Take-up and Targeting

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Program Take-up Rates

Incomplete take-up is an important feature of U.S. transfer programs

Yet hard to measure because full "denominator" of eligible non-enrollees is not observed by program administrators

Some estimates from linked admin–survey data:

- **SNAP:** 63% take-up in Texas in 2008 (Newman and Sherpf, 2009)
- **WIC:** 59%–82% take up in 15 states in 2019 (McBride et al., 2022)
- **TANF** thought to be much lower

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   - Transfer programs reach very needy people because of stringent eligibility rules
2. **Incomplete take-up as mechanism design problem** (Mirleesian view)
   - Welfare programs add value to tax system only if they relax an IC constraint
   - If the optimal take-up rate is 1, then they are a (negative) tax but are costly to administer
   - Related statement: Fixing the budget, targeting programs to the neediest among eligibles achieves more redistribution

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Some (by no means all) economists favor variations on interpretation #2. Related points:

- Welfare programs may solve political economy constraints on redistribution
- Why hold the program budget fixed anyway? One could argue for more "pure" redistribution on its own; our approach takes welfare weights as exogenous

Positive Explanations for Incomplete Take-up

Take-up "puzzle": take-up rates are not 1, but this is $20 left on the sidewalk

Three classic explanations (Currie, 2006):

1. Take-up costs are not zero ("ordeals") [but, program benefits usually exceed even conservative accounting of time and hassle costs]
2. Stigma (can construe as a classical ordeal)
3. Behavioral biases (especially misperceptions, but also mental health or procrastination)

Roadmap:

- Classical view $\rightarrow$ bandwidth $\rightarrow$ biases $\rightarrow$ stigma
- Starting with a benchmark model of targeting and building up
- Today's class is on take-up and targeting papers, (some) behavioral (mostly) PF focus

[Many papers on benefit take-up not covered: Kleven and Kopczuk, 2011; Lieber and Lockwood, 2019; and others, especially empirical studies of take-up and information treatments (see Rafkin et al., 2024 for citations). See Currie (2006) and Currie and Gahvari (2008) for older reviews.]

Example: Nichols and Zeckhauser, 1982

- Two types $\theta \in \{H, L\}$, pop. normalized to 1, share of each s_θ, benefit B
- Money-metric benefit utility $u_\theta(B)$, with overall utility $U_\theta = u_\theta - c$
- Utilitarian social welfare with social cost of B: $u_L(B) > B > u_H(B)$
  - Obtains if B is financed w/ lump-sum tax on average hh with welfare weight of 1
- **Implication**: In first best, government distributes to L and not to H
- Individuals take up if $u_\theta(B) > c$, write $\mathbf{1}_\theta := \mathbf{1}(u_\theta > c)$
- Social welfare is $W = \mathbf{1}_H s_H(u_H - c) + \mathbf{1}_L s_L(u_L - c) - \mathbf{1}_H s_H B - \mathbf{1}_L s_L B$
- Assumption baked into framework: Individuals have private info on their "need" (MU) relative to govt $\rightarrow$ perhaps less relevant in age of big data

Example continued

What should the government set the ordeal at? Three options:

1. Complete take-up: $c = 0$, so social value is:

$$W = s_H u_H(B) + s_L u_L(B) - B \tag{1}$$

2. Separating: $c = u_H$, so social value is $W = s_L[\underbrace{u_L(B) - u_H(B)}_{\text{social value}} \underbrace{-B}_{\text{social cost}}]$

3. No program: $c = \infty$, so social value is 0

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3. No program: $c = \infty$, so social value is 0

- Incomplete take-up is optimal $\iff s_H B - u_H > 0$ and $u_L - u_H - B > 0$
- No program can be optimal: $W_{\text{Complete}} \lessgtr W_{\text{Sep}} \lessgtr 0 = W_{\text{NoProg}}$

Lessons from Nichols and Zeckhauser (1982)

Separation: $W = s_L[\underbrace{u_L(B) - u_H}_{\text{social value}} \underbrace{-B}_{\text{social cost}}]$; and $W_{\text{Sep}} > W_{\text{Complete}} \iff s_H B - u_H > 0$

- If $u_L(B) - B - \underbrace{u_H}_{\text{ordeal cost}} \gg 0$: then minor ordeal achieves lots of redistribution!
- If $u_L(B) - B - \underbrace{u_H}_{\text{ordeal cost}} < 0$: then deadweight loss of ordeal erodes social value, to the point where it's better to just have complete take-up, or no program
- Key statistics: DWL of optimal ordeal ($= u_H$) and utility wedge $\Delta u = u_H - u_L$
- **Envelope intuition**: new enrollees are "just indifferent" so confer negative social value
  - Because they get 0 in private utility, but they cost the government B
  - Raising take-up reduces social value to first order

Example 2: Nichols and Zeckhauser, 1982

- Now suppose utility is $U_\theta = u_\theta(B) - \beta_\theta c$, where β_θ is a fixed constant, known to govt
- Maintain benefit utility $u_L > u_H$
- To separate types, government sets ordeal which makes H indifferent: $c^* = u_H/\beta_H$.
- $W_{\text{Sep}} = s_L\left[u_L - \underbrace{u_H\frac{\beta_L}{\beta_H}}_{=c^*\beta_L} - B\right]$, while $W_{\text{Complete}} = s_L u_L + s_H u_H - B$
- New condition: $W_{\text{Sep}} > W_{\text{Complete}} \iff s_H B - u_H\left[s_H + \frac{s_L\beta_L}{\beta_H}\right] > 0$
- As $\frac{\beta_H}{\beta_L}$ rises, that pushes toward separation, and vice-versa
- Example intuition for $\beta_H \lessgtr \beta_L$?

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- As $\frac{\beta_H}{\beta_L}$ rises, that pushes toward separation, and vice-versa
- Example intuition for $\beta_H \lesseqgtr \beta_L$? Some versions:
  - $\beta_H > \beta_L$: time cost is higher for high type
  - $\beta_L > \beta_H$: poor people find minor hassles more costly

Enter bandwidth

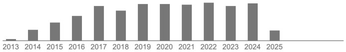
Enormously influential literature examining if poverty itself reduces cognitive function (Bertrand et al., 2004; Shah et al., 2012; Mullainathan and Shafir, 2013)

- If true, one interpretation is that $\beta_L \gg \beta_H$
- Provocative idea, empirical evidence is mixed
- "Behavioral," but no bias required: alternatively can be seen as about ratio β_H/β_L

Scarcity: Why having too little means so much

[PDF] from wordpress.com

Authors	Sendhil Mullainathan, Eldar Shafir
Publication date	2013/9/3
Publisher	Macmillan
Description	In this provocative book based on cutting-edge research, Sendhil Mullainathan and Eldar Shafir show that scarcity creates a distinct psychology for everyone struggling to manage with less than they need. Busy people fail to manage their time efficiently for the same reasons the poor and those maxed out on credit cards fail to manage their money. The dynamics of scarcity reveal why dieters find it hard to resist temptation, why students and busy executives mismanage their time, and why the same sugarcane farmers are smarter after harvest than before. Once we start thinking in terms of scarcity, the problems of modern life come into sharper focus, and Scarcity reveals not only how it leads us astray but also how individuals and organizations can better manage scarcity for greater satisfaction and success.
Total citations	Cited by 3768



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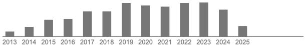
Some consequences of having too little

[PDF] from nber.org

Authors	Anuj K Shah, Sendhil Mullainathan, Eldar Shafir
Publication date	2012/11/2
Journal	Science
Volume	338
Issue	6107
Pages	682-685
Publisher	American Association for the Advancement of Science
Description	Poor individuals often engage in behaviors, such as excessive borrowing, that reinforce the conditions of poverty. Some explanations for these behaviors focus on personality traits of the poor. Others emphasize environmental factors such as housing or financial access. We instead consider how certain behaviors stem simply from having less. We suggest that scarcity changes how people allocate attention: It leads them to engage more deeply in some problems while neglecting others. Across several experiments, we show that scarcity leads to attentional shifts that can help to explain behaviors such as overborrowing. We discuss how this mechanism might also explain other puzzles of poverty.
Total citations	Cited by 2005



Scarcity evidence (a selective review)

Mixed evidence that poverty directly inhibits cognitive function, could go the other way

- Mani et al. (2013) lab study in NJ: induce thoughts about finances, test behavior on unrelated cognitive tasks
  - Results: treatment reduces cognitive function only among poor
  - Fails to replicate in Columbia (González-Arango et al., 2021)
- Mani et al. (2013) field study in India: cognitive performance before and after harvest, worse performance before
  - Does not replicate in U.S. paydays (Carvalho et al., 2016)
  - Goes the opposite direction in Zambia (Fehr et al., 2022)
- Duquennois (2022): 10 pp more word problems about money reduces test scores among low-income students by 0.026 s.d.
- Kaur et al. (2025) manipulate paydays and see 7% higher productivity after payday, & evidence of inattention before

What is the value of β_H/β_L?

Ideal regression: $x_i = \beta \text{ ordeal}_i + \varepsilon_i$, run among new applicants or enrollees only

- Identifying β requires exogenous variation in the ordeal
- x_i supposed to proxy for marginal utility
- Example x_i's: disability status, health status, income, benefit size (why?)
- Idea: if $\frac{dx}{\text{dordeal}} = \beta > 0$ where x is a bad thing, that implies $\beta_H/\beta_L > 0$
- No consensus on sign or magnitude of β across x's and programs
  (see Rafkin et al., 2024 for a more complete list of references)

Deshpande and Li, 2019: First Stage

- Applying for disability programs involves lots of paperwork
- Social Security Administration field offices provide application assistance
- Use disability office closures as a shock to ordeals
- Compare areas that experience a field office closing to areas that experience closings in the future

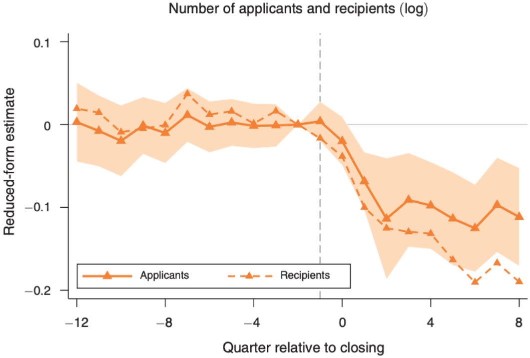
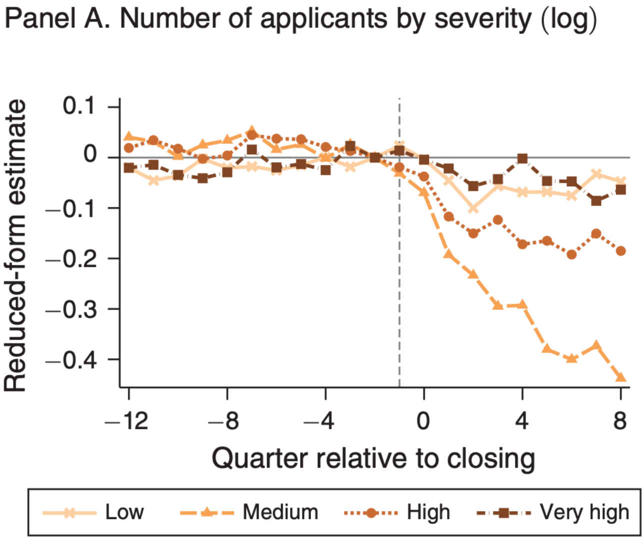
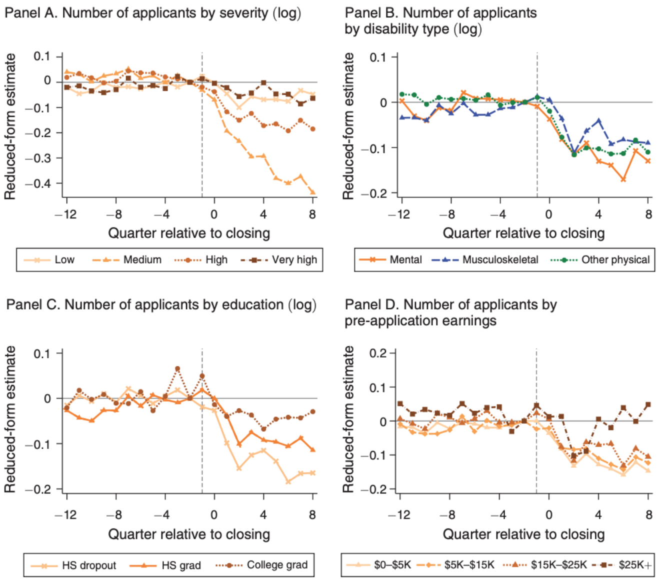


FIGURE 3. EFFECT OF CLOSINGS ON NUMBER OF DISABILITY APPLICATIONS AND ALLOWANCES

Deshpande and Li, 2019: Targeting



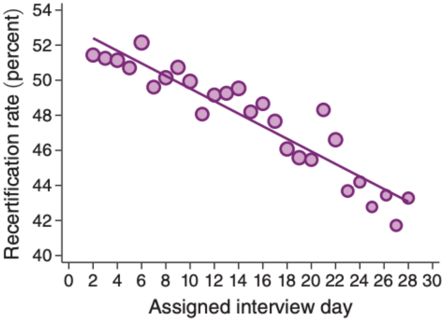
Deshpande and Li, 2019: Targeting



Homonoff and Somerville, 2021: First Stage

- Targeting impact of SNAP (food stamps) recertification (a second eligibility determination)
- Idiosyncratic variation to interview day
- Later interview day within the month $\rightarrow$ less time to reschedule

Panel A. Recertification rate



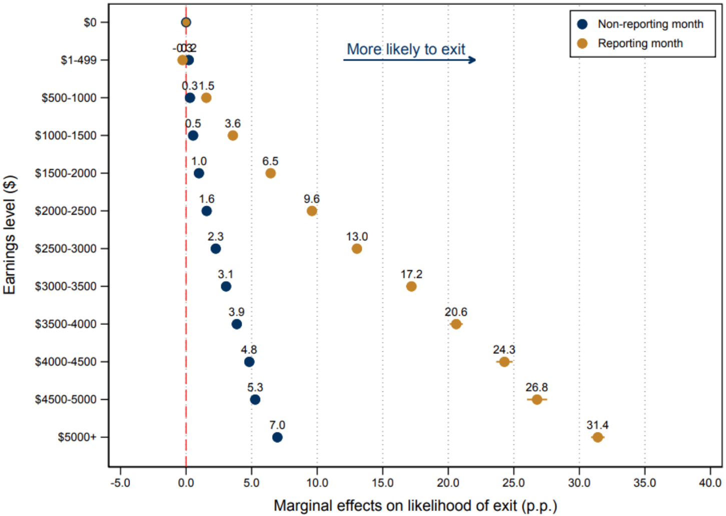
Homonoff and Somerville, 2021: Targeting

Outcome:	Recertified (1)	Post-recert. participation (2)
Interview day	−0.238	−0.074
	(0.067)	(0.057)
Benefit amount	4.571	5.073
	(0.452)	(0.368)
Interview day × benefit amount	−0.058	−0.004
	(0.026)	(0.019)
Max benefit		
Interview day × max benefit		
Outcome mean	48.3	77.6
Total cases	39,360	39,360

Marginally screened out person similar or more needy than average

Unrath, 2024: Characteristics of SNAP exiters

- SNAP recipients must undergo a semi-annual and annual report
- Relatively less poor recipients exit on the date of a report



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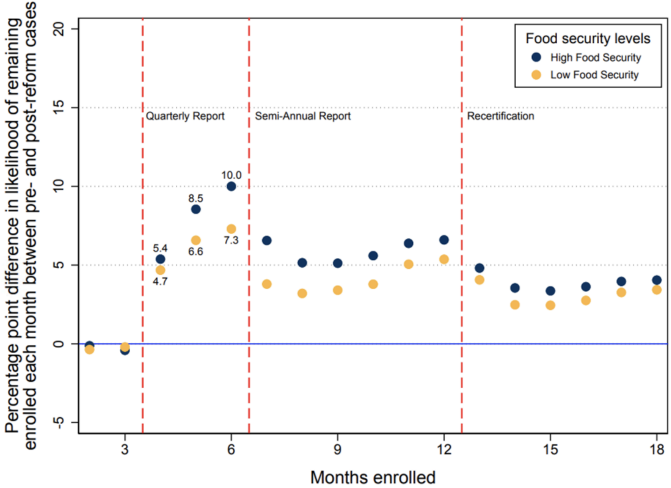
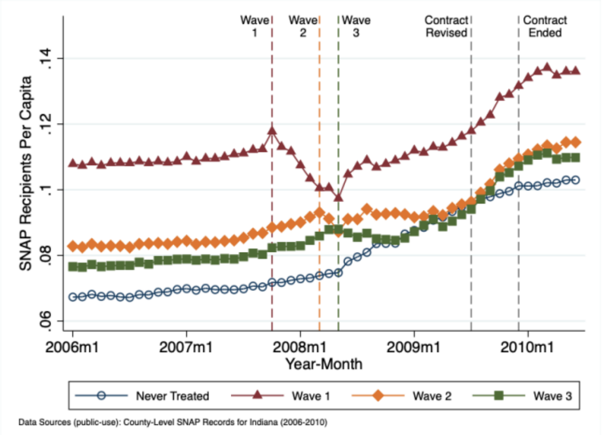


In 2013, changed the reporting frequency $\rightarrow$ seemed to reduce targeting efficiency

Wu and Meyer, 2024: First stage

- Botched roll out of new enrollment and recertification technology in Indiana
- Affecting SNAP, TANF (a cash welfare program), and Medicaid



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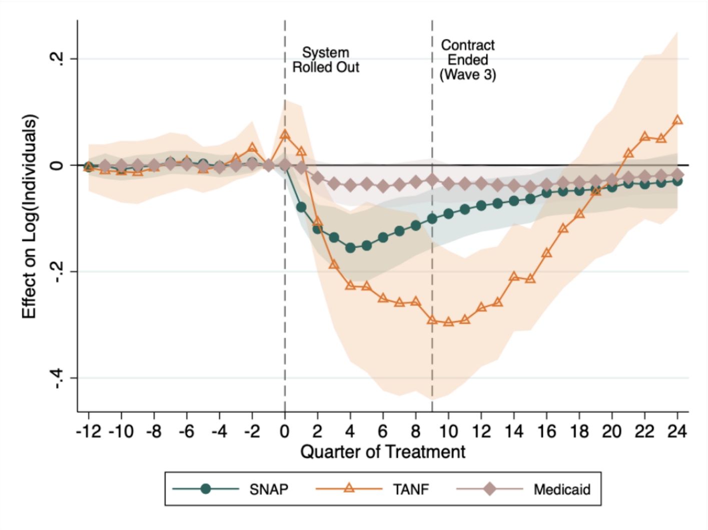

Wu and Meyer, 2024: Targeting

Table 5a. Treatment Effects on the Characteristics

Outcomes	All Remaining Recipients			
	Point Estimate	Std. Error	Baseline Mean	
	(1)	(2)	(3)	(4)
Log Benefit $s/Person	0.0149***	(0.0034)	103	+
Spell Length (mos.)				
Log 3-Year Tax Income[1]	-0.0277**	(0.0135)	38,620	+
Log Tax Income[1]	-0.0335**	(0.0153)	14,900	+
Log Wages (W-2)[1]	-0.0444***	(0.0152)	6,735	+
Has Earnings[1]	-0.0067**	(0.0028)	0.794	+
Has Asset Income[1]	-0.0007	(0.0012)	0.074	+
Years of Education	-0.0871***	(0.0268)	10.9	+
Has Elderly Member	0.0061***	(0.0016)	0.105	+
Has Disabled Member	0.0078***	(0.0027)	0.316	+
Single Parent	0.0076**	(0.0033)	0.328	+
Multiple Parents	-0.0075***	(0.0027)	0.161	+
Deprivation Index (SIPP)	-0.0002	(0.0002)	0.195	−
Non-White	0.0035	(0.0046)	0.178	+
County-Months		7,200		

Wu and Meyer, 2024: Targeting

Outcomes	All Remaining Recipients				Entrants				Exiters			
	Point Estimate	Std. Error	Baseline Mean		Point Estimate	Std. Error	Baseline Mean		Point Estimate	Std. Error	Baseline Mean	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log Benefit $s/Person	0.0149***	(0.0034)	103	+	0.0814***	(0.0097)	90	+	0.0355***	(0.0050)	100	–
Spell Length (mos.)					1.8740***	(0.2311)	15.1	+	1.1250***	(0.1369)	12.1	–
Log 3-Year Tax Income[1]	-0.0277**	(0.0135)	38,620	+	-0.0892***	(0.0170)	65,150	+	-0.0789***	(0.0133)	58,870	–
Log Tax Income[1]	-0.0335**	(0.0153)	14,900	+	-0.0915***	(0.0201)	25,200	+	-0.0807***	(0.0153)	24,540	–
Log Wages (W-2)[1]	-0.0444***	(0.0152)	6,735	+	-0.1112***	(0.0191)	12,160	+	-0.1017***	(0.0162)	12,310	–
Has Earnings[1]	-0.0067**	(0.0028)	0.794	+	-0.0138***	(0.0036)	0.869	+	-0.0109***	(0.0023)	0.850	–
Has Asset Income[1]	-0.0007	(0.0012)	0.074	+	-0.0072***	(0.0019)	0.101	+	-0.0046***	(0.0018)	0.086	–
Years of Education	-0.0871***	(0.0268)	10.9	+	-0.2259***	(0.0426)	11.1	+	-0.0918***	(0.0269)	11.1	–
Has Elderly Member	0.0061***	(0.0016)	0.105	+	0.0046***	(0.0014)	0.033	+	0.0030*	(0.0016)	0.046	–
Has Disabled Member	0.0078***	(0.0027)	0.316	+	0.0114***	(0.0027)	0.169	+	0.0107***	(0.0023)	0.211	–
Single Parent	0.0076**	(0.0033)	0.328	+	0.0254***	(0.0051)	0.337	+	0.0162***	(0.0044)	0.333	–
Multiple Parents	-0.0075***	(0.0027)	0.161	+	-0.0108***	(0.0035)	0.188	+	-0.0044	(0.0028)	0.197	–
Deprivation Index (SIPP)	-0.0002	(0.0002)	0.195	–	0.0015***	(0.0003)	0.191	+	0.0023***	(0.0003)	0.185	–
Non-White	0.0035	(0.0046)	0.178	+	0.0050	(0.0038)	0.168	+	0.0061**	(0.0028)	0.173	–
County-Months	7,200				7,200				7,200			

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

[1] All tax income measures are calculated for 2007 (the year before treatment was fully rolled out), and 3-year tax income is calculated for 2005-2007

Opposite-signed targeting by enrollment vs. recertification — possible synthesis?

Alatas et al., 2016: Ordeals Treatment

- 400 villages in Indonesia randomized into active application versus asset tests for benefit program
- Within active application treatment, ordeals treatment randomizes distance to application
- No interaction between ordeals treatment and consumption profile of applicants on applying (SEs large)

Close subtreatment	.275	.485
	(.168)	(2.920)
Log consumption		−1.446***
		(.144)
Close subtreatment × log consumption		−.023
		(.218)

DV: Show-up probability

No consensus across programs

Influential view: ordeals constitute an administrative burden and should be eliminated
(Herd and Moynihan, 2019, 2025)

- As we will see, the view is perfectly reasonable if the emphasis is on reducing costs for inframarginals, or if screening is costly to administer

- But sign of targeting for an (out-of-sample) ordeal is less clear an argument

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- But sign of targeting for an (out-of-sample) ordeal is less clear an argument

What would I recommend to a policymaker? No idea...

- Compelling set of applied micro results, but maddeningly inconsistent
- One view: This is social science. If you want consistency, take Physics 219B instead
- People marginal to ordeals could just differ — across ordeals, programs, & settings
- Still, we'd prefer not to run an expensive/time-consuming RCT for every ordeal
- My hope: New frameworks reconcile the evidence & enable out-of-sample predictions

Information frictions

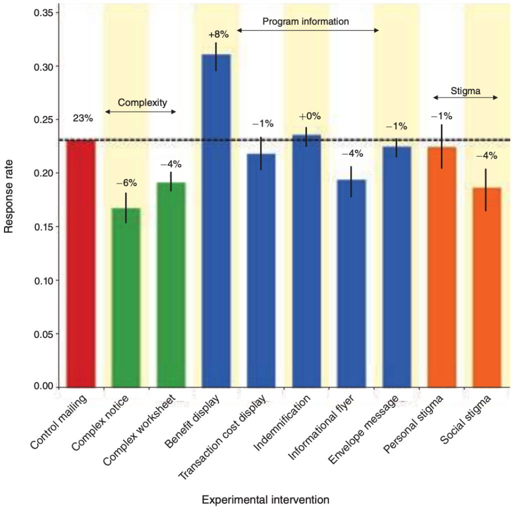
Previous analysis assumed household optimization:

- Under optimization, take up if $u(B, c) > 0$
- Households may not optimize for many reasons, but a candidate one is misperceptions
  - About benefit size
  - About eligibility
  - About awareness of program altogether

  $\rightarrow$ Caution: Minor differences in misperception modeling give different welfare impacts
- Why are information treatments popular?
  - Cheap
  - Relatively easier to find partners and scale (still very hard and impressive in absolute terms)
  - They seem normatively unambiguous (but actually are not, due to fiscal externalities)
- **Roadmap**: discuss some evidence, then circle back to the framework

Bhargava and Manoli, 2015: Main Findings

- 25% of households fail to claim the EITC
- Average amount forgone: ∼$1,100
- IRS experiment with three arms: Confusion, Complexity, Stigma
- Ordeals, including stigma, probably low (feature or bug?)



Bhargava and Manoli, 2015: Benefit Subtreatments

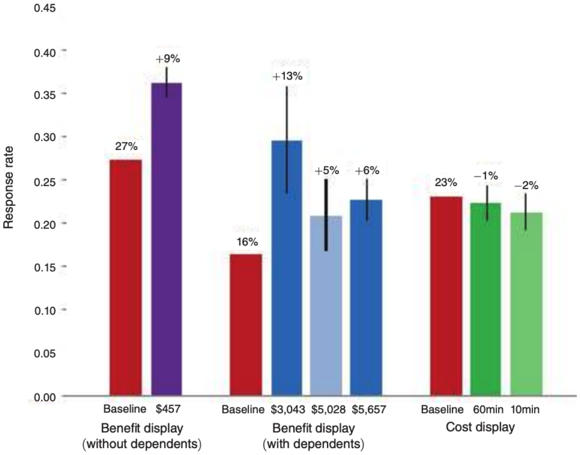


Figure 5. Response and Marginal Effects for Benefit and Cost Display Interventions

What could explain non-monotonicity in benefit size?

Bhargava and Manoli, 2015: Targeting

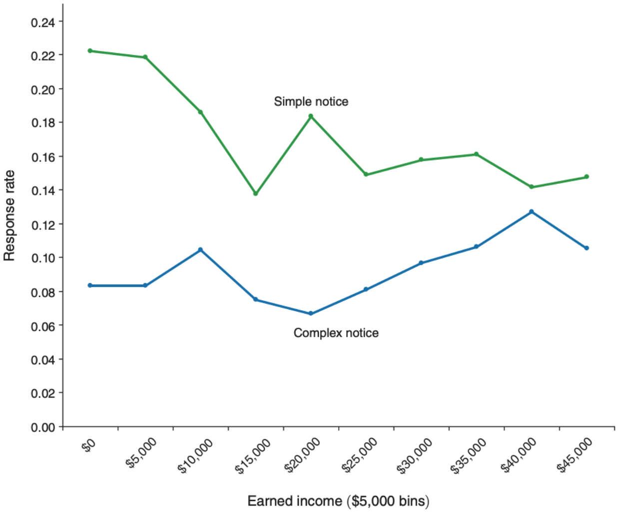
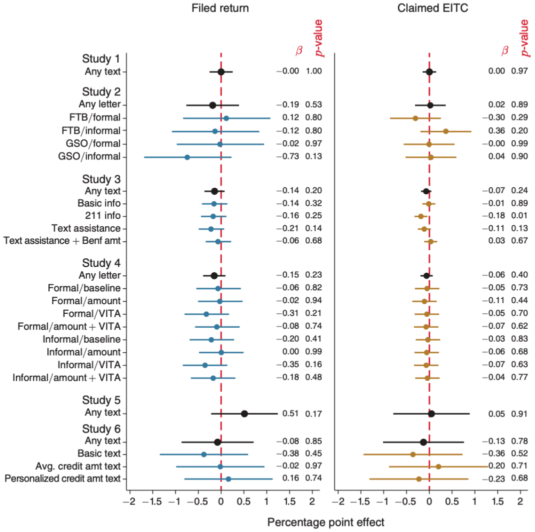


FIGURE 6. HETEROGENEITY IN RESPONSE TO SIMPLIFICATION BY EARNED INCOME
(*For recipients with dependents*)

But null results from other EITC nudges

Linos et al. (2022)

- Randomize other information or nudges to 1.5 million EITC nonfilers
- Null across ∼all treatments
- Also small absolute impacts in Linos et al. (2025) nudges for Child Tax Credit (large relative impacts)
- Possible explanation for discrepancy: Bhargava-Manoli sample had already filed something so more malleable



Other biases (in the opposite direction?) (Chan, 2017)

Welfare programs often motivated by paternalism (e.g., time limits & welfare dependence)

- **Present-focused preferences**: Underrate option value of banking extra time and value of work experience, but also delay take-up
- Program time limits affects dynamic continuation values but not present payoffs $\rightarrow$ identifies present focus and discounting
  (Magnac and Thesmar, 2002, related arguments in Fang and Silverman, 2009)
- Work and welfare choice identifies naifs vs. sophisticates
- Data: 1990's experiment on TANF time limits in Florida
- **Results**:
  - Present focus: 0.59 (quarterly), with wide dispersion; substantial naiveté
  - Eliminating present focus would raise take-up more than work
  - Revenue-neutral sanctions that forbid repeat enrollment can raise utility ($\sim$ commitment)

Putting it all together: Finkelstein and Notowidigdo, 2019

[Slightly different notation and emphasis than in FN]

- Continuum of types $\theta \sim U[0,1]$, benefit B_θ, ordeal cost $c_\theta = \beta_\theta c$
- Utility gain from take-up is $u_\theta(B_\theta, c)$
- Takes up if decision utility $\tilde{u}_\theta(B_\theta, c) \geq 0$, where $\tilde{u}_\theta$ can differ from u_θ
  - E.g., lack of awareness: $\tilde{u}(B, c) = -\infty$;
  - Present focus: $\tilde{u}(B, c) = \beta u(B) - c$
  - "Bandwidth"-type overestimation of costs due to stress: $\tilde{u}(B, c) = u(B, c) - 100c$
- Utilitarian welfare with marginal cost of public funds $= 1$
- ($\sim$ WLOG) sort types s.t. $d\tilde{u}_\theta / d\theta \leq 0$, gives marginal type $\tilde{\theta}(B_{\tilde{\theta}}, c)$ with $\tilde{u}_{\tilde{\theta}}(B_{\tilde{\theta}}, c) = 0$

$$W = \underbrace{\int_0^{\tilde{\theta}(B_{\tilde{\theta}}, c)} u_\theta(B_\theta, c) d\theta}_{\text{Social benefit to enrollees}} - \underbrace{\int_0^{\tilde{\theta}(B_{\tilde{\theta}}, c)} B_\theta d\theta}_{\text{Social cost of enrollment}}$$

Welfare impact of a marginal change in costs

$$\frac{dW}{dc} = \underbrace{\frac{d\tilde{\theta}}{dc} u_{\tilde{\theta}}(B_{\tilde{\theta}}, c)}_{\Delta \text{ welfare for marginals}} + \underbrace{\int_0^{\tilde{\theta}(B_{\tilde{\theta}}, c)} \frac{du_\theta}{dc} d\theta}_{\Delta \text{ DWL of ordeals for inframarginals}} - \underbrace{\frac{d\tilde{\theta}}{dc} B_{\tilde{\theta}}}_{\text{Fiscal cost of marginals}}$$

- **Envelope theorem in background**
  - Suppose $\tilde{u} = u$, so $u_{\tilde{\theta}}(B_{\tilde{\theta}}, c) = 0$: no welfare gain from behavioral response, but fiscal cost
  - Under optimization ($\tilde{u} = u$), bigger take-up responses among low types with bigger benefits *reduces* welfare, relative to having higher take-up responses among high types
  - Gains to new enrollees only if marginal $\tilde{u} \neq u$ (inframarginals' bias does not matter either)
- Reducing ordeals unambiguously reduces deadweight loss (note: du_θ/dc varies via β_θ)
- Take-up responses to change in ordeals are not a sufficient-statistic for welfare
  - Directly suggests large fiscal cost (note: fiscal cost does not depend on mechanism ✓)
  - However, new take-up possibly implies deadweight loss reductions for inframarginals

✓ If other fiscal externalities beyond take-up, then last term is $\int_0^1 \frac{dFE_\theta}{dc} d\theta$

Pop quiz

My destigmatization intervention raises take-up by 20 pp. I send a delighted email to my advisor and take the afternoon off to celebrate. My email was:

1. Justified, as I am celebrating that the intervention raised welfare
2. Cruel, as I am celebrating when the intervention reduced welfare
3. Hasty, as the impact is ambiguous

Pop quiz

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1. Justified, as I am celebrating that the intervention raised welfare
2. Cruel, as I am celebrating when the intervention reduced welfare
3. Hasty, as the impact is ambiguous

Answer: 3, get back to work

- If stigma is just like any other ordeal, the welfare impact of raising take-up is ambiguous
- $\uparrow$ take-up is **worrisome** because new enrollees are "just indifferent" (envelope)
- $\uparrow$ take-up is **encouraging** if it suggests $\downarrow$ DWL of ordeals among inframarginal
- **Null results**, in principle, could be better for welfare if they actually destigmatize
- Still, not that many economists care about this "gotcha": What are the best retorts?

Bias and information

Household take-up choice maximizes true utility w.p. $q_\theta p$, where $q_\theta \in [0, 1/p]$

$$\tilde{u}_\theta(B_\theta, c) = \begin{cases} u_\theta(B_\theta, c) & \text{with probability } q_\theta p \\ \hat{u}_\theta(B_\theta, c) & \text{with probability } 1 - q_\theta p \end{cases} \tag{2}$$

(Written so common change to information dp is more impactful on θ for large q_θ)

Let θ_1, θ_2 be such that $u_{\theta_i}(B_{\theta_1}, c) = 0$, $\hat{u}_{\theta_2}(B_{\theta_2}, c) = 0$

- Assume bias reduces take-up, so $u_\theta(B_\theta, c) > \hat{u}_\theta(B_\theta, c)$ (easy to relax)
- Then, $\theta_1 > \theta_2$
- Counterargument?

Bias and information

Household take-up choice maximizes true utility w.p. $q_\theta p$, where $q_\theta \in [0, 1/p]$

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- Assume bias reduces take-up, so $u_\theta(B_\theta, c) > \hat{u}_\theta(B_\theta, c)$ (easy to relax)
- Then, $\theta_1 > \theta_2$
- Counterargument? (Chan, 2017)

Welfare impact of a marginal change in information

$$W = \underbrace{\int_0^{\theta_1(B_{\theta_1},c)} q_\theta p u_\theta(B_\theta, c) d\theta}_{\text{Enrolls if unbiased}} + \underbrace{\int_0^{\theta_2(B_{\theta_2},c)} (1 - q_\theta p) u_\theta(B_\theta, c) d\theta}_{\text{Enrolls if biased}}$$

$$- \underbrace{\int_0^{\theta_1(B_{\theta_1},c)} q_\theta p B_\theta d\theta}_{\text{Cost if unbiased}} - \underbrace{\int_0^{\theta_2(B_{\theta_2},c)} (1 - q_\theta p) B_\theta d\theta}_{\text{Cost if biased}}$$

$$\frac{dW}{dp} = \underbrace{\int_{\theta_2(B_{\theta_2},c)}^{\theta_1(B_{\theta_1},c)} q_\theta u_\theta(B_\theta, c) d\theta}_{\text{Welfare gains of newly enrolled (formerly biased)}} - \underbrace{\int_{\theta_2(B_{\theta_2},c)}^{\theta_1(B_{\theta_1},c)} q_\theta B_\theta d\theta}_{\text{Cost of newly enrolled (formerly biased)}}$$

Welfare impact of a marginal change in information: intuition

$$\frac{dW}{dp} = \underbrace{\int_{\theta_2(B_{\theta_2},c)}^{\theta_1(B_{\theta_1},c)} q_\theta u_\theta(B_\theta, c) d\theta}_{\text{Welfare gains of newly enrolled (formerly biased)}} - \underbrace{\int_{\theta_2(B_{\theta_2},c)}^{\theta_1(B_{\theta_1},c)} q_\theta B_\theta d\theta}_{\text{Cost of newly enrolled (formerly biased)}}$$

- **Why do "true" welfare gains of new enrollees enter?**

Welfare impact of a marginal change in information: intuition

$$\frac{dW}{dp} = \underbrace{\int_{\theta_2(B_{\theta_2}, c)}^{\theta_1(B_{\theta_1}, c)} q_\theta u_\theta(B_\theta, c) d\theta}_{\text{Welfare gains of newly enrolled (formerly biased)}} - \underbrace{\int_{\theta_2(B_{\theta_2}, c)}^{\theta_1(B_{\theta_1}, c)} q_\theta B_\theta d\theta}_{\text{Cost of newly enrolled (formerly biased)}}$$

- **Why do "true" welfare gains of new enrollees enter?** People no longer optimize $\rightarrow$ off envelope condition
- Comparison with dW/dc: Reducing costs confers direct impacts to already enrolled (DWL reduction), whereas reducing bias confers direct impacts to newly enrolled
- **Targeting matters!**: information is not always good/debiasing people can be bad
  - If $u_\theta(B_\theta, c) < B_\theta$ for $\theta_2 < \theta < \theta_1$ (a flavor of Allcott et al. (2024) on nudges)
- Per usual, fiscal externality is "easy": does not require taking a stance on bias, but do need to measure social costs of **new** enrollees

✓ Model insights beyond PF: in-kind benefits (devo), job training (labor), etc.

Finkelstein-Notowidigdo: First Stage

- Two interventions, partnering with a SNAP assistance nonprofit

- Info Plus Assistance and Information Only

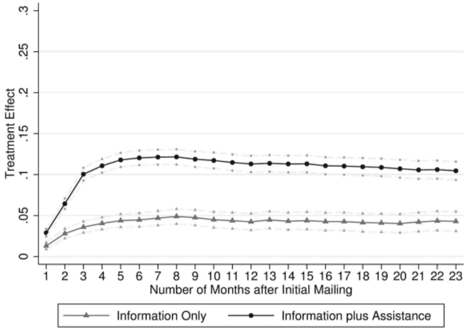


FIGURE I

Time Pattern of Enrollment Responses

Figure shows, by month, the (cumulative) estimated treatment effects on enrollment (relative to the control) for the Information Only arm and the Information Plus Assistance arm. Ninety-five percent confidence intervals on these estimates are shown in the dashed light gray lines.

Finkelstein-Notowidigdo: Targeting

	Control (1)	Information Only (2)	Information Plus Assistance (3)	p-value of difference (column (2) versus (3)) (4)
Benefit amount ($)	145.94	115.38	101.32	
		[.000]	[.000]	[.013]
Share $16 benefit	0.192	0.312	0.367	
		[.000]	[.000]	[.021]
Share $194 benefit	0.206	0.164	0.147	
		[.076]	[.003]	[.352]
Share $357 benefit	0.060	0.052	0.040	
		[.587]	[.077]	[.259]
Share missing benefit	0.073	0.043	0.028	
		[.025]	[.000]	[.139]
Predicted benefit for enrollees w/ actual benefit	140.20	112.49	102.93	
		[.000]	[.000]	[.086]
Predicted benefit for all enrollees	138.65	114.01	104.03	
		[.000]	[.000]	[.068]
Share of enrollees in household size of 1	0.657	0.714	0.760	
		[.038]	[.000]	[.036]
Benefit amount for enrollees in household size of 1	116.97	93.35	85.82	
		[.000]	[.000]	[.134]
Observations (N)	613	559	1,861	

Finkelstein-Notowidigdo: Targeting

TABLE V

Demographic and Health Characteristics: Applicants and Enrollees

	Applicants				Enrollees			
	Means			p-value	Means			p-value
	Control (1)	Info Only (2)	Info Plus Assistance (3)	Info Plus Assistance versus Info Only (4)	Control (5)	Info Only (6)	Info Plus Assistance (7)	Info Plus Assistance versus Info Only (8)
Panel A: Predicted benefits								
Predicted benefits	148.26	125.65	115.36		138.65	114.01	104.03	
		[.000]	[.000]	[.037]		[.000]	[.000]	[.068]
Panel B: (Annual) healthcare measures, 2015								
Total healthcare	9,424	8,605	8,334		10,238	9,532	8,603	
spending ($)[a]		[.517]	[.300]	[.781]		[.661]	[.208]	[.459]
Total number of visits	13.33	11.67	9.92		14.79	10.90	9.92	
and days		[.331]	[.018]	[.166]		[.058]	[.008]	[.467]
Weighted total number of	4,661	3,273	2,818		5,407	3,288	2,779	
visits and days		[.128]	[.022]	[.442]		[.064]	[.011]	[.461]
Number of chronic	6.21	5.55	5.27		6.54	5.43	5.37	
conditions		[.094]	[.006]	[.383]		[.019]	[.005]	[.875]
Panel C: Demographics								
Share age above	0.41	0.46	0.46		0.39	0.43	0.46	
median = 65		[.072]	[.014]	[.764]		[.282]	[.006]	[.159]
Share age 80+	0.06	0.11	0.14		0.07	0.12	0.14	
		[.001]	[.000]	[.042]		[.005]	[.000]	[.085]
Male	0.41	0.40	0.38		0.39	0.42	0.38	
		[.983]	[.232]	[.250]		[.446]	[.444]	[.104]

Finkelstein-Notowidigdo: Targeting

TABLE V
CONTINUED

	Applicants				Enrollees			
	Means			p-value Info Plus Assistance versus Info Only	Means			p-value Info Plus Assistance versus Info Only
	Control (1)	Info Only (2)	Info Plus Assistance (3)	(4)	Control (5)	Info Only (6)	Info Plus Assistance (7)	(8)
Share white[b]	0.67	0.73	0.74		0.71	0.78	0.78	
		[.005]	[.000]	[.554]		[.004]	[.001]	[.958]
Share black[b]	0.10	0.08	0.11		0.11	0.07	0.10	
		[.103]	[.577]	[.011]		[.011]	[.833]	[.004]
Share primary language not English	0.08	0.06	0.04		0.06	0.05	0.03	
		[.141]	[.000]	[.012]		[.242]	[.002]	[.067]
Share living in Pittsburgh	0.05	0.06	0.07		0.05	0.06	0.07	
		[.385]	[.066]	[.459]		[.374]	[.028]	[.310]
Share last Medicaid spell starting before 2011	0.25	0.30	0.29		0.26	0.33	0.31	
		[.022]	[.017]	[.704]		[.009]	[.026]	[.348]
Observations (N)	817	781	2,519		613	559	1,861	

Finkelstein-Notowidigdo: Welfare

Rewrite welfare propositions using MVPF ($\sim$ ratio of social benefits to social costs) ✓

Sample of assumptions for empirical calibration for information only:

- Two types w/ same social cost, corresponding to minimum benefit and average benefit
- Misperceptions that rationalize non-applying are very large
- Divide by each type's MU $\rightarrow$ society's WTP for \$1 is \$1 for each

Results:

- Absent bias, targeting to low types reduces welfare, as they have bigger benefits
- Even with misperceptions, MVPF < 1 (because dividing by MU & admin costs)
- MVPF higher for low types (0.93) than high types (0.5)
- Higher for information plus assistance

Finkelstein-Notowidigdo: Assessment & Next Steps

Why is this paper important?

- Provides a new and portable lens for interpreting this whole take-up literature
- Tight connection between simple theory and rigorous empirics
- Clear mapping to welfare (and connection to Allcott et al., 2024 on nudges)

What comes next?

- Empirical covariances between bias and treatment effects are key, but not collected
- Evidence on welfare impacts of ordeal reductions less clear
- Pure redistributive benefits not considered but probably important

One Step Further: Shepard and Wagner, 2025

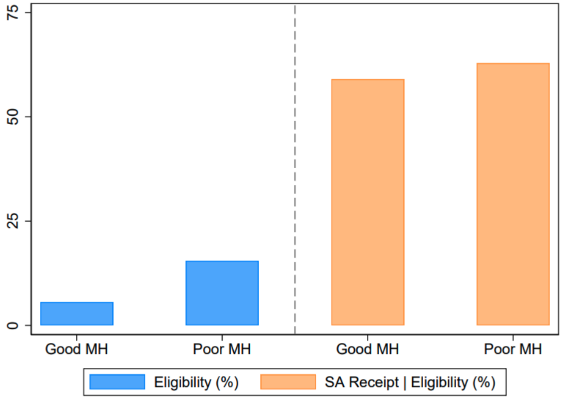
Beautiful application and extension of FN

- **Theory**: FN-type model applied to adverse selection in public health insurance
- **Insight**: Ordeals screen out low-utilization people, amplifying adverse selection
- **Variation**: Ending auto-enrollment for health care for low-income households in MA
- **Empirics**: Ordeals screen out younger, healthier, and poorer ✓
- **Model calibration**:
  - Applies "rational consumer benchmark" approach in Allcott et al. (2019) to value healthcare among passive enrollees
  - Projects demand from high-income demographic cells that face positive prices
- **Normative results**:
  - Passive enrollees have lower private value...
  - ... but higher social value, because they lessen adverse selection

Recent JMP: Naik, 2025

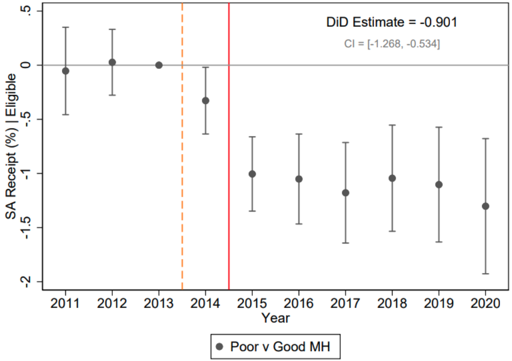
Mental health and benefit take-up:

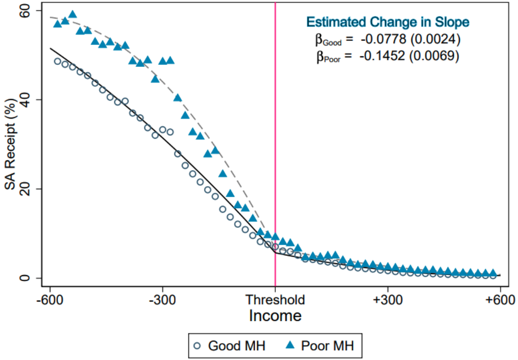
- High prevalence of poor mental health in eligible population
- How to target people w/ poor MH: $\uparrow$ benefits or $\downarrow$ ordeals?
- Adapt FN to study Dutch social assistance
- Three key ingredients: levels of take-up (s_θ) by MH type $\theta \in \{H, L\}$, ds_θ/dc, ds_θ/dB



Step 1: Levels are similar

Steps 2–3: Poor MH & elasticities





Step 2: Poor MH more elastic to ordeals

Step 3: Poor MH more elastic to benefits

$\implies$ **Reducing ordeals is more efficient than raising benefits**

- $\uparrow$ benefits is coarse: transfers to those with relatively low need
- $\downarrow$ ordeals confers gains to inframarginals
- Very classical set-up: Much to do on mental health and optimization failures

A Different Perspective: Rafkin, Solomon, and Soltas (2024)

Desired estimand in ordeal literature: dW/dc

- Recall ordeal regression: $x_i = \beta \text{ ordeal}_i + \varepsilon_i,$ run among new applicants only, e.g.
- Regression tells us about targeting at the margin of an ordeal
- Conceptual exercise: if we remove page 352 of 420 page document, who joins

Alternative question: What if we make programs automatic but held budget fixed?

- Transfers from inframarginal enrollees to inframarginal non-enrollees

[Antecedents to this approach: Alatas et al. (2016), Deshpande and Lockwood (2022), and others]

Run the right regression

Ideal object: Δ in marginal utility between recipients and "similar" eligible nonrecipients

$$\beta = \frac{\mathsf{E}[u'_{c,1}] - \mathsf{E}[u'_{c,0}]}{\mathsf{E}[u'_c]}$$

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Ideal object: Δ in marginal utility between recipients and "similar" eligible nonrecipients

$$\beta = \frac{\mathrm{E}[u'_{c,1}] - \mathrm{E}[u'_{c,0}]}{\mathrm{E}[u'_c]}$$

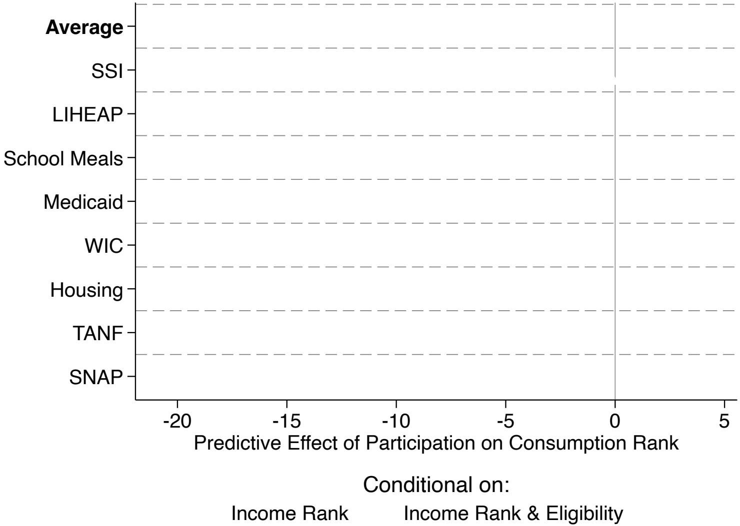
Regression analog:

$$\frac{u'_{c,it}}{\mathrm{E}[u'_c]} = \beta D_{it} + f(x_{it}) + u_{it}$$

Data and design:

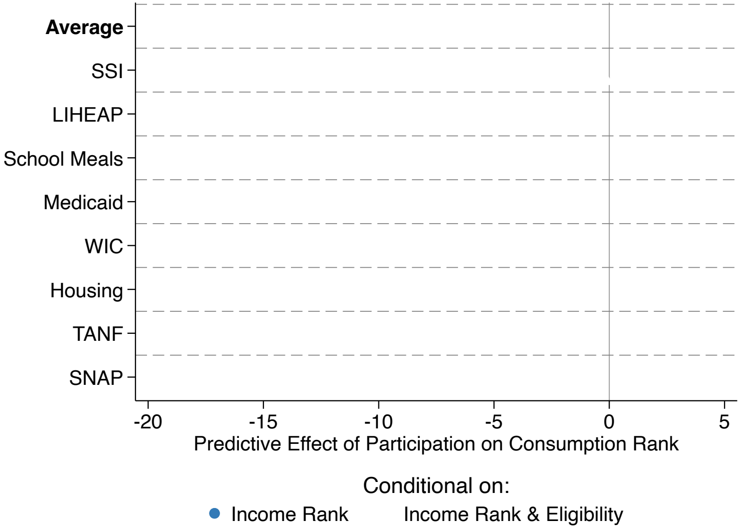
- PSID consumption (1997–2019), eight transfer programs
- Simple comparison of means: no quasi-experiment necessary

Self-Targeting: Consumption



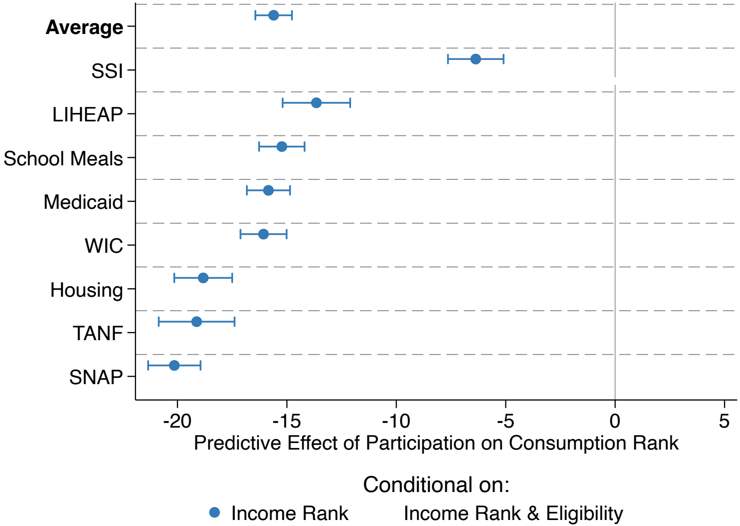
Self-Targeting: Consumption

$$r_{it}^{c} = \tilde{\beta} D_{it} + f(r_{it}^{y}) + u_{it}$$



- r_{it}^{c} : consumption
- D_{it} : transfer receipt
- r_{it}^{y} : income

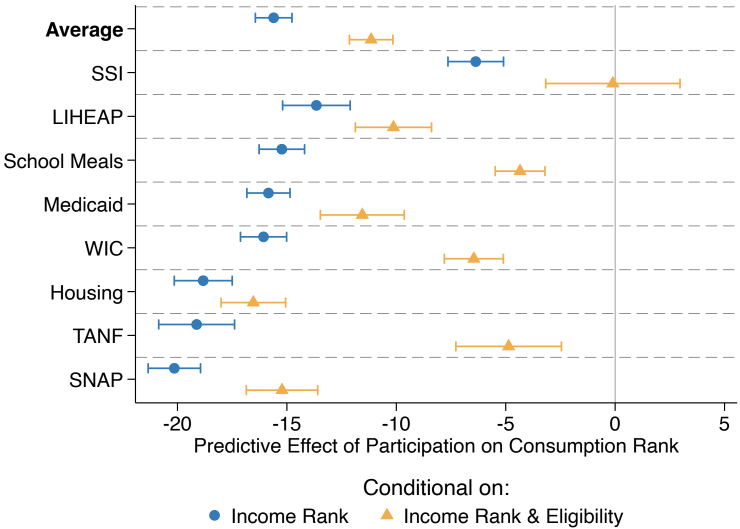
Self-Targeting: Consumption



$$r^c_{it} = \tilde{\beta} D_{it} + f(r^y_{it}) + u_{it}$$

- r^c_{it} : consumption
- D_{it} : transfer receipt
- r^y_{it} : income

Self-Targeting: Consumption



Full population:

$$r^c_{it} = \tilde{\beta} D_{it} + f(r^y_{it}) + u_{it}$$

Among eligibles only:

$$r^c_{it} = \tilde{\beta} D_{it} + f(r^y_{it}) + u_{it}$$

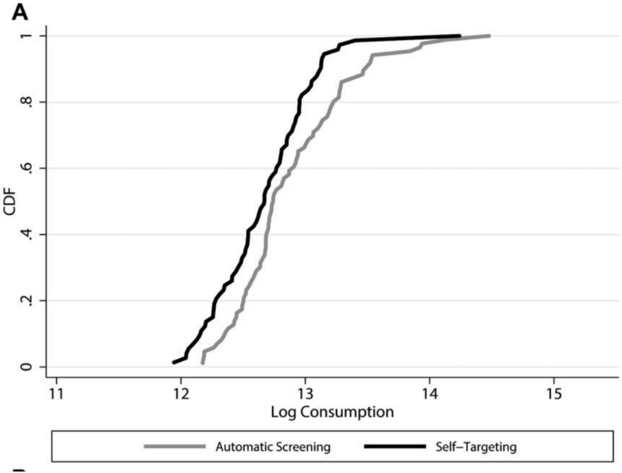
- r^c_{it} : consumption
- D_{it} : transfer receipt
- r^y_{it} : income

Levels/Logs + Controls

Months Other Transfers CEX

Self-Targeting on Consumption (Alatas et al., 2016)

- Remember: 400 villages in Indonesia randomized into active application versus asset tests
- Ground-truth data on consumption
- Positive self-targeting on observable and unobservable component



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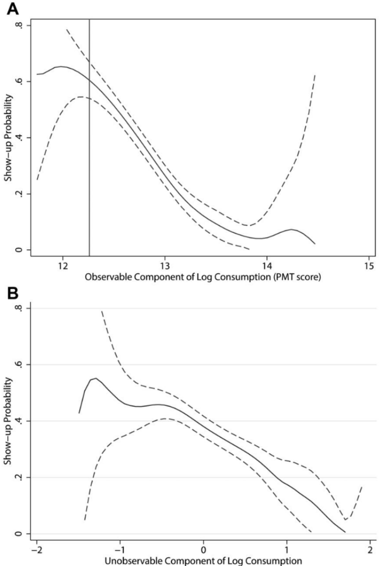
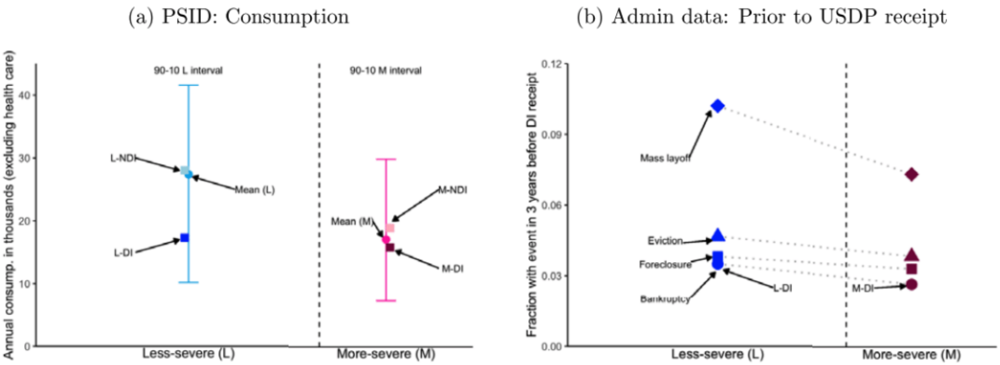


Self-Targeting on Consumption (Deshpande and Lockwood, 2022)



DI recipients with Less-severe health conditions:

- Have as low consumption as those with More-severe conditions
- Much worse off than Non-recipients (NDI)

Rafkin et al.: Voluntary or Automatic? Theory

What is the Δ in welfare between two policy alternatives?

1. Voluntary: flat increase dB in size of transfer B
2. Automatic: equal-cost increase (incl. behavioral response to voluntary)

Rafkin et al.: Voluntary or Automatic? Theory

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1. Voluntary: flat increase dB in size of transfer B
2. Automatic: equal-cost increase (incl. behavioral response to voluntary)

$$\frac{dW}{dB} = \underbrace{M(B)\mathrm{E}[\alpha(i) \,|\, \kappa(i) \leq B] \cdot ((1+\varepsilon_b)M(B) - 1)}_{\text{recipients}}$$
$$+ \underbrace{(1 - M(B))\mathrm{E}[\alpha(i) \,|\, \kappa(i) > B] \cdot (1+\varepsilon_b)M(B)}_{\text{nonrecipients}}$$

where, with households $i \in [0, 1]$

- $\alpha(i)$: welfare weight on household i
- $\kappa(i)$: take-up cost of household i
- $M(B)$: take-up rate at size s
- ε_b: elasticity of take-up w.r.t. benefit

Rafkin et al.: Voluntary or Automatic? Theory

What is the Δ in welfare between two policy alternatives?

1. Voluntary: flat increase dB in size of transfer B
2. Automatic: equal-cost increase (incl. behavioral response to voluntary)

$$\frac{dW}{dB} = \underbrace{\beta\sigma_M^2}_{\text{benefits}} - \underbrace{M(B)\varepsilon_b}_{\text{costs}}$$

where

- Self-targeting intensity: $\beta = \mathrm{E}[\alpha(i)|\kappa(i) \leq B] - \mathrm{E}[\alpha(i)|\kappa(i) > B]$
- Variance in take-up rate: $\sigma_M^2 = M(B)[1 - M(B)]$

Rafkin et al.: Voluntary or Automatic? Theory

What is the Δ in welfare between two policy alternatives?

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- Variance in take-up rate: $\sigma_M^2 = M(B)[1 - M(B)]$

Generalizations in the paper: (1) labor supply, (2) risk aversion, (3) dynamics

Rafkin et al., 2024: Welfare Calibration & Implications

Table 3: Welfare Effects of Budgetary Shifts Toward Automatic Transfers (Cents per Transfer Dollar)

	Self-Targeting Gains		Other Forces		Total
	Redistribution (1)	Insurance (2)	Upper Bound on Ordeals (3)	Labor-Supply Effects (4)	(5)
Panel A: Primary Estimates					
Dollar-Weighted Average	**-27.6**	**-3.3**	**15.9**	**-0.6**	**-15.6**
SNAP	-39.2	-5.6	17.3	-0.8	-28.2
Medicaid	-29.8	-2.2	21.0	-0.6	-11.6
Housing Assistance	-22.2	-3.2	6.2	-0.4	-19.7
TANF	-7.2	-0.8	4.1	-0.7	-4.6
SSI	7.3	-2.4	25.0	-0.8	29.1
School Lunch	-7.9	-0.8	18.2	-0.7	8.7
WIC	-14.1	-3.6	19.1	-1.5	-0.0
LIHEAP	-13.8	-1.5	7.5	-0.4	-8.3

Implications for behavioral economics and take-up:

- At the margin of a given ordeal, targeting is unclear: scarcity, β_H/β_L, and other forces
- Integrating over all margins, seems $\beta_H \gg \beta_L$
- Still consistent with scarcity (e.g., Fehr et al., 2022)

Alternative to “Self”-Targeting: Machine Learning

Predict need & impact of transfer (Haushofer et al., 2022)

- **Govt trade off**: Transfer based on deprivation (high MU) or impact (TEs)
- In Kenya cash transfer setting, impact $\gg$ need for reasonable utility calibration
- Interpretation of TE of cash?

✓ Shows broad relevance of targeting framework

	(1)	(2)	(3)	(4)	(5)
CARA: α	CE	Most deprived	Most impacted	Choice	α_c
Panel A: Consumption					
0.0000	\$50	0.26	1.00	I	
0.0005	\$49	0.27	0.95	I	
0.0010	\$49	0.29	0.92	I	
0.0075	\$41	0.35	0.81	I	0.01
0.0150	\$33	0.36	0.79	D	

Cells in (2)/(3) show % SWF should treat

Welfare Stigma

What is stigma?

- Social psych definition: $\sim$ social or self signaling (Goffman, 1963)
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Moffitt (1983): Canonical econ formalization

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Welfare Stigma

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- $u(h, y, B) = u(h, y + \gamma \mathbf{1}_{\text{TakesUp}} B) - \phi \mathbf{1}_{\text{TakesUp}}$
- What are reasonable values of (γ, ϕ)? Answer: $\gamma \in [0, 1)$, $\phi > 0$
- 80s labor econ tricks to obtain estimating equations for participation given fade out
- $\phi = 0.65$ (s.d. of shock), $\gamma > 1$ (!) [but results are heavily structural and outdated]

Experimental proof of concept: Friedrichsen et al., 2019

- Take-up for benefit, in public or private
- Eligibility based on performance in quiz task, or luck
- If take-up, non-enrollees' pay is lower
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Task	Private transfer	Public transfer	Difference (paired)
Quiz	0.879	0.576	0.303***
	(0.025)	(0.039)	(0.038)
	[165]	[165]	[165]
Random	0.862	0.673	0.189***
	(0.027)	(0.037)	(0.032)
	[159]	[159]	[159]
Difference	0.017	-0.097*	DiD=0.114**
(unpaired)	(0.037)	(0.054)	(0.050)
	[324]	[324]	[324]

Stigma & Political Economy of Welfare State: Lindebeck et al., 1999

- Net utility from transfer T and tax rate t: $u(T, t, x)$; x is % of pop on transfer
- Fixed-point equation in x, possibly multiple equilibria
- Tax $f(x)$ and transfer $F(x)$ no longer monotonic in x (intuition?)
- Two "political equilibria" that majority support: no transfer or high tax and welfare society

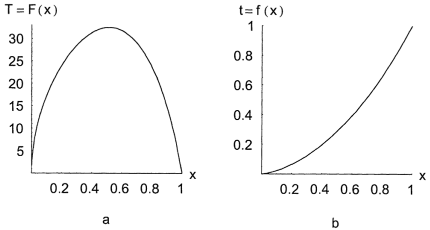


FIGURE II
A Transfer Function F with Associated Tax Function f

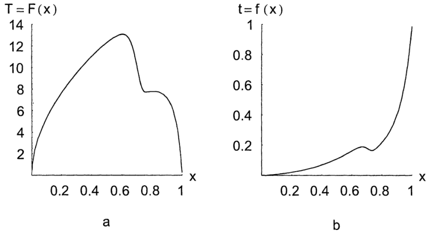
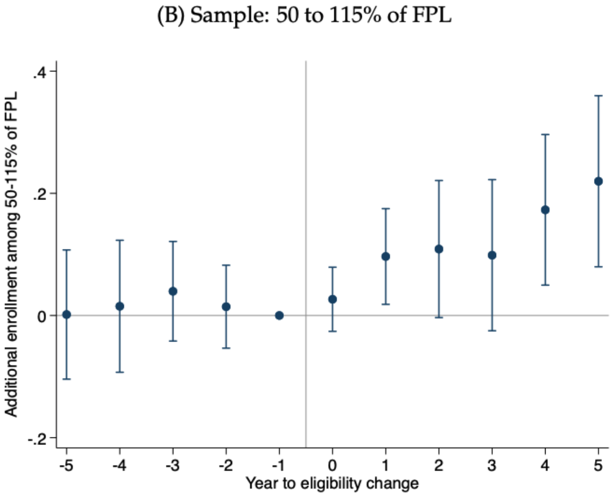


FIGURE III
A Nonconcave Transfer Function F and the Associated Nonmonotonic Tax Function f

Stigma versus information: Anders and Rafkin, Forthcoming

"Woodwork effects":

- ↑ the SNAP eligibility threshold could ↑ take-up among already-eligible inframarginals
- Use idiosyncratic variation in SNAP eligibility expansions
- Public-use anonymized admin data, the Quality Control files (Ganong and Liebman, 2019)



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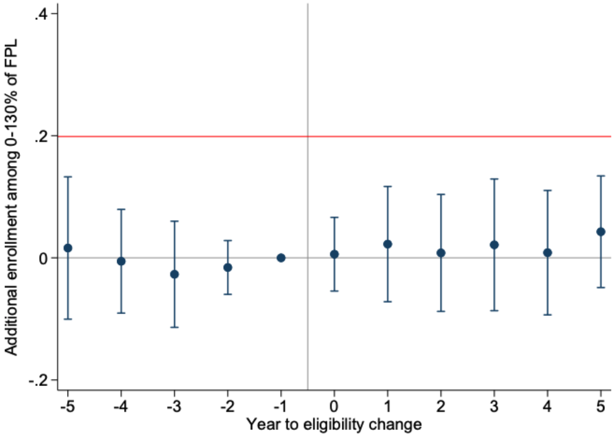
(C) Placebo: BBCE States that Do Not Expand Eligibility



Stigma versus information

Main explanations: stigma (Michael B. Katz, *In the Shadow of the Poorhouse*, 1986), or information

- Stigma: inconclusive lab experiment manipulating beliefs about eligibility threshold
- Information: dredged up old (internal) USDA data on SNAP information $\rightarrow$ some evidence of misperceptions

Normative interpretation: build on FN

- Welfare impacts of woodwork effects are mixed
- If from stigma, then new take-up reduces welfare, but could confer gains to inframarginal enrollees
- If from information, then new take-up is probably good (if newly enrolled are needy)

Anders and Rafkin: Stylized calibration

	At Threshold		Already Eligible			Social Welfare		
	Social benefits (1)	Social costs (2)	Social benefits from take-up (3)	Social benefits from stigma reduction (4)	Social costs (5)	At threshold (= 1 - 2) (6)	Already eligible (= 3 + 4 - 5) (7)	Overall (= 6 + 7) (8)
1. Primary	**66.7**	**66.7**	**753**	**176**	**232**	**0**	**697**	**697**
2. Half woodwork elasticity	66.7	66.7	377	176	116	0	437	437
3. Double woodwork elasticity	66.7	66.7	1,507	176	463	0	1,219	1,219
4. Heterogeneous woodwork elasticity	66.7	66.7	527	176	298	0	404	404
5. No woodwork from stigma	66.7	66.7	1,130	0	232	0	898	898
6. Double woodwork from stigma	66.7	66.7	377	352	232	0	497	497
7. All woodwork from stigma	66.7	66.7	0	527	232	0	296	296
8. Half WTP for stigma change	66.7	66.7	753	87.9	232	0	610	610
9. Double WTP for stigma change	66.7	66.7	753	352	232	0	873	873
10. Half risk aversion	196	66.7	379	88.4	232	129	236	365
11. Double risk aversion	0.89	66.7	749	175	232	-65.8	692	626
12. Half income floor	28.5	66.7	737	172	232	-38.2	678	639
13. Double income floor	119	66.7	594	139	232	52.5	501	553
14. Half hassle costs	75.6	66.7	764	178	232	8.8	711	719
15. Double hassle costs	49.6	66.7	733	171	232	-17.2	672	655
16. Uniform idiosyncratic costs	4.6	66.7	346	80.8	232	-62.1	195	133

Highlights role of different mechanisms, and need for more evidence

General problem and aside: DWL of ordeals

DWL could be massive: most people are inframarginal

- Small changes in an ordeal, summed over share s enrolled, could greatly exceed the fiscal cost of new just-indifferent enrollees

Hard to measure. Several strategies:

- Calibration (e.g., Finkelstein and Notowidigdo, 2019; Anders and Rafkin, 2024; Unrath, 2024)
- Parametric extrapolation: ds/dc recovers du/dc (Anders and Rafkin, 2022 WP; Naik, 2025)
- Envelope theorem: ds/dB yields upper bound on c for marginals (Rafkin et al., 2024)
  - Non-parametric estimation to inframarginals requires a lot of variation in B
  - Inherent tension with the above, because assumes optimization
  - Envelope ordeal costs are perhaps an upper bound depending on the reform in question
- Other options: Elicit inframarginals' WTP for an ordeal reduction (never done??)

One Last Thing: Program Selection on Altruism (Rafkin-Soltas 2024)

- ERAP is a benefit program that helps tenants facing eviction
- Potential reason for small ERAP effects: **Altruists enroll but never evict**

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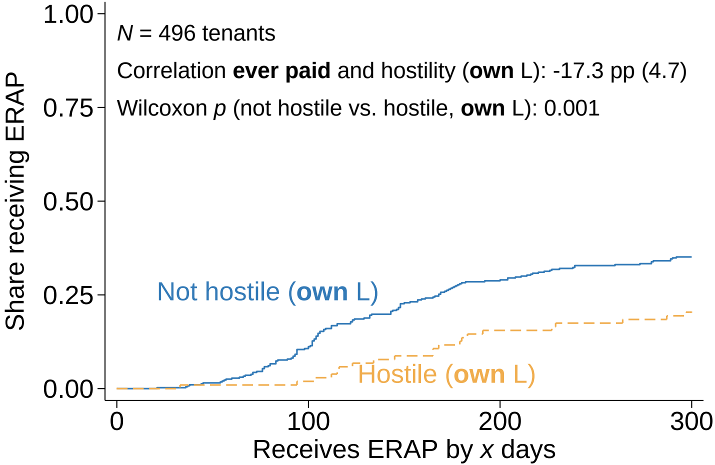
- ERAP is a benefit program that helps tenants facing eviction
- Potential reason for small ERAP effects: **Altruists enroll but never evict**
- **Test**: link experiment on social preferences to administrative data on payment
- Other applications? Old-age assistance, divorce settlements, child care...



Next steps for the literature

Exciting space! Non-classical forces have big positive and normative implications

- Positive: behavioral forces (misperceptions, maybe stigma) likely shape take-up
- Normative: implications are rich and run counter to common policy refrains

New frontiers:

- Positive evidence on classical and non-classical wedges (mental health? procrastination? misperceptions? self-stigma?)
- Monetizing wedges, especially covariance between take-up and bias
- Measuring deadweight loss of ordeals
- Synthesizing results across programs
- Policy margins beyond ordeals