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Don't trust, verify: The economics of scams in initial coin offerings

Kenny Phua[a] Bo Sang[b] Chishen Wei[c,d] Gloria Yang Yu[c]

[a]University of Technology Sydney
[b]University of Bristol
[c]Singapore Management University
[d]Hong Kong Polytechnic University

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THE STRAITS TIMES

$12.8m OCBC phishing scams: 20-year-old is first person to plead guilty

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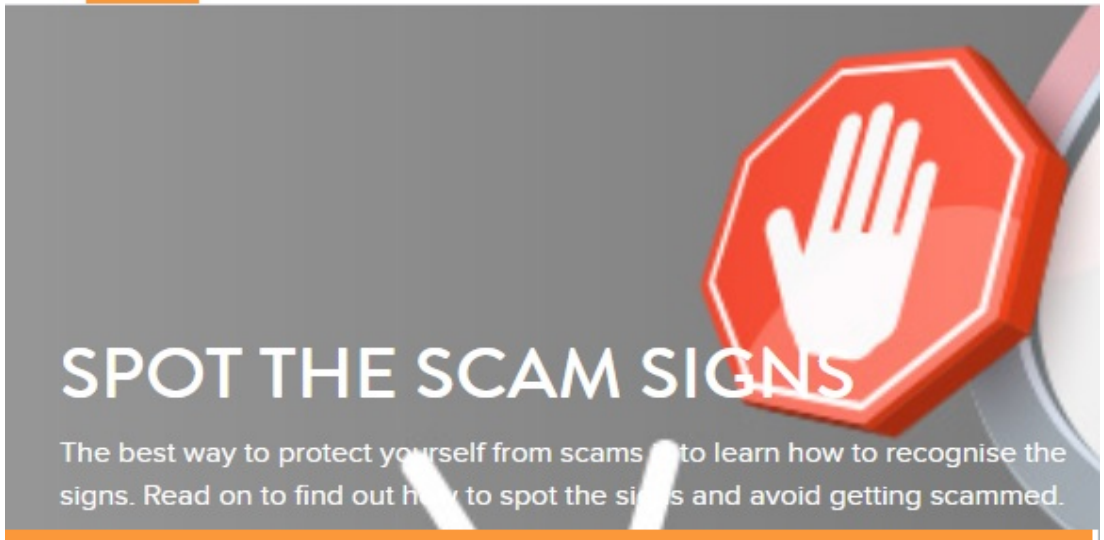
SINGAPORE - The first person linked to the OCBC phishing scams involving about $12.8 million has admitted in a district court to offences including money laundering.

Described as a "serial and prolific offender" by the prosecution, Leong Jun Xian, 20, had his own agents working under him to source for bank accounts which would be provided to the syndicates involved in the scams.

ANTI-SCAM HELPLINE: **1800-722-6688** (Mon – Fri, 9am – 5pm, exc

SCAM ALERT



SPOT THE SCAM SIGNS

The best way to protect yourself from scams is to learn how to recognise the signs. Read on to find out how to spot the signs and avoid getting scammed.

COULD THIS BE A SCAM?

Do you suspect that you are involved in a scam? Search our site to see if there are similar stories that match your circumstances. Search with key words such as 'online love', 'transfer money' or via email addresses, phone numbers, bank account numbers, etc.

search for scam | Search by Type | Search

Financial frauds and scams are widespread

Global costs of fraud and scams exceed $5 trillion annually.

- Large social and psychic costs.
- From a welfare perspective, some important issues to understand are:
  - Prevalence of fraud (Egan et al. 2019)
  - Circumstances under which fraud arises (Dimmock et al. 2021)

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Empirical challenge:
We rarely observe interactions between perpetrators and victims.

ICOs are a unique lab to study the economics of scams

Initial coin offering (ICO): Crowdfunding for blockchain projects.

Exploit the richness of data in the ICO market.

- $\sim$ \$50 billion dollars raised through 2020.
- "Rife with fraud, scams, and abuses" (Gensler 2021).

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Unique features:

- We observe how issuers market ICOs to investors.
- Public availability of blockchain data.

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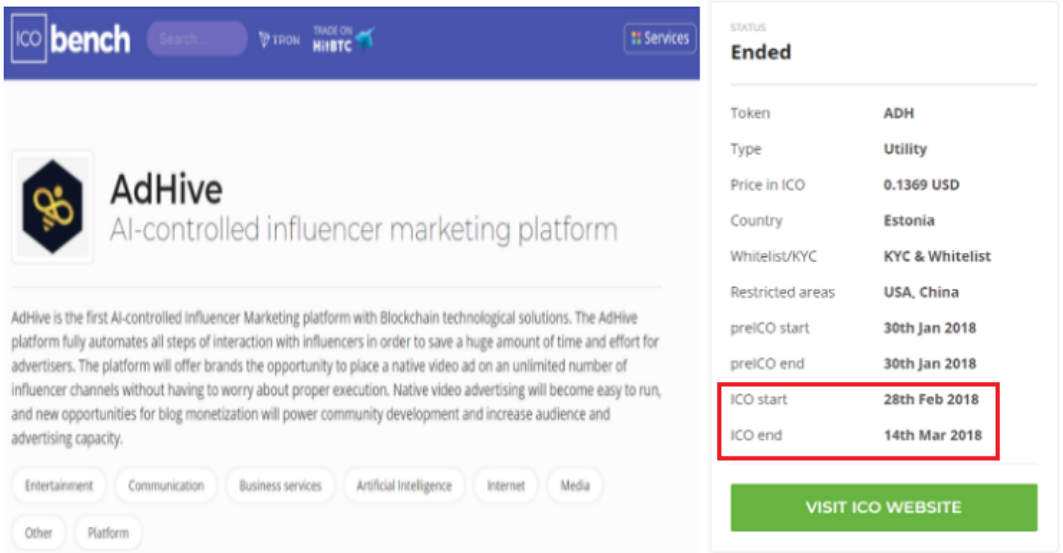
Our paper aims to do two things:

- Shed light on the economics of financial scams.
- Show how malicious actors/scammers target their victims.

AdHive ICO on ICOBench.com



Financial

Token info

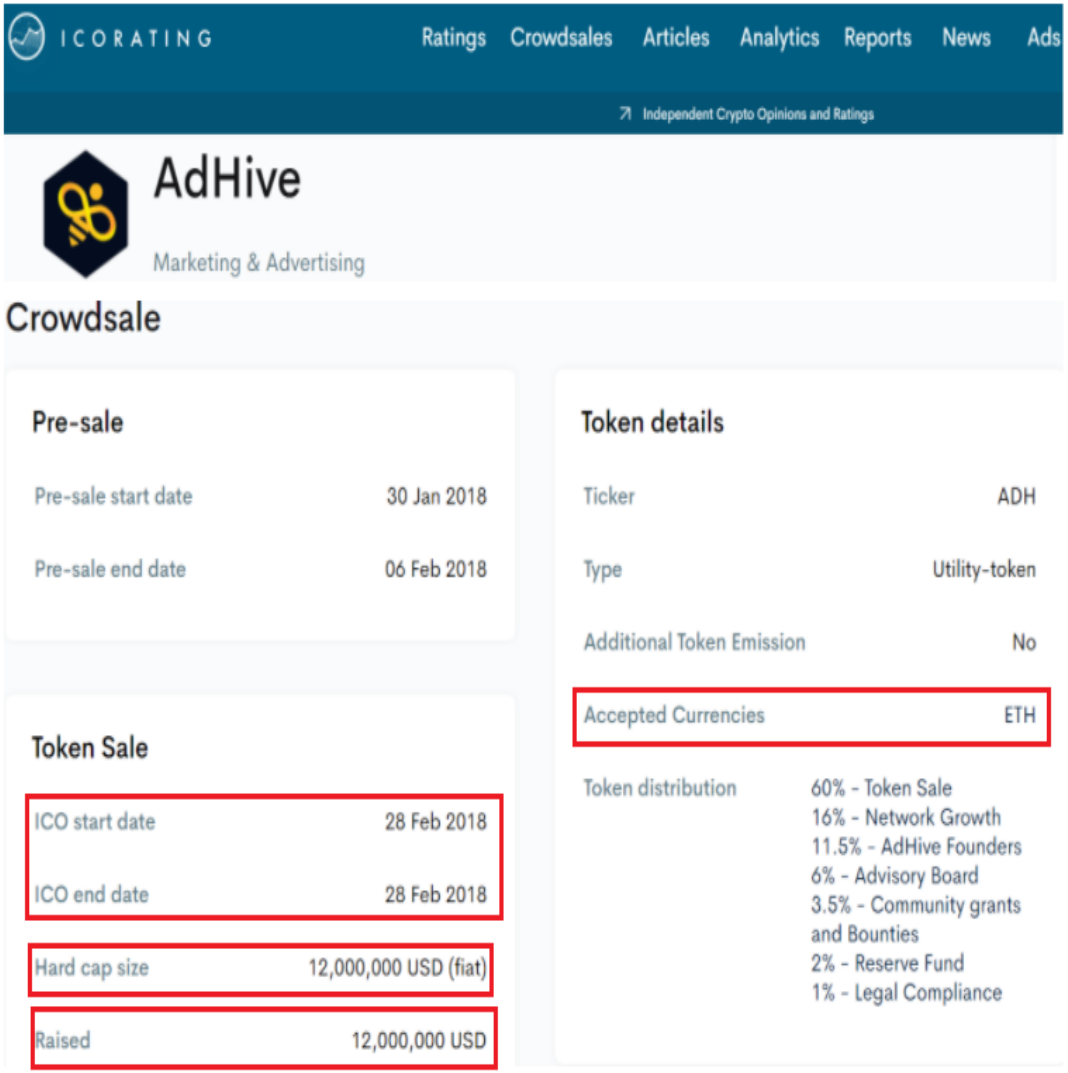
Token	ADH
Platform	Ethereum
Type	ERC20
Price in ICO	0.1369 USD

BONUS
Pre-sale: 15%-30% Bonus Token Sale Phase #1: 0%-15% Bonus

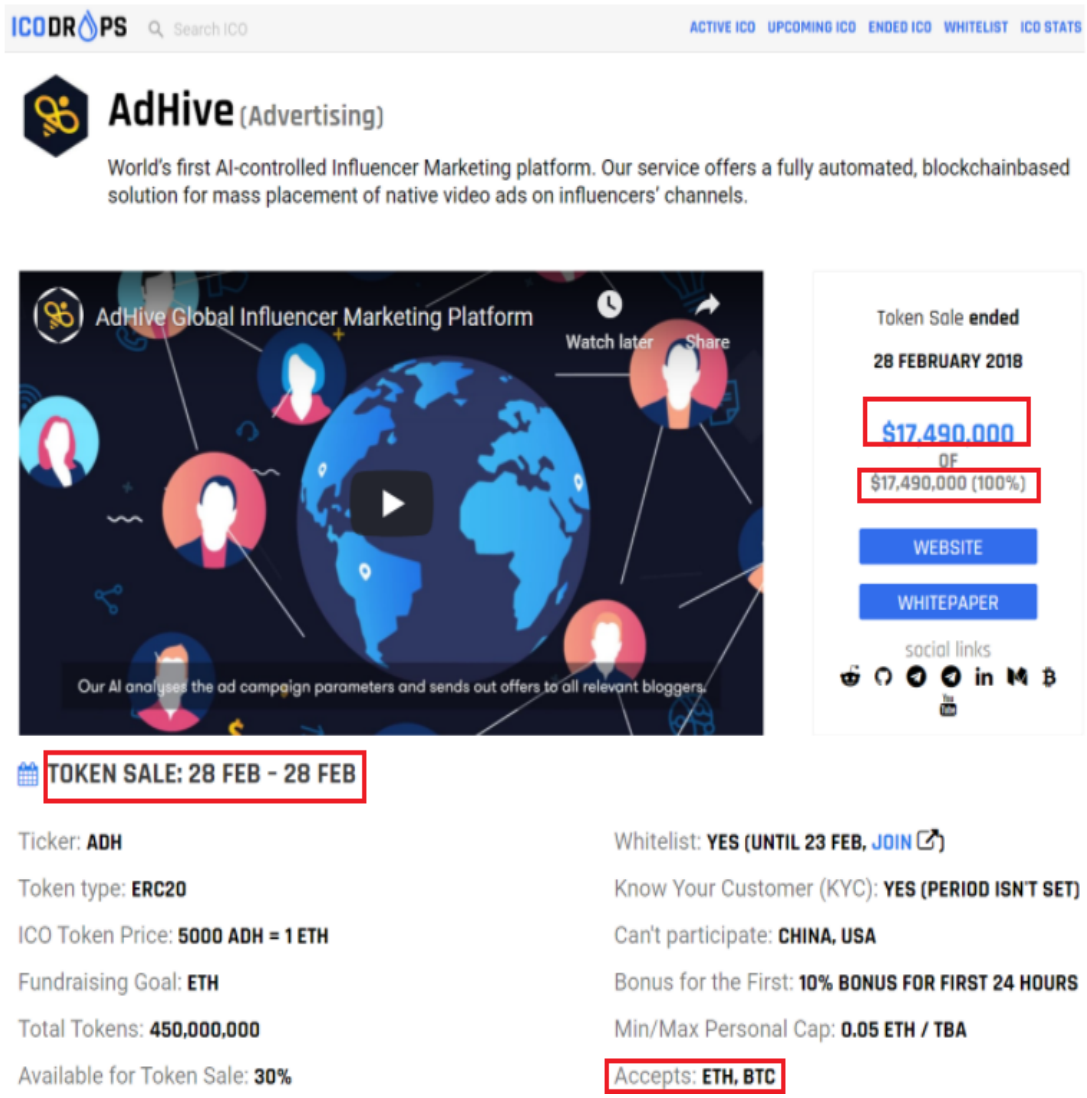
Investment info

Min. investment	0.05 ETH, 0.005 BTC
Accepting	ETH, BTC, Fiat
Distributed in ICO	60%
Soft cap	2,000,000 USD
Hard cap	12,000,000 USD
Raised	$12,000,000

AdHive ICO on ICORating.com



AdHive ICO on ICODrops.com

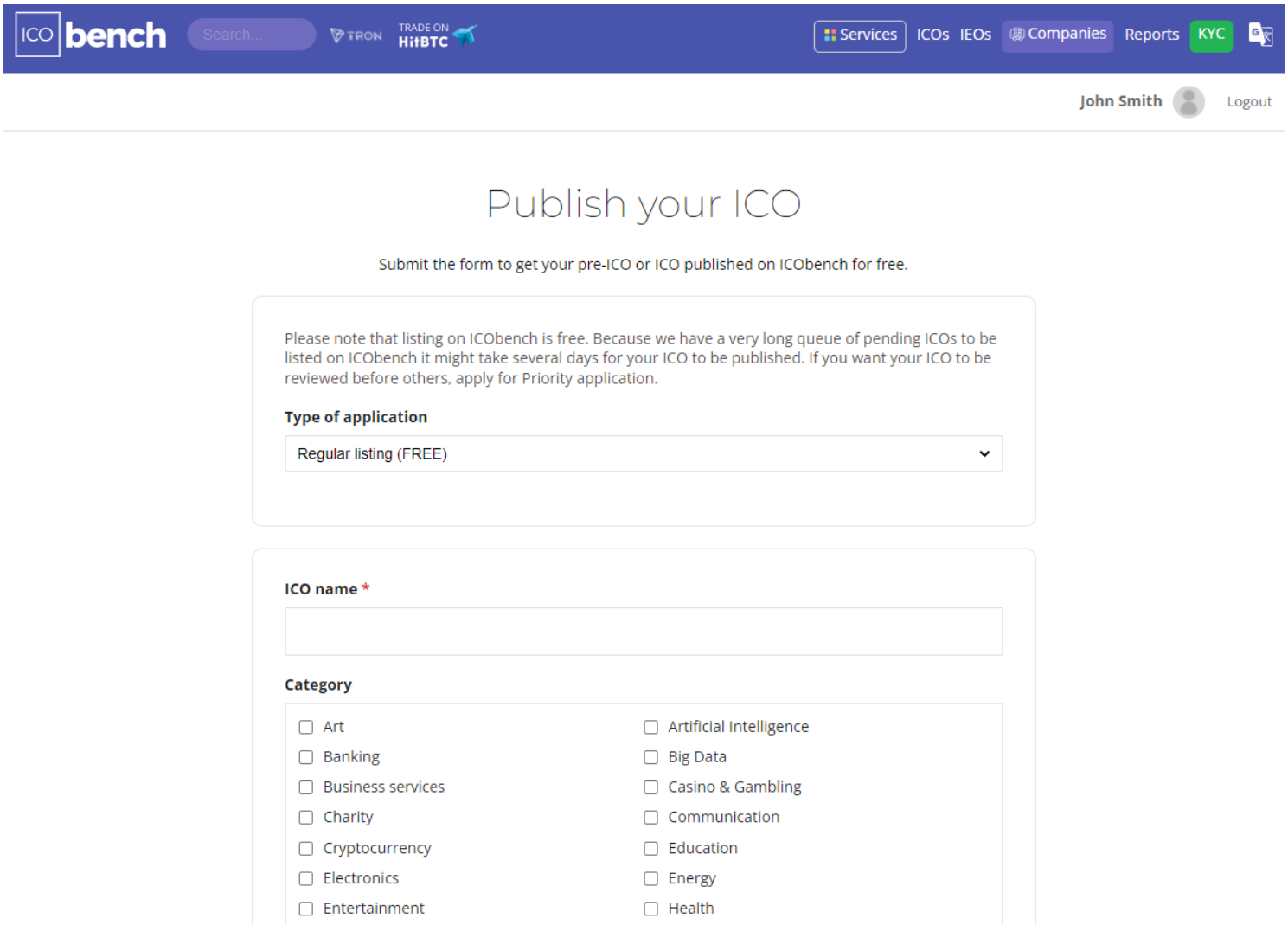


Example: The AdHive ICO across 3 websites

	ICOBench	ICORating	ICODrops
Start date	28 Feb 2018	28 Feb 2018	28 Feb 2018
End date	14 Mar 2018	28 Feb 2018	28 Feb 2018
Softcap	-	$2 M	-
Hardcap	$12 M	$12 M	$17.49 M
Raised funds	$12 M	$12 M	$17.49 M
Accept BTC	Y	N	Y
Accept ETH	Y	Y	Y
Accept USD	Y	N	N

Note: Listing websites are not exchanges/brokerages.

Creating an ICO listing is straightforward



Puzzling phenomenon

34% of ICOs in our sample have at least one discrepancy.

- Under U.S. securities laws, misrepresentations (misreps) are mis-statements of material facts.

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Why do so many issuers fail to accurately report ICO details?

- Carelessness is an unsatisfying explanation.
- We work hard to address this story.

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- We work hard to address this story.

Our hypothesis:
Misreps are used as a screening device to screen out astute investors and retain naïve investors.

Screening model and main results

A malicious issuer runs a financial scam

Issuer faces a mass m of investors.

- n naïve and $(m - n)$ astute investors.
- Investor types are unobservable, ex ante.

Naïve vs. astute investors

- Naïve investors fund the ICO scam.
- Astute investors ultimately do not fund it.

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- Astute investors ultimately do not fund it.

Both types can seek information and ask questions.

- To answer questions, issuer must expend effort to respond.
- Astute types are undesirable because they ask questions but ultimately don't fund the ICO.

Scammers hate questions

"it is important for everyone to know [...] how much these scammers hate when you ask questions"

—Kitboga (alias), Youtube (2.4M subscribers) vigilante

"We embrace new technologies, but we also want investors to see what fraud looks like. I encourage investors to do their diligence and ask questions."

—Former SEC Chairman Jay Clayton

Malicious issuer's targeting strategy

- Investor i tolerates d_i misreps before dismissing a ICO.
- Naïve investors are more tolerant on average.
- Issuer forms a targeting strategy by choosing d^*.

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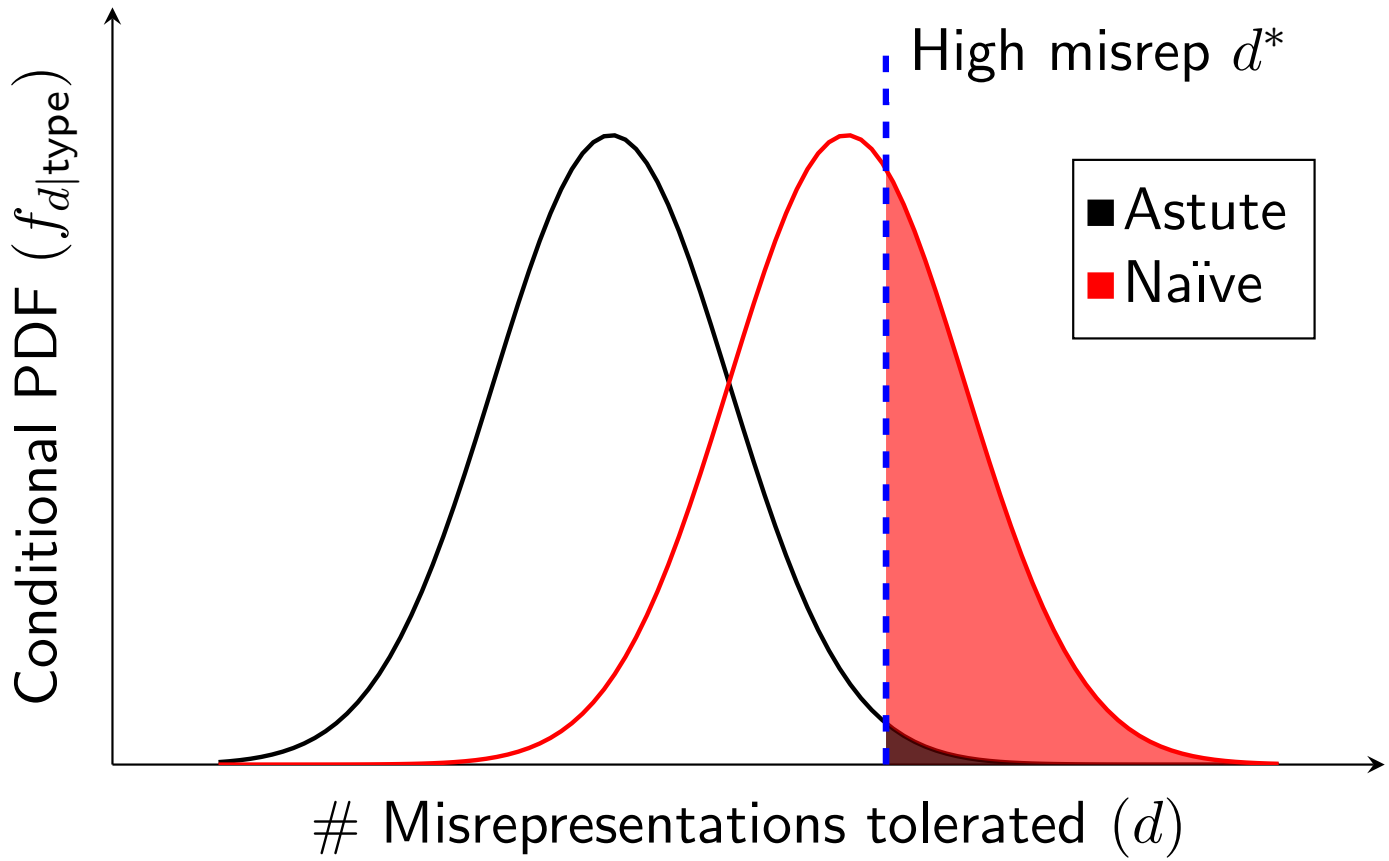
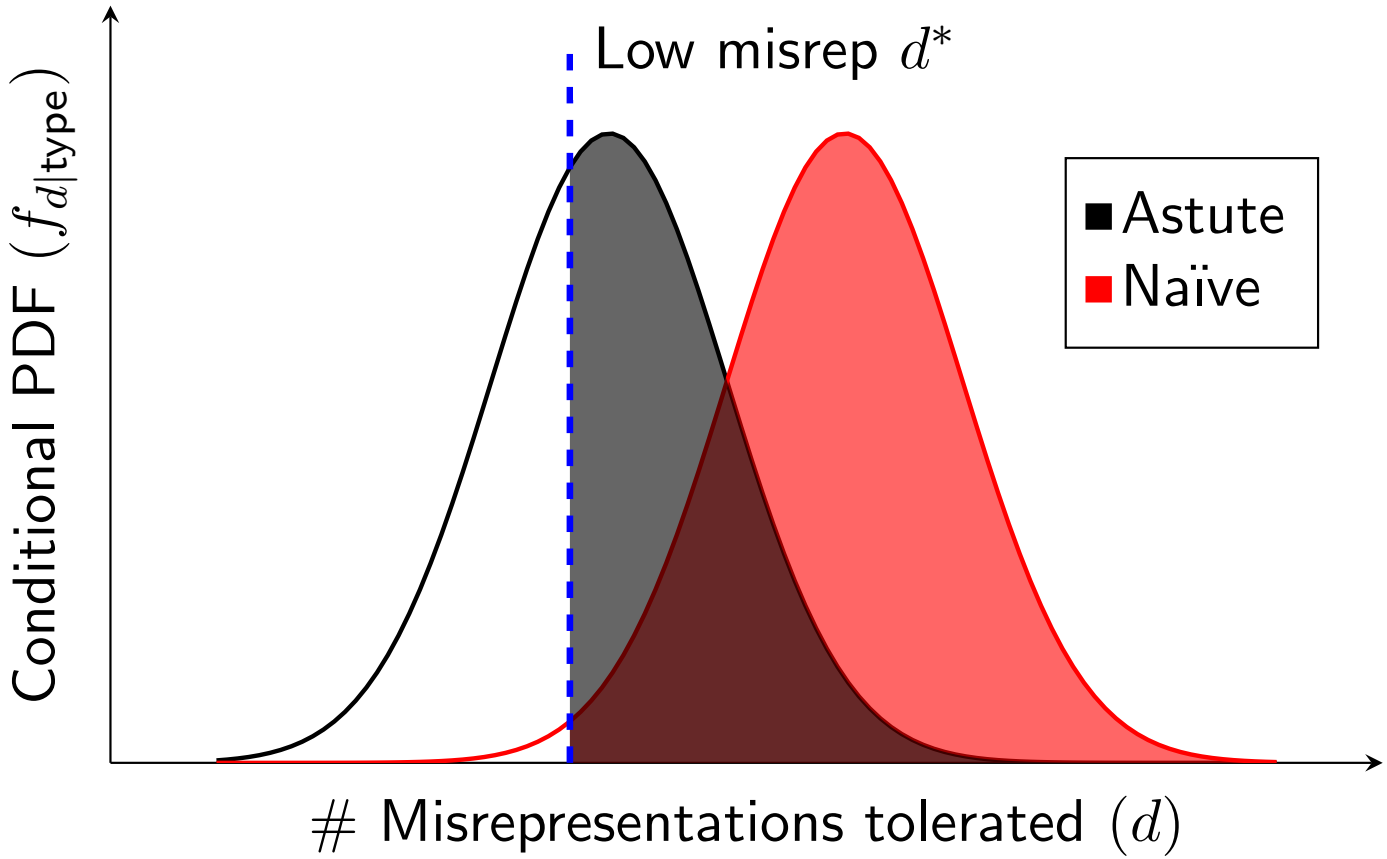
- Issuer forms a targeting strategy by choosing d^*.
- Potential investors may ask questions, which impose cost C on the issuer.
- Our story: Misrep acts as a screen for investor type.
  - Issuer sets misrep to target an optimum where they attract enough naïve investors and also screen out astute investors.

High misrep d^* targeting strategy



Screens out most of the astute investors. But also screens out many profitable naïve investors.

Low misrep d^* targeting strategy



Targets most of the naïve investors. But fails to screen out many costly astute investors who don't fund the ICO.

Misrepresentations act as a screening device

- High d^* avoids many astute investors.
  - "Safe" strategy in minimizing cost, but forgoes many profitable victims.
- Low d^* targets many naïve investors, but also attracts many astute investors.
  - Incurs high costs and is suboptimal when C is high.

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- This screening mechanism is found in other financial scams and frauds.
  - Nigerian Prince email hoax.
  - Online phishing attacks.

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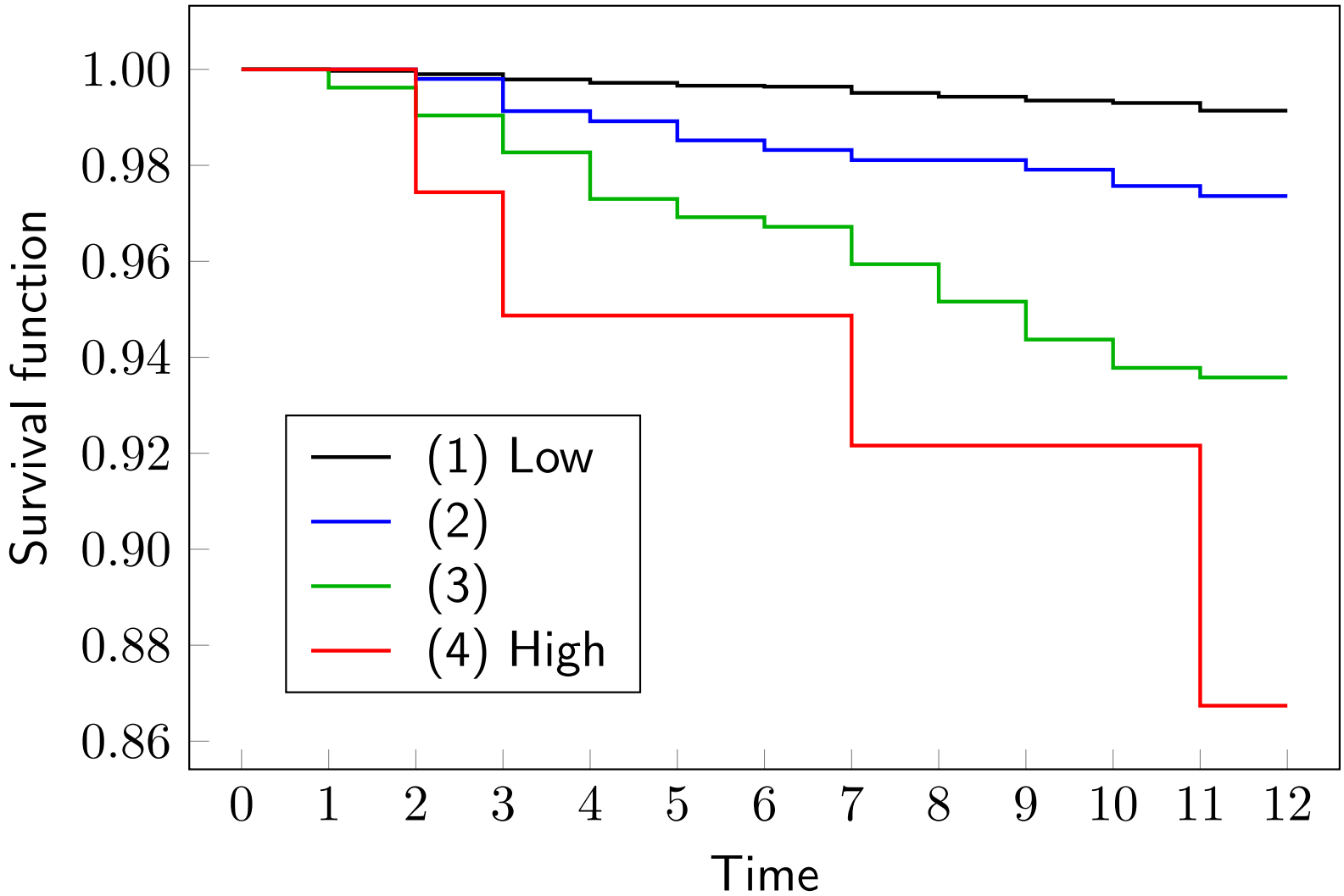
  - Online phishing attacks.
  - 1800s Letters of Jerusalem scam in France.

Data

- On the 15^{th} of every month from Aug 2018 to Aug 2019, we scrape data of ICOs listed on 5 listing websites.
- Collect data on ICO characteristics:
  - Basic: ticker, country, banned, start date, end date, duration, and accept (BTC/ETH/USD)
  - Nonbasic: softcap, hardcap, whitelist, and presale
- $\text{misrep}_i = \sum_c (\#\text{ distinct values of characteristic}_{i,c} - 1)$
- 5,935 unique ICOs; 115 are alleged scams (`DeadCoin.com`).

Distrib. misreps | Summary statistics | △ means

Misrepresented ICOs have poorer survival rates



Hazard of ICO scam rises with misreps

Event: ICO scam

	(1)	(2)	(3)	(4)
$\mathbb{1}(\text{Misrep} > 0)$	3.740			
	(5.46)			
Misrep		1.253	1.140	
		(6.71)	(2.18)	
$\text{Misrep}^{\text{basic}}$				1.240
				(4.86)
Controls	Y	Y	Y	Y
# ICOs	5,935	5,935	5,935	5,935
Cohort strata	N	N	Y	Y
Coverage-quartile FE	N	N	Y	Y
Clustered SE	N	N	Y	Y

* Cox regressions, hazard ratios

Using the blockchain: What do victims look like?

- We expect that the token holders of misrepresented ICOs are less sophisticated.
- From the Ethereum blockchain, we extract these wallet traits:
  - Value: $ value of all holdings
  - Diversity: # distinct tokens
  - Activity: # blockchain transactions
- These traits are proxies for investor sophistication.

Holders of misrepresented tokens are less sophisticated

	(1)	(2)	(3)
Dependent variable:	Value	Diversity	Activity
$\mathbb{1}(\text{Misrep} > 0)$	0.399	0.803	0.910
	(2.61)	(2.88)	(2.62)
Controls	Y	Y	Y
# ICOs	1,996	1,996	1,996
Cohort FE	Y	Y	Y
Clustered SE	Y	Y	Y

* Poisson regressions, incidence rate ratios

Are misrepresentations just unintentional mistakes?

3 sets of tests to address this explanation

Test 1 Network test: Unusual patterns of misrepresentation behavior

- Network analysis of ICOs linked by common advisors.
- Labor market outcomes of advisors.

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Test 2 Regulatory scrutiny test

- If motives are nefarious, regulatory action should deter malicious issuers.

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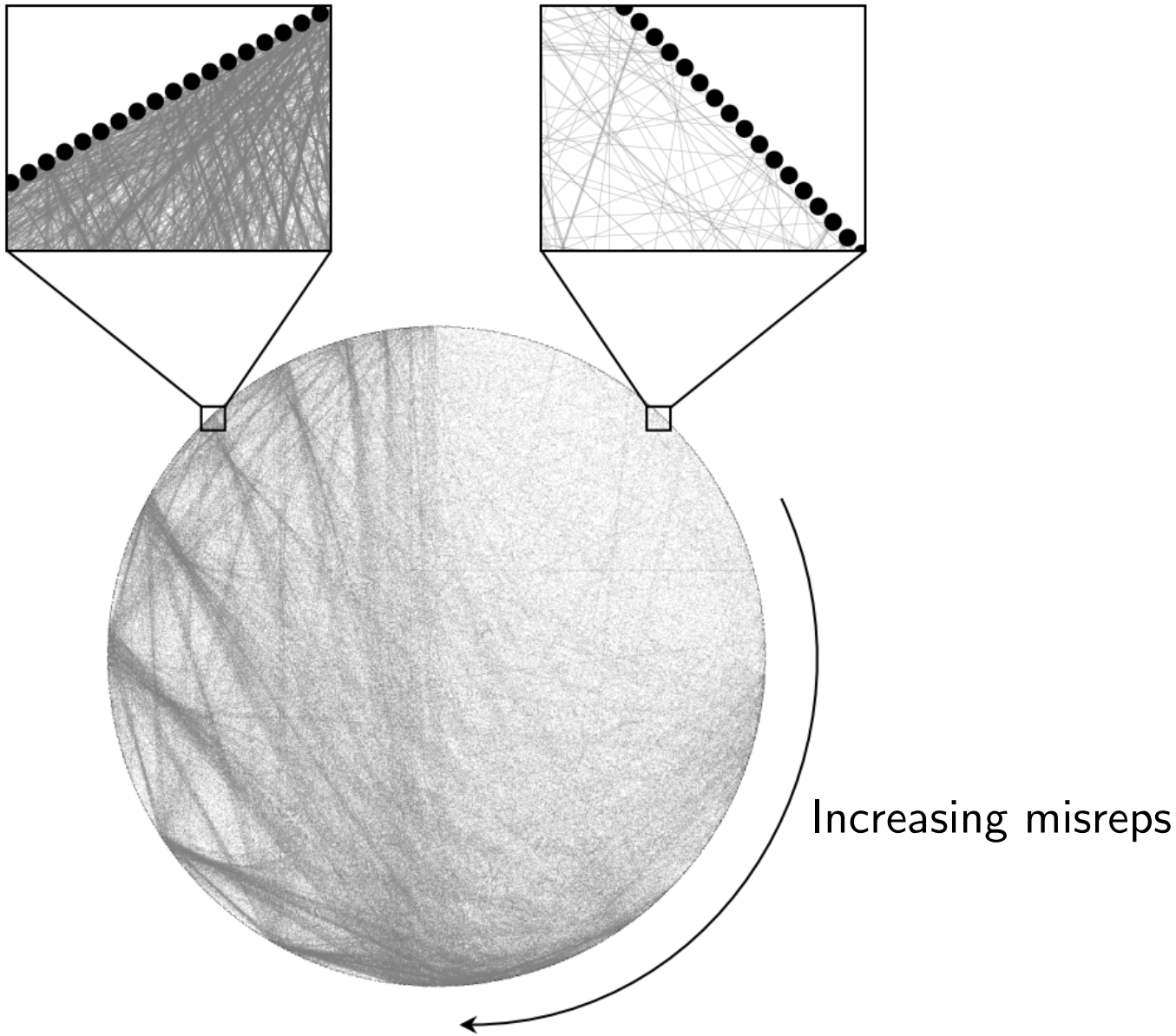
Test 3 ICO quality test

- Low quality issuers may fail to ensure their offerings are accurately marketed on websites.

Network test: Systemic patterns of misrep behavior

- If the use of misrep is intentional and strategic, we should find systematic footprints in the ICO ecosystem.
- Focus on ICO advisors who often work on multiple ICOs.
  - Pathway for complementarities: Learning and/or social norms.
  - Misrep behavior may be transmitted via common advisors.
- If so, network theory predicts that misrep behavior of an ICO is associated with its network position. Details

Central ICOs have more misreps



Central ICOs have more misreps (cont'd) Details

Dependent variable: Misrep				
	(1)	(2)	(3)	(4)
Weighted links	N	Y	N	Y
$\log$(Centrality)	1.485	1.567		
	(2.27)	(2.17)		
$\mathbb{1}$(High centrality)			1.061	1.067
			(1.96)	(2.25)
Controls	Y	Y	Y	Y
# ICOs	2,271	2,271	2,271	2,271
Cohort FE	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y

* Poisson regressions, incidence rate ratios

Advisors are not penalized for misrep in labor market

Event: Subsequent ICOs

	(1)	(2)	(3)	(4)
Consider recurrent events	N	N	Y	Y
Misrep	1.025		1.008	
	(2.94)		(2.79)	
$\mathbb{1}(\text{Misrep} > 0)$		1.172		1.090
		(2.42)		(1.75)
Controls	Y	Y	Y	Y
# ICOs	2,271	2,271	2,271	2,271
Cohort strata	Y	Y	Y	Y
Event-order strata	N	N	Y	Y
Coverage FE	N	N	Y	Y
Clustered SE	N	N	Y	Y

* Standard Cox and PWP-TT regressions, hazard ratios

Reputational costs may be insufficient deterrents (Egan et al. 2019).

Test 2: Regulatory scrutiny reduces misrep behavior

	(1)	(2)	(3)	(4)
Dependent variable:	$\mathbb{1}(\text{Misrep} > 0)$		Misrep	
$\mathbb{1}(\text{News})$	0.540		0.644	
	(3.23)		(3.90)	
News intensity		0.795		0.838
		(2.13)		(2.91)
Controls	Y	Y	Y	Y
# ICOs	5,935	5,935	5,935	5,935
Cohort FE	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y

* Poisson regressions, incidence rate ratios

Test 3: Misrep is unrelated to ICO quality

	(1)	(2)	(3)
	Source code		
Dependent variable:	$\mathbb{1}$(Posted)	$\mathbb{1}$(Audited)	Raised
Misrep	0.984	1.011	1.058
	(0.31)	(0.26)	(1.04)
Controls	Y	Y	Y
# ICOs	4,604	4,604	2,985
Cohort FE	Y	Y	Y
Clustered SE	Y	Y	Y

* Logit (Poisson) regressions, odds (incidence rate) ratios

Conclusions

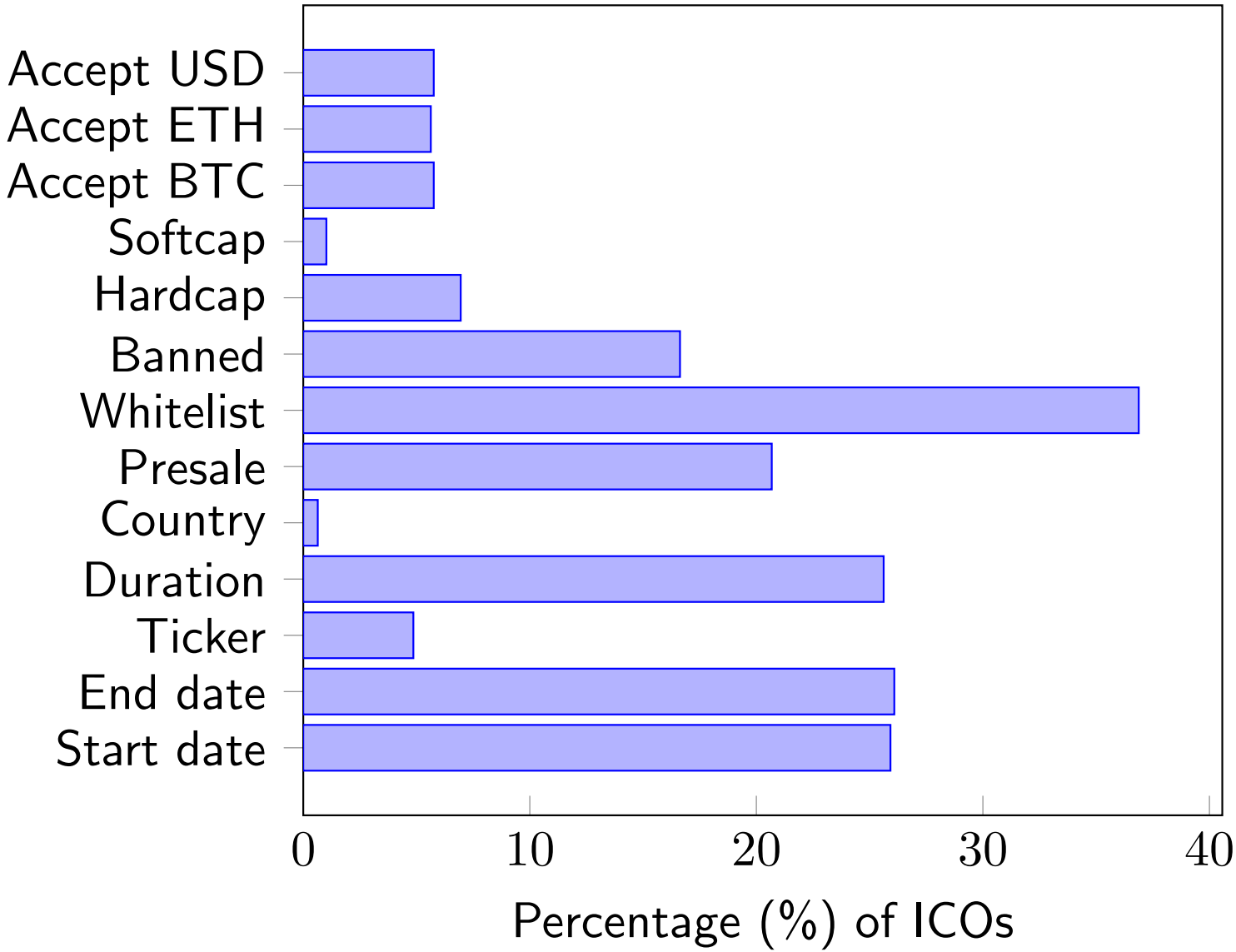
- We study the economics of scams using the ICO market as a unique lab.
- We propose a screening-based mechanism of misreps.
- Misrepresented ICOs have higher scam risk and attract less sophisticated investors.
- Misrep behavior is unlikely to be unintentional mistakes.
  - Response to regulatory scrutiny
  - No observable differences in ICO quality
  - Systematic patterns of misrep behavior

Additional content

- Model stages Figure
- Are misreps the only trick in the book? Details
- Welfare analysis Details

Appendix

Distribution of misrepresented ICO characteristics



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Summary statistics

	N	μ	σ	p10	p50	p90
Misrep	5,960	1.26	2.16	0	0	4
$\mathbb{1}_{\text{Misrep}>0}$	5,960	0.35	0.48	0	0	1
Banned	5,960	0.95	0.22	1	1	1
Whitelist	5,960	0.55	0.50	0	1	1
Presale	5,960	0.47	0.50	0	0	1
Hardcap	5,960	0.70	0.46	0	1	1
Softcap	5,960	0.26	0.44	0	0	1
Accept BTC	5,960	0.28	0.45	0	0	1
Accept ETH	5,960	0.58	0.49	0	1	1
Accept USD	5,960	0.10	0.30	0	0	0
SEC filing (%)	5,960	0.89	9.38	0	0	0
Enforcement	5,960	0.26	0.42	0	0	1
Disclosure	5,960	1.20	1.23	0	0.73	2.92
Duration (days)	5,960	54.38	50.25	15	37	109

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Differences in means

	(1)	(2)	$\Delta_{(1)-(2)}$	t
ICO scam	0.04	0.01	0.03	6.88
Banned	0.95	0.95	−0.01	0.90
Whitelist	0.46	0.60	−0.15	10.96
Presale	0.68	0.36	0.32	25.15
Hardcap	0.89	0.60	0.29	27.58
Softcap	0.29	0.25	0.04	3.16
Accept BTC	0.39	0.22	0.16	12.99
Accept ETH	0.80	0.46	0.34	28.82
Accept USD	0.12	0.09	0.04	4.21
SEC filing (%)	1.21	0.72	0.49	1.79
Duration (days)	47.71	57.91	−10.20	8.29
Enforcement	0.33	0.22	0.11	9.52
Disclosure	1.44	1.07	0.37	11.11

(1): ICOs with at least one misrepresentation
(2): ICOs with no misrepresentations

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Details of network model

A simple network model

- Consider a set of ICOs $N = \{1, \ldots, n\}$ that are members of a network g.
- Link two ICOs if they have at least one common advisor.
- For two ICOs i and j, define:

$$g_{ij} = \begin{cases} 1, & \text{share a direct link} \\ 0, & \text{do not share a direct link or } i = j \end{cases}$$

- There is a square symmetric matrix $\mathbf{G} = [g_{ij}]$, which tracks the direct links in the network.

Model: Katz centrality

- The Katz-Bonacich centrality is useful in game-theoretic applications because it accounts for indirect links in the network.
- Let $\mathbf{G}^k$ be the k-th power of $\mathbf{G}$, where k is an integer.
  - Special case: $\mathbf{G}^0 = \mathbf{I}$
- $\mathbf{G}^k$ tracks indirect links in the network.
  - A nice result in graph theory
  - $g_{ij}^{[k]}$ gives the number of walks of length $k \geq 1$ from i to j in the network.
- The "prominence" of a network node (i.e., an ICO) is the weighted sum of walks that emanate from it.

Model: Katz centrality (cont'd)

- Consider a matrix $\mathbf{M}$ that tracks the number of walks of ALL lengths between any two ICOs.

$$\mathbf{M} = \sum_{k=0}^{+\infty} \theta^k \mathbf{G}^k \quad m_{ij} = \sum_{k=0}^{+\infty} \theta^k g_{ij}^{[k]}$$

- θ^k is the decay factor applied to walks of length k.

- The Katz-Bonacich centrality of ICO i, denoted as $b_i(g, \theta)$, is the sum of the elements of the i-th row in $\mathbf{M}$.

$$b_i(g, \theta) = \sum_{j=1}^{n} m_{ij} = \sum_{j=1}^{n} \sum_{k=0}^{+\infty} \theta^k g_{ij}^{[k]} \tag{1}$$

Model: Katz centrality (cont'd)

- The $(n \times 1)$ vector of Katz-Bonacich centralities is hence:

$$\mathbf{b}(g, \theta) = \mathbf{M} \cdot \mathbf{1} = [\mathbf{I} - \theta \mathbf{G}]^{-1} \cdot \mathbf{1} \tag{2}$$

- To see the equivalence, consider:

$$\mathbf{M} = \mathbf{I} + \theta \mathbf{G} + \theta^2 \mathbf{G}^2 + \theta^3 \mathbf{G}^3 + \ldots$$
$$\theta \mathbf{G} \mathbf{M} = \theta \mathbf{G} + \theta^2 \mathbf{G}^2 + \theta^3 \mathbf{G}^3 + \ldots$$

- Taking their difference gives

$$\mathbf{M} - \theta \mathbf{G} \mathbf{M} = \mathbf{I}$$
$$\mathbf{M} = [\mathbf{I} - \theta \mathbf{G}]^{-1}$$

Model: Katz-Bonacich centrality (cont'd)

- We can also slightly modify (1) to obtain weighted Katz-Bonacich centrality.

$$b_i(g,\theta) = \sum_{j=1}^{n} m_{ij} = \sum_{j=1}^{n}\sum_{k=0}^{+\infty} \theta^k g_{ij}^{[k]} \alpha_j \tag{3}$$

- α_j is the weight assigned to walks from i to j.

- Likewise, (2) can be slightly modified to get:

$$\mathbf{b}(g,\theta) = \mathbf{M}\boldsymbol{\alpha} = [\mathbf{I} - \theta\mathbf{G}]^{-1}\boldsymbol{\alpha} \tag{4}$$

Complementarities in misrep behavior

- Two channels of complementarities in malignant behavior:
  - Informal learning
  - Acceptable norms

- Issuer's utility function is linear-quadratic.

$$u_i(d_i, d_{-i}, g) = \underbrace{\alpha_i d_i}_{\text{ICO-specific propensity to misrep}} - \overbrace{\frac{1}{2} d_i^2}^{\text{Cost}} + \underbrace{\theta \sum_{j=1}^{n} g_{ij} d_i d_j}_{\text{Complementarities when } g_{ij} = 1}$$

- Perspective: Network has formed, and issuer i chooses d_i.

Model: Solution

- An ICO chooses d_i to maximize utility. The first-order condition of (10) gives the best-response function:

$$d_i^* = \alpha_i + \theta \sum_{j=1}^{n} g_{ij} d_j^*, \quad \forall i = 1, 2, \ldots, n \tag{5}$$

  In matrix form,

$$\mathbf{d}^* = \boldsymbol{\alpha} + \theta \mathbf{G} \mathbf{d}^* \tag{6}$$

- Solving (6) and using (4), the Nash equilibrium vector $\mathbf{d}^*$ is the vector of weighted Katz-Bonacich centralities:

$$\mathbf{d}^* = [\mathbf{I} - \theta \mathbf{G}]^{-1} \boldsymbol{\alpha} = \mathbf{M} \boldsymbol{\alpha} \tag{7}$$

Back

Estimating θ with spatial autoregressive models

- We estimate θ with spatial autoregressive models.

$$\text{misrepresent}_i = \text{const.} + \theta \sum_{j=1}^{n} g_{ij} \text{misrepresent}_j + \epsilon_i$$

- For unweighted network $\mathbf{G}$,

$$\hat{\theta} = 0.00138 \ (t = 2.07) \qquad \frac{1}{\rho(\mathbf{G})} = 0.00962$$

- For weighted network $\mathbf{G}$,

$$\hat{\theta} = 0.00182 \ (t = 2.53) \qquad \frac{1}{\rho(\mathbf{G})} = 0.00795$$

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Our model has three periods

Issuer selects d^*	Ask questions	Gross funding
Targeted investors $mz \cdot \mathcal{T}(d^*)$ $m(1-z) \cdot \mathcal{F}(d^*)$ Dismissed investors $mz \cdot (1-\mathcal{T}(d^*))$ $m(1-z) \cdot (1-\mathcal{F}(d^*))$	$mz \cdot \mathcal{T}(d^*) \times C$ $m(1-z) \cdot \mathcal{F}(d^*) \times C$	$mz \cdot \mathcal{T}(d^*) \times Q$
Period (1) ICO launches	Period (2) ICO in progress	Period (3) ICO completes

Note: $z = n/m$ is the density of naïve investors

Back

Are misreps the only trick in the book?

- We examine 2 other potential screens for investor naïvety.
- The SEC warns that celebrity endorsements are a red flag for investment scams.
- A malicious issuer may choose listing websites based on the characteristics of their web traffic.
  - Passive traffic:
    Paid advertisements, 3rd party referral links, search engines
  - Active traffic:
    Direct access via URLs or browser bookmarks

Looking out for misreps is incrementally useful

Event: ICO scam

	(1)	(2)	(3)	(4)
$\mathbb{1}$(Celebrity)	25.780	27.027		
	(10.64)	(9.37)		
Web traffic ratio			1.265	1.254
			(2.23)	(2.07)
Misrep		1.145		1.136
		(2.04)		(2.12)
Controls	Y	Y	Y	Y
# ICOs	5,935	5,935	5,935	5,935
Cohort strata	Y	Y	Y	Y
Coverage-quartile FE	Y	Y	Y	Y
Clustered SE	Y	Y	Y	Y

* Cox regressions, hazard ratios

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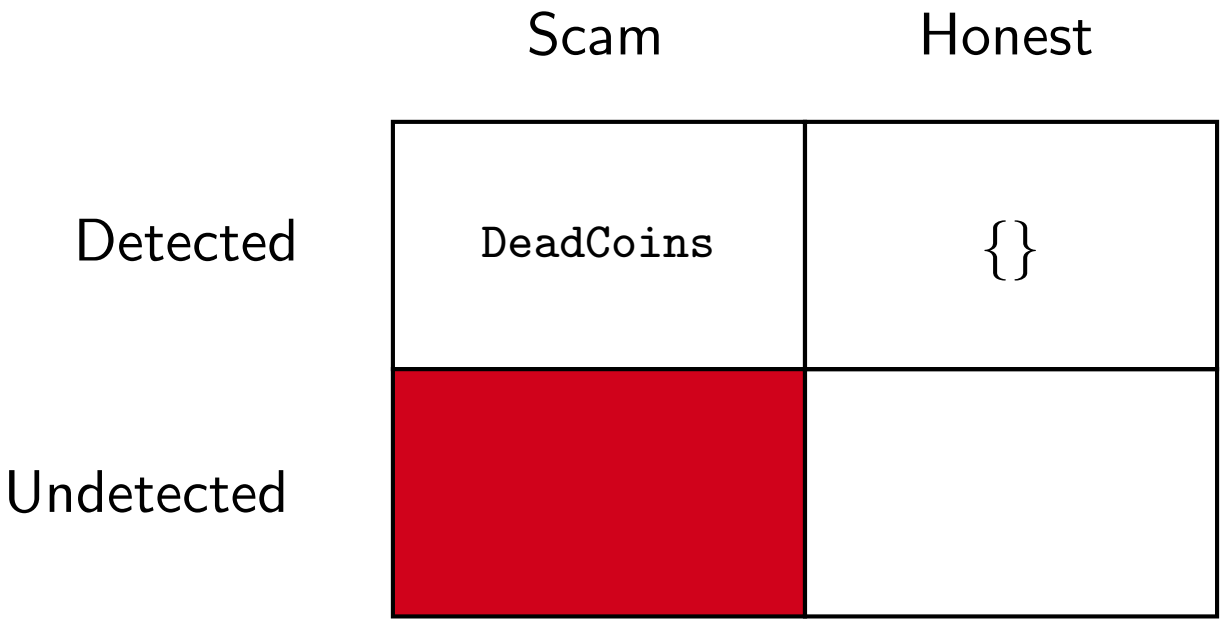
Welfare analysis

We only observe ICO scams that are detected



The partial observability problem

- 2 implications of imperfect detection:
  - Underestimate welfare losses to ICO scams.
  - Overestimate the predictive effect of misreps on scam risk.

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  - Overestimate the predictive effect of misreps on scam risk.
- Probabilistically identify ICO scams
  - Detection controlled estimation (DCE) framework
  - Instrumental variables for propensity to be an ICO scam.
- Identification: Malicious issuers ride strong sentiment in crypto markets to launch scams.
  - Pre-launch Google search volume for "Bitcoin" ("ICO").
  - Pre-launch Bitcoin (Alt-coin) returns.

Misreps remain a powerful predictor of scam risk

	(1)	(2)	(3)	(4)
	Model A		Model B	
	Scam	Detection	Scam	Detection
BTC search	1.030			
	(4.74)			
BTC returns	2.428			
	(4.63)			
Altcoin search			1.023	
			(5.20)	
Altcoin returns			1.362	
			(5.06)	
Misrep	1.113	1.110	1.130	1.116
	(6.16)	(6.32)	(6.65)	(6.60)
Controls	Y	Y	Y	Y
# ICOs	5,935	5,935	5,935	5,935

* DCE models, odds ratios

Welfare losses to ICO scams could be large

- About 40% of our sample ICOs could be scams.
  - vs. `DeadCoins.com` (2%) and practitioners (78%)
- Potential losses of $12.03 billion in our sample to ICO scams.

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- About 40% of our sample ICOs could be scams.
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- Potential losses of $12.03 billion in our sample to ICO scams.
- ICOs as another risky gambling device?
  - State lotteries have U.S. $76.4 billion sales in 2018 alone.
- Overall, we are agnostic on net welfare losses.
  - But, prevalence and potential costs of ICO scams may justify tougher regulatory actions.

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