Predictive Crypto Crashes and Asset Pricing Implications: An Inelastic Market Perspective

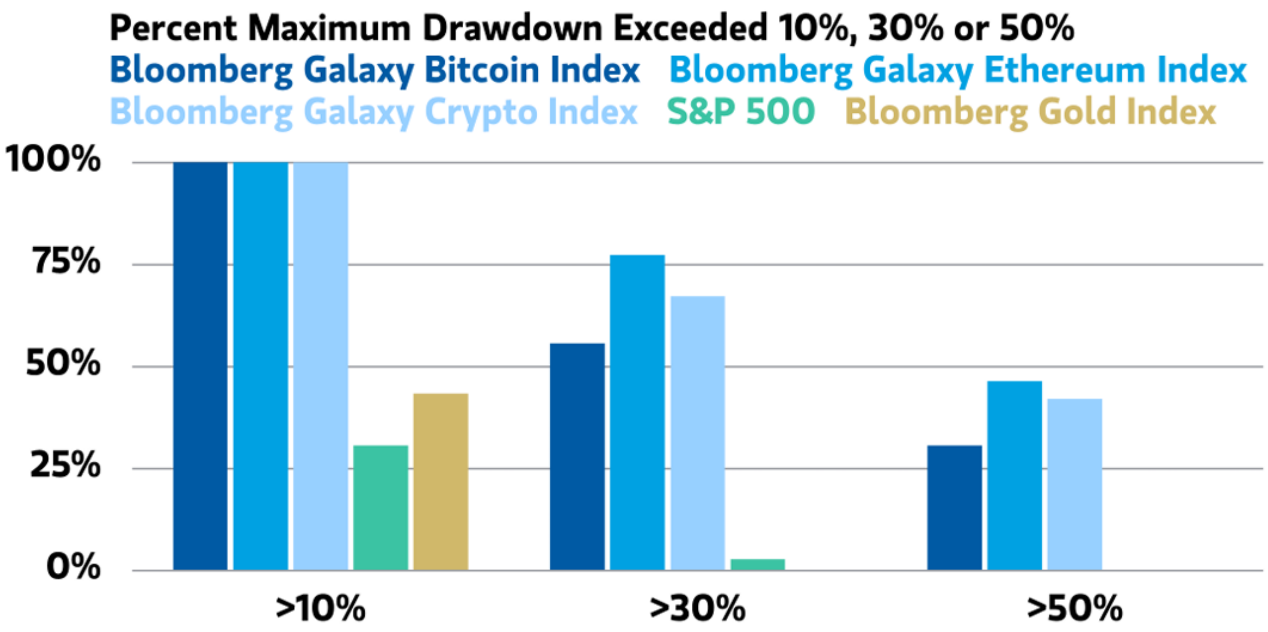
Jennifer (Jie) Li[1] **Li Liao**[2] **Siyuan Yang**[3] **Hong Zhang**[4]

[1] University of Macau
[2] Tsinghua University
[3] University of International Business and Economics
[4] Singapore Management University

2026 ABFER

Motivation: Crypto Crashes

Source: Coinmarketcap

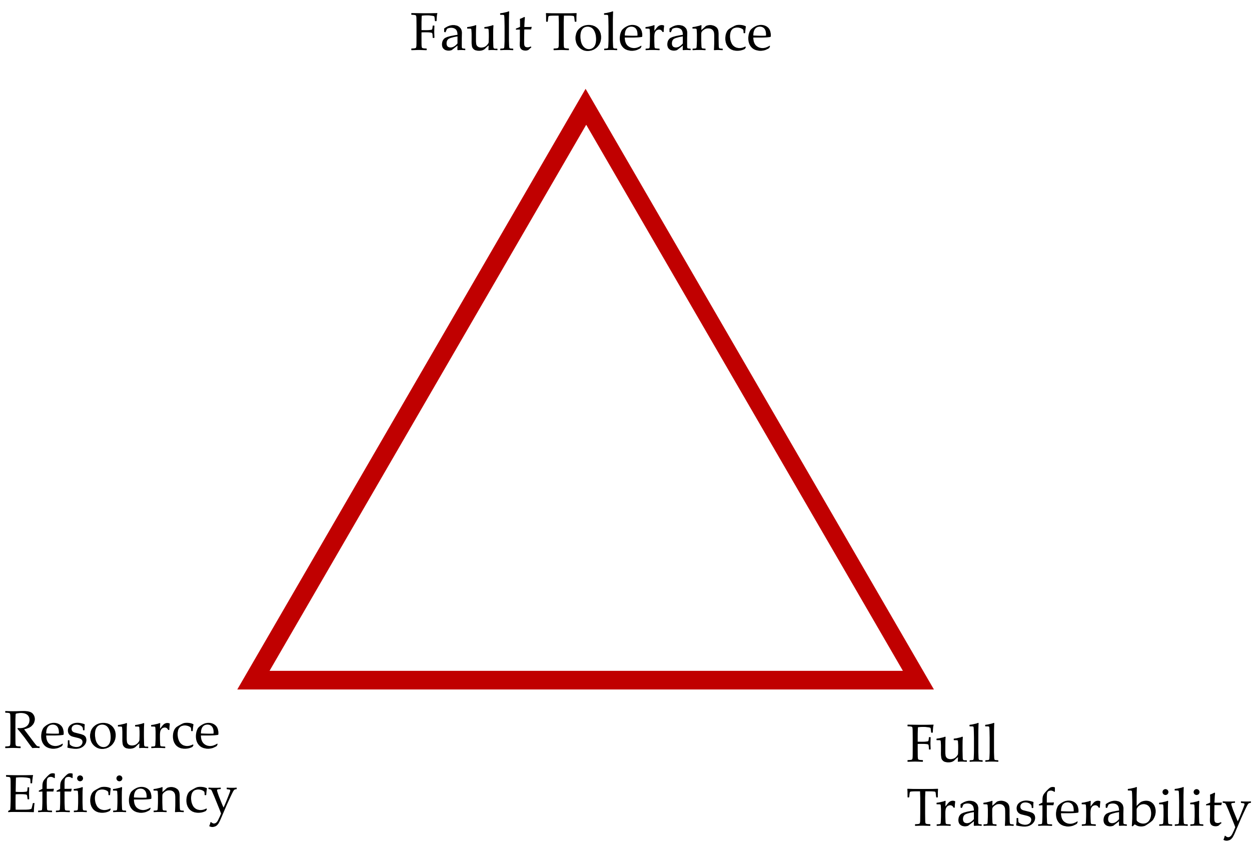


Source: Morgan Stanley, *Asset Allocation Considerations for Cryptocurrency*

- Bubbles and crashes are hallmarks of cryptocurrencies:
  - During the "Great Crypto Crash" in 2018, the price of Bitcoin dropped by around 80%.
  - Over a rolling 6-month holding period, a drawdown of 30% or greater is observed in 50% of such periods
- Our Question: Are crypto crashes predictable?
  - If so, what feature of blockchain contributes to the crashes?

Motivation: A Key Limitation of Blockchain Technologies

Buterin's Trilemma on Scalability, Decentralization, and Security



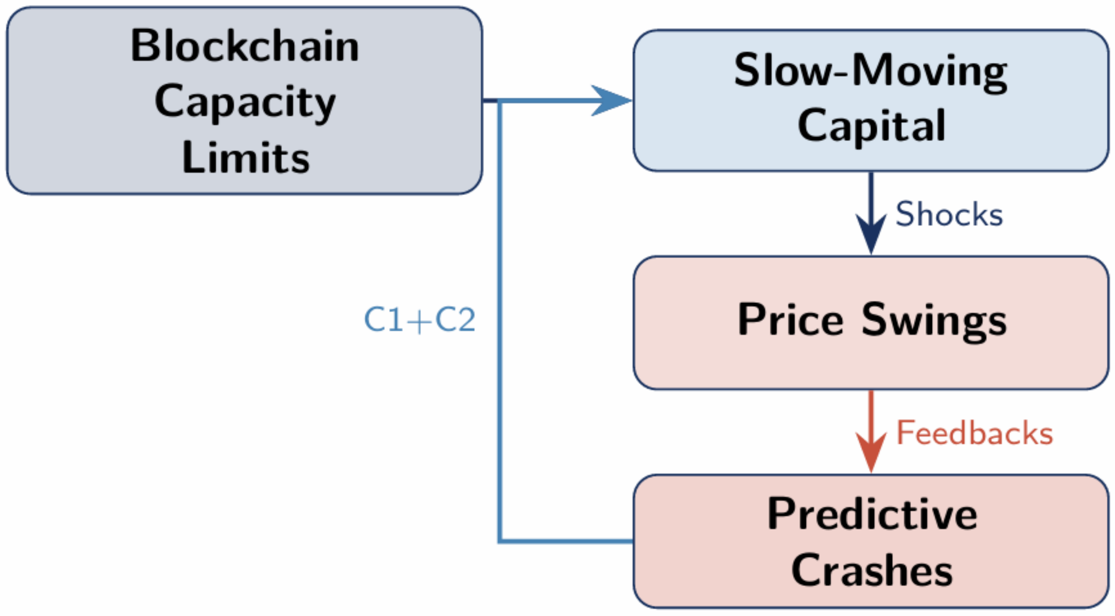
Abadi and Brunnermeier's Blockchain Trilemma

- From a capital flow perspective, these properties limit the speed and scale at which capital can move across the market to join transactions, naturally giving rise to *slow-moving* capital

An Inelastic Market Perspective: Slow Moving Capital

The Economic Chain:

1. **Blockchain capacity constraints** limit transaction processing speed
2. Capital cannot move fast enough → **Slow-moving capital (SMC)**
3. Shocks generate **large price swings** (jump reversal patterns)
4. **Two feedback channels** transform swings into **predictable crashes**



Two Feedback Channels:

C1 Valuation Gap Widens: large swings → Buyer & seller gap ↑ → Matching rate ↓

C2 Negative Network Effect: Deteriorating conditions → investor exit → active investor pool contraction

Key Insights:

C1+C2 **transform temporary capital dislocations into persistent crashes**: demand weakens when capital is already slow, making decline far more severe than in elastic markets

What We Do and What We Find

- Built on a search-based model of crypto crashes (Slow-moving capital + search frictions), we construct a measure for inelastic capital, namely, *Inelasticity Rank* (***InRank***).
  - InRank predicts larger crash risks and negative returns:
    - Validated against blockchain congestion data
    - The Elastic-minus-Inelastic strategy (EMI) generates a weekly return of 2.5%
- **Enhanced Momentum:**
  - WML fails to deliver significant positive returns among the most inelastic cryptos
  - EWIL: Elastic-Winner-minus-Inelastic-Loser: 3.4%
    - No momentum crash risk (Daniel and Moskowitz, 2016);
    - Persistent at 52 weeks
- **Identification**:
  - ICO-induced blockchain congestion on Ethereum blockchain as exogenous shocks. The ICO-affected cryptos built on Ethereum exhibit:
    - higher inelasticity ranks and negative cumulative abnormal returns.
    - more time between transactions, lower number of transactions, and higher Google search volume, consistent with the slow-moving capital hypothesis.

Related Literature

- Asset pricing in cryptocurrencies
  - Anomalies (Hubrich, 2017; Rohrbach, Suremann, and Osterrieder 2019), experience bubbles and crashes (Corbet, Lucey, and Yarovaya 2018), fit into factor models (Liu and Tsyvinski 2021; Liu, Tsyvinski and Wu, 2022; Cong, Karolyi, Tang and Zhao, 2023), subject to the influence of market frictions (Makarov and Schoar, 2019; Borri and Shakhnov, 2022), and network effect (Cong, Li, and Wang 2021).
  - cryptocurrency crashes as a sunspot: flawed protocol or attacks (see, e.g., Garratt and Wallace, 2018; Bias et al., 2023). Investor belief about the future value and adoption of cryptocurrencies (e.g., Benetton and Compiani, 2021; Kogan, Makarov, Niessner, and Schoar, 2022) also helps explain cryptocurrency returns.
  - Our paper: limited capacity of blockchains and slow-moving capital (e.g., Rubinstein and Wolineky 1985; Mitchell, Pedersen, and Pulvino 2007; Duffie 2010)

- Bubble/Crashes and Momentum
  - industry crashes and financial crises can be largely predicted using a list of economically motivated yet sophisticated characteristics (Greenwood, Shleifer, and You, 2018 and Greenwood, Hanson, Shleifer, and Sørensen, 2022)
  - Crypto momentum: Cong, Li, and Wang (2021), Liu and Tsyvinski (2021); Liu, Tsyvinski and Wu, (2022), Cong, Karolyi, Tang and Zhao, (2023)

Model Setup

- DGP (2005) benchmark: continuous time, four types $\{ho, hn, lo, ln\}$, pairwise meetings at rate λ_0. Nash bargaining (seller power: q). $dv_t = \mu_v dt + \sigma_v dB_t$
  - $l\ type\ (holding\ cost\ \delta_L) \rightarrow h\ type: \lambda_u(t);$ $h\ type\ \rightarrow l\ type: \lambda_d$
  - $\mu_{ho} + \mu_{lo} = s$ (supply)
  - **Our departure** ❶ : trade completion is endogenous, controlled by the no-trade zone

$$Z_t \geq 0$$

The trade completion probability $\pi(Z_t)$, where $\pi(0) = 1$ and $\pi'(.) < 0$

  - The effective trade rate:

$$\lambda_t^{eff} = \lambda_0 \times \pi(Z_t)$$

→ A level wedge

Equilibrium price (DGP + λ_t^{eff})

$$P = \frac{v}{r} - \frac{\delta_L}{r}\Phi(\lambda_u, \lambda_d, \lambda^{\text{eff}}, \mu; q)$$

Illiquidity discount

- $\uparrow \lambda_d \Rightarrow \uparrow \Phi \Rightarrow \downarrow$ P
- $\uparrow Z_t \Rightarrow \downarrow \lambda^{eff} \Rightarrow \uparrow \Phi \Rightarrow \downarrow$ P
  - wider no-trade zone → fewer completed trades → lower price (higher required discount)

Channel 1: Network-instability Channel

Intuition: Infrastructure shocks (ICOs, protocol upgrades, exchange events) widen buyer-seller valuation gap

Two microfoundations:

1. Cross-sectional dispersion in investor reservation values

- After shocks, the remaining pool is selected to have reservation values further from any feasible transaction price

2. Crypto-specific amplifier: venue fragmentation

- Multi-venue trading + stress-period arbitrage constraints
- Price formation becomes locally determined (Hautsch et al, 2024)

Since Z_t is latent, we need an observable proxy.
Realized swing:

$$s_\tau \equiv |p_\tau - p_{\tau-\Delta}|$$

Lemma A.1 (Monotone Identification)

$$s_\tau = \frac{\delta_L}{r}\left|\frac{\partial \Phi}{\partial \lambda^{\text{eff}}}\right| |\pi'(0)| Z_\tau + O(Z_\tau^2)$$

To first order, s_τ is monotonic in Z

s_τ serves as a revealed-state statistic for Z_τ .

Channel 2: Network Effects

Network adoption A_t enters via Markov up-transition rate:

$$\lambda_u(t) = \lambda_u^0 + \psi(A_t), \psi'(\cdot) > 0$$

2

Three reinforcing mechanisms:

- Search externalities: larger network ⇒ more counterparties ⇒ lower search costs
- Information formation: larger network ⇒ more public info ⇒ tighter Z_t
- Infrastructure: custody, derivatives, regulatory clarity widen feasible pool

"Negative network effect": investor exit ⇒ contraction ⇒ mechanisms reverse.

Network adoption dynamics:

$$\frac{dA_t}{dt}$$

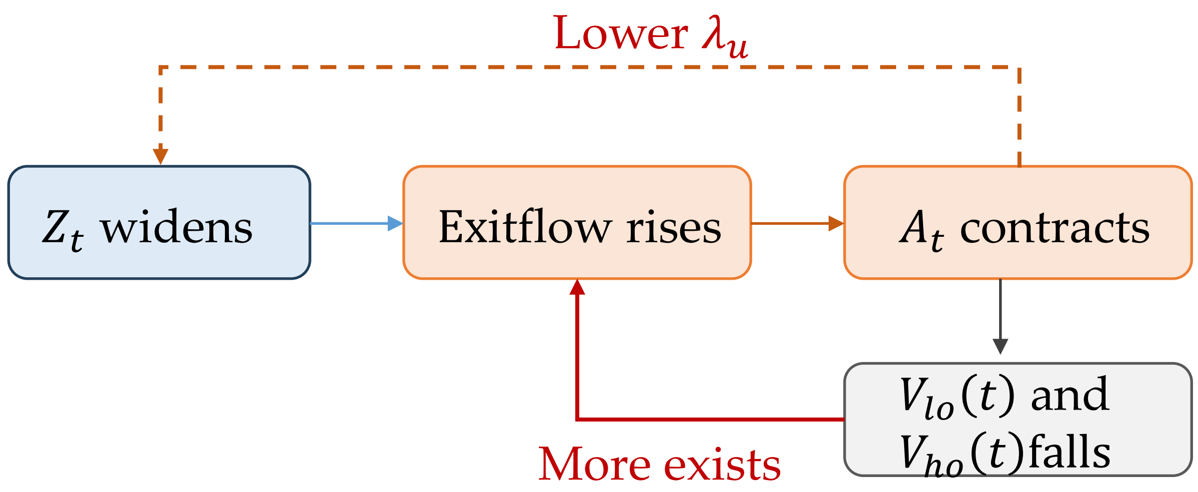
$$= \beta(A* - A_t)$$ Mean reversion

$$- \gamma\left[F_W\left(V_{lo}^{SS}\right) - F_W(V_{lo}(t))\right] \cdot \mu_{lo}(t)$$

$$- \gamma_e\left[F_W\left(V_{ho}^{SS}\right) - F_W(V_{ho}(t))\right] \cdot \mu_{ho}(t)$$

Exit flow

The feedback loop



Two Feedback Channels: From Swings to Crashes

Large price swings do NOT merely reflect SMC — they feed back to cause crashes:

Channel 1: Valuation Gap Widens

- Large swings → buyers/sellers valuation gap widens
- Reservation prices diverge further
- ⇒ Matching rate λ drops further
- Amplification: lower λ → lower prices → wider gap

Channel 2: Negative Network Effects

- Deteriorating conditions → some investors exit
- Active investor pool contracts
- Remaining investors: fewer matches, worse prices, more risk
- ⇒ Further exits → vicious cycle

Key Insight

- Combined, C1+C2 transform temporary capital dislocations into persistent, predictive crashes: demand weakens when capital is already slow, making decline far more severe than in elastic markets

Key Results

Proposition A.2: Supply shock Ω ⇒ realized swing

- $s_\tau = |P_{\tau+} - P_{\tau-}| = \frac{\delta_L}{r} \left|\frac{\partial \Phi}{\partial \mu_{hn}}\right| \cdot \Omega + O(\Omega^2)$

Proposition A.3 (Monotonic and Convex Exit Flow). The exit flow one period after the shock satisfies

- $ExitFlow_{\tau+\Delta} = \left[F_W\left(V_{lo}^{SS}\right) - F_W\left(V_{lo}^{SS} - \Delta V_{lo}(s_\tau)\right)\right] \cdot \mu_{lo},$

The exit flow is monotonically increasing in s_τ

Proposition A.5: (Persistent Crash)

- $E[P_{\tau+2\Delta} - P_{\tau+\Delta} \mid s_\tau] = -\frac{\delta_L}{r} \cdot \Psi(s_\tau) < 0$

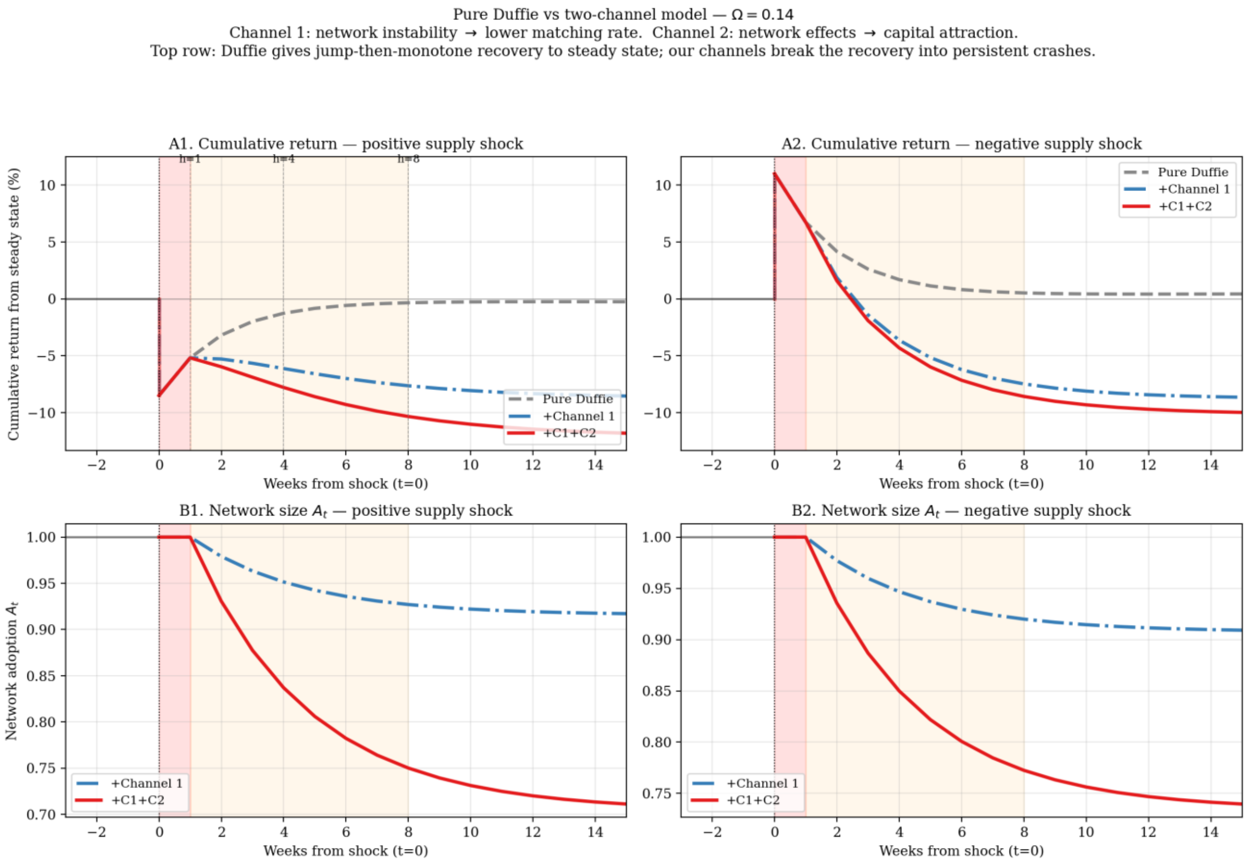
$$\Psi(s_\tau) = \left|\frac{\partial \Phi}{\partial \lambda_u}\right| \cdot \psi' \cdot \gamma \cdot ExitFlow_{\tau+\Delta} + \left|\frac{\partial \Phi}{\partial \mu_{hn}}\right| \cdot h(ExitFlow_{\tau+\Delta})$$

CH 2's network-amplification term   direct counterparty-pool contraction

Recovery half-life: exceeds 8 weeks

$$t_{1/2} = \frac{ln\ 2}{min\{\lambda_{u'}^0 + \lambda_d\ \beta\}}$$

Model Calibration



- **Setup**: Supply shock Ω = 0.14, calibrated simulation
- **Three Configurations**:
  - – Pure Duffie (gray): Both channels OFF
  - -. +Channel 1 (blue): Matching friction
  - — +C1+C2 (red): Both channels ON
- **Key Takeaways**:
  - Pure Duffie: Jump → monotone recovery to steady state
  - +Channel 1: Recovery broken
  - +C1+C2: Crash is deepened → persistent crash!

Bi-directional Crash

- Both positive shocks (A1: drawdown) & negative shocks (A2: runup) produce crashes. Network (B1/B2) contracts under C2

Empirical Predictions

	Predictions	Empirical Tests
P1	***InRank predicts negative forward returns***	EMI portfolio: high InRank → crash; 2.5%/wk
P2	***ICO shocks identify the network-instability channel***	InRank ↑, CulRet ↓
P3	***Asymmetric winner–loser response (EWIL)***	EWIL = 3.4% vs. WML = 2.2%
P4	***EWIL persistence at long horizons***	EWIL persists at 52 weeks; WML turns to zero
P5	***Network contraction channel***	Time ↑, #AbTrans ↓, Google↑

Data

- Trading data: from Coinmarketcap:
  - Jan, 2014 – May, 2024, 26,127cryptocurrencies in original sample.
  - Filters:
    - No missing price, volume, or market cap
    - Exclude market cap < 1M (week *t*-1) & weekly volume < $1
    - Require continuous data from week t–12 to t–1 to compute inelasticity
  - --- 4,284 cryptocurrencies left
- On-chain data: from Sentora Research (Intotheblock)
  - Average Time between Transactions, Number of Transactions, Active Addresses, and Total Addresses
  - Over 600 cryptocurrencies, combining augmented on-chain data and trading data.
- ICO dataset
  - ICO database from Lyandres et al. (2022) covers over 5,400 completed ICOs from 2015 to 2019
  - Augmented with ICO data and coinmarketcap records from 2020 onward
  - Missing ICO start dates and public blockchain information manually verified
  - --- 4,715 Ethereum-based ICOs from October 2015 to May 2024

Constructing InRank (Inelasticity Rank)

Key Insights (Proposition A.2)

When capital is slow, shocks generate jump-reversal patterns. We accordingly proxy the slow-moving capital by a realized observable price swing.

1 Calculate MaxRunup and MaxDrawdown

- MaxRunup: price runup from the lowest price to week-end, scaled by the time interval
- MaxDrawdown: price drawdown from the highest price to week-end, scaled by the time interval

2 Rank and Standardize

- Rank both measures cross-sectionally, standardize to [0,1]: $\widehat{R_i}$ and $\widehat{D_i}$

3 Construct InRank

$$\boldsymbol{InRank} = \frac{\widehat{R_i} + \widehat{D_i}}{\mathbf{2}}$$

- High InRank: Sequential large runup & drawdown ⇒ inelastic capital

Validation: InRank and Blockchain Congestion

Dep. Var = InRank	(1)	(2)	(3)	(4)
Time (avg. between transactions)	0.040***	0.035***	0.031***	0.041***
	(4.49)	(4.13)	(3.54)	(4.32)
#Transactions	0.059***	0.035***	0.061***	0.089***
	(5.92)	(3.45)	(4.09)	(5.18)
Time × #Transactions		0.005***	0.003***	0.003***
		(5.29)	(3.48)	(2.66)
Coin FE	YES	YES	YES	YES
Time FE	YES	YES	YES	NO
Blockchain×Time FE	NO	NO	NO	YES
Controls (ActAdr, BA)	NO	NO	YES	YES
Observations	7,407	7,397	6,933	6,933
Adj R^2	0.205	0.210	0.214	0.214

- InRank is positively associated with blockchain processing time and its interaction with transaction volume.

Diagnostic: Runup and Drawdown Double Sort

Panel A: Excess Returns (Runup × Drawdown)

	Drawdown		
MaxRunup	Low	Mid	High
Low	0.008	0.011	-0.003
Mid	0.023	0.011	0.011
High	0.011	0.003	**-0.015**

Panel B: Top/Top vs. Mid/Mid Spread

	Excess Ret	CAPM α	3-Factor α	5-Factor α
Spread	**-0.026**	**-0.024**	**-0.023**	**-0.021**
	(-3.75)	(-3.71)	(-4.46)	(-5.25)

Key Finding

The top/top portfolio (highest InRank) significantly underperforms by 2.6% per week—exactly the jump-reversal pattern predicted by the slow-moving capital model

Portfolio Analysis: Quintile Sorts on InRank

Test P1: Inelastic Crypto Crash

Panel A: The Portfolio Performance of Groups Sorted by Inelasticity

	1 (Elastic)	**2**	**3**	**4**	**5 (Inelastic)**	**EMI (Elastic-minus-Inelastic)**		
	h = 1 week						h=4week	h=8week
Excess Return	0.013	0.016	0.006	0.009	-0.011	0.025***	0.019***	0.023***
	(2.55)	(2.22)	(0.87)	(1.12)	(-1.42)	(4.71)	(3.17)	(4.35)
CAPM Alpha	0.004	0.005	-0.005	-0.003	-0.023	0.026***	0.022***	0.026***
	(1.58)	(1.05)	(-1.13)	(-0.72)	(-4.30)	(5.27)	(4.02)	(5.28)
Three Factor	0.004	0.005	-0.005	-0.002	-0.021	0.026***	0.021***	0.025***
	(1.63)	(1.10)	(-0.99)	(-0.34)	(-4.41)	(5.53)	(3.94)	(5.10)
Five Factor	-0.001	-0.002	-0.010	-0.009	-0.026	0.024***	0.019***	0.023***
	(-0.31)	(-0.58)	(-2.71)	(-2.48)	(-5.30)	(5.38)	(3.43)	(4.64)

Economic Magnitude:

- The EMI strategy generates 2.5% weekly returns, robust to risk adjustments and longer holding periods.
- The return spread is persistent

Fama-MacBeth Regressions

Test P1: Return Predictability

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var =			Ret			
InRank	**-0.016***** (-3.77)	**-0.015***** (-2.98)	**-0.055***** (-8.55)			
Inelasticity Dummy				**-0.012***** (-3.76)	**-0.010***** (-3.14)	**-0.025***** (-7.25)
Control	No	Basic	Full	No	Basic	Full
Adj R^2	0.004	0.044	0.093	0.007	0.049	0.095
Weeks	540	540	540	540	540	540
obs	388,955	388,953	388,948	388,955	388,953	388,948

Basic: Size, Ret[-12,-3], Ret[-2,-1] | **Full**: + lnAmihud, Turnover, IVOL, Skewness, Kurtosis

Economic Magnitude:

- A one-standard-deviation increase in InRank (SD = 0.289) is associated with

$$0.289 \times (-0.055) = -1.59\% \text{ lower weekly returns}$$

Predicting Crashes by InRank

Test P1: Crash Probability

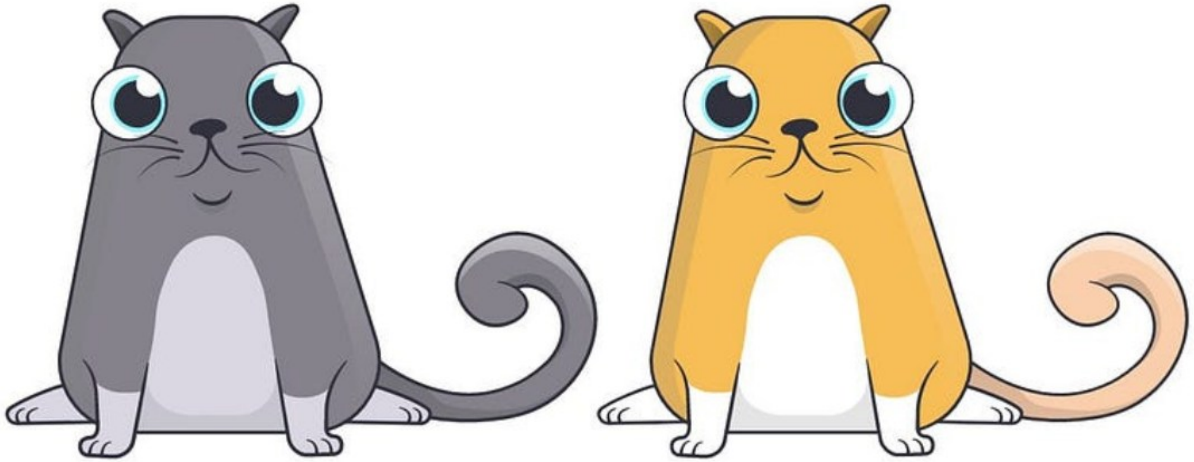
	Predicting Crashes					
	(1)	(2)	(3)	(4)	(5)	(6)
	Holding Period=1 Week		Holding Period=4 Weeks		Holding Period=8 Weeks	
InRank	0.152***		0.128***		0.098***	
	(32.33)		(15.32)		(9.12)	
Inelasticity Dummy		0.087***		0.077***		0.063***
		(27.34)		(14.44)		(9.82)

Economic Magnitude:

- Top 20% most inelastic cryptos have 8.7% higher crash probability.
- Robust to alternative specifications (Logit model, non-overlapping sample)

Identification Attempt: ICO-induced Inelasticity

- ICO-induced congestion (background)
  - On November 28, 2017, Ethereum was stuck by the ICO of CryptoKitties.
  - the CryptoKitties game accounts for over 10% of network traffic on Ethereum. As traffic increases, transactions become more expensive to execute quickly.



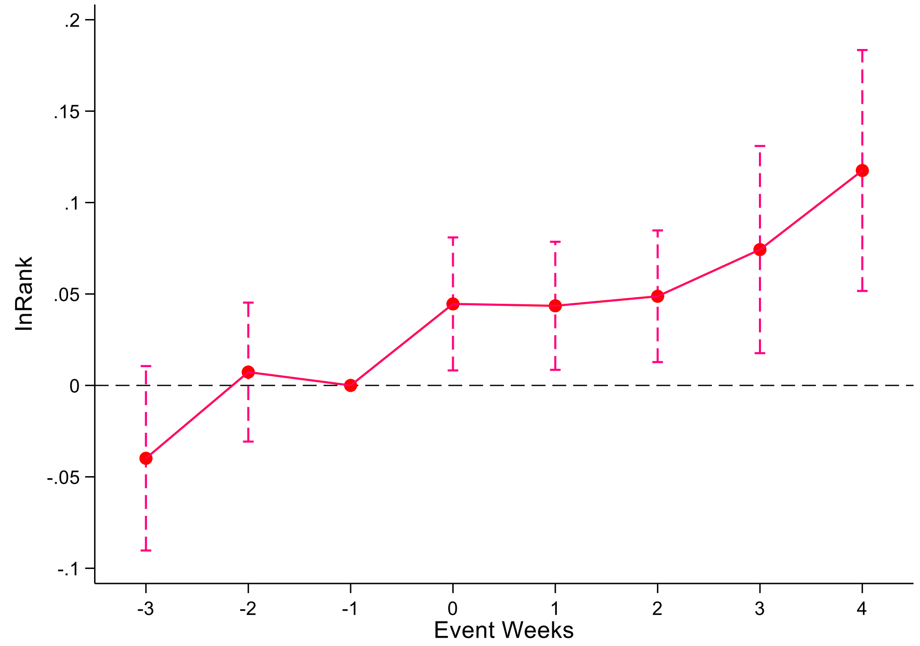
ICO Shocks and DiD Framework

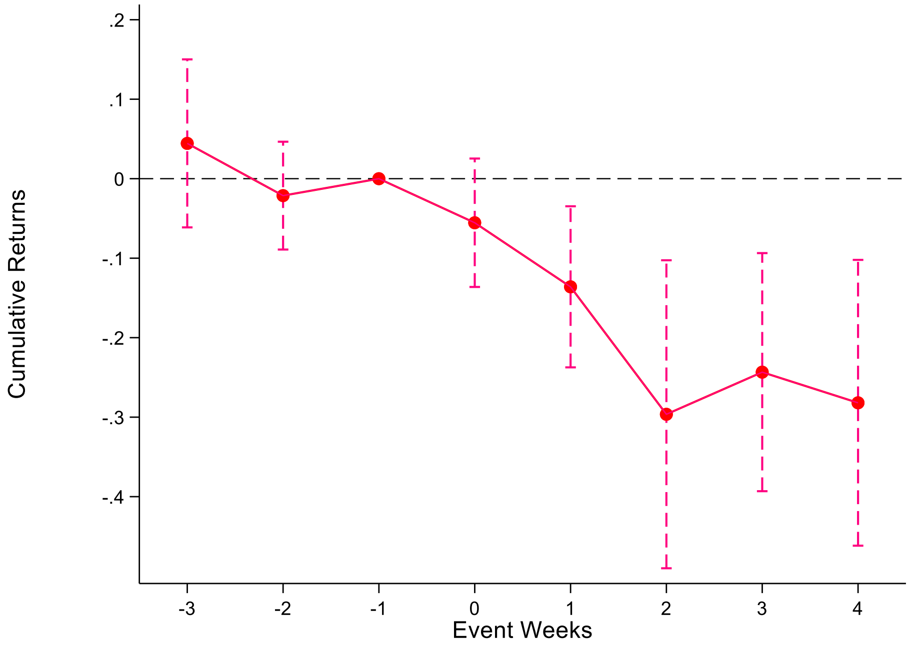
- Large ICOs on Ethereum occupy significant blockchain capacity, creating plausibly exogenous congestion shocks for other Ethereum-based cryptos.
- DiD Framwork:
  - Treatment: Cryptos built on Ethereum (excluding ETH)
  - Control: Non-Ethereum cryptos (Mahalanobis distance matched)
  - Event: Top 50 ICOs by amount raised per day
  - Window: [-3, +4] weeks around ICO

DiD Regressions

Test P2: ICO Shocks

$$Dep\,Var_{i,t} = a + \beta \times DiD_{i,t} + \gamma \times X_{i,t} + u_{i \times Event} + v_{t \times Event} + \varepsilon_{i,t}$$





DiD Results:

- lnRank increases immediately during ICO week
- Significant negative returns start one week later

DiD Regressions

Test P5: ICO Joint Response

$$Dep\,Var_{i,t} = a + \beta \times DiD_{i,t} + \gamma \times X_{i,t} + u_{i\times Event} + v_{t\times Event} + \varepsilon_{i,t}$$

Panel B: Average time, Abnormal Transactions, and Google Search around ICO Events			
	(1)	(2)	(3)
	Time	AbVolume	Google Search
Treat	0.282**	-0.147***	0.245***
	(2.31)	(-2.73)	(3.47)

DiD Results:

- Rising Time, reflecting matching-rate degradation
- ICOs reduce on-chain activity
- Rising investor search volume (Google Trend), reflecting active re-evaluation of the asset during the instability episode
    - Not less attention

How Inelasticity Affects Momentum

Test P3: Elastic momentum vs. Inelastic momentum

The Economic Logic

- Standard momentum: past winners → future winners
- But if winner's gains came from SMC-induced swings → crash risk offsets continuation
- **Elastic winners**: continue delivering returns
- **Inelastic winners**: underperform due to crash risk

Double-sort Results (MOM × InRank)

		InRank					
	Momentum	1 (Elastic)	2	3 (Inelastic)	EMI	EMI Average	Momentum Average
Excess Return	1 (Loser)	0.002	0.001	-0.007	0.008		
		(0.40)	(0.12)	(-1.02)	(1.43)		
	2	0.012	0.007	0.004	0.010		
		(2.07)	(0.96)	(0.38)	(1.56)		
	3 (Winner)	0.023	0.016	-0.003	0.027***		
		(3.24)	(1.80)	(-0.35)	(4.08)		
	WML	0.021***	0.015**	0.004		0.013***	0.014***
		(4.11)	(2.41)	(0.62)		(3.34)	(3.30)

The EWIL Strategy

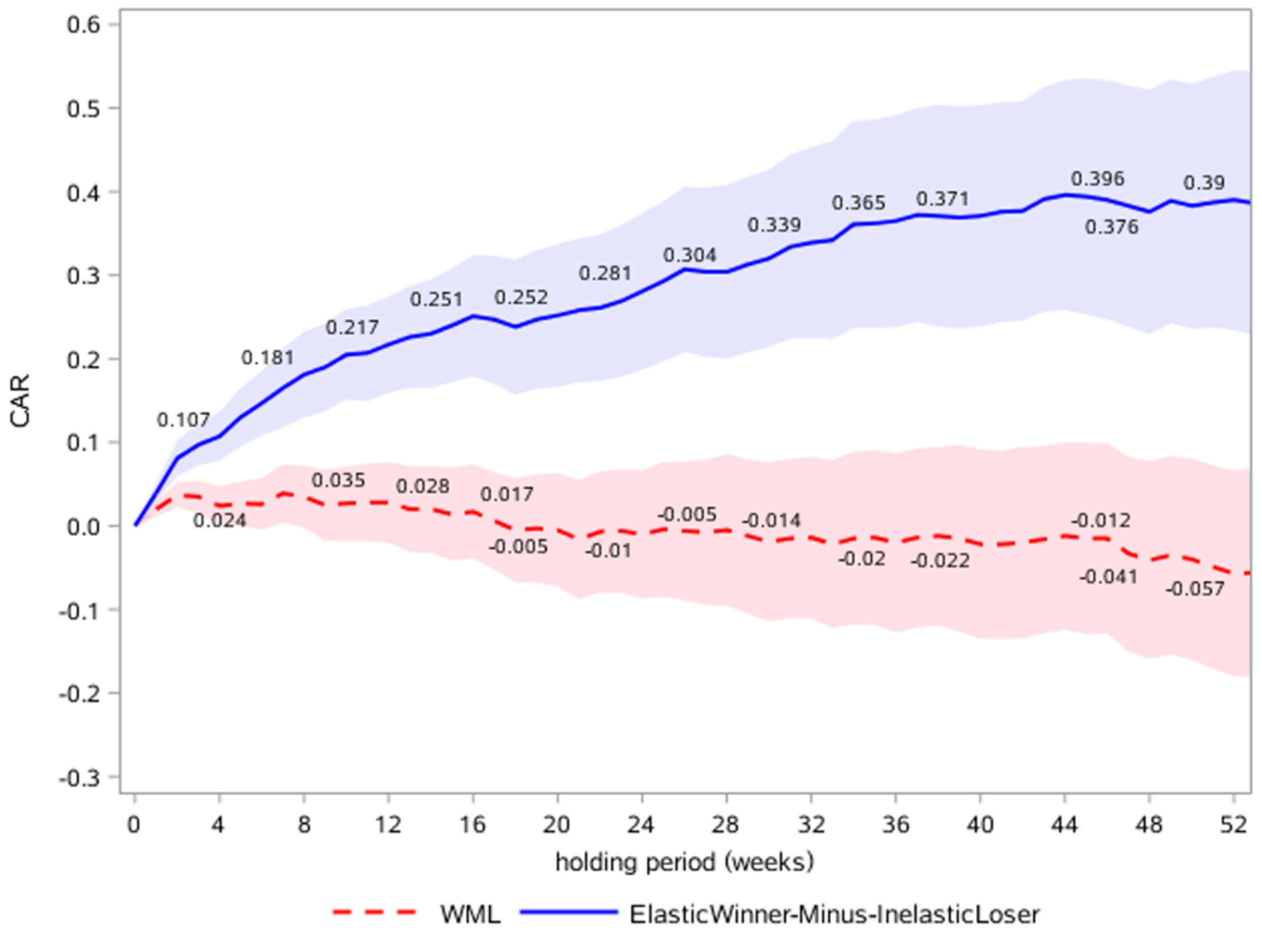
Test P3: Elastic momentum vs. Inelastic momentum

EWIL = Elastic Winners − Inelastic Losers → 3.4%***

EWIL Performance:

- Weekly return: **3.4%*****
- 3-Factor α: 3.3%***
- 5-Factor α: 3.2%***

The EWIL Strategy v.s. Momentum Strategy



Test P4: EWIL persistence at long horizons

- Blue (**EWIL**): Monotonically increasing, no sign of dissipation even at 52 weeks
- Red dashed (**WML**): Peaks at week 9, then declines; turns negative after week 20
- **Economic Interpretation**:
  - EWIL captures both **elastic momentum** (long winners) and **inelastic crash risk** (short losers)
  - Shorting inelastic losers hedges crash risk & generates persistent alpha
  - Momentum alone lacks the crash-risk hedge → eventual reversal

Model Link

Matches Figure A.1: EWIL's persistence ≈ +C1+C2 channels creating hysteresis inefficiency that Duffie baseline cannot explain.

Momentum Crashes

Coef.	Dep. Var = Indep. Var	R_{WML} (1)	EMI (2)	EWIL (3)	R_{WML} (4)	EMI (5)	EWIL (6)
$\tilde{\beta}_0$	$\tilde{R}_{Mkt,t}$	-0.018	-0.159***	-0.010	-0.216**	-0.212***	-0.300***
		(-0.29)	(-2.65)	(-0.11)	(-2.42)	(-3.33)	(-3.01)
$\tilde{\alpha}_B$	$I_{B,t-1}$				0.021	-0.016	0.001
					(1.44)	(-0.98)	(0.07)
$\tilde{\beta}_B$	$I_{B,t-1}\tilde{R}_{Mkt,t}$				0.455**	-0.105	0.270
					(2.20)	(-0.80)	(1.62)
$\tilde{\beta}_{B,U}$	$I_{B,t-1}\tilde{I}_{U,t}\tilde{R}_{Mkt,t}$				-0.088	0.365	0.533**
					(-0.31)	(1.14)	(2.10)
$\tilde{\alpha}_0$		0.022***	0.026***	0.035***	0.009	0.027***	0.019**
		(4.27)	(5.19)	(6.53)	(1.14)	(4.00)	(2.54)

Our Finding:

Unlike momentum which has negative market timing during bear markets (like written call options), EWIL exhibits positive market timing — shorting inelastic losers hedges against crashes!

Alternative Explanations and Robustness Checks

■ Tested and Ruled Out

- Inattention: Google searches increased for treated cryptos
- Volatility Timing: Vol.-managed portfolios add no info
- Prospect Theory: Controls for max daily returns
- Sequence Effects: RunupFirst dummy insignificant

Outlier treatment	No winsor	0.023*** (0.025***)
	Truncate 0.5%/99.5% (Fieberg et al. 2025)	0.026*** (0.025***)
Latent confounding	Doubly Debiased LASSO	-0.068***

Conclusion

1. **New Mechanism:** Blockchain capacity constraints → slow-moving capital → predictable crashes
2. **New Measure**: InRank captures capital inelasticity using observable price swing patterns, validated against on-chain blockchain data
3. **New Strategy**: EWIL (Elastic Winner − Inelastic Loser) generates 3.4% weekly returns, more than doubling momentum, with no traditional momentum crashes
4. **Causal Evidence**: ICO-induced Ethereum blockchain congestion causes higher inelasticity and subsequent crashes
5. **Implications**: Constrained transaction capacity imposes fundamental limits on price efficiency in blockchain-based markets

Thank You