Can you spot a scam?
Measuring and improving scam identification ability

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EEA
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Motivation

- Expansion of digital financial services in developing countries
  - increases access to finance (e.g., Pazarbasioglu et al. 2020, Balyuk 2022)
  - increases consumer protection issues (Garz et al. 2021): high and hidden prices, over-indebtedness, post-contract exploitation, fraud, ...

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- We focus on a large digital financial market: Kenya (Koyama et al 2021)

Fraud in Kenya

- Predominant type of fraud in Kenya: phone scams (Blackmon et al. 2021)
- 56% reported they had been contacted by scammers in the past six months (Blackmon et al. 2021)
- 90% of the adult population is concerned about fraud when using digital services (Koyama et al. 2021)
- 71% of the self-employed report limiting their usage of DFS due to concerns about fraud (Koyama et al. 2021)

Prevention of Victimization

- A common approach to tackle fraud: Education and awareness campaigns

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- How effective are they?

This Study

Research Questions

- How well can individuals distinguish genuine from fraudulent contact attempts? Who is more susceptible to scams?
- How confident are individuals in their scam identification ability? Who is very confident?
- Can a light-touch educational intervention increase scam identification ability?

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1. Scoping: stakeholder interviews, focus groups, social media analysis
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Main Take-Aways

- women and less experienced users are more susceptible
- a light-touch educational intervention does not increase scam identification ability, but it makes individuals more cautious

Contributions

1. Financial fraud in developing countries
   Annan (2022a, 2022b), Garz et al. (2021), Blackmon et al. (2021), Fu and Mishra (2022)
   → Measure of *relative* ability to distinguish scams and genuine official communication

2. Approaches to fraud prevention
   e.g., Burke et al. (2022), Scheibe et al. (2014), Sheng et al. (2007)
   → Test common policy response in a digital financial market

3. Correlates of fraud susceptibility and victimization
   e.g., Moustafa et al. (2021), Norris et al. (2019), Engels et al. (2020), Chen et al. (2018)
   → Document that more susceptible groups do not differentially benefit from education

Data collection

Scoping

Overview of Activities

- Qualitative data: understand perceptions of scams
  - 6 interviews with stakeholders
  - 5 focus group discussions with DFS users
- Social media data: examples of scams and genuine messages
  - Twitter: 427,121 original post; public facebook groups: 18,022 posts
  - survey in Kenya's largest fraud-detection facebook group: 919 responses more
  - analysis: topic clustering and manual classification of 1,836 examples regarding topics , actions , senders

Main insights

- Scam Types
  - Impersonation of agents/family/friends
  - False loan or investment offers/promotions/prizes
  - Erroneous transfer/shipment
- Goals of scammers: acquire personal info, money, or identity

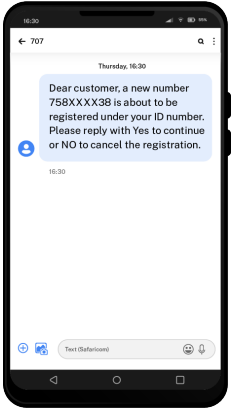
Measure of Scam Identification Ability

- labeled Twitter data and survey data of examples for scams and official messages ($N = 1,836$)
  - keep only copy-pasted text or text extracted from pictures

- Idea: generate variation by choosing rather hard-to-classify messages
  1. build database of more ambiguous messages
  2. stratified by topic, randomly select 13 scam and 7 official messages examples
  3. pilot in 2 convenience samples ($N = 39$)
  4. final selection based on topics, classification, and certainty rating: 8 scam and 4 official messages examples
  5. vary the display of the sender

Measuring Scam Identification Ability & Confidence

- Is this a scam message? (Yes/No)



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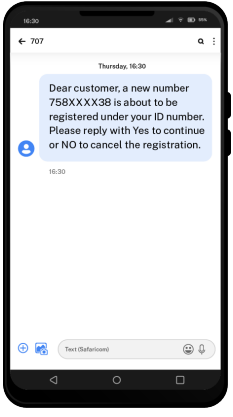

- How confident are you in your answer? (Scale from 1 to 5)

Overview of Vignettes

	Content	Intention	Sender
Block A	M-PESA transfer receipt	Genuine	Displayed
	Offer to use the new M-PESA app and get cash back	Genuine	Not displayed
	Random message to encourage contact	Fraudulent	Displayed
	Investment opportunity	Fraudulent	Displayed
	Suspended bank account	Fraudulent	Not displayed
	Notification as emergency contact	Fraudulent	Not displayed
Block B	M-PESA reversal request	Genuine	Displayed
	Notification of new registered SIM	Genuine	Displayed
	Job offer	Fraudulent	Displayed
	Lottery win	Fraudulent	Displayed
	Covid-19 relief fund	Fraudulent	Not displayed
	Notification as loan grantor	Fraudulent	Displayed

Implementation

- Online experiment
  - 1000 Kenyan respondents from a consumer panel of Geopoll
  - Quotas for gender, age, and location
  - Survey questions: demographics, the use of DFS, and scam experiences

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  - 2 blocks with 4 scam messages and 2 official messages each
  - random order of blocks and messages within blocks
    - share of correctly classified messages
    - share of correctly classified scams
    - share of correctly classified non-scams

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  - random order of blocks and messages within blocks
    - share of correctly classified messages
    - share of correctly classified scams
    - share of correctly classified non-scams
- Logistics
  - Participation fee: 500 KES (4.4 USD)
  - Average duration: about 21 minutes
  - AEA Registry No: AEARCTR-0008754
  - January 2022

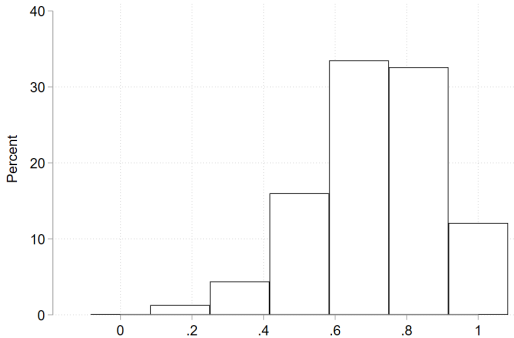
Descriptive Statistics

Descriptive Statistics

	N	Mean	SD	Min.	Max.
Demographics					
Female (0/1)	1000	0.50	0.50	0	1
Age	1000	32.28	9.84	18	67
Urban (0/1)	999	0.50	0.50	0	1
Post secondary education (0/1)	1000	0.73	0.44	0	1
Low income	1000	0.78	0.41	0	1
Formal employment (0/1)	997	0.36	0.48	0	1
Internet on phone (0/1)	999	0.99	0.09	0	1
Social media on phone (0/1)	999	0.99	0.09	0	1
Financial transactions w/ phone in the past 90 days	980	0.96	0.21	0	1
DFS Use					
Number of DFS used	1000	4.78	2.52	0	9
Scam Experience					
Have you ever been contacted by a scammer?	999	0.96	0.18	0	1
Ever been a victim of a scammer?	960	0.56	0.50	0	1
Anyone you know ever been a victim of a scammer?	1000	0.85	0.35	0	1
Scam Identification Ability (Block 1)					
Share of correctly identified messages (SIA)	1000	0.71	0.18	0	1
Share of correctly identified scams	1000	0.74	0.24	0	1
Share of correctly identified non-scams	1000	0.66	0.35	0	1
Average confidence in SIA	1000	4.23	0.63	1	5

Heterogeneity in SIA and Confidence

Block 1



mean SIA=0.71 or 4.23 messages

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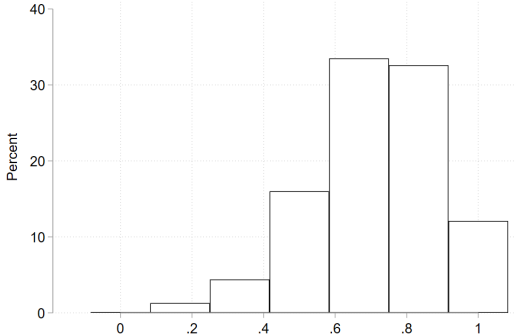

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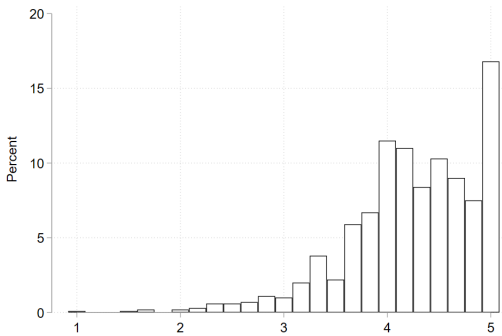


mean confidence=4.23

Who is doing better? Who is more confident?

Block 1

Who is doing better? Who is more confident?

Block 1

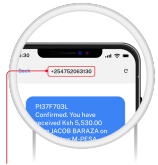
	SIA			Confidence in SIA		
	(1)	(2)	(3)	(1)	(2)	(3)
Demographics:						
Female	-0.03***	-0.03***	-0.03***	-0.11***	-0.10***	-0.12***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)
Age in Years	0.00	0.00	0.00	0.01**	0.01**	0.00*
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Post-Seconday Education	0.03*	0.02	0.01	0.11**	0.10*	0.13**
	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)	(0.06)
Low Income	0.02	0.02	0.02	0.04	0.03	0.04
	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)	(0.05)
Formal Employment	-0.00	-0.01	-0.00	0.06	0.04	0.03
	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.04)
DFS Use:						
Low Trust in DFS		0.01	0.01		-0.11**	-0.09**
		(0.01)	(0.01)		(0.05)	(0.04)
Above average use of different DFS		0.03**	0.03**		0.05	0.03
		(0.01)	(0.01)		(0.04)	(0.04)
Scam Experience:						
Contacted less than 1 week ago			-0.01			-0.01
			(0.02)			(0.06)
Victim of a Scammer			-0.01			-0.05
			(0.01)			(0.04)
N	997	997	956	997	997	956
R-Squared	0.05	0.05	0.05	0.03	0.04	0.04

Effects of Scam Education

Light-Touch Scam Education

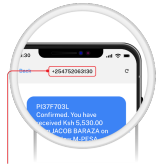
- After completing block 1, 50% of participants receive a light-touch scam education
- Consumers are encouraged to look for **scam markers**
  - typos and grammar mistakes
  - an unknown sender
  - a shortened link
  - requests for private information such as PIN codes or passwords
- Based on Kenyan information campaigns
- Randomized at the individual level
- On average, participants spend more than one minute reviewing the information

Scam Identification Tips



Pay attention to the sender!

- Do you recognize the sender?



Pay attention to the sender!

- Do you recognize the sender?
- **Safaricom will only SMS you from MPESA and Safaricom.**

Pay attention to the text!

- Beware of spelling mistakes, wrong tense or wrong punctuation.

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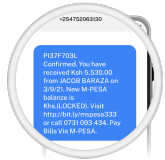
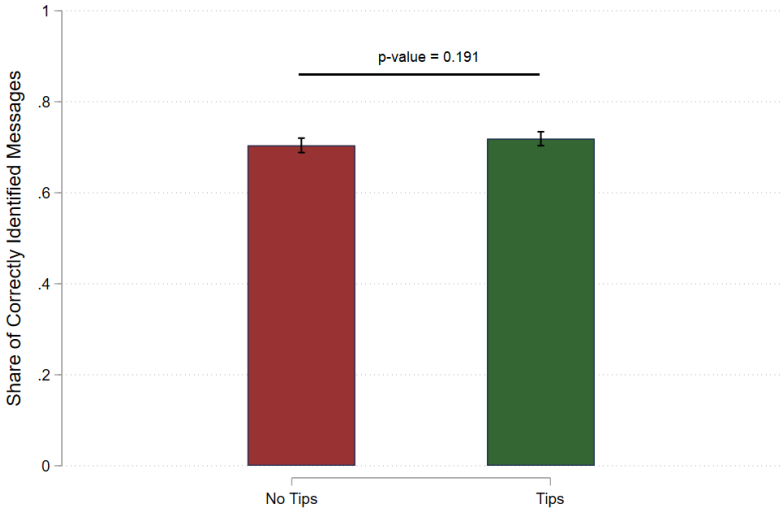
- Beware of spelling mistakes, wrong tense or wrong punctuation.
- **Do not click on shortened links.**



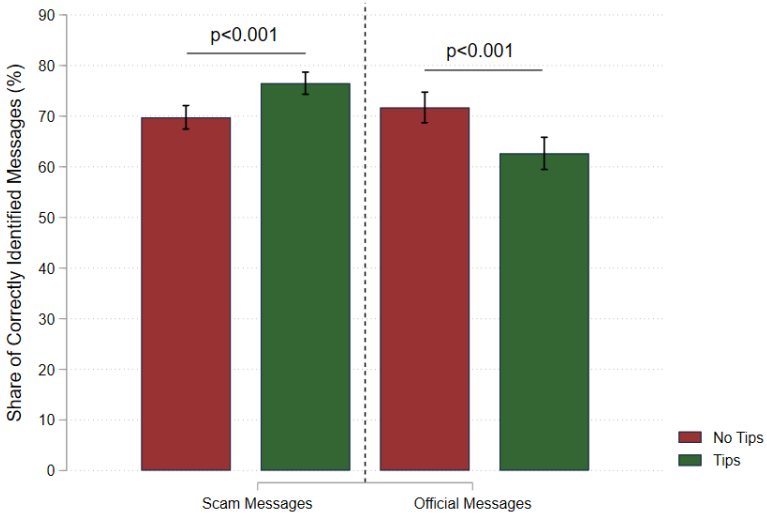
Your bank will never text to ask for your PIN or password!

Tips don’t increase scam identification ability



Share of correctly identified messages in block 2

Tips make participants more likely to say a given message is scam



Additional results

- Little treatment effect heterogeneity in SIA
  - individuals with higher education benefit from tips more
- Tips make participants more confident
  - driven by an increase in confidence for scam messages
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  - individuals with higher education benefit from tips more
- Tips make participants more confident
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- No treatment effect heterogeneity in confidence more
- Robustness
  - slightly larger effects when excluding those who failed attention check tables
  - control variables are balanced across treatments tables
  - no effect of inclusion/exclusion of control variables table

Discussion

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1. Do individuals provide effort in our measure?
2. Why do individuals become more likely to say any given message is a scam?
3. How to think about the effect sizes?

Do individuals provide effort? Incentive treatment

- Additional payment (10 KSH) for each correctly classified message
- For all 12 vignettes
- Randomized at the individual level
- Feedback at the very end of the survey

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Effect of Incentives in Block 1

	SIA	Scams Identified	Non-scams Identified	Confidence
Incentives	-0.01	-0.02	0.00	0.06
	(0.02)	(0.02)	(0.03)	(0.06)
Control Mean	0.71	0.75	0.63	4.23
N	956	956	956	956
R-Squared	0.05	0.04	0.09	0.04

Notes: Coefficients from OLS regressions and robust standard errors in parenthesis. Asterisks indicate that the estimate is statistically significant at the 1% ***, 5% **, and 10% * levels.

No difference between tips with incentives and without

Treatment Effects in Block 2

	Correctly Identified Messages			Confidence		
	SIA	Scams	Non-scams	SIA	Scams	Non-scams
Tips (unincentivized)	0.02	0.08***	-0.09***	0.13***	0.16***	0.07
	(0.02)	(0.02)	(0.03)	(0.04)	(0.05)	(0.06)
Tips (incentivized)	0.03*	0.08***	-0.07**	0.09**	0.09*	0.09
	(0.02)	(0.02)	(0.03)	(0.04)	(0.05)	(0.06)
Control Mean	0.70	0.69	0.71	4.20	4.20	4.33
p-value ($Tips^U = Tips^I$)	0.56	0.89	0.40	0.43	0.18	0.78
N	956	956	956	956	956	956
R-Squared	0.04	0.10	0.16	0.46	0.40	0.26

Notes: The displayed coefficients are from OLS regressions. Robust standard errors are in parenthesis. Asterisks indicate that the estimate is statistically significant at the 1% ***, 5% **, and 10% * levels.

Why do individuals become more likely to say any given message is a scam?

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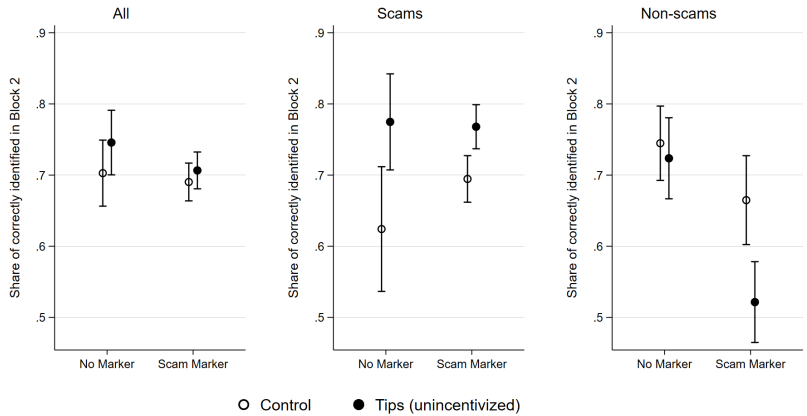

Interpretation of effect sizes

- Absolute levels of SIA are hard to interpret
  - would need to capture all messages and their frequency
  - abstract away from situational circumstances

  $\rightarrow$ focus on differences between groups
    - treatment groups
    - socio-demographics

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    - treatment groups
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- Magnitude of treatment effects
  - upper bound: literate and relatively educated sample, tips are provided when needed and in a salient way
  - lower bound: participants are alert, use of common tips, difficulty of vignettes more

  $\rightarrow$ focus on the direction of the treatment effects

Conclusion

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Education Campaigns

- Popular policy response
- No significant effects of information on correctly identified messages
- Respondents become overly cautious: the share of messages categorized as scams increases

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Several reasons why information might not be effective

- Official communication includes scam-like features
- Not targeted at specific audiences
- Static

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Several reasons why information might not be effective

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- Not targeted at specific audiences
- Static

Can we find a better way to increase DFS use sustainably?

Thank you!

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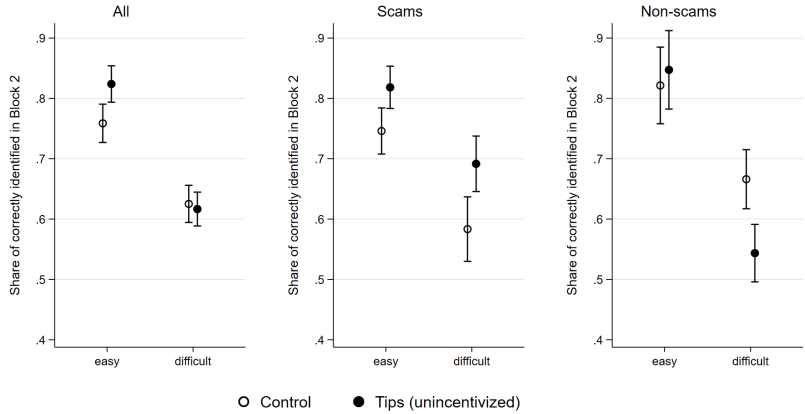
Appendix

Exploring the difficulty of the vignette

Vignette-level effects by baseline difficulty of the vignette



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Treatment Effect Heterogeneity: SIA

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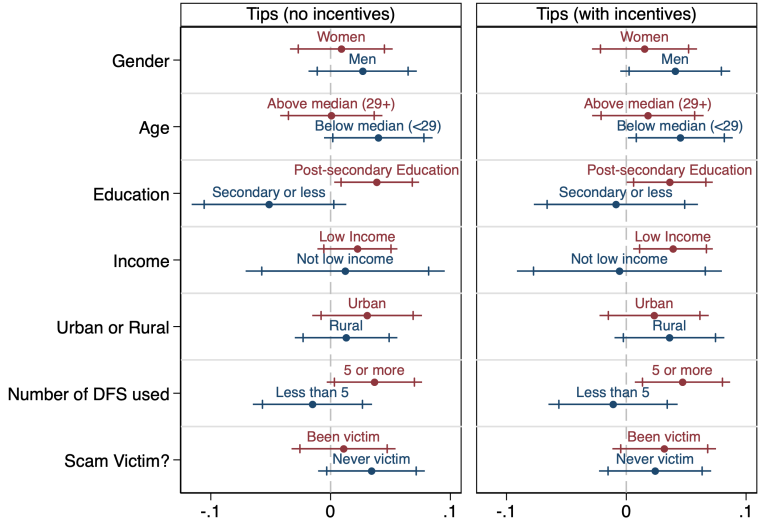
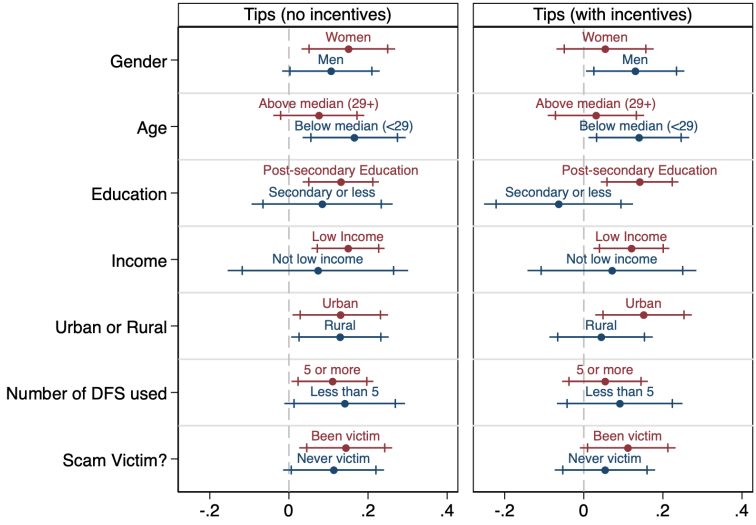


Treatment Effect Heterogeneity: Confidence

back



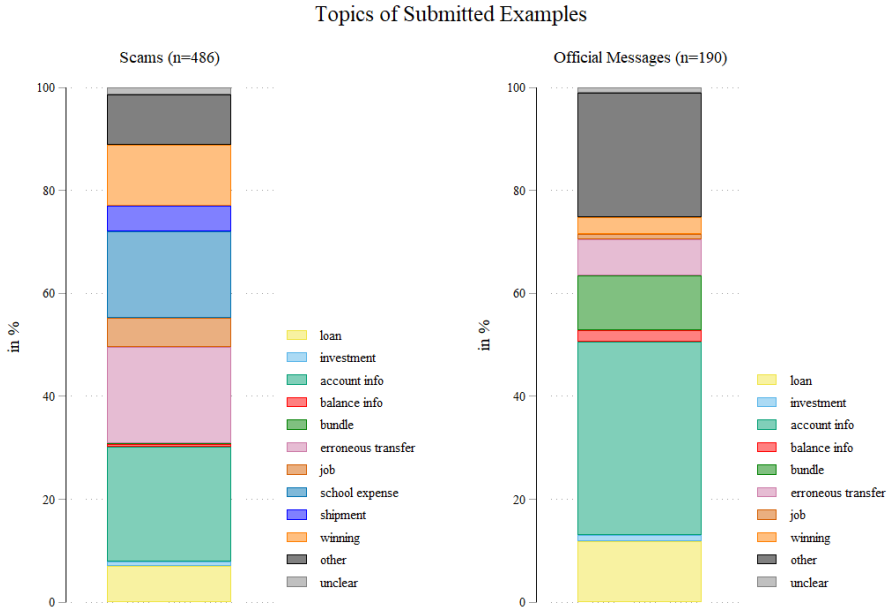
Scoping: Social Media Analysis

- Twitter (via brandwatch)
  - January 2020 - August 2021
  - 427,121 posts
- Public facebook groups (via crowdtangle)
  - June 2020 - June 2021
  - 18,022 posts
- Survey in private fraud-detection facebook group
  - September 2021, $N = 919$
  - main focus, best data quality: example, classification and confidence of respondent
  - use RAs to classify topics, actions, senders

back

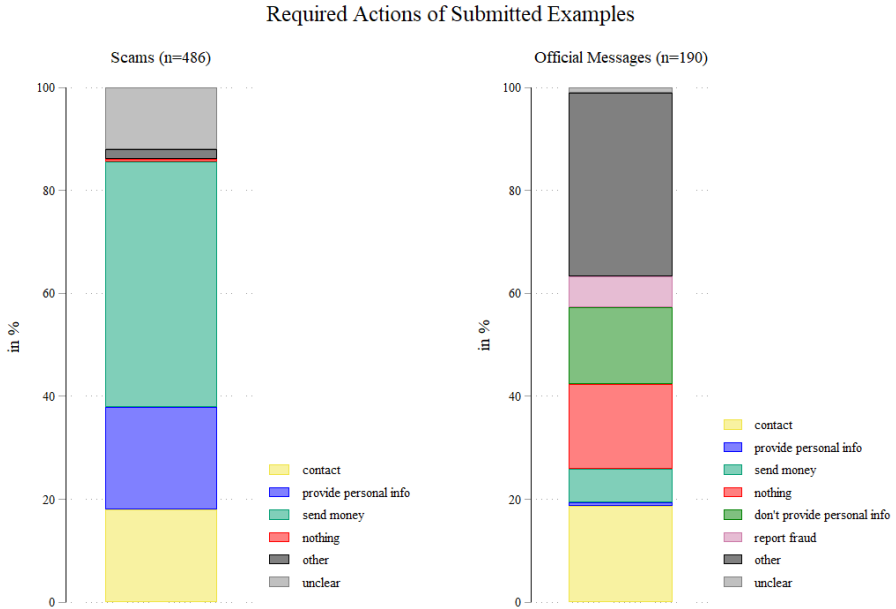
Survey data

back



Survey data

back



Survey data

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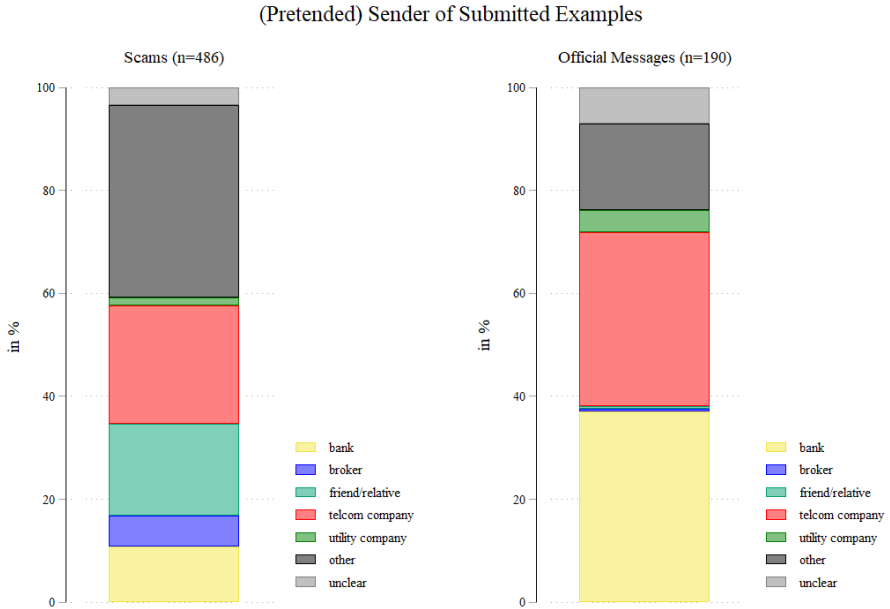

No difference for secondary outcomes

Treatment Effects in Block 2

	Trust in DFS	Response Time SIA	All Scams Identified	All Non-scam Identified
Tips (unincentivized)	0.01	0.12	0.10**	-0.11***
	(0.07)	(0.08)	(0.04)	(0.04)
Tips (incentivized)	-0.00	0.23**	0.11**	-0.08*
	(0.07)	(0.10)	(0.04)	(0.05)
Control Mean	2.02	2.21	0.30	0.52
p-value ($Tips^U = Tips^I$)	0.92	0.26	0.99	0.42
N	956	956	956	956
R-Squared	0.03	0.34	0.07	0.11

Notes: The displayed coefficients are from OLS regressions. Robust standard errors are in parenthesis. Asterisks indicate that the estimate is statistically significant at the 1% ***, 5% **, and 10% * levels.

Scam features

Scam prediction

- off-the-shelf internationally trained model over-predicts in Kenyan data
- Train Electra model to predict which messages are scam
- based on survey and Twitter data, manually labeled by three RAs
- 93% accuracy on test dataset

Scam features

- Scam: locked, win, congratulations, received, hi, hello, interested, kindly
- Official messages: enquiries, queries, dial, transaction, paybill

DFS Use: Balance

	N	Control Mean	Treatment Mean	p-value
Any financial transactions on the phone in the past 90 days	980	0.95	0.96	0.76
Low trust in DFS (0,1)	1000	0.32	0.31	0.69
Financial transactions ever done with phone:				
Sending/receiving funds with mobile money	1000	0.89	0.88	0.73
Accessing a bank account via your mobile phone	1000	0.50	0.52	0.49
Paying a bill or paying for something with mobile money	1000	0.72	0.71	0.94
Taking a mobile loan	1000	0.39	0.42	0.50
Conducting a financial transaction using an agent (includes withdrawing funds)	1000	0.55	0.55	0.94
Mobile money used for:				
Send money to friends or family	1000	0.82	0.83	0.72
Receive money	1000	0.79	0.79	0.88
Receive salary	1000	0.22	0.22	0.84
Receive payments for business	1000	0.30	0.29	0.73
Make payments for business	1000	0.39	0.38	0.77
Pay bills/purchase items	1000	0.74	0.74	0.77
Save or keep money	1000	0.52	0.52	0.91
Buy airtime	1000	0.79	0.79	0.94
Gambling	1000	0.19	0.21	0.49
Other	1000	0.00	0.01	0.18

back

Scam Experience: Balance

	N	Control Mean	Treatment Mean	p-value
Have you ever been contacted by a scammer?	999	0.96	0.97	0.41
Last time you were contacted by a scammer:				
Less than a week ago	962	0.14	0.14	0.98
Between 1 week and 4 weeks ago	962	0.22	0.23	0.78
Between 1 month and 12 months ago	962	0.46	0.47	0.70
More than 12 months ago	962	0.18	0.16	0.40
How did you encounter these scams or fraud?				
By phone call	1000	0.67	0.66	0.62
By SMS	1000	0.69	0.73	0.11
On Whatsapp	1000	0.18	0.16	0.30
On social media (Facebook, Instagram, ..)	1000	0.20	0.19	0.85
Other	1000	0.01	0.01	0.54
What did the scammers ask you to do?				
Send money	1000	0.58	0.54	0.23
Share my password or PIN	1000	0.21	0.21	0.99
Share my personal information	1000	0.37	0.35	0.49
Share account details	1000	0.22	0.18	0.11
Asked for a payment reversal	1000	0.42	0.40	0.46
Asked to help relative or a friend in need	1000	0.28	0.27	0.74
Other	1000	0.05	0.05	0.98

back

Scam Experience (cont'd)

	N	Control Mean	Treatment Mean	p-value
How did you know that this was a scam?				
Regular number	1000	0.16	0.15	0.70
From others' experiences	1000	0.48	0.43	0.13
Requested personal information	1000	0.40	0.40	0.97
No recent transactions	1000	0.24	0.24	0.89
Personal awareness	1000	0.47	0.44	0.34
Incorrectly identified me	1000	0.24	0.24	0.95
Never used the service	1000	0.23	0.20	0.19
I did not know the caller/sender	1000	0.34	0.36	0.40
Unusual time	1000	0.07	0.05	0.09
Poor language or grammar	1000	0.21	0.26	0.04
Other	1000	0.02	0.01	0.23
What did you do?				
I fell for it	964	0.62	0.65	0.48
I ignored it	964	0.08	0.07	0.46
I deleted it	964	0.26	0.24	0.67
I reported it	964	0.04	0.04	0.87
Have you alerted any of your family members of friends?	961	0.90	0.88	0.30
Have you ever been a victim of a scammer?	960	0.54	0.57	0.22
Have you alerted any of your family members of friends?	532	0.93	0.94	0.58
Has anyone you know ever been a victim of a scammer?	1000	0.84	0.87	0.12

back

Balancing Checks

	N	Control Mean	Treatment Mean	p-value
Female	1000	0.51	0.49	0.57
Age	1000	32.15	32.41	0.68
Urban (0,1)	999	0.50	0.50	0.96
Post Secondary Education (0,1)	1000	0.75	0.72	0.38
Low Income (0,1)	1000	0.77	0.79	0.36
Formal Employment (0,1)	997	0.37	0.36	0.94
Internet on Phone (0,1)	999	0.99	0.99	0.47
Social Media on Phone (0,1)	999	0.99	0.99	0.75
Shared Phone (0,1)	1000	0.12	0.12	0.81
Own SIM Card (0,1)	997	0.94	0.96	0.25
Shared SIM Card (0,1)	1000	0.03	0.05	0.14
Correctly Identified Messages (Part 1)	1000	4.25	4.31	0.43
Average Confidence in SIA (Part 1)	1000	4.25	4.21	0.31
Correctly Identified Scam Messages (Part 1)	1000	2.96	2.94	0.64
Correctly Identified Official Messages (Part 1)	1000	1.29	1.37	0.06
Attention Check	1000	0.28	0.26	0.51

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Control Variables

	SIA				Confidence in SIA			
Information	0.13	0.13	0.10	0.11	0.12***	0.11***	0.12***	0.12***
	(0.09)	(0.09)	(0.10)	(0.10)	(0.04)	(0.04)	(0.04)	(0.04)
Incentives	0.11	0.14	0.11	0.12	0.06	0.07*	0.07	0.07*
	(0.10)	(0.10)	(0.10)	(0.10)	(0.04)	(0.04)	(0.04)	(0.04)
Inf. + Inc.	0.15	0.18*	0.18*	0.18*	0.08*	0.08*	0.09**	0.09**
	(0.09)	(0.09)	(0.10)	(0.10)	(0.04)	(0.04)	(0.05)	(0.05)
DV in Control	4.2	4.2	4.2	4.2	4.2	4.2	4.2	4.2
N	1000	997	937	937	1000	997	937	937
R-Squared	.014	.03	.033	.039	.45	.46	.45	.45
Individual Controls		✓	✓	✓		✓	✓	✓
Experience Controls			✓	✓			✓	✓
Design Controls				✓				✓

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Only those who passed attention check

	SIA				Confidence in SIA			
Information	0.21*	0.21*	0.19	0.20*	0.15***	0.14***	0.15***	0.15***
	(0.11)	(0.11)	(0.12)	(0.11)	(0.05)	(0.05)	(0.06)	(0.06)
Incentives	0.16	0.19	0.16	0.16	0.07	0.08	0.09*	0.09*
	(0.12)	(0.12)	(0.12)	(0.12)	(0.05)	(0.05)	(0.05)	(0.05)
Inf. + Inc.	0.14	0.16	0.19*	0.19*	0.05	0.05	0.07	0.07
	(0.11)	(0.11)	(0.11)	(0.11)	(0.05)	(0.05)	(0.05)	(0.05)
DV in Control	4.2	4.2	4.2	4.2	4.2	4.2	4.2	4.2
N	732	731	685	685	732	731	685	685
R-Squared	.02	.043	.039	.051	.44	.45	.43	.44
Individual Controls		✓	✓	✓		✓	✓	✓
Experience Controls			✓	✓			✓	✓
Design Controls				✓				✓

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Only those who passed attention check

	Over-Identified	Under-Identified
Information	0.08**	-0.09***
	(0.03)	(0.03)
Incentives	-0.02	-0.03
	(0.04)	(0.03)
Inf. + Inc.	0.08**	-0.09***
	(0.03)	(0.03)
DV in Control	.27	.33
Inf=Inc	.0024	.021
Inf=Inf+Inc	.98	.95
Inc=Inf+Inc	.003	.028
N	685	685
R-Squared	.18	.11

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