Oil-Driven Greenium

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Abstract

As climate attention grows, many argue that investors discipline carbon-intensive firms by increasing their costs of capital, creating a "greenium" favoring green firms. We challenge this view, demonstrating that the observed greenium variation is largely driven by oil demand fluctuations, which boost product prices and growth options for carbon-intensive firms, reducing the greenium. This pattern holds across U.S. bonds, equities, and international markets. Revisiting key climate-related events, like the Paris Agreement, we find that once oil's impact is considered, investor discipline often plays a negligible role. Our findings indicate investors may be less responsive to the climate crisis than anticipated.

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

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The question of whether investors effectively price in carbon transition risk is central to climate finance. At the heart of this issue is the "greenium," the notion that carbon-intensive firms face a higher cost of capital during the transition to net zero, while less carbon-intensive firms benefit from a lower cost of capital. Such investor commitment can potentially aid efforts to combat climate change without heavy-handed government intervention (Hong, Wang and Yang, 2023). Over the past decade, the greenium has grown, reflecting a higher relative cost of capital faced by carbon-intensive firms (Pástor, Stambaugh and Taylor, 2022; Gormsen, Huber and Oh, 2023). Furthermore, the greenium appears to be responsive to climate-related events, such as the Paris Agreement (Monasterolo and De Angelis, 2020; Seltzer, Starks and Zhu, 2022). This evidence is often interpreted as indicating that investors have begun to price in carbon transition risk, driven by increasing climate regulatory pressure and sustainable investing.

In this paper, we challenge this prevailing narrative that the documented greenium variation reflects genuine investor commitment to climate-aware investments. Many carbon-intensive firms are concentrated in oil and gas industries, where their product price, valuation, and cost of capital are closely tied to fluctuations in the oil market. The oil price has experienced several booms and busts over the past two decades, which coincide with periods of various climate events. Hence, fluctuations in the greenium might be mistakenly attributed to the repricing of carbon transition risk or impact of sustainable investors when in fact they reflect changes in the risks that affect oil-dependent firms. Indeed, our analysis reveals that these oil-related shocks play a significant role in explaining variations in the greenium. After accounting for the influence of oil prices, we find that investor discipline surrounding key climate-related events, such as the Paris Agreement, has only modest, if any, effects. These findings suggest that financial markets may not be as responsive to climate crises as previously assumed.

To understand the dynamics behind oil price fluctuations and their impact on the greenium, we first examine sources of oil price variations. The real price of oil can vary due to distinct reasons, such as supply shocks, aggregate economic activity shocks, and oil demand shocks. This paper first interprets the oil price variations through the structural VAR framework (Baumeister and Hamilton, 2019) and shows that oil price variations are primarily driven by oil demand shocks in the past two decades. We then study an investment-based model with oil demand shocks in which the oil price is the relative price between brown and green products. In the model, higher oil demand results in higher prices for brown products, elevated Q and asset growth of brown firms, thereby lowering costs of capital for brown firms relative to green firms. In contrast, lower oil demand is associated with lower product prices, lower Q, and higher costs of capital for brown firms relative to green firms. Thus, the model predicts that the greenium is decreasing in the demand-driven fluctuations in oil prices.

Our empirical analysis supports these model predictions with robust evidence. First, we observe a significant pass-through of the real oil price to the relative output prices between brown and green firms. Second, the real price of oil positively correlates with various measures of growth options, including the Tobin's Q spread, return on equity (ROE) spread, asset growth spread, and sales growth spread between brown and green firms. Empirically, controlling for various firm characteristics, including Q, momentum, profitability, asset growth, sales growth, etc., can only partially account for the relation between oil price and future firm growth. This underscores the necessity of explicitly considering the impact of oil price changes in event studies, as firm characteristics alone cannot adequately capture the dynamics at play.

Next, we test the prediction on the negative relation between oil prices and the forward-looking greenium in ex-ante expected returns. We measure the ex-ante cost of debt as duration-matched bond yield spreads and the cost of equity as implied cost of capital estimates. In the baseline panel analysis, we find that a one-standard-deviation increase in the oil price is associated with a bond greenium decrease of 7 basis points (bps) per annum for per standard deviation increase in carbon intensity for both scopes 1 and 2. For equity, a one-standard-deviation increase in the oil price is associated with a greenium decrease of 9 bps and 14 bps per annum for scope 1 and 2 intensity, respectively. This negative relationship robustly holds in different specifications, including the incorporation of characteristic controls, portfolio sorting, subsample analysis, direct use of decomposed oil shocks, and replacing the oil price with the natural gas price.

We further turn to international markets and find that the local real price of oil is negatively related to the greenium across countries, consistent with the baseline. It is important to emphasize that the negative impact of oil prices on greenium arises through product price variations even without shifts in climate regulation and investor preferences. However, it remains possible that regulatory risks and sustainable preferences, whether related to investment or consumption, could influence both firms' cost of capital and oil prices, particularly in the more recent period. Since oil prices are determined globally and predominantly invoiced in U.S. dollars, fluctuations in exchange rates introduce variation in the local real price of oil across countries. We thus use exchange rate variations as an instrumental variable (IV) for the local real price of oil, isolating the exogenous component of oil price fluctuations unaffected by climate policies or investor preferences. The IV estimates are similar to the OLS estimates, suggesting that potential endogeneity concerns are minimal.

After establishing the relation between oil prices and the greenium, we revisit several commonly studied climate events in the literature and assess whether oil price fluctuations might have biased existing estimates. We focus on the corporate bond market, in which the cost of capital estimates are more precisely measured. The Paris Agreement (PA) adopted at the UN Climate Change Conference (COP21) in December 2015 is likely the most studied event in the climate literature (Monasterolo and De Angelis, 2020). Consistent with Seltzer, Starks and Zhu (2022), we find that the bond greenium significantly increases following the Paris Agreement. However, the increase is not driven by increased climate policy risk or climate attention, but by dramatic oil price fluctuations around the event. The PA coincided with the bottom of the 2014 oil price crash. After controlling for oil price movements, the estimated impact of the PA on the greenium is no longer significantly positive for either scope. Next, we study the election of President Trump in November 2016 (Ilhan, Sautner and Vilkov, 2021). Consistent with the perceived decline in climate policy risk, we document a significant decline in greenium. Note that this event occurred as oil prices recovered from the 2014 crash and the Organization of the Petroleum Exporting Countries (OPEC) and Russia decided to cut their production in the same month. After the oil price variation is controlled for, the impact of the election is attenuated.

Furthermore, we investigate whether estimates of the impact of climate attention on the greenium are affected by changes in oil prices. Higher climate attention can increase the greenium either through perceived regulatory risk or flow-driven valuation changes, and vice versa for lower climate attention. We measure the climate attention among the general public with the Google search volume or GSV (Choi, Gao and Jiang, 2020) and among investors with the share of fixed-income environmental, social and governance (ESG) funds (Pástor, Stambaugh and Taylor, 2022). Without controlling for oil prices, these measures have mixed relations with the greenium. After controlling for oil price variations, both measures become positively associated with the greenium as hypothesized, although the magnitudes appear modest compared to the impact of oil.

This paper fits in the literature that studies the ex ante green premium. Hsu, Li and Tsou (2023) examine environmental policy risk. Pedersen, Fitzgibbons and Pomorski (2021)and Pástor, Stambaugh and Taylor (2021, 2022) emphasize the role of green preferences, whereas Berk and van Binsbergen (2021) report negligible impacts and Chen, Garlappi and Lazrak (2023) find opposite effects with the green consumption preference. To the best of our knowledge, this paper is the first to characterize the impact of oil, a force that persists even without climate-related shocks, on the ex ante greenium explicitly. Indeed, the effects remains strong in the earlier sample when climate concerns are minimal. Moreover, the literature actively debates the magnitude of the average greenium (Bolton and Kacperczyk, 2021; Aswani, Raghunandan and Rajgopal, 2024; Zhang, 2024). Our finding show that the concept of an "average greenium" across firms is elusive, as the estimated greenium is highly sensitive to the prevailing oil price levels in the sample. Related, Blitz (2022) and Bolton, Kacperczyk and Wang (2024) find that oil prices positively affect realized carbon returns, and this paper instead focuses on the ex ante cost of capital.

A substantial body of literature conducts event studies and explores how aggregate shifts affect the greenium. Key events examined include the Paris Agreement (Monasterolo and De Angelis, 2020; Bolton and Kacperczyk, 2021; Seltzer, Starks and Zhu, 2022; Duan, Li and Wen, 2023), the surprise election of President Trump in 2016 (Ilhan, Sautner and Vilkov, 2021), as well as the COVID-19 pandemic and the outbreak of the Ukraine-War. The literature also examines in implications of shifts in climate attention and sustainable investing (Ardia et al., 2023; Van der Beck, 2021; Pástor, Stambaugh and Taylor, 2022). Notably, these aggregate events coincide with different episodes of oil price fluctuations. This paper revisits these studies and shows that failing to account for oil price effects leads to biased estimates of their impact on greenium.

The literature acknowledges the potential contamination from oil prices, and a common approach in existing studies is to control for oil beta, which is estimated as the sensitivity of security returns on oil price innovations. However, this method has two key limitations. First, the oil beta for individual securities is often noisily estimated, making it difficult to fully account for the impact of oil. Second, and more importantly, the oil beta primarily captures the contemporaneous risk exposure to oil shocks. This paper instead introduces a different economic mechanism that ties the level of oil prices to time-varying risk premium, a dynamic that the oil beta alone cannot sufficiently capture.

The remainder of the paper is as follows. Section 1 examines what drives oil price variations and presents a stylized model to characterize the relation between the oil price and the greenium. Section 2 explains the data and conducts the preliminary evidence. Section 3 studies the relation between the oil price and the greenium in various markets. Section 4 revisits existing event studies in the literature. Section 5 concludes.

1 A Conceptual Framework

This section studies the linkage between oil prices and greenium conceptually. First, we decompose various driving forces of oil price fluctuations and show that the oil demand shocks play the most important role in the past two decades. Second, we study a highly stylized model with oil demand shocks to analyze the relationship between the oil price and greenium. The framework predicts that oil demand is negatively associated with the greenium, because oil demand is positively associated with the growth option and asset growth of brown firms relative to green firms.

1.1 Drivers of Oil Price Fluctuations

The oil price can fluctuate for several reasons: oil supply, aggregate economic activity, and oil-specific demand shocks. Oil supply shocks represent shocks that affect the global supply of oil. Examples include OPEC announcements, attacks on Libyan oil fields in 2011, Hurricane Katrina and Rita that disrupted U.S. oil production in 2005, and shale revolution that significantly boosted U.S. oil output in subsequent years, as well as the Russia-Ukraine war in 2022. Economic activity shocks are fluctuations in aggregate economic conditions, such as the U.S. recession following the Global Financial Crisis. The oil-specific demand shocks include oil consumption shocks and oil inventory shocks and are orthogonal to oil supply and aggregate economic activity shocks. Examples include demand shocks from downstream industries, pandemics and natural disasters, such as COVID-19, seasonal variations and weather conditions, technological advancements in energy efficiency and alternative energy sources, economic incentives aimed at promoting renewable energy use, and shifts in consumer preference.

To evaluate the contribution of each shock quantitatively, we follow the structural model in Baumeister and Hamilton (2019) to decompose oil price fluctuations into individual shocks. This model allows for contemporaneous supply response and identifies greater contributions of oil supply shocks than Kilian (2009). We construct the real price of oil, which is the U.S. CPI-adjusted nominal price of oil. The nominal oil price is the refiner acquisition cost of crude oil imports from U.S. Energy Information Administration and the U.S. CPI data come from FRED at St. Louis Fed. The Appendix contains details of the structural model.

With decomposed oil shocks, the variance of oil price shocks can be rewritten as

$$
\begin{aligned}
var(\text{Shock}_{Oil}) &= cov(\text{Shock}_{Oil}, \text{Shock}_{Supply}) \\
&+ cov(\text{Shock}_{Oil}, \text{Shock}_{Economic\ activity}) + cov(\text{Shock}_{Oil}, \text{Shock}_{Oil\ demand}),
\end{aligned}
\tag{1}
$$

where Shock_{Oil} is the monthly growth in the real price of oil, and Shock_i is the impact of shock i in the real price of oil, where $i = Supply$, *Economic activity*, and *Oil demand*. For simplicity, the impact of oil demand shocks is the sum of oil consumption shocks and oil inventory shocks. The contribution of i shocks to oil price fluctuations can be calculated as

$$cov(\text{Shock}_{Oil}, \text{Shock}_i)/var(\text{Shock}_{Oil}).$$

Figure 1 plots the percentage contribution over a rolling 12-month window. Over the past two decades, oil demand shocks have played a dominant role, with supply shocks playing a less important role than historically. The average contribution of supply, economic activity, and oil demand shocks over the sample is 12%, 4%, and 82%, respectively. This pattern of weakened supply shocks is consistent with the increased supply of U.S. shale oil alongside evolving dynamics within OPEC, as the U.S. surpassed both Saudi Arabia and Russia to become the world's largest crude oil producer in mid 2010s. In the time series, the contribution of oil supply shocks reached its highest point of 35% during the periods with intensive supply shocks, such as the oil bust of 2014 to 2016 and the COVID-19 pandemic (Känzig, 2021).[1] In short, oil demand shocks drive most oil price variations in the past two decades except for a few episodes.

In addition, it is worth noting that the main analysis studies U.S. firms. Oil supply shocks from non-U.S. entities, such as the OPEC announcements (Känzig, 2021), constitute effective demand shocks for U.S.-produced oil and gas. As such, we interpret oil price shocks mostly as oil demand shocks in the rest of the paper. We conduct robustness analysis with decomposed shocks and find that the results are indeed driven by oil demand shocks.

[1] The Internet Appendix figures plot the decomposed 12-month oil price shocks and deliver the same message.

1.2 Model

This section now presents a highly stylized model to analyze the relation between oil prices and the greenium. Consider an economy in which agents consume brown goods, which are oil and gas products, and green goods or other products.[2] There is no renewable energy in this economy. The green good is the numeraire in the economy. In the spirit of Kogan, Livdan and Yaron (2009) and Ready (2018), the demand for both goods is represented by

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

where P_B is the real price of oil, changes in A denote unexpected oil demand shocks, Y_B and Y_G are aggregate oil and green production, respectively, and ϵ is the elasticity of demand.

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

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

where $i = B, G$ and K_i is the level of capital in each sector. The capital in each sector accumulates as follows,

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

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

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

Firms take product prices as given, invest, produce, and generate profits π,

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

[2] There is no renewable energy in this economy for simplicity. As a substitute for the traditional energy, renewable energy prices comove with oil prices. As such, oil price fluctuations also negatively affect the cost of capital for the renewable energy sector, as documented in D'Amico, Klausmann and Pancost (2023).

The firm can be financed with debt b_{t+1} and equity s_{t+1}. Taking the stochastic discount factor M_{t+1} as given, firm i chooses its investment I_{it}, its future capital K_{it+1}, and debt b_{it+1} to maximize its cum-dividend market value of equity,

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

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

1.2.1 Model Dynamics

The demand follows an auto-regressive process as follows,

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

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

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

where γ is risk loading.

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

$$Greenium_{it+1} = \left(w^b_{Bt} r^b_{Bt+1} + w^s_{Bt} r^s_{Bt+1}\right) - \left(w^b_{Gt} r^b_{Gt+1} + w^s_{Gt} r^s_{Gt+1}\right). \tag{9}$$

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

1.2.2 Equilibrium and Investment Return

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

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

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

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

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

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

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

As such, the greenium equals the investment return difference between brown and green firms

$$Greenium_{t+1} = r^K_{Bt+1} - r^K_{Gt+1}. \tag{13}$$

1.2.3 Greenium Analysis

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

$$
\begin{aligned}
& Greenium_{t+1} \\
= & \frac{(1-\tau)\left(\alpha A_{t+1} K_{Bt+1}^{\alpha\left(1-\frac{1}{\epsilon}\right)-1} + \delta\tau + \frac{\chi}{2}\left(\frac{I_{Bt+1}}{K_{Bt+1}}\right)^2\right) + (1-\delta)\left(1 + (1-\tau)\chi\frac{I_{Bt+1}}{K_{Bt+1}}\right)}{1 + (1-\tau)\chi\frac{I_{Bt}}{K_{Bt}}} - r_G^K.
\end{aligned}
\tag{14}
$$

The equation shows that current asset growth, future profitability $(1-\tau)\alpha A_{t+1} K_{Bt+1}^{\alpha\left(1-\frac{1}{\epsilon}\right)-1}$, and future investment growth all play a role in determining the green premium. However, the oil demand A_t jointly determine all these variables.

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

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

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

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

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

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

The presence of physical adjustment cost ϕ is a key force that generates greenium variations. If we assume away the adjustment cost $\chi \to 0$, brown firms' marginal Q stays constant, and the greenium does not vary with the oil demand $\frac{\partial E_t Greenium_{t+1}}{\partial A_t} \to 0$. Equation (16) also highlights the role of demand elasticity. If the oil demand is perfectly inelastic $\epsilon \to 0$, firms barely change their investment in response to oil demand and the greenium stays the same. In addition, if the oil demand is not persistent $\rho \to 0$, the current oil price is not informative about future oil prices and does not drive greenium variations.

1.2.4 Numerical Results

This section solves the model numerically and presents quantitative results. We calibrate the model at a quarterly frequency and present parameters in Panel A, Table 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.

For oil-related variables, we set the oil demand elasticity ϵ to 0.1, matching the low estimates in Kilian (2022). The persistence of aggregate oil demand ρ_A is set to 0.91, matching the empirical persistence of the real oil price. The conditional volatility of the oil demand σ is set to 0.087 to match the empirical volatility of the real oil price. The adjustment cost

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

coefficient χ is set to 7 such that the oil supply elasticity is 0.02, within the range of estimates obtained in Kilian and Murphy (2014) and Baumeister and Hamilton (2019). We set the price of oil demand risk λ to 0.5.

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

In sum, the model predicts that oil demand is negatively associated with the greenium. Higher oil demand is associated with higher marginal Q, asset growth, sales, and profitability for brown firms compared to green ones. In contrast, lower oil demand is associated with lower brown-minus-green Q spread, lower asset growth spread, lower profitability spread, and higher greenium.

2 Data and Preliminary Evidence

This section conducts preliminary empirical analysis. First, we explain various data used in this study. Second, we document the significant pass through of oil prices to brown product prices. Finally, we show that the growth option of brown firms increases more with oil prices than that of green firms, as the model predicts.

2.1 Data and Summary Statistics

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

Our primary metric for assessing climate profile is carbon intensity, calculated as the logarithm of total emissions scaled by sales over the period of emission. We use the most recent carbon emission and accounting data based on their respective data release dates following Zhang (2024) when combining various datasets. Given that Trucost conducted a review and updated all data prior to 2008 in May 2009, we assume the original release date of the data to be October of the subsequent year, coinciding with the Carbon Disclosure Project's October release cycle.

For corporate bond pricing, we extract month-end pricing data from the ICE Index Platform following Bekaert and De Santis (2021); Huang, Nozawa and Shi (2024). We supplement the bond pricing information with additional issuance information from Refinitiv Eikon. The international segment includes an extensive roster of 42 countries, and most prolific issuing countries are Japan, the UK, France, Germany, and Canada, collectively accounting for 70% of the international sample.

The estimation of firm-level equity implied cost of capital (ICC) is challenging due to the inherent noise associated with assumptions regarding expected future cash flows and the potential for non-unique numerical solutions. Following the methodological recommendations of Lee, So and Wang (2021), we employ Gebhardt, Lee and Swaminathan (2001) (GLS) estimates as our primary metric for ICC. We also conduct robustness analysis using the average of the four published residual-income-model-based estimates. Firm-level equity and accounting data come from CRSP and Compustat N.A. for the U.S. and Canada and come from Compustat Global for the global sample. We focus on the primary common stocks listed on the primary exchange.

Panel A, Table 1 presents the summary statistics for cost of capital measures. The corporate yield spread has an annualized mean of 2.05% and a standard deviation of 3.31%, comparable to the quantities reported in previous studies on the US corporate bond market. The GLS ICC has an annualized mean of 8.55% and a standard deviation of 3.94%, whereas the average ICC has both lower means and standard deviations, 2.26% and 1.34%. The differences in these statistics confirm the noise in ICC estimates as highlighted in Lee, So and Wang (2021). The international credit spreads have lower means and standard deviations of 1.39% and 1.43%, compared to the U.S. sample. The difference is largely driven by the differential composition of bond issuers in the U.S. and internationally (Huang, Nozawa and Shi, 2024).

Panel B of Table 1 shows that the average carbon intensities for Scope 1 and Scope 2 emissions are 3.08 and 2.78 logarithmic tons of CO2e per million U.S. dollars, respectively. Our regression models incorporate a variety of control variables to ensure robustness. Bond-specific characteristics include duration, bond age, amount outstanding and credit ratings. Firm and equity attributes include market beta estimated over a 60-month rolling window, size as the log market capitalization, (log) book-to-market ratio, momentum, and idiosyncratic volatility as derived from the Fama-French three-factor model. To mitigate the influence of outliers, carbon-related variables, and control variables are subjected to winsorization at the 1st and 99th percentiles before their inclusion as explanatory variables in our empirical analyses.

2.2 Producer Prices

In this section, we examine the key assumption of the model that oil price increases raise the product prices of brown firms relative to green firms. We focus on the industry evidence, employing the PPI data from the U.S. Bureau of Labor Statistics. Because price levels are non-stationary, our analysis instead studies the relationship using price changes,

$$\Delta PPI_{it} = a + b \cdot Intensity_{it} + c \cdot Intensity_{it} \times \Delta Oil_t + \iota_t + e_{it+\tau}, \tag{17}$$

where $Intensity$ denotes carbon intensity, $\Delta PPI_t = \log(PPI_t/PPI_{t-1})$ measures changes in the producer product price index (PPI) of the NAICS4 level that the firm belongs to, $\Delta Oil_t = \log(Oil_t/Oil_{t-1})$ and X signifies firm-level characteristic controls. The carbon intensity is standardized to have zero mean and unit variance each year. The regression model incorporates time fixed effects, with standard errors double clustered at both the industry and month levels.

Columns (1) and (2) of Table 3 find that oil price variations positively pass through to the relative price of carbon-intensive products. Specifically, we examine the price differential between two industries with distinct environmental profiles, as represented by a one-standard-deviation difference in scope 1 carbon intensity. Our estimates indicate that a one-percent increase in oil prices results in a 2.37 bps increase in the average product price of brown industries relative to green ones. And this quantity is 1.03 bps if we use scope 2 intensity to measure the climate performance of different industries.

One possible concern is that the input price might also vary with oil prices, potentially exceeding the magnitude of changes in output prices. To address this, we build the input price index changes by using the 71 industry-level input-output table from the Bureau of Economic Analysis (BEA), which is the finest industry level with annually-updated data. We run a similar regression as in Eq. (17), with the results presented in columns (3) and (4). A one-percent increase in the oil price is associated with 1.04 bps and 0.16 bps increases in the input price of brown industries compared to green industries measured by scope 1 and 2 intensity, respectively.

Furthermore, given that the cost of goods sold constitutes a fraction of total sales, the impact on total input costs is somewhat mitigated. To evaluate the weighted impact on the input cost for per dollar sales, we calculate the average fraction of cost of goods (COGS) to total sales (SALE) for each industry using the Compustat data. Then, we scale the input price change with this fraction. Columns (5) and (6) show that the estimated impact now decreases to 0.78 bps, which is less than a third of the output price increase of 2.37 bps. In essence, our analysis demonstrates that oil price variations significantly pass through to output prices of brown firms, consequently widening their profit margins.

2.3 Growth Opportunities

This section now builds on the evidence and tests the model prediction that growth options of brown firms increase more with the oil price. We estimate the relation between brown firms' growth opportunities relative to green firms' and the oil price as

$$Y_{it+\tau} = a + b \cdot Intensity_{it} + c \cdot Intensity_{it} \times Oil_t + d \cdot X_{it} + \iota_t + e_{it+\tau}, \tag{18}$$

where Y denotes measures of growth opportunities, *Intensity* denotes the standardized carbon intensity and *Oil* denotes the standardized real price of oil. The quarterly estimation includes time fixed effects and standard errors are double clustered at the firm and quarter levels.

The theoretical framework in Section 1.2 predicts that brown firms have greater growth options than green firms in periods of high oil prices, shown as both higher return on equity (ROE) and asset growth for brown firms relative to green ones. We use Tobin's average Q as a proxy for marginal Q in our model and consider actual firm growth indicators, such as 4-quarter sales and asset growth, to gauge the growth options. Panel A of Table 4 provides robust evidence that higher oil prices are associated with a widening disparity in growth options between brown and green firms, as indicated by Tobin's Q, asset growth, and sales growth. Panel B further documents the sustained impact of oil prices on asset and sales growth over the next year. In particular, the magnitude of estimated coefficients indicates that the influence of oil prices on future growth metrics is more pronounced than on current growth metrics because firms take time to adjust their investment.

For instance, a one-standard-deviation increase in the oil price is projected to amplify the brown-green asset growth gap in the subsequent year by 0.13 for scopes 1, versus 0.08 in the current quarter. The effects on asset and sales growth are greater and statistically significant for scope 1, in line with the higher pass-through of oil prices for scope 1 emission-intensive firms. Collectively, these results highlights the differential impacts of oil prices on the growth options of brown and green firms, with brown firms benefiting more from elevated oil prices.

From an empirical point of view, when assessing the impact of a market-level treatment on the greenium, it would be imperative to control for time-varying oil prices. It is possible that investors have priced in the effects and controlling for various characteristics can account for the impact. Columns (5) to (8) in Panel B control for various firm characteristics. The magnitude of coefficients slightly decreases compared to the estimates in columns (1) to (4), and the effect remains highly significant for scope 1.

In summary, our findings underscore the importance of explicitly controlling for the oil price level when conducting empirical studies. Merely incorporating firm characteristics as control variables is insufficient. Instead, the impact of oil price levels needs to be accounted for explicitly.

3 Oil Price and Greenium

In this section, we provide evidence that the oil price has a negative impact on the greenium across various markets. We first examine the U.S. bond and equity and then conduct various robustness tests. Finally, we turn to the international evidence.

3.1 Bond and Equity Greenium

We now test the prediction of the model that the oil price negatively correlates with the level of greenium at the firm level. We start with the bond greenium, of which the cost of capital is measured more precisely. We estimate the following panel regression,

$$YieldSpread_{it} = a + b \cdot Intensity_{it} + c \cdot Intensity_{it} \times Oil_t + d \cdot X_{it} + \iota_t + e_{it}. \qquad (19)$$

where *Intensity* is the standardized carbon intensity, *Oil* is the standardized real price of oil, X represents the bond- and bond-level characteristics. The regression is conducted at the monthly frequency and includes time fixed effects. Standard errors are double clustered as the bond and month levels.

The model predicts that fluctuations in oil prices have a negative impact on the greenium ($c < 0$). Results in Table 5 lend strong support to the hypothesis. Columns (1) and (2) show that a one-standard-deviation rise in oil prices leads to a reduction of 7.80 and 11.91 bps in the greenium for scopes 1 and 2, respectively. The magnitudes are substantial, as the distribution of oil prices has long tails. For example, the 2014 oil crash, which is a three-standard deviation crash, would lead to a rough reduction of 23 and 35 bps for per standard deviation increase in scopes 1 and 2 intensity, respectively.

In columns (3) and (4), we control for a range of bond and firm characteristics. The magnitude of coefficients decreases slightly to -3.58 and -5.49 and remains highly significant. This finding is consistent with the results presented in Table 4, suggesting that firm-level controls capture only a portion of the oil price's influence on the growth options of brown firms. For the controls, credit spreads widen as the bond duration increases and credit rating decreases. Proxies for bond illiquidity, such as the amount outstanding and bond age, are also priced in corporate yield spreads. Finally, credit spreads are positively associated with the firm's leverage and equity volatility, consistent with existing evidence.

Next, we turn to the equity greenium and we measure the ex-ante cost of equity as the GLS mechanical estimates. Panel A of Table 6 summarizes the findings. Consistent with the evidence obtained from the corporate bond market, higher oil prices are associated with a widening disparity in the ICC between brown and green firms. In the specification without firm-level controls, a one-standard-deviation increase in oil prices is estimated to reduce the annualized equity greenium by 11.21 and 22.36 bps for scopes 1 and 2, respectively. These coefficient magnitudes are slightly greater than the corresponding bond-based estimates of -7.8 and -11.91 bps. Incorporating controls for a broader set of firm characteristics again moderate these estimated coefficients to -5.34 and -9.62 bps, yet the coefficients remain highly significant. Most controls significantly explain ICC variations. In the multivariate setting, firms with a higher beta, smaller size, higher book-to-market ratio, profitability, and lower asset growth have higher ICCs.

To mitigate the concern regarding the measurement error inherent in ICC estimates, we perform a robustness check using the simple average of four different ICC measures as studied in Lee, So and Wang (2021). Panel B of Table 6 presents these results, which corroborate the primary findings from Panel A: oil prices exhibit a robust inverse relation with the equity greenium. Collectively, these results suggest that oil prices exert a negative influence on the greenium, thereby reducing the cost of capital spread between brown and green firms.

3.2 Robustness Analysis

We conduct a few robustness analyses below. First, we extend our focus beyond crude oil to encompass natural gas. While petroleum has been the most important form of global energy for the longest time, natural gas has come to account for a share comparable, at least in the U.S.[4] Therefore, we also examine the impact of natural gas prices on the greenium using the CPI-deflated Henry Hub natural gas spot price from FRED. Panel A of Table 7 shows that the natural gas price also has a significant negative impact on the greenium. The magnitudes are slightly larger than the baseline estimates with oil prices, in line with the greater importance of natural gas in the U.S. in recent years.

Second, the model predicts that oil price variations driven by oil demand shocks have a negative impact on oil prices. The baseline analysis directly uses the real price of oil as oil demand shocks drive most oil price variations in the sample. We now explicitly use shocks decomposed in Section 1.1 and proxy for oil price variations driven by individual shocks as the cumulative 12-month impact of each shock. We then conduct the following regression

$$R_{it} = a + b \cdot Intensity_{it} + \mathbf{c} \cdot Intensity_{it} \times \mathbf{CumShock}_t + d \cdot X_{it} + \iota_t + e_{it}, \qquad (20)$$

[4] According to the EIA, the market share of natural gas in the U.S. is around 38% of the total primary energy production as of 2023, while petroleum (crude oil and natural gas plant liquids) represents roughly 34%. In contrast, unrefined petroleum alone makes up half of the market globally.

where R denotes the cost of capital measures, such as the yield spread and ICC, and $Intensity$ denotes the standardized carbon intensity. **CumShock** is a vector of rolling 12-month oil price changes driven by each shock and is not standardized, allowing for a direct comparison of the estimated coefficients across different shocks. We include same characteristic controls as in the baseline bond and equity regressions, respectively. Again, the regression includes time fixed effects, and standard errors are double clustered as the bond and month levels. Panel B of Table 7 presents the results. Oil price fluctuations driven by oil demand shocks have a strong negative impact on the greenium. The estimated coefficients are similar for bonds and equity, similar to the baseline. In contrast, the coefficients relating to supply shocks and economic activity shocks are mostly statistically indifferent from zero.

Finally, as a complement to the panel regressions in our baseline analyses, we construct the time series of bond and equity greenium and estimate time series regressions. We sort firms into three terciles based on the cabon intensity and then calculate the bond and equity greenium b_t as the value-weighted high-minus-low difference in yield spreads and GLS ICC estimates, respectively. The time series regression of the greenium on the standardized oil price follows

$$b_t = \alpha + \beta Oil_t + \varepsilon_t. \tag{21}$$

Panel C of Table 7 corroborates the panel regression findings, showing a negative relation between the oil price and greenium. The scope 1 coefficients are -14.44 and -25.32 for bonds and equity, respectively. The coefficients for the value-weighted greenium are slightly larger than the baseline estimates, suggesting a greater impact on larger firms.

Figure 2 plots the time series of the greenium and oil price. Consistent with the regression evidence, the oil price has a correlation of -0.49 with both scope 1 and 2 bond greenium, and a correlation of -0.32 and -0.19 with scope 1 and 2 equity greenium, respectively. Visual inspection of the plot yields several insights. First, the greenium varies substantially throughout the sample but becomes more elevated from mid 2014 onward. For example, the bond greenium has been mostly positive since this period, a trend that aligns with the below-mean real oil prices observed over the same interval. Second, past two decades have witnessed two significant boom-and-bust cycles in the greenium. The oil price crashes closely coincide with peaks in the bond greenium. The first oil bust occurred from 2014 to 2016, with oil prices bottoming out in January 2016, coinciding with the bond greenium peak. Similarly, the second oil bust took place in 2020, with oil prices reaching their lowest point in April and the bond greenium peaking in March.[5] A analogous pattern, albeit less pronounced, is observed in the ICC-based equity greenium. Third, the greenium becomes more elevated from 2018 to 2020 and experiences a reversal subsequently, mirroring the rise and fall of sustainable investing. The figure shows that the oil price briefly peaked in 2018 before dropping to the sample low in 2020 and steadily recovering afterward, a movement that accounts for the rise and fall of greenium.

Lastly, our analysis covers both the recent period marked by climate-related shocks and an earlier period starting in 2003 before significant attention to climate issues emerged. Additional results in the Internet Appendix demonstrate that the negative relationship persists across the entire sample. The negative relationship is more pronounced for equities during the earlier period, characterized by higher oil prices, and stronger for bonds in the later period, when lower oil prices pushed carbon-intensive firms closer to the default boundary.

In summary, fluctuations in the real price of oil significantly impact the greenium, explaining key dynamics observed over the past two decades. This relationship is robust across various tests and persists even in the absence of shocks from climate regulations or sustainable investing.

3.3 International Evidence

The baseline analysis studies the U.S. securities. One concern is that the negative relation between the oil price and greenium may arise coincidentally in the short U.S. sample. In this section, we turn to the international markets beyond the U.S. securities for an out-of-sample test. Our analysis in the international setting focuses on corporate bonds given the

[5] Ready, Roussanov and Taillard (2023) provide an excellent analysis of this period and explore its long-lasting impact on oil prices.

availability of reliable ICC estimates. We estimate the following regression model,

$$YieldSpread_{ijt} = a + b \cdot Intensity_{ijt} + \beta \cdot Intensity_{ijt} \times Oil_{jt}^{LOC} + c \cdot X_{ijt} + d_j + e_t + \varepsilon_{it}, \quad (22)$$

where Oil_j^{LOC} represents the real local oil price for country j, defined as the local price of oil deflated by the local inflation. X encompasses bond and firm characteristics. The regression includes country and time fixed effects, with standard errors double-clustered at the firm and year-month levels. The variable $Intensity$ is standardized to a zero mean and unit variance for each country each year, and the Oil^{LOC} series is also standardized to have a zero mean and unit variance for each country.

Panel A of Table 8 documents a negative correlation between oil prices and the greenium, consistent with the U.S. findings. Columns (1) and (2) find that a one-standard-deviation increase in the local real oil price reduces the greenium by 7.19 and 4.8 bps in regressions for scope 1 and 2 intensity, respectively. These estimates remain robust and significant at -6.02 and -4.09 after incorporating additional controls. This finding suggests that the negative association between oil prices and the greenium is not limited to the U.S. but is also evident in international markets.

It is notable that this negative relation can arise without shifts in climate regulation and investor preferences. It is possible that climate regulations and shifts in green preferences could influence both the oil price and greenium. We address the possibility in two ways. First, we study the subsample with little climate regulations or sustainable investing in the Internet Appendix and again find a robust negative relation. Second, we employ an instrument variable (IV) approach. Since oil prices are determined globally and predominantly invoiced in U.S. dollar, a shift towards green preferences could decrease the demand for fossil fuels and lower oil prices in U.S. dollars. However, exchange rate fluctuations introduce additional variability in the local real price of oil across countries. Therefore, we employ exchange rate variations as an IV for the local real price of oil, thereby isolating the exogenous component of oil price fluctuations that are not influenced by climate policies or investor preferences.[6]

[6] We exclude oil-reliant countries whose oil export share in their total export is greater than 20% in the

The first stage of the two-stage least squares (2SLS) estimation is included in the Internet Appendix. The results show a strong relationship between exchange rate fluctuations and real price of oil variations. The subsequent 2SLS estimates, as reported in Panel B, indicate that a one-standard-deviation increase in the oil price reduces the greenium by 7.16 and 4.30 bps in the specification with all controls for scopes 1 and 2, respectively. These coefficients are not only highly significant but also slightly larger than the OLS estimates detailed in Panel A, suggesting that the endogeneity or reverse causality issue is less important in this context.

In summary, oil price variations driven by oil demand shocks pass through to relative product price variations and have a negative impact on the greenium. This relation takes place even without climate-related shocks and is robust both in the U.S. and internationally.

4 Event Studies

Thus far, our analysis has established that oil prices can significantly influence the greenium, independent of climate-related shocks. This finding is critical because it suggests that failing to account for oil prices in climate-related event studies could introduce bias in the estimated impact of various events. In particular, the sign and magnitude of this bias depend on the covariance between the shocks under consideration and oil prices. In this section, we revisit the impact of commonly studied climate-related events to assess whether movements in oil prices have confounded prior conclusions. This analysis focuses on bond yield spreads, as ICC measures are often sluggish and imprecisely estimated.

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

Internet Appendix, and results are robust.

below 2°C above pre-industrial levels" and to "limit the temperature increase to 1.5°C above pre-industrial levels." A typical hypothesis is that the agreement provides an exogenous positive shock to expectations of future climate regulations, thereby increasing the cost of capital for brown firms and widening the greenium (Monasterolo and De Angelis, 2020).

Following Bolton and Kacperczyk (2021), we employ a difference-in-difference specification to isolate the impact of the PA:

$$YieldSpread_{it} = a + b \cdot Intensity_{it} \times AfterPA_t + c \cdot X_{it} + d_i + e_t + \varepsilon_{it}, \tag{23}$$

where $AfterPA$ 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 bond and time fixed effects, with standard errors double-clustered at the firm and month levels. Columns (1) to (2) in Panel A of Table 9 presents the baseline results. The greenium based on scope 1 intensity increased significantly by 15.99 bps after the PA in a specification without additional controls, a finding comparable to the 30 bps estimated in Seltzer, Starks and Zhu (2022).

However, the timing of the PA coincided with the oil bust that began in 2014. On the supply side, the crash was related to a general oversupply of shale oil and the response of the OPEC not to cut production in an attempt to maintain market share[7]. On the demand side, the demand growth slowed due to improved energy efficiency as well as weak global demand from China and Europe. The oil price reached its bottom in January 2016, immediately following COP 21. The recovery in oil prices from January 2016 onwards is attributable to the decline of the U.S. shale production, OPEC production cuts, and a resurgence in global demand. The average oil price in the 12-month window following the PA was lower by 0.45 standard deviations compared to the 12 months preceding the PA, contributing to a greenium increase. As such, the oil price shock confounds the PA event, necessitating explicit control for oil price variations.

[7]The OPEC decided not to reduce production in November 2014. This strategy was interpreted by analysts as an attempt to remove higher-cost producers, like US shale oil, from the market.

To address this confounding effect, we incorporate in our DiD estimation the interaction of carbon intensity with oil prices,

$$YieldSpread_{it} = a+b\cdot Intensity_{it}\times AfterPA_t+\beta\cdot Intensity_{it}\times Oil_t+c\cdot X_{it}+d_i+e_t+\varepsilon_{it}, \quad (24)$$

Columns (3) to (4) in Panel A present the refined results. Within the event window, a one-standard-deviation increase in oil prices is associated with a substantial reduction of 23.35 and 32.55 bps in the greenium for scopes 1 and 2, respectively. Upon accounting for these oil price movements, the impact of the Paris Agreement on the greenium becomes statistically insignificant for scope 1 and even significantly negative for scope 2. In other words, the greenium did not experience significant increases following the PA after controlling for oil price variations. The previously documented positive impact is driven by oil price fluctuations instead of increased climate policy risk. Notably, oil price variations not only explain the higher average greenium following the PA, but also explain the reverse-V-shaped dynamics in the greenium as shown in Figure 2. Columns (5) and (6) incorporate further controls for additional bond characteristics, and our results remains robust.

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, the oil price level differentially influences conditional expected returns of brown and green firms, an effect that the oil beta fails to capture. Supplementary results presented in the Internet Appendix confirm that the oil beta is inadequate to account for the oil impact.

The analysis above documents a strong impact of oil prices which drives out the impact of the PA. As an alternative, it can be hypothesized that the PA simultaneously affects both the oil price and greenium. For instance, the PA suggests increased future subsidies for renewable energy thereby depressing oil prices. However, this effect is likely more pronounced in future oil prices than in contemporaneous ones.[8] Alternatively, the PA might shift con-

[8] While the long-run supply of renewable energy is relatively elastic (e.g., over a five-year horizon (Johnson, 2011)), short-run supply is inelastic and may even slope downward in some cases (La Nauze, 2019).

sumer preferences, steering them away from "brown" products and potentially reducing oil prices. Yet, the literature offers inconclusive evidence on corporate and retail responses to ESG or CSR news(see Dai, Liang and Ng (2021), Dube, Lee and Wang (2023), and Meier et al. (2023)), with scant findings specifically pertaining to the PA. More importantly, oil price movements around the PA do not align with these hypotheses. The low oil prices preceding the PA were part of a broader downturn that initiated in 2014. Following the PA, oil prices experienced a sustained recovery, contradicting the hypotheses based on subsidies or preferences.

To summarize, the significant impact of the PA on the greenium, as documented in prior studies, is primarily a reflection of dramatic oil price variations during the event window rather than an increase in the carbon-transition risk. This finding highlights the necessity of controlling for oil price movements when assessing the impact of climate policy events on the greenium.

4.2 The 2016 Election of President Trump

Another commonly studied event is the 2016 election of President Trump on November 9th, 2016 (Ilhan, Sautner and Vilkov, 2021). The event is unexpected and reduces the climate policy uncertainty in the short term. We follow the literature and hypothesize that the climate policy risk decreases and the greenium drops following the surprise election.

To assess the election's impact on the greenium, we employ the regression model outlined in Eq. (23) and examine the 12 months surrounding the event. Panel B of Table 9 details the findings. In the wake of the election, the greenium exhibits a decline of -15.27 and -26.6 bps for scopes 1 and 2, respectively. These results are consistent with the option-based findings reported by Ilhan, Sautner and Vilkov (2021).

Paralleling the election's influence, the oil market experienced a continued recovery from the 2014 oil bust. In particular, the OPEC and non-OPEC countries, led by Russia, agreed to cut their production during the 171st OPEC Conference on November 30, 2016, which lead to higher oil prices and higher demand for the U.S.-produced oil. The average oil price during the 12-month post-election period surpassed the pre-election 12-month average by 0.35 standard deviations, contributing to the observed reduction in the greenium.

To account for this, we incorporate oil price fluctuations into our regression model as specified in Eq. (24). Columns (3) to (4) of Panel B display the adjusted results, where the coefficients diminish to -7.25 and -18.18 for scopes 1 and 2, respectively, with marginal significance for the latter. Upon further inclusion of bond characteristics in Columns (5) and (6), the estimated impacts are refined to -12.96 and -14.71 basis points, with only scope 1 coefficient retaining its significance. Collectively, these refined estimates indicate that, the 2016 presidential election may have influenced the greenium, but the magnitudes are attenuated relative to the initial estimates.

4.3 Climate Attention and Sustainable Investing

This section examines the influence of climate attention and investor awareness on the greenium, a phenomenon that has been linked to the performance of green assets and the expected returns of brown firms from 2013 to 2020 (Van der Beck, 2021; Pástor, Stambaugh and Taylor, 2022). The underlying hypothesis is that heightened climate attention leads to increased demand for green assets, thereby depressing the expected returns on brown stocks and raising the greenium.

We employ two measures to quantify climate attention: the first, denoted as GSV, is the logarithm of national Google search volume for the term "climate change," which captures the general public's interest in climate change and its associated risks (Choi, Gao and Jiang, 2020; Alekseev et al., 2022). The second measure, ESGShare, reflects investor preference or attention (Pástor, Stambaugh and Taylor, 2022; Van der Beck, 2021) and is calculated as the proportion of ESG funds within the fixed-income mutual fund segment.

We estimate the relation between climate attention and the greenium, with and without controlling for oil prices, using the following regression models,

$$\begin{aligned}
YieldSpread_{it} =& a + b \cdot Intensity_{it} + c \cdot Intensity_{it} \times Attention_t + d \cdot X_{it} + e_t + \varepsilon_{it}, \\
YieldSpread_{it} =& a + b \cdot Intensity_{it} + c \cdot Intensity_{it} \times Attention_t + \beta \cdot Intensity_{it} \times Oil_t \\
& + d \cdot X_{it} + e_t + \varepsilon_{it}.
\end{aligned} \tag{25}$$

Panel A of Table 10 presents the results for GSV. The GSV metric is significantly positively associated with the greenium without controlling for the oil price. Notably, the oil price has a moderate negative correlation of -0.33 with GSV and ignoring oil price variations can lead to an overestimation of the impact of climate attention. After controlling for oil price variations in columns (3) to (6), the positive association between the climate attention and greenium mostly persists, though the coefficients are attenuated. For example, estimates in columns (5) and (6) suggest that the cumulative effects of GSV over the sample period are about 9 and 6 bps for scopes 1 and 2, respectively.

Panel B reports the findings on sustainable investing. Columns (1) and (2) suggest no significant link between the share of ESG investment and greenium without controlling for the oil price. Because of the late onset of sustainable investing in fixed-income markets in 2017 and its rapid growth despite strong oil price performance from 2020 to 2022, the ESGShare has a positive correlation of 0.52 with the oil price. Failing to account for oil price variations can bias the estimated impact of sustainable investing downward. Upon controlling for oil prices in columns (3) to (6), the ESGShare now becomes significantly positively associated with the greenium. The cumulative impact of sustainable investing on the greenium over the sample period is roughly 9 and 17 bps increase for scopes 1 and 2, respectively. From 2020 to 2022, as ESG funds saw significant inflows and ESGShare rose from nearly zero to one percent, the oil price experienced a three-standard-deviation recovery, reducing the greenium by 35 and 60 basis points for scopes 1 and 2, respectively. As such, while shifts in climate attention and sustainable investing are associated with increases in the greenium, the overall effect is relatively modest compared to the substantial impact of oil price volatility.

In conclusion, this section revisits key events and drivers influencing the greenium. Our analysis underscores that ignoring oil price fluctuations can bias the estimated impact of targeted events, with the direction of this bias depending on the correlation between the event and oil prices. After accounting for the influence of oil prices, we find that investor discipline surrounding key climate-related events, such as the Paris Agreement, has ab best modest effects.

5 Conclusion

Our analysis challenges the prevailing view that greenium variation primarily reflects investor commitment to climate-aware investments. Instead, we show that oil demand fluctuations play a dominant role in driving these variations. When oil demand rises, growth opportunities improve for carbon-intensive firms, such as those in the oil-and-gas sector, thereby reducing the greenium in both U.S. and international markets. This suggests that financial markets are more responsive to oil demand shocks than to climate-related regulatory risks or sustainability preferences. While this paper focuses on the greenium, oil prices have broader implications for carbon pricing, firms' capital budgeting, bank lending, and corporate behavior. Further research on the role of oil prices will deepen our understanding of climate regulation, sustainable investing, and the transition towards net-zero economies.

These results raise concerns about how effectively financial markets are pricing in the risks associated with the carbon transition. In light of this, stronger policy interventions may be required to ensure that the financial sector takes a more proactive role in addressing climate change. By recognizing the influence of oil demand on the greenium, policymakers can better tailor regulations to encourage consistent and accurate pricing of carbon risks in financial markets.

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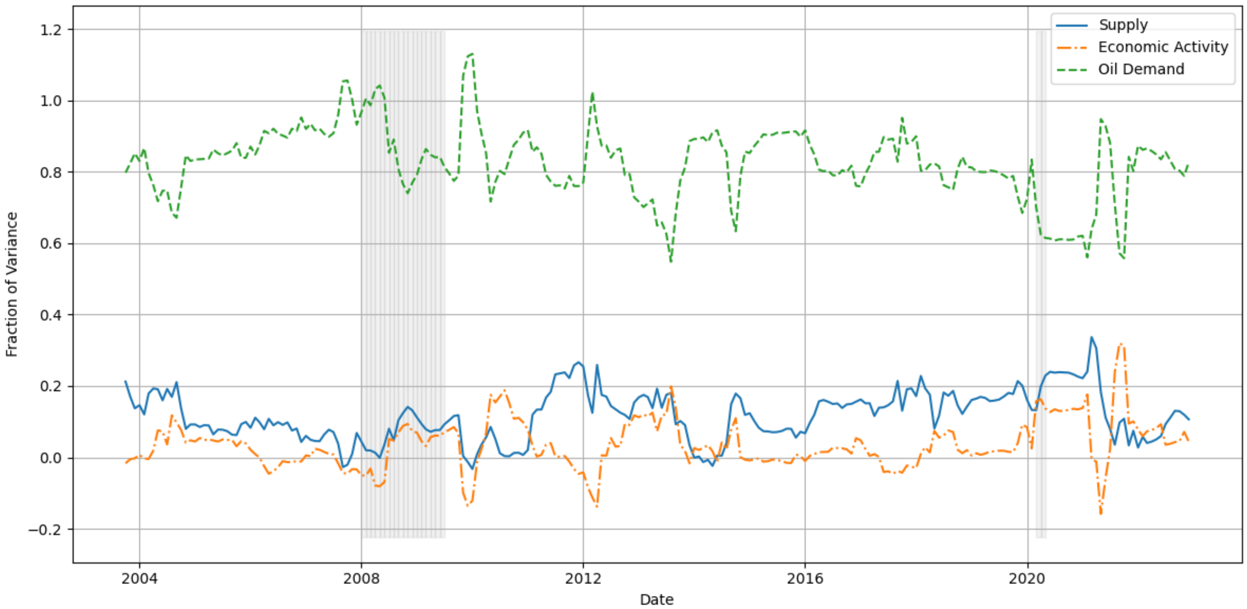
Figure 1: Contribution to 12-Month Oil Price Shocks



Notes: This figure plots the fraction of real oil price shocks explained by supply shocks, economic activity shocks, and oil demand shocks, respectively. The sample period is 2003:10 to 2022:12.

Figure 2: Ex-Ante Greenium and Oil Price

Notes: This figure plots the ex ante greenium and standardized real price of oil. The bond greenium is the value-weighted yield spread difference 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 GLS mechanical ICC estimate difference 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	AR	P25	P50	P75
	Panel A: Cost of Capital Measures (bps)					
Yield Spread	205.43	330.98	0.97	82.00	135.00	223.00
GLS ICC (Annualized)	854.94	394.31	0.97	612.23	808.73	1051.34
Average ICC (Annualized)	226.05	133.88	0.95	155.87	205.51	268.57
International Yield Spread	139.40	143.08	0.97	62.00	104.00	172.00
	Panel B: U.S. Carbon and Financial Information					
Scope 1 Intensity	3.08	2.68	1.00	1.33	2.84	5.03
Scope 2 Intensity	2.78	1.41	0.99	2.01	2.90	3.68
Duration	6.77	4.38	1.00	3.47	5.58	8.99
Bond Age	3.75	3.34	1.00	1.27	2.84	5.33
Rating	8.21	2.91	1.00	6.00	9.00	9.00
Beta	0.99	0.57	1.00	0.58	0.94	1.30
Size	9.67	1.09	1.00	8.99	10.08	10.60
BE/ME	-0.93	0.91	0.99	-1.43	-0.80	-0.29
Momentum	0.13	0.33	0.89	-0.05	0.11	0.28
ROE	0.14	0.28	0.95	0.07	0.13	0.22
Asset Growth	0.10	0.29	0.92	-0.00	0.05	0.12
Sales Growth	0.07	0.23	0.95	-0.01	0.05	0.12
Leverage	0.79	1.47	0.99	0.19	0.36	0.77
IVol	1.35	0.91	0.60	0.79	1.10	1.61
	Panel C: Aggregate Variables					
Oil	28.91	10.58	0.97	20.47	26.52	37.64
CumShock_{Supply}(%)	0.14	1.09	0.94	-0.44	0.18	0.81
$\text{CumShock}_{Economic\ Activity}$ (%)	-0.03	0.59	0.96	-0.32	-0.04	0.30
$\text{CumShock}_{Oil\ Demand}$(%)	-0.14	2.03	0.92	-1.57	-0.17	1.18
CumShock_{Oil}(%)	-0.03	2.62	0.94	-1.40	-0.14	1.68
Natural Gas	20.22	10.88	0.94	12.25	16.68	26.93
GSV	1.58	0.62	0.82	1.10	1.61	2.08
ESGShare (%)	0.39	0.36	1.01	0.06	0.27	0.78

Notes: This table presents summary statistics of cost of capital measures, firms' carbon and financial performance, and aggregate variables. The autocorrelation is calculated as the monthly frequency. Carbon intensity is the log total emissions scaled by the dollar sales during the emitting period. The implied cost of capital estimates (ICCs) are GLS mechanical estimates and the average of all four published measures. Oil and natural gas denotes the real prices of oil and natural gas, GSV is the log Google search index of "climate change". ESGShare is calculated as the fraction of ESG fixed income fund flows scaled by the total market capitalization of fixed income funds.

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	0.5

Panel B: Simulated Moments		
Moment	Data	Simulation
Oil Demand Elasticity	0.1	0.1
Oil Supply Elasticity	$0 - 0.04$	0.02
Mean Asset Growth		3.00%
σ(Oil Price)/Mean(Oil Price)	0.19	0.19
Mean Greenium		0.21%
σ(Greenium)		1.51%
Corr(A_t, P_t)		0.99
Corr(P_t, Marginal Q_t^{B-G})		0.17
Corr($P_t, (I_{it}/K_{it})^{B-G}$)		0.17
Corr(P_t, Greenium$_{t+1}$)		-0.97

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

Table 3: Oil Price and Producer Price

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔOutput PPI		ΔInput PPI		Scaled ΔInput PPI	
Scope 1 Intensity	0.08***		-0.03		-0.01	
	(3.04)		(-1.29)		(-0.48)	
Scope 2 Intensity		0.04***		-0.02		-0.00
		(2.92)		(-1.00)		(-0.32)
×ΔOil	2.37***	1.03***	1.04**	0.16	0.78**	0.15
	(8.67)	(5.03)	(2.23)	(0.93)	(2.28)	(1.26)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26498	26498	10200	10200	10200	10200
R^2	0.059	0.049	0.513	0.511	0.478	0.476

Notes: This table estimates the impact of real oil price changes (ΔOil) on changes in producers price index (ΔPPI×100). The dependent variables are output PPI changes (columns (1) and (2)), input PPI changes (columns (3) and (4)), and input PPI changes scaled by the share of cost of goods sold in in total sales (columns (5) and (6)). 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 2003:11 to 2022:12.

Table 4: Oil Price and Growth Opportunities

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Contemporaneous Relation							
	ME/BE		ROE		ΔAT		ΔSales	
Scope 1 Intensity	-0.41***		-0.02***		-0.01***		-0.00	
	(-4.11)		(-4.66)		(-3.38)		(-0.27)	
Scope 2 Intensity		0.83***		-0.00		-0.00		0.02*
		(6.15)		(-0.53)		(-0.31)		(1.97)
$\times$Oil$\times 10^{-1}$	1.21***	1.13*	0.09***	0.12***	0.09***	0.07*	0.07	0.17***
	(2.96)	(1.76)	(2.89)	(2.73)	(2.80)	(1.84)	(1.61)	(2.77)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	79530	79503	79536	79509	81883	81856	81644	81617
R^2	0.032	0.034	0.019	0.017	0.019	0.018	0.044	0.045
	Panel B: Predicting Future Growth							
	ΔAT_{t+12}		$\Delta\text{Sales}_{t+12}$		ΔAT_{t+12}		$\Delta\text{Sales}_{t+12}$	
Scope 1 Intensity	-0.01***		-0.00		-0.01**		-0.00	
	(-2.79)		(-0.21)		(-2.59)		(-0.15)	
Scope 2 Intensity		0.00		0.02*		-0.03***		-0.01
		(0.23)		(1.91)		(-6.63)		(-1.38)
$\times$Oil$\times 10^{-1}$	0.13***	0.04	0.13***	0.08	0.12***	0.00	0.12***	0.04
	(5.28)	(0.92)	(3.42)	(1.36)	(4.73)	(0.10)	(3.29)	(0.82)
Beta					-0.01***	-0.01*	0.01*	0.01**
					(-3.26)	(-1.92)	(1.74)	(2.27)
Size					-0.01***	-0.01***	0.00	0.00
					(-2.99)	(-2.89)	(0.50)	(0.49)
BE/ME					-0.07***	-0.07***	-0.04***	-0.04***
					(-14.39)	(-15.11)	(-10.33)	(-11.04)
Momentum					0.12***	0.12***	0.12***	0.12***
					(8.60)	(8.56)	(9.55)	(9.57)
ROE					-0.01	-0.01	-0.11***	-0.11***
					(-0.99)	(-0.76)	(-6.02)	(-5.86)
Asset Growth					0.02*	0.02*	0.17***	0.17***
					(1.96)	(1.98)	(10.77)	(10.79)
Sales Growth					0.09***	0.08***	0.07**	0.07**
					(6.00)	(6.00)	(2.29)	(2.29)
Leverage					-0.02***	-0.02***	-0.01**	-0.01**
					(-5.68)	(-6.09)	(-2.37)	(-2.57)
IVol					0.02***	0.03***	0.01**	0.01**
					(5.70)	(5.96)	(2.52)	(2.48)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70137	70110	70020	69993	65230	65203	65156	65129
R^2	0.019	0.017	0.049	0.049	0.106	0.108	0.186	0.186

Notes: This table regresses measures of growth opportunities on the standardized carbon intensity and its interaction with the standardized real price of oil (Oil). 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:Q4 to 2022:Q4.

Table 5: Oil Price and Bond Greenium

	(1)	(2)	(3)	(4)
Scope 1 Intensity	10.78**		-4.52*	
	(2.18)		(-1.91)	
Scope 2 Intensity		10.63		-1.70
		(1.55)		(-0.45)
× Oil	-7.80***	-11.91**	-3.58**	-5.49*
	(-3.25)	(-2.42)	(-2.15)	(-1.84)
Duration			6.80***	6.79***
			(27.47)	(28.09)
Bond Age			2.67***	2.56***
			(8.07)	(8.47)
Rating			21.71***	20.82***
			(9.15)	(9.25)
Beta			13.22***	16.65***
			(3.29)	(4.52)
Size			-27.78***	-28.18***
			(-6.47)	(-6.51)
BE/ME			-4.66	-5.55*
			(-1.62)	(-1.89)
Momentum			-41.31***	-42.27***
			(-7.47)	(-7.74)
ROE			-34.60***	-34.43***
			(-3.00)	(-3.02)
Asset Growth			-0.14	0.64
			(-0.03)	(0.16)
Sales Growth			-17.50***	-16.79***
			(-2.73)	(-2.70)
Leverage			19.03***	19.06***
			(4.27)	(4.08)
IVol			0.40***	0.40***
			(8.51)	(8.66)
Time FE	Yes	Yes	Yes	Yes
Observations	529536	529232	505272	504968
R^2	0.209	0.210	0.609	0.620

Notes: This table examines the co-variation of bond greenium with the oil price by regressing yield spreads on the standardized carbon intensity, its interaction with the standardized real price of oil (Oil), as well as bond and issuer characteristics. 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 2003:11 to 2022:12.

Table 6: Oil Price and Equity Greenium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: GLS Estimates				Panel B: Average ICC Estimates			
Scope 1 Intensity	-35.53***		-38.21***		-8.91***		-9.60***	
	(-5.45)		(-9.57)		(-4.43)		(-7.59)	
Scope 2 Intensity		-46.06***		-14.79***		-12.61***		-4.33***
		(-7.72)		(-3.67)		(-6.86)		(-3.41)
×Oil	-8.65***	-13.52***	-4.28**	-6.22***	-3.19***	-6.38***	-1.63*	-4.23***
	(-2.85)	(-4.24)	(-2.06)	(-2.64)	(-2.86)	(-5.31)	(-1.86)	(-4.07)
Beta			8.72	17.59***			8.10***	10.59***
			(1.51)	(2.76)			(3.52)	(4.16)
Size			-13.90***	-13.70***			-3.08***	-3.04***
			(-4.03)	(-3.68)			(-2.82)	(-2.63)
BE/ME			181.04***	174.93***			48.87***	47.21***
			(29.15)	(28.20)			(23.70)	(23.70)
Momentum			-62.85***	-67.76***			-19.29***	-20.57***
			(-8.46)	(-8.94)			(-8.48)	(-8.85)
ROE			281.95***	289.85***			54.35***	56.53***
			(12.43)	(12.64)			(8.54)	(8.81)
Asset Growth			-15.76***	-14.03**			-5.84**	-5.47**
			(-2.91)	(-2.58)			(-2.49)	(-2.34)
Sales Growth			6.82	6.04			6.41	6.42
			(0.83)	(0.73)			(1.37)	(1.37)
Leverage			69.35***	70.46***			24.37***	24.51***
			(8.47)	(8.56)			(7.12)	(7.17)
IVol			16.69***	15.06***			6.58***	6.17***
			(4.92)	(4.20)			(5.31)	(4.78)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	209955	209873	200774	200692	209955	209873	200774	200692
R^2	0.115	0.123	0.509	0.498	0.571	0.574	0.704	0.702

Notes: This table regresses the ICC measures on the standardized carbon intensity, its interaction with the standardized real price of oil (Oil), and firm characteristics. Panel A focuses on the Gebhardt-Lee-Swaminathan mechanical estimates, and Panel B studies the average of four commonly used ICC measures. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period spans from 2003:10 to 2022:12.

Table 7: Robustness Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Bond				Equity			
	Panel A: Real Price of Natural Gas							
Scope 1 Intensity	9.83**		-6.46***		-46.68***		-50.51***	
	(2.06)		(-2.72)		(-5.59)		(-10.21)	
Scope 2 Intensity		10.09		-2.64		-86.04***		-28.81***
		(1.52)		(-0.72)		(-8.10)		(-3.94)
×Gas	-6.95***	-6.18*	-8.17***	-5.97**	-10.08**	-25.88***	-10.42***	-19.81***
	(-3.01)	(-1.88)	(-4.76)	(-2.09)	(-2.37)	(-4.46)	(-3.65)	(-4.81)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	529536	529232	505272	504968	209955	209873	200774	200692
R^2	0.208	0.209	0.611	0.620	0.115	0.123	0.510	0.498
	Panel B: Decomposed Oil Shocks							
Scope 1 Intensity	0.88**		-0.33		-3.55***		-4.07***	
	(2.01)		(-1.54)		(-5.14)		(-9.61)	
Scope 2 Intensity		0.74		-0.12		-6.82***		-2.05***
		(1.20)		(-0.38)		(-7.46)		(-3.26)
$\times\text{CumShock}_{Supply}$	0.23	0.54*	-0.10	-0.01	-0.31	0.28	0.13	0.13
	(1.46)	(1.89)	(-0.95)	(-0.09)	(-1.20)	(0.62)	(0.68)	(0.42)
$\times\text{CumShock}_{Economic\ activity}$	0.00	-0.23	-0.17	-0.25	0.64	0.76	0.18	1.10*
	(0.01)	(-0.67)	(-1.23)	(-1.14)	(1.36)	(0.92)	(0.49)	(1.80)
$\times\text{CumShock}_{Oil\ demand}$	-0.24***	-0.33***	-0.16***	-0.25***	-0.23**	-0.32	-0.12	-0.25*
	(-3.80)	(-3.31)	(-4.27)	(-3.82)	(-2.25)	(-1.62)	(-1.52)	(-1.94)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	529536	529232	505272	504968	209955	209873	200774	200692
R^2	0.209	0.210	0.610	0.620	0.115	0.122	0.509	0.498
	Panel C: Time-Series Regression							
	Scope 1		Scope 2		Scope 1		Scope 2	
Oil	-14.44***		-16.98***		-25.32**		-17.98	
	(-2.61)		(-3.29)		(-2.56)		(-1.63)	
Observations	231		231		231		231	
R^2	0.236		0.244		0.099		0.033	

This table conducts robustness analysis on the relation between the greenium and oil prices. Panel A examines the impact of the standardized real natural gas prices on the greenium, and Panel B assesses the role of decomposed oil price shocks. Standard errors are double clustered at the firm and month levels. Panel C studies time series of the greenium, which is calculated as the value-weighted spread between high and low carbon intensity tercile portfolios. Newey-West standard errors account for 12 lags. 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 8: International Bonds

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Ordinary Least Squares				Panel B: Two-Stage Least Squares			
Scope 1 Intensity	3.10		-3.45		3.08		-3.40	
	(0.88)		(-1.13)		(0.87)		(-1.11)	
Scope 2 Intensity		8.44***		-2.15		8.46***		-2.14
		(2.88)		(-0.77)		(2.89)		(-0.76)
$\times$Oil^{LOC}	-7.18***	-4.81***	-6.03***	-4.09***	-6.05	-5.30***	-7.16***	-4.30***
	(-4.55)	(-4.91)	(-4.67)	(-5.61)	(-1.57)	(-4.13)	(-4.04)	(-4.06)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	320959	320916	305910	305873	320959	320916	305910	305873
R^2	0.274	0.276	0.532	0.531	0.008	0.011	0.361	0.360

Notes: This table examines the variation of international greenium with the oil price. The analysis regresses duration-matched yield spreads on the carbon intensity, its interaction with the local real price of oil, and bond characteristics. Panel A studies the ordinary-least-squares (OLS) specification, and Panel B reports two-stage least squares (2SLS) estimates. The carbon intensity is standardized within each country each year and the oil price is standardized to have zero mean and unit variance for each country. 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 9: Event Study

	(1) Scope 1	(2) Scope 2	(3) Scope 1	(4) Scope 2	(5) Scope 1	(6) Scope 2
			Panel A: Paris Agreement			
Intensity×Post PA	15.99**	7.38	4.56	-9.02*	1.44	-10.48
	(2.35)	(0.91)	(0.77)	(-1.77)	(0.21)	(-1.69)
Intensity×Oil			-23.35**	-32.55**	-20.93***	-23.54**
			(-2.56)	(-2.34)	(-3.28)	(-2.26)
Controls	No	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	69627	69559	69627	69559	66012	65944
R^2	0.618	0.651	0.619	0.652	0.702	0.751
			Panel B: Trump Surprise Election			
Intensity×Post Election	-15.27*	-26.60**	-7.25	-18.18*	-12.96**	-14.71
	(-1.98)	(-2.52)	(-1.35)	(-1.96)	(-2.45)	(-1.60)
Intensity×Oil			-24.97**	-30.25*	-24.34***	-32.82**
			(-2.56)	(-1.72)	(-3.41)	(-2.31)
Controls	No	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	73777	73742	73777	73742	70335	70300
R^2	0.573	0.593	0.574	0.593	0.678	0.701

Notes: This table studies the greenium variation around the Paris Agreement and 2016 Election of President Trump. The analysis regresses duration-matched yield spreads on the standardized carbon intensity's interaction with the post-event dummy and interaction with the standardized real price of oil. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table 10: Climate Attention and Sustainable Investing

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Google Search Volume					
Scope 1 Intensity	0.97		7.46		-12.17**	
	(0.11)		(0.94)		(-2.35)	
Scope 2 Intensity		-9.55		0.19		-6.97
		(-0.66)		(0.02)		(-0.98)
×GSV	6.18*	12.28*	1.91	6.19	4.42**	3.12
	(1.92)	(1.92)	(0.79)	(1.44)	(2.04)	(1.09)
×Oil			-7.36***	-10.76**	-2.66	-4.94*
			(-3.25)	(-2.48)	(-1.64)	(-1.82)
Controls	No	No	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	527246	526942	527246	526942	503066	502762
R^2	0.208	0.209	0.209	0.211	0.609	0.620
	Panel B: Sustainable Investing					
Scope 1 Intensity	19.15***		2.73		-8.28**	
	(3.47)		(0.76)		(-2.64)	
Scope 2 Intensity		28.55***		6.78		-11.06**
		(3.40)		(1.00)		(-2.42)
×ESGShare	-5.55	-4.69	11.90**	19.04*	9.25***	17.53***
	(-1.20)	(-0.69)	(2.14)	(1.76)	(2.81)	(3.26)
×Oil			-18.38***	-24.83**	-11.72***	-19.89***
			(-3.60)	(-2.44)	(-3.64)	(-3.36)
Controls	No	No	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225922	225922	225922	225922	213434	213434
R^2	0.109	0.108	0.113	0.110	0.613	0.613

Notes: This table studies the greenium co-variation with climate attention and sustainable investing. The analysis regresses corporate yield spreads on the standardized carbon intensity, its interaction with the climate attention measures and its interaction with the standardized real price of oil. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

A Appendix

A.1 Structural Estimation

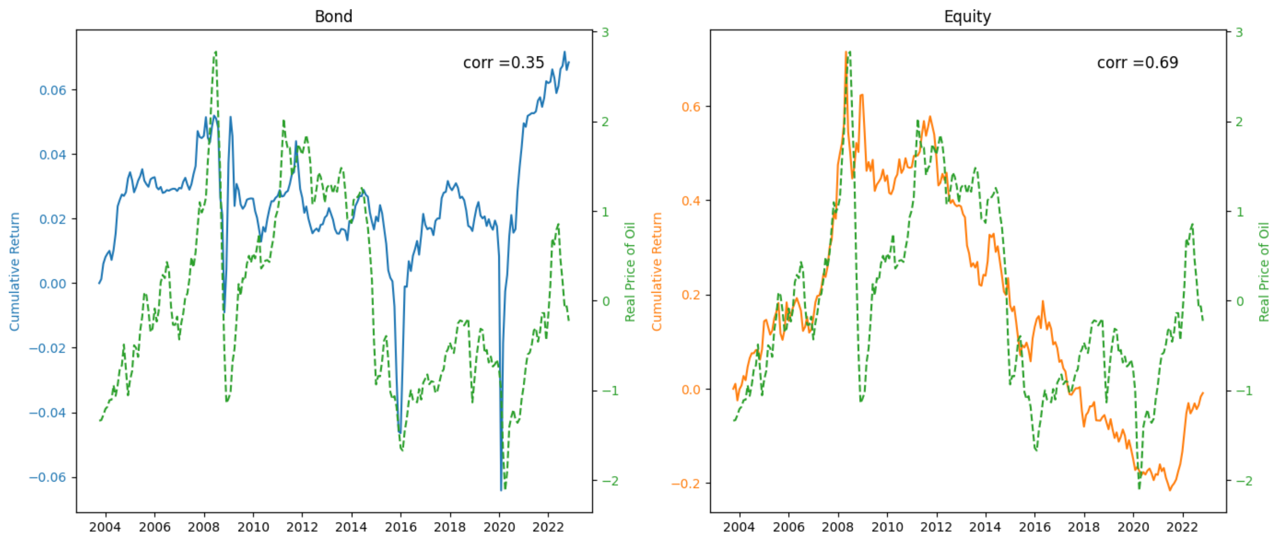
We follow Baumeister and Hamilton (2019) and use a three-element observed vector $\mathbf{y_t}$ to summarize the global oil market. The first element is the quantity of oil produced, the second is a measure of real economic activity, and the third captures the real price of oil: $\mathbf{y}_t = (q_t, y_t, p_t)'$. The structural model consists of the following four equations:

$$
\begin{aligned}
q_t &= \alpha_{qy} p_t + \mathbf{b}_1' \mathbf{x}_{t-1} + u_{1t}^*, \\
y_t &= \alpha_{yp} p_t + \mathbf{b}_2' \mathbf{x}_{t-1} + u_{2t}^*, \\
q_t &= \beta_{qy} y_t + \beta_{qp} p_t + \chi^{-1} \Delta i_t + \mathbf{b}_3' \mathbf{x}_{t-1} + u_{3t}^* - \chi^{-1} e_t, \\
\Delta i_t &= \psi_1 q_t + \psi_2 y_t + \psi_3 p_t + \mathbf{b}_4' \mathbf{x}_{t-1} + \chi u_{4t}^* + e_t,
\end{aligned}
\tag{A.1}
$$

where $q_t = 100 \ln(Q_t/Q_{t-1})$ is the observed monthly growth rate of world crude oil production, p_t is the log difference between the refiner acquisition cost of crude oil imports and the US CPI, y_t is an extended version of the OECD's index of monthly industrial production in the OECD and six major other countries, $\Delta i_t^* = 100 \Delta I_t^* / Q_{t-1}$ denotes our estimate of the change in OECD crude oil inventories as a percent of the previous month's world production, As such, $q_t - \Delta i_t^*$ denotes the growth in consumption demand. Oil supply is also presumed to be influenced by lagged values of all the variables over the preceding two years, with $\mathbf{x}_{t-1} = (\mathbf{y}_{t-1}', \mathbf{y}_{t-2}', \mathbf{y}_{t-3}', ..., \mathbf{y}_{t-24}', 1)'$. The oil inventory demand is often described as a "speculative demand shock" in the literature and inventory decisions are typically made by oil refiners. e_t reflects measurement error which is assumed to be serially uncorrelated and uncorrelated with $\mathbf{u}_t$ and captures the fact that the global oil inventories are not observable. The shocks u_{1t}^* and u_{2t}^* represent shocks to oil supply and economic activity. u_{3t}^* and u_{4t}^* represent oil-specific consumption demand and inventory demand, acknowledging that oil produced but not consumed in the current periods goes into inventories.

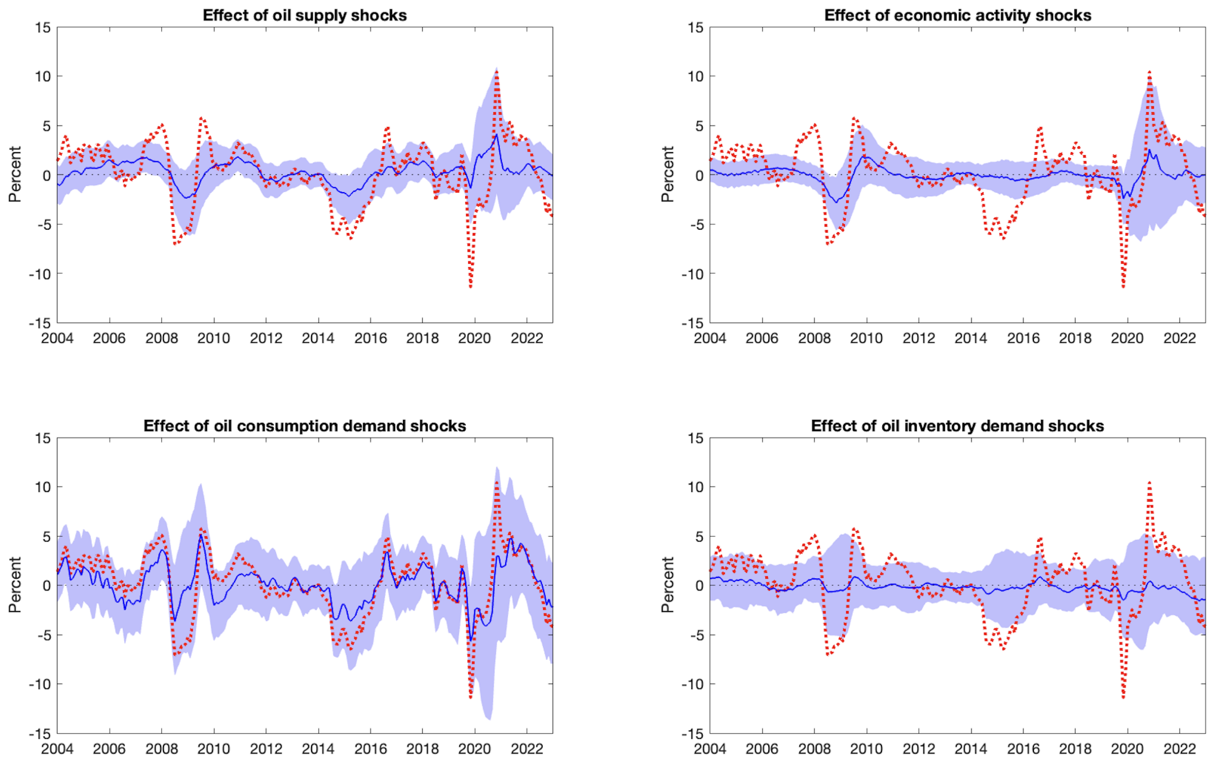
Internet Appendix

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: Decomposed 12-Month Oil Price Shocks

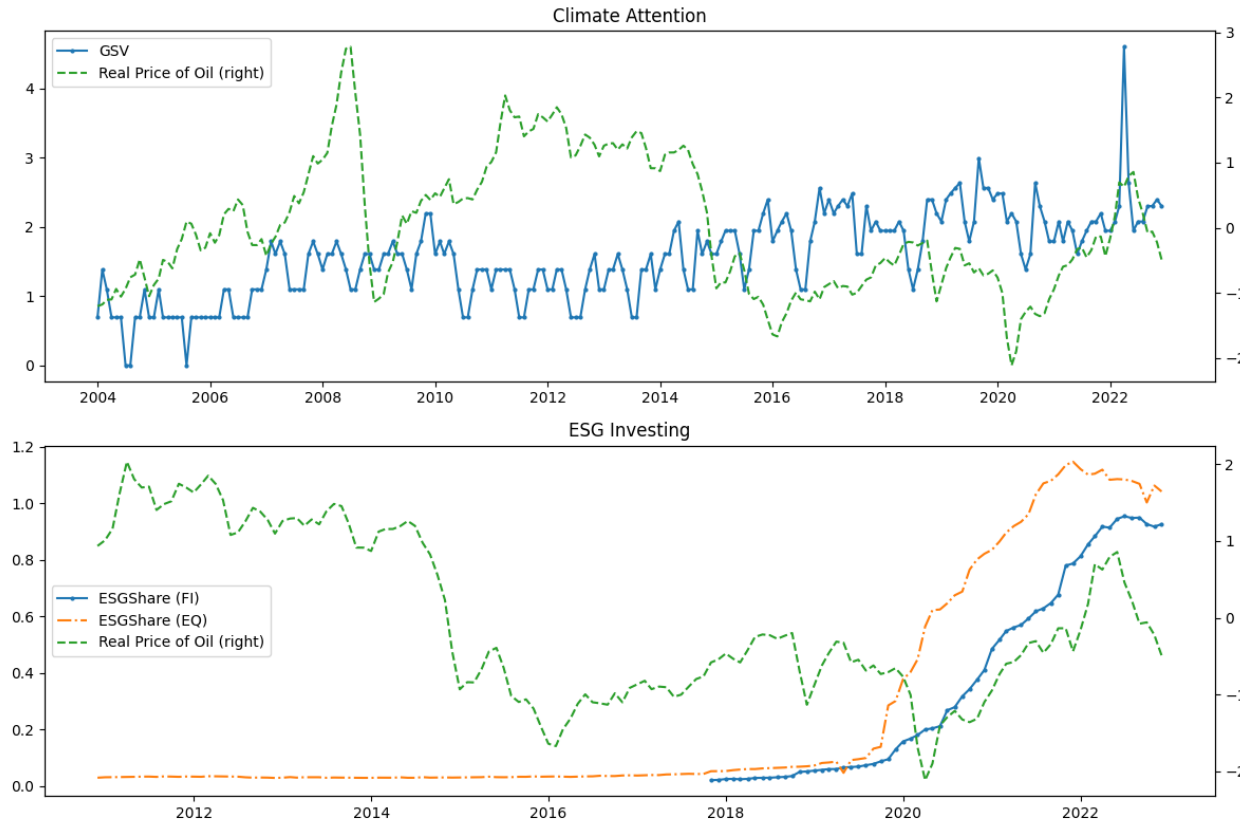


Notes: This figure plots actual 12-month changes in oil prices (red dotted lines) and the median estimate of the historical contribution of separate structural shocks (blue lines) for the baseline four-variable model. Blue shaded regions indicate 95 percent posterior credibility regions.

Figure IA.3: Growth Opportunities and Oil Price

Notes: This figure plots the standardized Tobin's Q spread between brown and green firms and the standardized real price of oil. The Tobin's Q spread is the Tobin's Q difference between the top tercile of firms with the highest carbon intensity and the bottom tercile for scopes 1 and 2, respectively. All series are standardized to have zero mean and unit variance. The sample period is 2003:10 to 2022:12.

Figure IA.4: Climate Attention and Sustainable Investing



Notes: This figure plots the series of climate attention (GSV) and ESGShare together with the standardized real price of oil.

Table IA.1: U.S. Greenium: Subsample Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Before 10/2009		11/2009-12/2015		Post 12/2015	
			Bond			
Intensity×Oil	-1.50	-2.73	-3.53	-8.49*	-15.02***	-12.56*
	(-0.54)	(-0.80)	(-1.34)	(-1.68)	(-3.25)	(-1.86)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Intensity Control	Yes	Yes	Yes	Yes	Yes	Yes
Characteristic Controls	No	No	No	No	No	No
Observations	77164	77152	155614	155352	296758	296728
R^2	0.406	0.406	0.062	0.062	0.097	0.092
			Equity			
Intensity×Oil	-12.42**	-6.61	-18.74***	-19.71**	-3.44	10.42
	(-2.31)	(-0.83)	(-4.50)	(-2.43)	(-0.55)	(1.23)
Intensity Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	36083	36079	55187	55115	118685	118679
R^2	0.157	0.193	0.087	0.107	0.044	0.042
			Panel B: With Characteristic Controls			
			Bond			
Intensity×Oil	0.73	-3.86	-2.36	-6.31*	-11.25***	-12.01**
	(0.29)	(-0.96)	(-1.30)	(-1.76)	(-3.15)	(-2.33)
Intensity Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	74863	74851	149436	149174	280973	280943
R^2	0.671	0.665	0.668	0.673	0.539	0.559
			Equity			
Intensity×Oil	2.54	1.45	-9.25***	-12.32**	1.76	2.87
	(0.63)	(0.22)	(-3.20)	(-2.07)	(0.38)	(0.45)
Intensity Control	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	34652	34648	53830	53758	112292	112286
R^2	0.585	0.565	0.488	0.473	0.482	0.473

Notes: This table examines the variation of greenium with the oil price during different sub-sample periods. The carbon intensity is standardized within each country each year and the oil price is standardized to have zero mean and unit variance for each country. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period spans from 2003:10 to 2022:12.

Table IA.2: First Stage Regression Estimates in the Instrumental Variable Inference

	(1)	(2)	(3)	(4)
Scope 1 Intensity	0.02		0.04	
	(0.29)		(0.48)	
Scope 2 Intensity		0.01		-0.00
		(0.10)		(-0.01)
×FX	0.56***	0.72***	0.58***	0.73***
	(2.67)	(5.10)	(2.87)	(5.46)
Controls	No	No	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	320959	320916	305910	305873
R^2	0.350	0.592	0.377	0.611

This table presents the first stage of the 2SLS analysis presented in Table 8. The interaction of carbon intensity with real oil prices in domestic currencies is regressed on the carbon intensity and its interaction with the exchange rate corresponding to the issuer's country of origin. The carbon intensity is standardized within each country each year, and the oil price is standardized to have zero mean and unit variance for each country. 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: International Bonds: Subsample Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	Before 10/2009		11/2009-12/2015		Post 12/2015	
	Scope 1	Scope 2	Scope 1	Scope 2	Scope 1	Scope 2
	Panel A: No Bond Controls					
Scope 1 Intensity	-13.09**		6.96		4.97	
	(-2.55)		(1.59)		(1.23)	
Scope 2 Intensity		5.93		9.77**		8.01**
		(1.44)		(2.29)		(2.32)
$\times\text{Oil}^{LOC}$	1.32	-2.05*	-8.24*	-3.43	-7.92***	-5.08***
	(0.44)	(-1.72)	(-1.90)	(-0.99)	(-5.55)	(-5.48)
Controls	No	No	No	No	No	No
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	45211	45175	101323	101368	172746	172694
R^2	0.432	0.427	0.363	0.365	0.205	0.204
	Panel B: With Bond Controls					
Scope 1 Intensity	-13.98**		-2.38		-2.57	
	(-2.61)		(-0.68)		(-0.87)	
Scope 2 Intensity		-2.22		-2.67		-2.13
		(-0.50)		(-0.73)		(-0.76)
$\times\text{Oil}^{LOC}$	-0.24	-3.08*	-6.16**	-2.25	-6.28***	-3.91***
	(-0.08)	(-1.94)	(-2.09)	(-0.81)	(-4.80)	(-4.68)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	42935	42903	96520	96565	164884	164834
R^2	0.551	0.545	0.626	0.624	0.526	0.524

Notes: This table examines the variation of international greenium with the oil price during different sub-sample periods. The carbon intensity is standardized within each country each year and the oil price is standardized to have zero mean and unit variance for each country. 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.4: International Bonds: Excluding Oil-Reliant Economies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Ordinary Least Squares				Panel B: Two-Stage Least Squares			
Scope 1 Intensity	2.54		-3.78		2.57		-3.65	
	(0.71)		(-1.22)		(0.71)		(-1.18)	
Scope 2 Intensity		8.18***		-2.03		8.22***		-1.99
		(2.74)		(-0.71)		(2.75)		(-0.70)
$\times$Oil^{LOC}	-7.19***	-4.76***	-6.10***	-4.07***	-8.62***	-6.03***	-8.69***	-4.85***
	(-4.55)	(-4.80)	(-4.78)	(-5.51)	(-4.36)	(-5.97)	(-8.08)	(-6.39)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	312148	312091	299750	299699	312148	312091	299750	299699
R^2	0.270	0.272	0.535	0.534	0.008	0.010	0.368	0.367

Notes: This table examines the variation of international greenium with the oil price, excluding countries whose oil export share is higher than 20% in 2013. The analysis regresses duration-matched yield spreads on the carbon intensity, its interaction with the local real price of oil, and bond characteristics. Panel A studies the ordinary-least-squares (OLS) specification, and Panel B reports two-stage least squares (2SLS) estimates. The carbon intensity is standardized within each country each year and the oil price is standardized to have zero mean and unit variance for each country. 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.5: Event Study with Oil Beta Controls

	Panel A: Paris Agreement							
	Equity Oil Beta				Bond Oil Beta			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Scope 1	Scope 2	Scope 1	Scope 2	Scope 1	Scope 2	Scope 1	Scope 2
Intensity×Post PA	11.46**	0.30	10.69	-2.84	16.50**	5.06	12.03*	0.89
	(2.10)	(0.05)	(1.67)	(-0.47)	(2.39)	(0.68)	(1.82)	(0.14)
Oil Beta×Post PA	265.39**	228.04**	231.65**	182.15**	39.09*	40.90*	-1.32	0.87
	(2.39)	(2.68)	(2.28)	(2.64)	(1.78)	(2.00)	(-0.10)	(0.08)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65750	65688	62444	62382	67097	67033	63670	63606
R^2	0.630	0.657	0.707	0.750	0.622	0.651	0.702	0.748
	Panel B: 2016 Election of President Trump							
Intensity×Post Election	-10.87	-20.22**	-17.74**	-18.87*	-14.77*	-26.15**	-20.54***	-23.17**
	(-1.55)	(-2.30)	(-2.68)	(-1.96)	(-1.91)	(-2.56)	(-2.95)	(-2.29)
Oil Beta×Post Election	-234.60**	-235.18**	-203.89***	-205.81***	-43.48***	-43.87***	-33.78***	-33.43***
	(-2.73)	(-2.73)	(-4.52)	(-4.55)	(-3.04)	(-3.09)	(-3.87)	(-4.08)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	70028	69999	66857	66828	71326	71295	68049	68018
R^2	0.581	0.596	0.683	0.701	0.578	0.593	0.681	0.700

Notes: This table studies the bond greenium variation around the Paris Agreement (PA) and 2016 election of President Trump. The analysis regresses duration-matched yield spreads on carbon intensity's interaction with the post-event dummy and oil beta's interaction with the post-event dummy. Oil beta is estimated as the loading of bond and equity returns on oil price changes in a rolling 60-month window, respectively. The carbon intensity are standardized each year to have zero mean and unit variance each year. We report t-statistics in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

Table IA.6: Climate Attention with Oil Beta Controls

	Panel A: Climate Attention							
	Equity Oil Beta				Bond Oil Beta			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Scope 1	Scope 2	Scope 1	Scope 2	Scope 1	Scope 2	Scope 1	Scope 2
Scope 1 Intensity	2.35		-13.99**		1.19		-14.34***	
	(0.29)		(-2.58)		(0.14)		(-2.62)	
Scope 2 Intensity		-7.39		-9.88		-9.78		-11.24
		(-0.54)		(-1.14)		(-0.68)		(-1.30)
×GSV	3.95	8.65	5.29**	4.73	6.03*	11.95*	5.94**	5.83
	(1.30)	(1.48)	(2.13)	(1.23)	(1.87)	(1.91)	(2.38)	(1.50)
×Oil Beta	183.80***	182.39***	58.11***	54.36***	16.50***	16.53***	-0.40	-0.48
	(7.71)	(7.84)	(4.96)	(5.00)	(4.09)	(4.10)	(-0.25)	(-0.29)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	499889	499595	477652	477358	509383	509085	486504	486206
R^2	0.257	0.259	0.610	0.620	0.215	0.216	0.607	0.617
	Panel B: Sustainable Investing							
Scope 1 Intensity	18.95***		2.20		19.25***		2.28	
	(3.49)		(0.75)		(3.50)		(0.77)	
Scope 2 Intensity		27.47***		6.27		28.20***		6.30
		(3.32)		(1.29)		(3.35)		(1.29)
×ESGShare	-6.53	-5.17	-1.70	-1.24	-5.97	-4.83	-1.63	-1.09
	(-1.37)	(-0.73)	(-0.54)	(-0.20)	(-1.28)	(-0.70)	(-0.53)	(-0.18)
×Oil Beta	264.97***	266.55***	39.01	39.01	16.89	17.06	-17.28**	-17.28**
	(2.66)	(2.67)	(1.27)	(1.27)	(0.98)	(1.00)	(-2.36)	(-2.39)
Controls	No	No	Yes	Yes	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	215612	215612	203942	203942	219290	219290	207359	207359
R^2	0.119	0.118	0.607	0.608	0.110	0.108	0.609	0.609

Notes: This table studies the greenium variation with climate attention, controlling for the oil beta. Oil beta is estimated as the loading of bond and equity returns on oil price changes in a rolling 60-month window, respectively. The carbon intensity are standardized each year to have zero mean and unit variance each year. We report t-statistics in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.