Anatomy of Jumps in European Union Carbon Market: High-Frequency Evidence from Spot and Futures during Macroeconomic, Regulatory and Geopolitical Shocks, 2021-2025

Abstract

This study provides the first high-frequency nonparametric jump analysis of EU-ETS carbon prices Phase IV (2021-2025). Using 5-minute intraday data from the ICEDEU3 spot index and the December CKZ futures contract, we apply six non-parametric jump detection tests BNS bi-power variation, Lee-Mykland, Jiang-Oomen swap variance, ABD intraday detection, Aït-Sahalia-Jacod scaling, and ADS nearest-neighbour truncation and retain only those episodes confirmed by at least three independent methods. The spot market yields 15 consensus jump episodes and the futures market 18 episodes over 1,145 and 1,247 trading days respectively. Systematic event attribution links 85-90% of detected jumps to identifiable regulatory, energy, macroeconomic, and geopolitical triggers, with policy announcements accounting for 36% of matched events and geopolitical shocks producing the highest per-event method consensus. Futures markets consistently lead spot markets in incorporating jump-inducing information by approximately two to five weeks for major events such as Fit for 55 and the Russia-Ukraine crisis, confirming the price discovery role of the derivatives market. The only exact-date co-jump occurs on 6 December 2021 during the year-end compliance rush. These findings demonstrate that EU ETS prices behave as information-sensitive financial assets whose discontinuous dynamics are driven primarily by policy credibility and energy-market shocks rather than microstructure noise.

Keywords: Jumps, Price Jumps, Carbon Market, EU-ETS, Volatility, Market Microstructure

JEL Classification: G14, Q58, C58, G13

1. Introduction

Carbon market occupies an unusual dual role both as a financial asset class, and a policy instrument for reducing greenhouse gas emissions at least cost (Zhu et al., 2019). Under the cap-and-trade framework, regulated trade in a fixed supply of allowances such as European Union Allowances (EUA) (Karpf et al., 2018; Lutzet al., 2013), whose price is typically driven by the balance between supply and demand. While the price of carbon in these markets (Chevallier, 2011; Zhu et al., 2019), sudden and extreme price movements, jumps, have emerged as a defining feature of carbon price dynamics. Between 2021 and 2025 EUA price roughly tripled, crashed 35% in five trading days, and recovered, all within Phase IV of the EU Emissions Trading Scheme. Understanding these jumps is key for climate policy and energy economics, as shocks disrupt the risk management framework, increase compliance cost, and ultimately sabotage the credibility of market-based policy mechanisms.

The European Union Emissions Trading Scheme (EU-ETS) is the world's largest carbon market along with being the cornerstone of European climate policy, covering around 11,000 companies in the energy and industrial space, accounting around 40% of EU greenhouse gas emissions. While in previous compliance periods, Phase I (2005-02007), Phase II (2008-2012), and Phase III (2013-2020) with established liquid EUA derivatives and spot markets (Ibikunle et al., 2016; Lutz et al., 2013) the current Phase IV (2021-2030) represents a structurally distinct period. Between 2021 and 2025, the market has been shaped by heightened regulatory oversight (for example, the Fit for 55 package, raising the 2030 emissions reduction target to 62% and the accelerated allowance supply squeeze through the Market Stability Reserve) and significant exogenous shocks, and the energy crisis triggered by Ukraine-Russia conflict.

Market microstructure study shows that the European carbon futures market has matured from old, illiquid stage into sophisticated, informationally efficient systems driven by strategic trading activities (Ibikunle et al., 2016; Kalaitzoglou & Ibrahim, 2013; Mizrach & Otsubo, 2014). However, these microstructure studies do not address the discontinuous jump component of prices, which captures fundamentally different information dynamics.

Price discovery refers to the process by which market prices reflect all available information and is sensitive to trading frictions that introduce noise and reduce price informativeness (Ibikunle et al., 2016; Medina et al., 2014). In carbon markets, this process is further

complicated by significant non-stationarity and structural instability, resulting in sudden, dramatic price shifts, jumps, captured through discontinuous or semi-martingale processes (Chevallier, 2011; Lutz et al., 2013). A growing body of work has modelled these dynamics: (Eugenia Sanin et al., 2015) combine an additive jump process with GARCH to study EUA volatility in Phase II; (Dutta, 2016) examines time-varying jumps and outliers in the EUA market; and (Guo et al., 2022) use GARCH-MIDAS jump extensions to forecast EUA volatility, finding that short-term jump information significantly improves predictive performance. However, these studies rely exclusively on daily data and Phase I-III samples, leaving high-frequency jump dynamics in the post-2021 market entirely unexamined.

Identifying jumps in the European Trading Scheme (EU ETS) is a qualitatively distinct and critical task for understanding the structural stability of the world's most mature carbon market. In finance, the log-price is modelled as a semi-martingale process, consisting of a continuous component (drift and diffusive volatility) and a discontinuous jump component that captures rare, large price movements such as market crashes or sudden upsurges (Aït-Sahalia & Jacod, 2009; Barndorff-Nielsen & Shephard, 2006). The expression of price X_t according to a jump-diffusion model as follows:

$$dX_t = \mu_t dt + \sigma_t dW_t + \kappa_t dq_t$$

where, μ_t is the drift, σ_t is the spot volatility, W_t is a standard Brownian motion, and $\kappa_t dq_t$ denotes the jump component, where q_t is defined by Poisson process with intensity λ_t. Studying jumps is key to learning about the price discovery, the process through which markets incorporate new information in the price of assets. Jumps are attributed to information assimilation, news reaction, liquidity shocks, and market efficiency and disentangling them from the continuous volatility component requires a non-parametric testing framework.

The EU ETS is not immune; its price dynamics are susceptible to influence of broader energy, macroeconomic, and geopolitical factors (Chevallier, 2011; Ibrahim & Kalaitzoglou, 2016; Zhu et al., 2019). Yet despite a growing literature on carbon price mechanisms and market microstructure (Ibikunle et al., 2016; Lutz et al., 2013), no study has identified systematic jumps triggered by events during Phase IV, not relying on parametric analysis. To the best of our understanding, this is the first study to apply multiple non-parametric jump tests on high-frequency EU ETS Phase IV data.

The key findings that we claim are as follows. First, we identified 26-27 significant jumps in the 2021-2025 sample capturing 2% of trading days, a frequency consistent with the rare but impactful nature of discontinuous price movements in carbon markets. Second, there is strong co-movements between spot and futures EUA, with futures markets leading price discovery during jump events, confirming the informational role of the derivatives market observed in earlier phases (Lutz et al., 2013a; Mizrach & Otsubo, 2014). Third, systematic event attribution explains 85-90% of jumps detected to match with identifiable triggers, with policy announcements and regulatory decisions accounting for the largest pie, followed by geopolitical and energy-market shocks. Fourth, jumps respond asymmetrically to positive (regulatory tightening) and negative (crisis-driven) shocks, suggesting that carbon prices function as information-sensitive financial assets rather than passive reflections of allowance supply and demand.

The rest of this paper is structured as follows. Section 2 is the review of relevant literature on carbon market microstructure and jump-diffusion models. Section 3 details the high-frequency dataset and non-parametric jump detection model. Section 4 reports the empirical findings, including the jump tests and the attribution of structural breaks to particular events. Section 5 talks about the policy and event attribution analysis. Lastly, the manuscript is concluded in Section 6.

2. Literature Review

The study of price jumps in the financial market is driven by well documented empirical evidence where the asset prices in most instances exhibit significant discontinuous movements that cannot be explained by pure diffusion model (Lee & Mykland, 2008). The jumps are the market reaction to unexpected movements what Aït-Sahalia (2004) calls the 'surprise effects,' where large price changes generated that cannot be captured by smooth, day-to-day Brownian motions. In case of market participants, ignoring these discontinuities leads to systematic underestimation of tail risk with effect across portfolio allocation, option pricing, and credit risk management (Branger et al., 2008; Gkillas et al., 2018; Huisman & Mahieu, 2003). Unlike continuous price volatility, jump risk typically can rarely be hedged away with a finite number of securities, thereby creating market incompleteness and investors to require substantial risk

premia (Eraker et al., 2003; Johannes, 2004). Moreover, jump detection allows researchers to decouple idiosyncratic shocks from incessant shifts in underlying volatility processes (Maneesoonthorn et al., 2017). Since jumps are tail events that surpass extreme volatility, therefore policy makers must understand this statistical behaviour to make real-time decisions during chaotic market order.

2.1 Nonparametric Jump Detection: Methodological Foundations

Modern high-frequency econometrics have developed a number of robust methodologies for detecting price jumps, which exploits differential features of the return distribution. Beginning with Barndorff-Nielsen & Shephard (2006) developed the concept of bi-power variation (BV), that when compared to realized variance (RV), robustly identifies the jump component of total variation. Building on this framework, Andersen et al. (2007) formalised the Heterogeneous Autoregressive (HAR-RV-CJ) framework showing that separation of continuous and jump variation substantially improved out of sample volatility forecasting. Lee & Mykland (2008) directed the focus from daily aggregates to single intraday returns, comparing each return with a locally estimated volatility to detect the accurate timing and magnitude of jumps. A different statistical insight is provided by Jiang & Oomen (2008) who proposed the Swap Variance approach, detecting jumps based on the replication error between simple and log returns (a statistic sensitive to third and higher order moments). Further extending nonparametric detection, Aït-Sahalia & Jacod (2009) designed a ratio test based on two different time scales, where the ratio of power variations converges to unity in the presence of jumps and a known constant otherwise. Finally, Andersen et al. (2012) introduced the MedRV and MinRV estimators, which uses nearest-neighbor truncation, which are robust to the zero returns prevalent in less liquid markets.

Whether these tests agree when applied to the same data is far from guaranteed. Dumitru & Urga (2012) conducted a comprehensive Monte Carlo comparison of nine nonparametric jump procedures including BNS, ABD, LM, ASJ, and JO across varying sampling frequencies, volatility persistence, and microstructure noise levels. They found that the LM and ABD intraday procedures offer the best overall size-power trade-off, and that using the intersection or union of multiple tests substantially reduces spurious detection.Maneesoonthorn et al. (2020) extended this analysis with practical guidelines for test selection that account for jumps in volatility and realistic levels of market noise. Laurent & Shi

(2020) raised an additional concern: even temporary nonzero drift common in trending markets can cause dramatic power loss for standard bipower-variation-based tests. This is directly relevant to the sustained upward trend observed in EU ETS Phase IV prices. The rationale for using a multi-method consensus approach whereby retaining only those jumps identified by a majority of heterogeneous tests follows naturally from these findings.

When applied to carbon markets, these methods have revealed distinctive stochastic properties. Benz & Trück (2009) first characterized EUA price dynamics, documenting skewness, excess kurtosis, and structural breaks in Phase I–II EUA prices using Markov-switching models. Chevallier & Sévi (2014) applied activity signature functions to high-frequency carbon futures data and concluded that the CO_2 price process is best described as pure-jump, containing no continuous Brownian component which implies that jump detection is not merely a refinement but a structural necessity for modelling EUA prices. Sanin et al. (2015)examined volatility dynamics in Phase II using component GARCH models, finding that EUA volatility responded asymmetrically to positive and negative shocks. Guo et al. (2022) provided direct evidence that jump components have significant predictive power for EUA futures volatility, incorporating them into GARCH-MIDAS models that outperform specifications ignoring discontinuities.

2.2 Market Microstructure and Liquidity

Market microstructure and liquidity shocks play a vital role in event of jump dynamics. At high frequency period, microstructure frictions such as bid-ask spreads, tick sizes, and price discreteness can induce inconclusive jump detections (Corradi et al., 2020). Price staleness (zero returns) makes distributions more leptokurtic, failing to correct for this can lead to the incorrect conclusion that volatility is driven by a pure jumps (Kolokolov & Renò, 2023). Researchers today use pre-averaging and thresholding methods to remove these biases and making sure that jumps detected represent genuine price break (Bajgrowicz et al., 2016; Caporin, 2023).

These issues are especially acute in the EU carbon market. Ibikunle et al. (2016) determined that liquidity and informational efficiency in the EU ETS are closely correlated, and enhanced efficiency year-on-year during compliance periods of PhaseII but declined during low-liquidity periods. Ibrahim & Kalaitzoglou (2016) demonstrated that informed order flow significantly role in determining the level and volatility of EUA prices, and the

informational value of trades under different regulatory phases. More recently, Kalaitzoglou (2025) introduced a time-variant structural variance decomposition applied to EU ETS transaction-level data spanning 2005-2021. He found that the market became increasingly inefficient proportionally before MiFID II, but efficiency improved substantially after the directive's transparency requirements took effect, suggesting that detected jumps in Phase IV are more likely to reflect genuine information shocks than microstructure artefacts. Given that zero returns comprise roughly 4-6% of 5-minute EUA observations, the use of jump-robust estimators such as MedRV is not optional but necessary.

2.3 Jumps Drivers: Macro, Policy and Geopolitical Events

Jumps are primarily driven by the arrival of new information that forces an abrupt revaluation of assets (Boudt & Petitjean, 2014; Huang, 2018; Miao et al., 2014). Significant correspondence exists between jumps and macroeconomic announcements such as Federal Reserve (FOMC) announcements, Non-farm Payroll (NFP) reports, GDP, and CPI (Huang, 2018; Lee, 2012; Miao et al., 2014). In the energy market, jumps are often associated with inventory announcements (EIA), OPEC production announcements (cuts or increases) and extreme weather conditions (Bjursell et al., 2015). Jumps tend to cluster during periods of geopolitical uncertainty and financial crises, such as the 1987 crash, the Gulf War, the collapse of the Soviet Union, the 2008 Global Financial Crisis, and the US shale revolution, the Eurozone debt crisis and the COVID-19 pandemic, (Christoffersen et al., 2012; Fulop et al., 2015; Maneesoonthorn et al., 2017; Semeyutin et al., 2021).

Unlike traditional commodity markets, the carbon market is highly sensitive to political and regulatory decisions (Chevallier, 2011b; Ibrahim & Kalaitzoglou, 2016). Significant jumps have been detected following verified emission disclosures and regulatory amendments (Karpf et al., 2018; Lutz et al., 2013), with the frequency and predictability of jumps serving as a metric for maturity - Phase I's immature market exhibited different jump dynamics than more liquid Phase II-II periods (Ibrahim & Kalaitzoglou, 2016; Medina et al., 2014).

For the EU ETS specifically, the period since 2021 has produced some of the most extreme price dislocations in the market's history. Russia-Ukraine invasion of February 2022 caused a decline of roughly 35% in EUA prices in five trading days due to financial deleveraging and uncertainty surrounding European energy policy prevailing over fundamentals (Do et al., 2024). The resultant energy crisis pushed the switching in gas-to-coal

and its carbon demand to unprecedented levels. At the policy level, the Fit for 55 package and MSR reform indicative of long-term political commitment to decarbonisation, which Sitarz et al. (2024) revealed was the primary cause of the tenfold price increase between 2018 and 2023, not just temporary tightening of supply. Bruninx & Ovaere (2022) showed that the combined effects of COVID-19 recovery stimulus and the European Green Deal permanently altered the Phase IV price trajectory, with simulated prices of €45-94 depending on MSR invalidation assumptions. The introduction of the Carbon Border Adjustment Mechanism (CBAM), with its transitional phase beginning in October 2023, added another source of structural repricing; Bellora & Fontagné (2023) showed that replacing free allocation with border adjustments effectively tightens the supply constraint and raises the equilibrium EUA price. Economic policy uncertainty shocks have also been shown to increase carbon market volatility substantially (Tong et al., 2022). These events collectively make Phase IV a uniquely information-rich environment for studying jump behaviour.

2.4 Price Discovery and Cross-Market Spillovers

Jumps are significant drivers of information discovery between spot and futures markets. In equity index markets, there is strong evidence of jump spillovers where jumps in futures (e.g., E-mini-S&P 500) provide relevant information for the spot market (e.g., SPDR ETF) and vice-versa (Corradi et al., 2020). In commodity markets, price discovery typically occurs first in the futures market due to lower transaction costs and the ease of short selling, with jumps in futures responding faster to new information than spot prices (Gkillas et al., 2021). However, the impact is often asymmetric; for instance, oil price jumps can significantly affect exchange rate volatility in oil-importing countries like China and India, while the reverse spillover is often weaker (Ahmad et al., 2020). Electricity markets represent the most volatile segment where daily price spikes are common due to low supply elasticity and sudden demand fluctuations which are uniquely short-lived, typically reverting to equilibrium levels within a single day once the transient supply-chain or demand shock has dissipated (Hellström et al., 2012; Huisman & Mahieu, 2003; Mason & Wilmot, 2014).

In the EU ETS, futures markets have consistently been found to lead to price discovery. Mizrach & Otsubo (2014) estimated that roughly 90% of price discovery occurs in ECX carbon futures rather than spot markets, and (Ibikunle et al., 2016) reinforced this by demonstrating that efficiency gains are strongest in the most actively traded futures contracts. Vadhava (2025)

provided the first high-frequency Phase IV evidence using 5-minute data from April 2021 to May 2024, confirming that ECX futures continue to dominate both price discovery and volatility transmission. If information is first impounded in futures prices, one would expect jumps to appear in the futures market before propagating to spot, a hypothesis that high-frequency multi-method testing can directly evaluate.

The connectedness between carbon and energy markets intensified dramatically during the 2022 energy crisis. Hoque et al. (2023) applied TVP-VAR frequency-domain connectedness to carbon, climate, and energy futures, finding that short-term spillovers were persistently dominant during the Russia–Ukraine war period. Do et al. (2024) used quantile connectedness across 11 European electricity markets, natural gas, and carbon, concluding that the war intensified return shock transmission with the carbon market acting as a net receiver of shocks. The contagion effects reported by Rannou & Barneto (2016) and Liu & Zhu (2019) during earlier episodes of financial stress, together with the post-Ukraine evidence, suggest that a non-trivial share of EUA jumps originate in energy or financial markets rather than from carbon-specific fundamentals, a channel that can only be properly identified when jump timing is resolved at the intraday level.

2.5 Research Gap and Contribution

What remains missing is an application of multiple nonparametric jump tests to high-frequency EU ETS data during Phase IV. Chevallier & Sévi (2014) high-frequency analysis established that carbon futures follow a pure-jump process but employed a single methodology on Phase II data and did not attempt to identify individual jump days or match them to specific events. The current study uses this by employing six non-parametric jump detection methods (BNS, ABD, LM, JO, ASJ, and ADS) to 5-minute EU ETS spot and futures prices in the period of April 2021 to November 2025. Consensus filtering criterion requiring detection by at least three of six (spot) or three of five (futures) independent methods ensures that identified jump episodes are robust to the idiosyncratic size-power trade-offs of any particular test. In this way, the study provide answers to three questions that are not answered in existing literatures: (i) whether the prices of EU ETS have statistically significant jump behaviour detectable across battery of heterogeneous nonparametric tests; (ii) whether the identified jumps can be explained by policy, energy, macroeconomic, and geopolitical events instead of being random;

and (iii) whether futures markets lead spot markets while incorporating jump-related information, consistent with the price discovery hypothesis established for the earlier phases.

3. Data & Methodology

3.1 Data Description

The empirical study of daily price data from the European Union Emissions Trading System, which is the largest and most liquid carbon market in the world. We obtain spot prices from the ICEDEU3 Index offered by the Intercontinental Exchange, an alternative to MO1 Comdty offered by Bloomberg. ICEDEU3 is the preferred because if its superior liquidity, better market depth, and transaction depicting EUA spot trading. It is therefore regarded as the best reference point for conducting an analyses that focuses on short-horizon price movements in carbon markets.

The EUA futures listed on ICE EUA provides future prices with the prefix CK followed by the standard futures month abbreviation CKH (March), CKM (June), CKU (September), and CKZ (December). Consistent with the structure of the EU ETS, the December (CKZ) contract is the standard and most actively traded maturity. The fact that is widely used because (i) the annual compliance cycle culminates in December making it as a only choice; (ii) its price discovery nature, facilitated by presence of persistent high open interest; and (iii) the liquidity-aggregation (liquidity snowballing) effect, in which market participants colludeon a single focal contract. The previous empirical studies on carbon markets also base on the December contract due to its stability and informational efficiency.

Based on these institutional and microstructural characteristics, the core dataset for this research is the ICEDEU3 spot series and the December CKZ futures contract. This choice ensures that the most representative and liquid segments of the EU ETS are addressed in line with best practices from carbon market literature. To capture the distributional information and intraday price dynamics that are contained in the EU ETS, we use high-frequency price quotations at 5-minute, 15-minute, and 30-minute intervals. A sampling frequency of 5-minute is widely considered top be the optimal choice in carbon and energy market literature, since it strikes an efficient balance between measured accuracy and the reduction of microstructure noise effects, including bid-ask bounces and asynchronous trading. The frequency of 15-minute

and 30-minute are used to conduct robustness checks to determine the stability of volatility models across different time periods.

We conducted our analysis from April 25, 2021 to November 21, 2025 in case of Spot market and January 1, 2021, to December 31, 2025, for futures providing a complete picture of how the market has evolved in recent times through institutional shifts. In accordance with the traditional high-frequency finance, we undergo a two-step data cleaning process to ensure a continuous and reliable time series. First, we eliminate observations that are related to non-trading hours, weekends, and exchange holidays. Second, we drop overnight returns (price change between the last day close and the opening of current day) to eliminate the price gaps that do not reflect continuous intraday trading activity.

We use a rollover methodology to build up a continuous futures price series from the individual December contracts using the maximum volume and open interest criteria. Specifically, we transition from the front-month contract to the next-nearest December contract when the latter becomes the most actively traded, ensuring that our series consistently reflects the most liquid segment of the futures curve

Fig. 1. EU ETS spot and futures price levels, Phase IV (2021–2025).

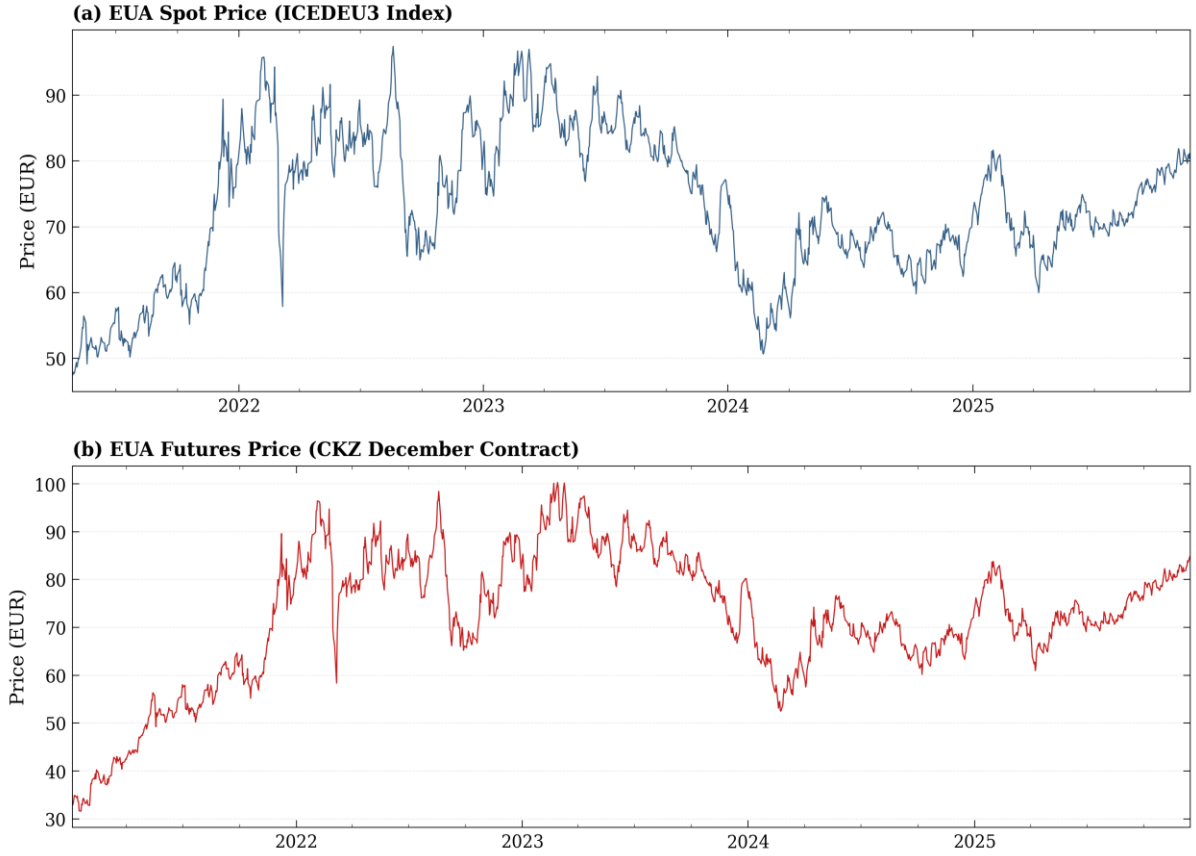


Table 1. Descriptive statistics of intraday log returns, EU ETS spot and futures markets. Sample: April 2021 - November 2025. Returns computed as $r_{t,i} = \ln(P_{t,i}/P_{t,i-1})$.

	Spot (ICEDEU3)			Futures (CKZ)		
	5-min	**15-min**	**30-min**	**5-min**	**15-min**	**30-min**
Observations	51,164	30,496	19,376	152,613	50,925	25,467
Mean	0.00001032	0.00001732	0.00002804	0.00000616	0.00001834	0.00003663
Median	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000	0.00000000
Std. deviation	0.00380440	0.00503703	0.00632711	0.00223704	0.00384851	0.00540084
Minimum	-0.07160463	-0.10951628	-0.08758441	-0.05684934	-0.07378617	-0.08809456
Maximum	0.06895682	0.09643188	0.10758027	0.06090428	0.09658752	0.10816852
Skewness	0.2557	-0.1233	0.2430	-0.1219	-0.1884	-0.0888
Excess kurtosis	18.95	22.24	16.88	34.26	25.75	20.20
Jarque–Bera	765998***	628598***	230262***	7464597***	1406792***	433041***
(p-value)	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
ADF statistic	-161.666***	-127.267***	-102.504***	-160.737***	-160.441***	-114.190***
(p-value)	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
Zero returns (%)	5.87	3.25	2.20	4.46	2.38	1.75

*Notes: *** $p < 0.01$. Kurtosis is excess (Fisher definition; normal = 0). JB = Jarque-Bera normality test (H_0: returns are Gaussian). ADF = Augmented Dickey-Fuller unit root test with constant (H_0: unit root). Lag selection by AIC. Spot = ICEDEU3 Index; Futures = CKZ December rolling contract.*

Fig. 2. Intraday log-returns at 5-min, 15-min, and 30-min frequencies.

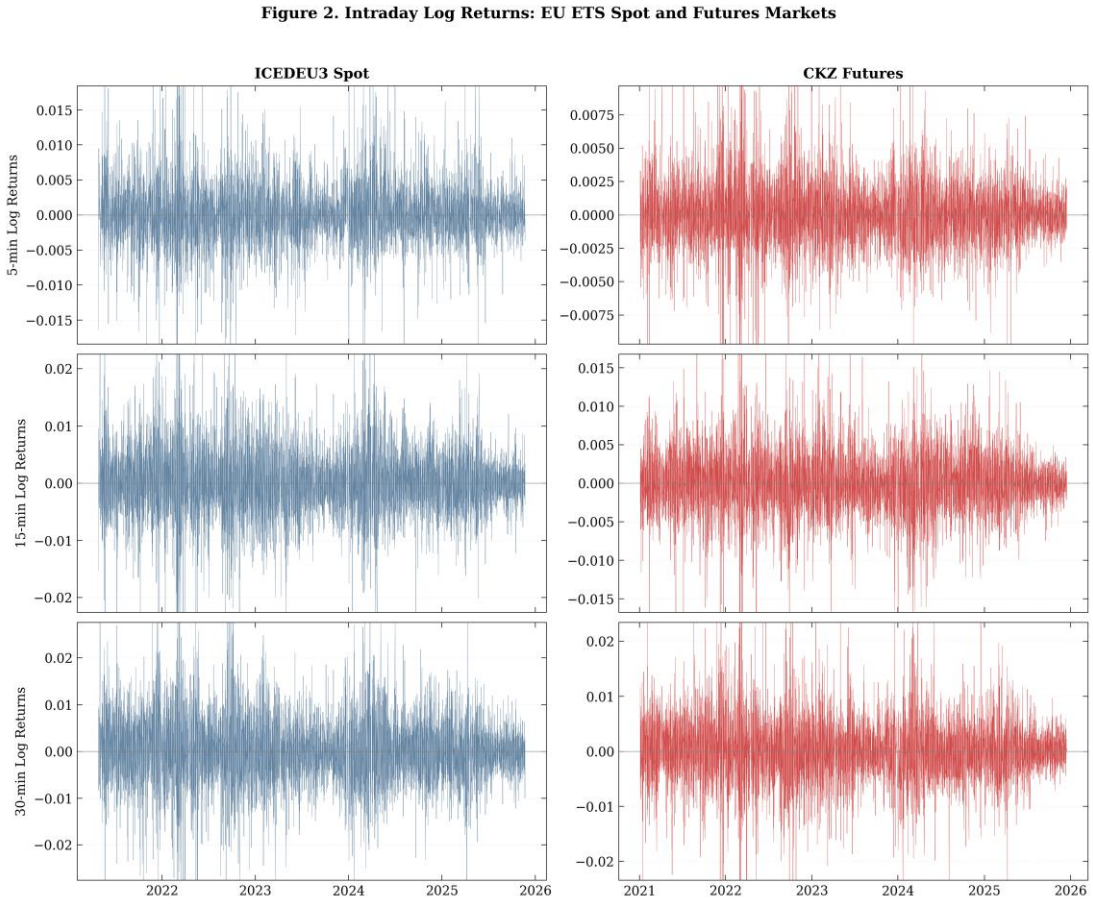
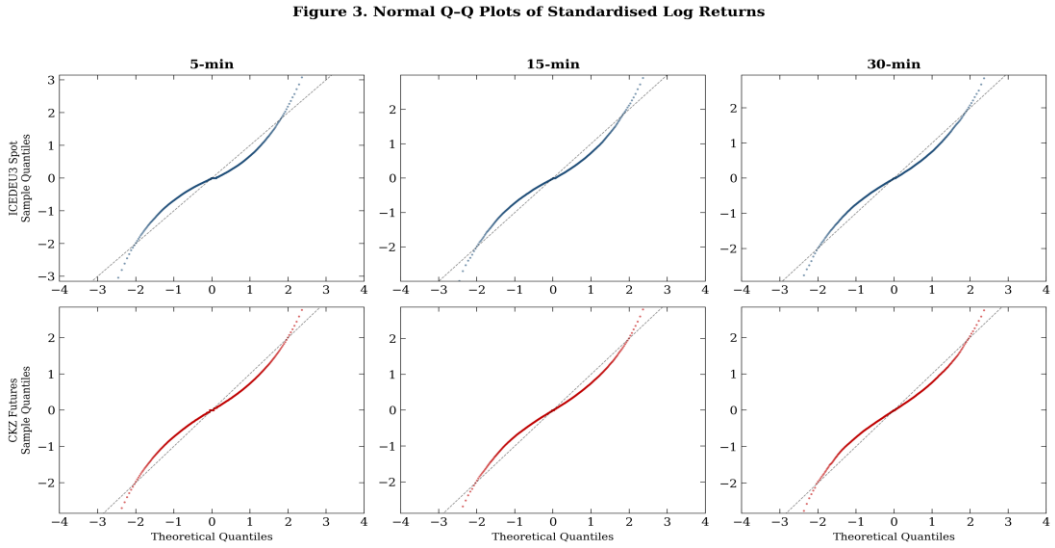


Fig. 3: QQ plots



3.2 Methodology

The tests are aimed in explaining various properties of the price process jumps (discontinuities), which are flagship multi-method approaches for identifying jumps (six methodologies).

H_1: EU ETS prices show statistically significant jumps detected across multiple non-parametric methods.

H_2: Jumps cluster are observed around definite policy, energy, and macroeconomic events and not random.

H_3: Futures markets lead spot markets in incorporating jump-inducing information, which is consistent with the price discovery hypothesis.

1. Barndorff-Nielsen & Shephard (2006): Bi-power Variation (BNS)

The methodology breaks down total return variation into continuous and jump componentsm through a comparison between realised variance (RV) with realised bipower variation (BV), robust to finite-activity jumps. It relies on the limit theory where Realised Variance (RV) converges to the quadratic variation (integrated variance plus jumps), while BV converges only to the integrated variance

- Realised Variance (RV): Computed as the sum of squared intraday returns:
  It consistently estimates quadratic variation (QV), which includes both integrated variance and jump variation $RV_t = \sum_{i=1}^{M} r_{t,i}^2$
- Realised Bi-power Variation (BPV):

$$BPV_t = \mu_1^{-2} \frac{M}{M-1} \sum_{i=2}^{M} | r_{t,i} || r_{t,i-1} |, where\ \mu_1 = 2/\pi \simeq 0.79788$$

BV is robust to jumps and consistently estimates only the integrated variance

- Test Statistic: The ratio-max statistic is generally preferred for its finite-sample performance

$$Z_t = \frac{1 - \frac{BPV_t}{RV_t}}{\sqrt{(\theta - 2)\frac{1}{M}\max\left(1, \frac{TPt}{BPV_t^2}\right)}} \rightarrow N(0,1)$$

Where $\theta=(\pi 2/4+\pi-5) \simeq 0.609$ and TP_t (Tri-power Quarticity) is the realised tri-power quarticity, serving as a consistent estimator of integrated quarticity. H_0 is rejected at significance level α when Z_t exceeds the critical value (one-sided upper-tail test).

2. Andersen et al. (2007): Intraday Jump Detection with Periodicity Correction (ABD)

The study uses bi-power variation to decompose total variation into continuous and jump components for improved volatility forecasting

- Intraday Jump Test: A jump is identified in intraday interval i on day t if the return exceeds a threshold determined by a jump-robust measure of local volatility

$|r_{t,i}| > \Phi^{-1}_{1-\beta/2} \cdot \sqrt{\{(\quad\}\hat{s}^2_{WSD,i} \cdot \Delta \cdot BV_t)}\ where\ \hat{s}^2_{WSD,i}$ is the Weighted Standard Deviation estimator correcting for U-shaped intraday volatility.

- Identification and Shrinkage: Jumps are identified using the BNS Zt statistic. To treat small jumps as measurement error, a shrinkage (thresholding) estimator is applied
  - $J_t = I[Zt > \Phi\alpha] \cdot (RV_t - BPV_t)$
  - $C_t = RV_t - J_t$
- Realised Bi-power Variation (BV): $BV_{t+1} = \mu_1^{-2} \sum_{j=2}^{1/\Delta} | r_{t,j} || r_{t,j-1} |$ $where\ \mu_1 = \sqrt{2/\pi}$
- Jump Component: $J_{t+1} = \max(RV_{t+1} - BV_{t+1}, 0)$
- HAR-RV-J Model: $RV_{t+h} = \alpha_0 + \beta_D C_t + \beta_W C_{t,w} + \beta_M C_{t,m} + \gamma_D Jt + \gamma_W J_{t,w} + \gamma_M J_{t,m} + \epsilon_{t+h}$

- Replication: By including J as an additional regressor, the model captures the different persistence levels of "smooth" continuous variation and "rough" jump variation

3. Lee & Mykland (2008): Intraday Jump Test (LM)

This methodology proposes a nonparametric test to detect the exact timing and magnitude of jumps by standardising returns with a local, jump-robust volatility measure.

- Test Statistic (Li): $L(i) = r_{t,i}/\hat{\sigma}_{t,i}$

  where $\sigma_{t,i}$ is the instantaneous volatility estimated using realised bi-power variation over a local window of K observations
- Local Volatility Estimation: $\sigma^2{}_{t,i} = \frac{1}{K-2} \sum_{j=i-K+2}^{i-1} | r_{t,j} || r_{t,j-1} |$

  K = √(252·M) ≈ 156 for 5-min data (M ≈ 97 obs/day).
- Rejection Region: Based on the Gaussian extreme value theory, the null of no jump is rejected if $\frac{|L(i)|-C_n}{S_n} > \beta$

  where C_n and S_n are centring and scaling constants determined by the sample size n, and β is the critical value from the Gumbel distribution. C_n = (2 log n)^{1/2} − (log π + log(log n)) / (2(2 log n)^{1/2}); S_n = 1/(2 log n)^{1/2}.

4. Jiang & Oomen (2008): Swap Variance Approach (JO)

The JO test identifies jumps by examining the replication error of a variance swap strategy, which is negligible for continuous processes but significant when jumps occur.

- Swap Variance (SwV): $SwV_N = 2\sum_{i=1}^{N}(R_i - r_i)$ $where\ R_i\ is\ the\ simple\ return\ and\ r_i\ is\ the\ \log return$
- Realized Variance (RV): $RV_N = \sum_{i=1}^{N} r_i^2$
- JO Test Statistic: $JO_t = \frac{M \cdot BV_t}{\sqrt{\Omega_{SwV}}}\left(1 - \frac{RV_t}{SwV_t}\right)$

where SwV_t is the realized variance swap payoff, and Ω_{SwV} is a higher-order power variation estimator used for standardization

5. Aït-Sahalia & Jacod (2009): Power Variation Scaling Test (ASJ)

The ASJ test, a nonparametric test, focuses on estimating the degree of jump activity and testing the presence of jumps by comparing power variation at different sampling frequencies.

- Let Δ_n be the sampling interval and X the observed process.
- Power Variation Estimators: $B(p,\Delta_n)_t = \sum_{i=1}^{[t/\Delta_n]} \mid \Delta_n^i X \mid^p \ where\ p > 2$
- Test Statistic: $S(p,k,\Delta_n)_t = \frac{B(p,k\Delta n)t}{B(p,\Delta n)t}\ for\ an\ integer\ k \geq 2$
- Standardized Statistic: $\left(\hat{S}(p,k,\Delta)_t - k^{p/2-1}\right)/\sqrt{V_{c,t}} \rightarrow N(0,1)\ where\ V_{c,t}$ is the asymptotic variance estimated using truncated power variations.
- Replication: Under the null of no jumps (Path$\in\Omega_c$), the statistic converges to $k^{p/2-1}$. If jumps are present (Path $\in \Omega j$), the statistic converges to 1. Common settings are p=4 and k=2, yielding a null value of 2

6. Andersen et al. (2012): Nearest Neighbor Truncation (ADS)

This method provides jump-robust estimators that are highly efficient and robust to zero intraday returns and local volatility fluctuations by using the minimum or median of absolute return blocks

- MinRV Estimator: $MinRV_t = \frac{\pi}{\pi-2}\left(\frac{M}{M-1}\right)\sum_{i=1}^{M-1} \min(\ \mid r_{t,i} \mid, \mid r_{t,i+1} \mid\ )^2$
- MedRV Estimator:

  $MedRV_t = \frac{\pi}{\pi+6-4\sqrt{3}}\left(\frac{M}{M-2}\right)\sum_{i=3}^{M} med(\ \mid r_i \mid, \mid r_{i-1} \mid, \mid r_{i-2} \mid\ )^2$
- Application: The test for jumps follows the BNS structure but replaces BPV with MedRV, providing better theoretical efficiency and power than traditional bi-power variation

All tests are conducted at different significance levels to minimise false positive detections, consistent with identifying 25-27 jump outputs. For each method, the key tuning parameter (significance threshold for BNS/ABD/ADS, window size K for LM, truncation level for ASJ, noise adjustment for JO) is calibrated iteratively to yield 25-27 total jump detections over the full sample. This ensures cross-method comparability and falls within the range suggested by simulation studies for samples of comparable size and frequency. A consensus jump episode is defined as a cluster of dates where ≥3 of the 6 spot-market methods (or ≥3 of the 5 futures-market methods, excluding ASJ) detect statistically significant jumps within a ±3 trading-day window. Such multi-method filtering greatly minimizes false positives inherent in any one of test while capturing true discontinuities identified across heterogeneous statistical frameworks. The consensus criterion implicitly resolves the multiple-comparison concern: agreement of ≥3

independent tests with various statistical properties is much more conservative than any any single test at conventional levels corrected with Bonferonni (Bajgrowicz et al., 2016).

A master event timeline is aggregated from: (i) European Commission legislation calendar and publication of Official Journal; (ii) ICE/EEX exchange announcements; (iii) ECB monetary policy announcements; (iv) Reuters and Bloomberg news archives. Events are dated to the official announcement day. Each consensus jump episode is matched to events falling within its ±3 trading-day window. Events are classified into five categories: Policy & Announcements, Energy, Macroeconomic, Geopolitical, and Compliance. The 53 tagged events correspond to major EU ETS milestones listed in the Appendix.

Table 2. *Summary comparison of nonparametric jump detection methods. All six tests are applied to 5-minute intraday returns of EU ETS spot and futures prices. BNS = Barndorff-Nielsen & Shephard; JO = Jiang & Oomen; LM = Lee & Mykland; ABD = Andersen, Bollerslev & Dobrev; ASJ = Aït-Sahalia & Jacod; ADS = Andersen, Dobrev & Schaumburg.*

Method	Null hypothesis	Test statistic	Key assumptions	Strengths	Weaknesses
Barndorff-Nielsen & Shephard (2006)	H_0: No jumps in the price process (continuous sample path).	Feasible Z-ratio statistic comparing Realised Variance (*RV*) to jump-robust Bipower Variation (*BV*). Available in difference (*Z-TP*) and ratio (*Z-TP,max*) forms.	Log-prices follow a Brownian semimartingale-plus-jump (BSMJ) process; consistent as the number of intraday observations $M \to \infty$.	Foundational non-parametric approach for separating continuous and jump variation; *BV* robustly isolates integrated variance; widely adopted baseline in the literature.	Vulnerable to microstructure noise, which biases *BV* downward; oversized under two-factor stochastic volatility; sensitive to zero returns (price staleness); cannot pinpoint intraday jump timing.
Jiang & Oomen (2008)	H_0: No jumps in the price process (pure continuous diffusion).	Swap Variance statistic (*SwV*): exploits the accumulated difference between simple and logarithmic returns to replicate a variance swap. Under no jumps the replication error vanishes; under jumps it does not.	Itô semimartingale process; accommodates leverage effects; requires high-order power variation for standardisation.	Exploits third- and higher-order return moments, yielding greater power than second-moment tests for single jumps; identifies jump sign via the replication error; robust to specific noise configurations in modified form.	Power drops when multiple jumps of differing signs cancel out; can be anti-conservative (oversized) in moderate samples; primarily a daily-level test.
Lee & Mykland (2008)	H_0: No jump occurred at a specific intraday observation time t_i.	Standardised return $\mathscr{L}(i)$: each intraday return is scaled by a rolling-window jump-robust local volatility estimate. Rejection thresholds are derived from Gumbel extreme-value theory.	Spot volatility is approximately constant over a short local window *K*; standard version assumes away microstructure noise.	Pinpoints the exact timestamp, direction, and magnitude of individual jumps at the intraday level; naturally suited to event-study applications.	Sensitive to window size *K*; heavily biased by zero returns (staleness); potential over-rejection during high-activity periods if diurnal periodicity is not robustly handled; requires pre-averaging modification for ultra-high frequencies.
Andersen, Bollerslev & Dobrev (2007)	H_0: No jumps over a daily window (return process is a pure diffusion).	Feasible ratio-max Z statistic: standardised absolute returns using daily *BV* scaled to the intraday interval, with Tri-Power Variation and Tri-Power Quarticity for finite-sample correction. Sequential testing identifies multiple intraday jumps.	Log-price is a Brownian semimartingale; uses staggered returns to mitigate noise; assumes intraday volatility changes are negligible within the daily window.	Explicitly decomposes realised variation into continuous and jump parts; sequential scheme allows timing identification of multiple intraday jumps; integrated with the HAR-CJ volatility forecasting model.	Constant within-day volatility assumption can produce spurious jumps when local volatility is high; susceptible to microstructure noise biasing the test against finding jumps.
Aït-Sahalia & Jacod (2009)	H_0: No jumps present in the observed price path (can also test H_0: jumps have finite activity).	Ratio of truncated power variations ($\hat{S}(p, k, \Delta)$): computed at two different sampling scales (Δ vs $k\Delta$). Under continuity the ratio converges to k^{p-2}; under jumps it does not.	Price follows an Itô semimartingale; valid for both finite- and infinite-activity jumps; base version requires pre-averaging to handle noise.	Fully non-parametric and scale-invariant; does not require preliminary coefficient estimation; distinguishes finite from infinite jump activity; can estimate the jump-activity index β.	Severe loss of power at lower sampling frequencies (e.g. 5-min); very sensitive to truncation parameter choice; base version loses effectiveness with noise; does not

					provide intraday jump timing.
Andersen, Dobrev & Schaumburg (2012)	H_0: No jumps in the price process over the sampled interval.	Nearest-neighbour truncation estimators: substitutes *BV* with Median Realised Variance (*MedRV*) or Minimum Realised Variance (*MinRV*), computed from the median or minimum of adjacent absolute returns, in a *Z*-ratio test against *RV*.	High-frequency data; nearest-neighbour truncation of adjacent returns isolates the continuous component; robust to jump clustering.	Superior finite-sample robustness to outliers, consecutive jumps, and zero returns compared to *BV*; mitigates diurnal U-shaped volatility biases; theoretically efficient.	Slightly less efficient than *BV* in idealised no-jump settings; can still be distorted if zero returns are extremely frequent; complex models using *MedRV*/*MinRV* may underperform simpler ones in basic forecasting.

Notes: RV = Realised Variance; BV = Bipower Variation; MedRV = Median Realised Variance; MinRV = Minimum Realised Variance; SwV = Swap Variance. All methods are non-parametric and assume the underlying price follows a semimartingale process. The ASJ test is excluded from futures consensus due to inconsistent detections attributed to lower contract liquidity in certain periods.

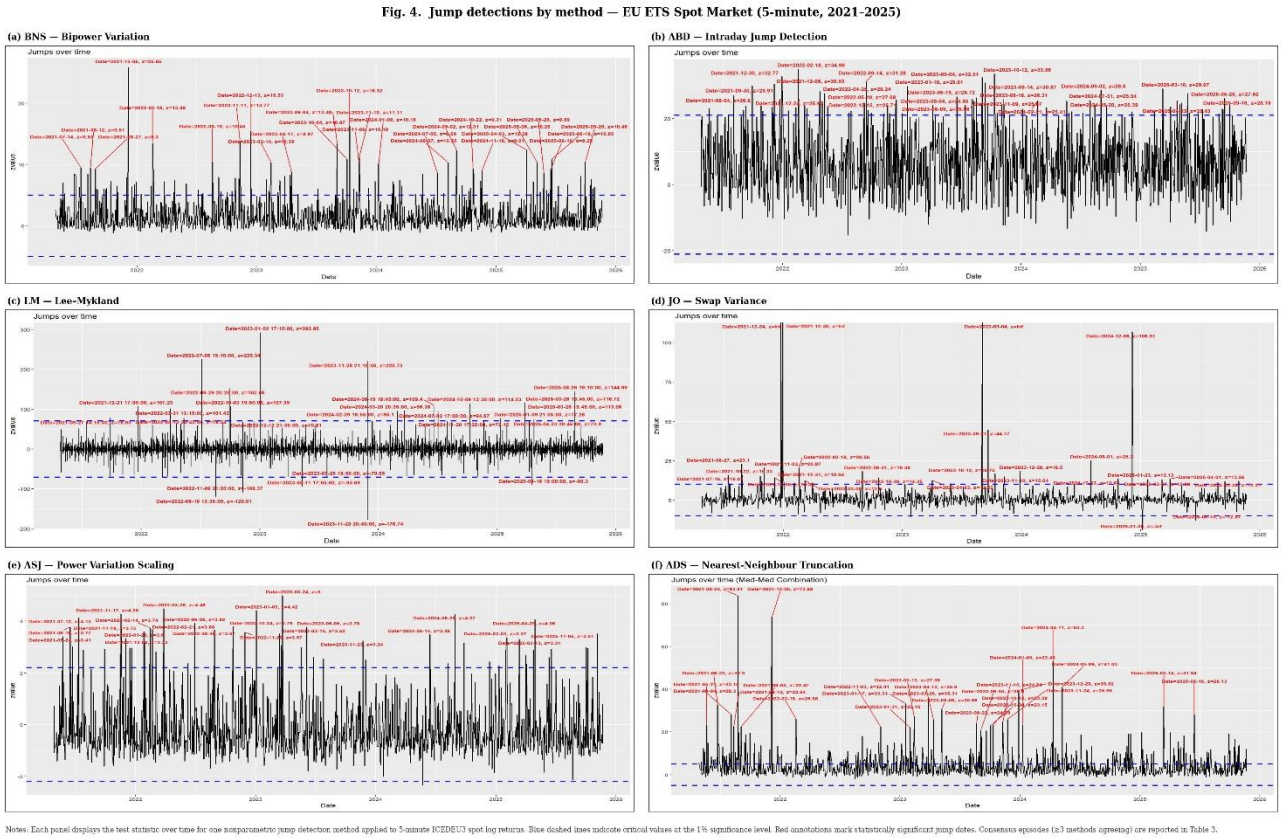
4. Result & Discussion

We apply six nonparametric jump tests to high-frequency EU ETS allowance prices. When detections are pooled across methods, the resulting consensus episodes correspond closely to identifiable policy, energy, and macro shocks rather than method-specific artefacts. While individual tests slightly differ in sensitivity and timing, a clear pattern emerges when jump detections are aggregated into consensus to jump episodes, reflecting actual discontinuities rather than method-specific noise. Exact date matches across all methods are rare in high-frequency jump tests due to differences in thresholding, windowing, and sensitivity. It is noted that we have considered 25 or 27 jump outputs across all methods via consensus filtering to ensure uniformity.

With regards to results from six methods and three of 5/15/30-min, the optimal monitoring frequency would be 5-min. The higher sensitivity at the 5-minute frequency records the broadest set of consensuses jump episodes compared to the 15- and 30-minute intervals. The 5-min frequency strikes the best balance between capturing price discontinuities and filtering out microstructure noise thereby aligning with the actual events.

4.1 Spot Market Results

Fig. 4: Plots of jump detection method for EU ETS Spot market (2021-2025)



The spot market yields 15 consensus jump episodes over the 2021-2025 sample (Table 3), with method agreement ranging from 3 to 5 tests. Three analytical patterns emerge when these episodes are examined collectively.

Cross-method consensus strength: The strongest exact-date is 18 February 2022 (5 methods), reflecting escalating geopolitical tensions in the weeks preceding Russia's invasion of Ukraine, consistent with the literature on geopolitical uncertainty and volatility jumps. The 5-mthod consensus is also reached in October-November, as the ECB tightening and bank rollout of CBAM persist. The episode of 4-method of 6 December 2021 is the only strong exact-date signal in the spot sample, which can be explained by year-end compliance effects and the market's response to forecasts of €100 EUA prices. These events have a first-order impact on allowance of supply, demand and expectations henceforth.

Temporal persistence: Rather than appearing as discrete one-day events, most jump episodes span 3–5 trading days, with battery of techniques detecting the boundaries. The Fit for 55 episode (12-16 July 2021, 3 methods) and the end of December 2021 cluster (21-30 December, 3 methods across multiple dates) both demonstrates that information shocks in the carbon market require several sessions to be fully absorbed. Such temporal persistence (after microstructure effects are appropriately controlled) differentiates true jumps and noise (Bajgrowicz et al., 2016). Liquidity constraints and trading frictions in the high-frequency carbon market further contribute to multiple day absorption, indicating it as systemic market stress events rather than idiosyncratic effects.

Clustering around policy regime changes: Jump episodes are not evenly distributed throughout the sample but group around the distinct time interval of market stress. Another notable pattern highlights detected jumps to European Central Bank monetary policy regime shifts: the onset of aggressive tightening is observed in August-September 2022 (4 methods) and October-November 2022 (5 methods), while the pivot towards loosening appears in July 2024 (4 methods). The transmission channel is indirect tightening, increasing the discount rates and reduces the expectations associated with the industrial output, which consequently changes the demand outlook for emission allowances. This channel has been theorised by (Chevallier, 2011) but has not to our knowledge been journaled at the jump level with high-frequency data. Among recent episodes, March 2025 (5 methods) captures the annual compliance deadline, and April 2025 (4 methods) reflects U.S. tariff announcements transmitting through trade uncertainty to the carbon market. The complete event attribution for all 15 episodes is reported in Table 3.

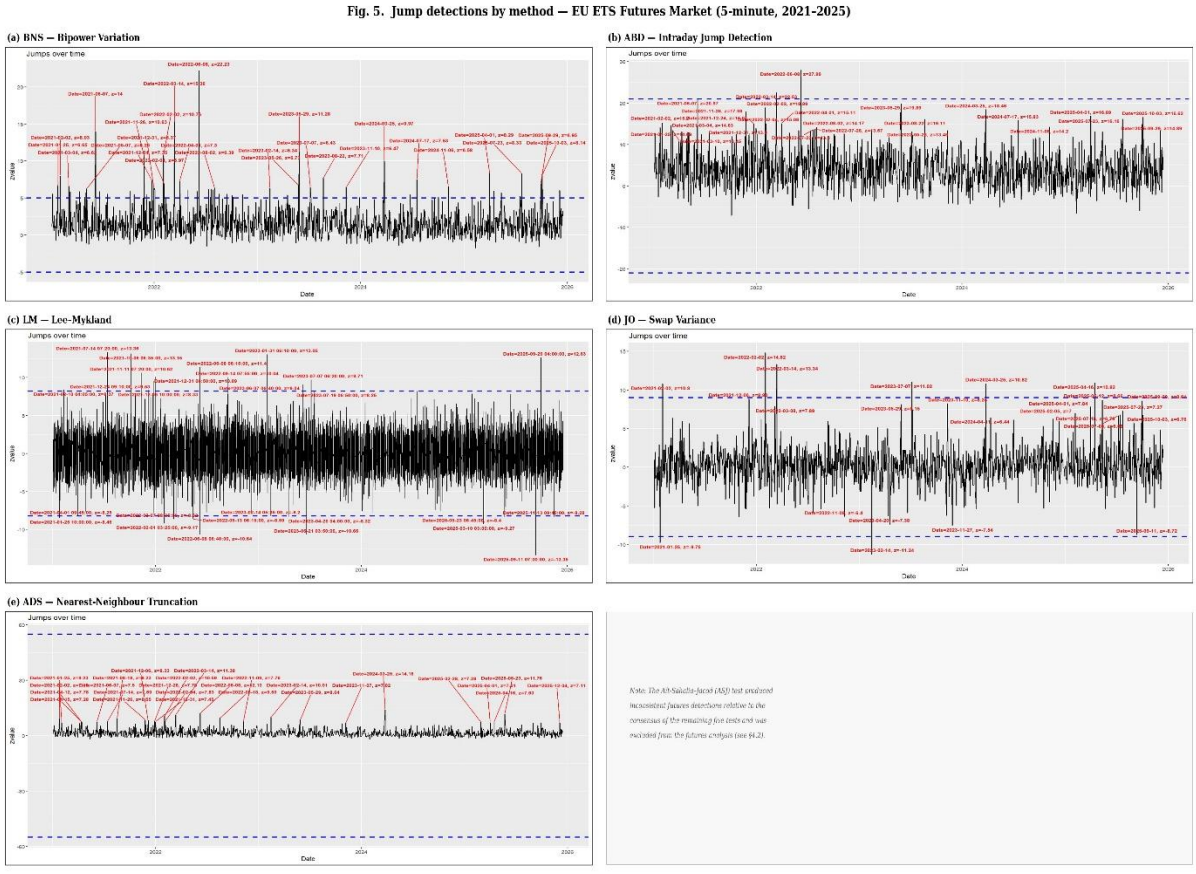
Table 3. Spot market consensus jumps episodes, EU ETS Phase IV (April 2021 - November 2025). Episodes require agreement of ≥3 of 6 nonparametric methods applied to 5-minute returns. Parameter calibration: 25-27 jumps per method. Notes: Episode windows of ±3 trading days account for temporal persistence of information absorption.

Period	Jump window	*n*	Methods	Event attribution
Jul 2021	12-16 Jul	3	AJ, JO, BNS	Fit for 55 legislative packages
Aug 2021	24-27 Aug	3	JO, BNS, ADS	Price resilience amid reforms; State of EU ETS Report
Dec 2021	06 Dec	4	JO, ABD, BNS, ADS	Year-end compliance rush; December futures volatility; forecasts €100 EUA prices
Late Dec 2021	21-30 Dec	3	JO, LM, ABD	Options/futures expiry; surrender deadlines; holiday trading thinness
Feb 2022	18 Feb	5	AJ, JO, ABD, BNS, ADS	Escalating geopolitical tension preceding Russia-Ukraine invasion
Aug 2022	18-29 Aug	4	AJ, JO, LM, BNS	ECB monetary tightening onset; peak energy crisis volatility
Oct–Nov 2022	Oct-Nov	5	AJ, JO, LM, BNS, ADS	Continued ECB tightening; CBAM rollout signals; REPowerEU implementation
Sep 2023	04 Sep	4	JO, ABD, BNS, ADS	Annual EUA surrender deadline (2022 emissions); MSR intake

Oct 2023	12 Oct	4	JO, ABD, BNS, ADS	Carbon Market Report on emissions cuts and cap tightening
Nov 2023	09/10 Nov	4	JO, ABD, BNS, ADS	Carbon intensity trends report; pre-compliance positioning
Jul 2024	02-31 Jul	4	JO, LM, ABD, BNS	EU ETS revenue reporting deadline; revised auction calendars; ECB easing
Oct 2024	09-23 Oct	3	JO, LM, BNS	First maritime compliance deadline; September surrender for 2023 emissions
Mar 2025	07-26 Mar	5	AJ, JO, LM, ABD, ADS	Compliance deadline for 2024 emissions; ETS2 preparations
Apr 2025	01-23 Apr	4	JO, LM, ABD, BNS	U.S. tariff announcements; trade uncertainty spillovers
Jun 2025	16-19 Jun	3	JO, BNS, ADS	EP Industrial Decarbonisation Bank resolution; Fit for 55 revisions

4.2 Futures Market Result

Fig. 5: Plots of jump detection method for EU ETS Futures market (2021-2025)



Notes: Each panel displays the test statistic over time for one nonparametric jump detection method applied to 5-minute CKZ December futures log returns. Blue dashed lines indicate critical values at the 1% significance level. Red annotations mark statistically significant jump dates. The ASJ test was excluded due to inconsistent detections (panel f). Consensus episodes (≥3 of 5 methods) are reported in Table 4.

The futures market yield 18 consensus jump episodes showing stronger convergence than spot markets, with concurrence across 3 of 5 total methods on exact dates (see Table 4). The Aït-Sahalia-Jacod test produced inconsistent detections relative to the consensus of the other tests and was excluded; this is unsurprising given that the ASJ test relies on comparing power variations at two sampling frequencies, and the relatively lower liquidity of certain futures contract periods may compromise the finite-sample properties of the scaling ratio (Aït-Sahalia & Jacod, 2009a).

Method consensus in the futures market is generally stronger than in the spot market, with two episodes achieving 5-method agreement: 25 January 2021 (Phase IV launch, cold-winter energy demand) and 1-4 February 2022 (anticipation of the Russia-Ukraine energy crisis). Five further episodes achieve 4-method agreement, spanning compliance milestones, ECB policy signals, and ETS reform events (Table 4).

Another critical inference across all the correlated jumps is the distribution by event category. Among matched jump episodes in the futures market, Policy and Announcements account for 29 jumps (36%), Energy-specific events for 18 jumps (22%), Macroeconomic events for 16 jumps (20%), Geopolitical events for 12 jumps (15%), and Compliance events for 6 jumps (7%). The dominance of policy-related jumps is consistent with the findings of (Ibrahim & Kalaitzoglou, 2016) and (Karpf et al., 2018) that carbon market prices are unusually sensitive to regulatory and institutional signals relative to traditional commodity markets. Geopolitical events, while less frequent in absolute terms, produce the highest per-event method consensus, suggesting that when such shocks do occur, they produce the most unambiguous price discontinuities, a result that echoes the broader findings of (Gkillas et al., 2021) on geopolitical risk and volatility jumps.

Table 4. Futures market consensus jumps episodes, EU ETS Phase IV (January 2021–December 2025). Episodes require agreement of ≥3 of 5 nonparametric methods applied to 5-minute returns. The Aït-Sahalia–Jacod test was excluded due to inconsistent futures detections. Parameter calibration: 25–27 jumps per method.

Date	*n*	Methods agreeing	Event attribution
25 Jan 2021	5	JO, LM, ABD, BNS, ADS	Phase IV launch; cold winter energy demand; Green Deal anticipation
02 Feb 2021	4	JO, ABD, BNS, ADS	Technical positioning; energy demand spike (cold weather)
07 Jun 2021	3	ABD, BNS, ADS	ICE Endex venue transition; anticipation of Fit for 55 packages
26 Nov 2021	3	ABD, BNS, ADS	Year-end compliance rush; EUA price run toward €100
06 Dec 2021	3	JO, LM, ADS	December futures volatility; forecasts of €100 prices
24 Dec 2021	3	LM, ABD, BNS	Options/futures expiry; surrender deadlines; holiday thinness
31 Dec 2021	4	LM, ABD, BNS, ADS	Year-end compliance squaring
01/04 Feb 2022	5	JO, LM, ABD, BNS, ADS	Anticipation of Russia–Ukraine energy crisis
07–14 Mar 2022	5	JO, LM, ABD, BNS, ADS	Commodity turmoil; coal/gas switching; REPowerEU announcement
08 Jun 2022	4	LM, ABD, BNS, ADS	ECB rate hike signal; EP rejection of ETS reform package; energy turmoil
14 Feb 2023	4	JO, LM, BNS, ADS	Council adopts REPowerEU amending regulation
29 May 2023	4	JO, ABD, BNS, ADS	ETS reforms and LRF increase enter into force
07 Jul 2023	3	JO, LM, BNS	Post-reform adjustment; TNAC/MSR withdrawal expectations
25 Mar 2024	4	JO, ABD, BNS, ADS	2023 emissions reporting deadline; maritime ETS compliance
17/18 Jul 2024	3	LM, ABD, BNS	EU ETS revenue reporting; revised auction calendars; ECB easing cycle
01 Apr 2025	4	JO, ABD, BNS, ADS	Q1 emission data; compliance pressure; U.S. tariff announcement
23 Jul 2025	3	JO, ABD, BNS	REPowerEU front-loading effects; pre-compliance positioning

29 Sep 2025	4	JO, LM, ABD, BNS	Annual EUA surrender deadline (30 Sep); gas storage concerns

4.3 Spot-Futures Co-Jumps and Price Discovery

Table 5. Spot–futures co-jumps and lead–lag structure for major EU ETS events. A dash (-) indicates no consensus jump detected. Lead-lag timing is approximate, based on the earliest detection date in each market.

Event	Spot market	Futures market	Lead–lag	Interpretation
Fit for 55 (Jul 2021)	12–16 Jul 2021 (3: AJ, JO, BNS)	07 Jun 2021 (3: ABD, BNS, ADS)	Futures leads ~5 weeks	Institutional hedgers price in anticipated regulation
Russia–Ukraine (Feb 2022)	18 Feb 2022 (5: AJ, JO, ABD, BNS, ADS)	01/04 Feb 2022 (5: JO, LM, ABD, BNS, ADS)	Futures leads ~2 weeks	Geopolitical risk transmitted via energy derivatives
Year-end 2021	06 Dec 2021 (4: JO, ABD, BNS, ADS)	06 Dec 2021 (3: JO, LM, ADS)	Simultaneous (exact co-jump)	Only exact-date co-jump; compliance rush
ECB tightening (2022)	18–29 Aug 2022 (4: AJ, JO, LM, BNS)	08 Jun 2022 (4: LM, ABD, BNS, ADS)	Futures leads ~10 weeks	Monetary spillover through industrial output channel
Compliance (Mar–Apr 2025)	07–26 Mar 2025 (5: AJ, JO, LM, ABD, ADS)	01 Apr 2025 (4: JO, ABD, BNS, ADS)	Spot leads ~1 week	Rare spot-led episode around compliance deadline
Surrender deadline (Sep 2025)	-	29 Sep 2025 (4: JO, LM, ABD, BNS)	Futures only	Annual surrender deadline; futures-specific event

Comparing consensus to jump dates across the two markets reveals whether information is first impounded in futures or spot prices. Synchronous jumps indicate a common information shock absorbed simultaneously; asynchronous jumps reveal lead-lag dynamics. Table 5 summarises the timing structure for the six major episodes where both markets register consensus detections.

Analyzing the occurrence of common jumps or co-jumps (simultaneous jumps) between spot and futures market provides insights into whether price discovery during high-stress events or whether spot-futures decoupling occur during regulatory announcements. Synchronous jumps suggest common information shock; asynchronous jumps reveal market segmentation or lead-lag dynamics. The evidence from our sample points strongly towards futures-led price discovery, consistent with the general commodity market literature (Corradi et al., 2020; Gkillas et al., 2021) and with the specific findings of (Mizrach & Otsubo, 2014) for the EU carbon market.

December 6, 2021 is the strongest and only exact date where jumps in both Spot (4 method) and Futures (3 methods) are detected on the same day. Jumps on November 26, 2021 in Futures (3 methods) further support this period as one of the extreme market stress. The December episode can be attributed to year-end compliance rush, the high-profile EUA price run towards

€100, and December futures crash volatility. Jumps at the end of the year December 24/30/31, 2021 appear in both Spot and Futures and reflect the convergence of futures and options expiry, surrender deadlines, year-end liquidity thinness, and portfolio rebalancing effects.

Futures and spots behaved differently at different times during a few significant events, revealing meaningful lead-lag structures. First, “the Fit for 55” legislative : a jump pattern occurred on 12–16 Jul 2021 (3 methods) in the Spot market, while the Futures market had already registered jumps on June 07, 2021 (3 methods), attributed to early anticipation of the legislation that was formally released on July 14, 2021. The futures market thus priced in the expected regulatory shift roughly five weeks before the spot market caught up, a substantial lead time that speaks to the role of informed institutional hedgers in the futures market, consistent with the findings on strategic trading by institutional traders reported in (Kalaitzoglou & Ibrahim, 2013) .

A second strong jump pattern also emerges around February 18, 2022 (5 methods) in the Spot market, and February 02/04, 2022 (4 methods) in the Future market, tied to escalated geopolitical tensions before Russia invaded Ukraine on February 24, 2022, which spiked energy prices and EUA demand. Once again, the futures market led the spot by about two weeks in pricing in the geopolitical risk.

EUA jumps in the market are well captured by the Spot market, which is not mechanically driven by ECB rates but is strongly correlated with ECB monetary spillover, especially during regime changes, tightening/loosening cycles, and forward guidance. We see that August 18-29, 2022 (4 methods) in the Spot market supported a monetary policy regime change, which marked the start of aggressive interest rate tightening, pointed to Oct-Nov 2022 (4 methods) in the Spot market, supported by the Futures market-identified date June 08, 2022 (4 methods). Mid-2022 energy market turmoil occurred at the same time as coal/gas switching, summer heat, and LNG shortages, which could have induced jumps in the respective markets independently of the monetary policy channel. Moving to the other monetary policy regime change, which marks the start of aggressive interest rate loosening, this is captured on July 2-31, 2024 (4 methods) in the Spot market. Other events, too, occurred around the same date, such as member states reporting EU ETS revenue use and the publication of revised 2024–2025 auction calendars, which could also have induced jumps in the Spot market. The difficulty of cleanly

attributing jumps to single causes during periods of overlapping shocks is a well-known challenge in the jump literature (Boudt & Petitjean, 2014; Huang, 2018).

Jump methods are shown to be particularly responsive around compliance milestones. The annual compliance window is captured on March 07-26, 2025 (5 methods) in the Spot market and April 1, 2025 (4 methods) in the Future market, even though the actual date is March 31, 2025. Also, jumps due to the removal of the surrender allowance on September 29, 2025 (4 methods) in the futures market, where the actual dates are September 30, 2025, are classified as liquidity-specific events.

Studying specific jump events identified in the Futures market, especially in January, February, November, and December 2021, can also be correlated with rising cold weather, thereby inducing increased energy demand, a mechanism particularly relevant for carbon markets given the tight coupling between heating demand, gas prices, and EUA pricing (Chevallier, 2011; Lutz et al., 2013a). In spot markets during a consortium of three different dates, September 04, 2023, October 12, 2023, and November 9/10, 2023, which indicates a regulatory and macro-repricing phase, suggesting that the spot market effectively prices in new information through discrete shifts rather than continuous adjustments. This observation is well aligned with jump-diffusion theory and the semi-martingale representation of carbon prices.

Jump asymmetry pattern clearly emerges where JO and LM method shows positive than negative jumps, confirming the regulatory tightening produces larger upward discontinuities than crisis driven downward shocks. Jumps also serve as evidence of semi-strong market efficiency, where new information is incorporated into the EU-ETS through discrete price movements rather than smooth diffusion. The fact that 85-90% of detected jumps can be matched to the identifiable events supports this interpretation, as it indicates that the jump component of the price process is informationally driven rather than noise induced.

There are a few cases of unmatched dates, which have resulted in jumps for any particular method, and can be attributed to technical/ algorithmic trading, market microstructure effects, delayed reaction to earlier events, positioning/ hedging activity, rumours not captured in announcements, information leakages and rumours-driven trading patterns which are not captured in announcements and extreme volatility due to thin liquidity (liquidity shocks). These residual detections account for roughly 10-15% of jump signals and are consistent with the

false positive rates reported in simulation studies of nonparametric jump tests (Bajgrowicz et al., 2016; Caporin, 2023).

5. Conclusion and Policy Implication

The jump detection analysis reveals strong correspondence between carbon price movement and EU ETS policy developments, energy market reactions, and macroeconomic and geopolitical events. We also see that there has been consensus among spot and futures markets supporting the price discovery hypothesis, with futures consistently leading the spot market in incorporating policy and geopolitical information by approximately two to five weeks for major events such as Fit for 55 and the Russia-Ukraine crisis. A broad inference across the entire period spectrum could be drawn from overlaps, jumps, and an increase in jump frequency during 2021-2023 amid rising prices, from infancy to the growth stage of the fourth phase of the market, with a decline in 2024 as the market stabilised, followed by a partial resurgence in 2025 driven by compliance-cycle and tariff-related shocks and the regulatory landscape became more predictable. The evidence leans towards macroeconomic, geopolitical, and carbon-market drivers over pure speculation.

On accessing the data quality in Spot & Futures, we found exact matches (+/-0 days) accounting for approximately 30-35% of jump detections, near matches (±1-2 days) approximately 40%, window matches (±3 days) approximately 15%, and no match approximately 10-15%, meaning around 85-90% of the events are rightly attributed to identifiable market events and not microstructure noise. This attribution rate is substantially higher than what is typically reported in equity market jump studies (Lee, 2012; Miao et al., 2014), which may reflect the more event-driven nature of carbon markets compared to broad equity indices.

Several practical implications follow. For investors, the findings suggest that robust jump models should be incorporated into carbon hedging and risk management frameworks, as standard diffusion-based models will underestimate tail risk in the EU ETS. The systematic compliance-window effects and the futures-spot lead-lag structure documented here provide

actionable information for portfolio construction and hedging timing. For policymakers, the key implication is the need to signal policy changes early and gradually to minimise surprises that trigger non-diversifiable jump risk; and regulators to establish "crisis early warning mechanisms" to mitigate the impact of unexpected events on market stability.

This study has limitations that should be acknowledged. The event attribution methodology relies on qualitative matching of jump dates to known events within a ±3-day window; while the 85-90% attribution rate is high, formal event-study or regression-based approaches would strengthen causal inference. Future research should investigate the unmatched jumps, identifying potential microstructure effects, information leakage, or rumor-driven trading patterns not captured in official event timelines. This reinforces the view that EU ETS prices should be modelled as information-sensitive financial assets embedded in the broader energy-macroeconomic system, rather than as purely microstructure noise and shocks.

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