Oil-Driven Greenium

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Abstract

Driven by climate policy risk and investor pressure, many argue that carbon-intensive firms face higher costs of capital, creating a "greenium" favoring greener firms. We challenge this view, showing that oil demand fluctuations drive key dynamics in greenium variation by raising product prices and growth opportunities for carbon-intensive, oil-dependent firms, thereby lowering their relative cost of capital. This effect holds across U.S. bonds, equities, and global markets. Revisiting major climate-related events like the Paris Agreement, we find that investor discipline plays a minor role once oil's impact is considered. These findings suggest markets may be less climate-responsive than previously expected.

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

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One of the most pressing questions in climate finance is whether financial markets truly factor firms' carbon footprint into asset prices. At the heart of this issue is the concept of "greenium," which posits that, during the transition to net zero, carbon-intensive firms face a higher cost of capital due to increased climate policy risk and investor preference shifts, while less carbon-intensive firms benefit from a lower cost of capital. Such investor commitment can potentially aid efforts to combat climate change without extensive government intervention (Hong, Wang and Yang, 2023). Over the past decade, the greenium has grown in general, reflecting a higher relative cost of capital faced by carbon-intensive firms (Gormsen, Huber and Oh, 2023). More importantly, the greenium appears to be responsive to climate-related events, such as the Paris Agreement (Monasterolo and De Angelis, 2020). This evidence is often interpreted as indicating that investors have begun to incorporate firms' environmental, social, and governance (ESG) performance in asset prices.

In this paper, we challenge this prevailing narrative that the documented greenium variation reflects genuine investor commitment to climate-aware investments. Carbon-intensive firms are concentrated in oil and gas industries, where their product price and valuation are closely tied to fluctuations in the oil market (see Figure 1). As such, fluctuations in oil prices can directly impact their cost of capital. The oil price has experienced several booms and busts over the past two decades, which coincide with various climate events. Hence, fluctuations in the greenium might have been mistakenly attributed to climate policy risk or sustainable investing when, in fact, they reflect time-varying risks that affect oil-dependent firms. Indeed, our analysis reveals that 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. Overall, financial markets may not be as responsive to climate shocks as previously assumed.

To understand the impact of oil price fluctuations on the greenium, we first examine sources of oil price variations. Structural VAR frameworks (Kilian, 2009; Baumeister and Hamilton, 2019; Känzig, 2021) show that oil price variations are primarily driven by oil

demand shocks in the past two decades. We thus focus on oil demand shocks and study an investment-based model with brown and green firms. In the model, brown firms produce oil, green firms produce green goods, and the oil price represents the relative price of brown versus green products. Higher demand for oil, the brown product, raises brown goods' prices and boosts brown firms' growth opportunities, lowering their cost of capital, while lower demand has the opposite effect.

Our empirical analysis supports these model predictions with robust evidence. First, the real price of oil is associated with higher relative product prices of brown goods. Second, the real price of oil positively correlates with brown firms' growth options relative to green firms', measured by Tobin's Q, return on equity, asset growth, and sales growth. Empirically, controlling for various firm characteristics, such as market-to-book ratios, profitability, and investment, can only partially account for the relation between the oil price and future firm growth. This underscores the need to explicitly consider the level of oil price in climate-related event studies.

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. Figure 2 shows that oil price fluctuations closely track key greenium dynamics over the past two decades, including the higher average greenium in recent years and additional greenium booms and busts.

It is important to emphasize that the negative impact of oil prices on greenium arises through growth opportunity variations without shifts in climate regulation and investor preferences. However, it remains possible that shifts in regulatory risks and sustainable preferences could influence both firms' cost of capital and oil prices simultaneously. Robustness

tests confirm that results hold robustly in the earlier sample when the attention to carbon transition is minimal. In addition, results also hold when replacing the oil price with the natural gas price, which is a key driver of brown firm profits but is often considered a transition energy unlike crude oil.

Furthermore, we 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. We further 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 carbon transition shocks. 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. 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, and the V-shaped oil price dynamics well explains the tent-shaped greenium dynamics in the event window. After controlling for oil price movements, the estimated impact of the PA on the greenium is no longer significantly positive. Next, we study the election of President Trump in November 2016 (Ilhan, Sautner and Vilkov, 2021), which reduced the perceived climate policy risk. This event coincided with the oil price recovery following the 2014 crash, marked by the Organization of the Petroleum Exporting Countries (OPEC) and Russia's decision to cut production that same month. We document a significant greenium decline following the election without controlling for the oil price and the effect is attenuated after the oil effect is controlled for.

Furthermore, we investigate whether estimates of the impact of climate attention 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 climate attention among the general public with Google search volume (Choi, Gao and Jiang, 2020) and among investors with the share of fixed-income 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, although the magnitudes appear minor compared to the impact of oil.

This paper fits in the literature that studies time-varying ex ante green premium. Hsu, Li and Tsou (2023) examine environmental policy risk, and Hartzmark and Shue (2022) investigate the role of past stock returns. Pedersen, Fitzgibbons and Pomorski (2021) and Pástor, Stambaugh and Taylor (2021, 2022) emphasize the role of green preferences, whereas Berk and van Binsbergen (2025) and De Angelis, Tankov and Zerbib (2023) report negligible impacts and Chen, Garlappi and Lazrak (2023) find opposite effects with the responsible consumption preference. To the best of our knowledge, this paper is the first to characterize the impact of oil prices on the ex-ante greenium, extending the focus beyond realized returns explored in studies like Blitz (2022) and Bolton, Kacperczyk and Wang (2024).[1] The channel we propose is the variation of growth opportunities, which persists even in the absence of carbon transition shocks, but fits in the investment-based literature (Liu, Whited and Zhang, 2009; Kuehn and Schmid, 2014). Our analysis adds to this literature by allowing for output heterogeneity and demand shocks.

Meanwhile, 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 implications of climate attention and sustainable

[1]Related, Sautner et al. (2023) and D'Amico, Klausmann and Pancost (2023) link the pricing of other climate-related risks to oil prices.

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 key climate events and shows that failing to account for oil price effects leads to biased estimates of the true impact of climate-related shocks.

The literature also actively debates the magnitude of the average greenium (Bolton and Kacperczyk, 2021; Aswani, Raghunandan and Rajgopal, 2024; Zhang, 2024). Our findings 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. One needs to exercise caution when interpreting the greenium estimates in a specific sample.

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 the oil price and greenium conceptually. First, we dissect the various drivers of oil price fluctuations and show that 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 through boosting the product prices and growth options of brown 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 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. Policy interventions like carbon taxes and emissions trading systems are also categorized under oil supply shocks. Aggregate economic activity shocks refer to fluctuations in aggregate economic conditions that influence the aggregate demand for all goods, exemplified by the U.S. recession following the Global Financial Crisis. Oil-specific demand shocks, which are orthogonal to oil supply and aggregate economic activity shocks, include oil consumption shocks and oil inventory shocks. These can result from industry-level demand shocks that disproportionally affect brown and green industries, such as demand shocks from China, pandemics and natural disasters, including shifts to remote work due to the COVID-19, and changes in responsible consumption preferences. In addition, technological advancements in energy efficiency and alternative energy sources, as well as seasonal variations and weather conditions, also affect oil demand.

We construct the real price of oil by adjusting the nominal price of oil using the U.S. Consumer Price Index (CPI). The nominal oil price is derived from the refiner acquisition cost of crude oil imports, as reported by the U.S. Energy Information Administration, while the U.S. CPI data are sourced from FRED at the St. Louis Fed. To quantitatively assess the contribution of each shock, we decompose oil price fluctuations using structural vector autoregression (SVAR) models proposed in Kilian (2009), Baumeister and Hamilton (2019), and Känzig (2021), respectively. Baumeister and Hamilton (2019) extend Kilian (2009)'s work by allowing for contemporaneous supply responses, and Känzig (2021) studies the role of oil supply news shocks in place of actual oil supply shocks, without decomposing other shocks. For detailed methodologies, we direct readers to the original papers and authors' websites. The Internet Appendix plots the time series of decomposed oil prices.

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 ease of exposition, the impact of oil demand shocks encompasses both oil consumption shocks and oil inventory shocks. The contribution of shock i to oil price fluctuations is quantified as:

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

Table 1 shows that oil supply shocks explain 5% and 17% of oil price variations according to Kilian (2009) and Baumeister and Hamilton (2019), respectively. Aggregate economic activity shocks explain a small fraction, no more than 6%. In contrast, oil demand shocks explain more than 75% of oil price variations in both models. Känzig (2021) finds that oil supply news shocks, which capture both actual supply shocks and oil-inventory demand shocks (Kilian and Zhou, 2023), explain 40% of oil price variations. Other orthogonal shocks, likely dominated by oil consumption demand shocks, play a significant role, accounting for 60%.

In short, oil demand shocks are the primary drivers of oil price variations over the past two decades. Consequently, we interpret oil price shocks as oil demand shocks in the rest of the paper. We conduct robustness analysis with decomposed shocks and confirm that the findings are indeed driven by oil demand shocks.

1.2 Model

This section now presents a highly stylized model to analyze the relation between the oil prices and greenium. Consider an economy in which agents consume brown goods, which are oil and gas products, and green goods or other products.[2] The green good is the numeraire in the economy. In the spirit of Kogan, Livdan and Yaron (2009) and Ready (2018), the

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

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

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

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

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

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

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

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

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 return or 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 $E_t\left[M_{t+1}r_{it+1}^K\right]=1$, in which r_{it+1}^K is the physical capital investment return,

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

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

$$r_{it+1}^K=w_{it}^b r_{it+1}^b+w_{it}^s r_{it+1}^s.\tag{12}$$

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

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

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 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 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

[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.

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 comovement between oil prices and brown product prices. Finally, we show that the growth option of brown firms increases more with the oil price 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) and 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. We employ Gebhardt, Lee and Swaminathan (2001) (GLS) estimates as our primary metric for ICC and then conduct robustness analysis using the average of the four published ICC 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 3 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%. 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 3 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 model assumption that the oil price is positively associated with product prices of brown firms. We examine the relation empirically using industry-level analysis employing the PPI data from the U.S. Bureau of Labor Statistics. We start with the mining industry in which the oil-and-gas companies belong. Because price levels are non-stationary, our analysis studies the relationship using price changes,

$$\Delta PPI_{it} = a + b \cdot 1(Mining)_{it} + c \cdot 1(Mining)_{it} \times \Delta Oil_t + \iota_t + e_{it+\tau}, \tag{17}$$

where $\Delta PPI_t = \log(PPI_t/PPI_{t-1})$ measures changes in the producer product price index (PPI) of the NAICS4 level that the firm belongs to, $1(Mining)$ equals one for the mining industry and zero otherwise, and $\Delta Oil_t = \log(Oil_t/Oil_{t-1})$ and X signifies firm-level characteristic controls. The regression model incorporates time fixed effects, with standard errors double clustered at both the industry and month levels. Columns (1) of of Table 4 lends strong support to the model assumption. A one-percent increase in the oil price increases the output price of the mining industry by 14 bps.

We further hypothesize that this relation holds not only for the oil-and-gas industries but

also general brown industries, because time-varying sectoral demand for brown-versus-green products is an important driver of oil price variations.[4] We run the following regression

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

where $Intensity$ denotes standardized carbon intensity. Columns (2) and (3) of Table 4 find that oil price variations positively affect the relative price of carbon-intensive products. Our estimates indicate that a one-percent increase in oil prices results in a 2 bps increase in the brown product price relative to green ones. And this estimate is 1 bp for scope 2 intensity. Overall, the effect is significantly positive but modest quantitatively, potentially due to the price rigidity as well as firm-level hedging of oil price shocks.

One possible concern is that the input price for brown industries also varies with the oil price, and the magnitude might exceed the changes in output prices. To address this, we build the input price index changes using the 71 industry-level input-output table from the Bureau of Economic Analysis (BEA). We scale the input price change by the cost of goods sold (COGS) share in total sales (SALE) for each industry using Compustat data. Columns (4) to (6) show that although the oil price positively impacts the COGS, the impact is minor and less than a third of the out price increase in all cases. In essence, our analysis demonstrates that oil price variations is significantly associated with 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

$$Y_{it+\tau} = a + b \cdot Intensity_{it} + c \cdot Intensity_{it} \times Oil_t + d \cdot X_{it} + \iota_t + e_{it+\tau}, \tag{19}$$

[4]Katz and Rosen (1985) and Kimmel (1992) show that a negative productivity shock or an increase in the input price, such as oil, can lead to higher output prices and higher profits in an oligopolistic industry, even without demand shocks for brown products.

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 5 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 start with the corporate bond market, in which the cost of capital is measured more precisely. We estimate the following panel regression:

$$YieldSpread_{it} = a + b \cdot Intensity_{it} + c \cdot Intensity_{it} \times Oil_t + d \cdot X_{it} + \iota_t + e_{it}. \tag{20}$$

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

Consistent with the model prediction, Panel A of Table 6 shows that oil price fluctuations negatively impact the greenium ($c < 0$). Columns (1) and (2) show that a one-standard-deviation increase in oil prices leads to a reduction of 7.80 bps and 11.91 bps in the greenium for scopes 1 and 2, respectively. Because of the fat-tailed distribution of oil prices, the realized impact of oil prices can be large. For example, the 2014 oil crash, a three-standard deviation event, would lead to a reduction of approximately 23 bps and 35 bps 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 to -3.58 and -5.49 and remains highly significant. This finding is consistent with the earlier results that

firm-level controls capture only a portion of the oil price's influence on the growth options of brown firms.

For other variables, the mean greenium (b) tends to be positive without bond controls in this sample, but turns negative after these controls are included. Credit spreads widen as bond duration increases and credit ratings decline. 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 firm leverage and equity volatility as expected.

We next turn to equity and measure the ex-ante cost of equity with GLS mechanical estimates (Gebhardt, Lee and Swaminathan, 2001). Lee, So and Wang (2021) show that these implied cost of capital (ICC)-based estimates are most reliable in the time series analysis. Results in Panel B of Table 6 further corroborate the primary findings in corporate bonds: the oil price exhibits a robust inverse relationship with the equity greenium. 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 bps 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 bps and -11.91 bps. Incorporating controls for a broader set of firm characteristics again moderates these estimated coefficients to -5.34 and -9.62 bps, yet the coefficients remain highly significant. For the mean greenium, carbon-intensive firms' mean ICCs tend to be lower than those of less carbon-intensive firms in this sample.

Furthermore, to mitigate concerns about potential measurement error in the ICC estimates, we perform a robustness check using the simple average of four different ICC measures as studied in Lee, So and Wang (2021) in the Table IA.1 in Internet Appendix and find a robust negative relation between the oil price and greenium

In summary, 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. COnsequently, the greenium variation over time cannot be simply interpreted as the repricing of carbon transition risk in financial markets. Instead, it can reflect variations in expected returns driven by oil demand shocks through changes in growth opportunities.

3.2 Time Series Analysis

In this section, we extend the baseline analysis with a time series approach to the greenium, providing a narrative discussion of its time variation. We first sort firms into three terciles based on the carbon intensity and then calculate the greenium b_t as the value-weighted high-minus-low difference in yield spreads and GLS ICC estimates for bonds and equity, respectively. 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. The time series regression of the greenium on the standardized oil price follows

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

Panel A of Table 7 confirms the negative relation. 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 and shows that the greenium rise and fall well accords with oil price variations. First, the greenium varies substantially throughout the sample but becomes more elevated from mid 2014 onward, a trend that aligns with the below-mean oil price observed over the same interval. Second, the past two decades, two major boom-and-bust cycles in oil prices have closely aligned with greenium fluctuations. The first oil price bust occurred between 2014 and 2016, while the second took place in 2020. These dramatic crashes and recoveries in oil prices are mirrored by sharp rallies and reversals in the bond greenium and similar, albeit less pronounced, patterns in the equity greenium.

3.3 Robustness Analysis

We conduct a few robustness analyses below. First, 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 oil price shocks decomposed in Baumeister and Hamilton

(2019), the most flexible SVAR model that decomposes oil demand shocks, and proxy for oil price variations driven by individual shocks as the cumulative 12-month impact of each shock. We conduct the following regression

$$R_{it} = a + b \cdot Intensity_{it} + \mathbf{c} \cdot Intensity_{it} \times \mathbf{CumShock}_t + d \cdot X_{it} + \iota_t + e_{it}, \qquad (22)$$

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. 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.

It is worth highlighting that the impact of oil prices can arise through product price variations even without carbon transition shocks, such as shifts in climate regulation and investor preferences. However, it remains possible that regulatory risks and sustainable preferences influence both firms' cost of capital and oil prices simultaneously. In the second robustness tests, we conduct additional subsample analyses to futher address the concern regarding carbon transition shocks. Before 2010, discussions of carbon transition were minimal. Google Trends labeled "carbon transition" or "decarbonization" as having "not enough data for this term", and no databases provided point-in-time carbon emissions data.[5] The concept of "carbon transition" began to emerge in 2009, but did not gain significant public attention until the Paris Agreement brought policymakers together in December 2015. Indeed, Google Trends reported mostly "not enough data" for terms like "decarbonization" and "ESG investing" from 2009 to 2015. From the Paris Agreement onward, transition discussions expanded to a broader audience, aligning with the sample periods examined in

[5]S&P Trucost backfilled emissions data prior to 2009 in May 2009.

existing event studies. Panel C of Table 7 shows that the negative relationship between the oil price and greenium 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. Table IA.2 in the Internet Appendix includes the analysis with further controls and results remain robust.

Next, we extend our analysis beyond crude oil to 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 comparable share in the U.S. and become a key revenue source of U.S. oil-and-gas companies. In addition, the natural gas is the fossil fuel with the lowest emission intensity and is often perceived as a transition energy and less exposed to transition shocks.[6] Results in Panel D again document that a negative impact of the natural gas prices on the greenium. The magnitudes tend to be even slightly larger than the baseline estimates, suggesting that the results are less driven by carbon transition-related shocks.

In summary, fluctuations in the real price of oil significantly impact the greenium explaining key greenium 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.

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

$$YieldSpread_{ijt} = a + b \cdot Intensity_{ijt} + \beta \cdot Intensity_{ijt} \times Oil_{jt}^{LOC} + c \cdot X_{ijt} + d_j + e_t + \varepsilon_{it}, \quad (23)$$

[6]For example, natural gas is included as a clean energy source in the Clean Energy Standards, which are first introduced during the Obama administration.

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, 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.

The international sample further allows us to zoom in on the relation between oil price variations and carbon transition-related shocks through an instrument variable (IV) approach. Since oil prices are determined globally and predominantly invoiced in U.S. dollar, a shift toward green preferences could decrease the demand for fossil fuels and lower oil prices in U.S. dollars. However, fluctuations in exchange rates 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 carbon transition-related shocks.[7] The first stage of the two-stage least squares (2SLS) estimation shows a strong relationship between exchange rate fluctuations and real price of oil variations and is included in the Table IA.3 of the Internet Appendix. The subsequent 2SLS estimates in Panel B of Table 8 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 in Panel A, suggesting

[7]We exclude oil-reliant countries whose oil export share in their total export is greater than 20% in Table IA.4 of the Internet Appendix, and results are robust.

that the endogeneity or reverse causality issue is less important in this context.

In summary, oil price variations driven by demand shocks correlate with relative product price variations and have a negative impact on the greenium. This relation takes place even without carbon transition-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 results on ICC measures, which are less imprecisely estimated, are deferred in the Internet Appendix and discussed toward the end of this section.

4.1 The Paris Agreement

The most studied event in the climate literature is arguably the Paris Agreement. Adopted by 196 Parties at the UN Climate Change Conference (COP21) in Paris on December 12, 2015, the agreement aims to hold "the increase in the global average temperature to well below 2°C above pre-industrial levels" and to "limit the temperature increase to 1.5°C above pre-industrial levels." A 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 specifica-

tion to isolate the impact of the PA:

$$YieldSpread_{it} = a + b \cdot Intensity_{it} \times AfterPA_t + c \cdot X_{it} + d_i + e_t + \varepsilon_{it}, \tag{24}$$

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 PA well coincides with the oil bust and recovery from 2014 to 2016. Figure 2 shows that the oil price crash began in mid 2014, reached its bottom in January 2016, and recovered strongly from that point onward. This V-shaped pattern in the oil price mirrors the tent-shaped dynamics in the greenium in the event window. The oil crash was related to a general oversupply of U.S. shale oil, the response of the OPEC not to cut production in an attempt to maintain market share[8], as well as weakened demand growth due to improved improved energy efficiency and weak Chinese economy. The oil rebound was driven more by a resurgence in global demand. In short, the oil price shock confounds the PA event, necessitating explicit control for oil price variations.

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

$$YieldSpread_{it} = a + b \cdot Intensity_{it} \times AfterPA_t + \beta \cdot Intensity_{it} \times Oil_t + c \cdot X_{it} + d_i + e_t + \varepsilon_{it}, \tag{25}$$

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

[8]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.

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. 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, 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 price level differentially influences expected returns of brown and green firms through a conditional risk premium channel, an effect that an unconditional oil beta fails to capture. Supplementary results presented in Table IA.5 of 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 through potential subsidies to green energy or investor and consumer preference shifts. However, oil price movements around the PA do not align with these hypotheses. The sustained 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 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.

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 boosted oil prices and demand for the U.S.-produced oil. As such, this oil market development would lead to a reduction in the greenium directly and should be controlled for.

We now assess the election's impact on the greenium without and with the oil control. First, we employ the regression model outlined in Eq. (24) and examine the 12 months surrounding the event. 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). To account for the oil impact, we incorporate oil price fluctuations into our regression model as specified in Eq. (25). 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 strong performance of green assets and

higher expected returns of brown firms in recent years. 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.

Figure 3 shows that the greenium rose sharply from 2017 to 2020, mirroring the rise of sustainable investing, but reversed subsequently, despite record sustainable inflows in 2021 and stable sustainable assets in 2022. In contrast, the oil price dynamics aligns more closely with greenium trends, as the oil price plunges to a sample low in 2020 and recovered steadily thereafter. This pattern underscores the need to account for oil prices when estimating the impact of climate attention and sustainable investing.

We employ two measures to quantify climate attention and sustainable investing: 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.

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

$$\begin{aligned} YieldSpread_{it} =& a + b \cdot Intensity_{it} + c \cdot Intensity_{it} \times Attention_t + d \cdot X_{it} + e_t + \varepsilon_{it}, \\ YieldSpread_{it} =& a + b \cdot Intensity_{it} + c \cdot Intensity_{it} \times Attention_t + \beta \cdot Intensity_{it} \times Oil_t \\ & + d \cdot X_{it} + e_t + \varepsilon_{it}. \end{aligned} \tag{26}$$

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. After controlling for oil price variations in columns (3) to (6), the positive association between 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, broadly in line with the insignificance of ESG flow and ESG asset in Pástor, Stambaugh and Taylor (2022). Because 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. For comparison, the oil price experienced a three-standard-deviation recovery from 2020 to 2022, reducing the greenium by 35 and 60 bps 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 minor compared to the substantial impact of oil price volatility.

Finally, we repeat the event study analysis above in equity in Table IA.7 and IA.8 of the Internet Appendix, with the caveat that ICCs are measured with noise. Consistent with the evidence in bonds, the greenium does not respond to climate-related events with the intended signs in most exercises. The only exception is the impact of "climate attention", which generates a small positive impact. As such, the evidence on the repricing of carbon footprint in asset prices around key events is scarce.

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 only minor, if any, effects on asset prices.

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 policy risks or sustainability preferences. The evidence underscores challenges of relying solely on time series shocks in climate finance event studies, highlighting the need to carefully account for oil price dynamics. Cross-sectional shocks across multiple entities can serve as valuable complementary evidence. In addition, while this paper focuses on the greenium, oil prices have broader implications for carbon pricing, firms' capital budgeting, bank lending, and corporate behavior.

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

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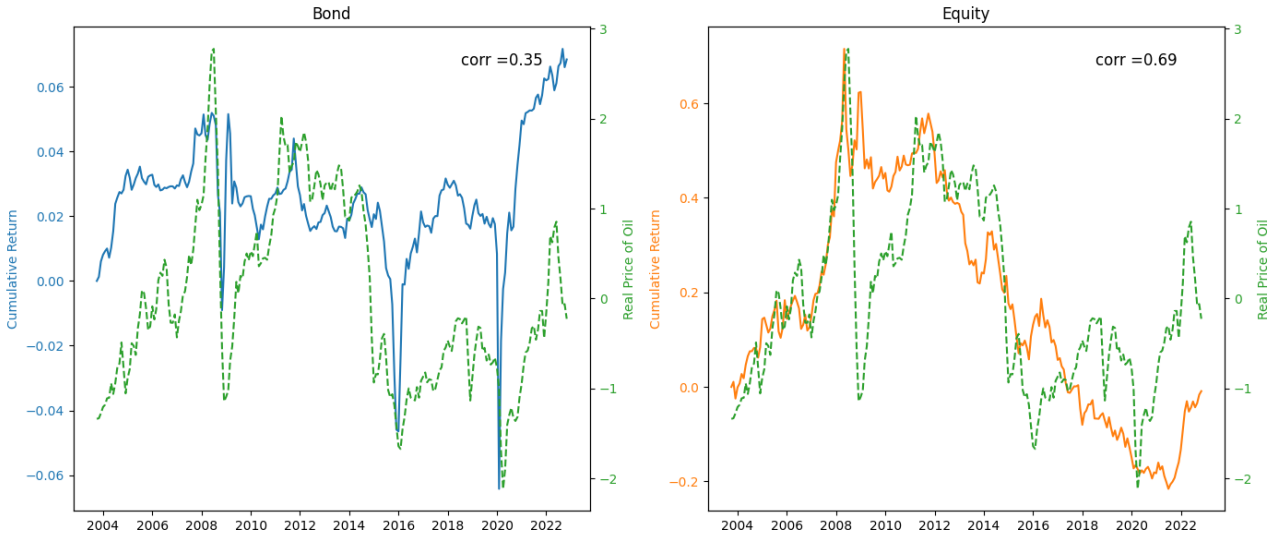
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Figure 1: Brown Return and Oil Price



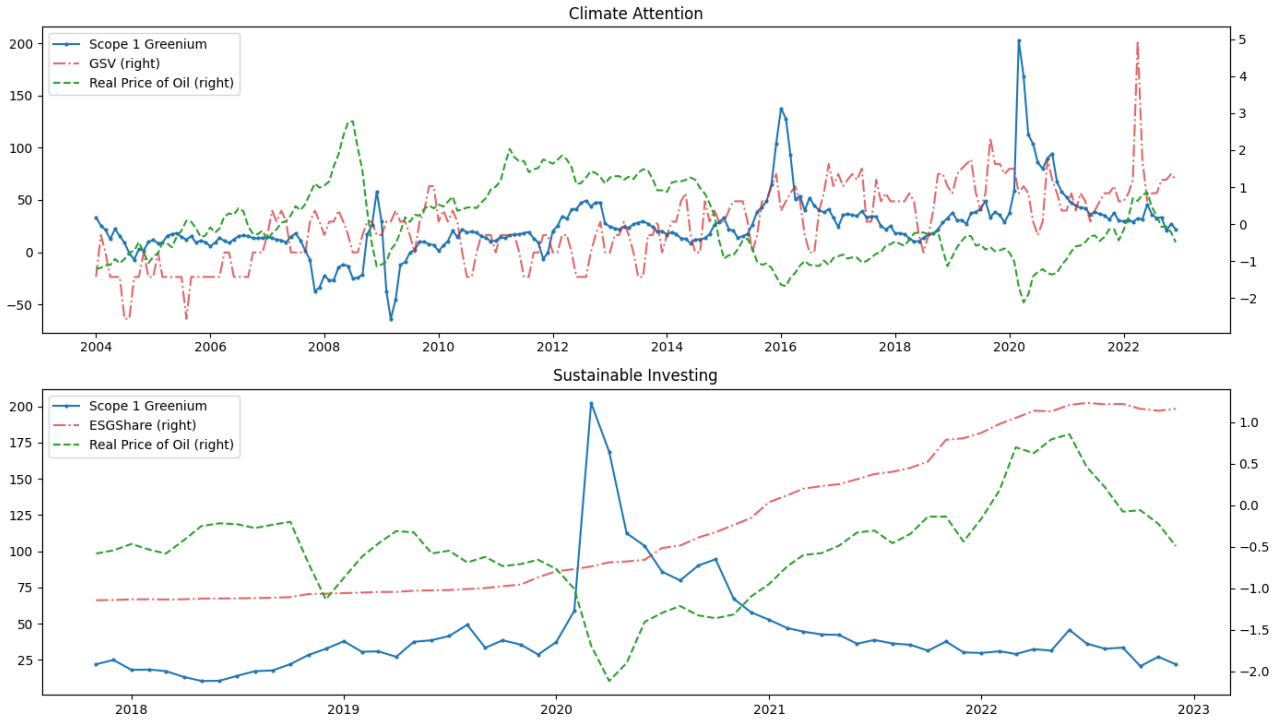
Notes: This figure plots the cumulative brown return and the standardized real price of oil. The monthly brown return is the value-weighted return difference between the top tercile of firms with the highest scope 1 carbon intensity and the bottom tercile. The real price of oil is standardized to have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

Figure 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 (bps) between the top tercile of firms with the highest carbon intensity and the bottom tercile for scopes 1 and 2, respectively. The equity greenium is the value-weighted GLS mechanical ICC estimate difference (bps) between the top tercile of firms with the highest carbon intensity and the bottom tercile for scopes 1 and 2, respectively. The first vertical line denotes the Paris Agreement and the second vertical line denotes the 2016 election of President Trump. The sample period is 2003:10 to 2022:12.

Figure 3: Climate Attention and Sustainable Investing



Notes: This figure plots the series of standardized climate attention (GSV), ESGShare, real price of oil together with the time series of scope 1 bond greenium (bps). The scope 1 bond greenium is the value-weighted yield spread difference (bps) between the top tercile of firms with the highest scope 1 carbon intensity and bottom tercile, respectively.

Table 1: Decomposition of Oil Price Shocks

	Oil Supply	Economic activity	Oil demand
Kilian (2009)	0.05	0.03	0.92
Baumeister & Hamilton (2019)	0.17	0.06	0.77
	Oil Supply News	Other	
Känzig (2021)	0.40	0.60	

This table presents historical contribution of separate structural shocks to oil price innovations from 2003:10 to 2022:12, quantified using different models. The reported contribution of oil demand shocks in Baumeister and Hamilton (2019) model represents the total contribution of oil speculative and consumption shocks.

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$(P_t, \text{Marginal } Q_t^{B-G})$		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: 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
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
$\text{CumShock}_{Supply}(\%)$	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
$\text{CumShock}_{Oil}(\%)$	-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 4: Oil Price and Producer Price

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔOutput PPI			Scaled ΔInput PPI		
1(Mining)	0.25**			0.02		
	(2.29)			(0.39)		
Scope 1 Intensity		0.08***			-0.01	
		(3.02)			(-0.48)	
Scope 2 Intensity			0.04***			-0.00
			(2.90)			(-0.32)
×Oil	13.79***	2.37***	1.03***	1.41*	0.78**	0.15
	(11.41)	(8.65)	(5.01)	(1.94)	(2.28)	(1.23)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26498	26498	26498	10200	10200	10200
R^2	0.063	0.059	0.049	0.476	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) to (3)), and input PPI changes scaled by the share of cost of goods sold in in total sales (columns (4) to (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 5: 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)
×Oil×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}		$\Delta Sales_{t+12}$		ΔAT_{t+12}		$\Delta Sales_{t+12}$	
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)
×Oil×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 6: Oil Price and Greenium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Yield Spread Estimates				Panel B: ICC Estimates			
Scope 1 Intensity	10.78**		-4.52*		-45.65***		-48.87***	
	(2.18)		(-1.91)		(-5.48)		(-9.71)	
Scope 2 Intensity		10.63		-1.70		-83.61***		-26.20***
		(1.55)		(-0.45)		(-7.74)		(-3.56)
×Oil	-7.80***	-11.91**	-3.58**	-5.49*	-11.21***	-22.36***	-5.34**	-9.62**
	(-3.25)	(-2.42)	(-2.15)	(-1.84)	(-2.93)	(-3.91)	(-2.04)	(-2.23)
duration			6.80***	6.79***				
			(27.47)	(28.09)				
Bond Age			2.67***	2.56***				
			(8.07)	(8.47)				
Bond Rating			21.71***	20.82***				
			(9.15)	(9.25)				
Beta			13.22***	16.65***			8.81	17.69***
			(3.29)	(4.52)			(1.52)	(2.77)
Size			-27.78***	-28.18***			-14.41***	-13.98***
			(-6.47)	(-6.51)			(-4.20)	(-3.78)
BE/ME			-4.66	-5.55*			181.02***	174.87***
			(-1.62)	(-1.89)			(29.15)	(28.21)
Momentum			-41.31***	-42.27***			-62.68***	-67.76***
			(-7.47)	(-7.74)			(-8.44)	(-8.94)
ROE			-34.60***	-34.43***			281.82***	289.86***
			(-3.00)	(-3.02)			(12.42)	(12.64)
Asset Growth			-0.14	0.64			-15.57***	-13.91**
			(-0.03)	(0.16)			(-2.87)	(-2.55)
Sales Growth			-17.50***	-16.79***			7.00	6.03
			(-2.73)	(-2.70)			(0.85)	(0.73)
Leverage			19.03***	19.06***			69.11***	70.40***
			(4.27)	(4.08)			(8.42)	(8.54)
IVol			0.40***	0.40***			16.65***	15.02***
			(8.51)	(8.66)			(4.91)	(4.19)
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	0.609	0.620	0.115	0.123	0.510	0.497

Notes: This table regresses the maturity-matched yield spreads and ICC measures on the standardized carbon intensity, its interaction with the standardized real price of oil (Oil), and bond or firm characteristics. Panel A focuses on the maturity-matched yield spread estimates and Panel B studies the Gebhardt-Lee-Swaminathan mechanical estimates. 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 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	
	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)
$\times$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)
$\times$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)
$\times$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: Sub-sample Analysis							
	Before 10/2009		11/2009-12/2015		Post 12/2015			
	Bond							
Intensity$\times$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)		
Intensity Control	Yes	Yes	Yes	Yes	Yes	Yes		
Characteristic Controls	No	No	No	No	No	No		
Time FE	Yes	Yes	Yes	Yes	Yes	Yes		
Observations	77164	77152	155614	155352	296758	296728		
R^2	0.406	0.406	0.062	0.062	0.097	0.092		
	Equity							
Intensity$\times$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		
Characteristic Controls	No	No	No	No	No	No		
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		

(*Continued*)

Table 7: Robustness Analysis—*Continued*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel D: 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

This table conducts robustness analysis on the relation between the greenium and oil prices. Panel A studies time series of the greenium, which is calculated as the value-weighted spread between high and low carbon intensity tercile portfolios. Panel B assesses the role of decomposed oil price shocks and Panel C conducts the subsample analysis. Panel D examines the standardized real natural gas prices. Newey-West standard errors for Panel A account for 12 lags and standard errors for Panel B - D are double clustered at the firm and month levels. 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)
$\times \text{Oil}^{LOC}$	-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

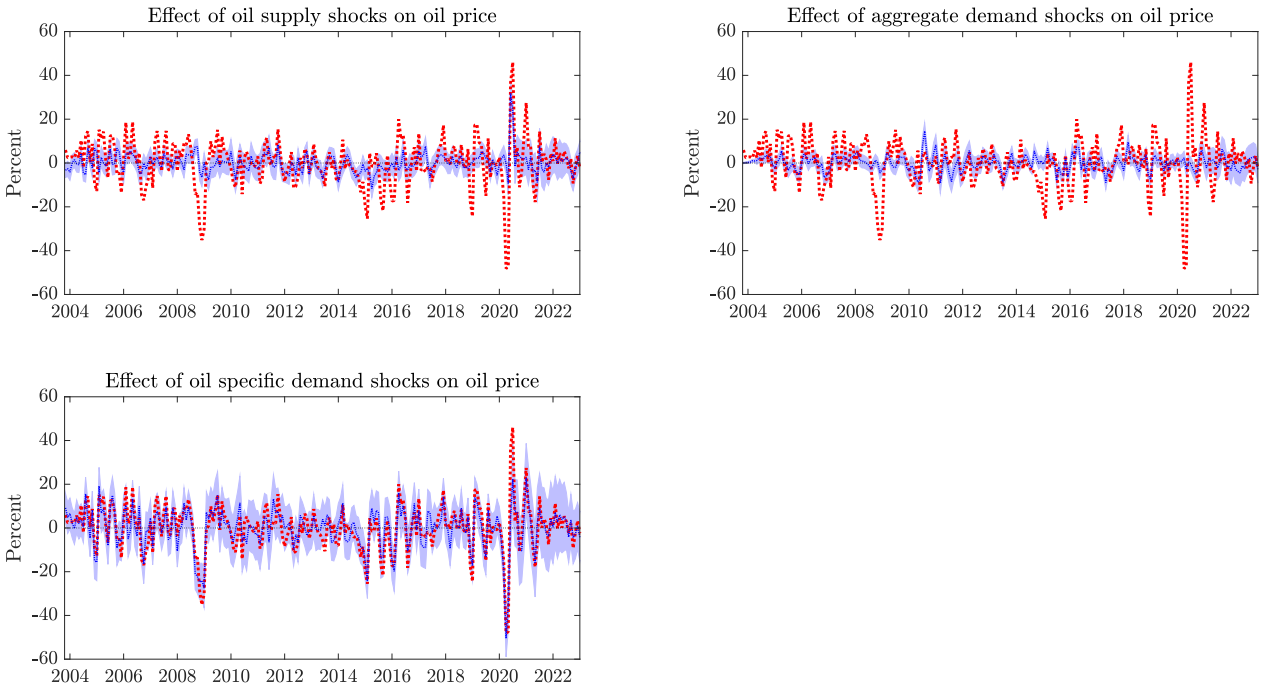
Notes: This table studies the greenium variation around the Paris Agreement and 2016 Election of President Trump. The analysis regresses duration-matched yield spreads on the standardized carbon intensity's interaction with the post-event dummy and interaction with the standardized real price of oil. 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

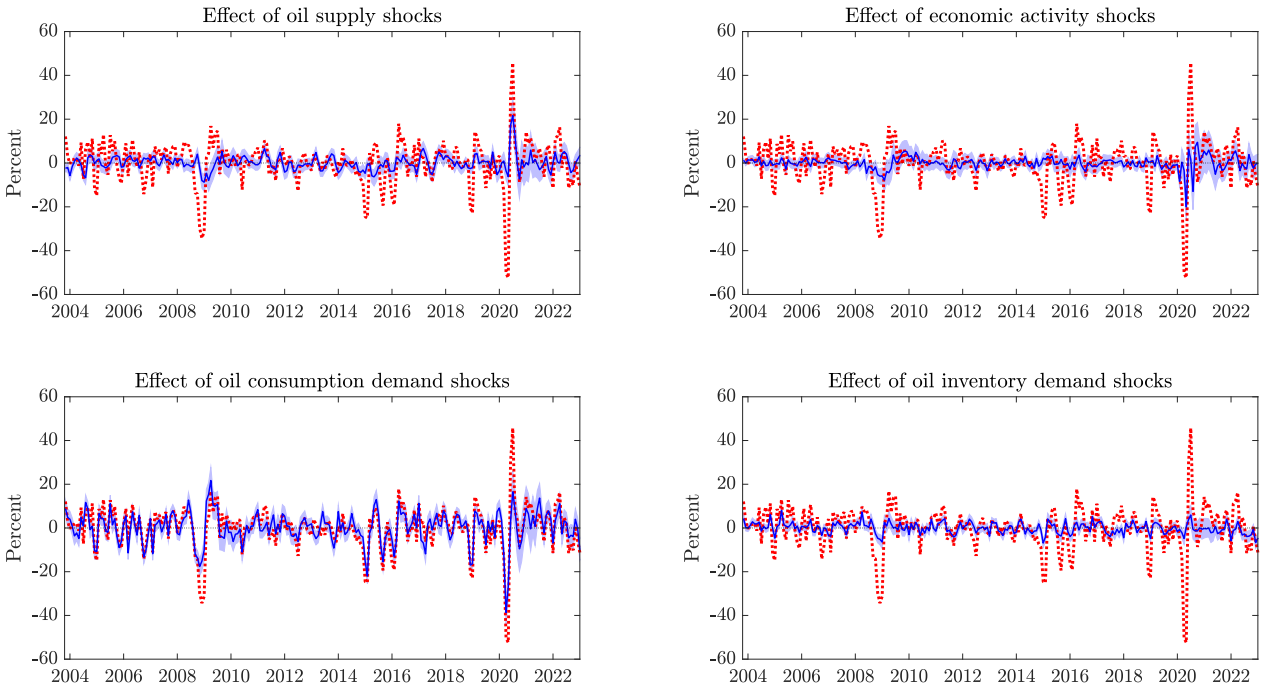
Notes: This table studies the greenium co-variation with climate attention and sustainable investing. The analysis regresses corporate yield spreads on the standardized carbon intensity, its interaction with the climate attention measures and its interaction with the standardized real price of oil. Reported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

Figure IA.1: Kilian (2009) Decomposition



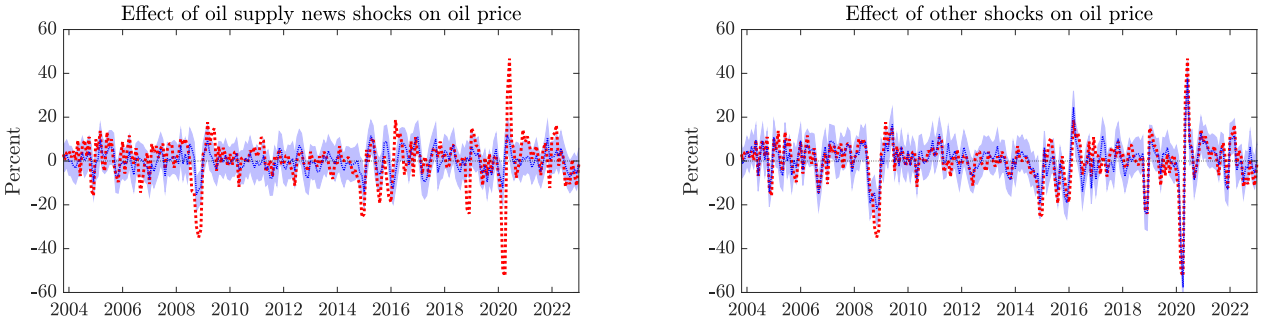
Notes: This figure plots innovations in the real price of oil (red dotted lines) and the median estimate of the historical contribution of separate structural shocks (blue lines) for the baseline Kilian (2019) model. Blue shaded regions indicate 95 percent posterior credibility regions.

Figure IA.2: Baumeister and Hamilton (2019) Decomposition



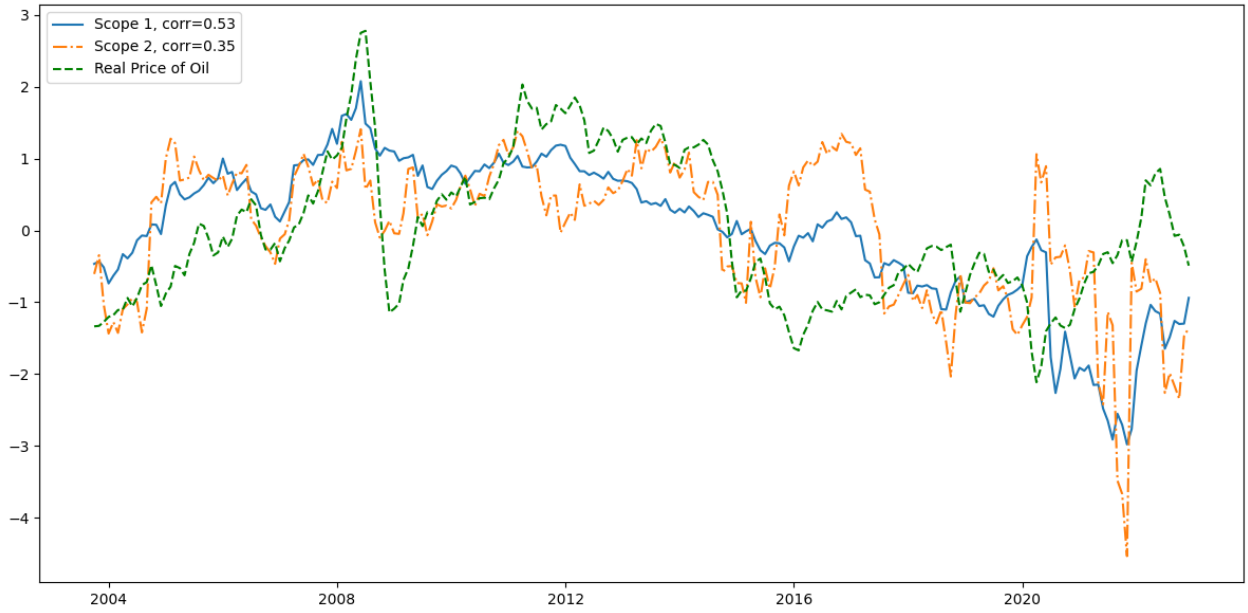
Notes: This figure plots innovations in the real price of oil (red dotted lines) and the median estimate of the historical contribution of separate structural shocks (blue lines) for the baseline Baumeister and Hamilton (2019) model. Blue shaded regions indicate 95 percent posterior credibility regions.

Figure IA.3: Känzig (2021) Decomposition



Notes: This figure plots innovations in the real price of oil (solid blue lines) and the contribution of non-oil supply news shocks for the baseline Känzig (2021) model.

Figure IA.4: 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.

Table IA.1: Oil Price and Average ICC Greenium

	(1)	(2)	(3)	(4)
Scope 1 Intensity	-11.55***		-12.38***	
	(-4.49)		(-7.78)	
Scope 2 Intensity		-22.72***		-7.52***
		(-6.89)		(-3.32)
×Oil	-4.18***	-10.73***	-2.07*	-6.91***
	(-2.98)	(-5.10)	(-1.88)	(-3.81)
Beta			8.11***	10.61***
			(3.53)	(4.17)
Size			-3.21***	-3.10***
			(-2.95)	(-2.70)
BE/ME			48.87***	47.21***
			(23.71)	(23.65)
Momentum			-19.24***	-20.57***
			(-8.47)	(-8.86)
ROE			54.31***	56.53***
			(8.53)	(8.81)
Asset Growth			-5.80**	-5.44**
			(-2.48)	(-2.33)
Sales Growth			6.46	6.39
			(1.38)	(1.37)
Leverage			24.30***	24.50***
			(7.10)	(7.17)
IVol			6.58***	6.16***
			(5.31)	(4.77)
Time FE	Yes	Yes	Yes	Yes
Observations	209955	209873	200774	200692
R^2	0.571	0.574	0.704	0.702

Notes: This table regresses the average ICC measures on the standardized carbon intensity, its interaction with the standardized real price of oil (Oil), and bond or firm 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 2003:10 to 2022:12.

Table IA.2: Subsample Analysis with Controls

	(1)	(2)	(3)	(4)	(5)	(6)
	Before 10/2009		11/2009-12/2015		Post 12/2015	
			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
Characteristic Controls	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
Characteristic Controls	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 with the full set of bond or equity characteristic controls. 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: 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.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)
$\times \text{Oil}^{LOC}$	-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.

Table IA.7: Event Study In Equity

	(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	-37.41***	-11.22	-47.90***	-19.13	-17.89**	-7.34
	(-3.80)	(-0.90)	(-4.18)	(-1.28)	(-2.37)	(-0.73)
Intensity×Oil			-20.78**	-15.40	3.86	5.93
			(-2.22)	(-1.48)	(0.58)	(0.87)
Controls	No	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	19939	19921	19939	19921	19212	19194
R^2	0.768	0.766	0.769	0.766	0.854	0.853
	Panel B: Trump Surprise Election					
Intensity×Post Election	5.06	26.71**	6.79	24.92**	-0.93	16.34*
	(0.52)	(2.30)	(0.71)	(2.12)	(-0.14)	(1.83)
Intensity×Oil			-5.46	6.61	3.52	4.39
			(-0.57)	(0.63)	(0.45)	(0.55)
Controls	No	No	No	No	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20606	20599	20606	20599	19875	19868
R^2	0.821	0.822	0.821	0.822	0.879	0.879

Notes: This table studies the equity greenium variation around the Paris Agreement and 2016 Election of President Trump. The analysis regresses annualized GLS mechanical ICC estimates 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 IA.8: Climate Attention and Sustainable Investing in Equity

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Google Search Volume					
Scope 1 Intensity	-62.19***		-54.11***		-65.82***	
	(-4.04)		(-3.94)		(-7.63)	
Scope 2 Intensity		-154.72***		-143.36***		-60.05***
		(-7.27)		(-7.49)		(-4.23)
× Attention	10.05	42.36***	4.90	35.01***	10.02**	19.80***
	(1.47)	(4.03)	(0.86)	(3.89)	(2.49)	(2.99)
×Oil			-10.05***	-15.70***	-3.43	-5.86
			(-2.95)	(-2.90)	(-1.39)	(-1.40)
Controls	No	No	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	208954	208872	208954	208872	199817	199735
R^2	0.115	0.124	0.115	0.124	0.510	0.498
	Panel B: Sustainable Investing					
Scope 1 Intensity	-27.68***		-28.43***		-34.64***	
	(-2.99)		(-3.11)		(-5.64)	
Scope 2 Intensity		-45.52***		-47.05***		1.34
		(-3.68)		(-3.92)		(0.17)
×ESGShare$_{EQ}$	-34.36***	-30.28**	-38.08***	-35.92***	-24.10***	-37.14***
	(-3.79)	(-2.33)	(-4.28)	(-2.74)	(-3.39)	(-4.07)
×Oil			-11.89***	-19.97***	-6.99**	-11.03**
			(-3.04)	(-3.28)	(-2.54)	(-2.52)
Controls	No	No	No	No	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	163935	163870	163935	163870	156425	156360
R^2	0.081	0.081	0.082	0.082	0.499	0.488

Notes: This table studies the equity greenium co-variation with climate attention and sustainable investing. The analysis regresses GLS mechanical ICC estimates 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.