The Limits of ESG Preferences
Pricing Carbon or Salience?

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Abstract

Whether investors price carbon or salience is unresolved: in equities, preference-based pricing is confounded with hedging of future emissions taxation. Cryptocurrency removes the confound: no carbon regulation exists, so any ESG pricing is purely a preference. Using this market as a unique frictionless economic laboratory, I develop an equilibrium model capitalizing the carbon liability into the asset price and derive the threshold over which ESG investors divest. Carbon liability is discounted by time preference, emissions decay, and beliefs about technology upgrades, falling convexly in the latter two. Crypto's extreme volatility pushes the divestment threshold orders of magnitude above rational carbon valuations, leaving the boundary entirely slack; were ESG investors to exit, the risk compensation required by remaining holders to absorb the additional supply would be enormous. An exogenous shock eliminating 99.95% of carbon externality overnight reallocates no capital toward the now-green asset; the same attribute, when made salient, moves liquidity transiently. Investors price salience, not carbon, in assets with a high-risk return profile.

I. Introduction

A central identification challenge in sustainable finance is whether investors' environmental preferences price an asset's carbon footprint itself, or merely their attention to it. In equity markets, carbon intensity typically proxies for future carbon liability, so any pricing attributed to preferences may partly reflect hedging of transition risk. This paper resolves this tension by moving the test to the cryptocurrency market, which is structurally free of carbon taxation liability, serving as a unique economic laboratory to isolate pure preference-based pricing. The setting has two other features that make it an unusually clean environment to study investor environmental preferences. First, the externality is real, large, and precisely measurable. Bitcoin's market capitalization alone is over trillion dollars, larger than all but a handful of public companies. Bitcoin mining consumes electricity on the scale of a midsize industrial economy and emits on the order of sixty million tonnes of CO_2 per year (Conklin and Malone, 2024). Second, the externality is embedded in internal design and varies sharply across otherwise similar assets that trade side by side: proof-of-work coins (Bitcoin, pre-Merge Ethereum) are energy-intensive, while proof-of-stake (POS) coins consume negligible energy, hence are considered green.

To formalize the preference-based pricing mechanism in this setting, I develop a parsimonious, continuous-time, partial-equilibrium carbon pricing model. The mean-variance investor allocates between the crypto token and a riskless asset with interest rate r_f; a fraction μ of investors with ESG preferences bear a non-pecuniary flow disutility of d dollars per tonne of CO_2 financed, in the taste-based tradition of Pástor et al. (2021); per-coin emissions $\kappa(t)$ decay deterministically at rate λ as the network gains efficiency; and news about a technology upgrade arrives at Poisson hazard η that further reduces the private valuation of carbon. Market clearing yields a price equal to the carbon-free fundamental minus a capitalized carbon claim: the present value of all future emissions, priced at a known carbon valuation following (Rennert et al., 2022) and discounted by time preference, emissions decay, and technology transition anticipation. Convexity in λ and η confirms the absence of an interior maximum. Thus, preferences can enter the price through any of these channels. Rational investors' private valuation of the claim is largest at the corner solution of the pricing model - full internalization at the social cost of carbon following (Rennert et al., 2022), no efficiency decay, no anticipation - worth \$254 per coin for Ethereum, 17% of its price, and a valuation of \$30.6 billion.

The carbon claim is one of two channels through which preferences can operate. The second,

and the one the sustainable-investing mechanism ultimately leans on, is exclusion: when investors with ESG preferences hold none of the asset, the remaining investors must absorb the entire supply. Consequently, they demand higher compensation for bearing the concentrated risk, and the brown asset's price falls by the limited-risk-sharing discount of Merton et al. (1987) and Heinkel et al. (2001). Whether exclusion can operate at all is a quantitative question, and the model answers it by providing a threshold above which ESG investors divest. Carbon enters the ESG investor's demand as a private per-coin tax on the dividend, so she holds an interior long position while her private carbon valuation stays below an exit threshold; above it her no-short constraint binds, she exits, and the unconstrained pool absorbs the entire supply at a discounted price. The threshold is the equilibrium risk compensation per tonne of carbon financed, denominated in dollars per tonne of CO2 emissions, and therefore is directly comparable to the social cost of carbon.

Crypto's payoff variance and realized excess returns, two measurements of the same equilibrium object, place it orders of magnitude above that benchmark: no private valuation within the social-cost schedule of Rennert et al. (2022) makes the constraint bind, and investors hold brown assets such as Bitcoin, however strong their environmental preferences. Yet were the constraint ever to bind, that same volatility would make the exclusion discount enormous- with so few unconstrained investors left to absorb the entire supply, each demands large compensation for the concentrated risk, a discount of hundreds of percent even at a small excluded mass. The discount is thus never triggered: for an investor to exit, she would have to value carbon two to three orders of magnitude more than its social cost, far beyond the private carbon valuation for any rational investor. Even where it binds, the limited-risk-sharing discount depends on the mass of constrained capital, risk aversion, and payoff variance. Once the exclusion binds, the level of carbon emissions is irrelevant to the price. Divestment therefore cannot be triggered at any rational valuation of carbon social costs, and cannot scale with carbon even once triggered, a structural property of the exclusion equilibrium itself. This mechanism applies to any asset that has a high risk-return profile.

I use the Ethereum technology upgrade, the Merge, as a natural experiment to empirically[1] test the model. The setting provides the cleanest experiment in the carbon-pricing literature. On September 15, 2022, at block 15,537,393 (05:42:42 UTC), the Ethereum network upgraded its technology and replaced proof-of-work consensus with proof-of-stake, cutting the network's energy consumption by 99.95% and its emissions from roughly 11 million tonnes of CO_2 per year to

[1] Existing work on the Merge documents changes in liquidity, volatility, transaction fees, and cross-asset connectedness. None values the eliminated externality or derives the price response that an equilibrium model admits.

approximately zero. The treatment is total, permanent, and precisely dated: the technology upgrade eliminated Ethereum's entire carbon externality at a single verifiable block, so the entire value of the carbon claim is extinguished overnight. It was pre-announced twenty-two days ahead, so the arrival of the news and its implementation are observed separately. I use Bitcoin as a robust control that shares Ethereum's trading venues and its exposure to every macro and crypto-wide shock. Bitcoin remained proof-of-work and differs from Ethereum ex-post only in whether the carbon claim survives.

I find that post-technology upgrade, no capital was reallocated toward the now-green Ethereum. In difference-in-differences specifications with asset and date fixed effects and treatment scaled by the dollar value of the per-coin claim eliminated, order-flow imbalance, the dollar-weighted buy ratio, and volume are statistically indistinguishable from zero in every trade-size bucket on both Kraken and Binance, the most liquid venues in the market. The results are consistent with what the model predicts: because the exit threshold lies orders of magnitude above any rational carbon valuation and an enormous exclusion discount required by remaining holders to absorb the additional supply, no ESG capital is excluded from Ethereum. Therefore, even as the technology upgrade eliminates the entire carbon claim, order flow does not move. However, I find liquidity-supply effects: adverse selection falls by 0.89 standard deviations on Kraken, while illiquidity and the spread rise on Binance. This is consistent with liquidity providers contracting liquidity following a huge and permanent exogenous shock.

Returns provide a consistent story and validate the model and ESG preferences. At the announcement, the hazard η resolves, the execution date becomes common knowledge, and a forward-looking market front-loads the entire revaluation. Hence, the announcement is where returns are identified. Anticipation of the technology update governs the carbon liability claim. Under full internalization with no efficiency decay, a market that had never expected the transition ($\eta = 0$) should have gained +15.3% on the announcement. A market expecting it within four years on average ($\eta = 0.25$) should have gained only 1.6% at the same carbon price - an order of magnitude smaller, from anticipation alone. The observed announcement cumulative abnormal returns are indistinguishable from zero. Its 95% confidence band excludes +15.3% but contains every prediction with $\eta \geq 0.25$ (Figure 4). Between the announcement and execution of the technology upgrade, the claim amortizes to three basis points for any revealed carbon price, so the model predicts no repricing at execution, and none is observed from data. The realized response is instead negative.

I estimate the single-factor market model on a six-month window ending two months before the Ethereum Merge. I focus on short horizons as they are the appropriate test window: post Merge a repricing should appear immediately, and longer windows accumulate variance and post-event confounds without adding additional identifying information. I show that Ethereum's cumulative abnormal return relative to Bitcoin on Kraken Post-Merge is -7.2% at day one ($t = -2.66$), -10.8% at day three ($t = -2.18$), and -12.0% at day five ($t = -1.91$). Results from Binance yield -7.9% ($t = -2.61$), -12.0% ($t = -2.32$), and -14.0% ($t = -2.20$) at the same horizons. The estimates are uniformly negative and significant at the 5% level or better on both venues, with the exception of the five-day Kraken estimate, which is significant at 10%. Under the corner calibration $(D, \lambda, \eta) = (\text{SCC} = 80, 0, 0)$, full internalization implies an Ethereum abnormal return of +17.3%, and +36.7% under the coal-only emissions scenario. The realized response results are inconsistent with the repricing mechanism: extinguishing a liability cannot reduce the price of an asset, so the elimination of the externality cannot account for a negative abnormal return, and the observed negative values should be attributed to factors outside the carbon repricing channel. The results confirm the model's prediction of no carbon repricing post-elimination of carbon externality.

A second experiment holds fundamentals fixed and moves only attention. On March 24, 2021, Elon Musk tweeted that Tesla would accept Bitcoin as payment[2]; on May 12, 2021, he suspended acceptance, citing Bitcoin's environmental footprint. The news was covered in major outlets[3]. Same actor, same channel, same market; the two announcements reverse the sign of the payment-utility news, and only the second carries carbon content. Neither changed fundamentals - Bitcoin and Ethereum remained proof-of-work throughout. The pair therefore disentangles the carbon-salience component: summing the treated-versus-control differentials across the two events cancels the mirrored utility component in signed outcomes (order flow, buy ratios), while differencing them cancels common attention in unsigned outcomes (trade-size composition, spreads), isolating the carbon-salience component in each. I show that the order flow and buy ratios carry no carbon component while the carbon signal concentrates in liquidity provision. The effective spread narrows by 2.2 pre-event standard deviations on the acceptance and widens by 3.0 standard deviations on the suspension, an asymmetry that symmetric attention cannot produce, yielding a carbon-salience component of +5.2 standard deviations ($t = 4.0$). Retail participation responds to both attention and carbon: it increases more on the carbon event (+5.87 SD) than on the pure-attention event

[2] https://www.reuters.com/business/autos-transportation/musk-says-can-now-buy-tesla-with-bitcoin-2021
[3] https://www.reuters.com/technology/tesla-stops-taking-bitcoin-cites-fossil-fuel-use-mining-cybercur

(+3.10 SD), leaving a positive and significant carbon-salience component (+2.77, $t = 2.06$). Hourly estimates show spreads and adverse-selection costs increasing at the tweet on May 12, and reverting within six to nine hours. Ethereum, proof-of-work but unnamed in the tweet, acts as a counterfactual. Results for Ethereum show no response to carbon salience, suggesting that the preferences run through salience to a specific asset's carbon attribute, not through crypto-wide market sentiment.

The paper makes three contributions. The first is theoretical: to my knowledge, the first equilibrium model that capitalizes a carbon externality into the price of an asset facing a stochastic technology transition. The claim's closed-form expression stacks the discount rate, carbon decay, and transition hazard additively in the denominator, a comparative static that can be applied to any asset. Beliefs about technology upgrades reduce the private valuation of carbon social costs, therefore increasing the asset's price. I also derive the endogenous exit threshold at which ESG investors divest and characterize the resulting equilibrium price discount on brown assets. Economically, this discount is what the remaining non-ESG investors demand for holding the entire supply once investors with ESG preferences exit the market: with fewer investors bearing the same total risk, each requires higher compensation, and the brown asset's price falls. The framework combines the exclusion equilibrium of Heinkel et al. (2001) and taste-based pricing of Pástor et al. (2021) and Pedersen et al. (2021), and the three-regime information structure converts an event study into a bound on the revealed carbon price.

The second contribution is identification. Equity-based tests cannot separate preferences from regulatory transition risk, and their findings turn on emissions measurement and on realized-versus-expected returns (Bolton and Kacperczyk, 2021, 2023; Pástor et al., 2022a; Aswani et al., 2024b). The technology upgrade, as a natural experiment, provides a precisely dated, complete elimination of carbon externalities overnight, and the ESG investors' exit-threshold estimates then explain the muted trading response following the technology upgrade. The results directly complement (Berk and van Binsbergen, 2025), who show that divestiture fails to shift the cost of capital due to the high substitutability of assets, and (Oehmke and Opp, 2025), who demonstrate that real economic impact requires mandates willing to absorb financial losses. I extend this frontier by showing that in high volatility settings, the divestment margin never activates: the boundary remains entirely slack at any plausible parameterization of investor taste. Crucially, I depart from standard models of stable ESG wealth shares; the empirical asymmetry documented here - the permanent shock does not price carbon while transitory salience events do - is an asymmetry no stable preference can generate.

The third contribution is the within-market comparison of structural and salience-driven ESG

pricing. Climate attention is known to move prices and flows (Hartzmark and Sussman, 2019a; Choi et al., 2020; Engle et al., 2020), and investor attention to move trading generally (Barber and Odean, 2008; Da et al., 2011), but no study disentangles the carbon component of a pure attention shock. This paper also resolves the systemic look-ahead bias inherent in delayed corporate disclosures (Zhang, 2025) by leveraging verified daily blockchain network carbon metrics. The paper also adds to work on cryptocurrency risk premia, arbitrage, and equilibrium valuation (Liu and Tsyvinski, 2021; Makarov and Schoar, 2020; Biais et al., 2023; Cong et al., 2021). I further add to the literature on Bitcoin's carbon footprint(Stoll et al., 2019; De Vries et al., 2022; Papp et al., 2023).

Several strands of literature ask whether investors price the environmental characteristics of the assets they hold. Hartzmark and Sussman (2019b) document that ESG fund flows respond to Morningstar Globe ratings, a demand-side investor response. Krueger et al. (2020) document that the average respondent believes that climate risk is not fully priced in a survey-based study. I provide complementary evidence on the cryptocurrency market. Hsu et al. (2023) provide a risk-based channel in which firms exposed to environmental or pollution policy risk command higher expected returns. Several other theories share a common implication: an asset's environmental attribute is a priced characteristic of its expected return, while (Görgen et al., 2020; Aswani et al., 2024a; Lindsey et al., 2021) report mixed patterns. This paper provides a plausible explanation for the mixed evidence observed in equity markets. More broadly, the paper identifies a boundary condition for preference based ESG pricing. When regulatory liability is absent, environmental preferences do not continuously price the carbon externality. They affect market outcomes only when attention makes the externality salient.

The remainder of the paper proceeds as follows. Section II describes the background. Section III describes the data. Section IV presents the model. Section V presents empirical methods and results. Section VI presents the salience channel. Section VII concludes. All proofs are in the appendices.

II. Background

A. Consensus Mechanisms and CO_2 Emissions

The carbon footprint of a cryptocurrency is determined primarily by its consensus mechanism. Under proof-of-work (PoW), miners used specialized computers to compete to solve cryptographic puzzles. The first miner to find a valid solution receives a cryptocurrency. Participation in the blockchain validation process requires specialized hardware and vast amounts of electricity, which translates into a significant carbon footprint: Bitcoin network consumed an estimated 130-150 terawatt-hours of electricity annually at its 2021 peak, comparable to the annual electricity consumption of Argentina (Stoll et al., 2019; De Vries et al., 2022). Ethereum's consumption was approximately 83 TWh. Network CO2 emissions depend on both total electricity use and the carbon intensity of the power mix supplying miners. Figure IA.1 shows carbon emissions over time for POW assets.

Proof-of-stake (PoS) removes this computational race. Validators are selected in proportion to the amount of the native token they stake, so securing the network does not require energy-intensive mining. Ethereum provides the clearest illustration. Ethereum operated under PoW until September 2022. Later, it transitioned to POS and reduced energy usage by 99.9%, reducing annualized emissions from about 11 million tonnes of CO_2 to roughly 870 tonnes (Crypto Carbon Ratings Institute, 2022). Because crypto's environmental externality is embedded in protocol design, it provides a clean setting to test whether investors price carbon.

B. The Merge as an Exogenous Carbon Shock

On 15 September 2022, at block 15,537,393 (05:42:42 UTC), Ethereum executed the Merge: a pre-announced, on-chain technology upgrade that replaced proof-of-work consensus with proof-of-stake. The Merge isolates the carbon claim from other parameters that move crypto prices. Merge wiped off Ethereum's carbon claim, worth roughly one-quarter to one-third of the asset's market value. Ethereum's carbon emissions became zero at a verifiable on-chain block, eliminating the entire carbon externality. Bitcoin retained proof-of-work and continued to emit at approximately 70–90 $MtCO_2$/yr depending on electricity-mix assumptions.

C. The Brown Attention Shock

On March 24,2021 Elon Musk tweeted that Tesla will accept Bitcoin for purchases. Two months later, on May 12, 2021, Elon Musk announced that Tesla would suspend Bitcoin payments, citing

concerns over the environmental footprint of Bitcoin mining. The announcement received global media coverage. I use the Musk announcement as the attention shock in the analysis.

III. Data & Summary Statistics

A. Trade Data

The core data set consists of tick-level transaction records from Kaiko for four cryptocurrency pairs: BTC/USDC and ETH/USDC on both Binance and Kraken, and ADA/USDC and XRP/USDC on Binance alone. The Binance and control samples span January 1, 2019, to March 14, 2023; the Kraken BTC/USDC and ETH/USDC series span January 8, 2020, to March 13, 2023. Each record includes a timestamp, trade price, quantity, signed direction (buyer-initiated or seller-initiated), and an exchange identifier. I aggregate these ticks to the asset- exchange- day level, yielding daily panels: Binance contributes 1,371 daily observations each for BTC/USDC and ETH/USDC, and 1,280 and 1,368 for ADA/USDC and XRP/USDC, respectively, while Kraken contributes 1,161 daily observations each for BTC/USDC and ETH/USDC. I classify trades as small and large by dollar volume, following Bybit trade size classification [4]: large ($\geq$ \$100K notional), medium (\$10K–\$100K), and small ($<$ \$10K). Large Share and Small Share are the fractions of daily volume in trades exceeding \$100K notional and below \$10K notional, respectively.

B. Emissions Data

I obtain historical greenhouse-gas emissions for Bitcoin and Ethereum from the Cambridge Centre for Alternative Finance (CCAF). Each series reports the network's annualized emissions in millions of tonnes of CO_2-equivalent ($MtCO_2e$) at daily frequency[5], under a common electricity-cost assumption of \$0.05/kWh. The Bitcoin series runs from July 18, 2010 through March 12, 2026; the Ethereum (proof-of-work) series runs from August 27, 2015 through September 14, 2022, terminating at the Merge, after which Ethereum's consensus emissions fall to approximately zero.

For each network and date, CCAF provides three estimates that bracket the uncertainty in the mining energy mix: a *Hydro-only* lower bound, an *Estimated* central case reflecting the realized geographic distribution of mining, and a *Coal-only* upper bound. I take the *Estimated* series as the baseline and use the *Coal-only* series as an upper bound to compute social costs of carbon. I

[4] https://docs.rs/rs_bybit/latest/bybit/prelude/enum.TradeSizeCategory.html
[5] https://ccaf.io/cbnsi/cbeci/ghg

convert network-level emissions to a per-coin attributable intensity κ_0 (tCO_2/coin/yr) by dividing the annualized emissions on a given date by the outstanding coin supply on that date. Evaluated at the Merge (T_M = September 15, 2022), the Bitcoin network emits 46.4 $MtCO_2e$/yr under the Estimated mix (91.7 under Coal-only), which against a supply of 19.14 million coins implies κ_0 = 2.590 tCO_2/coin/yr (5.050 under Coal-only). The Ethereum network emits 10.3 $MtCO_2e$/yr under the Estimated mix (21.4 under Coal-only), which against a supply of 120.52 million coins implies κ_0 = 0.0953 tCO_2/coin/yr (0.2022 under Coal-only).

Table I reports summary statistics. Panel A shows that BTC-Binance is the most liquid asset exchange, with the tightest Roll Spread (1.75 bps), highest Log Volume (17.34), and lowest Amihud illiquidity (0.008). Within each venue, ETH spreads are wider than BTC spreads; across venues, Kraken spreads are wider than Binance spreads for the same asset, consistent with Kraken's thinner USDC book. Order Flow Imbalance is mildly negative on Binance and close to zero on Kraken, and Buy Ratios are near 0.5 on both venues, consistent with clientele similarity across the two exchanges. Small trades, defined as those below \$10K notional, account for roughly 60 to 85 percent of daily volume, and large trades, defined as those exceeding \$100K, account for one to two percent of trading volume. Medium shares are unreported but account for the rest of the trading activity. Panel B reports the proof-of-stake controls data from Binance. Spreads are several multiples wider than on the treated cells (12.67 bps for ADA and 5.56 bps for XRP). Amihud illiquidity is correspondingly higher, and small trades make up 92 to 95 percent of volume; institutional participation is at most one-tenth of one percent of volume on both controls.

Table II reports G for Bitcoin and Ethereum - the carbon claim under full internalization of the social cost, zero efficiency decay, and zero anticipation. This is the corner solution for my model and generates the largest admissible claim and therefore the sharpest, most detectable price response. This forms the basis of my empirical test on carbon pricing. Every departure from the corner shrinks the claim. Figure 1 shows the impact of departure on carbon claim. Following the rate-matched SCC schedule of Rennert et al. (2022), Ethereum's corner claim is \$882 per coin at r = 2% (SCC = \$185) to \$254 at r = 3% (SCC = \$80)-60% to 17% of its price, or \$106 to \$30.6 billion market-wide, while Bitcoin's standing corner claim at these rates is \$23,958 to \$6,907 per coin, respectively. Rational investors adopt r = 3%, and I adopt the same. Figure IA.2 plots the present discounted value of social costs of carbon for Bitcoin and Ethereum. The externality is economically significant at any rate.

IV. Model

A. The Carbon Claim and Equilibrium Pricing Model

I now present the continuous-time asset pricing parsimonious model that I study in this paper. The model modifies a standard mean-variance portfolio choice framework and features non-pecuniary ESG flow disutilities, a deterministic carbon emissions decay, and a stochastic proof-of-stake stochastic technological transition hazard to capture key innovations from the recent sustainable finance literature (e.g., (Pástor et al., 2021)). Despite these enrichments, the model presented below is intentionally streamlined along various dimensions for simplicity and to maintain a closer connection to foundational limited-risk-sharing papers in the literature (Heinkel et al., 2001). Throughout this theoretical framework, I study portfolio allocation in partial equilibrium, focusing strictly on the market-clearing dynamics between unconstrained and ESG-sensitive investors. I restrict the focus to partial equilibrium because it perfectly isolates the tension between financial returns and environmental disutility. This focused setting is where the mechanics of the "greenium" and limited risk-sharing are most cleanly resolved. Once the capitalized carbon claim and exclusionary bounds are established here, expanding the framework to encompass multiple asset classes or general equilibrium effects follows standard theoretical practices.

I derive, from portfolio choice and market clearing, the dollar carbon discount embedded in the price of a crypto-asset. The derivation delivers three objects the empirical design uses. First, an equilibrium carbon claim $G^{\text{mkt}}(t) = D\,\kappa(t)/(r + \lambda + \eta)$, in which the *revealed* price of carbon D (dollars per tonne charged by the marginal investor), the network's efficiency-driven emissions-decay rate λ, and the POW to POS technology upgrade anticipation hazard η discount the claim. Second, an upper bound: the claim is maximized at the corner $(D, \lambda, \eta) = (\text{SCC}, 0, 0)$, full internalization of the social cost, no efficiency decay, no anticipation, which is the calibration reported in Table II and the sharpest testable prediction the framework admits. Third, the mapping from the two event windows to the model's parameters: the announcement window bounds $D/(r + \lambda + \eta)$, while the execution window is a specification check on which the predicted response is negligible for *any* value of D. Full internalization, $D = \text{SCC}$, is throughout a hypothesis to be tested.

B. The Per-Coin Carbon Claim

An investor holding one unit of proof-of-work cryptocurrency i at instant s finances the social cost of the network's emissions in proportion to her ownership share. Per-coin attributable emissions are

$\kappa_i(s) = E_i^{\text{net}}(s)/N_i(s)$, where $E_i^{\text{net}}(s)$ is the network emission rate and $N_i(s)$ the circulating supply. With the technological upgrades, the network gains efficiency, and the emissions from crypto mining decay exponentially,

$$E_i^{\text{net}}(s) \;=\; E_{i,0}\, e^{-\lambda s}, \qquad \text{so} \qquad \kappa_i(s) \;=\; \kappa_{i,0}\, e^{-\lambda s}, \qquad \lambda \geq 0, \tag{1}$$

which shows that continuous efficiency improvements act like an additional discount rate on the future carbon impact of the network.[6] Capitalizing a recurring flow into carbon liability follows standard valuation practice - the Modigliani and Miller (1963) capitalization of a permanent debt tax shield, or the balance-sheet capitalization of a long-term lease and mirrors the environmental-accounting evidence that equity markets impound carbon footprints as implicit financial penalties (Matsumura et al., 2014).The price at which that capitalization occurs when no regulations exist is derived below.

C. Environment

Assumption 1 (Fundamental Pecuniary Flow)**.** Each coin yields a net pecuniary flow Ψ per year, defined as the sum of validator priority fees and the burnt base fees - a mechanism often likened in market practice to a corporate buyback - net of new issuance dilution[7] (Cong et al., 2021). While the revenue from fees is highly volatile and endogenous to network utilization, I treat Ψ as a constant parameter to maintain analytical tractability (see Appendix A).

Assumption 2 (Emissions and Technology Upgrade)**.** While the network operates under proof of work, each coin finances $\kappa(t) = \kappa_0 e^{-\lambda t}$ tonnes of CO_2 per year, with $\lambda \geq 0$. The proof-of-stake transition occurs at a random date τ and eliminates a share χ of carbon emissions; post- transition emissions $(1-\chi)\kappa(t)$ are insignificant.[8]

Assumption 3 (Investors)**.** A unit mass of investors with common absolute risk aversion a makes instantaneous mean–variance portfolio choices over the token and a riskless asset paying rate r_f. The per-coin payoff variance is σ^2 per year. A fraction $1-\mu$ of investors is *unconstrained* and values only pecuniary payoffs. A fraction μ consists of *ESG investors*: identical, except that holding the token imposes a non-pecuniary flow disutility of d dollars per tonne financed, $d\,\kappa(t)$ dollars per

[6] The second equality in (B) treats circulating supply as constant over the valuation horizon. With growing supply $N_i(s)$, the per-coin rate $\kappa_i(s) = E_{i,0}e^{-\lambda s}/N_i(s)$ decays weakly *faster* than $E_i^{\text{net}}(s)$, so issuance acts as additional decay and the $\lambda = 0$ corner of Lemma 1 remains the upper bound *a fortiori*.

[7] The non-pecuniary convenience yield of the token is subsumed in investor utility rather than added to the cash flow.

[8] The residual is below 0.05% of the pre-Merge rate and is immaterial at any calibration considered.

coin per year, in the taste-based spirit of Pástor et al. (2021). The parameter d is a *private* valuation of the externality.

Assumption 4 (Beliefs about Technology Upgrade)**.** Before the announcement date T_A, investors believe that the upgrade arrives at a constant Poisson hazard $\eta \geq 0$, independent of payoff shocks. At T_A, the execution date T_M becomes common knowledge and beliefs collapse to a point mass at T_M, with $\Delta \equiv T_M - T_A$.

Assumption 5 (Unique Solution)**.** The token's per-capita supply is a constant q, and prices satisfy the condition $\lim_{T\to\infty} e^{-rT} P(T) = 0$, which restricts price bubbles and thereby selects the unique fundamental solution of the pricing equation.

D. Equilibrium Price and Portfolio Choice

In this section, I develop a partial equilibrium parsimonious continuous-time model of portfolio choice. Let $P(t)$ denote the token price and $\mu_P(t) \equiv \dot{P}(t)$ its deterministic drift. An investor holding x coins earns the expected excess flow $x\,[\mu_P + \Psi - r_f P]$ per year at variance $x^2\sigma^2$; an ESG investor additionally bears the carbon disutility $x\,d\,\kappa(t)$. Market clearing and first-order conditions give the demands

$$x_U(t) \;=\; \frac{\mu_P + \Psi - r_f P}{a\sigma^2}, \qquad x_I(t) \;=\; \frac{\mu_P + \Psi - r_f P - d\,\kappa(t)}{a\sigma^2}, \tag{2}$$

so the carbon disutility operates on the ESG investor as a private per-coin tax on the dividend.

Proof. Appendix A completes the proof. □

Proposition 1. *The equilibrium price of POW cryptocurrency increases as the underlying network gains efficiency and carbon emissions decay because of technology upgrades. The equilibrium carbon claim retains the present-value structure of the capitalized liability, with discounts stacked additively in the denominator: the rate of time preference r, and the emissions decay λ. Under Assumptions 1 - 5, the equilibrium price is*

$$P(t) = \underbrace{\frac{\Psi - a\sigma^2 q}{r}}_{\text{carbon-free value } P^*} - \underbrace{\frac{D\,\kappa(t)}{r+\lambda+\eta}}_{\text{carbon claim } G^{\text{mkt}}(t)} . \tag{3}$$

This shows that the carbon claim is a liability and reduces the asset's value. The pricing formula holds for any $r \in (0, \infty)$ *and* $\Psi \geq a\sigma^2 q + \frac{r\,D\,\kappa(t)}{r+\lambda+\eta}$. *Figure 1 & 2 presents the results.*

Proof. Appendix B completes the proof. □

Lemma 1 (Minimum Price and Maximum Carbon Claim)**.** *On the admissible set* $(D, \lambda, \eta) \in [0, \text{SCC}] \times [0, \infty) \times [0, \infty)$, *the claim* $G^{\text{mkt}}(t) = D\kappa_0 e^{-\lambda t}/(r + \lambda + \eta)$ *is strictly increasing in D and strictly decreasing and convex in each of λ and η. It attains its unique maxima, and the price attains its minima at the corner* (SCC, 0, 0)*, with value*

$$\bar{G} = \frac{\text{SCC}\,\kappa_0}{r}, \qquad P(t) = \underbrace{\frac{\Psi - a\sigma^2 q}{r}}_{\text{carbon-free value } P^*} - \bar{G}. \tag{4}$$

The value of carbon claim, $G^{\text{mkt}}(t) = D\kappa_0 e^{-\lambda t}/(r + \lambda + \eta)$, *implies that even small increases in emissions decay coefficient λ or anticipation η can dramatically reduce the carbon claim, which is the key mechanism behind the paper's argument that no change in trading behavior post technology upgrade announcement, the Ethereum Merge, is consistent with the model for a wide range of parameter values. The value* $D = 0$ *recovers carbon-indifferent pricing.*

Proof. Appendix C completes the proof. □

Figure 1. Private Valuation of Carbon claim

This figure shows the equilibrium carbon claim G as a function of the emissions decay rate λ for a grid of anticipation hazard values $\eta \in \{0.25, 0.5, 0.75, 1.0\}$, separately for BTC (Panel A) and ETH (Panel B). The claim is given by

$$G(t) = \frac{D\,\kappa(t)}{r + \lambda + \eta}, \qquad \kappa(t) = \kappa_0 e^{-\lambda t},$$

where r is the discount rate (set to 3%), D is the revealed carbon price (set to the Social Cost of Carbon, D = SCC = \$80/tCO$_2$) following (Rennert et al., 2022), and κ_0 is the per-coin attributable emission intensity (2.590 tCO$_2$/coin/yr for BTC; 0.0953 tCO$_2$/coin/yr for ETH). The corner solution $(\lambda, \eta) = (0, 0)$ reduces the claim to $G = D\kappa_0/r$, equal to \$6,907/coin for BTC and \$254/coin for ETH.

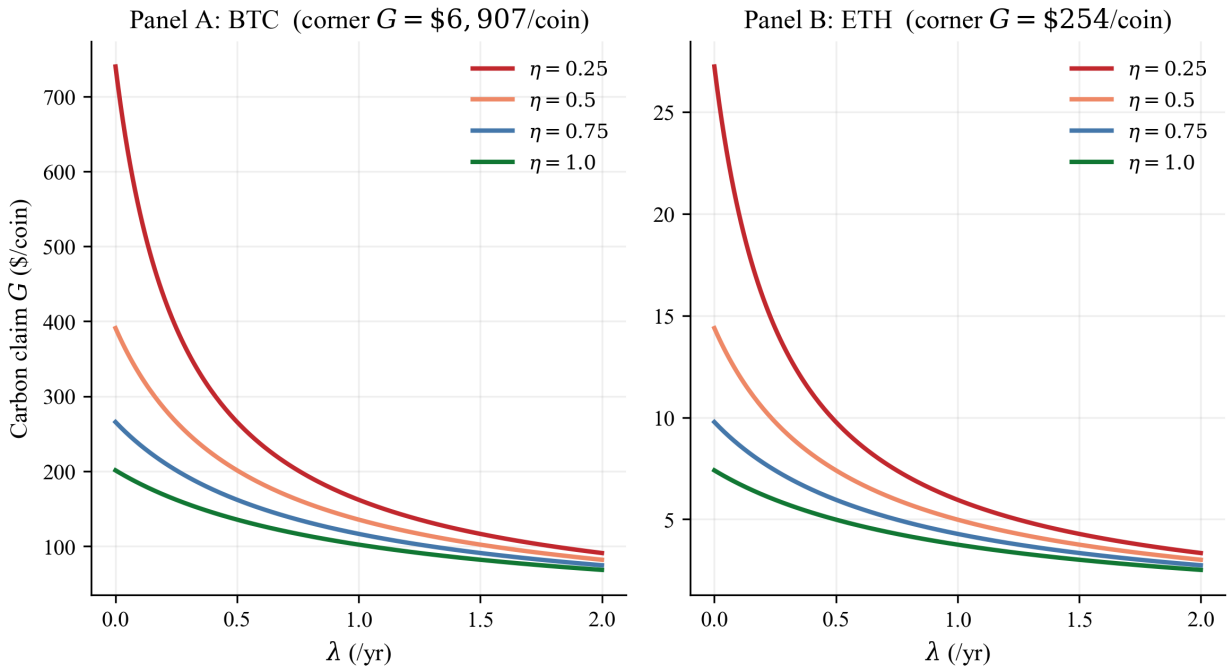
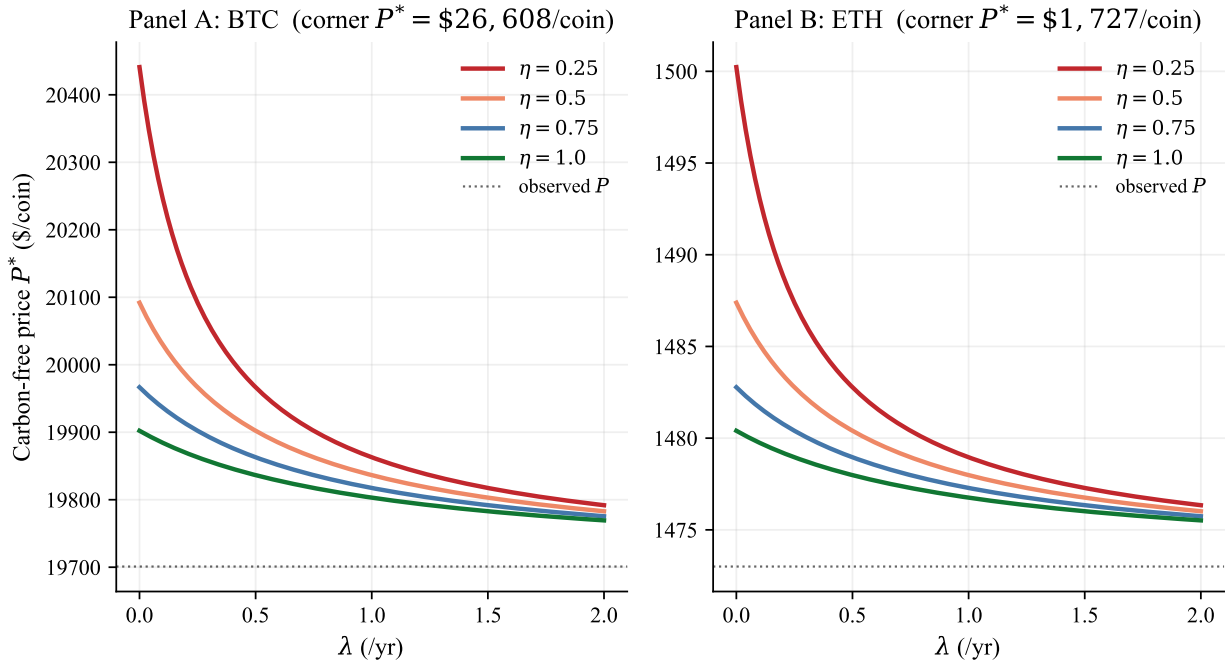


Figure 2. Carbon-Free Fundamental Price P^*

This figure shows the carbon-free fundamental price P^* as a function of the emissions decay rate λ for a grid of anticipation hazard values $\eta \in \{0.25, 0.5, 0.75, 1.0\}$, separately for BTC (Panel A) and ETH (Panel B). The carbon-free price is

$$P^* = P(t) + G(t), \qquad G(t) = \frac{D\,\kappa(t)}{r + \lambda + \eta}, \qquad \kappa(t) = \kappa_0 e^{-\lambda t},$$

where r is the discount rate (set to 3%), D is the revealed carbon price (set to the Social Cost of Carbon, D = SCC = \$80/tCO$_2$) following (Rennert et al., 2022), and κ_0 is the per-coin attributable emission intensity (2.590 tCO$_2$/coin/yr for BTC; 0.0953 tCO$_2$/coin/yr for ETH). The dotted line marks the observed reference price at the Merge execution date on September 15, 2022. The corner solution $(\lambda, \eta) = (0, 0)$ gives $P^* = P + D\kappa_0/r$, equal to \$26,608/coin for BTC and \$1,727/coin for ETH.



Proposition 2. *ESG investors in crypto markets don't divest because the exit threshold is too high. Whatever ESG preferences crypto investors have, those preferences are not strong enough to make them act - they hold Bitcoin and other POW regardless. When the per-coin disutility exceeds the exit threshold $d^*(t)$, the ESG investor's no-short constraint binds, the unconstrained pool absorbs the entire supply*

$$d\,\kappa(t) \;\le\; \frac{a\sigma^2 q}{1-\mu} \qquad \Longleftrightarrow \qquad d \;\le\; d^*(t) \equiv \frac{a\sigma^2 q}{(1-\mu)\,\kappa(t)}. \tag{5}$$

and the equilibrium price carries the discount. The ESG investor's no-short-price is

$$P \;=\; \frac{1}{r}\left(\Psi - \frac{a\sigma^2 q}{1-\mu}\right), \qquad \textit{and} \;\; \Delta_{\text{excl}} \;=\; \frac{a\sigma^2 q}{r}\,\frac{\mu}{1-\mu}, \tag{6}$$

is the limited-risk-sharing discount of Merton et al. (1987) and Heinkel et al. (2001). Δ_{excl} depends on the mass of constrained capital, risk aversion, and variance, not on κ and is economically negligible magnitudes for small values of μ. Once exclusion binds, the level of carbon emissions is irrelevant to pricing. This structural feature limits the model's ability to generate a continuous carbon-pricing mechanism through the exclusion channel. Figure 3 plots the variation of the limited risk-sharing discount with the mass of ESG investors.

Proof. Appendix D completes the proof. □

Lemma 2 (The exclusion discount is large)**.** *Under the CARA normalization $a = \gamma/W$, $W = PN$, $q = N$, and $\sigma^2 = \sigma^2_{\text{ret}} P^2$ (see Section V), the exclusion discount of Proposition 2 scales with the asset's return variance,*

$$\frac{\Delta_{\text{excl}}}{P} \;=\; \frac{\gamma\,\sigma^2_{\text{ret}}}{r}\,\frac{\mu}{1-\mu}, \tag{7}$$

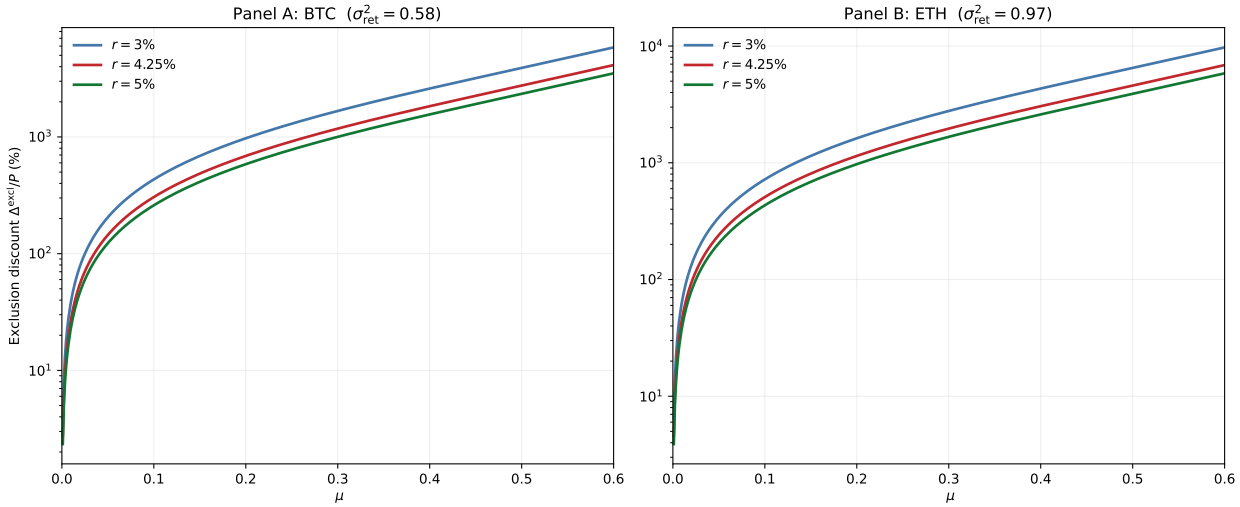
which is strictly increasing in μ and diverges as $\mu \to 1$. The discount is the risk compensation demanded by the $(1-\mu)$ unconstrained investors who remain and must absorb the entire supply once the ESG mass exits; as that pool shrinks, each holder bears a more concentrated position and the required discount grows without bound. If even a small fraction of ESG capital were excluded from Bitcoin or POW crypto, the required discount would be enormous - because crypto is so volatile that the few remaining holders would demand huge compensation for the concentrated risk. Therefore, exclusion never activates: the same extreme volatility that would make the discount huge also drives the exit threshold orders of magnitude above any rational carbon cost, so no ESG investor ever exits in the first place: $d < d^*(t)$ holds throughout.

Figure 3. Equilibrium Exclusion Discount and the Mass of Constrained Capital

The figure plots the limited-risk-sharing exclusion discount of Proposition 2 as a function of the mass of ESG-constrained capital μ, for Bitcoin (Panel A) and Ethereum (Panel B). When the per-coin disutility exceeds the exit threshold $d^*(t)$, the ESG investor's no-short constraint binds, the unconstrained pool absorbs the entire supply, and the equilibrium price carries the discount

$$\frac{\Delta^{\text{excl}}}{P} = \frac{\gamma\,\sigma^2_{\text{ret}}}{r} \cdot \frac{\mu}{1-\mu},$$

where the composite risk term is pinned by the CRRA normalization $a = \gamma/W$, $W = PN$, $q = N$, and $\sigma^2 = \sigma^2_{\text{ret}} P^2$, so that $a\sigma^2 q = \gamma\,\sigma^2_{\text{ret}}\,P$. Here $\gamma = 2$ is relative risk aversion and σ^2_{ret} is the annualized variance of daily log returns (0.58 for BTC, 0.97 for ETH). The three curves vary the discount rate r over the standard discounting range (3%, 4.25%, and 5%). The vertical axis is on a log scale, and μ is shown over $[0, 0.6]$. Daily closing prices for BTC/USDC and ETH/USDC on Binance over January 1, 2019 to March 14, 2023.



E. Information Regimes and Carbon Pricing

The carbon claim evolves through three regimes governed by the arrival of information, now with beliefs made explicit rather than assumed degenerate.

Regime 1 ($t < T_A$): anticipation. With the execution date unknown, the claim is the expected present value of the emission flow stopped at the random date τ,

$$G^{\text{mkt}}(t) = \mathbb{E}_t\left[\int_t^{\tau} e^{-r(u-t)}\, D\,\kappa(u)\, du\right] = \frac{D\,\kappa(t)}{r+\lambda+\eta}, \qquad t < T_A, \tag{8}$$

Regime 2 ($T_A \le t < T_M$): the dated annuity. At T_A the hazard resolves to a point mass at T_M and the claim truncates to the remaining brown window,

$$G^{\text{mkt}}(t) = \frac{D\,\kappa(t)}{r+\lambda}\Big(1 - e^{-(r+\lambda)(T_M-t)}\Big), \qquad T_A \le t < T_M. \tag{9}$$

Regime 3 ($t \ge T_M$): extinguishment. Execution sets κ to zero and $G^{\text{mkt}}(t) = 0$; the price is P^*.

The present value of the future carbon damages per coin eliminated is:

$$\Delta G_{T_A} \;=\; G(T_A^-) - G(T_A^+) \;=\; D\,\kappa(T_A)\left[\frac{1}{r+\lambda+\eta} - \frac{1-e^{-(r+\lambda)\Delta}}{r+\lambda}\right], \tag{10}$$

At $\lambda = \eta = 0$,

$$\Delta G_{T_A} = \frac{D\,\kappa_0}{r}\Big[1 - \big(1 - e^{-r\Delta}\big)\Big] = \frac{D\,\kappa_0}{r}\, e^{-r\Delta}, \tag{11}$$

Cumulative Abnormal Returns at the announcement date follow:

$$\text{CAR}(T_A) = \frac{D\,\kappa(T_A)}{P(T_A^-)}\left[\frac{1}{r+\lambda+\eta} - \frac{1-e^{-(r+\lambda)\Delta}}{r+\lambda}\right]. \tag{12}$$

Proof. Appendix E completes the proof. □

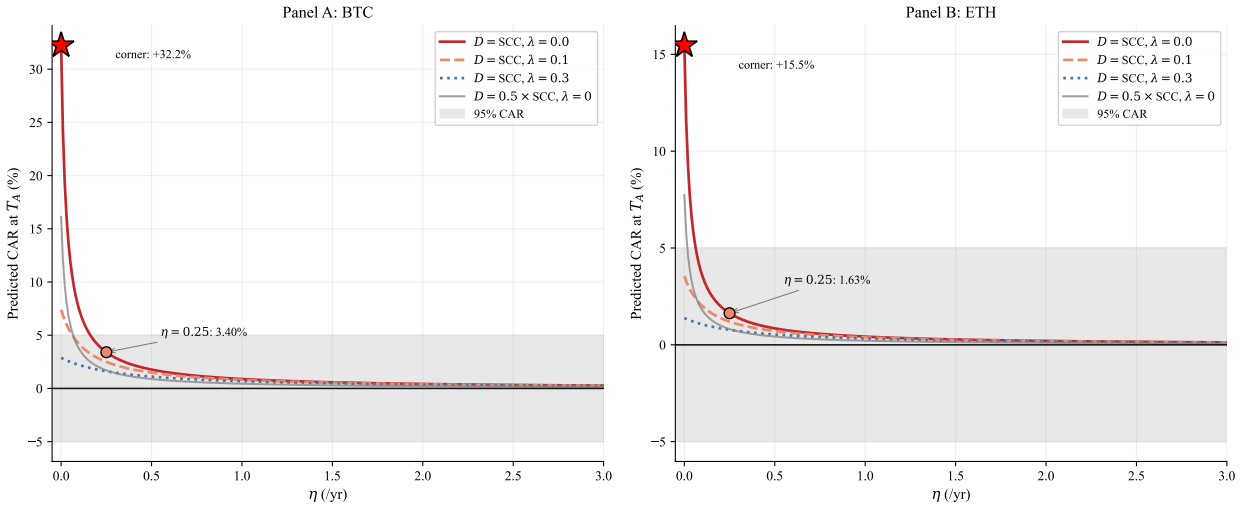
Lemma 3 (Announcement Response and Anticipation)**.** *At* $D = \text{SCC}$*,* $\lambda = 0$*,* $r = 3\%$*, the pre-announcement claim is* $\text{SCC}\,\kappa_0/(0.03 + \eta)$ *dollars per coin, equal to $254 per coin for ETH and $6,907 per coin for BTC at* $\eta = 0$*. Anticipation is decisive for the carbon claim and for returns. Evaluated at the announcement-date price* $P(T_A^-)$ *($1,657 for ETH, $21,369 for BTC on 24 August 2022), equation* (12) *gives a predicted announcement return of* 15.3% *for ETH (*32.3% *for BTC) at* $\eta = 0$*, falling to* 1.6% *for ETH (*3.4% *for BTC) at* $\eta = 0.25$ *(expected merge within four years) and* 0.4% *for ETH (*0.9% *for BTC) at* $\eta = 1$ *(expected merge within one year). A market that had long anticipated the transition would therefore exhibit an announcement response an order of magnitude below the corner prediction even under* full *internalization. Figure 4 presents the results.*

Figure 4. Predicted Announcement Return and Anticipation

This figure plots the model-predicted cumulative abnormal return at the announcement date T_A as a function of the anticipation hazard η, separately for BTC (Panel A) and ETH (Panel B). The predicted return is

$$\mathrm{CAR}(T_A) = \frac{D\,\kappa(T_A)}{P(T_A^-)}\left[\frac{1}{r+\lambda+\eta} - \frac{1-e^{-(r+\lambda)\Delta}}{r+\lambda}\right],$$

where D is the revealed carbon price, $\kappa(T_A)$ is the per-coin emission intensity at T_A, $P(T_A^-)$ is the pre-announcement price, r is the discount rate, λ is the emissions decay rate, η is the anticipation hazard, and $\Delta = T_M - T_A$ is the announcement-to-execution horizon. Curves are shown for $D = \mathrm{SCC}$ at $\lambda \in \{0, 0.1, 0.3\}$ and for $D = 0.5 \times \mathrm{SCC}$ at $\lambda = 0$. Parameters are set to $r = 3\%$, $D = \mathrm{SCC} = \$80/\mathrm{tCO_2}$, $\Delta = 22$ days, and $\kappa_0 = 2.590$ (BTC) and 0.0953 (ETH) $\mathrm{tCO_2}$/coin/yr; the pre-announcement price $P(T_A^-)$ is the close on 24 August 2022. The star marks the corner prediction at $\eta = 0$, the circle marks the value at $\eta = 0.25$, and the shaded band the 95% confidence interval for the observed CAR.



V. Empirical Methods & Results

A. Identification of $d^*(t)$

The exit condition characterizes the private valuation d above which an ESG-constrained investor's short-sale constraint binds, and the segment exits the market. This subsection derives the reduced form and the empirical estimation for the exit threshold.

Equation (5) contains three quantities that are not directly observable in market data: the CARA parameter a, the per-capita supply q under the "unit mass" normalization, and the constrained mass μ. Any numerical evaluation of $d^*(t)$ therefore requires either an external calibration of these primitives or a substitution that eliminates them through an equilibrium restriction implied by the model.

$$d\,\kappa(t) \;\le\; \frac{a\sigma^2 q}{1-\mu} \qquad \Longleftrightarrow \qquad d \;\le\; d^*(t) \equiv \frac{a\sigma^2 q}{(1-\mu)\,\kappa(t)}.$$

where σ^2_{ret} the variance of its return; since $dP = P\,(dP/P)$, scaling by P scales variance by P^2, giving $\sigma^2 = \sigma^2_{\text{ret}}\,P^2$. This converts the return variance into the dollar-payoff units, $\text{Var}(dW) = x^2\sigma^2$, where x is in coins and W in dollars. Expressing absolute risk aversion in relative terms, $a = \gamma/W$, with $W = PN$ and $q = N$. I set $W = PN$, a standard local CRRA matching and should be read as a calibration choice rather than a re-specification of preference, so the representative investor's wealth equals market capitalization. This is a normalization that fixes the scale at which the dimensionless coefficient γ maps to the absolute coefficient a via $a = \gamma/W$.

$$a\,\sigma^2\,q = \frac{\gamma}{W}\,\sigma^2\,q = \frac{\gamma}{PN}\left(\sigma^2_{\text{ret}}P^2\right)N = \gamma\,\sigma^2_{\text{ret}}\,P.$$

Under the normalization, the threshold reduces to $d^* = \gamma\sigma^2_{\text{ret}}P/[(1-\mu)\kappa]$. For a diversified investor holding crypto as a share $s = PN/W \le 1$ of wealth, the threshold scales to $s\,d^*$. The $s = 1$ case provides an upper bound. This upper bound already exceeds the SCC by two to three orders of magnitude. For realistic diversification ($s < 1$), the threshold is lower, yet remains above the SCC for a wide range of parameters. The $s = 0$ case is irrelevant because the investor holds no crypto. Thus, the exclusion constraint is slack under empirically plausible calibrations. For $d > d^*(t)$ the ESG pool exits.

Figure 5 plots the exclusion-regime exit threshold implied by the equilibrium model. Because crypto's risk-return profile is so extreme, the value of $d^*(t)$ is high, and the personal valuation of

carbon claim is a rounding error in the portfolio decision. An investor deciding whether to hold Bitcoin is weighing ±80% annual volatility and triple-digit expected returns against a few tonnes of CO2 per coin. Even investors with strong green preferences hold Bitcoin indefinitely. The high crypto volatility makes carbon unpriceable through preferences. Private valuation of carbon costs can't reach $d^*(t)$ for rational investors in crypto markets. Across both assets, the boundary exceeds the social cost of carbon by two to three orders of magnitude, so the exclusion constraint is slack throughout: under standard risk aversion, no empirically plausible private carbon valuation is large enough to induce divestment. Carbon preference is silent through exclusion.

A.1. Empirical Derivation of the Exit Threshold

The exit threshold equals the equilibrium excess payoff per coin per year, divided by the coin's carbon emissions per coin per year. Its units of dollars per tonne of CO_2 follow directly. In the cryptocurrency setting, Ψ is not directly observable. As noted in Assumption 1, the non-pecuniary convenience yield of the token is absorbed in investor utility rather than added to the cash flow, so Ψ captures only the residual pecuniary component of the flow per coin (validator/priority fees plus base-fee burn minus new-issuance dilution). Substituting Eq. (D4) directly into Eq. (D2) eliminates a, σ^2, q, and μ yielding

$$\boxed{d^*(t) \;=\; \frac{\mu_P + \Psi - r_f P(t)}{\kappa(t)}} \tag{13}$$

To obtain a numerical solution of Eq. (13), I adopt a reduced-form assumption that maps the (unobservable) equilibrium excess payoff to the (observable) realized excess return:

$$\mu_P + \Psi - r_f P(t) \;\approx\; \left(\bar{r} - r_f\right) P(t), \tag{14}$$

where $\bar{r}$ denotes the coin's realized total return over the sample period, and r_f is the risk-free rate. Equation (14) replaces the model's equilibrium excess payoff per coin with the empirical realized excess return per coin. In a rational-expectations sense, if realized average returns provide an unbiased proxy for equilibrium expected excess payoffs at the per-coin level, then the two are equal in expectation. Substituting Eq. (14) into Eq. (13) yields the reduced-form exit threshold used in the empirical framework.

$$\boxed{\widehat{d^*}(t) \;=\; \frac{\left(\bar{r} - r_f\right) P(t)}{\kappa(t)}} \tag{15}$$

Because realized crypto returns over the sample embed a large unexpected demand-driven component, $\bar{r} - r_f$ overstates the expected excess payoff (Pástor et al., 2022b), so $\hat{d}^*(t)$ is an upper bound; the point is immaterial here, since $d^*(t)$ exceeds the social cost of carbon by two to three orders of magnitude and remains above it even under an order-of-magnitude reduction in the assumed excess return. Figure 6 presents the results. Under the reduced-form Equation (15), $\widehat{d}^*(t)$ falls outside the range of plausible private ESG valuations by rational investors or those reported in (Rennert et al., 2022). The preference channel is quantitatively inoperative in either specification. The paper's identification of the exclusion regime relies on $\widehat{d}^*(t)$. In every interval, theory results coincide with the empirical results (Figures 5 & 6), corroborating the model.

At the Ethereum Merge transition, the threshold attains singularity. This means that an asset with zero emissions imposes no carbon disutility, so no investor would exit on environmental grounds given $(\bar{r} > r_f)$. As $\kappa(t) \to 0$, $\widehat{d}^*(t) \to \infty$ for any positive $(\bar{r} - r_f)P(t)$. This implies that even after the permanent elimination of carbon externality, the ESG investor's short-sale constraint remains infinitely slack. For ESG investors to change trading behavior at the Ethereum Merge, their private carbon valuation would have to be infinite or $(\bar{r} <= r_f)$.

Figure 5. Model-implied exclusion threshold $d^*(t)$ under the CARA calibration.

Description. The figure plots the exclusion-regime exit threshold implied by the equilibrium model,

$$d^*(t) \;=\; \frac{\gamma\,\sigma^2_{ret}(t)\,P(t)}{(1-\mu)\,\kappa(t)},$$

for Bitcoin and Ethereum on Binance and Kraken. The threshold is evaluated at the baseline calibration $\gamma = 2$ (moderate relative risk aversion) and $\mu = 1/2$ (the ESG-indifference benchmark), with aggregate wealth set to market capitalization of Bitcoin and Ethereum, respectively, so that the CARA coefficient satisfies $a = \gamma/(PN)$ and the per-coin supply cancels. The term $\gamma\sigma^2_{ret}(t)P(t)$ is the model's equilibrium compensation for risk and is strictly positive. Return variance $\sigma^2_{ret}(t)$ is the trailing-365-day annualized variance of hourly log returns, aggregated to daily frequency as the daily mean; $P(t)$ is the daily closing price; and $\kappa(t) = E(t)/N(t)$ is per-coin carbon intensity, computed from CCAF annualized emissions and the issuance-implied circulating supply. The solid line is the boundary $d^*(t)$: an ESG-constrained investor with private carbon valuation d holds an interior long position in the green region ($d < d^*(t)$) and is driven to the short-sale boundary in the red region ($d > d^*(t)$). Dotted horizontal lines mark the (Rennert et al., 2022) social cost of carbon at \$80 and \$185 per tonne. Ethereum panels terminate at the Merge (15 September 2022), after which $\kappa \to 0$ under proof-of-stake and the threshold diverges.

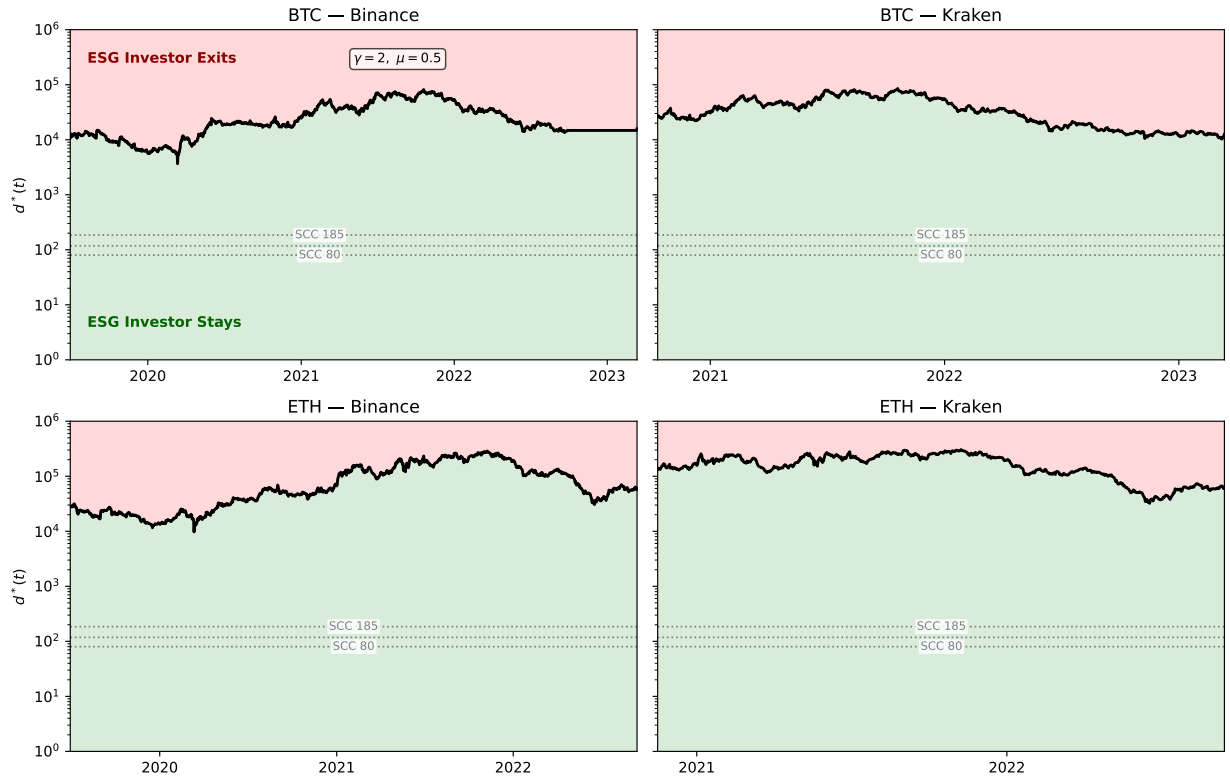
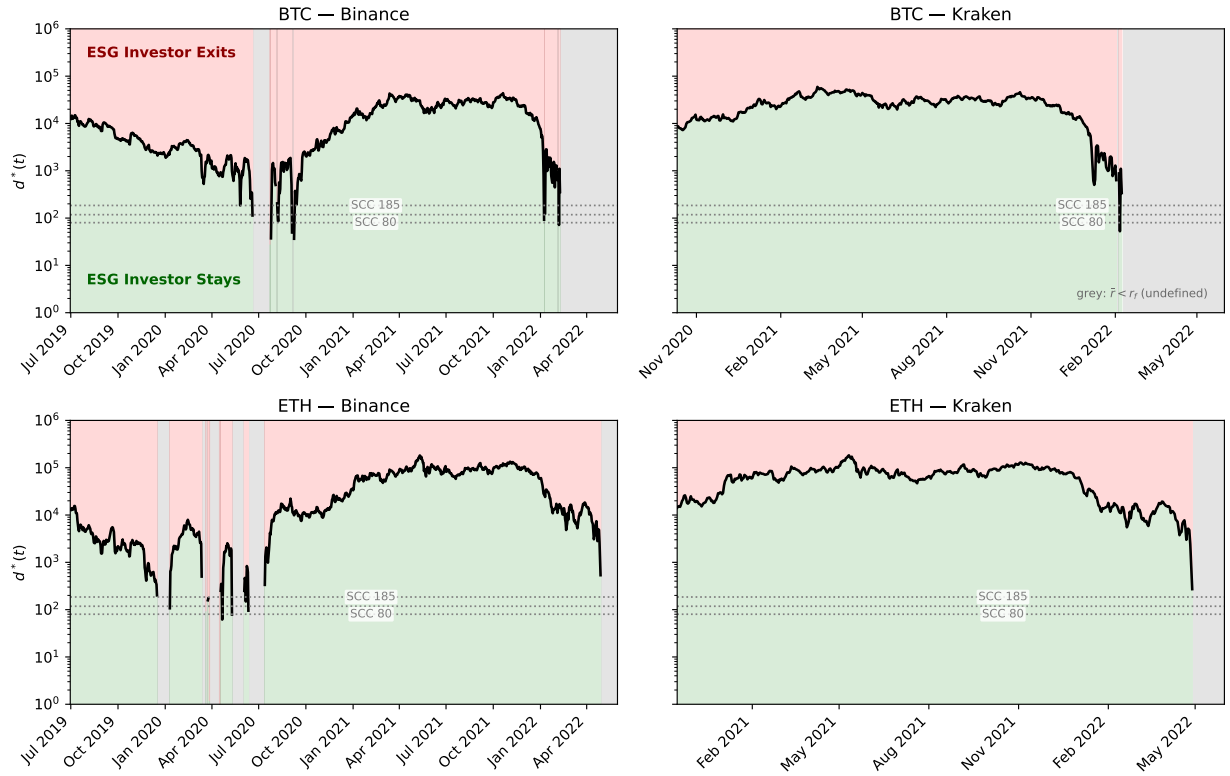


Figure 6. Reduced-form exclusion threshold $\widehat{d}^*(t)$

Description. The figure plots the reduced-form exit threshold

$$\widehat{d}^*(t) \;=\; \frac{\big(\bar{r}(t) - r_f\big)\, P(t)}{\kappa(t)},$$

which replaces the model's equilibrium risk premium $a\sigma^2 q/(1-\mu) = \Psi - rP$ with the observable realized excess return per coin. Here $\bar{r}(t)$ is the trailing-365-day annualized mean of hourly log returns, $r_f = 4\%$ is the risk-free rate, $P(t)$ is the daily closing price, and $\kappa(t) = E(t)/N(t)$ is per-coin carbon intensity from CCAF emissions and the issuance-implied supply. The solid line is the estimated boundary and the green and red regions denote the ESG-stay ($d < \widehat{d}^*$) and ESG-exit ($d > \widehat{d}^*$) sets; dotted horizontal lines mark the social cost of carbon at \$80 and \$185 per tonne. Grey bands cover intervals in which the trailing excess return is negative ($\bar{r} < r_f$), where the reduced-form proxy fails—the model requires a strictly positive equilibrium excess payoff, so the threshold is undefined rather than negative in these spans.



B. The Merge as a Natural Experiment

The premise of sustainable investing is that capital markets can internalize externalities on their own. If enough investors hold preferences over the external consequences of the assets they own, then the prices will come to embed those consequences: dirty producers face a higher cost of capital, clean producers a lower one, and capital reallocates toward the socially preferred technology - without any regulator setting a price or a quantity (Heinkel et al., 2001; Bolton and Kacperczyk, 2021). To examine this, I test whether technological abatement can reshape capital flows and trading behavior as investors move to green Ethereum following the elimination of carbon externality. I estimate Ethereum's differential trading response to Bitcoin around the Merge, scaling the treatment by the dollar magnitude of the carbon claim eliminated. While the Merge eliminated a huge portion of Ethereum's carbon claim overnight, Bitcoin's claim persisted. This gives a clean contrast: a large, permanent elimination of the carbon claim in the treated asset, against an untreated control whose claim persists. If the externality is priced through investor preferences, the elimination should impact Ethereum's returns, trading behavior, and market quality relative to Bitcoin's; if it does not, the externality is unpriced.

Let $i \in \{\text{BTC}, \text{ETH}\}$ index asset and t index date, let $\text{Post}_t = \mathbf{1}\{t \geq T_M\}$, and let $\overline{G}^{\text{pre}}_{\text{ETH}}$ denote the average pre-Merge per-coin carbon claim, i.e. the value removed at execution. The treatment intensity is $T_{i,t} = \text{ETH}_i \times \text{Post}_t \times G^{\text{pre}}_{\text{ETH}}$ or $\text{Post}_t \times \mathbf{1}\{i = \text{ETH}\} \times \overline{G}^{\text{pre}}_{\text{ETH}}$, which equals $\overline{G}^{\text{pre}}_{\text{ETH}}$ for Ethereum once the network turns green and zero otherwise. Scaling by \$1,000 yields the regressor $\tilde{T}_{i,t} = T_{i,t}/1000$, in which one unit corresponds to \$1,000 of eliminated per-coin carbon claim. I estimate

$$y^{(z)}_{i,t} = \gamma_i + \delta_t + \beta \tilde{T}_{i,t} + \varepsilon_{i,t}. \tag{16}$$

The outcome $y^{(z)}_{i,t}$ is standardized within asset on the pre-Merge window, so that β is expressed in standard deviations and the differential liquidity scales cannot confound the comparison. Asset fixed effects γ_i absorb permanent level differences between Bitcoin and Ethereum; date fixed effects δ_t absorb every common shock, so β is identified solely from the ETH-versus-BTC differential at the Merge. The coefficient β measures the change in the outcome per \$1,000 of ETH per-coin carbon claim eliminated. Within-asset standardization places coefficients in standard-deviation units and prevents differences in outcome scale from confounding the comparison. Multiplying by the

treatment magnitude $G^{\text{pre}}_{\text{ETH}}/1000$ yields the implied effect of the full Merge,

$$\widehat{\text{SD effect}} \;=\; \hat{\beta} \cdot G^{\text{pre}}_{\text{ETH}}/1000. \tag{17}$$

The estimate is invariant to the disputed carbon intensity of mining. The claim $G_{i,t} = \text{SCC}\,\kappa_{i,t}/r$ scales with the assumed electricity mix, for which CCAF reports a central ("estimated") and a coal-only upper-bound scenario. Moving between scenarios multiplies both the regressor $\tilde{T}_{i,t}$ and the treatment magnitude $\overline{G}^{\text{pre}}_{\text{ETH}}$ by the same mix factor, which cancels in the implied effect $\hat{\beta} \cdot \overline{G}^{\text{pre}}_{\text{ETH}}$. I therefore report both scenarios and the conclusion does not turn on which one is correct.

B.1. Kraken Venue

Estimating (16) on daily Bitcoin and Ethereum data, quoted against USDC on Kraken, over the window $[T_M - 90, T_M + 46]$. The 90-day pre-period maximizes baseline precision while staying short enough to limit anticipation contamination; the post-period runs through October 31, 2022, terminating a week before the 8 November 2022 collapse of FTX, which would otherwise contaminate later observations through market-wide liquidity spillovers and a flight from centralized exchanges. The outcomes span the channels through which a preference-driven reallocation toward the now-green asset would operate: directional demand and its institutional composition (order-flow imbalance, the buy ratio, and the large-, medium-, and small-trade shares) and the cost of liquidity (the Roll effective spread). If investors price the externality, eliminating ΔG_{ETH} should pull investors toward Ethereum and improve its liquidity relative to Bitcoin.

Table III reports the estimates. The preference-channel outcomes, order-flow imbalance, and the dollar-weighted buy ratio in the medium- and small-trade buckets, and small-trade volume, are uniformly indistinguishable from zero. The eliminated carbon claim thus explains almost none of the residual variation in how Ethereum is traded once common shocks and asset levels are removed, and several estimates carry the wrong sign for a repricing story (medium and small order-flow imbalance, −0.070 and −0.294 SD). Because these measures are built from executed trades, and Kraken trading was continuous throughout the window, the null reflects an absence of directional reallocation, not a trading gap because of the Merge.

The one significant coefficient is adverse selection, the permanent price-impact component, which *falls* by 0.89 standard deviations for Ethereum relative to Bitcoin. This is a liquidity-supply measure, not a preference one, and its sign matches the mechanics of the Merge rather than investor

demand: ending proof-of-work removed predictable, price-insensitive miner selling, lowering the adverse-selection risk liquidity providers had previously faced. The result is invariant to the emissions scenario by construction, as the Estimated and Coal-only assumptions rescale the regressor and treatment proportionally.

B.2. Binance Venue

My identification venue is Kraken, chosen for continuous trade coverage across the full event window. Because Binance is the most liquid cryptocurrency exchange and intermediates the largest share of global BTC and ETH volume, it is the natural venue on which to ask whether the main result generalizes. Estimating (16) on daily Bitcoin and Ethereum data, quoted against USDC on Binance, over the window $[T_M - 90, T_M + 14]$. The 90-day pre-period maximizes baseline precision while staying short enough to limit anticipation contamination; the post-period runs through 29 September 2022, terminating six weeks before the 8 November 2022 collapse of FTX, which would otherwise contaminate later observations through market-wide liquidity spillovers and a flight from centralized exchanges. Outcomes are standardized within asset on the pre-Merge window, so $\hat{\beta}$ is read in standard deviations per \$1,000 of Ethereum carbon claim eliminated. Binance trade coverage for the BTC/USDC and ETH/USDC pairs is continuous through the pre-Merge window, but terminates on 2022-09-29. The balanced panel, therefore, contains the full 90-day pre-Merge window but only 15 post-Merge days (September 15–29).

Table IV reports the estimates. On the most liquid venue in the market, the permanent removal of Ethereum's carbon claim produces no detectable shift in investor preferences. The only outcomes that load are the two liquidity-supply measures, Amihud illiquidity and the Roll spread, both positive: Ethereum became *less* liquid relative to Bitcoin after the Merge. The preference-channel outcomes - order-flow imbalance and the dollar-weighted buy ratio at every trade size - are statistically indistinguishable from zero. This is the opposite sign to a demand-side repricing of a now-green asset, and is most naturally read as the mechanical consequence of the proof-of-stake transition - the collapse of issuance, rather than as investors pricing carbon. The preference-channel measures (OFI, buy ratio) are computed solely from executed trades and are therefore unaffected by the post-Merge supply dynamics that impact liquidity outcomes. Trading was continuous on both venues, so these measures are fully observed. I find no shift in directional order flow toward Ethereum following the permanent removal of its carbon claim. Taken together, the elimination of a carbon externality worth \$30.6 billion, 17% of Ethereum's market value at the moment of its removal, produced no detectable

shift in order flow or trade composition toward Ethereum on Binance and Kraken, as Ethereum became green overnight. The estimates do not detect a post-Merge carbon-pricing response in secondary-market trading. I show that a forward-looking, informationally efficient market must front-load the multi-billion-dollar restructuring to the announcement date, leaving execution day to be governed purely by transitory microstructure liquidity frictions and supply shocks.

C. Return Response to the Merge

A rational, carbon-aware investor should price the elimination of an environmental externality through portfolio reallocation. The Ethereum Merge eliminated approximately $30.6 billion carbon liability on Ethereum and provides the cleanest possible setting to test this. If markets price the carbon externality through investor returns, the Merge should produce a positive abnormal return on Ethereum relative to Bitcoin, of a magnitude exceeding the normal noise floor of ETH-vs-BTC return volatility. The sample is the Kraken-USDC six-hour log returns for ETH and BTC, spanning $[T_M - 45d,\ T_M + 45d]$ around the Merge (T_M = September 15, 2022, 05:42:42 UTC). Six-hour binning provides higher resolution than daily returns without the microstructure noise of hourly returns. The bin spanning 00:00–06:00 UTC on September 15, which contains the Merge, is dropped to avoid contamination. The post-event window terminates on October 30, 2022, nine days before the FTX collapse on November 8, 2022, to avoid contamination by the exchange-driven dislocation that followed FTX's bankruptcy filing. I test this with an event-study CAR analysis under two specifications.

C.1. Specification 1: Simple Differential CAR

The simple differential abnormal return is

$$AR_t^{\text{simple}} = \left(r_t^{\text{ETH}} - r_t^{\text{BTC}}\right) - \hat{\mu}_{\text{pre}}, \tag{18}$$

where r_t^{ETH} and r_t^{BTC} are six-hour log returns and $\hat{\mu}_{\text{pre}}$ is the mean differential return over $[T_M - 45d,\ T_M - 1 \text{ bin}]$. The cumulative abnormal return is $\text{CAR}^{\text{simple}}(0, h) = \sum_{t=0}^{h} AR_t^{\text{simple}}$. This specification implicitly imposes $\beta_{\text{ETH,BTC}} = 1$.

C.2. Specification 2: CAPM-Adjusted CAR

To evaluate abnormal returns around the Ethereum Merge, and following the event-study methodology of (MacKinlay, 1997), I implement a single-factor market model using Bitcoin (r_{BTC}) as the market proxy. Bitcoin's dominant capitalization makes it highly correlated with the broader crypto market. I avoid a value-weighted index because Ethereum is its constituent; regression against such an index would endogenously embed the event into the risk factor. Because Ethereum co-moves strongly with Bitcoin, a simple return differential would misattribute normal systematic exposure to the event. I estimate

$$r_t^{\text{ETH}} - r_t^f = \alpha + \beta \left(r_t^{\text{BTC}} - r_t^f \right) + \varepsilon_t \tag{19}$$

on a pre-estimation window $[T_M - 180d,\ T_M - 60d]$, ending two months before the Merge to avoid anticipation contamination ($N = 478$ bins). I estimate this market model with the risk-free rate set to zero, $r_t^f \approx 0$, since the six-hour Treasury return is negligible at this frequency [9]. The CAPM-adjusted abnormal return is the out-of-sample residual of the pre-event market model,

$$AR_t^{\text{CAPM}} = r_t^{\text{ETH}} - \hat{\alpha} - \hat{\beta}\, r_t^{\text{BTC}}. \tag{20}$$

Because $\hat{\alpha}$ and $\hat{\beta}$ are estimated on the pre-event window $[T_M - 180d, T_M - 60d]$, which does not overlap the event window $[T_M - 45d, T_M + 45d]$, every AR_t^{CAPM} is evaluated out of sample. On the estimation window, the residuals are mean-zero and orthogonal to r^{BTC} by OLS construction; on the event window they are not, and their departures from zero are the abnormal returns of interest - ETH's return purged of its normal BTC comovement. For each horizon h, I report $\text{CAR}(0, h)$ and the corresponding t-statistic.

C.3. Results

I begin with the validation of the market-model benchmark that underlies the event study. Estimation over the pre-event window on Binance and Kraken yields $\hat{\beta} = 1.183, 1.165$ ($t = 12.32, 12.51$) and an intercept indistinguishable from zero ($\hat{\alpha} = 0.09\%$, $t = 1.58$), confirming that Ethereum's pre-Merge returns carry no drift once Bitcoin comovement is removed (Table V). Table VI reports endpoint

[9] The risk-free rate is annualized using the 4-week Treasury bill rate, which was approximately 4.5% during the sample period. Over a six-hour window $\left(\frac{1}{1460}\right.$ of a year, since there are $365 \times 4 = 1460$ six-hour periods in a year), the six-hour risk-free rate is $0.045 \times \frac{1}{1460} \approx 0.0000308 = 0.00308\%$. This is negligible relative to six-hour cryptocurrency returns, which are often several percentage points.

CARs and HAC t-statistics at horizons from +1 to +45 days under both specifications. The response is wrong-signed for the green-reward hypothesis at every horizon. Under the simple specification, peak underperformance is −25.5% at +30 days ($t = -2.26$), partially reversing to −15.3% by +45 days ($t = -0.92$). Under the CAPM-adjusted specification, which absorbs the systematic component of ETH's expected response to BTC's path, peak underperformance is −18.3% at +30 days ($t = -1.73$) and the +45-day endpoint is −7.1% ($t = -0.48$), statistically indistinguishable from zero. Figure 7 plots both CAR series. The pre-Merge window shows no anticipation effect; the post-Merge response is concentrated in the first three weeks following the event with partial mean reversion through late October. The CAPM-adjusted CAR remains within the 95% confidence band throughout. The realized direction is the opposite of the fundamentals-rational prediction. A market that prices the carbon externality through investor returns should produce a positive abnormal return on ETH proportional to the eliminated externality, on the order of +17% to +37% in the post-event window. The realized response is −7% to −18% depending on horizon and specification.

I repeat the event study on Binance, the most liquid venue. Figure 8 presents results. The market model is estimated on the $[-180, -60]$-day window with the Terra/Celsius/3AC cascade (5 May, 2022 - 1 July 2022) masked out, yielding $\hat{\alpha} = 0.086\%$ per six-hour bin, $\hat{\beta} = 1.18$, $\hat{\sigma}_\varepsilon = 0.84\%$, and $R^2 = 0.78$ on 253 clean bins (Table V). Binance trade coverage for the pair ends 29 September 2022, so the post window is limited to roughly +14 days and horizons beyond are not estimable; I therefore treat Binance as a diagnostic rather than an identification venue. Over the available window the response is wrong-signed for the green-reward hypothesis at every horizon and closely matches Kraken in sign and magnitude: cumulative ETH underperformance reaches −17.1% by +10 days under both the simple ($t = -1.92$) and CAPM-adjusted ($t = -1.98$) specifications; −8.0% at +1 day and −14.4% at +5 days. The CAR is wrong-signed for a green-reward hypothesis at every horizon on the deepest liquidity venue in the market. The negative direction is plausibly attributable to identifiable post-Merge non-carbon mechanisms. ETH miners had accumulated approximately $341 million of inventory in the weeks preceding the Merge and liquidated positions following the elimination of block rewards. The Federal Open Market Committee meeting on September 21, 2022 raised rates by 75 basis points; ETH fell 3% that day while BTC fell 1%, reflecting ETH's higher risk beta. The CAPM specification absorbs Fed component through $\hat{\beta}$; the miner-liquidation component remains in the residual. Neither is a preference response to the carbon transition.

VI. Carbon Salience and the Attention Channel

A. Attention Shocks and Trading Behavior

The equilibrium model of Section A does not incorporate the carbon preferences channel. A natural question arises: do environmental preferences influence investor behavior when news makes the carbon attribute salient? If they do, the news should move prices, and hence the trading behavior in proof-of-work assets, whose emission intensity κ is more than in otherwise-similar proof-of-stake assets, for which $\kappa \approx 0$ (see Equation 3). Because the price scales with κ, the differential response should load on the carbon attribute, not on characteristics common to large-capitalization cryptocurrencies.

I test this with a sudden, global attention shocks: Elon Musk's March 24, 2021 announcement that Tesla would accept Bitcoin payments for Tesla purchases[10] and his May 12, 2021 announcement that Tesla would suspend Bitcoin payments for Tesla purchases on environmental grounds[11]. The events are well-suited to identification because tweets (i) arrived without anticipation, (ii) impacted buyers globally, and (iii) didn't change underlying fundamentals: Bitcoin and Ethereum remained proof-of-work assets. Moreover, the two events originate from the same actor, transmit through the same channel (Musk's Twitter account), and impact the same market. Musk's tweet in March, therefore, identifies the investor response to pure Bitcoin utility and attention to news; the May tweet incorporates an additional carbon component. Any differential investor responses must therefore operate through attention to the asset's carbon footprint. This design helps separate the carbon salience component.

B. Empirical Design

For each event, I estimate for asset i on day t, a difference-in-differences specification with asset and date fixed effects,

$$Y_{it}^{(e)} = \gamma_i^{(e)} + \delta_t^{(e)} + \beta_3^e \left(\text{Post}_t \times \text{Treated}_i\right) + \varepsilon_{it}^{(e)}, \qquad e \in \{\text{Mar, May}\}, \tag{21}$$

where $Y_{it}^{(e)}$ is a microstructure outcome standardized within asset on event e's pre-window (units are pre-event standard deviations), the treated asset is proof-of-work (Bitcoin or Ethereum), the control is proof-of-stake (Cardano, with XRP as robustness), the date fixed effect $\delta_t^{(e)}$ absorbs the

[10] https://x.com/elonmusk/status/1374617643446063105

[11] https://x.com/elonmusk/status/1392602041025843203?lang=en

market-wide common shock, and standard errors are clustered by date. The coefficient β_3^e is the treated-versus-control differential for event e.

Decomposition of the differential. The key to isolating carbon salience is that each estimated differential β_3^e is a sum of the economic channels active at that event. Let C denote the carbon-salience component—the object of interest—and let U^e and A^e denote, respectively, the utility component (news about Bitcoin's value as a payment medium) and the attention component at event e. The March event is a positive utility shock accompanied by attention, with no carbon content; the May event is a negative utility shock accompanied by attention, *and* it carries the carbon content in tweet:

$$\beta_3^{\text{Mar}} = U^{\text{Mar}} + A^{\text{Mar}}, \qquad \beta_3^{\text{May}} = U^{\text{May}} + A^{\text{May}} + C. \tag{22}$$

Three features of the two announcements show how these components enter. *(i)* They concern the same actor, channel, and payment mechanism, but differ in the sign of the utility component: acceptance raises Bitcoin's payment value and suspension lowers it, so the utility component reverses, $U^{\text{May}} = -U^{\text{Mar}}$. *(ii)* Both announcements were comparably prominent, so the attention they generate is assumed to be the same across the events, $A^{\text{May}} = A^{\text{Mar}} \equiv A$. *(iii)* A utility shock is directional—good news draws net buying, bad news net selling—whereas attention is directionless, impacting trading activity and adverse-selection risk without a sign. Consequently, a *signed* outcome (order-flow imbalance, buy ratio) loads on the utility component but not on attention, while an *unsigned* outcome (trade-size shares, effective spread) loads on attention but not on the utility component.

Applying these features and solving Equation (22) isolates C. For a signed outcome, attention does not enter and the reversing utility terms cancel in the *sum*:

$$\beta_3^{\text{May}} + \beta_3^{\text{Mar}} = \big(U^{\text{May}} + C\big) + U^{\text{Mar}} = \big(-U^{\text{Mar}} + C\big) + U^{\text{Mar}} = C. \tag{23}$$

For an unsigned outcome, the utility component does not enter and the common attention term cancels in the *difference*:

$$\beta_3^{\text{May}} - \beta_3^{\text{Mar}} = \big(A + C\big) - A = C. \tag{24}$$

Under the identifying assumption that disutility from suspension equals utility from acceptance,

the carbon-salience component is therefore the linear combination

$$C = \begin{cases} \beta_3^{\text{May}} + \beta_3^{\text{Mar}}, & \text{signed outcomes (order-flow imbalance, buy ratio),} \\ \beta_3^{\text{May}} - \beta_3^{\text{Mar}}, & \text{unsigned outcomes (trade-size shares, effective spread).} \end{cases} \tag{25}$$

Because C combines coefficients from two separately windowed regressions, its variance involves their covariance,

$$\text{Var}(C) = \text{Var}\big(\hat{\beta}_3^{\text{May}}\big) + \text{Var}\big(\hat{\beta}_3^{\text{Mar}}\big) \pm 2\,\text{Cov}\big(\hat{\beta}_3^{\text{May}}, \hat{\beta}_3^{\text{Mar}}\big), \tag{26}$$

and $\text{Cov}(\hat{\beta}_3^{\text{May}}, \hat{\beta}_3^{\text{Mar}})$ can't be computed from two independent regressions. To recover it and conduct joint inference on C, I stack the events into a single system,

$$y_{i,t,e} = \gamma_{i\times e} + \delta_{t\times e} + \beta_3^{\text{Mar}}\big(\text{Post}_t \times \text{Treated}_i \times \mathbf{1}_{e=\text{Mar}}\big) + \beta_3^{\text{May}}\big(\text{Post}_t \times \text{Treated}_i \times \mathbf{1}_{e=\text{May}}\big) + \varepsilon_{i,t,e}, \tag{27}$$

with asset-by-event and date-by-event fixed effects and standard errors clustered by calendar date. Estimating both coefficients in one system yields their joint covariance matrix, from which $\text{Var}(C)$ is computed directly; I report the Wald test of $H_0 : C = 0$.

C. The Carbon Signal in Liquidity Provision

Event windows are chosen to exclude every contemporaneous confound. The March window spans $[-25, +18]$ days (ending April 11), before the Coinbase direct listing (April 14) and the April 18 liquidation cascade. The May window spans $[-14, +5]$ days (ending May 17), *strictly before* the May 18 statement of the three Chinese financial associations and the May 21 State Council announcement that initiated the mining crackdown. This last restriction is essential rather than cosmetic: the crackdown differentially affected mined (proof-of-work) assets—precisely the treatment group—so any window extending past May 17 would attribute China-policy effects to carbon salience.[12]

Table VIII reports the per-event differentials and the carbon-salience component C for each treatment–control pair. Each row reports, for one microstructure outcome, the treated-versus-control differential at each event (β_3^{Mar}, β_3^{May}) and their carbon-salience combination C, with Bitcoin the treated proof-of-work asset and Cardano the proof-of-stake control. The pattern across rows separates

[12] I verify that the results below are unchanged under tighter symmetric windows of ±10 days for both events; the point estimates on the effective spread retain their sign and significance.

three distinct channels. Net order flow carries no carbon component: the signed combination θ for order-flow imbalance and the buy ratio is statistically zero (-0.17 and -0.97; $t = -0.17$ and -1.10), so the net selling observed on the suspension is the mirror of the acceptance's adoption flow and cancels. Retail participation responds to attention but not distinctively to carbon: the small-trade share rises sharply on *both* events, and while its combination is positive it reflects the generic prominence of Tesla–Musk news rather than environmental content. The carbon signal is concentrated in liquidity provision: the effective spread *narrows* on the acceptance (-2.22; $t = -3.09$) and *widens* on the suspension ($+3.00$; $t = +2.73$), yielding a large and precisely estimated carbon-salience effect ($C = +5.22$; $t = +4.02$). Because both announcements were comparably prominent, symmetric attention cannot produce liquidity improvement on the positive event and deterioration on the negative one; the asymmetry is attributable to the carbon framing that distinguishes them, and it indicates that market makers price additional adverse-selection risk into the high-emission asset precisely when its carbon attribute becomes salient.

Ethereum serves as a quasi-experimental counterfactual because it shares Bitcoin's market environment but was neither mentioned in Musk's announcement nor carries a comparable carbon liability. The absence of a price or flow response in Ethereum therefore isolates the salience channel from crypto-wide sentiment, confirming that the observed Bitcoin reaction reflects attention to carbon rather than fundamentals. Results from Table IX suggest that carbon was not priced in Ethereum following Musk's tweet. Overall, results from both tests show that carbon is priced when it is made salient.

D. Returns and Liquidity

The paired design isolates the carbon component of *unsigned* liquidity outcomes. For completeness, I also document the price reaction to the May announcement, while noting that the return, as a signed outcome, cannot be cleanly separated from the payment-suspension news by the same logic. Figure 9 & Table IA.3 reports cumulative abnormal returns benchmarked to the mean daily return over a $[-120, -11]$ estimation window. Bitcoin's reaction is large and immediate—a cumulative abnormal return of -20.0% over $[-1, +3]$ ($t = -2.02$) and -29.2% over $[0, +5]$ ($t = -2.70$)—and is essentially identical on Binance and Coinbase, ruling out any venue-specific explanation. Differencing each proof-of-work asset against the proof-of-stake control Cardano removes the market-wide May selloff; the differential decline occurs within 72 hours, well before the May 18 China announcement, so it reflects the tweet rather than the regulatory crackdown. These features establish that the price reaction is immediate, asset-level, and pre-regulatory; consistent with the paired-design evidence, however, I interpret the return as documenting the market's response to the bundled announcement rather than as a clean estimate of carbon repricing.

Finally, to trace the liquidity-provider channel at high frequency, I estimate an hourly event study around the May announcement,

$$Y_{it} = \alpha_i + \lambda_t + \sum_{\tau \neq -1} \beta_\tau \left(\text{Treated}_i \times D_t^\tau \right) + \varepsilon_{it}, \tag{28}$$

where Y_{it} is the effective spread or the adverse-selection cost, standardized within asset over the pre-event sample; α_i are asset fixed effects; λ_t are six-hour relative-time bin fixed effects that absorb the common shock; and the bin immediately preceding the tweet is the omitted reference. Figure 10 plots the estimated β_τ. Pre-event coefficients are near zero and insignificant, supporting the parallel-trends assumption. After the announcement, spreads and adverse-selection costs jump sharply and then revert within roughly six to nine hours. The transience of the response is itself informative: it is the signature of an attention-gated activation that decays as salience fades, not of a permanent change in the pricing of the carbon attribute—the dynamic analogue of the paper's central asymmetry between salience and fundamentals.

VII. Conclusion

The paper's findings demonstrate that voluntary ESG preferences are inherently episodic and ineffective mechanisms for pricing large-scale environmental externalities in high-volatility asset classes like cryptocurrency. Model and empirical results reveal that because high volatility and substantial expected returns drive the investor exclusion boundary orders of magnitude above the Social Cost of Carbon that rational investors would price, green preferences remain entirely slack following fundamental technology upgrades that eliminate huge carbon externalities. Instead, preference-driven capital reallocations are triggered purely by transient attention shocks. These insights extend the sustainable finance literature, including the foundational frameworks of (Pástor et al., 2021) by showing that voluntary market-based mechanisms cannot act as a friction-free substitute for direct Pigouvian carbon regulation in assets with a high risk-return profile.

The structural primitives identified in cryptocurrency markets map precisely onto Artificial Intelligence infrastructure companies managing energy-intensive data centers that consume enormous electricity and thereby have a significant carbon footprint. Operating under extreme growth expectations ($\bar{r}$) and immense idiosyncratic volatility (σ^2), the AI sector sits deep within the slack boundary regime. Energy-intensive infrastructure, extreme volatility, high expected returns, and thin direct carbon regulation characterize Artificial Intelligence firms as they do in crypto. The same slack-boundary logic implies that institutional capital will not ration nascent AI companies on carbon disutility. Carbon pricing in that sector arrives through episodic salience unless strict carbon regulations are placed. A price signal with these dynamics cannot generate the persistent investor carbon preferences that the sustainable-investing mechanism requires. Thus, the paper offers evidence relevant to the welfare question: in high-volatility asset classes, voluntary investor preferences appear unlikely to substitute effectively for Pigouvian intervention.

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Table I. Summary Statistics

Notes: Daily observations January 1, 2019, to March 14, 2023 (Binance, BTC/ETH); January 8, 2020, to March 13, 2023 (Kraken, BTC/ETH); March 29, 2019, to September 28, 2022 (ADA-Binance); and January 1, 2019, to September 29, 2022 (XRP-Binance). Roll Spread is in basis points. Log Volume is the natural log of daily USD volume. OFI is volume-weighted signed imbalance. Buy Ratio is the fraction of buyer-initiated trades. Large Share and Small Share are fractions of daily volume in trades exceeding $100K notional and trades below $10K notional, respectively. ADA and XRP are green assets.

Panel A: (BTC/USDC and ETH/USDC)

	BTC-Binance		ETH-Binance		BTC-Kraken		ETH-Kraken	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Roll Spread (bps)	1.748	1.220	2.661	2.120	3.367	4.828	5.894	15.765
Amihud ILLIQ	0.008	0.059	0.069	0.130	0.102	0.920	0.355	3.776
Log Volume	17.336	1.265	16.104	1.708	14.255	1.694	13.782	1.904
OFI	−0.015	0.159	−0.028	0.170	0.010	0.308	0.001	0.362
Buy Ratio	0.487	0.087	0.479	0.088	0.505	0.154	0.501	0.181
Large Share	0.009	0.011	0.006	0.011	0.016	0.039	0.012	0.036
Small Share	0.776	0.089	0.853	0.112	0.592	0.215	0.617	0.232
N (days)	1,371		1,371		1,161		1,161	

Panel B: (ADA/USDC and XRP/USDC in Binance)

	Cardano (ADA)-Binance		XRP-Binance	
	Mean	SD	Mean	SD
Roll Spread (bps)	12.667	9.754	5.561	3.227
Amihud ILLIQ	2.567	4.711	0.528	0.939
Log Volume	13.456	1.963	14.096	1.344
OFI	−0.052	0.189	−0.039	0.205
Buy Ratio	0.462	0.107	0.483	0.096
Large Share	0.001	0.004	0.000	0.002
Small Share	0.923	0.105	0.948	0.064
N (days)	1,280		1,368	

Table II. Present Value of Carbon Externality

Notes. $G_i = \mathrm{SCC}(r)\,\bar{\kappa}_i/r$ is the per-coin present value of the carbon externality, capitalizing the trailing-365-day average attributable emission rate $\bar{\kappa}_i$ as a perpetuity (the $\lambda = 0$ upper bound; any efficiency decay lowers it). Per-coin emissions $\bar{\kappa}_i$ are computed from hourly Cambridge CCAF annualized network emissions, averaged over the trailing 365 days, divided by circulating supply. Supply follows deterministic issuance schedules (block subsidy with halvings for Bitcoin; pre- and post-Merge issuance for Ethereum), anchored at the Ethereum Merge (T_M = September 15, 2022) with $N_{\mathrm{BTC}}(T_M) = 19{,}140{,}000$ and $N_{\mathrm{ETH}}(T_M) = 120{,}520{,}000$; Ethereum's emission rate is set to its post-Merge proof-of-stake level (≈ 0) after T_M. Social costs of carbon in USD are rate-matched to the discount rate following Rennert et al. (2022). The *Estimated* and *Coal-only* columns use the CCAF central and upper-bound electricity-mix scenarios, respectively. ETH price is approximately \$1,470 on T_M.

	$\bar{\kappa}$ (tCO_2/coin/yr)			G_i	
	Estimated	Coal-only	SCC(r)	Estimated	Coal-only
	Panel A: r = 2.0%, SCC=\$185				
Bitcoin	2.590	5.050	\$185	\$23,958	\$46,709
Ethereum, pre-Merge	0.0953	0.2022	\$185	\$882	\$1,870
Ethereum, post-Merge	≈ 0	≈ 0	\$185	\$0	\$0
ΔG_{ETH} (Merge)				**\$882**	**\$1,870**
	Panel B: r = 2.5%, SCC=\$118				
Bitcoin	2.590	5.050	\$118	\$12,225	\$23,834
Ethereum, pre-Merge	0.0953	0.2022	\$118	\$450	\$954
Ethereum, post-Merge	≈ 0	≈ 0	\$118	\$0	\$0
ΔG_{ETH} (Merge)				**\$450**	**\$954**
	Panel C: r = 3.0%, SCC=\$80				
Bitcoin	2.590	5.050	\$80	\$6,907	\$13,466
Ethereum, pre-Merge	0.0953	0.2022	\$80	\$254	\$539
Ethereum, post-Merge	≈ 0	≈ 0	\$80	\$0	\$0
ΔG_{ETH} (Merge)				**\$254**	**\$539**

Table III. The Ethereum Merge and the Pricing of the Carbon Externality - Kraken

Description. This table reports estimates of β from the two-way fixed-effects specification $y_{i,t}^{(z)} = \gamma_i + \delta_t + \beta \tilde{T}_{i,t} + \varepsilon_{i,t}$, where $\tilde{T}_{i,t} = \text{ETH}_i \times \text{Post}_t \times G_{\text{ETH}}^{\text{pre}}/1000$ is the per-coin Ethereum carbon claim eliminated at the Merge, measured in thousands of dollars. The sample consists of daily BTC and ETH against USDC on Kraken over the window $[T_M - 90,\ \text{October 31, 2022}]$ around the Ethereum Merge (T_M = September 15, 2022). The post window terminates before the FTX collapse on November 8, 2022 to avoid contamination. Outcomes are restricted to those for which parallel trends hold under HAC standard errors on the pre-Merge window; aggregate order-flow imbalance and aggregate buy ratio are excluded because their pre-trend failures are driven by a shifting trade-size composition that vanishes once size is conditioned, and the large-trade bucket is excluded because Kraken-USDC sees no trades above $100,000 on most days. Trade-size buckets are medium ($10K–$100K) and small (< $10K). The dollar-weighted buy ratio ("$-wt") is the share of dollar volume within a bucket attributable to buyer-initiated trades. Adverse selection is the Glosten-Harris permanent price-impact component estimated tick-by-tick within each hour and aggregated to daily by trade count; it is a market-maker liquidity-supply measure, not a preference-channel measure. Outcomes are standardized within asset on the pre-Merge window. "Estimated" and "Coal-only" correspond to alternative electricity-generation assumptions; because the two scenarios differ only by a constant rescaling, the t-statistics, R^2, and implied standard-deviation effects are identical across scenarios by construction. Standard errors are clustered by date.

	$\hat{\beta}$						
Outcome	Estimated	Coal-only	t	Implied SD	R^2_{total}	R^2_{within}	N
Panel A: Order-flow imbalance							
Medium	−0.070	−0.033	−0.09	−0.018	0.606	0.0000	1,004
Small	−0.294	−0.138	−0.55	−0.075	0.652	0.0009	1,094
Panel B: Buy ratio (dollar-weighted)							
Medium	+0.084	+0.040	+0.11	+0.021	0.602	0.0001	1,004
Small	−0.168	−0.079	−0.28	−0.043	0.593	0.0002	1,094
Panel C: Trade volume (dollar)							
Small	+0.605	+0.285	+1.60	+0.154	0.774	0.0073	1,094
Panel D: Liquidity providers							
Adverse selection	−3.492**	−1.646**	−2.26	−0.888	0.612	0.0409	1,091
Asset FE	Yes	Yes					
Date FE	Yes	Yes					

Table IV. The Ethereum Merge and the Pricing of the Carbon Externality - Binance

This table reports estimates on Binance, $y_{i,t}^{(z)} = \gamma_i + \delta_t + \beta\,(\mathrm{Post}_t \times \mathrm{ETH}_i \times \bar{G}_{\mathrm{ETH}}^{\mathrm{pre}}) + \varepsilon_{i,t}$, with Ethereum treated and Bitcoin as control around the Merge (15 September 2022, 05:42:42 UTC). The sample consists of daily BTC and ETH against USDC on Binance over the window $[T_M - 90, T_M + 14]$ around the Ethereum Merge (T_M = September 15, 2022). Outcomes are standardized within the asset on the pre-Merge window. β is expressed in standard deviations per \$1,000 of Ethereum carbon claim eliminated; *Implied SD* $= \hat{\beta} \cdot \bar{G}^{\mathrm{pre}}/1000$ is the implied full-Merge effect and is identical across the two carbon scenarios. Estimated and Coal-only correspond to alternative electricity-generation assumptions. $\bar{G}^{\mathrm{pre}}$ is the steady-state per-coin carbon claim SCC $\cdot\, \bar{\kappa}/r$ (trailing-365-day $\bar{\kappa}$; $r = 3\%$; rate-consistent SCC = \$80), equal to \$254.21 (Estimated) and \$539.18 (Coal-only). Outcomes are restricted to those passing a HAC parallel-trends screen on the pre-Merge window. Standard errors are clustered by date.

	$\hat{\beta}$						
Outcome	Estimated	Coal-only	t	Implied SD	R^2_{total}	R^2_{within}	N
Panel A: Order-flow imbalance							
Large	−2.035	−0.960	−0.62	−0.517	0.632	0.013	181
Medium	+0.862	+0.406	+0.24	+0.219	0.470	0.002	210
Small	−0.076	−0.036	−0.05	−0.019	0.466	0.000	210
Panel B: Buy ratio (dollar-weighted)							
Large	−1.758	−0.829	−0.59	−0.447	0.627	0.009	181
Medium	+0.845	+0.398	+0.20	+0.215	0.464	0.002	210
Small	+0.067	+0.032	+0.05	+0.017	0.455	0.000	210
Panel C: Trade volume (dollar)							
Large	−0.796	−0.375	−0.50	−0.202	0.694	0.004	210
Medium	−0.806	−0.380	−0.68	−0.205	0.858	0.009	210
Panel D: Liquidity providers							
Amihud illiquidity	+7.363	+3.472	+1.68*	+1.872	0.801	0.206	210
Roll spread (bps)	+3.308	+1.560	+2.53**	+0.841	0.907	0.147	210
Asset FE	Yes	Yes					
Date FE	Yes	Yes					

Table V. Pre-Event Market Model

Description. OLS estimates of the market model $r_t^{\mathrm{ETH}} = \alpha + \beta\, r_t^{\mathrm{BTC}} + \varepsilon_t$ on six-hour returns over the pre-event estimation window $[T_M - 180d,\ T_M - 60d]$, excluding the Terra/Celsius/3AC cascade (5 May–1 July 2022), estimated separately on each venue. α is the market-model intercept. t-statistics use Newey-West HAC standard errors (five-day maximum lag). *, **, *** denote significance at the 10%, 5%, 1% levels.

Venue	α	$t(\alpha)$	β_{BTC}	$t(\beta_{\mathrm{BTC}})$	R^2
Binance	+0.086%	(1.58)	$+1.183^{***}$	(12.32)	0.782
Kraken	+0.088%	(1.57)	$+1.165^{***}$	(12.51)	0.763

Table VI. Event-Study CAR around the Ethereum Merge (Kraken)

Description. The table reports cumulative differential abnormal returns and Newey-West HAC t-statistics at multiple horizons h after the Ethereum Merge (T_M = September 15, 2022, 05:42:42 UTC). The sample is Kraken-USDC six-hour log returns; the 00:00–06:00 UTC bin on September 15 (containing the Merge) is dropped. The post-event window terminates on October 30, 2022, before the FTX collapse. The simple differential CAR (columns 1–2) is $\sum_{t=0}^{h}(r_t^{\mathrm{ETH}} - r_t^{\mathrm{BTC}} - \hat{\mu}_{\mathrm{pre}})$ and implicitly assumes $\beta_{\mathrm{ETH,BTC}} = 1$. The CAPM-adjusted CAR (columns 3–4) is $\sum_{t=0}^{h}(r_t^{\mathrm{ETH}} - \hat{\alpha} - \hat{\beta}\, r_t^{\mathrm{BTC}})$, where $\hat{\alpha} = 0.088\%$ per six-hour bin, $\hat{\beta} = 1.17$, $\hat{\sigma}_{\varepsilon} = 1.02\%$ per six-hour bin, $R^2 = 0.763$, and $N = 478$ are OLS estimates over the pre-estimation window $[T_M - 180d,\, T_M - 60d]$. HAC standard errors use a maximum lag of twenty six-hour bins (five days). Coefficients in percent.

	Simple Differential ($\beta = 1$)		CAPM-Adjusted	
Horizon	CAR	t (HAC)	CAR	t (HAC)
$[0, +1d]$	$-7.79\%^{**}$	-2.47	$-7.21\%^{***}$	-2.66
$[0, +3d]$	$-11.73\%^{**}$	-2.12	$-10.82\%^{**}$	-2.18
$[0, +5d]$	$-14.19\%^{**}$	-2.09	$-12.02\%^{*}$	-1.91
$[0, +10d]$	$-17.03\%^{*}$	-1.92	-13.74%	-1.61
$[0, +15d]$	$-19.79\%^{**}$	-1.98	$-15.87\%^{*}$	-1.72
$[0, +30d]$	$-25.54\%^{**}$	-2.26	$-18.34\%^{*}$	-1.73
$[0, +45d]$	-15.28%	-0.92	-7.11%	-0.48

Table VII. Event-Study CAR around the Ethereum Merge (Binance)

The table reports the cumulative differential abnormal returns at multiple horizons h after the Ethereum Merge (T_M = September 15, 2022, 05:42:42 UTC), on Binance as an external check. The sample is BTC-USDC, ETH-USDC with six-hour log returns; the 00:00–06:00 UTC bin on September 15 (containing the Merge) is dropped. Binance trade coverage for the pair ends September 29, 2022. The simple differential CAR is $\sum_{t=0}^{h}(r_t^{\mathrm{ETH}} - r_t^{\mathrm{BTC}} - \hat{\mu}_{\mathrm{pre}})$. The CAPM-adjusted CAR is $\sum_{t=0}^{h}(r_t^{\mathrm{ETH}} - \hat{\alpha} - \hat{\beta}\, r_t^{\mathrm{BTC}})$, where $\hat{\alpha} = 0.086\%$ per six-hour bin, $\hat{\beta} = 1.18$, $\hat{\sigma}_{\varepsilon} = 0.84\%$ per six-hour bin, $R^2 = 0.78$, and $N = 253$ are OLS estimates over the pre-estimation window $[T_M - 180d,\, T_M - 60d]$, excluding the Terra/Celsius/3AC cascade (5 May–1 July 2022). HAC standard errors use a maximum lag of twenty six-hour bins (five days). Coefficients in percent.

	Simple Differential ($\beta = 1$)		CAPM-Adjusted	
Horizon	CAR	t (HAC)	CAR	t (HAC)
$[0, +1d]$	$-8.01\%^{**}$	-2.40	$-7.86\%^{***}$	-2.61
$[0, +3d]$	$-11.86\%^{**}$	-2.12	$-11.96\%^{**}$	-2.32
$[0, +5d]$	$-14.35\%^{**}$	-2.12	$-13.99\%^{**}$	-2.20
$[0, +10d]$	$-17.09\%^{*}$	-1.92	$-17.12\%^{**}$	-1.98
$[0, +13d]$	$-19.54\%^{**}$	-2.08	$-19.68\%^{**}$	-2.17

Table VIII. Separating Carbon Salience from Payment-Adoption News: The Tesla Reversal Pair

Notes: This table separates the carbon-salience component of the May 12, 2021 Musk suspension from its payment-adoption content, using the March 24, 2021 acceptance as the adoption benchmark. Bitcoin is the treated (proof-of-work) asset; Cardano is the proof-of-stake control. For each event, β_3 is the treated-versus-control differential from the two-way fixed-effects specification (asset and date fixed effects; equation 21). θ is the carbon-salience component (equation 25): $C = \beta_3^{\text{May}} + \beta_3^{\text{Mar}}$ for signed outcomes (OFI, Buy Ratio), which nets out the mirrored payment-utility flow, and $C = \beta_3^{\text{May}} - \beta_3^{\text{Mar}}$ for unsigned outcomes (trade-size shares, effective spread), which nets out event attention. Inference on θ is the Wald test of $H_0 : C = 0$ from the stacked specification (equation 27). Windows: March $[-25, +18]$ days (ending April 11, before the Coinbase listing and the April 18 liquidation cascade); May $[-14, +5]$ days (ending May 17, before the May 18 and May 21 China mining-crackdown announcements, which differentially affect mined assets). Outcomes are standardized within asset on each event's pre-window; coefficients are in pre-event standard-deviation units. t-statistics in parentheses; standard errors clustered by date. Trade data are from Binance.

Outcome	β_3 Accept (Mar 24)	β_3 Suspend (May 12)	C (carbon salience)
OFI	+0.122	-0.294^{*}	−0.172
	(+0.12)	(−1.78)	(−0.17)
Buy Ratio	−0.746	-0.226^{***}	−0.972
	(−0.86)	(−2.72)	(−1.10)
Small Share	$+3.098^{***}$	$+5.870^{***}$	$+2.772^{**}$
	(+4.98)	(+4.83)	(+2.06)
Effective Spread	-2.221^{***}	$+2.997^{***}$	$+5.218^{***}$
	(−3.09)	(+2.73)	(+4.02)
Asset FE (each event)	Yes	Yes	—
Date FE (each event)	Yes	Yes	—
Observations		88 (Mar), 40 (May); stacked 128	

Table IX. Carbon Salience: Ethereum vs. Cardano (Robustness)

Notes: This table repeats the paired-event design of Table VIII with Ethereum as the treated (proof-of-work, pre-Merge) asset and Cardano as the proof-of-stake control. For each event, β_3 is the treated-versus-control differential from the two-way fixed-effects specification (equation 21). θ is the carbon-salience component (equation 25): $C = \beta_3^{\text{May}} + \beta_3^{\text{Mar}}$ for signed outcomes and $C = \beta_3^{\text{May}} - \beta_3^{\text{Mar}}$ for unsigned outcomes, with inference from the Wald test of $H_0 : C = 0$ in the stacked specification (equation 27). Windows, standardization, and clustering are as in Table VIII. Coefficients are in pre-event standard-deviation units; t-statistics in parentheses; standard errors clustered by date. Trade data are from Binance.

Outcome	β_3 Accept (Mar 24)	β_3 Suspend (May 12)	C (carbon salience)
OFI	+1.455	−0.428*	+1.027
	(+1.35)	(−1.96)	(+0.92)
Buy Ratio	−0.041	−0.288*	−0.329
	(−0.05)	(−1.72)	(−0.42)
Small Share	+0.147	+1.679*	+1.531
	(+0.22)	(+1.95)	(+1.41)
Effective Spread	−0.224	+1.111	+1.335
	(−0.40)	(+1.02)	(+1.11)
Asset FE (each event)	Yes	Yes	—
Date FE (each event)	Yes	Yes	—
Observations	88 (Mar), 40 (May); stacked 128		

Figure 7. ETH−BTC Differential CAR around the Ethereum Merge (Kraken)

Description. The figure plots the cumulative differential abnormal return on Ethereum relative to Bitcoin around the Merge (T_M = September 15, 2022, 05:42:42 UTC) under two specifications. The sample is Kraken-USDC six-hour log returns over the window $[T_M - 45d,\ T_M + 45d]$, with the bin containing the Merge dropped. The post-event window terminates on October 30, 2022, before the FTX collapse on November 8, 2022, to avoid contamination. The left panel reports the simple differential CAR $\sum_t (r_t^{\mathrm{ETH}} - r_t^{\mathrm{BTC}} - \hat{\mu}_{\mathrm{pre}})$, which implicitly imposes $\beta_{\mathrm{ETH,BTC}} = 1$ and demeans by the pre-event sample mean. The right panel reports the CAPM-adjusted CAR $\sum_t (r_t^{\mathrm{ETH}} - \hat{\alpha} - \hat{\beta}\, r_t^{\mathrm{BTC}})$, where $\hat{\alpha}$ and $\hat{\beta}$ are estimated by OLS on the pre-estimation window $[T_M - 180d,\ T_M - 60d]$ (N = 478 six-hour bins, $\hat{\beta}_{\mathrm{ETH,BTC}} = 1.17$, $R^2 = 0.763$); this window ends two months before the Merge to avoid contamination by Merge anticipation. The vertical red line marks the Merge. The shaded band is the 95% confidence band of width $\pm 1.96\, \hat{\sigma}_\varepsilon \sqrt{k}$, where k is the number of six-hour bins cumulated and $\hat{\sigma}_\varepsilon$ is the market-model residual standard deviation from the pre-estimation window. Endpoint magnitudes and HAC t-statistics are reported in Table VI.

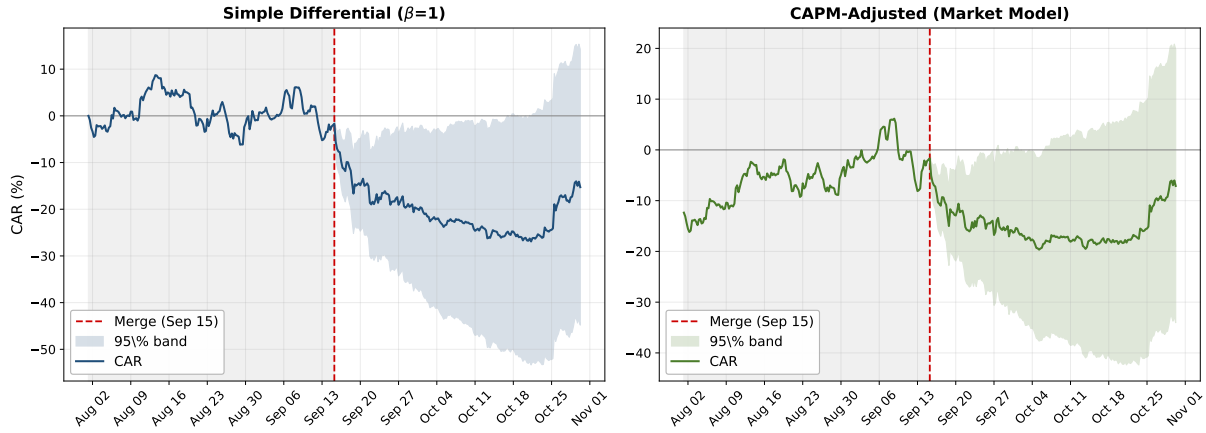


Figure 8. Cumulative Abnormal Returns around the Ethereum Merge (Binance)

This figure plots the cumulative abnormal returns (CAR) of Ethereum relative to Bitcoin around the Merge (15 September 2022, 05:42:42 UTC), at six-hour frequency on Binance. The left panel uses the simple differential specification ($\mathrm{AR}_t = r_{\mathrm{ETH},t} - r_{\mathrm{BTC},t}$, implicit $\beta = 1$); the right panel uses the CAPM-adjusted market model ($\mathrm{AR}_t = r_{\mathrm{ETH},t} - \hat{\alpha} - \hat{\beta}\, r_{\mathrm{BTC},t}$), with $\hat{\alpha}, \hat{\beta}$ estimated on the $[-180, -60]$-day pre-event window. Shaded regions are 95% confidence bands ($1.96\, \hat{\sigma}_\varepsilon \sqrt{k}$). The vertical dashed line marks the Merge; the shaded left region is the pre-event estimation window.

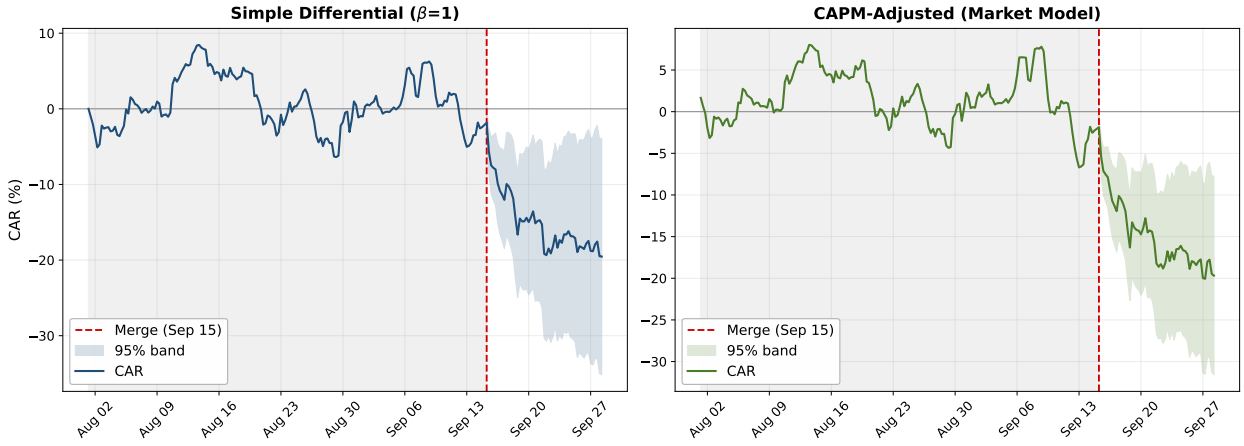


Figure 9. Differential Cumulative Abnormal Returns around the Musk Tweet

Notes: This figure plots the differential cumulative abnormal return (CAR) of each proof-of-work asset relative to the proof-of-stake control Cardano (ADA), accumulated from the hour of Elon Musk's May 12, 2021 tweet suspending Bitcoin payments (event time 22:00 UTC). Abnormal returns are measured relative to the mean differential return over a pre-event estimation window. Returns are hourly and trade data is from Binance. The shaded region marks the 48 pre-event hours and the vertical dashed line marks the tweet hour; shaded bands are pointwise 95% confidence intervals. Endpoint differentials over $[0, +3\text{d}]$ are -35.2% (Bitcoin, $t = -2.7$) and -32.8% (Ethereum, $t = -1.9$), with Newey–West standard errors at a 24-hour lag.

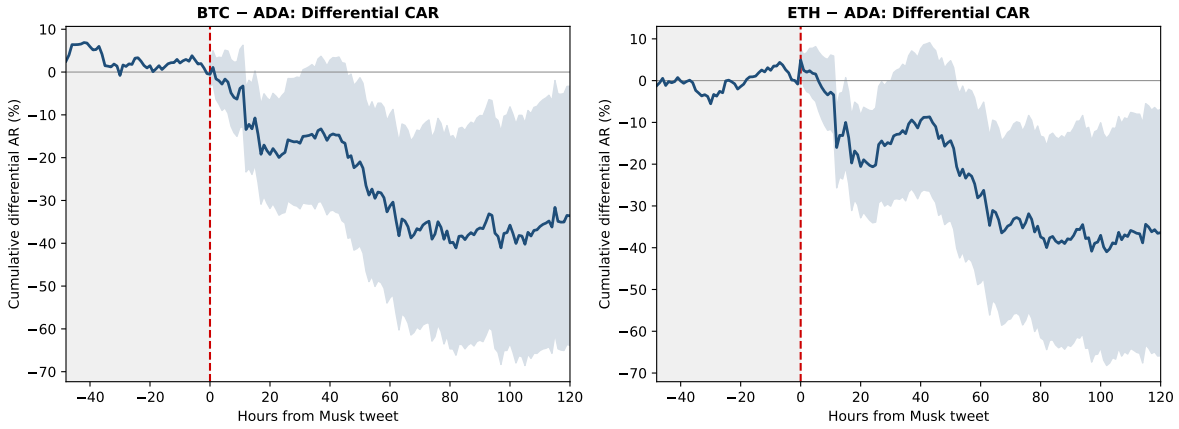
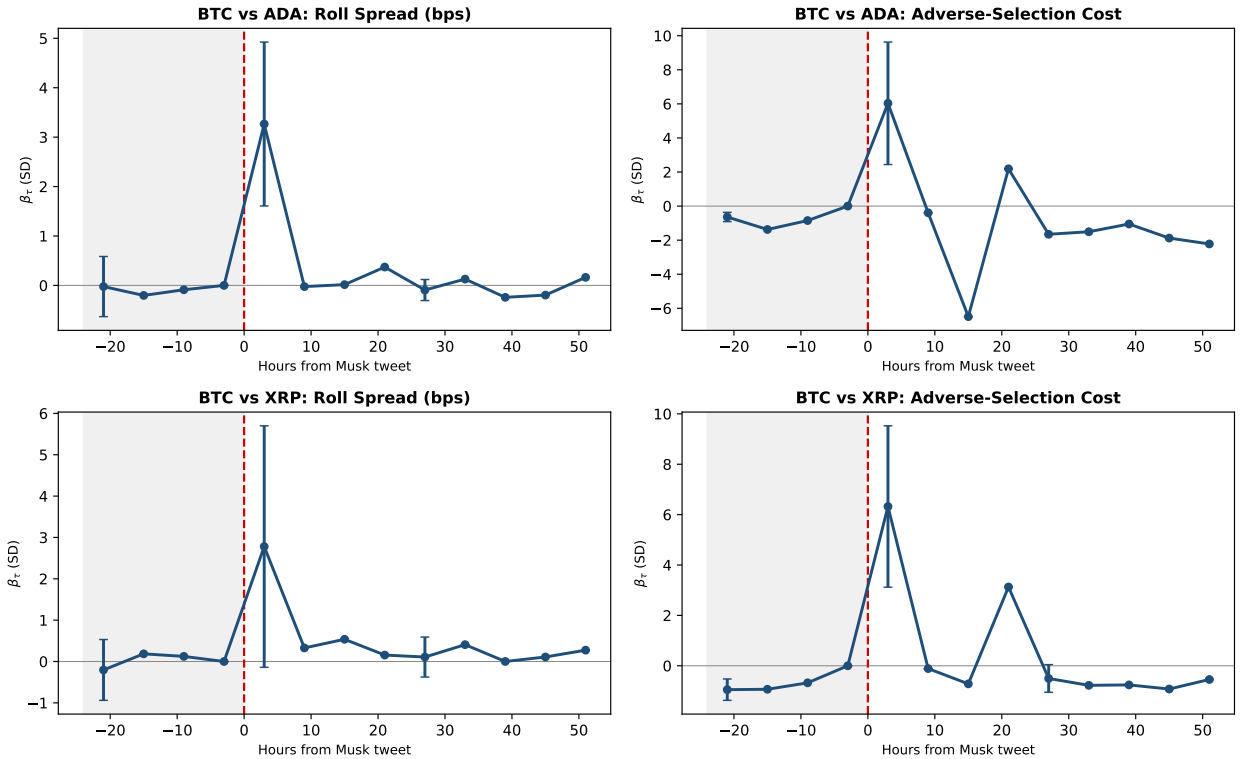


Figure 10. Hourly Market-Maker Response around the Musk Tweet

Notes: This figure plots the dynamic difference-in-differences coefficients β_τ from Equation (28), with 95% confidence intervals, around Elon Musk's May 12, 2021 tweet suspending Bitcoin payments. The event time is 22:00 UTC. The coefficients trace the differential response of proof-of-work assets relative to low-carbon controls, Cardano (ADA) and XRP. The top row reports Bitcoin versus Cardano, and the bottom row reports Bitcoin versus XRP. Coefficients are measured in pre-event standard-deviation units. The vertical dashed line marks the tweet hour; the shaded region marks the 24 pre-event hours; and the omitted reference category is the six-hour bin immediately preceding the event. Standard errors are clustered by calendar day. Trade data are from Binance.



Appendix

Proofs for "The Carbon Claim and Its Equilibrium Pricing"

A. Portfolio Choice and the Demand Functions

Fix an instant t and horizon dt. Assuming W_t is normally distributed with mean m and variance v,

$$W_t \sim \mathcal{N}(m, v), \tag{A1}$$

An investor with wealth W allocates xP dollars to the token (x coins) and $W - xP$ dollars to the riskless asset with interest rate r_f. Over $[t, t + dt]$ the token pays the pecuniary flow $\Psi\, dt$ per coin and delivers a per-coin capital gain dP. I assume a constant pecuniary flow ψ for tractability, permitting a closed-form solution to the ordinary differential equation defining the carbon liability - $G^{\text{mkt}}(t)$. If instead fees follows the process $d\psi_t = \theta_\psi(\bar{\psi} - \psi_t)\, dt + \sigma_\psi\, dW_t$, the per-coin payoff loads on the fee innovation and total payoff variance rises to $\tilde{\sigma}^2_{\text{total}} = \sigma^2 + w^2\sigma^2_\psi + 2\rho\, w\, \sigma\, \sigma_\psi$, where w is the payoff's exposure to ψ and ρ the fee–payoff correlation. For any $\rho \geq 0$, $\tilde{\sigma}^2_{\text{total}}$ strictly increases. Because $d^*(t) \propto \gamma\sigma^2$, the constant-$\psi$ threshold understates the true one, $\tilde{d}^*(t) > d^*(t)$; constant ψ is thus a conservative (lower) bound, placing the true threshold even further above the social cost of carbon and strengthening the conclusion that the constraint does not bind.

The equilibrium price path $P(t)$ is deterministic, with drift $\mu_P \equiv \dot{P}$; investors nonetheless perceive per-coin payoff risk of variance σ^2 per year (Assumption 3) carried by the innovation $\sigma\, dZ$ with dZ mean-zero and $\text{Var}(dZ) = dt$.Wealth evolves as

$$dW \;=\; x\,(dP + \Psi\, dt) + (W - xP)\, r_f\, dt \;=\; \big[x(\mu_P + \Psi - r_f P) + r_f W\big]dt + x\,\sigma\, dZ. \tag{A2}$$

An ESG investor additionally experiences the non-pecuniary flow disutility $x\, d\, \kappa(t)\, dt$, measured in dollar equivalents (Assumption 3).

Let the investor's end-of-interval wealth be $W_{t+dt} \sim \mathcal{N}(m, v)$ with $m = \mathbb{E}[W_{t+dt}]$ and $v = \text{Var}(W_{t+dt})$. For CARA utility $u(W) = -e^{-aW}$, the moment-generating function of a normal variable gives the expected utility

$$\mathbb{E}\big[-e^{-aW_{t+dt}}\big] = -\exp\!\Big(-a\, m + \tfrac{1}{2}a^2 v\Big)\,. \tag{A3}$$

Maximizing (A3) is equivalent to *minimizing* the exponent $-a\,m + \frac{1}{2}a^2 v$. This is equivalent to maximizing $am - \frac{1}{2}a^2 v$ or $\mathbb{E}[dW] - \frac{a}{2}\mathrm{Var}(dW)$ per unit time. Since dZ is a standard Brownian motion increment, it has expected value $\mathbb{E}[dZ] = 0$ and variance $\mathrm{Var}(dZ) = dt$. Applying these to the wealth dynamics (A2) gives the per-interval mean and variance of the wealth change,

$$\begin{aligned}\mathbb{E}[dW] &= \left[\, x(\mu_P + \Psi - r_f P) + r_f W_t \,\right] dt,\\ \mathrm{Var}(dW) &= \mathrm{Var}(x\,\sigma\,dZ) = x^2\sigma^2\,dt.\end{aligned}$$

For the unconstrained investor,

$$\max_x \;\; x\,(\mu_P + \Psi - r_f P) + r_f W_t \;-\; \frac{a}{2}\,x^2\sigma^2, \tag{A4}$$

with first-order condition $\mu_P + \Psi - r_f P - a\sigma^2 x = 0$, i.e.

$$x_U \;=\; \frac{\mu_P + \Psi - r_f P}{a\sigma^2}. \tag{A5}$$

For the ESG investor, the objective function subtracts the disutility flow $x\,d\,\kappa(t)$:

$$\max_{x\geq 0} \;\; x\left(\mu_P + \Psi - r_f P - d\,\kappa(t)\right) + r_f W_t \;-\; \frac{a}{2}\,x^2\sigma^2, \tag{A6}$$

whose interior first-order condition gives

$$x_I \;=\; \frac{\mu_P + \Psi - r_f P - d\,\kappa(t)}{a\sigma^2}, \qquad \text{valid when } x_I \geq 0. \tag{A7}$$

The carbon disutility thus enters the ESG demand as a private per-coin tax of $d\,\kappa(t)$ on the dividend.

B. Equilibrium Price

To solve for a general equilibrium to this pricing model, token market clearing is imposed. Let the total number of tokens held by an ESG and a non-ESG holder be q. The mass of ESG investors is μ. Market clearing requires $\mu\, x_I + (1-\mu)\, x_U = q$. Substituting values from (A5) and (A7),

$$\begin{aligned} &\frac{1}{a\sigma^2}\Big[\mu\big(\mu_P + \Psi - r_f P - d\kappa(t)\big) + (1-\mu)\big(\mu_P + \Psi - r_f P\big)\Big] = q \\ &\qquad\Longleftrightarrow \quad \mu_P(t) + \Psi - r_f P(t) - \underbrace{\mu d}_{\equiv D}\,\kappa(t) = a\sigma^2 q. \end{aligned} \tag{B1}$$

Only the wealth-weighted disutility $D = \mu d$ enters: the market prices carbon at the *average* marginal taste and the perceived ESG investor's carbon price.

Rearranging (B1), the equilibrium price $P(t)$ satisfies:

$$\frac{dP(t)}{dt} - r_f P(t) = -\Big[(\Psi - a\sigma^2 q) - D\kappa(t)\Big] \tag{B2}$$

This is a linear first-order non-homogeneous ODE of the form:

$$\frac{dP}{dt} + AP = Q(t), \tag{B3}$$

where $A = -r_f$ is constant, and $Q(t) = -\Psi + a\sigma^2 q + D\kappa(t)$. Using the integrating factor $\text{IF} = e^{\int A dt} = e^{-rt}$, the general solution is:

$$e^{-r_f t} P(t) = \int e^{-r_f t} Q(t)\, dt + C. \tag{B4}$$

Solving the above equation,

$$e^{-r_f t} P(t) = \int e^{-r_f t}\Big[-\big(\Psi - a\sigma^2 q\big) + D\,\kappa(t)\Big] dt \;+\; C, \tag{B5}$$

where C is the constant of integration.

$$\begin{aligned} e^{-r_f t}P(t) &= -\int e^{-r_f t}(\Psi - a\sigma^2 q)dt + D\int \kappa(t)e^{-rt}dt + C \\ &= \frac{e^{-r_f t}(\Psi - a\sigma^2 q)}{r_f} + D\kappa_0 \int e^{-\lambda t}e^{-r_f t}dt + C \\ &= \frac{e^{-r_f t}(\Psi - a\sigma^2 q)}{r_f} - \frac{D\kappa_0 e^{-(r_f+\lambda)t}}{r_f + \lambda} + C \end{aligned}$$

Applying the transversality condition $\lim_{t\to\infty} e^{-rt}P(t) = 0$ to rule out explosive bubbles and taking limits $t \to \infty$ on both sides, I obtain:

$$0 = 0 + 0 + C \implies C = 0 \tag{B6}$$

Thus, the equilibrium price is given by

$$P(t) = \frac{\Psi - a\sigma^2 q}{r_f} - \frac{D\,\kappa_i(t)}{r_f + \lambda}, \tag{B7}$$

$$\kappa_i(t) = \kappa_{i,0}\, e^{-\lambda t}, \quad \lambda \geq 0,$$

where $\kappa_i(t)$ denotes per-coin attributable emissions at time t, $\kappa_{i,0}$ denotes the initial emissions at $t = 0$, and λ is the emission decay rate due to technological improvement of the network.

.1. *Carbon Claim under Technology Upgrade*

The technology upgrade news arrives with Poisson hazard η (Assumption 4), independent of payoff shocks and unpriced (Assumption 5). η represents the rate at which the market expects a clean-technology transition. Before the transition, the token is "brown" and carries the carbon claim. After the transition, emissions drop close to zero, and the token becomes "green." I derive carbon claim as follows:

Let $P_b(t)$ denote the pre-Merge (brown) price and $P^* = (\Psi - a\sigma^2 q)/r_f$ the post-Merge (green) price (B7) applies with no carbon term. Over dt, the technology upgrade occurs with probability $\eta\, dt$, in which case the price jumps to P^*. The expected capital gain is therefore $\dot{P}_b + \eta\,(P^* - P_b)$

per year, and the clearing restriction (B1) becomes

$$\dot{P}_b(t) + \eta\big(P^* - P_b(t)\big) + \Psi - r_f P_b(t) - D\kappa(t) \;=\; a\sigma^2 q. \tag{B8}$$

Let $P_b(t) = P^* - G(t)$. Then $\dot{P}_b = -\dot{G}$ and $\eta(P^* - P_b) = \eta\, G$. Substituting, and using $\Psi - r_f P^* = a\sigma^2 q$,

$$-\dot{G}(t) + \eta\, G(t) + r_f\, G(t) - D\kappa(t) = 0 \quad \Longleftrightarrow \quad \dot{G}(t) = (r_f + \eta)\, G(t) - D\,\kappa(t). \tag{B9}$$

Solving ODE and applying $\lim_{t\to\infty} e^{-r_f t} P(t) = 0$ yields carbon claim

$$G(t) \cdot e^{-(r_f+\eta)t} = -D\kappa_0 \int e^{-\lambda t} \times e^{-(r_f+\eta)t} dt + C \tag{B10}$$

$$G(t) = \frac{D\kappa(t)}{(r_f + \lambda + \eta)} \tag{B11}$$

Equivalently, by independence of τ and the payoff shocks and the law of iterated expectations,

$$\begin{aligned} G(t) &= \mathbb{E}_t\left[\int_t^\tau e^{-r(u-t)} D\kappa(u)\, du\right] = \int_t^\infty e^{-r(u-t)}\, D\kappa(u)\, \Pr(\tau > u \mid \tau > t)\, du \\ &= \int_t^\infty e^{-r(u-t)} \times D\kappa_0 e^{-\lambda(u-t)} \times e^{-\eta(u-t)}\, du = \frac{D\,\kappa(t)}{r + \lambda + \eta}, \end{aligned} \tag{B12}$$

where $\Pr(\tau > u \mid \tau > t) = e^{-\eta(u-t)}$ is the exponential survival function.
Price can never be negative, hence

$$P(t) \;=\; \underbrace{\frac{\Psi - a\sigma^2 q}{r}}_{\text{carbon-free value } P^*} \;-\; \underbrace{\frac{D\,\kappa(t)}{r + \lambda + \eta}}_{\text{carbon claim } G^{\text{mkt}}(t)} \;\geq\; 0 \quad \Longleftrightarrow \quad \Psi \;\geq\; a\sigma^2 q \;+\; \frac{r\,D\,\kappa(t)}{r + \lambda + \eta}, \tag{B13}$$

The proofs establish Proposition 1.

C. Proof of Lemma 1

For $\kappa_0 > 0$ and for $t \geq 0$,

$$G(\lambda, \eta; D) \;=\; \frac{D\, e^{-\lambda t}}{r + \lambda + \eta}, \qquad D \geq 0, \lambda \geq 0,\ \eta \geq 0,\ D \in (0, \text{SCC}].$$

Taking logs of $G(\lambda) = \dfrac{De^{-\lambda t}}{r + \lambda + \eta}$:

$$\ln G = \ln D - \lambda t - \ln(r + \lambda + \eta).$$

The first derivative follows directly:

$$\begin{aligned} \frac{1}{G}\frac{\partial G}{\partial \lambda} &= -t - \frac{1}{r + \lambda + \eta}, \\ \frac{\partial G}{\partial \lambda} &= -De^{-\lambda t}\left[\frac{t}{r + \lambda + \eta} + \frac{1}{(r + \lambda + \eta)^2}\right] \;<\; 0. \end{aligned} \tag{C1}$$

For the second derivative, differentiate again:

$$-\frac{1}{G^2}\left(\frac{\partial G}{\partial \lambda}\right)^2 + \frac{1}{G}\frac{\partial^2 G}{\partial \lambda^2} = \frac{1}{(r + \lambda + \eta)^2}, \tag{C2}$$

$$\frac{\partial^2 G}{\partial \lambda^2} = G(\lambda)\left[\frac{1}{(r + \lambda + \eta)^2} + \frac{1}{G^2}\left(\frac{\partial G}{\partial \lambda}\right)^2\right] > 0. \tag{C3}$$

Thus, G is strictly decreasing and strictly convex in λ. G is also strictly decreasing and convex in η

$$\frac{\partial G}{\partial \eta} = -\frac{D\, e^{-\lambda t}}{(r + \lambda + \eta)^2} \;<\; 0, \qquad \frac{\partial^2 G}{\partial \eta^2} = \frac{2\, D\, e^{-\lambda t}}{(r + \lambda + \eta)^3} \;>\; 0,$$

Since G is strictly increasing in D and strictly decreasing in each of λ and η everywhere on the admissible set, and the partial derivatives do not reach zero in the interior, the interior optimum does not exist. Maxima is attained at the corner with the highest density of ESG investors ($\mu = 1$ at the corner while $\mu < 1$ elsewhere), yielding $(D, \lambda, \eta) = (\text{SCC}, 0, 0)$, where $G = \text{SCC}\,\kappa_0/r$. Convexity in λ and η confirms the absence of an interior maximum. This proves Lemma 1.

D. ESG Pool and Exit Threshold

In the interior equilibrium, using $D = \mu d$ gives

$$x_I = \frac{a\sigma^2 q + D\kappa(t) - d\kappa(t)}{a\sigma^2} = q \; - \; \frac{(1-\mu)\, d\, \kappa(t)}{a\sigma^2}, \tag{D1}$$

Hence $x_I \geq 0$ if and only if

$$d\,\kappa(t) \;\leq\; \frac{a\sigma^2 q}{1-\mu} \qquad \Longleftrightarrow \qquad d \;\leq\; d^*(t) \equiv \frac{a\sigma^2 q}{(1-\mu)\,\kappa(t)}. \tag{D2}$$

where σ^2 is the variance of a coin's dollar payoff.

.1. *The Equilibrium Restriction*

Under the exclusion regime, the constrained segment holds $x_I = 0$ and market clearing requires the unconstrained segment to hold the entire per-capita supply, so that $(1-\mu)\, x_U = q$. This reduction in the effective risk-sharing pool necessitates a price discount to compensate the remaining investors for the increased exposure. The unconstrained investor's optimum is,

$$x_U \;=\; \frac{\mu_P + \Psi - r_f P(t)}{a\,\sigma^2}, \tag{D3}$$

so that the clearing condition becomes

$$\frac{q}{1-\mu} \;=\; \frac{\mu_P + \Psi - r_f P(t)}{a\,\sigma^2} \quad \Longleftrightarrow \quad \frac{a\,\sigma^2\, q}{1-\mu} \;= \mu_P + \; \Psi - r_f P(t), \tag{D4}$$

where $q/(1-\mu)$ accounts for the limited risk-sharing pool with ESG investors excluded. The composite $a\sigma^2 q/(1-\mu)$ that appears in the exit threshold *equals* the equilibrium excess payoff per coin per year at any exclusion-regime equilibrium.

.2. *Exclusion Discount*

The equilibrium price $P(t)$ is governed by equation D4

$$\frac{dP(t)}{dt} - r_f P(t) = -\left(\Psi - a\sigma^2 \left(\frac{q}{1-\mu}\right)\right) \tag{D5}$$

Steady-State

Assuming a static environment ($\dot{P} = 0$), the price collapses to the exclusion-only benchmark:

$$\Psi - r_f P = \frac{a\sigma^2 q}{1-\mu} \quad \Longrightarrow \quad P = \frac{1}{r_f}\left(\Psi - \frac{a\sigma^2 q}{1-\mu}\right). \tag{D6}$$

Dynamic Equilibrium

I solve (D5) using the integrating factor $e^{-r_f t}$ and the transversality condition $\lim_{T\to\infty} e^{-r_f T} P(T) = 0$:

$$\begin{aligned} e^{-r_f t} P(t) &= -\int e^{-r_f t}\left[\left(\Psi - \frac{a\sigma^2 q}{1-\mu}\right)\right] dt + C \\ P(t) &= \frac{\Psi}{r_f} - \frac{a\sigma^2 q}{r_f(1-\mu)} \end{aligned}$$

The total price is decomposed into the fundamental value and the time-invariant exclusion discount. Relative to the frictionless price $(\Psi - a\sigma^2 q)/r_f$, the exclusion discount is

$$\Delta_{\text{excl}} = \frac{a\sigma^2 q}{r_f}\left(\frac{1}{1-\mu} - 1\right) = \frac{a\sigma^2 q}{r_f}\,\frac{\mu}{1-\mu}, \tag{D7}$$

The proofs establish Proposition 2.

E. Information Regimes and Carbon Pricing Derivations

In an efficient market, investors update their beliefs and reprice carbon claims when new information arrives. The information arrives at a constant Poisson hazard η. The survival function is:

$$\Pr(\tau > u \mid \tau > t) = e^{-\eta(u-t)}, \qquad u \geq t.$$

Before the announcement T_A, with the transition date (because of a technology update) unknown, the holder prices the emission stream as a perpetuity.

$$\begin{aligned} G^{\text{mkt}}(t) &= \mathbb{E}_t \left[\int_t^{\tau} e^{-r(u-t)} D\kappa(u)\, du \right] \\ &= \int_t^{\infty} e^{-r(u-t)} D\kappa(u)\ \Pr(\tau > u \mid \tau > t)\, du \\ &= \int_t^{\infty} e^{-r(u-t)} D\kappa(u)\, e^{-\eta(u-t)}\, du \\ G(T_A^-) &= \frac{D\kappa(t)}{r+\lambda+\eta}. \end{aligned} \tag{E1}$$

Between announcement and execution, investors holding Ethereum update their beliefs, and the carbon claim reduces to a finite annuity, the present value of the emission flow over the remaining brown window of length $T_M - t \leq 22$ days:

$$G^{\text{mkt}}(t) = \int_t^{T_M} e^{-r(s-t)} D\kappa(s)\, ds = \frac{D\kappa(t)}{r+\lambda} \left(1 - e^{-(r+\lambda)(T_M-t)}\right), \qquad T_A \leq t < T_M. \tag{E2}$$

$$G(T_A^+) = \int_{T_A}^{T_M} e^{-r(u-T_A)}\, D\,\kappa(u)\, du = D\,\kappa(T_A)\, \frac{1 - e^{-(r+\lambda)\Delta}}{r+\lambda}, \qquad \Delta = T_M - T_A, \tag{E3}$$

After the technology update is completed, the network becomes PoS and turns green, $\kappa_{\text{ETH}}(s) = 0$ for all $s \geq T_M$, and the carbon claim vanishes:

$$G_{\text{ETH}}(t) = \int_{T_M}^{\infty} e^{-r(s-t)}\, D\,\kappa_{\text{ETH}}(s)\, ds = \int_{T_M}^{\infty} e^{-r(s-t)}\, D \cdot 0\, ds = 0, \qquad t \geq T_M. \tag{E4}$$

The present value of the future carbon damages per coin eliminated is:

$$\Delta G_{T_A} \;=\; G(T_A^-) - G(T_A^+) \;=\; D\,\kappa(T_A)\left[\frac{1}{r+\lambda+\eta} - \frac{1-e^{-(r+\lambda)\Delta}}{r+\lambda}\right], \tag{E5}$$

At $\lambda = \eta = 0$,

$$\Delta G_{T_A} = \frac{D\,\kappa_0}{r}\Big[1 - \big(1 - e^{-r\Delta}\big)\Big] = \frac{D\,\kappa_0}{r}\,e^{-r\Delta}, \tag{E6}$$

.1. *CAR Derivation*

Before the announcement, the price includes the full carbon claim:

$$P(T_A^-) = P^* - G^{\text{mkt}}(T_A^-), \tag{E7}$$

where $G^{\text{mkt}}(T_A^-)$ is the pre-announcement claim (with hazard η). At the announcement, the claim drops to $G^{\text{mkt}}(T_A^+)$, so the new price is:

$$P(T_A^+) = P^* - G^{\text{mkt}}(T_A^+). \tag{E8}$$

The abnormal return is the percentage change in price:

$$\text{CAR}(T_A) = \frac{P(T_A^+) - P(T_A^-)}{P(T_A^-)} = \frac{G^{\text{mkt}}(T_A^-) - G^{\text{mkt}}(T_A^+)}{P(T_A^-)}. \tag{E9}$$

$$\text{CAR}(T_A) = \frac{D\,\kappa(T_A)}{P(T_A^-)}\left[\frac{1}{r+\lambda+\eta} - \frac{1-e^{-(r+\lambda)\Delta}}{r+\lambda}\right]. \tag{E10}$$

Internet Appendix

A. Relevant Figures

Figure IA.1. Bitcoin and Ethereum Greenhouse Gas Emissions

Notes: This figure plots hydro-only, estimated, and coal-only greenhouse gas emissions for Bitcoin and Ethereum, measured in $MtCO_2e$. Panel (a) shows Bitcoin emissions from 2010 through 2026. Panel (b) shows Ethereum proof-of-work emissions from 2016 through the September 15, 2022 Merge, marked by the vertical dashed line. The Merge transitioned Ethereum from proof-of-work to proof-of-stake, eliminated proof-of-work mining on Ethereum, and reduced the network's energy consumption by approximately 99.95%. The hydro-only and coal-only paths provide lower- and upper-bound emissions scenarios, while the estimated path is the benchmark series. Data source: Cambridge Centre for Alternative Finance (CCAF).

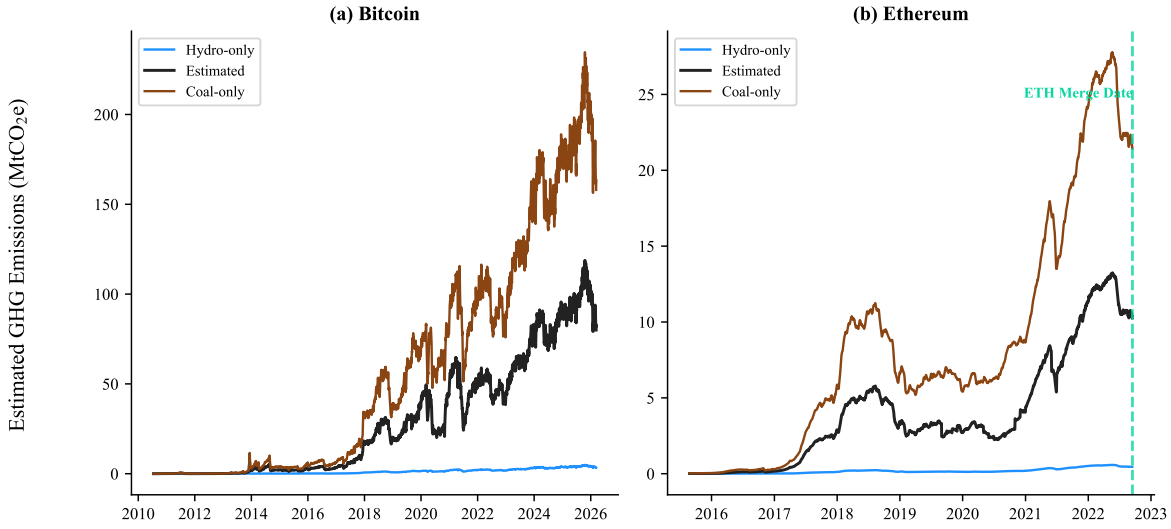


Figure IA.2. Per-coin carbon externality Social Costs present value

Notes. The figure plots the per-coin present discounted sum of all future carbon externality, $G_{i,t} = \mathrm{SCC}(r)\,\kappa_{i,t}/r$, valued at each date. Per-coin emissions are $\kappa_{i,t} = E_{i,t}/N_{i,t}$, where $E_{i,t}$ is the network's annualized CO_2 emissions and $N_{i,t}$ is circulating supply constructed from the issuance schedule. The social cost of carbon is taken from Rennert et al. (2022) and matched to the discount rate: \$185 at $r = 2.0\%$, \$118 at 2.5%, and \$80 at 3.0%. Ethereum's emission rate is set to its post-Merge proof-of-stake level (≈ 0) after 15 September 2022; the Bitcoin series begins in 2016 and the Ethereum series in 2019. The dashed line marks the Merge. Data Sources: (CCAF CO2 series for Bitcoin and Ethereum.)

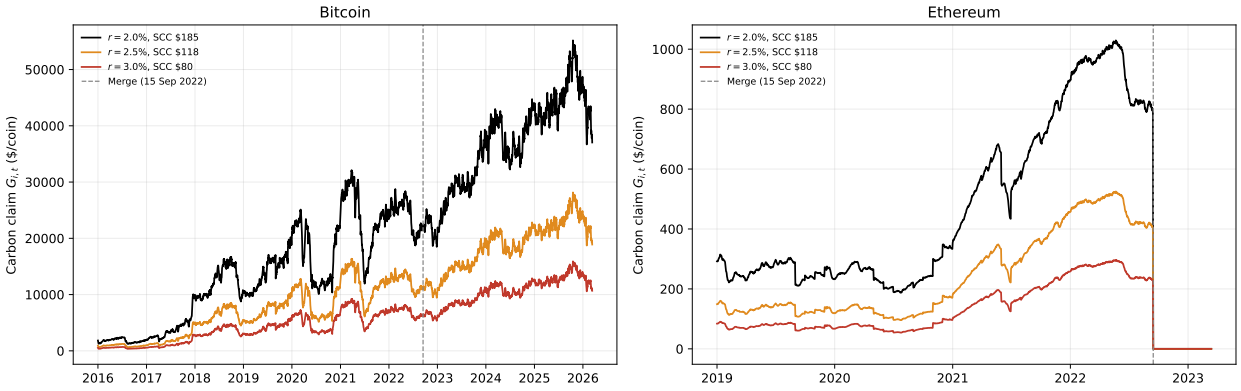


Figure IA.3. Parallel-Trends Check: Bitcoin vs. Cardano (ADA)

Notes: This figure plots raw, binned microstructure outcomes around the Musk tweet on May 12, 2021. The event window is ±30 days, and observations are averaged into three-day bins. The shaded region marks the pre-event period, and the vertical dashed line marks the Musk tweet. The plots assess pre-event co-movement and post-event divergence in raw values.

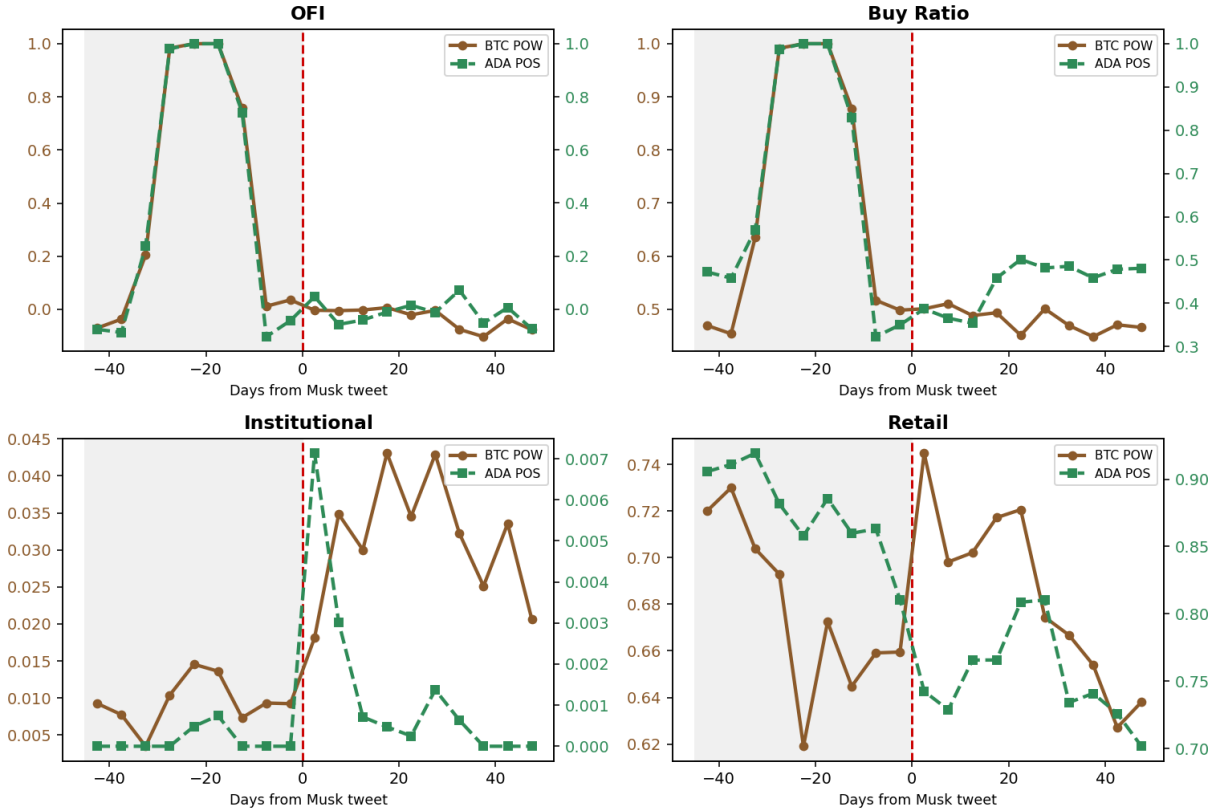


Figure IA.4. Parallel-Trends Check: Bitcoin vs. XRP

Notes: This figure plots raw, binned microstructure outcomes around the Musk tweet on May 12, 2021. The event window is ±30 days, and observations are averaged into three-day bins. The shaded region marks the pre-event period, and the vertical dashed line marks the Musk tweet. The plots assess pre-event co-movement and post-event divergence in raw values.

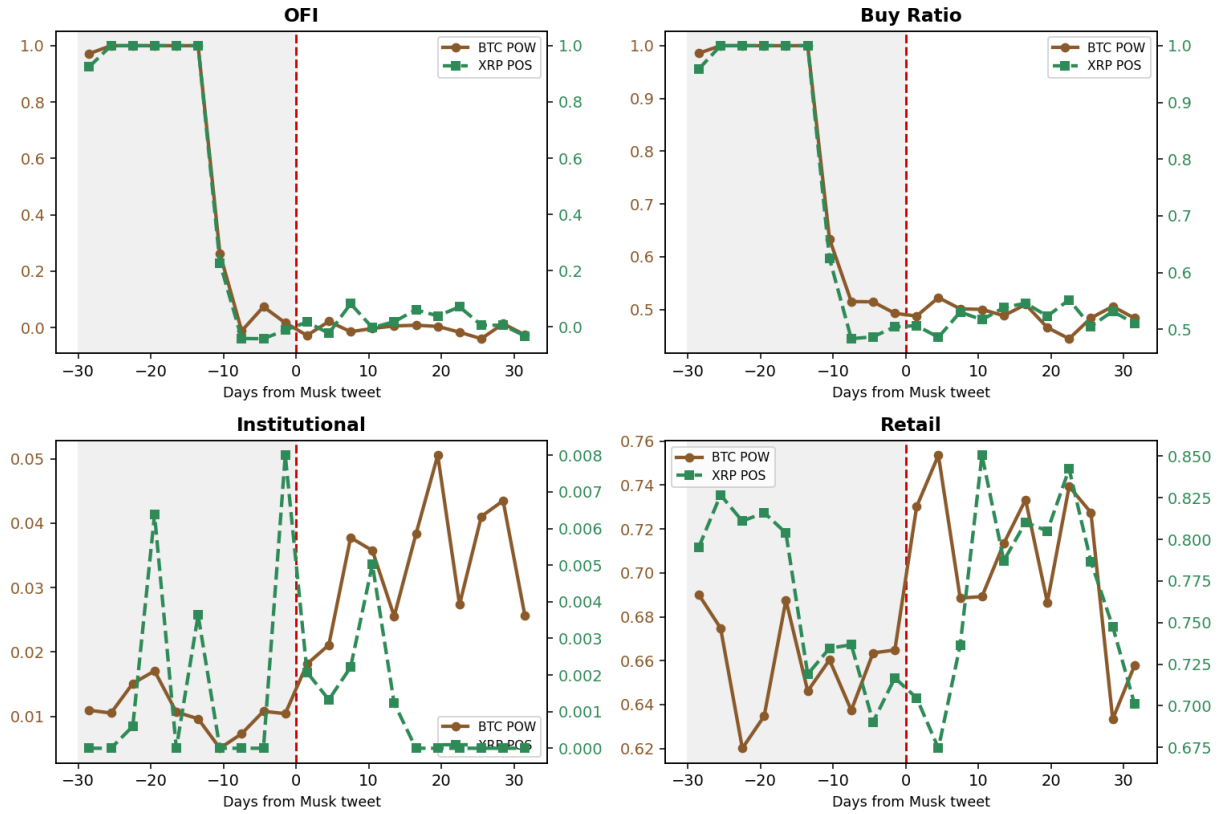


Figure IA.5. Parallel-Trends Check: Ethereum vs. Cardano (ADA)

Notes: This figure plots raw, binned microstructure outcomes around the Musk tweet on May 12, 2021, for Ethereum (a proof-of-work asset, plotted on the left axis) and Cardano (ADA, a proof-of-stake asset, plotted on the right axis). The event window is ±30 days and observations are averaged into three-day bins. The shaded region marks the pre-event period and the vertical dashed line marks the tweet. Because the two assets trade at different raw levels, each is shown on its own axis. The figure assesses pre-event co-movement and post-event divergence in raw values.

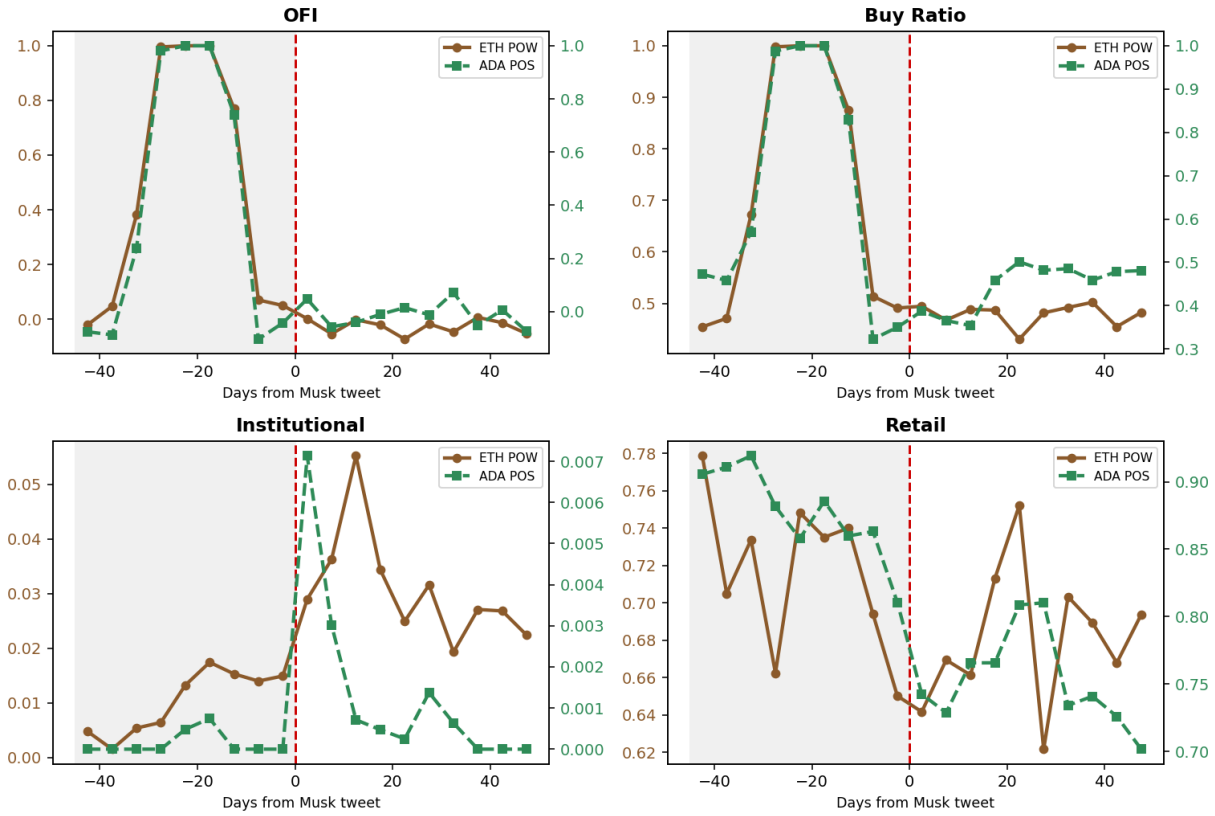
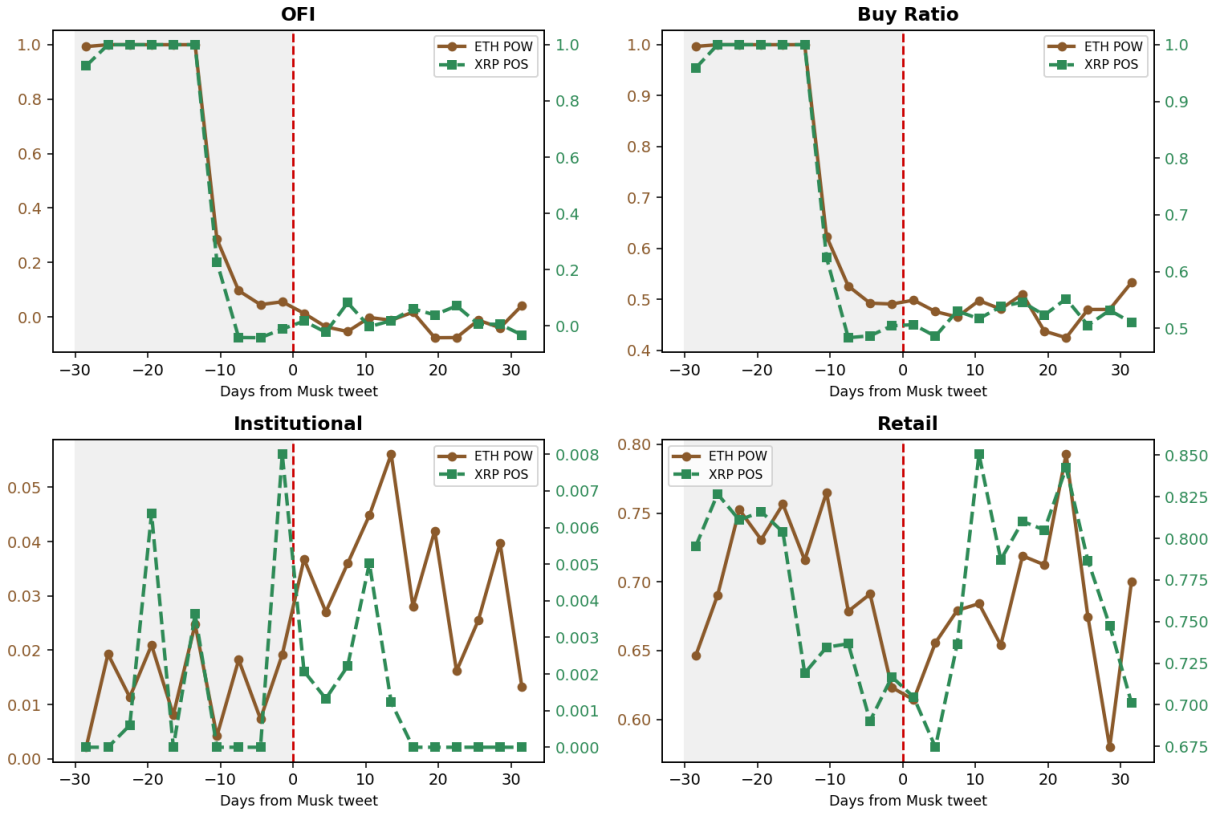


Figure IA.6. Parallel-Trends Check: Ethereum vs. XRP

Notes: This figure plots raw, binned microstructure outcomes around the Musk tweet on May 12, 2021, for Ethereum (a proof-of-work asset in 2021, plotted on the left axis) and XRP (a non-PoW asset used as a low-carbon robustness control, plotted on the right axis). The event window is ±30 days, and observations are averaged into three-day bins. The shaded region marks the pre-event period and the vertical dashed line marks the tweet. Because the two assets trade at different raw levels, each is shown on its own axis. The figure assesses pre-event co-movement and post-event divergence in raw values.



B. Attention Shocks and Trading Behavior

Does preference channel show that investors respond gradually to the *salience* of an asset's environmental profile, as opposed to liquidity providers who respond quickly to news by adjusting their quotes. I test this with a sudden, global attention shocks: Elon Musk's March 24,2021 and May 12, 2021 announcement that Tesla would accept and suspend Bitcoin payments for Tesla purchases. Bitcoin and Ethereum remained proof-of-work assets.

For asset i on day t I estimate

$$Y_{it} = \alpha + \beta_1 \,\text{Post}_t + \beta_2 \,\text{Treated}_i + \beta_3 \,(\text{Post}_t \times \text{Treated}_i) + \varepsilon_{it}, \tag{IA1}$$

where Y_{it} is a microstructure measure standardized within asset on the pre-event window (units are pre-event standard deviations), where treated assets are POW. The coefficient β_1 captures the *common shock*, the control's post-event change, which absorbs the market-wide movement. β_3 captures the POW asset differential, an estimate of the attention effect.

The treated asset is Bitcoin. The controls are Cardano (ADA) and XRP, large-cap cryptocurrencies[13] that are proof-of-stake and therefore do not carry any comparable carbon salience to the news. Figures IA.3, IA.4, IA.5, and IA.6 present co-movement and trends for Y_{it}. Table IA.1 reports the estimates. Three results hold for Bitcoin. The common shock β_1 is large and negative for these measures, confirming the similar impact on both. Second, order flow imbalance and the buy ratio fall sharply on Bitcoin relative to the controls ($\beta_3 < 0$, significant at one percent), suggesting that the buying interest withdraws from the assets whose environmental profile becomes salient. The differential β_3 isolates the *additional* investor retreat specific to POW assets. The large-trade share rises on the Bitcoin ($\beta_3 > 0$) on both controls: the composition of trading shifts toward larger participants. For retail traders (β_3) is positive but significant only when Cardano is control. The widening of the effective spread for Bitcoin ($\beta_3 > 0$) suggests that liquidity provision deteriorates precisely where attention spikes.

The consistent pattern across controls suggests an attention-driven demand shift when underlying asset fundamentals are intact. Nothing about Bitcoin's dirtiness changed on May 12; only attention did, following a widely reported tweet. Because the control assets are exposed to every market-wide shock that Bitcoin faces, as β_1 shows, the residual differential β_3 cannot be attributed to a common

[13]Both rank consistently among the largest cryptocurrencies by market capitalization. At the time of the event (May 2021), XRP and Cardano (ADA) had market capitalizations of approximately $70 billion and $50 billion, respectively.

crypto shock. It reflects investors re-evaluating Bitcoin specifically, on information about its environmental profile that was already known but suddenly became salient. The results slightly differ for β_1 for XRP as it was subject to ongoing SEC litigation [14] (SEC v. Ripple, filed December 2020), which may add asset-specific variation unrelated to the environmental channel.

B.1. Return Response: Event-Study CARs

For each asset on each venue, I compute the cumulative abnormal return over an event window relative to the mean daily return over a $[-120, -11]$ estimation window preceding the event. The Musk announcement produced a sharp, statistically significant return reaction in Bitcoin: a cumulative abnormal return of -20.1% over $[-1, +3]$ ($t = -2.02$) and -29.2% over $[0, +5]$ ($t = -2.69$). Ethereum is less impacted in the days immediately following the announcement, consistent with Musk's explicit reference to Bitcoin. The impact is identical on Binance and Coinbase, indicating an asset-level response to environmental attention rather than a venue-specific event. Table IA.3 reports the results.

Because these raw returns coincide with the broad May 2021 selloff, I difference each proof-of-work asset against the proof-of-stake control Cardano (ADA), which faces the same market shock but carries no carbon salience. The differential $D_t = r_{i,t} - r_{\text{ADA},t}$ nets out the common crash. Figure 9 plots the differential CAR at hourly resolution. Over $[0, +3]$ days, Bitcoin falls -35.2% relative to ADA ($t = -2.7$) and Ethereum -32.8% ($t = -1.9$). I see a sharp decline within 72 hours, well before the May 18, 2021, China's announcement to ban Cryptocurrencies. The reaction reflects the tweet, not the regulatory crackdown. The return evidence corroborates CAR results: an immediate, asset-specific repricing of proof-of-work coins once their carbon footprint became salient.

[14] https://www.sec.gov/newsroom/press-releases/2020-338

Figure IA.7. Parallel Trends ETH vs. BTC on Kraken Around the Ethereum Merge

Description. The figure plots the daily evolution of order-flow imbalance (top row) and the dollar-volume-weighted buy ratio (bottom row) for Bitcoin (blue) and Ethereum (green) against USDC on Kraken, disaggregated by trade-size bucket (medium: \$10K–\$100K; small: < \$10K). The sample window is June 17, 2022 through October 31, 2022; the post-Merge window terminates before the FTX collapse on November 8, 2022 to avoid contamination. The vertical red line marks the Ethereum Merge (T_M = September 15, 2022). Solid lines are five-day centered rolling means; light dots are raw daily values. Each panel reports the p-value of the differential pre-trend test (ETH $\times\, t$ interaction) on the pre-Merge window with HAC-robust standard errors; in every panel the assumption of parallel pre-trends is not rejected at conventional levels, so the identifying assumption for the difference-in-differences estimator holds. The large-trade bucket (≥ \$100K) is omitted because Kraken-USDC sees no trades of that size on most days, leaving the test underpowered. The visual co-movement of ETH and BTC across the Merge, and the absence of a discrete shift at the event date, foreshadow the null preference-channel difference-in-differences estimates reported in Table III.

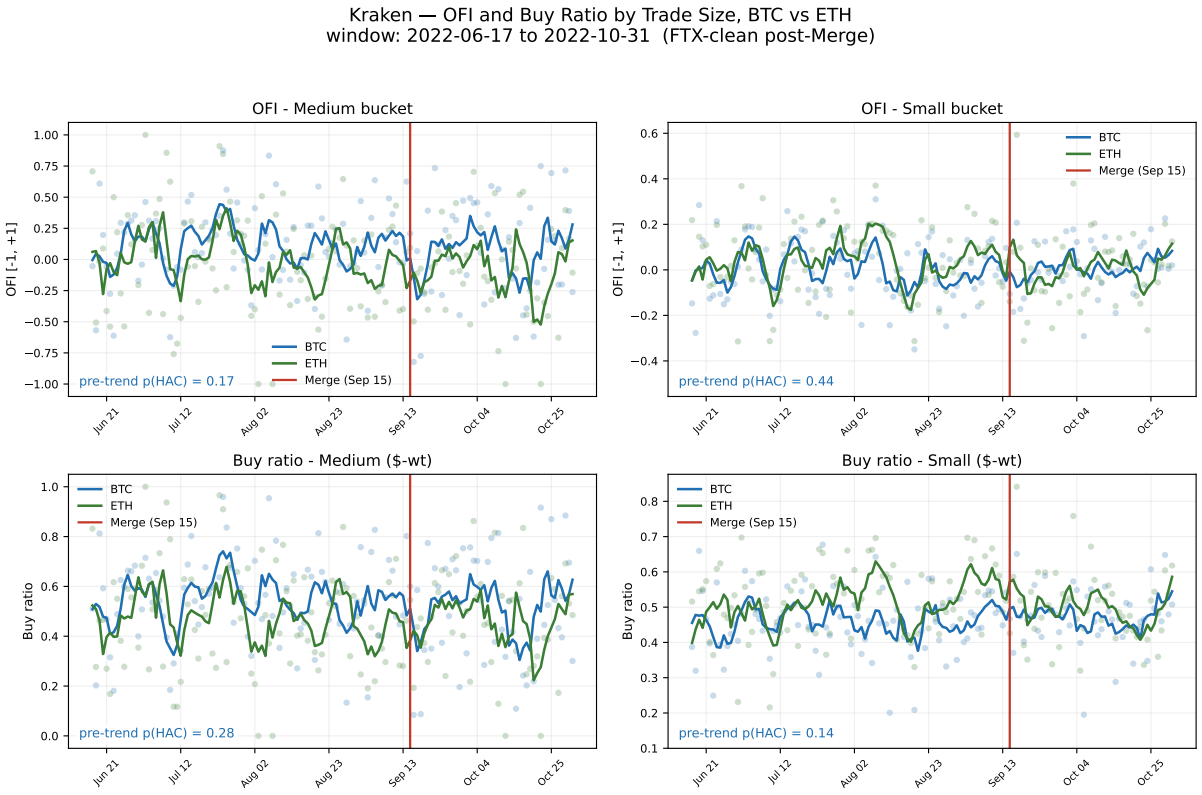


Table IA.1. Trading Behavior around the Musk Announcement Suspending BTC

Notes: This table reports difference-in-differences estimates around the Musk tweet on May 12, 2021, using a ±30-day window. Bitcoin is the treated asset. Cardano and XRP serve as control assets in Panels A and B, respectively. The simple DiD specification reports β_1, the post-event change for the control asset, and β_3, the differential post-event change for Bitcoin relative to the control. The TWFE specification includes asset and date fixed effects, so the reported β_3 captures the within-date differential response of Bitcoin relative to the control. Outcomes are standardized within the asset using the pre-event window, so coefficients are in pre-event standard-deviation units. t-statistics in parentheses. Trade data are from Binance. Standard errors are clustered by date.

Outcome	β_1 (common shock)	β_3 (simple DiD)	β_3 (TWFE)
Panel A: Bitcoin vs. Cardano, ±30 days			
OFI	-2.613^{***}	-0.723^{***}	-0.723^{***}
	(−6.12)	(−6.95)	(−4.91)
Buy Ratio	-2.666^{***}	-0.472^{***}	-0.472^{**}
	(−5.25)	(−3.09)	(−2.19)
Large Share	$+0.836^{*}$	$+1.312^{**}$	$+1.312^{*}$
	(+1.83)	(+2.45)	(+1.73)
Small Share (retail)	-1.663^{***}	$+2.214^{***}$	$+2.214^{***}$
	(−8.18)	(+10.05)	(+7.11)
Roll Spread (bps)	−0.104	$+1.240^{***}$	$+1.240^{***}$
	(−0.75)	(+8.50)	(+6.01)
Asset FE	No	No	Yes
Date FE	No	No	Yes
Observations	122	122	122
Panel B: Bitcoin vs. XRP, ±30 days			
OFI	-2.467^{***}	-0.869^{***}	-0.869^{***}
	(−6.22)	(−9.51)	(−6.73)
Buy Ratio	-2.527^{***}	-0.611^{***}	-0.611^{***}
	(−6.20)	(−7.22)	(−5.11)
Large Share	−0.366	$+2.513^{***}$	$+2.513^{***}$
	(−0.69)	(+4.47)	(+3.16)
Small Share (retail)	+0.143	+0.408	+0.408
	(+0.45)	(+1.22)	(+0.86)
Roll Spread (bps)	−0.028	$+1.164^{***}$	$+1.164^{***}$
	(−0.12)	(+7.26)	(+5.14)
Asset FE	No	No	Yes
Date FE	No	No	Yes
Observations	122	122	122

Table IA.2. Trading Behavior around the Musk Announcement Accepting BTC

Notes: This table reports difference-in-differences estimates around the Musk tweet on March 24, 2021, using a ±45-day window. Bitcoin is the treated asset. Cardano and XRP serve as control assets in Panels A and B, respectively. The simple DiD specification reports β_1, the post-event change for the control asset, and β_3, the differential post-event change for Bitcoin relative to the control. The TWFE specification includes asset and date fixed effects, so the reported β_3 captures the within-date differential response of Bitcoin relative to the control. Outcomes are standardized within the asset using the pre-event window, so coefficients are in pre-event standard-deviation units. t-statistics in parentheses. Trade data are from Binance. Standard errors are clustered by date.

Outcome	β_1 (common shock)	β_3 (simple DiD)	β_3 (TWFE)
Panel A: Bitcoin vs. Cardano, ±45 days			
OFI	$+2.909^{***}$	$+0.639^{***}$	$+0.639^{**}$
	(+5.60)	(+3.08)	(+2.18)
Buy Ratio	$+2.947^{***}$	−0.151	−0.151
	(+5.34)	(−0.67)	(−0.47)
Large Share	-1.616^{***}	$+1.165^{**}$	+1.165
	(−3.08)	(+2.23)	(+1.58)
Small Share (retail)	$+0.968^{***}$	+0.239	+0.239
	(+4.63)	(+1.11)	(+0.79)
Roll Spread (bps)	-0.543^{***}	-0.450^{***}	-0.450^{**}
	(−3.47)	(−3.19)	(−2.25)
Asset FE	No	No	Yes
Date FE	No	No	Yes
Observations	182	182	182
Panel B: Bitcoin vs. XRP, ±45 days			
OFI	$+2.613^{***}$	$+0.935^{***}$	$+0.935^{**}$
	(+6.08)	(+3.55)	(+2.51)
Buy Ratio	$+2.863^{***}$	−0.067	−0.067
	(+6.00)	(−0.43)	(−0.30)
Large Share	$+0.523^{**}$	-0.974^{***}	-0.974^{***}
	(+2.07)	(−3.84)	(−2.72)
Small Share (retail)	-3.797^{***}	$+5.004^{***}$	$+5.004^{***}$
	(−7.23)	(+10.12)	(+7.15)
Roll Spread (bps)	$+0.604^{***}$	-1.597^{***}	-1.597^{***}
	(+3.61)	(−10.76)	(−7.61)
Asset FE	No	No	Yes
Date FE	No	No	Yes
Observations	182	182	182

Table IA.3. Cumulative Abnormal Returns around Musk Announcement

Notes: Cumulative abnormal returns around the Musk announcement of May 12, 2021, benchmarked to the mean daily return over the $[-120, -11]$ estimation window. t-statistics in parentheses. The Bitcoin reaction is large, significant, and essentially identical across venues.

	Coinbase		Binance	
Window	Bitcoin	Ethereum	Bitcoin	Ethereum
$[-1, +1]$	−13.1%	−8.6%	−13.1%	−8.6%
	(−1.70)	(−0.93)	(−1.71)	(−0.92)
$[-1, +3]$	−20.1%	−12.3%	−20.0%	−12.3%
	(−2.02)	(−1.02)	(−2.02)	(−1.02)
$[0, +3]$	−21.2%	−17.1%	−21.1%	−17.0%
	(−2.38)	(−1.59)	(−2.38)	(−1.58)
$[0, +5]$	−29.2%	−29.3%	−29.2%	−29.3%
	(−2.69)	(−2.23)	(−2.70)	(−2.22)

IA.1. Robustness

A. Generalization to Ethereum

The baseline establishes the attention response for Bitcoin, the asset Musk named explicitly in his tweet. If the response reflects attention to the carbon attribute rather than to Bitcoin specifically, it should appear on the other major proof-of-work asset as well. I therefore re-estimate equation IA1 specification with Ethereum as the treated asset.

Table IA.4 reports the Ethereum estimates. Every margin that responds for Bitcoin also responds for Ethereum, with the same sign and at the same significance level. Order flow imbalance and buy ratio falls ($\beta_3 = -0.69$ against ADA, -0.84 against XRP), and (-0.58, -0.72) respectively, the institutional share increases (+2.97, +4.17), and the spread widens (+0.56, +0.48). The TWFE specification with date fixed effects, which absorbs the market-wide post-event movement is strongly significant. Two points about magnitude are worth noting. The institutional reallocation is larger on Ethereum than Bitcoin (+2.97 vs. +1.31 against ADA; +4.17 vs. +2.51 against XRP), consistent with institutions repricing the proof-of-work *class* rather than only the named asset. The spread response by liquidity providers is correspondingly smaller, in line with Ethereum's lower trading volume than Bitcoin. The retail (small-trade) share is the only outcome that does not cleanly replicate, is positive and significant against ADA but insignificant against XRP, suggestive of ongoing SEC litigation for XRP (SEC v. Ripple, filed December 2020). That the same outcomes move in the same direction for both Bitcoin and Ethereum, against POS currencies, further suggests that traders respond to carbon salience.

Table IA.4. Attention around the Musk Tweet Rejecting BTC

Notes: DiD estimates around the Musk tweet on May 12, 2021, using a ±30-day window. Ethereum is treated; Cardano and XRP are controls in Panels A and B. Simple DiD reports β_1 (control's post-event change) and β_3 (Ethereum's differential change). TWFE includes asset and date fixed effects; β_3 is the within-date differential response. Outcomes are standardized within the asset on the pre-event window. t-statistics are in parentheses. Trade data are from Binance; standard errors are clustered by date.

Outcome	β_1 common	β_3 simple DiD	β_3 TWFE
Panel A: Ethereum vs. Cardano			
OFI	-2.613^{***}	-0.692^{***}	-0.692^{***}
	(-6.12)	(-5.79)	(-4.09)
Buy Ratio	-2.666^{***}	-0.583^{***}	-0.583^{**}
	(-5.25)	(-3.48)	(-2.46)
Large Share	$+0.836^{*}$	$+2.969^{***}$	$+2.969^{***}$
	$(+1.83)$	$(+3.75)$	$(+2.65)$
Small Share	-1.663^{***}	$+1.383^{***}$	$+1.383^{***}$
	(-8.18)	$(+5.73)$	$(+4.05)$
Roll Spread	-0.104	$+0.559^{***}$	$+0.559^{***}$
	(-0.75)	$(+4.82)$	$(+3.41)$
Asset FE	No	No	Yes
Date FE	No	No	Yes
Observations	122	122	122
Panel B: Ethereum vs. XRP			
OFI	-2.467^{***}	-0.838^{***}	-0.838^{***}
	(-6.22)	(-8.90)	(-6.29)
Buy Ratio	-2.527^{***}	-0.721^{***}	-0.721^{***}
	(-6.20)	(-7.01)	(-4.96)
Large Share	-0.366	$+4.170^{***}$	$+4.170^{***}$
	(-0.69)	$(+4.66)$	$(+3.29)$
Small Share	$+0.143$	-0.423	-0.423
	$(+0.45)$	(-1.36)	(-0.96)
Roll Spread	-0.028	$+0.482^{***}$	$+0.482^{**}$
	(-0.12)	$(+2.95)$	$(+2.08)$
Asset FE	No	No	Yes
Date FE	No	No	Yes
Observations	122	122	122

Table IA.5. Attention around the Musk Tweet Accepting BTC

Notes: DiD estimates around the Musk tweet on March 24, 2021, using a ±45-day window. Ethereum is treated; Cardano and XRP are controls in Panels A and B. Simple DiD reports β_1 (control's post-event change) and β_3 (Ethereum's differential change). TWFE includes asset and date fixed effects; β_3 is the within-date differential response. Outcomes are standardized within the asset on the pre-event window. t-statistics are in parentheses. Trade data are from Binance; standard errors are clustered by date.

Outcome	β_1 common	β_3 simple DiD	β_3 TWFE
Panel A: Ethereum vs. Cardano			
OFI	$+2.909^{***}$	$+0.725^{***}$	$+0.725^{***}$
	(+5.60)	(+4.30)	(+3.04)
Buy Ratio	$+2.947^{***}$	$+0.485^{**}$	+0.485
	(+5.34)	(+2.19)	(+1.55)
Large Share	-1.616^{***}	$+2.058^{***}$	$+2.058^{**}$
	(−3.08)	(+3.08)	(+2.18)
Small Share	$+0.968^{***}$	-0.453^{**}	−0.453
	(+4.63)	(−2.07)	(−1.46)
Roll Spread	-0.543^{***}	$+0.266^{*}$	+0.266
	(−3.47)	(+1.92)	(+1.36)
Asset FE	No	No	Yes
Date FE	No	No	Yes
Observations	182	182	182
Panel B: Ethereum vs. XRP			
OFI	$+2.613^{***}$	$+1.021^{***}$	$+1.021^{***}$
	(+6.08)	(+5.11)	(+3.62)
Buy Ratio	$+2.863^{***}$	$+0.569^{***}$	$+0.569^{**}$
	(+6.00)	(+3.02)	(+2.14)
Large Share	$+0.523^{**}$	−0.082	−0.082
	(+2.07)	(−0.19)	(−0.14)
Small Share	-3.797^{***}	$+4.312^{***}$	$+4.312^{***}$
	(−7.23)	(+8.66)	(+6.12)
Roll Spread	$+0.604^{***}$	-0.881^{***}	-0.881^{***}
	(+3.61)	(−6.08)	(−4.30)
Asset FE	No	No	Yes
Date FE	No	No	Yes
Observations	182	182	182

Table IA.6. Variable Definitions and Construction

Term	Definition / Construction
Panel A: Assets and Technology	
Cryptocurrency	Digital bearer asset recorded on a decentralized blockchain and secured by a consensus protocol rather than an intermediary. Carries no exposure to carbon taxation or mandatory emissions disclosure.
Proof-of-Work (PoW)	Consensus by competitive computational mining; energy-intensive, large carbon footprint (BTC, pre-Merge ETH).
Proof-of-Stake (PoS)	Consensus by validators selected in proportion to staked tokens; negligible energy use, treated as green (ADA, XRP, post-Merge ETH).
Ethereum Merge	Pre-announced protocol upgrade replacing PoW with PoS at block 15,537,393, 15 September 2022, 05:42:42 UTC (T_M); cut network energy use by 99.95% and annualized emissions from ≈10 $MtCO_2$/yr to ≈0. Announced 24 August 2022 (T_A), $\Delta = T_M - T_A = 22$ days.
Musk event pair	Tesla Bitcoin-acceptance tweet (24 March 2021) and suspension tweet on environmental grounds (12 May 2021).
Panel B: Model objects	
$\kappa_i(t)$	Per-coin attributable emission intensity, $E_i^{\text{net}}(t)/N_i(t)$ in tCO_2/coin/yr; CCAF annualized network emissions divided by issuance-implied circulating supply. Decays as $\kappa_i(t) = \kappa_{i,0}e^{-\lambda t}$.
λ	Deterministic emissions-decay rate from network efficiency gains; acts as an additional discount on the carbon claim.
η	Poisson hazard of the technology upgrade anticipation.
d	ESG investor's private valuation of the externality: non-pecuniary flow disutility of d dollars per tonne financed.
D	The wealth-weighted marginal taste $D = \mu d$ ($/$tCO_2$); the price at which the market capitalizes carbon.
SCC	Social cost of carbon, rate-matched following Rennert et al. (2022): $185 at $r = 2\%$, $118 at 2.5%, $80 at 3%.

Continued on next page

Table IA.6 (continued)

Term	Definition / Construction
$G^{\text{mkt}}(t)$	Capitalized carbon claim, $D\kappa(t)/(r+\lambda+\eta)$; strictly decreasing and convex in λ and η. The corner $(D,\lambda,\eta) = (\text{SCC}, 0, 0)$ gives the upper bound $\bar{G} = \text{SCC}\,\kappa_0/r$.
Ψ	Net pecuniary flow per coin per year: priority fees plus base-fee burn, net of new-issuance dilution; treated as constant in model.
P^*	Carbon-free fundamental price, $(\Psi - a\sigma^2 q)/r$, with $P(t) = P^* - G^{\text{mkt}}(t)$.
μ, γ, σ^2_{ret}	Mass of ESG-constrained investors; relative risk aversion ($\gamma = 2$ baseline); annualized variance of log returns. CARA normalization $a = \gamma/W$, $W = PN$, $q = N$, $\sigma^2 = \sigma^2_{\text{ret}} P^2$.
$d^*(t)$	Exit threshold, $a\sigma^2 q/[(1-\mu)\kappa(t)] = \gamma\sigma^2_{\text{ret}}(t)P(t)/[(1-\mu)\kappa(t)]$; the ESG investor's no-short constraint binds for $d > d^*(t)$. Denominated in \$/tCO$_2$ and directly comparable to the SCC.
$\widehat{d^*}(t)$	Reduced-form exit threshold, $(\bar{r}(t) - r_f)P(t)/\kappa(t)$, replacing the equilibrium excess payoff with the realized one; $\bar{r}(t)$ is the trailing-365-day annualized mean of hourly log returns and r_f is risk free rate. Undefined where $\bar{r} < r_f$.
Δ^{excl}	Limited-risk-sharing exclusion discount (Merton et al., 1987; Heinkel et al., 2001): $\Delta^{\text{excl}}/P = (\gamma\sigma^2_{\text{ret}}/r)\cdot\mu/(1-\mu)$. Depends on constrained mass, risk aversion, and variance, not on κ.
Panel C: Treatment and event-study design	
Treated / Control	Merge test: treated ETH, control BTC (both USDC pairs, Kraken and Binance). Salience test: treated PoW (BTC, ETH), control PoS (ADA, XRP) on Binance.
$\tilde{T}_{i,t}$	Treatment intensity, $\text{ETH}_i \times \text{Post}_t \times G^{\text{pre}}_{\text{ETH}}/1000$: thousands of dollars of per-coin carbon claim eliminated at the Merge; zero otherwise.
Implied SD	Full-Merge effect, $\hat{\beta}\cdot G^{\text{pre}}_{\text{ETH}}/1000$, in pre-event standard deviations. Invariant to the CCAF electricity-mix scenario by construction.
Simple differential CAR	$\sum_t (r^{\text{ETH}}_t - r^{\text{BTC}}_t - \hat{\mu}_{\text{pre}})$ on six-hour log returns; implicitly imposes $\beta_{\text{ETH,BTC}} = 1$.
CAPM-adjusted CAR	$\sum_t (r^{\text{ETH}}_t - \hat{\alpha} - \hat{\beta} r^{\text{BTC}}_t)$, with $\hat{\alpha}, \hat{\beta}$ from the single-factor market model estimated out of sample on $[T_M - 180d,\ T_M - 60d]$.

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Table IA.6 (continued)

Term	Definition / Construction
Signed / unsigned outcome	Signed outcomes (OFI, buy ratio) load on the directional utility component and not on attention; unsigned outcomes (trade-size shares, effective spread) load on attention and not on utility.
C (carbon salience)	Carbon-salience component of the Musk pair: $\beta_3^{\text{May}} + \beta_3^{\text{Mar}}$ for signed outcomes, $\beta_3^{\text{May}} - \beta_3^{\text{Mar}}$ for unsigned outcomes. Inference from the Wald test of $H_0 : C = 0$ in the stacked specification.
Panel D: Microstructure outcomes	
Roll Spread (bps)	Effective spread from the serial covariance of price changes (Roll, 1984).
Amihud ILLIQ	Daily |return| / dollar volume.
OFI	Volume-weighted signed imbalance of buyer- vs. seller-initiated trades.
Buy Ratio	Fraction of buyer-initiated trades; the dollar-weighted version is the share of within-bucket dollar volume from buyer-initiated trades.
Large / Medium / Small Share	Fractions of daily volume in trades ≥ \$100K, \$10K–\$100K, and < \$10K notional (Bybit size classification). Small Share proxies retail participation.
Adverse selection	Permanent price-impact component (Glosten and Harris, 1988), estimated tick-by-tick within each hour: a liquidity-supply measure, not a preference-channel measure.
CCAF	Cambridge Centre for Alternative Finance annualized network emissions ($MtCO_2e$, daily, \$0.05/kWh): Hydro-only lower bound, Estimated central case, Coal-only upper bound. Estimated is the baseline; Coal-only bounds the claim from above.