization efforts. Consequently, stronger policy interventions may be necessary to ensure that carbon-intensive firms take meaningful steps to address climate change. Recognizing the influence of oil shocks on the greenium can help policymakers better assess the impact of regulations on firms' cost of capital and progress in the carbon transition.

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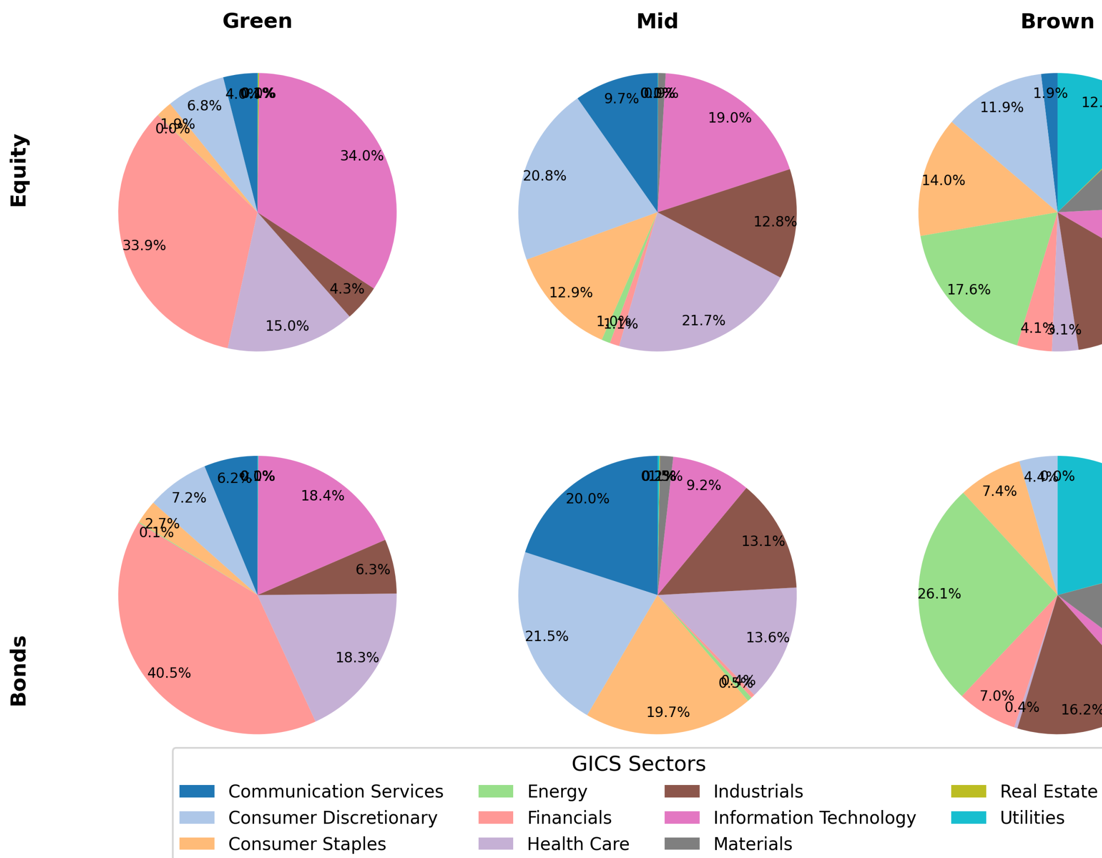
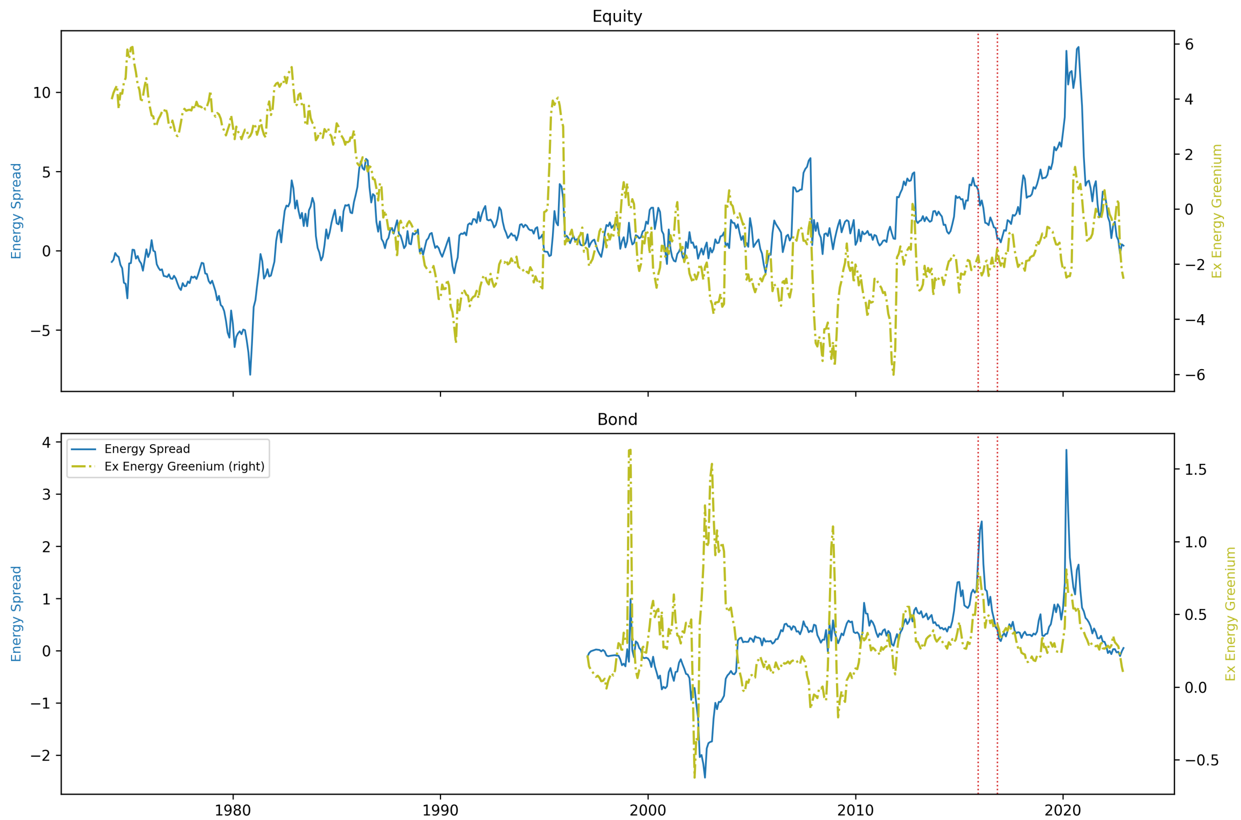
Figure 1: Sectoral Distribution across Carbon-Sorted Portfolios



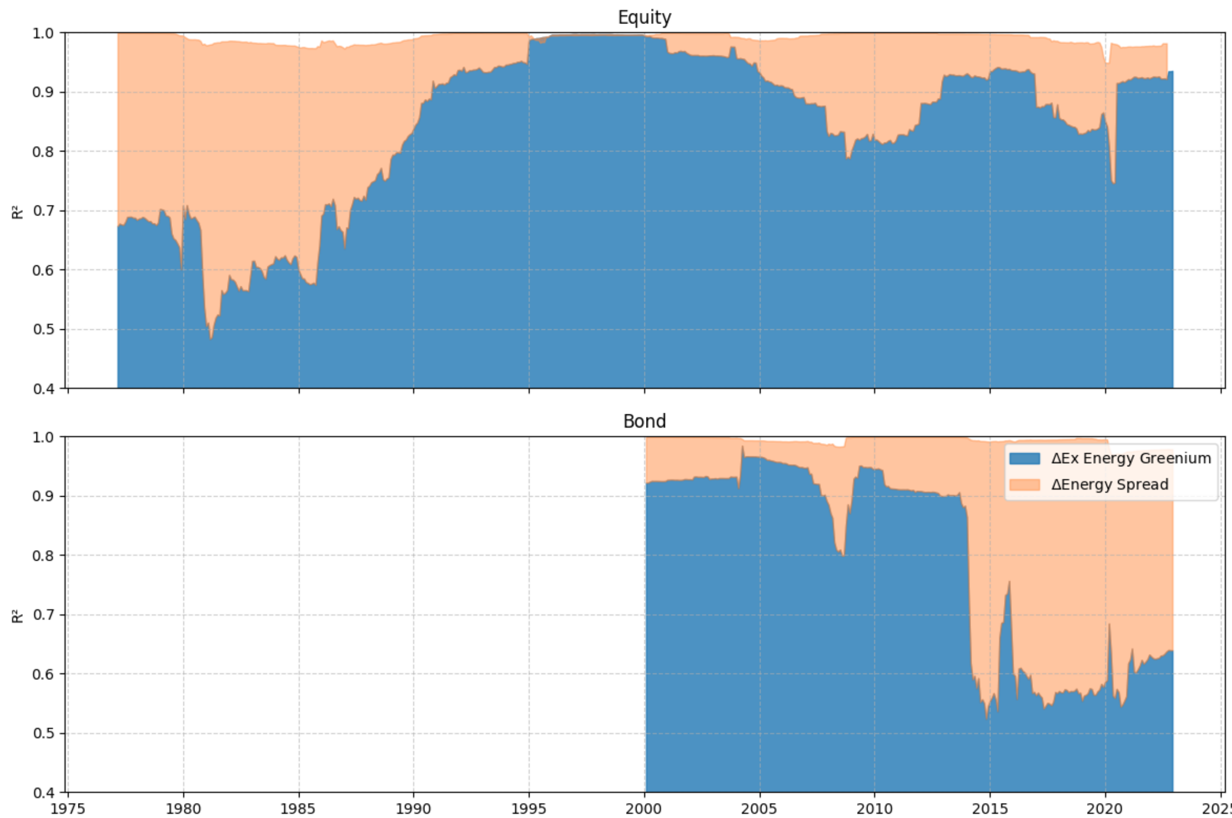
Notes: This figure plots the average portfolio weight of Global Industry Classification Standard (GICS) sectors across portfolios sorted by carbon emission intensity. Portfolio weights reflect the proportional representation of each sector within intensity-sorted terciles. The sample period spans from 2003:10 to 2022:12.

Figure 2: Greenium and Energy Spread



Notes: This figure plots the time series of the greenium's two constituent spreads: (1) the non-energy greenium (solid line), measured as the difference in cost of capital between non-energy brown firms (top tercile in terms of carbon intensity) and green firms (bottom tercile), and (2) the energy spread (dashed line), defined as the differential between energy firms and other non-energy brown firms. Panel A illustrates the equity greenium, calculated using value-weighted estimates of implied cost of equities. Panel B depicts the bond greenium, measured as the value-weighted yield spread differential for corporate bonds. The sample period for the equity greenium spans from 1974:02 to 2022:12, while the bond greenium covers the period from 1997:01 to 2022:12.

Figure 3: Historical Contribution of Greenium Components

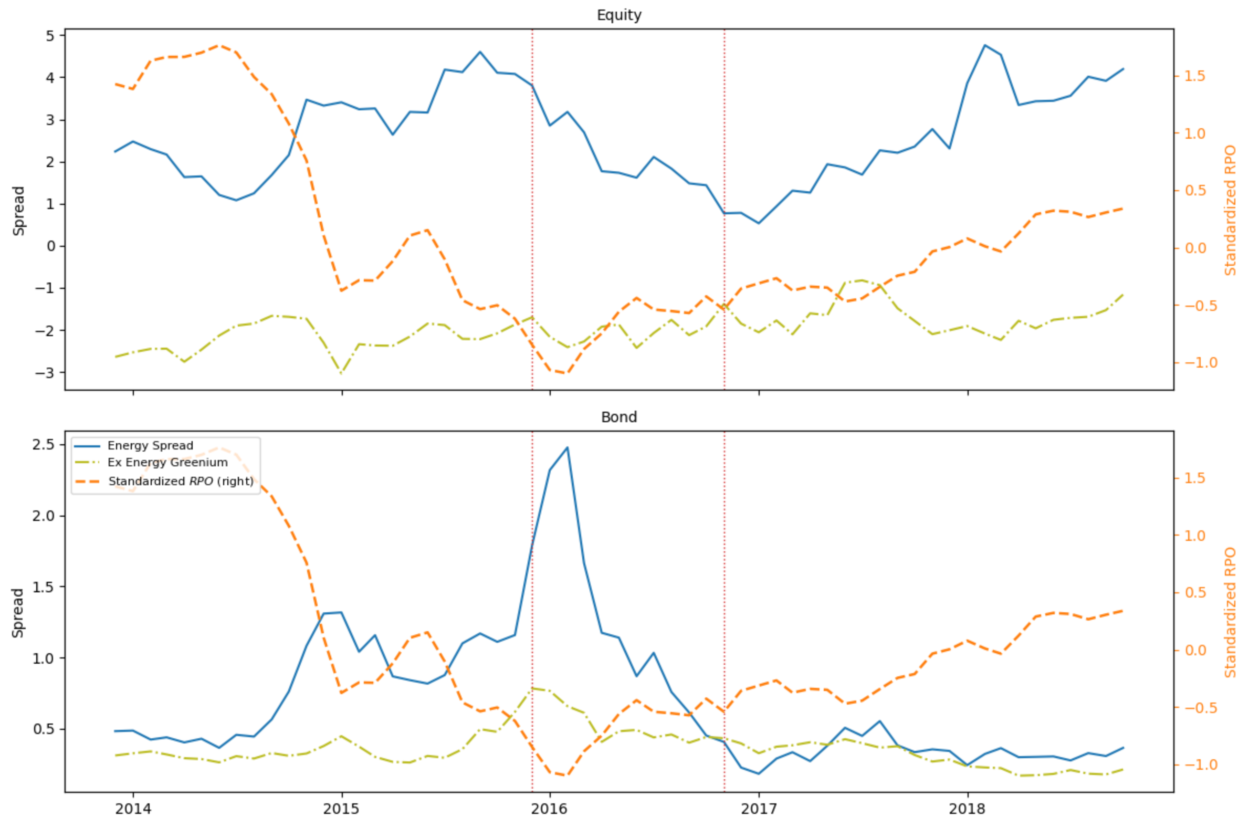


Notes: This figure plots the time-series R^2 from two regressions over 60-month rolling windows (minimum 36 months): (1) the aggregate greenium ($\Delta \text{Spread}^{B-G}$), defined as the spread between brown and green firms, regressed on the non-energy greenium ($\Delta \text{Spread}^{BNE-G}$); and (2) the same regression augmented with the energy sector spread ($\Delta \text{Spread}^{Energy-BNE}$). The incremental R^2 (shaded area) quantifies the additional explanatory power contributed by energy sector dynamics. The sample period for the equity greenium spans from 1974:02 to 2022:12, while the bond greenium covers the period from 1997:01 to 2022:12.

Figure 4: Energy Spread and Oil Price

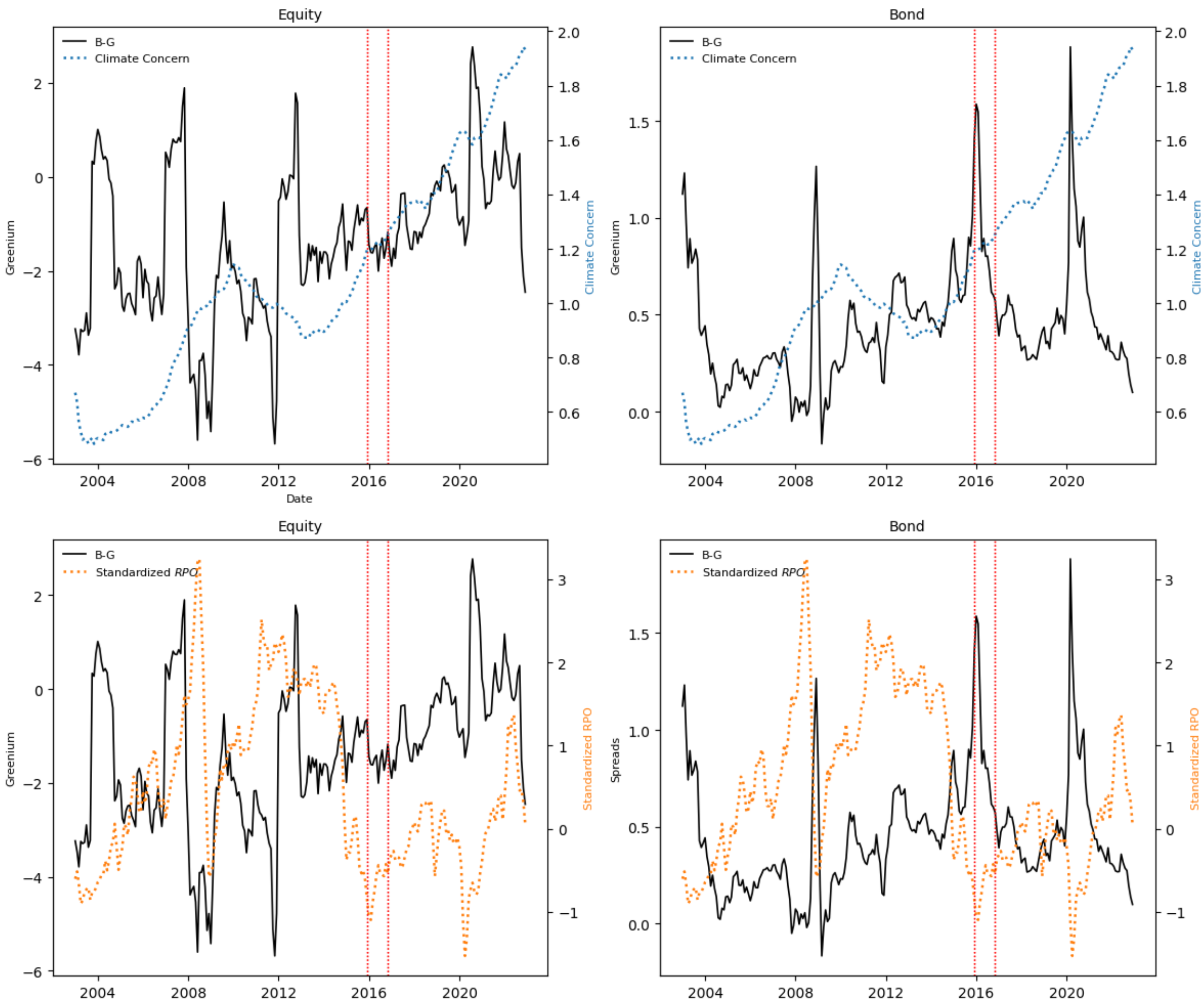
Notes: This figure plots the ex ante greenium and real price of oil. The bond greenium is the value-weighted yield spread difference (bps) between the top tercile of firms with the highest carbon intensity and the bottom tercile for scopes 1 and 2, respectively. The equity greenium is the value-weighted average mechanical ICC estimate difference (bps) between the top tercile of firms with the highest carbon intensity and the bottom tercile for scopes 1 and 2, respectively. The first vertical line denotes the Paris Agreement and the second vertical line denotes the 2016 election of President Trump. The sample period is 2003:10 to 2022:12.

Figure 5: Greenium Dynamics During the Event Windows



Notes: This figure plots the energy spread, ex energy greenium, and real price of oil variations around the Paris Agreement and the 2016 presidential election. The first vertical line denotes the Paris Agreement and the second vertical line denotes the 2016 election of President Trump. The sample period is 2013:12 to 2018:10.

Figure 6: Greenium, Climate Concern, and Oil Prices



Notes: This figure plots the co-movement of bond greenium, climate concern, and real oil prices over time. The aggregate greenium (B-G, solid line) is defined as the difference in the cost of capital between the top tercile (highest emission intensity) and bottom tercile (lowest intensity) of firms. The sample period spans from 2003:6 to 2022:12.

Table 1: Summary Statistics

Panel A: Annualized Cost of Capital (%)					
	Mean	SD	P25	P50	P75
ICC	7.39	11.34	0.27	6.20	13.24
ΔICC	0.03	2.96	-0.75	0.00	0.76
Yield Spread	1.93	1.94	0.82	1.35	2.23
ΔYield Spread	-0.00	0.50	-0.10	0.00	0.08
Panel B: Carbon and Financial Information					
(Log) Emission Intensity	4.10	2.03	2.84	3.82	5.33
Beta	1.14	0.71	0.65	1.06	1.53
Log Assets	5.24	2.35	3.49	5.12	6.90
BE/ME	-0.51	0.94	-1.05	-0.42	0.11
Momentum	0.13	0.56	-0.21	0.05	0.34
ROE	-0.09	0.67	-0.04	0.08	0.14
Investment	0.23	0.66	-0.02	0.08	0.23
Sales Growth	0.21	0.62	-0.02	0.09	0.25
Leverage	0.83	1.69	0.04	0.25	0.81
IVol	3.03	2.33	1.45	2.33	3.82
Duration	6.60	4.27	3.41	5.44	8.41
Bond Age	3.90	3.46	1.33	2.97	5.53
Rating	8.51	3.09	6.00	9.00	9.00
Panel C: Aggregate Variables					
ΔRPO	0.00	0.08	-0.03	0.00	0.04
Equity $\Delta Spread^{B-G}$	-0.01	0.66	-0.26	-0.02	0.22
Equity $\Delta Spread^{Energy-BNE}$	0.00	0.73	-0.33	0.01	0.36
Equity $\Delta Spread^{BNE-G}$	-0.01	0.55	-0.23	-0.03	0.21
Bond $\Delta Spread^{B-G}$	-0.00	0.18	-0.05	-0.00	0.04
Bond $\Delta Spread^{Energy-BNE}$	0.00	0.26	-0.08	-0.00	0.07
Bond $\Delta Spread^{BNE-G}$	-0.00	0.16	-0.04	-0.00	0.04
Climate Concern	1.15	0.45	0.89	1.04	1.43
ΔClimate Concern	0.07	0.30	-0.13	0.04	0.24
Equity ESG Flow (%)	0.01	0.02	0.00	0.00	0.01
Bond ESG Flow (%)	0.02	0.02	0.00	0.01	0.03
Equity ESG Assets (%)	0.30	0.41	0.03	0.04	0.69
Bond ESG Assets (%)	0.47	0.39	0.07	0.39	0.92

Notes: This table presents summary statistics of cost of capital measures, firms' carbon and financial performance, and aggregate variables. Implied cost of capital estimates (ICCs) are average mechanical estimates and the average of all four published measures and yield spread estimates are the duration-matched corporate bond yield spreads. Carbon intensity is the log total emissions scaled by the dollar sales during the emitting period. Beta is estimated over a 60-month rolling window; the (log) book-to-market ratio is the log ratio of book value of equity to market value of equity; ROA is net income scaled by total assets; asset growth is the percentage change of total assets; momentum is past 12-month return skipping the most recent month; leverage is book leverage defined as the book value of debt divided by the book value of assets; sales growth is log four-quarter sales sales growth; and ivol is idiosyncratic volatility from the Fama-French 3-factor model. Greenium, energy, and ex energy greenium spreads are constructed following section 2.2. Climate concern is calculated following Pástor, Stambaugh and Taylor (2022) using data provided by Ardia et al. (2023). ESG flow and assets are calculated as the fraction of ESG income fund flows and assets scaled by market-level counterparts.

Table 2: Industry Structure in Carbon Emission Intensity

	Intensity (Level)	Intensity (Log)	%N Stocks	%Market Cap
Utilities	3288	8.10	0.04	0.03
Materials	686	6.53	0.06	0.03
Energy	539	6.29	0.06	0.05
Industrials	154	5.03	0.15	0.10
Consumer Staples	109	4.70	0.05	0.09
Real Estate	70	4.26	0.00	0.00
Consumer Discretionary	61	4.12	0.16	0.13
Health Care	39	3.65	0.14	0.14
Information Technology	38	3.65	0.15	0.22
Communication Services	23	3.13	0.03	0.05
Financials	10	2.34	0.16	0.15

Notes: This table presents sector-level statistics on carbon emission intensity, along with firm distribution and market capitalization shares for Global Industry Classification Standard (GICS) sectors. Emission intensity is measured in absolute terms (Intensity (Level)) and natural logarithm (Intensity (Log)). The columns "%N Stocks" and "%Market Cap" display the proportion of firms and market capitalization, respectively, within each sector. The sample period spans from 2003:10 to 2022:12.

Table 3: Model Parameters

Panel A: Calibration Parameters		
Variable	Notation	Number
Oil Demand Elasticity	ϵ	0.1
Return to Scale	α	0.33
Depreciation Rate	Δ	0.03
Tax Rate	τ	0.14
Adjustment Cost	χ	7
Persistence	ρ	0.91
Volatility	σ	0.087
Discount Rate	β	0.99
Price of Oil Demand Risk	γ	0.5

Panel B: Simulated Moments		
Moment	Data	Simulation
Oil Energy Supply Elasticity	$0 - 0.04$	0.02
Mean Investment		3.00%
σ(Oil Price)/Mean(Oil Price)	0.19	0.19
Mean Energy Spread^{E-NE}		0.21%
σ(Spread^{E-NE})		1.51%
Corr(A_t, P_t)		0.99
Corr(P_t, Marginal Q_t^{E-NE})		0.17
Corr(P_t, $(I_{it}/K_{it})^{E-NE}$)		0.17
Corr(P_t, Spread$_{t+1}^{E-NE}$)		-0.97

Notes: This table summarizes the calibrated parameters in the baseline model and simulated moments at quarterly frequency.

Table 4: Transmission of Oil Price Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Industry-Level Output and Input Price					
	ΔOutput PPI (%)			Weighted ΔInput PPI (%)		
ΔRPO×1(Energy)	38.79***	37.56***	37.58***	2.81***	2.35***	2.48***
	(15.97)	(15.83)	(15.83)	(2.79)	(2.80)	(2.87)
ΔRPO×Intensity		1.50***			0.42	
		(5.78)			(1.59)	
ΔRPO×1(Brown)			2.26***			0.70
			(5.05)			(1.48)
Industry & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26183	26183	26183	10062	10062	10062
R^2	0.278	0.282	0.280	0.531	0.532	0.532
	Panel B: Firm-Level Outcome					
	ΔQ			ΔSales		
ΔRPO×1(Energy)	0.32***	0.35***	0.31***	0.31***	0.32***	0.29***
	(4.44)	(3.87)	(4.72)	(3.26)	(5.38)	(3.12)
ΔRPO×Intensity		0.00			0.02**	
		(0.41)			(2.37)	
ΔRPO×1(Brown)			0.03			0.05***
			(1.06)			(3.41)
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	172019	128125	172019	176277	131540	176277
R^2	0.162	0.164	0.162	0.215	0.252	0.215
	ΔInvestment			ΔROE		
ΔRPO×1(Energy)	0.15***	0.12**	0.15***	0.21***	0.20***	0.21***
	(3.20)	(2.59)	(3.50)	(3.14)	(4.21)	(3.14)
ΔRPO×Intensity		-0.00			0.00	
		(-0.06)			(0.69)	
ΔRPO×1(Brown)			-0.01			0.00
			(-0.28)			(0.04)
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	176787	130972	176787	174174	129751	174174
R^2	0.086	0.104	0.086	0.098	0.113	0.098

Notes: This table examines the pass-through of oil price shocks to industry-level producer price indices (PPI) and their implications for firm-level growth metrics. Panel A estimates regressions of quarterly NAICS4-level PPI changes (ΔPPI) on interactions between oil price changes (ΔRPO) and energy sector indicators ($1(Energy)$), carbon intensity ($Intensity$), and brown industry status ($1(Brown)$). Panel B analyzes firm-level outcomes—sales growth ($\Delta Sales$), return on equity (ΔROE), Tobin's Q (ΔQ), and investment growth ($\Delta Investment$)—regressed on energy sector interactions with oil price changes. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period spans from 1974:Q1 to 2022:Q4.

Table 5: Oil Price and Greenium Components

	(1)	(2)	(3)	(4)	(5)	(6)
		Equity			Bond	
			Panel A: Time Series Analysis			
	Energy-BNE	BNE-G		Energy-BNE	BNE-G	
ΔRPO	-1.75***	0.14		-0.84***	-0.30***	
	(-4.94)	(0.50)		(-6.50)	(-3.17)	
Observations	585	585		310	310	
R^2	0.039	0.000		0.107	0.034	
			Panel B: Panel Analysis			
ΔRPO×1(Energy)	-2.84***	-2.66**	-2.72**	-1.25**	-1.19*	-1.23**
	(-3.55)	(-2.34)	(-2.45)	(-1.99)	(-1.85)	(-2.08)
ΔRPO×Intensity		-0.10			-0.02	
		(-1.43)			(-0.48)	
ΔRPO×1(Brown)			-0.13			-0.03
			(-1.15)			(-0.38)
Beta	0.01	0.02	0.02	-0.02***	-0.02***	-0.02***
	(0.40)	(1.20)	(1.20)	(-3.60)	(-3.49)	(-3.60)
Log Assets	0.11***	0.11***	0.11***	0.01**	0.01**	0.01**
	(12.82)	(12.01)	(12.01)	(2.54)	(2.36)	(2.53)
BE/ME	-0.11***	-0.11***	-0.11***	-0.01	-0.01	-0.01
	(-7.58)	(-5.86)	(-5.86)	(-1.49)	(-1.09)	(-1.48)
Momentum	0.17***	0.18***	0.18***	-0.02	-0.02	-0.02
	(6.20)	(5.46)	(5.45)	(-1.54)	(-1.29)	(-1.54)
ROE	0.07***	0.06***	0.06***	0.02***	0.03***	0.02***
	(3.23)	(2.63)	(2.63)	(2.90)	(2.86)	(2.90)
Asset Growth	0.10***	0.10***	0.10***	0.00	0.00	0.00
	(7.31)	(6.79)	(6.79)	(0.80)	(0.68)	(0.80)
Sales Growth	0.05***	0.07***	0.07***	0.02	0.02	0.02
	(4.24)	(4.14)	(4.14)	(1.53)	(1.46)	(1.52)
Leverage	-0.20***	-0.19***	-0.19***	-0.03	-0.02	-0.03
	(-4.96)	(-4.49)	(-4.49)	(-1.55)	(-1.05)	(-1.55)
IVol	0.00	-0.00	-0.00	-0.00*	-0.00*	-0.00*
	(0.16)	(-0.53)	(-0.53)	(-1.77)	(-1.88)	(-1.77)
Duration				0.00	0.00	0.00
				(1.57)	(1.48)	(1.57)
Bond Age				-0.00***	-0.00***	-0.00***
				(-2.66)	(-2.63)	(-2.66)
Rating				-0.01***	-0.01***	-0.01***
				(-3.81)	(-3.70)	(-3.81)
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1354319	995467	995467	634205	584269	634205
R^2	0.078	0.090	0.090	0.308	0.319	0.308

This table conducts analysis on the relation between the greenium and oil prices. Panel A conducts time series analysis on the impact of oil price shocks (ΔRPO) on two components of the greenium premium variations: (1) changes in the spread between energy and non-energy brown firms ($\Delta Spread^{Energy-BNE}$) and (2) changes in the spread between non-energy brown and green firms ($\Delta Spread^{BNE-G}$). Panel B regresses security-level cost of capital changes on the interaction of oil price shocks with energy sector dummy and log carbon intensity or brown firm status. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period spans from 1974:2 to 2022:12.

Table 6: Differential Impact of Oil Shocks: Event Studies

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity			Bond		
	Panel A: OPEC Announcements					
	Energy-BNE	BNE-G		Energy-BNE	BNE-G	
ΔRPO	-6.88***	0.95		-1.74***	-0.50	
	(-2.71)	(0.50)		(-2.76)	(-1.02)	
Observations	419	419		250	250	
R^2	0.341	0.016		0.191	0.044	
	Panel B: COVID-19 Pandemic Lockdown					
Post Lockdown×1(Energy)	2.98***	4.80***	3.41***	0.65	0.61	0.59
	(3.32)	(5.06)	(3.78)	(1.43)	(1.40)	(1.33)
Post Lockdown×Intensity		-0.95***			0.03	
		(-8.42)			(1.14)	
Post Lockdown×1(Brown)			-1.11***			0.10*
			(-4.27)			(1.82)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56582	47632	56582	80102	79633	80102
R^2	0.878	0.865	0.879	0.835	0.838	0.836
	Panel C: Russian-Ukraine Military Conflict					
Post Outbreak×1(Energy)	-2.15**	-2.14**	-2.15**	-0.21**	-0.25**	-0.25**
	(-2.37)	(-2.28)	(-2.37)	(-2.22)	(-2.59)	(-2.67)
Post Outbreak×Intensity		0.15			0.03*	
		(1.35)			(2.06)	
Post Outbreak×1(Brown)			0.01			0.08**
			(0.03)			(2.36)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52566	46383	52566	84448	84346	84448
R^2	0.886	0.875	0.886	0.854	0.854	0.854

Notes: This table presents causal estimates of oil price shocks on energy sector premiums (Energy-BNE) and non-energy greenium (BNE-G) using two identification strategies. Panel A employs an instrumental variables (IV) approach, instrumenting oil price changes (ΔRPO) with OPEC announcement surprises (first principal component of WTI crude futures price changes around OPEC meetings). Panels B and C utilize quasi-natural experiments in a difference-in-differences (DiD) framework: the COVID-19 lockdown (Panel B) and the Russia-Ukraine conflict (Panel C). The Post-Lockdown indicator in Panel B captures the pandemic period after March 2020, while the Post-Outbreak indicator in Panel C marks the conflict period after February 2022. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period spans from 2003:10 to 2022:12.

Table 7: Climate Event Study: Paris Agreement

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Equity			
Post PA×Intensity	-0.06	-0.10	-0.08			
	(-0.45)	(-0.70)	(-0.53)			
Post PA×1(Brown)				-0.17	-0.26	-0.30
				(-0.59)	(-0.85)	(-0.98)
Post PA×1(Energy)		0.69			0.73	
		(0.57)			(0.59)	
ΔRPO×Intensity			-0.04			
			(-0.30)			
ΔRPO×1(Brown)						-0.29
						(-1.16)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20128	20128	20128	20128	20128	20128
R^2	0.865	0.865	0.865	0.865	0.865	0.865
			Panel B: Bond			
Post PA×Intensity	0.06*	0.04	-0.05*			
	(1.73)	(1.30)	(-1.92)			
Post PA×1(Brown)				0.18**	0.09	-0.10
				(2.08)	(1.63)	(-1.71)
Post PA×1(Energy)		0.64**			0.61**	
		(2.17)			(2.11)	
ΔRPO×Intensity			-0.26***			
			(-3.52)			
ΔRPO×1(Brown)						-0.61***
						(-3.72)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64971	64971	64971	69655	69655	69655
R^2	0.850	0.853	0.852	0.871	0.872	0.872

Notes: This table examines the impact of the 2015 Paris Agreement (PA) on greenium using a difference-in-differences framework. The dependent variable is the implied cost of capital estimates (ICCs) for equity and duration-matched yield spreads for corporate bonds. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period spans from 2015:05 to 2016:05.

Table 8: Climate Event Study: The 2016 Trump Election

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Equity			
Post Election×Intensity	0.05	0.10	0.05			
	(0.46)	(0.82)	(0.50)			
Post Election×1(Brown)				0.09	0.19	0.28
				(0.38)	(0.76)	(1.25)
Post Election×1(Energy)		-0.78			-0.78	
		(-0.80)			(-0.79)	
ΔRPO×Intensity			-0.01			
			(-0.06)			
ΔRPO×1(Brown)						-0.70*
						(-1.96)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20593	20593	20593	20593	20593	20593
R^2	0.878	0.878	0.878	0.878	0.878	0.878
			Panel B: Bond			
Post Election×Intensity	-0.13***	-0.07**	-0.06**			
	(-3.42)	(-2.41)	(-2.72)			
Post Election×1(Brown)				-0.36***	-0.18**	-0.26***
				(-4.02)	(-2.50)	(-3.28)
Post Election×1(Energy)		-0.89***			-0.87***	
		(-3.61)			(-3.60)	
ΔRPO×Intensity			-0.23***			
			(-3.23)			
ΔRPO×1(Brown)						-0.36*
						(-2.06)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	69282	69282	69282	73045	73045	73045
R^2	0.814	0.821	0.815	0.837	0.842	0.837

Notes: This table examines the impact of 2016 Election of President Trump on greenium using a difference-in-differences framework. The dependent variable is the implied cost of capital estimates (ICCs) for equity and duration-matched yield spreads for corporate bonds. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period spans from 2016:05 to 2017:05.

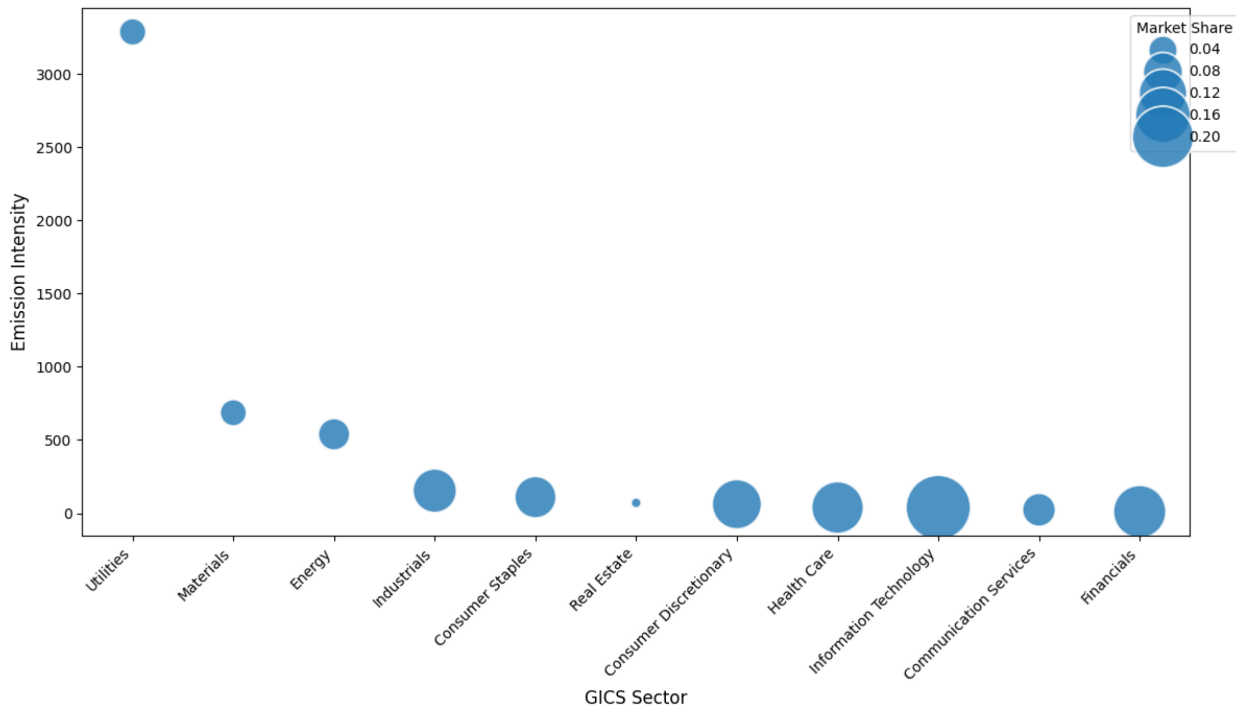
Table 9: Climate Concern Shocks and Greenium Dynamics

	(1)	(2)	(3)	(4)	(5)	(6)
		Equity			Bond	
	ΔSpread^{B-G}	ΔSpread^{BNE-G}	ΔSpread^{B-G}	ΔSpread^{B-G}	ΔSpread^{BNE-G}	ΔSpread^{B-G}
			Panel A: November 2012 - June 2018			
ΔClimate Concern	0.47*	0.41*	0.50**	0.11**	0.07**	0.09**
	(1.88)	(1.98)	(2.02)	(2.42)	(2.60)	(2.43)
Lagged ΔClimate Concern	-0.25	-0.14	-0.18	0.17***	0.05*	0.11***
	(-1.02)	(-0.66)	(-0.73)	(3.54)	(1.83)	(2.90)
ESG Share	87.67	33.17	109.02	-20.03	-7.86	-5.18
	(1.15)	(0.52)	(1.41)	(-0.89)	(-0.60)	(-0.29)
Lagged ESG Asset	4.23	5.63	1.92	4.05*	1.59	3.35**
	(0.50)	(0.78)	(0.22)	(1.94)	(1.30)	(2.02)
ΔRPO			1.09			-0.73***
			(1.37)			(-6.15)
Observations	68	68	68	68	68	68
R^2	0.082	0.069	0.109	0.234	0.145	0.524
			Panel B: June 2006 - December 2022			
ΔClimate Concern	-0.01	0.03	-0.01	-0.01	-0.00	-0.01
	(-0.03)	(0.19)	(-0.03)	(-0.21)	(-0.02)	(-0.22)
Lagged ΔClimate Concern	-0.29	-0.23	-0.27	0.06	0.01	0.05
	(-1.53)	(-1.48)	(-1.44)	(1.63)	(0.48)	(1.50)
ESG Share	0.21	0.70	0.84	-1.07	-0.31	-0.21
	(0.06)	(0.25)	(0.25)	(-0.96)	(-0.42)	(-0.21)
Lagged ESG Asset	-0.07	-0.05	-0.09	-0.01	-0.01	-0.03
	(-0.40)	(-0.37)	(-0.54)	(-0.28)	(-0.38)	(-0.68)
ΔRPO			0.53			-0.61***
			(1.07)			(-7.26)
Observations	203	203	203	203	203	203
R^2	0.016	0.013	0.021	0.025	0.005	0.231

Notes: This table examines the impact of climate concern shocks and ESG investment flows on the greenium. The analysis estimates time-series regressions of differentials in the cost of capital—between high-intensity and low-intensity firms (B-G), and high-intensity non-energy and green firms (BNE-G)—on standardized climate concern (ΔClimate Concern), ESG capital allocations (ESG Share), and lagged controls. ΔRPO denotes the oil price innovations. Panel A (2012–2018) and Panel B (2006–2022) report results for both equity and bond greeniums, with Spread^{o} capturing oil price interactions. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Internet Appendix

Figure IA.1: Carbon Intensity Variations Across Sectors



Notes: This figure plots mean carbon intensity (scope 1 and 2 emissions/sales) and average market share of each GICS sector.

Figure IA.2: All Spreads

Notes: This figure plots aggregate green premium, non-energy greenium premium, and the energy spread.

Table IA.1: Industry Structure in Carbon Intensity

	(1)	(2)	(3)
Beta		-0.07	0.05
		(-0.83)	(1.70)
Log Assets		-0.18***	-0.02
		(-6.87)	(-1.19)
BE/ME		0.22***	0.11***
		(4.41)	(4.79)
Momentum		0.06	0.02
		(0.74)	(0.93)
ROE		0.18***	0.01
		(3.95)	(0.69)
Investment		-0.15***	-0.03
		(-2.89)	(-1.63)
Sales Growth		0.09	0.08***
		(1.01)	(3.43)
Leverage		3.22***	0.64***
		(16.12)	(6.43)
IVol		0.04	0.03***
		(1.59)	(3.32)
GICS Sector FE	Yes	No	Yes
Time FE	Yes	Yes	Yes
Observations	26206	23624	23624
R^2	0.679	0.144	0.694

Notes: This table reports results from regressions of firm-level carbon emission intensity on Global Industry Classification Standard (GICS) sector fixed effects and firm characteristics. Column (1) includes GICS sector and time fixed effects, Column (2) incorporates firm characteristics (e.g., leverage, book-to-market ratio, ROE), and Column (3) combines both. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period spans from 2003:10 to 2022:12.

Table IA.2: Transmission of Oil Price Shocks (With Controls)

	(1)	(2)	(3)	(4)	(5)	(6)
		ΔQ			ΔSales	
ΔRPO×1(Energy)	0.09***		0.09***	0.22***		0.23***
	(2.87)		(2.85)	(2.72)		(4.06)
ΔRPO×Intensity		0.00	0.00		0.02***	0.01**
		(0.53)	(0.03)		(3.33)	(2.31)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122539	87466	87466	122852	87615	87615
R^2	0.596	0.614	0.614	0.280	0.333	0.335
		ΔInvestment			ΔROE	
ΔRPO×1(Energy)	0.06**		0.03	0.10*		0.09**
	(2.03)		(1.07)	(1.88)		(2.17)
ΔRPO×Intensity		0.00	-0.00		0.00	-0.00
		(0.04)	(-0.28)		(0.86)	(-0.35)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	123361	87949	87949	122530	87437	87437
R^2	0.667	0.680	0.680	0.361	0.393	0.393

This table examines how oil price shocks (ΔRPO) asymmetrically affect growth metrics for (a) energy firms versus non-energy firms and (b) brown versus green firms. The analysis estimates firm-level regressions of changes in Tobin's Q (ΔQ), sales (ΔSales), investment (ΔInvestment), and return on equity (ΔROE) on interactions between oil price changes and (i) an energy sector indicator (1(Energy)) or (ii) carbon intensity (Intensity). All specifications include firm characteristics, firm fixed effects, and time fixed effects. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period spans from 2003 to 2022.

Table IA.3: Energy-Utility Spread

	(1)	(2)	(3)	(4)
	Dependent Variable: ΔSpread$^{Energy-Utility}$			
	Full Sample		Post-PA Sample	
	Equity	Bond	Equity	Bond
ΔRPO	-1.69***	-0.92***	-1.81*	-1.52***
	(-3.28)	(-5.95)	(-1.97)	(-5.31)
Observations	582	282	85	85
R^2	0.018	0.112	0.045	0.253

Notes: This table examines the impact of oil price shocks (ΔRPO) on the spread between energy and utility sectors' cost of capital. The dependent variable is the equity and bond yield spread differential (ΔSpread$^{Energy-Utility}$). Results are reported using time-series regressions for the full sample (2003:10–2022:12) and the post-Paris Agreement (PA) subsample (2016–2022). Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table IA.4: First-Stage Estimates of OPEC Announcement Shocks

	(1)	(2)
	Dependent Variable: ΔRPO	
	Equity Sample	Bond Sample
OPEC Surprise	1.09***	1.57***
	(4.02)	(4.19)
Observations	419	251
R^2	0.037	0.066

Notes: This table reports the first-stage results of an instrumental variable (IV) regression examining the relationship between OPEC announcement surprises and oil price changes (ΔRPO). The instrument is constructed as the first principal component of daily changes in WTI crude futures prices (contract maturities: 1–12 months) around OPEC meetings, capturing exogenous supply-driven oil price variation. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The equity sample spans the 1983-2017 period, and bond sample spans 1997 to 2017.

Table IA.5: Differential Impact of Oil Shocks: OPEC Price War

	(1)	(2)	(3)	(4)	(5)	(6)
		Equity			Bond	
Post Meeting×1(Energy)	3.06***	1.05	3.11***	0.64***	0.58***	0.66***
	(4.10)	(1.30)	(4.06)	(4.52)	(4.33)	(4.49)
Post Meeting×Intensity		0.17*			-0.01	
		(1.73)			(-0.38)	
Post Meeting×1(Brown)			-0.17			-0.04
			(-0.74)			(-0.82)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62684	19956	62684	63315	58221	63315
R^2	0.897	0.869	0.897	0.892	0.880	0.892

Notes: This table presents difference-in-differences estimates of oil shocks' effects on the cost of capital for energy/brown firms during the quasi-natural experiment, the OPEC surprise price war. The analysis regresses equity implied cost of capital (ICC) and bond yield spreads on interactions between an energy sector indicator ($1(Energy)$), carbon intensity (Intensity), brown industry status ($1(Brown)$), and a post-November 2014 conflict period (Post Meeting) in 12-month event window.

Table IA.6: The Paris Agreement and Greenium Dynamics: Controlling for Oil Beta

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Equity			
Post PA×Intensity	-0.04	-0.07	-0.01			
	(-0.28)	(-0.55)	(-0.05)			
Post PA×1(Brown)				-0.05	-0.04	-0.44
				(-0.15)	(-0.11)	(-1.17)
Post PA×Equity Oil Beta		-2.84**			-0.67	
		(-2.22)			(-0.72)	
Post PA×Bond Oil Beta			-4.33			-0.83
			(-1.35)			(-0.33)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20191	20189	9994	60412	60405	12046
R^2	0.869	0.870	0.894	0.912	0.913	0.890
			Panel B: Bond			
Post PA×Intensity	0.06*	0.07*	0.05			
	(1.73)	(1.92)	(1.66)			
Post PA×1(Brown)				0.18**	0.18**	0.13*
				(2.08)	(2.10)	(1.81)
Post PA×Equity Oil Beta		0.89**			0.76*	
		(2.11)			(1.98)	
Post PA×Bond Oil Beta			2.78***			2.64***
			(4.09)			(4.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64971	63958	61403	69655	68414	65705
R^2	0.850	0.851	0.860	0.871	0.872	0.880

Notes: This table examines the impact of the Paris Agreement (PA) on greenium dynamics while controlling for firms' exposure to oil price fluctuations, proxied by oil beta. The analysis estimates regressions of equity implied cost of capital (ICC) and bond yield spreads on interactions between carbon intensity (Intensity), a brown industry indicator (1(Brown)), and a post-PA dummy (PostPA), augmented with oil beta interactions. Oil beta is estimated as the loading of bond and equity returns on oil price changes over a rolling 60-month window. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period spans from 2015:05 to 2016:05.