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(Citation)

International Review of Finance, 26(3):e70099

(Issue Date)

2026-09

(Resource Type)

journal article

(Version)

Version of Record

(Rights)

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SPECIAL ISSUE ARTICLE OPEN ACCESS

Intraday and Daily Price Discovery in Carbon Markets: EUA Futures Versus Carbon ETFs

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ABSTRACT

We investigate intraday price discovery between EUA futures and a US-listed carbon ETF (KEUA) using hourly data and a state-space model that separates efficient-price innovations from transitory noise and allows adjustment speeds to differ across trading-hour regimes. Results show that intrinsic-value-relevant innovations are concentrated when the futures market is active: during ETF-only hours, efficient-price innovations are small and the ETF exhibits little contemporaneous adjustment, implying largely transitory quote dynamics. During overlapping hours, both markets incorporate innovations rapidly, with the ETF adjusting at least as quickly as futures on average, while time variation in relative efficiency is linked to cross-market liquidity and policy regimes. Around major within-sample Fit-for-55/EU ETS reform milestones, price discovery shifts relatively toward EUA futures, suggesting that policy-sensitive information is incorporated primarily through the futures market. At the daily frequency, auctions, futures, and the ETF are tightly integrated: shocks transmit bidirectionally, and longer-horizon variation is increasingly associated with ETF-related innovations, consistent with a venue-interactive EU ETS pricing system.

JEL Classification: G10, G14, Q58, C32, G15

1 | Introduction

Efficient price discovery is central to the functioning of cap-and-trade systems. In the EU Emissions Trading System (EU ETS), the allowance price guides abatement decisions, compliance planning, and investment in low-carbon technologies. As carbon markets have matured, trading has become increasingly financialised, raising a natural question: how is the EU ETS price formed across the growing set of trading venues and instruments, and when do different venues lead the incorporation of new information?

A substantial literature documents the prominent role of EUA futures in EU ETS price discovery. Following the introduction and rapid growth of futures trading, studies such as Mizrach

and Otsubo (2014) and Rittler (2012) show that futures prices are central to the information aggregation process for EU Allowances (EUAs). More recently, financialisation has extended to exchange-traded funds (ETFs), which broaden access to carbon exposure and may deepen liquidity, but also create new cross-market linkages. Related ETF theory emphasizes that ETF effects on underlying market quality depend on *market accessibility* and the strength of the *arbitrage linkage* between the ETF and the underlying asset. In particular, Holden and Nam (2024) predict that when the underlying market is relatively inaccessible, ETF trading can attract new uninformed participation and improve underlying price formation via arbitrage spillovers, whereas when arbitrage capacity is weak, the ETF can instead transmit more noise than signal. This mechanism-based view motivates our focus on session dependence: in our setting,

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arbitrage feasibility varies mechanically across non-overlapping and overlapping trading hours.

Because EUAs are a regulated asset with supply determined by policy and auction schedules, ETF demand and inventory management can plausibly interact with underlying futures pricing and, ultimately, with primary-market price formation. Moreover, unlike conventional financial assets, EUAs are policy-created assets whose long-run scarcity value is shaped by regulatory decisions on emissions caps, auction supply, and market design. Major EU ETS reform milestones can therefore alter not only price levels but also the informational environment in which different trading venues incorporate value-relevant news. Despite this institutional relevance, direct evidence on how carbon ETFs affect the price discovery process of their underlying EUA futures is still limited. Existing work on carbon ETFs, including Shrestha et al. (2023), focuses primarily on comparing price discovery across ETFs rather than assessing how an ETF interacts with, and potentially contributes to, price discovery in the underlying futures market. This paper addresses that gap by studying price discovery between EUA futures traded on ICE and a leading EUA-focused ETF traded on NYSE. We focus on the KraneShares European Carbon Allowance Strategy ETF (KEUA), which provides direct exposure to EUA futures and therefore offers a clean setting to study ETF–futures interaction.¹ Unlike most studies that examine basket ETFs, our setting features an ETF with near single-asset exposure to EUA futures. This substantially reduces confounding forces—such as index reconstitutions, multi-constituent stale pricing, and diversification-driven flows—so that deviations between the ETF-implied synthetic EUA price and the futures price can be interpreted mainly as reflecting ETF-specific microstructure and limits to arbitrage. As a result, we can more sharply identify how the informational content of ETF prices varies across non-overlapping versus overlapping trading sessions.

A key practical challenge is that the two markets operate on different trading schedules: EUA futures trade from 07:00 to 17:00 UK time, whereas KEUA trades from 10:00 to 16:00 US Eastern Time, implying substantial non-overlap. This asynchronicity is economically meaningful: information arrival, liquidity provision, and the ability of market makers and arbitrageurs to hedge exposures differ sharply across sessions. It also poses a methodological challenge, because standard reduced-form price discovery approaches based on cointegration and VECM frameworks (e.g., Hasbrouck (1995); Gonzalo and Granger (1995)) are designed for continuously and simultaneously traded prices and do not naturally accommodate informational dynamics when one market is closed.

To capture these session-specific dynamics, we use intraday quotes and adopt a state-space framework in which observed prices are decomposed into an efficient (latent) price component and transitory microstructure noise. We estimate the model by Kalman filtering and recover (i) the volatility of efficient-price innovations, which measures the size of intrinsic-value-relevant information flow, (ii) the volatility of transitory pricing noise, and (iii) market-specific adjustment coefficients that quantify how rapidly each observed price incorporates efficient-price innovations. Crucially, we estimate

these objects separately for (a) non-overlapping intervals (futures-only and ETF-only trading hours) and (b) the overlap interval when both markets are simultaneously open. This design allows us to distinguish limited information flow from limited adjustment, and to evaluate when the ETF can meaningfully participate in price discovery.

Beyond secondary-market interaction, EU ETS price formation also reflects the primary market for allowances. EUAs are supplied through auctions whose clearing price is economically meaningful: it reflects market-clearing demand for compliance instruments and is monitored by market participants as a key reference. We therefore complement the intraday analysis with a daily three-venue analysis of auctions, futures, and the ETF, aligning secondary-market prices to 4pm UK time (the time at which the ETF's NAV is computed). Using cointegration tests, a VECM, generalized impulse responses, and generalized forecast error variance decompositions, we assess long-run integration and bidirectional information transmission between the primary market and secondary markets.

Our findings can be summarized as follows. Intraday efficient-price innovations are concentrated in periods when the main futures market is active, whereas ETF-only hours exhibit little intrinsic-value-relevant information flow and little measurable ETF adjustment to latent innovations. During overlapping hours, however, information arrival is substantial and both markets incorporate innovations rapidly, with the ETF's price discovery at least as quickly as futures on average. Time variation in relative efficiency is systematically related to cross-market liquidity: larger futures trading volume and frequency are associated with relatively stronger ETF price discovery, whereas larger futures trade size is associated with futures-led price discovery, consistent with the greater informativeness of institutional or compliance-related futures trading. Around major Fit-for-55/EU ETS reform milestones, price discovery shifts relatively toward EUA futures, suggesting that policy-sensitive information is incorporated primarily through the futures market. At the daily frequency, auctions, futures, and the ETF are tightly integrated, and shocks transmit meaningfully across venues, consistent with a jointly price-discovering EU ETS system in which secondary-market pricing feeds back into primary-market clearing and auction outcomes convey scarcity information back to secondary markets.

This paper contributes to the growing literature on carbon-market microstructure and financialisation in four ways. First, it provides intraday evidence on ETF–futures price discovery under asynchronous trading, showing that the informational role of carbon ETFs is strongly session-dependent. Second, it offers a structural decomposition of information flow, transitory noise, and adjustment speed using a state-space model, suited to non-synchronous trading. Third, it shows that relative price discovery varies with relative trading volume and size, and policy-induced information. Fourth, it links secondary-market dynamics to primary-market price formation via auctions. More broadly, it adapts and extends state-space approaches used in fragmented and cross-listed markets (e.g., Menkveld et al. (2007); Otsubo (2014)) to the institutional setting of the EU ETS and to the new financial layer created by carbon ETFs.

The remainder of the paper proceeds as follows. Section 2 reviews the literature. Section 3 presents the intraday state-space model, estimation via Kalman filtering, and the interpretation of the key parameters capturing information arrival, transitory noise, and adjustment speed. Section 4 describes the data, including intraday quote construction, trading-hour definitions (futures-only, ETF-only, and overlap intervals), and the daily 4pm UK alignment used to incorporate auctions and the ETF NAV timing. Section 5 reports the empirical results, including regime-specific intraday price discovery, the determinants of relative efficiency, policy-event regimes, daily auction–futures–ETF interactions, and practical and policy implications. Section 6 concludes. Section 6 concludes.

2 | Literature Review

Price discovery—the process by which dispersed information is incorporated into traded prices—is central to market microstructure. In carbon markets it has particular policy salience: allowance prices guide compliance decisions and abatement incentives, so frictions that delay or distort information incorporation can weaken the efficiency and credibility of cap-and-trade.

Early EU ETS evidence highlights the leading role of EUA futures in carbon price formation. Using cointegration-based frameworks and information-share measures, Mizrach and Otsubo (2014) show that futures dominate price discovery relative to other carbon instruments, consistent with futures markets concentrating liquidity and informational trading. Using higher-frequency data, Rittler (2012) documents strong information transmission and spillovers in EUA markets, underscoring the importance of microstructure and trading intensity for short-run carbon price dynamics. Since these first works, a strand of literature has been devoted to this research question Alberola et al. (2008), Chevallier (2009), Bredin et al. (2014), Schultz and Swieringa (2014), Ibikunle et al. (2016), Stefan and Wellenreuther (2020), quite recently Vadhava (2025) has confirmed the high contribution of futures with the recent data.

This literature motivates treating futures as a benchmark while examining how newer vehicles interact with the futures-led process.

The growth of carbon-linked ETFs has expanded access to carbon exposure and may deepen secondary-market liquidity, but it can also introduce non-compliance demand, portfolio flows, and intermediary constraints into allowance pricing. Direct evidence on *ETF–underlying* price discovery in carbon markets remains limited. Shrestha et al. (2023) study price discovery across “carbon” ETFs using daily data and generalized information-share measures. However, the daily frequency and ETF-to-ETF focus leave open the key mechanism for allowance valuation: how a carbon ETF interacts with EUA futures at intraday horizons when liquidity, hedging capacity, and arbitrage are time-varying.

A broad ETF literature studies how creation–redemption and authorized-participant arbitrage link ETF prices to underlying values, and when those links weaken. ETF effects on informational efficiency depend on liquidity in both the ETF and the

hedge market, and premia/discounts can arise when intermediaries face balance-sheet or liquidity constraints (Madhavan and Sobczyk 2016). ETFs can also transmit demand shocks and amplify non-fundamental components of price dynamics when short-horizon trading and arbitrage flows are strong (Ben-David et al. 2018; Brown et al. 2021). Importantly, these mechanisms do not require a multi-asset basket: arbitrage operates through hedging and the creation–redemption channel, so they apply equally to near single-exposure ETFs.

Holden and Nam (2024) reconcile mixed evidence on ETF-linked trading and market quality Subrahmanyam (2015), Gorton and Pennacchi (1993), Jegadeesh and Subrahmanyam (1993), Israeli et al. (2017) by emphasizing *market accessibility*. In their framework, arbitrage-induced liquidity spillovers—potentially amplified by investor entry when the underlying is costly to access—can outweigh liquidity-trader migration from the underlying into the ETF; empirically, corporate bond ETF introductions improve underlying liquidity mainly for less accessible bonds and when ETF arbitrage activity is high. These insights speak naturally to carbon ETFs, where futures and ETF markets differ in trading hours, participant bases, and hedging opportunities. Asynchronous sessions mechanically vary arbitrage capacity, implying that ETF informativeness may be *session dependent*.

Standard price discovery metrics rely on cointegration and VAR/VECM representations. Seminal contributions include Hasbrouck (1995) and Gonzalo and Granger (1995), with later extensions such as generalized information-share measures (Lien and Shrestha 2014). These reduced-form approaches are typically applied when markets operate contemporaneously; when one venue is closed, lead–lag relations, liquidity provision, and arbitrage constraints differ sharply across sessions.

State-space models estimated by Kalman filtering address non-synchronous trading explicitly by separating efficient-price innovations from transitory noise while allowing market-specific adjustment. Menkveld et al. (2007) study cross-listed equities and show that leadership varies systematically with trading hours and market conditions. Otsubo (2014) similarly models price discovery across non-overlapping sessions with market-specific adjustment dynamics. This class of models is well-suited to carbon ETFs, where asynchronous trading is economically meaningful.

EU ETS price formation also involves the primary market (auctions). Auction outcomes reflect regulated supply and market-clearing costs of obtaining compliance instruments, so linking auctions to secondary-market price discovery complements the futures–ETF perspective by tracing information transmission between continuously traded venues and periodic primary-market clearing.

Building on these literatures, we contribute in three ways. First, we provide intraday evidence on ETF–futures price discovery under asynchronous trading, distinguishing futures-only, ETF-only, and overlapping sessions to identify when the ETF can meaningfully participate in information incorporation. Second, we connect the EU ETS setting to the ETF literature by focusing on arbitrage capacity, liquidity conditions, and flow-driven trading in a carbon ETF with concentrated exposure to EUA

futures. Third, we link secondary-market dynamics to primary-market price formation by incorporating daily auction prices and assessing long-run integration and bidirectional information transmission among auctions, futures, and the ETF using cointegration, VECM-based impulse responses, and forecast error variance decompositions.

Several mechanisms yield distinct predictions. A migration/adverse-selection view suggests liquidity traders substitute from the underlying into the ETF, potentially worsening adverse-selection in the underlying and shifting leadership toward the ETF even when both markets are open. An information-aggregation view emphasizes that ETF trading can concentrate information and improve price discovery, with gains transmitted to the underlying via arbitrage. Limits-to-arbitrage and flow-based channels imply that ETF flows can generate price pressure that is only imperfectly arbitrated away, making ETF variation noisier when arbitrage capital is constrained or the hedge market is unavailable. Holden and Nam (2024) unify these perspectives by highlighting *market accessibility* and the strength of the *arbitrage linkage*: ETF effects are most likely to be beneficial when the underlying is relatively inaccessible and arbitrage activity is strong, but can be noise-amplifying when arbitrage capacity is weak. Finally, a primary-market dominance mechanism is plausible in the EU ETS, whereby auctions reveal scarcity and compliance demand and secondary prices adjust to auction outcomes. These channels imply testable patterns in our setting: whether ETF leadership is persistent or *session dependent* (overlap vs. non-overlap), whether it co-moves with trading activity and quoted liquidity (arbitrage capacity) rather than volatility alone, and whether information transmission between auctions and secondary markets is bidirectional or predominantly from auctions to traded prices.

3 | The State Space Model for Price Discovery Analysis

We model intraday price discovery between EUA futures and the KEUA ETF using a state-space framework with a latent efficient price that follows a random walk and observed prices that partially adjust to efficient-price innovations and contain transitory microstructure noise. The model is estimated by maximum likelihood via the Kalman filter.

The specification follows the state-space price discovery approach used in cross-listed and fragmented markets (Menkveld et al. 2007; Otsubo 2014). It is well suited to our setting because EUA futures (ICE Europe, 07:00–17:00 UK time) and KEUA (NYSE, 10:00–16:00 ET) trade with substantial non-overlap, implying time-varying arbitrage capacity and mechanically missing observations when one venue is closed. We represent the ETF as a synthetic EUA price implied from KEUA and estimate regime-specific parameters for futures-only, ETF-only, and overlapping hours: efficient-price innovation volatility σ_η , transitory noise volatilities σ_ϵ , and adjustment coefficients θ . This decomposition separates information arrival from price adjustment and allows us to quantify how price discovery shifts across trading sessions.

Observed log prices are noisy, market-specific signals about the common efficient price. A key feature of our specification is *partial adjustment*: at time t , each observed price is anchored at the previous efficient price m_{t-1} and incorporates only a fraction of the current-period efficient-price innovation, plus transitory microstructure noise. This formulation cleanly separates (i) *information arrival* in the efficient price from (ii) *how quickly* each market incorporates that information and (iii) *quote-level noise*.

Let $p_{1,t}$ denote the log EUA futures mid-quote and $p_{2,t}$ denote the log *synthetic* EUA price implied by the KEUA ETF (constructed to reflect the ETF's fundamental exposure to EUA futures; see Section 4.2). The latent efficient price m_t follows a random walk with a session-dependent innovation volatility (defined in the state equation below). Define three mutually exclusive trading-hour regimes:

$$s(t) \in \{\text{EUA-only}, \text{KEUA-only}, \text{overlap}\},$$

corresponding to intervals in which only the EUA futures market is open, only the ETF market is open, or both markets are simultaneously open.

Efficient-price innovation input. Write the efficient-price increment as follows:

$$\Delta m_t \equiv m_t - m_{t-1} = \sigma_{\eta,s(t)} \eta_t, \quad \eta_t \sim \mathcal{N}(0, 1),$$

where $\sigma_{\eta,s(t)}$ is regime-specific:

$$\sigma_{\eta,s(t)} = \begin{cases} \sigma_{\eta,\text{EUAonly}} & \text{if } s(t) = \text{EUA-only}, \\ \sigma_{\eta,\text{KEUAonly}} & \text{if } s(t) = \text{KEUA-only}, \\ \sigma_{\eta,\text{overlap}} & \text{if } s(t) = \text{overlap}. \end{cases}$$

Partial-adjustment observation equations. Conditional on the regime, observed prices satisfy

$$p_{j,t} = m_{t-1} + \theta_{j,s(t)} \Delta m_t + \sigma_{\epsilon_j,s(t)} \epsilon_{j,t}, \quad \epsilon_{j,t} \sim \mathcal{N}(0, 1), \quad j \in \{1, 2\},$$

where $\theta_{j,s(t)}$ captures the *speed of price discovery* (how much of Δm_t is impounded contemporaneously), and $\sigma_{\epsilon_j,s(t)}$ captures *transitory pricing noise* in market j in that regime. We allow both θ and σ_ϵ to differ across trading-hour regimes to reflect changes in arbitrage capacity and liquidity provision.

Writing the equations explicitly by regime gives:

- i. EUA-only hours (non-overlap). Only the futures market is observed:

$$p_{1,t} = m_{t-1} + \theta_{1,\text{EUAonly}} \cdot \sigma_{\eta,\text{EUAonly}} \eta_t + \sigma_{\epsilon 1,\text{EUAonly}} \epsilon_{1,t}, \quad s(t) = \text{EUA-only}, \quad (1)$$

and $p_{2,t}$ is missing (ETF market closed).

- ii. KEUA-only hours (non-overlap). Only the ETF-implied synthetic price is observed:

$$p_{2,t} = m_{t-1} + \theta_{2,\text{KEUAonly}} \cdot \sigma_{\eta,\text{KEUAonly}} \eta_t + \sigma_{\epsilon 2,\text{KEUAonly}} \epsilon_{2,t}, \quad s(t) = \text{KEUA-only}, \quad (2)$$

and $p_{1,t}$ is missing (futures market closed).

- iii. Overlapping hours. Both markets are observed and may incorporate information at different speeds and noise levels:

$$p_{1,t} = m_{t-1} + \theta_{1,\text{overlap}} \cdot \sigma_{\eta,\text{overlap}} \eta_t + \sigma_{\epsilon_{1,\text{overlap}}} \epsilon_{1,t}, \quad (3)$$

$$p_{2,t} = m_{t-1} + \theta_{2,\text{overlap}} \cdot \sigma_{\eta,\text{overlap}} \eta_t + \sigma_{\epsilon_{2,\text{overlap}}} \epsilon_{2,t}, \quad s(t) = \text{overlap}. \quad (4)$$

Interpretation. When $\theta_{j,s(t)} = 1$, market j fully incorporates the contemporaneous efficient-price innovation within the interval; values below one indicate sluggish incorporation. As θ can occasionally exceed one indicating “over-adjustment”, for cross-market comparisons we therefore also use absolute deviations from full adjustment, $|1 - \theta|$, as a robust inefficiency metric. Transitory noise $\sigma_{\epsilon_{j,s(t)}}$ captures deviations from the intrinsic value and need not move one-for-one with informational efficiency; hence we also consider the noise-to-information ratio $\sigma_{\epsilon_{j,s(t)}} / \sigma_{\eta,s(t)}$.

Distributional assumptions. Innovations η_t , $\epsilon_{1,t}$, and $\epsilon_{2,t}$ are i.i.d. standard normal and mutually independent. Missing observations arise mechanically when a market is closed and are handled naturally by the Kalman filter.

4 | Data

The dataset comprises intraday best bid and offer prices of EUA futures and the KEUA ETF, along with exchange rate data, spanning 3 years, observed at hourly frequency. All the data are obtained from LSEG Tick History. EUA futures are standardized contracts for EUA, obligating the holder of a long position to purchase EUAs at a predetermined price on the contract's expiry date. The most actively traded EUA futures contracts are December expiry and are traded on the ICE during European trading hours. The KEUA is a carbon credit ETF that exclusively holds December-expiry EUA futures contracts. KEUA issues shares, which investors can trade on the secondary market. As an actively traded US-listed ETF, KEUA is primarily traded on NYSE. The fund continuously rolls its holdings to maintain exposure to the nearest December-expiry EUA futures contract. A key advantage of selecting KEUA ETF for this study is its exclusive focus on EUA futures, simplifying the computation of the synthetic EUA futures price. Unlike carbon ETFs that hold multiple asset classes, KEUA's structure eliminates the need to estimate the proportional weight of EUA futures within a broader portfolio. If the market is efficient, the NAV should reflect the intrinsic value of KEUA per share, corresponding to the value of its EUA futures holdings. Using this relationship, we compute the EUA futures price implied by KEUA's trading price and incorporate it into our analysis.

A precise synthetic EUA futures price is essential for testing price discovery, as errors in computation can lead to misleading conclusions about arbitrage efficiency. Since EUA futures trade on ICE Europe, while KEUA ETF trades on NYSE with non-overlapping sessions, direct price comparisons require careful synchronization of timestamps, NAV updates, and currency conversions. For each year under study, we focus on

the EUA futures contracts expiring in December 2022, 2023, and 2024. We obtain hourly best bid and ask prices to compute mid-quotes for EUA futures and KEUA ETF prices. Similarly, for currency conversion, we extract hourly best bid and ask prices for the EUR/USD exchange rate and compute mid-quotes accordingly.

While KEUA's NAV per share is available, it is only reported daily at the London closing time (4PM UK local time). Additionally, we incorporate records of KEUA's outstanding shares, which are updated whenever changes occur, aligning them with the daily NAV data. In this study, NAV per share is aligned to London closing prices (4PM UK time), while ETF market prices are recorded during NYSE trading hours (10:00–16:00 US Eastern Time). The number of ETF shares issued is forward-filled to account for infrequent updates, and synthetic EUA prices are computed using bid-ask mid-quotes.

All datasets are timestamped in Coordinated Universal Time (UTC), requiring adjustments for trading hours and market-specific time zones. To mitigate bid-ask bounce, we compute the mid-quote for EUA futures and KEUA ETF prices as follows:

$$\text{Mid-Quote} = \frac{\text{Best Bid Price} + \text{Best Ask Price}}{2} \quad (5)$$

The best bid and best ask prices at the beginning of each 1-h window are used for this calculation. The model is estimated using these intraday mid-quotes for EUA futures and the KEUA ETF, which undergo the following preprocessing steps. The KEUA rolls its futures contracts before expiration by selling expiring contracts and reinvesting in later-dated ones, but the exact timing is not specified in the fund's prospectus. KraneShares notes that the rollover depends on the adviser's discretion to optimize yield, implying that the transition likely occurs before December expiration to avoid last-minute execution risks and potential liquidity constraints (KraneShares (2024)). Therefore, December observations were excluded from the empirical analysis to avoid distortions from rollover effects.

4.1 | Trading Hours and Session Definitions

EUA futures trade on ICE Europe from 07:00 to 17:00 London local time, while the KEUA ETF trades on NYSE Arca from 09:30 to 16:00 U.S. Eastern Time. Because the UK and U.S. switch to and from daylight saving time on different dates, the overlap between these two trading sessions varies within the calendar year. We therefore determine trading-hour regimes using exchange-local clocks (London time for ICE; Eastern time for NYSE), applying the appropriate daylight saving time conventions.

Figure 1 illustrates the three hourly regimes used in the intraday model: *EUA-only* hours (ICE open, NYSE closed), *KEUA-only* hours (NYSE open, ICE closed), and *overlap* hours (both open). In most of the year, the overlap window is 09:30–12:00 Eastern time (14:30–17:00 London time), that is, 2.5 h of simultaneous trading. During the UK–U.S. daylight-saving transition weeks,

the overlap shifts by 1 h in London time, but the regime classification remains correct because it is defined by each venue's local trading schedule.

For model estimation, we work with hourly observations and set prices outside a venue's trading hours to missing. Weekends are excluded. We also remove days that are holidays for the relevant venue(s). Missing observations arising from market closure are treated as missing and are handled naturally by the Kalman filter.

4.2 | Synthetic EUA Price Computation

Unlike direct EUA futures prices, which trade on ICE Europe, the KEUA ETF provides an alternative means of accessing EUA price exposure through an ETF structure on NYSE. To ensure a valid price comparison and enable robust price discovery analysis, the synthetic EUA futures price is computed by integrating the KEUA ETF price, the EUR/USD exchange rate, the number of KEUA shares issued, and the NAV per share.

The synthetic EUA futures price, denoted as P'_E , is derived as follows:

$$P'_E = \frac{X \cdot P_K \cdot Q}{N} \quad (6)$$

where P_K represents the KEUA price in USD (computed as NAV per share), X is the EUR/USD exchange rate at the corresponding time, Q is the number of KEUA ETF shares issued, and N represents the number of EUA futures contracts

held by KEUA. Since N is not explicitly recorded, it is estimated as:

$$N = \frac{X \cdot \text{NAV}}{P_E} \quad (7)$$

where P_E is the observed EUA futures mid-price at 4 PM UK time, the time at which NAV is officially recorded.

Given the importance of ensuring data consistency and time alignment, missing NAV and shares issued values are forward-filled to maintain continuity in the dataset. Furthermore, synthetic EUA prices are computed only during NYSE trading hours (10:00–16:00 US Eastern Time), ensuring that the derived price aligns with the active trading window of KEUA ETF. This approach mitigates distortions that could arise from stale NAV updates or misaligned exchange rate conversions.

By using the synthetic price instead of the directly observed KEUA market price, we ensure that the ETF's valuation reflects its fundamental exposure to EUA futures rather than transient market frictions or NAV timing discrepancies. This adjustment enhances the robustness of the price discovery analysis by aligning the KEUA ETF with the underlying EUA futures contract more accurately.

Table 1 presents summary statistics for key variables used in the analysis. EUA futures and KEUA ETF prices exhibit similar mean values and standard deviations. The EUR/USD exchange rate remains relatively stable during the sample period. KEUA's market price closely tracks the NAV per share. The number of KEUA shares issued varies over time but is updated infrequently,

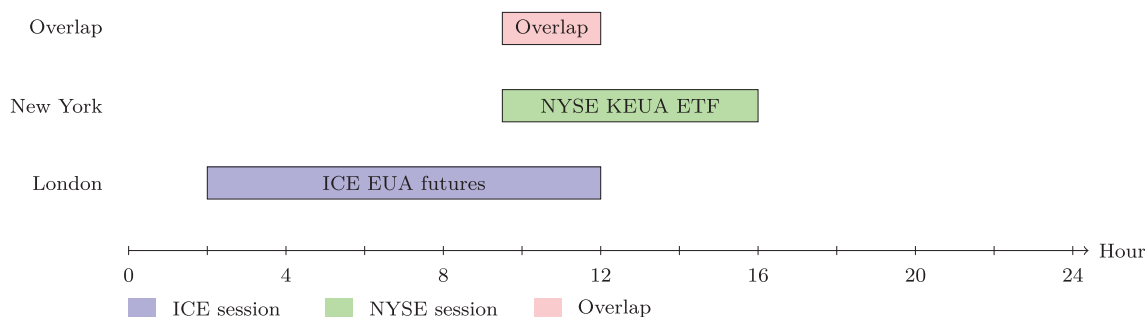


FIGURE 1 | Trading hours and overlap (New York local time). Sessions are defined in New York's local clock.

TABLE 1 | Summary statistics of key variables (January–November).

Variable	Mean	Std. Dev.	Min	Max	Observations
EUA Futures Mid-Quote Price (EUR)	77.75	10.64	51.47	101.13	7557
Synthetic EUA Futures Price (EUR)	77.71	10.63	52.10	100.65	4809
KEUA ETF Mid-Quote Price (USD)	28.01	4.62	17.83	37.89	4809
EUR/USD Exchange Rate	1.07	0.04	0.95	1.15	10,256
KEUA NAV per Share (USD)	28.02	4.61	17.86	37.41	687
KEUA Shares Issued (Millions)	0.64	0.24	0.05	1.03	10,256

Note: This table presents summary statistics for key variables used in the analysis, based on hourly observations from January to November. The synthetic EUA futures price is derived from KEUA ETF data using NAV per share, shares issued, and the EUR/USD exchange rate. The number of KEUA shares issued is updated infrequently and was forward-filled in the model to maintain consistency with high-frequency price data.

TABLE 2 | Table intraday state-space parameter estimates.

Parameters	2022	2023	2024	Average
Panel A: Non-overlap				
$\sigma_{\eta\text{EUAonly}}$	0.0107***	0.0064***	0.0075***	0.0082
$\sigma_{\eta\text{KEUAonly}}$	0.0021***	0.0009***	0.0006***	0.0012
$\sigma_{e1,\text{EUAonly}}$	0.0041***	0.0029***	0.0033***	0.0034
$\sigma_{e2,\text{KEUAonly}}$	0.0014***	0.0004***	0.0004***	0.0008
$\theta_{1,\text{EUAonly}}$	0.8219***	0.7054***	0.7098***	0.7457
$\theta_{2,\text{KEUAonly}}$	0.2549*	0.0000	0.0002	0.0850
Panel B: Overlap				
$\sigma_{\eta,\text{overlap}}$	0.0096***	0.0055***	0.0069***	0.0073
$\sigma_{e1,\text{overlap}}$	0.0062***	0.0031***	0.0033***	0.0042
$\sigma_{e2,\text{overlap}}$	0.0022***	0.0012***	0.0008***	0.0014
$\theta_{1,\text{overlap}}$	0.9299**	0.9718	0.9322***	0.9446
$\theta_{2,\text{overlap}}$	1.0237	1.0669***	1.0230**	1.0379
Panel C: Model fit				
Sample size	3375	3435	3446	3419
Log Likelihood	14329.2	17128.4	17016.5	16,158
AIC	−28636.4	−34234.8	−34011.0	−32,294
BIC	−28569.0	−34167.2	−33943.4	−32,227

Note: Panel A reports estimates for non-overlapping trading hours (EUA-only and KEUA-only sessions). Panel B reports estimates for overlapping hours when both markets are open. Statistical significance is denoted by ***, **, and * for $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively. Average values are simple means across years and are not starred. Panel C reports model fit statistics.

requiring forward-filling for consistency in the synthetic EUA futures price computation.

5 | Empirical Results

We begin with intraday price discovery between EUA futures and the EUA ETF, distinguishing ETF-only trading hours from periods when both markets are simultaneously open. This split is economically meaningful because information arrival, liquidity provision, and arbitrage capacity differ sharply across sessions.

5.1 | Intraday: Non-Overlapping Trading Hours

5.1.1 | Information Arrival: σ_{η}

We first examine the size of information arriving during non-overlapping trading hours using the volatility of the efficient price process. Table 2 (Panel A) shows that the estimated standard deviation of the efficient price innovations during the EUA-only session, $\sigma_{\eta,\text{EUAonly}}$, is economically meaningful, averaging 0.0082 across years. By contrast, the corresponding estimate for the ETF-only session, $\sigma_{\eta,\text{KEUAonly}}$, is substantially smaller, averaging 0.0012. The implied information-arrival ratio reported in Table 3 indicates that the size of information during the

EUA-only session is several times larger than that in the ETF-only session, between five times and 12 times depending on the year. Taken together, these estimates suggest that intrinsic-value-relevant information arrival during ETF-only hours is limited. This implies that, over our sample, there is little economically meaningful arrival of intrinsic-value news overnight (in European hours); that is, shocks that would move the underlying EUA valuation tend to materialize predominantly during active market hours. This timing is not mechanically obvious. In many asset classes, especially equities, important value-relevant information (e.g., earnings announcements and annual reports) is frequently released after-hours. Our evidence indicates that, in the EU carbon market, the bulk of valuation-relevant innovations is concentrated in periods when the main market is open.

5.1.2 | Transitory Noise: σ_e

Next, we examine the magnitude of transitory pricing noise during non-overlapping trading hours using the volatility of observed price innovations. The observation-noise parameter for futures, $\sigma_{e1,\text{EUAonly}}$, ranges from 0.0029 to 0.0041, whereas the corresponding ETF noise, $\sigma_{e2,\text{KEUAonly}}$, is smaller in magnitude, ranging from 0.0004 to 0.0014. However, a smaller σ_e does not necessarily imply better informational content if σ_{η} is even smaller. Hence, these estimates are best interpreted jointly with the information-arrival estimates above by

TABLE 3 | Derived intraday measures.

	2022	2023	2024	Average
Panel A: Non-Overlap				
$\sigma_{e1,EUAonly}/$ $\sigma_{\eta,EUAonly}$	0.38	0.45	0.44	0.43
$\sigma_{e1,KEUAonly}/$ $\sigma_{\eta,KEUAonly}$	0.67	0.48	0.71	0.62
$ 1 - \theta_{1,EUAonly} $	0.18	0.29	0.29	0.25
$ 1 - \theta_{2,KEUAonly} $	0.75	1.00	1.00	0.91
$ 1 - \theta_{1,EUAonly} $ $- 1 - \theta_{2,KEUAonly} $	-0.57	-0.71	-0.71	-0.66
$\sigma_{\eta,EUAonly}/$ $\sigma_{\eta,KEUAonly}$	5.10	6.88	11.99	7.99
Panel B: Overlap				
$\sigma_{e1,overlap}/\sigma_{\eta,overlap}$	0.65	0.56	0.48	0.56
$\sigma_{e2,overlap}/\sigma_{\eta,overlap}$	0.23	0.22	0.12	0.19
$ 1 - \theta_{1,overlap} $	0.07	0.03	0.07	0.06
$ 1 - \theta_{2,overlap} $	0.02	0.07	0.02	0.04
$ 1 - \theta_{1,overlap} $ $- 1 - \theta_{2,overlap} $	0.05	-0.04	0.04	0.02

Note: This table reports derived diagnostics constructed from the intraday state-space parameter estimates.

considering the noise-to-information ratio, σ_e/σ_η . The ratios reported in Table 3 indicate that, during ETF-only hours, the ETF exhibits a higher noise-to-information ratio (0.62 on average) than futures (0.43 on average) across the sample period, implying that transitory noise is large relative to efficient-price innovations for the ETF.

5.1.3 | Price Discovery Speed: θ

Turning to price discovery speed, Table 2 shows a sharp contrast in the partial-adjustment coefficients. Futures prices incorporate information efficiently during futures-only hours, with $\theta_{1,EUAonly}$ ranging from 0.71 to 0.82 across years. In contrast, the ETF adjusts only weakly during ETF-only hours: $\theta_{2,KEUAonly}$ averages 0.09 across subsamples. Correspondingly, the implied inefficiency measures are large for the ETF during ETF-only hours ($|1 - \theta_{2,KEUAonly}| = 0.92$), whereas futures prices are much closer to full adjustment ($|1 - \theta_{1,EUAonly}| = 0.25$). These estimates imply that, when the underlying futures market is closed, ETF prices do not meaningfully track changes in the latent efficient price. Combined with the low information-arrival volatility in ETF-only hours, the near-zero $\theta_{2,KEUAonly}$ suggests that observed ETF quote dynamics in this session are dominated by transitory components rather than fundamental valuation updates. In other

words, the ETF contributes little to price discovery when it trades in isolation. The negligible adjustment of the ETF during ETF-only hours is consistent with the mechanism emphasized by Holden and Nam (2024): when the arbitrage/hedging linkage to the underlying market is weak or unavailable, ETF trading can reflect transitory demand and inventory effects more than fundamental information, implying that ETF price changes may add more noise than signal for the underlying valuation.

5.1.4 | Why ETF-Only Hours Show Little Price Discovery

From the results above, we can summarize that during ETF-only hours: (i) intrinsic-value-relevant innovations are small, and (ii) the ETF exhibits virtually no measurable adjustment to latent innovations. The lower level of σ_e during ETF-only hours does not imply superior informational efficiency, because efficient-price innovations are also markedly smaller in this session and the ETF's adjustment coefficient is close to zero. Taken together, these results imply that the ETF has little scope to contribute to price discovery when the underlying futures market is closed, consistent with the low overall volatility of ETF prices in this window.

5.2 | Intraday Overlapping Trading Hours

We next examine overlapping trading hours, when both EUA futures and the ETF are simultaneously open.

5.2.1 | Information Arrival

Table 2 (Panel B) reports the estimated efficient-price innovation volatility, $\sigma_{\eta,overlap}$, ranging from 0.0055 to 0.0096 (averaging 0.0073 across years), which is comparable in magnitude to the innovation volatility observed during futures-only hours. This indicates that overlap periods are characterized by substantial information flow, which would attract active price discovery in both markets.

5.2.2 | Transitory Noise

We next examine the magnitude of transitory noise during overlapping trading hours. Table 2 (Panel B) shows that noise increases for both instruments relative to non-overlapping hours. For futures, $\sigma_{e1,EUAoverlap}$ ranges from 0.0031 to 0.0062 (0.0042 on average), exceeding the corresponding non-overlap estimates. For the ETF, the increase is particularly pronounced: $\sigma_{e2,KEUAoverlap}$ lies between 0.0008 and 0.0022 (0.0014 on average), compared with 0.0004–0.0014 in ETF-only hours. Because we use mid-quotes, these patterns reflect quote-level microstructure variation rather than bid-ask bounce in transaction prices, and are consistent with more active quote updating and trading intensity when both markets are simultaneously open. Importantly, a higher level of σ_e in overlap does not by itself imply lower informational efficiency, as efficient-price innovations are also larger during these trading hours. We therefore interpret σ_e jointly with σ_η using the noise-to-information ratio in Table 3. Interpreting

these estimates relative to information flow yields a sharp contrast across instruments. As shown in Table 3, the futures noise-to-information ratio rises in overlapping hours relative to futures-only hours, indicating that transitory noise increases more than efficient-price innovations for futures during these trading hours. In contrast, the ETF's noise-to-information ratio falls markedly in overlapping hours relative to ETF-only hours.

5.2.3 | Price Discovery Speed

Table 2 (Panel B) shows rapid incorporation of efficient-price innovations in both markets during overlapping hours. The futures adjustment coefficient, $\theta_{1,\text{EUAoverlap}}$, is close to unity across subsamples (0.93–0.97), and the ETF coefficient, $\theta_{2,\text{KEUAoverlap}}$ is also close to unity and slightly exceeds one (1.02–1.07). To compare adjustment speed in a way that is robust to estimates above one, Table 3 reports $|1 - \theta|$. The implied deviations from full adjustment are small for both instruments in overlap, and on average the ETF is closer to unity than futures (0.04 vs. 0.06). Overall, the estimates indicate that during overlapping hours the ETF contributes to price discovery at a similar—and on average marginally faster—speed than the futures contract. This finding is consistent with stronger cross-market arbitrage and hedging activity when both markets are simultaneously open, which helps align the ETF price closely with the underlying efficient price.

5.2.4 | Contrast With ETF-Only Hours

The contrast with ETF-only hours is stark. When the underlying futures market is closed, efficient-price innovations are limited and the ETF does not measurably adjust to latent shocks; when both markets are open, information arrival is substantial and both prices adjust rapidly, with the ETF showing lower noise. This shift is consistent with the restored ETF-futures arbitrage and hedging channel. When the hedge market is open, liquidity providers can manage inventory risk more effectively and mispricings can be corrected more quickly, tightening the connection between ETF prices and efficient prices. This pattern is consistent with Holden and Nam (2024)'s prediction that ETF-induced spillovers depend on arbitrage capacity: when the hedge market is open and cross-market arbitrage is feasible, ETF trading becomes tightly linked to underlying price formation and can contribute meaningfully to information incorporation. We next examine whether our findings are sensitive to market conditions and time variation.

5.3 | Volatility Regime Dependence in Intraday Price Discovery

Price discovery is likely to be state dependent. Periods of elevated volatility are typically associated with more intense information arrival and changes in market functioning, including liquidity provision and the informativeness of order flow. A key question is therefore whether the relative price discovery roles of EUA futures and the ETF during overlapping

hours are stable across tranquil and volatile conditions. To address this, we split the sample into low- and high-volatility regimes based on the median daily realized volatility of EUA futures and re-estimate the intraday model by regime. In this specification, the observation-noise parameters σ_e are constrained to be identical across regimes; we therefore focus on regime dependence in efficient-price innovations and adjustment speeds.

5.3.1 | Volatility-Regime-Dependent State-Space Model

Volatility regime definition. Let $d(t)$ denote the trading day containing hour t . We classify each day into a low- or high-volatility regime using the median of daily realized volatility of EUA futures:

$$r(d) \in \{L, H\}, \quad r(d) = \begin{cases} L & \text{if } RV_d \leq \text{median}(RV), \\ H & \text{if } RV_d > \text{median}(RV). \end{cases}$$

The regime indicator $r(d)$ is treated as observed (non-latent) and is constant within a day.

State equation with regime-dependent information arrival. We retain the random-walk efficient price,

$$m_t = m_{t-1} + \Delta m_t,$$

but allow the efficient-price innovation volatility to vary jointly with the trading-hour session $s(t) \in \{\text{EUA-only, KEUA-only, overlap}\}$ and the daily volatility regime $r(d)$:

$$\Delta m_t = \sigma_{\eta, s(t), r(d(t))} \eta_t, \quad \eta_t \sim \mathcal{N}(0, 1). \quad (8)$$

Equivalently,

$$\sigma_{\eta, s(t), r(d)} = \begin{cases} \sigma_{\eta, \text{EUAonly}, r(d)} & \text{if } s(t) = \text{EUA-only}, \\ \sigma_{\eta, \text{KEUAonly}, r(d)} & \text{if } s(t) = \text{KEUA-only}, \\ \sigma_{\eta, \text{overlap}, r(d)} & \text{if } s(t) = \text{overlap}. \end{cases}$$

Thus, the extension allows the *size of intrinsic-value-relevant information arrival* to differ across low- and high-volatility days within each trading-hour session.

Observation equations with regime-dependent adjustment speed. Observed prices remain partially adjusting signals of m_t :

$$p_{j,t} = m_{t-1} + \theta_{j,s(t), r(d(t))} \Delta m_t + \sigma_{e_j, s(t)} \varepsilon_{j,t}, \quad \varepsilon_{j,t} \sim \mathcal{N}(0, 1), \quad j \in \{1, 2\}.$$

To focus the extension on state dependence in information arrival and price discovery *during active two-sided trading*, we impose two parsimonious restrictions that match the empirical specification in Table 4:

- Observation-noise invariance across volatility regimes:

$$\sigma_{e_j, s(t), L} = \sigma_{e_j, s(t), H} \equiv \sigma_{e_j, s(t)}.$$

That is, quote-level noise may differ between non-overlap and overlap hours, and across markets j , but is held constant across low- and high-volatility days.

TABLE 4 | Volatility regime-switching model.

Panel A: Parameter estimates		
Parameter	Estimate	
$\sigma_{\eta,\text{EUAonly},L}$	0.0050***	
$\sigma_{\eta,\text{overlap},L}$	0.0048***	
$\sigma_{\eta,\text{KEUAonly},L}$	0.0015***	
$\sigma_{\eta,\text{EUAonly},H}$	0.0107***	
$\sigma_{\eta,\text{overlap},H}$	0.0098***	
$\sigma_{\eta,\text{KEUAonly},H}$	0.0013***	
$\theta_{1,\text{EUAonly}}$	1.0073	
$\theta_{1,\text{KEUAonly}}$	0.0037	
$\theta_{1,\text{overlap},L}$	0.9363***	
$\theta_{2,\text{overlap},L}$	1.0383***	
$\theta_{1,\text{overlap},H}$	0.9744***	
$\theta_{2,\text{overlap},H}$	1.0089*	
Panel B: Derived measures		
Measure	Low	High
$\left 1-\theta_{1,\text{overlap},r(d)}\right $	0.0637	0.0256
$\left 1-\theta_{2,\text{overlap},r(d)}\right $	0.0383	0.0089
$\left 1-\theta_{1,\text{overlap},r(d)}\right -\left 1-\theta_{2,\text{overlap},r(d)}\right $	0.0254	0.0167
$\sigma_{\eta,\text{EUAonly},r(d)}/\sigma_{\eta,\text{KEUAonly},r(d)}$	3.3333	8.2308
Panel C: Model fit		
Sample size	10,256	
Log likelihood	48111.6	
AIC	−96191.2	
BIC	−96075.5	

Note: Low (high) denotes the subsample of days below (above) the median daily realized volatility of EUA futures. Statistical significance is denoted by ***, **, and * for $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

- Regime dependence in overlap adjustment only:

$$\theta_{1, \text{EUAonly}, L} = \theta_{1, \text{EUAonly}, H} \equiv \theta_{1, \text{EUAonly}},$$

$$\theta_{2, \text{KEUAonly}, L} = \theta_{2, \text{KEUAonly}, H} \equiv \theta_{2, \text{KEUAonly}},$$

while allowing overlap adjustment speeds to differ across volatility regimes:

$$\theta_{1, \text{overlap}, r(d)} \text{ and } \theta_{2, \text{overlap}, r(d)} \text{ for } r(d) \in \{L, H\}.$$

Writing the overlap equations explicitly:

$$p_{1,t} = m_{t-1} + \theta_{1, \text{overlap}, r(d(t))} \cdot \sigma_{\eta, \text{overlap}, r(d(t))} \eta_t + \sigma_{e1, \text{overlap}} \varepsilon_{1,t}, \quad (9)$$

$$p_{2,t} = m_{t-1} + \theta_{2, \text{overlap}, r(d(t))} \cdot \sigma_{\eta, \text{overlap}, r(d(t))} \eta_t + \sigma_{e2, \text{overlap}} \varepsilon_{2,t}, \quad s(t) = \text{overlap}. \quad (10)$$

5.3.2 | Information Arrival

Table 4 Panel A shows that efficient-price innovations are larger on high-volatility days, as expected. In particular, $\sigma_{\eta, \text{overlap}}$ increases from 0.0048 in the low-volatility regime to 0.0098 in the high-volatility regime. The futures-only innovation volatility exhibits a similar pattern ($\sigma_{\eta, \text{EUA only}}$: 0.0050–0.0107). In contrast, the ETF-only innovation volatility remains small in both regimes ($\sigma_{\eta, \text{KEUA only}}$: 0.0015 in low volatility and 0.0013 in high volatility). The information-arrival ratio, $\sigma_{\eta, \text{EUA only}} / \sigma_{\eta, \text{KEUA only}}$, rises from 3.33 in the low-volatility regime to 8.23 in the high-volatility regime (Table 4 Panel B), confirming that intrinsic-value-relevant innovations are concentrated in the futures-only session, especially on volatile days. These results further strengthen our conclusion from the previous section that intrinsic-value-relevant innovations are scarce during ETF-only trading hours.

5.3.3 | Price Discovery in Overlap

The main question is whether the relative price discovery speed between futures and the ETF during overlapping hours depends on volatility conditions. Table 4 shows that adjustment coefficients remain close to unity in both regimes. For futures, $\theta_{1, \text{overlap}}$ increases from 0.94 in low volatility to 0.97 in high volatility. For the ETF, $\theta_{2, \text{KEUA, overlap}}$ is also close to unity (1.04 in low volatility; 1.01 in high volatility). Using $|1 - \theta|$ to compare deviations from full adjustment, both markets are closer to full adjustment in the high-volatility regime, and the ETF remains at least as close as futures in both regimes (low volatility: 0.04 vs. 0.06; high volatility: 0.01 vs. 0.03). Overall, the relative price discovery speed between the two markets is not volatility-regime dependent. The ETF contributes to price discovery at a similar, if anything slightly faster, speed than futures in both tranquil and volatile market conditions. This stability is consistent with overlap trading hours being the period in which the ETF–futures hedging and arbitrage channel is active. When both markets are open, cross-market trading can align ETF prices with efficient-price innovations even under elevated volatility.

Although price discovery speed is stable across volatility regimes, it may still vary over time with other factors such as market development and trading activity. We therefore estimate the model using a rolling-window approach to assess time variation in overlap-hour price discovery and to examine the determinants of these variations.

5.4 | Rolling Window Analysis

Figure 2 plots daily 60-trading-day rolling estimates of the adjustment coefficients $\theta_{1, \text{overlap}}$ and $\theta_{2, \text{overlap}}$ (top panel, blue and red line respectively) and the implied relative inefficiency measure, the difference in Absolute Inefficiency:

$$\text{dAINEFF} = |1 - \theta_{1, \text{overlap}}| - |1 - \theta_{2, \text{overlap}}|$$

(bottom panel). Positive values of dAINEFF indicate that the ETF's adjustment coefficient is closer to the model benchmark

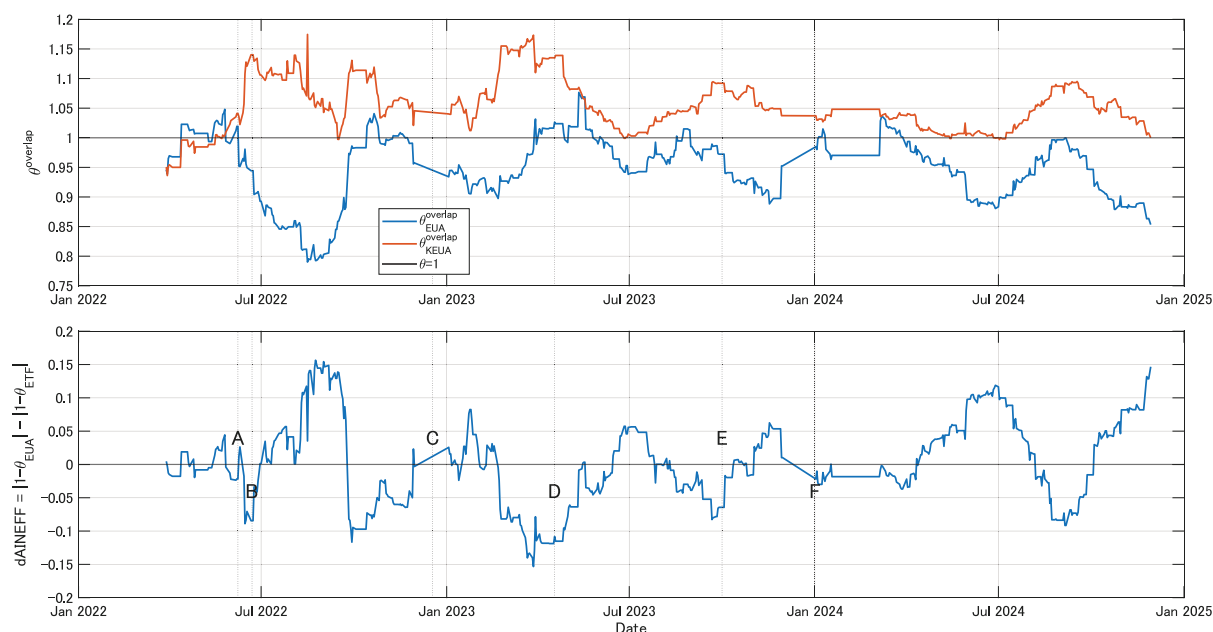


FIGURE 2 | Rolling-window estimates of θ and relative inefficiency during overlapping hours. The figure reports daily estimates from a 60-trading-day rolling-window version of the intraday state-space model, focusing on the overlapping trading-hours interval when both EUA futures and the KEUA ETF are simultaneously open. The top panel plots the rolling estimates of the adjustment (market reaction) coefficients $\theta_{1,overlap}$ and $\theta_{2,overlap}$, where $\theta = 1$ corresponds to full contemporaneous adjustment to latent efficient-price innovations. The bottom panel plots the relative inefficiency measure $dAINEFF = |1 - \theta_{1,overlap}| - |1 - \theta_{2,overlap}|$. Positive values of $dAINEFF$ indicate that the ETF adjusts closer to $\theta = 1$ (i.e., is relatively more efficient) than the futures contract during overlap hours; negative values indicate the opposite. Vertical dashed lines mark selected within-sample Fit-for-55/EU-ETS reform milestones; letter codes (A, B, C, ...) correspond to the event list reported in the accompanying (Table 5).

$\theta = 1$ than the futures during overlapping trading hours, whereas negative values indicate the opposite. The series exhibits pronounced time variation. In particular, $dAINEFF$ rises during parts of mid-2022 (suggesting relatively higher ETF efficiency) and subsequently reverses, turning negative through late-2022 and into early-2023 (suggesting relatively higher futures efficiency). We annotate major within-sample Fit-for-55/EU ETS reform milestones, including the European Parliament's June 2022 legislative votes, the December 2022 provisional ETS agreement, the April 2023 final approval of the ETS and Carbon Border Adjustment Mechanism (CBAM) reforms, the start of the CBAM transitional phase, and the implementation of revised ETS rules in 2024. Because our sample begins in 2022, these events do not capture the initial Paris Agreement shock or the original July 2021 launch of Fit for 55. Instead, they capture the within-sample policy-resolution process through which expectations about allowance scarcity, cap tightening, and market design were updated. The visual correspondence should therefore be interpreted as suggestive rather than definitive; below, we examine these policy-event regimes more formally.

5.5 | Determinants of Relative Efficiency

The rolling-window estimates reveal substantial time variation in which venue adjusts more closely to the latent efficient price during overlapping trading hours. To investigate whether this variation is systematically related to market conditions, we regress the relative inefficiency measure on cross-market

TABLE 5 | Event list for Figure 2.

Code	Date	Event
A	08-Jun-22	European Parliament ETS vote fails (Fit for 55)
B	22-Jun-22	European Parliament ETS negotiating position
C	18-Dec-22	Provisional ETS deal (Council–Parliament)
D	18-Apr-23	European Parliament final approval (ETS + CBAM)
E	01-Oct-23	CBAM transitional starts
F	01-Jan-24	Revised ETS applies from 2024

differences in trading activity and quoted liquidity, controlling for volatility.

Explanatory variables. All covariates are computed from hourly data during the *overlap* interval and then aggregated to the same daily frequency as the dependent variable (one observation per day). Let V_d^{EUA} and V_d^{KEUA} denote total traded volume during overlap hours on day d for EUA futures and the ETF, respectively, and let N_d^{EUA} and N_d^{KEUA} denote the corresponding number of trades. We measure relative trading activity using log ratios:

$$\text{RelVol}_d = \ln\left(\frac{V_d^{EUA}}{V_d^{KEUA}}\right), \quad \text{RelTrade}_d = \ln\left(\frac{N_d^{EUA}}{N_d^{KEUA}}\right).$$

To capture trade-size composition, we compute volume per trade (VPT) for each venue during overlap hours.

$$\text{VPT}_d^{EUA} = \frac{V_d^{EUA}}{N_d^{EUA}}, \quad \text{VPT}_d^{KEUA} = \frac{V_d^{KEUA}}{N_d^{KEUA}},$$

and define relative volume per trade as follows:

$$\text{RelVPT}_d = \ln\left(\frac{\text{VPT}_d^{EUA}}{\text{VPT}_d^{KEUA}}\right).$$

Quoted liquidity is measured using average quoted spreads during overlap hours. Let $\overline{QS}_d^{EUA}$ and $\overline{QS}_d^{KEUA}$ denote the day- d mean of the quoted spread (ask minus bid, in the same units as prices) computed from intraday quotes within overlap hours for each venue. We define relative quoted spreads as

$$\text{RelQS}_d = \ln\left(\frac{\overline{QS}_d^{EUA}}{\overline{QS}_d^{KEUA}}\right).$$

Finally, to control for market-wide conditions we use relative realized volatility computed from intraday log returns during overlap hours. Let RV_d^{EUA} and RV_d^{KEUA} denote realized volatility for each venue (e.g., square root of the sum of squared intraday returns within overlap hours). The relative volatility control is

$$\text{RelRV}_d = \ln\left(\frac{\text{RV}_d^{EUA}}{\text{RV}_d^{KEUA}}\right).$$

We use log ratios so that coefficients can be interpreted as semi-elasticities and to mitigate scale differences between futures and ETF trading activity.

Table 6 examines the determinants of the relative inefficiency measure dAINEFF during overlapping trading hours, where positive values indicate that the ETF's adjustment coefficient is closer to full adjustment than that of EUA futures. The results show that relative trading activity is systematically related to relative price discovery, but the interpretation depends on the dimension of activity considered. Relative futures volume and the relative number of futures trades enter positively and significantly. Since a positive coefficient implies a shift toward relatively greater ETF efficiency, this result suggests that higher futures trading intensity per se does not necessarily correspond to futures-led information incorporation. Instead, high relative futures volume or trade counts may partly reflect liquidity trading, inventory rebalancing, quote updating, or short-horizon hedging activity, all of which increase trading intensity without necessarily increasing the informational content of each trade.

By contrast, relative volume per trade enters with a large negative and statistically significant coefficient. This result indicates that when the average futures trade is large relative to the average ETF trade, futures prices adjust more closely to the latent efficient price. This pattern is consistent with a

market-microstructure interpretation in which trade size is more informative about the presence of institutional or compliance-related trading than aggregate trading intensity alone. EUA futures are the natural venue for compliance entities, professional hedgers, and institutional traders managing direct allowance-price exposure. Larger futures trades are therefore more likely to contain information about expectations of allowance scarcity, policy developments, or hedging demand. ETF trading, by contrast, provides equity-market access to carbon exposure and may attract portfolio-flow or retail-access demand, which can be informative during overlap hours but may also contain a larger transitory component. Because we do not observe trader identities, this interpretation should be viewed as indirect evidence based on the microstructure meaning of trading intensity, trade size, and venue choice rather than as a direct classification of traders.

The results for quoted spreads are also consistent with this interpretation. Relative quoted spreads are insignificant on their own but become positive and significant after controlling for trading activity. Wider futures spreads relative to ETF spreads are associated with higher dAINEFF , implying that the ETF becomes relatively closer to full adjustment when futures quoted liquidity deteriorates. Finally, relative realized volatility is statistically insignificant across specifications. Thus, the time variation in relative efficiency during overlap hours is not primarily a volatility phenomenon. Rather, it is shaped by the composition of trading activity, the likely informativeness of trade size, and the relative state of quoted liquidity across the two venues.

5.6 | Policy-Event Regimes and Relative Efficiency

To address whether relative price discovery also varies with the policy-driven information environment, we conduct a supplementary event-window analysis around major within-sample EU ETS and Fit-for-55 policy milestones (Table 5). These events include the European Parliament's June 2022 ETS votes, the December 2022 provisional ETS agreement, the April 2023 final approval of the ETS and CBAM reforms, the start of the CBAM transitional phase, and the implementation of revised ETS rules in 2024. Because our intraday sample begins in 2022, we cannot directly examine the original Paris Agreement shock or the July 2021 launch of the Fit-for-55 package. Instead, we focus on major within-sample EU ETS policy milestones associated with the legislative negotiation, approval, and implementation of the Fit-for-55 ETS reform and CBAM.

These milestones are appropriate for our setting because they represent policy-resolution events through which market participants updated expectations about allowance scarcity, cap tightening, auction supply, and future compliance costs. Because the rolling-window dependent variable is not available for all calendar dates, we use only events for which a rolling-window estimate is available within five calendar days of the actual event date. We then define policy-event regimes as observations whose rolling-window end dates fall within ± 10 observed rolling-window dates around usable policy milestones.²

TABLE 6 | Determinants of relative efficiency.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Intercept	−0.0051 (0.0104)	0.0016 (0.0135)	0.0133 (0.0265)	−0.1141*** (0.0436)	−0.5989*** (0.1089)	−0.0008 (0.0096)	−0.1259*** (0.0440)	−0.5963*** (0.1093)	0.0135 (0.0282)	−0.1087 (0.0664)	−0.5666*** (0.1477)
RelVol	0.0214** (0.0100)					0.0258*** (0.0098)			0.0248** (0.0106)		
RelTrade				0.0218** (0.0088)			0.0250*** (0.0090)			0.0242*** (0.0097)	
RelVPT					−0.1154*** (0.0202)			−0.1150*** (0.0202)			−0.1118*** (0.0247)
RelQS		0.0295 (0.0561)				0.1029** (0.0421)	0.0964** (0.0454)	0.01 (0.0424)	0.1254** (0.0506)	0.1170** (0.0564)	0.0337 (0.0410)
RelRV			0.0046 (0.0092)						0.0045 (0.0091)	0.0041 (0.0089)	0.0041 (0.0067)
Adj. R ²	0.133	0.002	0.011	0.168	0.246	0.173	0.205	0.245	0.181	0.211	0.252
N	592	592	592	592	592	592	592	592	592	592	592

Note: The dependent variable is the relative inefficiency measure $d_{\text{AINEFF}} = |1 - \theta_{\text{EUA}}^{\text{overlap}}| - |1 - \theta_{\text{KEUA}}^{\text{overlap}}|$ computed from 60-trading-day rolling estimates during overlapping trading hours. Standard errors are reported in parentheses. Statistical significance is denoted by ***, **, and * for $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

TABLE 7 | Policy-event regimes and relative efficiency: ± 10 trading-day windows.

	(1)	(2)	(3)	(4)	(5)
Intercept	0.0072 (0.0122)	0.0327 (0.0273)	0.0211 (0.0269)	−0.0891 (0.0604)	−0.5120*** (0.1246)
PolicyWindow10	−0.0585*** (0.0200)	−0.0684*** (0.0205)	−0.0566*** (0.0142)	−0.0555*** (0.0137)	−0.0553*** (0.0173)
RelVol			0.0219** (0.0094)		
RelTrade				0.0217** (0.0086)	
RelVPT					−0.1026*** (0.0206)
RelQS		0.1215*** (0.0449)	0.1607*** (0.0489)	0.1531*** (0.0538)	0.0774* (0.0412)
RelRV		0.0063 (0.0082)	0.0039 (0.0087)	0.0034 (0.0085)	0.0034 (0.0062)
Adj. R^2	0.089	0.136	0.253	0.280	0.321
N	592	592	592	592	592

Note: The dependent variable is $dAINEFF = |1 - \theta_{EUA}^{overlap}| - |1 - \theta_{KEUA}^{overlap}|$. PolicyWindow10 equals one for observations whose rolling-window end date falls within ± 10 observed rolling-window end dates of a usable within-sample EU ETS/Fit-for-55 policy milestone. If an event date is not an observed rolling-window end date, the nearest available rolling-window end date is used only when it is within five calendar days of the actual event date; otherwise the event is reported in the event-summary file but excluded from the event-window dummy. Newey–West/HAC standard errors with bandwidth 60 are reported in parentheses. Statistical significance is denoted by ***, **, and * for $p < 0.01$, $p < 0.05$, and $p < 0.10$, respectively.

The results in Table 7 show that the policy-event indicator enters negatively and significantly across all specifications. This implies that, during major EU ETS policy-event windows, EUA futures prices adjust closer to the latent efficient price than the ETF. The magnitude is economically meaningful: the coefficient ranges from approximately -0.058 to -0.071 , compared with the sample mean of $dAINEFF$ close to zero. This pattern is consistent with the view that policy-related information about allowance scarcity, cap tightening, and regulatory design is incorporated primarily through the futures market, where compliance entities, professional hedgers, and institutional traders are more likely to concentrate their trading activity.

Importantly, this policy-event effect remains significant after controlling for relative trading volume, number of trades, volume per trade, quoted spreads, and realized volatility. Thus, regime shifts in relative price discovery are not fully captured by volatility or liquidity conditions alone. Instead, policy-induced information regimes appear to alter the relative informational roles of futures and ETFs. This finding highlights a distinctive feature of carbon markets: because allowances are policy-created assets, major regulatory announcements can shift the venue through which value-relevant information is incorporated.

5.7 | Daily Analysis

While the intraday analysis focuses on overlapping continuous trading between EUA futures and the carbon ETF, the EU

ETS market also features an important primary-market price formation mechanism: the EUA auctions. We use the daily auction clearing price as a practical and economically meaningful proxy for primary-market demand conditions. In the daily analysis, we align EUA futures and ETF prices to 4 pm UK time (when the ETF's NAV is computed) and examine the joint dynamics among futures, ETF, and auction prices. Futures prices are widely viewed as a key benchmark for auction participants, whereas the auction clearing price reflects the market-clearing price of allowances and the cost of obtaining compliance instruments. Consequently, all three prices can plausibly interact and transmit information in the daily price discovery process.

5.7.1 | Vector Error Correction Model (VECM) Specification

Let

$$\mathbf{L}_t = \begin{pmatrix} L_{AUC,t} \\ L_{EUA,t} \\ L_{KEUA,t} \end{pmatrix}$$

denote the 3×1 vector of log daily prices aligned to 4 pm UK time. Given Johansen rank $r = 2$, the system admits a VECM representation with two error-correction terms:

$$\Delta \mathbf{L}_t = \alpha \beta' \mathbf{L}_{t-1} + \sum_{i=1}^{K-1} \Gamma_i \Delta \mathbf{L}_{t-i} + \mathbf{c} + \mathbf{u}_t, \quad \mathbf{u}_t \sim (0, \Sigma), \quad (11)$$

where $K = 3$ is the VAR lag order in levels (so the VECM contains $K - 1 = 2$ lags of first differences), β is a 3×2 matrix whose columns span the cointegration space, and α is a 3×2 loading matrix governing the speed and direction of adjustment back to the long-run equilibrium space. The term $\beta' L_{t-1}$ yields the two error-correction terms, denoted $ECT_{1,t-1}$ and $ECT_{2,t-1}$, and Γ_i are 3×3 matrices capturing short-run dynamics in daily changes. We include a constant c consistent with the Johansen specification, and conduct inference using HAC/Newey–West covariance estimates in subsequent Wald tests.

Writing the system equation-by-equation highlights the error-correction channels:

$$\Delta L_{AUC,t} = \alpha_{AUC,1} ECT_{1,t-1} + \alpha_{AUC,2} ECT_{2,t-1} + \sum_{i=1}^2 \gamma_{AUC}^{(i)} \Delta L_{t-i} + c_{AUC} + u_{AUC,t}, \quad (12)$$

$$\Delta L_{EUA,t} = \alpha_{EUA,1} ECT_{1,t-1} + \alpha_{EUA,2} ECT_{2,t-1} + \sum_{i=1}^2 \gamma_{EUA}^{(i)} \Delta L_{t-i} + c_{EUA} + u_{EUA,t}, \quad (13)$$

$$\Delta L_{KEUA,t} = \alpha_{KEUA,1} ECT_{1,t-1} + \alpha_{KEUA,2} ECT_{2,t-1} + \sum_{i=1}^2 \gamma_{KEUA}^{(i)} \Delta L_{t-i} + c_{KEUA} + u_{KEUA,t}, \quad (14)$$

TABLE 8 | Johansen cointegration test and VECM adjustment coefficients.

Panel A: Johansen trace test					
Null hypothesis	Trace stat	10%	5%	1%	Decision (5%)
($r = 0$)	87.04	32.00	34.91	41.07	Reject
($r \leq 1$)	27.01	17.85	19.96	24.60	Reject
($r \leq 2$)	4.10	7.52	9.24	12.97	Fail to reject
Panel B: Cointegrating vectors (β ; one normalization)					
	CI(1)		CI(2)		
L_{AUC}	1.0000		1.0000		
L_{EUA}	−1.0439		3.4124		
L_{KEUA}	0.0252		−3.4163		
Constant	0.1259		−7.8233		
Panel C: Adjustment coefficients (loading matrix α)					
	ECT ₁		ECT ₂		
ΔL_{AUC}	−0.2831		−0.0258		
ΔL_{EUA}	0.0607		−0.0428		
ΔL_{KEUA}	0.0512		−0.0352		

Note: Panel A reports Johansen trace statistics and critical values. Panel B reports two cointegrating vectors under the standard normalization from the Johansen procedure; when $r > 1$, the cointegration space is identified but individual vectors are not unique. Panel C reports the corresponding loading (adjustment) coefficients associated with the two error-correction terms (ECTs) in the VECM representation.

where $\gamma_j^{(i)}$ denotes the 3×1 vector of coefficients on $(\Delta L_{AUC,t-i}, \Delta L_{EUA,t-i}, \Delta L_{KEUA,t-i})'$ in equation $j \in \{AUC, EUA, KEUA\}$.

In this representation, long-run price discovery is reflected in the loading coefficients α (which venues correct disequilibria), while short-run predictive linkages are governed by the Γ_i matrices (which lagged returns help forecast other returns). Because $r = 2$, the individual cointegrating vectors are not unique; our empirical interpretation focuses on the strength and pattern of adjustment through α and on impulse responses and forecast error variance decompositions derived from the estimated VECM.

5.7.2 | Cointegration

Table 8 reports the results. With three prices, the Johansen trace test indicates a cointegration rank of $r = 2$, implying that the auction clearing price (L_{AUC}), EUA futures price (L_{EUA}), and the carbon ETF price (L_{KEUA}) share a two-dimensional long-run equilibrium space. Because $r > 1$, individual cointegrating vectors are not uniquely identified; only the cointegration space is identified. We therefore report the Johansen estimates under the standard normalization and interpret long-run comovement primarily through the presence of two stationary equilibrium relations and the associated loading (adjustment) matrix. The estimated loading matrix indicates economically meaningful error correction across venues, with the auction price exhibiting relatively strong adjustment to long-run deviations and the secondary-market prices also adjusting to restore equilibrium, consistent with tight long-run integration among auctions, futures, and the ETF at the daily frequency.

5.7.3 | Vector Error Correction Model

Estimating a VECM with cointegration rank $r = 2$ and lag order $K = 3$, we find strong and asymmetric error-correction dynamics across the three markets (Table 8). The auction clearing price displays pronounced mean reversion to the long-run equilibrium space: the error-correction terms enter the $\Delta L_{AUC,t}$ equation with relatively large magnitudes and are statistically significant, indicating that the auction mechanism plays an important role in absorbing equilibrium deviations at the daily horizon. In contrast, EUA futures and the carbon ETF exhibit weaker and more selective adjustment, with their responses concentrated on one of the two error-correction components, consistent with joint equilibrium restoration occurring primarily through the continuously traded secondary markets for certain deviations. In terms of short-run dynamics, auction returns load positively on lagged changes in both futures and ETF prices, and futures returns also respond to lagged ETF changes, indicating economically meaningful feedback across venues in the short run.

5.7.4 | Granger Causality

We next examine short-run predictive relationships within the VECM using Wald tests for Granger causality based on the

TABLE 9 | VECM Granger causality tests (Wald tests with HAC/Newey–West covariance).

Null hypothesis	df	F-stat	p-value
EUA does not Granger-cause AUC	2	4.797	0.009
KEUA does not Granger-cause AUC	2	3.635	0.027
KEUA does not Granger-cause EUA	2	1.651	0.193
AUC does not Granger-cause EUA	2	2.359	0.095
EUA does not Granger-cause KEUA	2	0.895	0.409
AUC does not Granger-cause KEUA	2	2.329	0.098

Note: The table reports Wald F -tests of Granger causality based on the coefficients on lagged differences in the VECM. HAC/Newey–West covariance estimates are used.

coefficients on lagged differences (with HAC/Newey–West covariance estimates). The results (Table 9) indicate that both the EUA futures and the carbon ETF contain short-run predictive information for the auction clearing price: lagged changes in futures prices jointly predict changes in the auction price ($F = 4.80$, $p = 0.009$), and lagged ETF price changes also predict auction price changes ($F = 3.63$, $p = 0.027$). In contrast, we find little evidence that the ETF leads the futures market, as ETF innovations do not predict futures returns ($p = 0.193$). Feedback from auctions to secondary-market returns is weak: auction price changes predict futures and ETF returns only at the 10% level ($p = 0.095$ and $p = 0.098$, respectively). Overall, the short-run dynamics suggest that information embedded in secondary-market trading—particularly futures—tends to be incorporated into auction outcomes, while auction-specific demand signals feed back into secondary markets more gradually.

5.7.5 | Impulse Response Functions

Figure 3 reports generalized impulse response functions (GIRFs) from the VECM Pesaran and Shin (1998). The auction clearing price responds strongly and quickly to innovations in secondary-market prices. A one-standard-deviation shock to EUA futures raises the auction log price on impact (0.013) and the response peaks after 1–2 trading days at about 0.027–0.028 before slowly decaying, remaining positive even after 20 days (0.016). The response to an ETF shock is nearly identical in magnitude and persistence. These patterns suggest rapid pass-through from the secondary market to the primary-market price formation mechanism, consistent with auction participants conditioning bids on prevailing secondary-market valuations (with futures acting as a benchmark). The persistence of the response further indicates gradual adjustment toward the long-run cointegrating relations rather than purely transitory comovement.

Generalized impulse responses also show that the primary market feeds back into secondary-market pricing. A

one-standard-deviation innovation in the auction clearing price increases both EUA futures and the ETF price immediately by about 0.018 in logs ($\approx 1.8\%$), with a peak around day 2 (≈ 0.020) and a gradual decay that remains positive after 20 days (≈ 0.010 – 0.012). The near-identical responses of futures and the ETF suggest that, at the daily frequency and 4pm UK alignment, both markets absorb auction information in a similar way. Together with the strong response of auction prices to futures/ETF innovations, these results point to a bidirectional price-discovery mechanism: secondary markets provide a benchmark that anchors auction bidding, while auction outcomes reveal demand and scarcity conditions that subsequently update valuations in futures and ETF markets.

5.7.6 | Forecast Error Variance Decomposition

Table 10 reports generalized forecast error variance decompositions (GFEVD) from the daily VAR among auction, futures, and ETF prices Diebold and Yilmaz (2012), Diebold and Yilmaz (2014). Across horizons ($H = 5, 20, 60$), spillovers are large: the auction price's forecast error variance is largely associated with innovations in secondary-market prices, with the ETF accounting for an increasing share as the horizon lengthens (37.0% at $H = 5$ vs. 45.6% at $H = 60$). Futures innovations also contribute materially to auction variance (around 36%–37% across horizons). Overall, the decomposition suggests that auction-price uncertainty is strongly linked to the broader information set embedded in futures and ETF markets, while longer-horizon variation is increasingly dominated by ETF-related innovations.

5.7.7 | Summary

Daily results broadly corroborate the intraday evidence that price discovery is shared across venues. Futures, the carbon ETF, and auctions are jointly price-discovering: in the short run, innovations in futures and the ETF are strongly linked to auction outcomes, while at longer horizons the forecast error variance of each price is increasingly explained by shocks associated with the other venues, especially the ETF. This pattern is consistent with persistent components of secondary-market pricing feeding back into primary-market clearing and the broader EU ETS price formation process. Overall, the daily analysis supports a tightly integrated EU ETS pricing system in which auctions and secondary markets interact meaningfully.

While Holden and Nam (2024) do not model a primary-market auction mechanism, their framework suggests that any ETF influence on primary-market outcomes should operate through the strength of the arbitrage linkage to the underlying benchmark market. Interpreted through this lens, our daily results—showing strong integration among auctions, futures, and the ETF and substantial transmission from secondary-market innovations to auction outcomes—are consistent with a channel in which ETF-related demand shocks matter for price formation primarily when they are transmitted into the underlying EUA valuation via secondary-market trading and arbitrage.

TABLE 10 | Generalized forecast error variance decomposition (GFEVD) and connectedness measures.

Panel A: GFEVD shares (%), by horizon						
<i>Horizon H = 5</i>						
AUC		26.3		36.6		37.0
EUA		18.6		40.7		40.7
KEUA		17.4		39.3		43.3
<i>Horizon H = 20</i>						
AUC		21.4		37.4		41.3
EUA		17.7		39.2		43.1
KEUA		16.6		37.9		45.6
<i>Horizon H = 60</i>						
AUC		18.2		36.1		45.6
EUA		16.1		37.2		46.7
KEUA		15.0		35.9		49.1
Panel B: Connectedness summary measures (%)						
Horizon	TCI	AUC FROM	AUC TO	AUC NET	EUA NET	KEUA NET
<i>H = 5</i>	63.2	73.6	36.0	− 37.6	16.6	21.0
<i>H = 20</i>	64.6	78.7	34.3	− 44.4	14.5	29.9
<i>H = 60</i>	65.2	81.7	31.1	− 50.6	9.2	41.4

Note: Panel A reports generalized forecast error variance decomposition (GFEVD) shares (in %) from the daily VAR for the auction clearing price (AUC), EUA futures (EUA), and the carbon ETF (KEUA), at horizons $H \in \{5, 20, 60\}$ trading days. The first, second, and third columns report the contribution to the GFEVD share from AUC, EUA, KEUA, respectively. Panel B reports summary connectedness measures based on the GFEVD: TCI is the total connectedness index; *AUC FROM* (*AUC TO*) is the share of AUC's forecast error variance explained by shocks from other variables (the share of other variables' variance explained by AUC shocks); *NET* measures are defined as *TO* minus *FROM*, so negative values indicate net shock absorption.

5.8 | Practical and Policy Implications

The results have several implications for ETS market design and for the interpretation of carbon prices by regulators and market participants. First, the evidence suggests that primary and secondary markets should not be viewed as separate price-formation mechanisms. The daily analysis shows that auction prices, EUA futures prices, and ETF-implied prices are tightly integrated, with innovations transmitting across venues. This implies that auction clearing prices are formed in an informational environment in which secondary-market prices provide important reference valuations, while auction outcomes themselves feed back into secondary-market prices by revealing demand and scarcity conditions. For ETS market design, this highlights the importance of maintaining transparent, regular, and predictable auction mechanisms, since auctions operate not only as an allocation device but also as part of the broader information-production system of the carbon market.

Second, the findings clarify how regulators should interpret the growing role of carbon ETFs. The ETF does not appear to be uniformly informative across all trading sessions. During ETF-only hours, efficient-price innovations are small and the ETF's adjustment to latent innovations is limited, suggesting that ETF price movements in this window are more likely to contain transitory components. During overlapping trading hours, however, the ETF adjusts rapidly and can contribute meaningfully to price discovery. The policy implication is therefore not

that ETF trading is either purely beneficial or purely destabilizing. Rather, its informational value depends on whether the arbitrage and hedging link to the underlying futures market is active. Regulators monitoring carbon-market financialisation should therefore distinguish between ETF price movements that occur when the futures hedge market is open and those that occur when the ETF trades in isolation.

Third, the results are relevant for compliance entities, hedgers, and speculative investors. For firms using EUA futures to manage compliance-cost risk, the evidence confirms that futures remain the main venue through which value-relevant information is incorporated, especially when trade size is large and around policy-event windows. For ETF investors, the results suggest that ETF prices are most informative during overlap hours, when cross-market arbitrage can align ETF prices with the underlying EUA valuation. ETF-only price changes should be interpreted more cautiously as signals about fundamental EUA scarcity. More generally, market participants should pay attention not only to which instrument they observe, but also to when the price is observed and whether the underlying hedge market is open.

Finally, the policy-event analysis reinforces the distinctive nature of carbon markets. Because EUAs are policy-created assets, major regulatory announcements can shift the informational environment and alter the relative roles of trading venues. The finding that futures become relatively more efficient around

Generalized Impulse Response Functions (GIRFs)

Daily VAR/VECM-based GIRFs, horizon $H = 20$

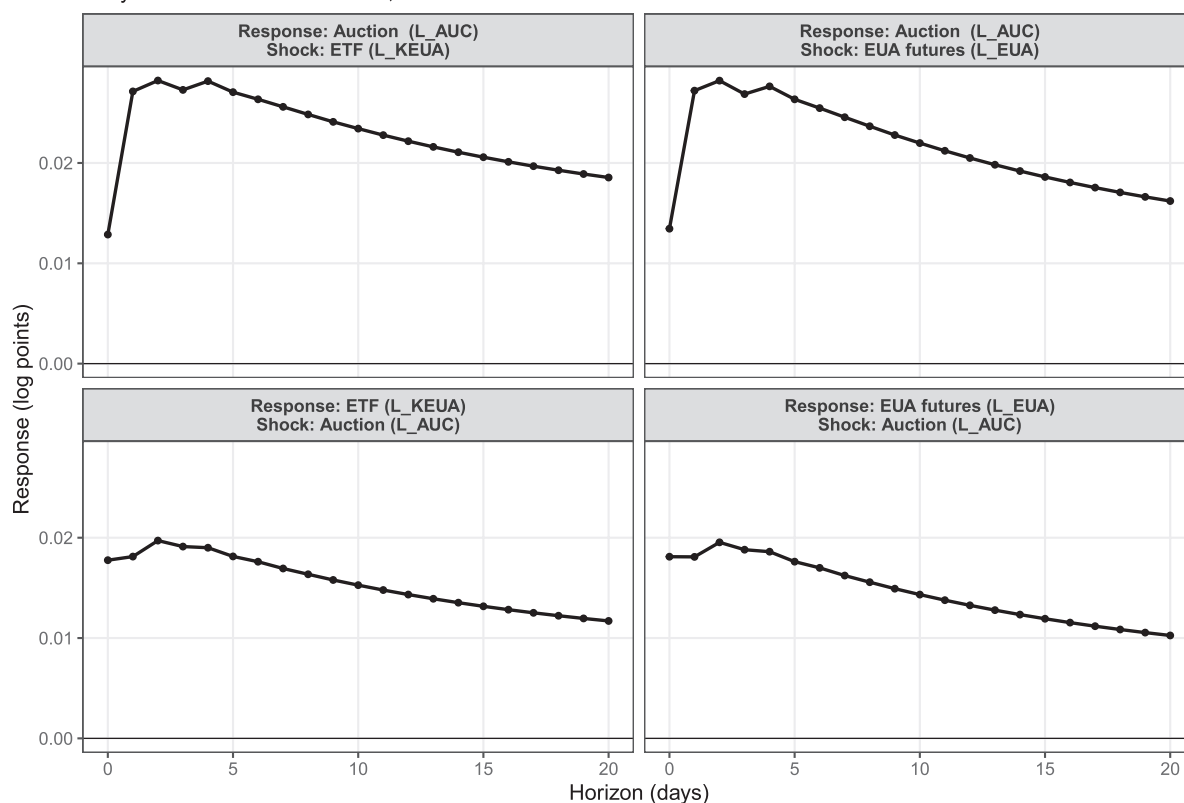


FIGURE 3 | Generalized impulse response functions from the VECM. The figure reports generalized impulse response functions (GIRFs) computed from the estimated VECM for $(L_{AUC}, L_{EUA}, L_{KEUA})$, where all series are aligned to 4pm UK time. Each panel plots the response of the variable on the vertical axis to a one-standard-deviation innovation in the variable named in the panel title. Responses are expressed in log units and are traced over trading days following the shock. GIRFs are invariant to variable ordering.

major EU ETS and Fit-for-55 policy milestones suggests that policy-sensitive information is incorporated primarily through the futures market, where compliance entities, professional hedgers, and institutional traders are likely to concentrate. This underscores the importance of transparent policy communication and careful coordination between regulatory announcements, auction design, and secondary-market functioning.

6 | Conclusion

This paper studies price discovery in the EU ETS across two key secondary-market venues—EUA futures and a US-listed carbon ETF—and links their interaction to primary-market price formation through EUA auctions. To accommodate sharp cross-session differences in information flow and arbitrage capacity, we distinguish ETF-only trading hours from periods when both markets are simultaneously open, and we model intraday prices with a state-space framework that separates efficient-price innovations from transitory microstructure noise. We then complement the intraday evidence with a daily three-venue analysis (futures, ETF, and auctions) aligned to 4pm UK time.

Three findings emerge from the intraday analysis. First, intrinsic-value-relevant information arrival is highly concentrated in periods when the main futures market is active. Efficient-price innovation volatility is economically meaningful

during futures-only hours but markedly smaller during ETF-only hours, implying that overnight (European-hours) innovations in the underlying EUA valuation are limited in our sample. Second, when the ETF trades in isolation it exhibits little measurable price discovery. Although quote noise is not large in absolute terms, the ETF's noise-to-information ratio is high and its adjustment coefficient is close to zero, indicating that ETF quote dynamics during ETF-only hours are dominated by transitory components rather than fundamental valuation updates. Third, when both markets are open the picture reverses: efficient-price innovations are substantial and both venues adjust rapidly, with the ETF's adjustment coefficient at least as close to full contemporaneous adjustment as futures on average and with a lower noise-to-information ratio. In economic terms, overlap hours are the interval in which the ETF-futures hedging and arbitrage channel is restored, allowing liquidity provision and cross-market trading to tightly align prices with latent innovations.

The regime and time-variation results reinforce this interpretation. Splitting the sample into low- and high-volatility regimes shows larger efficient-price innovations on volatile days, but the relative adjustment speed of futures and the ETF during overlap hours remains stable: both prices remain close to full adjustment, and the ETF is at least as close as futures in both regimes. Rolling-window estimates nevertheless reveal pronounced time variation in relative efficiency within overlap hours. Cross-sectional liquidity and activity metrics help explain

this variation. Relative trading intensity (volume and number of trades) tends to coincide with periods in which the ETF appears relatively more efficient, whereas higher relative volume per trade—a proxy for more informative trading—is associated with futures prices adjusting more closely to the latent efficient price than the ETF. Relative quoted liquidity also matters once trading activity is controlled for, while relative realized volatility is not a robust determinant. Overall, within the overlap session, which venue leads is shaped less by volatility per se than by the composition of trading and the relative state of quoted liquidity. In addition, policy-event windows are associated with relatively stronger futures-led price discovery, indicating that policy-induced information regimes affect the venue through which value-relevant information is incorporated.

At the daily frequency, incorporating the auction clearing price highlights that EU ETS price discovery is not confined to secondary markets. Johansen tests indicate strong long-run integration among auctions, futures, and the ETF, and VECM dynamics suggest meaningful error correction across venues. Short-run predictability points to futures and ETF innovations being incorporated into auction outcomes, consistent with auction participants conditioning bids on prevailing secondary-market valuations. Generalized impulse responses and GFEVDs further support bidirectional interaction: auctions respond strongly to secondary-market shocks, and auction shocks feed back into both futures and the ETF. The variance decompositions imply a tightly connected pricing system in which auctions are a net receiver of shocks, while longer-horizon variation is increasingly associated with ETF-related innovations, consistent with persistent components of secondary-market pricing feeding back into primary-market clearing and broader EU ETS price formation.

These findings have practical and policy implications. Carbon ETFs can contribute to price discovery, but their informational content is conditional on the trading session and the availability of the futures-market hedge. For regulators, this means that ETF price movements should be interpreted in relation to market-opening conditions and the strength of the ETF–futures arbitrage link. For compliance entities, hedgers, and investors, the results imply that futures remain the central venue for policy-sensitive information, while ETF prices are most informative during overlap hours. More broadly, the evidence suggests that EU ETS price formation is a venue-interactive process in which auctions, futures, and ETFs jointly contribute to the production of the carbon price.

Several limitations suggest avenues for future work. Our evidence is based on a particular ETF and sample period and relies on mid-quote dynamics rather than transaction-level order flow. Extending the framework to additional carbon-linked instruments, incorporating order flow and inventory measures, and modeling time-varying (or event-driven) constraints on arbitrage capacity would deepen understanding of when and why leadership shifts across venues.

Acknowledgments

We would like to thank Jie Cao and Katsumasa Nishide for their helpful comments. We are grateful for participants at the TDRI research

seminar, International Review of Finance Conference, Japanese Economic Association Annual Meeting, and Annual International Conference in Hawaii.

Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from LSEG. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the author(s) with the permission of LSEG.

Endnotes

¹ See the product information at KraneShares KEUA ETF.

² Results using ± 5 observed rolling-window dates are qualitatively similar and are available upon request.

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