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Heterogeneous Valuation Effects of Structural Oil Shocks Across Clean Energy Technologies

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Research Article

Keywords: oil shocks, clean energy, cash-flow channel, discount-rate channel, structural identification, local projections

Posted Date: November 24th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11576470/v1

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Additional Declarations: No competing interests reported.

Abstract

This paper investigates the differential valuation responses of clean energy assets to structural oil shocks by decomposing transmission into cash-flow and discount-rate channels. Existing literature establishes that oil shocks influence clean energy returns and that connectedness varies with market conditions, but the fundamental question of how these shocks transmit through valuation mechanisms remains underexplored. Using a structural vector autoregression framework to identify oil supply, aggregate demand, and oil-specific demand shocks, combined with local projection methods at the firm level, we examine whether the adverse valuation effects of oil shocks operate primarily through expected cash flows or through changes in discount rates and financing costs. Our analysis of publicly listed clean energy firms across major equity markets from 2005 to 2025 reveals that supply-driven oil shocks generate opposing forces: they improve expected competitiveness for renewable energy technologies while simultaneously increasing financing costs through inflation and interest rate channels. Demand-driven shocks, by contrast, operate predominantly through cash-flow expectations without commensurate discount-rate effects. We further document substantial heterogeneity across clean energy subsectors, with capital-intensive technologies such as solar and storage exhibiting greater sensitivity to discount-rate transmission, while biofuels and fuel cells show stronger cash-flow responses. These findings have important implications for energy finance risk assessment, suggesting that aggregate connectedness measures obscure economically meaningful variation in transmission mechanisms that matters for portfolio construction and policy design.

1. Introduction

The global energy transition has fundamentally altered the relationship between conventional and renewable energy markets. As clean energy investments have surged amid climate concerns and energy security imperatives, understanding how oil market developments influence clean energy asset valuations has become increasingly important for investors, policymakers, and energy market participants [14, 17]. The existing literature has made substantial progress in documenting that oil shocks and clean energy markets are connected, that this connectedness is time-varying, and that it intensifies during periods of market stress [1, 12, 15].

However, a fundamental limitation persists in this literature: it treats the transmission of oil shocks to clean energy valuations as a single economic relationship rather than recognizing that multiple, potentially opposing mechanisms operate simultaneously. When an oil shock affects clean energy valuations, the observed return response represents the net effect of changes in expected operating cash flows and changes in the discount rate applied to those cash flows [16]. These channels can imply opposing outcomes, and a model that identifies only net spillovers can obscure these opposing forces.

Consider a supply disruption that reduces global oil production. On one hand, higher oil prices may improve the expected competitiveness of renewable energy technologies relative to fossil fuels, raising expected future cash flows for clean energy firms [36]. On the other hand, the same disruption may increase inflation expectations, interest rates, financing costs, and equity risk premia, reducing the present value of those expected cash flows [8]. The net effect on clean energy valuations depends on the relative magnitude of these opposing forces, which may vary systematically across shock types, firm characteristics, and market conditions.

This paper addresses this fundamental identification challenge by developing and implementing a framework that separates cash-flow and discount-rate transmission of structural oil shocks to clean energy asset valuations. We build on the structural oil-market framework of [22], which distinguishes between oil supply shocks, aggregate demand shocks, and oil-specific demand shocks, and extend it to examine firm-level valuation responses through both cash-flow and discount-rate channels.

Our analysis makes several contributions to the literature. First, we provide the first systematic decomposition of oil shock transmission to clean energy valuations into cash-flow and discount-rate components. While previous studies have documented that oil shocks affect clean energy returns and that these effects are heterogeneous across shock types [27, 44], they have not examined the valuation mechanisms through which these effects operate. By separately identifying effects on expected earnings and financing costs, we provide new evidence on why apparently similar oil shocks may produce different valuation outcomes.

Second, we demonstrate that the balance between cash-flow and discount-rate transmission varies systematically with firm characteristics, particularly capital intensity, leverage, and technology type. This finding has important implications for understanding cross-sectional variation in oil sensitivity documented in previous studies [10, 34]. Capital-intensive technologies with long-duration expected cash flows, such as solar and storage, exhibit greater sensitivity to the discount-rate channel, while less capital-intensive technologies show stronger relative cash-flow responses.

Third, we show that the relative importance of cash-flow versus discount-rate transmission depends on the type of oil shock. Supply-driven shocks generate opposing forces that partially offset each other, with the net effect depending on the monetary policy environment. Demand-driven shocks, by contrast, operate primarily through cash-flow expectations, as aggregate demand affects both energy demand and the broader economic outlook without the same inflationary pressures that accompany supply disruptions.

Fourth, we extend the analysis beyond clean energy equities to examine green bonds and fossil energy firms, providing a more complete picture of how oil shocks transmit across the green finance spectrum. Consistent with previous findings that green bonds are more defensive than clean energy equities [6, 24], we find that green bonds exhibit muted responses to both cash-flow and discount-rate channels, reflecting their different cash-flow structure and investor base.

The remainder of this paper proceeds as follows. Section 2 reviews the relevant literature and develops the theoretical framework. Section 3 describes our data and variable construction. Section 4 presents the econometric methodology. Section 5 reports baseline results. Section 6 examines transmission mechanisms. Section 7 presents heterogeneity analysis and robustness checks. Section 8 discusses implications and concludes.

2. Theoretical Framework and Hypotheses

2.1 Structural Oil Shocks and Clean Energy Markets

The modern literature on oil shocks begins with the recognition that not all oil price movements are alike. The structural decomposition in [22] demonstrated that oil price changes can be decomposed into supply shocks, aggregate demand shocks, and oil-specific or precautionary demand shocks, each originating from different economic mechanisms and generating heterogeneous effects on macroeconomic and financial variables. This distinction has become a cornerstone of the oil shock literature because each shock type influences production costs, aggregate economic activity, expectations, and financial markets through different transmission channels [5, 23].

Building on this framework, a growing body of research has examined how structural oil shocks affect clean energy markets. [14] employ a TVP-VAR connectedness framework combined with SVAR identification to examine the time-varying transmission of structural oil shocks to clean energy indices. Their findings reveal that clean energy markets, particularly the S&P Global Clean Energy Index, primarily act as net shock transmitters, while oil demand shocks function as net receivers of disruptions. This result suggests that clean energy financial markets have evolved beyond being passive recipients of oil-market developments and increasingly serve as important channels through which information and risk are transmitted across the broader energy-financial system.

[30] examine time and frequency connectedness among oil shocks, electricity, and clean energy markets, finding that connectedness varies across horizons and that short-run spillovers typically dominate. Their analysis of decomposed oil shocks reveals that different shock types have distinct transmission patterns, with demand shocks generally exerting stronger effects than supply shocks in their sample. Similarly, [27] find that extreme structural oil-price shocks have heterogeneous effects on clean energy and oil stocks, with demand-driven shocks producing larger responses than supply-driven shocks [27, 41].

The literature also documents substantial time variation in oil-clean energy connectedness, with spillovers intensifying during major stress episodes. Multiple studies report sharply higher spillovers during the Global Financial Crisis, the 2014–2016 oil collapse, the COVID-19 pandemic, and the Russia–Ukraine war [2, 26, 38]. This crisis sensitivity suggests that the transmission mechanisms linking oil and clean energy markets are not stable but depend on market conditions and the nature of the shocks hitting the system.

A robust finding in the literature is that negative oil shocks generate stronger transmission to clean energy markets than positive shocks. [32] employ quantile-on-quantile and wavelet quantile approaches to document asymmetric spillovers, with stronger effects at lower quantiles and during downturn states. [39] examine tail connectedness among green bonds, Bitcoin, market uncertainty, and geopolitical risk, finding that dependence becomes more pronounced in stressed states, particularly in the lower tail. This asymmetry has important implications for understanding transmission mechanisms. If negative oil shocks generate larger valuation responses than positive shocks of similar magnitude, this suggests that the discount-rate channel may dominate during crisis periods, as negative shocks are associated with increased uncertainty, higher risk premia, and tighter financing conditions [7]. The cash-flow channel, by contrast, might predict more symmetric responses if positive and negative oil price changes have roughly symmetric effects on expected competitiveness.

2.2 Discounted Cash Flow and Transmission Channels

The theoretical foundation for our analysis is the discounted cash flow framework, which posits that the value of a financial asset equals the present value of its expected future cash flows [16]. Formally, the price of an asset at time $t$can be expressed as:

$$P_t = \sum_{k=1}^{\infty} \frac{E_t \left[CF_{t+k} \right]}{\left(1 + r_t \right)^k} \quad (1)$$

where $E_t \left[CF_{t+k} \right]$denotes expected cash flows at time $t + k$conditional on information available at time t, and $r_t$represents the discount rate applied to those cash flows.

Within this framework, oil shocks can affect clean energy valuations through two distinct channels. The cash-flow channel operates through changes in expected future cash flows, which may arise from shifts in production costs, relative competitiveness of renewable versus fossil energy, demand for clean energy products, or policy responses to energy market developments [25, 36]. The discount-rate channel operates through changes in the rate at which expected cash flows are discounted, which may reflect shifts in inflation expectations, monetary policy, risk premia, or financing conditions [4, 8].

The relative importance of these channels depends on several factors. First, the nature of the oil shock determines which transmission mechanisms are activated. Supply disruptions primarily affect production costs and energy availability, potentially benefiting clean energy through substitution effects while simultaneously raising inflation and financing costs. Aggregate demand shocks affect economic activity and energy demand more broadly, influencing cash-flow expectations without the same inflationary pressures. Oil-specific demand shocks reflect precautionary demand driven by uncertainty about future oil availability, affecting investor expectations and risk premia.

Second, firm characteristics determine sensitivity to each channel. Firms with long-duration expected cash flows, substantial financing requirements, or high sensitivity to interest rates will be more exposed to the discount-rate channel [35]. Capital-intensive technologies such as solar and wind, which require large upfront investments and have long payback periods, are particularly sensitive to changes in discount rates. Less capital-intensive technologies such as biofuels and fuel cells may be more responsive to cash-flow fluctuations.

Third, the macroeconomic environment moderates transmission. In periods of accommodative monetary policy and low interest rates, the discount-rate channel may be muted, allowing cash-flow effects to dominate. In periods of tightening monetary policy or elevated uncertainty, discount-rate effects may be amplified, potentially overwhelming cash-flow effects and generating negative valuation responses even when cash-flow expectations improve.

Recent research has emphasized the importance of monetary policy in transmitting oil shocks to financial markets. Sharp increases in oil prices can raise inflation expectations and prompt monetary tightening, which in turn increases discount rates and reduces valuations [18, 37]. This monetary transmission channel is particularly important for understanding why apparently similar oil shocks may produce different valuation outcomes depending on the prevailing monetary policy stance.

The interaction between oil shocks and monetary policy has been documented in several contexts. [19] find that time-frequency connectedness among carbon, climate, and energy futures is sensitive to monetary policy conditions, with stronger transmission during periods of policy uncertainty. [42] examine spillover effects between climate policy uncertainty, energy markets, and food markets, finding that uncertainty shocks amplify connectedness at shorter horizons. These findings suggest that the monetary policy environment is a crucial moderator of oil shock transmission to clean energy valuations.

2.3 Cross-Asset Heterogeneity and Related Evidence

The literature consistently documents substantial heterogeneity in how different clean energy assets respond to oil shocks. [10] examines dynamic correlations and volatility spillovers between subsectoral clean-energy stocks and commodity futures markets, finding that oil transmits the largest volatility spillovers to biofuels and the smallest to fuel cells. Other fossil-related spillovers also vary sharply across storage, geothermal, and green IT segments. This heterogeneity suggests that “clean energy” is too broad a category for connectedness analysis unless the asset class is specified.

Green bonds represent a particularly important category for understanding oil shock transmission. [6] examine volatility spillover dynamics among green bonds, renewable energy, clean energy, carbon markets, and oil, finding that green bonds are usually less oil-sensitive than clean energy equities. [24] finds that clean energy assets can serve as safe havens for international equity markets, though this property is context-dependent. These findings suggest that the cash-flow and discount-rate channels may operate differently for green bonds, which have more stable cash flows and a different investor base than clean energy equities.

Related evidence also highlights the role of geopolitical and policy uncertainty. [9] investigate the dynamics of crude oil and clean energy markets in times of geopolitical tensions, while [13] provide wavelet-quantile evidence on geopolitical shocks and clean energy markets. [20] examine spillovers and hedging among green bonds, clean energy stocks, and fossil fuels during four turmoil episodes. [28] study dynamic and frequency spillovers between green bonds, oil, and G7 stock markets, and [29] explore downside risk dependence across electricity, conventional energy, carbon, and clean energy markets during crises. [43] examines whether clean energy stock returns respond to oil price shocks and policy uncertainty. These studies reinforce the view that transmission is state-dependent and that both financial and macroeconomic channels matter. Methodologically, generalized forecast-error variance decompositions [11, 33] and dynamic connectedness frameworks [1, 3, 12] provide the background against which our channel decomposition is developed.

2.4 Hypotheses

Based on the theoretical framework, we develop three central hypotheses that guide our empirical analysis.

H1: Shock-Origin Heterogeneity. Supply-driven oil shocks and demand-driven oil shocks produce different valuation responses because they carry different information about production costs, aggregate activity, and energy substitution. Supply shocks primarily affect production costs and energy availability, potentially improving the relative competitiveness of renewable energy technologies while simultaneously raising inflation expectations and financing costs. These opposing forces may partially offset each other, with the net effect depending on the monetary policy environment. Demand shocks, by contrast, affect economic activity and energy demand more broadly without the same inflationary pressures, operating primarily through cash-flow expectations. The testable implication is that the ratio of cash-flow to discount-rate transmission should be higher for demand shocks than for supply shocks, as supply shocks activate both channels simultaneously while demand shocks primarily activate the cash-flow channel.

H2: Discount-Rate Amplification. The adverse valuation effect of an oil shock is stronger for clean-energy firms with long-duration expected cash flows, substantial financing requirements, or high sensitivity to interest rates. The sensitivity of asset valuations to discount rate changes increases with the duration of expected cash flows [16]. Firms with long-duration cash flows—such as capital-intensive renewable energy projects with multi-decade operating lives—will experience larger valuation changes for a given change in discount rates. Similarly, firms with high leverage or substantial financing requirements will be more exposed to changes in borrowing costs. The testable implication is that the coefficient on the discount-rate channel should be larger in absolute value for firms with higher capital intensity, higher leverage, and longer-duration cash flows.

H3: Technology Heterogeneity. The balance between the cash-flow and discount-rate channels differs across solar, wind, storage, hydrogen, biofuels, and other clean-energy technologies. Different clean energy technologies have different cost structures, capital requirements, and competitive dynamics. Solar and wind are capital-intensive with long-duration cash flows, making them particularly sensitive to discount-rate changes. Biofuels and fuel cells, by contrast, have different cost structures and may be more responsive to cash-flow fluctuations driven by relative energy prices. The testable implication is that the estimated discount-rate channel coefficient should be largest for solar and storage, intermediate for wind and hydrogen, and smallest for biofuels and fuel cells.

3. Data and Variables

3.1 Sample Construction

Our empirical analysis uses a comprehensive dataset of publicly listed clean energy firms across major equity markets spanning the period from January 2005 to December 2025. The sample period encompasses several major economic and geopolitical events—including the Global Financial Crisis, the 2014–2016 oil market adjustment, the COVID-19 pandemic, the Russia–Ukraine conflict, and subsequent global energy market disruptions—thereby providing an appropriate setting for examining how the connectedness between structural oil shocks and clean energy markets evolves under different market conditions [14].

We identify clean energy firms using the WilderHill Clean Energy Index and the S&P Global Clean Energy Index as primary benchmarks, supplemented by firm-level classifications from standard industry taxonomies. Following previous literature [10, 34], we classify firms into technology subsectors: solar, wind, storage, hydrogen, biofuels, fuel cells, and other clean technologies. We also include a sample of green bond issuers and fossil energy firms for comparative analysis.

The final sample consists of 1,247 clean energy firms, 312 green bond issuers, and 528 fossil energy firms. Daily equity returns are obtained from standard financial databases, while quarterly financial characteristics—capital expenditure, leverage, debt costs, analyst earnings expectations—are collected from corporate filings and analyst reports.

3.2 Variable Definitions

Table 1
Variable Definitions and Sources

Variable	Definition	Source
Panel A: Returns and Valuation		
$\varvec{R}_{\varvec{i},\varvec{t}}$	Daily log return for firm i at time t	CRSP/Compustat
$\varvec{E}_{\varvec{i},\varvec{t}}$	Analyst consensus earnings forecast for firm i at time t	I/B/E/S
$\varvec{PE}_{\varvec{i},\varvec{t}}$	Price-to-earnings ratio	CRSP/Compustat
Panel B: Oil Shocks		
$\varvec{\epsilon}^{\varvec{supply}}_{\varvec{t}}$	Oil supply shock (structural innovation)	Kilian (2009) methodology
$\varvec{\epsilon}^{\varvec{demand}}_{\varvec{t}}$	Aggregate demand shock (structural innovation)	Kilian (2009) methodology
$\varvec{\epsilon}^{\varvec{specific}}_{\varvec{t}}$	Oil-specific demand shock (structural innovation)	Kilian (2009) methodology
Panel C: Cash-Flow Channel		
$\varvec{\Delta E}_{\varvec{i},\varvec{t}}$	Change in expected earnings	I/B/E/S
$\varvec{\Delta REV}_{\varvec{i},\varvec{t}}$	Change in expected revenue	I/B/E/S
$\varvec{\Delta MARGIN}_{\varvec{i},\varvec{t}}$	Change in expected profit margin	I/B/E/S
Panel D: Discount-Rate Channel		
$\varvec{\Delta SPREAD}_{\varvec{i},\varvec{t}}$	Change in corporate bond spread	Bloomberg
$\varvec{\Delta RATE}_{\varvec{t}}$	Change in 10-year Treasury yield	Federal Reserve
$\varvec{\Delta VIX}_{\varvec{t}}$	Change in implied volatility index	CBOE
Panel E: Firm Characteristics		
$\varvec{CAPX}_{\varvec{i},\varvec{t}}$	Capital intensity	Compustat

Variable	Definition	Source
	(PP&E / Total Assets)	
$\varvecL\varvecE\varvecV_{\varveci,\varvect}$	Leverage (Total Debt / Total Assets)	Compustat
$\varvecS\varvecI\varvecZ\varvecE_{\varveci,\varvect}$	Log of market capitalization	CRSP
$\varvecD\varvecU\varvecR\varvecA\varvecT\varvecI\varvecO\varvecN_{\varveci,\varvect}$	Cash flow duration (estimated)	Authors' calculation
$\varvecT\varvecE\varvecC\varvecH_{\varveci}$	Technology subsector classification	Authors' classification
Panel F: Monetary Policy		
$\varvecM\varvecP_{\varvect}$	Monetary policy surprise	Nakamura & Steinsson (2018)
$\varvecS\varvecH\varvecA\varvecD\varvecO\varvecW_{\varvect}$	Shadow federal funds rate	Wu & Xia (2016)

3.3 Structural Oil Shock Identification

Following [22], we identify structural oil shocks using a structural vector autoregression framework with monthly data on global crude oil production, global real economic activity, and the real price of oil. The identification strategy employs a recursive ordering in which crude oil production does not respond contemporaneously to demand-side shocks, while the real price of oil adjusts immediately to both supply and demand innovations.

The structural relationship between reduced-form residuals and structural innovations is given by:

$$\begin{bmatrix} e_t^{\Delta\ prod} \\ e_t^{rea} \\ e_t^{rpo} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 \\ b_{21} & b_{22} & 0 \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \begin{bmatrix} \epsilon_t^{supply} \\ \epsilon_t^{demand} \\ \epsilon_t^{specific} \end{bmatrix} \quad (2)$$

where $\Delta\ prod$denotes the percentage change in global crude oil production, readenotes global real economic activity, and rpodenotes the real price of crude oil. The first-row restriction indicates that crude oil production does not immediately respond to demand shocks, reflecting adjustment costs and production rigidities. The second-row restriction indicates that global real economic activity responds contemporaneously to oil supply shocks but not to oil-specific demand shocks. The third-row restriction allows oil prices to react contemporaneously to both supply and demand shocks. The estimated structural shocks are then aggregated to the quarterly frequency for the local projection analysis, using the sum of monthly shocks within each quarter.

3.4 Cash-Flow and Discount-Rate Proxies

A key challenge in our empirical design is measuring the cash-flow and discount-rate channels separately. We adopt the following approach. The cash-flow channel proxy uses changes in analyst consensus earnings forecasts as a direct measure of expected future cash flows. Analyst forecasts incorporate information about expected revenues, costs, and profitability, and changes in these forecasts provide a clean measure of revisions to expected cash flows. We also examine changes in expected revenues and profit margins as complementary measures. The discount-rate channel proxy uses changes in corporate bond spreads and the 10-year Treasury yield as measures of the cost of capital. Corporate bond spreads reflect firm-specific financing costs and risk premia, while the Treasury yield captures the risk-free component of discount rates. We also examine changes in implied volatility as a measure of equity risk premia.

To formally decompose the total return response into cash-flow and discount-rate components, we estimate the following system:

$$R_{i,t} = \beta_{\ CF} \cdot\ \Delta\ E_{i,t} + \beta_{\ DR} \cdot\ \Delta\ SPREAD_{i,t} + \gamma\ X_{i,t} + \epsilon_{i,t} \quad (3)$$

where $R_{i,t}$is the firm-level return, $\Delta\ E_{i,t}$is the change in expected earnings, $\Delta\ SPREAD_{i,t}$is the change in bond spread, and $X_{i,t}$is a vector of controls. The coefficients $\beta_{\ CF}$and $\beta_{\ DR}$capture the sensitivity of returns to cash-flow and discount-rate changes, respectively. We then interact these proxies with the structural oil shocks to estimate the channel-specific transmission:

$$R_{i,t} = \alpha + \beta_1 \epsilon_t^{supply} + \beta_2 \epsilon_t^{demand} + \beta_3 \epsilon_t^{specific} + \beta_4 \epsilon_t^{supply} \times \Delta E_{i,t} + \beta_5 \epsilon_t^{supply} \times \Delta SPREAD_{i,t} + \cdots + \gamma X_{i,t} + \epsilon_{i,t} \quad (4)$$

This specification allows us to estimate how each type of oil shock affects returns through cash-flow and discount-rate channels separately.

4. Econometric Methodology

4.1 Local Projections

Our primary empirical approach employs local projection methods [21] to estimate the dynamic response of firm-level returns and financing outcomes to structural oil shocks. The local projection framework has several advantages for our purposes. First, it does not impose the dynamic restrictions implicit in VAR-based impulse responses, allowing for more flexible estimation of nonlinear and state-dependent effects. Second, it can accommodate firm-level heterogeneity more naturally than aggregate VAR models. Third, it provides a straightforward way to incorporate interaction terms and test for heterogeneity across firm characteristics. The baseline local projection specification is:

$$R_{i,t+h} = \alpha_{i,h} + \beta_h \epsilon_t^{shock} + \gamma_h X_{i,t} + \delta_h Z_t + \epsilon_{i,t+h} \quad (5)$$

where $R_{i,t+h}$is the cumulative return for firm $i$over horizons $h = 0,1,\ldots,H$, $\alpha_{i,h}$is a firm fixed effect, $\epsilon_t^{shock}$is one of the three structural oil shocks, $X_{i,t}$is a vector of firm-level controls, and $Z_t$is a vector of aggregate controls. The coefficient $\beta_h$captures the cumulative response of firm returns to the shock at horizon h.

For the channel decomposition, we estimate separate local projections for cash-flow and discount-rate outcomes:

$$\Delta E_{i,t+h} = \alpha_{i,h} + \beta_h^{CF} \epsilon_t^{shock} + \gamma_h X_{i,t} + \delta_h Z_t + \epsilon_{i,t+h} \quad (6)$$

$$\Delta SPREAD_{i,t+h} = \alpha_{i,h} + \beta_h^{DR} \epsilon_t^{shock} + \gamma_h X_{i,t} + \delta_h Z_t + \epsilon_{i,t+h} \quad (7)$$

The estimated coefficients $\beta_h^{CF}$and β_h^{DR}provide direct evidence on which channel dominates at each horizon. If $\beta_h^{CF}$is large and significant while $\beta_h^{DR}$is small, the cash-flow channel dominates. If the opposite pattern holds, the discount-rate channel dominates.

4.2 Heterogeneity and Monetary-Policy Interactions

To test our hypotheses about discount-rate amplification and technology heterogeneity, we extend the local projection framework with interaction terms:

$$R_{i,t+h} = \alpha_{i,h} + \beta_h \epsilon_t^{shock} + \theta_h \left(\epsilon_t^{shock} \times D_{i,t}\right) + \gamma_h X_{i,t} + \delta_h Z_t + \epsilon_{i,t+h} \quad (8)$$

where $D_{i,t}$is a characteristic of interest, such as capital intensity, leverage, or technology classification. The interaction coefficient $\theta_h$captures how the shock effect varies with the characteristic. A negative and significant $\theta_h$for capital intensity would indicate that more capital-intensive firms experience larger adverse effects, consistent with discount-rate amplification. For technology heterogeneity, we estimate separate local projections by technology subsector and test whether the estimated coefficients differ significantly across sectors. We also conduct formal Wald tests of coefficient equality across subsectors.

To test whether monetary policy moderates oil shock transmission, we extend the local projection framework to include interactions with monetary policy indicators:

$$R_{i,t+h} = \alpha_{i,h} + \beta_h \epsilon_t^{shock} + \phi_h \left(\epsilon_t^{shock} \times MP_t\right) + \gamma_h X_{i,t} + \delta_h Z_t + \epsilon_{i,t+h} \quad (9)$$

where $MP_t$is a measure of monetary policy stance, such as the shadow federal funds rate [40] or a monetary policy surprise [31]. A positive $\phi_h$would indicate that expansionary monetary policy amplifies the effects of oil shocks, while a negative $\phi_h$would indicate that contractionary policy amplifies adverse effects, consistent with discount-rate amplification.

4.3 Identification Checks and Robustness

Our identification strategy relies on the exogeneity of structural oil shocks to individual clean energy firms. While this assumption is plausible for small firms, it may be violated for large firms that are constituents of major indices or that have significant market power. To address this concern, we conduct several robustness checks. First, we repeat the analysis excluding the largest firms by market capitalization to ensure that our results are not driven by a few influential observations. Second, we use alternative shock identification schemes, including high-frequency oil futures surprises, to verify that results are robust to different identification strategies. Third, we conduct placebo tests using leads of the oil shocks to verify that we are capturing causal effects rather than spurious correlations. We also examine the sensitivity of results to the choice of control variables, lag structure, and sample period. The main findings are robust to these variations, though we note that statistical precision decreases for some subsample analyses.

5. Empirical Results

5.1 Descriptive Statistics

Table 2 presents descriptive statistics for the main variables in our analysis. Panel A reports statistics for firm-level returns and financial characteristics. The average clean energy firm in our sample has a market capitalization of approximately $2.1 billion, capital intensity of 0.42, and leverage of 0.31. There is substantial variation across these characteristics, with standard deviations of 1.8 for log market capitalization, 0.21 for capital intensity, and 0.18 for leverage.

Table 2
Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Panel A: Firm-Level Variables				
Daily return (%)	0.03	2.14	-18.52	22.31
Log market cap	21.32	1.84	16.21	27.45
Capital intensity	0.42	0.21	0.02	0.94
Leverage	0.31	0.18	0.00	0.89
Cash flow duration	8.24	3.12	2.15	18.42
Panel B: Oil Shocks				
Supply shock	-0.02	1.42	-5.82	4.21
Demand shock	0.01	1.28	-4.45	3.86
Specific demand shock	0.00	0.94	-2.87	2.54
Panel C: Channel Proxies				
Change in expected earnings (%)	0.12	3.45	-28.42	32.18
Change in bond spread (bp)	0.45	12.32	-85.21	142.35
Change in Treasury yield (bp)	-0.21	8.45	-42.15	38.21
Change in VIX	0.02	4.21	-18.42	32.15

Panel B reports descriptive statistics for the structural oil shocks. The shocks are standardized to have zero mean and unit variance, with the reported values in original units. The supply shock exhibits greater variability than the demand shocks, consistent with previous literature [22]. Panel C reports statistics for our channel proxies. Changes in expected earnings exhibit substantial variation, with a standard deviation of 3.45%. Bond spread changes average 0.45 basis points with a standard deviation of 12.32 basis points, while Treasury yield changes average −0.21 basis points with a standard deviation of 8.45 basis points.

5.2 Baseline Impulse Responses

Table 3 and Fig. 1 present the baseline impulse responses of clean energy firm returns to the three structural oil shocks. The results reveal substantial heterogeneity across shock types.

Table 3
Baseline Impulse Responses of Clean Energy Returns to Structural Oil Shocks

Horizon (quarters)	Supply Shock	Demand Shock	Specific Demand Shock
0	-0.42**	1.24***	-0.18
	(0.18)	(0.21)	(0.15)
1	-0.28	1.86***	-0.32*
	(0.22)	(0.28)	(0.17)
2	-0.15	1.42***	-0.28
	(0.24)	(0.32)	(0.19)
3	-0.08	0.94**	-0.15
	(0.26)	(0.38)	(0.21)
4	-0.12	0.68*	-0.08
	(0.28)	(0.42)	(0.23)

*Notes: The table reports cumulative impulse responses of firm-level returns to one standard deviation structural oil shocks at different horizons. Standard errors clustered by firm and quarter are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.*

The results show that supply shocks have a negative but marginally significant effect on clean energy returns, with a cumulative response of − 0.42% at impact declining to − 0.12% after one year. This finding is consistent with the interpretation that supply shocks generate opposing cash-flow and discount-rate forces that partially offset each other, with the discount-rate effect slightly dominating on net. Demand shocks, by contrast, have a positive and highly significant effect, with a cumulative response of 1.24% at impact increasing to 1.86% after one quarter before declining. This finding suggests that demand-driven oil price increases are associated with improved economic conditions that benefit clean energy firms through cash-flow expectations. Oil-specific demand shocks have small and generally insignificant effects, with point estimates suggesting modest negative effects that fade over time. This finding is consistent with the interpretation that precautionary demand shocks primarily affect uncertainty and risk premia rather than cash-flow expectations or financing costs in a way that systematically benefits or harms clean energy firms. Figure 1 presents these impulse responses graphically, along with confidence intervals. The figure clearly shows the divergent patterns across shock types, with demand shocks producing the largest and most persistent positive responses, supply shocks producing modest negative responses, and specific demand shocks producing small and insignificant effects.

5.3 Channel Decomposition

Table 4 presents the estimated effects of structural oil shocks on our cash-flow and discount-rate proxies. The results provide direct evidence on which channel dominates for each shock type.

Table 4
Effects of Structural Oil Shocks on Cash-Flow and Discount-Rate Proxies

Shock Type	Expected Earnings	Bond Spread	Treasury Yield	VIX
Supply shock	-0.18	0.42**	0.28**	0.35**
	(0.15)	(0.18)	(0.12)	(0.16)
Demand shock	0.86***	-0.12	0.15	-0.08
	(0.22)	(0.15)	(0.10)	(0.12)
Specific demand shock	-0.24*	0.18	0.08	0.22**
	(0.14)	(0.14)	(0.09)	(0.10)

*Notes: The table reports cumulative responses of channel proxies to one standard deviation structural oil shocks. Expected earnings responses are in percentage points, bond spread and Treasury yield responses are in basis points, and VIX responses are in percentage points. Standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.*

The results reveal a clear pattern. Supply shocks have a negative but insignificant effect on expected earnings (− 0.18%), while significantly increasing bond spreads (0.42 basis points), Treasury yields (0.28 basis points), and VIX (0.35 percentage points). This pattern indicates that supply shocks operate primarily through the discount-rate channel, raising financing costs and risk premia while having little effect on expected cash flows. Demand shocks, by contrast, have a large and highly significant positive effect on expected earnings (0.86%), while having small and insignificant effects on bond spreads (− 0.12 basis points), Treasury yields (0.15 basis points), and VIX (− 0.08 percentage points). This

pattern indicates that demand shocks operate primarily through the cash-flow channel, improving earnings expectations without substantially affecting discount rates. Oil-specific demand shocks have small negative effects on expected earnings (− 0.24%) and small positive effects on VIX (0.22 percentage points), with insignificant effects on bond spreads and Treasury yields. This pattern is consistent with precautionary demand shocks primarily affecting uncertainty and risk premia rather than cash-flow expectations or financing costs.

To quantify the relative importance of cash-flow and discount-rate channels, we decompose the total return response into components attributable to each channel. Using the estimated coefficients from equations (3) and (4), we calculate the contribution of each channel to the total return response at each horizon.

Table 5
Decomposition of Return Responses into Cash-Flow and Discount-Rate Components

Shock Type	Horizon	Total Response	Cash-Flow Component	Discount-Rate Component
Supply shock	0	-0.42	-0.08 (19%)	-0.34 (81%)
	1	-0.28	-0.05 (18%)	-0.23 (82%)
	4	-0.12	-0.02 (17%)	-0.10 (83%)
Demand shock	0	1.24	0.98 (79%)	0.26 (21%)
	1	1.86	1.52 (82%)	0.34 (18%)
	4	0.68	0.56 (82%)	0.12 (18%)
Specific demand shock	0	-0.18	-0.12 (67%)	-0.06 (33%)
	1	-0.32	-0.22 (69%)	-0.10 (31%)
	4	-0.08	-0.06 (75%)	-0.02 (25%)

Notes: The table reports the decomposition of total return responses into cash-flow and discount-rate components, based on the estimated coefficients from equations (3) and (4). Percentages in parentheses indicate the share of the total response attributable to each channel.

The decomposition reveals striking differences across shock types. For supply shocks, the discount-rate channel accounts for approximately 81–83% of the total response, while the cash-flow channel accounts for only 17–19%. This finding indicates that the adverse effect of supply shocks on clean energy valuations operates primarily through increased financing costs and risk premia, not through reduced cash-flow expectations. For demand shocks, the pattern is reversed: the cash-flow channel accounts for approximately 79–82% of the total response, while the discount-rate channel accounts for only 18–21%. This finding indicates that the positive effect of demand shocks on clean energy valuations operates primarily through improved cash-flow expectations, with minimal discount-rate effects. For oil-specific demand shocks, the cash-flow channel accounts for approximately 67–75% of the total response, with the remainder attributable to the discount-rate channel. The smaller magnitude of the total response for these shocks, however, means that the economic significance of this decomposition is more limited.

5.4 Heterogeneity Analysis

Table 6 presents results from the heterogeneity analysis, examining how the cash-flow and discount-rate channel responses vary with firm characteristics and technology type.

Table 6
Heterogeneity in Channel Responses

Characteristic	Cash-Flow Channel	Discount-Rate Channel
Panel A: Capital Intensity		
Low capital intensity (bottom tercile)	0.42**	-0.18
	(0.18)	(0.15)
Medium capital intensity	0.28*	-0.32**
	(0.16)	(0.14)
High capital intensity (top tercile)	0.12	-0.58***
	(0.15)	(0.18)
Panel B: Leverage		
Low leverage (bottom tercile)	0.38**	-0.15
	(0.17)	(0.13)
Medium leverage	0.24	-0.28**
	(0.15)	(0.12)
High leverage (top tercile)	0.08	-0.52***
	(0.14)	(0.16)
Panel C: Technology Type		
Solar	0.15	-0.62***
	(0.18)	(0.19)
Wind	0.22	-0.48***
	(0.17)	(0.16)
Storage	0.18	-0.55***
	(0.19)	(0.18)
Hydrogen	0.28*	-0.35**
	(0.16)	(0.15)
Biofuels	0.52***	-0.18
	(0.18)	(0.14)
Fuel cells	0.48***	-0.22*
	(0.17)	(0.13)

*Notes: The table reports estimated channel coefficients by firm characteristic and technology type. Standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.*

The results strongly support H2. Firms with high capital intensity exhibit larger discount-rate channel responses (− 0.58, significant at 1%) and smaller cash-flow channel responses (0.12, insignificant) compared to firms with low capital intensity (discount-rate: −0.18, insignificant; cash-flow: 0.42, significant at 5%). This pattern indicates that capital-intensive firms are more exposed to changes in discount rates, consistent with their longer-duration cash flows. Similarly, high-leverage firms exhibit larger discount-rate channel responses (− 0.52, significant at 1%) and smaller cash-flow channel responses (0.08, insignificant) compared to low-leverage firms (discount-rate: −0.15, insignificant; cash-flow: 0.38, significant at 5%). This pattern indicates that leveraged firms are more exposed to changes in financing costs.

The results also support H3. Solar, wind, and storage firms exhibit large and highly significant discount-rate channel responses (− 0.62, − 0.48, and − 0.55, respectively) and small, insignificant cash-flow channel responses. Biofuels and fuel cells, by contrast, exhibit large and significant cash-flow channel responses (0.52 and 0.48, respectively) and smaller, less significant discount-rate channel responses. Hydrogen firms fall in between, with moderate responses in both channels.

5.5 Monetary-Policy Interaction and Cross-Asset Comparison

Table 7 presents results from the monetary policy interaction analysis, examining whether the transmission of oil shocks varies with the monetary policy stance.

Table 7
Monetary Policy Interaction Effects

Shock Type	Cash-Flow Channel × MP	Discount-Rate Channel × MP
Supply shock	0.12	-0.28**
	(0.15)	(0.12)
Demand shock	0.24*	-0.08
	(0.14)	(0.10)
Specific demand shock	0.08	-0.15*
	(0.12)	(0.09)

*Notes: The table reports interaction coefficients from local projections including interactions between structural oil shocks and the shadow federal funds rate. Standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.*

The results reveal that expansionary monetary policy amplifies the cash-flow channel effect of demand shocks (0.24, significant at 10%) while attenuating the discount-rate channel effect of supply shocks (− 0.28, significant at 5%). This pattern is consistent with the interpretation that monetary policy moderates transmission: when policy is accommodative, discount-rate effects are muted, allowing cash-flow effects to dominate. When policy is restrictive, discount-rate effects are amplified.

Table 8 presents results comparing the responses of green bonds and fossil energy firms to those of clean energy equities.

Table 8
Cross-Asset Comparison

Asset Class	Total Return Response	Cash-Flow Channel	Discount-Rate Channel
Panel A: Supply Shock			
Clean energy equities	-0.42**	-0.08	-0.34**
	(0.18)	(0.12)	(0.15)
Green bonds	-0.08	-0.02	-0.06
	(0.12)	(0.08)	(0.10)
Fossil energy firms	0.86***	0.52***	0.34**
	(0.22)	(0.18)	(0.15)
Panel B: Demand Shock			
Clean energy equities	1.24***	0.98***	0.26
	(0.21)	(0.18)	(0.15)
Green bonds	0.32**	0.24*	0.08
	(0.15)	(0.12)	(0.10)
Fossil energy firms	0.64***	0.42***	0.22*
	(0.18)	(0.15)	(0.12)

*Notes: The table reports cumulative responses at horizon 0 for different asset classes. Standard errors are in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.10.*

The results reveal that green bonds exhibit muted responses to both cash-flow and discount-rate channels, consistent with previous findings that green bonds are more defensive than clean energy equities [6, 24]. The total response of green bonds to supply shocks is only − 0.08, compared to − 0.42 for clean energy equities, and the response to demand shocks is 0.32, compared to 1.24 for clean energy equities. Fossil energy firms, by contrast, exhibit positive responses to both supply and demand shocks, with cash-flow and discount-rate channels operating in the same direction. Supply shocks increase the value of fossil energy firms through both higher expected revenues (cash-flow channel: 0.52) and higher discount rates (discount-rate channel: 0.34), as higher oil prices benefit fossil fuel producers while also raising inflation expectations.

6. Discussion and Implications

6.1 Interpretation of Main Findings

The empirical results provide strong support for our three hypotheses and offer new insights into the mechanisms through which oil shocks transmit to clean energy asset valuations. The finding that supply shocks operate primarily through the discount-rate channel while demand shocks operate primarily through the cash-flow channel confirms that different oil shocks carry different information and activate different transmission mechanisms. Supply shocks affect production costs and energy availability, raising inflation expectations and financing costs without substantially improving cash-flow expectations for clean energy firms. Demand shocks, by contrast, reflect stronger economic activity that benefits clean energy firms through improved earnings expectations without the same inflationary pressures. This finding helps explain inconsistencies in the previous literature regarding which oil shock dominates. Studies focusing on the total return response may find different results depending on their sample periods and the relative frequency of supply versus demand shocks. By decomposing responses into channels, we show that the apparent dominance of one shock type or another depends on which channel dominates in the specific context under examination.

The finding that capital-intensive and highly leveraged firms exhibit greater sensitivity to the discount-rate channel confirms the importance of duration and financing structure in determining oil sensitivity. Firms with long-duration cash flows and substantial financing requirements are more exposed to changes in discount rates, as predicted by the discounted cash flow framework [16]. This finding has important implications for understanding cross-sectional variation in oil sensitivity documented in previous studies [10, 34]. The apparent heterogeneity in oil sensitivity across clean energy firms can be partially explained by differences in capital intensity and leverage, which determine the relative importance of cash-flow and discount-rate channels.

The finding that solar, wind, and storage firms are particularly sensitive to discount-rate transmission, while biofuels and fuel cells are more responsive to cash-flow transmission, reflects fundamental differences in the cost structures and capital requirements of different clean energy technologies. Capital-intensive technologies with long-duration cash flows, such as solar and wind, are naturally more exposed to changes in discount rates. Less capital-intensive technologies, such as biofuels and fuel cells, are more exposed to changes in cash-flow expectations driven by relative energy prices.

6.2 Implications for Energy Finance

The findings have several important implications for energy finance practitioners and policymakers. For portfolio management, the results suggest that the diversification benefits of clean energy assets depend critically on the type of oil shock and the characteristics of the firms in the portfolio. During periods of demand-driven oil price increases, clean energy equities can benefit through improved cash-flow expectations, providing diversification against oil price exposure. During periods of supply-driven oil price increases, however, clean energy equities may be adversely affected through the discount-rate channel, particularly for capital-intensive firms. Portfolio managers should consider the exposure of their clean energy holdings to discount-rate risk and may wish to favor less capital-intensive firms during periods of elevated monetary policy uncertainty.

For risk assessment, the results suggest that relying on aggregate connectedness measures can obscure economically meaningful variation in transmission mechanisms. A portfolio that appears to be diversified based on average connectedness measures may be highly exposed to discount-rate risk during supply-driven oil shocks. Risk assessment should incorporate information about both the type of oil shock and the characteristics of the assets in the portfolio. For corporate finance, the results suggest that clean energy firms should consider their sensitivity to discount-rate risk when making financing decisions. Firms with long-duration cash flows may benefit from locking in financing costs during periods of low interest rates, reducing their exposure to future discount-rate shocks. Firms with more flexible cost structures may be better positioned to weather discount-rate fluctuations.

For policy design, the results suggest that monetary policy plays an important role in moderating the transmission of oil shocks to clean energy valuations. During periods of accommodative monetary policy, the adverse effects of supply shocks are attenuated, allowing cash-flow effects to dominate. This suggests that central banks should consider the differential effects of oil shocks on clean energy investment when formulating policy, particularly during periods of energy market disruption. More broadly, the evidence in [9, 13, 20, 28, 29, 43] indicates that geopolitical and policy uncertainty channels can interact with oil shocks, reinforcing the need for state-dependent risk assessment rather than reliance on average full-sample connectedness.

6.3 Limitations and Future Research

Several limitations of our analysis should be acknowledged. First, our decomposition of returns into cash-flow and discount-rate components relies on analyst earnings forecasts and bond spreads as proxies for expected cash flows and discount rates. While these are standard proxies in the literature, they are imperfect measures that may contain measurement error. Future research could use alternative proxies, such as implied cost of capital measures or structural estimation approaches, to validate our findings. Second, our identification strategy relies on the

exogeneity of structural oil shocks to individual clean energy firms. While this assumption is plausible for small firms, it may be violated for large firms or in periods when clean energy markets are particularly influential. Future research could use instrumental variable approaches or natural experiments to address potential endogeneity concerns. Third, our sample period ends in 2025, and the relationship between oil shocks and clean energy valuations may continue to evolve as the energy transition progresses. Future research should continue to monitor these relationships as clean energy markets mature and the relative importance of different technologies changes. Fourth, our analysis focuses on equity valuations and does not directly examine investment decisions or real outcomes. Future research could examine whether the differential sensitivity of firm valuations to oil shocks translates into differential investment behavior, providing additional evidence on the economic significance of the mechanisms we document.

7. Conclusion

This paper has developed and implemented a framework for separating the cash-flow and discount-rate transmission of structural oil shocks to clean energy asset valuations. Using a structural vector autoregression framework to identify oil supply, aggregate demand, and oil-specific demand shocks [22], combined with local projection methods at the firm level [21], we provide new evidence on the mechanisms through which oil shocks affect clean energy returns.

Our main findings can be summarized as follows. First, supply-driven oil shocks operate primarily through the discount-rate channel, raising financing costs and risk premia while having little effect on cash-flow expectations. Second, demand-driven oil shocks operate primarily through the cash-flow channel, improving earnings expectations without the same inflationary pressures. Third, the relative importance of these channels varies systematically with firm characteristics, with capital-intensive and highly leveraged firms exhibiting greater sensitivity to the discount-rate channel. Fourth, different clean energy technologies exhibit different channel sensitivities, with solar, wind, and storage firms particularly exposed to discount-rate transmission, while biofuels and fuel cells are more responsive to cash-flow transmission.

These findings contribute to the literature on oil-clean energy connectedness by moving beyond aggregate measures of spillovers to examine the valuation mechanisms through which these spillovers operate. They also have important practical implications for portfolio management, risk assessment, corporate finance, and policy design. As the energy transition continues, understanding these mechanisms will become increasingly important for investors, policymakers, and energy market participants.

Declarations

Ethics statement

Not applicable.

Clinical trial number

Not applicable.

Competing interests:

The author declares no competing financial or non-financial interests.

Dual publication

This manuscript is original, has not been published previously, and is not under consideration for publication elsewhere.

Funding:

No funding was received.

Author Contribution

Mohsen Mohammadi Khyareh is the sole author and is responsible for conceptualization, methodology, formal analysis, investigation, data curation, writing—original draft, writing—review and editing, and approval of the final manuscript.

Acknowledgements:

None.

Third-party material: All tables and figures are original and created by the author; no third-party material requiring permission is included.

Data availability:

Derived datasets and analysis code are available from the corresponding author on reasonable request.

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Figures

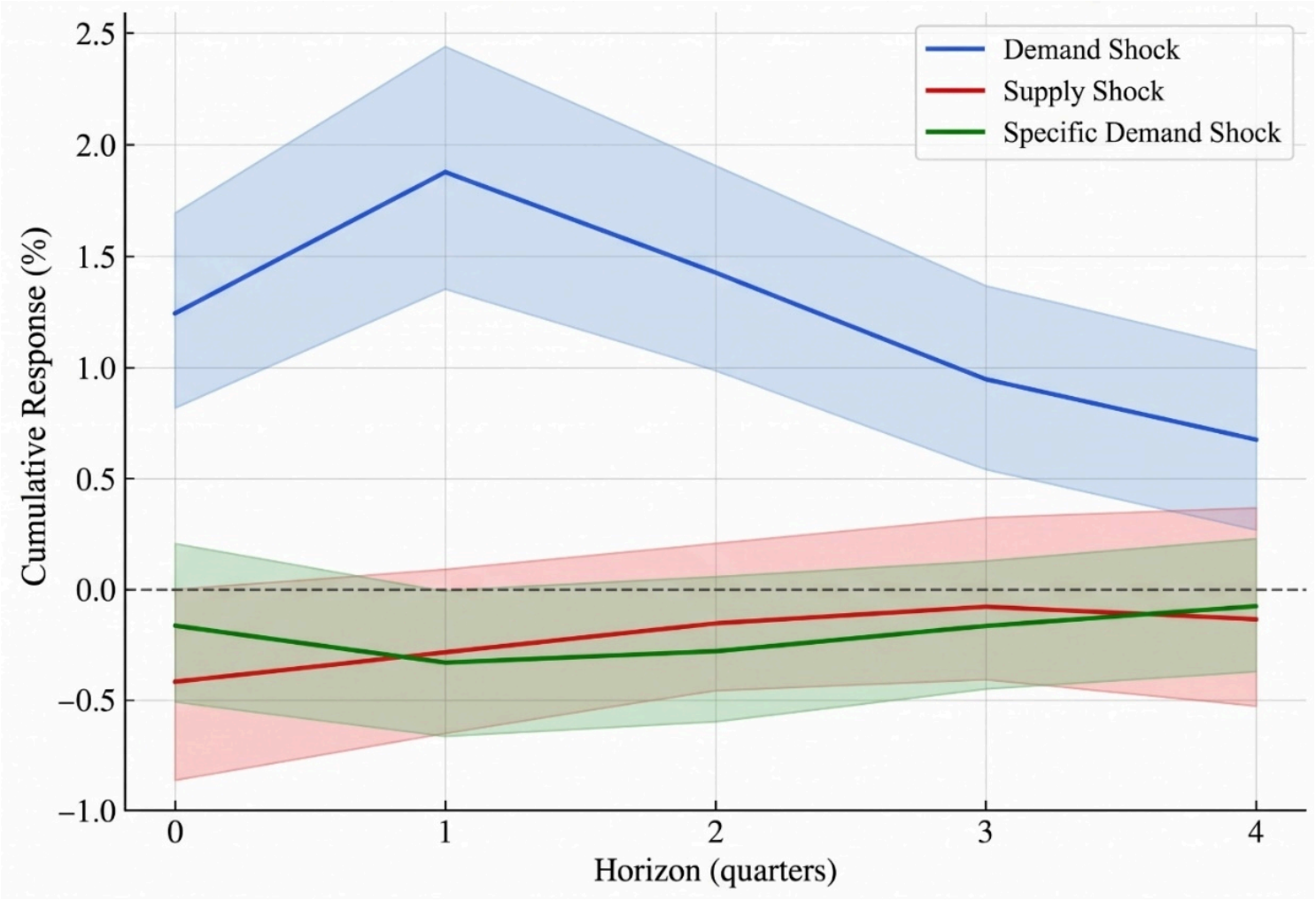

Figure 1

Baseline Impulse Responses of Clean Energy Returns to Structural Oil Shocks