Blockchain Analytics for Intraday Financial Risk Modeling

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with

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Resources

Publications:

- *BHeist: Topological Data Analysis for Ransomware Payment Detection on the Bitcoin Blockchain*, in preparation.
- *Blockchain Analytics for Intraday Financial Risk Modeling*, to appear in Digital Finance, 2019
- *Blockchain Data Analytics*, Journal of IEEE Intelligent Informatics, 20(1), 2019
- *Bitcoin Risk Modeling with Blockchain Graphs*, Economic Letters 173 (1), 138-142, 2018. arxiv:1805.04698

Source code and data:

github.com/cakcora/CoinWorks

Workshops:

samsi — Workshop on Blockchain Analytics, Fall 2019

IEEE ICDM 2019
November 8-11, 2019 in Beijing — Workshop @ IEEE International Conference on Data Mining

Core Blockchain

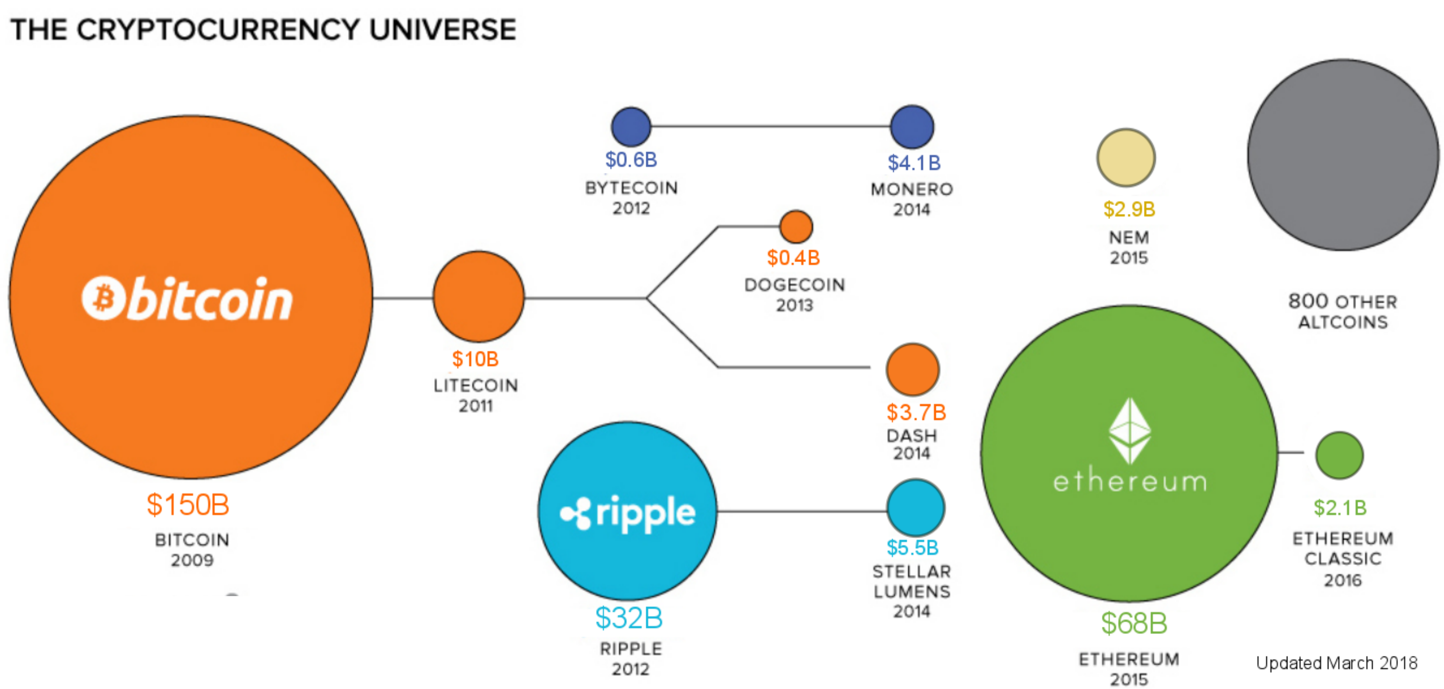
10/31/2008: Satoshi Nakamoto posts the Bitcoin white paper to a forum.

1/3/2009: The first data block in the Bitcoin.

Bitcoin: A peer to peer Electronic Cash System

Smart contracts, lightning networks, added privacy

Coin Timeline*



* By JEFF DESJARDINS. Image retrieved from VisualCapitalist.com and updated.

Cryptocurrency Trading

#	Name	Market Cap	Price	Volume (24h)	Circulating Supply	Change (24h)	Price Graph (7d)	
1	Bitcoin	$141,703,109,313	$7,982.30	$18,583,900,996	17,752,162 BTC	4.52%		···
2	Ethereum	$26,229,392,181	$246.43	$8,080,519,571	106,437,814 ETH	6.53%		···
3	XRP	$16,868,460,900	$0.399358	$1,474,509,708	42,238,947,941 XRP *	3.77%		···
4	Litecoin	$7,976,855,249	$128.31	$5,348,424,694	62,169,426 LTC	12.50%		···
5	Bitcoin Cash	$7,030,723,936	$394.30	$1,527,313,887	17,830,988 BCH	4.37%		···
6	EOS	$5,879,483,425	$6.40	$2,290,513,919	918,595,097 EOS *	4.61%		···
7	Binance Coin	$4,520,728,581	$32.02	$455,474,332	141,175,490 BNB *	4.82%		···
8	Bitcoin SV	$3,419,203,486	$191.78	$514,926,505	17,828,773 BSV	4.13%		···
9	Tether	$3,292,759,247	$1.01	$18,988,729,218	3,276,289,280 USDT *	0.31%		···
10	Stellar	$2,394,238,688	$0.123850	$350,213,802	19,331,690,041 XLM *	3.89%		···

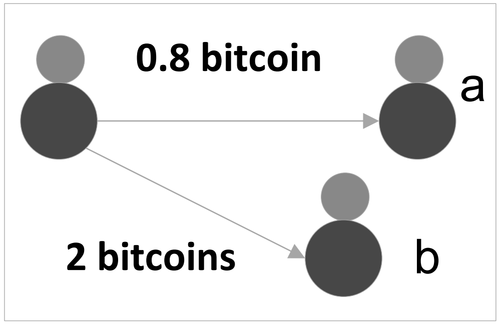
Blockchain Graph Analytics

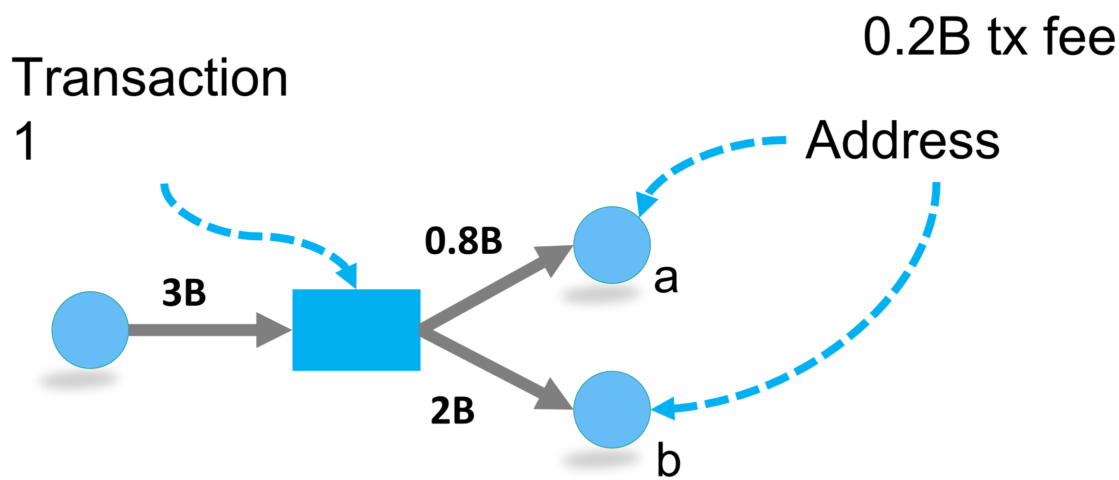
- For data modeling, blockchains can be divided into two major categories:

Transaction output (TXO) based blockchains (e.g., Bitcoin, Litecoin)

Account based blockchains (e.g., Ethereum)

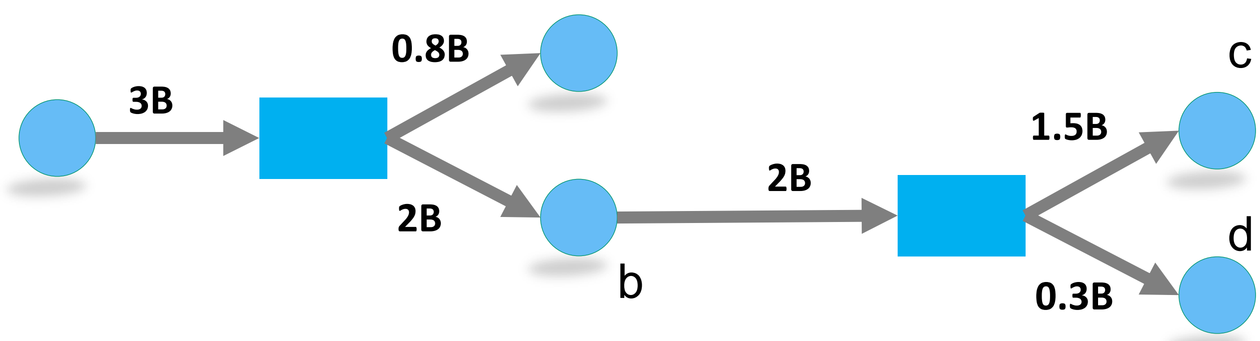
Transaction output (TXO) based blockchains





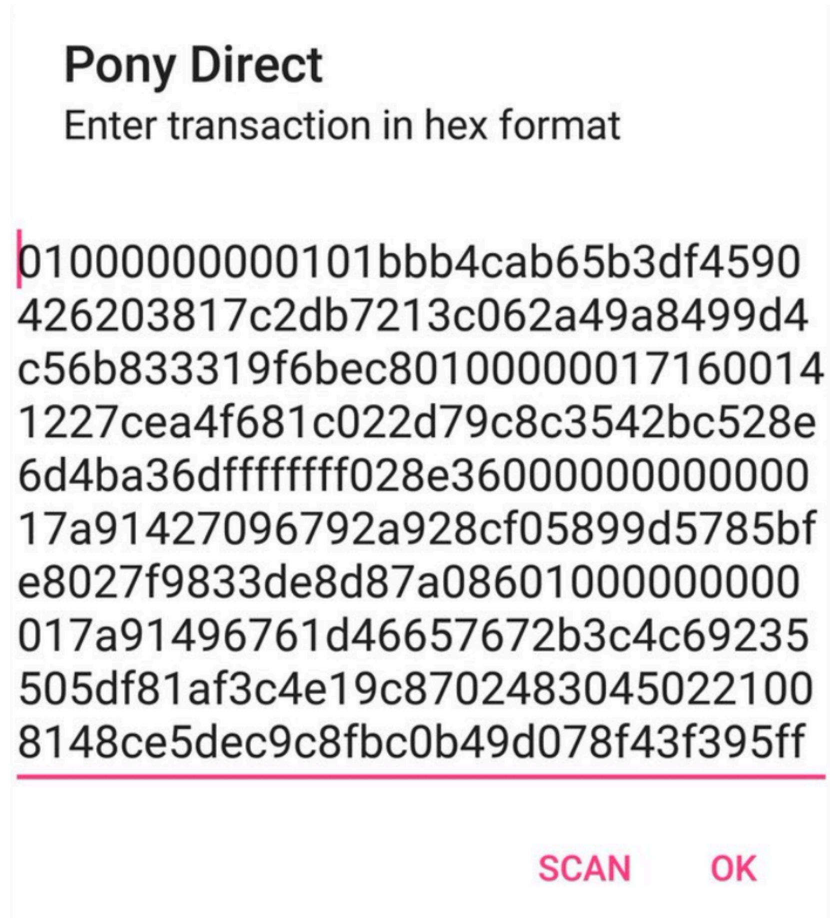
Next, if address b wants to spend its received 2B, it needs to show proof of funds:

“Use the 2B I received from Block 1, transaction 1, to pay 1.5B to c and 0.3B to d”.



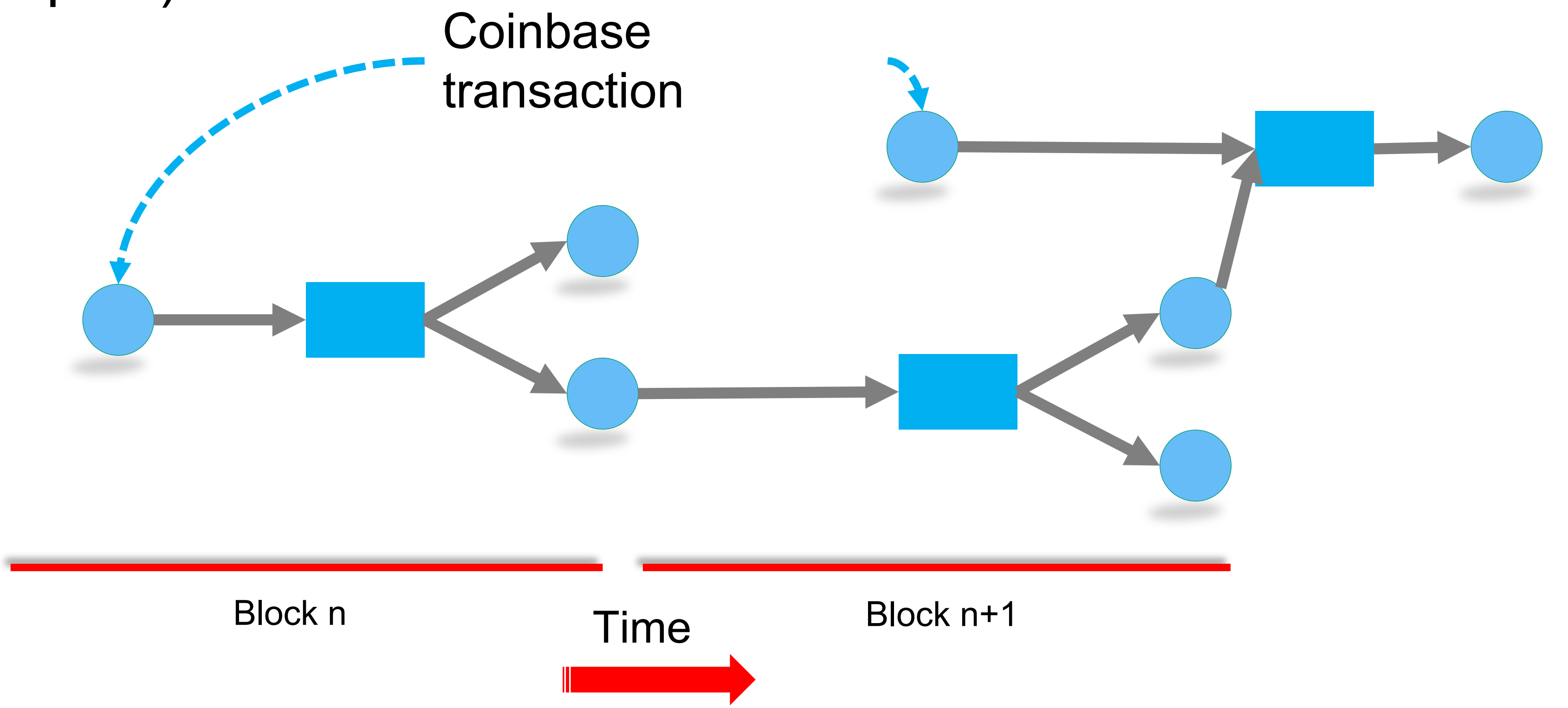
Bitcoin ⇔ Cow?


BARCLAYS BANK
St. PAUL'S BRANCH
PAY A.P. HERBERT


Pony Direct
Enter transaction in hex format
0100000000101bbb4cab65b3df4590
426203817c2db7213c062a49a8499d4
c56b833319f6bec80100000017160014
1227cea4f681c022d79c8c3542bc528e
6d4ba36dffffffff028e3600000000000
17a91427096792a928cf05899d5785bf
e8027f9833de8d87a0860100000000000
017a91496761d46657672b3c4c69235
505df81af3c4e19c870248304502210
8148ce5dec9c8fbc0b49d078f43f395ff
SCAN
OK

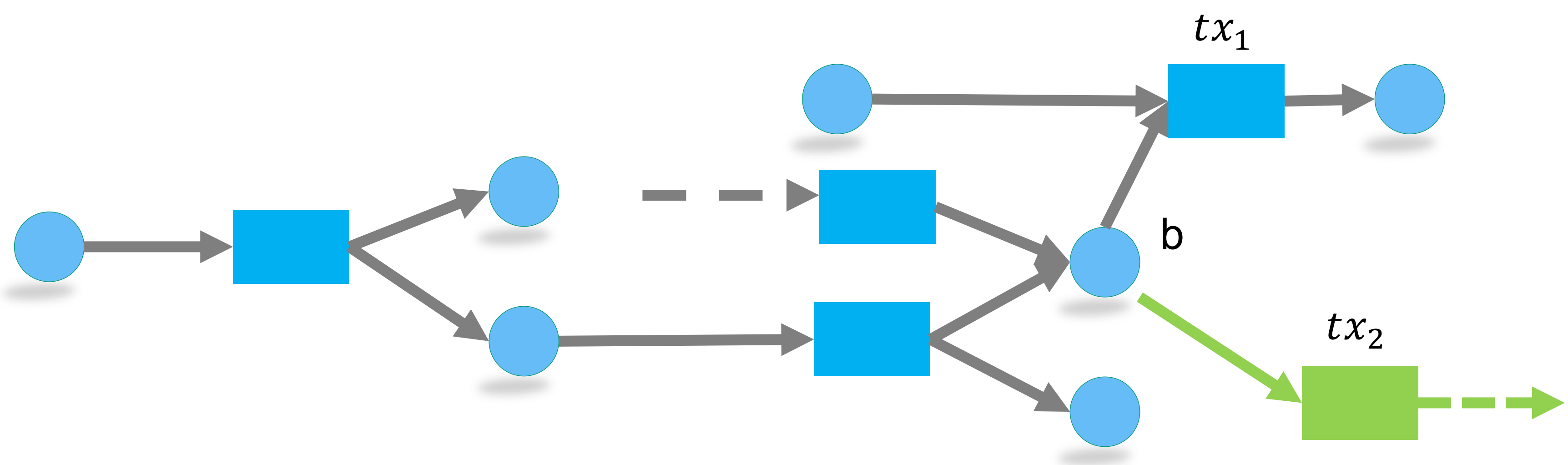
Transaction output (TXO) based blockchains

- Genesis block 0: The first block, created by Nakamoto.
- Every block has one coinbase transaction that creates bitcoins (sum of block reward + transaction fees).
- All other payments must show proof of funds (previous outputs).



Three Graph Rules for TXO

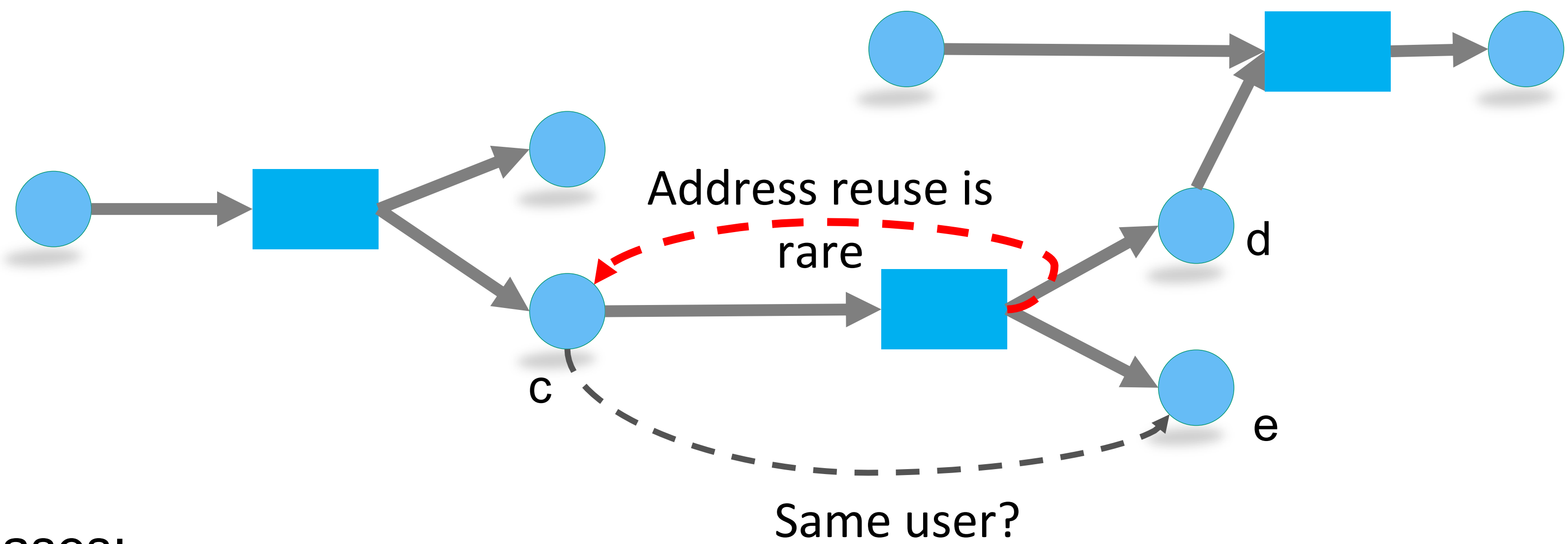
1- **Source Rule**: Coins can be sourced from multiple transactions. These can be spent at once or separately (dashed edges connect to unspecified addresses).



Address b can spend bitcoins at tx_1(once), or at tx_1 and tx_2.

Three Graph Rules for TXO

2- **Balance Rule**: All coins gained from a transaction must be spent in a single transaction. Addresses cannot keep change, must forward it.



Two cases:

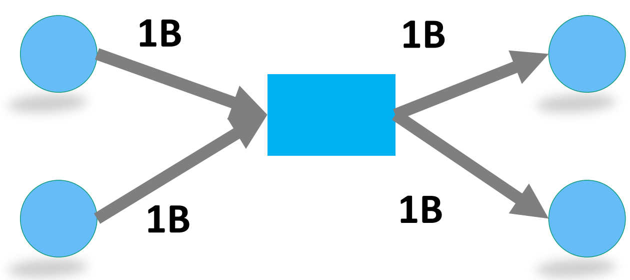
i - c sold all its coins: c, d and e all belong to different people, or
ii - c paid to d, and forwarded the change to its new address e.

In many scenarios, we have to identify which addresses belong to the same entity.

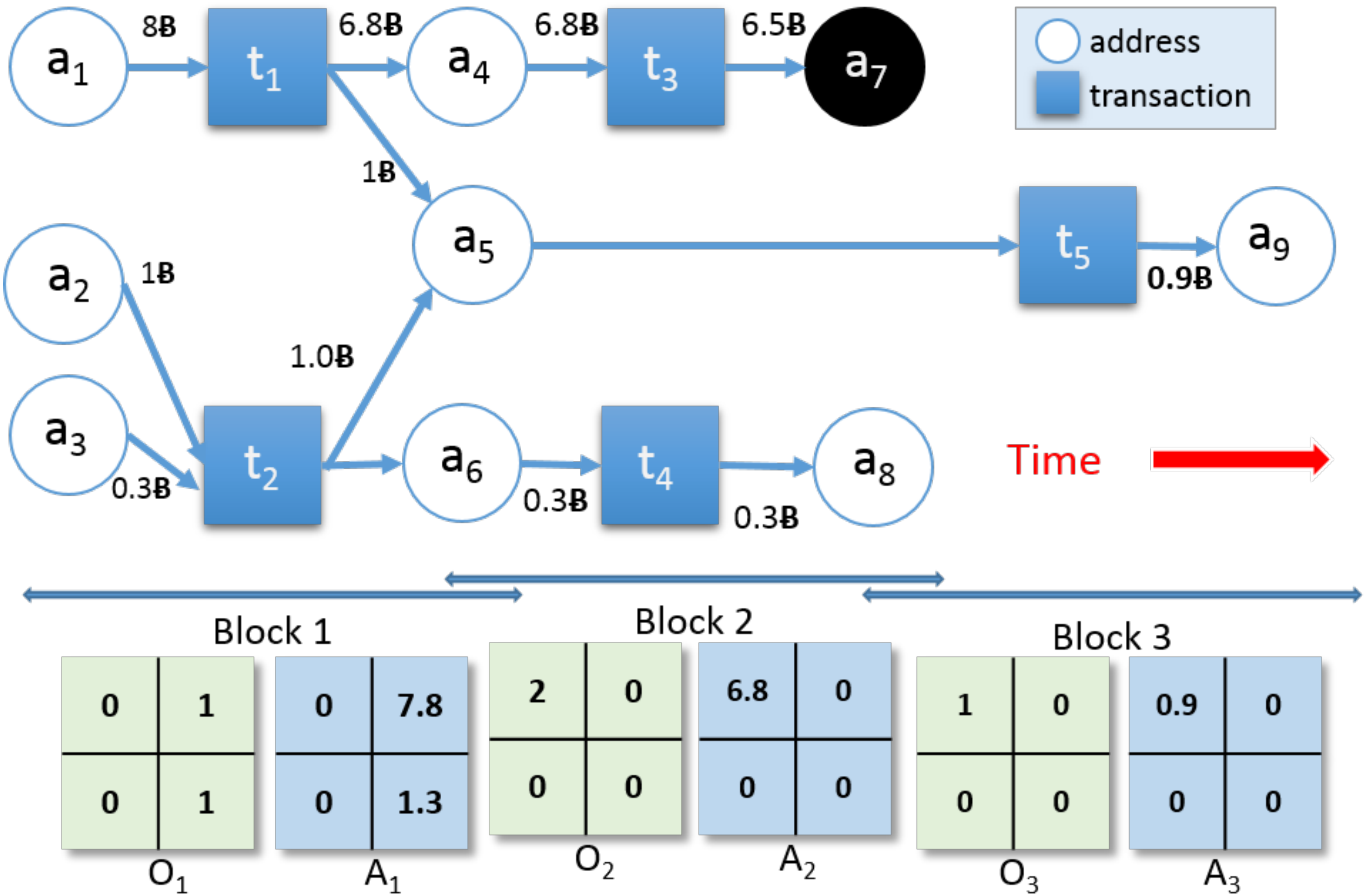
Three Graph Rules for TXO

3 – **Mapping Rule**: Multiple inputs can be signed separately and merged, but the input-output address mappings are not recorded.

A transaction can be considered a lake with incoming rivers, and outgoing emissaries. Coins mix in this lake.



A Toy TXO Graph



Blockchain Analysis - The Graph

- Graphs provide a high fidelity representation of Blockchain transactions between addresses and entities.

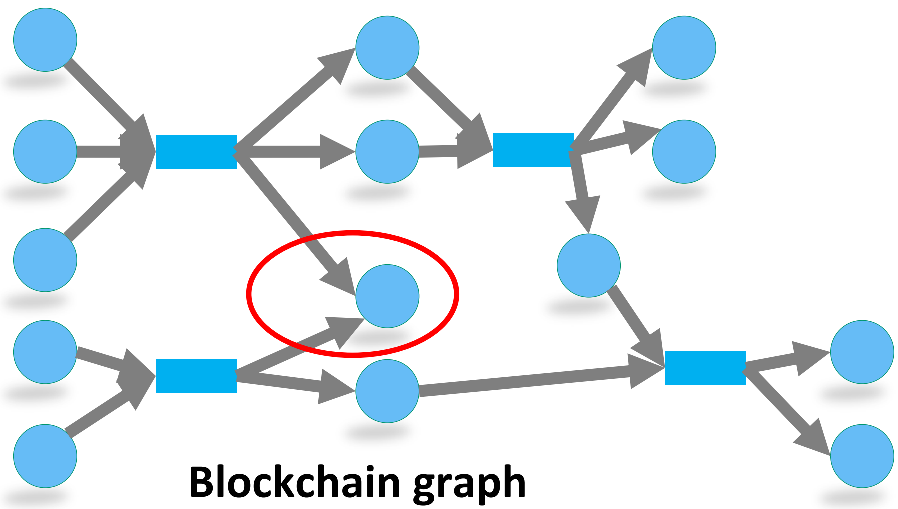
- Existing works extract global network characteristics and compute features such as:
  average degree, clustering coefficient, subgraph patterns.

1- Chartalist: Initial Coin Offerings on Ethereum: A topological analysis of coin offerings on Ethereum: a smart contract based blockchain.

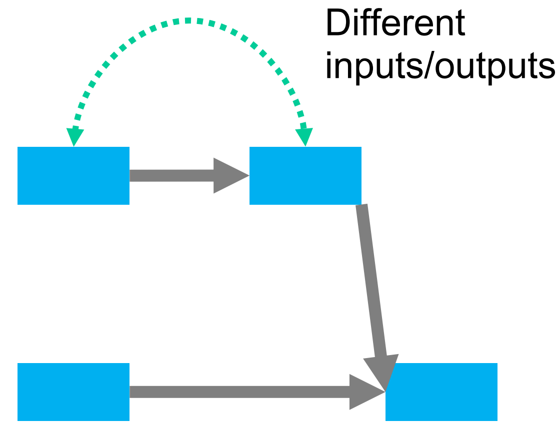
2- Watching the Circus in Action: Tracking Anomalies on Blockchain Graphs with Yuzhou Chen (SMU Stats)

3- Tracking Illegal Sales on the Bitcoin Dark markets: Statistical models to link block data to temporal graph analysis.

Existing Graph Approaches



Blockchain graph



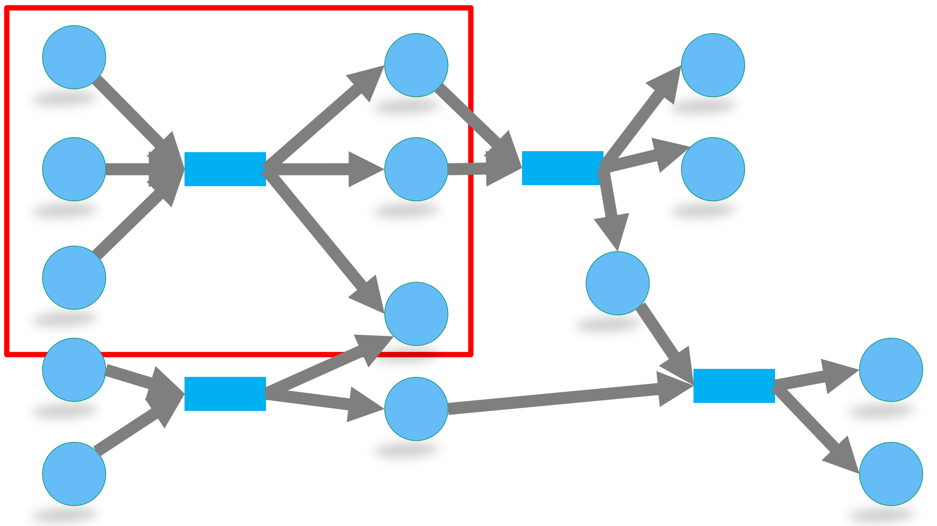
Transaction graph

Transaction graph: Edges between transactions only.

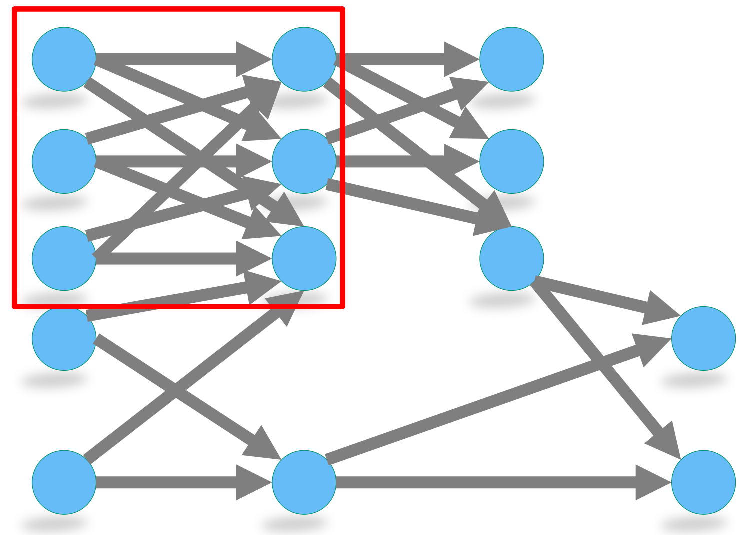
- ❖ Cannot capture unspent coins.
- ❖ Cannot discern transactions with differing inputs/outputs.

Dorit Ron and Adi Shamir. 2013. **Quantitative analysis of the full bitcoin transaction graph**. In International Conference on Financial Cryptography and Data Security. Springer, 6–24.

Existing Graph Approaches



Blockchain graph



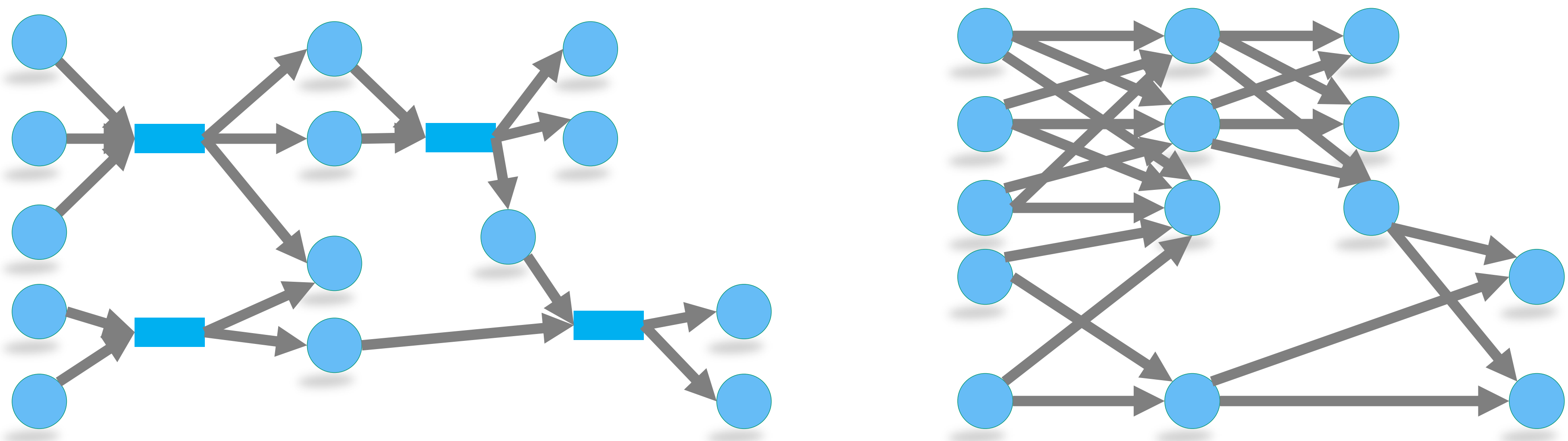
Address graph

2- **Address graph:** Edges between addresses only.

- ❖ Edges are multiplied between inputs and outputs: creates 1 million edges for a 1000 input, 1000 output transaction.
- ❖ Creates bias for average degree, even for median degree.

Michele Spagnuolo, Federico Maggi, and Stefano Zanero. 2014. **Bitiodine: Extracting intelligence from the bitcoin network**. In International Conference on Financial Cryptography and Data Security. Springer, 457–4

Existing Graph Approaches



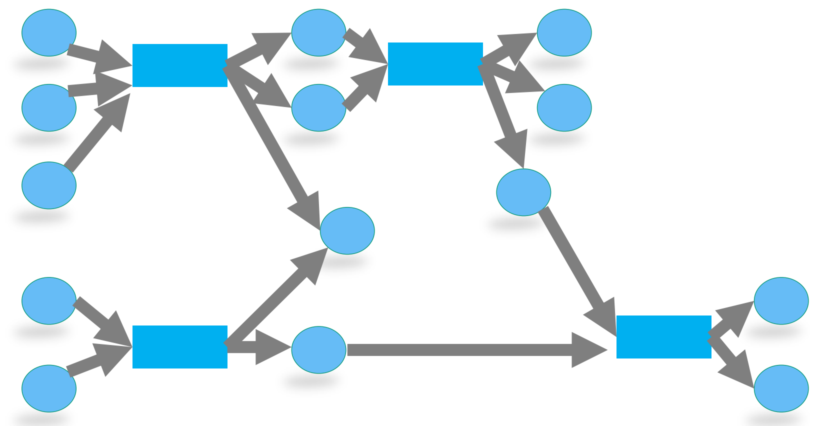
2- **Address graph:** is it worth the trouble searching for graph motifs?

- ❖ Addresses are not supposed to re-appear in future.
- ❖ Closed triangles are very rare.
- ❖ Output/input address sets do not have edges to each other – our tools do not consider this, and search for edges in vain (linked transactions within a block are possible but rare).

Graph Analysis with single node type:
Not always useful for the forever forward branching tree of Bitcoin.

Blockchain Graph – Substructure mining

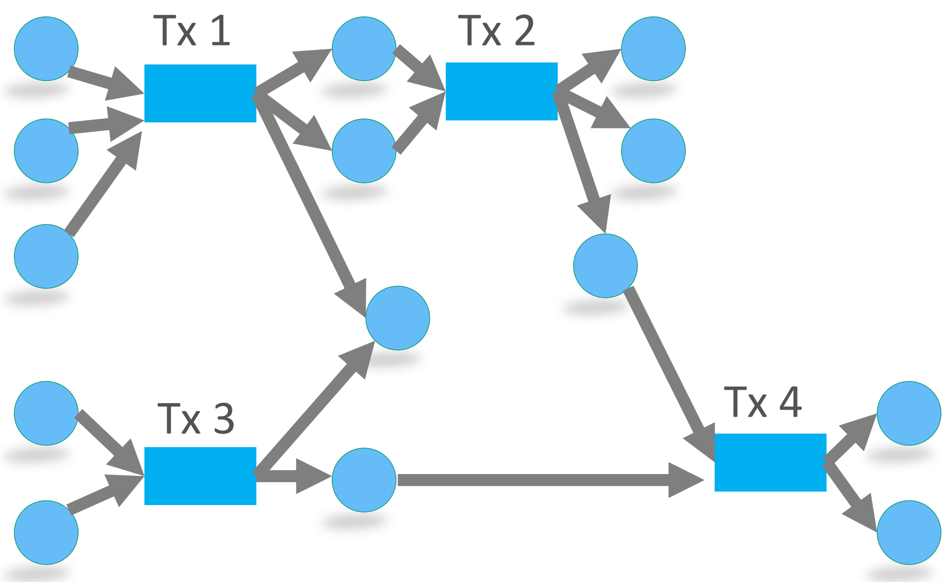
- Rather than individual edges or nodes, we use a subgraph as the building block in our Bitcoin analysis.
- We use the term **chainlet** to refer to such subgraphs.



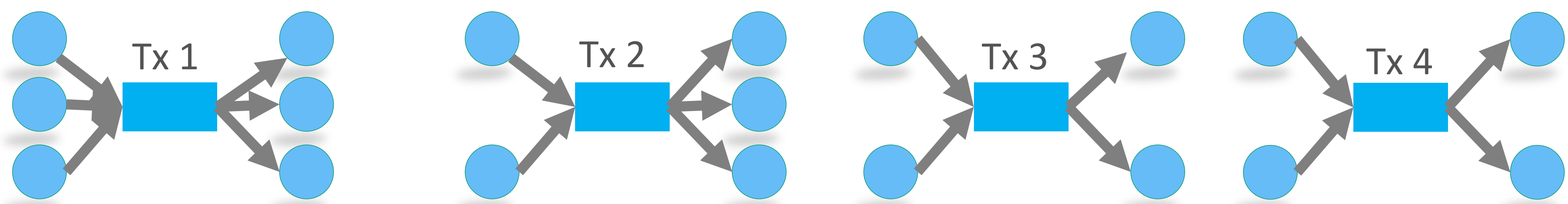
Definition [**K-Chainlets**]:
Let **k-chainlet** $G_k = (V_k, E_k, B)$ be a subgraph of G with **k** nodes of type {**Transaction**}. If there exists an isomorphism between G_k and G', G' ∈ G, we say that there exists an occurrence, or embedding of G_k in G.

If a G_k occurs more/less frequently than expected by chance, it is called a Blockchain k-chainlet. A k-chainlet signature $f_G(G_k)$ is the number of occurrences of G_k in G.

Blockchain Chainlets

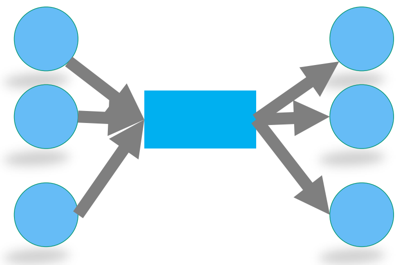


- Chainlets have distinct shapes that reflect their role in the network.
- We aggregate these roles to analyze network dynamics.

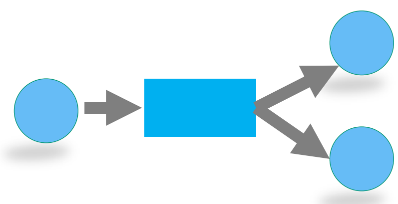


Three distinct types of 1-chainlets!

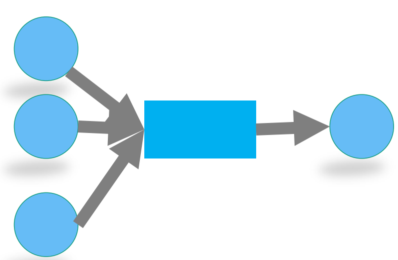
Aggregate Chainlets



Transition. Ex: Chainlet $C_{3\to3}$



Split. Ex: Chainlet $C_{1\to2}$



Merge. Ex: Chainlet $C_{3\to1}$

$C_{x\to y}$: chainlet with x inputs and y outputs.

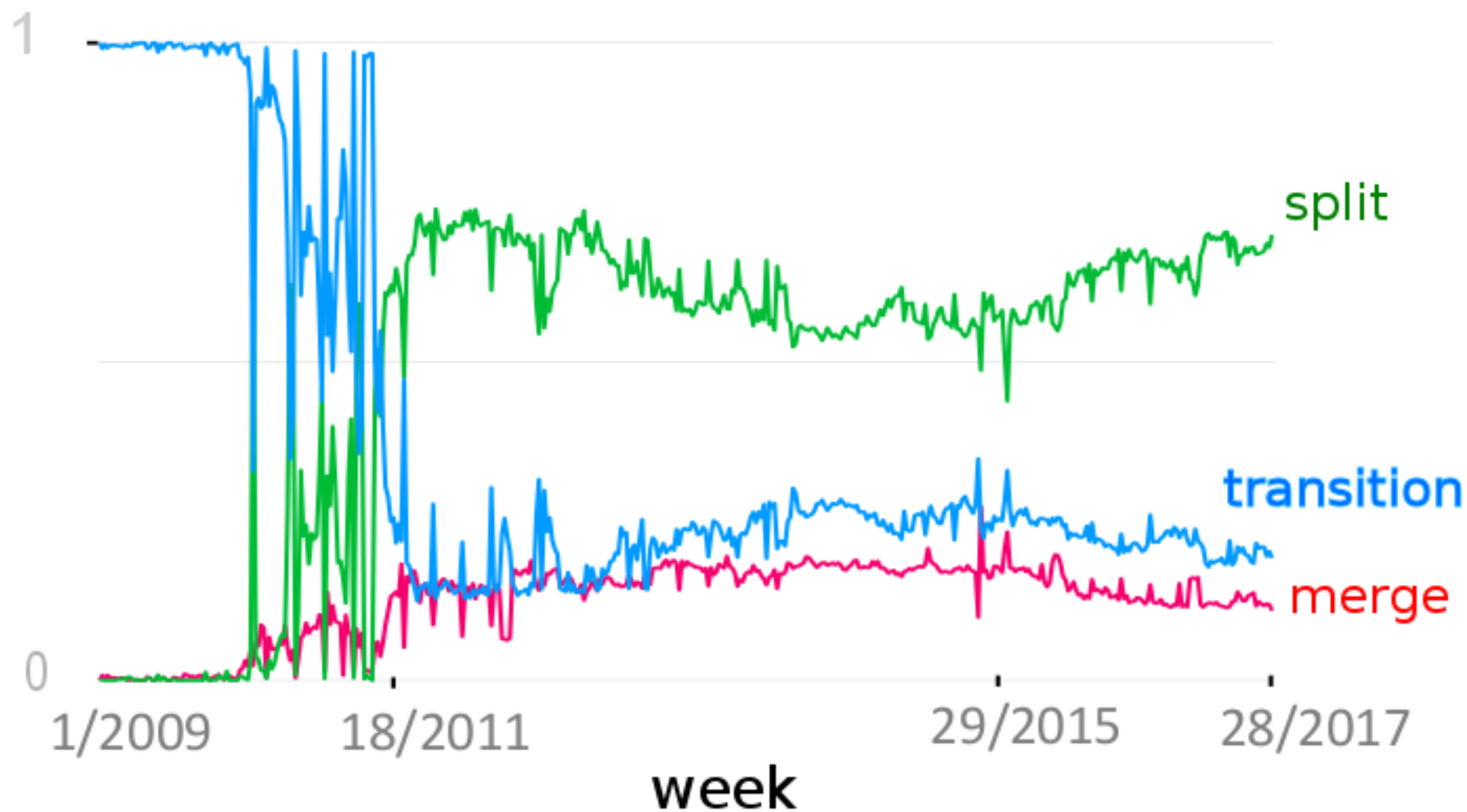
- **Transition Chainlets** imply coins changing address: $x = y$.

- **Split Chainlets** may imply spending behavior: $y > x$.

  But, community practice against address reuse can also create split chainlets.

- **Merge Chainlets** imply gathering of funds: $x > y$.

Aggregate Chainlets

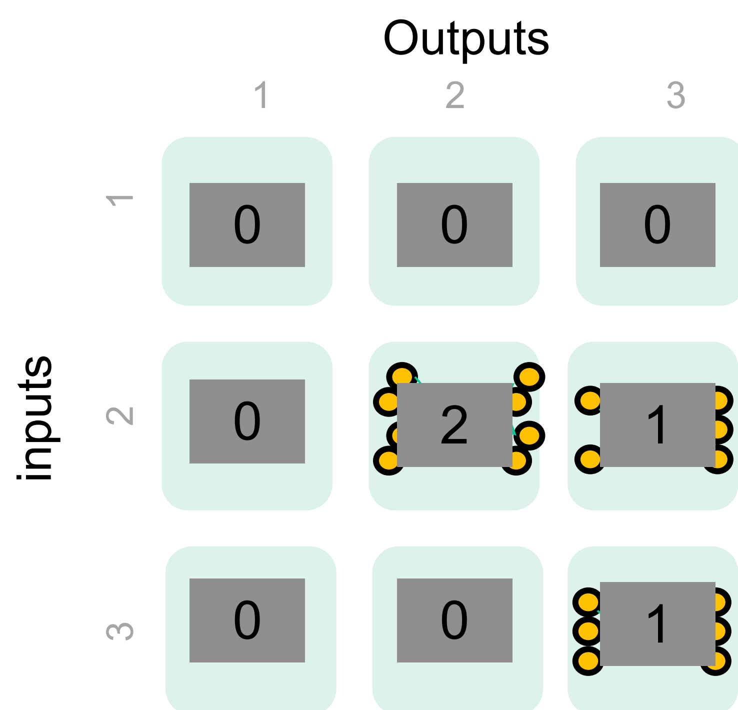


Percentage of aggregate chainlets in the Bitcoin Graph (weekly snapshots)

Chainlet Matrix

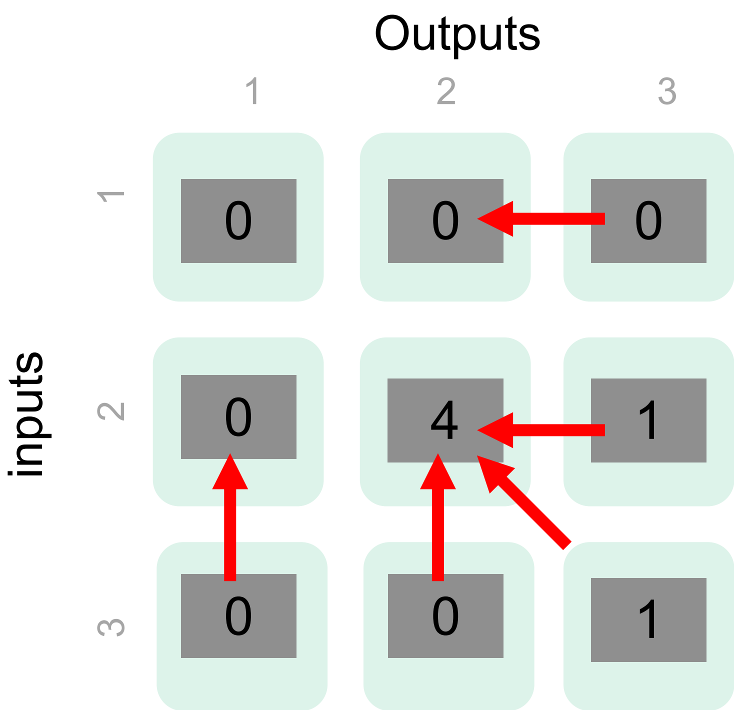
Representing the network in time

- For a given time granularity, such as one day, we take snapshots of the Bitcoin graph.
- Chainlet counts obtained from the graph are stored in an N×N matrix.



N: How big should the matrix be?

Extreme Chainlets



- N can reach thousands, the matrix can be 1000×1000.
- On Bitcoin, % 90.50 of the chainlets have N of 5 ($x < 5$ and $y < 5$), and % 97.57 for N of 20.

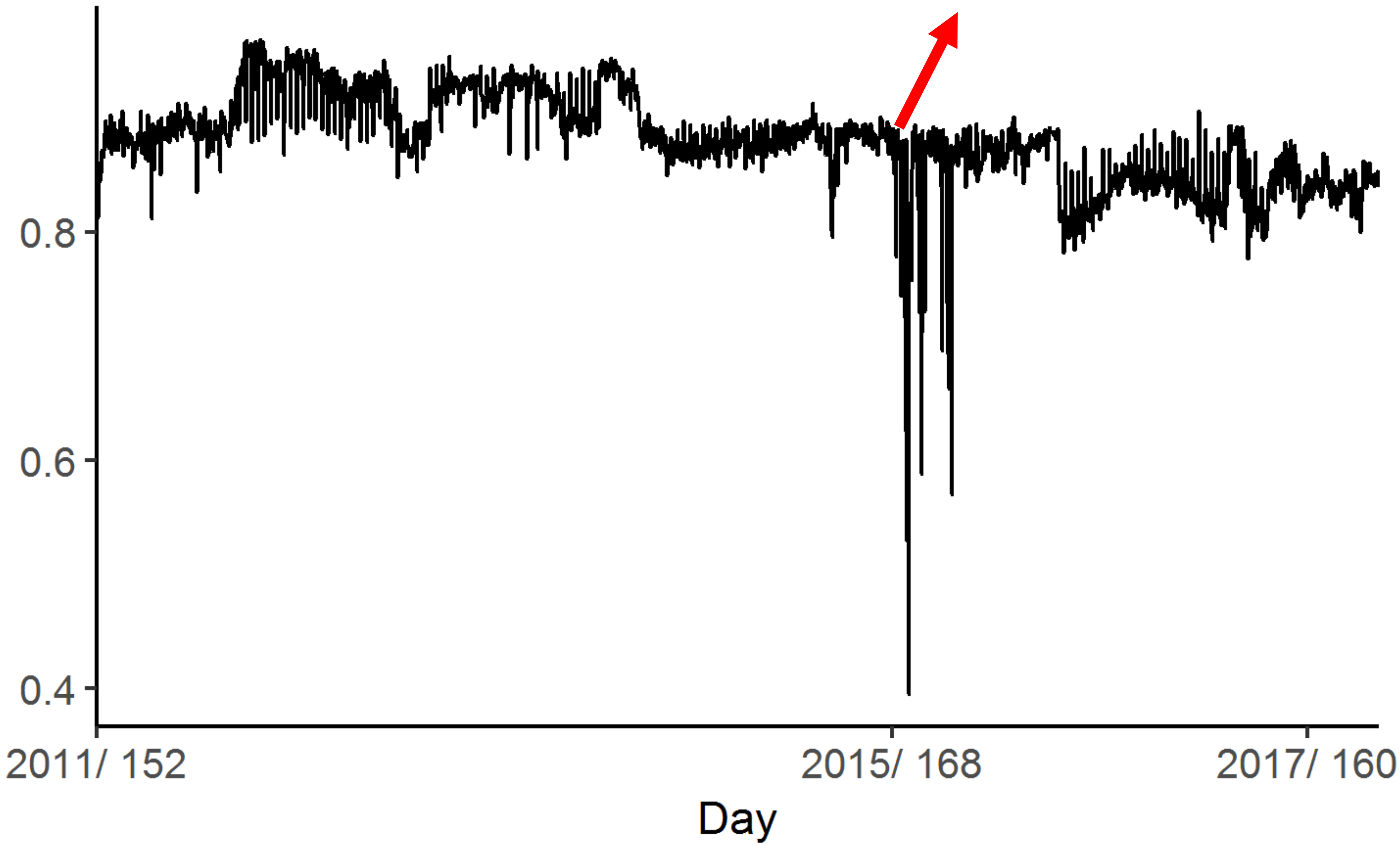
Occurrence matrix

$$O[i,j] = \begin{cases} \#C_{i\to j} & \text{if } i < N \text{ and } j < N \\ \sum_{z=N}^{\infty} \#C_{i\to z} & \text{if } i < N \text{ and } j = N \\ \sum_{y=N}^{\infty} \#C_{y\to j} & \text{if } i = N \text{ and } j < N \\ \sum_{y=N}^{\infty} \sum_{z=N}^{\infty} \#C_{y\to z} & \text{if } i = N \text{ and } j = N \end{cases}$$

Extreme chainlets are the last column/row of the chainlet matrix.
They imply big coin movements in the graph!

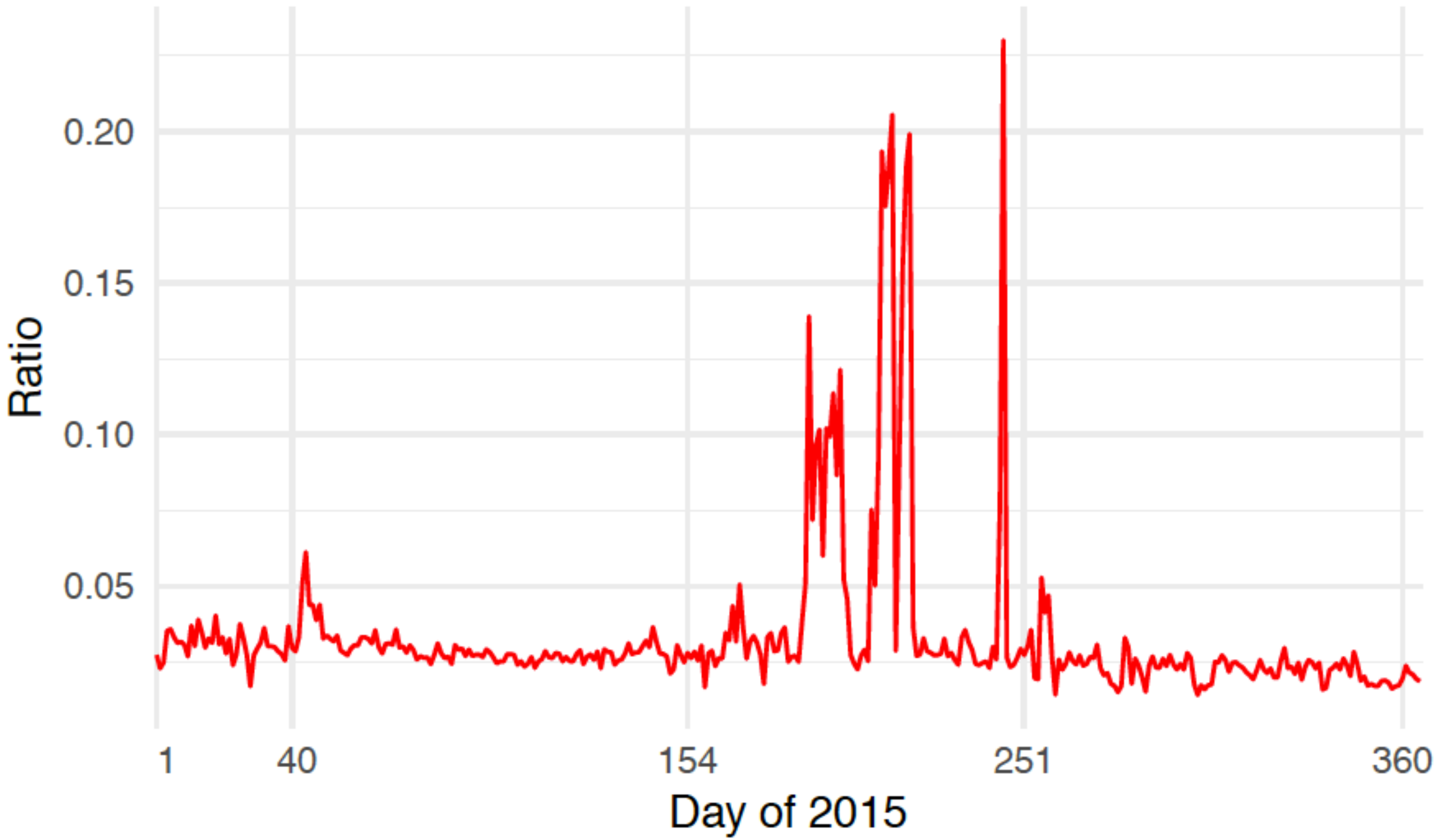
Extreme Chainlets

Bitcoin companies stopped all business in New York State because of new regulations.
The New York Business Journal called this the "Great Bitcoin Exodus".



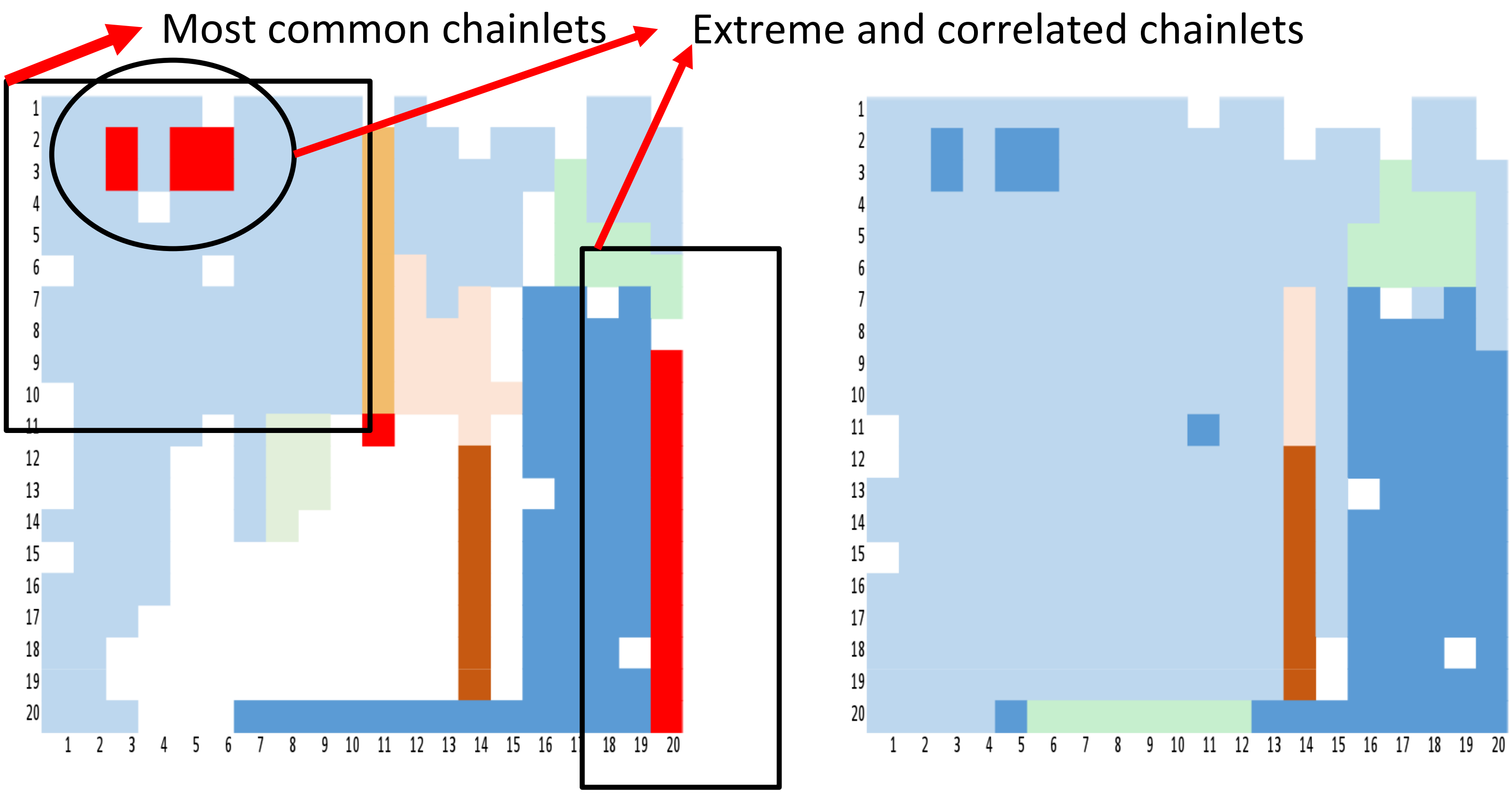
Percentage of non-extreme chainlets in the Bitcoin Graph (N = 20, daily snapshots)

Extreme Chainlet Occurrences



Clustering the Chainlets

- A hierarchical clustering of chainlets by using Cosine Similarity over chainlet signatures in time.
- We used a similarity cut threshold of 0.7 to create clusters from the hierarchical dendrogram.

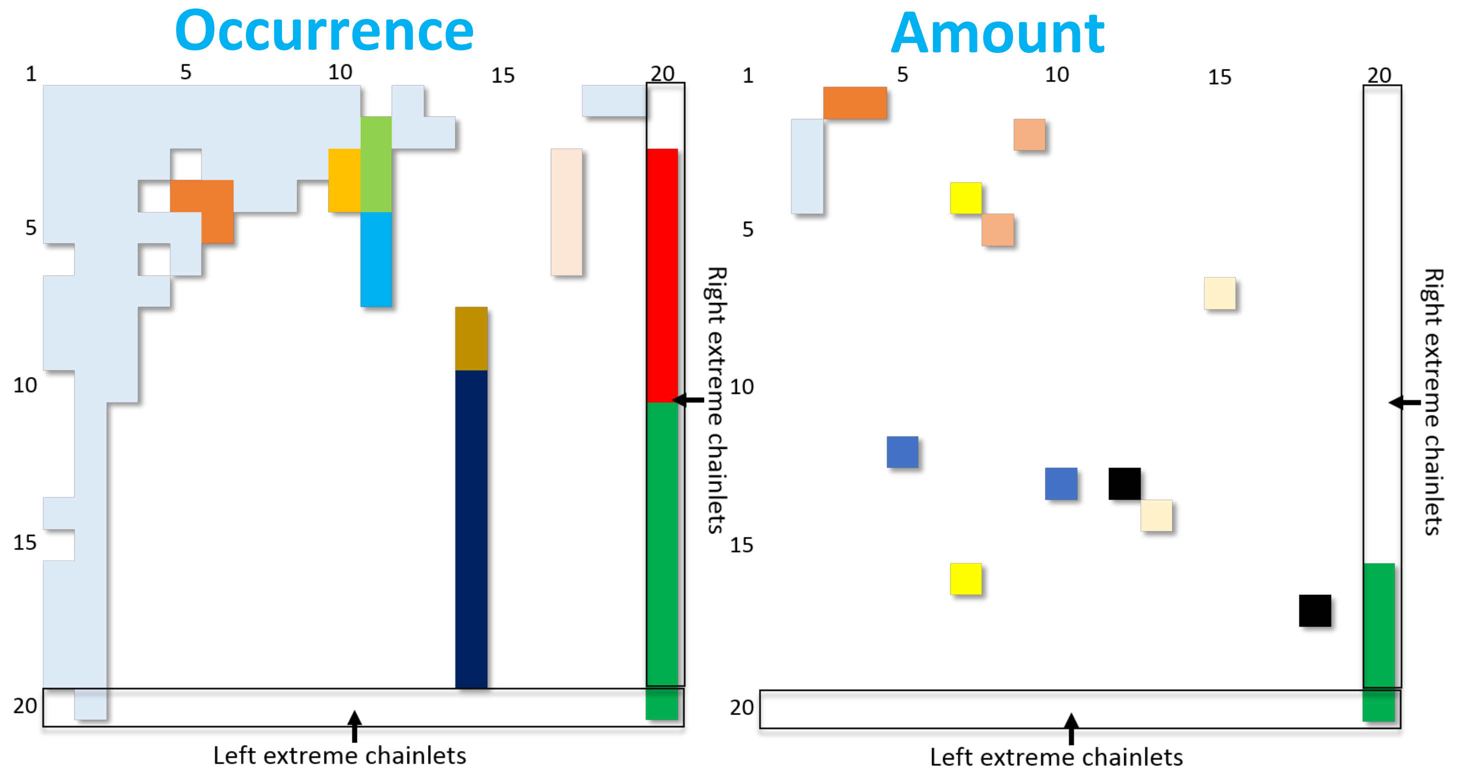


Chainlet clusters for daily snapshots **Chainlet clusters for weekly snapshots**

Definition: Extreme Chainlets

Left extreme chainlets are the subset $\mathcal{C}^l := \{\mathbb{C}_{i\to j} \mid i = N,\ j \in \{1,\ldots,N\}\}$ highlighted in the bottom row in the figure. They represent transactions from of a large number of accounts to fewer addresses. They represent bitcoin *investment* – transfer of Bitcoin from a large number of wallets to a relatively few number of wallets represents the supply of liquidity at an exchange.

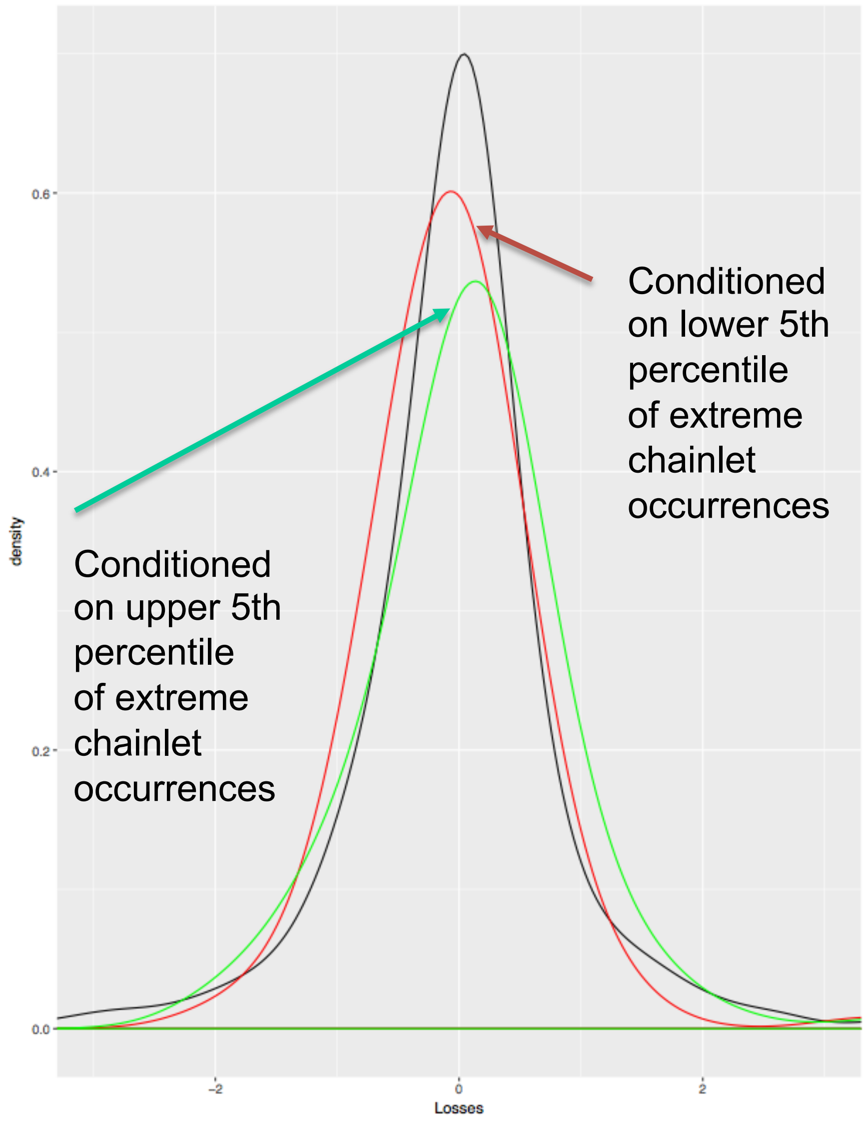
Right extreme chainlets are the subset $\mathcal{C}^r := \{\mathbb{C}_{i\to j} \mid i \in \{1,\ldots,N-1\},\ j = N\}$ highlighted in the far right column in the figure. They represent the *sale* of a large sum of bitcoins across the market – the seller divides the balance and sends them to potentially hundreds of Bitcoin addresses.



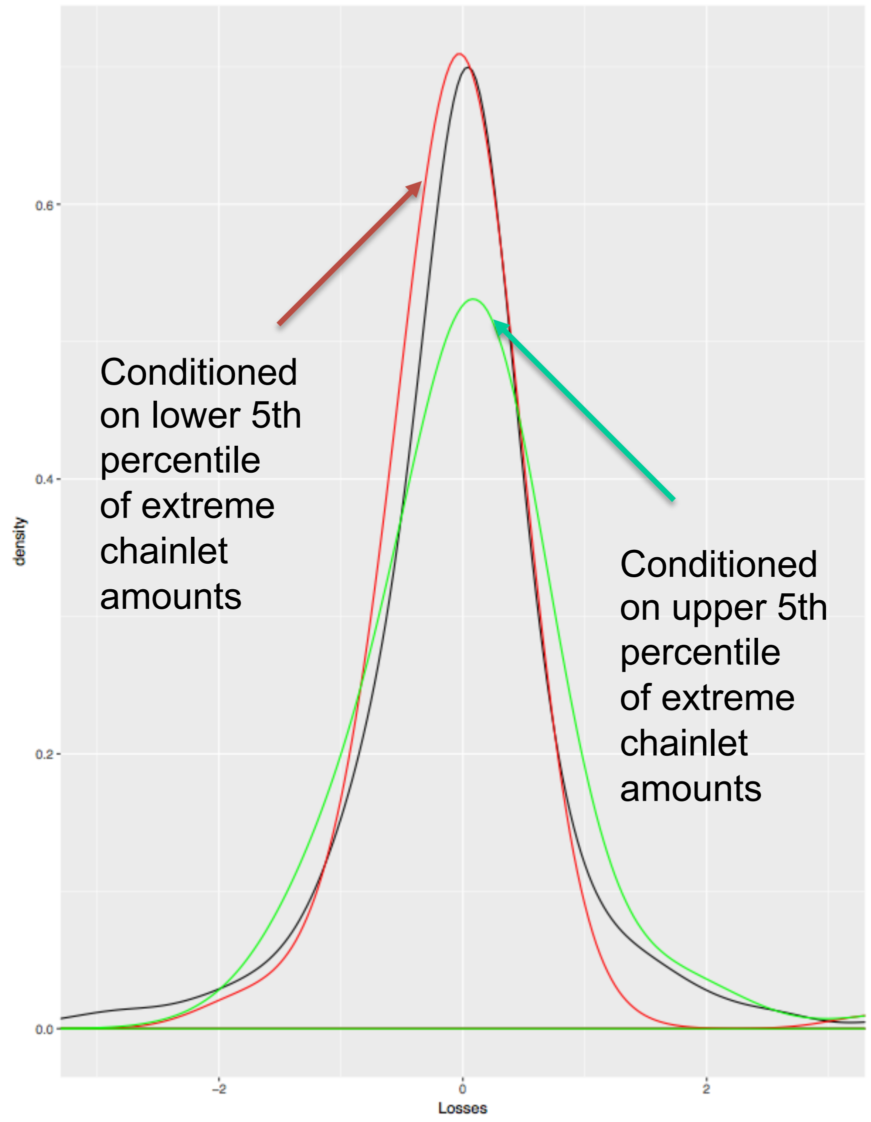
This figure illustrates how the 400 chainlets (i.e., N=20) are related to each other in terms of their occurrence (left) and amount (right). The occurrence and amount matrices are formed by taking daily snapshots of the Bitcoin graph and counting the occurrences and summing amounts of Ci→j,∀i,j, respectively (over the period 2015 to 2018). The color scale denotes cluster membership.

Conditional Loss Distributions (daily)

Occurrences



Amounts



Conditional Loss Distributions (daily)

pdf	mean	std.dev.	skewness	kurtosis
$\phi(L_t)$	0	1	0.518	12.082
$\phi(L_t \mid A_t^x < \Phi_{A_t^x}^{-1}(0.05))$	-0.047	1.107	3.283	31.618
$\phi(L_t \mid A_t^x > \Phi_{A_t^x}^{-1}(0.95))$	0.0861	0.843	1.590	6.046
$\phi(L_t \mid O_t^x < \Phi_{O_t^x}^{-1}(0.05))$	-0.081	0.633	1.296	8.114
$\phi(L_t \mid O_t^x > \Phi_{O_t^x}^{-1}(0.95))$	0.118	0.930	2.025	10.457

Comparison of the empirical densities of the standardized daily losses conditioned on the lower and upper α = 0.05 percentiles of extreme chainlet activity by amount (Ax) and occurrences (Ox).

Conditional Loss Distributions (intra-day)

Interval (min)	pdf	mean	std.dev.	skewness	kurtosis
15	$\phi(L_t)$	0	1	9.154	1056.313
15	$\phi(L_t \mid A_t^x < \Phi_{A_t^x}^{-1}(0.05))$	-0.013	0.907	-14.93	918.836
15	$\phi(L_t \mid A_t^x > \Phi_{A_t^x}^{-1}(0.95))$	0.008	1.181	**9.706**	839.024
15	$\phi(L_t \mid O_t^x < \Phi_{O_t^x}^{-1}(0.05))$	-0.01	0.931	-11.531	764.131
15	$\phi(L_t \mid O_t^x > \Phi_{O_t^x}^{-1}(0.95))$	0.041	1.641	**22.525**	1034.844
30	$\phi(L_t)$	0	1	7.181	498.262
30	$\phi(L_t \mid A_t^x < \Phi_{A_t^x}^{-1}(0.05))$	-0.039	0.971	-15.781	**519.805**
30	$\phi(L_t \mid A_t^x > \Phi_{A_t^x}^{-1}(0.95))$	0.018	1.124	**13.496**	**526.045**
30	$\phi(L_t \mid O_t^x < \Phi_{O_t^x}^{-1}(0.05))$	-0.014	0.787	-6.176	209.604
30	$\phi(L_t \mid O_t^x > \Phi_{O_t^x}^{-1}(0.95))$	0.028	1.127	**14.669**	**528.621**
60	$\phi(L_t)$	0	1	4.723	227.521
60	$\phi(L_t \mid A_t^x < \Phi_{A_t^x}^{-1}(0.05))$	-0.034	0.761	-6.031	107.801
60	$\phi(L_t \mid A_t^x > \Phi_{A_t^x}^{-1}(0.95))$	0.029	1.362	**11.197**	**255.048**
60	$\phi(L_t \mid O_t^x < \Phi_{O_t^x}^{-1}(0.05))$	-0.024	0.77	-4.014	99.398
60	$\phi(L_t \mid O_t^x > \Phi_{O_t^x}^{-1}(0.95))$	-0.006	1.182	**11.231**	**297.34**
120	$\phi(L_t)$	0	1	4.615	228.85
120	$\phi(L_t \mid A_t^x < \Phi_{A_t^x}^{-1}(0.05))$	-0.025	0.749	-5.148	112.134
120	$\phi(L_t \mid A_t^x > \Phi_{A_t^x}^{-1}(0.95))$	0.027	1.37	**11.155**	**253.848**
120	$\phi(L_t \mid O_t^x < \Phi_{O_t^x}^{-1}(0.05))$	-0.022	0.781	-3.575	98.738
120	$\phi(L_t \mid O_t^x > \Phi_{O_t^x}^{-1}(0.95))$	-0.019	0.906	3.781	148.533
240	$\phi(L_t)$	0	1	4.642	229.758
240	$\phi(L_t \mid A_t^x < \Phi_{A_t^x}^{-1}(0.05))$	-0.021	0.802	-2.709	106.828
240	$\phi(L_t \mid A_t^x > \Phi_{A_t^x}^{-1}(0.95))$	0.025	1.712	**11.622**	**351.914**
240	$\phi(L_t \mid O_t^x < \Phi_{O_t^x}^{-1}(0.05))$	-0.023	0.768	-3.164	98.804
240	$\phi(L_t \mid O_t^x > \Phi_{O_t^x}^{-1}(0.95))$	-0.016	0.957	4.071	130.399
1440	$\phi(L_t)$	0	1	1.38	11.512
Daily	$\phi(L_t \mid A_t^x < \Phi_{A_t^x}^{-1}(0.05))$	-0.102	0.712	-0.693	5.881
Daily	$\phi(L_t \mid A_t^x > \Phi_{A_t^x}^{-1}(0.95))$	0.186	1.356	1.309	6.623
Daily	$\phi(L_t \mid O_t^x < \Phi_{O_t^x}^{-1}(0.05))$	-0.026	0.919	**2.056**	**13.222**
Daily	$\phi(L_t \mid O_t^x > \Phi_{O_t^x}^{-1}(0.95))$	-0.119	1.047	-1.072	5.619

Comparison of the empirical densities of the standardized losses conditioned on the lower and upper α = 0.05 percentiles of extreme chainlet activity by amount (Ax) and occurrences (Ox). Each row represents different time intervals of 15, 30, 60, 120, 240 minutes and days. The standardized unconditional loss densities for these time intervals are also given.

Augmented Dickey Fuller Test

Interval (min)	Lag Order	Dickey-Fuller	p-value
15	68	-41.2958	0.01
30	57	-31.4344	0.01
60	51	-26.5716	0.01
120	43	-18.0825	0.01
240	36	-16.3109	0.01

The Augmented Dickey-Fuller test with a maximum lag specified by Lag Order.

ARCH Effects with Ljung Box Test

Interval (min)	X-squared	df	p-value
15	2420.3	15	$< 2.2e-16$
30	890.29	15	$< 2.2e-16$
60	1273.9	15	$< 2.2e-16$
120	1727.6	15	$< 2.2e-16$
240	1335	15	$< 2.2e-16$

The Ljung-Box test results for ARCH effects using the residuals squared at various intervals.

Intraday Risk Model

- E-Garch model (Nelsen91) with exogeneous regressors:

$$ln(\sigma_t^2) = \omega + \sum_{j=1}^{q} \alpha_j \epsilon_{t-j} + \gamma_j(|\epsilon_{t-j}| - \mathbb{E}|\epsilon_{t-j}|) + \sum_{j=1}^{p} \beta_j ln(\sigma_{t-j}^2) + \sum_{j=1}^{|x_t|} \beta_j^x x_{t,j}$$

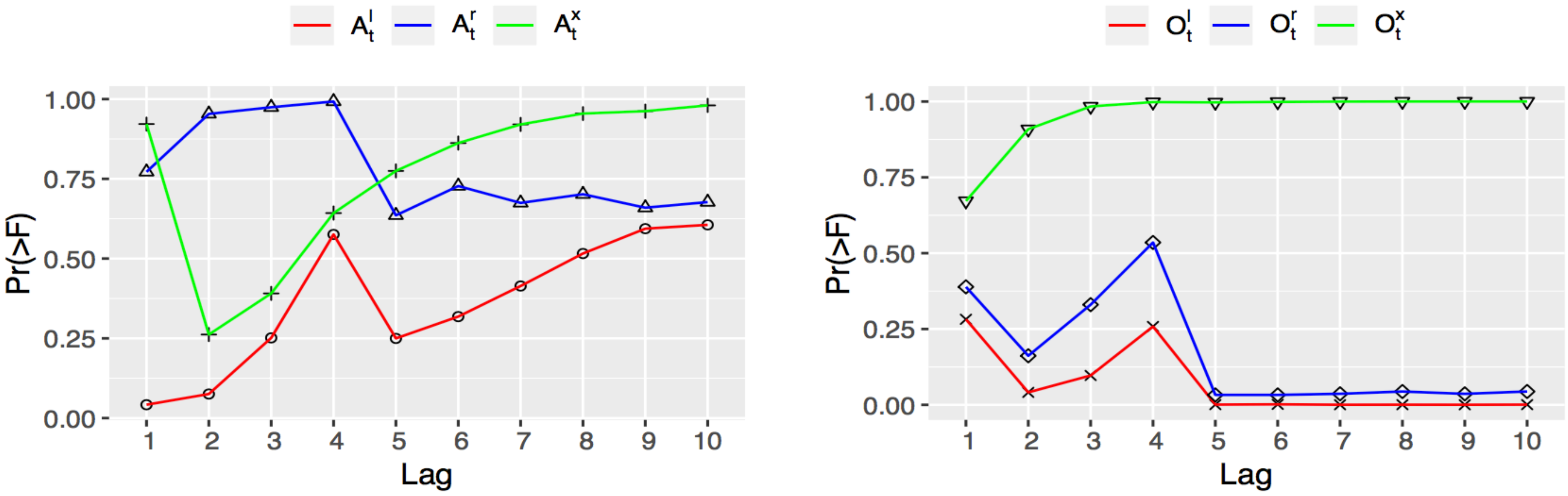
sign effect

size effect

chainlet regressors

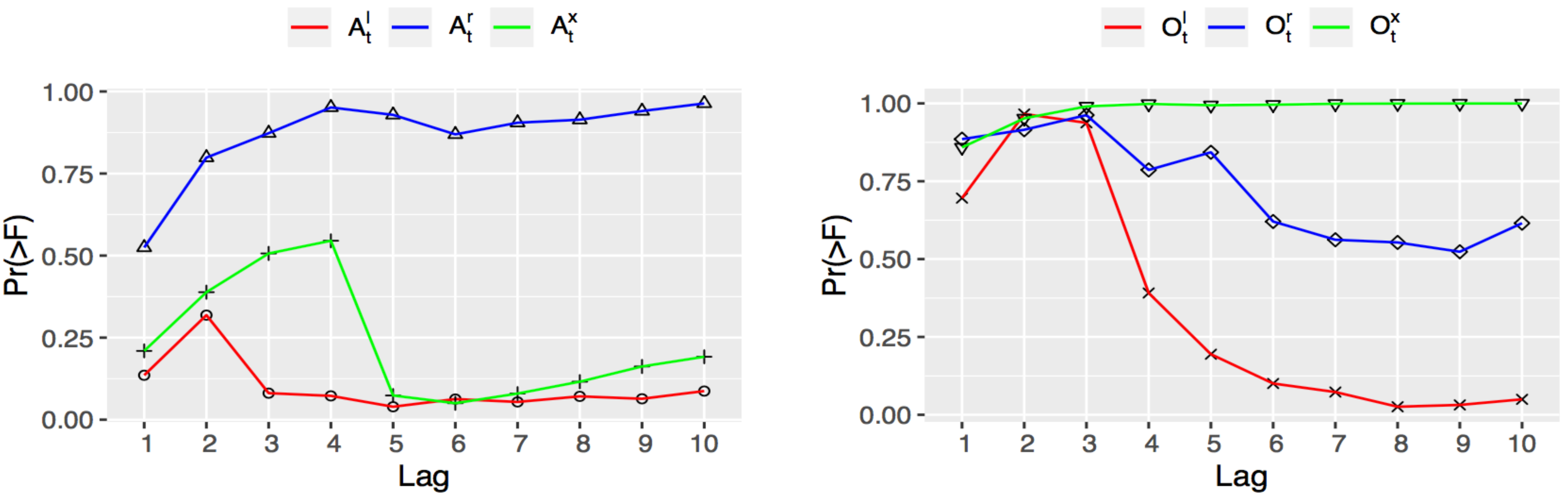
	Estimate	Std. Error	t-value	Pr(> $|t|$)	
(Intercept)	0.9995	0.0807	12.385	< 2e-16	***
A_t^l	0.7248	0.1063	6.818	1.21e-11	***
A_t^r	0.2959	0.1278	2.316	0.02068	*
A_t^x	-0.5348	0.1313	-4.073	4.82e-05	***
O_t^l	-0.5699	0.1074	-5.304	1.25e-07	***
O_t^r	-0.4541	0.1644	-2.762	0.00579	**
O_t^x	0.5043	0.1832	2.753	0.00595	**

Granger Causality (15 mins)



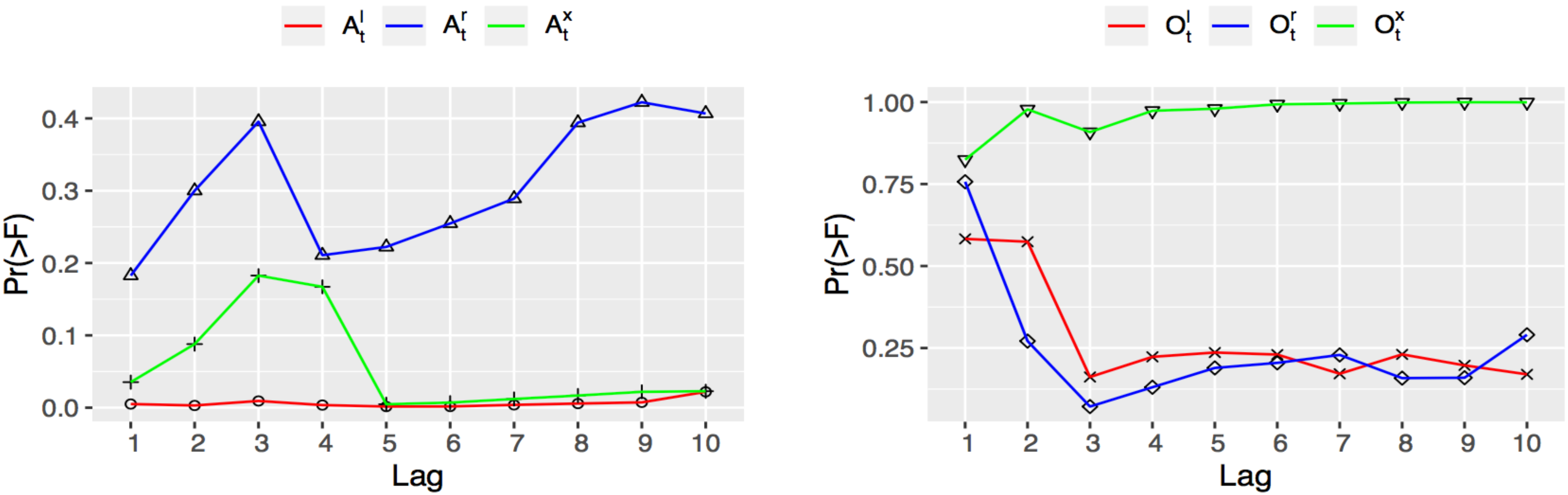
The results from applying a Granger Causality test of extreme chainlet amounts (left) and extreme chainlet occurrences (right) as predictors of volatility. Each plot shows the p-value of accepting the null hypothesis that there is no causal effect of lagged extreme chainlets. The x-axis shows the maximum lag chosen in each test. The time intervals is 15 minutes.

Granger Causality (30 mins)



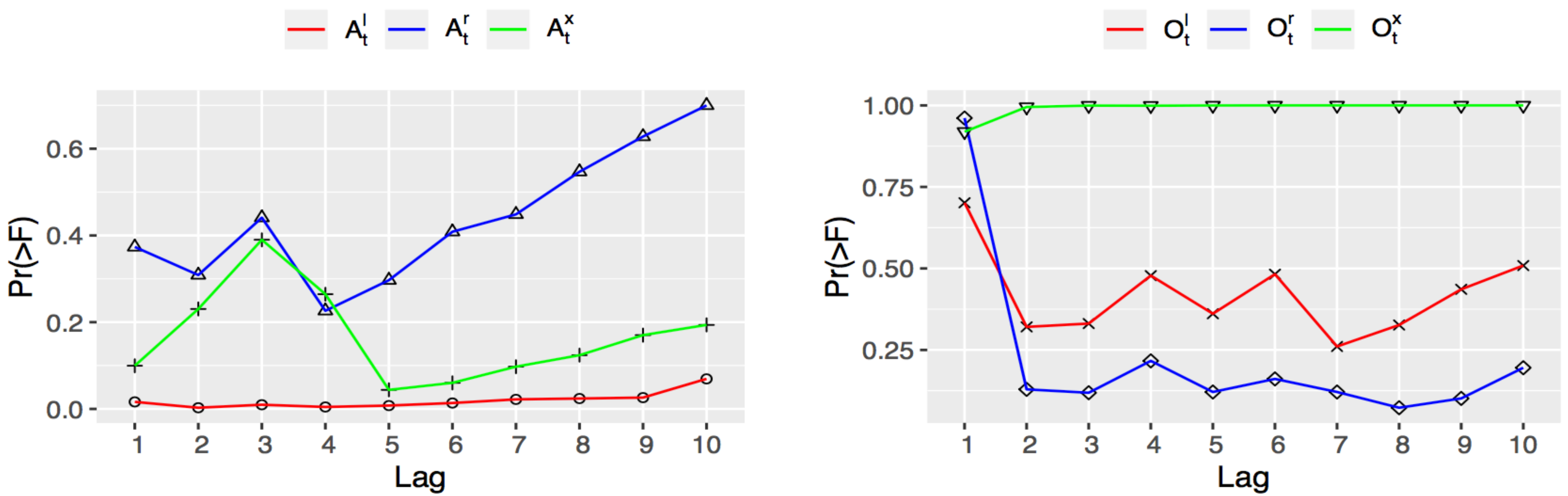
The results from applying a Granger Causality test of extreme chainlet amounts (left) and extreme chainlet occurrences (right) as predictors of volatility. Each plot shows the p-value of accepting the null hypothesis that there is no causal effect of lagged extreme chainlets. The x-axis shows the maximum lag chosen in each test. The time intervals is 30 minutes.

Granger Causality (60 mins)



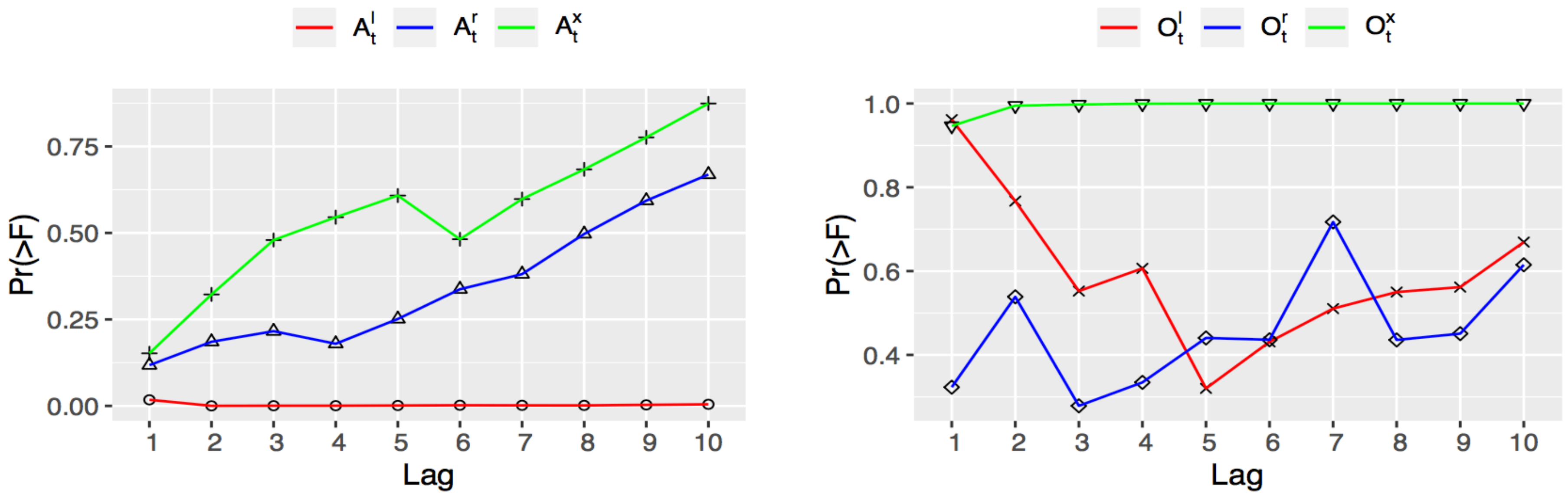
The results from applying a Granger Causality test of extreme chainlet amounts (left) and extreme chainlet occurrences (right) as predictors of volatility. Each plot shows the p-value of accepting the null hypothesis that there is no causal effect of lagged extreme chainlets. The x-axis shows the maximum lag chosen in each test. The time intervals is 60 minutes.

Granger Causality (120 mins)



The results from applying a Granger Causality test of extreme chainlet amounts (left) and extreme chainlet occurrences (right) as predictors of volatility. Each plot shows the p-value of accepting the null hypothesis that there is no causal effect of lagged extreme chainlets. The x-axis shows the maximum lag chosen in each test. The time intervals is 120 minutes.

Granger Causality (240 mins)



The results from applying a Granger Causality test of extreme chainlet amounts (left) and extreme chainlet occurrences (right) as predictors of volatility. Each plot shows the p-value of accepting the null hypothesis that there is no causal effect of lagged extreme chainlets. The x-axis shows the maximum lag chosen in each test. The time intervals is 240 minutes.

Risk Model

Interval (mins)	ARMA	eGARCH	# observations
15	(4,5)	(3,5)	99795
30	(5,0)	(2,2)	49923
60	(4,3)	(1,0)	24967
120	(5,5)	(1,0)	12483
240	(4,4)	(2,5)	5985
Daily	(5,4)	(4,4)	1040

The selected ARMA-eGARCH(X) models together with the training set size for each time interval

Sign Bias Test

Interval (mins)	Sign Bias	Negative Sign Bias	Positive Sign Bias	Joint Effect
15	3.573***	2.562**	15.411***	244.357***
30	3.452***	3.204***	1.841*	17.932***
60	12.259***	8.041***	41.833***	1816.407***

Comparison of the sign bias test results across different intervals using the ARMA- eGARCHX model.

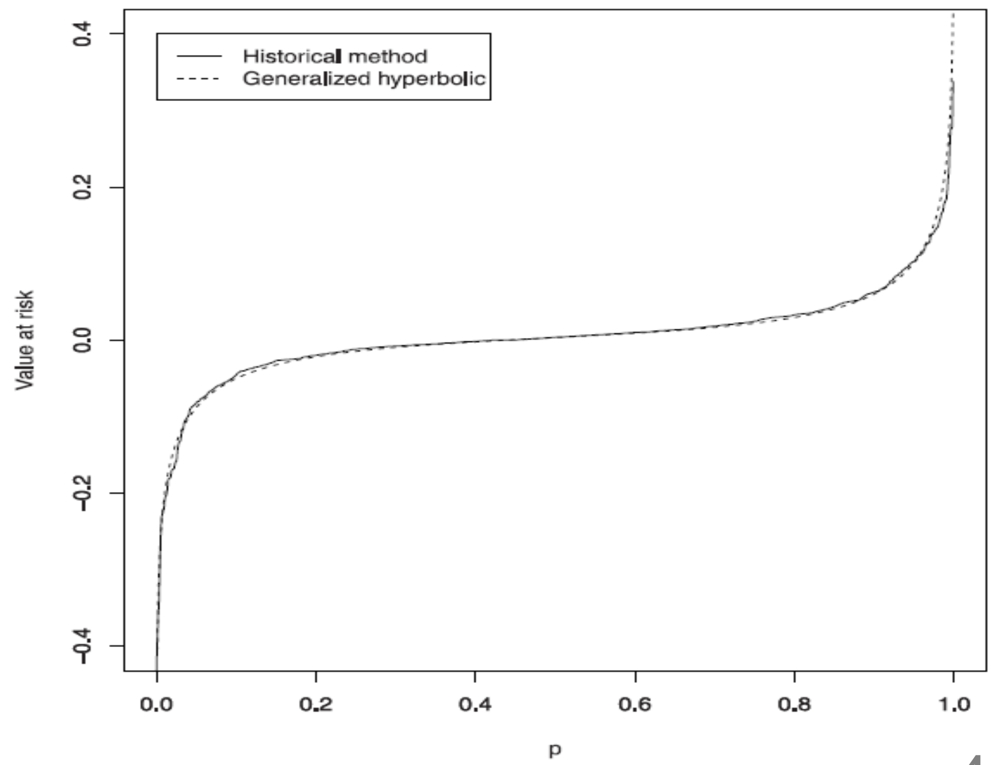
Bitcoin Value at Risk (VaR)

Value at Risk is the maximum loss, which should not be exceeded during a specified period of time with a given probability level. Let $f(x)$ be the probability density function of this distribution.

$$P\big(X \leq -VaR(1-\alpha)\big) = \alpha$$

$$\int_{-\infty}^{-VaR(1-\alpha)} f(x)\,dx = \alpha$$

The fitted values for the daily VaR appear very close to the historical estimates (Chu et al., 2015).



Backtesting Risk Model

Interval (mins)	Backtest Length	Expected Breaches	Actual VaR Breaches w/o chainlets	Actual VaR Breaches with chainlets
15	99545	995.5	1023	1014
30	49673	496.7	512	501
60	24717	247.2	261	249
120	12233	122.3	141	126
240	5735	57.4	74	59
Daily	790	7.9	19	12

Comparison of the VaR backtesting performance with and without the chainlet regressors.
Each row represents different time intervals of 15, 30, 60, 120, 240 minutes and days.

Backtesting Risk Model

Interval (mins)	Unconditional Coverage Null-Hypothesis:	Kupiec Correct Breaches	
		w/o chainlets	with chainlets
15	LR.uc Statistic:	11.306	7.291
	LR.uc Critical:	3.841	3.841
	LR.uc p-value:	0.001	0.005
	Reject Null:	YES	YES
30	LR.uc Statistic:	8.060	1.854
	LR.uc Critical:	3.841	3.841
	LR.uc p-value:	0.003	0.210
	Reject Null:	YES	NO
60	LR.uc Statistic:	4.671	1.755
	LR.uc Critical:	3.841	3.841
	LR.uc p-value:	0.035	0.223
	Reject Null:	YES	NO
120	LR.uc Statistic:	3.771	1.317
	LR.uc Critical:	3.841	3.841
	LR.uc p-value:	0.056	0.259
	Reject Null:	NO	NO
240	LR.uc Statistic:	28.515	1.516
	LR.uc Critical:	3.841	3.841
	LR.uc p-value:	0	0.242
	Reject Null:	YES	NO
Daily	LR.uc Statistic:	11.306	1.955
	LR.uc Critical:	3.841	3.841
	LR.uc p-value:	0.001	0.195
	Reject Null:	YES	NO

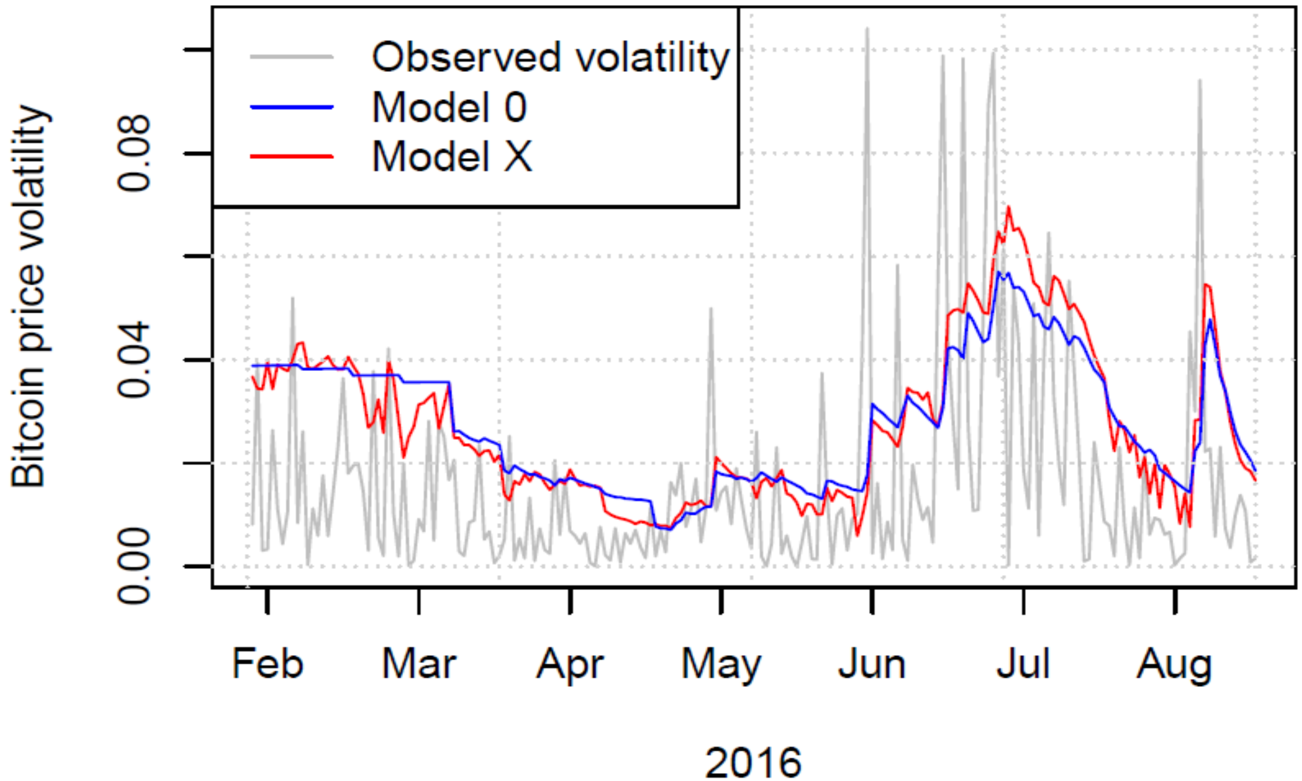
Comparison of Kupiec's unconditional coverage test results for the VaR breaches, with and without the chainlet regressors. Each row represents different time intervals of 15, 30, 60, 120, 240 minutes and days.

Backtesting Risk Model

	Unconditional Coverage	Christoffersen	
Interval (mins)	Null-Hypothesis:	Correct Breaches & Independence of Failures	
		w/o chainlets	with chainlets
15	LR.uc Statistic:	9.124	6.899
	LR.uc Critical:	5.991	5.991
	LR.uc p-value:	0.007	0.029
	Reject Null:	YES	YES
30	LR.uc Statistic:	14.025	2.105
	LR.uc Critical:	5.991	5.991
	LR.uc p-value:	0.001	0.157
	Reject Null:	YES	NO
60	LR.uc Statistic:	6.982	1.592
	LR.uc Critical:	5.991	5.991
	LR.uc p-value:	0.03	0.213
	Reject Null:	YES	NO
120	LR.uc Statistic:	9.773	2.547
	LR.uc Critical:	5.991	5.991
	LR.uc p-value:	0.008	0.141
	Reject Null:	YES	NO
240	LR.uc Statistic:	32.487	1.855
	LR.uc Critical:	5.991	5.991
	LR.uc p-value:	0	0.173
	Reject Null:	YES	NO
Daily	LR.uc Statistic:	14.389	2.738
	LR.uc Critical:	5.991	5.991
	LR.uc p-value:	0.001	0.154
	Reject Null:	YES	NO

Comparison of Christoffersen's conditional coverage test results for the VaR breaches, with and without the chainlet regressors. Each row represents different time intervals of 15, 30, 60, 120, 240 minutes and days

Analyzing Price Volatility with Chainlets cont...



Out of sample Bitcoin price volatility forecast for 2016.

The model with chainlet covariates, *Model X*, tends to describe the Bitcoin price volatility more accurately than the volatility model without chainlet covariates i.e., *Model 0* (Akcora et al., 2018).

Diebold-Mariano Test

In empirical applications it is often the case that two or more time series models are available for forecasting a particular variable of interest.

- actual values $\{y_t; t = 1, ..., T\}$
- two forecasts: $\{\hat{y}_{1t}; t = 1, ..., T\}$ $\{\hat{y}_{2t}; t = 1, ..., T\}$

Question: Are the forecasts equally good?

Diebold-Mariano Test

We define the loss differential between the two forecasts by

$$d_t = g(e_{1t}) - g(e_{2t})$$

and say that the two forecasts have equal accuracy if and only if the loss differential has zero expectation for all t.

Diebold-Mariano Test

So, we would like to test the null hypothesis

$$H_0 : E(d_t) = 0 \;\; \forall t$$

versus the alternative hypothesis

$$H_1 : E(d_t) \neq 0$$

The null hypothesis is that the two forecasts have the same accuracy. The alternative hypothesis is that the two forecasts have different levels of accuracy

Diebold-Mariano Test

Under the null hypothesis, the test statistics DM is asymptotically $N(0,1)$ distributed. The null hypothesis of no difference will be rejected if the computed DM statistic falls outside the range of $-z_{\alpha/2}$ to $z_{\alpha/2}$, that is if

$$|DM| > z_{\alpha/2},$$

where $z_{\alpha/2}$ is the upper (or positive) z-value from the standard normal table corresponding to half of the desired α level of the test.

Under a quadratic loss function, we reject H0 (DM=-2.2728) and conclude that the differences in the model residuals are significant at the 95% level (p = 0.023)

Summary and Outlook

Extreme chainlets capture information on conjunctive bitcoin transaction scenarios which are leading indicators of price and volatility movement

Combining chainlets with econometric models leads to a more comprehensive analysis of market risk

Current work is investigating the use of chainlets as an early warning indicator to stabilize Bitcoin markets

Resources

Publications:

- *BHeist: Topological Data Analysis for Ransomware Payment Detection on the Bitcoin Blockchain*, in preparation, 2019
- *Blockchain Analytics for Intraday Financial Risk Modeling*, to appear in Digital Finance, 2019
- *Blockchain Data Analytics*, Journal of IEEE Intelligent Informatics, 20(1), 2019
- *Bitcoin Risk Modeling with Blockchain Graphs*, Economic Letters 173 (1), 138-142, 2018. arxiv:1805.04698

Source code and data:

github.com/cakcora/CoinWorks

Workshops:

samsi — Workshop on Blockchain Analytics, Fall 2019

IEEE ICDM 2019 — November 8-11, 2019 in Beijing — Workshop @ IEEE International Conference on Data Mining