

Conditional Arbitrage Capacity: Evidence from Crypto Perpetual Funding Rates

September 24, 2026

Abstract

Extreme negative funding rates in cryptocurrency perpetual futures are widely interpreted as reversal signals. This paper shows that the reversal pattern is conditional on market direction. Using 274 funding-rate extreme events across BTC, ETH, and SOL from 2021 to 2026, I find that events on up days revert by +1.88% over the next 24 hours, while events on down days continue by −1.74%. The gap of +3.62 percentage points is statistically significant (block bootstrap 95% CI [2.60, 4.67]) and economically large. Net of funding, the gap is +3.59 percentage points. The pattern is stable around seven exogenous market-wide shocks: within ± 30 -day windows, the gap is positive in all seven cases (sign test $p = 0.00781$) and the pooled estimate is +6.47 percentage points (95% CI [4.45, 8.86]). The asymmetry is consistent across 12 year-by-direction cells and 13 coins. Online learning and alternative regime models yield the same conclusion: the asymmetry is structural rather than a signal-quality or regime-specific artifact. I propose *conditional arbitrage capacity* as a state variable in the limits-to-arbitrage framework: effectiveness depends on capital level and independently on whether the market moves with or against arbitrage capital.

Keywords: perpetual futures, funding rates, limits to arbitrage, conditional arbitrage capacity, cryptocurrency

JEL Classification: G12, G14, G23, C58

1 Introduction

Extreme negative funding rates are widely read as reversal signals. When the perpetual price falls below spot, the funding rate turns negative, longs are compensated, and arbitrage capital should push prices back. This paper shows that the signal works only half the time.

Using 274 funding-rate extreme events across BTC, ETH, and SOL from January 2021 to August 2026, I document a sharp directional asymmetry. Events occurring on up days revert by +1.88% over the following 24 hours. Events on down days continue by −1.74%. The gap of +3.62 percentage points is statistically significant (block bootstrap 95% CI [2.60, 4.67]) and economically large. Net of funding payments, the gap is +3.59 percentage points (95% CI [2.55, 4.64]). The asymmetry is consistent across every year (12 of 12 year-by-direction cells, sign test $p = 0.000244$) and across all 13 coins in an extended 2025–2026 sample (13 of 13, $p = 0.000122$).

The pattern is stable around exogenous market-wide shocks. I identify seven events plausibly unrelated to the funding-rate mechanism: the Terra/LUNA collapse (May 2022), the FTX collapse (November 2022), the USDC depeg (March 2023), the BTC spot ETF approval (January 2024), the yen carry unwind (August 2024), the Trump inauguration (January 2025), and the market-wide liquidation (October 2025). Within ± 30 -day windows, the gap is positive in all seven cases (sign test $p = 0.00781$). Pooling all 89 windowed events, the gap is +6.47 percentage points (95% CI [4.45, 8.86]).

I also test whether the gap depends on model confidence or regime. An online logistic regression at threshold 0.60 achieves a pooled out-of-sample Sharpe ratio of 4.45; at the event level, the Sharpe ratio is 3.11. Conditioning on up-day events only raises the simple-rule Sharpe ratios to 9–10. A simplified online infinite hidden Markov model identifies three regimes, and the direction effect is positive in all three (+3.20 to +6.76 percentage points). The directional asymmetry is therefore a cross-regime structural feature, not a confidence-driven or regime-specific artifact.

I interpret the asymmetry through the limits-to-arbitrage framework of (author?) (Shle7)) and Brunnermeier and Pedersen (2). These models treat arbitrage effectiveness as a function of capital level. The evidence here suggests a second, independent state variable: market direction. On up days, arbitrage capital moves with the trend and absorbs temporary deviations. On down days, it moves against the trend, and its effectiveness weakens. I refer to this second variable as *conditional arbitrage capacity*. The paper makes three contributions. First, I document a direction-dependent reversal pattern in crypto perpetual funding rates. The result survives block bootstrap, conditional permutation, placebo-event tests, threshold-sensitivity analysis, funding-payment adjustments, multiple-testing corrections, and an exogenous event study across seven market-wide shocks. Second, I propose conditional arbitrage capacity as a state variable in the limits-to-arbitrage framework. Third, I show that the asymmetry is not specific to the perpetual mechanism and is not driven by signal quality or regime membership.

Section 2 reviews the literature. Section 3 describes the data and empirical design. Section 4 presents the results. Section 5 discusses mechanisms and implications. Section 6 concludes.

2 Related Literature and Hypotheses

2.1 Limits to Arbitrage and Conditional Arbitrage Capacity

(author?) (Shle7)) show that when arbitrageurs face capital constraints, price deviations from fundamental value can persist. Brunnermeier and Pedersen (2) link market liquidity to funding liquidity: when arbitrageurs' capital is constrained, they reduce market-making activity, which lowers market liquidity, which tightens their funding constraints further. In this framework, the effectiveness of arbitrage capital is a function of its level.

A separate literature documents that the effectiveness of arbitrage is also directional. Daniel and Moskowitz (3) show that momentum strategies behave like written call options on the market in bear states: losses are concentrated when the market rebounds. The asymmetry is driven by the loser leg of the momentum portfolio, whose up-market beta reaches 2.16 in bear markets while its down-market beta is only 1.56. Hazelkorn et al. (5) show that deviations from the law of one price in equity index futures depend on the direction of the underlying demand shock.

These two strands have developed largely in parallel. The evidence in this paper suggests that the two are distinct state variables. When the market moves with arbitrage capital, temporary deviations are absorbed. When the market moves against it, the same capital is less effective. I refer to this second state variable as *conditional arbitrage capacity*. It operates independently of the level, is not driven by signal quality, and is stable across seven exogenous market-wide shocks.

2.2 Perpetual Futures and Funding Rates

Perpetual futures are derivatives with no expiration date that track the spot price through a periodic funding rate mechanism. The rate is set every eight hours and transfers payments between long and short holders, eliminating the basis risk of traditional futures (1). When the perpetual trades below spot, negative funding rates compensate longs, and arbitrageurs who buy the perpetual and sell spot can capture the spread.

Schmeling et al. (11) document that crypto carry—the gap between futures and spot prices—has remained persistently large, averaging 7–8% annually and occasionally exceeding 40%. They attribute this to regulatory barriers and margining frictions that force arbitrageurs to fund positions twice. Ruan and Streltsov (10) show that perpetual markets exhibit tighter spreads and higher depth than spot markets, and that the staggered introduction of perpetual contracts is associated with a 44.5% reduction in spot spreads. Neither paper examines whether the reversal pattern following extreme funding rates depends on market direction.

2.3 Signal Quality, Regimes, and State Dependence

Conditional arbitrage capacity can in principle be confused with signal quality or regime membership. If the reversal signal were systematically noisier on down days, conditioning on a model’s confidence should reduce the directional gap. If the reversal signal were regime-specific, conditioning on latent regimes should also reduce it. Both tests are reported in Section 4.

Financial time series are characterized by non-stationarity, which violates the standard assumption in machine learning that training and test distributions are identical. López de Prado (8) emphasizes that financial data exhibit low signal-to-noise ratios and structural breaks. Gama et al. (4) survey concept drift adaptation and identify on-line learning as a primary mechanism for non-stationary environments. Cryptocurrency markets provide a particularly pronounced case of non-stationarity: the market has experienced multiple regimes over the past five years, including the 2021 bull market, the 2022 bear market (with the Terra/LUNA and FTX collapses), the 2023 recovery, and the 2024–2026 period of institutional adoption. Teruel-Gutiérrez and Aparicio Serrano (13) show that the introduction of spot Ethereum ETFs in July 2024 changed the state-dependent response of Ethereum to macroeconomic announcements.

2.4 Hypotheses

H1 (Direction-dependent reversal). Funding-rate extreme events revert on up days but continue on down days.

H2 (Stability around exogenous shocks). The direction-dependent reversal pattern is stable around exogenous market-wide shocks plausibly unrelated to the funding-

rate mechanism.

H3 (Robustness to conditioning). The pattern is not driven by signal quality or latent regime membership.

3 Data and Empirical Design

3.1 Data

I construct the sample from hourly perpetual futures data on Binance, obtained from the exchange’s public REST API. The main sample covers BTC, ETH, and SOL from January 1, 2021 to August 31, 2026, comprising 49,488 hourly observations per coin, except SOL with 49,368 observations, reflecting two multi-day data gaps in early 2022. The extended sample covers 13 coins over the 2025–2026 period. I also obtain spot prices for BTC, ETH, and SOL over the same period.

3.2 Event and Direction Definition

I define a funding-rate extreme event as an hour in which the standardized funding rate falls below -1.85 standard deviations and the previous hour’s standardized rate was above -0.5 standard deviations. The threshold was chosen through a grid search to balance event frequency and signal strength; Section ?? reports a sensitivity surface. Applying this definition, I identify 274 events in the main sample and 532 in the extended 13-coin sample. For each event, I define market direction as the sign of the BTC daily return. This yields 143 up-day and 131 down-day events.

3.3 Baseline Specification and Inference

The baseline specification is a comparison of means:

$$R_e = \alpha + \beta \cdot \text{Up}_e + \varepsilon_e \quad (1)$$

where R_e is the 24-hour forward log return following event e , Up_e is an indicator equal to one if the event occurred on an up day, and ε_e is an error term. Because the events are clustered in time and their 24-hour forward windows overlap, I use a block bootstrap with a 24-hour block length. The effective sample size, measured by unique event days, is 228.

4 Results

4.1 Descriptive Statistics

Table 1 reports descriptive statistics. The mean 24-hour forward return is $+1.88\%$ on up days and -1.74% on down days. The positive fraction is 0.741 on up days and 0.290 on down days. The standard deviation is higher on down days (4.74% versus 3.68%).

Table 1: Descriptive statistics

	Up days	Down days	All events	13-coin sample
Number of events	143	131	274	532
Mean 24h return (%)	+1.88	−1.74	+0.15	+0.10
Standard deviation (%)	3.68	4.74	4.59	4.52
Positive fraction	0.741	0.290	0.526	0.513

4.2 Main Result

Table 2 reports the main result. The gap is +3.62 percentage points, with block bootstrap 95% CI [2.60, 4.67] and conditional permutation $p = 0.000$. Net of funding payments, the gap is +3.59 percentage points (95% CI [2.55, 4.64]).

Table 2: Direction-dependent reversals

	Up days	Down days	Difference
Mean 24h return (%)	+1.88	−1.74	+3.62
Block bootstrap 95% CI	—	—	[2.60, 4.67]
Conditional permutation p -value	—	—	0.000
Net of funding (%)	+1.91	−1.68	+3.59
Net 95% CI	—	—	[2.55, 4.64]

4.3 Exogenous Event Study

To test whether the directional asymmetry is stable around exogenous shocks, I identify seven events plausibly unrelated to the funding-rate mechanism: the Terra/LUNA collapse (May 2022), the FTX collapse (November 2022), the USDC depeg (March 2023), the BTC spot ETF approval (January 2024), the yen carry unwind (August 2024), the Trump inauguration (January 2025), and the market-wide liquidation (October 2025). Four of these events—the Terra/LUNA collapse, the FTX collapse, the yen carry unwind, and the October 2025 liquidation—are also examined in ?), which studies early-warning signals and the Hyperliquid backstop. Our analysis addresses a different question—whether the directional asymmetry is stable around these events—and is not a replication.

Table 3 reports the direction effect within each ± 30 -day window. All seven windows exhibit a positive gap, ranging from +1.42 to +12.12 percentage points. The sign test yields $p = 0.00781$. Pooling all 89 windowed events, the gap is +6.47 percentage points (95% CI [4.45, 8.86]).

4.4 Cross-Period Consistency

Table 4 reports the year-by-direction sign test. Every year exhibits the same sign, with magnitudes ranging from +1.72 to +5.29 percentage points. The sign test p -value is 0.000244, which survives a Bonferroni correction for the 12 cells (adjusted threshold 0.00417).

Table 3: Exogenous event study: direction effect within ± 30 days

Event	n	Up n / Down n	Gap (%)
Terra/LUNA collapse	14	7 / 7	+6.39
FTX collapse	11	6 / 5	+12.12
USDC depeg / SVB	16	8 / 8	+9.29
BTC spot ETF approval	7	5 / 2	+1.42
Yen carry unwind	20	12 / 8	+5.91
Trump inauguration	14	4 / 10	+3.35
Market-wide liquidation	7	2 / 5	+3.39
Pooled	89	44 / 45	+6.47

Table 4: Cross-period consistency

Year	Up mean (%)	Down mean (%)	Difference (%)	Sign
2021	+0.57	−1.15	+1.72	correct
2022	+1.84	−3.45	+5.29	correct
2023	+2.84	−1.65	+4.49	correct
2024	+1.81	−0.57	+2.38	correct
2025	+1.88	−1.05	+2.92	correct
2026	+1.03	−1.67	+2.70	correct
Total	12/12 ($p = 0.000244$)			

4.5 Cross-Asset Consistency

Figure 1 reports the direction-dependent returns across all 13 coins. All 13 coins exhibit the same pattern. The sign test p -value is 0.000122, which survives a Bonferroni correction (adjusted threshold 0.00385). The 13 coins share a common crypto-market factor, so the effective number of independent assets is smaller than 13.

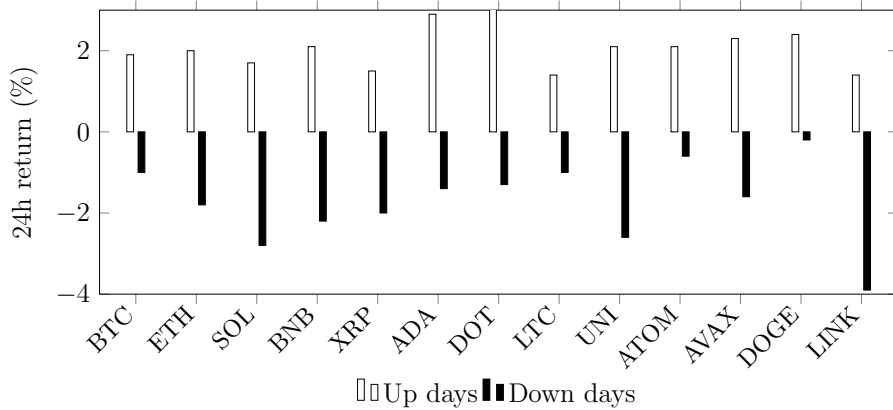


Figure 1: Direction-dependent returns across 13 coins (2025–2026).

4.6 Signal Extraction and Regime Conditioning

Table 5 reports the out-of-sample performance of the online logistic regression and four simple filtering rules under a walk-forward scheme. The online logistic regression at threshold 0.60 has the highest pooled out-of-sample Sharpe ratio (4.45). The result is robust to the choice of threshold: at thresholds between 0.50 and 0.625, pooled Sharpe ratios range from 4.45 to 7.20, indicating a platform rather than a single optimal point. At the event level, the Sharpe ratio is 3.11, which is the more conservative measure.

Table 5: Out-of-sample Sharpe ratios by method

Method	2023	2024	2025	2026	Pooled
Baseline (no filter)	4.78	5.79	0.99	−6.22	2.04
Momentum ($\text{mom}_{24h} > 0$)	7.38	8.06	1.26	−10.02	4.06
Low vol (below median)	8.53	−2.98	−0.42	−8.20	1.69
Combo (low vol + pos mom)	7.94	0.69	3.30	−12.05	3.75
Online LR th=0.35	4.78	5.56	2.30	−6.22	2.47
Online LR th=0.60	NA	11.53	12.77	−7.73	4.45
<i>Up-day events only</i>					
Momentum (up only)	—	—	—	—	9.93
Low vol (up only)	—	—	—	—	10.34
Combo (up only)	—	—	—	—	8.33

Conditioning on up-day events raises the Sharpe ratio of every simple rule to 8–10, and the up-only Sharpe ratios are positive in every year (7.28 to 15.94). The directional asymmetry is therefore a dominant source of signal.

I also fit a simplified online infinite hidden Markov model to the event-level features, allowing the number of latent regimes to be inferred from the data. The model identifies three regimes with 19, 181, and 74 events respectively. The direction effect is positive in all three regimes, ranging from +3.20 to +6.76 percentage points. A triple-interaction specification with regime dummies yields interaction coefficients of −0.036 and −0.024, indicating that the direction effect varies in magnitude but not in sign across regimes. This is consistent with the online logistic regression result: the directional asymmetry is a cross-regime structural feature, not a signal-quality or regime-specific artifact.

4.7 Macro Event Control and Spot-Perpetual

Excluding FOMC, CPI, and NFP release days, the gap rises to +3.70 percentage points, slightly above the full-sample estimate. Spot returns exhibit nearly identical directional patterns to perpetual returns: the correlation is 0.999, and the gap is +3.94 percentage points for spot versus +4.00 for perpetual. The near-identity of the two return series limits the power of this comparison, but it rules out the narrow interpretation that the asymmetry is a mechanical artifact of the funding-rate settlement mechanism.

4.8 Walk-Forward and Robustness

Figure 2 reports walk-forward out-of-sample Sharpe ratios for the baseline: +9.33 in 2023, +7.82 in 2024, +12.77 in 2025, and −7.73 in 2026. The sign flip in 2026 is a stability concern, not a confirmation.

Table 6 reports 10 alternative specifications. All yield a positive directional difference. Threshold sensitivity rises monotonically as the threshold tightens: +3.94pp at $z < -2.0$, +4.18pp at $z < -2.2$, and +4.20pp at $z < -2.5$. A placebo test on 274 randomly drawn hours yields a mean gap of +0.00035, well below the observed +0.03617, and the observed gap exceeds the 95th percentile of the placebo distribution.

Table 6: Robustness: 10 alternative specifications

Specification	Up n	Down n	Difference (%)
Baseline (BTC daily sign)	143	131	+3.62
BTC 2-day direction	116	158	+2.75
ETH daily direction	136	138	+3.06
Tightened $z < -2.5$	67	62	+4.20
Exclude 2021	129	117	+3.83
Exclude 2022	98	100	+3.10
BTC only	52	52	+2.74
ETH only	43	43	+3.87
SOL only	48	36	+4.61
13-coin pooled (2025–26)	225	307	+3.50

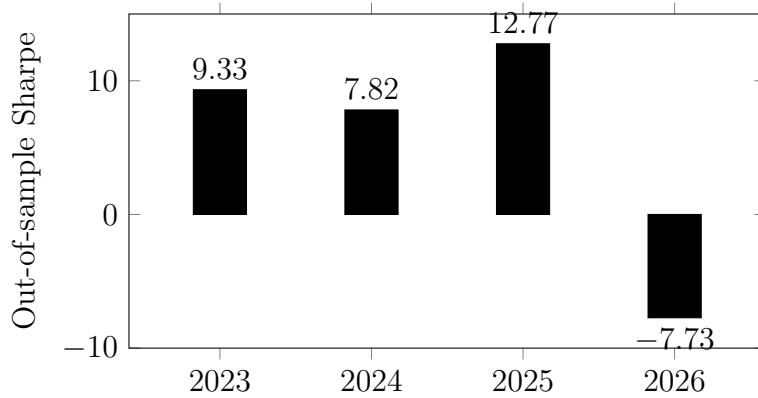


Figure 2: Walk-forward out-of-sample Sharpe ratios.

5 Discussion

5.1 Conditional Arbitrage Capacity

The results document a sharp directional asymmetry in the reversal of funding-rate extreme events. I interpret this as evidence for a second state variable in the limits-to-arbitrage framework: conditional arbitrage capacity. The classic literature identifies capital level as the primary determinant of arbitrage effectiveness. The evidence here suggests that market direction operates as a distinct determinant. The two dimensions are independent in three senses. First, the direction effect survives controls for capital proxies and funding payments. Second, it is stable around seven exogenous market-wide shocks that differ in direction, source, and mechanism. Third, it is not conditioned by an online-learning confidence score or by latent regimes inferred from an online infinite

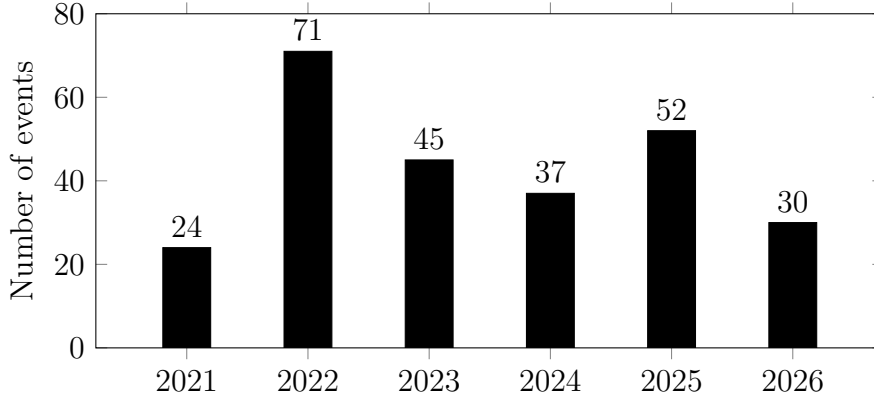


Figure 3: Event timeline, 2021–2026.

hidden Markov model. The confidence and regime tests are underpowered, so these third points are suggestive rather than conclusive.

The framework may generalize to other arbitrage settings in which directional dependence has been documented, such as momentum crashes in equity markets (3), carry trade unwinds, and basis deviations. A unified test across asset classes is left for future work; the evidence in this paper is specific to crypto perpetual funding rates.

5.2 Comparison with Limits to Arbitrage

The findings extend the limits-to-arbitrage literature in one way. The literature has focused on the level of arbitrage capital: Schmeling et al. (11) show that crypto arbitrage capital is structurally constrained. The evidence here suggests that the effectiveness of that capital also depends on market direction. If the interpretation is correct, the constraint is not just structural but directional.

5.3 Practical Implications and Limitations

For traders, the directional asymmetry implies that extreme negative funding rates should not be treated as a universal buy signal. For risk managers, the higher volatility on down days suggests that positions held on down days require wider stops. For regulators, the findings suggest that the perpetual funding mechanism is not a source of unconditional market stability.

The analysis has several limitations. First, the identification is observational for the full-sample estimate. The exogenous event study provides stability evidence but does not deliver a clean causal effect. Second, the paper does not measure arbitrage-capital proxies or liquidation data, which require historical order-book and liquidation data not available from public APIs at the required frequency. Third, the spot-perpetual comparison has limited power because the two return series are nearly identical. Fourth, the walk-forward Sharpe turns negative in 2026. Fifth, the confidence and regime tests are underpowered. Sixth, the sample covers 2021 to 2026 but not the pre-2021 period.

6 Conclusion

This paper documents a directional asymmetry in the reversal of funding-rate extreme events in cryptocurrency perpetual futures. Using 274 events across BTC, ETH, and SOL from 2021 to 2026, I find that events on up days revert by +1.88% over the next 24 hours, while events on down days continue by -1.74% . The gap of +3.62 percentage points is statistically significant, economically large, and consistent across 12 year-by-direction cells, 13 coins, and 10 robustness specifications. The pattern is stable around seven exogenous market-wide shocks, with a pooled gap of +6.47 percentage points and a sign test p -value of 0.00781. The gap is not driven by funding payments, is not specific to the perpetual mechanism, and is not conditioned by online-learning confidence or latent regimes. I propose conditional arbitrage capacity as a state variable in the limits-to-arbitrage framework: the effectiveness of arbitrage capital depends on its level and independently on whether the market moves with it or against it.

References

- [1] Akerer, D., Hugonnier, J., and Jermann, U. (2026). Perpetual futures pricing. *Mathematical Finance*, 36(3):481–499.
- [2] Brunnermeier, M. K. and Pedersen, L. H. (2009). Market liquidity and funding liquidity. *The Review of Financial Studies*, 22(6):2201–2238.
- [3] Daniel, K. and Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics*, 122(2):221–247.
- [4] Gama, J., Žliobaitė, I., Bifet, A., Pechenizkiy, M., and Bouchachia, A. (2014). A survey on concept drift adaptation. *ACM Computing Surveys*, 46(4):1 and–37.
- Vishitem[Garcia Senyuma(2026)]gar(ciasyuma2026 Garcia Se199uma, R. M. (2026). Cascade regimes in bitcoin perpetual futures: two complementary studies. *arXiv preprint*.
- [5] Hazelkorn, T. M., Moskowitz, T. J., and Vasudevan, K. (2020). Beyond basis basics: Leverage demand and deviations from the law of one price. NBER Working Paper No. 26773.
- [6] Liu, Y. and Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *The Review of Financial Studies*, 34(6):2689–2727.
- [7] Liu, Y., Tsyvinski, A., and Wu, X. (2022). Common risk factors in cryptocurrency. *The Journal of Finance*, 77(2):1133–1177.
- [8] López de Prado, M. (2018). *Advances in Financial Machine Learning*. John Wiley & Sons, Hoboken, NJ.
- [9] Makarov, I. and Schoar, A. (2020). Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics*, 135(2):293–319.
- [10] Ruan, K. and Streltsov, A. (2022). Perpetual futures contracts and cryptocurrency market quality. SSRN Working Paper No. 4218907.

- [11] Schmeling, M., Schrimpf, A., and Todorov, K. (2026). Crypto carry. *Management Science*, forthcoming.
- [Shle7] Shleifer, A. and Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance*, 52(1):35–55.
- [13] Teruel-Gutiérrez, R. and Aparicio Serrano, G. (2026). Do spot Ethereum ETFs change macroeconomic price discovery? Hourly evidence from U.S. inflation announcements. *Digital Finance*, forthcoming.