Crowdsourcing Peer Information to Change Spending Behavior

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Research Agenda on Robo-Advising

1. **Common Perception:**
   Robo-advising = automated advice for portfolio allocation

wealthfront
Betterment
FutureAdvisor
Schwab Intelligent Portfolios
Vanguard
SIGFIG
PERSONAL CAPITAL

Research Agenda on Robo-Advising

- BUT households' decisions are more complex!
  Robo-Advising: automated advice for ANY household choice

The Balance Sheet View of Households

ASSETS	LIABILITIES
Financial Assets - Equities - Bonds - Funds Retirement.. **Human Capital** - Produces income **Durable Assets** - Cars, Housing… - Produce consumption value	**Financial Liabilities** - Mortgages - Credit Card Debt - Student Loans - Car Payments… EQUITY

(D'Acunto and Rossi, 2021)

Research Agenda on Robo-Advising

Robo-advising for Investment Decisions

- "*Robo-advising*," D'Acunto & Rossi
- "*The Promises and Pitfalls of Robo-advising*," D'Acunto, Prabhala & Rossi
- "*Who Benefits from Robo-advising? Evidence from Machine Learning*" Rossi & Utkus
- "*The Needs and Wants in Financial Advice: Human vs Robo-Advising*," Rossi&Utkus
- "*Algorithmic Aversion: Theory and Evidence from Robo-advice*," Ramadorai et. al

Robo-advising/FinTech for Consumption, Saving, Debt & Lending

- "*New Frontiers of Robo-Advising: Consumption, Saving, Debt Management, and Taxes*," D'Acunto and Rossi
- "*Crowdsourcing Peer Information to Change Spending,*" D'Acunto, Rossi & Weber
- "*Goal Setting and Saving in the FinTech Era*" Gargano & Rossi
- "*How Costly Are Cultural Biases? Evidence from FinTech*" D'Acunto, Ghosh & Rossi
- "*Improving Households' Debt Management with Robo-advising*" D'Acunto, et. al

Motivation

Low savings limit wealth accumulation for retirement

Households have little information about optimal savings rate

Likely to acquire information from the spending of others

Potential role for **visibility bias** (Han, Hirshleifer, Walden, 2018)

- People make inference based on **others**' spending choices
- BUT, mostly conspicuous part visible
- Might overestimate the overall spending of others
- Especially in times of social media

Luxury on Instagram...

Sad and cheap everyday dinner...

Motivation

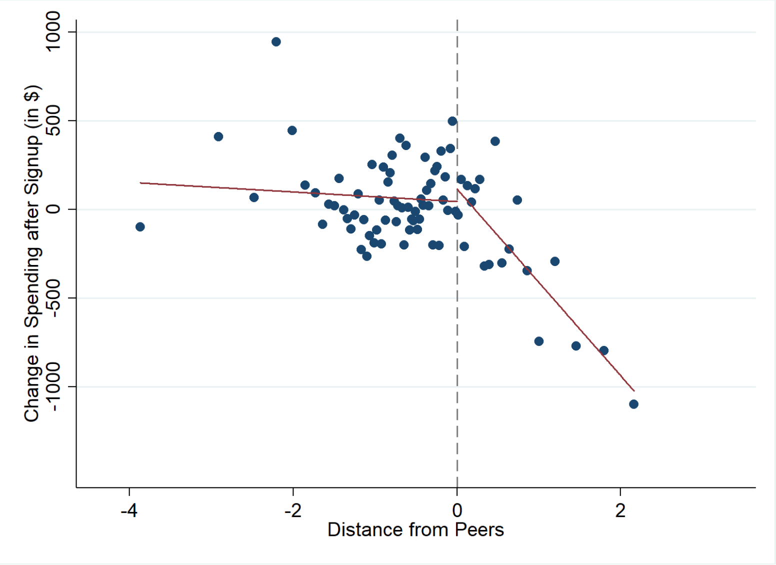
- Biased inference can lead to severe over-consumption
- How to correct this biased inference, and choices?
- Provide info on the **overall spending** of others

$\rightarrow$ VERY DIFFICULT to implement with traditional tools

This Paper

- Income aggregator application (app) called *Status*
- **Robo-advisor** for consumption. Provides users with:
  - information on spending similar individuals (*peers)*
  - information crowdsourced from representative US data
- Do users react to this information? If yes, how?
- Allows us to study peer effects in a setting we can rule out
  - common shocks
  - socialization

Spending Reaction to Information about Peers



Preview of Our Main Findings

1. Users who are told they spend
   - more than peers reduce spending
   - less than peers increase spending
2. Asymmetry: cuts are three times larger than increases
3. Distance from peers affects reaction monotonically
4. Stronger reaction if signal more informative
5. Lower-income users react more
6. External validity using RCT on non-selected population

The STATUS APP
(INPUTS)

At Signup, users provide Status with:

- Annual Income (can be verified from accounts ex post)
- Age
- Homeownership status
- Location of residence
- Location type—Urban or Rural
- Social Security Number $\rightarrow$ STATUS obtains credit report

Users link their:

- Debit and credit account(s)
- Retirement and investment account(s)

The STATUS APP

(PEER GROUPS)

You

Age
42

Income
$140K

Location
New York, NY

Location Type
Urban

Credit Score
769

Housing Type
Pay Rent

Your Peers

9.9K people

Age Range
40 – 49

Income Range
$100K – $150K

Location
New York, NY

Location Type
All

Credit Score Range
720 – 779

Housing Type
Pay Rent

The STATUS APP

Using the information provided, the STATUS APP:

- Constructs a peer group for each client
- Peers matched on 5 characteristics & w > 5,000 individuals
- STATUS purchases spending data for random US sample
- Compares the client's consumption to that of the peer group
- Information is easy-to-understand and salient

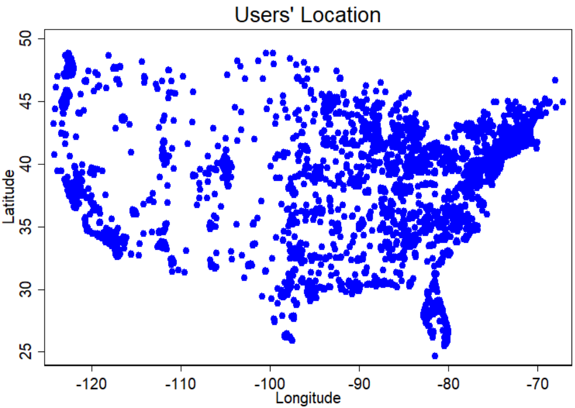
The STATUS APP

(PEER SPENDING)

Status Users Characteristics

	Main sample		
	Observations	Mean	St. Dev.
Age	20,679	32.01	7.80
Credit Score	19,051	736.20	74.34
Home Ownership	20,679	0.39	0.49
Annual Income ($)	20,679	92,633	62,838
Distance Peers	20,679	-0.53	0.97
Monthly Spending Before (30 Days, $)	20,679	4,963	4,007
Monthly Spending Before (60 Days, $)	20,679	4,886	4,040
Monthly Spending Before (90 Days, $)	20,679	4,671	3,894

Status Users Location

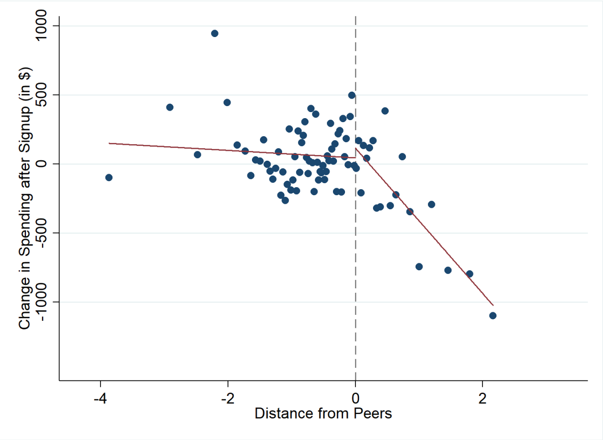


Spending Reaction to Information about Peers-I

- Study change in spending behavior around sign up
- Use three months prior and after signup (similar for two, one)
- Split sample into individuals spending above and below peers
- Seasonally-adjusted Δ spending using time-fixed effects

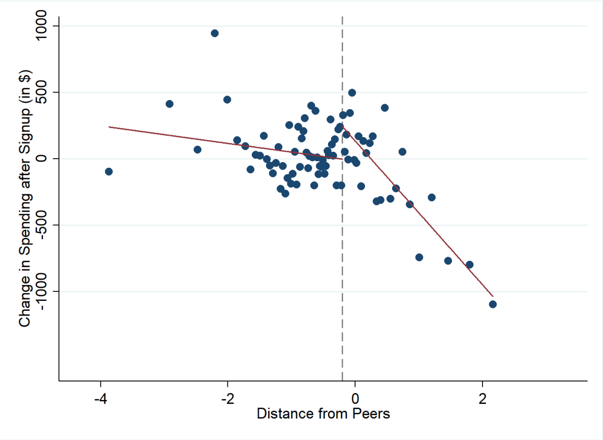
Spending Reaction to Information about Peers-II

- Exogenous Threshold at “0”



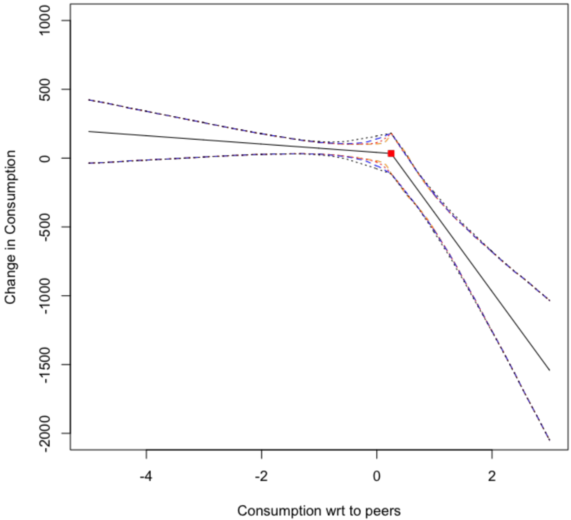
Spending Reaction to Information about Peers-III

- Endogenous Threshold Regressions (Hansen, 2000)

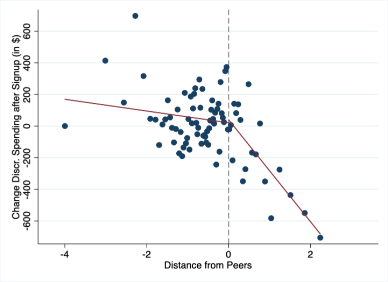


Spending Reaction to Information about Peers-IV

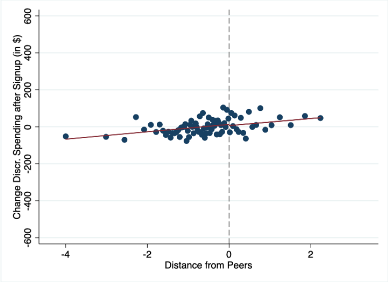
- Kink Regression Results (Hansen, 2015)



Spending Reaction to Information about Peers-V



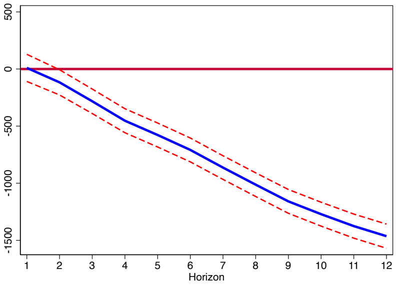
(a) Discretionary Spending



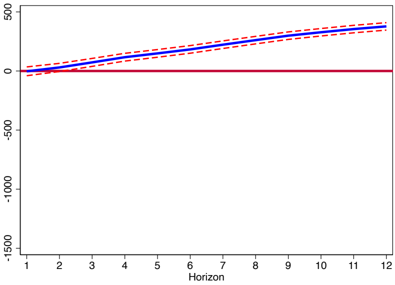
(b) NonDiscretionary Spending

Dynamic Effect of Peer Spending After Sign-up

- Tracking Spending up to 12 months post signup



(a) Overspenders



(b) Underspenders

Multivariate Results

- **Raw results:** don't account for differences in spending levels across users
- **Dep. variable:** normalized ratio of 90 days post spending to 90 days pre
- **Estimate (in Columns 3-4):**

$$\frac{Spending_{i,post}}{Spending_{i,pre}} = \alpha + \gamma\ Distance\ Peers_i + \delta\ \boldsymbol{x}_i + \epsilon_i,$$

	Above	Below	Distance Above	Distance Below
Average Change	**-0.233***** **(-42.00)**	**0.074***** **(8.34)**		
Distance Peers			**-0.103***** **(-11.31)**	**-0.086***** **(-7.03)**
Observations	5,012	15,667	5,012	15,667

- Results are robust to adding additional controls

Controlling for Mean Reversion

- Are we capturing a **mean reversion** effect for over-spenders?
  - Directly control for pre-signup spending
  - Use spending 2 or 3 months before signup for Δ peer spending

	30 Days before Signup		60 Days before Signup		90 Days before Signup	
	(1)	(2)	(1)	(2)	(1)	(2)
Distance Peers	**-0.103*****	**-0.039*****	**-0.110*****	**-0.083*****	**-0.099*****	**-0.075*****
	(-11.31)	**(-3.54)**	**(-13.83)**	**(-8.61)**	**(-11.75)**	**(-7.38)**
Spend Before		-0.096***		-0.062***		-0.058***
		(-13.11)		(-8.91)		(-8.25)
Other controls		✓		✓		✓
Observations	5,012	4,179	4,791	3,970	4,473	3,697

$$\frac{Spending_{i,post}}{Spending_{i,pre}} = \alpha + \gamma\ Distance\ Peers_i + \zeta\ Spending_{i,pre} + \delta\ \boldsymbol{x}_i + \epsilon_i,$$

Identification Strategy

Identification Concerns:

- Individuals who sign-up for STATUS may *know* they are:
  - Over-spending
  - Under-spending

$\rightarrow$ They might have changed spending anyway

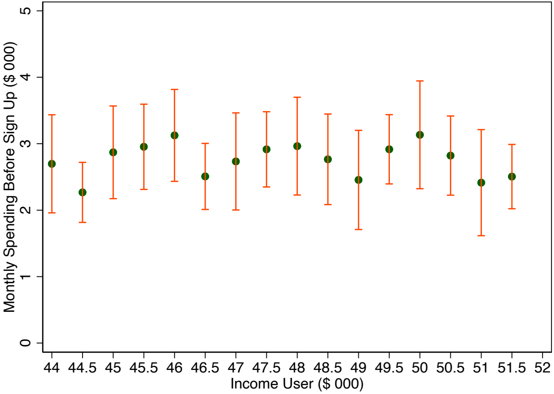
Identification Strategy:

- Exploit cutoffs to assign users to peer groups
- Most important are Income Buckets:
  $35K, $50K, $75K, $100K, and $150K
- Users around cutoffs, very similar income & spending profiles
- Above cutoff$\rightarrow$peer group with higher spending
- Below cutoff$\rightarrow$peer group with lower spending

Assessing Identifying Assumptions: Spending Before

No detectable differences in pre-spending around all thresholds

Example: Income Threshold **$50,000**



Assessing Identifying Assumptions: Other variables

	Home ownership	log of Credit Score	log of Age	log of Asset Balance	log of Debt Balance
	Panel A: Income Threshold: $35,000				
Above Dummy	0.031	-0.009	0.018	-0.160	0.324**
	(1.06)	(-0.95)	(1.02)	(-0.85)	(2.10)
Observations	896	834	896	675	837
	Panel B: Income Threshold: $50,000				
Above Dummy	0.038	-0.001	0.014	0.021	0.009
	(1.63)	(-0.09)	(1.31)	(0.17)	(0.08)
Observations	1,516	1,410	1,516	1,227	1,415
	Panel C: Income Threshold: $75,000				
Above Dummy	0.013	0.002	0.012	0.017	0.027
	(0.49)	(0.25)	(0.14)	(-0.03)	(0.23)
Observations	1,546	1,435	1,546	1,278	1,457
	Panel D: Income Threshold: $100,000				
Above Dummy	0.004	0.019	0.024**	0.199	-0.163
	(0.14)	(1.24)	(2.09)	(1.62)	(-1.21)
Observations	1,128	1,047	1,128	954	1,065
	Panel E: Income Threshold: $150,000				
Above Dummy	-0.015	0.002	-0.000	-0.074	-0.322
	(-0.35)	(0.24)	(-0.00)	(-0.44)	(-1.54)
Observations	543	510	543	482	516

Identification Strategy

- Keep only clients close the threshold: -$6K to +$2K
- Use the random assignment to instrument for peer spending
- Estimate the following 2SLS specification

$$\textit{Peer Spending}_i = \alpha + \gamma \textit{ Dummy Above}_i + \zeta \textit{ Spending Before}_i + \epsilon_i, \quad (\textit{First Stage})$$

$$\frac{\textit{Spending}_{i,post}}{\textit{Spending}_{i,pre}} = \alpha + \beta \widehat{\textit{Peer Spending}_i} + \zeta \textit{ Spending Before}_i + \epsilon_i, \quad (\textit{Second Stage})$$

- Expect: $\hat{\beta} > 0$, increase if above cutoff seeing higher spending

Two-stage Least Squares

			Placebo IV	
	First Stage	Second Stage	First Stage	Second Stage
Above Dummy	**0.743*** (24.62)**		0.078 (0.795)	
Peer Spending		**0.111*** (3.08)**		0.942 (0.432)
Spending Before	0.344*** (23.33)	-0.305*** (-15.63)	0.120*** (3.46)	-0.566*** (-2.02)
First stage F-stat	606.1			
Observations	5,629	5,629	678	678

- Thresholds: $35K, $50K, $65K, $75K, $100K, and $150K
- Placebo Thresholds: $45K, $60K, $90K, $110K, and $140K

Reaction by Signal Informativeness

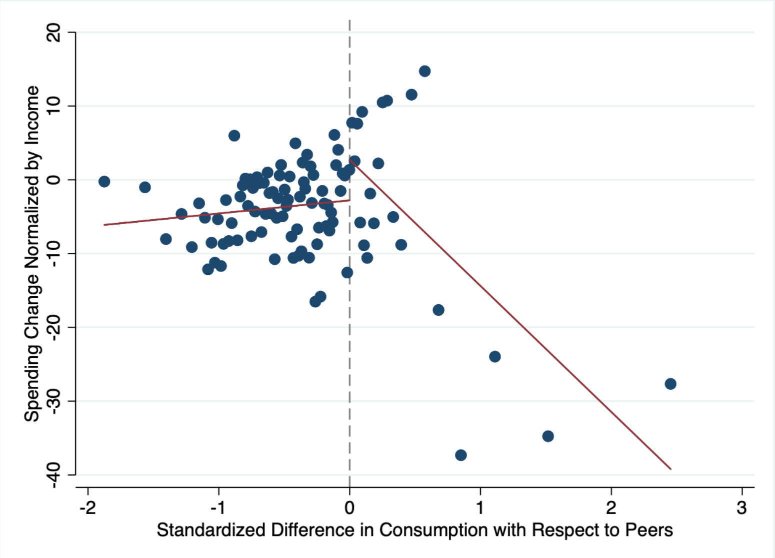
Users react more to more informative signals, i.e., when:

1. peer groups comprise more similar people
2. the number of people in the peer group is larger
3. peer groups income width is smaller
4. users are unlikely to have peer info before adopting the App

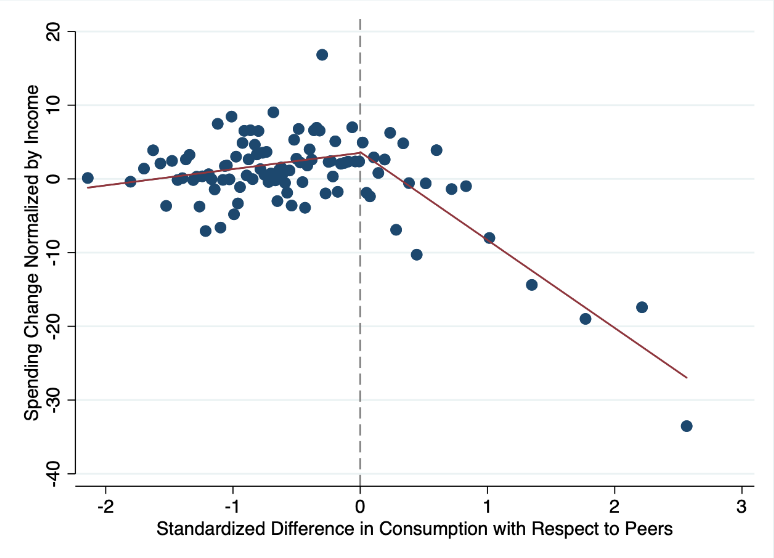
Reactions by Income Levels

- Low-income households ex-ante less access to information
- But a larger part of their income is spent on discretionaries
- Ex-ante not clear which direction, if any, heterogeneity goes

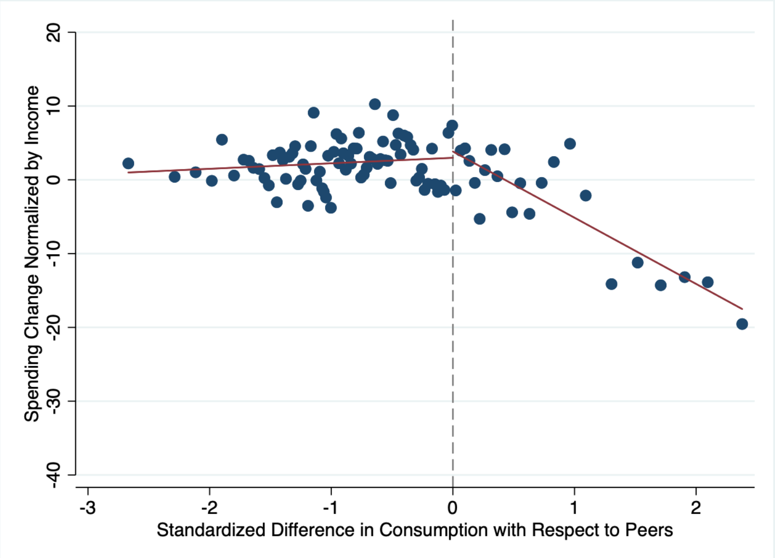
Reactions by Income Levels (INCOME GROUP 1)



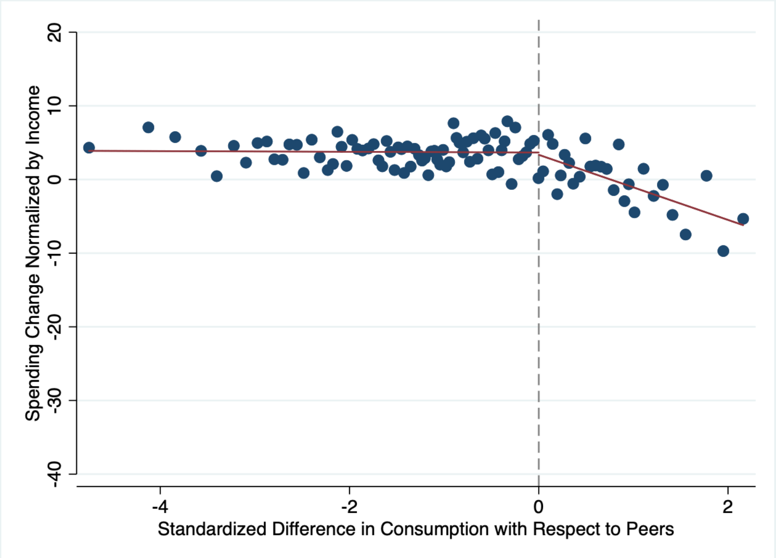
Reactions by Income Levels (INCOME GROUP 2)



Reactions by Income Levels (INCOME GROUP 3)



Reactions by Income Levels (INCOME GROUP 4)



Robustness

Results robust to (many!!) checks:

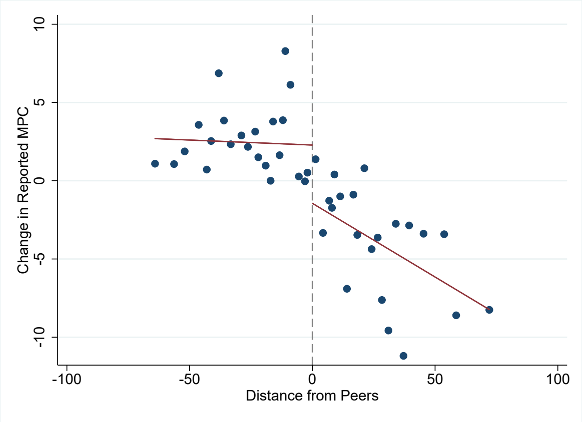
1. Limiting the sample to users
   - with more than 2 accounts linked
   - under 35 years of age
   - with income below $200K
   - other filters based on spending/login activity
2. Showing users react to peer info and not other information
3. Alternative regression specifications
4. Alternative statistical inference
5. Alternative bandwidths for IV strategy

The Problem of External Validity

- All the results so far are within a specific population...
- ... those who decide to sign up for Status
  - They might care more than others about own financials
  - They might care more than others about peers
- Are results also externally valid?
  - If we did the same intervention on the whole population, would people react in the same way?

External Validity? Randomized Control Trial

Replicate results on a representative US population, RCT



- Overconsumers cut, underconsumers increase MPC
- Asymmetric response
- Result robust conditioning on demos unobserved on Status

Conclusions

1. Users who spend
   - more than peers reduce spending significantly
   - less than peers keep constant or increase their spending
2. More informative signal$\rightarrow$stronger reaction
3. Caveat: reacting is likely not optimal!