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ORIGINAL RESEARCH ARTICLE

Environmental penalties and commodity market dynamics: Empirical evidence from Chinese listed companies and associated futures price volatility

Guohua Wu*

School of Management, Hefei University of Technology, Hefei, Anhui, China
***Corresponding author:** Guohua Wu (2021010099@mail.hfut.edu.cn)

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Abstract: As ecological civilization and dual carbon goals advance, environmental risk has emerged as a crucial factor influencing corporate performance and financial market stability. This study examines whether and how firm-level environmental penalty events transmit into commodity futures markets, identifying the underlying transmission mechanisms and moderating factors. We manually collect a comprehensive dataset of 982 environmental penalty announcements issued to Chinese A-share listed companies from 2010 to 2023, matching these with price data from the most directly linked commodity futures (e.g., industrial metals and agricultural products). The results show that environmental penalties significantly induce negative price reactions and elevate volatility in corresponding commodity futures markets. This effect is particularly pronounced for penalties in pollution-intensive industries. Within 1–3 trading days following a penalty announcement, cumulative abnormal returns of related futures contracts are significantly negative (p<0.01). Generalized autoregressive conditional heteroskedasticity model estimates confirm a notable increase in conditional volatility on the announcement day, accompanied by stronger risk-averse sentiment in the market. This study elucidates the micro-transmission mechanism of corporate environmental risk to commodity markets, offering investors a fresh lens for risk pricing and providing empirical support for regulators in constructing environmental risk monitoring systems. The findings carry important policy implications: (1) Commodity futures markets serve as an effective channel for pricing environmental risk; (2) regulators should consider cross-market spillover effects when designing environmental penalty disclosure policies; and (3) commodity market participants should incorporate environmental risk assessments into their trading strategies. These insights support enhancing financial markets' role in the green transition.

Keywords: Environmental risk; Environmental penalty; Commodity futures; Event study; Market response

1. Introduction

Under the dual context of increasingly severe global climate change challenges and China's transition toward high-quality development, the concept of green development has been deeply integrated into the national strategic agenda. The report of the 20th National Congress of the Communist Party of China explicitly states that we must firmly establish and practice the philosophy of "lucid waters and lush mountains are invaluable assets," and advance carbon reduction, pollution reduction, greening, and coordinated economic growth. Under this overarching policy orientation, environmental regulations are reshaping corporate production and operation behavior and value-creation logic with unprecedented intensity. A company's environmental performance is no longer merely an embodiment of its social responsibility; it directly impacts a company's operating costs, financing ability, brand reputation, and even its survival and development, making environmental performance one of the core risks faced by the enterprise.[1] When a company is penalized by regulators for environmental violations, this negative event not only directly shocks the company's stock value[2,3] but also whether and how its impact transmits through the supply chain and market expectations to the broader financial market—particularly the commodity futures market most closely connected to the real economy—has become a theoretical and practical question urgently requiring in-depth research.

Commodity futures markets, as primary venues for pricing and risk management, are highly sensitive to shifts in supply–demand expectations. Environmental penalties against listed companies—especially in pollution-intensive industries—signal potential production constraints and cost increases, thereby affecting commodity supply and, in turn, futures prices.[4,5] Therefore, exploring the association between listed companies' environmental penalty events and the volatility of related commodity futures prices not only deepens our understanding of the financial effects of environmental risks but also opens a new window to observe how environmental information is transmitted and priced across different market levels.

However, existing literature on the financial market effects of environmental risk has mostly focused on the equity market. A large number of studies have examined the impact of environmental information disclosure,[6] environmental, social, and governance (ESG) ratings, and negative environmental events on company stock prices,[7] stock returns, and crash risk, generally finding that poor environmental performance imposes a negative shock on a firm's market value. At the same time, research on macro-level environmental risks, such as climate risk and environmental disasters, and their impact on banking systems and cross-border capital flows has been growing.[8-10] However, few studies have treated high-frequency, firm-level environmental penalty events as identifiable environmental-risk shocks and systematically examined their impact on the commodity futures market. This research gap limits our complete understanding of the transmission chain of environmental risk. As a bridge between finance and the real economy, the futures market's response mechanism to environmental risk is critical for understanding the effectiveness of green financial policies, assessing the cost of environmental risk for real-economy firms, and preventing systemic financial risks. Since the implementation of the new Environmental Protection Law in 2015, the intensity and scope of China's environmental enforcement have continued to deepen. According to statistics from the Ministry of Ecology and Environment, the total amount of fines imposed in environmental administrative penalty cases nationwide from 2015 to 2023 reached a substantial 86.02 billion CNY, sending a persistent and strong policy signal to market participants. Simultaneously, existing research has confirmed that environmental production restriction policies targeting high-pollution industries, such as steel and non-ferrous metals, can quickly transmit to the futures market through supply contraction expectations, causing significant volatility in related futures contracts. Against this backdrop, investigating the specific impact of firm-level environmental penalty events on the broader commodity futures market is of significant theoretical and practical importance.

In view of this, this paper endeavors to fill the above research gap and construct a novel analytical perspective. We manually collected and compiled environmental penalty announcements issued by Chinese A-share listed companies from 2010 to 2023, building a precise, detailed database of environmental penalty events. Unlike traditional research, the core innovation of this study is that instead of examining the impact of these events on the penalized company's stock price, we focus on the commodity futures markets closely related to these companies' main businesses. By matching each environmental penalty event to its directly corresponding commodity futures variety (such as steel, chemicals, non-ferrous metals, and agricultural products), we can test the macro-market response to micro-level environmental risk events across a broader, fundamental asset class. We adopt a research approach that combines the event study method with generalized autoregressive conditional heteroskedasticity (GARCH) family models, aiming to answer the following key questions: (i) Do listed companies' environmental penalty events trigger abnormal price movements and heightened volatility in the related commodity futures markets? (ii) What are the magnitude and persistence of this market response? Is there a significant "announcement effect"? (iii) What is the underlying transmission mechanism? Is it through changing market expectations of future supply and demand, or through contagion of risk sentiment? (iv) Does this market response exhibit heterogeneity? In other words, do different types of penalties, different industries, or different market environments lead to varying market reactions?

The contributions of this paper are reflected mainly in the following aspects: First, in terms of research perspective, this study connects firm-level environmental penalties with the macro-level commodity futures market, bridging the research gap in tracing environmental risk transmission from the micro (firm) level to the macro (commodity) level, and expanding the boundaries of research in green finance and risk management. Second, in data construction, through meticulous manual data collection and matching, we establish a unique database that contains detailed information on environmental penalties (e.g., cause, amount, measures) and the corresponding commodity futures varieties, providing a solid data foundation and new opportunities for subsequent research. Third, in research methodology, this study makes comprehensive use of the event study method (capturing short-term price shocks) and GARCH models (characterizing dynamic volatility changes), allowing a comprehensive and multidimensional capture of the futures market's complex response patterns to environmental risk events. Finally, in terms of policy implications, our conclusions provide regulators with a "sentinel" signal from the futures market, demonstrating that environmental regulation not only impacts the firms but also quickly transmits to fundamental commodity markets. This offers new perspectives and strong empirical evidence for regulatory authorities to build cross-market environmental risk monitoring systems, improve environmental information disclosure regimes, guide financial resources toward green industries, and utilize futures market tools to hedge and manage environmental risk, all of which have important practical significance.

2. Literature review and theoretical basis

2.1. Financial market effects of environmental risk

Environmental risk, a non-traditional risk, is attracting increasing attention in academia and practice for its impact on financial markets. According to the Financial Stability Board, environmental risks are primarily divided into physical risk and transition risk. Physical risk refers to direct economic losses caused by extreme weather events or long-term climate change;[8] transition risk refers to the financial risks brought about by the process of society transitioning to a low-carbon economy, due to changes in policy, technology, market preferences, etc.[11] The listed companies' environmental penalty events examined in this study have characteristics of both risk types. On one hand, the reasons for the penalties are often related to actions such as pollutant emissions or ecological damage, which are root causes of environmental physical risk; on the other hand, the penalties reflect a tightening of environmental policy, falling under transition risk, as they send a clear signal to the market of regulators' "zero tolerance" for environmental violations.

Existing literature on the financial effects of environmental risk unfolds along two main lines. The first line focuses on the impact of environmental risk on corporate value. Early research focused on major environmental disasters (e.g., the Exxon Valdez oil spill and British Petroleum's Deepwater Horizon spill), finding that such events can cause significant market-value losses for the companies involved.[12] With improvements in environmental information disclosure regimes, research shifted to more general environmental performance indicators. For example, utilizing ESG rating data, scholars have found that higher ESG scores—particularly excellent performance in the environmental dimension—typically correlate with lower firm risk, higher stock returns, and lower financing costs.[13-16] Conversely, poorer environmental performance or being identified as having environmental risk increases a firm's stock price crash risk. The empirical study by Lo *et al.*[3] directly examined the negative impact of environmental incidents on firm market value, providing direct evidence of the value relevance of corporate environmental performance. These studies collectively demonstrate that capital markets, especially the stock market, can discern and price firms' environmental risk.[17-19]

The second line of research, from a macro perspective, examines the impact of environmental risk on the stability of the financial system. Studies have found that environmental disasters not only cause direct economic losses but also destabilize the banking system by impairing firms' asset quality and raising default probabilities.[8] Climate transition risks may lead to a revaluation of high-carbon assets and pose climate vulnerability challenges to commercial banks holding large portfolios of such assets.[11] At the global level, divergences in climate policies across countries can, via capital markets, redirect cross-border capital flows, posing potential threats to the financial stability of developing countries.[9] In addition, several studies have begun to focus on the impact of climate risk on different asset prices.[20] For example, studies have found that clean energy stocks versus traditional fossil fuel stocks exhibit significantly different responses to physical and transition risks.[10] Consistent with this, evidence shows that investors price carbon risk in the cross-section of equity returns.[21] Moreover, firm-level climate-risk disclosures and related communications can materially affect stock market reactions.[22] Event-level global climate policy signals may also move markets; for example, stock market expectations and reactions around the 26th Conference of the Parties have been documented.[23] Related work also exploits policy instruments, such as green public procurement, to identify market responses in bidding and pricing behavior.[24]

Despite the abundance of existing research, clear gaps remain. First, research subjects have mainly focused on the stock market; there is relatively scarce attention on how environmental risk transmits to other important financial markets, especially the commodity futures market, which serves as a "barometer" of the real economy. Stock prices primarily reflect expectations of a company's future profitability, whereas commodity futures prices more directly reflect expectations of physical supply–demand fundamentals. The mechanisms and sensitivities of their responses to information differ substantially. Second, numerous studies have used low-frequency data (annual or quarterly ESG ratings or environmental disclosure scores) or focused on one-off major disasters, whereas research on the frequently occurring, cumulatively significant environmental administrative penalty events in routine regulation remains insufficient. These penalty events are high-frequency, clear, and officially confirmed, making them an ideal quasi-natural experiment for observing market responses to environmental regulatory policy. Finally, the existing literature's exploration of mechanisms of environmental risk transmission often remains theoretical, lacking a complete empirical chain from micro events to macro-market response.

2.2. Linkage between environmental penalty events and the commodity futures market

Beyond firm-level penalties, a growing strand of literature highlights how transition policies reshape real-economy behavior and, by extension, commodity-market expectations. For example, China's carbon emissions trading pilots have been linked to improvements in firm value,[25] and the carbon trading system has been shown to generate externalities and promote industrial green transformation.[26] Carbon price signals can also influence firms' green investment decisions and credit risks.[27] At the international level, global green trade and environmental rule governance are becoming increasingly salient for industrial upgrading and competitiveness,[28] and environmental clauses in free trade agreements may affect carbon emissions through trade and technology channels.[29] Relatedly, border carbon tariff shocks interact with the expansion and pricing of domestic carbon markets,[30] and global value chain restructuring can reshape the embodied economic-environmental effects of trade.[31] Within China, binding environmental constraints and accountability-style audits can accelerate firms' green transformation,[32] while the design of environmental regulation tools affects green innovation incentives and industrial green development.[33] Because environmental enforcement intensity and decentralization vary across regions, environmental decentralization may further condition the quality of economic growth and environmental outcomes.[34] Finally, investor belief formation and extrapolative expectations can amplify market reactions to policy and firm-level news, contributing to pricing anomalies.[35] Together, these insights motivate our focus on how firm-level environmental penalty announcements—an identifiable and frequent enforcement shock—may transmit into commodity futures pricing and volatility.

This study aims to address the research gap outlined above. Its theoretical logic is built on the premise that a listed company's environmental penalty event triggers futures price volatility by influencing market expectations of the future supply–demand balance of related commodities. This logical chain unfolds through the following channels:

First, the expected supply shock channel. This is the most direct transmission mechanism. When a listed company with significant market share in a given industry is hit with a severe environmental penalty—such as an order to suspend production for rectification, production restrictions, or a shutdown—it directly causes a sharp short-term reduction in the market supply of the commodity produced by that firm. The futures market, driven by expectations, will quickly incorporate this information, and participants will anticipate a future shortage in that commodity's supply. According to classical supply–demand theory, with demand relatively stable, an expected tightening of supply will push futures prices up. Conversely, if the penalty is only a fine, but the market expects the firm to increase environmental protection investments or improve production processes to avoid harsher penalties in the future, this could lead to a short-term decline in production efficiency or the exit of some capacity, similarly creating an expectation of supply contraction. Moreover, a penalty event at one company may be interpreted by the market as the start of an industry-wide regulatory crackdown; investors might expect the entire industry to face stricter environmental inspections, leading to widespread capacity cuts and amplifying the expected supply shock.

Second, the expected cost pass-through channel. Environmental penalties—especially fines—directly increase a firm's production costs. More importantly, the issues revealed by the penalty often require the firm to invest heavily in environmental equipment upgrades, process improvements, and pollution abatement. These compliance costs become internalized as part of the firm's production costs. In a perfectly competitive market, increased costs compress profit margins; but in industries with certain market power, firms have an incentive to pass these added costs on to downstream customers through higher product prices. Futures market participants, especially traders and producers along the supply chain, will anticipate this cost pass-through and adjust their expectations of future commodity price trends accordingly. The expectation that future spot prices will rise due to cost-push factors will motivate them to initiate buy hedges or speculative long positions in the futures market, thereby driving futures prices upward.

Third, the risk premium and sentiment contagion channel. An environmental penalty event is not merely isolated information about a specific firm's operations; it is also a risk signal. The event exposes the regulatory, reputational, and operational risks facing the firm and even the entire industry. For futures investors, this increase in uncertainty raises the risk premium they require for holding long positions in related commodities. Worried that more unforeseen negative events may follow (such as broader industry crackdowns or more stringent policies), investors may become more cautious or even pessimistic. This sentiment can spread across the market through trading behavior, leading some investors to close long positions or short sell to hedge potential risks, thereby putting downward pressure on futures prices. At the same time, rising uncertainty naturally amplifies price volatility.

It is noteworthy that the direction of environmental penalty events' impact on futures prices depends on the penalized firm's position in the supply chain. If the penalized firm is a producer of the commodity, supply contraction expectations will push prices up; if the penalized firm is a consumer/downstream user of the commodity, demand contraction expectations will cause prices to fall. In our sample, listed companies are predominantly manufacturing enterprises occupying mid-to-downstream positions in the supply chain, serving as demanders rather than suppliers of bulk commodity raw materials. Therefore, when these firms face environmental penalties, the market expects their demand for raw materials to decline, leading to negative price reactions in related commodity futures.

2.3. Theoretical contribution and research hypotheses

This paper constructs a framework linking corporate environmental penalties to commodity futures responses via three channels: supply shocks, cost pass-through, and risk premiums. This reveals the short-term market volatility triggered by environmental regulation.

Based on the above theoretical analysis, this paper proposes the following core research hypotheses:

H_1: Announcements of listed companies' environmental penalty events will trigger significant abnormal fluctuations in the prices of related commodity futures in the short term.

Specifically, we expect that around the event announcement date, the returns of related commodity futures contracts will exhibit volatility that deviates from normal patterns. Given that expected supply contraction and higher costs could drive prices up, while risk aversion and pessimistic sentiment could drive prices down, the direction of price change is uncertain; however, a surge in volatility is highly likely. Therefore, we further refine the hypothesis:

H_1a: Announcements of listed companies' environmental penalty events will significantly increase the conditional volatility of related commodity futures prices.

H_1b: Since penalized firms are predominantly demanders of commodity raw materials (mid-to-downstream manufacturing enterprises), environmental penalties will reduce market expectations for their raw material procurement, thereby leading to significantly negative cumulative abnormal returns (CARs) in related commodity futures prices.

Furthermore, the strength of the market's reaction to information usually depends on the information's importance and clarity, as well as firm- and industry-specific fundamentals. We thus expect heterogeneous market responses and propose the following hypothesis:

H_2: The impact of environmental penalty events on the commodity futures market is moderated by the penalty's severity, firm characteristics, and industry attributes.

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In particular, we conjecture that, compared to general warnings or small fines, penalty events involving production suspensions or large fines have a more substantial impact on supply and costs, and will elicit stronger market reactions (H_2a). Compared to non-pollution-intensive industries, environmental penalty events occurring in industries such as steel, chemicals, and mining (highly polluting industries) are more likely to be interpreted by the market as signals of systemic industry risk, thus causing greater market shocks (H_2b). Compared to firms that are not crucial in the industry chain, if an industry leader or a firm with a large market share is penalized, the actual impact on market supply is larger, and thus the market reaction will be more intense (H_2c). Testing these hypotheses constitutes the core of the empirical analysis in this paper.

3. Research design

3.1. Methodological justification

This study employed a combination of event study methodology and GARCH-family models, a choice driven by both theoretical considerations and practical advantages over alternative approaches.

- Why event study methodology? Event study is the standard approach in finance literature for assessing market reactions to discrete information events.[36,37] Unlike regression-based approaches that examine average relationships across periods, event studies isolate the causal impact of specific events (environmental penalties) by comparing actual returns against expected returns derived from a pre-event estimation window. This is particularly appropriate for our research question, as environmental penalty announcements represent clearly identifiable information shocks with precise timing.
- Why GARCH models? We complemented the event study with GARCH models because environmental penalty events may not only affect price levels but also alter market uncertainty and volatility patterns. Standard event study methodology focuses primarily on abnormal returns (ARs) and may miss volatility effects. GARCH models are well-established for capturing time-varying volatility and volatility clustering in financial time series,[38] making them ideal for testing our hypothesis that environmental penalties increase conditional volatility in related futures markets. and its multivariate extensions have been widely applied to energy and commodity markets, including evidence that multivariate specifications can outperform univariate benchmarks in forecasting energy-market volatility.[39] Moreover, commodity futures volatility may exhibit long-memory features, motivating alternative forecasting approaches, such as random long memory models for realized volatility.[40]

We considered alternative volatility models, including stochastic volatility models and realized volatility measures based on intraday data. However, GARCH models offered better tractability and have been extensively validated in commodity futures research. Moreover, our data frequency (daily) was more suitable for GARCH estimation than for realized volatility measures, which typically require tick-level data for reliable estimation.

3.2. Sample selection and data sources

The aim of this study is to investigate the impact of environmental penalty events involving listed companies on related commodity futures prices. We constructed a multidimensional dataset spanning time, companies, events, and futures varieties.

3.2.1. Environmental penalty event data collection

We manually collected environmental penalty events from temporary announcements issued by Chinese A-share listed companies between January 1, 2010, and December 31, 2023. The data collection process proceeded as follows: First, using keywords such as “environmental pollution,” “environmental protection,” “emissions,” “penalty,” “violation,” “rectification,” and “inspection,” we performed a comprehensive search of all A-share companies’ temporary announcements on the CNINFO website (http://www.cninfo.com.cn). Next, we read each retrieved announcement in full and screened for events that clearly disclosed the company (or its significant subsidiaries) that was subjected to administrative penalties by environmental authorities (including various local environmental protection bureaus and Departments of Ecology and Environment). To ensure the validity of events, we excluded announcements that were merely risk warnings or media reports without company confirmation, or cases where the penalizing entity was not an official environmental agency. After this stringent screening, we identified 1,256 distinct environmental penalty events involving 478 listed companies. For each event, we recorded details including: the company code, company name, announcement date, penalizing authority, a summary of the reason for the penalty, the penalty measures (e.g., fines, orders to rectify, and production suspension), and the fine amount (if disclosed).

3.2.2. Commodity futures data matching and acquisition

The innovation of this paper lies in matching the above environmental penalty events with specific commodity futures varieties. The matching principle is based on the penalized company's main business and its position in the industry chain. First, using information from annual reports, we identified the core products of the penalized company. Then we matched these products to futures contracts traded on China's three major commodity futures exchanges (Shanghai Futures Exchange, Dalian Commodity Exchange, and Zhengzhou Commodity Exchange). For example, an environmental penalty event for a steel company would be matched to rebar and hot-rolled coil futures; an event for a chemical enterprise would be matched to purified terephthalic acid (PTA), polyvinyl chloride, or methanol futures, depending on its primary products; a penalty event for a pig farming company would be matched to live hog futures. To ensure accurate matching, we excluded event samples whose primary business was overly diversified or had no direct corresponding futures contract. After matching and filtering, our final analysis sample comprises 982 event–futures pairs.

The relevant futures market data were obtained from the Wind Financial Terminal (WIND) database, covering all commodity futures varieties matched to the above events. For each futures variety, we retrieved daily trading data for the primary continuous contract from January 1, 2010, to December 31, 2023, including the opening price, highest price, lowest price, closing price, trading volume, and open interest. Daily returns are calculated as $R_t = ln(P_t/P_{t-1})$, where P_t is the closing price on day t.

3.2.3. Company–futures matching protocol

To ensure rigorous and replicable matching between environmental penalty events and commodity futures contracts, we established the following matching protocol:

For companies penalized for environmental violations, the upstream raw materials used in their product production corresponded to the most heavily traded primary contract. Regardless of the amount of materials used by a company, it qualified as long as the raw material product met two conditions in futures trading: First, being the main contract, and second, having normal trading activity. One event could involve multiple futures products, but each futures product corresponded to only one futures contract. No threshold was set for primary products. If the main contract involved a month rollover, a continuous contract was used instead. Matching examples are provided in Table 1, illustrating how companies subjected to environmental penalties were matched with futures contracts.

3.2.4. Control variable data

In the regression analysis, we introduced a series of control variables to account for other factors that might affect futures price volatility. These data are also from the WIND database, including: (i) Macro-level variables: the daily Shibor overnight rate to control for liquidity conditions in the money market and the daily USD/CNY exchange rate to control for the impact of exchange rate fluctuations on commodity prices. (ii) Market sentiment: the daily return of the WIND All-A Share Index to control for systemic risk and overall market sentiment in the stock market. (iii) Commodity market characteristics: the logarithm of daily trading volume and the logarithm of daily open interest for the corresponding commodity futures contract, to control for market liquidity and trading activity.

3.3. Variable definitions

3.3.1. Core explanatory variable

We defined the date a listed company published an environmental penalty announcement (day T) as the event date. The dummy variable, environmental penalty event (Penalty), equals 1 on the event day and 0 otherwise. Based on severity, we defined the variables Severe_Penalty (involving production suspension or a large fine) and Minor_Penalty (warnings or small fines).

3.3.2. Dependent variables: Futures market response

We characterize the commodity futures market response along three dimensions:

- Cumulative AR: This is the core metric of the event study. To estimate the normal return, we used the market model, specified as Equation (1):

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \quad (1)$$

where R_{it} is the return of commodity i on day t, and R_{mt} is the market benchmark return. Considering the characteristics of China's commodity market, we selected the Nanhua Commodity Index (NHCI) as the market benchmark. Using data from the estimation window before the event window (set in this paper as

Table 1. Examples of matching environmental penalty events with futures contracts

Penalized company (affiliated entity)	Matched futures product	Event date	Futures symbol	Main contract code	Price date
Hainan Huanyu New Energy Co., Ltd.	Crude oil	November 10, 2023	SC	SC2312.INE	November 10, 2023
Hainan Huanyu New Energy Co., Ltd.	Asphalt	November 10, 2023	BU	BU2401.SHF	November 10, 2023
Hainan Huanyu New Energy Co., Ltd.	Fuel oil	November 10, 2023	FU	FU2401.SHF	November 10, 2023
Hainan Huanyu New Energy Co., Ltd.	Low-sulfur fuel oil	November 10, 2023	LU	LU2402.INE	November 10, 2023
Hainan Huanyu New Energy Co., Ltd.	Liquefied petroleum gas	November 10, 2023	PG	PG2312.DCE	November 10, 2023

Notes: Each row represents a single environmental penalty event matched to a major futures contract based on the firm's core products. For diversified firms, multiple related futures contracts may be matched simultaneously. The main contract is defined as the most liquid contract on the event date.

the 120 trading days to 11 trading days before the event announcement, i.e., T−120 to T−11), we ran ordinary least squares regressions to obtain the parameters $\hat{\alpha}_i$ and $\hat{\beta}_i$.

Then, within the event window (set as T−10 to T+10 in this paper), we calculated the daily AR as in Equation (2):

$$AR_{it} = R_{it} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{mt}\right) \tag{2}$$

Finally, we computed the CAR over a given interval $[t_1,t_2]$ within the event window (Equation [3]):

$$CAR_i\left(t_1,t_2\right) = \sum_{t=t_1}^{t_2} AR_{it} \tag{3}$$

We focused on intervals around the announcement day, such as $CAR(0,1)$ and $CAR(0,3)$, and examined their values and significance.

- Conditional volatility: To capture the event's impact on market price volatility, we employed a GARCH(1,1) model. This model effectively captured the volatility clustering commonly observed in financial time series. The model is specified as shown in Equations (4) and (5):

$$R_t = \mu + \sum_{k=1}^{p} \phi_k X_{kt} + \epsilon_t \tag{4}$$

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta\, Penalty_t \tag{5}$$

where R_t is the futures' daily return, and X_{kt} represents a series of control variables. In the variance equation, σ_t^2 is the conditional variance of interest. The core explanatory variable, Penalty, is included in the variance equation, and its coefficient δ measures the instantaneous impact of the environmental penalty announcement on conditional volatility on that day. If δ is significantly positive, it indicates that the event increased market volatility, supporting hypothesis H_1a.

- Market sentiment proxy: To indirectly gauge market sentiment, we followed related literature and constructed a volatility-based indicator using high-frequency data. Specifically, we used the intraday highest and lowest prices to calculate the Parkinson volatility (Equation [6]):

$$Vol_{Parkinson} = \frac{\left(lnH_t - lnL_t\right)^2}{4ln\left(2\right)} \tag{6}$$

This indicator utilizes the intraday high–low price range and better captures the intensity of intraday price swings than realized volatility, which is based only on closing prices, and can serve as a proxy for market panic or uncertainty.

3.4. Event study design: Windows and benchmark selection

3.4.1. Estimation window

We employed an estimation window of 110 trading days, spanning from T−120 to T−11 relative to the event date (T = 0). This window length follows standard practice in event study methodology[37] and provides sufficient observations for reliable parameter estimation while maintaining temporal proximity to the event. The 10-day gap between the estimation window and the event date prevents potential information leakage from contaminating the normal return estimation.

3.4.2. Event window

The event window spans from T−10 to T+10, capturing both potential anticipation effects and delayed market responses. We focused on the short-term windows CAR(0,1), CAR(0,3), and CAR(0,5) that aligned with the typical information incorporation speed in commodity futures markets.

3.4.3. Handling overlapping events

When multiple environmental penalty events occur for the same company–futures pair within overlapping event windows (i.e., within 21 trading days of each other), we applied the following rules: (i) If the events occurred within five trading days, we treated them as a single clustered event, using the first announcement date as T = 0; (ii) If the events were separated by 6–20 trading days, we excluded the later event to avoid contamination of the estimation window; (iii) Events separated by more than 20 trading days were treated as independent observations. This procedure resulted in the exclusion of 43 events due to window overlap.

3.4.4. Market benchmark selection

We selected the NHCI as the market benchmark for estimating normal returns. The NHCI is a value-weighted composite index that covers all major commodity futures contracts traded on China's three commodity exchanges, making it the most comprehensive representation of systematic factors affecting China's commodity futures market. This choice is preferable to: (i) equity market indices (e.g., China Securities Index 300), which capture different risk factors than commodity markets; (ii) single-commodity sector indices, which would introduce selection bias; and (iii) equal-weighted commodity indices, which would over-represent illiquid contracts.

3.4.5. Robustness to alternative benchmarks

We conducted robustness tests using three alternative benchmark specifications: (i) The constant mean return model, which assumed expected return equaled the historical mean from the estimation window; (ii) an equal-weighted commodity index constructed from our sample contracts; and (iii) Sector-specific sub-indices (e.g., Nanhua Industrial Index for steel-related events). Results remain qualitatively unchanged across all specifications, with CAR(0,3) ranging from −0.35% to −0.41% (all significant at $p<0.05$).

3.5. Model specification

3.5.1. Event study model

As described above, we computed CAR to assess the value effect of an event. To test the statistical significance of CAR, we calculated the average CAR (ACAR) across all events and employed a standardized t-test. For the i-th event, the standardized AR is defined as $SAR_{it} = AR_{it}/s(AR_{it})$, where $s(AR_{it})$ is the standard deviation of the forecast error. The test statistic for the ACAR is shown in Equation (7):

$$t = \frac{\sum_{i=1}^{N} CAR_i\left(t_1, t_2\right)}{\sqrt{N \cdot \left(t_2 - t_1 + 1\right) \cdot \sigma^{-2}}} \tag{7}$$

where N is the total number of events, and σ^{-2} is the average variance of ARs in the estimation period.

3.5.2. Generalized autoregressive conditional heteroskedasticity model

To test hypothesis H_1a more precisely—namely, the impact of environmental penalty events on volatility—we constructed the following GARCH(1,1) model (Equation [8]):

$$\begin{cases} R_{it} = \mu_i + \phi_1 WIND\_A_t + \phi_2 \Delta Shibor\_ON_t + \\ \phi_3 \Delta USDCNY_t + \phi_4 ln\left(Volume_{it}\right) + \epsilon_{it} \\ \sigma_{it}^2 = \omega_i + \alpha_i \epsilon_{it-1}^2 + \beta_i \sigma_{it-1}^2 + \delta_i Penalty_{it} \end{cases} \tag{8}$$

We estimated this model on the time-series data of each event–futures pair. The mean equation controls for macroeconomic factors, stock market influences, and the futures contract's own trading activity. The key parameter in the variance equation is δ_i. We focused on whether the average of all estimated δ_i across events was significantly >0. If $\bar{\delta} > 0$ it was statistically significant, it indicated that environmental penalty events indeed systematically exacerbated the price volatility of the related commodity futures.

3.5.3. Distributional assumption

The baseline GARCH(1,1) model was estimated under the assumption that the standardized residuals followed a standard normal distribution, i.e., $\varepsilon t \mid \Omega t{-}1 \sim N(0, \sigma t^2)$, where $\Omega t{-}1$ denotes the information set available at time t−1. Maximum likelihood estimation was performed using the Broyden–Fletcher–Goldfarb–Shanno optimization algorithm, with robust (quasi-maximum likelihood) standard errors to account for potential mild departures from normality.

3.5.4. Robustness to alternative distributions

Given that commodity futures returns often exhibit heavier tails than the normal distribution, we reestimated all models using Student's *t*-distribution and the generalized error distribution for the standardized residuals. The results demonstrate that our main finding—environmental penalty events significantly increase conditional volatility—is robust to alternative distributional assumptions. The magnitude and significance of the penalty effect coefficient (δ) remained stable across all three specifications, providing confidence in the reliability of our inference.

Of the 982 event–futures pairs, 883 (89.9%) yielded valid GARCH(1,1) estimates. The remaining 99 pairs were excluded due to insufficient trading days, missing data around the event date, or model non-convergence.

Table 2 reports summary statistics for the GARCH(1,1) variance equation parameters estimated separately for each event–futures pair. The substantial standard deviations relative to means indicate considerable heterogeneity across pairs. For instance, the standard deviation of ω (0.96) exceeds its mean (0.65), reflecting substantial variation in baseline volatility across commodity futures. The persistence parameter (α + β) ranges from near zero to unity, suggesting diverse volatility dynamics across different commodity markets. The penalty effect coefficient (δ), which captures the instantaneous impact of environmental penalty announcements on conditional volatility, is reported separately in Section 4.3: mean δ = 0.158, *t*-statistic = 4.76, significant at the 1% level.

3.5.5. Panel regression model

To test the heterogeneity hypothesis H_2, we used the event's CAR as the dependent variable and built a cross-sectional (or panel) regression model. Since CAR was calculated for each event, we used different event characteristics as explanatory variables (Equation [9]):

$$CAR_i\ (t_1,t_2) = \gamma_0+\gamma_1\text{Penalty\_Severity}_i+\gamma_2\text{Firm\_Char}_i+\gamma_3\text{Industry\_Char}_i+\text{Controls}+\varepsilon_i \quad (9)$$

where $CAR_i\ (t_1,t_2)$ is the CAR of event i over window $[t_1,t_2]$. Penalty_Severity captures the severity of the penalty (e.g., the logarithm of the fine amount, or a dummy for production suspension). Firm_Char includes firm-level characteristics, such as firm size (log of total assets) and profitability (return on assets). Industry_Char includes industry attributes, such as a dummy for whether the industry is classified as highly polluting. Controls include macroeconomic conditions at the time of the event, among others. By examining the significance of $\gamma_1,\gamma_2,\gamma_3$,, we revealed the moderating effects of various factors on the market reaction.

4. Empirical analysis

4.1. Descriptive statistics

Table 3 presents the descriptive statistics of the main variables. In the 982 effective event–futures paired samples, the mean daily return of commodity futures was close to 0, but the standard deviation indicates a certain level of volatility. The mean CARs, CAR(0,1) and CAR(0,3), were both negative, providing preliminary support for H_1b—namely, that the market overall reacted negatively to environmental penalty events. Regarding the control variables, all indicators were within reasonable ranges, with no notable outliers. The mean of the penalty severity dummy Severe_Penalty was 0.28, indicating that about 28% of the environmental penalty events in our sample were classified as severe (involving production suspension or a fine amount over 10 million CNY). The mean of the heavy-pollution industry dummy Heavy_Pollution was 0.63, indicating that the majority of penalty events occurred in heavy-pollution industries, which aligned with intuition.

Table 2. Summary statistics of the GARCH (1,1) parameter estimates

Parameter	*n*	Mean	Standard deviation	Min	Median	Max
ω (Constant)	883	0.6475	0.9633	0.0000	0.0811	4.2568
α (ARCH)	883	0.0610	0.0698	0.0000	0.0477	0.5680
β (GARCH)	883	0.6712	0.3782	0.0000	0.8746	1.0000
Persistence (α+β)	883	0.7322	0.3519	0.0018	0.9223	1.0000

Abbreviations: ARCH: Autoregressive conditional heteroskedasticity; GARCH: Generalized autoregressive conditional heteroskedasticity.

4.2. Event study analysis

To test hypothesis H_1b, we computed the average AR and ACAR of the full sample over the event window (T−10 to T+10). Figure 1 shows the ACAR trend around the event.

From Figure 1, before the announcement day (T = 0), ACAR fluctuated slightly around zero, indicating that our market model was specified reasonably and that there was no information leakage or model misspecification before the event. Starting from T = 0, the ACAR curve

Table 3. Descriptive statistics of main variables

Variable name	Observations	Mean	Standard deviation	Min	Max
R (futures daily return, %)	245,500	0.012	1.854	−10.23	9.87
AR (%)	245,500	−0.003	1.762	−9.98	9.54
CAR (0,1) (%)	982	−0.215	2.134	−8.76	7.92
CAR (0,3) (%)	982	−0.387	3.011	−11.23	9.88
Penalty (event dummy)	245,500	0.004	0.063	0	1
Severe_Penalty (dummy for severe penalty)	982	0.28	0.45	0	1
Heavy_Pollution (high-pollution industry dummy)	982	0.63	0.48	0	1
Ln (Fine) (log of fine amount)	345	12.87	1.76	9.21	16.81
Ln (Asset) (log of total assets)	982	22.54	1.32	19.87	25.43
WIND_A (return, %)	245,500	0.021	1.543	−8.87	9.12
Volume (log trading volume)	245,500	12.67	1.89	8.11	16.54
Open_Interest (log open interest)	245,500	11.98	1.55	7.65	15.87

Notes: The 245,500 daily observations represent the pooled panel dataset across 982 event–futures pairs, where each pair includes approximately 250 trading days covering both the estimation window (T−120 to T−11) and the extended event window. Event-level variables (CAR, Severe_Penalty, Heavy_Pollution, Ln (Asset)) are calculated at the event–futures pair level (*n*=982). Data are based on daily observations of 982 event–futures pairs from 2010 to 2023. Ln (Fine) is calculated for the 345 samples that disclosed fine amounts. Abbreviations: AR: Abnormal return; CAR: Cumulative abnormal return; WIND_A: WIND All-A share index.

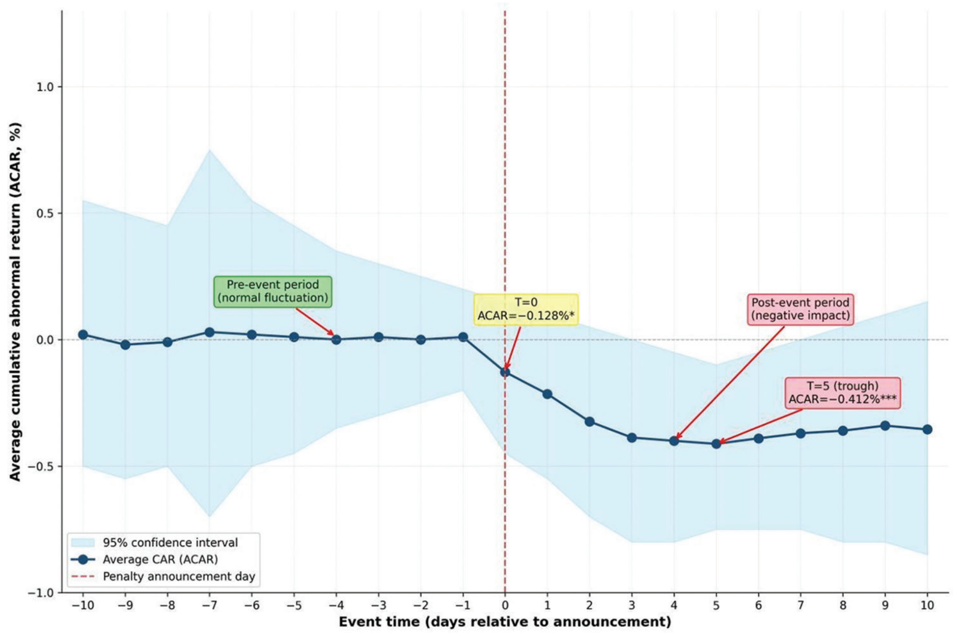

Figure 1. ACAR (%) throughout the event time. The chart shows ACAR fluctuating near 0 before day T = 0; starting at T = 0, ACAR declined sharply and continued to fall for the next few days, reaching a trough around T+3, then slightly rebounded but remained in negative territory.

Notes: *p < 0.1, ***p < 0.01.

Abbreviation: ACAR: Average cumulative abnormal return.

sloped sharply downward and continued to decline over the next few trading days, reaching a low around T+3. This clearly demonstrated that the market responded swiftly and significantly negatively to the environmental penalty announcement.

Table 4 shows ACAR and *t*-test statistics for several key windows. On the event day itself, CAR(0,0) averages −0.128%, significant at the 10% level. For the window including the day after the announcement, CAR(0,1) and ACAR fell to −0.215%, with the significance level rising to 5%. Extending the window to three days post-announcement, CAR(0,3) and ACAR reached −0.387%, which was highly significant at the 1% level. This indicated that the negative shock persisted to a certain extent and that the market took a few days to fully digest the information. However, over a longer window, such as CAR(0,10), although ACAR remained negative, its significance diminished, suggesting that the short-term overreaction may be partially corrected. Overall, the event study results strongly support hypothesis H_1b: environmental penalty events, in general, cause a negative price shock in the related commodity futures market.

4.3. Generalized autoregressive conditional heteroskedasticity model analysis

To test hypothesis H_1a, we estimated the specified GARCH(1,1) model for each event–futures pair's time series, focusing on the coefficient δ on the event dummy in the variance equation. From 982 regressions, we obtained 982 estimated δ values. We then conducted a *t*-test to assess whether the mean of these estimates was significantly >0.

The results show that the mean of δ was 0.158, with a corresponding *t*-statistic of 4.76, which was highly significant at the 1% level. This result provides strong evidence that on the day of an environmental penalty announcement, the conditional volatility of the related commodity futures market rose significantly. This finding is fully consistent with hypothesis H_1a. It indicates that the occurrence of an environmental penalty event injects new uncertainty into the market, causing greater dispersion in investors' expectations of future price trends and more active trading behavior, thereby sharply amplifying market volatility. Together, the negative price shock (from the CAR analysis) and the significantly heightened volatility (from the GARCH analysis) formed a complete picture of the market's response to an environmental risk event: the market became not only bearish but also more "panicky" and unstable.

Table 4. Average cumulative abnormal returns (ACAR) around environmental penalty events

Event window	ACAR (%)	*t*-statistic	*n*
CAR(−1, −1)	−0.021	−0.54	982
CAR (0, 0)	−0.128*	−1.88	982
CAR (0, 1)	−0.215**	−2.45	982
CAR (0, 2)	−0.324***	−3.12	982
CAR (0, 3)	−0.387***	−3.56	982
CAR (0, 5)	−0.412***	−3.01	982
CAR (0, 10)	−0.355**	−2.23	982

Notes: *p<0.1; **p<0.05; ***p<0.01.
The *t*-statistics were calculated based on the standardized residuals.
Abbreviation: ACAR: Average cumulative abnormal returns.

4.4. Water-related environmental penalty: Case study of Tongliao Jinmei Chemical Co., Ltd.

4.4.1. Case background and industry context

To illustrate the transmission mechanism from water-related environmental penalties to commodity futures markets, we examined a representative case involving Tongliao Jinmei Chemical Co., Ltd., a subsidiary associated with the listed company (stock code: 600844). This case exemplified how environmental enforcement actions against water-intensive manufacturing enterprises could propagate to upstream commodity markets through the expected supply shock channel.

Tongliao Jinmei Chemical is a large-scale coal chemical enterprise located in the Inner Mongolia Autonomous Region, primarily engaged in coal-to-chemical conversion processes. The coal chemical industry is characterized by high water consumption and significant wastewater generation, making it a focal point for environmental regulation under China's water pollution control framework. Such facilities are major consumers of chemical feedstocks, including PTA and related intermediates, while simultaneously being subject to stringent discharge standards for industrial effluents. Table 5 shows the details of the environmental penalty event involving Tongliao Jinmei Chemical Co., Ltd.

4.4.2. Transmission mechanism: From water pollution penalty to upstream futures price

The transmission from this water-related environmental penalty to PTA futures operates through the expected supply shock channel. When Tongliao Jinmei Chemical received the environmental penalty for water pollution violations, market participants rationally anticipated

Table 5. Environmental penalty event summary

Item	Details
Penalized entity	Tongliao Jinmei Chemical Co., Ltd.
Associated listed company	Stock code: 600844
Announcement date	June 24, 2023 (Saturday; market impact from June 26)
Penalty amount	1,000,000 CNY
Penalty type	Fine
Industry classification	Chemical raw materials and chemical products manufacturing
Location	Inner Mongolia Autonomous Region
Matched futures contract	Purified terephthalic acid futures (TA2309.ZCE)

several downstream consequences that would affect upstream commodity demand:

(i) Production disruption expectations: Environmental penalties, particularly those of significant magnitude (1,000,000 CNY), often signal regulatory pressure for operational adjustments. Market participants anticipate that the penalized facility may need to temporarily reduce or suspend production to implement rectification measures, directly reducing its demand for upstream chemical inputs, including PTA

(ii) Industry-wide regulatory spillover: A high-profile penalty against a major coal chemical enterprise signaled intensified environmental enforcement across the sector. Futures market participants reassessed environmental exposure across the coal–chemical industry supply chain, anticipating that similar enforcement actions may affect other major PTA consumers

(iii) Cost structure adjustment expectations: Beyond immediate production impacts, the penalty signaled that coal–chemical enterprises may face increased compliance costs for wastewater treatment and emission control. These anticipated cost increases may lead to reduced production margins and, in the medium term, potentially lowered output levels, further dampening upstream input demand.

4.4.3. Market response analysis

We employed the constant mean return model to estimate ARs, using an estimation window of 108 trading days (January 4, 2023, to June 15, 2023). The mean daily return during the estimation period was 0.0214%, with a standard deviation of 1.4473%. The event window spanned from one day before to three days after the announcement (t = −1 to t = +3), with June 26, 2023 (Monday) designated as the event day (t = 0) since the penalty was announced on Saturday, June 24 (Tables 6 and 7).

4.4.4. Case study discussion

The case study results reveal several noteworthy patterns. On the event day (t = 0, June 26, 2023), PTA futures experienced a substantial negative AR of −1.5637%, representing a price drop from 5,576 CNY to 5,490 CNY. This immediate price reaction was consistent with the expected supply shock hypothesis: market participants responded to the environmental penalty announcement by revising downward their expectations of demand from the penalized enterprise and potentially similar firms in the coal chemical sector.

The CARs across all event windows were consistently negative, ranging from −1.59% to −1.00%. The largest single-day impact occurred on the event day itself (CAR[0,0] = −1.5637%), suggesting that the market incorporated the penalty information relatively quickly. The subsequent partial price recovery on t = +1 (+0.5615%) indicates some market correction, though the overall CAR[0,+3] remained negative at −1.5869%.

While the *t*-statistics did not achieve conventional significance levels, this was expected in single-case analysis, where the high daily volatility of commodity futures (standard deviation of 1.4473%) made it difficult to detect statistically significant effects from individual events. The economic magnitude of the effect, however, was notable: a 1.56% single-day decline represented a substantial price movement in PTA futures, translating into approximately 86 CNY per ton price drop.

4.4.5. Policy implications

This case study carried important implications for water pollution prevention policy and environmental-financial linkages: First, the case demonstrated that

Table 6. Purified terephthalic acid futures price movement around the event date

Day	Date	Closing price (CNY)	AR (%)
t = −1	June 21, 2023	5,576	+0.3386
t=0	June 26, 2023	5,490	−1.5637
t = +1	June 27, 2023	5,522	+0.5615
t = +2	June 28, 2023	5,482	−0.7458
t = +3	June 29, 2023	5,492	+0.1610

Abbreviation: AR: Abnormal return.

Table 7. Event study results

Event window	CAR (%)	*t*–statistic
[0, 0]	−1.5637	−1.0804
[0, +1]	−1.0022	−0.4896
[0, +3]	−1.5869	−0.5482
[−1, +3]	−1.2483	−0.3857

Notes: Estimation window: Jan 4–Jun 15, 2023 (108 trading days). Mean daily return: 0.0214%, standard deviation: 1.4473%. Abbreviation: CAR: Cumulative abnormal return.

commodity futures markets responded to firm-level environmental penalty information, suggesting that futures prices could serve as a complementary channel for environmental risk pricing beyond equity markets. Second, the transmission operated through the expected supply shock channel, where downstream manufacturing penalties affected upstream commodity demand expectations. This highlights the importance of considering supply chain effects in environmental policy design. Third, as environmental regulators intensified enforcement against industrial wastewater violations—a key priority under China's water pollution control framework—the resulting market responses in commodity futures may reinforce financial incentives for corporate environmental compliance in water-intensive industries.

4.4.6. Concluding remarks on the case study

This case study of Tongliao Jinmei Chemical illustrated the micro-to-macro transmission mechanism through which water-related environmental penalties at manufacturing enterprises propagated to upstream commodity futures markets. The negative ARs observed in PTA futures following the penalty announcement provided empirical support for incorporating environmental risk factors into commodity market analysis. These findings offer relevant insights for coordinating environmental enforcement with financial market monitoring, particularly in sectors with significant water pollution profiles.

5. Further analysis

To gain a deeper understanding of the underlying logic of the market reaction, this section tests hypothesis H_2, which concerns the heterogeneity of market responses. We used the 3-day window CAR, CAR(0,3), as the dependent variable and conducted panel regressions for analysis.

5.1. Impact of penalty severity

We introduced two variables to measure the severity of the penalty: one was the dummy variable Severe_Penalty, which equaled 1 if the penalty involved a production suspension or a fine amount over 10 million CNY, and 0 otherwise; the other was the continuous variable Ln(Fine), the natural logarithm of the fine amount (for those events where the fine amount is disclosed). Regression results were presented under models (1) and (2) in Table 8.

In model (1), the coefficient of Severe_Penalty was −0.451, and it was significant at the 1% level. This indicated that, compared to general penalties, events involving severe penalties triggered a much larger negative shock in futures prices—the 3-day CAR was on average 0.451% lower for severe penalty events. In model (2), the coefficient of Ln(Fine) was −0.082, significant at the 5% level, suggesting that the larger the fine, the stronger the market's negative reaction. Both results align with expectations and support H_2a. This demonstrated that the futures market can effectively distinguish environmental penalty events by severity: events with greater information content (implying larger shocks to supply and cost) lead to more pronounced price reactions.

5.2. Impact of industry attributes

We divided the sample into two groups—heavy-pollution industries vs. non-heavy-pollution industries—for a comparative analysis. The classification of heavy-pollution industries follows the "Guidelines for Environmental Information Disclosure of Listed Companies," which lists 16 industry categories, including thermal power, steel, cement, chemicals, petrochemicals, and mining. Model (3) in Table 8 introduced a heavy-pollution industry dummy, Heavy_Pollution, and its interaction with penalty severity.

The results of model (3) show that the coefficient of Heavy_Pollution itself is not significant, but its

Table 8. Regression analysis of heterogeneous effects on cumulative abnormal return(0,3)

Variables	Model (1)	Model (2)	Model (3)	Model (4)
Core variables				
Severe_Penalty	−0.451*** (−3.87)		−0.211* (−1.76)	−0.205* (−1.88)
Ln(Fine)		−0.082** (−2.33)		
Heavy_Pollution			−0.054 (−0.65)	−0.061 (−0.72)
Severe_Penalty×Heavy_Pollution			−0.316** (−2.51)	−0.308**(−2.45)
Ln(Asset)				−0.109*(−1.92)
Industry_Leader				−0.562*** (−3.98)
Control variables				
WIND_A	Yes	Yes	Yes	Yes
Shibor_ON	Yes	Yes	Yes	Yes
USD/CNY exchange rate	Yes	Yes	Yes	Yes
Constant	0.087 (0.98)	0.876** (2.11)	0.123 (1.21)	2.134* (1.79)
Observations	982	345	982	982
R^2	0.124	0.156	0.187	0.254

Notes: *p<0.1; **p<0.05; ***p<0.01. The t-statistics are in parentheses. All models control for macroeconomic conditions (stock market returns, interest rates, and exchange rates).

Abbreviations: Shibor_ON: Daily Shibor overnight rate; WIND_A: WIND All-A share index.

interaction with Severe_Penalty has a coefficient of −0.316, significant at the 5% level. This suggested a deeper insight: the market impact of an environmental penalty event did not depend solely on the industry attribute, but rather on a "severe penalty in a heavy-pollution industry." In other words, when a company in a highly pollution-intensive industry was hit with a severe penalty, the market interpreted it as a strong policy signal, expecting that a broader industry crackdown may follow. This led to panic and selling pressure far exceeding that of similar events in less-polluting industries. This finding strongly supports H_2b.

5.3. Impact of firm characteristics

We further examined whether firm size (Ln(Asset)) and the firm's position in the supply chain influence the market reaction. We used the natural logarithm of total assets as a proxy for firm size. Meanwhile, by manually reviewing company reports, we identified 35 penalized companies as industry leaders or top-five in market share, and constructed a dummy variable Industry_Leader for these. Regression results were shown in Table 8, model (4).

Model (4) showed that the coefficient for firm size, Ln(Asset), was −0.109, significant at the 10% level, indicating that the larger the penalized firm, the stronger the market's negative reaction. This may be because a large firm's operational disruptions had a greater impact on industry-wide supply. It was noteworthy that the coefficient for the industry leader dummy Industry_Leader was −0.562, highly significant at the 1% level. This suggested that when an industry-leading company experienced an environmental scandal, the shock to the commodity futures market was enormous. This finding validates H_2c and again highlights the market's capability to gauge an event's impact based on the firm's position in the industry chain.

6. Robustness checks

To ensure the reliability of our conclusions, we conducted a series of robustness checks.

6.1. Changing the event window and the estimation window

We shortened the event window in the event study to (−5, +5) and extended the estimation window to (−200, −21) (relative to the event date), then recalculated CAR and reran the analyses. The results showed that the sign, magnitude, and significance of the coefficients for the core explanatory variables did not change substantively, indicating that our conclusions are not sensitive to the choice of event/estimation window.

6.2. Replacing the dependent variable

We used the change in Parkinson volatility on the announcement day T (denoted $\Delta Vol_{Parkinson}$ as defined earlier) as an alternative dependent variable to test the event's impact on intraday volatility. The regression results show that the coefficients for variables, such as Severe_Penalty and Heavy_Pollution, were all significantly positive, indicating that penalty events with those characteristics significantly exacerbate intraday price volatility. This finding is consistent with the conclusion from the GARCH model, reinforcing the evidence.

6.3. Propensity score matching–difference-in-differences test

To mitigate concerns about sample selection bias, we employed a propensity score matching combined with a difference-in-differences approach. We treated penalized "company–commodity" pairs as the treatment group, and from all unpenalized "company–commodity" pairs, we used firm size, industry, profitability, etc., as covariates to perform 1:1 propensity score matching, finding a control group with the closest characteristics. We then constructed a difference-in-differences model (Equation [10]):

$$Y_{it} = \beta_0 + \beta_1(\text{Treat}_i \times \text{Post}_t) + \text{Controls} + \varepsilon_{it} \tag{10}$$

where Y_{it} is the futures return or volatility, treat is a dummy for the treatment group, and post is a time dummy for the post-event period. The results show that the coefficient β_1 on the interaction term (Treat×Post) is significantly negative in the return model and significantly positive in the volatility model, which is fully consistent with our baseline findings. This further strengthens the causal interpretation of our conclusions.

6.4. Excluding other events

We carefully checked whether the penalized companies released any other major announcements (such as earnings forecasts, major asset restructurings) during the event window. After excluding samples with confounding events and rerunning the analysis, the conclusions remained unchanged. This suggests that our results are indeed driven by the environmental penalty events, rather than by other firm-specific information.

7. Discussion

This study reveals a transmission channel from corporate environmental penalties to commodity futures prices. The market responded with negative returns and heightened volatility, reflecting supply chain and sentiment effects. The negative ARs were consistent with supply chain transmission logic. The penalized listed companies in our sample were primarily concentrated in manufacturing industries (such as steel, chemicals, and building materials), which are the major consumers of bulk commodities, including iron ore, coke, and PTA. When these firms were penalized or even suspended due to environmental violations, the market anticipated a significant decline in their demand for upstream raw materials, thereby triggering negative adjustments in related futures prices. This finding reveals an important mechanism of reverse transmission of environmental risk along the supply chain.

Compared to existing studies focused on equity markets,[3,6] our findings carry unique significance. The stock market's reaction to negative events is primarily a revaluation of the affected firm's value. In contrast, the reaction of the commodity futures market reveals the impact of the event on the entire industry chain's supply–demand expectations. For example, when a large steel enterprise is suspended due to environmental issues, the decline in rebar futures prices and the surge in volatility reflect not just the loss of that company's value, but the market's reassessment of the future supply, costs, and even policy environment risks for the entire steel industry. This indicates that the externality of environmental risk, through the futures market as an efficient information aggregation platform, is rapidly transmitted and diffused, with an impact scope far beyond the penalized firm. It provides a concrete example of the transmission path by which environmental risk can evolve from a micro-level issue to a macro-level systemic risk.

The heterogeneous market responses we uncovered are equally insightful. The especially strong reactions to "severe penalties" and "penalties in heavy-pollution industries" suggest that the market does not react blindly and uniformly to all negative news, but rather has considerable ability to discriminate among information. Futures market participants—composed of professional industrial investors and speculators—have a deep understanding of the substantive impacts of different penalty measures on real production, as well as the vulnerabilities of different industries under the current environmental policy regime. In particular, the huge market shock when an "industry leader" is penalized indicates that the market is highly attentive to systemically important firms, and that their environmental performance is seen as an industry "weathervane." This echoes findings in global supply chain research that uncertainty in key node firms significantly affects the entire chain.

Our research also provides new evidence on the applicability of the efficient market hypothesis to environmental information. Although we observed significant short-term shocks, prices stabilized after a few days, suggesting that while the market may overreact in the very short term, it has the ability to self-correct in the longer term. However, whether this correction is complete, and whether the market has fully priced in long-term transition risks (such as asset stranding risks under carbon peak and carbon neutrality goals), remains an open question. This study focused on the short-term shock of penalty events; future research could employ longer time series and more sophisticated models to explore the long-term pricing effects of environmental risk.

Furthermore, our study resonates with broader macro-policy studies. For instance, environmental regulatory decentralization might influence local governments' regulatory incentives, thereby affecting firms' environmental behavior and the quality of economic growth.[34] From the market's perspective, our study verifies the visibility and impact of local environmental enforcement actions. Each environmental penalty is a display of local governments' determination in environmental governance, and the futures market has become the "loudspeaker" and "amplifier" of that determination.

8. Conclusion

By manually collecting environmental penalty events for Chinese listed companies and matching them with related commodity futures prices, this paper employs a case study and GARCH model to empirically test the impact of micro-level environmental risk events on the macro-level commodity market. The findings are as follows: First, announcements of environmental penalties imposed on listed companies lead to significantly negative ARs and a significant rise in conditional volatility in related commodity futures prices in the short term—the market reaction is swift and intense. Second, this market response exhibits notable heterogeneity: the more severe the penalty and the larger the fine, the greater the negative shock; environmental penalty events in heavy-pollution industries involving industry-leading companies trigger far greater market volatility than similar events. Third, a series of robustness checks supports the above conclusions, indicating that the results are robust and reliable.

Our findings carry rich policy implications. This study also finds that the price effects of environmental risk are closely related to firms' positions in the supply chain, providing a new perspective on the supply chain transmission effects of environmental regulation.

First, for regulators, this study reveals the strong market penetration of environmental regulatory policies. Every enforcement action by environmental authorities affects not only the penalized enterprise but also rapidly spreads to the entire industry chain and macroeconomic level through the futures market, as an efficient information platform. This provides new perspectives and tools for environmental policy formulation and implementation. On one hand, regulators should fully recognize the spillover effects of environmental enforcement—when designing policies, they need to assess the short-term volatility such actions might cause in related commodity markets and establish corresponding risk contingency plans. On the other hand, they can leverage futures market price signals in a feedback manner. The futures market's sensitive response to environmental events makes it an effective environmental risk "early warning system" and policy impact "barometer." Regulators can closely monitor price fluctuations of commodity futures related to high-pollution industries as an auxiliary indicator to identify potential buildups of environmental risk and to evaluate the effectiveness of regulatory policies.

Second, for investors, this study makes clear that corporate environmental risk is an important factor influencing commodity investment decisions. When trading commodity futures, investors should no longer focus solely on traditional macroeconomic data and supply–demand fundamentals; they should also incorporate environmental performance, ESG ratings, and potential regulatory risks into their analysis and pricing models for key companies in the relevant industry. Ignoring environmental risk could expose their portfolios to unanticipated "black swan" events. At the same time, our study provides ideas for developing quantitative trading strategies and risk management tools based on environmental risk. For example, one could build systems to monitor high-frequency environmental news and penalty announcements as sources of trading signals.

Third, for companies, this study uses market-based evidence to quantify the enormous external costs of environmental non-compliance. An environmental penalty not only entails direct fines and rectification expenses but also, by altering market expectations, delivers a negative shock to the entire industry chain, ultimately harming the interests of all stakeholders. This serves as a warning for corporate managers: strengthening environmental risk management and advancing green transformation are no longer "optional," but a "mandatory course" for a company's long-term survival and development. Companies should internalize environmental compliance as a core operating principle, increase investment in green technology innovation, and proactively disclose environmental information, thereby earning the trust of the market and investors under increasingly stringent environmental constraints.[1]

Finally, from the perspective of improving the financial market system, our study demonstrates that the commodity futures market can play a more active role in facilitating the green transition of the real economy. Regulatory bodies should encourage and guide the development of additional futures and derivatives related to green development, such as carbon-emission futures and green-electricity futures, providing enterprises with a richer toolkit for managing environmental risks. Meanwhile, the environmental information disclosure system for listed companies should be further improved to enhance the timeliness, accuracy, and comparability of information, enabling the market to more effectively price environmental risk. This will help channel financial resources toward more environmentally friendly and sustainable economic activities, supporting the smooth achievement of the "dual carbon" goals.

This study has several limitations. For example, due to data availability, we could not fully quantify the impact of penalty events on firms' actual output, so the transmission chain from "announcement" to "actual supply change" involves several inferences. Future research could incorporate higher-frequency production data (such as satellite remote sensing data or electricity consumption data) to directly verify the supply shock channel. In addition, this study mainly focused on the short-term market response to penalty events; their long-term impacts and interactions with other macro variables merit further exploration.

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Conflict of interest

The author declares no competing interests.

Author contributions

This is a single-authored article.

Availability of data

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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