

Article

Reconciling the Energy-Exposure and Sectoral-Risk Hypotheses: Spillover Effects of Oil Shocks to Clean and Dirty Chinese Stocks

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Abstract

This paper develops a new direction of study oil-shocks with two competing hypotheses: (i) the Energy-exposure hypothesis, which posits that clean stocks with less direct reliance on fossil fuel should be less sensitive to oil shocks; and (ii) the Sectoral-risk hypothesis, which argues that dirty stocks are less sensitive to oil shocks because they exhibit more defensive characteristics and can act as safe-haven assets during oil-induced market stress. Our study constructs clean and dirty portfolios based on firm-level carbon intensity for stocks in the Hang Seng Stock Connect China A 300 (HSCA300) Index, decomposes oil shocks into supply, aggregate demand, and oil-specific demand components, and measures return and volatility spillovers with the connectedness framework. The results show that directional spillovers from all three types of oil shocks to the clean portfolio generally exceed those to the dirty portfolio in both returns and volatility, supporting the sectoral-risk hypothesis. However, volatility spillovers from oil-specific demand shocks are stronger for the dirty portfolio, aligning with the energy-exposure hypothesis.

Keywords: oil shocks; carbon intensity; energy-exposure hypothesis; sectoral-risk hypothesis; market connectedness; China stocks

1. Introduction

There is a conventional wisdom that low-carbon (“clean”) stocks tend to be more resilient to oil shocks than high-carbon (“dirty”) stocks. This perspective derives from an energy-exposure framework, in which low-carbon companies are assumed to have less direct exposure to fossil fuel inputs, so their financial performance is less sensitive to fluctuations in oil prices (Dutta et al., 2020). Conversely, oil shocks are expected to have a greater negative impact on carbon-intensive sectors such as energy and utilities, given their heavy dependence on fossil fuels (Khan et al., 2023; Joo & Park, 2021). This prevailing view suggests that clean stocks should be less adversely affected by oil price spikes, while the spillover of oil shocks should be stronger toward dirty, high-carbon stocks than toward clean, low-carbon counterparts.

However, empirical evidence indicates that this “conventional wisdom” does not always hold, with the Russia–Ukraine conflict in 2022 serving as a notable counterexample. As a major exporter of oil and gas, Russia’s involvement in the conflict led to significant disruptions in global energy markets. Sanctions on Russian energy exports and fears of supply shortages drove crude oil prices from about \$ 77 to over \$ 120 per barrel in the first half of 2022, a surge



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of more than 50% that signaled severe supply-side stress. This shock triggered widespread declines across global equity markets, with major indexes such as the MSCI World, the S&P 500, and the Euro Stoxx 50 dropping by approximately 20%. When comparing the performance of low-carbon and high-carbon stocks (Table 1), the MSCI USA Low Carbon Target Index, which has a weighted average carbon intensity of 393 tons of CO₂e per US\$ million in sales, declined by 21.9% during the first half of 2022 (MSCI, 2025a). In contrast, the MSCI USA Value Index, characterized by a higher concentration of high-carbon stocks with a weighted average carbon intensity of 837 tons of CO₂e per US\$ million in sales, experienced a smaller decline of 12.7% over the same period (MSCI, 2025b).

Table 1. Statistics of MSCI USA Low Carbon Target and MSCI USA Value Indexes.

	MSCI USA Low Carbon Target Index	MSCI USA Value Index
Index change from 31 December 2021 to 30 June 2022	−21.9%	−12.7%
Weighted average carbon intensity	393 tons of CO ₂ e per US\$ million in sales	837 tons of CO ₂ e per US\$ million in sales
Price-to-earnings ratio	28.43	21.04
5-year annualized volatility	16.15%	15.27%
Dividend Yield	1.19%	2.13%

Note: These figures are drawn from the MSCI website (MSCI, 2025a, 2025b). The reported weighted average carbon intensity, price-to-earnings ratio, five-year annualized volatility, and dividend yield refer to values as of 28 November 2025.

This empirical evidence prompted us to develop a new direction of study oil-shocks with two competing hypotheses: (i) the Energy-exposure hypothesis, which posits that clean stocks with less direct reliance on fossil fuel should be less sensitive to oil shocks; and (ii) the Sectoral-risk hypothesis, which argues that dirty stocks are less sensitive to oil shocks because they exhibit more defensive characteristics and can act as defensive assets during oil-induced market stress. When we compare the MSCI USA Low Carbon Target Index and the MSCI USA Value Index, it reveals that the latter has a lower price-to-earnings ratio (28.43 vs. 21.04), lower volatility (16.15% vs. 15.27%), and a higher dividend yield (1.19% vs. 2.13%) (Table 1). These figures indicate that low-carbon sectors behaved as high-risk assets during the oil shock, amplifying rather than mitigating macro-financial stress in investor portfolios. This pattern offers a salient illustration of a case where the sectoral-risk hypothesis appears to hold.

The core idea of the sectoral-risk hypothesis is: many stocks with low carbon intensity are typically concentrated in high-technology, healthcare, pharmaceuticals, online consumer platforms, IT and communication services, which are characterized by considerable uncertainty stemming from innovation cycles, evolving regulatory environments, intense competition, and shifting consumer preferences. These firms frequently exhibit high betas well above one and annualized volatility above 20 percent. In contrast, high-carbon dirty stocks, such as those in utilities and traditional energy production, often operate under regulated or quasi-regulated frameworks, benefit from stable demand, and provide consistent dividend streams. These features typically produce betas below one and volatilities often under 10 percent, positioning them as defensive or “safe haven” assets during periods of systemic market stress. When oil shocks impact global markets, growth-oriented low-carbon stocks sometimes experience larger drawdowns and more persistent volatility than traditional high-carbon sectors, as investors rotate out high-beta, high-volatility clean assets into perceived safe-haven, high-carbon industries.

This dynamic reveals a fundamental tension between the energy-exposure and sectoral-risk hypotheses, yet existing empirical studies have not systematically reconciled these views. Implementing this perspective requires (i) classification of stocks into clean and dirty portfolios based on carbon intensity; and (ii) decomposition of oil shocks into supply-

and demand-driven components. Although research on oil shocks and stock returns is extensive, most studies rely on aggregate indexes or broad sector classifications and do not differentiate firms by carbon intensity. Empirical research following Kilian (2009, 2014) and Ready (2018) demonstrates that oil supply and demand shocks have distinct macro-financial effects, but typically ignores the clean–dirty portfolio dimension. A growing strand of research investigates oil shocks and clean or low-carbon assets (Elsayed et al., 2024; Zhou & Geng, 2021), yet most of these contributions concentrate only on green or renewable indexes, leaving the behavior of explicitly high-carbon portfolios underexplored. Zhang and Xu (2023) are among the few to construct clean and dirty portfolios based on carbon emissions and to study spillovers using a connectedness framework. However, the study treats oil shocks as a single variable, which does not disentangle the effects of different oil shock components.

Our study addresses these gaps in three ways. First, we follow Zhang and Xu (2023) in constructing clean and dirty portfolios from the Hang Seng Stock Connect China A 300 (HSCA300) Index based on firm-level carbon intensity, thereby providing a direct comparison of low- and high-carbon Chinese A-share equities, rather than relying on aggregate indexes or sectoral proxies. We focus on extending the literature to China's low-carbon A-share market, which is of particular significance, as China is the world's largest emitter of carbon dioxide, which accounts for roughly 27% of global carbon dioxide emissions (World Bank Group, 2022). Second, we adopt Kilian's (2009, 2014) structural approach to decompose oil shocks into supply, aggregate demand, and oil-specific demand shocks, allowing an assessment of whether clean and dirty portfolios respond differently to fundamentally distinct types of oil disturbances. Third, we combine these structural shocks with the total and directional connectedness measures of Diebold and Yilmaz (2012, 2014) to quantify the magnitude and direction of spillovers between each oil shock component and the clean/dirty portfolios in both returns and volatility. By jointly conditioning on carbon intensity and the nature of the oil shock, the paper aims to distinguish between carbon-risk and market-risk channels and to clarify whether, and under which types of oil shocks, low-carbon stocks are in fact more or less resilient than their high-carbon counterparts. In this respect, the 2022 Russia–Ukraine conflict is used as an illustrative motivation, while the empirical results are derived from a long sample that spans both tranquil and crisis periods, so that the main findings are not driven by any single episode but reflect the broader dynamics of oil shocks and equity-market connectedness.

We organize the rest of the paper as follows. Section 2 presents a summary of the literature review. Section 3 discusses the data and the measurement methods employed. Section 4 explains the methodology. Section 5 reports and interprets the empirical results. Section 6 concludes.

2. Literature Review

Empirical studies have established that oil price movements play a significant role in influencing stock market activity and returns. The empirical toolkit has evolved from simple linear time-series models to richer, time-varying, and multi-scale frameworks that capture asymmetries, volatility dynamics, connectedness, and structural breaks. Early work, such as Sadorsky (1999), employed a vector autoregressive (VAR) framework to examine how changes in oil prices and volatility affect the U.S. stock market. The results indicate that positive oil price shocks dampen real stock returns and impact economic activity; however, changes in economic activity have only a limited feedback effect on oil prices.

Subsequent research applied GARCH-type models, extending the analysis to multivariate and asymmetric specifications. Elyasiani et al. (2011) employ a GARCH(1,1)

technique to examine thirteen U.S. industrial sectors, demonstrating that sensitivity to oil price shocks varies significantly across sectors. Both oil returns and their volatility significantly influence excess industry returns, with asymmetric effects indicating oil can act as a cost shock for some sectors and a revenue shock for others. [Filis et al. \(2011\)](#) employ a multivariate asymmetric DCC-GARCH model using Brent oil prices and stock indexes of six countries, and find that oil prices have a generally negative effect on all stock markets, regardless of the source of the shock, with the exception of the 2008 global financial crisis, during which lagged oil prices exhibit a positive correlation with stock markets.

More recent work adopts wavelet decomposition to analyze the oil–stock price relationship across various time scales and frequency bands, revealing contagion and interdependence between oil and equity markets. [Reboredo and Rivera-Castro \(2014\)](#) apply discrete and continuous wavelet multiresolution methods to U.S. and European stock returns, finding that oil price changes did not affect stock market returns at either the aggregate or sectoral level before the 2008 crisis. However, since July 2008, there has been clear evidence of contagion and interdependence between oil and stock markets. [Martín-Barragán et al. \(2015\)](#) use wavelet correlations to show that oil–stock correlations are typically near zero and stable during calm periods, but increase significantly at both high and low frequencies during oil and financial shocks.

Building on the connectedness and spillover framework of [Diebold and Yilmaz \(2012, 2014\)](#), a newer strand of literature maps how shocks propagate between oil and stock markets. [Li et al. \(2021\)](#) document robust connectedness between oil, commodities, and financial assets, and find that U.S. markets are more strongly connected to these prices than Chinese markets. [Asadi et al. \(2022\)](#) provide evidence that the Shanghai stock market is significantly affected by WTI oil prices, whereas spillovers from coal and natural gas have almost no impact on Chinese equities. [Mensi et al. \(2023\)](#) analyze the connectedness between WTI crude oil and ten Chinese stock market sectors from 2007 to 2021, showing that the consumer discretionary and industrial sectors are net transmitters of return spillovers, while utilities and telecommunication services are net receivers. [Yang et al. \(2023\)](#) examined exogenous oil supply shocks triggered by events such as the 2022 Russia–Ukraine conflict and found that these episodes increase connectedness and risk spillovers in the global system, as well as in China’s equity market. [Wang et al. \(2023\)](#) develop a connectedness network model to study dynamic spillovers between China’s crude oil futures and sectoral stock indexes, concluding that total spillovers are predominantly short-run (high-frequency) effects operating over horizons of 1 to 5 days.

Another strand of the literature disentangles oil price movements into structural shocks, particularly distinguishing between supply and demand shocks, with two influential approaches by [Kilian \(2009, 2014\)](#) and [Ready \(2018\)](#). Kilian’s framework develops an “Index of Global Real Economic Activity”, providing a direct proxy for real global demand for industrial commodities over the business cycle. This index is grounded in observable shipping transactions and is intended to reflect actual movements in real activity rather than financial sentiment. In contrast, [Ready \(2018\)](#) relies on the VIX derived from S&P 500 options prices, which reflects market expectations of future volatility and is influenced by sentiment, financial uncertainty, and risk aversion, rather than real economic activity or commodity demand.

Distinguishing between oil supply and demand shocks is crucial, as they lead to different macro-financial outcomes. Supply-driven shocks, typically triggered by geopolitical events or production disruptions, raise uncertainty and usually depress equity markets. Demand-driven shocks, stemming from changes in global oil consumption and industrial activity, often signal stronger global conditions that can support stock prices despite higher energy costs. To compare the approaches of [Kilian \(2009, 2014\)](#) and [Ready \(2018\)](#), Kil-

ian's approach identifies oil demand shocks through real-side global conditions, whereas Ready's method anchors identification in forward-looking financial-market expectations, offering a complementary view of how oil shocks interact with equity markets and macro-financial risk.

A new research direction extends the oil–stock market literature by explicitly distinguishing between low-carbon (“clean”) and high-carbon (“dirty”) equity portfolios when analyzing the impact of oil shocks. Rather than using aggregate stock indexes, this strand constructs portfolios using sectoral or firm-level carbon emissions and environmental characteristics, enabling a direct comparison between clean and dirty assets. Clean portfolios typically contain stocks with low carbon intensity and relatively strong environmental performance, such as those in the renewables, technology, and finance sectors. In contrast, dirty portfolios comprise carbon-intensive sectors, including oil, gas, utilities, materials, and heavy industry.

Zhang and Xu (2023) classify Chinese industries into clean, dirty, and ordinary portfolios based on sectoral carbon emissions and, using a Diebold–Yilmaz spillover framework, find that the Clean portfolio is typically a net transmitter of spillovers to both dirty industries and Brent crude, whereas the dirty portfolio is more often a net receiver, especially under tighter climate regulation. This pattern contrasts with Lam et al. (2025), who construct low- and high-carbon portfolios from Hang Seng constituents and find that both low-carbon and high-carbon portfolios primarily behave as net receivers of volatility. Liu et al. (2023) examine spillovers between three types of oil shocks and high- and low-carbon assets, showing that WTI and heating oil futures act as spillover senders to clean energy stocks, while natural gas futures are net receivers of shocks from the clean energy sector. Dutta et al. (2023) study crude-oil volatility jumps and show that such jumps significantly increase the realized volatility of green portfolios, but with different magnitudes and persistence compared to broader, more carbon-intensive benchmarks, indicating distinct risk dynamics for sustainable stocks. Mahadeo (2024) finds that clean energy stocks react mainly to oil demand shocks tied to real activity, whereas dirty energy stocks respond more strongly to oil supply and price shocks, implying that clean and dirty energy equities cannot be treated as homogeneous hedging assets against oil-market risk.

The existing literature on oil shocks and stock returns is extensive, and methodological advances from VAR and GARCH to wavelets and connectedness networks document time-varying, asymmetric spillovers that intensify around crises and geopolitical disruptions. Nonetheless, prior studies have rarely framed their analysis through the lens of the energy-exposure and sectoral-risk hypotheses, which require simultaneously classifying equities into clean and dirty portfolios by carbon intensity and decomposing oil shocks into distinct supply- and demand-driven components. Most studies focus on either structural oil shock decomposition or carbon-based portfolio construction, with few examining the combined effects of shock type and carbon intensity within a single empirical framework.

3. Data and Measures

3.1. Carbon Intensity

The study spans a period of 19.5 years from January 2006 to June 2025, focusing on companies within the HSCA300 index to identify those with high and low carbon intensities. Carbon intensity refers to the amount of carbon dioxide (CO₂) or equivalent greenhouse gases emitted per unit of economic activity, typically measured in tons of CO₂ emission per million dollars of revenue. In line with the current Greenhouse Gas Protocol, organizational greenhouse gas emissions are classified into three distinct scopes to provide a comprehensive view of a company's climate impact. As disclosure of Scope 3 emissions remains optional and is not widely reported by A-share companies, this study defines

carbon intensity as the sum of Scope 1 and Scope 2 greenhouse gas (GHG) emissions per RMB 1 million of revenue.

Our primary source for company-level carbon intensity is the Wind ESG database, which supplies data for 235 out of the 300 constituent companies. For the remaining stocks, we manually searched for Scope 1 and Scope 2 GHG emission data from various company-specific sources, including annual reports, official websites, and sustainability disclosures. By combining these emissions data with revenue figures from annual reports, carbon intensity was calculated for an additional 29 companies, yielding reliable carbon intensity data for a total of 264 firms within the HSCA300 Index.

Table 2 presents the average carbon intensity of HSCA300 constituent stocks across different industries. The Utilities, Properties & Construction, and Materials sectors exhibit significantly higher carbon intensities, reflecting their dependence on fossil fuels, energy-intensive operations, and intensive raw material processing. Energy and Industrial firms also record high emissions due to the combustion of fuels and extensive manufacturing activities. In contrast, Financials and Information Technology display notably low carbon intensities, as their business models rely more on services, digital processes, and office-based operations with minimal physical production. Healthcare and Telecommunications lie in the mid-range, influenced by energy use in laboratories and data networks, but benefiting from relatively efficient energy management systems.

Table 2. Average carbon Intensity of the HSCA300 constituent stocks, by industry.

Industry	No. of HSCA300 Constituent Stocks	Carbon Intensity (Scope 1 and Scope 2 GHG Emissions per RMB 1 Million Revenue)
Financials	46	0.90
Information Technology	37	10.96
Consumer Staples	16	14.65
Healthcare	24	20.00
Telecommunications	4	23.59
Consumer Discretionary	25	37.58
Industrials	53	48.36
Energy	8	173.38
Materials	26	234.83
Properties and Construction	12	325.21
Utilities	13	490.32
Grand Total	264	85.33

3.2. Clean and Dirty Portfolios

The next step is to rank the stocks in the HSCA300 Index by carbon intensity in descending order. Following the approach of Zhang and Xu (2023), we construct two distinct portfolios based on this ranking:

- Clean portfolio: Consists of the 50 stocks with the lowest carbon intensity.
- Dirty portfolio: Consists of the 50 stocks with the highest carbon intensity.

Table 3 summarizes the Clean portfolio, which comprises 50 stocks from the HSCA300 Index with the lowest carbon intensity. These companies, primarily from the financials, information technology, and clean energy sectors, typically have lower direct emissions and are less dependent on fossil fuels in their operations.

Table 3. The Clean portfolio consists of the 50 stocks in the HSCA300 Index with the lowest carbon intensity.

Stock Code	Company Name	Industry	Carbon Intensity
600989.SH	BAOFENG ENERGY	Materials	0.00062
600547.SH	SD GOLD	Materials	0.00150
603369.SH	KING'S LUCK	Consumer Staples	0.01700
601319.SH	PICC GROUP	Financials	0.03000
600025.SH	HUANENG HYDROPOWER	Utilities	0.03400
002555.SZ	SANQI HUYU	Information Technology	0.04200
000002.SZ	CHINA VANKE	Properties & Construction	0.04200
002142.SZ	BANK OF NINGBO	Financials	0.05700
600926.SH	HZBANK	Financials	0.09400
601878.SH	ZHESHANG SECURITIES	Financials	0.10000
600000.SH	SPD BANK	Financials	0.12000
601901.SH	FOUNDER SECURITIES	Financials	0.13053
000617.SZ	CNPCCCL	Financials	0.18000
603019.SH	SUGON	Information Technology	0.19687
601336.SH	NCI	Financials	0.20000
003816.SZ	CGN POWER	Utilities	0.27000
688041.SH	HYGON	Information Technology	0.29000
601818.SH	CEB BANK	Financials	0.36000
688036.SH	TRANSSION	Information Technology	0.38000
601318.SH	PING AN	Financials	0.43000
600030.SH	CITIC SEC	Financials	0.43000
600900.SH	CYPC	Utilities	0.45000
600016.SH	MINSHENG BANK	Financials	0.47000
000166.SZ	SWHY	Financials	0.47000
300059.SZ	EASTMONEY	Financials	0.48000
601881.SH	CGS	Financials	0.50000
600011.SH	HUANENG POWER	Utilities	0.50037
601888.SH	CTG DUTY-FREE	Consumer Discretionary	0.50537
600958.SH	DFZQ	Financials	0.51000
000977.SZ	IEIT	Information Technology	0.51919
601601.SH	CPIC	Financials	0.53000
601136.SH	CAPITAL SECURITIES	Financials	0.54000
601066.SH	CSC	Financials	0.55000
300628.SZ	YEALINK	Information Technology	0.56000
000776.SZ	GF SEC	Financials	0.58000
688008.SH	MONTAGE TECHNOLOGY	Information Technology	0.60000
601658.SH	PSBC	Financials	0.62000
603986.SH	GIGADEVICE	Information Technology	0.70000
600919.SH	BANK OF JIANGSU	Financials	0.73000
300413.SZ	MANGO	Consumer Discretionary	0.77000
601377.SH	IS	Financials	0.80000
601916.SH	CZBANK	Financials	0.83000
600436.SH	PIEN TZE HUANG	Healthcare	0.83519
601688.SH	HTSC	Financials	0.88000
002230.SZ	IFLYTEK	Information Technology	0.92319
688111.SH	KINGOFTOFFICE	Information Technology	0.93659
601009.SH	NJCB	Financials	0.98000
601229.SH	BANK OF SHANGHAI	Financials	1.00000
601998.SH	CITIC BANK	Financials	1.00000
601211.SH	GTHT	Financials	1.04000
Average			0.46431

Table 4 presents the Dirty portfolio, which consists of the 50 stocks in the HSCA300 Index with the highest carbon intensity. This group encompasses traditional sectors such as materials, industrials, energy, and utilities. Companies in this portfolio typically provide essential services, such as electricity, water, and gas, or are engaged in large-scale industrial production, resulting in higher carbon emissions per unit of revenue. The firms in the Dirty portfolio exhibit significantly higher carbon intensity values, averaging 404.04, which is

approximately 870 times greater than those in the Clean portfolio. This stark difference underscores the substantial disparities in both direct and indirect emission levels between the two portfolios.

Table 4. The Dirty portfolio consists of the 50 stocks in the HSCA300 Index with the highest carbon intensity.

Stock Code	Company Name	Industry	Carbon Intensity
000100.SZ	TCL TECH.	Consumer Discretionary	58.51
000792.SZ	QHSI	Materials	61.23
002460.SZ	GANFENGLITHIUM	Materials	68.37
688599.SH	TRINA SOLAR	Industrials	71.16
002714.SZ	MUYUAN	Consumer Staples	72.51
601816.SH	BJ-SH HIGH SPEED RAILWAY	Industrials	74.72
002493.SZ	RSPC	Materials	80.90
002812.SZ	ENERGY TECHNOLOGY	Materials	81.10
601919.SH	COSCO SHIP HOLD	Industrials	94.55
603799.SH	HUAYOU COBALT	Materials	101.11
000408.SZ	ZANGGE HOLDING	Materials	107.75
300274.SZ	SUNGROW POWER SUPPLY	Industrials	117.00
002001.SZ	NHU	Healthcare	128.81
002422.SZ	KELUN PHARMA	Healthcare	130.46
000786.SZ	BNBMPLC	Properties & Construction	135.47
002648.SZ	SATLPEC	Materials	135.51
600176.SH	CJS	Materials	151.83
600309.SH	WANHUA	Materials	153.95
600188.SH	YANKUANG ENERGY	Energy	163.92
600221.SH	HNA	Consumer Discretionary	166.16
601111.SH	AIR CHINA	Consumer Discretionary	167.26
600029.SH	CHINA SOUTH AIR	Consumer Discretionary	168.01
600026.SH	COSCO SHIP ENGY	Industrials	168.47
002129.SZ	TZE	Industrials	173.79
600115.SH	CHINA EAST AIR	Consumer Discretionary	181.44
001289.SZ	CHINA LONGYUAN	Utilities	198.39
000301.SZ	CESM	Energy	218.64
600346.SH	HLGF	Materials	228.21
600236.SH	GGEP	Utilities	233.13
601872.SH	CMES	Industrials	234.98
600438.SH	TONGWEI	Industrials	244.29
601898.SH	CHINA COAL	Energy	248.58
600219.SH	NANSHAN ALUMINIUM	Materials	252.57
600160.SH	ZJJH	Materials	262.36
600089.SH	TBEA	Industrials	289.15
601865.SH	FLAT GLASS	Industrials	311.55
000708.SZ	CITIC STEEL	Materials	326.11
600019.SH	BAOSTEEL	Materials	342.24
601600.SH	CHALCO	Materials	491.00
000807.SZ	YNALCO	Materials	513.21
601088.SH	CHINA SHENHUA	Energy	589.20
688303.SH	DAQO	Materials	596.66
603260.SH	HOSHINE SILICON INDUSTRY	Materials	670.75
600886.SH	SDIC POWER	Utilities	844.40
600426.SH	HUALU-HENGSHENG	Materials	1357.64
600027.SH	HUADIAN POWER	Utilities	1567.61
000877.SZ	TSM	Properties & Construction	1685.21
600023.SH	ZZEPC	Utilities	1725.12
600795.SH	GDPD	Utilities	1755.94
600585.SH	CONCH CEMENT	Properties & Construction	2001.11
Average			404.04

Figure 1 shows the sectoral composition of the clean and dirty portfolios: the clean portfolio is predominantly composed of financials and information technology, while the

dirty portfolio is dominated by materials, industrials, utilities, and energy. This composition underscores the interaction between carbon intensity and sectoral characteristics. Since high- and low-carbon firms tend to cluster within particular sectors, sector-level analysis such as comparing firms' oil shock sensitivity relative to sector peers with explicit controls for sector membership, should not be well suited to address the core research question of this study. The primary goal of this study is to examine the combined effects of carbon intensity and sectoral risk, specifically how low-carbon, growth-oriented sectors compare with high-carbon, defensive sectors in transmitting oil shocks, rather than to treat sectoral effects as noise. Therefore, using broad clean and dirty portfolios sorted by emissions and reflecting actual sectoral composition is the most appropriate empirical approach, while granular within-sector analyses are better suited for future research rather than as a core component of this study.

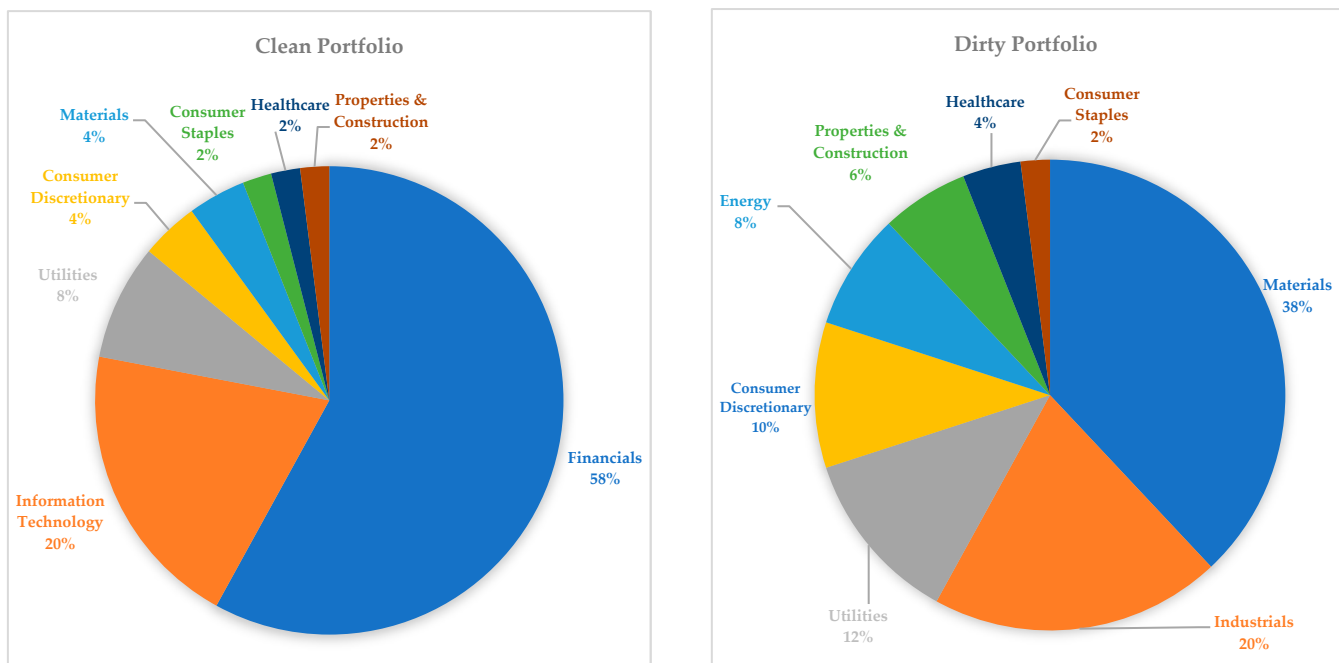


Figure 1. Sector composition of the Clean and Dirty portfolios.

3.3. Portfolio Return and Volatility

For each stock, a monthly table is compiled that highlights two key dimensions:

- (i) Stock return is assessed using logarithmic returns, calculated as the natural logarithm of the ratio between the closing price at the end of the current month and the closing price at the end of the previous month:

$$r_{i,m} = \ln \left(\frac{P_{i,m}}{P_{i,m-1}} \right) \quad (1)$$

where r_{im} and P_{im} are the monthly return and closing price of stock i on the last trading day of month m .

- (ii) Volatility is measured by calculating the standard deviation of returns:

$$\sigma_{i,m} = \sqrt{243 \frac{1}{Nm-1} \sum_{t=1}^{Nm} (r_{it} - \bar{r}_{i,m})^2} \quad (2)$$

where r_{it} is the daily logarithmic return of stock i on day t , $\bar{r}_{i,m}$ be the average logarithmic return of stock i in month m , and Nm denotes the number of trading days

in month m . During the sample period from January 2006 to June 2025, the total number of trading days is 4733, and the average number of trading days per year is $4733/19.5 = 243$.

After calculating monthly volatility for each stock, the mean monthly volatility of the Clean and Dirty portfolios is computed as the simple average across the 50 stocks. Table 5 reports the descriptive statistics for the variables in Clean and Dirty portfolios, while Figure 2 displays the charts for the period from January 2006 to June 2025.

Table 5. Descriptive statistics of Clean and Dirty portfolios.

	Clean Portfolio	Dirty Portfolio
Stock Monthly Return		
- Mean	0.0111	0.0096
- Median	0.0061	0.0141
- Maximum	0.2234	0.2497
- Minimum	−0.2825	−0.3410
- Standard deviation	0.0797	0.0882
- Skewness	−0.2831	−0.6042
- Kurtosis	1.6312	2.1740
Volatility		
- Mean	0.3674	0.3955
- Median	0.3369	0.3573
- Maximum	0.8534	0.9430
- Minimum	0.1645	0.1950
- Standard deviation	0.1193	0.1363
- Skewness	1.2519	1.1928
- Kurtosis	1.5826	1.2633



Figure 2. The monthly return and volatility of Clean and Dirty portfolios from January 2006 to June 2025.

3.4. Oil Supply, Aggregate Demand, and Oil-Specific Demand Shocks

Kilian (2009, 2014) and Ready (2018) propose two prominent frameworks for separating oil supply and demand shocks. This study adopts Kilian’s approach because it relies on physical measures of global oil production and demand, which are directly interpretable and regularly updated by the Federal Reserve Bank of Dallas, making them suitable for policy analysis and long-horizon forecasting. In contrast, the VIX-based measures in Ready

(2018) are more susceptible to financial market noise and option-pricing assumptions, which may not accurately reflect actual changes in economic fundamentals. For these reasons, the analysis follows Kilian's Structural VAR (SVAR) framework to identify oil supply shocks, aggregate demand shocks, and oil-specific demand shocks:

$$A_0 z_t = \alpha + \sum_{i=1}^{24} A_i z_{t-i} + \varepsilon_t \quad (3)$$

where

$$z_t = (\Delta prod_t, rea_t, rpo_t)'$$

ε_t denotes the vector of serially and mutually uncorrelated structural innovations

- $\Delta prod_t$ represents the logarithmic change in global crude oil production, with data sourced from the U.S. Energy Information Administration (EIA).
- rea_t refers to the "Index of Global Real Economic Activity," which is obtained from the website of the Federal Reserve Bank of Dallas. This index is constructed from a panel of dollar-denominated global bulk dry cargo shipping rates and serves as a proxy for the volume of shipping in global industrial commodity markets.
- rpo_t denotes the real price of oil. The monthly nominal oil price data are sourced from the U.S. Energy Information Administration (EIA). These nominal prices are adjusted for inflation using the Consumer Price Index (CPI) data from the Federal Reserve Bank to derive real oil prices. While Kilian (2009) used the "Refiner Acquisition Cost of Crude Oil, Imported (USD per Barrel)" from the EIA for calculations, Fernandez-Perez et al. (2023) recommend utilizing the "Refiner Acquisition Cost of Crude Oil, Composite (USD per Barrel)" for research with a global market focus. Given that this study investigates the Chinese stock market rather than the U.S. market, the approach advocated by Fernandez-Perez et al. (2023) is deemed more suitable for our analysis.

According to Kilian (2009), A_0^{-1} has a recursive structure such that the reduced-form errors e_t can be decomposed according to $e_t = A_0^{-1} \varepsilon_t$:

$$e_t = \begin{pmatrix} e_t^{\Delta prod} \\ e_t^{rea} \\ e_t^{rpo} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{oil \text{ supply shock}} \\ \varepsilon_t^{aggregate \text{ demand shock}} \\ \varepsilon_t^{oil-specific \text{ demand shock}} \end{pmatrix} \quad (4)$$

This approach distinguishes three important structural shocks in the global crude oil market, each with different origins and economic implications:

1. Oil supply shocks: Defined as an unpredictable change in global oil production, typically due to exogenous factors such as geopolitical events, natural disasters, or technical failures. These shocks can either reduce or increase the physical availability of crude oil, leading to short-term fluctuations in the oil price.
2. Aggregate demand shocks: Represent changes in global real economic activity that influence the demand for all industrial commodities, including but not limited to oil. Such shocks are typically driven by fluctuations in the global business cycle, such as periods of robust economic expansion or recession.
3. Oil-specific demand shocks: Separate from aggregate demand shocks as they result from market expectations of future oil supply shortages, often driven by heightened uncertainty or risk, such as geopolitical tensions or fears of disruption. Known as precautionary demand shocks, they are not caused by current changes in production or consumption but by concerns over potential future scarcity, leading to immediate and lasting effects on oil prices.

Figure 3 presents oil supply shocks, aggregate demand shocks, and oil-specific demand shocks from January 2006 to June 2025, with values expressed as annual averages to improve the readability of the charts.

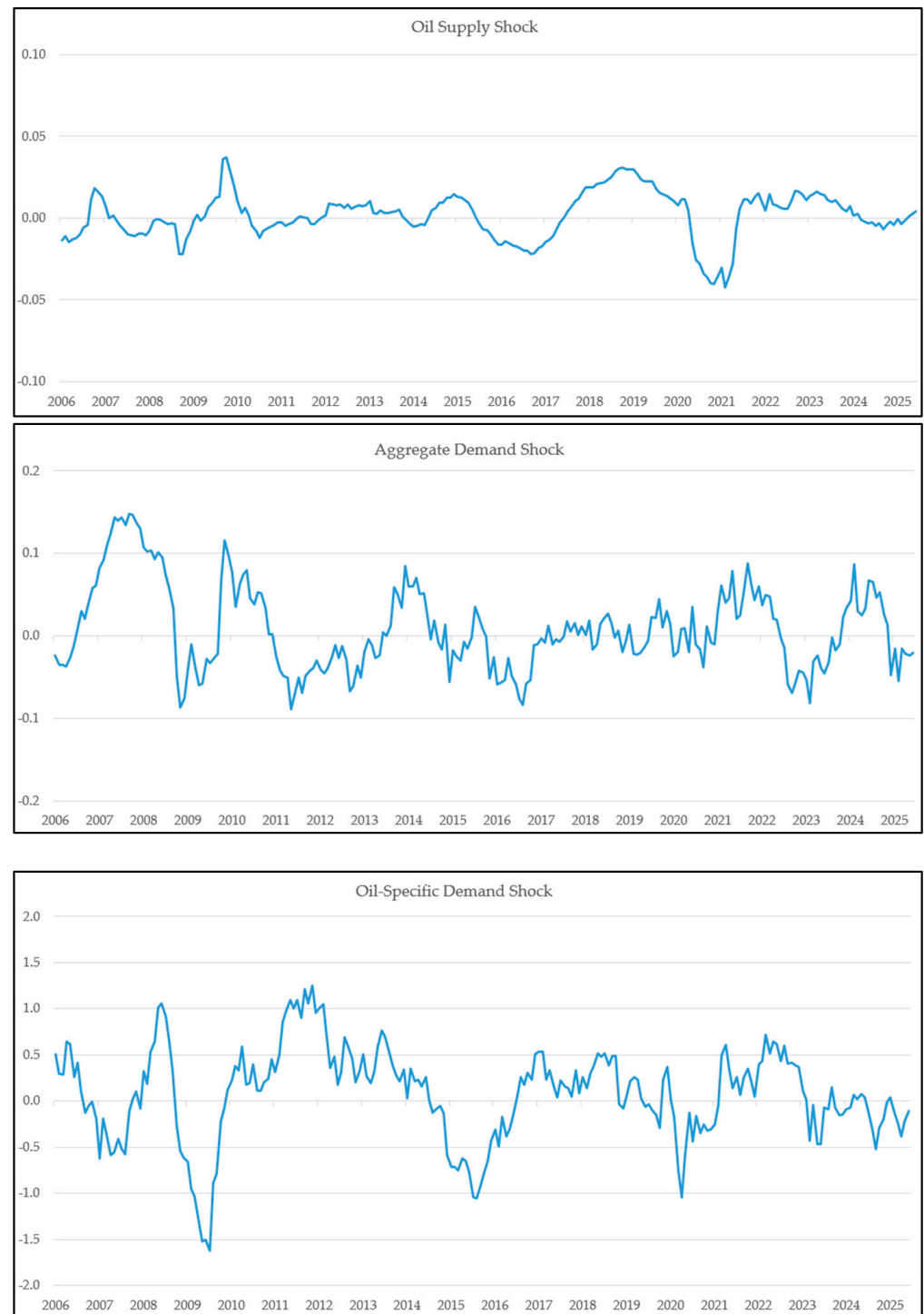


Figure 3. The Oil supply shocks, Aggregate demand shocks, and Oil-specific demand shocks from January 2006 to June 2025.

4. Methodology

This study employs the connectedness measurement framework developed by Diebold and Yilmaz (2012, 2014), which is based on dynamic variance decomposition from vector autoregressive models. A key advantage of this approach, compared to orthog-

onalization schemes like Cholesky decomposition, is that the resulting forecast-error variance decompositions are invariant to the ordering of variables in the VAR, ensuring consistent and interpretable connectedness metrics. Consider a covariance stationary N -variate process described by the VAR(p) framework as $x_t = \sum_{i=1}^p \Phi_i x_{t-i} + \varepsilon_t$, where $\Phi_1, \dots, \Phi_p$ coefficient matrices are $x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, A_i obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p}$, $\varepsilon_t \sim (0, \Sigma)$ = white noise, $A_0 = N \times N$ identity matrix, and $A_i = 0$ for $i < 0$. The H -step-ahead generalized forecast-error variance

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \quad (5)$$

where σ_{ij} is the standard deviation of the disturbance and e_i is the selection vector. The Koop-Pesaran-Potter-Shin generalized VAR framework—that is, $\sum_{j=1}^N \theta_{ij}^g(H) \neq 1$. The row sum to obtain pairwise directional connectedness is $\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^N \theta_{ij}^g(H)}$, which normalized the entry of the generalized variance decomposition matrix. The $\tilde{\theta}_{ij}^g(H)$ is converted to $C_{i \leftarrow j}^H$ with $\sum_{j=1}^N \tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H) = N$ for less cumbersome and directional informative. The total directional connectedness from all other variables j to firm i will equal to

$$C_{i \leftarrow \cdot}^H = \frac{\sum_{j=1}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} = \frac{\sum_{j=1}^N \tilde{\theta}_{ij}^g(H)}{N} \quad (6)$$

and the total directional connectedness of the variable i to all other variables j will be

$$C_{\cdot \leftarrow i}^H = \frac{\sum_{j=1}^N \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ji}^g(H)} = \frac{\sum_{j=1}^N \tilde{\theta}_{ji}^g(H)}{N} \quad (7)$$

The final step in Diebold and Yilmaz's framework is to measure system-wide connectedness. This is accomplished by using the normalized entries of the generalized variance decomposition matrix: the total directional connectedness measure is calculated as the ratio of the sum of all off-diagonal elements to the sum of all elements in the entire variance decomposition matrix. This yields a single index that summarizes the overall degree of interconnectedness among all variables in the system, regardless of their order or groupings:

$$C^H = \frac{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)} = \frac{\sum_{i,j=1}^N \tilde{\theta}_{ij}^g(H)}{N} \quad (8)$$

5. Empirical Findings

We follow the methodology of Diebold and Yilmaz (2012) to build the VARs of order 2 and an H -step ahead forecast horizon of 10 for the connectedness analysis. Given the sample size of 234 observations in our data, we select a rolling window size of 50. The connectedness analysis first evaluates the monthly returns of the Clean and Dirty portfolios in response to oil supply shocks, aggregate demand shocks, and oil-specific demand shocks, and then follows with an analysis of volatility.

5.1. Performance Returns

Table 6 presents the relationship between oil shocks and portfolio returns, and Figures 4–9 show the spillover diagram. The directional spillover from oil supply shocks to the Clean Portfolio return ($C_{Clean_Ret \leftarrow Oil_Supp}^H$) is 4.53%, which is higher than the Dirty portfolio return ($C_{Dirty_Ret \leftarrow Oil_Supp}^H$) of 3.92%. This suggests that oil supply shocks may prompt investors and policymakers to focus on alternatives and renewable energy sources. This increases the attractiveness and perceived growth potential of clean energy firms, translating into stronger returns. Clean stocks are also seen as more resilient to fossil fuel market volatility, so they react more positively when oil supply is disrupted. Dirty stocks, although directly linked to oil, may not benefit as much due to increased costs and regulatory headwinds.

Table 6. Spillover in portfolio returns.

	Oil Supply Shocks	Aggregate Demand Shocks	Oil-Specific Demand Shocks	Clean Portfolio Return	Dirty Portfolio Return	FROM
Oil supply shocks	74.00	7.15	7.16	6.37	5.32	26.00
Aggregate demand shocks	11.34	69.60	4.84	7.82	6.40	30.40
Oil-specific demand Shocks	6.05	5.48	71.54	8.02	8.92	28.46
Clean portfolio return	4.53	3.25	4.60	50.94	36.69	49.06
Dirty portfolio return	3.92	2.60	3.63	38.30	51.56	48.44
TO	25.84	18.47	20.23	60.51	57.33	182.37
NET	−0.16	−11.93	−8.24	11.45	8.88	

The directional spillover from aggregate demand shocks to the Clean Portfolio return ($C_{Clean_Ret \leftarrow Agg_D}^H$) of 3.25% is higher than the Dirty portfolio return ($C_{Dirty_Ret \leftarrow Agg_D}^H$) of 2.60%. The directional spillover from oil-specific demand shocks to the Clean Portfolio return ($C_{Clean_Ret \leftarrow Agg_D}^H$) of 4.60% is also higher than the Dirty portfolio return ($C_{Dirty_Ret \leftarrow Agg_D}^H$) of 3.63%. Clean stocks are typically high-tech and financial companies, which are known for their innovation, scalability, and sensitivity to global business cycles. During periods of oil shocks, especially driven by strong aggregate demand or oil-specific demand, these conditions often signal global economic expansion. Capital tends to flow into high-tech and financial assets, leading to higher returns for clean stocks. Dirty stocks, which are more reliant on traditional industries, may not experience the same level of investor enthusiasm or growth during periods of expansion. Therefore, the aggregate demand shocks have a greater directional spillover to Clean portfolios, reflecting investor preference for sectors poised to benefit most from global growth.

Oil-specific demand shocks have a stronger spillover effect than aggregate demand shocks because they arise from abrupt changes in market expectations about future oil scarcity, often driven by geopolitical tensions or anticipated supply disruptions. These shocks induce precautionary buying, which immediately impacts oil prices and investor sentiment, generating greater volatility and uncertainty in financial markets. Dirty portfolio stocks, being more directly involved in oil-related industries, are especially sensitive to these shocks; their cash flows and risk exposure react sharply to price surges and uncertainty. Clean stocks, while somewhat affected, are less exposed, so the overall system's connectedness to oil-specific demand shocks is dominated by dirty assets. In contrast, aggregate demand shocks reflect slower changes in economic activity, influencing all sectors gradually. Therefore, the magnitude of directional spillover is greater for oil-specific demand shocks due to their immediacy, market-wide implications, and disproportionate effect on oil-sensitive portfolios.

For the analysis of net directional spillovers, oil supply shocks, aggregate demand shocks, and oil-specific demand shocks are all identified as net receivers with a magnitude

of -0.16% (25.84% minus 26.00%), -11.93% (18.47% minus 30.40%), and -8.24% (20.23% minus 28.46%), respectively. This aligns with the research conducted by Umar et al. (2020), which investigated the connectedness between the returns of stock indexes and oil prices. The research concludes that oil shocks typically act as net receivers, meaning they exert limited influence on other assets and are more affected by external factors.

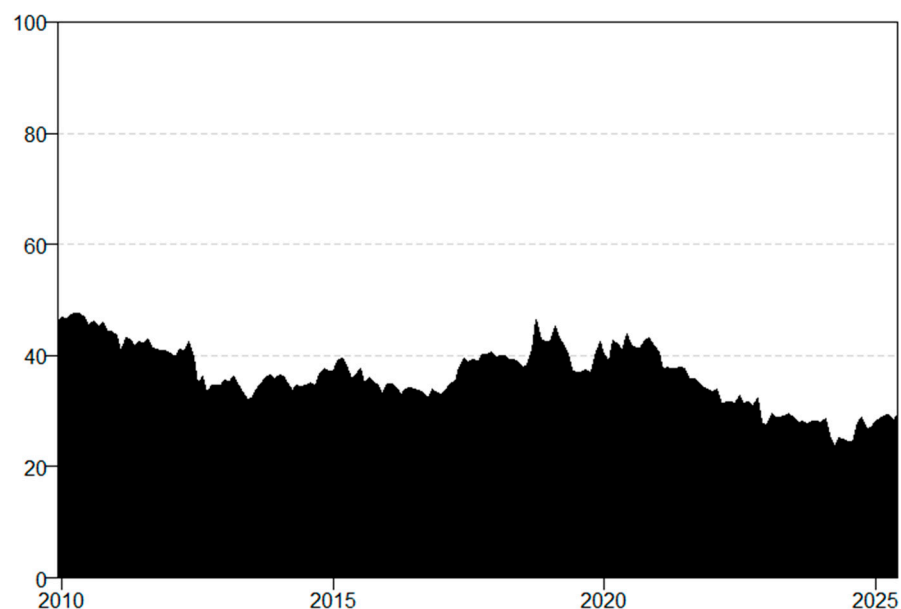


Figure 4. Total spillover in portfolio returns.

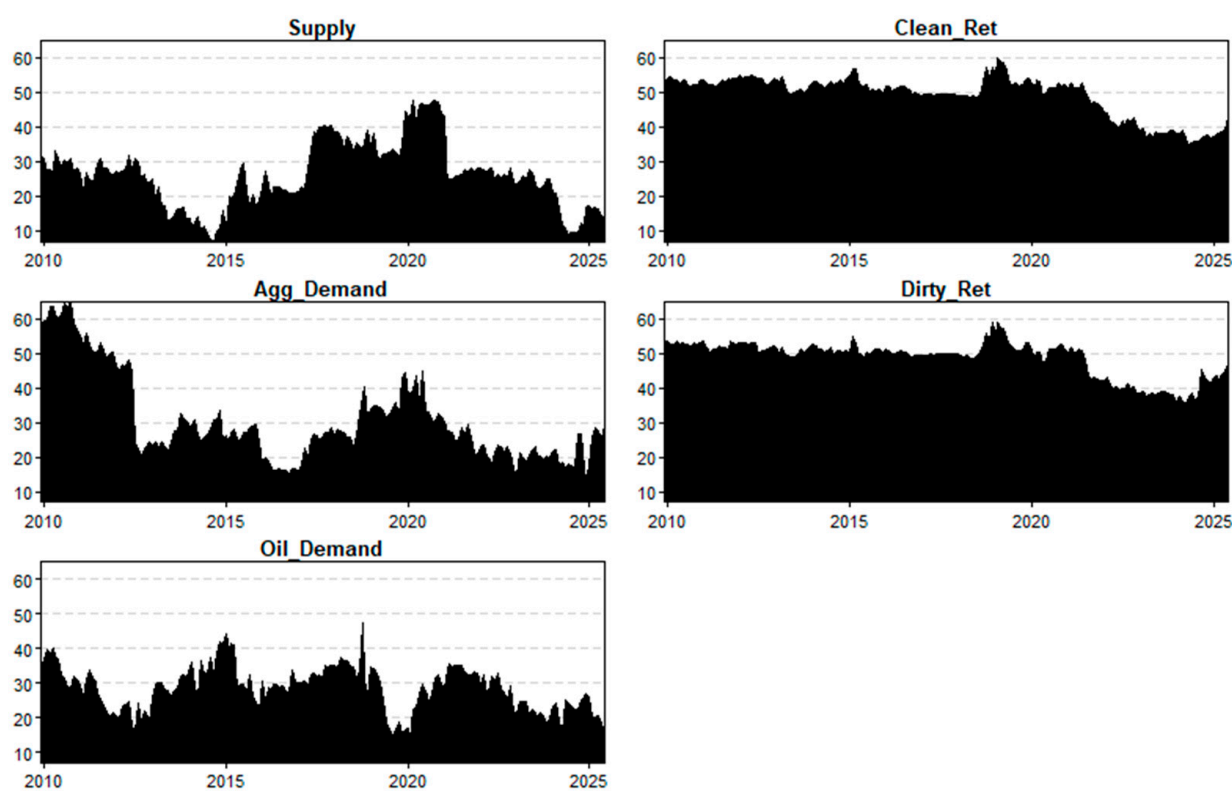


Figure 5. Directional spillover in portfolio returns—FROM.

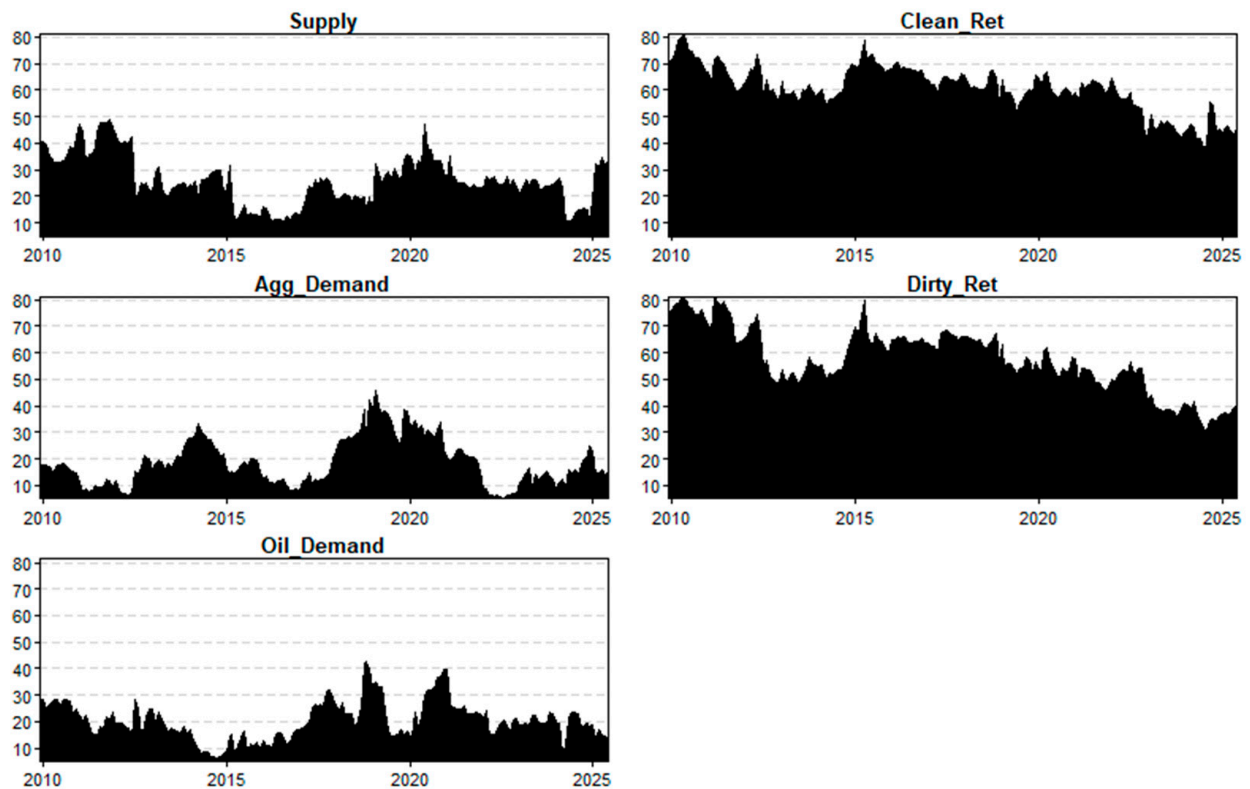


Figure 6. Directional spillover in portfolio returns—TO.

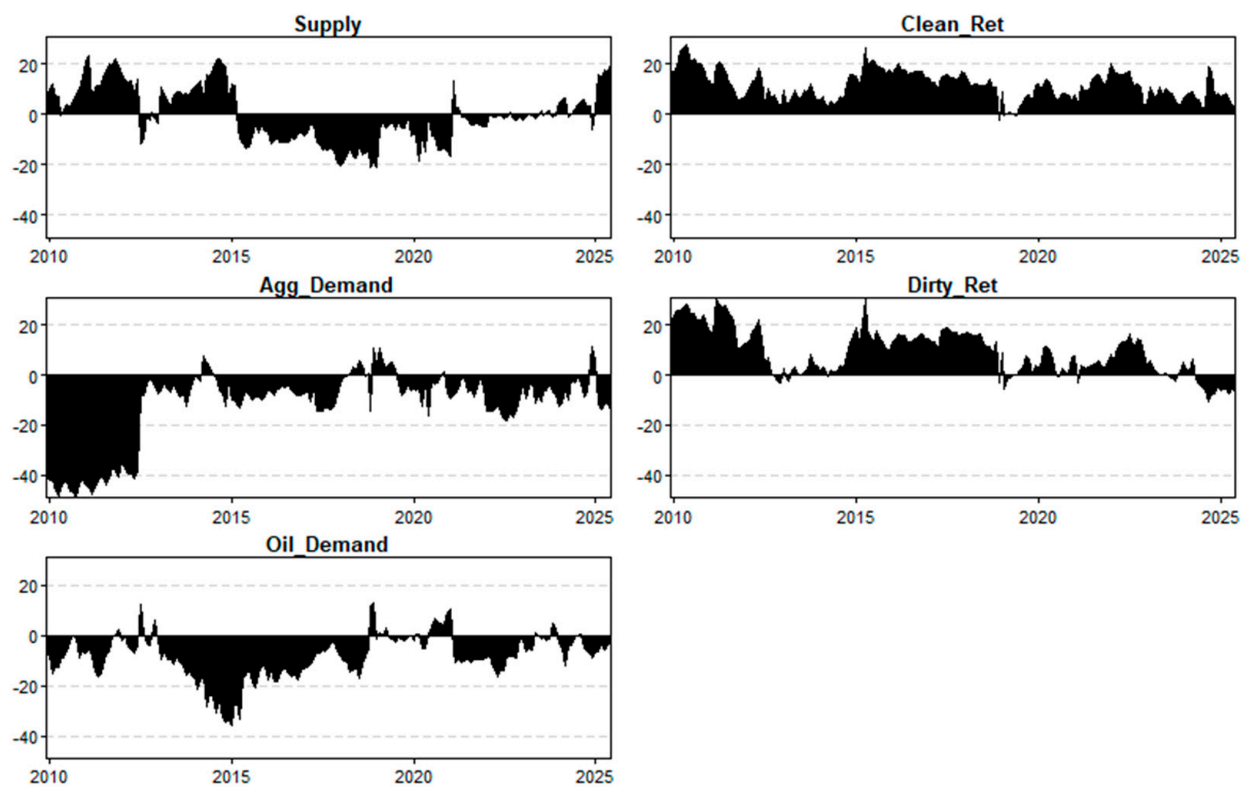


Figure 7. Directional spillover in portfolio returns—NET.

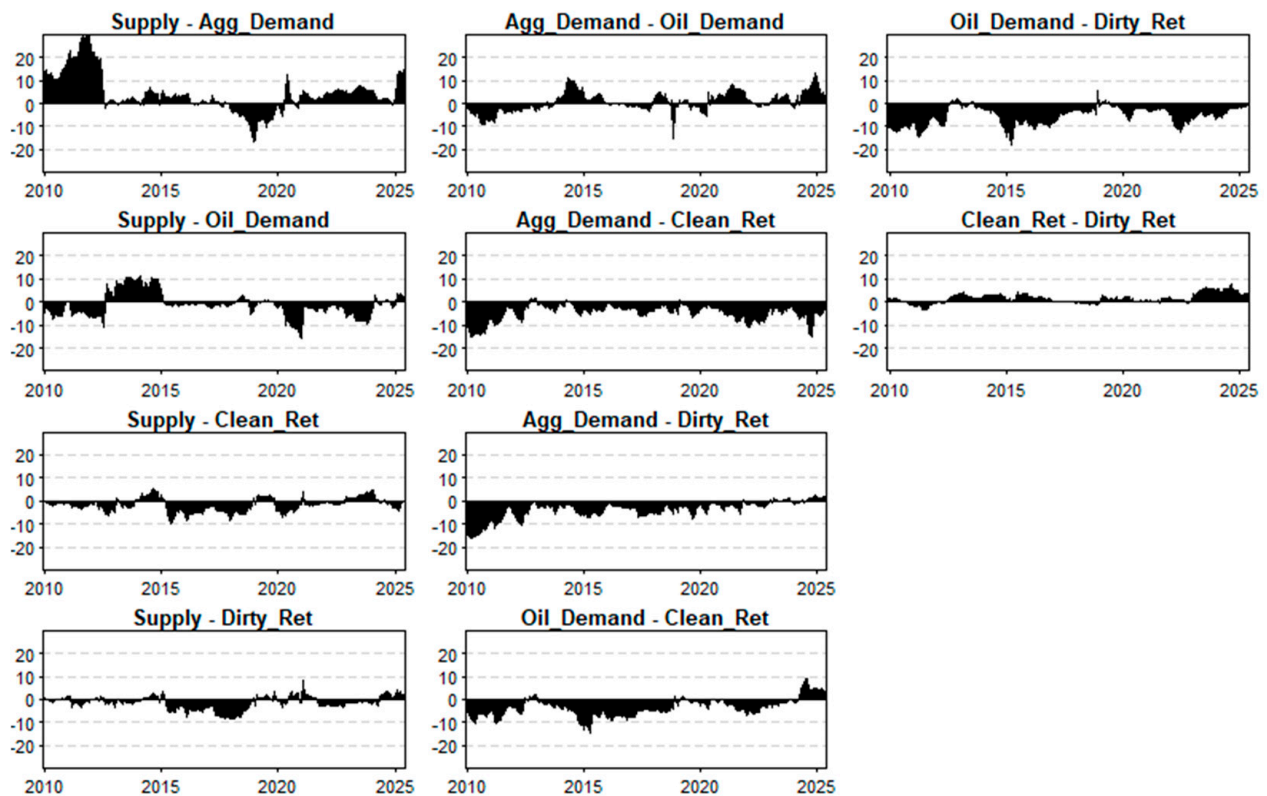


Figure 8. Directional spillover in portfolio returns—NET Pairwise.

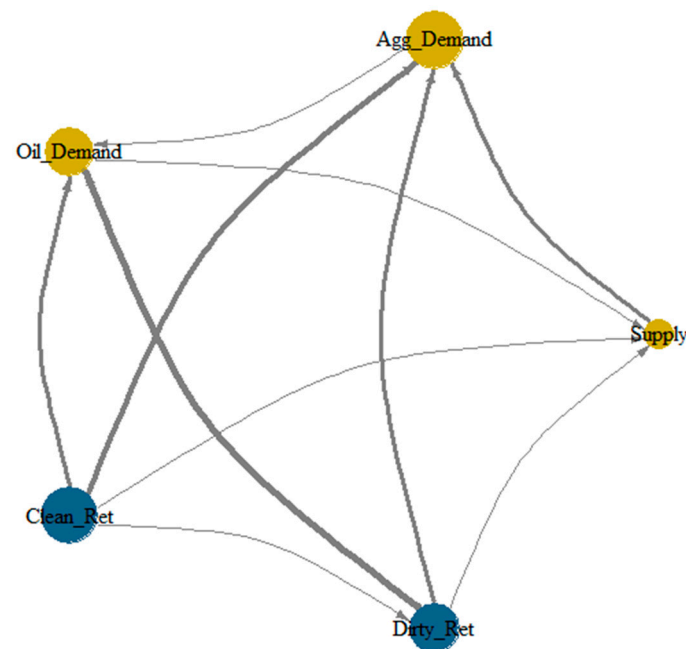


Figure 9. NET Pairwise connectedness network in portfolio returns. Note to Figure 9: This figure follows the methodology of Diebold and Yilmaz (2012, 2014) to present network graphs depicting the net pairwise directional return connectedness among three shocks and the performance returns of two portfolios. Arrowheads indicate the direction of positive net direct connectedness from the source variable to others, while arrow thickness represents the strength of the net pairwise directional connectedness.

For the robustness test, we reassess return connectedness using a range of forecast horizons (3, 5, 6, 8, 10, 15, and 20 months) and plot the minimum, maximum, and median

values. As shown in Figure 10, the spillover plot remains consistent across different forecast horizons, confirming the robustness of our results.



Figure 10. Sensitivity of the spillover in portfolio returns to the forecast horizon (maximum, minimum, and median values for 3-, 5-, 6-, 8-, 10-, 15-, and 20-month forecast horizons).

5.2. Volatility

Table 7 presents the connectedness among oil shocks and portfolio volatilities. Compared to Table 6, which examines the connectedness between oil shocks and portfolio returns, the direction of spillovers remains largely consistent across both tables, but the magnitude of volatility spillovers reported in Table 7 is generally higher than that of return spillovers in Table 6. For instance, the spillover from oil supply shocks to the Clean portfolio ($C_{Clean_Ret \leftarrow Oil_Supp}^H$) and Dirty portfolio ($C_{Dirty_Ret \leftarrow Oil_Supp}^H$) is 4.53% and 3.92% in terms of returns, but rises to 6.79% for the Clean portfolio ($C_{Clean_Vol \leftarrow Oil_Supp}^H$) and 4.75% for the Dirty portfolio ($C_{Dirty_Vol \leftarrow Oil_Supp}^H$) when measured by volatility. The difference is even more marked for oil-specific demand shocks: the return spillovers to the Clean portfolio ($C_{Clean_Ret \leftarrow Oil_D}^H$) and Dirty portfolio ($C_{Dirty_Ret \leftarrow Oil_D}^H$) are 4.60% and 3.63%, while the corresponding volatility spillovers are 6.52% ($C_{Clean_Vol \leftarrow Oil_D}^H$) and 7.26% ($C_{Dirty_Vol \leftarrow Oil_D}^H$). This pattern is consistent with established observations in financial markets, where volatility tends to be more sensitive and persistent in response to shocks than returns, which tend to adjust more quickly and subsequently revert to equilibrium. Volatility spillovers offer a more pronounced and lasting indication of interconnection within and across portfolios when compared to spillovers measured in returns. This underscores the importance of monitoring volatility, as it provides key insight into the potential for systemic transmission and amplification of shocks throughout the financial system.

Table 7. Spillover in portfolio volatility.

	Oil Supply Shocks	Aggregate Demand Shocks	Oil-Specific Demand Shocks	Clean Portfolio Volatility	Dirty Portfolio Volatility	FROM
Oil supply shocks	69.06	6.20	7.60	9.62	7.53	30.94
Aggregate demand shocks	12.18	72.05	4.81	6.09	4.87	27.95
Oil-specific demand shocks	6.42	5.97	71.03	9.32	7.27	28.97
Clean portfolio volatility	6.79	3.89	6.52	47.88	34.92	52.12
Dirty portfolio volatility	4.75	3.46	7.26	34.17	50.35	49.65
TO	30.13	19.53	26.18	59.20	54.58	189.62
NET	−0.81	−8.42	−2.79	7.08	4.94	

Another notable difference between return spillovers (Table 6) and volatility spillovers (Table 7) is that the Clean portfolio generally receives higher spillovers from oil shocks than the Dirty portfolio, but with an exception of oil-specific demand shocks that volatility spillover to the Dirty portfolio ($C_{Dirty_Vol \leftarrow Oil_D}^H$) is higher at 7.26% than to the Clean portfolio ($C_{Clean_Vol \leftarrow Oil_D}^H$) at 6.52%. This can be attributed to the Dirty portfolio's greater exposure to oil price risk and its vulnerability to abrupt changes in energy market expectations, often driven by geopolitical events or concerns about future supply. When oil-specific demand shocks occur, the direct linkage between dirty assets and oil market dynamics makes these stocks the primary recipients of sector volatility, even surpassing the clean segment in this scenario.

In the analysis of net directional spillovers, the volatility figures exhibit a pattern similar to returns, with all oil shocks serving as net receivers. The net directional spillover from aggregate demand shocks is particularly notable at −8.42% (19.53% minus 27.95%), which is substantially larger than that from oil supply shocks at −0.81% (30.13% minus 30.94%) and oil-specific demand shocks at −2.79% (26.18% minus 28.97%). For returns, the net receiver effects are greater for aggregate demand shocks at −11.93% and oil-specific demand shocks at −8.24% compared to oil supply shocks at −0.16%. This indicates that oil-specific demand shocks are strong net receivers in the return network, but this pattern does not hold for volatility. While precautionary oil-specific shocks significantly absorb return spillovers from the broader market, likely due to their influence on expectations and sentiment, they are less influential in absorbing volatility. Instead, aggregate demand shocks play a dominant role in volatility spillovers.

The charts in Figures 11–16, which illustrate spillovers in portfolio volatilities, clearly show that spillovers reached record highs in several charts during 2015. This was primarily driven by volatility surging to over 80% in both the Clean and Dirty portfolios, which then spilled over to other variables throughout the year. In the first half of 2015, widespread margin lending and speculative activity among retail investors fueled a rapid rise in equity prices, resulting in a significant stock market bubble in China. The CSI 300 Index soared from 3533.71 at the end of December 2014 to a peak of 5380.43 on 9 June 2015, representing an extraordinary 52.3% increase in just six months. However, this trend reversed sharply in June 2015 when regulators imposed strict controls on margin financing, particularly targeting shadow banking activities. Many leveraged investors unwound their positions amid heightened regulatory scrutiny, resulting in massive sell-offs and a rapid market decline. The CSI 300 Index plummeted to a low of 2952.01 on August 26, erasing nearly half its value in a matter of weeks. The crash was exacerbated by the suspension of trading for several listed companies, which led to a loss of confidence and caused extreme volatility in the A-share market during this period.

For the robustness test, we reassess volatility connectedness using a range of forecast horizons (3, 5, 6, 8, 10, 15, and 20 months) and plot the minimum, maximum, and median values. As shown in Figure 17, the spillover plot remains consistent across different forecast horizons, confirming the robustness of our results.

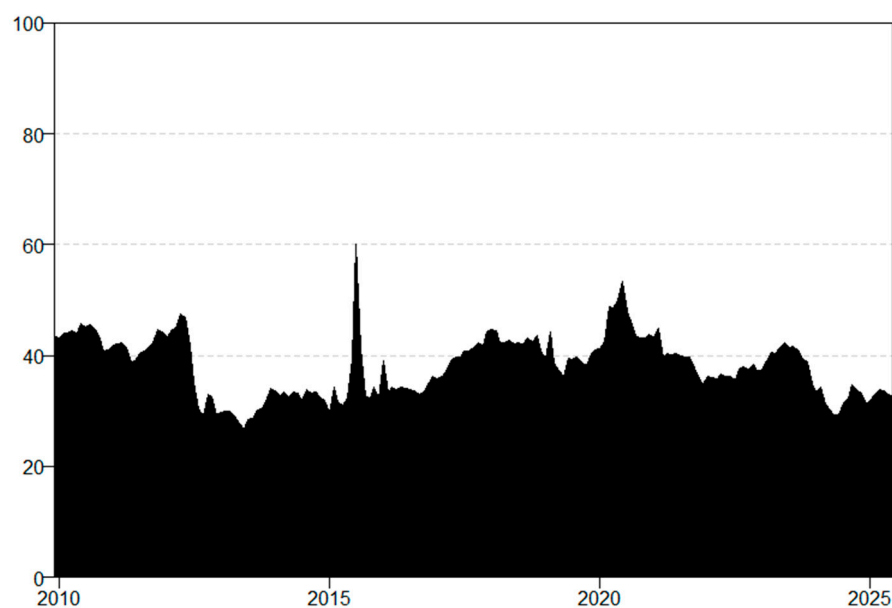


Figure 11. Total spillover in portfolio volatilities.

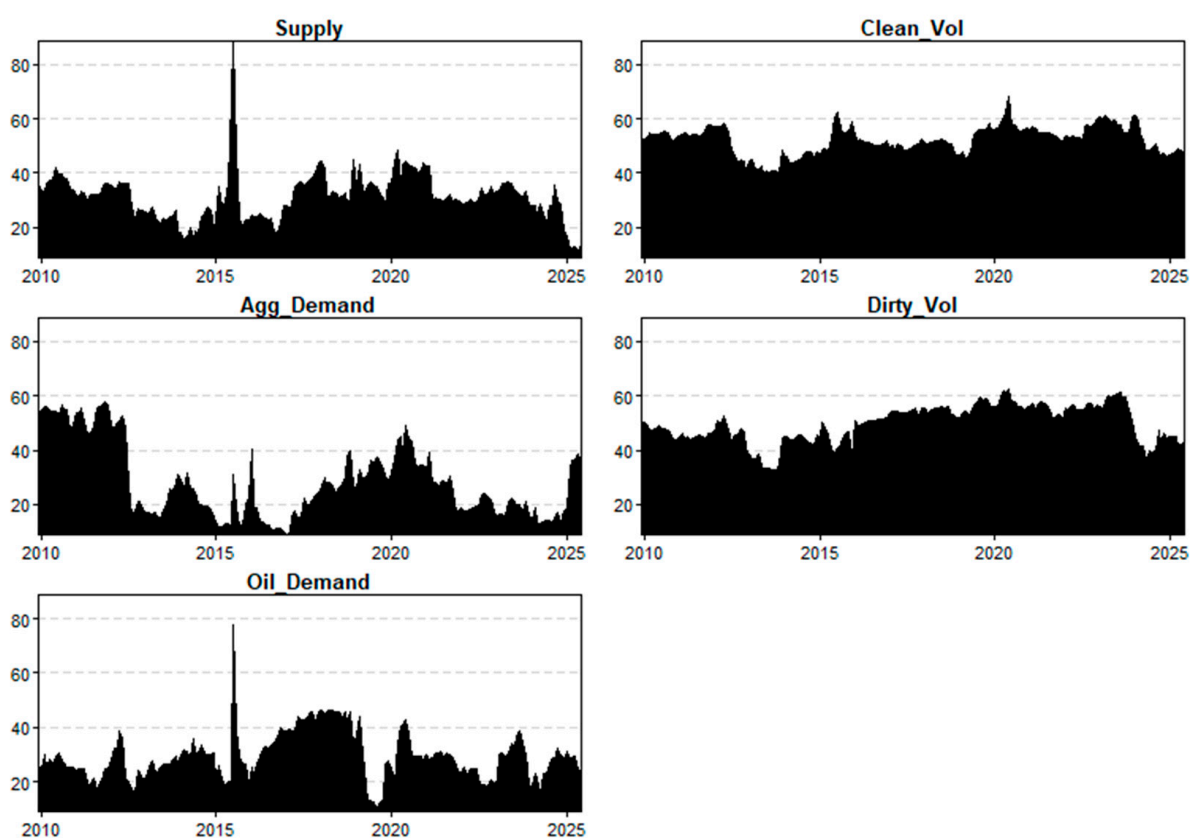


Figure 12. Directional spillover in portfolio volatilities—FROM.

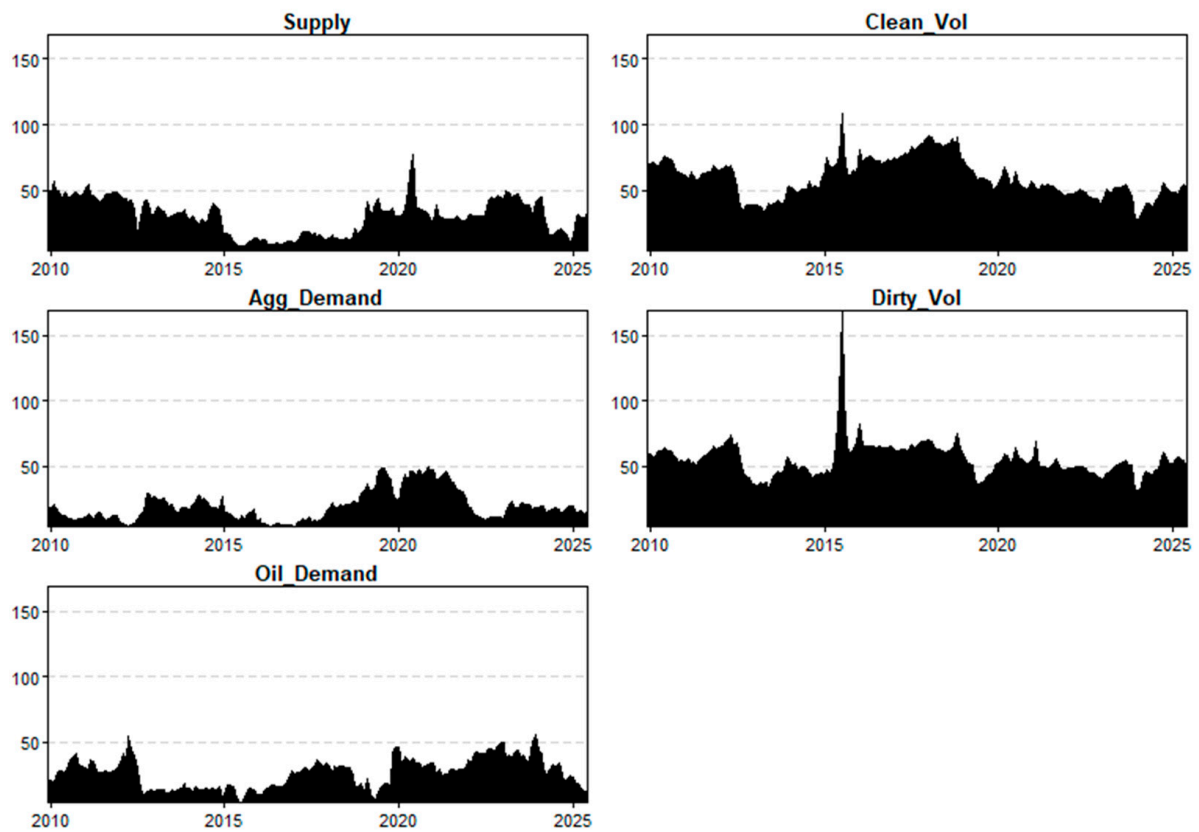


Figure 13. Directional spillover in portfolio volatilities—TO.

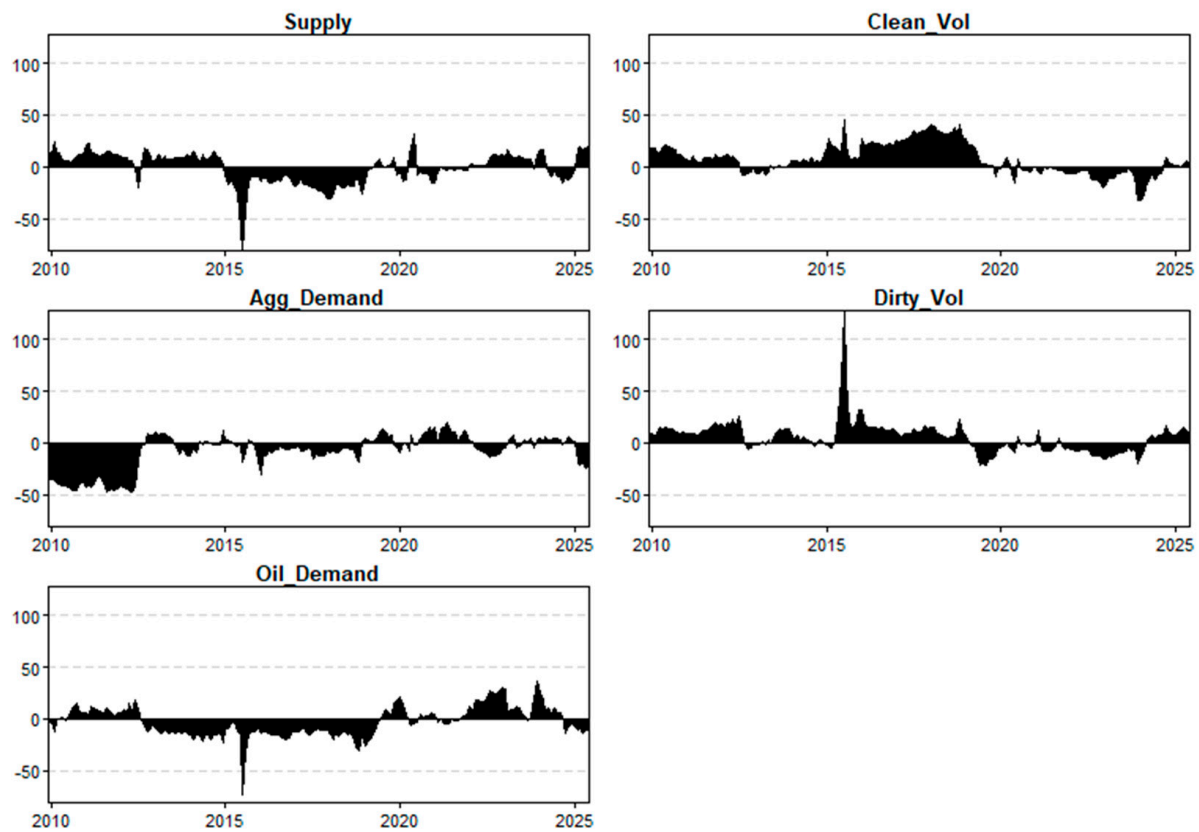


Figure 14. Directional spillover in portfolio volatilities—NET.

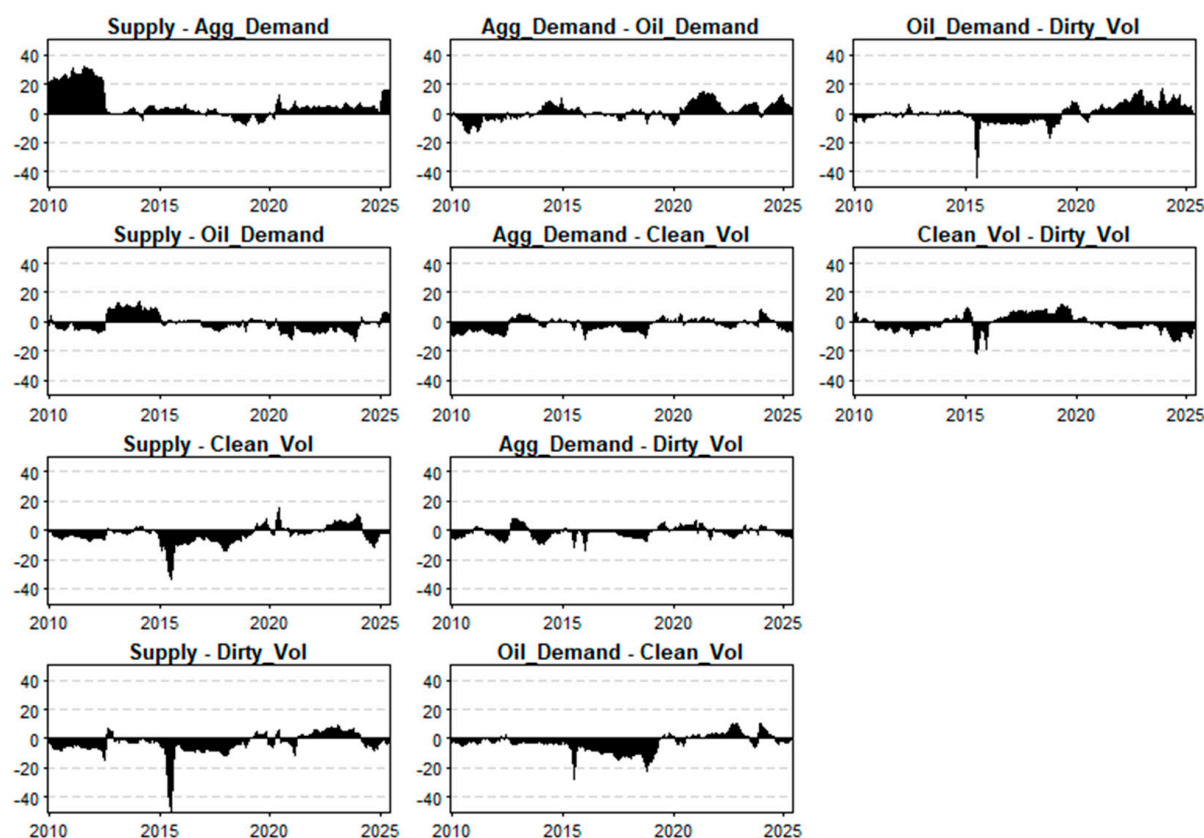


Figure 15. Directional spillover in portfolio volatilities—NET Pairwise.

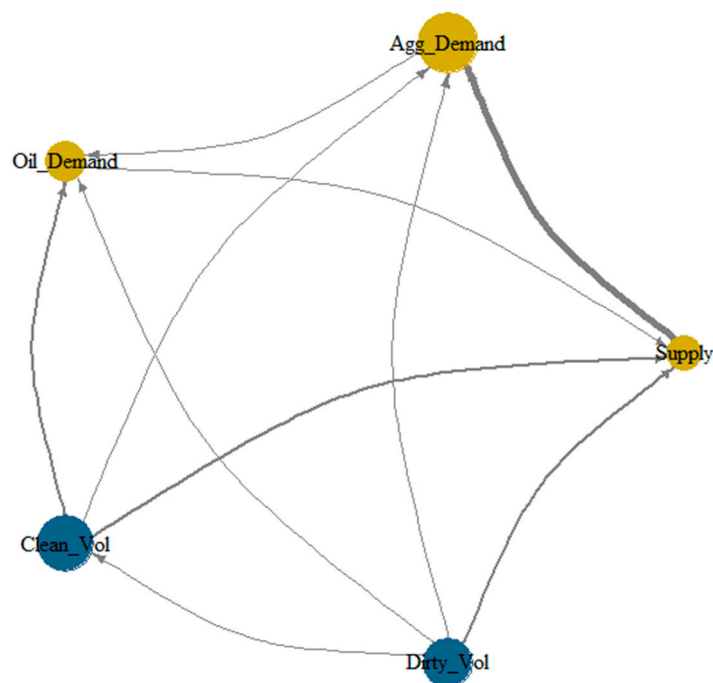


Figure 16. NET Pairwise connectedness network in portfolio volatilities. Note to Figure 16: This figure follows the methodology of Diebold and Yilmaz (2012, 2014) to present network graphs depicting the net pairwise directional return connectedness among three shocks and the volatilities of two portfolios. Arrowheads indicate the direction of positive net direct connectedness from the source variable to others, while arrow thickness represents the strength of the net pairwise directional connectedness.

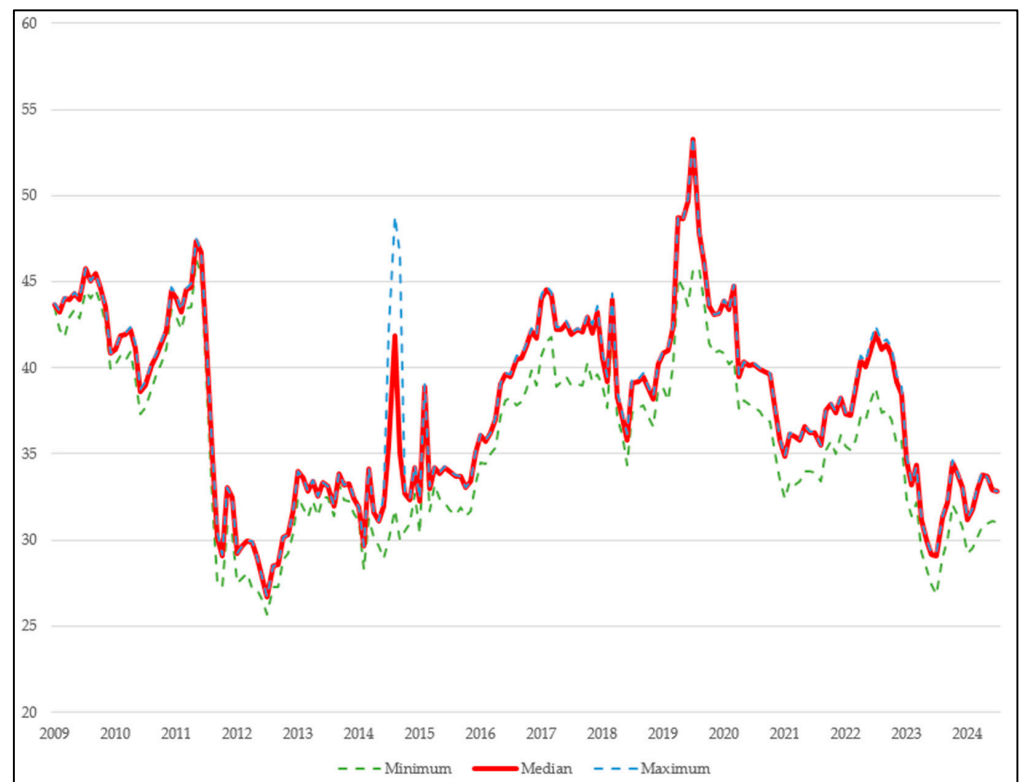


Figure 17. Sensitivity of the spillover in portfolio volatilities to the forecast horizon (maximum, minimum, and median values for 3-, 5-, 6-, 8-, 10-, 15-, and 20-month forecast horizons).

6. Conclusions

This paper demonstrates that structural oil shocks produce systematic and asymmetric spillovers to both clean and dirty Chinese A-share portfolios, thereby challenging the conventional view that low-carbon assets are uniformly more resilient to oil-market disruptions. By jointly conditioning on firms' carbon intensity and the structural decomposition of oil shocks into supply, aggregate demand, and oil-specific demand components, the following are the key insights obtained from this study:

- (1) Across all types of shocks—oil supply, aggregate demand, and oil-specific demand shocks—the directional spillovers toward the Clean portfolio are consistently higher than toward the Dirty portfolio in both returns and volatility (except the volatility spillover from oil-specific demand shocks, please refer to the second insight). This finding aligns with the sectoral-risk hypothesis, suggesting that low-carbon industries are more sensitive to oil price shocks than high-carbon industries. This increased sensitivity is likely due to the fact that the Clean portfolio primarily consists of high-technology and financial companies, which tend to have higher beta and greater volatility.
- (2) An exception to the above pattern is that volatility spillover from oil-specific demand shocks is higher to the Dirty portfolio than the Clean portfolio. This result aligns with the energy-exposure hypothesis, indicating that oil-specific demand shocks are often triggered by concerns over future oil shortages or unexpected changes in global precautionary demand, all of which directly impact the costs and risk perceptions of firms with high carbon intensity. When these shocks occur, Dirty portfolio companies are more likely to face heightened uncertainty regarding input costs and market outlook, resulting in greater volatility in their asset prices.
- (3) The magnitude of spillovers from oil shocks to volatility is significantly higher than that measured in return. Volatility responds more vigorously and persistently to

market disruptions, making it a more sensitive barometer of systemic risk transmission. When markets experience oil shocks, investors not only reprice assets but also swiftly adjust their risk expectations and trading activities, resulting in amplified and prolonged volatility even after returns have stabilized. Volatility thus captures both the immediate and lasting effects of uncertainty, influenced by feedback loops and behaviors such as herding and risk aversion, allowing oil shocks to propagate more vigorously and persistently through financial networks than price changes alone would suggest.

- (4) The net directional spillover analysis reveals that all oil shocks serve as net receivers, absorbing more influence from other assets than they transmit. Notably, oil supply shocks have the smallest net receiver values, while aggregate demand shocks are the most significant net receivers. This highlights the dominant role of aggregate demand shocks in absorbing systemic risk within the network under analysis.

These findings provide a more nuanced understanding of both the energy-exposure and sectoral-risk hypotheses. While the evidence challenges the simplistic view that clean stocks reliably hedge against oil shocks, as clean portfolios in the market are often concentrated in high-growth, high-volatility industries that tend to transmit rather than absorb oil-related risk. On the other hand, the results support a more refined sectoral risk perspective: regulated and asset-heavy dirty firms, particularly in utilities and traditional energy, exhibit lower betas and more stable volatility, which allow them to function as relative safe havens when oil shocks tighten financial conditions, except during periods of acute oil-specific demand uncertainty when their direct exposure dominates. Taken together, the results suggest that a portfolio's resilience to oil shocks depends less on its carbon footprint alone and more on its sectoral composition, cash flow cyclicity, and its role in investors' risk-taking cycles.

These insights have important implications for policy and investment practice. For regulators and central banks conducting climate-related stress tests, the findings caution that portfolios tilted toward clean or low-carbon stocks may not always mitigate vulnerability to energy-market shocks and could even amplify systemic risk if these holdings are concentrated in high-beta growth sectors. For asset managers pursuing decarbonization strategies, the results highlight the importance of considering oil shock heterogeneity and sectoral risk characteristics when constructing green portfolios, as indiscriminate reallocation into low-carbon indexes may inadvertently increase exposure to oil-driven volatility. For corporate issuers, the evidence suggests that transitioning to lower carbon intensity should be evaluated in conjunction with changes in business models and cash flow cyclicity, since decarbonization alone may not lower perceived exposure to energy market shocks in the eyes of investors.

Several limitations point to directions for future research. First, our study focuses on Chinese A-share companies within the HSCA300. Extending this framework to other markets, such as the United States, Europe, or other emerging economies, would help test the external validity of the energy-exposure and sectoral-risk hypotheses. Second, the study relies on a specific connectedness and structural VAR framework, and exploring alternative econometric approaches such as wavelet methods, high-frequency identification, or local projection regressions etc. could help assess the robustness of the observed spillover patterns across different model specifications. Third, this analysis uses monthly data, as daily oil decomposition is not available with the Kilian approach. Applying alternative oil decomposition methods to daily data would allow for a more detailed examination of the robustness and dynamics of these spillover effects. Fourth, further work could compare outcomes across alternative structural identification schemes, incorporate transition risk variables such as carbon prices, and explore nonlinear effects across different market stress

regimes to better understand the interplay among oil shocks, carbon intensity, and sectoral risk in shaping equity market connectedness.

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Conflicts of Interest: The authors declare no conflict of interest.

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