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Introduction to Web3 Economics and Oracle Networks

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FinTech@Cornell | IC3 | NBER

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Goal of the talk:

1. The economics of blockchain/crypto/defi is relevant and important.
2. Marrying the rich data from blockchain/DeFi/CeFi/Web3 with economic analyses is a fruitful path.

Roadmap:

1. Blockchain Economics
2. Digital Nations and Tokenomics.
3. Oracle Networks, Interoperability, and Off-Chain Economy Integration.

Why is economics relevant for blockchain/crypto/web3? And how to apply it?

Game theory, mechanism design, market microstructure, monetary supply.

Asset pricing, corporate finance, international economics, contracting theory, banking, currencies and commodities, etc.

Treating digital networks as cyber countries/digital nations. Then tokens are domestic currencies and assets.

1. Blockchain Economics

Blockchains as decentralized consensus and mining as an allocation mechanism.

Smart contracts enable automation and enforceability of contract terms w.r.t. the system states (consensus).

Pros and cons of decentralization:

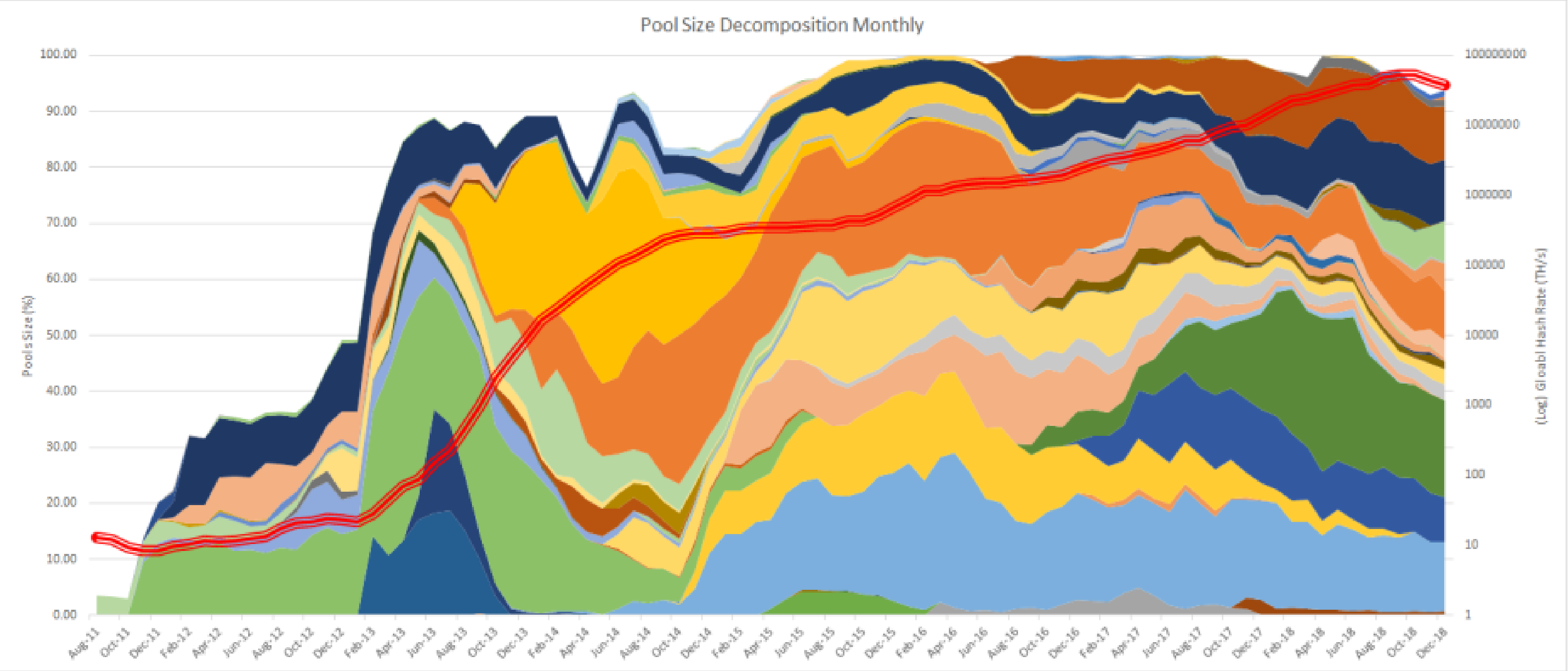
- Economic single point of failure
- Dynamic market power
- Infrastructure for MPC

Vertical Integration and Mining Concentration

Economics of Cybercrimes and Forensic Finance

Fee mechanisms and Financial Inclusion

Decentralized Mining in Centralized Pools (Cong, He, and Li, 2018)



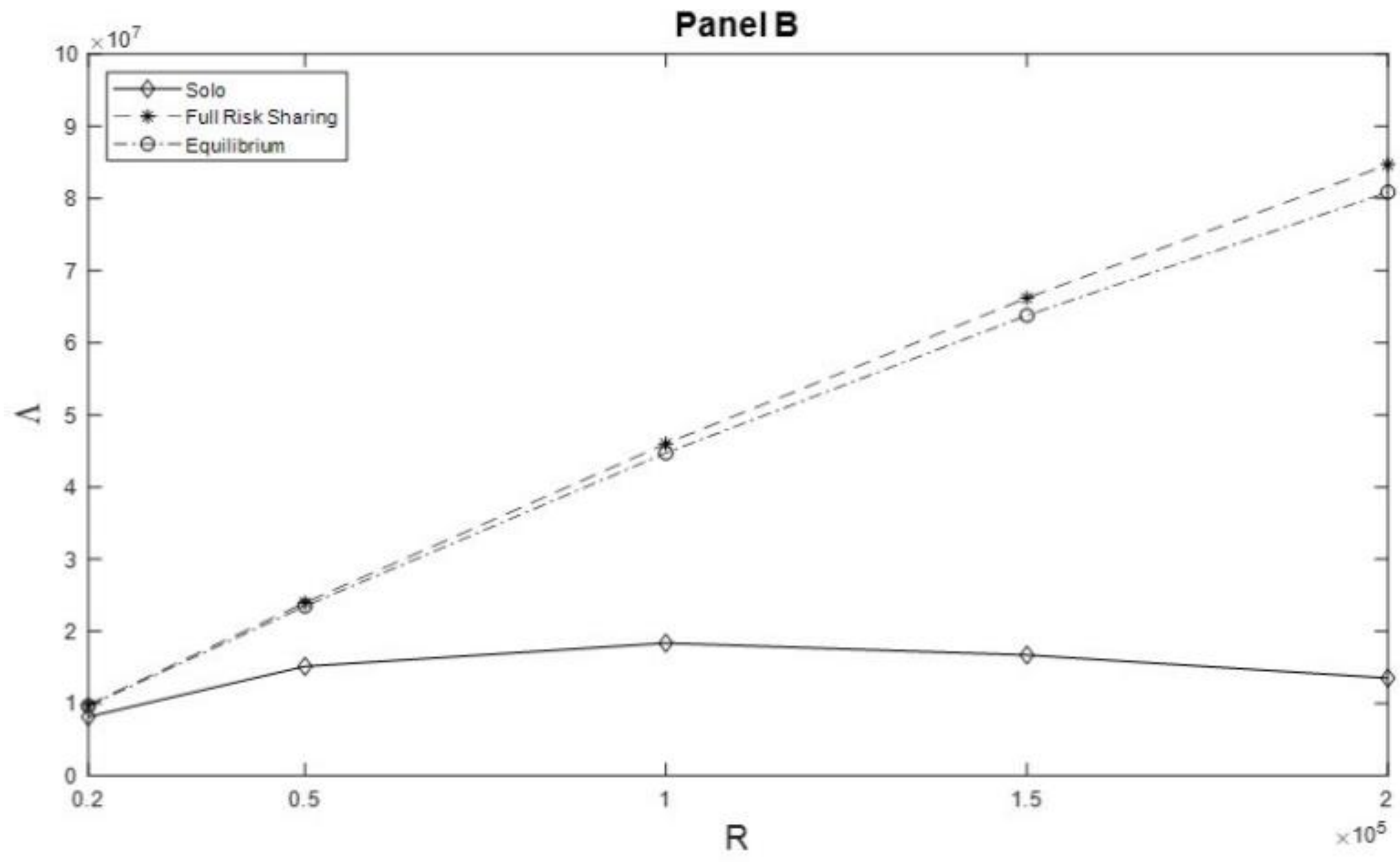
1. Pool dominance coincides with explosive growth in hash power.
2. Pools grow but no long-term over-concentration.

Industrial Organization and Environmental Impact

- Risk-aversion → pooling: significant risk-sharing benefits.

1. Rise of pools not accompanied by over-concentration.
   - Diversification as a counter-centralization force.
   - IO force: larger pools charge higher fees and grow slower.
2. Financial innovation that potentially reduces welfare.
   - Risk-sharing drastically aggravates mining arms race and multiplies egregious energy use.

Mining Arms Race and Energy Consumption



Economics of Crypto-Related Crimes & Forensic Finance: Incentives Matter

Exchange Manipulation: "Crypto Wash Trading" (Cong, Li, Tang, & Yang, 2019).

Trader Manipulation: "Tax-Loss Harvesting with Cryptocurrencies" (Cong, Landsman, Maydew, & Rabetti, 2021).

Cybercrimes: "An Anatomy of Crypto-Enabled Cybercrimes" (Cong, Harvey, Rabetti, & Wu, 2022)

"Blockchain Forensics and Crypto-Related Cybercrimes" (Cong, Grauer, Rabetti, & Updegrave)

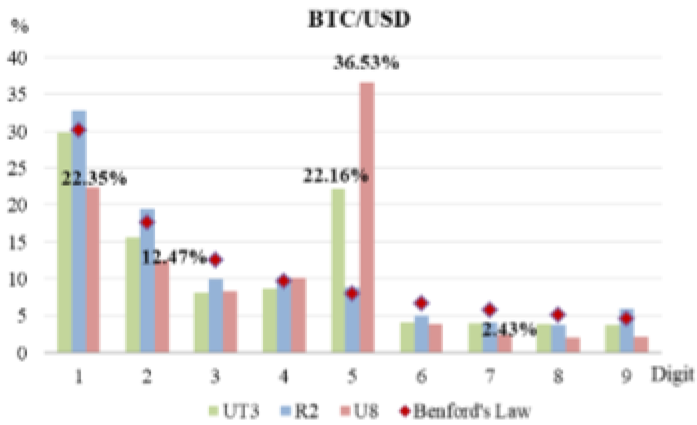
Crypto Wash Trading

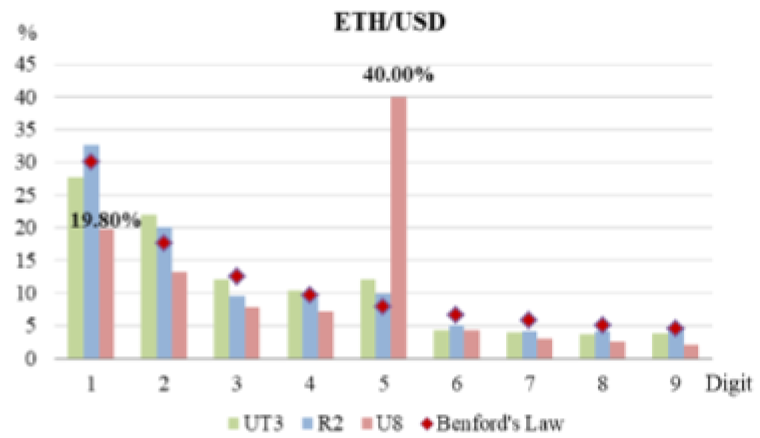
Traders fabricating trades and acting as the transaction counterparty on both sides:

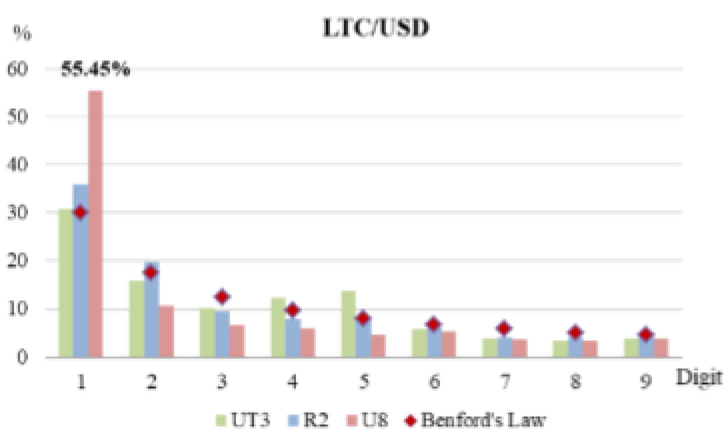
Data

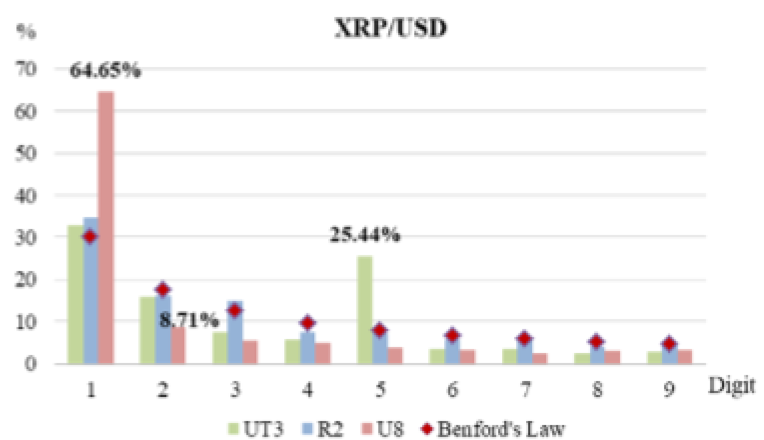
- Trading history from TokenInsight
- Exchange info, transaction ID, timestamp, price, amount traded, trade pair symbol.
- July 9, 2019 to Nov 3, 2019; focus on BTC, ETH, XRP, LTC; 448,475,535 observations.
- Exchange-related data from official websites, tracking platforms.
- Ranking data from SimilarWeb, Alexa, CoinMarketCap
- 3 regulated and 26 unregulated based on NYSDFS licensing.

Distribution of First Significant Digits



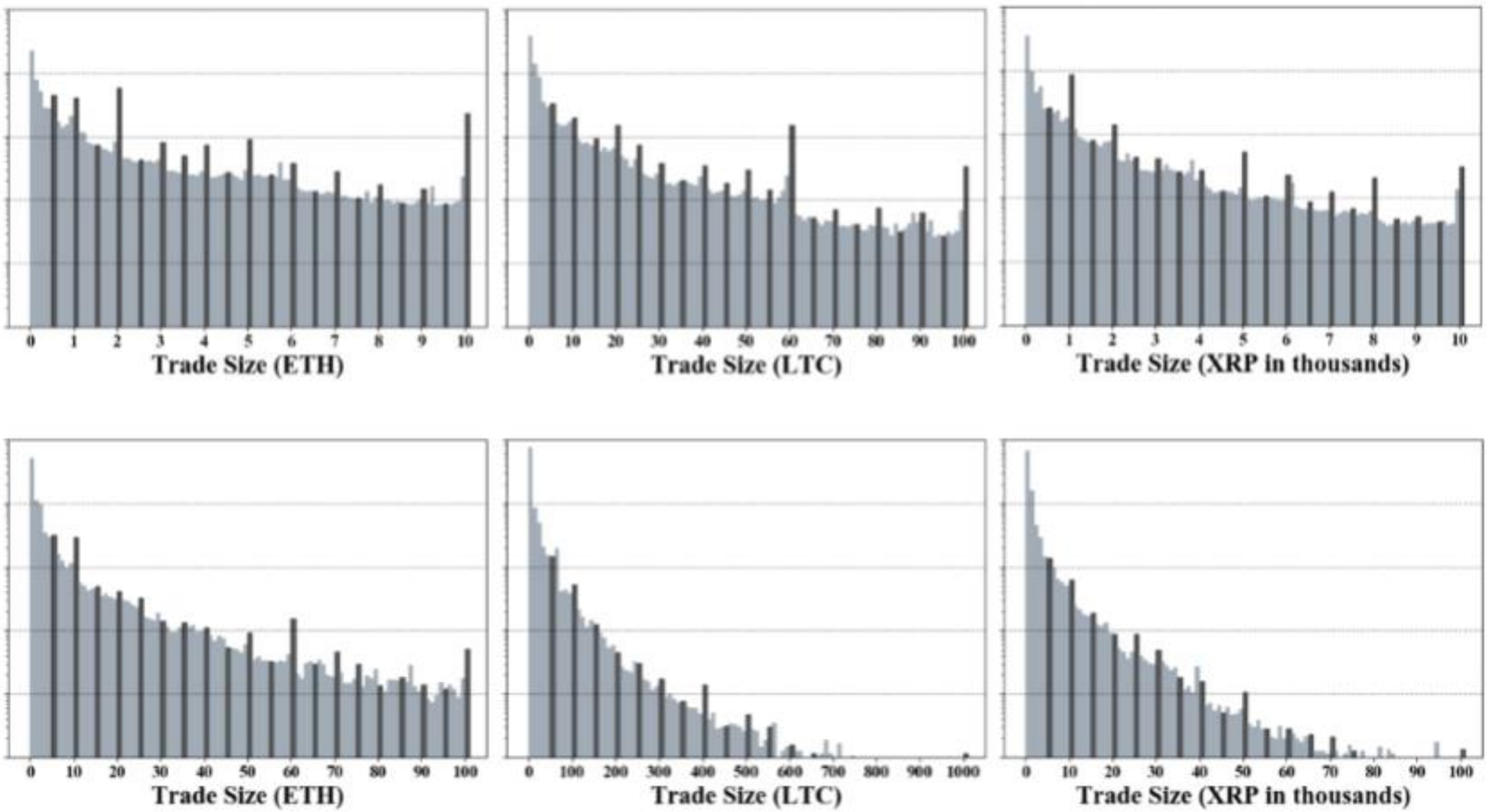






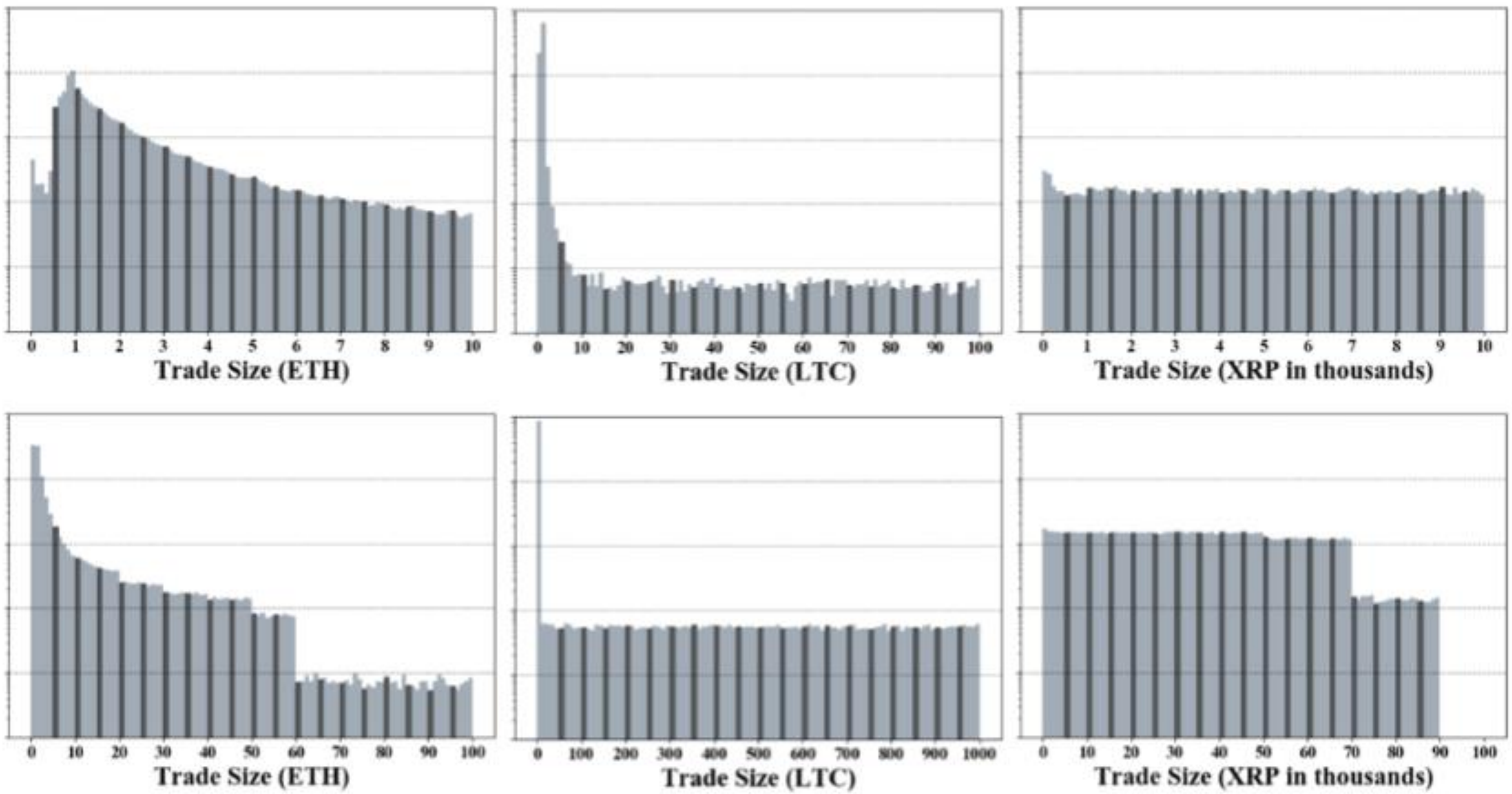
Rounding & Clustering

Regulated exchanges: R2



Rounding & Clustering

Unregulated tier-2 exchanges: U14



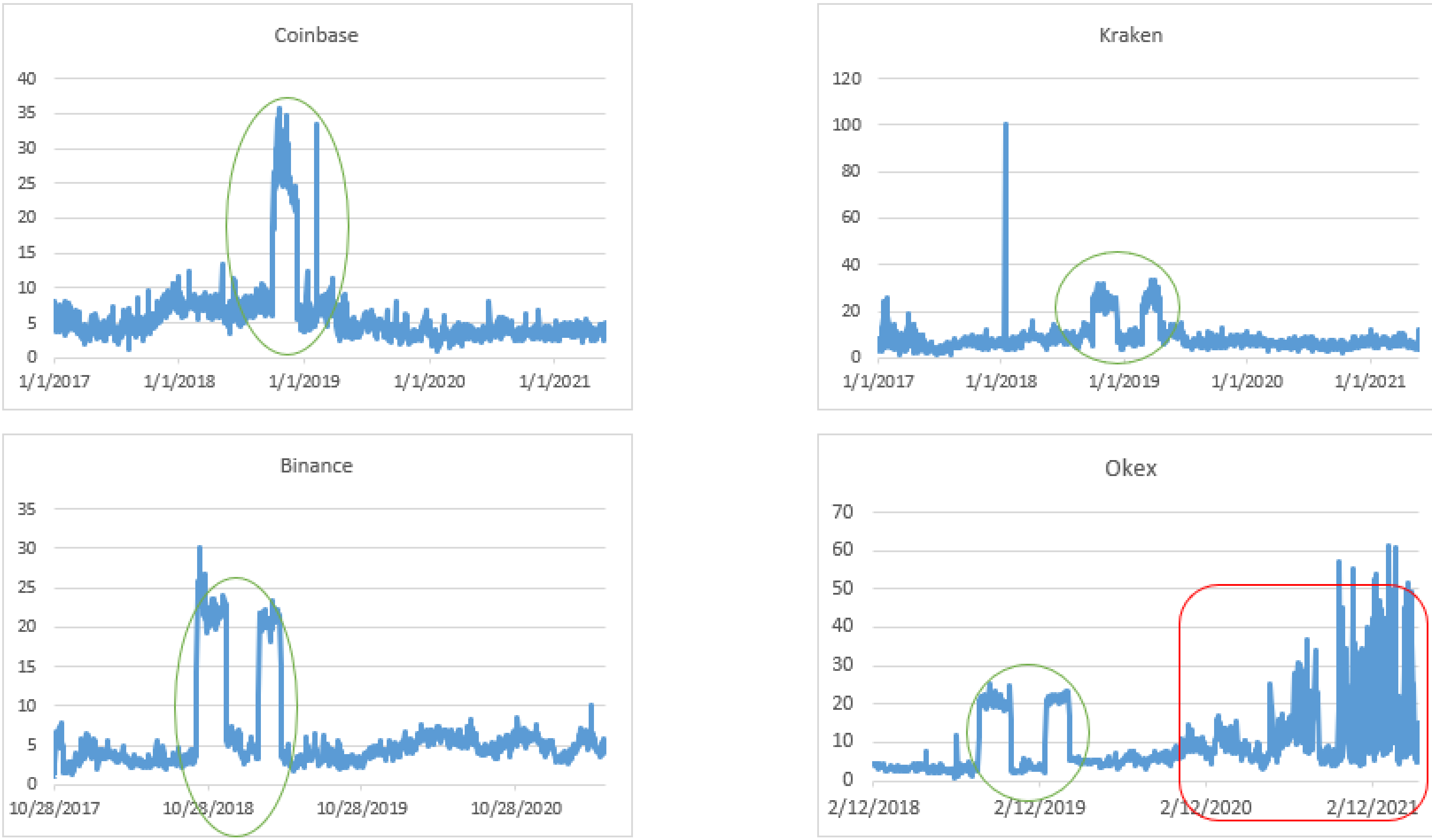
Quantifying Wash Trading

Round to unrounded trades ratio and regulated/traditional exchanges as benchmark.

	Wash Volume Percentage	
	Average	Standard Deviation
Unregulated exchanges	69.72%	29.71%
Unregulated Tier-1 exchanges	52.52%	29.41%
Unregulated Tier-2 exchanges	80.48%	25.13%

Exchange Code	Wash Volume Percentage
Panel A Unregulated Tier-1 Exchanges	
UT1	51.76%
UT2	51.73%
UT3	1.12%
UT4	92.60%
UT5	44.87%
UT6	66.3%
UT7	18.95%
UT8	66.12%
UT9	37.49%
UT10	94.31%
Panel B Unregulated Tier-2 Exchanges	
U1	99.99%
U2	98.30%
U3	72.72%
U4	95.50%
U5	89.71%
U6	98.13%
U7	77.20%
U8	77.09%
U9	81.12%
U10	98.45%
U11	21.48%
U12	98.08%
U13	65.42%
U14	96.78%
U15	94.36%
U16	23.27%

Tax-Loss Harvesting Evidence: BTC ↓



Exogenous Wash Trade ≈ Tax-Loss Harvesting

Endogenous Wash Trade ≈ Volume Inflation

Estimated Tax-Loss Harvesting Revenue

Panel A - Tax-Loss Harvesting Estimates

Volume-Weighted		Equally-Weighted	
Harvest	**Regular**	**Harvest**	**Regular**
21.56	4.25	19.34	5.24

Panel B - Estimated Loss to the Government

Exchanges	Pair	Volume-Weighted		Equally-Weighted	
		Wash	**Revenue**	**Wash**	**Revenue**
All	BTC-USDT	25.52	5.36	20.80	4.37
Regulated	BTC-USDT	19.37	4.07	15.78	3.31
All	ALL	77.14	16.20	62.85	13.20
Regulated	ALL	58.53	12.29	47.69	10.02

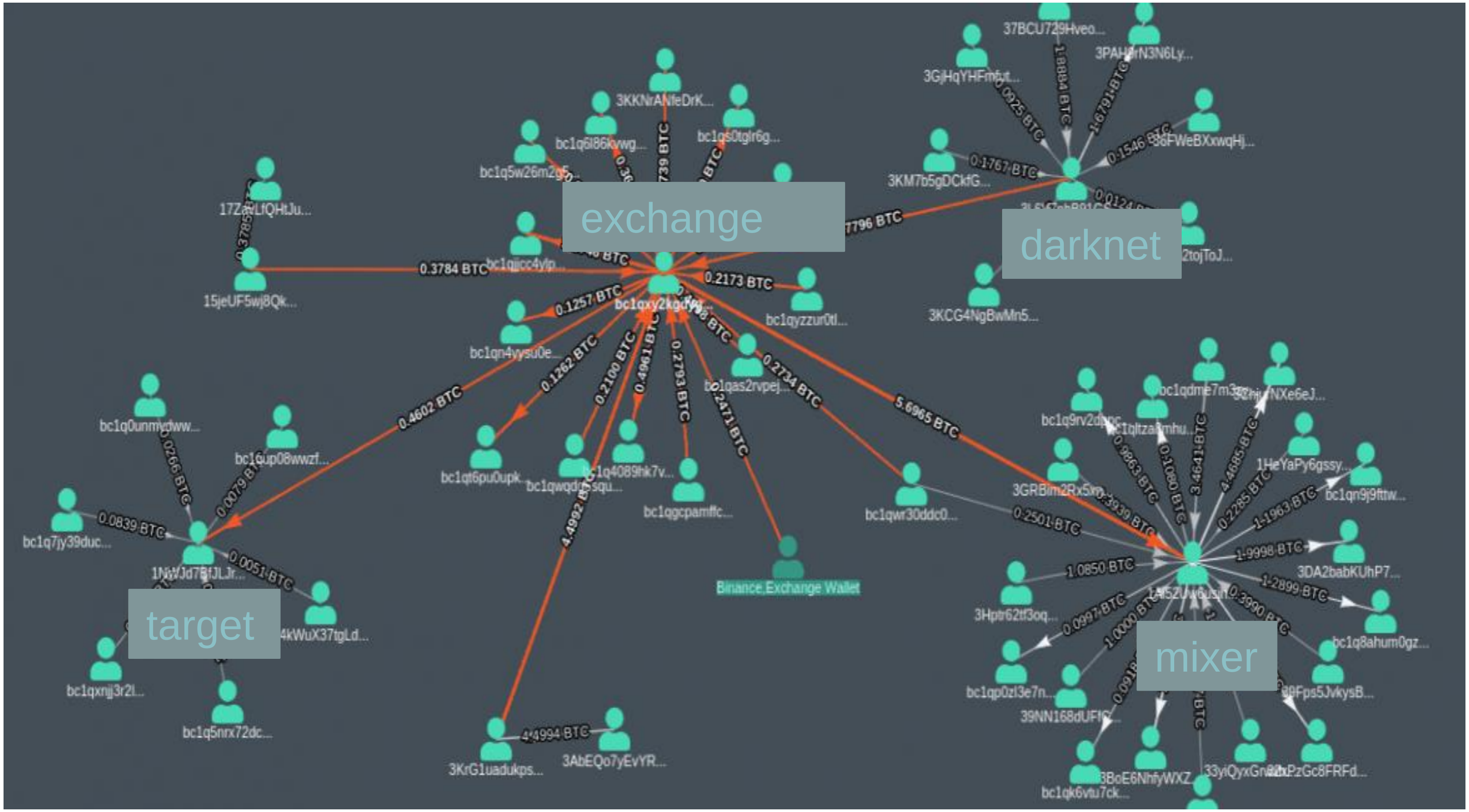
Table 7. Estimating the Size of Revenue Loss from Tax-Loss Harvesting. Estimating the Size of Revenue Loss from Tax-Loss Harvesting. This table reports estimates of tax revenue loss arising from tax-loss harvesting in 2018. Panel A reports volume-weighted and equally-weighted estimates of the percentage of trades that are wash trades during tax-harvesting regular periods. Panel B reports the estimated wash volume and revenue loss to the government (in billions). All variables are reported at the regulated-exchanges level. See section 5.2 for computational details.

In 2018, federal capital gains tax revenue was **$158.4 billion**
-> Potential: **Increase** of about **5-10% tax revenue [only BTC].**

Crypto-Enabled Cybercrimes

- Diverse set of public, proprietary, and hand-collected data (dark web conversations in Russian).
- An anatomy of crypto-enabled cybercrimes and relevant economic issues.
- A few organized ransomware gangs dominate with sophisticated corporate-like operations with physical offices, franchising, and affiliation programs.
- Techniques have also become more aggressive over time, entailing multiple layers of extortion and reputation management.
- Blanket restrictions on cryptocurrency usage may prove ineffective in tackling crypto-enabled cybercrime and hinder innovations.

Mapped Addresses



Ransomware-As-A-Service (RaaS)

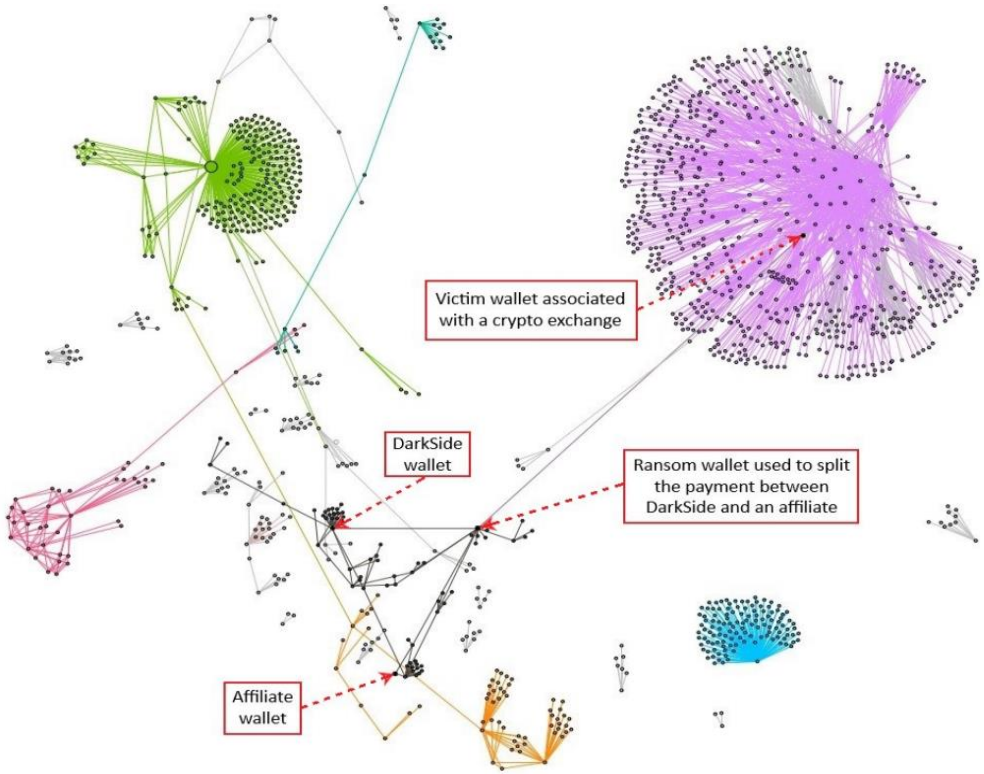


Figure 5: A Ransomware Gang's (DarkSide) Network Analysis

Ransom	Split (%)
<500k	25%
500k to 2m	20%
2m to 5m	15%
>5m	10%
fixed	20%

Table 3: DarkSide revenue splits
(Source: Compiled from dark web forums)

Pricing

- Attacker gives high priority to the company's financials. They will know how much cash is available.

- Attacker will look for cybersecurity insurance and sometimes make the case that paying the attacker is "free" given the insurance policy

- Pricing is often a function of the number of computers connected to the network

Total received in BTC payments and the problem of underreporting

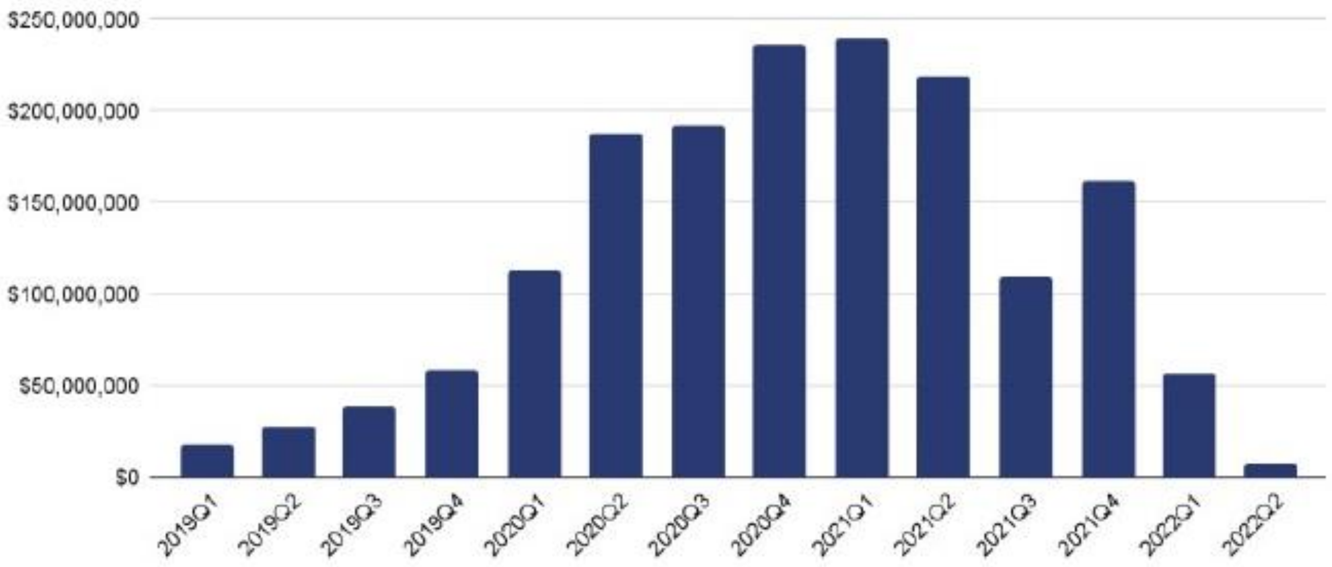


Fig. 1.1 Total quartely value received by ransomware attackers, Q1 2019 – Q2 2022.

U.S. DEPARTMENT OF THE TREASURY

ABOUT TREASURY | POLICY ISSUES | DATA | SERVICES | NEWS

PRESS RELEASES

Treasury Sanctions Evil Corp, the Russia-Based Cybercriminal Group Behind Dridex Malware

December 5, 2019

Washington – Today the U.S. Treasury Department's Office of Foreign Assets Control (OFAC) took action against Evil Corp, the Russia-based cybercriminal organization responsible for the development and distribution of the Dridex malware. Evil Corp has used the Dridex malware to infect computers and harvest login credentials from hundreds of banks and financial institutions in over 40 countries, causing more than $100 million in theft. This malicious software has caused millions of dollars of damage to U.S. and international financial institutions and their customers. Concurrent with OFAC's

Rebranding Strategy

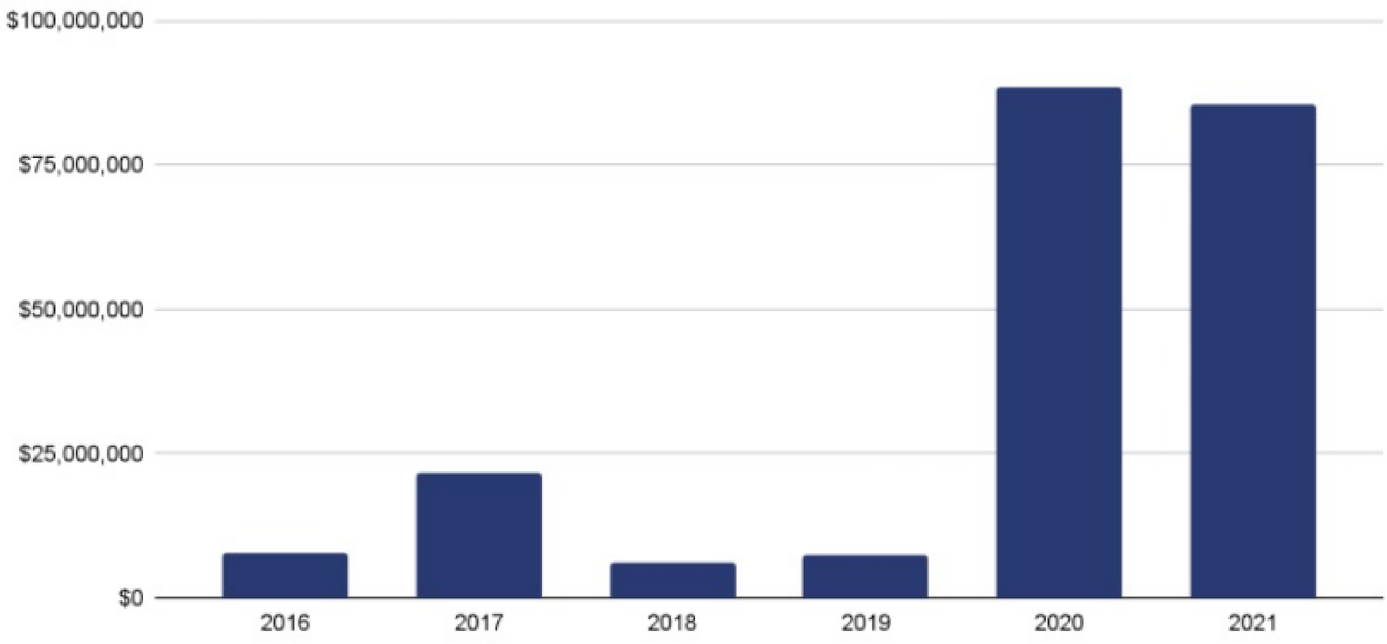


Fig. 1.8 Ransomware payment rule to strains associated with Evil Corp, 2016-2021.

Inclusion and Democratization Through Web3 and DeFi? Initial Evidence from the Ethereum Ecosystem

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- Description of Ethereum Ecosystem using Big Data
  - General Trends/Stylized Patterns in the Network
  - Data Sharing and Visualization
  - Distribution of Mining Income
  - Distribution of Token Ownership
  - Distribution of Transactions

Data

- Ethereum blockchain
  - Aug 15-Feb 22, 14 million blocks, 1.7+4.6 billion transactions, etc.; big datacomputing clusters.
  - Value of tokens transferred, the time when transaction bundled into the block, gas used, gas price and gas limit (set by the initiator), status of transaction.

- Block information (e.g., address of block verifier, mining pool, block number, etc.)

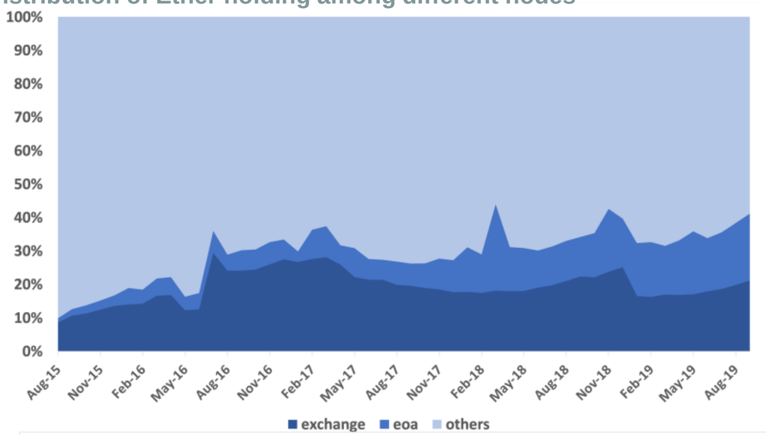
- Addresses associated with DeFi/ DApps
  - DApp Radar, DApponline, and Etherscan
  - Classified into 9 groups: exchanges, DeFi, gambling, games, collectibles, etc.
  - 166 DeFi protocols, 2,820 DApps.

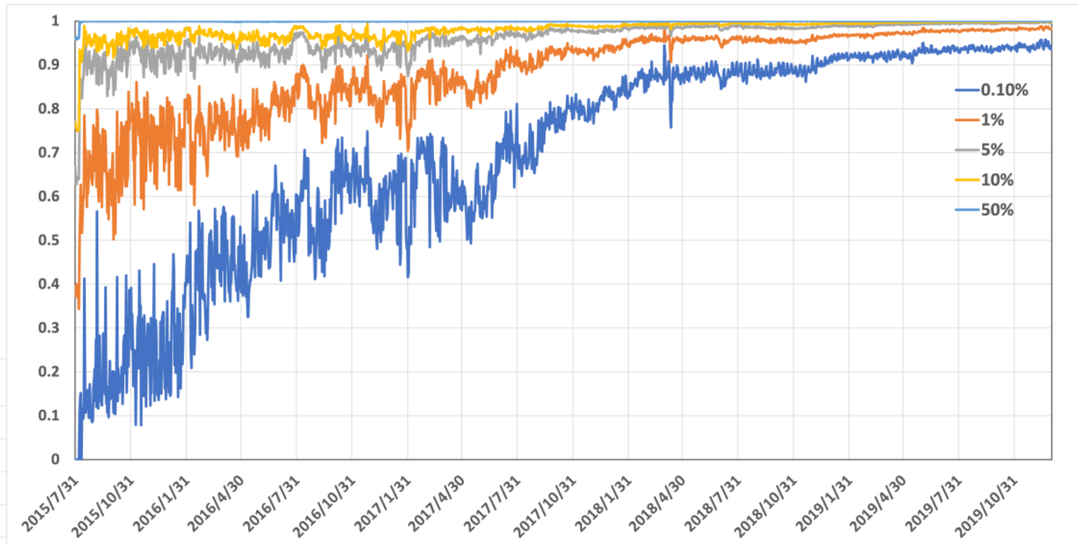
- ETH Gas Station, CoinMarketCap, Google Trends
  - Recommended gas prices, etc.
  - Token prices, popularity metrics, etc.

Description of Ethereum Ecosystem—*Distribution of On-Chain Token Ownership*

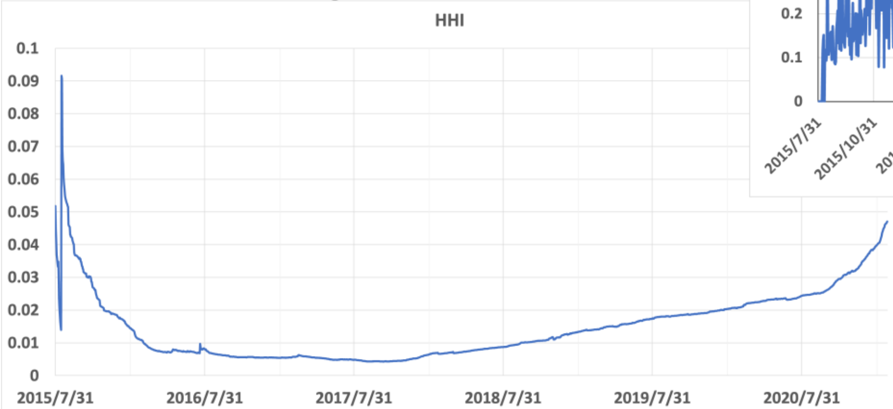
- Token ownership is heavily concentrated at a few nodes of institutions and individual users.

Distribution of Ether holding among different nodes





The concentration of EOA addresses (without exchanges)



HHI for EOA address (without exchanges)

Transaction Fees and Undemocratic and Exclusive Usage—*Percentage Transaction Fee*

$$PercentageTransactionFee = \frac{GasPrice*GasUsed}{Value} \times 100\%$$

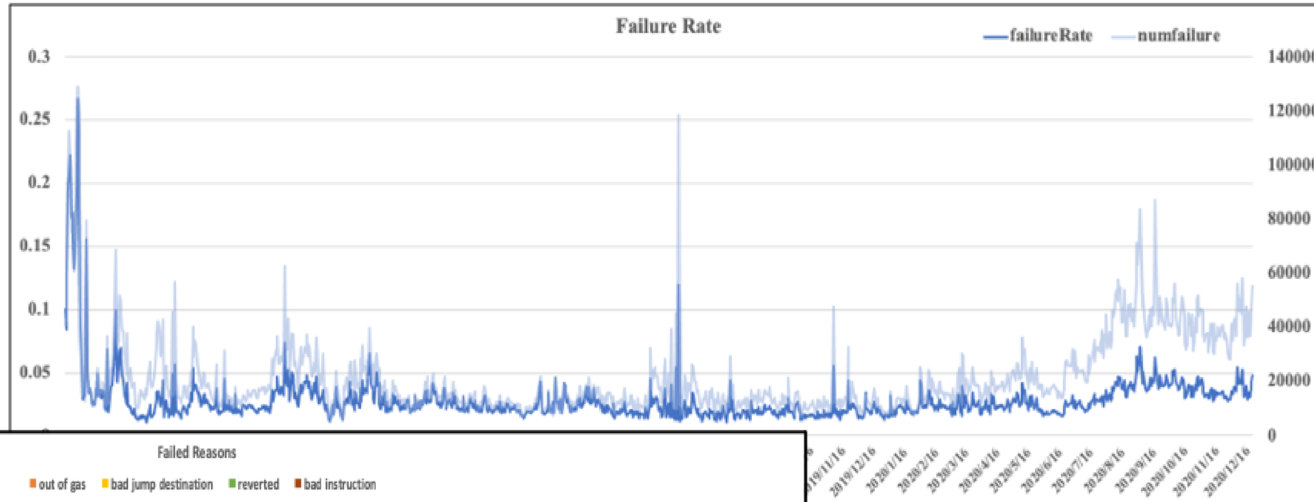
- The percentage transaction fee for small amount transactions using DeFi is too high and volatile for inclusive finance.

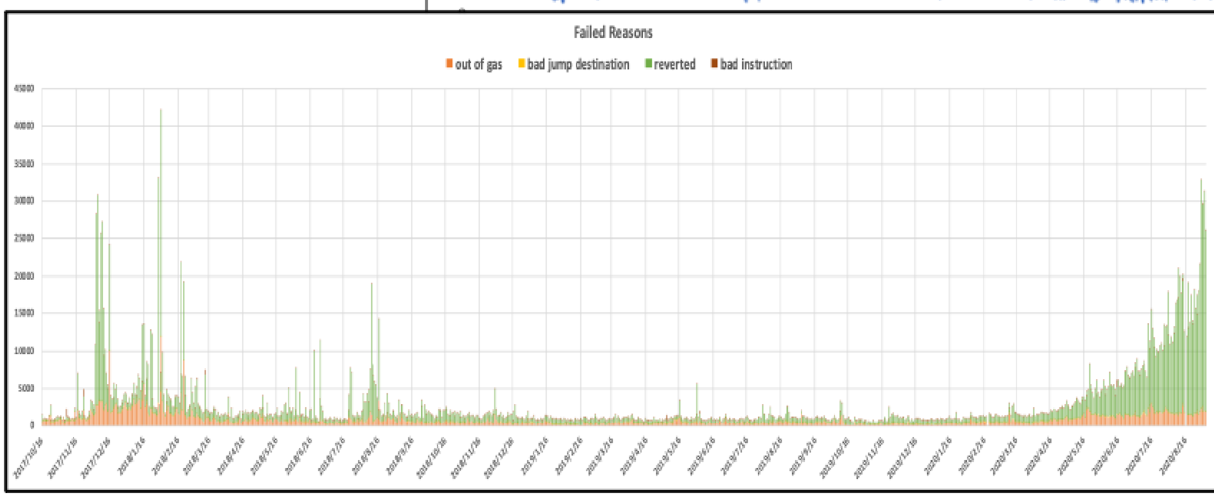
Table 2—: Percentage Transaction Fee (continued)

(c) Ether and Tokens on Ethereum

	Percentage transaction fee of transactions with Ether						Percentage transaction fee of transactions with tokens					
value ($)	mean (%)	median (%)	25% (%)	75% (%)	standard deviation	count	mean (%)	median (%)	25% (%)	75% (%)	standard deviation	count
0-0.01	2.05*1016	1549.53	121.75	6.4*104	3.38*1015	1,802,606	6.56*1031	15757.34	2108.71	8.68*105	3.16*1032	1,020,664
0.01-0.1	150.45	37.82	21.00	70.00	39.14	10,828,833	863.32	239.92	87.87	384.17	37.96	3,096,112
0.1-1	31.54	16.80	7.19	32.38	6.49	33,110,009	96.47	29.41	9.86	76.24	8.43	5,838,297
0-1	8.07*1014	21.00	10.11	44.10	6.73*1014	45,741,448	6.68*1030	69.84	18.11	287.03	1.01*1032	9,955,073
1-10	7.81	2.11	0.42	8.75	7.60	53,548,484	17.88	4.15	1.42	11.45	2.54	10,608,388
10-100	1.24	0.15	0.04	0.64	2.01	109,237,500	2.53	0.58	0.21	1.67	0.19	23,077,554
100-1000	0.18	0.04	0.01	0.13	2.19	78,726,642	0.36	0.09	0.03	0.26	0.01	43,924,023
1000-	0.02	0.00	0.00	0.01	0.03	52,759,079	0.05	0.01	0.00	0.03	0.00	38,500,612
1-	1.93	0.08	0.02	0.53	3.65	294,271,705	2.29	0.08	0.01	0.51	0.78	116,110,577
General	1.09*1014	0.13	0.02	1.84	2.47*1014	340,013,153	5.29*1029	0.11	0.02	0.91	2.84*1031	126,065,650

Transaction Failures

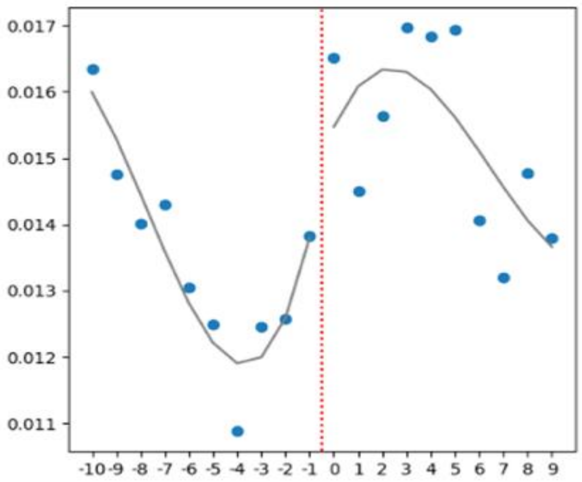




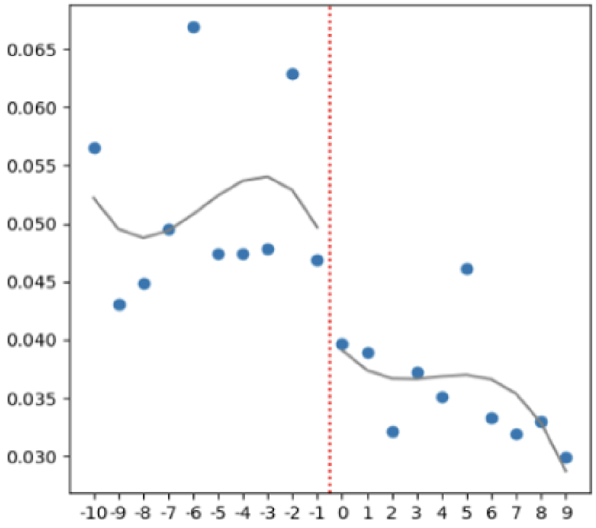
- **Major Reasons for Failure**
  a) “Out of gas”(30%)
  b) “Reverted” (73%)
  c) “Bad Instruction”
  d) “Bad jump destination

The EIP-1559 Fee Mechanism—*Background and Identification Strategy*

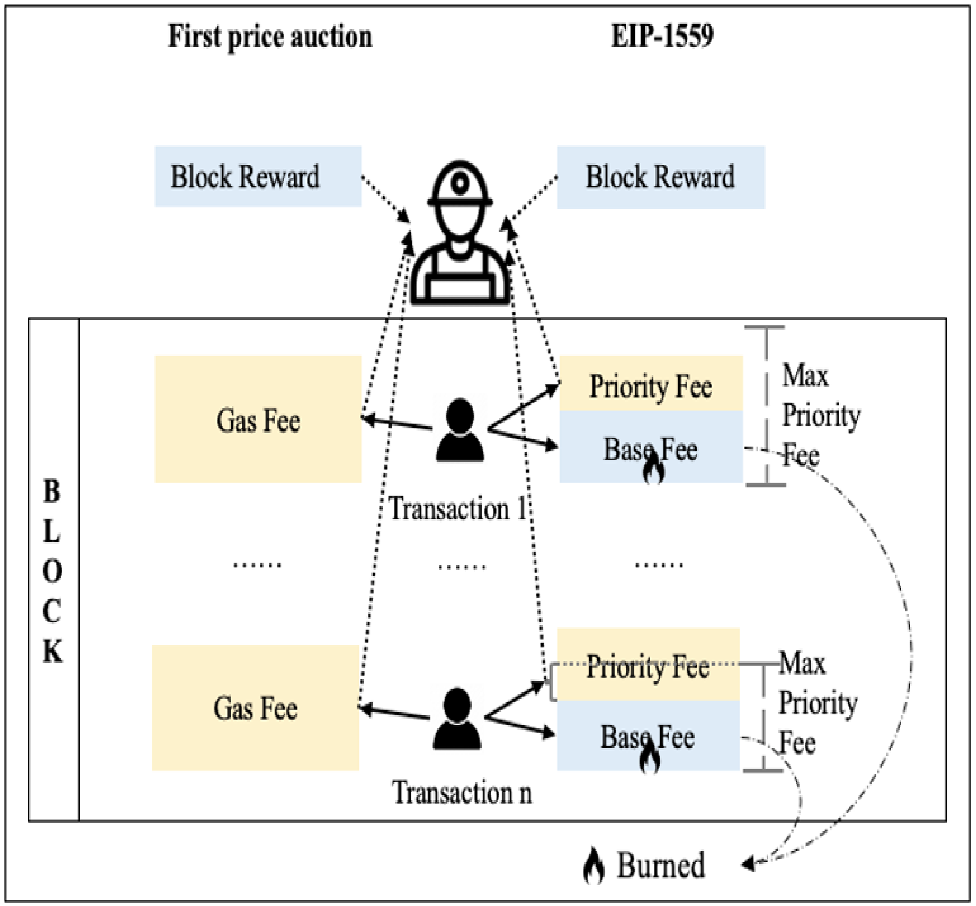
- **EIP-1559**
  - ✓ Burnt base fee
  - ✓ Max priority fee and priority fee (tips)
  - ✓ Block size



(b) The Log of Weekly Transaction Volume



(a) The Log of Weekly Mining Rewards



EIP-1559 Fee Mechanism

2. Digital Nations and The Tokenomics of Staking

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Viewing Web3 Networks as Digital Nations

Monetary economics meets asset pricing and corporate finance.

International economics, financial integration, risk-sharing, forex, etc.

Protocol designs, token issuance policies, incentive programs, connection to other networks, etc., are not isolated decisions.

Asset Pricing, Corporate Finance, and Optimal Monetary Policy

Tokenomics: Dynamic Adoption and Valuation

Token-Based Platform Finance

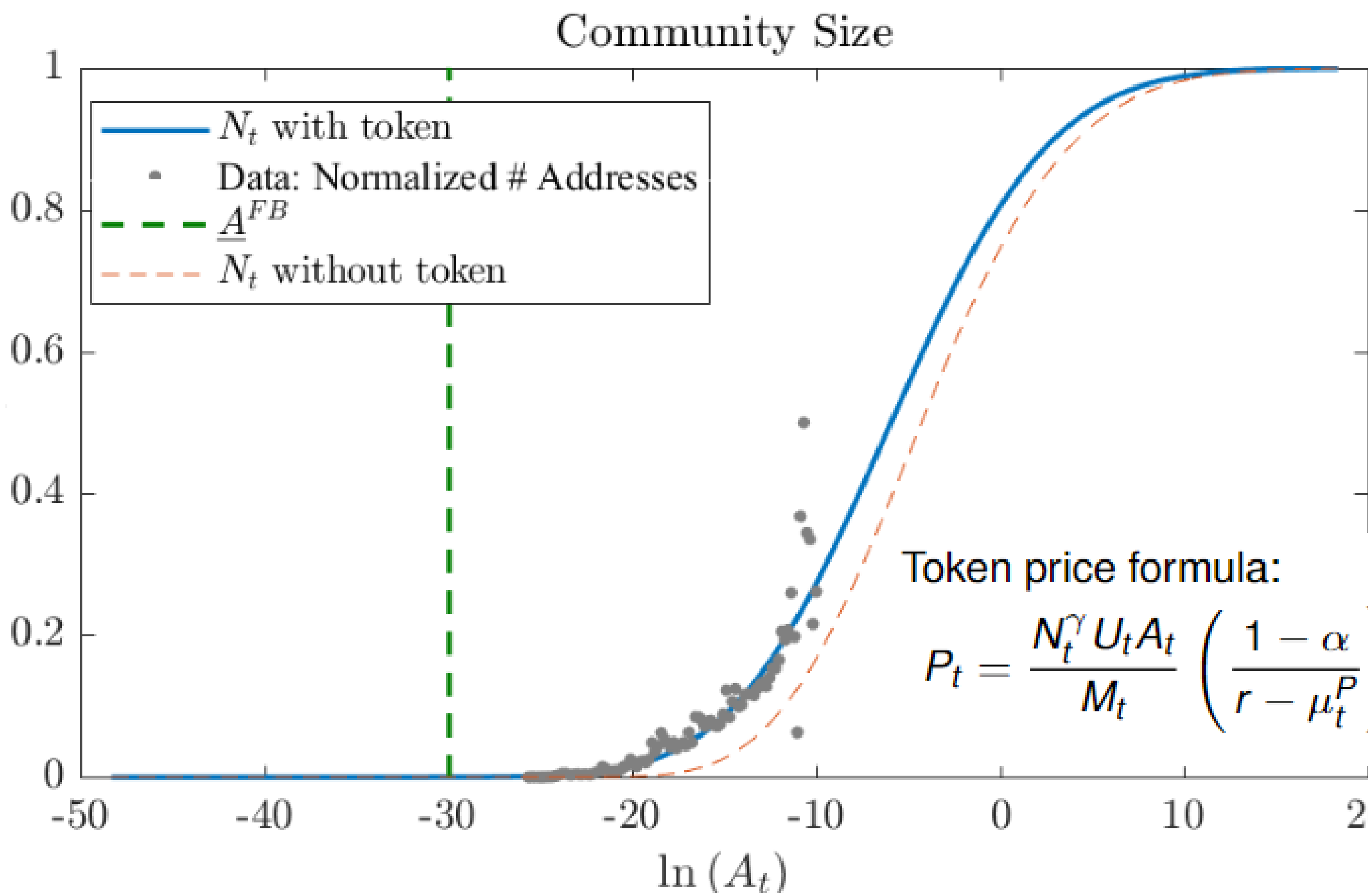
Lin William Cong, Ye Li, & Neng Wang

Tokenomics Landscape

Tokenomics: Dynamic Adoption and Valuation (Cong, Li, Wang, 2018)

- What tokens are?
  - General payment tokens, platform tokens, product tokens, security tokens.
  - Hybrid between money and investable asset.
  - CBDC, DCEP, monetary policy, etc.

- Token valuation and crypto vol:
  1. Pillars of token value:
     1.1 Means of payment to realize unique trade surplus on the platform;
     1.2 Token burning/buyback policy by insiders and designers.
  2. Sources of volatility:
     2.1 Fundamental technology/productivity/policy shocks.
     2.2 Speculation and behavioral factors.
     2.3 Endogenous adoption.
     2.4 Countercyclical/stabilizing token supply/allocation policy.
  3. Fundamental-based token pricing formula, possibly with endogenous token supply policy.



Token price formula:

$$P_t = \frac{N_t^{\gamma} U_t A_t}{M_t} \left(\frac{1-\alpha}{r-\mu_t^P} \right)^{\frac{1}{\alpha}}$$

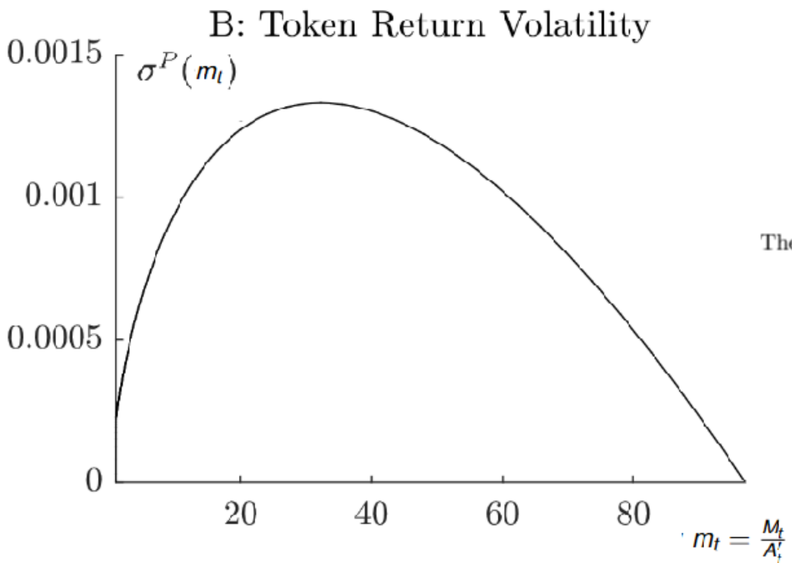
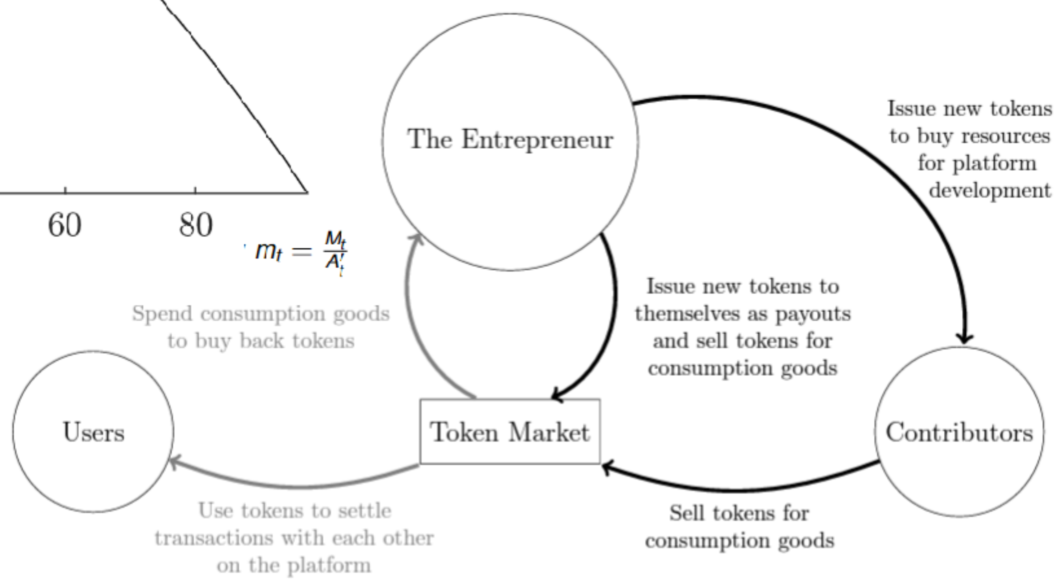


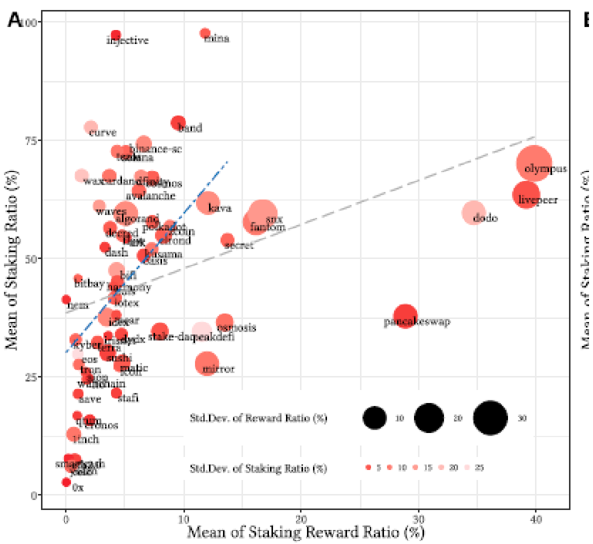
Figure 1: **Token Ecosystem**.

The black and gray arrows represent token supply and demand, respectively.



The Tokenomics of Staking (Cong, He, and Tang, 2022)

- Daily observations from stakingrewards.com;
- 48 pan-PoS + 29 DeFi, July 2018-Nov 2022.



Staking Ratio Predicting Token Price Returns

Dependent:	$r_{price_{i,t}}$								
	Daily			7-Day			30-Day		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$StakingRatio_{i,t-1}$	0.009**	0.027***	0.022**	0.066***	0.172**	0.138*	0.208*	0.347*	0.372**
	(0.004)	(0.007)	(0.008)	(0.023)	(0.068)	(0.071)	(0.121)	(0.197)	(0.139)
MKT_t	0.968***	1.029***		0.844***	0.685*		2.445*	2.201	
	(0.031)	(0.043)		(0.264)	(0.352)		(1.435)	(1.496)	
$\hat{\beta}_{i,t}$			-0.002			-0.037			-0.132
			(0.002)			(0.031)			(0.104)
$\log(Cap)_{i,t-1}$	-0.002***	-0.002**	-0.005***	-0.027***	-0.031***	-0.038***	-0.120***	-0.121***	-0.113***
	(0.000)	(0.001)	(0.001)	(0.006)	(0.009)	(0.009)	(0.034)	(0.043)	(0.021)
$r_{price_{i,t-1}}$		0.021	0.035		0.008	-0.075*		0.127*	-0.076
		(0.050)	(0.060)		(0.040)	(0.042)		(0.062)	(0.074)
$\Delta Network_{i,t-1}$		0.167***	0.224***		0.195	0.366		0.992	0.996
		(0.058)	(0.068)		(0.207)	(0.259)		(1.393)	(1.216)
$a_{i,t-1}$		0.047	0.069		0.603**	0.306		1.007	0.614
		(0.030)	(0.041)		(0.258)	(0.235)		(0.825)	(0.946)
$Whale_{i,t-1}$		-0.010	-0.013		-0.006	-0.103		-0.179	-0.253
		(0.009)	(0.009)		(0.086)	(0.073)		(0.341)	(0.201)
$NotLaunched_{i,t}$		-0.003	0.011***		0.075***	0.108**		0.119	0.159
		(0.002)	(0.004)		(0.024)	(0.040)		(0.154)	(0.126)
$Y^0_{i,t}$		0.002	0.007**		0.021	0.056**		-0.073	0.114
		(0.002)	(0.003)		(0.021)	(0.020)		(0.084)	(0.107)
Token FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE			Yes			Yes			Yes
Observations	41,544	10,887	9,991	5,872	1,530	1,434	1,347	334	322
R^2	0.267	0.346	0.478	0.043	0.054	0.507	0.120	0.207	0.640

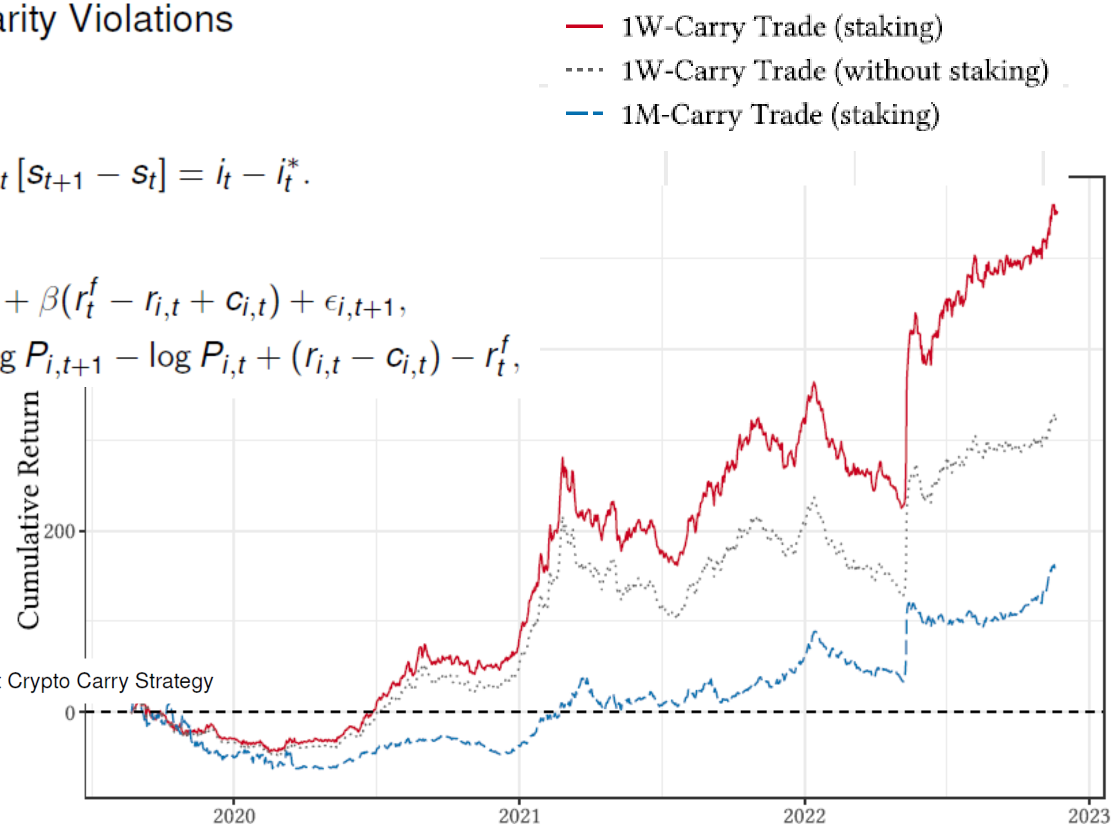
Uncovered Interest Rate Parity Violations

$$\mathbb{E}_t[s_{t+1} - s_t] = i_t - i_t^*.$$

Fama (1984):

$$\lambda_{i,t+1} = \alpha + \beta(r_t^f - r_{i,t} + c_{i,t}) + \epsilon_{i,t+1},$$

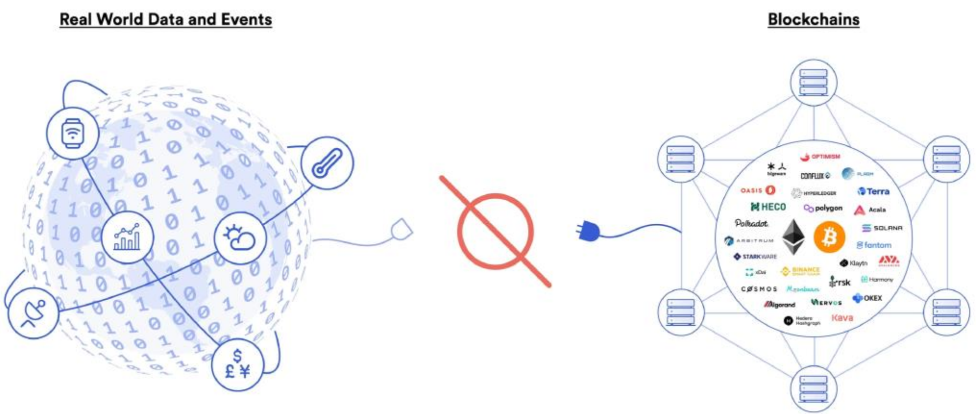
where $\lambda_{i,t} = \log P_{i,t+1} - \log P_{i,t} + (r_{i,t} - c_{i,t}) - r_t^f,$

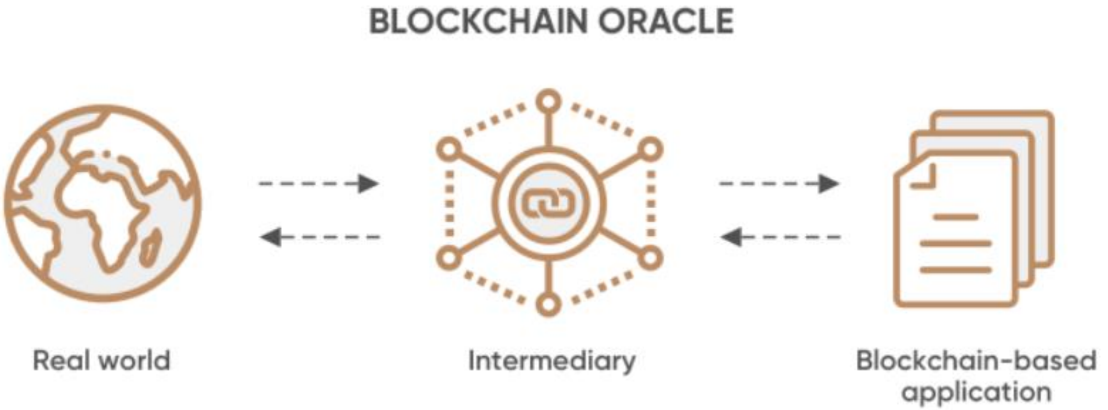


Cumulative Returns of a Long-Short Crypto Carry Strategy

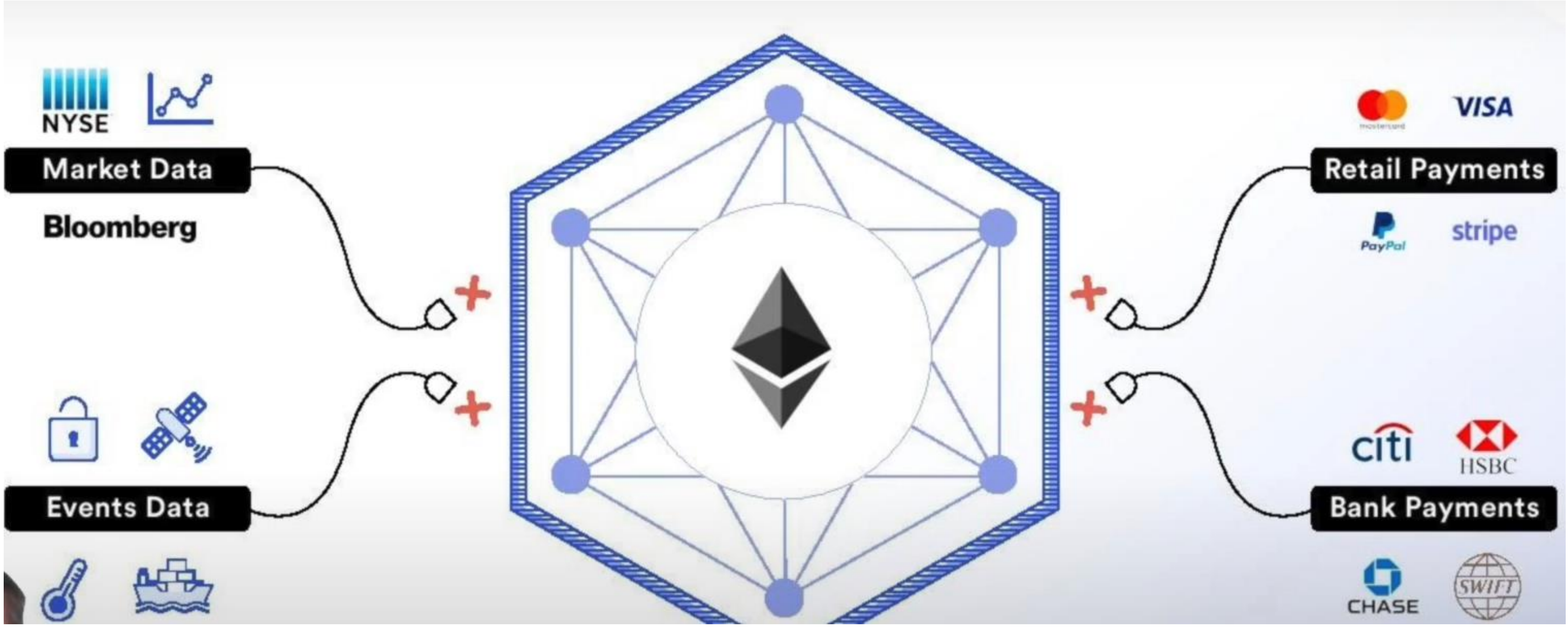
3. Introduction to Oracle Networks

Oracle: Bridge between blockchains/smartcontracts and with real world; a device or entity that connects a deterministic blockchain with off-chain data





The Oracle Problem
to centralized or decentralize?

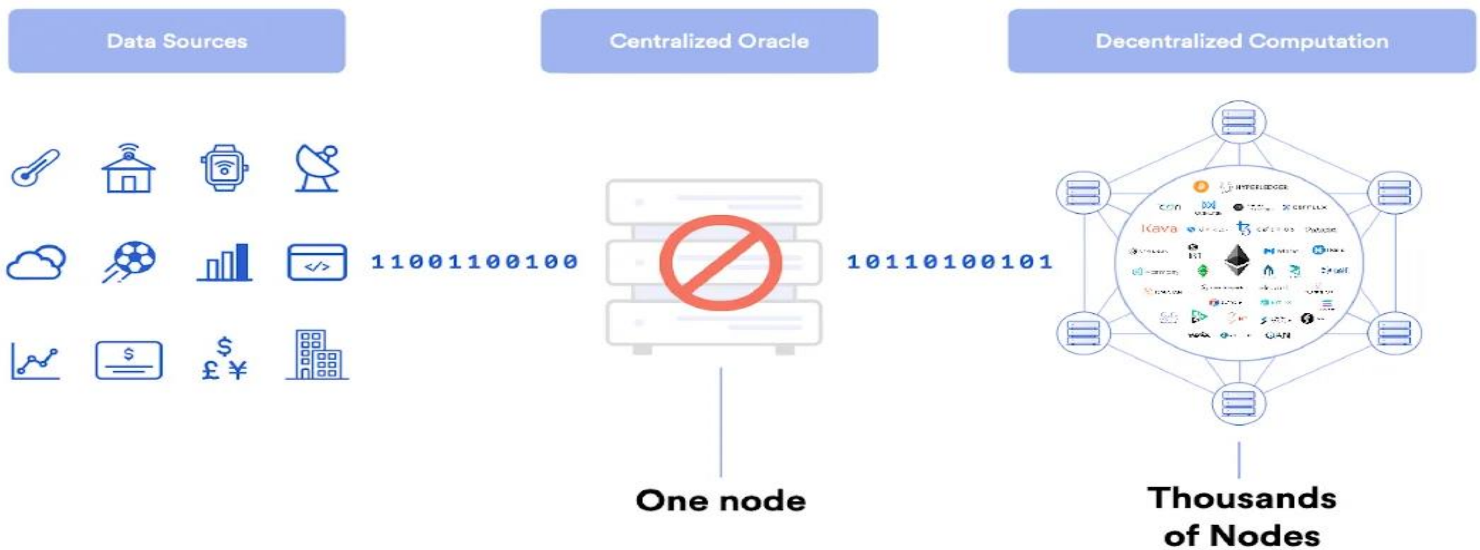


Financial and Information Integration Through Oracles

– Decentralized oracle networks (DON) administrators provide a potential solution by authenticating data from multiple oracles and feeding their combined output.

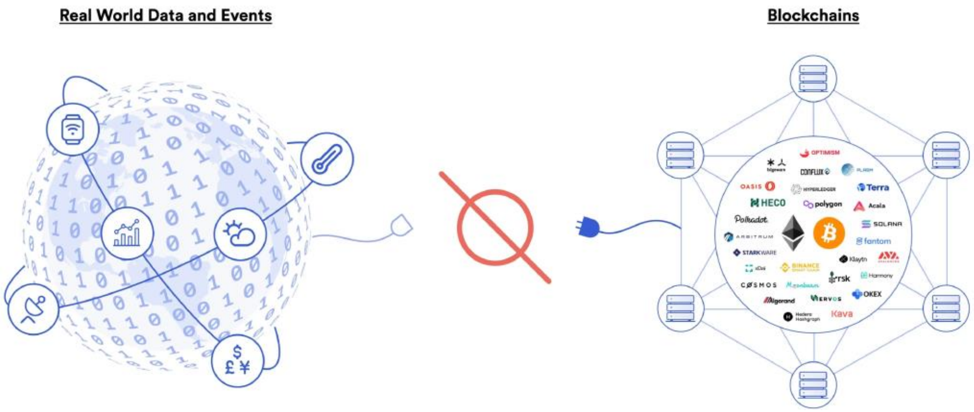
– To ensure data accuracy and reliability, DONs may use trusted hardware, consensus algorithms, or reputation systems.

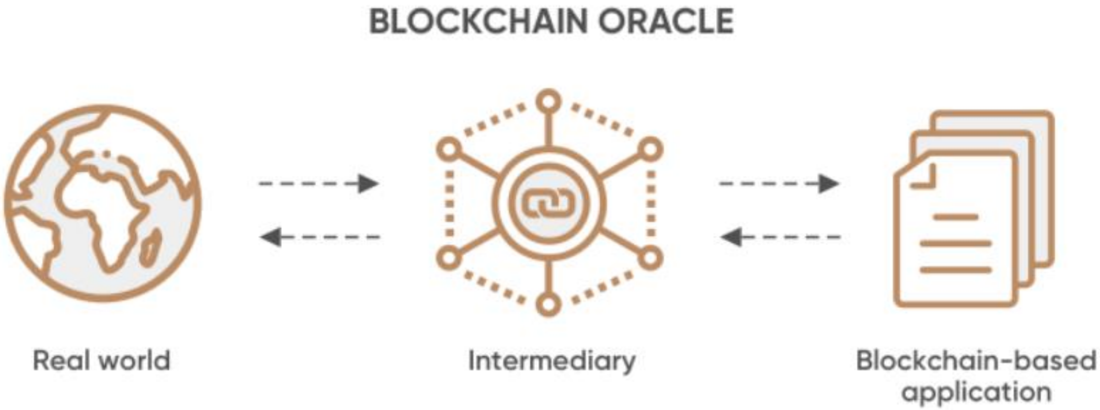
– Fully decentralized?



Financial and Information Integration Through Oracle Networks (Cong, Prasad, Rabetti, 2023)

Bridge between blockchains/smartcontracts and with real world





Integration Effects

$$TVL_i = \alpha + \beta DON + \gamma CON + \eta FDV + \iota Staking + \delta Chains + \zeta Oracles + \Theta + \Lambda + \epsilon, \quad (2)$$
$$MCap_i = \alpha + \beta DON + \gamma CON + \eta FDV + \iota Staking + \delta Chains + \zeta Oracles + \Theta + \Lambda + \epsilon, \quad (3)$$

	Panel A: Total Value Locked				Panel B: Market Capitalization			
	Day	Week	Month	Quarter	Day	Week	Month	Quarter
DON	10.84	35.12 *	74.85 ***	92.21 **	2.65	25.50 *	42.63 **	75.57 ***
	(11.53)	(20.96)	(28.64)	(38.18)	(9.14)	(15.10)	(21.37)	(28.49)
CON	5.52	-16.84	-46.10	-40.51	-6.96	34.47	34.34	81.35 *
	(19.35)	(35.24)	(50.54)	(67.86)	(16.42)	(26.81)	(38.55)	(49.35)
log(1 + FDV)	1.43 ***	2.34 **	3.08 **	5.53 ***	0.34	-0.22	1.44	3.15 **
	(0.54)	(0.98)	(1.34)	(1.78)	(0.46)	(0.76)	(1.08)	(1.46)
log(1 + Staking)	0.67	1.09	3.63 **	5.89 **	0.83	-0.02	1.07	4.87 ***
	(0.73)	(1.32)	(1.83)	(2.47)	(0.57)	(0.93)	(1.34)	(1.83)
log(1 + # Chains)	-0.92	-26.77	-42.80	-56.74	-3.76	2.55	-13.84	23.47
	(17.40)	(31.44)	(43.37)	(55.54)	(14.78)	(24.13)	(34.25)	(42.50)
log(1 + # Oracles)	5.57	13.85	29.90	29.88	-11.43	-8.09	15.56	60.25
	(15.98)	(29.55)	(41.31)	(57.09)	(13.55)	(22.61)	(32.66)	(45.31)
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Blockchain	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,373	1,349	1,273	1,047	745	739	710	579
Adj.r^2	0.08	0.08	0.12	0.16	0.18	0.19	0.19	0.27

Table 6. Post-live performance responses to oracle adoption

Interoperability Effects

Correlations tend to increase post-integration. For instance, correlation between Avalanche and Ethereum's TVL increased by one-third post-integration.

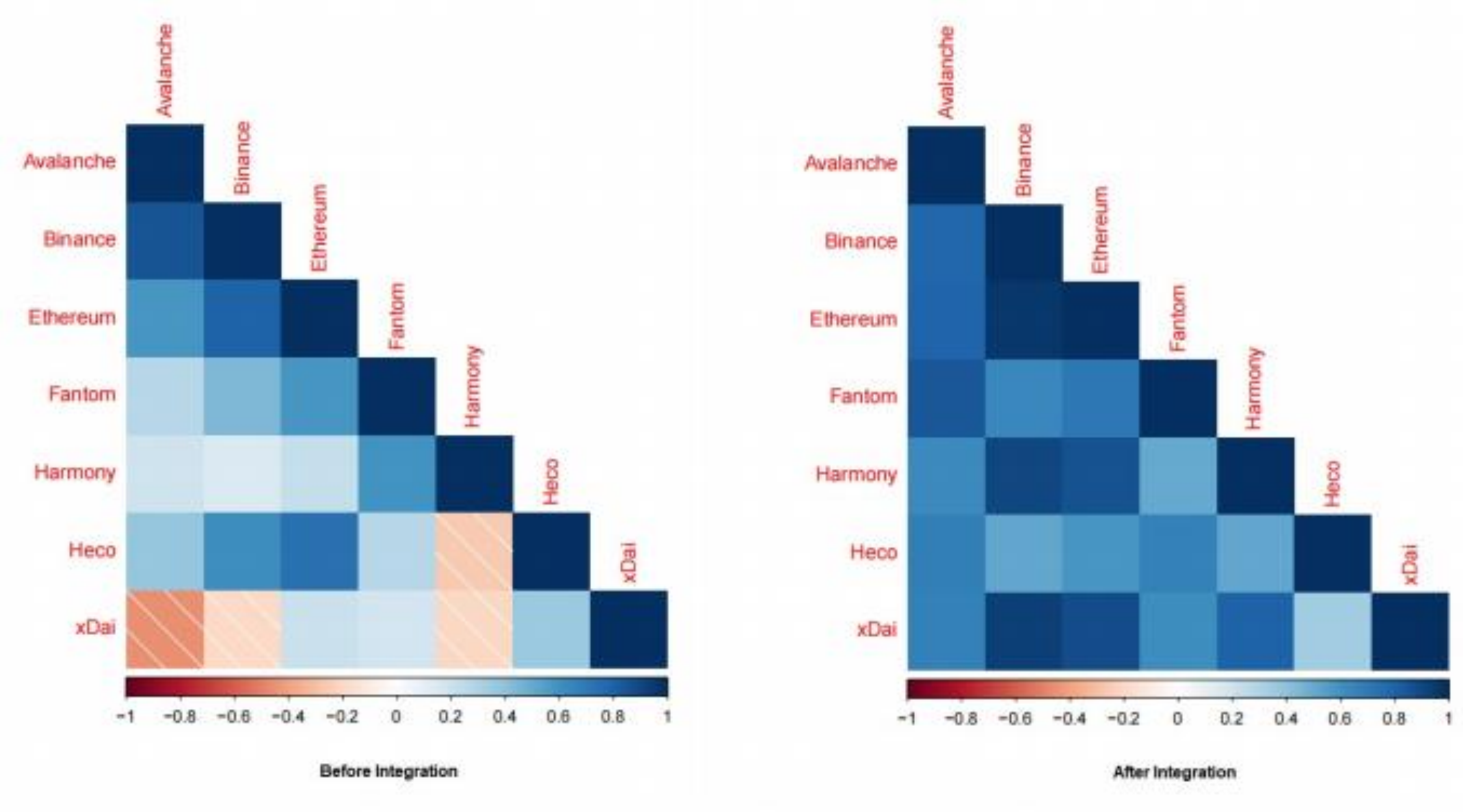


Figure 3. TVL correlations (Avalanche)


ANY
QUESTIONS?

Goal of the talk:

1. The economics of blockchain/crypto/defi is relevant and important.
2. Marrying the rich data from blockchain/DeFi/CeFi/Web3 with economic analyses is a fruitful path.

Roadmap:

1. Blockchain Economics
2. Digital Nations and Tokenomics.
3. Oracle Networks, Interoperability, and Off-Chain Economy Integration.

Thank you for the questions, comments, and discussion.

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