Beyond Brown: Oil Shocks and Carbon Premium

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Abstract

This paper shows that the aggregate "carbon premium"—the higher cost of capital for carbon-intensive firms—is confounded by oil shocks. We decompose it into an energy premium (Energy minus non-energy brown) and a non-energy carbon premium (non-energy brown minus green). Oil shocks primarily move the energy premium by shifting output prices, growth options, and risk exposures, while other brown firms are insulated because they pass input-cost shocks through to prices. Re-examining the 2015 Paris Agreement, we show that the previously documented post-event premium increase largely reflects the 2014–2016 oil crash rather than a broad repricing of transition risk.

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

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How do financial markets price the risks of carbon transition? With trillions of dollars now allocated to sustainable investment strategies, this question has become one of the most pressing in modern finance. A large and rapidly expanding literature addresses it by studying the "carbon premium"—the systematic difference in the cost of capital between carbon-intensive ("brown") firms and their cleaner ("green") counterparts. The prevailing view is that this premium, and its recent increase, reflect investors' demand for compensation for bearing carbon-transition risk (Figure 1). In principle, such market-driven pricing could help facilitate the net-zero transition with limited government intervention.

However, this interpretation may be overstated. Many of the climate events used to study the carbon premium coincide with sharp oil price movements, often driven by oil-demand collapses or foreign supply shocks. For instance, the landmark Paris Agreement occurs near the trough of the 2014–2016 oil price collapse. As a result, movements in the measured carbon premium may be misattributed to transition risk when they instead reflect changes in the risks faced by oil-dependent firms.

This confounding channel is reinforced by the composition of "brown" portfolios, which are dominated by Energy, Utilities, and Materials firms. Although Energy firms are less carbon-intensive than Utilities and Materials, they account for the largest share of brown assets. Because Energy firms have direct exposure to oil price movements, the aggregate carbon premium can reflect oil-market dynamics rather than genuine transition risk.

In this paper, we show that oil shocks are a major and underappreciated driver of the observed carbon premium. Once these shocks are accounted for, the explanatory power commonly attributed to the Paris Agreement largely disappears. We also identify periods in which the influence of oil shocks is particularly pronounced and should be interpreted with caution.

To investigate the role of oil shocks, we first distinguish the direct economic mechanisms through which oil price fluctuations affect different types of brown firms. For the Energy sector, comprising traditional oil-and-gas firms, crude oil is a primary output. Consequently, oil price movements directly shape these firms' output prices, fundamentals, and risk exposures, including their growth opportunities (Tobin's Q and realized future growth) and their value factor (HML) loadings, relative to other firms. For other brown firms, such as Utilities and Materials, the channel is quite different. These firms are exposed to oil price changes primarily through input costs. However, they are often able to pass these costs through to output prices in competitive markets, leaving a smaller net effect on their profit margins. Hence, a shock that represents a relative windfall for oil producers constitutes only a secondary effect on other brown firms, even though both are classified as "brown."

This fundamental heterogeneity implies that aggregating all brown firms into a single portfolio obscures their distinct responses to oil and climate shocks. The asymmetry, however, provides a valuable identification opportunity: oil shocks predominantly affect energy firms, while genuine carbon transition shocks influence the broader expected return variation across all brown firms.

A central case study in the literature linking financial markets to carbon transition risk is the Paris Agreement (PA) of December 2015. The PA is widely interpreted as a pivotal moment shaping climate policy expectations, with heterogeneous implications for firms depending on their carbon intensity. As of October 2025, more than 1,700 studies have employed event-study designs to assess market or firm reactions to the PA (e.g., Monasterolo and De Angelis (2020); Bolton and Kacperczyk (2021, 2023); Seltzer, Starks and Zhu (2025)). However, this interpretation faces a fundamental identification challenge: the Agreement coincides with the trough of the historic 2014–2016 oil price collapse. Driven by the U.S. shale expansion and OPEC's November 2014 decision to initiate a price war, this collapse fundamentally altered the financing conditions of energy firms that dominate "brown" portfolios. Our event study of the OPEC announcement reveals that the cost of capital for energy firms rises sharply relative to other sectors, and such an adjustment is absent among non-energy carbon-intensive firms. This divergence serves as a crucial cautionary tale: if an econometrician were to mistakenly take this period of energy sector distress as a baseline for a climate event study, they would erroneously attribute the widening spread to transition risk. This confounding scenario is not merely hypothetical; it directly prefigures the identification challenge surrounding the 2015 Paris Agreement.

Standard event studies document a significant increase in the bond carbon premium following the Paris Agreement, with mixed response in equity markets, typically interpreted as evidence that bond investors internalized higher transition risk. We argue this interpretation is misleading. The upward trend in carbon premia began as early as mid-2014, aligning with the onset of the oil price collapse. When we explicitly account for the asymmetric response of the energy sector, whose cost of capital is tightly linked to oil price fluctuations, the post-PA rise in the carbon premium vanishes. Similarly, specifications incorporating sector-by-time fixed effects, which capture broad cross-sector movements, yield the same null result. In contrast, conventional approaches such as controlling for security-level oil betas prove insufficient: these backward-looking measures are imprecise and fail to capture the highly non-linear dynamics that characterized the 2014–2016 oil cycle. Taken together, these findings suggest that what has often been interpreted as a landmark market response to a global climate policy shock primarily reflects leading and contemporaneous energy market dynamics, rather than a genuine repricing of carbon transition risk.

We extend our analysis beyond the Paris Agreement by decomposing the aggregate carbon premium into an "energy premium" (the excess cost of capital of energy firms over non-energy brown firms) and a "non-energy carbon premium" (non-energy brown vs. green). In our main sample (October 2003–December 2022), oil price increases strongly reduce the energy premium but exhibit a small, inconsistent correlation with the non-energy carbon premium. Using a structural vector autoregression (SVAR) decomposition, we further identify that demand-like oil shocks are the key drivers of these variations, lowering the cost of capital for energy firms without spilling over into the non-energy carbon premium. This asymmetry indicates that oil fluctuations affect the aggregate premium through energy-sector fundamentals rather than a broad-based pricing of transition risk.

To further rule out reverse causality from transition risk, we examine renewable energy firms as a falsification test. We find that higher oil prices significantly reduce renewable firms' financing costs, mirroring the response of oil-and-gas firms. This pattern indicates that the market prices these episodes as sector-wide energy economics rather than as a divergence between green and brown assets. This interpretation is further supported by a historical sample (1974–2003) predating the modern climate era, in which the negative oil–energy-premium relationship remains structural and robust. Finally, oil price innovations are nearly uncorrelated with climate-concern shocks and sustainable flows, reinforcing that climate sentiment is not a first-order driver of oil prices in the long sample.

We further quantify the impact of these energy-specific shocks on the aggregate carbon premium over time. To do this, we attribute any aggregate premium variations not explained by the non-energy carbon premium to the energy sector. This orthogonalization method conservatively attributes shocks common to all brown firms (such as climate shocks, which would move both the non-carbon brown premium and energy premium) to the non-energy carbon premium. This contribution is highly aligned with the oil cycle. During periods of intense oil shocks, such as the 1980s oil glut, the Global Financial Crisis, the 2014-2016 crash, the COVID-19 lockdown, and the 2022 Russo-Ukrainian war, these orthogonal movements in the energy sector can account for more than half of total carbon premium variations. The results underscore the significant risk of omitted variable bias when analyzing the carbon premium without controlling for energy-specific shocks. We confirm the oil impact with event studies and find that these oil shocks do not significantly move the market-wide pricing of the carbon premium.

Our paper contributes to a few strands of literature. First, we add to the growing literature on climate event studies. Much of this line investigates the market's response to major events like the Stern Review (Painter, 2020), the Paris Agreement (Monasterolo and De Angelis, 2020; Bolton and Kacperczyk, 2021; Seltzer, Starks and Zhu, 2025; Duan, Li and Wen, 2025), the 2016 U.S. election (Ilhan, Sautner and Vilkov, 2021), or shifts in climate concern (Ardia et al., 2023; Van der Beck, 2021). A common feature of these studies is to treat brown firms as a homogeneous group. Our analysis reveals that this approach is vulnerable to a critical omitted variable bias, as many landmark climate events coincided with substantial oil market volatility. To isolate the causal impact of climate policy, empirical tests must therefore explicitly control for oil price confounds and demonstrate robustness to the exclusion of the energy sector or cross-industry variations.

To do this, we build on the extensive literature on oil price dynamics (Kilian, 2022; Baumeister and Hamilton, 2019; Fang, Liu and Roussanov, 2025) beyond mere environmental considerations (D'Amico, Klausmann and Pancost, 2023). In particular, Känzig (2021) and Ready, Roussanov and Taillard (2023) study the OPEC surprise announcements and COVID-19 episodes. This paper highlights that these oil shocks are not only cash flow shocks, but also discount rate shocks through growth option variations. This novel growth option channel shows that oil prices affect both fossil fuel and renewable energy firms similarly, complementing the legacy investment or stranded asset channel (Acemoglu et al., 2023; Barnett, 2024).

Second, we contribute to the literature on the ex-ante carbon premium. While prior studies have identified environmental policy risk (Hsu, Li and Tsou, 2023), shifting investor preferences (Pedersen, Fitzgibbons and Pomorski, 2021; Pástor, Stambaugh and Taylor, 2021), or shifting consumer preferences (Chen, Garlappi and Lazrak, 2023). Our central contribution is to identify oil price shocks as a first-order determinant, especially during volatile oil shock periods. This novel mechanism also helps reconcile large carbon premium variations and quantitative plausibility of sustainability forces highlighted in Berk and van Binsbergen (2025). In other words, a significant, time-varying "oil premium" is embedded within the aggregate carbon premium (Bolton and Kacperczyk, 2021; Aswani, Raghunandan and Rajgopal, 2024; Zhang, 2025). When calculating the genuine carbon premium, researchers must account for the fact that it is not a constant value but rather one that fluctuates significantly with the state of the energy cycle.

Our work is most closely related to, but stands in contrast with, Bolton, Kacperczyk and Wang (2024). The differences are both economic and methodological. Economically, our key innovation is the explicit distinction between energy and non-energy brown firms, which uncovers a sharp asymmetry in their response to oil shocks. Methodologically, we measure transition risk using lagged carbon intensity (emissions scaled by sales) rather than total emissions, consistent with institutional practice and the literature (Aswani, Raghunandan and Rajgopal, 2024; Zhang, 2025). We also focus on expected returns rather than realized returns to avoid confounding from in-sample shocks (Pástor, Stambaugh and Taylor, 2022; Atilgan et al., 2024).

The remainder of the paper is as follows. Section 1 explains the data and decomposes the carbon premium into sectoral contributions. Section 2 revisits the Paris Agreement and evaluates the impact of oil shocks, and Section 3 studies the impact oil shocks in more general time series. Section 4 examines the importance of these energy-specific contribution over time and examine whether these oil shocks shift the market-wide pricing of carbon-transition risk. Finally, Section 5 concludes.

1 Data, Carbon Performance, and Oil Exposures

This section presents the data and preliminary evidence. First, we describe the datasets used in the analysis. Second, we characterize the sector composition of carbon-sorted portfolios and highlight the key role of energy firms. Third, we document firms' differential exposures to oil price movements.

1.1 Data and Summary Statistics

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

Our primary metric for assessing a firm's climate profile is carbon intensity, calculated as total emissions scaled by sales over the emitting period. This choice is also consistent with institutional practices for carbon-aware portfolio management (Hartzmark and Shue, 2022). We use the most recent carbon emission and accounting data based on their respective release dates when combining various datasets following Zhang (2025). Given that Trucost conducted a review of all data from 2002 to 2008 in May 2009 and no longer provides original data release dates, we assume the original release date of the data to be October of the subsequent year, according to the Carbon Disclosure Project's October release cycle. In addition, we classify firms as part of the energy sector if they belong to the MSCI energy sector (code 10), which represents a congregation of enterprises dedicated to the exhaustive exploration, extraction, refinement, and marketing of fuel and associated energy products. For firm and security characteristic information, we extract bond issuance details from Merget FISD, stock data from CRSP, and accounting data from Compustat N.A., focusing on primary common stocks listed on major exchanges.

We measure firms' cost of capital using both bonds and equity. To measure the ex-ante cost of debt, we extract option-adjusted duration-matched yield spreads for bonds ($YieldSpread$) included either in the ICE Corporate Master index or the ICE Corporate High Yield index (Schaefer and Strebulaev, 2008; Huang, Nozawa and Shi, 2024). For the ex-ante cost of equity, we employ two measures. The first measure is the average of four published implied cost of capital-based estimates (ICC) (Gebhardt, Lee and Swaminathan, 2001; Claus and Thomas, 2001; Easton, 2004; Ohlson and Jüttner-Nauroth, 2005). These estimates are shown to be most reliable in the time series analysis (Lee, So and Wang, 2021), and the averaging of various ICC measures helps mitigate the inherent noise in assumptions regarding expected future cash flows and the potential for non-unique numerical solutions. These ICC estimates are available for the broad cross-section of firms over a long historical sample, allowing us to characterize the impact of oil shocks before the climate change enters the public discourse. The second measure is the 12-month option-implied expected equity return (IER) for constituents of the S&P 500 index, following Martin and Wagner (2019).

We construct the real price of oil by adjusting the nominal price of oil using the U.S. Consumer Price Index (CPI) sourced from FRED at the St. Louis Fed. The nominal oil price is derived from the refiner acquisition cost of crude oil imports, as reported by the U.S. Energy Information Administration, and extended back historically using the WTI index before 1983 following Baumeister and Hamilton (2019).

Panel A, Table 1 presents summary statistics for cost of capital measures. We winsorize all carbon intensity, security characteristics, and cost of capital measures at the 1% and 99% level to mitigate the impact of potential estimate outliers. The yield spread, corresponding to an average duration of 6.6 years, has an annualized mean of 1.93% and a standard deviation of 1.94%, comparable to quantities reported in previous studies on the US corporate bond market. The ICC measure has an annualized mean of 7.39% and a standard deviation of 11.34%. The 12-month IER measure for S&P 500 firms has a comparable mean of 6.54% but lower dispersion.

Panel B shows that the average (log) scope 1 and 2 carbon intensities are 4.10 logarithmic tons of CO2e per million U.S. dollars, respectively. Our regression models incorporate a variety of control variables to ensure robustness. Firm and equity attributes include market beta estimated over a 60-month rolling window, log assets, (log) book-to-market ratio, momentum, ROE, investment, sales growth, leverage (debt/total assets), and idiosyncratic volatility as derived from the Fama-French three-factor model. Bond-specific characteristics include duration, bond age, and credit ratings. To mitigate the influence of outliers, carbon and control variables are subjected to winsorization at the 1st and 99th percentiles before their inclusion as explanatory variables in our empirical analyses. Finally, Panel C presents the summary statistics of aggregate variables. The log growth of the real price of oil (ΔRPO) has a monthly standard deviation of 8%.

1.2 Carbon Intensity and Sectoral Heterogeneity

We measure a company's environmental performance using its carbon emission intensity. We find that variation in carbon intensity across companies is overwhelmingly driven by industry structure. The eleven GICS sectors alone explain nearly 70% of the variation in (log) carbon intensity, whereas firm-specific characteristics add only another 2% of explanatory power (see Table IA.1 of the Internet Appendix).

To supplement this continuous measure and allow for potential asymmetric effects, we sort firms into tercile portfolios based on their carbon intensity, labeling the top tercile as "brown." As shown in Panel A, Table 2, sector heterogeneity is again the crucial factor in this designation. The brown firm portfolio is dominated by the Utilities, Materials, and Energy sectors. Each of these sectors represents more than 10% of the portfolio, and they are largely absent from the non-brown portfolios. In contrast, the Industrials and Consumer Staples sectors have considerable weight in both the brown and non-brown portfolios, suggesting significant within-sector variation in carbon intensity for these sectors.

These three primary "brown sectors" (Utilities, Materials, and Energy) account for approximately two-thirds of the brown bond portfolio's weight and half of the brown equity portfolio's weight. However, they exhibit substantial differences in their carbon intensities, with means of 3,334, 684, and 538 metric tons of CO2e per million U.S. dollars, respectively. Notably, the Energy sector, while only the third most carbon-intensive, carries the largest single weight in the brown portfolio (25% in bonds and 18% in equity). This low industry granularity and high concentration in a single sector suggest that movements specific to the Energy sector can significantly impact the aggregate carbon premium, even when unrelated to climate transition risk.

1.3 Exposure to Oil Shocks

Crude oil is a foundational element of the global economy and can have a cost push effect along the supply chain. Carbon-intensive firms tend to be more oil-dependent on the input side, though these input shares are generally modest. On average, energy firms use about 4% more oil and gas extraction inputs than other industries, while non-energy brown firms exhibit 1.2% higher input shares for oil and gas extraction products and 1% higher for petroleum and coal products (Table IA.2).[1]

[1] The most oil-intensive industry is petroleum and coal product manufacturing within the Energy sector, where oil and gas extraction products account for roughly 24% of total inputs. Among non-energy industries, transportation and manufacturing are the most exposed, with petroleum and coal products comprising less

We begin by examining the supply chain effect of oil price fluctuations. We measure industry-level output prices using producer price index (PPI) data from the U.S. Bureau of Labor Statistics and construct weighted input prices using BEA input–output tables. The following specification measures how industry-level prices respond to oil price changes:

$$\Delta PPI_{i,t} = \alpha + \beta \cdot \Delta RPO_t + \gamma \cdot \text{Energy}_{i,t} \times \Delta RPO_t + \delta \cdot \text{Carbon}_{i,t} \times \Delta RPO_t + \kappa_i + e_{i,t}, \tag{1}$$

where $\Delta PPI_{i,t}$ denotes the log change in input or output prices for NAICS4 industry i, ΔRPO_t is the log change in the real oil price, $Energy_i$ is an Energy-sector indicator, and Carbon_i measures either standardized carbon intensity or a binary "brown" indicator. Panel B of Table 2 first reports the results on input prices. Oil price increases are broadly inflationary, raising input prices across industries by about 0.03% for each 1% increase in the oil price. The effect is somewhat stronger for carbon-intensive and energy firms, about 0.01% and 0.03%, respectively, consistent with their limited oil input shares.

We next turn to output prices. Two mechanisms are at play. First, energy firms, which are engaged in the exploration, extraction, refinement, and marketing of fuel products, directly produce commodities benchmarked to global oil prices. Second, non-energy brown industries may partially pass higher input costs through to output prices if product markets are competitive. Panel B of Table 2 shows that crude oil price changes have a pronounced effect on Energy-sector output prices: a 1% oil price increase raises Energy output prices by an additional 0.4%. For non-energy brown sectors, output prices rise only modestly and largely offset higher input costs, consistent with cost pass-through in competitive markets. These findings underscore that oil shocks transmit directly to Energy-sector output prices, making the sector uniquely exposed among brown firms.

We then examine whether these price sensitivities translate into financial exposures by estimating security-level oil betas (β_{Oil}) using 60-month rolling regressions:

$$R_{j,t} = \alpha_j + \beta_{j,MKT} Mkt_t + \beta_{j,Oil} \Delta RPO_t + \varepsilon_{j,t}, \tag{2}$$

than 7% of inputs and oil and gas extraction products contributing only marginally.

where $R_{j,t}$ is the month-t return on security j and Mkt_t is the corresponding market return. Columns (6) and (7) in Panel A of Table 2 show that average oil betas are close to zero for most sectors. The Energy sector is the clear outlier, with average bond and equity oil betas of 0.11 and 0.28, respectively, reflecting its direct exposure to oil revenues. In contrast, the Utilities sector, despite its high carbon intensity, shows negligible exposure, likely due to regulated rate-of-return structures that require complete input cost pass-through to consumers. Table IA.3 further confirms that carbon intensity outside the Energy sector do not comove with oil betas in an economically significant way.

Overall, these results demonstrate that not all brown sectors are alike. The Energy sector's direct linkage between output prices and crude oil makes it uniquely sensitive to oil shocks, while other carbon-intensive industries experience only muted and indirect effects through input costs.

1.4 Growth Option and Risk Variations

We next investigate how these differential exposures to oil shocks translate into firm valuations and risk profiles. To isolate these cross-sectional relationships, we estimate the following firm-level regression:

$$\Delta Y_{j,\tau} = \alpha + \beta \cdot \text{Energy}_{j,t} \times \Delta RPO_t + \gamma \cdot \text{Carbon}_{j,t} \times \Delta RPO_t + \kappa_j + \iota_t + e_{j,t+1}, \quad (3)$$

where Y_j denotes measures of firm j's growth opportunities, and ΔRPO denotes log oil price changes. Our primary interest lies in the interaction terms, which capture the heterogeneous responses to oil shocks. The model is again conducted in difference, because the oil price series is not stationary. The model includes firm fixed effects (κ_j) to absorb time-invariant characteristics and year fixed effects (ι_t) to control for market-wide trends, including the average impact of oil shocks as well as broad market risk premium variations. Standard errors are clustered at both the firm and year levels.

Panel A of Table 3 reveals a stark divergence in growth opportunities driven by oil price shocks. Following a 1% oil price increase, energy firms' sales grow by an additional 0.23%. This realized growth is reflected in market valuations contemporaneously: the Tobin's Q of energy firms, a forward-looking proxy for their growth options, increases significantly (coefficient of 0.14) when oil prices increase. In contrast, non-energy brown firms experience only minor expansions in sales growth relative to other firms, and the magnitudes are second-order (a coefficient of 0.03, compared to 0.23 for energy), consistent with the price pass-through evidence.

Given that a firm's growth-option profile is a key determinant of its expected returns, these findings imply that oil price shocks should alter the factor loadings of energy firms. We hypothesize that as their growth opportunities expand, energy firms will behave more like growth stocks and less like value stocks. This shift should manifest as a decrease in their loading (beta) on the HML value factor. To test this, we estimate time-varying factor betas for each security using 5-year rolling regressions using the Fama-French three-factor model,

$$r_{j,t} = a_j + \beta_j^{MKT} MKT_t + \beta_j^{HML} HML_t + \beta_j^{SMB} SMB_t + e_{j,t},$$

where HML and SMB denote equity value and size factors. We then use these estimated HML betas as the dependent variable in our main regression, Equation (3). As predicted, Panel B of Table 3 confirms that energy firms' HML betas are significantly negatively related to contemporaneous oil price innovations, relative to non-energy firms.[2]

2 Revisiting The Paris Agreement

The Paris Agreement is arguably the most studied event in the climate literature. As of October 2025, there are 1,710 papers conducting Paris Agreement event studies in Google Scholar. Its timing, however, presents a significant empirical challenge: the Agreement coincides almost perfectly with the trough of a historic oil price collapse and subsequent

[2]Additional results in Table IA.4 show that the market and SMB beta estimates are largely stable cross-sectionally.

recovery that spanned from 2014 (nearly two years before the PA) to 2016. This powerful, pre-existing oil shock creates a classic omitted-variable problem for event studies of the PA. In this section, we first summarize the oil-market developments leading into the PA and then re-evaluate the event-study evidence using a framework designed to disentangle oil-driven effects from carbon-policy effects.

2.1 Theoretical Prediction

The preliminary empirical analysis shows that the energy sector—a large component of typical "brown" portfolios—is uniquely sensitive to oil price fluctuations, which in turn affects its growth prospects and risk exposures. Rather than a complication, this asymmetry is an identification opportunity: oil shocks should primarily reprice energy firms, whereas genuine transition-risk shocks should affect carbon-intensive firms outside Energy as well.

To formalize this distinction, we develop a quantitative model in Internet Appendix Section A. The economy features three representative firms: Energy (E), Non-Energy Brown (NB), and Green (G). These firms are subject to two distinct aggregate shocks. The first is an oil demand shock (e.g., OPEC supply constraints) that selectively affects energy prices and profitability, while non-energy firms remain insulated via cost pass-through mechanisms. The second is a carbon tax shock that imposes a direct cost on all high-emission firms (E and NB), mimicking shifts in regulation or sustainable consumption preferences.

We decompose the aggregate "carbon premium", the expected return spread between brown and green firms, into two components: the "energy premium" (the spread between energy E and non-energy brown NB firms) and the "non-energy carbon premium" (the spread between non-energy brown NB and green G firms).

The model yields a sharp, testable prediction regarding the asymmetric impact of these shocks. An oil shock affects only the energy premium. Mechanically, a positive oil shock acts as a profitability windfall for sector E, expanding its growth options and lowering its risk exposure (and consequently its cost of capital), without materially affecting the NB sector. In contrast, a carbon tax shock widens both the energy premium and the non-energy carbon premium. Because a carbon tax acts as a negative profitability shock for all high-emission sectors, it raises the cost of capital for both E and NB firms simultaneously.

Although the model abstracts from the potential for climate shocks to directly affect oil prices, it crucially predicts that the energy premium widens following a climate shock. This implies that observing variations in the energy premium alone is insufficient to identify a climate event. Consequently, a significant response in the non-energy carbon premium is a necessary condition to isolate the impact of carbon transition shocks from standard oil price volatility.

2.2 The 2014 Oil Crash

The 2014 oil crash, representing a three-standard-deviation oil price drop, is one of the largest in modern history. It ended the commodity "super-cycle" and the era of $100 oil, signaling a new market paradigm defined by supply abundance. The crash followed a massive supply glut, primarily driven by the U.S. shale oil revolution. Advanced technologies like fracking unlocked vast new reserves, causing American production to surge, almost doubling from 5.0 million barrels per day (bpd) in 2008 to 8.7 million bpd in 2014. This boom, combined with slowing economic growth and weakening demand in key markets like China and Europe, disrupted a period of stability where prices had remained comfortably above $100 per barrel. By June 2014, this multi-year structural oversupply became apparent, and Brent crude began a steady slide, falling from a high of $115 per barrel to the $75–$80 range by early November.

The steady decline turned into a full-blown crash on November 27, 2014. As prices weakened, the market expected OPEC to perform its traditional role as the global "swing producer" and cut output. However, at its critical meeting in Vienna, OPEC, led by Saudi Arabia, made a pivotal decision. Faced with the threat of U.S. crude production, which had surged from 50% of Saudi output in 2008 to almost 90% by 2014, the cartel announced it would maintain its production ceiling. This signaled a dramatic strategy shift: OPEC was initiating a price war, abandoning price management to defend its market share against the new, higher-cost US shale producers. The market reacted instantly; without OPEC as the "swing producer", prices went into freefall, plummeting below \$50 per barrel by early 2015 and ultimately bottoming out near \$26 per barrel in early 2016.[3]

Our theoretical model predicts that this oil crash, triggered by OPEC's surprise announcement in November 2014, substantially increases the cost of capital for oil-and-gas (energy) firms. To test this prediction, we study the 12-month event window around November 2014 and estimate the following difference-in-differences (DiD) regression:

$$ER_{j,t} = \alpha + \beta \cdot \text{Energy}_{j,t} \times \text{PostEvent}_t + \gamma \cdot \text{Carbon}_{j,t} \times \text{PostEvent}_t + X_{j,t} + \kappa_j + \iota_t + \varepsilon_{j,t}, \quad (4)$$

where $ER_{j,t}$ is the expected return for firm j, and PostPriceWar_t is an indicator for the 6-month window following OPEC's strategic action in November 2014. $X_{j,t}$ indicates additional controls, such as the interactions of the carbon performance with the post event dummy. The firm fixed effects (κ_j) absorb all stable, time-invariant differences between firms, such as their underlying business model, average risk profile, or sector-specific attributes. The time fixed effects (ι_t) control for any market-wide shocks or macroeconomic trends in a given period t that affect all firms, such as changes in GDP forecasts or general market sentiment. Standard errors are double-clustered by firm and month levels.

Panel A of Table 4 presents the results. The 2014 OPEC meeting triggered a sharp, statistically significant increase in the cost of capital for Energy firms. Specifically, bond yield spreads widened by approximately 1%, and the cost of equity—measured by either the implied cost of equity (ICC) or option-implied expected returns (IER)—increased by 2–3% relative to non-energy firms. Crucially, we observe no significant variation in the cost of capital for other carbon-intensive (Brown) firms. This suggests the market reaction was not driven by a broad repricing of climate risk. The absence of such a pattern indicates the market's reaction was a fundamental reassessment of systematic risk specific to the oil and gas sector's competitive landscape, rather than a generic re-evaluation of environmental

[3] See Baffes et al. (2015); Behar and Ritz (2016); Fantazzini (2016) for excellent discussions of the Shale revolution, OPEC's price war response, and the 2014-2016 oil saga. Känzig (2021) examines the impact of OPEC surprise announcements in general historical contexts.

liabilities.

Figure 2 plots the monthly energy sector coefficients relative to the base period of October 2014 ($t = -1$). Broadly, the energy premium is negatively correlated with oil prices. From $t-12$ to $t-2$, the premium remains stable and negative, reflecting a favorable cost of capital while oil prices were high. However, this trend breaks at $t-1$, where coefficients rise as the market anticipates weakening prices due to early OPEC discounts. The primary structural break occurs at $t = 0$ (November 2014), when coefficients surge across the zero line following OPEC's surprise decision. This pattern confirms that the post-event divergence is not a continuation of a pre-existing trend, but a sharp risk reassessment triggered specifically by the supply shock.

Panel B of Table 4 illustrates the potential for misidentification. Here, we estimate the aggregate carbon premium using a misspecified naive model that treats the oil price war as a generic climate shock:

$$ER_{j,t} = \alpha + \gamma \cdot \text{Carbon}_{j,t} \times \text{PostEvent}_t + X_{j,t} + \kappa_j + \iota_t + \varepsilon_{j,t}. \tag{5}$$

Under this specification, the aggregate carbon premium appears to increase across all cost of capital measures. The estimated premium for high-emission firms rises by 19 basis points (bps) for bonds, and by 79 bps and 91 bps for ICC and IER measures, respectively. This highlights that omitting the energy-specific interaction yields a spurious "carbon premium." In short, failing to isolate the energy sector's unique distress can conflate a specific oil shock with a broader repricing of carbon transition risk.

2.3 Firm Dynamics Around the Paris Agreement

The Paris Agreement, adopted in December 2015, marked the first time global leaders joined forces on climate issues. The agreement aims to hold "the increase in the global average temperature to well below 2°C above pre-industrial levels" and to "limit the temperature increase to 1.5°C above pre-industrial levels." A prevailing hypothesis is that the agreement provides an exogenous positive shock to expectations of future climate regulations, thereby increasing the cost of capital for brown firms and widening the carbon premium (Monasterolo and De Angelis, 2020; Bolton and Kacperczyk, 2021; Seltzer, Starks and Zhu, 2025). At the same time, the agreement coincided almost perfectly with the trough of the historic 2014–2016 oil price collapse discussed above. This overlap creates a classic omitted-variable problem: absent a clean separation of these forces, post-PA movements in measured premia may simply reflect the oil cycle rather than a repricing of transition risk.

2.3.1 Baseline Specification and Pre-Event Trends

First, we estimate the impact of the PA event in a standard difference-in-difference (DiD) specification as in Eq. (5). Similar specifications have been adopted in Seltzer, Starks and Zhu (2025) and Bolton and Kacperczyk (2021, 2023). Panel B of Table 5 reports the results. Following the Paris Agreement, the bond carbon premium significantly increases by 12 bps for per standard deviation increase in the carbon intensity and as much as 37 bps for the top brown firms. The result well replicates the findings in Seltzer, Starks and Zhu (2025) and is consistent with the return-based evidence such as in Duan, Li and Wen (2025). In contrast, Panel B and C show that the equity-based carbon premium does not increase robustly. The ICC and IER carbon premium estimates find inconsistent patterns for top brown firms (coefficients of -0.58% for ICCs and 0.83% for IERs) and there are no significance for the continuous carbon intensity measures. This result is largely consistent with Seltzer, Starks and Zhu (2025), but differs from the post-PA carbon premium increase documented Bolton and Kacperczyk (2021, 2023) due to differences in the construction of expected return measures and carbon variables.[4] Taken at face value, only the bond market evidence seems to support the climate policy hypothesis.

However, attributing the estimated post-PA movements to the Paris Agreement itself is undermined by a key identification failure: the parallel-trends assumption. Figure 4

[4] Specifically, Bolton and Kacperczyk (2021, 2023) study realized returns, instead of expected returns, and focus on contemporaneous total emissions and emission growth, instead of lagged emission intensity(Zhang, 2025).

plots the carbon premium, estimated using the carbon intensity measures, month-by-month over a longer event window and shows that the premium was far from stable before the PA. Instead, the carbon premium across all three measures was already in the midst of a dramatic, systematic rise for roughly a year and a half before the agreement.[5]

This pre-trend is not random. As the figure demonstrates, the estimated carbon premium moves in near-perfect lockstep with the 2014-2016 oil price collapse. By mid 2015, the energy sector is already in a full-blown crisis. A total of 42 exploration and production companies filed for bankruptcy in 2015, representing $17.4 billion in aggregate secured and unsecured debt. Notable examples include major operators like Quicksilver Resources Inc., which filed in March 2015 with roughly $4 billion in debt, and Samson Resources Corp., one of the largest private producers and backed by KKR, which filed in September 2015, among others. In short, The high carbon premium around December 2015 simply represents the moment of maximum financial distress for the energy sector, which happens to coincide with the oil price trough and the PA signing.

A potential alternative explanation for this pre-trend is that it reflects other anticipatory climate news or regulatory events that occurred prior to the PA, which might have coincidentally correlated with oil prices. To test this, we plot the real price of oil and the climate concern index (Ardia et al., 2023) in Figure 3 from the onset of the oil crash. The visual evidence offers a sharp contrast: while oil prices exhibit a distinct V-shaped pattern, climate awareness follows a strong, monotonic upward trend throughout this period of time. In particular, these trends are established more than 18 months before the Paris Agreement, longer than the typical anticipatory period.

Panel A in Table 5 further examines the dynamics of these two series. We find that the growth in climate concern does not significantly change following the Paris Agreement; in fact, the coefficients tend to be negative. Simultaneously, oil price growth displays no significant correlation with either climate concern growth or the occurrence of the Paris Agreement.[6] This orthogonality confirms that the pre-trend visible in Figure 2 is driven

[5] Figure IA.3 plots the carbon premium for top brown firms and finds consistent patterns.

[6] As shown in Table IA.6, oil price innovations exhibit near-zero correlation with climate concern inno-

by oil market economics—specifically the supply glut and price war—rather than a gradual pricing in of climate transition risk.

Consequently, the standard DiD model (Eq. (5)) is falsely attributing the peak of a pre-existing oil industry crisis to the Paris Agreement. Triggered by the oil crash, U.S. supply responded aggressively, and prices eventually bottomed out and started rebounding in February 2016. As a result, the carbon premium starts declining immediately after the event time in January 2016 for equity and March 2016 for bonds, and quickly reverts to pre-PA levels. These post-event dynamics lend further support to the oil shock hypothesis over the carbon transition risk hypothesis.

2.3.2 Accounting for the Oil Shock

This pattern indicates that the naive DiD model falsely attributes the peak of a pre-existing oil crisis to the Paris Agreement. The existing literature often acknowledges this confound and attempts to control for it using an oil beta (e.g., Seltzer, Starks and Zhu, 2025). This approach has critical limitations: (1) security-level oil betas are notoriously imprecise; (2) a linear beta fails to capture the highly nonlinear dynamics of a market crash; and (3) the linear regression cannot account for the fact that the oil beta of energy firms is a clear outlier as shown in Section 1. Indeed, Panel C adds an oil-beta control:

$$ER_{j,t} = \alpha + \beta \cdot \text{Carbon}_{j,t} \times \text{AfterPA}_t + \gamma \cdot \text{Oil Beta}_j \times \text{AfterPA}_t, +\kappa_j + \iota_t + \varepsilon_{j,t}. \quad (6)$$

The results confirm that the oil-beta control does little to alter the baseline estimates.

A robust identification strategy must disentangle the specific distress of the energy sector from broader climate risk. Guided by our theoretical prediction that oil shocks drive the energy premium while climate shocks drive the non-energy carbon premium, we augment the baseline specification and estimate Eq. (4). Panel D shows that controlling for the energy sector's unique exposure dramatically alters the results. The bond market premium

vation $\Delta MCCC$ (Ardia et al., 2023), nor do they correlate with ESG fund flows or other carbon policy shifts.

for non-energy brown firms shrinks from 12 bps to an insignificant 4 bps. Similarly, the equity risk premium for non-energy brown firms flips signs, becoming negative across both ICC and IER measures.

These findings indicate that the aggregate "carbon premium" observed in the baseline model is mechanically driven by the energy sector. Indeed, we find that the shock is fully absorbed by energy firms: their cost of debt increases by over 100 bps, and their cost of equity spikes by up to 400 bps relative to peers. As shown in Figure IA.4 of the Internet Appendix, the coefficients for non-energy brown firms show no reaction to the event, while the energy coefficients exhibit a sharp, persistent jump. This confirms that the shock is sector-specific rather than a broad-based climate signal.

As a final, more conservative test, we employ a specification that includes GICS sector-by-time fixed effects. This non-parametric approach absorbs all time-varying shocks common to a sector, including those from oil prices, while leaving the within-sector carbon intensity variations, such those in industrials. As shown in Columns (4) and (8) of Table 5, this specification confirms our main result: the carbon premium increase largely disappears. In summary, while the carbon premium appears to rise following the Paris Agreement, our analysis reveals that this variation is an artifact of concurrent oil price fluctuations. Once the confounding oil shock is properly accounted for, we find no evidence of a systematic repricing of carbon risk around this landmark climate event.

It is worth noting that the analysis here examines expected return dynamics, as higher-than-annual-frequency data help identify the response timing more precisely. However, an oil shock not only affects expected returns but also pervasively drives valuation, sales growth, investment, and other corporate decisions. Any analysis of this period, including those relying on accounting data, must therefore carefully account for this powerful confound to avoid misattributing oil-driven effects to the climate policy announcement.

3 Oil Shocks, Energy Premium, and Carbon Premium

The Paris Agreement analysis reveals that the oil price dynamics are associated with a strong increase in the cost of capital for energy firms relative to other firms—an effect that could be confused with the repricing of the carbon transition risk. We now test the relation between oil price shocks and expected returns to establish that oil shocks are a general, first-order driver of carbon premium fluctuations that are not limited to the Paris Agreement period.

3.1 Time-Series Evidence

Empirically, we sort firms into tercile portfolios based on carbon intensity, with the top tercile classified as brown firms and the bottom tercile as green. The aggregate carbon premium (Spread^{B-G}) is computed as the value-weighted differential in the cost of capital between these brown and green portfolios. The energy premium (Spread^{E-NB}) is defined as the cost of capital difference between energy firms and non-energy brown firms, both of which exhibit similar levels of carbon intensity but different exposure to the oil shocks. The non-energy carbon premium (Spread^{NB-G}), is the value-weighted cost of capital difference between non-energy brown firms and green firms. Figure 5 plots these components for each measure. The energy premium and non-energy carbon premium exhibit small negative correlations, ranging from -0.03 to -0.25, for all measures, suggesting distinct economic forces drive their variations.

We now test the empirical prediction of the energy price channel in the general context: higher oil prices should reduce the energy premium but remain orthogonal to the non-energy carbon premium. Our baseline specification estimates the dynamic relationship between oil price variations and financing cost spreads:

$$\Delta ER_{j,t} = \alpha_j + \beta_j \Delta RPO_t + \varepsilon_t, \tag{7}$$

where ER denotes the energy premium or non-energy carbon premium, and ΔRPO represents log changes in oil prices. Standard errors are adjusted for autocorrelation up to 12 lags.

Panel A of Table 6 reports results for the period from October 2003 to December 2022. Oil price increases consistently reduce the energy premium across markets and measures. The magnitude is smallest for the yield spreads (-0.95% for per 10% oil price increase) due to its less volatile nature, and largest for the option-implied expected returns (-2.13%), which focuses on the one-year near term expected returns. The results suggest that higher oil prices substantially compress the energy premium or the excess cost of capital for energy firms.

In sharp contrast, the non-energy carbon premium (Spread^{NB-G}) exhibits no consistent response to oil prices. The coefficients are statistically insignificant and flip signs across yields (negative), ICCs (insignificant), and IERs (positive). This asymmetry supports our model's mechanism: oil price variations drive fluctuations in the aggregate carbon premium solely through the energy component, without spilling over into the non-energy carbon premium.[7]

Figure 5 presents the findings visually. A few boom-and-bust cycles in oil prices have closely aligned with carbon premium fluctuations in the past two decades. The first oil price bust occurred during the Global Financial Crisis, and the second occurred between 2014 and 2016 as discussed in the Paris Agreement, leading to prolonged downturns. The third oil bust took place in 2020 following the outbreak of COVID-19, while the outbreak of the Russo-Ukrainian military conflict led to sharp rallies in oil prices. These dramatic crashes and recoveries in oil prices are mirrored by sharp rallies and reversals in the bond carbon premium and similar, albeit less pronounced, patterns in the equity carbon premium.

3.2 Disentangling Transition Risk from Energy Price Shock

A critical alternative explanation is that our results are driven by reverse causality: specifically, that heightened transition risk depresses oil demand, lowers prices, and simultaneously widens the energy premium. Theoretically, if the market prices in a rapid shift away from fossil fuels, this could manifest as an "oil shock" driven by climate expectations. However, this hypothesis yields a specific testable prediction: if transition risk were the primary driver

[7] Table IA.5 shows that oil price increases are associated with lower financing costs across all portfolios, showing that the oil shocks are aggregate shocks as in the model.

of oil price dynamics, it should also move the non-energy carbon premium. A shock powerful enough to reprice the entire oil sector due to climate risk should necessarily impact other high-carbon sectors. The absence of any significant response in the non-energy carbon premium, as documented above, fails to support this hypothesis.

To formally rule out this channel and isolate the energy price mechanism, we employ three distinct empirical tests. First, we examine the orthogonality of shocks. As shown in Internet Appendix Table IA.6, oil price innovations exhibit near-zero correlation with established proxies for transition risk, including climate concern shocks, ESG fund flows, and carbon policy shifts. This suggests that oil shocks represent a distinct source of variation independent of climate sentiment.

Second, to further disentangle sector exposure from environmental profiles, we utilize renewable energy firms as a falsification test. This allows us to distinguish between a "transition risk feedback loop" and a standard "energy market shock." Under the transition risk hypothesis, a drop in oil prices would reflect a structural shift away from fossil fuels. This should trigger a reallocation of capital: demand for renewables should rise, lowering their cost of capital while oil firms suffer. Conversely, under the energy price channel, renewables and fossil fuel firms are economic substitutes that share exposure to aggregate energy prices. In this scenario, a drop in oil prices depresses profitability across the entire energy complex, raising the cost of capital for both sectors.

The data strongly rejects the transition risk hypothesis in favor of the energy price channel. We find that renewable financing costs move in lockstep with oil prices: a 10% increase in oil prices significantly lowers renewable financing costs by 1.25% (bonds) and 2.02% (equity).[8] Despite their superior environmental credentials, renewable firms react to oil shocks with the same directionality as oil firms and significantly more negatively than non-energy brown firms. This confirming correlation demonstrates that the market is pricing these events as sector-wide energy economics, not as a climate-driven divergence between

[8]Renewable energy firms are identified via major green energy ETFs (ICLN, PBW, QCLN, TAN). While they exhibit emission intensities comparable to broad brown firms ($\approx$ 400), they are much less carbon intensive than traditional utilities. IERs are omitted due to the scarcity of renewable firms in the S&P 500.

brown and green assets.

Third, we perform an out-of-sample test using historical data predating the "climate era" (Panel C). We impute firm-level emissions for the 1974–2002 period using Fama–French 49 industry intensities. If the oil-energy premium relationship were a product of modern climate era, it should be absent in historical data. Instead, we find the negative relationship is structural and robust even in the 1970s and 1980s, especially for ICCs which cover the longest sample. Notably, Figure 1 shows that the carbon premium was highest during the oil glut of the early 1980s, a period void of climate concerns, driven by the elevated energy premium. Throughout this historical sample, the non-energy carbon premium remains statistically indistinguishable from zero.

In summary, the evidence indicates that oil shocks drive the carbon premium through a unique energy price channel. This relationship is structurally distinct from carbon transition risk, affects renewable and traditional energy firms symmetrically, and has persisted since the 1970s.

3.3 Panel Evidence

We next turn to firm-level panel regressions to control for security characteristics and absorb common shocks with time fixed effects. We estimate the following model:

$$\Delta ER_{j,t} = \alpha + \beta \cdot \text{Energy}_{j,t} \times \Delta RPO_t + \gamma \cdot \text{Carbon}_{j,t} \times \Delta RPO_t + \delta \cdot X_{j,t} + \kappa_j + \iota_t + e_{j,t} \tag{8}$$

where ER denotes the cost of capital measures, $Energy$ is the energy sector indicator, and X represents the security-level controls. We include the interaction between the firm's emission profile $Carbon$ with the oil price shock for comparison. The regression is conducted at the security-month level and includes firm and time-fixed effects. The firm fixed effect absorbs the firm-specific return variations, including unconditional returns of each firm. The time fixed effect absorbs the common return variations over time, including the average effect on an oil shock on all firms. Standard errors are double-clustered at the firm and month levels.

Table 7 shows that, consistent with the baseline analysis, oil price shocks negatively impact the cost of capital for energy firms. The coefficients are -1.2 for yield spreads, -2.7 for ICCs, and -4.4 for IERs, respectively, which are consistent with but greater than the baseline estimates. By contrast, we do not see significant impacts on any of the carbon intensive or brown firms. In short, oil price shocks have a consistently significant negative impact on energy firms' cost of financing, but not on other carbon-intensive firms.

3.4 Decomposing Oil Shocks

While our baseline analysis treats oil price variations as homogeneous, price fluctuations are endogenously driven by a mix of supply and demand factors. Disentangling these drivers is critical because their implications differ. We decompose oil price fluctuations using a five-dimensional structural vector autoregression (SVAR) model based on (Baumeister and Hamilton, 2019). We extend their framework by splitting global oil supply into U.S. and foreign components. This distinction is crucial because foreign supply cuts (e.g., OPEC) effectively act as demand shocks for U.S. oil-and-gas producers, where U.S. supply shocks, affecting both the firm productivity and oil prices, may have different effects. Our model identifies five orthogonal shocks: (i) U.S. supply, (ii) foreign supply, (iii) aggregate economic activity, (iv) speculative inventory demand, and (v) oil-specific consumption demand.[9] Figure IA.6 of the Internet Appendix plots the time series of the decomposed oil price shocks.

Table 8 reports the results. Demand-like shocks, including foreign supply and oil-specific consumption demand shocks, significantly lower U.S. energy firms' cost of capital across markets relative to other brown firms, thereby narrowing the energy premium. This finding aligns with the evidence from the 2014 OPEC price war event study. In contrast, these same shocks have little effect on the non-energy carbon premium.

U.S. supply shocks show weak or mixed effects. For example, the U.S. shale revolution simultaneously increases domestic productivity (a positive supply effect) but simultaneously

[9]The identification follows standard sign restrictions where U.S. supply shocks are characterized by a contemporaneous increase in U.S. production with no immediate effect on foreign production or global economic activity, foreign supply shocks have no immediate effect on U.S. production or global activity, and economic activity shocks have no immediate effect on oil production.

puts downward pressure on the global oil price, and these offsetting effects largely negate each other. Furthermore, Table IA.7 in the Internet Appendix shows that speculative oil inventory shocks have no significant effects on either premium, and aggregate economic shock-driven oil shocks tend to affect both premiums positively.

As an additional robustness test, we test the relation using the firm-level cost of capital in Table IA.8 of the Internet Appendix. For example, the U.S. shale revolution was fueled by debt, which makes leverage a crucial factor (Fantazzini, 2016). We construct a firm-level weighted average cost of capital (WACC) and find that our baseline results hold: oil prices are negatively associated with the leverage-adjusted energy premium but unrelated to the non-energy carbon premium.

Overall, these robustness tests consistently demonstrate that the negative relationship between oil prices and the energy premium is structural and persistent, reflecting the fundamental role of energy price shocks that operate independently of climate-related factors.

4 Temporal Attribution and Additional Oil Shocks

Our analysis has established that the energy sector, the largest sector in brown portfolios, can contribute significantly to aggregate carbon premium variations, through its unique exposure to oil shocks. Similarly, other energy-sector-specific shocks beyond the aggregate oil price series—such as different supply and demand forces discussed in Section 3.4, as well as energy market structure changes and fossil fuel policy changes—could also affect the energy sector in a unique way and mechanically drive carbon premium variations.

In this section, we assess the temporal contribution of these energy-specific shocks to the aggregate carbon premium. We isolate periods when the assumption of homogeneity across brown firms is most problematic. Then, we examine market reactions during these periods to determine if oil shocks systematically shift the market-wide pricing of carbon-transition risk.

4.1 Quantitative Temporal Attribution

To isolate the independent contribution of the energy sector, we first strip out the common variations shared by all brown firms by regressing the aggregate carbon premium on the non-energy carbon premium:

$$\text{Spread}_t^{B-G} = \alpha + \beta \cdot \text{Spread}_t^{NB-G} + e_t. \tag{9}$$

The R^2 from this regression captures how much of the aggregate premium's variation is explained by broad, market-wide forces affecting all brown firms. Consequently, the unexplained portion, $1 - R^2$, isolates the contribution of movements unique to the energy sector.

This framework is deliberately conservative. Any shock that affects brown firms simultaneously, such as the potential impact of climate-related shocks or energy efficiency improvement, is attributed to the common non-energy premium. As a result, our $1 - R^2$ measure should be interpreted as a lower bound on the energy sector's unique contribution. We apply this methodology to premiums derived from different asset classes to build a comprehensive picture of this contribution over time.

Figure 6 plots these contributions estimated over 3-year rolling windows. It reveals that the unique contribution of the energy sector is not constant but rather spikes during major market dislocations. We observe sharp increases in the energy-specific contributions coinciding with the 2008 Global Financial Crisis, the 2014-2016 oil price collapse, the 2020 COVID-19 lockdown shock, and the 2022 Russo-Ukrainian War. In these periods, the energy sector's unique dynamics frequently account for over 40-50% of the premium's fluctuations, reflecting a severe divergence in riskiness between energy and other brown firms.

Historical data back to 1974 reinforces this pattern. In the pre-1990 period—an era characterized by repeated oil supply shocks and substantial price volatility—the energy sector routinely explains more than 40% of the aggregate premium's variation. This influence diminishes during the relatively stable oil-market environment of the 1990s, only to rise again following the Global Financial Crisis as the oil cycle becomes more volatile. Taken together, the evidence shows that the aggregate carbon premium often reflects shocks that are specific to the energy sector. Failing to separate these sector-specific dynamics leads to a significant overstatement of the true, market-wide carbon premium.

4.2 Event Studies of Recent Oil Shocks

The attribution results highlight that several recent volatile periods that are particularly salient for potential omitted variable bias. Among them, the 2014-2016 oil shock and the Global Financial Crisis were the most severe, with peak-to-trough price fluctuations of approximately three standard deviations. The COVID-19 lockdown and the 2022 outbreak of the Russo-Ukrainian War were also intense shocks of about 1.5 standard deviations.

We now study these two recent shocks by directly examine the market response to recent oil shocks in the DiD framework as in Equation (4). In particular, we also examine the responses of brown firms to assess whether oil shocks shift broad market sentiment regarding the carbon transition. Two competing possibilities exist. On one hand, high oil prices could accelerate the transition by making it economically, not just environmentally, attractive, thereby increasing market support for less oil-dependent greener firms. On the other hand, high oil prices may signal periods of high demand and low supply for oil-intensive products, potentially making markets more tolerant of firms' poor carbon performance.

We begin with the COVID-19 lockdown in March 2020, which triggers an unprecedented collapse in global oil demand. WTI futures prices briefly turn negative in April 2020, pushing many U.S. producers into financial distress. As Panel A of Table 9 shows, energy firms' financing costs rise sharply: the cost of debt increases by about 1.5%, while ICCs and 12-month IERs rise by roughly 5% and 7%, respectively. In contrast, non-energy brown firms experience no significant increase, and in some cases a decline, in their financing costs.

Next, the 2022 Russo-Ukrainian War provides the opposite quasi-experiment. The conflict drives a rapid spike in global oil and natural gas prices, with sanctions on Russia redirecting demand toward U.S. producers–especially in the LNG market. The result is a substantial profitability shock to the U.S. energy sector.[10] Panel B of Table 9 shows that energy firms' cost of debt falls by about 0.3%, while their equity financing costs decline by roughly 3% for ICCs and 0.5% for IERs. Again, non-energy brown firms display no significant reaction. Together, these two large but opposite oil shocks demonstrate a consistent pattern: oil-market disruptions causally affect energy firms, and have yet to materially change the pricing of carbon-transition risk across the broader market.

5 Conclusion

The existence of a carbon premium is a central question in climate finance. This paper provides a new perspective, showing that the observed premium is substantially driven by the unique influence of oil price shocks, an effect distinct from a uniform repricing of carbon transition risk.

We illustrate this by re-examining the 2015 Paris Agreement, a landmark event widely believed to have triggered a repricing of carbon risk. Our analysis reveals that the documented increase in brown firms' cost of capital during this period is almost entirely driven by the energy sector's response to a historic oil price collapse and subsequent recovery. Once this confounding factor is controlled for, we find no statistically significant evidence of a systematic repricing of carbon transition risk.

These findings imply that what is often measured as a "carbon premium" is frequently an "oil premium" in disguise. In particular, these energy-specific shocks can explain over half of the premium's variation during periods with intense oil shocks. This finding poses a significant challenge for researchers and serves as a cautionary tale for investors and policymakers.

While this paper focuses on the carbon premium, the confounding role of oil shocks has implications for broader climate finance, including capital budgeting, bank lending, and corporate behavior. Future research can address these challenges and achieve clearer identification by implementing several remedies. First and foremost, studies should explicitly

[10] For example, ExxonMobil reports $55.7 billion in profit in 2022, the highest annual earnings in the history of western oil companies. Chevron's $36.5 billion in 2022 is more than double its 2021 earnings and also a record.

control for oil shocks and distinguish the energy sector from other brown firms. Furthermore, exploiting within-industry variations can provide more robust insights. Last but not least, evidence based on cross-sectional shocks, such as cross-country or cross-region temperature shocks (Choi, Gao and Jiang, 2020), can improve the identification and offer valuable complementary analysis to time-series event studies and better isolate true carbon transition effects.

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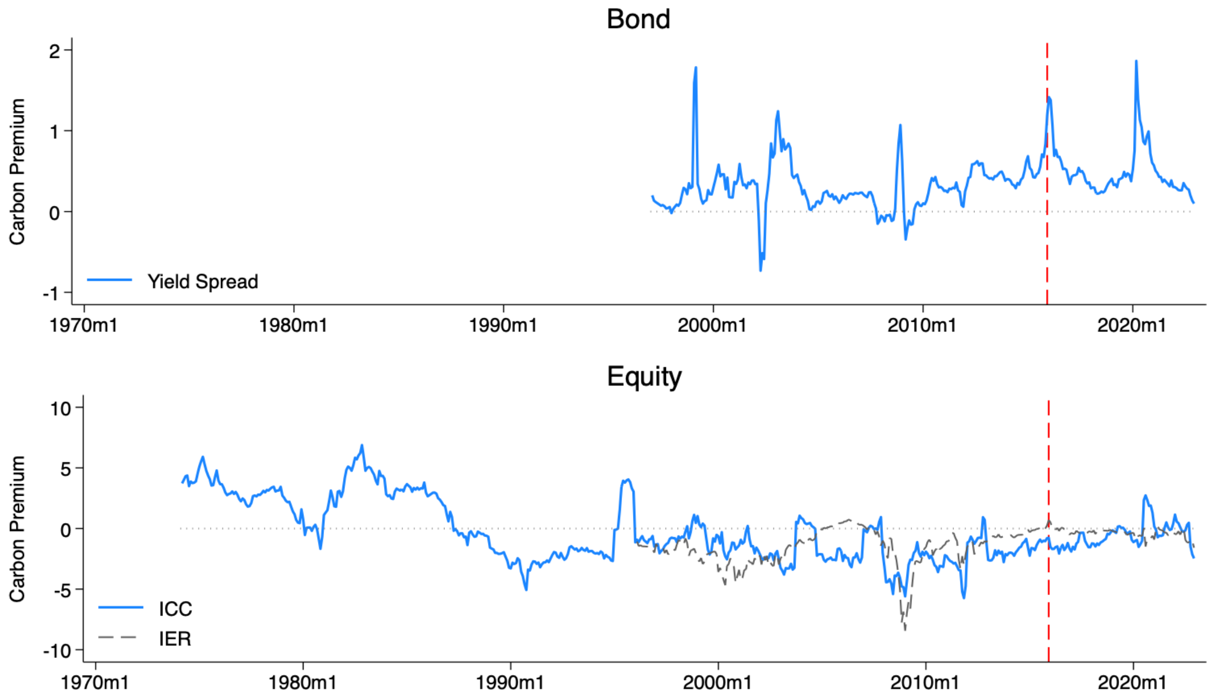
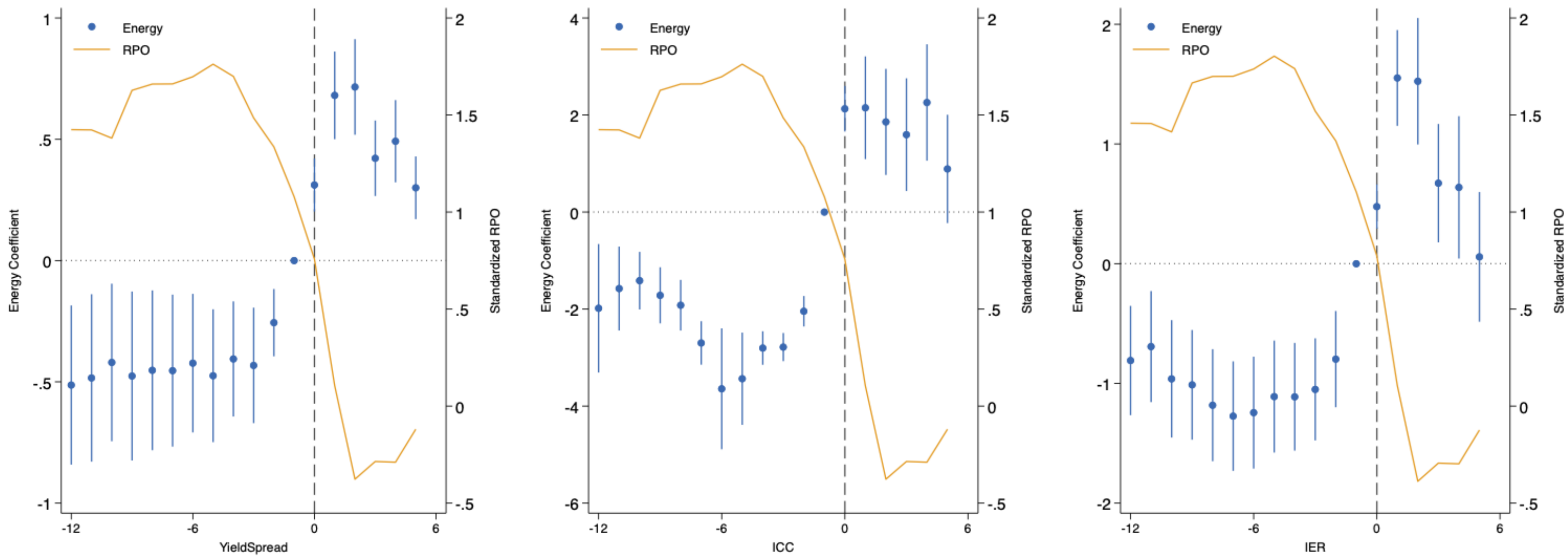
Figure 1: Time Variation in the Carbon Premium



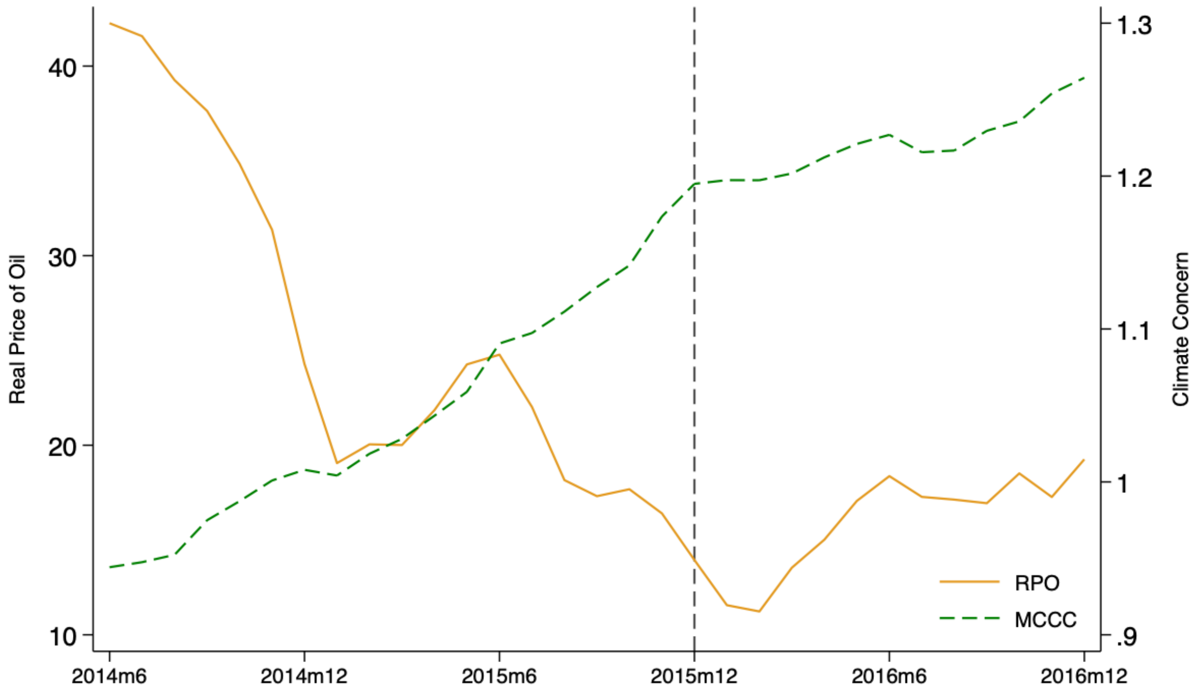
Notes: This figure plots the monthly value-weighted high-minus-low carbon premium in equity and corporate bond markets, constructed from portfolios sorted on firm-level carbon intensity. The bond carbon premium (top panel) is calculated analogously using option-adjusted yield spreads. The equity carbon premium (bottom panel) is computed as the difference in implied cost of equity or option-implied expected equity returns between the highest and lowest carbon intensity terciles. The dashed vertical lines indicate the adoption of the Paris Agreement (December 12, 2015). The sample period for the equity carbon premium spans from 1974:02 to 2022:12, while the bond carbon premium covers the period from 1997:01 to 2022:12.

Figure 2: Energy Premium Around the OPEC Price War



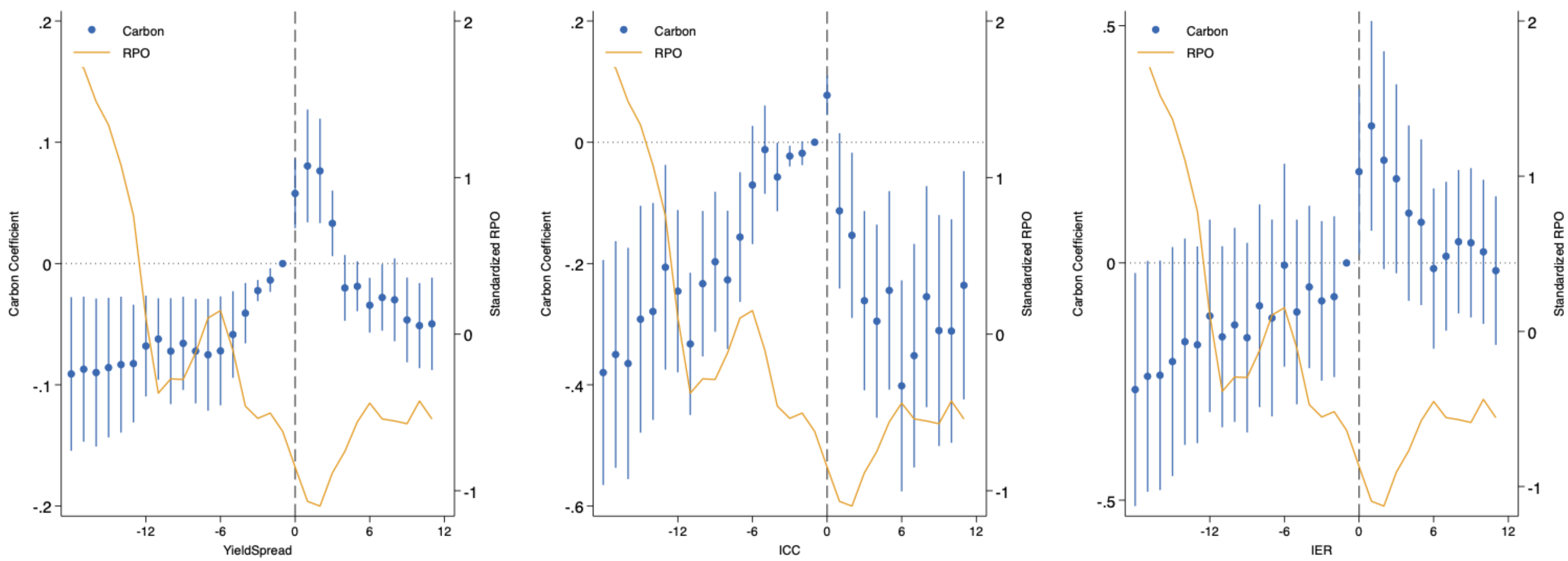
Notes: The figure plots monthly coefficients from event study regressions around the OPEC price war (November 2014, $t = 0$) for three cost of capital measures—corporate bond yield spreads (left panel), implied cost of equity capital (middle panel), and option-implied expected equity returns (right panel). Each panel plots coefficients (blue dots) for the interaction term between log emission intensity and monthly time dummies from a two-way fixed effects model with firm and month fixed effects. The month prior to the event, October 2014 ($t = -1$), is the omitted base period, and its coefficient is normalized to zero. Vertical spikes indicate 95% confidence intervals based on two-way clustered standard errors by firm and month. The orange line tracks the concurrent standardized real oil price. The sample period spans from September 2013 to October 2015.

Figure 3: Climate Concern and Oil Price Around the Paris Agreement



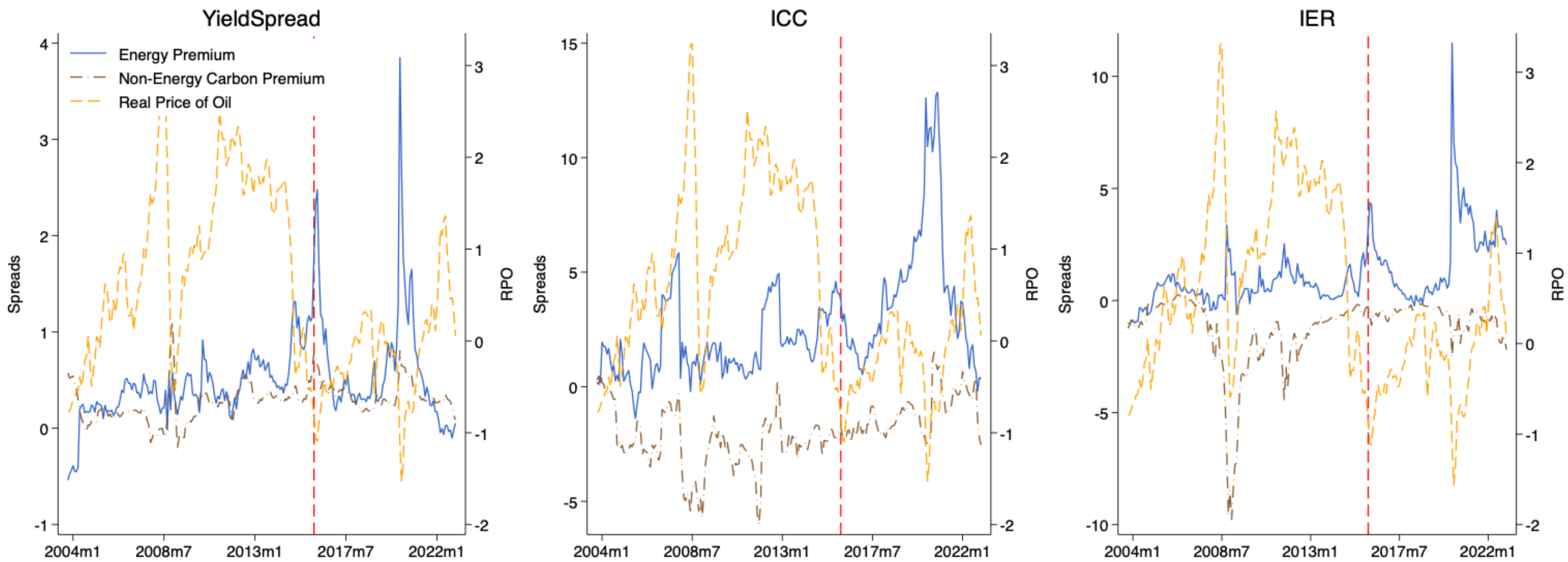
Notes: This figure plots the real price of oil (RPO) and the climate concern index (MCCC) around the Paris Agreement (December 2015).

Figure 4: Carbon Premium Around the Paris Agreement



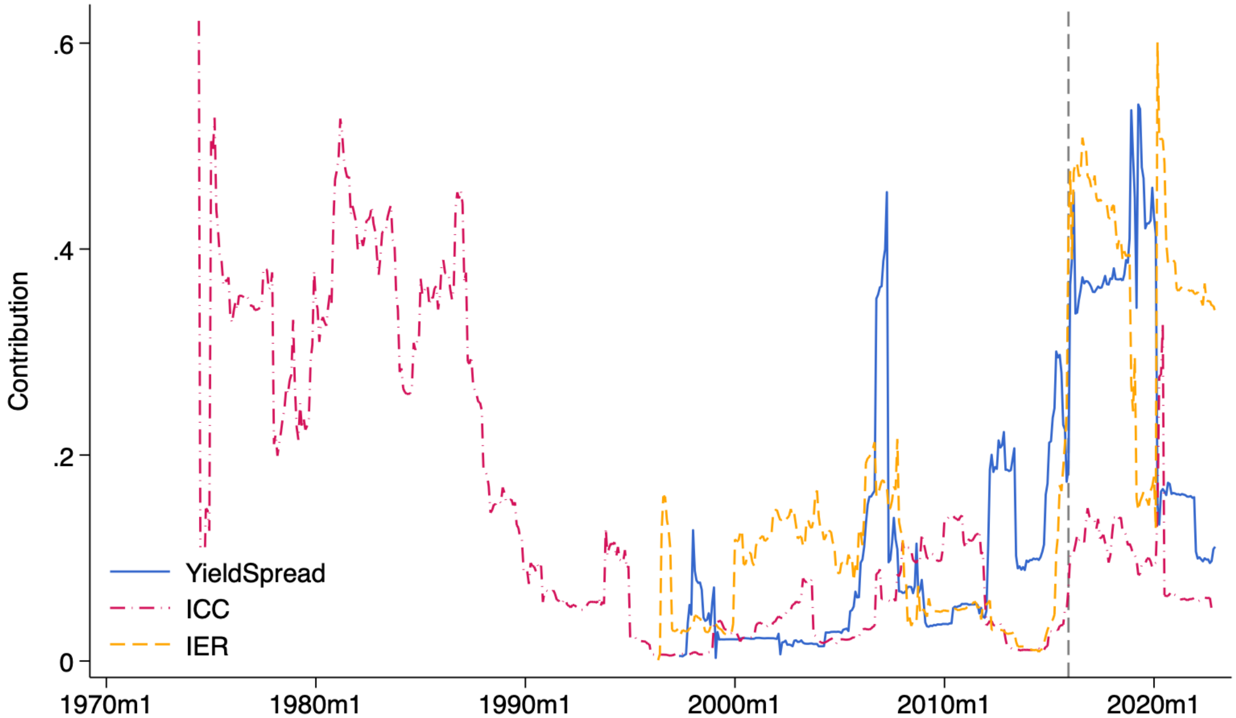
Notes: The figure plots monthly coefficients from event study regressions around the Paris Agreement (December 2015, $t = 0$) for three cost of capital measures—corporate bond yield spreads (left panel), implied cost of equity capital (middle panel), and option-implied expected equity returns (right panel). Each panel plots coefficients (blue dots) for the interaction term between log emission intensity and monthly time dummies from a two-way fixed effects model with firm and month fixed effects. The month prior to the event, November 2015 ($t = -1$), is the omitted base period, and its coefficient is normalized to zero. Vertical spikes indicate 95% confidence intervals based on two-way clustered standard errors by firm and month. The orange line tracks the concurrent standardized real oil price. The sample period spans from June 2014 to November 2016.

Figure 5: Oil Price and Carbon Premium Components



Notes: This figure presents monthly time series of decomposed carbon premium components alongside the real oil price for three cost of capital measures—corporate bond yield spreads (left panel), implied cost of equity capital (middle panel), and option-implied expected equity returns (right panel). In each panel, the solid line represents the energy premium, defined as the cost of capital differential between energy firms and non-energy brown firms. The dotted line represents the non-energy carbon premium, defined as the cost of capital differential between non-energy brown firms (top carbon intensity tercile) and green firms (bottom tercile). The right-hand axis displays the U.S. Refiner Acquisition Cost of Crude Oil deflated by the U.S. CPI, normalized to have zero mean and unit variance for visual comparability. Vertical dashed lines indicate the adoption of the Paris Agreement (December 2015). The sample period spans from 2003:10 to 2022:12.

Figure 6: Contribution of Energy Sector Dynamics to Carbon Premium Variation



Notes: This figure displays the time-varying explanatory power of energy-sector dynamics for the aggregate carbon premium. For each month t, the time-series regression $Spread_t^{B-G} = a + b \cdot Spread_t^{NB-G} + e_t$ is estimated over 60-month rolling windows, where Spread^{B-G} denotes the aggregate carbon premium (the value-weighted high-minus-low spread of carbon-intensity-sorted portfolios) and Spread^{NB-G} represents the non-energy carbon premium (the difference between non-energy brown firms and green firms). The contribution of energy-specific movements is measured as the proportion of $Spread^{B-G}$ variation unexplained by $Spread^{NB-G}$. The dashed vertical lines indicate the adoption of the Paris Agreement (December 12, 2015).

Table 1: Summary Statistics

	Mean	SD	P25	P50	P75
Panel A: Annualized Cost of Capital (%)					
Yield Spread	1.93	1.94	0.82	1.35	2.23
ICC	7.39	11.34	0.27	6.20	13.24
IER	6.54	8.13	2.29	4.18	7.45
Panel B: Carbon and Financial Information					
(Log) Emission Intensity	4.10	2.03	2.84	3.82	5.33
Beta	1.14	0.71	0.65	1.06	1.53
Log Assets	5.24	2.35	3.49	5.12	6.90
BE/ME	-0.51	0.94	-1.05	-0.42	0.11
Momentum	0.13	0.56	-0.21	0.05	0.34
ROE	-0.09	0.67	-0.04	0.08	0.14
Investment	0.23	0.66	-0.02	0.08	0.23
Sales Growth	0.21	0.62	-0.02	0.09	0.25
Leverage	0.83	1.69	0.04	0.25	0.81
IVol	3.03	2.33	1.45	2.33	3.82
Bond Duration	6.60	4.27	3.41	5.44	8.41
Bond Age	3.90	3.46	1.33	2.97	5.53
Rating	8.51	3.09	6.00	9.00	9.00
Panel C: Aggregate Variables					
ΔRPO	0.00	0.08	-0.03	0.00	0.04
Yield Carbon Premium (%)	0.36	0.32	0.19	0.33	0.46
ICC Carbon Premium (%)	-2.45	2.47	-1.04	-0.85	1.53
IER Carbon Premium (%)	-1.23	2.21	-0.61	-1.95	0.09
Yield Energy Premium (%)	0.25	0.68	0.00	0.30	0.53
ICC Energy Premium (%)	1.27	2.55	0.11	1.06	2.29
IER Energy Premium (%)	0.56	2.86	-1.00	0.05	1.16
Yield Non-Energy Carbon Premium (%)	0.31	0.28	0.16	0.28	0.40
ICC Non-Energy Carbon Premium (%)	-0.41	2.60	-2.35	-1.22	2.35
IER Non-Energy Carbon Premium (%)	-1.41	2.27	-1.76	-0.82	-0.17

Notes: This table presents summary statistics of cost of capital measures, firms' carbon and financial performance, and aggregate variables. Yield spreads measure corporate bonds' yield premium over the Treasury curve, adjusted for embedded options such as calls or puts. Implied cost of capital estimates (ICCs) combine the four published mechanical ICC estimates. Option-implied expected returns (IER) are expected equity returns, computed as bounds implied by risk-neutral variances from options. Carbon intensity is the log of total emissions scaled by dollar sales during the emitting period. Beta is estimated over a 60-month rolling window; the (log) book-to-market ratio is the log ratio of the book value of equity to the market value of equity; ROA is net income scaled by total assets; asset growth is the percentage change in total assets; momentum is the past 12-month return skipping the most recent month; leverage is book leverage, defined as the book value of debt divided by the book value of assets; sales growth is log four-quarter sales growth; and ivol is idiosyncratic volatility from the Fama-French three-factor model. Carbon premium, energy premium, and non-energy carbon premium spreads are constructed following Section 3.1.

Table 2: Carbon Intensity and Oil Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Panel A: Sectors and Carbon Portfolios					
		Brown Firms (%)		Other Firms (%)		Avg Oil Beta	
Sector	Intensity (level)	Bond	Equity	Bond	Equity	Bond	Equity
Utilities	3334	22	13	0	0	0.01	0
Materials	684	15	13	1	0	0.03	0.05
Energy	538	25	18	0	1	0.11	0.28
Industrials	157	15	13	10	9	0.01	0.01
Consumer Staples	107	6	15	13	8	0.01	0.01
Real Estate	70	0	0	0	0	0	0.11
Consumer Discretionary	61	4	10	13	13	0.03	0
Information Technology	39	3	9	11	24	0.01	0.02
Health Care	38	1	3	15	19	0	0
Communication Services	23	0	2	12	6	0.01	0.02
Financials	10	10	5	24	20	0.01	0

	Panel B: Product Price Response			
	ΔWeighted Input PPI		ΔOutput PPI	
ΔRPO	0.03***	0.02***	0.01***	0.00
	(3.06)	(2.97)	(5.57)	(0.87)
ΔRPO×Energy	0.03***	0.03***	0.36***	0.36***
	(2.83)	(2.77)	(13.38)	(13.29)
ΔRPO×Intensity	0.00*		0.02***	
	(1.78)		(5.96)	
ΔRPO×Brown		0.01*		0.02***
		(1.86)		(5.41)
Industry FE	Yes	Yes	Yes	Yes
Observations	9442	9442	24981	24981
R^2	0.159	0.159	0.246	0.244

Notes: This table examines the relationship between carbon intensity, portfolio weights, and the response of product prices to oil price shocks. Panel A displays the equity and bond portfolio weights of U.S. firms across sectors, classified into three carbon-intensity terciles: Brown (high), Mid (medium), and Green (low). Panel B presents regression results for quarterly industry-level producer price index changes (ΔPPI) on oil price changes (ΔRPO) and interactions with an energy-sector indicator (*Energy*), carbon intensity (*Intensity*), and brown-firm status (*Brown*). Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period spans from 1974 to 2022.

Table 3: Oil Price Shocks, Growth Options, and Risk Exposures

	(1)	(2)	(3)	(4)
	Panel A: Growth Options			
	ΔSales		ΔQ	
ΔRPO×Energy	0.23***	0.23***	0.14***	0.14***
	(4.77)	(4.61)	(4.27)	(4.55)
ΔRPO×Intensity	0.01*		0.00	
	(1.97)		(0.54)	
ΔRPO×Brown		0.03***		-0.00
		(3.15)		(-0.03)
Controls	Yes	Yes	Yes	Yes
Firm&Time FE	Yes	Yes	Yes	Yes
Observations	87615	87615	1078180	1078180
R^2	0.335	0.335	0.407	0.407
	Panel B: Security HML Beta			
	Equity		Bond	
ΔRPO×Energy	-0.67***	-0.61***	-0.06***	-0.08***
	(-9.20)	(-9.65)	(-2.77)	(-3.66)
ΔRPO×Intensity	0.01		0.00	
	(1.15)		(1.09)	
ΔRPO×Brown		-0.00		0.01
		(-0.09)		(1.04)
Firm&Time FE	Yes	Yes	Yes	Yes
Observations	1875668	2520548	483904	570638
R^2	0.219	0.202	0.157	0.159

Notes: This table examines the transmission of oil price shocks to firm-level growth opportunities and security risk characteristics. Panel A reports firm-level responses of growth metrics—sales growth ($\Delta Sales$) and Tobin's Q (ΔQ)—to oil price innovations (ΔRPO), interacted with an energy-sector indicator ($Energy$), carbon intensity ($Intensity$), and brown-firm status ($Brown$). Panel B presents regressions of security-level loadings on the High-Minus-Low (HML) factor on the same set of oil shock interactions. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Event Study: OPEC Price War

	(1)	(2)	(3)	(4)	(5)	(6)
	Bond		Equity			
	YieldSpread		ICC		IER	
			Panel A: Baseline			
Post Price War×Energy	0.91***	0.89***	3.00***	2.96***	2.18***	2.07***
	(4.54)	(4.53)	(3.61)	(3.45)	(4.36)	(4.23)
Post Price War×Intensity	-0.00		0.10		0.09	
	(-0.05)		(0.96)		(0.83)	
Post Price War×Brown		0.01		0.30		0.34**
		(0.27)		(1.09)		(2.08)
Firm&Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	65444	65444	21467	21467	9301	9301
R^2	0.760	0.760	0.845	0.845	0.745	0.746
			Panel B: Only Brown/Green			
Post Price War×Intensity	0.06		0.28**		0.28	
	(1.64)		(2.48)		(1.42)	
Post Price War×Brown		0.19**		0.79***		0.91**
		(2.68)		(2.82)		(2.60)
Observations	65444	65444	21467	21467	10093	10093
R^2	0.752	0.753	0.842	0.842	0.595	0.596

Notes: This table presents difference-in-differences estimates of the effect of the 2014 OPEC price war on the carbon premium in equity and bond markets. The analysis examines how the price war differentially affected firms based on their oil price exposure and carbon intensity. The dependent variables are yield spreads for corporate bonds and implied cost of capital (ICC) and option-implied expected returns (IER) for equities. The Post Price War indicator equals one for periods after November 2014. The regressions interact the post-treatment indicator with an energy-sector indicator (Energy), carbon intensity (Intensity), and brown-firm status (Brown). Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period spans from 2014:05 to 2015:05.

Table 5: Event Study: The Paris Agreement

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Climate Concern and Oil Price Patterns					
	ΔMCCC			ΔRPO		
	12M	24M	36M	12M	24M	36M
Post PA	-0.31	-0.18	-0.13	0.08	0.07	0.06
	(-1.48)	(-1.52)	(-1.17)	(0.98)	(1.28)	(1.34)
ΔMCCC				-0.02	-0.01	-0.03
				(-0.18)	(-0.06)	(-0.41)
Observations	13	25	31	13	25	31
R^2	0.165	0.091	0.045	0.119	0.078	0.076
	Bond		Equity		Option	
	Panel B: Baseline Regression					
Post PA×Intensity	0.12*		-0.24		0.38	
	(2.06)		(-1.65)		(1.33)	
Post PA×Brown		0.37**		-0.58*		1.17*
		(2.90)		(-1.79)		(1.88)
Firm&Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38320	38320	11454	11454	5252	5252
R^2	0.788	0.789	0.883	0.883	0.726	0.726
	Panel C: Controlling for Oil Beta					
Post PA×Intensity	0.13**		-0.25		0.47	
	(2.35)		(-1.62)		(1.61)	
Post PA×Brown		0.35**		-0.58*		1.17*
		(2.95)		(-1.79)		(1.99)
Post PA×Oil Beta	1.55**	1.45**	-0.97	-0.92	9.65**	9.39**
	(2.77)	(2.71)	(-0.62)	(-0.59)	(2.77)	(2.79)
Firm&Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37614	37614	11429	11429	5252	5252
R^2	0.792	0.793	0.883	0.883	0.739	0.739
	Panel D: Controlling for Energy Sector					
Post PA×Intensity	0.04		-0.26*		-0.04	
	(1.05)		(-2.00)		(-0.19)	
Post PA×Brown		0.14*		-0.64*		-0.06
		(1.81)		(-2.10)		(-0.15)
Post PA×Energy	1.11***	1.06***	0.34	0.38	5.97***	5.96***
	(3.38)	(3.28)	(0.28)	(0.31)	(3.22)	(3.19)
Firm&Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38320	38320	11454	11454	5252	5252
R^2	0.795	0.795	0.883	0.883	0.743	0.743
	Panel E: Controlling for Sector×Time FE					
	Bond		Equity		Option	
Post PA×Intensity	0.03		0.14		0.39	
	(0.48)		(0.69)		(1.50)	
Post PA×Brown		0.10		0.01		0.23
		(1.25)		(0.01)		(0.72)
Firm&Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector×FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38320	38320	11454	11454	5252	5252
R^2	0.805	0.805	0.888	0.888	0.772	0.772

Notes: This table presents evidence on the effect of the Paris Agreement (PA). Panel A studies the time-series relation between climate concern (MCCC), oil prices (RPO), and the PA. Panels B–E present difference-in-differences estimates of the effect of the 2015 Paris Agreement on the carbon premium in equity and bond markets. The analysis examines how the Agreement differentially affected firms based on their oil price exposure and carbon intensity. The dependent variables are bond yield spreads, average implied cost of capital, and option-implied expected equity returns, respectively. The Post PA indicator equals one for periods after December 2015. The regressions interact the post-treatment indicator with carbon intensity (Intensity), brown-firm status (Brown), oil beta (β_{Oil}), and an energy-sector indicator (Energy). Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period spans from 2015:06 to 2016:06.

Table 6: Time-Series Analysis on Oil Shocks and Carbon Premiums

	Panel A: Baseline Regressions					
	Energy Premium			Non-Energy Carbon Premium		
	YieldSpread	ICC	IER	YieldSpread	ICC	IER
ΔRPO	-0.95***	-1.51***	-2.13***	-0.30***	0.47	1.29***
	(-6.71)	(-2.92)	(-4.73)	(-4.70)	(1.09)	(4.13)
Observations	231	231	231	231	231	231
R^2	0.149	0.034	0.067	0.109	0.006	0.066
	Panel B: Renewable Energy					
	Renewable			Renewable-NB		
	Yield Spread	ICC		Yield Spread	ICC	
ΔRPO	-1.25***	-2.02**		-0.52***	-1.22*	
	(-5.97)	(-2.01)		(-3.36)	(-1.78)	
Observations	149	231		149	231	
R^2	0.179	0.018		0.060	0.015	
	Panel C: Early Sample Analysis					
	Energy Premium			Non-Energy Carbon Premium		
	Yield Spread	ICC	IER	Yield Spread	ICC	IER
ΔRPO	-0.21	-2.02***	-1.21*	-0.36	-0.36	0.03
	(-0.77)	(-3.64)	(-1.65)	(-0.89)	(-0.91)	(0.05)
Observations	79	354	91	79	354	91
R^2	0.007	0.031	0.023	0.010	0.002	0.000

This table reports time-series regressions of carbon premium components on oil price changes. The dependent variables are the Energy Premium (the cost of capital spread between energy and non-energy brown firms) and the Non-Energy Carbon Premium (the spread between non-energy brown and green firms). Panel A presents baseline results for the main sample (2003:10–2022:12). Panel B examines renewable energy firms, comparing their cost of capital with that of non-energy brown firms. Panel C extends the analysis to a pre-climate-finance sample (1974:04–2003:09) using imputed emissions data. t-statistics, based on Newey-West standard errors with 12 lags, appear in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Panel Regressions of Firm-Level Cost of Capital

	(1)	(2)	(3)	(4)	(5)	(6)
	Bond		Equity			
	YieldSpread		ICC		IER	
ΔRPO×Energy	-1.24*	-1.21*	-2.78*	-2.73*	-4.49**	-4.34**
	(-1.82)	(-1.80)	(-1.66)	(-1.69)	(-2.07)	(-2.04)
ΔRPO×Intensity	-0.02		0.03		0.11	
	(-0.64)		(0.38)		(0.83)	
ΔRPO×Brown		-0.08		-0.02		0.00
		(-1.08)		(-0.14)		(0.02)
Beta	-0.03***	-0.03***	-0.08**	-0.08**	-0.13***	-0.13***
	(-3.96)	(-3.95)	(-2.47)	(-2.47)	(-5.27)	(-5.26)
Log Assets	0.01*	0.01*	0.13***	0.13***	0.02	0.02
	(1.88)	(1.89)	(2.91)	(2.91)	(0.46)	(0.45)
BE/ME	-0.01	-0.01	-0.08**	-0.08**	-0.01	-0.01
	(-1.21)	(-1.20)	(-2.16)	(-2.16)	(-0.36)	(-0.36)
Momentum	-0.01	-0.01	0.25***	0.25***	-0.02	-0.02
	(-0.70)	(-0.70)	(4.35)	(4.36)	(-0.32)	(-0.33)
ROE	0.02**	0.02**	0.20***	0.20***	0.12***	0.12***
	(2.45)	(2.45)	(3.96)	(3.96)	(2.93)	(2.93)
Asset Growth	0.01	0.01	0.06***	0.06***	-0.00	-0.00
	(1.22)	(1.20)	(2.65)	(2.64)	(-0.09)	(-0.09)
Sales Growth	0.01	0.01	0.11***	0.11***	-0.02	-0.02
	(0.43)	(0.43)	(4.28)	(4.27)	(-0.39)	(-0.40)
Leverage	-0.03	-0.02	-0.32**	-0.32**	-0.01	-0.01
	(-1.08)	(-1.07)	(-2.54)	(-2.54)	(-0.08)	(-0.08)
IVol	-0.00	-0.00*	-0.04**	-0.04**	-0.05*	-0.05*
	(-1.65)	(-1.66)	(-2.24)	(-2.24)	(-1.88)	(-1.90)
Duration	0.00	0.00				
	(1.38)	(1.37)				
Bond Age	-0.00**	-0.00**				
	(-2.03)	(-2.02)				
Rating	-0.01***	-0.01***				
	(-3.60)	(-3.60)				
Firm&Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	498054	498054	237154	237154	78383	78383
R^2	0.369	0.369	0.172	0.172	0.630	0.630

This table presents panel regressions of firm-level changes in the cost of capital on interactions between oil price shocks and sector/carbon indicators. The dependent variables are bond yield spreads (Columns 1–2), the implied cost of equity (Columns 3–4), and option-implied expected equity returns (Columns 5–6). ΔRPO×Energy is an interaction of oil price changes with an energy-sector indicator; ΔRPO×Intensity and ΔRPO×Brown interact oil changes with carbon intensity and a brown-firm dummy, respectively. All specifications include firm and year-month fixed effects and control for firm and security characteristics. Standard errors are two-way clustered by firm and year-month. 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: Oil Shock Decomposition and Carbon Premium Components

	(1)	(2)	(3)	(4)	(5)	(6)
	Energy Premium			Non-Energy Carbon Premium		
	Panel A: Bond Yield Spread					
US Supply Shock	0.05***			0.00		
	(2.68)			(0.39)		
Foreign Supply Shock		-0.06***			-0.00	
		(-3.78)			(-0.62)	
Consumption Demand Shock			-0.10***			-0.03***
			(-6.69)			(-4.35)
Observations	230	230	230	230	230	230
R^2	0.031	0.059	0.165	0.001	0.001	0.079
	Panel B: Implied Cost of Capital					
US Supply Shock	0.06			-0.01		
	(1.05)			(-0.34)		
Foreign Supply Shock		-0.10*			0.03	
		(-1.73)			(0.72)	
Consumption Demand Shock			-0.16***			0.03
			(-2.94)			(0.67)
Observations	230	230	230	230	230	230
R^2	0.005	0.013	0.036	0.000	0.002	0.002
	Panel C: Option-Implied Expected Equity Return					
US Supply Shock	0.05			-0.03		
	(0.80)			(-0.76)		
Foreign Supply Shock		-0.18***			0.03	
		(-3.05)			(0.80)	
Consumption Demand Shock			-0.26***			0.13***
			(-4.83)			(3.75)
Observations	230	230	230	230	230	230
R^2	0.003	0.043	0.093	0.003	0.003	0.057

This table reports the impact of structural oil price shocks on the energy premium and non-energy carbon premium for three cost of capital measures—corporate bond yield spreads (Panel A), implied cost of equity capital (Panel B), and option-implied expected equity returns (Panel C). The independent variables are U.S. supply shocks, foreign supply shocks, and oil-specific demand shocks (consumption demand), identified using an extended Baumeister and Hamilton (2019) SVAR. All independent variables are standardized to facilitate cross-shock comparison. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period spans from 2003:10 to 2022:12.

Table 9: Event Study: Additional Oil Shocks

	(1)	(2)	(3)	(4)	(5)	(6)
	Bond		Equity			
	Yield Spread		ICC		IER	
	Panel A: COVID-19 Pandemic Lockdown					
Post Lockdown×Energy	1.47**	1.45**	5.35***	4.49***	7.38***	7.32***
	(2.72)	(2.63)	(6.92)	(5.84)	(4.71)	(4.71)
Post Lockdown×Intensity	0.05		-0.81***		0.08	
	(1.11)		(-5.38)		(0.38)	
Post Lockdown×Brown		0.12		-0.65**		0.28
		(1.13)		(-2.26)		(0.53)
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43031	43031	25560	25560	4907	4907
R^2	0.771	0.771	0.897	0.896	0.829	0.829
	Panel B: Russo-Ukrainian War					
Post Outbreak×Energy	-0.27***	-0.28***	-3.28***	-3.00***	-0.47	-0.47
	(-3.53)	(-3.71)	(-3.78)	(-3.48)	(-1.44)	(-1.44)
Post Outbreak×Intensity	0.00		0.10		-0.05	
	(0.33)		(0.93)		(-0.77)	
Post Outbreak×Brown		0.03		-0.28		-0.13
		(1.05)		(-1.20)		(-0.82)
Firm & Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	47598	47598	26333	26333	5036	5036
R^2	0.759	0.759	0.877	0.877	0.899	0.899

Notes: This table presents difference-in-differences estimates of the causal effect of oil price shocks on financing costs using two quasi-natural experiments. Panel A examines the COVID-19 pandemic lockdown (Post-Lockdown indicator starting March 2020), and Panel B examines the Russo-Ukrainian war (Post-Outbreak indicator starting February 2022). The dependent variables include corporate bond yield spreads, implied cost of equity capital (ICC), and option-implied expected equity returns. The regressions estimate differential changes for energy firms (Energy), high-carbon-intensity firms (Intensity), and brown firms (Brown) relative to other firms following these oil market shocks, with analysis conducted over 12-month windows around each shock. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Internet Appendix to
"Beyond Brown: Oil Shocks and Carbon Premium"

A A Quantitative Model with Oil and Carbon Shocks

In this section, we study a quantitative model to the distinct channels through which oil and carbon tax shocks operate and derive empirical predictions.

A.1 Model Setup

We consider an economy with three types of representative firms: Energy (E), Non-Energy Brown (NB), and Green (G). These firms produce two types of goods. Energy firms produce oil and gas, whose price, P_{Et}, is determined in a global market where domestic firms are price takers:

$$P_{Et} = e^{A_t}, \tag{IA.1}$$

where A_t reflects global demand for domestic oil, incorporating both aggregate demand for oil-specific consumption and the availability of foreign supply.

Non-energy goods can be produced by non-energy brown firms (NB) or green firms (G). The model comprises a representative firm in each sector $i = E, NB$ or G. The production function is

$$Y_{i,t} = e^{z_{i,t}} K_{i,t}^{\alpha}, \tag{IA.2}$$

where z_i is the productivity, and K_i is the level of capital in sector. The capital accumulates as follows,

$$K_{i,t+1} = (1-\delta)K_{i,t} + I_{i,t}, \tag{IA.3}$$

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

$$\Phi_{i,t} = \chi \frac{I_{i,t}^2}{K_{i,t}}. \tag{IA.4}$$

The greenhouse emission level of each firm is

$$GHG_{it} = \phi_i Y_{i,t}. \tag{IA.5}$$

We assume that $\phi_E = \phi_{NB} > \phi_G$. That is, both energy firms and non-energy brown firms have high carbon intensity, and green firms have low carbon intensity, as in the data.

The firms pay a tax rate τ on their profit and a carbon tax rate τ_{ct} on their emissions. The firm can be financed with debt b_{t+1} and equity s_{t+1}. Dividends $D_{i,t}$ derive from firms' production, investment, and financing,

$$D_{i,t} = (1-\tau)(P_{i,t}Y_{i,t} - \Phi_{i,t}) - I_{i,t} + \delta\tau K_{i,t} + b_{i,t+1} - r^b_{i,t}b_{i,t} - \tau_{ct}GHG_{it}, \tag{IA.6}$$

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

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

subject to $\lim_{T\to\infty} E_t\left[M_{t+T}b_{i,t+T+1}\right] = 0$ (the transversality condition), which prevents the firm from borrowing an infinite amount of debt. There is a key simplifying assumption of no tax shield or financial friction, including issuance costs or bankruptcy costs. As such, the capital structure is indeterminate, and the Modigliani-Miller theorem holds, allowing us to calculate the firm's cost of capital without explicitly solving for the capital structure.

A.2 Model Dynamics

The global oil demand follows an auto-regressive process, which pins down the global oil price,

$$A_{t+1} = \rho_a A_t + \sigma_a e_{a,t+1}, \tag{IA.7}$$

where e denotes the i.i.d. unexpected oil shocks that follow a standard normal distribution. In essence, e shocks represent oil demand shocks, distinct from z supply shocks or productivity shifts in oil firms. These oil shocks include sudden, significant changes in global oil demand or disruptions that drive oil prices, and constitute effective demand shocks for U.S. oil-and-gas firms. Positive e shocks include the 1970s oil embargo and the Russia–Ukraine war, both of which curtailed global supply, raised oil prices, and boosted U.S. energy firms' profitability. Another example is the surge in demand from China's manufacturing-driven economy. Negative e shocks include the 1980s oil glut, which eroded U.S. energy firms' profitability. Similarly, the COVID-19 lockdown sharply reduced transportation demand, dealing a heavy blow to the oil sector.

The carbon tax rate is uncertain and follows an auto-regressive process

$$\tau_{c,t+1} = \rho_c \tau_{c,t} + \sigma_c e_{c,t+1}. \tag{IA.8}$$

The carbon tax can be positive or negative, depending on whether the policy encourages green transition or manufacturing development. Finally, we assume the sector-specific log productivity shocks are transitory, $z_{i,t+1} = \sigma_z e_{z,i,t+1}$. The shocks in this model $[e_a, e_c, e_{z,E}, e_{z,NB}, e_{z,G}]$ are identically and independently distributed and follow a joint standard normal distribution.

We assume the stochastic discount factor varies with oil and carbon tax shocks as follows:

$$\frac{M_{t+1}}{M_t} = \beta \left(1 + \gamma_a e_{a,t+1} + \gamma_c e_{c,t+1}\right). \tag{IA.9}$$

The loading γ_a reflects the impact of oil shocks, which can disrupt the aggregate economy and drive risk premium fluctuations, given oil's role as a key input across sectors (Kilian, 2009; Baumeister and Hamilton, 2019; Känzig, 2021; Gao et al., 2022). The loading γ_c captures exposure to carbon tax shocks, reflecting the potential tradeoff between environmental policy efforts and economic growth.

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

We define $w^b_{i,t} = B_{i,t+1}/(P_{i,t} + B_{i,t+1})$ as the market leverage and $w^s_{i,t} = 1 - w^b_{i,t}$. The Euler equation for equity is $E_t[\frac{M_{t+1}}{M_t} r^s_{i,t+1}] = 1$.

A.3 Carbon Premium and Energy Premium

The expected cost of capital for the firm i equals the weighted sum of cost of equity and debt, $Er_{i,t+1} = w^b_{i,t+1} r^b_{i,t+1} + w^s_{i,t} r^s_{i,t+1}$. Following Liu, Whited and Zhang (2009), we can derive that the average cost of capital equals the investment return, $r^K_{i,t+1} = Er_{i,t+1} = w^b_{i,t+1} r^b_{i,t+1} + w^s_{i,t} r^s_{i,t+1}$. This insight allows us to abstract from modeling the entire firmn cross section to reconstruct the value factor and estimate the value beta loadings. Instead, we can focus on a representative firm in each sector and effectively construct their expected returns using the Q theory.

The energy premium $Spread^{E-NB}$ and non-energy carbon premium $Spread^{NB-G}$ are defined as

$$\begin{aligned} Spread^{E-NB}_t &= E_t[r_{E,t} - r_{NB,t}] = E_t[r^K_{E,t} - r^K_{NB,t}], \\ Spread^{NB-G}_t &= E_t[r_{NB,t} - r_{G,t}] = E_t[r^K_{NB,t} - r^K_{G,t}]. \end{aligned} \tag{IA.10}$$

The aggregate carbon premium is a weighted sum of these terms.

$$\begin{aligned} Spread^{B-G}_t &= W \cdot E_t r_{E,t+1} + (1 - W) E_t r_{NB,t+1} - E_t r_{G,t+1} \\ &= Spread^{NB-G}_t + W \cdot Spread^{E-NB}_t, \end{aligned} \tag{IA.11}$$

where W denotes the weight of energy firms in the brown portfolio. This decomposition highlights that both the energy premium and the non-energy carbon premium drive fluctuations in the overall carbon premium. As long as the energy sector weight is substantial, the energy premium can make a sizeable contribution. The overall impact thus depends on the portfolio share of energy firms (W) and the variability of the energy premium.

A.4 Equilibrium and Investment Return

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

$$1+(1-\tau)\chi\frac{I_{i,t}}{K_{i,t}}=E_t\frac{M_{t+1}}{M_t}$$
$$\cdot\left(\left((1-\tau)P_{i,t+1}-\tau_c\phi_i\right)\alpha e^{z_{i,t+1}}K_{i,t+1}^{\alpha-1}+(1-\tau)\left(\delta\tau+\frac{\chi}{2}\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^2\right)+(1-\delta)\left(1+(1-\tau)\chi\frac{I_{i,t+1}}{K_{i,t+1}}\right)\right). \tag{IA.12}$$

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

The first-order condition of physical investment also implies that $E_t\left[M_{t+1}r_{i,t+1}^K\right]=1$,

$$r_{i,t+1}^K=$$
$$\frac{\overbrace{\left((1-\tau)P_{i,t+1}-\tau_c\phi_i\right)\alpha e^{z_{i,t+1}}K_{i,t+1}^{\alpha-1}}^{MPK}+(1-\tau)\left(\delta\tau+\frac{\chi}{2}\left(\frac{I_{i,t+1}}{K_{i,t+1}}\right)^2\right)+(1-\delta)\left(1+(1-\tau)\chi\frac{I_{i,t+1}}{K_{i,t+1}}\right)}{\underbrace{1+(1-\tau)\chi\frac{I_{i,t}}{K_{i,t}}}_{\text{Investment, Marginal Q}}}. \tag{IA.13}$$

The equation states that firms' current asset growth, future profitability, and future investment growth all play a role in determining the expected return. The profitability is impacted directly by the oil and policy shocks and the firms endogenously adjust their capital and Tobin's Q, which further drives expected return variations. We thus solve the model numerically below to characterize these firm responses.

A.5 Numerical Results

We calibrate the model at a quarterly frequency and present parameters in Panel A, Table IA.9. 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 capital depreciation rate δ is 0.03, implying an annual rate of 0.12 as in Cooper and Haltiwanger (2006), and the adjustment cost coefficient χ is set to 10.

For the oil price process, the demand elasticity (ϵ) is set to 0.1, in line with estimates from Kilian (2022). The persistence (ρ) and volatility (σ_A) of the oil demand shock are calibrated to 0.98 and 0.087, respectively, to match the empirical persistence and volatility of the quarterly real oil price. The price of oil risk (γ_A) is set to -1.05, a value that allows the model to replicate the observed average annual energy premium of 0.25%.

For the carbon tax process, we face the challenge that a federal carbon tax has not yet been implemented in the U.S. Therefore, this part of the calibration is designed to explore a plausible future scenario. We set the carbon tax parameters to generate a positive non-energy carbon premium of approximately 1.3% annually, which is a generous estimate relative to empirical estimates.

Panel B of Table IA.9 confirms that the model's simulated moments align well with the data. A key result from our calibration is that the energy sector has the lowest steady-state investment rate and capital stock among all sectors. This is an endogenous outcome driven by a precautionary motive: because energy firms are exposed to two independent sources of risk (oil price and carbon tax), the heightened uncertainty about their future cash flows makes them inherently more cautious. They optimally choose to maintain a smaller scale of operations in the long run.

Figure IA.5 plots the dynamic responses of the model's key variables to a negative oil demand shock and a positive carbon tax shock. The left panel shows the response to a negative oil demand shock. The fall in oil prices directly reduces the profitability and growth options of energy firms. A negative oil demand shock, which reduces the energy firms' marginal Q, makes their returns more exposed to future shocks according to equation (IA.13). Consequently, their risk and expected return both increase.

In contrast, an unexpected increase in the carbon tax (right panel) acts as a broad shock to the costs of all carbon-intensive firms. This tax directly increases operating expenses, which squeezes profit margins for both energy and non-energy brown firms and reduces their marginal Q. The reduced marginal Qs again make all brown firms more exposed to future shocks, and this heightened risk further drives up the cost of capital for all of them. However, the magnitude of this effect varies across sectors. Because the energy sector is already exposed to significant background risk from oil price volatility, the carbon tax shock adds to its already high-risk profile. The conditional oil premium increases, and investors demand an even larger risk premium from energy firms than from their non-energy counterparts. In other words, an increased carbon tax simultaneously widens the non-energy carbon premium and energy premium in a correlated fashion.

A.6 Simulated Results

We further simulate the model for 300 periods and regress the expected return variations on oil demand and carbon tax innovations,

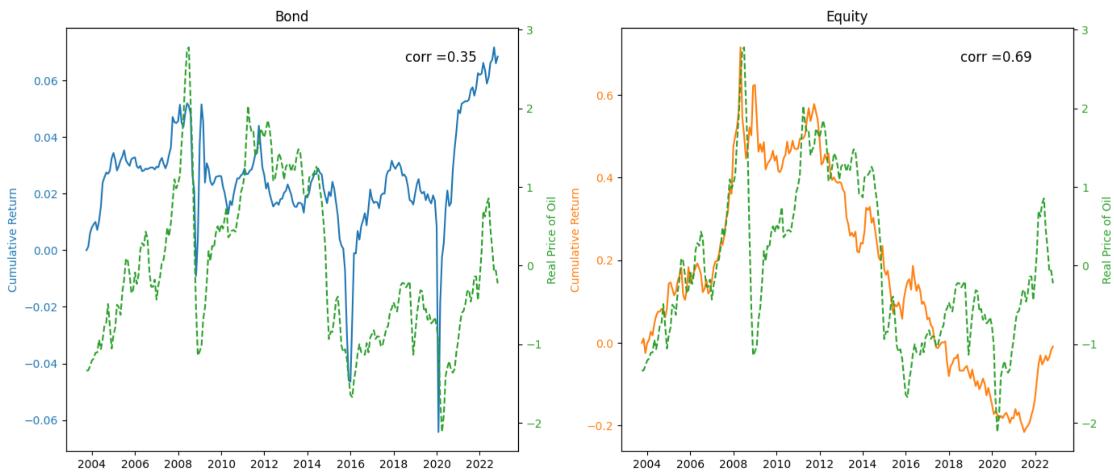
$$\Delta Er_{i,t} = \alpha + \beta \cdot \Delta A_t + \gamma \cdot \Delta \tau_t + e_{i,t}. \tag{IA.14}$$

Panel C presents the results. Consistent with the impulse responses, carbon tax shocks raise expected returns of both energy and non-energy brown firms, thereby increasing both the energy premium and the non-energy carbon premium. Oil demand shocks, by contrast, reduce expected returns of energy firms and narrow the energy premium, with little effect on non-energy firms.

In summary, the model's predictions provide a clear interpretive lens for our Paris Agreement findings. The documented V-shape pattern mainly derives from an oil demand shock, not a carbon policy shock. A true climate policy shock, like an unanticipated carbon tax, would have raised the cost of capital for all brown firms, including utilities and materials. The complete absence of this effect for non-energy brown firms around the PA is inconsistent with a broad repricing of carbon transition risk. Instead, the evidence is fully consistent with the energy sector's recovery from the preceding negative oil demand shock.

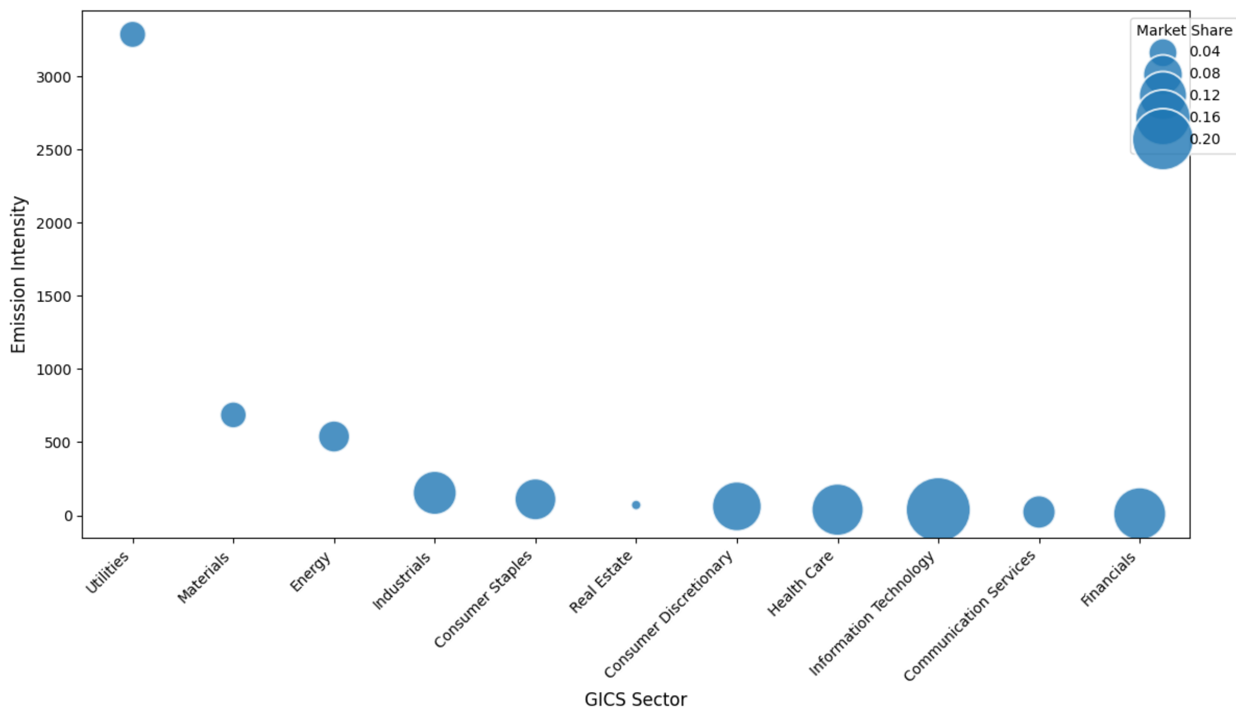
B Supplementary Tables and Figures

Figure IA.1: Brown Return and Oil Price



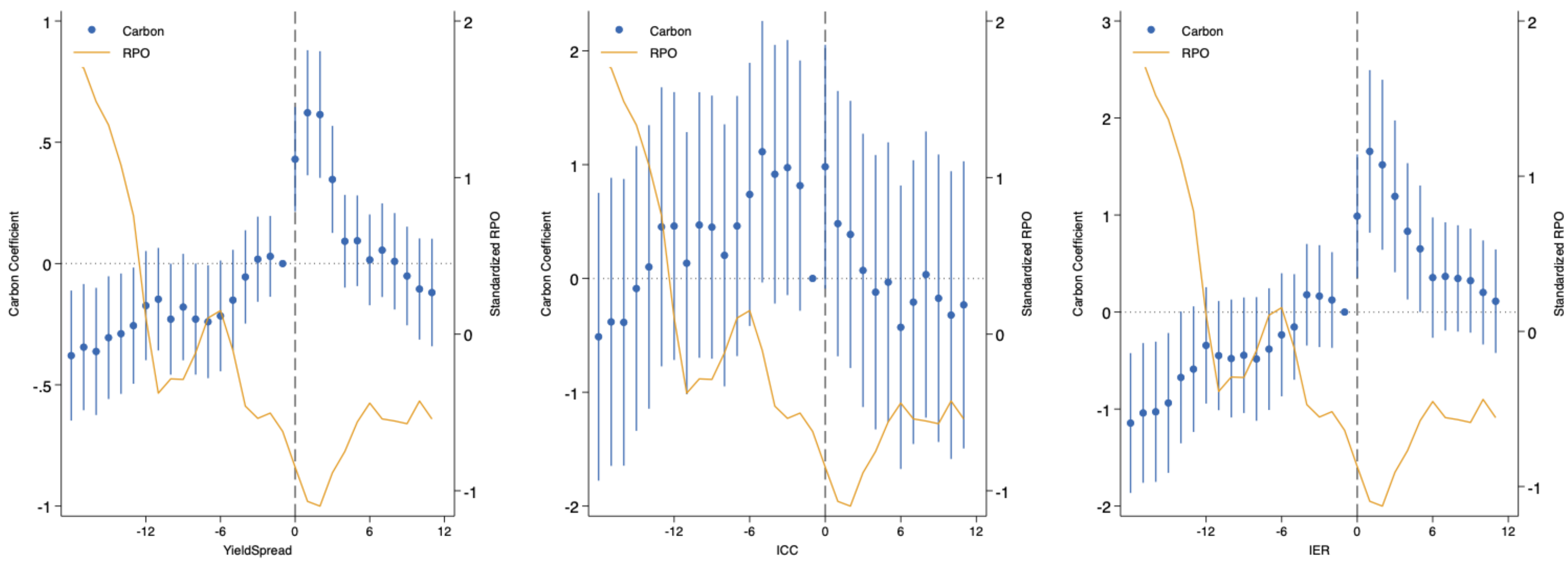
Notes: This figure plots the cumulative brown return and the standardized real price of oil. The monthly brown return is the value-weighted return difference between firms in the top tercile of carbon intensity and those in the bottom tercile. The real price of oil is standardized to have zero mean and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

Figure IA.2: Carbon Intensity Variations Across Sectors



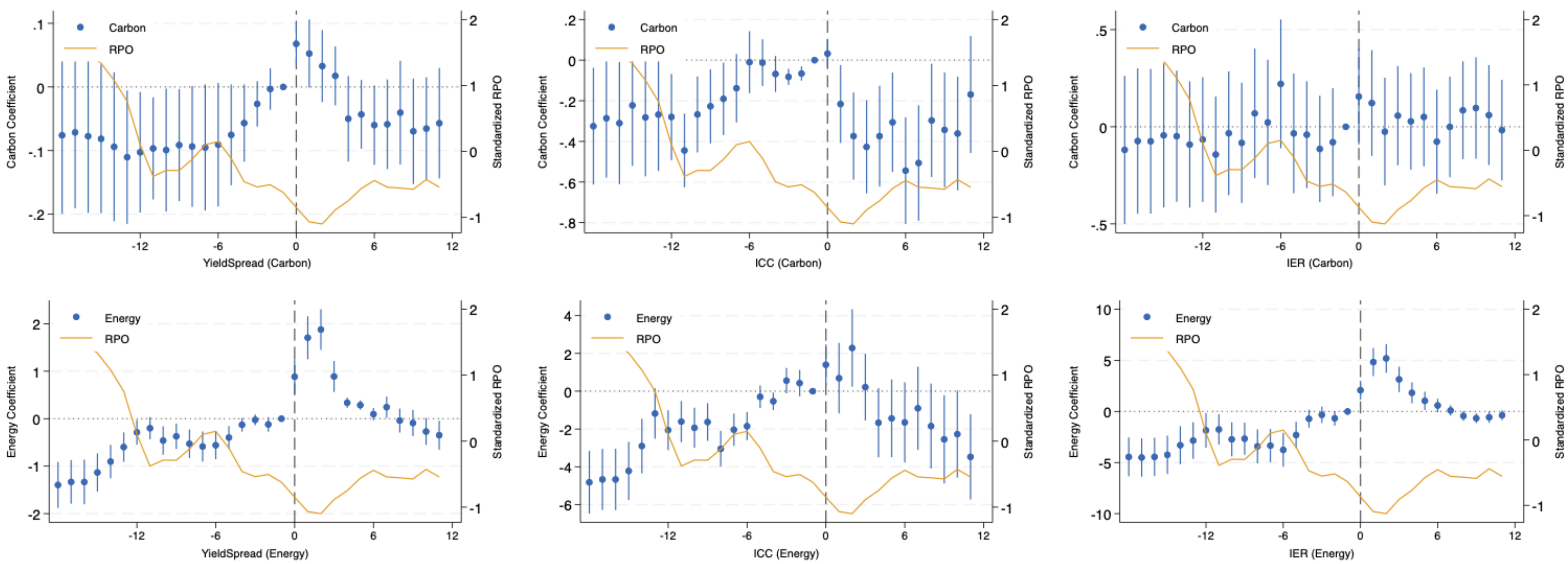
Notes: This figure plots mean carbon intensity (scope 1 and 2 emissions/sales) and the average market share of each GICS sector.

Figure IA.3: Brown Firm Carbon Premium Around the Paris Agreement



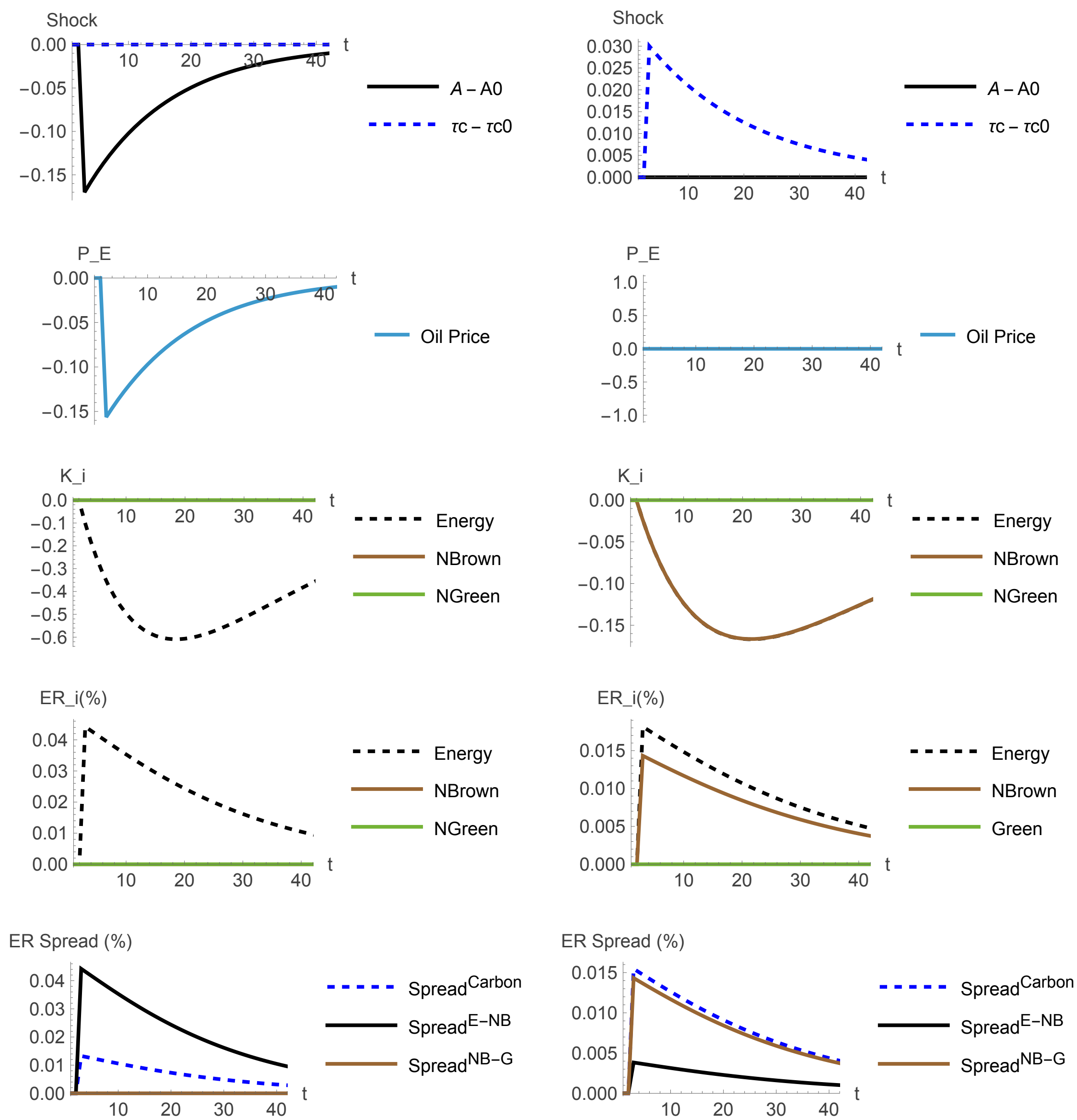
Notes: The figure plots monthly coefficients from event study regressions around the Paris Agreement (December 2015) for three cost of capital measures—corporate bond yield spreads (left panel), implied cost of equity capital (middle panel), and option-implied expected equity returns (right panel). Each panel plots coefficients (blue dots) for the interaction between the brown-firm indicator and monthly time dummies from a two-way fixed effects model with firm and month fixed effects. The month prior to the event, November 2015 ($t = -1$), is the omitted base period, and its coefficient is normalized to zero. Vertical spikes indicate 95% confidence intervals based on two-way clustered standard errors by firm and month. The orange line tracks the concurrent standardized real oil price. The sample period spans from June 2014 to November 2016.

Figure IA.4: Controlled Carbon Premium Around the Paris Agreement



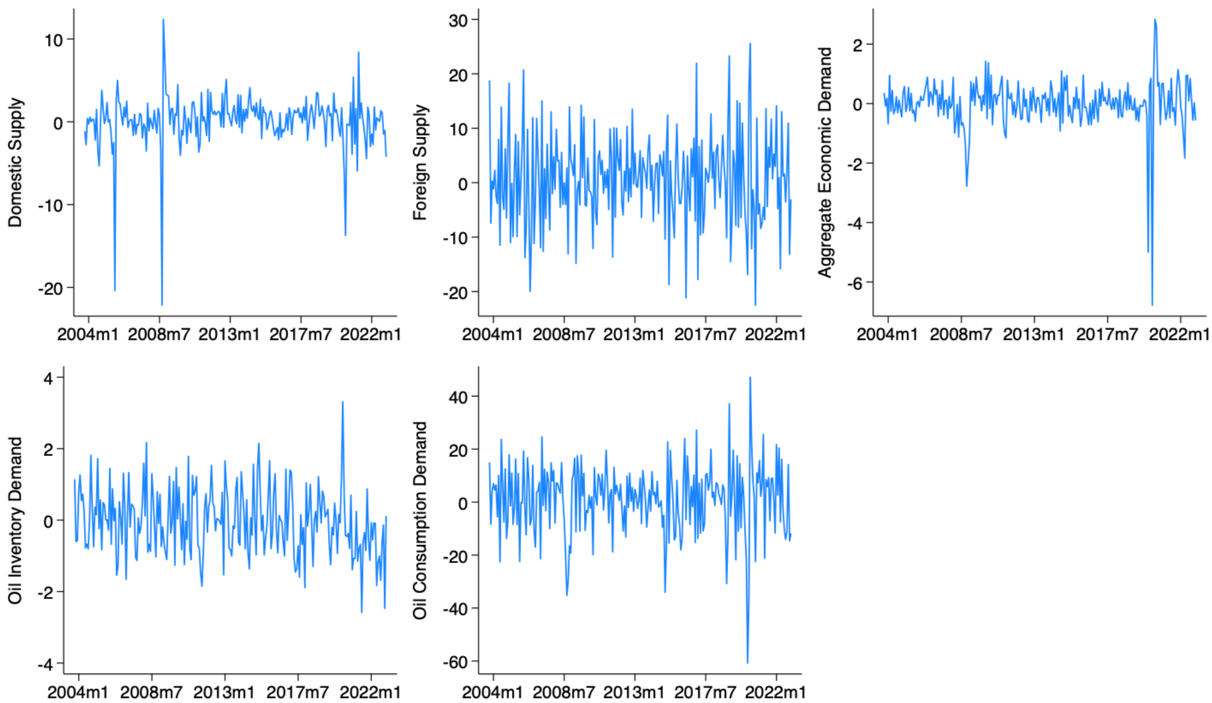
Notes: The figure plots monthly coefficients from event study regressions around the Paris Agreement (December 2015) for three cost of capital measures—corporate bond yield spreads (left panels), implied cost of equity capital (middle panels), and option-implied expected equity returns (right panels). Each figure plots coefficients (blue dots) for the interaction between firm carbon intensity and monthly time dummies or for the interaction between the energy-firm indicator and monthly time dummies, estimated in a two-way fixed effects model with firm and month fixed effects. The month prior to the event, November 2015 ($t = -1$), is the omitted base period, and its coefficient is normalized to zero. Vertical spikes indicate 95% confidence intervals based on two-way clustered standard errors by firm and month. The orange line tracks the concurrent standardized real oil price. The sample period spans from June 2014 to November 2016.

Figure IA.5: Model-Implied Dynamic Responses to Structural Shocks



Notes: This figure presents simulated impulse responses of key model variables to two structural shocks: a negative oil demand shock (left panel) and a positive carbon tax shock (right panel). The responses are derived from the calibrated model with parameters reported in Table IA.9. Key variables shown include oil prices, investment, and expected returns for energy and non-energy firms, as well as the carbon premium and its components (energy spread and non-energy carbon premium).

Figure IA.6: SVAR-Decomposed Oil Shocks



Notes: This figure plots the monthly time series of five structural oil price shocks identified using an extended Baumeister and Hamilton (2019) SVAR model. The shocks include U.S. supply shocks, foreign supply shocks, oil-specific consumption demand shocks, inventory demand shocks, and aggregate economic activity shocks. These shocks form the basis of the analysis in Tables 8 and IA.7. The sample period spans from 2003:10 to 2022:12.

Table IA.1: Industry Structure in Carbon Intensity

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

Notes: This table presents firm-level regressions of carbon emission intensity on sector fixed effects and firm characteristics. Column (1) includes GICS sector and time fixed effects. Column (2) incorporates firm characteristics, including market beta, log assets, book-to-market ratio, momentum, return on equity (ROE), investment, sales growth, leverage, and idiosyncratic volatility. Column (3) includes both firm characteristics and sector and time fixed effects. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period spans from 2003:10 to 2022:12.

Table IA.2: Energy Supply Chain and Carbon Intensity

	(1)	(2)	(3)	(4)
Panel A: Oil and Gas Extraction Product Input Share				
Energy	0.037***		0.038***	
	(6.07)		(6.48)	
Intensity	0.008***	0.011***		
	(5.16)	(7.81)		
Brown			0.012***	0.019***
			(4.79)	(6.49)
Time FE	Yes	Yes	Yes	Yes
Observations	10563	10563	10563	10563
R^2	0.249	0.136	0.229	0.105
Panel B: Petroleum and Coal Product Input Share				
Energy	-0.000		0.002*	
	(-0.14)		(1.99)	
Intensity	0.005***	0.005***		
	(9.89)	(10.78)		
Brown			0.007***	0.007***
			(6.24)	(7.06)
Time FE	Yes	Yes	Yes	Yes
Observations	18268	18268	18268	18268
R^2	0.266	0.266	0.145	0.143

Notes: This table examines the relationship between energy-related input shares and carbon intensity. Carbon intensity is normalized to have a mean of zero and a unit standard deviation. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period spans from 2003 to 2022.

Table IA.3: Oil Beta, Carbon Intensity, and Energy Supply Chain

Panel A: Oil Beta and Carbon Performance

	(1)	(2)	(3)	(4)
	Bond Oil Beta		Equity Oil Beta	
Energy	0.09***	0.20***	0.09***	0.20***
	(4.05)	(4.63)	(4.00)	(4.57)
Intensity	-0.00	-0.00		
	(-0.67)	(-0.35)		
Brown			-0.00	0.00
			(-0.23)	(0.10)
Time FE	Yes	Yes	Yes	Yes
Observations	7725	25680	7725	25680
R^2	0.083	0.051	0.083	0.051

Panel B: Oil Beta and Input Share

	Bond Oil Beta		Equity Oil Beta	
Energy	0.12***	0.29***	0.10***	0.28***
	(4.44)	(7.91)	(4.36)	(8.16)
Input Share	-0.01***	-0.01***		
(Oil and Gas Extraction Products)	(-3.35)	(-4.21)		
Input Share			-0.00	-0.01***
(Petroleum and Coal Products Manufacturing)			(-0.98)	(-8.55)
Time FE	Yes	Yes	Yes	Yes
Observations	4391	28221	7321	48904
R^2	0.095	0.046	0.076	0.038

Notes: This table examines the relationship between oil beta and carbon intensity or energy-related input shares. Carbon intensity and input shares are normalized to have a mean of zero and a unit standard deviation. Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period spans from 2003 to 2022.

Table IA.4: Oil Price Shocks and Security-Level Market and Size Betas

	(1)	(2)	(3)	(4)
	Panel A: Security MKT Beta			
	Equity		Bond	
ΔRPO×Energy	0.03	-0.05	-0.26***	-0.25***
	(0.46)	(-1.21)	(-3.32)	(-3.69)
ΔRPO×Intensity	0.01**		-0.01	
	(2.03)		(-1.04)	
ΔRPO×Brown		0.00		-0.05**
		(0.42)		(-2.13)
Firm&Time FE	Yes	Yes	Yes	Yes
Observations	1875668	2520548	483904	570638
R^2	0.180	0.177	0.179	0.189
	Panel B: Security SMB Beta			
ΔRPO×Energy	-0.24**	-0.02	-0.03	-0.03
	(-2.17)	(-0.21)	(-1.24)	(-1.46)
ΔRPO×Intensity	0.01		0.00	
	(1.44)		(1.28)	
ΔRPO×Brown		-0.03		0.01
		(-1.51)		(1.45)
Firm&Time FE	Yes	Yes	Yes	Yes
Observations	1875668	2520548	483904	570638
R^2	0.196	0.194	0.177	0.156

Notes: This table examines the effect of oil price shocks (ΔRPO) on security-level loadings of the market (MKT) and size (SMB) factors. The dependent variables are rolling MKT betas (Panel A) and rolling SMB betas (Panel B). The regressions estimate interactions between oil price shocks and an energy-sector indicator (Energy), carbon intensity (Intensity), or brown-firm status (Brown). Reported in parentheses beneath the coefficients are t-statistics. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period spans from 1974:02 to 2022:12 for equity and 1997:01 to 2022:12 for corporate bonds.

Table IA.5: Oil Price and Carbon-Sorted Portfolios

	(1)	(2)	(3)	(4)
	Green	Mid	Non-Energy Brown	Energy
		Bond Yield Spread		
ΔRPO	-0.64***	-0.70***	-0.94***	-1.89***
	(-4.14)	(-4.96)	(-5.47)	(-7.52)
Observations	231	231	231	231
R^2	0.073	0.100	0.122	0.182
		Implied Cost of Capital		
ΔRPO	-1.27**	-1.00	-0.80	-2.31**
	(-2.36)	(-1.38)	(-1.27)	(-2.38)
Observations	231	231	231	231
R^2	0.022	0.008	0.007	0.023
		Option-Implied Expected Return		
ΔRPO	-4.54***	-3.04***	-3.25***	-5.38***
	(-4.35)	(-3.61)	(-4.03)	(-4.82)
Observations	231	231	231	231
R^2	0.072	0.050	0.061	0.079

Notes: This table presents time-series regressions of portfolio-level cost of capital measures on oil price shocks. Firms are classified into four portfolios based on carbon intensity and sector: Green (lowest carbon intensity), Mid (medium), Non-Energy Brown (highest carbon intensity excluding energy sector), and Energy (energy sector firms). The dependent variables are three cost of capital measures: corporate bond yield spreads, the implied cost of equity, and option-implied expected equity returns. The independent variable is the log change in the real price of oil (ΔRPO). 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.6: Oil Shocks and Climate Concern: Time-Series Correlations

	ΔCC	Equity ESG Asset	Equity ESG Flow	Bond ESG Asset	Bond ESG Flow
Correlation(ΔRPO, x)	-0.00	-0.12	0.06	0.19	-0.00
	(-0.04)	(-1.52)	(0.71)	(1.64)	(-0.01)
	Environmental Policy Stringency			CO2 Trading	Low Carbon
	Overall	Market-Based	Non-Market Based	Scheme	R&D Expenditure
Correlation(ΔRPO, x)	0.00	-0.23	0.02	0.28	0.04
	(0.02)	(-1.46)	(0.20)	(1.06)	(0.22)

Notes: This table reports pairwise correlations between real oil price shocks (ΔRPO) and contemporaneous measures of climate concern and sustainable investing activity. Climate concern shocks (ΔCC) are constructed following Ardia et al. (2023). ESG flow and asset shares represent the fraction of monthly equity and bond fund flows and assets allocated to ESG-designated funds. P-values are reported in parentheses. The sample period spans from 2006:06 to 2022:12.

Table IA.7: Oil Shock Decomposition: Additional Structural Shocks

	(1)	(2)	(3)	(4)
	Energy Premium		Non-Energy Carbon Premium	
	Panel A: Yield Spreads			
Inventory Demand Shock	0.00		0.00	
	(0.08)		(0.41)	
Aggregate Demand Shock		0.04**		-0.00
		(2.42)		(-0.51)
Observations	230	230	230	230
R^2	0.000	0.024	0.001	0.001
	Panel B: Implied Cost of Capital			
Inventory Demand Shock	0.07		-0.03	
	(1.17)		(-0.67)	
Aggregate Demand Shock		0.12**		0.10**
		(2.08)		(2.50)
Observations	230	230	230	230
R^2	0.006	0.018	0.002	0.027
	Panel C: Option-Implied Expected Equity Return			
Inventory Demand Shock	-0.02		0.02	
	(-0.43)		(0.57)	
Aggregate Demand Shock		0.18***		0.02
		(3.17)		(0.64)
Observations	230	230	230	230
R^2	0.001	0.042	0.001	0.002

This table reports the impact of additional structural oil price shocks on the energy premium and the non-energy carbon premium for three cost of capital measures—corporate bond yield spreads (Panel A), implied cost of equity capital (Panel B), and option-implied expected equity returns (Panel C). The independent variables are inventory demand shocks (speculative demand shocks) and aggregate demand shocks (economic activity shocks), identified using an extended Baumeister and Hamilton (2019) SVAR. All independent variables are standardized to facilitate cross-shock comparison. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period spans from 2003:10 to 2022:12.

Table IA.8: Firm-Level Cost of Capital

	(1)	(2)	(3)	(4)	(5)	(6)
	Energy Premium			Non-Energy Carbon Premium		
	ICC	IER		ICC		IER
ΔRPO	-1.41***	-1.89***		0.34		0.32**
	(-3.34)	(-4.77)		(1.04)		(2.20)
Observations	231	231		231		231
R^2	0.041	0.079		0.005		0.019

This table reports time-series regressions of carbon premium components on oil price changes. The dependent variables are firm-level weighted-average costs of capital (leverage-adjusted). t-statistics, based on Newey-West standard errors with 12 lags, appear in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table IA.9: Model Calibration and Simulated Implications

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	0.05
Adjustment Cost	χ	10
Persistence	ρ_A	0.98
	ρ_c	0.99
Volatility	σ_A	0.087
	σ_c	0.02
	σ_z	0.05
Discount Rate	β	0.99
Risk Price	γ_A	-1.05
	γ_c	8

Panel B: Simulated vs. Empirical Moments

Variable	Data	Simulation
Oil Supply Elasticity	0–0.04	0.02
$\sigma(P_E)/\text{Mean}(P_E)$	0.19	0.13
Mean I_E/K_E	3.00%	3.04%
Mean I_{NB}/K_{NB}	3.00%	3.05%
Mean I_{NG}/K_{NG}	3.00%	3.09%
Mean ER_G	0%	8.12%
Mean Spread^{E-NB}	0.26%	0.24%
Mean Spread^{NB-G}	0.35%	1.31%
Vol Spread^{E-NB}	0.34%	0.02%
Vol Spread^{NB-G}	1.96%	0.02%

Panel C: Simulated Responses

	ΔER_{Energy}	ΔER_{NB}	$\Delta\text{Spread}^{E-NB}$	$\Delta\text{Spread}^{NB-G}$
ΔA	-0.24***	-0.00	-0.24***	-0.00
	(-236.39)	(-0.49)	(-256.08)	(-0.49)
$\Delta\tau_c$	0.60***	0.48***	0.12***	0.48***
	(205.33)	(332.34)	(45.33)	(332.34)
R^2	0.99	0.99	0.99	0.99

Notes: This table presents the calibration, simulated moments, and key implications from the proposed model linking oil price dynamics to the carbon premium. Panel A reports the calibrated parameters used in the baseline model. Panel B compares annualized moments in the data with those generated by the model simulation. Panel C presents the simulated response of annualized expected returns and expected return spreads to innovations in oil demand (ΔA) and the carbon tax ($\Delta\tau_c$). The regression is estimated at a quarterly frequency using 300 periods of simulated data. Reported in parentheses beneath the coefficients are t-statistics.