Airdrop games

And other blockchain launch models

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Launching a new blockchain

Several open questions

Success depends on enough people being convinced of value of the project and/or to contribute

Public good?

Public Goods

- Definition: Non rivalrous/non excludable (Samuelson 1954)
- Problem: free riding!
- Why?
- A. Smith (1776): Street lamps
  - One person enjoys, does not detract from other person’s enjoyment
  - Can’t charge every person for amount they use

Public goods games

- Classic type of game in experimental economics

- N players
- Endowment w
- Can contribute x, cost c(x)
- Contributions are summed, multiplied and distributed to all
- Output per capita o(X), $X=\Sigma x_i$
- Individual utility $U=w-c(x_i)+o(X)$
- O' is marginal per capita return
- Linear case w-x+mX
- Individual rationality: corner solution, invest all if m>1, else nothing

- Collective rationality: invest all if m>1/N

“Airdrop games”
logit dynamics in a contribution game

SUBMITTED

- A specific case of a public goods game
  - That we think corresponds well the the blockchain case with miners/SPOs
- Success depends on these players contributing
- Classic Nash: best response
  - Either contribute or not
  - Just do what gives higher payoff, even if difference is ε
- Logit: better response
  - Allows for experimentation
  - Logit dynamics select Nash equilibria (“good” equilibria)
  - Even if noise vanishing!

Why logit?

- Allows for experimentation
  - $P_i = \exp(\beta U_i)/\Sigma \exp(\beta U)$
  - where i=1,..,I all possible actions

- Plenty of support in experimental economics

- Nash + logit fits behavior well
  - In simple normal form games, mixed strategy equilibria, traveler's dilemma, auctions…
- Even better, logit equilibrium (QRE)

Logit dynamics

- Players choose sequentially
- In each period, one chosen and informed of number of contributors
- Decide on action
    - (Not a complete, contingent strategy)
    - But better respond, not best
    - According to logit rule

Parameters

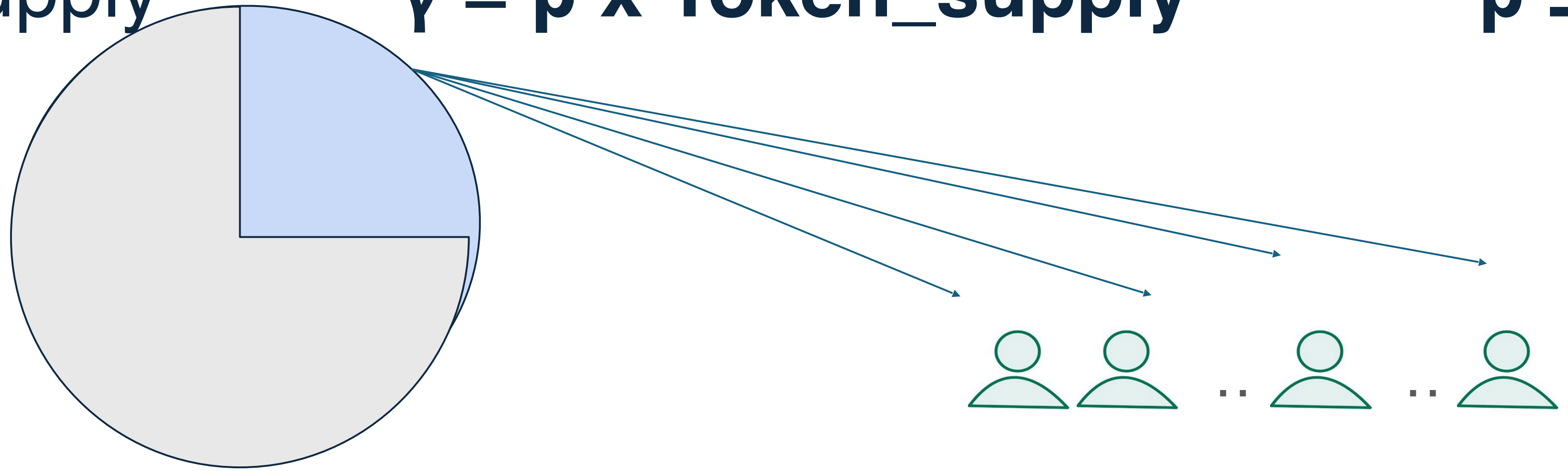
1. **γ** = rewards (anyway)
2. **α** = cost (if contributing)
3. **β** = rationality level

Limited → Interesting Considerations

Token_supply

γ = ρ x Token_supply

ρ ≤ 1



Example

Threshold “technology”

V(**a**) = “high” or “low” if at least 50% contribute

Quadratic “technology”

V(**a**) = l^2   for l = “number of contributors”

Bad and good Nash equilibria

None contributes

50% contribute

Why do good equilibria appear?

“Noisy” best response model

- Even in cases where free riding is best response, $m<1$ (threshold makes no difference)
- Some people might experiment
- If enough do, then the next player becomes pivotal
- For pivotal player contribution is clearly a best response

Results

Tradeoffs

1. Higher costs (and/or smaller noise) $\rightarrow$ More time
2. Rewards don’t accelerate convergence…
3. …but help to maintain good equilibrium

Non vanishing noise

Theorem 6. *For any threshold technology* (32) *with airdrop rewards* (2) *and any inverse noise parameter* $\beta > 0$*, the probability of selecting the high value outcome* (33) *is monotone increasing in the rewards* ρ *and, in particular, it has the following form:*

$$p_{high}(\rho) = \frac{1}{1 + C \cdot \exp(-\rho B)} \qquad B = \frac{\beta}{n} \cdot (V_{high} - V_{low}) \; , \tag{35}$$

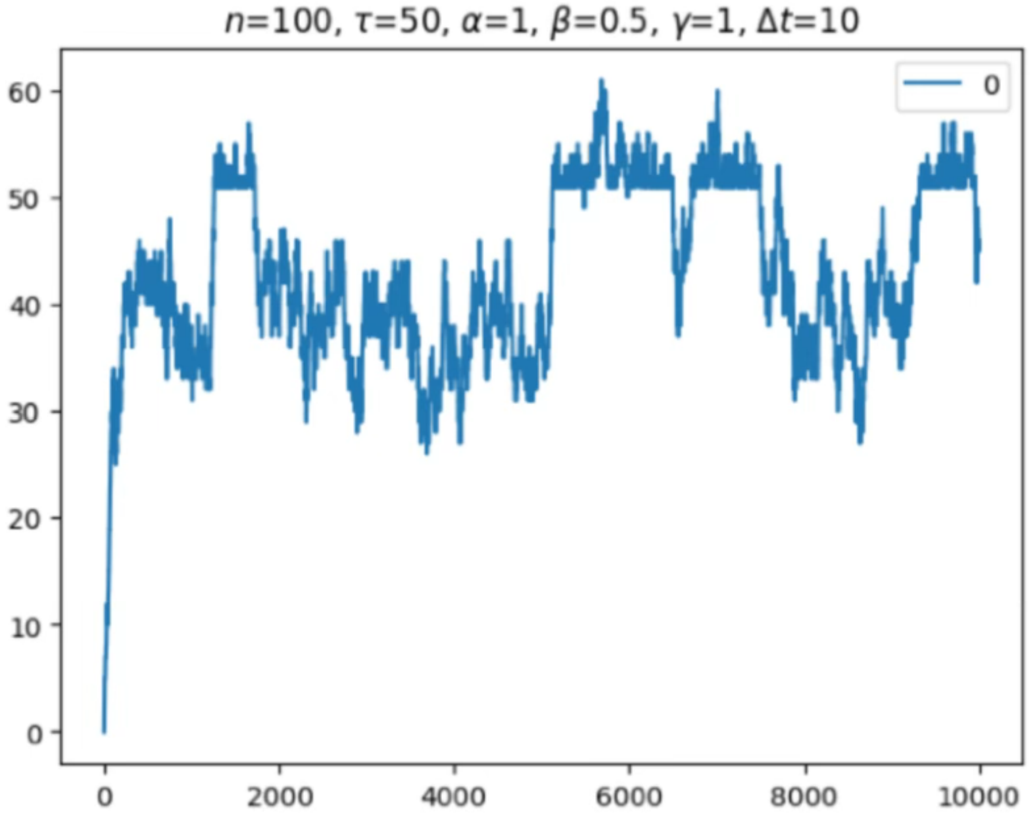
where $C = C(\alpha\beta, n, \tau) = \frac{1-p_{high}(0)}{p_{high}(0)}$ *does not depend on rewards* ρ *nor on the values* V_{low} *and* V_{high}.[4]

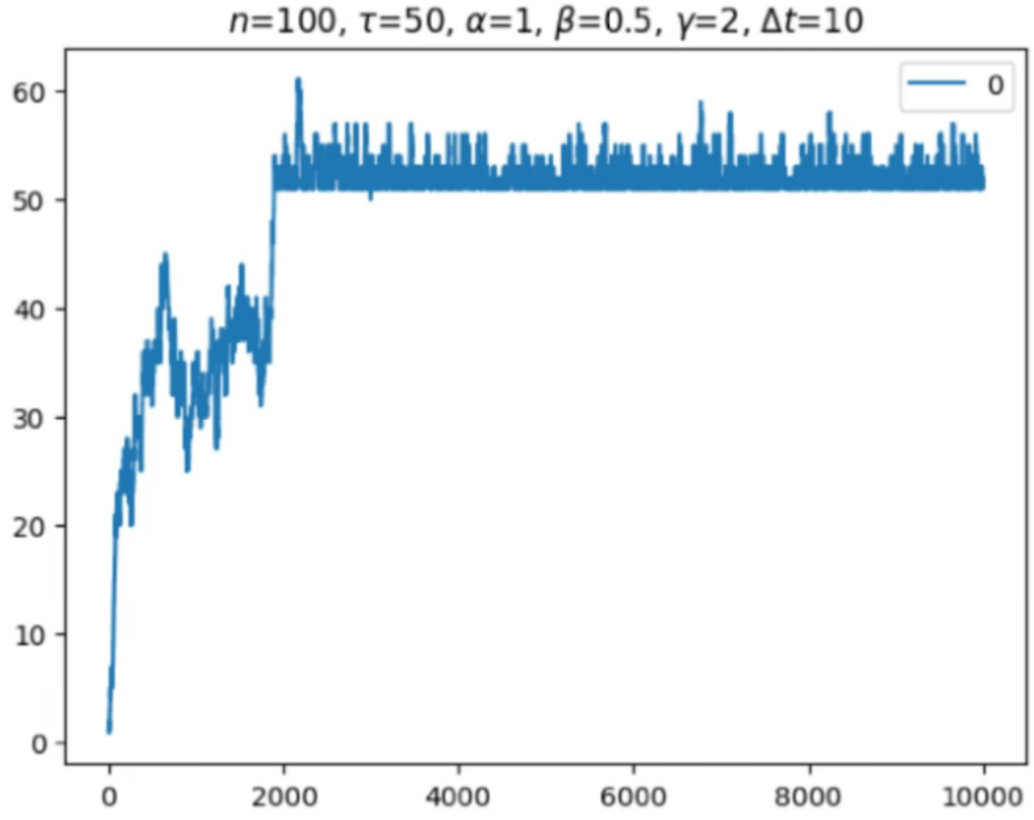
Average contribution level

$$\ell^* = n \cdot p_{\alpha\beta} \ , \qquad\qquad p_{\alpha\beta} := \frac{1}{1 + \exp(\alpha\beta)}$$

- Only depends on αβ

Rewards stabilize dynamics





Tradeoffs

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2. Rewards don't accelerate convergence…
3. …but help to maintain good equilibrium

"Technology" matters

1. Quadratic $\neq$ Threshold…

Partnerchain framework application

1. Reduced cost (Cardano SPOs), do not pay in ADA

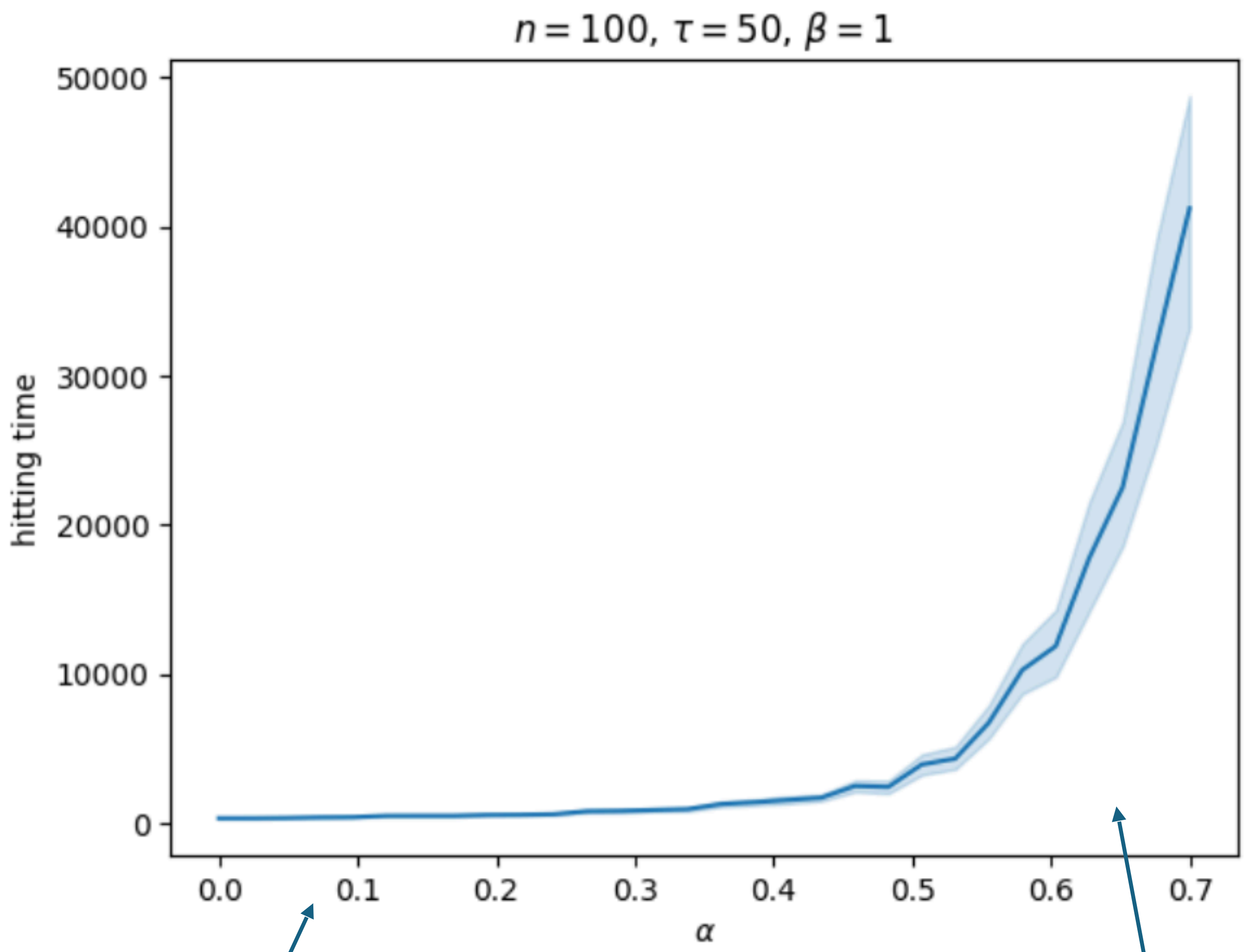
General Framework

1. Technology value V(a)
2. Good vs bad equilibria, role of rewards (and other parameters)

Designer Strategy

1. Low airdrop → No contribution → Fail
2. High → Contribution, but not convenient for designer
3. Medium → Contribution + good (profit) for designer ?

Application: 3 cases depending on contribution cost



Governance

Layer 2 projects/
sidechains

Brand new blockchains

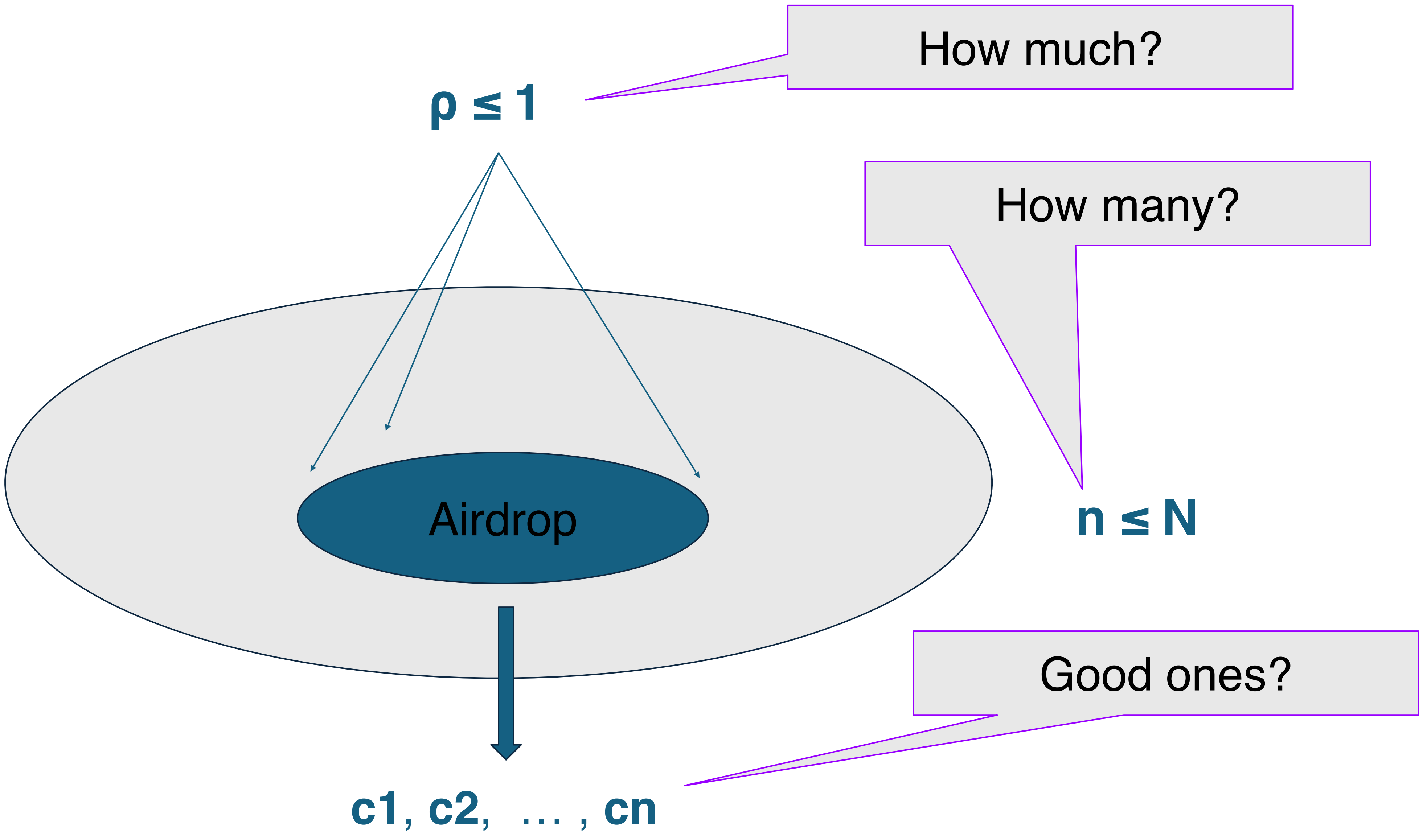
Newest results (next paper?)

- Suppose designer observes total contribution result in every period
- Gives every token holder rewards proportional to that sum
  - even if they didn't contribute
- This can help achieve the good equilibrium
- And can be beneficial for designer
  - (Making sure that rewards calibrated to not cause much inflation)

Conclusions

- Logit dynamics allow for high contribution equilibria (known)
- The exact technology matters
- In some cases partnering with an existing blockchain helps, because it lower costs of experimentation

Appendix



Dissipation of airdrop (rewards): ρ/n each vs costs c_i

1. Designer chooses **ρ**
2. Players reach some (pure Nash) **equilibrium a**
3. Value of system is V(**a**) and price of token

$$t(\mathbf{a}) = V(\mathbf{a}) / (\text{Token supply})$$

Further results:

1. **Characterization of equilibria** (higher **ρ** → higher contributions **a** → higher system value and token price), heterogeneous costs too.
2. **Highest possible system value** for **ρ = 1** ("bad" technologies/design result in "low" contribution →"low" value).
3. **Tradeoffs** (system value, social cost, social welfare, designer's profit)

Appendix
Model 2: Signalling

- The information that is provided by the issuers can be though of as a (potentially costly) signal

- How do receivers of the signal process it?
- Are they convinced to buy/contribute?

Spence (1973) job signalling

- Questions:
  - How much effort (time, cost) should signal sender spend?
  - How reliable is the signal?
  - Is there a good signalling equilibrium?

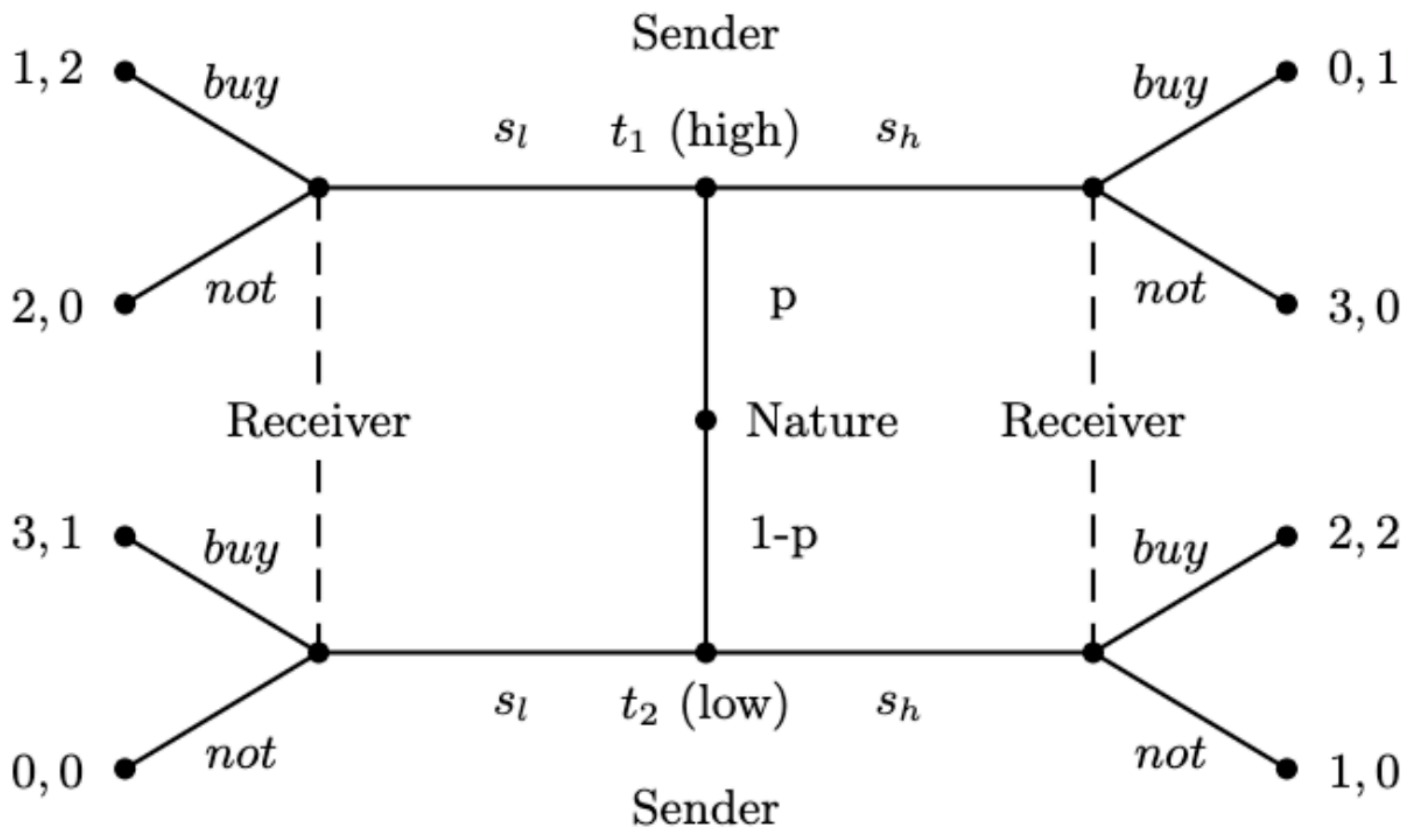
- Spence's application: education and jobs
  - How do job candidates signal skills?
  - What is the role of education?

Education signalling

- Two groups of people, I and II
    - Proportion p and 1-p
    - Cost of education level y is: y and y/2
    - Marginal productivity: 1 and 2
- Employer believes there is educ. threshold y* for which marginal productivity is:
    - 1 if $y<y^*$
    - 2 if $y>y^*$
    - Offers wages equal to MP

- If signalling effective
    - group I chooses y=0 if $1>2-y^*$
    - group II chooses y=y* if $2 - \frac{y}{2}>1$
- $1<y^*<2$, so beliefs are confirmed

Separating equilibria and effective signalling



Separation:
Each type sends a different signal
Bayesian receiver perfectly
knows who is who

High type happy not with separation

Low type also not!

From education to IPOs

- Leland & Pyle (1977) analyze signals in IPOs

- Good companies should send clear signals
    - the owner should keep control of a significant percentage of the company
- Signal needs to be reliable
    - Bad companies should find imitation hard

- Other strategies possible
    - Underpricing

What about ICOs

- Need to estimate payoffs and prior beliefs
  - Payoffs of good vs bad tokens
  - Belief that a given token, before seeing any signal, is of ”high quality”

- Also to consider what signals can be sent
  - How many?
  - Dimensions?
  - Types?

- Test the signals?

Getting data to check/test hypotheses

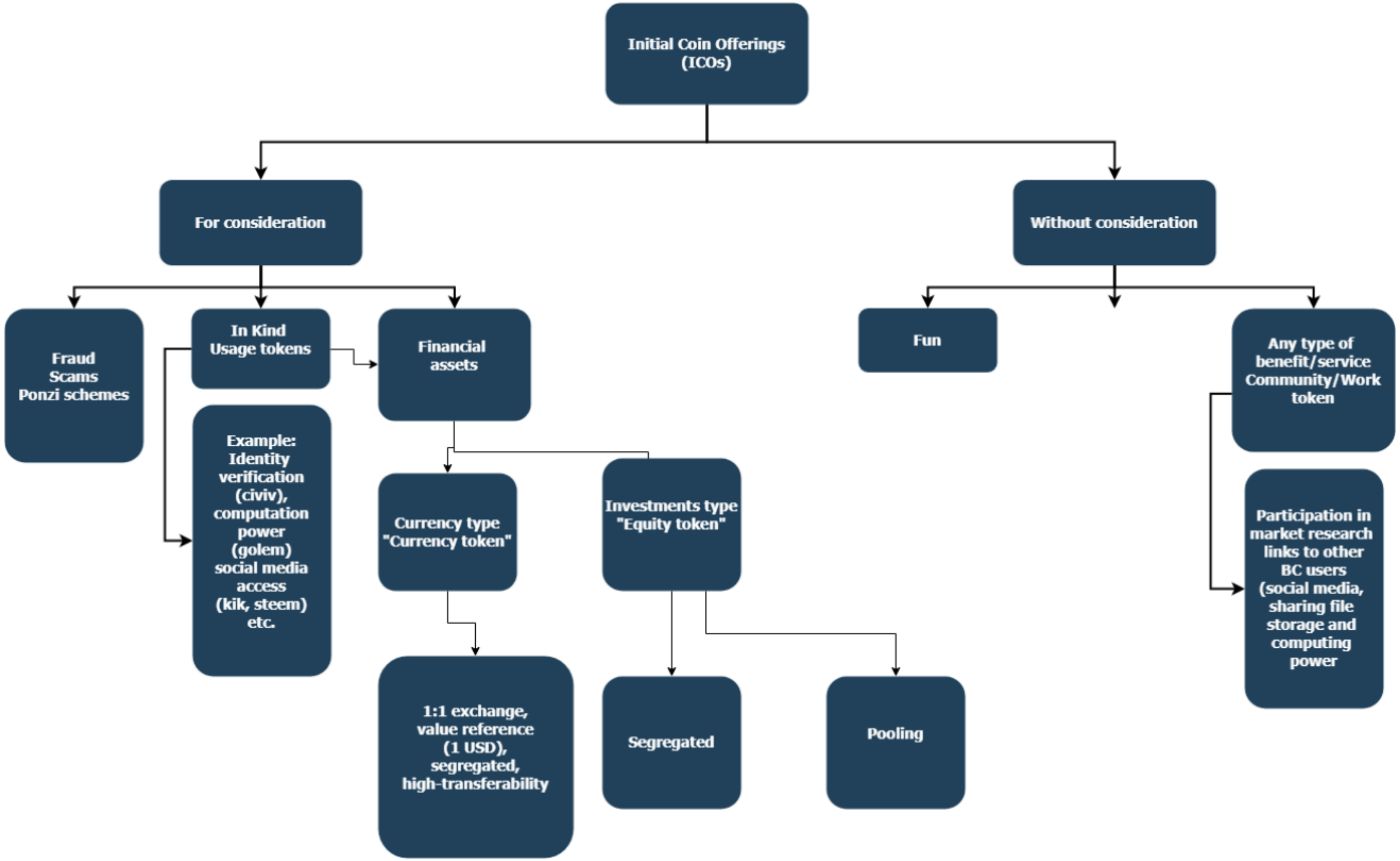
- Field data
  - Coinmarketcap
  - Coingecko
  - Other aggregators…

- Survey/experiment data
  - Who to target?

I. Field data
Building an ICO database

- It seems around 25,000 cryptocurrencies exist
- Large heterogeneity in
  - Quality
  - Purpose
  - Success!

ICO taxonomy



Current database

- 7200 ICOs
  - from 2016 to 2020
- 11 sources
  - Etherscan.io, coindesk, coingecko, cryptocompare, ICObench, ICODrops, ICOrating, ICOmarks, icodata, Foundic, TokenData
  - Merging info and choosing most trustworthy
- ICO characteristics
  - % for sale
  - Hardcap
  - Whitelist
  - Kyc
  - Team member size
  - Presale
- Socia media
  - Reddit
  - Twitter
  - Medium

Summary descriptives

Variable	Mean	Std. dev.	Min	Median	Max	Obs.
Panel A: ICO variables						
ICO characteristics						
hardcap	294.73	9,371.63	0.00	20.00	523,000.00	3,698
% for sale	0.56	0.24	0.00	0.57	1.00	3,938
presale	0.52	0.50	0.00	1.00	1.00	5,450
presale raised	0.04	0.19	0.00	0.00	1.00	5,450
kyc	0.50	0.50	0.00	1.00	1.00	5,450
whitelist	0.40	0.49	0.00	0.00	1.00	5,450
# team members	10.62	8.02	1.00	9.00	74.00	3,476
ICO outcomes						
raised dummy	0.45	0.50	0.00	0.00	1.00	5,450
amount raised, conditional on raising (US$ million)	13.11	89.68	0.00	3.80	4,197.96	2,473
raised-to-hardcap, conditional on raising	0.44	0.39	0.00	0.29	1.00	1,950
listing	0.41	0.49	0.00	0.00	1.00	2,473

How many ICOs are successful?

Variable	Mean	Std. dev.	Min	Median	Max	Obs.
ICO end-to-open returns						
ICO return, conditional on listing (%)	384.39	936.82	2.96	46.25	3,870.72	1,007
ICO return, unconditional (%)	99.75	646.98	−100.00	−100.00	3,870.72	2,442
ICO first-day returns						
ICO first day return (%)	9.71	22.82	−19.67	1.62	75.86	1,170
Longer-term cumulative post-ICO returns						
30-day return (%)	−2.64	80.38	−78.60	−29.69	233.42	1,159
90-day return (%)	−0.22	127.45	−94.33	−47.70	415.91	1,136
180-day return (%)	−7.74	149.40	−97.65	−70.43	489.57	1,083
365-day return (%)	−38.03	110.38	−99.28	−85.04	337.34	894

Analysis: what determines ICO success

Variable	(1) *raised dummy*	(2) log(*amount raised* + 1)	(3) *raised-to-hardcap*	(4) *listing dummy*
% for sale	−0.073*	−1.504**	−0.133***	−0.214***
	(−1.759)	(−2.240)	(−4.806)	(−6.333)
hardcap (log)	0.001	0.362***	−0.033***	0.010
	(0.179)	(2.877)	(−5.918)	(0.740)
whitelist	−0.021	−0.006	0.058***	0.034
	(−0.994)	(−0.017)	(2.921)	(0.901)
kyc	0.160***	2.580***	0.124***	0.221***
	(4.718)	(5.354)	(6.482)	(6.939)
white paper	0.039**	0.687**	0.051***	0.057**
	(2.024)	(2.560)	(4.208)	(2.205)
team members size (log)	0.084***	1.347***	0.043***	0.067***
	(6.079)	(5.905)	(3.467)	(3.877)
presale	−0.008	−0.179	−0.026*	0.033**
	(−0.369)	(−0.575)	(−1.740)	(2.088)
Commits at ICO start (log)	0.020***	0.298***	0.016***	0.021***
	(4.394)	(4.542)	(4.762)	(4.223)
Twitter at ICO start (log)	−0.002	−0.027	0.002	−0.010**
	(−0.442)	(−0.421)	(0.489)	(−2.190)
Reddit at ICO start (log)	−0.010**	−0.151**	−0.013***	−0.035***
	(−2.402)	(−2.376)	(−4.625)	(−5.342)
BTCTalk at ICO start (log)	0.029***	0.432***	0.006**	0.011***
	(10.135)	(8.988)	(2.120)	(2.950)
Medium at ICO start (log)	0.009	0.178	0.021***	0.021***
	(1.025)	(1.472)	(3.435)	(3.591)
Observations	2,322	2,364	2,364	1,292
R^2	0.201	0.284	0.310	0.333
Year-month fixed effects	Yes	Yes	Yes	Yes
Industry sector fixed effects	Yes	Yes	Yes	Yes
Geographical region dummy	Yes	Yes	Yes	Yes

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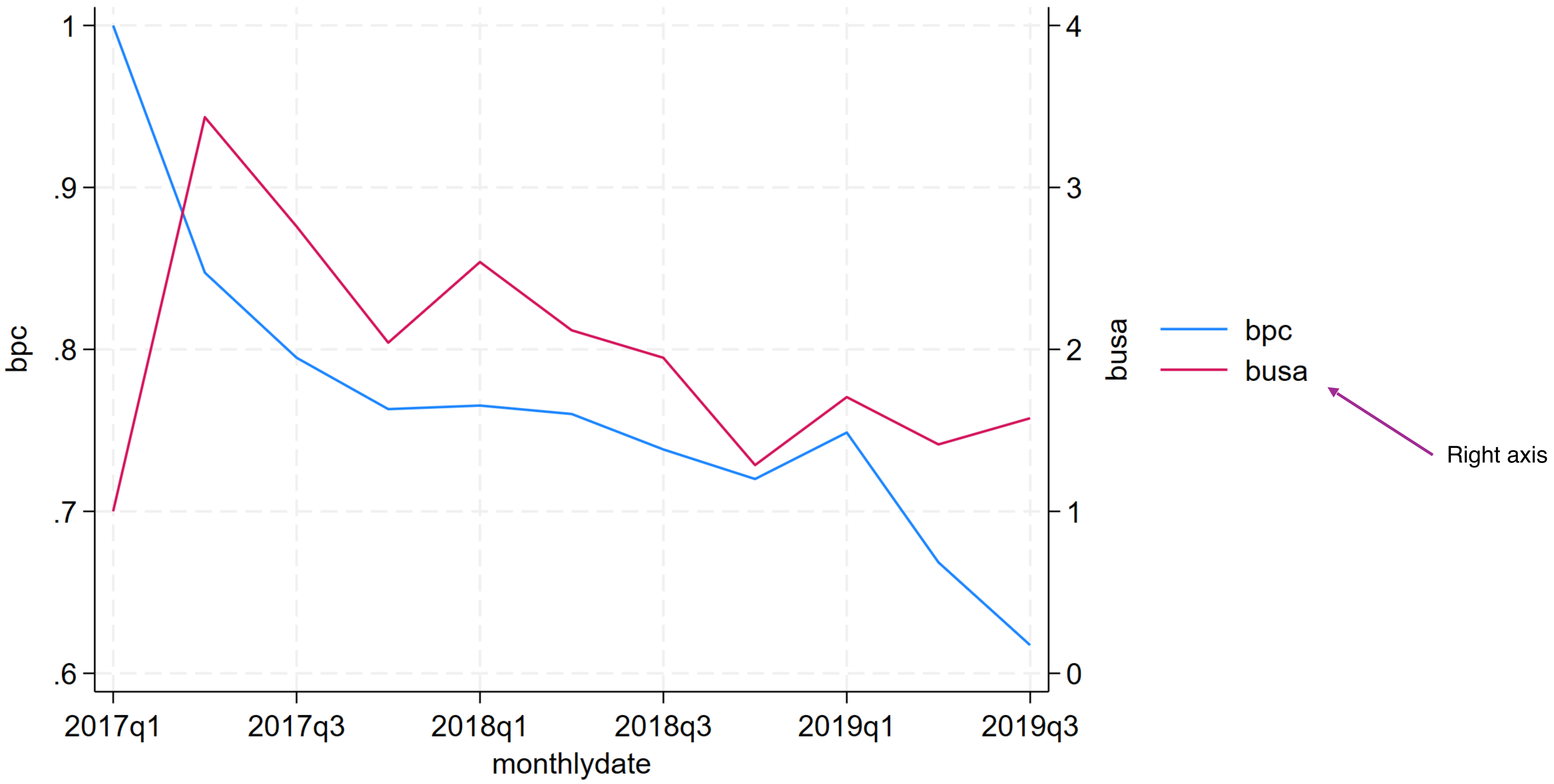
?

Timeseries

- What changes over time?
  - Presale?
  - % sale?
  - Team size
  - Kyc
  - Others?

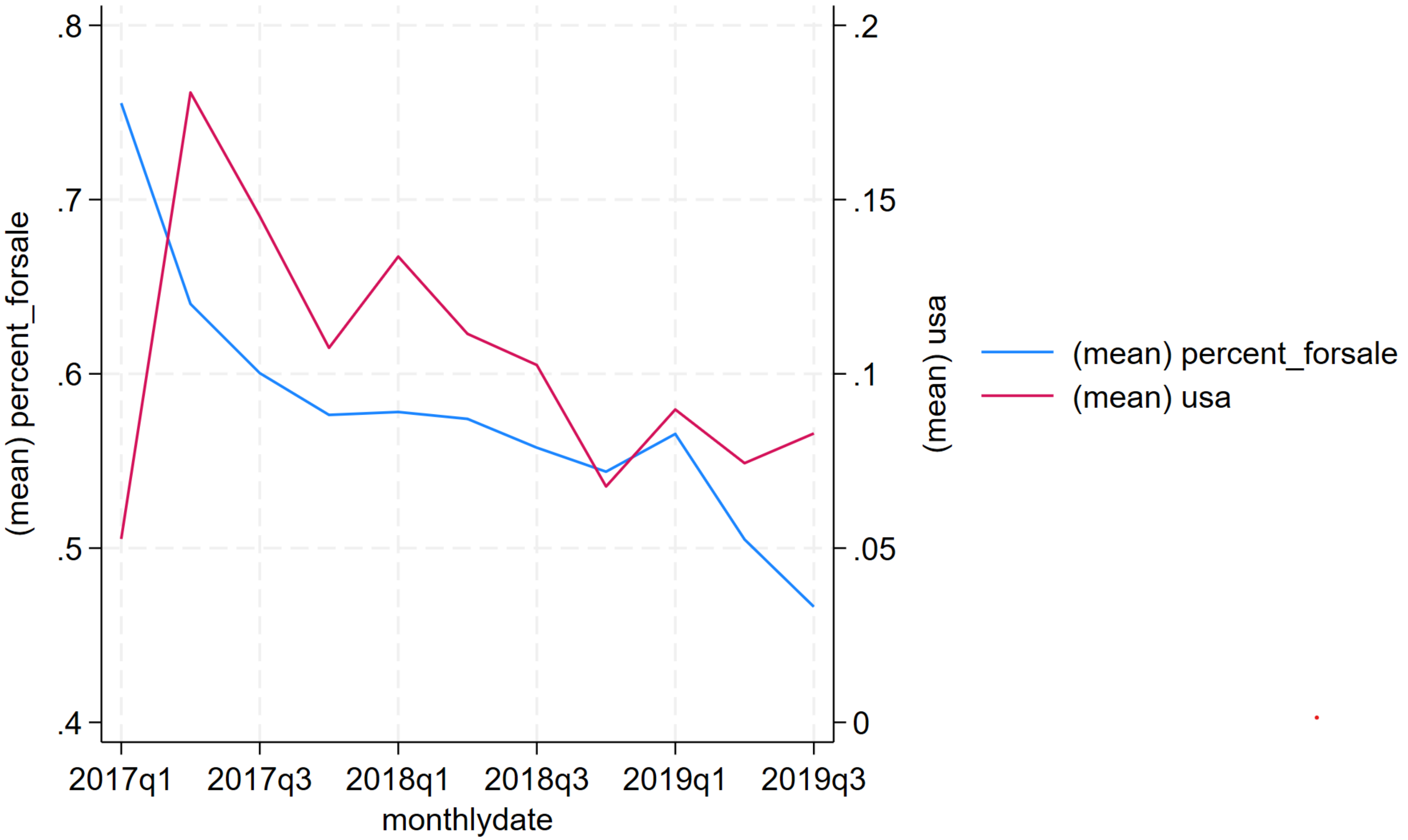
Timeseries

2017 q1 as baseyear



Timeseries

absolute



Expanding the ICO database

- Newer data
  - Harder because variety increased, NFT, defi etc

- Getting data (in the case of the major ICOs?) on exact airdrop strategy, relation with previous blockchains (partnerchain) etc