Oil-Driven Greenium

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Abstract

A prevailing 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 sudden disruptions in global oil supply or oil-demand surge, 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

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One of the central questions in climate finance is whether financial markets materially incorporate firms' environmental, social, and governance (ESG) performance into asset prices. At the core of this debate is the "greenium," the notion that carbon-intensive firms face higher costs of capital during the transition to net zero due to climate policy risks and shifting investor preferences, while less carbon-intensive firms enjoy lower costs. Such market-driven incentives could support climate change mitigation with minimal government intervention, aligning with Hong, Wang and Yang (2023) and Milton Friedman's 1970 view that markets, rather than regulations, should address societal challenges.

The greenium seems to have widened over the past decade, as shown in Figure 1, with carbon-intensive firms facing higher costs of capital relative to greener firms (Pástor, Stambaugh and Taylor, 2022; Gormsen, Huber and Oh, 2023; Eskildsen et al., 2024). This trend, coupled with greenium responses to events like the Paris Agreement (Monasterolo and De Angelis, 2020), has led many to conclude that investors are increasingly incorporating ESG performance and climate risks in asset prices.

In this paper, we challenge this influential view that greenium variations primarily reflect investor commitment to climate goals. Many carbon-intensive firms operate in the oil-and-gas sector, where product prices closely track oil market fluctuations. As a result, oil shocks significantly influence ESG investment returns (Blitz, 2022), as evidenced by ESG returns' sharp shift during the Russia-Ukraine conflict, and may also drive greenium changes by altering firms' cost of capital. Additionally, climate-related events have frequently coincided with oil price movements, which may have led researchers to mistakenly attribute greenium changes to climate policy risk or sustainable investing rather than the direct impact of oil shocks.

Our analysis documents that oil shocks are a significant driver of greenium variations. By influencing oil-and-gas producers' profit margins and growth options, oil shocks generate substantial variations in their expected returns, which further drive greenium variations. Once these effects are accounted for, investor discipline around climate events like the Paris Agreement appears to have only a modest impact, if any. Ultimately, financial markets may

be less responsive to climate shocks than previously concluded.

To investigate the potential contribution of oil shocks , we first decompose the aggregate greenium—the cost-of-capital spread between brown and green firms—into two components: the ex-energy greenium (non-energy brown vs. green firms) and the energy spread (energy vs. non-energy brown firms). These components move nearly independently, with the energy spread explaining an additional 20% of equity greenium variation and 15% of bond greenium variation beyond the ex-energy greenium on average. Since the 2014 oil price collapse, the energy spread accounts for more than 40% additional variations in bond greenium, as sustained low oil prices increased energy firms' credit risk.

To formalize the mechanism underlying the impact of oil shocks, we develop a stylized Q-theory model distinguishing oil-dependent energy firms from non-energy brown firms producing other goods. Oil shocks, such as sudden foreign supply disruptions or sector-specific demand surges, raise energy firms' output prices and enhance their growth opportunities. This force lowers their cost of capital relative to non-energy brown firms, narrowing the energy spread and thus the aggregate greenium without altering the ex-energy greenium. Unlike climate risk or green preference shocks, which affect all brown firms relative to green ones regardless of sectors (Pástor, Stambaugh and Taylor, 2021; Hsu, Li and Tsou, 2023), this oil-shock mechanism is unique to oil-dependent energy firms.

Our empirical analysis, covering a half-century sample from 1974 to 2022, strongly supports the model's theoretical predictions. Consistent with the framework, positive oil price shocks are associated with rising relative product prices in the energy sector and significant improvements in energy firms' growth opportunities—measured by Tobin's Q, sales growth, asset growth, and profitability. Conversely, adverse oil price shocks dampen these performance indicators. Most importantly, energy firms' cost of capital is highly sensitive to oil shocks: rising oil prices significantly reduce their costs of equity and bonds. In contrast, non-energy brown firms' expected returns only show limited sensitivity to oil price shocks, as supply chain price passthrough to their products at only about 10% of the direct impact on energy firm outputs.

To establish causality, we leverage 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 impact global energy prices, shift demand for U.S. hydrocarbons, and change growth prospects for domestic energy firms. For instance, following the COVID-19 outbreak, energy firms' cost of equity and bonds increase by 3% and nearly 1% per annum, respectively. In contrast, non-energy brown firms show muted response. This asymmetry underscores oil shocks as a primary driver of energy-sector return dynamics, driving greenium variations independently of climate shocks.

We then revisit key climate events widely 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), with over 3 million search results for the "Paris Agreement event study" on Google Scholar. Consistent with Seltzer, Starks and Zhu (2022), the bond greenium increases significantly following the PA, but the equity greenium remains unchanged. However, this bond greenium increase stems not from heightened climate policy risk or investor attention but from energy-sector dynamics tied to oil price fluctuations. Specifically, the PA coincides with the 2014 oil price crash's trough, and the V-shaped oil price recovery drives the bond greenium's reverse V-shaped pattern. After excluding energy firms or controlling for oil prices, the PA's effect becomes statistically insignificant.

Next, we examine the election of President Trump in November 2016, an event associated with reduced perceived climate policy risk (Ilhan, Sautner and Vilkov, 2021). The equity greenium shows no significant change, while the bond greenium declines post-election. The decline aligns with the ongoing oil price recovery, further fueled by OPEC and Russia's decision to cut production that same month. The bond greenium response weakens considerably once oil shocks are accounted for.

Finally, we assess climate concern shocks and sustainable investing, which prior studies suggest increase brown firms' cost of capital relative to green firms as discount rate shocks (Pástor, Stambaugh and Taylor, 2022). Nevertheless, when examining the period from 2006

to 2022, the influence of these factors on greenium variations appears statistically insignificant. In contrast, oil price shocks, through the energy-specific component, account for an additional 15% of equity greenium variation and 38% of bond greenium variation. These findings highlight the need to contextualize climate risk premia within broader commodity cycles and sectoral exposures, emphasizing the role of oil shocks.

This paper contributes to three key strands of literature. First, we add to the growing research on climate-related event studies by emphasizing the broad commodity cycle and industry heterogeneity. Much of the existing literature examines how key climate events shape the greenium, including the Stern Review (Painter, 2020), 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. Our analysis reveals these climate events coincide with significant oil shocks in the past two decades, and failing to account for oil shocks can bias the estimated climate effects, particularly for energy firms.

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) and green preferences (Pedersen, Fitzgibbons and Pomorski, 2021; Pástor, Stambaugh and Taylor, 2021). More recent literature, such as Berk and van Binsbergen (2025) and Chen, Garlappi and Lazrak (2023), casts more doubts, documenting negligible or opposite effects of green preferences on the greenium. To our knowledge, this paper is the first to highlight the role of oil shocks in shaping the ex-ante greenium through the energy sector. Related works by Sautner et al. (2023), D'Amico, Klausmann and Pancost (2023), and Bolton, Kacperczyk and Wang (2024) link the pricing of climate-related risks to oil prices. We propose a novel mechanism through growth opportunity variations, which persists without climate-related shocks and beyond the climate-aware sample.

Third, we contribute to the debate on the average magnitude of the 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 analysis uncovers that the perceived rise in the greenium over the past decade (Pástor, Stambaugh and Taylor, 2022; Sautner et al., 2023; Gormsen, Huber and Oh, 2023; Eskildsen et al., 2024) comes mostly from energy firms, coinciding with prolonged low oil prices following the 2014 oil crash. This underscores the need for caution when interpreting greenium estimates from any specific sample.

The remainder of the paper is as follows. Section 1 explains the data and decomposes the greenium into sectoral contributions. Section 2 presents a stylized model to characterize the relation between oil shocks and the greenium. Section 3 studies the pricing relation empirically. Section 4 revisits existing event studies in the literature. Section 5 concludes.

1 Data and Greenium Decomposition

This section presents data and conducts preliminary empirical analysis. First, we explain various data used in this study. Second, we construct the greenium for equity and bonds. Finally, we decompose the greenium and quantify the contribution of the energy sector to aggregate greenium variations.

1.1 Data and Summary Statistics

Our empirical analysis leverages firm-level climate performance data from S&P Trucost, a leading provider of annual carbon emission metrics, carbon dioxide equivalent (tCO2e). We focus on emissions categorized under Scope 1 and 2. Scope 1 greenhouse gas (GHG) emissions encompass direct emissions from sources 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

total emissions scaled by sales over the emitting period (Aswani, Raghunandan and Rajgopal, 2024; Zhang, 2025). This choice is also consistent with institutional practices for carbon-aware portfolio management (Bolton and Kacperczyk, 2021; Hartzmark and Shue, 2022). We use the most recent carbon emission and accounting data based on their respective release dates when combining various datasets following Zhang (2025). Given that Trucost conducted a review of all data from 2002 to 2008 in May 2009 and no longer provides original date release dates, 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.

To measure the ex-ante cost of equity, we employ the average of four published implied cost of capital (ICC)-based estimates.[1] The ICC estimates are shown to be most reliable in the time series analysis (Lee, So and Wang, 2021), and the averaging of various ICC measures helps mitigate the inherent noise in assumptions regarding expected future cash flows and the potential for non-unique numerical solutions. To measure the ex-ante cost of debt, we extract option-adjusted spreads (OAS) for bonds included either in the ICE Corporate Master index or the ICE Corporate High Yield index (Schaefer and Strebulaev, 2008; Huang, Nozawa and Shi, 2024) and winsorize the spreads at the 1% level following Kaviani et al. (2020).

In addition, we source stock data from CRSP and accounting data from Compustat N.A., focusing on primary common stocks listed on major exchanges. Bond issuance details come from Mergen FISD. We classify firms as part of the energy sector if they belong to the MSCI energy sector (sector code 10). The energy sector represents a congregation of enterprises dedicated to the exhaustive exploration, extraction, refinement, and marketing of fuel and associated energy products. As an instrumental element of the global economic structure, this sector serves as a bellwether for industrial activity and economic health. 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 (CPI) sourced from FRED at the St. Louis Fed. The nominal oil

[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).

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 before 1983 following Baumeister and Hamilton (2019). 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 are calculated as the proportion of equity and bond funds with ESG considerations among all equity and bond funds,

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 (log) scope 1 and 2 carbon intensities are 4.1 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 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 the summary statistics of aggregate variables. The log growth of the real price of oil (ΔRPO) has a monthly standard deviation of 8%. The equity and bond ESG shares average 0.30% and 0.47%, respectively.

1.2 Constructing the Greenium

To construct measures of green premium (greenium), we sort firms into tercile portfolios based on the carbon intensity, with the top tercile being brown firms and the bottom tercile green peers. The aggregate greenium $Spread^{B-G}$ is then computed as the value-weighted differential in ICC between brown (top tercile) and green (bottom tercile) equity portfolios,

with an analogous yield spread differential computed for bond portfolios. Figure 1 presents the time-series evolution of this aggregate greenium for both asset classes.

Sectoral heterogeneity plays a significant role in explaining emission intensity. As shown in Figure 2, utility, materials, and energy sectors are concentrated in the brown tercile and 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. Notably, energy firms are not the most carbon-intensive entities but represent the median brown stocks in the top brown tercile. For comparison, utilities have an average carbon intensity of 3,288 tCO2e/$M, materials 688, and energy 539 (Table IA.1 of the Internet Appendix). The portfolio weight of the brownest two sectors, utilities and materials, in the brown tercile, is 24% for equity and 35% for bonds.

1.2.1 The Energy Spread and a Narrative on Oil Shocks

The energy sector is heavily oil-dependent due to its direct involvement in hydrocarbon production. As such, we focus on the energy sector to isolate the effect of oil shocks and compare it to other brown firms to isolate the potential impact of oil related shocks. 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 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. To further 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. For pre-2003 periods lacking firm-level emissions data, we impute Fama-French 49-industry-level emission intensities using post-2003 firm-level data.[2] Figure 3 demonstrates starkly divergent dynam-

[2]Robustness analysis in the Internet Appendix shows that the main results hold before 2003 as well as after 2003, respectively.

ics between these components over a half-century sample. The two equity series exhibit a small negative correlation of -0.27 ($p<0.01$), while bond correlations are similar to zero, at -0.17 ($p>0.1$).

A closer examination of historical episodes reveals distinct dynamics of the series 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 enjoyed substantially higher profits and 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 remained 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, collapsed oil demand and oil prices pushed energy firms' cost of capital to decade highs. Most recently, following the Russia-Ukraine military conflict in Februrary 2022, 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.

1.2.2 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, movements orthogonal to the ex-energy greenium, is measured by the incremental R^2 from adding $Spread_t^{Energy-BNE}$ to the regression analysis.

Figure 4 plots the contribution of the 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. It is worth noting that many downstream industries that rely on energy inputs are also classified as brown industries due to their carbon intensity. As such, the ex-energy greenium can be exposed to oil shocks.[3] Consequently, the additional explanatory power of the energy spread estimated here is a lower bound of the potential contribution of energy-specific shocks, only capturing the component *orthogonal* to the indirect impact on non-energy brown firms.

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 heightened credit risk differentials between energy and other brown firms.

These findings underscore that conventional greenium metrics, which aggregate all brown

[3]The exposure sign can be ambiguous, as the pricing power of downstream industries varies with their market power (Katz and Rosen, 1985).

firms, conflate climate transition risks with energy-related commodity cycles. By incorporating sectoral heterogeneity, our decomposition framework helps better identify "true" climate risk repricing and informs portfolio strategies in climate-aware investing.

2 A Stylized Model

The empirical observations highlight the tight linkage between oil shocks and the financing cost of energy firms. Because various oil shocks significantly impact the macroeconomy and risk premium, oil shocks not only constitute cash flow shocks to these firms but can also impact their expected return variations. This section develops a Q-theory framework to formalize how global oil shocks, conditional on energy firms' productivity, drive variations in their conditional risk premium relative to non-energy firms.

2.1 Model Setup

Consider an economy in which agents consume two types of goods: energy (oil/gas) products E and non-energy brown goods BNE. The non-energy good is the numeraire in the economy. In the spirit of Kogan, Livdan and Yaron (2009), the good demand is represented by

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

where P_E is the real price of oil, A denotes oil demand, Y_i denotes good i production, and ϵ is the elasticity of demand.

The model comprises a continuum of competitive firms in each sector. For simplicity, the production technology is deterministic,

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

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

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

with δ denoting the depreciation rate. The adjustment cost Φ equals

$$\Phi_{i,t} = \chi \frac{I_{i,t}^2}{K_{i,t}}. \tag{5}$$

The firm can be financed with debt b_{t+1} and equity s_{t+1}. Dividends $D_{i,t}$ derive from firms' production, investment, and financing,

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

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

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

subject to $\lim_{T\to\infty} E_t \left[M_{t+T} b_{i,t+T+1} \right] = 0$ (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.

2.2 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 denotes the i.i.d. unexpected oil shocks that follow a standard normal distribution. Oil shocks are sudden, significant disruptions in the global oil supply or sudden surges or collapse in oil-specific demand. Examples of positive e shocks include the 1970s oil embargo and the outbreak of the Russian-Ukraine military conflict, which disrupted the global oil supply, boosted oil prices and boosted U.S. energy firms' profitability. Examples of negative e shocks include the 1980s oil glut and the COVID-19 lockdown, which destroyed U.S. energy firms' profitability.

We assume the stochastic discount factor is exposed to the oil shocks as follows

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

to capture the idea that oil shock can disrupt the macroeconomy and push up risk premium variations (Kilian, 2009; Baumeister and Hamilton, 2019; Känzig, 2021; Gao et al., 2022).

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

2.3 The Energy Spread and Greenium

We define the energy spread as the expected return differential between energy and non-energy firms

$$Spread^{E-BNE}_t = E_t\left[\left(w^b_{E,t} r^b_{E,t+1} + w^s_{E,t} r^s_{E,t+1}\right) - \left(w^b_{BNE,t} r^b_{BNE,t+1} + w^s_{BNE,t} r^s_{BNE,t+1}\right)\right]. \tag{9}$$

The bond and equity energy spreads are defined as $E_t\left[r^b_{E,t+1} - r^b_{BNE,t+1}\right]$ and $E_t\left[r^s_{E,t+1} - r^s_{BNE,t+1}\right]$, respectively. Following Liu, Whited and Zhang (2009), we can derive that the average cost of capital equals the investment return, $r^K_{i,t+1} = w^b_{i,t} r^b_{i,t+1} + w^s_{i,t} r^s_{i,t+1}$. As such, the energy spread

equals the expected investment return difference between energy and non-energy firms

$$Spread_t^{E-BNE} = E_t\left[r_{E,t+1}^K - r_{BNE,t+1}^K\right]. \tag{10}$$

For model simplicity, we do not model the green firms but assume their cost of capital r_G^K is constant. As such, the greenium can be calculated as

$$\begin{aligned} Greenium_t &= \phi E_t r_{E,t+t}^K + (1-\phi) E_t r_{BNE,t+1}^K - r_G^K \\ &= \phi \underbrace{Spread_t^{E-BNE}}_{\text{Energy Spread}} + \underbrace{r_{BNE,t}^K - r_G^K}_{\text{Ex-Energy Greenium}} \end{aligned} \tag{11}$$

where ϕ is the weight of energy firms in the brown portfolio. The equation shows that higher energy spread contributes to higher aggregate greenium, and lower energy spread reduces the aggregate greenium. The total impact depends on the portfolio weight of energy firms in the brown portfolio (ϕ).

2.4 Equilibrium and Investment Return

The equilibrium consists of optimal investment decisions, $I_{E,t+1}$, $I_{BNE,t+1}$, $K_{E,t+1}$, $K_{BNE,t+1}$, and the product price $P_{E,t}$, consistent with aggregate quantities. The first-order condition concerning the optimal investment in sector i is

$$\begin{aligned} &1 + (1-\tau)\chi\frac{I_{i,t}}{K_{i,t}} \\ =&E_t\frac{M_{t+1}}{M_t}\cdot\left((1-\tau)\left(\alpha P_{i,t+1}K_{i,t+1}^{\alpha-1} + \delta\tau + \frac{\chi}{2}\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^2\right) + (1-\delta)\left(1 + (1-\tau)\chi\frac{I_{i,t+1}}{K_{i,t+1}}\right)\right). \end{aligned} \tag{12}$$

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 $E_t\left[M_{t+1}r^K_{i,t+1}\right]=1$, in which $r^K_{i,t+1}$ is the physical capital investment return,

$$r^K_{i,t+1}=\frac{(1-\tau)\left(\alpha P_{i,t+1}K^{\alpha-1}_{i,t+1}+\delta\tau+\frac{\chi}{2}\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^2\right)+(1-\delta)\left(1+(1-\tau)\chi\frac{I_{i,t+1}}{K_{i,t+1}}\right)}{1+(1-\tau)\chi\frac{I_{i,t}}{K_{i,t}}}. \quad (13)$$

Given that non-energy goods serve as the numeraire and technology is deterministic, non-energy firms maintain constant profitability, investment and capital level. As such, non-energy firms' cost of capital is constant. In contrast, the investment rule and investment return of energy firms vary with A. We can spell out the energy spread as

$$Spread^{E-BNE}_t=-r^K_{BNE}$$
$$+\frac{E_t\left[(1-\tau)\left(\overbrace{\alpha A_{t+1}K^{\alpha\left(1-\frac{1}{\epsilon}\right)-1}_{E,t+1}}^{\text{Profitability}}+\delta\tau+\overbrace{\frac{\chi}{2}\left(\frac{I_{E,t+1}}{K_{E,t+1}}\right)^2}^{\text{Investment Wedge}}\right)+(1-\delta)\left(\overbrace{1+(1-\tau)\chi\frac{I_{E,t+1}}{K_{E,t+1}}}^{\text{Future Investment}}\right)\right]}{\underbrace{1+(1-\tau)\chi\frac{I_{E,t}}{K_{E,t}}}_{\text{Investment, Marginal Q}}}. \quad (14)$$

The equation shows that energy firms' current asset growth, future profitability $(1-\tau)\alpha A_{t+1}K^{\alpha\left(1-\frac{1}{\epsilon}\right)-1}_{E,t+1}$, and future investment growth all play a role in determining the average spread. Higher A can increase the profitability and the energy spread. However, the marginal Q for energy firms, $1+(1-\tau)\chi\frac{I_{E,t}}{K_{E,t}}$, increases with their investment, and can reduce the energy spread. We thus solve the model numerically below to characterize these firm responses as well as the energy spread.

2.5 Numerical Results

We calibrate the model at a quarterly frequency and present parameters in Panel A, Table 2. 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. The oil demand elasticity ϵ is set to 0.1, matching the low estimates in Kilian (2022). The persistence of aggregate oil demand ρ is set to 0.91, matching the empirical persistence of the real oil price. The oil demand volatility 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 γ to 0.53 to match the average energy spread of 0.27%, weighted between equity and bonds. Panel B, Table 2 shows that moments well match the data.

Figure 5 plots the policy functions, illustrating that positive oil demand shocks raise oil prices, increase energy firms' growth options, and lower their cost of capital. As the energy demand and oil price increase, the energy profitability (P/MPK_E) increases due to the price effect. In addition, as the oil demand (A) is persistent, both the investment rate and marginal Q of energy firms increase, which ultimately drives a negative relationship between the oil price and the energy spread in expected returns.

Comparative statics in Figure IA.5, Internet Appendix further examines the channels. First, the presence of physical adjustment cost ($\chi > 0$) is a key force that generates the investment wedge in Eq. (14), driving energy spread variations. Without the adjustment cost ($\chi \to 0$), energy firms' marginal Q stays constant, and the energy spread no longer varies with oil demand A. Second, oil demand persistence ρ governs the investment response and the energy spread. If $\rho \to 0$, the energy spread no longer varies with oil demand A. Third, oil price elasticity χ governs the oil price response to oil quantities and thus the optimal investment response. A lower price elasticity χ weakens the investment response, reduces the investment friction incurred, and reduces the energy spread sensitivity to oil demand shocks.

In summary, our model suggests that rising oil demand narrows the energy spread. Because the energy spread directly contributes to the aggregate greenium as in Eq. (11), oil shocks can further aggregate greenium fluctuations without altering the cost of capital dif-

ference between non-energy brown firms and green firms.

3 Oil Shocks and Dynamics of Greenium Components

This section builds on model predictions and formally examines the relationship between oil shocks and the cost of capital empirically. The impact of oil shocks is largely confined to energy firms due to its oil-specific nature, distinguishing it from climate risk or green preference shocks that broadly affect the brown-versus-green spread across various sectors (Pástor, Stambaugh and Taylor, 2021; Hsu, Li and Tsou, 2023). The distinct sectoral effects allow us to differentiate the impact of oil shocks from climate-related channels.

Two caveats warrant consideration. First, climate-related shocks may affect energy and non-energy brown firms with varying intensities, but these effects are unlikely to be orthogonal to or driven solely by energy firms. We thus focus distinct movements in energy firm dynamics relative to non-energy brown firms and contrast these with movements in the ex-energy greenium. Second, oil shocks could influence non-energy brown firms via supply chain spillovers, particularly for carbon-intensive firms closely linked to the energy sector, which the model abstracts from. We empirically evaluate the magnitude of these spillovers in the analysis below.

3.1 Producer Prices and Growth Opportunities

We start by examining 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,

$$\Delta PPI_{i,t} = a + b \cdot 1(Energy)_{i,t} \times \Delta RPO_t + \kappa_i + \iota_t + e_{i,t+\tau}, \tag{15}$$

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.

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

$$\Delta PPI_{i,t} = a + b \cdot 1(Energy)_{i,t} \times \Delta RPO_t + c \cdot Carbon_{i,t} \times \Delta RPO_t + \kappa_i + \iota_t + e_{i,t+\tau}, \tag{16}$$

where $Carbon$ is measured by $Intensity$, the standardized log carbon intensity, or $1(Brown)$, which equals one for industries in the top third of carbon intensity and zero otherwise. Both regression models incorporate industry (κ_i) and time (ι_t) fixed effects, with standard errors double clustered at industry and month levels.

Table 3 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. Overall, our results show that oil price shocks significantly influence energy-sector output prices. However, their impact on other brown industries is more limited, likely due to lower operational exposure to oil shocks and regulatory constraints.

Oil price shocks may also impact oil-dependent firms' input prices and dampen the impact of their growth options and expected returns. To gauge the impact, 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 Eqs (15) and (16) 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, consistent with the model's Q-channel predictions.

Next, we turn to the key model mechanism that energy firms experience a greater ex-

pansion of growth opportunities than other firms following oil price increases. We conduct the following regression,

$$\Delta Y_{j,t+1} = a + b \cdot 1(Energy) \times \Delta RPO_t + d \cdot X_{j,t} + \kappa_j + \iota_t + e_{j,t+1}, \tag{17}$$

where Y_j denotes measures of firm j's 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 3 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 (0.33 for energy firms and 0.02 for non-energy brown firms). The disparity persists in real outcomes—energy firms exhibit a 0.32% increase in sales growth, 0.14% in investment rates, and 0.21% in ROE change following a one-percent oil price increase, compared to minimal effects for non-energy firms.

Additional results in Table IA.3 of the 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.

3.2 Time Series Evidence on Oil Shocks

We now evaluate the key prediction of the model on the impact of oil shocks on expected return differentials between energy and other firms. Our baseline specification estimates the

dynamic relationship between oil price variations and sectoral financing cost spreads:

$$\Delta Spread_t^u = \alpha + \beta \Delta RPO_t + \varepsilon_t, \tag{18}$$

where $u \in \{Energy - BNE, BNE - G\}$ denotes energy spread or ex-energy greenium, and ΔRPO represents log changes in oil prices. Standard errors are adjusted for autocorrelation up to 12 lags.

Consistent with the model prediction, Panel A of Table 4 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 for non-energy brown firms. Specifically, the coefficients are 0.14 and -0.31 for non-energy equity and bond greenium, respectively, compared to -1.75 and -0.82 for corresponding energy spreads. Similarly, the explanatory power for ex-energy greenium variations is also lower, with $R^2 = 0\%$ and 3% for equity and bonds, respectively. This weaker oil response in the ex energy greenium is consistent with the small oil price passthrough to non-energy brown products at about 10% of the direct passthrough to energy products.

The time-series dynamics shown in Figure 6 reveal a strong negative co-movement between oil prices and the energy spread. First, the negative relation between the energy spread and oil prices persisted before the rise of sustainable investing and any emission data. For example, the low oil prices in the 1980s, driven by the global oil glut, correspond to the peak in the energy spread, and the subsequent oil price recovery corresponds to the large decrease in the energy spread. Supplementary results in Tables IA.4 of Internet Appendix show that this relation robustly holds in across different subsamples, including before 2000s.

Second, a few boom-and-bust cycles in oil prices have closely aligned with greenium fluctuations in the past two decades. 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 conflict 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.

Third, oil prices have mostly remained below their historical average since the 2014 crash, consistent with increased aggregate greenium as in Figure 1, often documented in the literature. The decomposition in Figure 3 shows a persistent increase in the energy spread, mirroring the oil price dynamics, while the ex-energy greenium has risen much less over the same period. These trends indicate that oil price fluctuations have significantly influenced perceptions of greenium growth in recent years.

We conduct a few robustness tests below. First, the baseline analysis compares energy firms to other brown firms to isolate the impact of oil shocks. As an alternative, we compare energy and utility firms to disentangle dynamics unrelated to the energy transition. Utilities, the most carbon-intensive sector, are also directly targeted by decarbonization policies and sustainable investing like energy. However, unlike energy firms, they operate under strict regulatory constraints, such as rate-of-return regulations, that limit pricing flexibility and insulate their cash flows from oil price volatility. Table IA.5 of the Internet Appendix utilizes the energy-utility spread and finds consistent results.

Second, natural gas, like oil, significantly affects oil and gas profitability, although gas prices show greater geographic variability. Using the Henry Hub (Louisiana) gas price index as our reference in Table IA.6 of the Internet Appendix, we obtained results consistent with our baseline findings.

Finally, we examine alternative samples in Table IA.7 of the Internet Appendix, including the historical long sample of bonds,[4] as well as the CDS market, and find similar results as the baseline analysis. Together, these findings underscore the asymmetric impact of oil shocks across brown sectors and the role of commodity prices in shaping greenium dynamics.

[4]We follow Chordia et al. (2017) by assembling data from Lehman Brothers Fixed Income and Datastream databases to construct an extensive panel of corporate bonds back to 1974.

3.3 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:

$$\Delta ER_{j,t} = a + b \cdot 1(Energy)_{j,t} \times \Delta RPO_t + d \cdot X_{j,t} + \kappa_j + \iota_t + e_{j,t}, \tag{19}$$

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 security-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 4 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 -2.98 and -1.24, slightly greater than the baseline portfolio-based coefficients (-1.75 and -0.82). In short, oil price shocks have a consistent significant negative impact on energy firms' cost of financing. In contrast, we do not detect a significant impact on general carbon-intensive firms.

3.4 Event Studies of Oil Shocks

The earlier sections show that oil price innovations significantly impact the cost of capital for energy firms. Because the oil price price is an endogenous variable (Kilian, 2009; Baumeister and Hamilton, 2019; Känzig, 2021), we now exploit various quasi-natural oil shock experiments to isolate causal effects.

First, we adopt an instrumental variables (IV) approach following Känzig (2021), using OPEC announcement surprises as an exogenous shock to the global oil supply. The in-

strument is the first principal component of daily WTI crude futures price changes (1- to 12-month maturities) around OPEC meetings, which captures unanticipated shifts in foreign oil supply and demand for U.S. oil and gas products.

Specifically, we estimate a two-stage model:

$$\begin{aligned} \text{first stage: } \Delta RPO_t &= \gamma_0 + \gamma_1 Z_t + u_t, \\ \text{second stage: } \Delta Spread_t^u &= \alpha_{IV} + \beta_{IV} \widehat{\Delta RPO}_t + e_t, \end{aligned} \tag{20}$$

where Z_t denotes OPEC announcement surprises. First-stage results, as presented in Table IA.8 of Internet Appendix, confirm the instrument's strength (F-statistic > 10). The second-stage results in Panel A of Table 5 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 -11.64 ($t = -3.34$), and bond greenium from -0.82 to -4.14 ($t = -3.49$). This change in magnitude suggests that endogenous oil price fluctuations in the baseline model likely attenuate the true causal effect of oil shocks on greenium dynamics. These results underscore the importance of exogenous oil 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 study additional quasi-natural experiments, e.g., the COVID-19 pandemic lockdown and the Russia-Ukraine military conflict, to isolate the causal effects of oil shocks. For each event, we estimate a difference-in-differences specification in the panel setting,

$$ER_{j,t} = a + b \cdot 1(Energy)_{j,t} \times PostEvent_t + c \cdot X_{j,t} + \kappa_j + \iota_t + \varepsilon_{j,t}, \tag{21}$$

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 in the baseline panel analysis. The regression includes firm and time-fixed effects, with standard errors double-clustered at the firm and month levels.

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. 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 5 shows that following the pandemic lockdown, energy firms' equity cost of capital increased by 2.98% annually, and their bond yield spreads increased by almost 1% 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 5. 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 0.25% 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.

4 Climate Event Studies

Thus far, our analysis has established that oil shocks drive energy spread dynamics independent of climate-related shock. This finding carries critical implications for climate finance research: failing to account for oil shocks 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.

4.1 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 prevailing 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. 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.[5] The rebound in 2016 was fueled by a resurgence in global demand. Figure IA.6 in the Internet Appendix shows that this V-shaped oil price pattern mirrors the reverse V-shaped dynamics of the energy spreads, with the equity spread peaking in September 2015 and the bond spread peaking in December 2015. Similar dynamics are observed in the ex-energy greenium, but more muted. In short, 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,

$$ER_{j,t} = a + b \cdot Carbon_{j,t} \times AfterPA_t + c \cdot X_{j,t} + \kappa_j + \iota_t + \varepsilon_{j,t}, \tag{22}$$

where $Carbon$ denotes the log emission intensity or the brown dummy indicating the top

[5]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.9 in Internet Appendix).

third of emission intensity, and $AfterPA$ 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 6 presents the baseline results. After the Paris Agreement, brown firms' equity ICCs show a statistically insignificant decrease (Panel A), while their bond yield spreads rise significantly (Panel B), increasing by 6 bps per standard deviation in emission intensity or 17 bps for the top-third most carbon-intensive brown firms. The bond estimates translate to about 32 bps based on quartile sorting, similar to the 30 bps effect estimated in Seltzer, Starks and Zhu (2022). As such, only the bond market response is consistent with the hypothesis of reduced climate policy risk.

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 to allow for differential impacts on energy firms,

$$ER_{j,t} = a + b \cdot Carbon_{j,t} \times AfterPA_t + e \cdot 1(Energy)_{j,t} \times AfterPA_t + c \cdot X_{j,t} + \kappa_j + \iota_t + \varepsilon_{j,t}. \quad (23)$$

After adjusting for energy firms' distinct exposure to oil shocks, the cost of capital for non-energy brown firms aligns closely with that of greener firms for both equity and bonds post-December 2015, showing no statistically significant differences at conventional levels. In contrast, energy firms experience a 70 bps ICC increase ($p > 0.1$) and a 60 bps yield spread increase ($p < 0.05$), in line with the impact of oil shocks.

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

$$ER_{j,t} = a + b \cdot Carbon_{j,t} \times AfterPA_t + e \cdot Carbon_{j,t} \times RPO_t + c \cdot X_{j,t} + \kappa_j + \iota_t + \varepsilon_{j,t}. \quad (24)$$

Results in Columns (3) and (6) indicate 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 instead of increase following the PA through all specifications. This lack of 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.10 of the Internet Appendix show that oil beta fails to account for the oil effect, particularly for equity beta used in Seltzer, Starks and Zhu (2022).

In summary, 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.

4.2 The 2016 Election of President Trump

Donald Trump's unexpected election win on November 8, 2016, represents another canonical event for assessing climate policy risk dynamics, given market perceptions of reduced regulatory stringency under the Trump administration (Ilhan, Sautner and Vilkov, 2021). While prior studies interpret post-election greenium compression as evidence of diminished climate risk premia, 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, the first such agreement since 2008, boosting oil prices and demand for U.S. energy output. This structural shift in commodity markets necessitates

explicit controls for concurrent oil price effects when isolating the election's impact.

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. (22) and examine the 12 months surrounding the event. Table 7 details the findings. Following the election, the bond greenium decreases by 13 bps per standard deviation increase in emission intensity, or 36 bps for top brown firms, but the response of equity greenium is statistically insignificant. As such, only the bond market response is consistent with the hypothesis of reduced climate policy risk.

Next, we account for the oil effect by allowing for a differential impact on energy firms. The equity response remains positively insignificant, whereas the bond coefficients remain negative but shrink by half for more carbon-intensive and brown firms. In contrast, the cost of capital of energy firms decreases by nearly 0.8% for equity and 0.9% for bonds after November 2016. This pattern aligns with OPEC-induced profitability improvements rather than regulatory risk repricing. Collectively, these refined estimates indicate that the 2016 presidential election may have influenced the bond greenium. However, the magnitudes are attenuated and limited after controlling for oil's impact.

4.3 Climate Concern and Sustainable Investing

Finally, this section revisits the influence of climate concern shocks and sustainable investing, which recent literature links to ESG-related discount rate shocks. The underlying hypothesis is that heightened climate concern increases demand for green assets and expected returns on brown stocks, thereby raising the greenium. We conduct time series analysis as in Pástor, Stambaugh and Taylor (2022) but focus on discount rate variations directly

$$\Delta Spread_t^{B-G} = \alpha + \beta \mathbf{CConcern_t} + \varepsilon_{\mathbf{t}}, \tag{25}$$

where **CConcern** is a vector containing various measures of climate concerns and sustainable investment. Climate concern shocks are constructed in line with Ardia et al. (2023), and we study the sample of 2006:06 to 2022:12, the full period for which climate concern shocks can

be constructed.

Columns (1) and (4) of Table 8 find that climate concern shocks or sustainable investing have no significant impact on the greenium. The R^2s are less than 3% for both regressions. Supplementary evidence in Table IA.11 and Figure IA.7 of the Internet Appendix confirms that climate concern shocks appear to influence greenium variations from 2012:11 to 2018:06 as in Pástor, Stambaugh and Taylor (2022). However, these relationships are sample-period sensitive rather than representing a universal economic relationship.

We isolate the potential impact of oil shocks in two ways. First, we control for the energy spread innovations orthogonalized to ex-energy greenium innovations, $\Delta\text{Spread}^{Energy-BNE,o}$. Second, we control for oil price changes, ΔRPO, a highlighted channel of energy spread variations. These controls boost the explanatory power by up to 16% for equity and 40% for bonds, but the estimates of climate concern shocks remain largely insignificant.

In conclusion, our analysis suggests that financial markets do not respond to climate-related shocks as effectively as previously concluded. 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 over the longer sample. 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.

5 Conclusion

This study challenges the prevailing view that greenium variations primarily reflect investor commitment to climate-conscious investments. Instead, we demonstrate that oil shocks drive 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 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 account for oil price dynamics. Additionally, while this paper focuses on the greenium, oil shocks have broader implications for carbon pricing, firms' capital budgeting, bank lending, and corporate behavior.

Several remedies can address these challenges. First, controlling for oil shocks and distinguishing the energy sector from other brown firms allow for clearer analysis. Second, cross-sectional shocks across multiple entities offer valuable complementary evidence beyond a single time series event study. Additionally, within-industry variations can provide further insight, as sector-specific shocks may influence greenium variations alongside oil shocks.

From a policy perspective, our findings raise questions about the effectiveness of market mechanisms in facilitating the carbon transition. The muted response to climate risks and preference shifts suggests that tighter policy interventions, such as carbon pricing or disclosure mandates, may be necessary to help align capital allocation with decarbonization objectives. Importantly, our decomposition framework provides policymakers with tools to better distinguish between commodity-driven and climate policy-driven movements in corporate financing costs.

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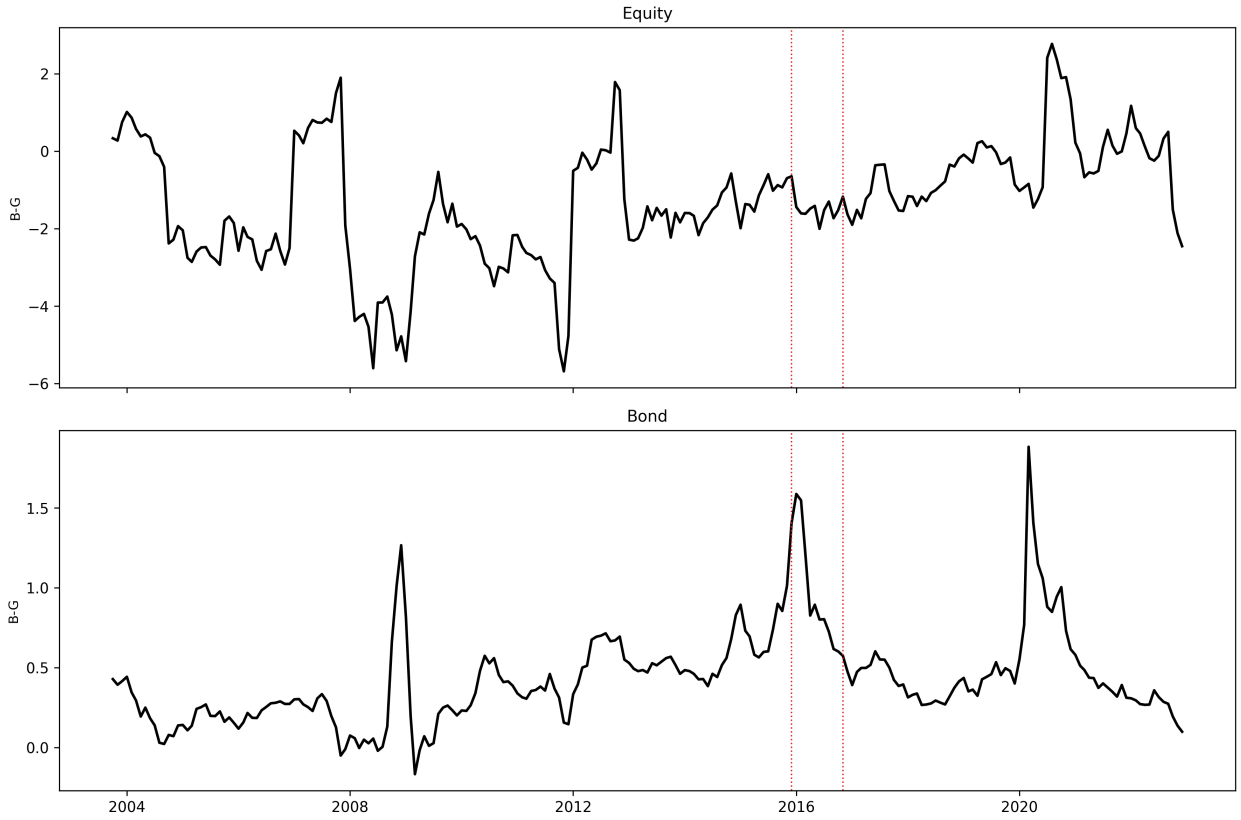
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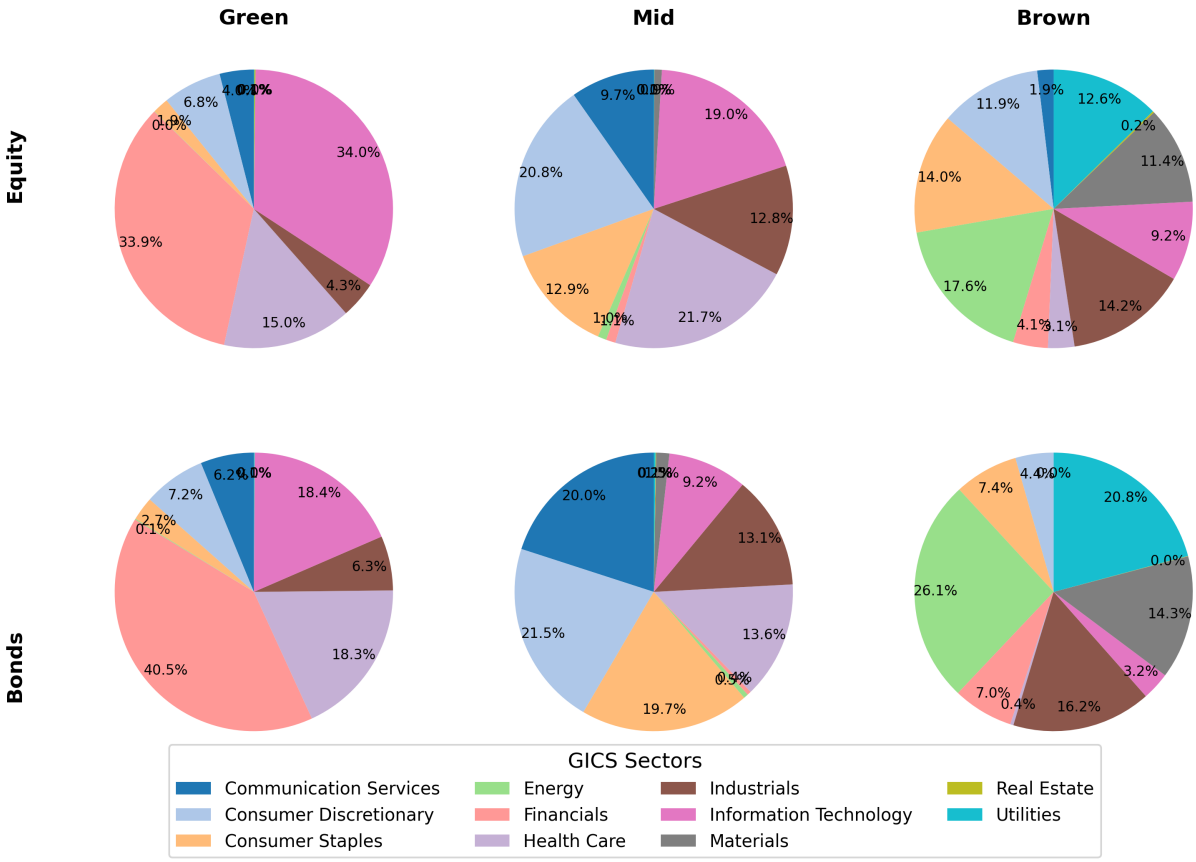
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Figure 1: Equity and Bond Greenium



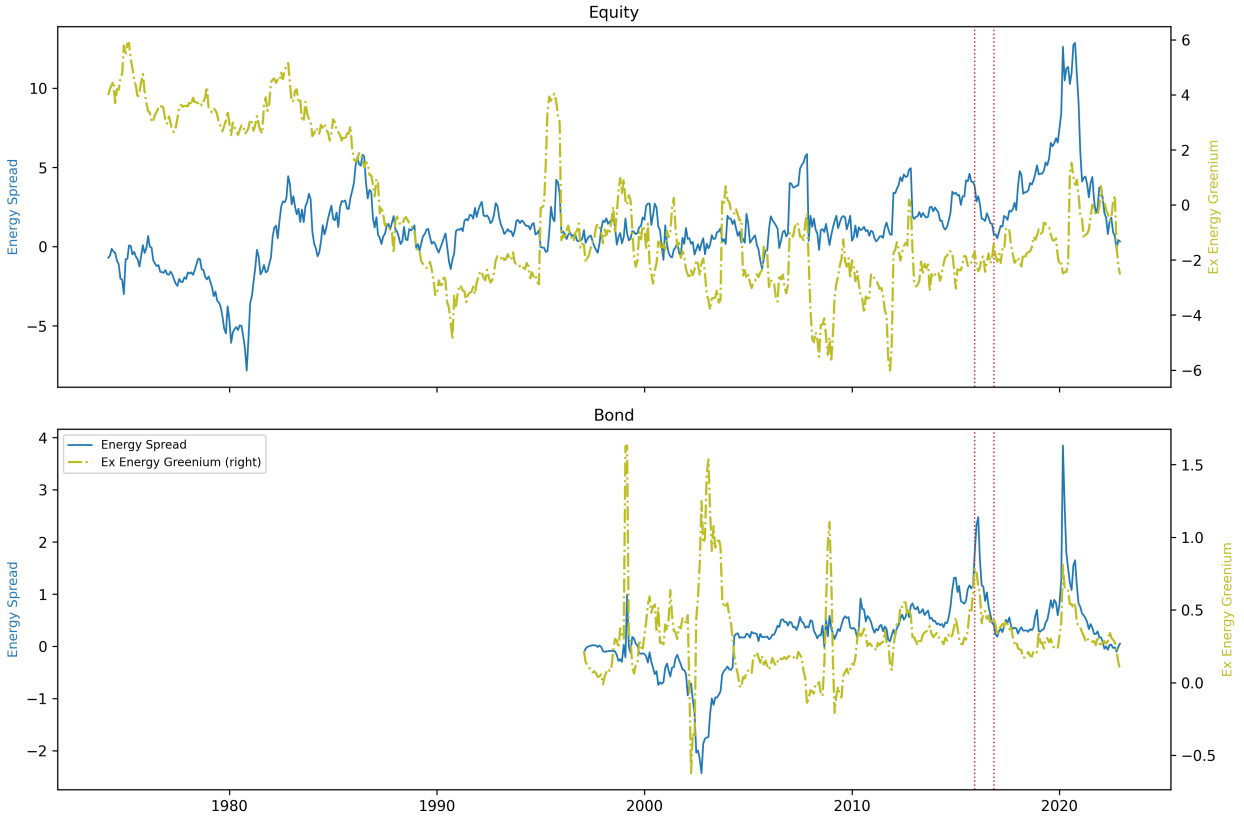
Notes: This figure plots the time series of equity and bond greenium, calculated as the value-weighted high-minus-low spread of carbon-intensity sorted portfolios. The first vertical line denotes the Paris Agreement and the second vertical line denotes the 2016 election of President Trump. The sample period spans from 2003:10 to 2022:12.

Figure 2: Sector Distribution across Carbon-Sorted Portfolios



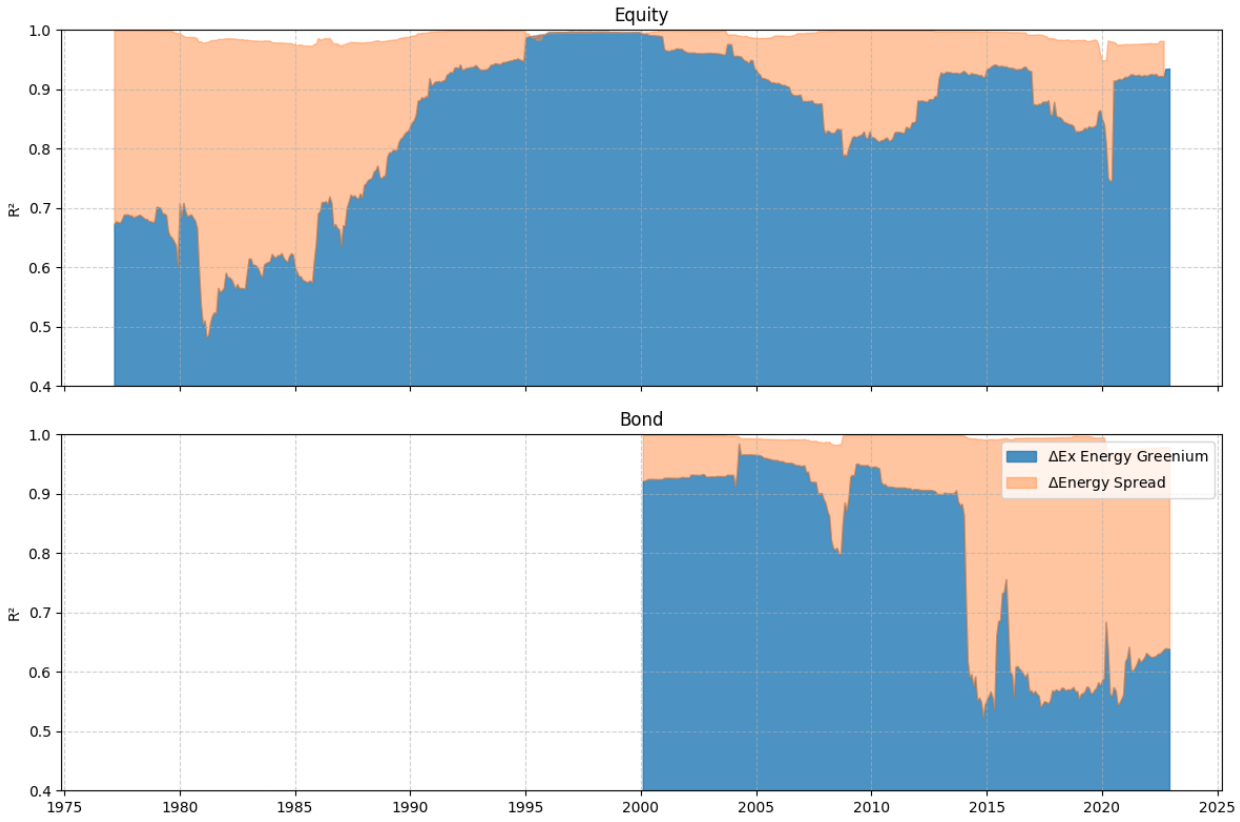
Notes: This figure plots the average portfolio weight of Global Industry Classification Standard (GICS) sectors across portfolios sorted by carbon emission intensity. Portfolio weights reflect the proportional representation of each sector within intensity-sorted terciles. The sample period spans from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

Figure 3: Greenium and Energy Spread



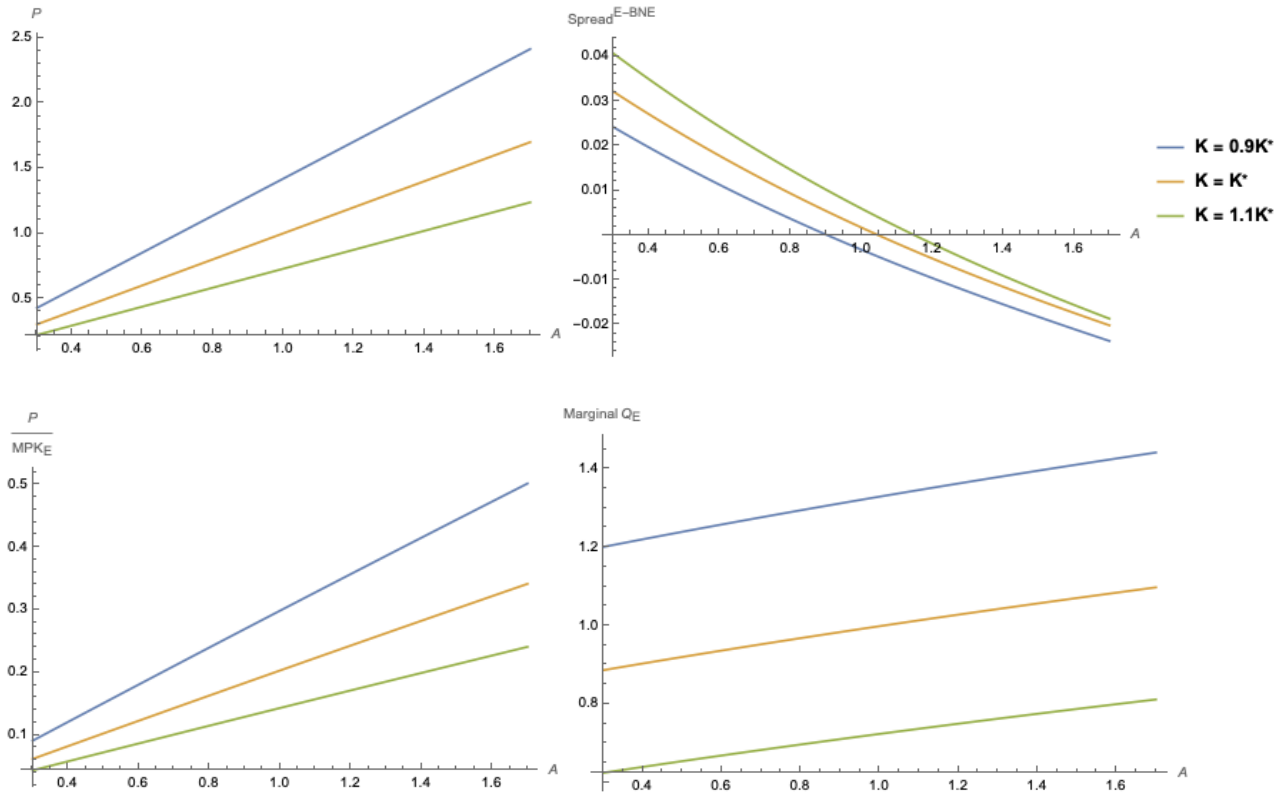
Notes: This figure plots the time series of the greenium's two constituent spreads: (1) the non-energy greenium (solid line), measured as the difference in cost of capital between non-energy brown firms (top tercile in terms of carbon intensity) and green firms (bottom tercile), and (2) the energy spread (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 4: 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 5: Policy Functions



Notes: This figure plots policy functions of the oil price (P), energy spread ($Spread^{E-BNE}$), energy firms' marginal Q, and energy firms' profitability (P/MPK_E) with respect to the state variable A under different levels of capital K. K^* denotes the steady-state level of capital for energy firms.

Figure 6: 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.

Table 1: Summary Statistics

	Mean	SD	P25	P50	P75
Panel A: Annualized Cost of Capital (%)					
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	0.63	-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	0.25	-0.08	0.00	0.07
Bond $\Delta Spread^{BNE-G}$	-0.00	0.17	-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 1.2. 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: 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	0.53

Panel B: Simulated Quarterly Moments		
Moment	Data	Simulation
Oil Energy Supply Elasticity	$0 - 0.04$	0.02
Mean Investment	5.75%	3.00%
σ(Oil Price)/Mean(Oil Price)	0.19	0.19
Mean Energy Spread^{E-BNE}	0.27%	0.24%
σ(Spread^{E-BNE})	1.14%	1.45%

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

Table 3: 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)	0.33***	0.36***	0.32***	0.32***	0.34***	0.31***
	(5.13)	(4.84)	(5.64)	(3.89)	(6.48)	(3.77)
ΔRPO×Intensity		-0.00			0.01*	
		(-0.08)			(2.00)	
ΔRPO×1(Brown)			0.02			0.04***
			(0.73)			(3.28)
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)	0.14***	0.12**	0.15***	0.21***	0.20***	0.21***
	(3.00)	(2.54)	(3.37)	(3.54)	(4.59)	(3.56)
ΔRPO×Intensity		-0.00			0.00	
		(-0.29)			(0.06)	
ΔRPO×1(Brown)			-0.01			-0.01
			(-0.48)			(-0.43)
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 4: 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		-0.82***	-0.31***	
	(-4.94)	(0.50)		(-6.47)	(-3.08)	
Observations	585	585		310	310	
R^2	0.039	0.000		0.109	0.032	
	Panel B: Panel Analysis					
ΔRPO×1(Energy)	-2.98***	-2.89***	-2.95***	-1.24**	-1.18*	-1.22**
	(-4.05)	(-2.89)	(-3.03)	(-2.00)	(-1.86)	(-2.09)
ΔRPO×Intensity		-0.07			-0.02	
		(-1.02)			(-0.48)	
ΔRPO×1(Brown)			-0.06			-0.03
			(-0.56)			(-0.37)
Beta	0.01	0.02	0.02	-0.02***	-0.02***	-0.02***
	(0.41)	(1.20)	(1.20)	(-3.60)	(-3.49)	(-3.60)
Log Assets	0.11***	0.11***	0.11***	0.01**	0.01**	0.01**
	(12.84)	(12.02)	(12.02)	(2.58)	(2.41)	(2.57)
BE/ME	-0.11***	-0.11***	-0.11***	-0.01	-0.01	-0.01
	(-7.59)	(-5.86)	(-5.86)	(-1.47)	(-1.08)	(-1.47)
Momentum	0.17***	0.18***	0.18***	-0.02	-0.02	-0.02
	(6.20)	(5.45)	(5.45)	(-1.54)	(-1.29)	(-1.54)
ROE	0.07***	0.06***	0.06***	0.02***	0.03***	0.02***
	(3.22)	(2.61)	(2.62)	(2.90)	(2.86)	(2.90)
Asset Growth	0.10***	0.10***	0.10***	0.00	0.01	0.00
	(7.31)	(6.80)	(6.80)	(0.81)	(0.69)	(0.80)
Sales Growth	0.05***	0.07***	0.07***	0.02	0.02	0.02
	(4.23)	(4.13)	(4.13)	(1.53)	(1.45)	(1.52)
Leverage	-0.20***	-0.19***	-0.19***	-0.03	-0.02	-0.03
	(-4.96)	(-4.50)	(-4.49)	(-1.54)	(-1.04)	(-1.54)
IVol	0.00	-0.00	-0.00	-0.00*	-0.00*	-0.00*
	(0.17)	(-0.53)	(-0.53)	(-1.76)	(-1.87)	(-1.76)
Duration				0.00	0.00	0.00
				(1.57)	(1.49)	(1.57)
Bond Age				-0.00***	-0.00***	-0.00***
				(-2.68)	(-2.66)	(-2.68)
Rating				-0.01***	-0.01***	-0.01***
				(-3.82)	(-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 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 5: 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	-11.64***	-0.25		-4.14***	-0.82*	
	(-3.34)	(-0.14)		(-3.49)	(-1.73)	
Observations	476	476		310	310	
	Panel B: COVID-19 Pandemic Lockdown					
Post Lockdown×1(Energy)	2.98***	4.81***	4.03***	0.91*	0.88*	0.86*
	(3.33)	(5.08)	(4.33)	(1.87)	(1.84)	(1.78)
Post Lockdown×Intensity		-0.87***			0.02	
		(-8.42)			(0.73)	
Post Lockdown×1(Brown)			-1.10***			0.07
			(-4.35)			(1.27)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	56581	47632	47632	80102	79633	79633
R^2	0.878	0.865	0.864	0.819	0.820	0.820
	Panel C: Russian-Ukraine Military Conflict					
Post Outbreak×1(Energy)	-2.15**	-2.15**	-1.93*	-0.25**	-0.27**	-0.28**
	(-2.37)	(-2.28)	(-2.05)	(-2.56)	(-2.68)	(-2.72)
Post Outbreak×Intensity		0.14			0.02	
		(1.34)			(1.05)	
Post Outbreak×1(Brown)			-0.02			0.05
			(-0.10)			(1.39)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52562	46381	46381	84448	84346	84346
R^2	0.886	0.875	0.875	0.843	0.844	0.844

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 6: Climate Event Study: The 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)	
RPO×Intensity			-0.04			
			(-0.30)			
RPO×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)	
RPO×Intensity			-0.26***			
			(-3.52)			
RPO×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 7: 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)	
RPO×Intensity			-0.01			
			(-0.06)			
RPO×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)	
RPO×Intensity			-0.23***			
			(-3.23)			
RPO×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.

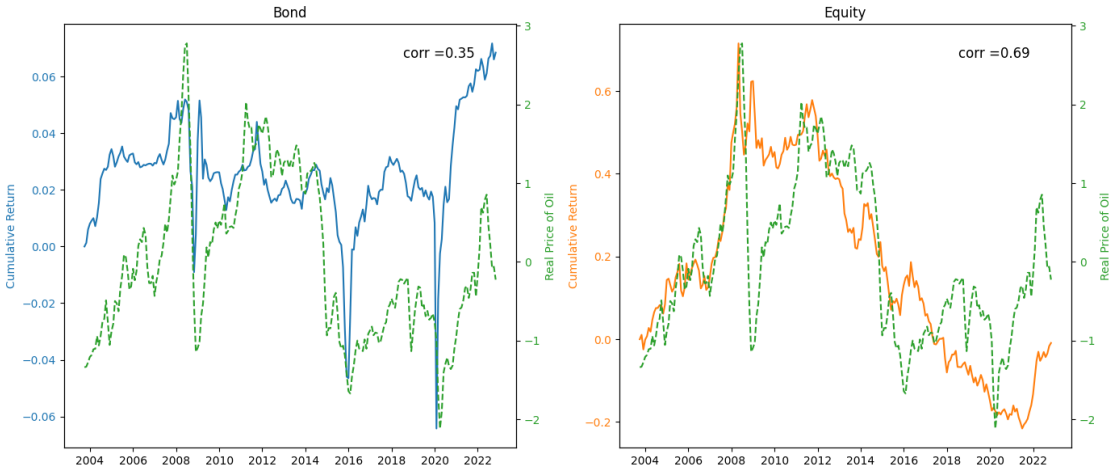
Table 8: Climate Concern Shocks and Greenium Dynamics

	(1)	(2)	(3)	(4)	(5)	(6)
		Equity			Bond	
ΔClimate Concern	-0.01	0.07	-0.01	-0.01	0.00	-0.01
	(-0.03)	(0.38)	(-0.03)	(-0.21)	(0.02)	(-0.22)
Lagged ΔClimate Concern	-0.29	-0.31*	-0.27	0.06	0.01	0.05
	(-1.53)	(-1.75)	(-1.44)	(1.63)	(0.29)	(1.50)
ESG Share	0.21	0.26	0.84	-1.07	-0.18	-0.21
	(0.06)	(0.08)	(0.25)	(-0.96)	(-0.21)	(-0.21)
Lagged ESG Asset	-0.07	0.03	-0.09	-0.01	-0.02	-0.03
	(-0.40)	(0.19)	(-0.54)	(-0.28)	(-0.43)	(-0.68)
$\Delta\text{Spread}^{Energy-BNE,o}$		0.33***			0.35***	
		(5.88)			(11.22)	
ΔRPO			0.53			-0.61***
			(1.07)			(-7.26)
Observations	203	203	203	203	203	203
R^2	0.016	0.163	0.021	0.025	0.405	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 the greenium on climate concern shocks, ESG flow share, and ESG assets. $\text{Spread}^{E-BNE,o}$ is the residual after regressing Spread^{E-BNE} on Spread^{BNE-G} and ΔRPO denotes the oil price innovations. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample spans 2006:06 to 2022:12.

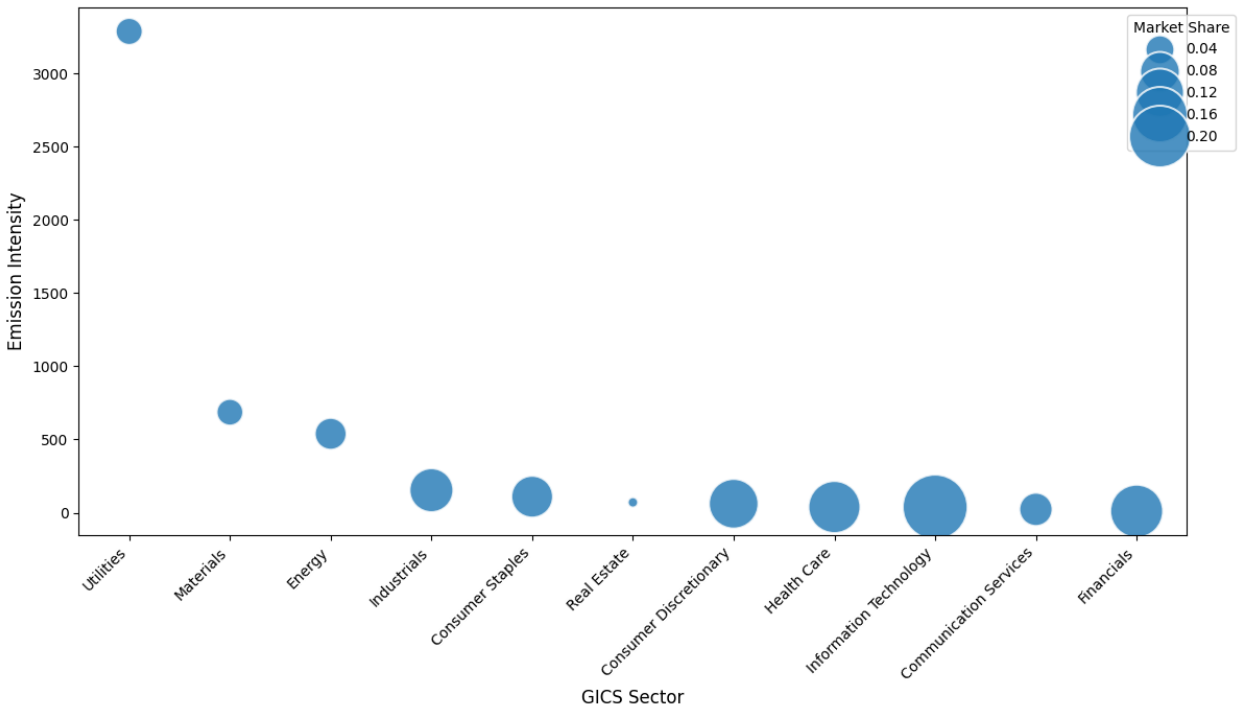
Internet Appendix

Figure IA.1: Brown Return and Oil Price



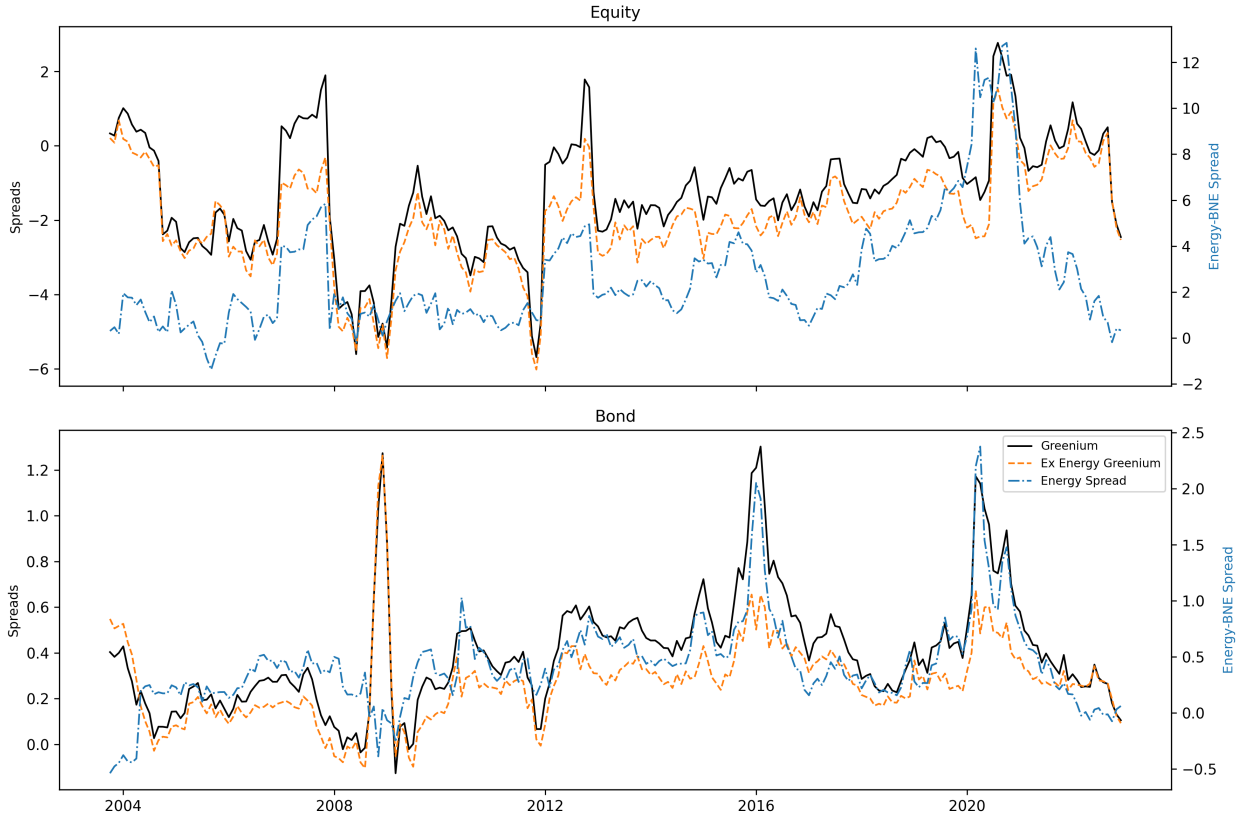
Notes: This figure plots the cumulative brown return and the standardized real price of oil. The monthly brown return is the value-weighted return difference between the top tercile of firms with the highest scope 1 carbon intensity and the bottom tercile. The real price of oil is standardized to have zero mean and unit variance. The sample period is 2003:10 to 2022:12.

Figure IA.2: 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.3: All Spreads



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

Figure IA.4: Model Mechanisms

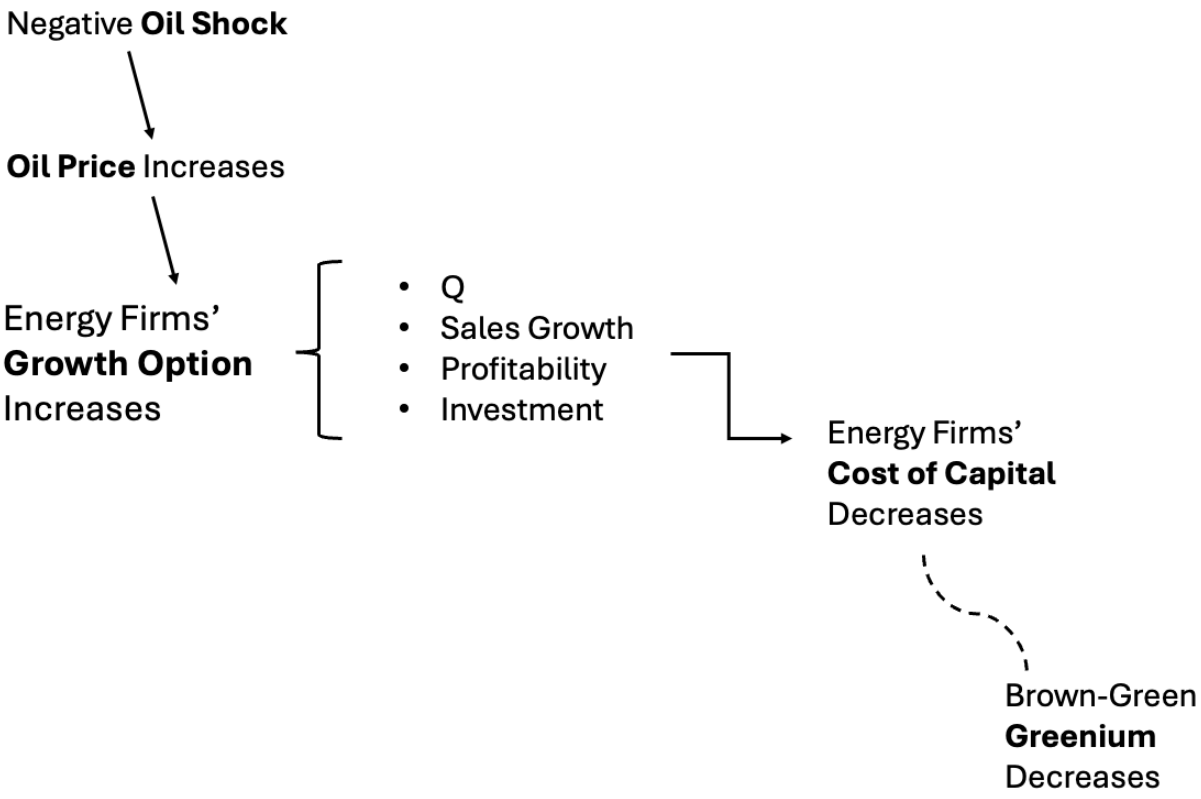
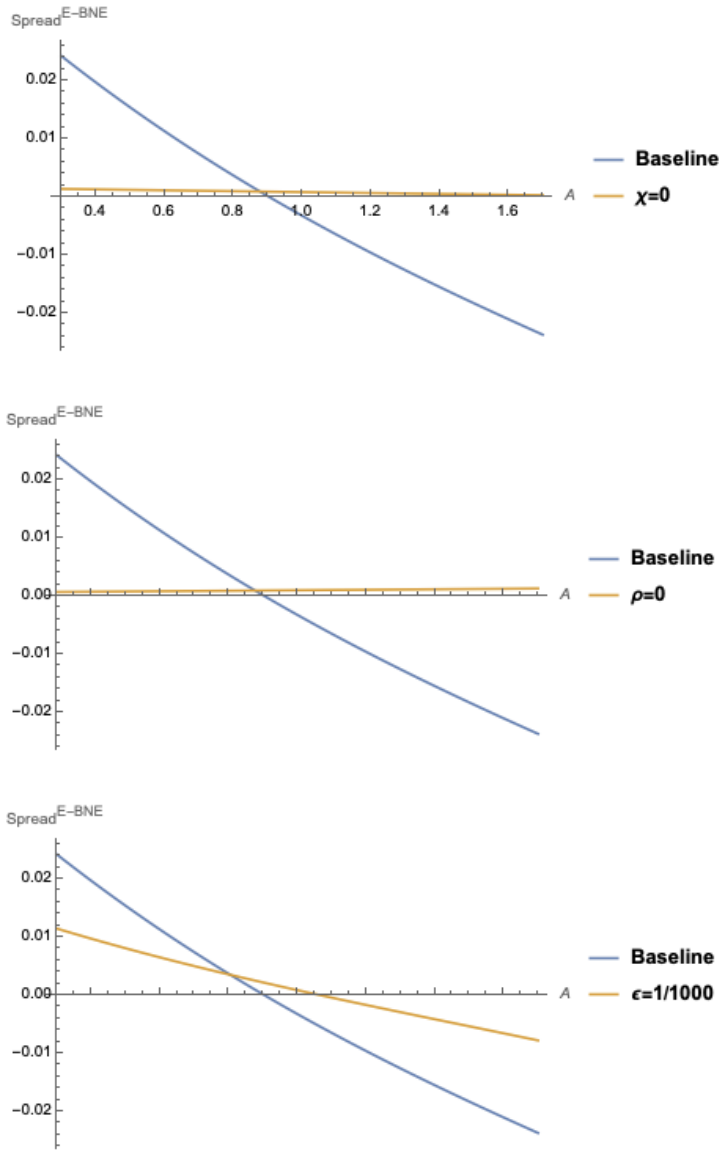
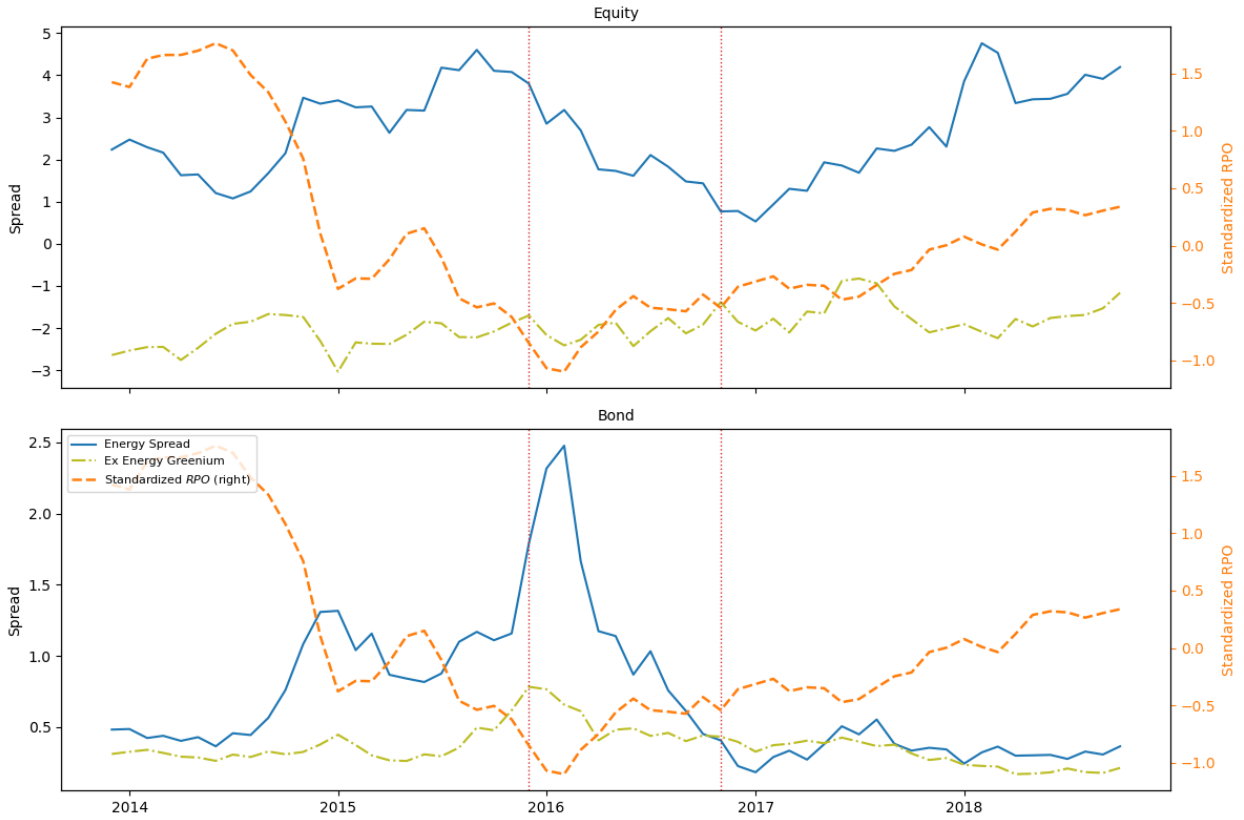


Figure IA.5: Comparative Statics



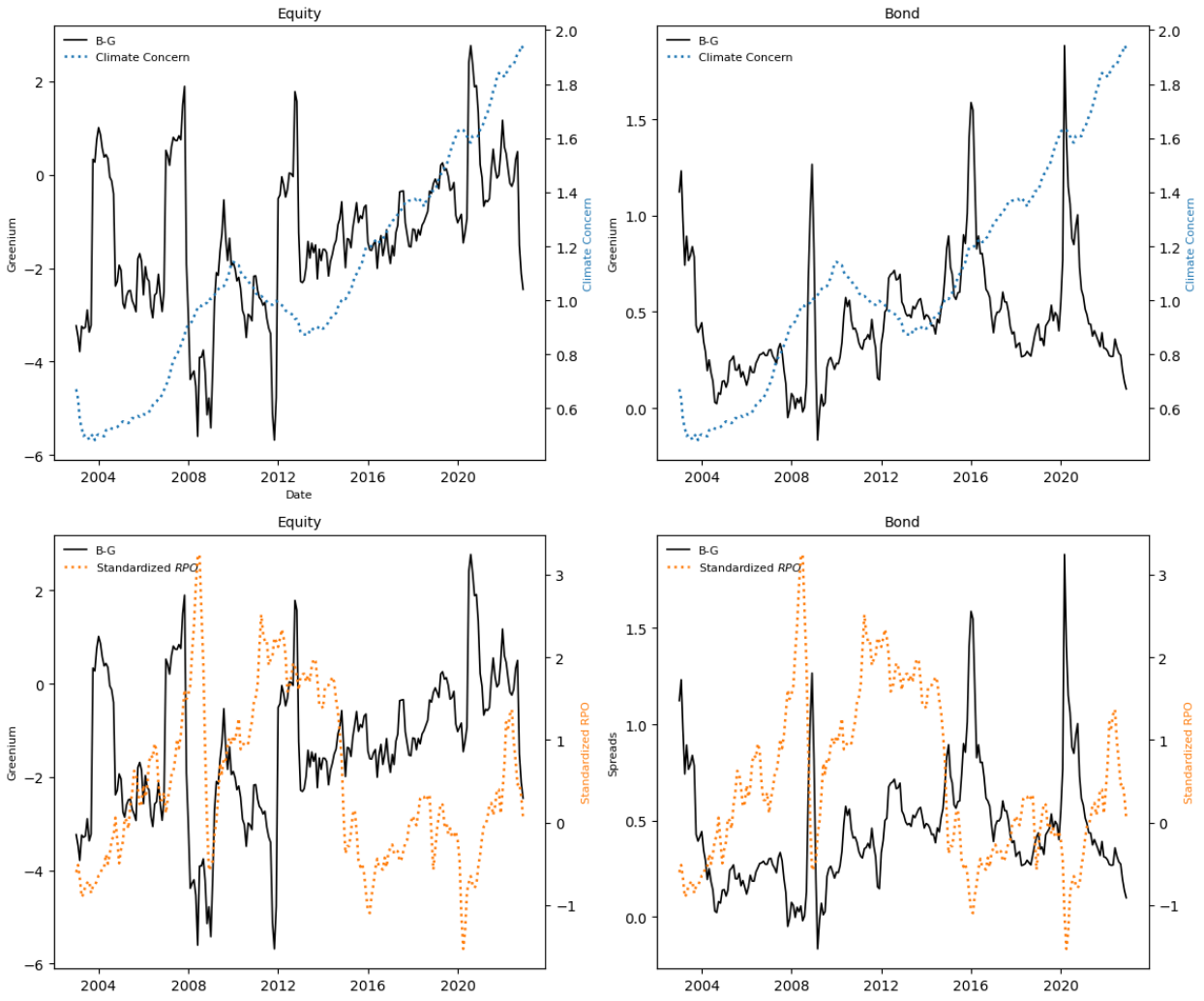
Notes: This figure the policy functions of various model variables, oil price P, energy spread $Spread^{E-NE}$, Marginal Q, and profitability P/MPK with respect to the state variable A under the steady-state level of capital K^* under benchmark parameters and alternative parameters.

Figure IA.6: Greenium Dynamics During 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 IA.7: 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 IA.1: 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 IA.2: 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.3: Transmission of Oil Price Shocks (With Controls)

	(1)	(2)	(3)	(4)	(5)	(6)
		ΔQ			ΔSales	
ΔRPO×1(Energy)	0.08**	0.07**	0.08***	0.22***	0.23***	0.21***
	(2.68)	(2.44)	(2.84)	(3.06)	(4.77)	(2.93)
ΔRPO×Intensity		0.00			0.01*	
		(0.05)			(1.97)	
ΔRPO×1(Brown)			-0.00			0.03***
			(-0.21)			(4.03)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	122539	87466	122539	122852	87615	122852
R^2	0.596	0.614	0.596	0.280	0.335	0.280
		ΔInvestment			ΔROE	
ΔRPO×1(Energy)	0.05**	0.03	0.05**	0.12**	0.12***	0.12**
	(2.07)	(1.10)	(2.06)	(2.34)	(3.09)	(2.38)
ΔRPO×Intensity		-0.00			-0.00	
		(-0.33)			(-1.24)	
ΔRPO×1(Brown)			-0.00			-0.01
			(-0.45)			(-1.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	123361	87949	123361	122530	87437	122530
R^2	0.667	0.680	0.667	0.361	0.393	0.361

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.4: Robustness: Subsample Analysis

	Equity		Bond	
	(1)	(2)	(3)	(4)
	Panel A: Pre 10/2003			
	Energy-BNE	BNE-G	Energy-BNE	BNE-G
ΔRPO	-2.20***	-0.26	-0.53**	0.30
	(-4.30)	(-0.61)	(-2.41)	(1.14)
Observations	355	355	350	350
R^2	0.049	0.001	0.004	0.012
	Panel B: 10/2003 - 11/2015			
ΔRPO	-0.81	0.50	-0.45***	-0.52***
	(-1.14)	(0.79)	(-3.59)	(-5.17)
Observations	146	146	146	146
R^2	0.008	0.005	0.071	0.199
	Panel C: 12/2015 - 12/2022			
ΔRPO	-2.02***	0.28	-1.36***	-0.10**
	(-2.66)	(0.60)	(-4.99)	(-2.05)
Observations	84	84	84	84
R^2	0.078	0.005	0.217	0.038

Notes: This table examines the impact of oil price shocks (ΔRPO) on the spread between energy spread and ex-energy greenium across equity and bond markets. The analysis is conducted over three subsample periods—1974:02-2003:09 (Panel A), 2003:10-2015:11 (Panel B), and 2015:12-2022:12 (Panel C)—which are selected to capture structural breaks in sustainability preferences and climate regulations. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table IA.5: Robustness: Energy-Utility Spread

	(1)	(2)	(3)	(4)
	Pre 12/2015		1/2016 - 12/2022	
	Equity	Bond	Equity	Bond
ΔRPO	-1.71***	-0.92***	-1.81*	-1.52***
	(-3.37)	(-5.95)	(-1.97)	(-5.31)
Constant	0.03	0.00	-0.02	-0.00
	(0.79)	(0.13)	(-0.13)	(-0.04)
Observations	582	282	85	85
R^2	0.019	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 ($\Delta\text{Spread}^{Energy-Utility}$). Results are reported using time-series regressions for the full sample 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.6: Robustness: Gas Price

	(1)	(2)	(3)	(4)	(5)	(6)
	Equity			Bond		
	Panel A: Time Series Analysis					
	Energy-BNE	BNE-G		Energy-BNE	BNE-G	
ΔGas	-0.97***	-0.11		-0.10	-0.05	
	(-3.11)	(-0.40)		(-1.00)	(-0.73)	
Observations	311	311		310	310	
R^2	0.030	0.001		0.003	0.002	
	Panel B: Panel Analysis					
ΔGas×1(Energy)	-1.40***	-1.49***	-1.45***	-0.15	-0.14	-0.13
	(-4.52)	(-3.78)	(-3.77)	(-1.56)	(-1.47)	(-1.44)
ΔGas×Intensity		0.03			-0.01	
		(0.66)			(-0.56)	
ΔGas×1(Brown)			0.01			-0.02
			(0.16)			(-1.17)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	861404	510203	510203	634205	584269	634205
R^2	0.076	0.096	0.096	0.302	0.313	0.302

This table conducts analysis on the relation between the greenium and gas prices. Panel A conducts time series analysis on the impact of gas price shocks (ΔGas) 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 1997:1 to 2022:12 for equity and 1997:2 to 2002:12 for bonds.

Table IA.7: Robustness: Alternative Debt Samples

	(1)	(2)	(3)	(4)	(5)	(6)
	Long-Sample Bond			CDS		
	Panel A: Time Series Analysis					
	Energy-BNE	BNE-G		Energy-BNE	BNE-G	
ΔRPO	−0.82***	−0.18		−1.95***	−0.01	
	(-2.76)	(-0.59)		(-3.53)	(-0.04)	
Observations	585	585		207	207	
R^2	0.013	0.001		0.057	0.000	
	Panel B: Panel Analysis					
	Yield Spreads			CDS Premium		
ΔRPO×1(Energy)	−1.47**	−1.46**	−1.46**	−2.83***	−1.89***	−2.76***
	(-2.57)	(-2.44)	(-2.57)	(-6.83)	(-4.62)	(-6.66)
ΔRPO×Intensity		0.00***			-0.00	
		(3.56)			(-0.10)	
ΔRPO×1(Brown)			-0.08			-0.01
			(-0.96)			(-0.24)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1059918	900529	1059918	89932	76587	89932
R^2	0.721	0.709	0.721	0.800	0.786	0.800

This table conducts analysis on the relation between firms' cost of debt and oil prices. Cost of debt is measured using yield spreads of corporate bonds (Columns (1)-(3)) and five-year CDS premiums (Columns (4)-(6)). Panel A conducts time series analysis on the impact of oil price shocks (ΔRPO) on two components of the debt greenium variations: (1) changes in the spread between energy and non-energy brown firms ($\Delta\text{Spread}^{Energy-BNE}$) and (2) changes in the spread between non-energy brown and green firms ($\Delta\text{Spread}^{BNE-G}$). Panel B regresses security-level cost of debt 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 for bond yield spreads spans from 1974:02 to 2022:12, while the CDS sample covers the period from 2002:01 to 2022:12.

Table IA.8: First-Stage Estimates of OPEC Announcement Shocks

	(1)	(2)
	Dependent Variable: ΔRPO	
	Equity Sample	Bond Sample
OPEC Surprise	0.98***	1.22***
	(3.71)	(3.53)
Observations	477	311
R^2	0.028	0.039

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.

Table IA.9: 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.10: 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.

Table IA.11: Climate Concern Shocks and Greenium Dynamics: November 2012 - June 2018

	(1)	(2)	(3)	(4)	(5)	(6)
		Equity			Bond	
ΔClimate Concern	0.47*	0.45*	0.50**	0.11**	0.08**	0.09**
	(1.88)	(1.94)	(2.02)	(2.42)	(2.39)	(2.43)
Lagged ΔClimate Concern	-0.25	-0.20	-0.18	0.17***	0.05	0.11***
	(-1.02)	(-0.89)	(-0.73)	(3.54)	(1.41)	(2.90)
ESG Share	87.67	44.27	109.02	-20.03	-8.06	-5.18
	(1.15)	(0.62)	(1.41)	(-0.89)	(-0.49)	(-0.29)
Lagged ESG Asset	4.23	4.57	1.92	4.05*	1.64	3.35**
	(0.50)	(0.58)	(0.22)	(1.94)	(1.06)	(2.02)
$\Delta\text{Spread}^{Energy-BNE,o}$		0.33***			0.38***	
		(3.38)			(7.58)	
ΔRPO			1.09			-0.73***
			(1.37)			(-6.15)
Observations	68	68	68	68	68	68
R^2	0.082	0.225	0.109	0.234	0.602	0.524

This table examines the impact of climate concern shocks and ESG investment flows on the greenium. The analysis estimates time-series regressions of the greenium on climate concern shocks, ESG flow share, and ESG assets. $\text{Spread}^{E-BNE,o}$ is the residual after regressing Spread^{E-BNE} on Spread^{BNE-G} and ΔRPO denotes the oil price innovations. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample spans 2006:06 to 2022:12. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample spans 2012:11 to 2018:6.