14.472 Public Finance II
VI.c: Takeup and Self-Targeting

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Incomplete take-up is widespread

- Well documented that take-up of social transfer programs is incomplete
- Currie (2006) review of takeup of various programs e.g.
  - 6-14% for SCHIP
  - ~75% for EITC

- Main explanations offered for limited take-up:
  - Informational barriers to takeup (eligibility, benefits, application process)
  - Transaction costs associated with enrollment
  - Stigma associated with participation (could be a form of transaction cost)

- Optimization?
  - optimizing models: take-up if expected benefits $>$ expected cost
  - non-optimizing models
Some key questions

- Positive / descriptive
  - What are key barriers to take-up?
    - Relative roles of information, transaction costs and stigma
  - Who is the marginal person deterred by barriers?
- Normative implications: Is low take up bad?
  - Normative implications of increasing takeup levels
  - Normative implications of self-targeting
Outline for lecture

- Barriers to take up:
  - Informational barriers: Bhargava and Manoli (2015) EITC experiment
  - Information and Transaction costs: Bettinger et al. (2012) FAFSA Experiment

- Self-Targeting properties of barriers:
  - Alatas et al. (2016) self-targeting experiment in Indonesia
  - Deshpande and Li (forthcoming) on disability insurance


- Some methodological themes:
  - A relatively large number of RCTs in this space (any thoughts on why?)
Consumers may have limited information about eligibility or benefits

- Costs involved in learning about eligibility and application rules (optimally may choose not to seek)
- "Psychological frictions" - confusion, complexity, inattention
"Why are Benefits Left on the Table?"

Randomized experiment on incomplete take-up of EITC

25% incomplete take-up

- 6.7 million non-claimants per year
- Forgo on average > one month’s income

Randomized experiment designed to assess various informational barriers to take-up

Modify the information content and complexity of IRS reminder notices to 35,000 tax filers in CA who failed to claim their EITC despite presumed eligibility (*and receipt of initial reminder*)
Complexity Interventions.—The first set of interventions, as depicted in Figure 4, indicates the stark effect of informational complexity on response. The complexity notice decreased response by 0.06 ($p < 0.01$), or 27 percent, relative to the 0.23 response of the control mailing, and the effect magnitude, in absolute terms, did not differ significantly across dependent status. The lengthened worksheet lowered response by 0.04 ($p < 0.01$) or 17 percent. The effect of worksheet complexity appears to be driven largely by those without dependents possibly because the treatment worksheet for this population is substantially “stronger” (due to the additional section of questions) than the same intervention for those with dependents. A separate estimate of the interaction of the two conditions reveals that the joint presence of both complexity elements reduced response by 0.09 ($p < 0.01$).

Figure 4. Response and Marginal Effects by Experimental Intervention

Notes: This figure depicts the response rates, and marginal treatment effects, associated with experimental interventions using estimates reported in column 1 of Table 4. The “Control mailing” refers to the simple notice and simple worksheet and reflects response averaged across the envelope and indemnity treatments.
Summary of results

- Take-up is sensitive to "frequency, salience and simplicity with which information is provided"
- Second mailing - just months after first - increases takeup by 14 percentage points!
- Nature of mailing has effects
  - Simplification (e.g. visually more appealing notice or shorter worksheet) raises enrollment from 0.14 to 0.23
    - Poorest individuals most deterred by complexity (Figure 6)
  - Stigma treatments have little effect.
    - Because they do not affect stigma or because stigma not important?
Interpretation

- Interpret results as evidence of low awareness of eligibility and benefits
  - Survey in which participants reviewed experimental interventions and then beliefs assessed suggest interventions shaped behavior by influencing beliefs (about eligibility and benefit size) and increasing attention paid to forms

- Difficult to rationalize with a traditional / rational model of takeup in which eligible individuals balance accurately perceived expectations of benefits and costs
  - Large impact of second notice
  - Large impact of reducing complexity or changing salience
  - Survey evidence suggested interventions increase awareness and reduce confusion

- Conclude there are "psychological frictions" and more work is needed to model and understand them
Bettinger et al. (2012) "The Role of Application Assistance and Information in College Decisions: Results from the H&R Block FAFSA Experiment"

- Randomized experiment on low-income individuals receiving tax preparation assistance
- Examining takeup of FAFSA (Free Application for Federal Student Aid)

Experimental design:

- Some individuals offered personalized aid estimates and immediate assistance filing forms
- Others just offered personalized aid estimates
- Controls (status quo)

Outcomes: Completing FAFSA; applying for financial aid, attending college; receiving aid at college
Summary of results

- Information + Assistance has real effects
  - Increased aid applications, college enrollment, receipt of aid, and college persistence
- Information by itself has no effect
Lack of effect of "information only" treatment

- Compare to EITC experiment.
  - Hassles may be greater with FAFSA so fewer people on margin
  - Outcome is different (getting a refund vs going to college)
- How did information treatment affect beliefs (about eligibility? expected benefits?)

Unfortunately, cannot say much about targeting as study population relatively homogeneous to begin with

- College persistence results could be suggestive
Is increased take-up a goal?

- Policy makers and advocates talk about goal of increasing takeup
- Private welfare gain from increased takeup depends critically on whether individuals are making optimal decisions
  - If so, no first order welfare gain from increasing takeup by reducing barriers (envelope theorem)
  - But if individuals are (sub-optimally) unaware / inattentive / failing to apply, could have first order welfare gain
- Social welfare: Incomplete takeup may actually be a desired (constrained) optimum
  - With imperfect information about individual’s type, takeup barriers may improve self-targeting efficiency of redistributive program (or they may not)
  - This is what the self-targeting literature is about
- Private takeup decisions impose a negative fiscal externality on government, creating wedge between private and social optimum
  - Public administrative costs, decreased tax revenue on earnings etc.
Recall Nichols and Zeckhauser (1982) - already covered

Want to redistribute based on an unobserved characteristic (e.g. ability).

- If demand for specific goods is correlated with unobserved characteristic, can transfer more efficiently by sacrificing productive efficiency
  - Exploit single crossing feature: people of different ability have different marginal utility (disutility) from specific goods

Previous example: in kind vs cash transfers

Now consider: pure deadweight costs - "ordeals"
Self-targeting: Ordeals

- NZ (1982) implies may be optimal to have “ordeals” in transfer programs: i.e. pure deadweight cost e.g.
  - Tedious administrative procedures
  - Stigma
- May enhance target efficiency if benefits from transfers vary across potential recipients
  - Suppose intended get 100 utils from transfer
  - Suppose imposters get 10 utils
  - Then ordeal that imposes an 11 util loss in order to qualify for the transfer would be an effective screening device
- Example: make people fill out lots of forms / wait in long lines to apply
  - Pure deadweight loss / ordeal
  - Nevertheless, may be a good screen for those whose marginal utility of receipt is low
An alternative take on ordeals

- Bertrand, Mullainthan and Shafir (AEA P&P 2004)
  - Hassle costs (e.g. 36 page food stamp application with confusing question) deter the low ability people you want to transfer to

- Mullainathan and Shafir (2013) "Scarcity"
  - Ordeals screen out those with limited "bandwidth" / consume cognitive resources
  - Poverty as a bandwidth tax: poor face many concerns and have to "tunnel" attention on a few
Research Questions:

- **Descriptive:** Who is the marginal person deterred by current program rules?
  - someone who looks like we wouldn’t want to redistribute to them (N-Z) or someone we would like to (BMS)

- **Normative:** How do the targeting properties of rules relate to their welfare implications?
"Self Targeting: Evidence from a Field Experiment in Indonesia"

Randomized evaluation across 400 Indonesian villages of different methods of enrolling in a large conditional cash transfer program

- Targets poorest 5% of population that also meet certain demographic requirements (e.g. pregnant woman or young kid in household)
- Cash assistance of about 4-13% of average yearly consumption
  - Requirements of school attendance, pre-postnatal checkup, and completed vaccinations
Self-targeting Experiment

- **Government problem:** determine who is eligible
  - Status quo: automatically screen for eligibility and enroll based on easy to observe assets (size of house, materials of roof etc)
  - "Proxy means test" (Imperfect proxy)

- **Experimental alternative to status quo**
  - Self-targeting: households have to apply to program
    - Note: Same asset tests applied. Key difference is active applying (self-targeting) vs automatic screening
  - Within self-targeting villages, also randomly vary application costs
    - Distance: Where application site is located relative to village center (max is 1/2 day’s time, which is trivial compared to benefits)

- **Researchers conduct their own detailed baseline consumption survey ("truth")**
Proxy means test an imperfect proxy for consumption

(A) Probability of Obtaining Benefits vs. Log Per Capita Consumption

Shows predicted probability of receiving benefit conditional on apply (from probit model of benefit receipt on log per capita consumption)
Uncertainty about benefit receipt even conditional on proxy

Figure 1. Probability of Obtaining Benefits vs. Log Per Capita Consumption and PMT score

(b) Probability of Obtaining Benefits vs. PMT score

Shows predicted probability of receiving benefit conditional on apply versus predicted consumption based on Proxy Means Test (PMT)
Information-based screening model

- Government program that delivers benefit $b$ if deemed eligible
- Government wants to target transfers based on consumption ($y$)
- Issue 1: Government only observes a part of consumption $y^o$, where $y = y^o + y^u$ and observes $y^o$
  - $y^o$ is the proxy means test
- Issue 2: Imperfect and costly measurement technology for $y^o$
  - Costly government survey / verification process to measure $y^o$
  - $y^o$ measured with error - conditional on applying, probability of being deemed eligible is $\mu(y^o)$ with $\mu'(y^o) \leq 0$
    - see preceding figure: uncertainty about benefit receipt conditional on proxy ($y^o$)
- Note: government faces two problems:
  - Costly verification process (fiscal externality on government from individual applying)
  - Unobservables (would like to target on $y$, not $y^0$)
Individual's problem

- Individuals:
  - know $y$
  - cost to individual of applying $c(l, y) - l$ is distance to application site

- Two types of individuals
  - Sophisticated: know that eligibility is determined by $\mu(y^o)$ - i.e. depends only on observable consumption
  - Unsophisticated: do not know what government observes; but see empirical probability of someone receiving program conditional on applying $\lambda(y)$

- Individuals apply if expected benefit exceeds expected cost
  - Note that sophisticated calculates expected benefit based on $y^o$, unsophisticated based on $y$
Government options: automatic screening vs. self-targeting

- **Automatic screening:**
  - Government incurs cost of measuring \( y^o \) for everyone and decides eligibility

- **Self-targeting:** people must apply before government will measure \( y^o \) and decide eligibility

- **Two theoretical advantages to self-targeting:**
  - Sophisticated individuals won’t apply if \( y^o \) is high - reduces fiscal externality on government
  - Unsophisticated individuals won’t apply if \( y \) is high - reduces fiscal externality and also improves selection on unobservable \( y^u \)
Self-targeting improves targeting

Figure 4. Experimental Comparison of Self-Targeting and Automatic Screening Treatments

Panel A shows the CDFs of log per capita consumption of beneficiaries in the self-targeting and automatic screening treatments. Kolmogorov-Smirnov test of equality yields a p-value of 0.10. Panel B presents non-parametric Fan regressions of benefit receipt on log per capita consumption in the two treatments. Bootstrapped pointwise 95 percent confidence intervals, clustered at the village level, are shown in dashes.
Self-targeting (applying) on observables

Figure 3. Show Up Rates Versus Observable and Unobservable Components of Log Per Capita Consumption

Notes: Figures provide non-parametric Fan regressions of the probability of applying for PKH against the observable and unobservable components of baseline log per capita consumption in the 200 self-targeting villages. The scales for the x-axis are both in logs, so are comparable. Bootstrapped pointwise 95 percent confidence intervals, clustered at the village level, are shown in dashes.

(A) Show Up as a Function of Observable Consumption ($y_{oi}$)
Self-targeting on unobservables (unsophisticated)

Figure 3. Show Up Rates Versus Observable and Unobservable Components of Log Per Capita Consumption

(a) Show Up as a Function of Observable Consumption ($y_{oi}$)

(b) Show Up as a Function of Unobservable Consumption ($y_{ui}$)

Notes: Figures provide non-parametric Fan regressions of the probability of applying for PKH against the observable and unobservable components of baseline log per capita consumption in the 200 self-targeting villages. The scales for the x-axis are both in logs, so are comparable. Bootstrapped pointwise 95 percent confidence intervals, clustered at the village level, are shown in dashes.
Summary of results

- Self targeting screens out higher consumption individuals relative to automatic screening
  - Savings on fiscal externality
  - Better selection on unobservables (unsophisticated self selection on \( y \), not \( y^o \))
- But marginal increases in application costs (via distance) do not further improve targeting (see paper). Why?
  - Long tail of people with low probability of passing screen = where mass of people are
  - So large mass of people w very small probability of receipt get weeded out by small application cost
Why additional application costs do not improve targeting

![Graph showing the distribution of log per capita consumption](image)

- **Automatic Screening**
- **Self-Targeting**
- **Poverty Line**
- **Log Consumption Distribution**
Possible US applications

- Medicare added to DI (w 2 yr wait period) in 1972
  - This increases “value” of DI. But is the marginal value of health insurance higher for the truly disabled or not? (Depends in part on access to health insurance through other means).
  - Similarly what about reducing two year waiting period
  - Gray (in progress): Adding prescription drug coverage to Medicare

- Food stamps: electronic benefit transfer
- Distance to social service office - Deshpande and Li (forthcoming)
"Who is screened out? Application Costs and Targeting of Disability Programs"

Natural experiment: timing of closing of 125 out of 1230 Social Security field offices between 2000 and 2014
- apply for SSDI and SSI in field office (or over phone or on line)
- field offices process applications

Study how closings affect level (and characteristics) of application and enrollment
Empirical strategy

- Examine outcomes in zips that experienced a closing
  - "The obvious concern with this empirical strategy is that SSA may be closing offices in areas where disability applications are already falling or where composition of disability applicants is already changing" (page 13)

- Therefore compare outcomes in areas that experienced a closing at a given time relative to areas that experience a closing at a future time
  - "The identifying assumption is that the exact timing of the closing is uncorrelated with changes in the number and type of disability applicants" (page 13)
  - i.e. requires that "timing of closings, rather than the closings themselves, be as good as random" (page 3)

- Exploit timing of closing of offices between 2000 and 2014
Figure 2: Timing of Field Office Closings

Source: Authors’ calculations based on Social Security Administration data.
Nice to start as close to raw data as can (as little "regression massaging" as possible)

Figure 4: Raw Plots of Number of Applications in Control and Treatment ZIPs

Notes: Figure plots raw (non-regression-adjusted) counts of applications in control and treatment ZIPs relative to the quarter of the closing. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.
Estimating equations

- Main estimating equation:

\[ Y_{isct} = \alpha_i + \gamma_{st} + \sum_{\tau} \lambda_{\tau} D_{ct}^{\tau} + \sum_{\tau} \delta_{\tau} (Treated_{ic} \times D_{ct}^{\tau}) + \epsilon_{isct} \]

- \( Y_{isct} \) is outcome for zip \( i \) in state \( s \) for closing \( c \) in quarter \( t \)
- control for zip fixed effects (\( \alpha_i \)) and calendar quarter by state fixed effects (\( \gamma_{st} \))

- Main results are presented as graphical plots of \( \delta_{\tau} \)
  - \( Treated_{ic} \) is indicator for whether Zip \( i \) is closing ZIP for closing \( c \)
  - \( D_{ct}^{\tau} \) are indicates if quarter \( t \) is \( \tau \) quarters after or before the quarter of closing

- For table estimates, report \( \beta \) from a more parsimonious pre-post regression:

\[ Y_{isct} = \alpha_i + \gamma_{st} + \sum_{\tau} \lambda D_{ct}^{\tau} + \beta (Treated_{ic} \times Post_{ct}) + \kappa (Treated_{ic} \times Zero_{ct}) + \epsilon_{isct} \]
Key Outcomes

- Counts of applicants or enrollees
- Characteristics of applicants or enrollees
  - Run application and enrollment regressions by type
  - Or put average characteristics of applicants or enrollees on LHS
    - Putting characteristics of endogeneous selected group on LHS a la cost curve test of EFC 2010
    - See Gruber, Levine and Staiger (QJE 1999) "Abortion Legalization and Child Living Circumstances: Who is the marginal child?"
Closings Decrease Applications and Enrollment

Figure 4: Raw Plots of Number of Applications in Control and Treatment ZIPs

-12 -8 -4 0 4 8
Quarter relative to closing
Control Treatment
Number of applications

Notes: Figure plots raw (non-regression-adjusted) counts of applications in control and treatment ZIPs relative to the quarter of the closing. Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Treatment ZIPs are ZIPs whose nearest office closes for a given closing, while control ZIPs are ZIPs whose nearest office closes in a future closing.

Figure 5: Effect of Closings on Number of Disability Applications and Allowances

-0.2 -0.1 0 0.1
Reduced form estimate
-12 -8 -4 0 4 8
Quarter relative to closing
Applicants Recipients
Number of applicants and recipients (log)

Notes: Figure plots estimates of $\delta_\tau$ coefficients from equation (1), where the dependent variable is the log number of disability applications (solid series) or the log number of disability recipients (dashed series). Shaded region is 95 percent confidence interval for disability applications (solid series). Sample is ZIP codes whose nearest office closes after 2000 and that have an average of at least three disability applications per quarter in the year before the closing. Regressions are weighted by application volume in the year before the closing.
Applications and enrollment decline more for lower SES (education, pre-application earnings etc)

Applications decline most among moderate (vs low or high) severity groups

- Severity can only be assessed through application process
- Low severity will be rejected, high severity accepted, moderate can appeal
Summary of results

- Compelling evidence of role of "transaction costs" in deterring applications and enrollment
  - Closings produce an 11% decline in applications and 13% decline in enrollment
- Heterogeneous response: Closings disproportionately affect low SES and lower severity conditions
- What is "mechanism" for decreased applications?
  - Closings increase travel time to nearest open field office by about 40 percent (10 minutes by drive; 36 minutes by public transit)
  - Also find evidence of congestion effect (i.e. increased walk-in time in neighboring offices)
  - Applicant time costs would have to be implausibly large to explain decline in applications
  - Perhaps update about overall costs of applying; perhaps "irrational"?
Normative analysis of take-up and self-targeting

- Will present model from Finkelstein and Notowidigdo (2019)
- Goals:
  - Framework for how to interpret the prior empirical results normatively
    - nests Nichols and Zeckhauser model as a special case
  - Provides guide to what empirical objects are needed for normative analysis
Overview of normative model

- Recall standard (i.e. Nichols and Zeckhauser) framework on "ordeal mechanisms:
  - Key assumptions: (1) Individual types (abilities) unobserved; (2) decisions are privately optimal and (3) labor supply responds to income tax
  - Result: ordeal that impose greater utility cost on high ability can improve social welfare over and above an optimal non-linear income tax

- This theoretical result does not generalize when we allow for either:
  - Individuals may not make privately optimal application decisions
  - OR flexible relationship between individual type and fiscal externality from her enrollment on government budget

- Key empirical questions for welfare implications of targeting:
  - Relative behavioral biases (if any) across types
  - Relative fiscal externalities across types
Model set up

- Individuals of type $j = L$ or $H$. Each type has unobserved wage $\theta_j$, with $\theta_H > \theta_L$
- Individuals make hours choice $h_j$ and also choose whether to apply to safety net program
- Net-of-tax earnings: $y_j = \theta_j h_j - \tau(\theta_j h_j)$
- Safety net program pays benefits $B$ if earnings are below some threshold $r^*$
Common utility function:

- If individual does not apply: $u(x_j) - v(h_j)$
- If individual applies: $u(x_j) - v(h_j) - (\Lambda \kappa_j + c)$
  - $(\Lambda \kappa_j + c)$ is private cost of applying
  - Type specific utility cost: $\kappa_j$
  - Individual-specific utility cost with type-specific distribution $f_j(c)$

- Individuals misperceive benefits from applying according to $(1 + \varepsilon_j)$
Application decision and private welfare

- Individuals make application and labor supply decisions to maximize private utility, given their (possibly incorrect) perceptions
  - Apply if EU from applying (given optimal hours choice if apply) > EU from not applying (again given optimal hours choice)

- For low-ability individuals, assume either hours choice would leave them below the earnings eligibility threshold $r^*$
  - For high ability individuals, assume hours choice if they do not apply puts earnings ability eligibility threshold $r^*$
    - Therefore if they apply set hours $= \frac{r^*}{\theta_H}$ so they are at income threshold

- Note: both types choose weakly fewer hours of work if apply (due to potential income effects) but for $H$ types there is an added reduction in hours from applying because of the need to reduce hours to meet income eligibility threshold
  - This will be important
Application decision and private welfare

- Individuals apply if expected utility from applying (given optimal hours choice if apply) exceeds expected utility from not applying (again given optimal hours choice).
- $V_j$ denotes private welfare of type $j$.

We define $c_j^*$ to be the threshold level of $c$ such for $c < c_j^*$, type $j$ chooses to apply. Total private welfare of type $j$, $V_j$, can therefore be written:

$$V_j = Pr(apply) \ast E[u()|apply] + Pr(\neg apply) \ast E[u()|\neg apply]$$

$$= \int_0^{c_j^*} (u(y_j^A + B) - v(h_j^A) - (\tilde{\Lambda}_{\kappa_j} + c))dF_j(c)$$

$$+ \int_{c_j^*}^{\infty} [u(y_j^{-A}) - v(h_j^{-A})]dF_j(c)$$
Assume a utilitarian SWF

Total social welfare, $W$, can therefore be written:  
\[ G_j^A = \tau(h_j^A \theta_j) \text{ and } G_j^{-A} = \tau(h_j^{-A} \theta_j) \]

\[
W = \underbrace{V_L + V_H}_{\text{Private Welfare}} - \underbrace{[B(A_L + A_H)]}_{\text{Program Cost}} + \underbrace{[A_L G_L^A - (1 - A_L) G_L^{-A} + A_H G_H^A + (1 - A_H) G_H^{-A}]}_{\text{Fiscal Externality}}
\]

where $A_j = F_j(c_j^*)$ is the expected number of applications from type $j$ individuals.
Note that instead of subtracting mechanical program costs from \( W \) could instead "close" the government budget by having these costs "paid for" out of individual consumption.

Our approach assumes costs of program born by someone with average marginal utility of consumption in society (i.e. \( W \) is a "money metric" SWF, normalized by average marginal utility of consumption in the population).
"Standard" negative fiscal externality: if individuals choose fewer hours of work as a result of applying for benefits, applying imposes a social cost - above and beyond the mechanical program cost ($B$) - via reduced income tax revenue.

- and note this fiscal externality is greater for $H$ type (why?)

- if individuals privately optimize with accurate beliefs, too many people will apply relative to social optimum.
Nests standard result

- Social optimum will involve a non-zero ordeal utility cost (i.e. $\Lambda > 0$) even in the presence of an optimal nonlinear income tax (Currie and Gahvari 2008)
  - Intuition: with unobserved ability $\theta_j$ and endogenous hours choices, optimal non-linear income tax has binding IC on high ability (prevent $H$ from mimicking $L$) that prevents first best amount of redistribution (equal consumption across types)
  - Adding ordeals that are more costly to high ability types ($\kappa_H > \kappa_L$) can relax IC constraint and allow for more redistribution

- Key assumptions for standard result:
  - Ordeals impose higher utility costs on high ability type ($\kappa_H > \kappa_L$)
  - Individual choices are privately optimal ($\epsilon_j = 0$)
  - Only source of fiscal externality is through tax revenue (therefore high ability impose greater fiscal externality)

- These are all empirically testable
Definition. Define $\mu_j \equiv u(y_j^A + B) - u(y_j^A + (1 + \epsilon_j)B)$

Proposition 1. The effect of the Information Only treatment on welfare is given by:

$$\frac{dW}{dT}^{\text{Information Only}} = \mu_L \frac{dA_L}{dT} + \mu_H \frac{dA_H}{dT} - B \left( \frac{dA_L}{dT} + \frac{dA_H}{dT} \right) + [G^A_L - G^{-A}_L] \frac{dA_L}{dT} + [G^A_H - G^{-A}_H] \frac{dA_H}{dT}$$

Change in Private Welfare \hspace{1cm} Change in Mechanical Program Costs
\hspace{2cm} \hspace{2cm}
Change in Fiscal Externality \hspace{1cm} \hspace{1cm} > 0 > 0 > 0 > 0 > 0 > 0
Neoclassical setting

- Assume no misperceptions \((\epsilon_H = \epsilon_L = 0)\). Therefore intervention has no effect on private welfare \((\mu_L = \mu_H = 0)\)
  - Individual decisions are already privately optimal
  - marginal individuals is indifferent between applying and not, so change in behavior has no first-order impact on private welfare
  - with misperception (e.g. \(\epsilon_j < 0\)) intervention increases private welfare for marginal applicants of each type by \(\mu_j\)
    - Size of private welfare gain increasing in amount of under-estimation
- Assumes change in fiscal externality for marginal applicant is larger (more negative) for \(H\) type
  - Remember he changes hours more in response to applying (bc needs to mimic \(L\))
Some definitions

- Treatments (i.e. ordeal reductions) ($T$):
  - "Information only": reduces misperceptions ($dT = d\epsilon$)
  - "Information plus assistance": reduces misperceptions and private application costs ($dT = d\epsilon, -d\Lambda$)

- Targeting $e = (E_L / (E_H + E_L))$
  - Share of enrollees who are low type (low ability / productivity)
  - Treatment $T$ increases targeting if $de / dT > 0$

- $\mu_j = u(y_j^A + B) - u(y_j^A + (1 + \epsilon_j)B)$
  - difference for type $j$ between the actual and perceived utility when applying
  - if individuals under-estimate benefits of applying ($\epsilon_j < 0$), $\mu_j > 0$
Proposition 2. Holding constant the change in applications due to an intervention, the change in social welfare in response to an improvement in targeting \((de/dT > 0)\) from an Information Only (or Information Plus Assistance) treatment is given by the following expression:

\[
\frac{\partial}{\partial(dW/dT)} \left( \frac{dW}{dT} \right) \bigg|_{\text{df}} = \left[ (\mu_L - \mu_H) + (G_L^A - G_L^-A) - (G_H^A - G_H^-A) \right] (E_H + E_L)
\]  

\(\text{(3)}\)

- In neoclassical case: the targeting property is
  - Unrelated impact on private welfare (which is zero by envelope theorem)
  - Depends solely on fiscal externality (which is larger for H by assumption)

- Once allow for misperceptions, can increase private welfare
  - \(u'(y_j)\) higher for \(L\)-types
  - But, welfare gain also depends on \(\epsilon_j\) which could have any relationship with type
Proposition 2. Holding constant the change in applications due to an intervention, the change in social welfare in response to an improvement in targeting \((\frac{de}{dT} > 0)\) from an Information Only (or Information Plus Assistance) treatment is given by the following expression:

\[
\frac{\partial}{\partial(\frac{de}{dT})} \left( \frac{dW}{dT} \right) \bigg|_{\frac{dA}{dt}} = \left[ (\mu_L - \mu_H) + (G_L^A - G_L^A) - (G_H^A - G_H^A) \right] (E_H + E_L)
\]

- Even without misperceptions \((\epsilon_j = 0)\) another “free parameter” in relationship between targeting and welfare is how size of fiscal externality varies with type
  - By assumption it’s higher for H than L in standard model
  - What if there are other fiscal externalities such as impact of program enrollment on health and public health expenditures?
    - Empirically ambiguous which type creates bigger fiscal externalities
Relationship between targeting and social welfare

- Without misperceptions ($\epsilon_H = \epsilon_L = 0$)
  - $\mu_L - \mu_H = 0$
    - Change in targeting has no effect on private welfare
  - Relationship between change in social welfare and change in targeting therefore depends solely on how change in targeting changes fiscal externality from applying

- "standard" setting (i.e. Nichols and Zechkhauser): no misperceptions and only fiscal externality is through earnings margin
  - improved targeting (i.e. inducing $L$ to apply instead of $H$) lowers the (negative) fiscal externality from applying
    - recall: reductions in earnings for $H$ types induced to apply are larger than for $L$ types induced to apply
  - therefore an increase in targeting increases social welfare

- Could break this if generalize $G$ to include other fiscal externalities from applying
  - Could be positive or negative
  - relative magnitude across types also ambiguous
Relationship between targeting and social welfare

- With misperceptions ($\epsilon_j \neq 0$), change in social welfare from an increase in targeting is also increasing in $(\mu_L - \mu_H)$
  - Intuition: thought experiment of increasing targeting "swaps" an $H$ applicant for an $L$ applicant so $\mu_L$ enters positively and $\mu_H$ enters negatively
- For $\epsilon_j < 0$, $\mu_j$ increasing in two type-specific factors: marginal utility of consumption, and magnitude of underestimation
- Sufficient condition for an increase in targeting to increase private welfare is that under-estimation is non-zero for at least one type and weakly higher (in absolute value) for $L$ type (i.e. $\epsilon_L \leq \epsilon_H \leq 0$, with at least one inequality strict)
  - e.g. behavioral frictions larger for $L$ type (Mullainathan and Shafir)
  - e.g. both underestimate by same (proportional) amount: $\epsilon_H = \epsilon_L < 0$
Empirical objects for welfare analysis of targeting

- Misperceptions by type
- Fiscal externality by type
- But "type" ($\theta$) is inherently unobserved. So can you do empirically?
  - Need joint distribution of misperceptions and fiscal externalities
  - And perhaps marginal utility of consumption (if there are misperceptions)
Questions about targeting

- Empirical: who is screened out?
  - i.e. what is the impact of a given intervention on targeting ($d e / d T$)
  - neoclassical theories assume ordeals improve targeting, while behavioral theories assume they worsen targeting
  - e.g. NZ assume ($\kappa_H > \kappa_L$) while "scarcity" hypothesis is opposie ($\kappa_L > \kappa_H$)

- Conceptual: how does the targeting impact of the intervention relate to its social welfare impact?
SNAP (Food stamp) takeup particularly low among elderly (~40% compared to 80% overall)

Non-profit (Benefits Data Trust) tries to increase takeup
- Gets information from state on people not enrolled in SNAP (SNAP enrollment data) but likely eligible (enrolled in Medicaid)
- Contacts these individuals to inform them of their potential eligibility and offer to assist them with document collection and application

RCT on ~30,000 elderly not enrolled in SNAP but likely eligible
- Information only: informs of likely eligibility
- Information plus assistance: also provides help with application
- Control group: status quo

Questions:
- how does takeup respond to these interventions
- who is the marginal person affected (targeting properties)
- what are the normative implications?
Figure A1: Standard Outreach Materials: Information Plus Assistance

Letter

Postcard

Envelope

Figure A1: Standard Outreach Materials: Information Plus Assistance

Letter

Postcard

Envelope
Figure A1: Standard Outreach Materials: Information Plus Assistance

Letter

Envelope

Figure A1: Standard Outreach Materials: Information Plus Assistance

Letter Postcard

Envelope

Information Plus Assistance

Figure A1: Standard Outreach Materials: Information Plus Assistance

Letter Postcard

Envelope

men ts in the Information Plus Assistance arm, and the con trol. W e do wn-w eigh t the individuals in
the standard treatmen tin the Information Plus Assistance arm so that the (w eigh ted) share in stan-
dard vs. mark eting is the same (50 p ercen t) in the Information Only arms.

B: DHS Data

Data sharing proto cols

To construct our study p opulation, DHS supplied BDT with a Medicaid outreac h le of appro x-
imately 230,000 individuals aged 60 and older who w ere enrolled in Medicaid as of Octob er 31,
2015. BDT remo v ed the Medicaid recipien t ID and created a unique, non-iden tifying scram bled
study ID that uniquely iden ties eac h individual. W e receiv ed de-iden tied data les from DHS for
all individuals on the initial outreac h list (see T able 1, column 1). The data consist of: Medicaid
enrollmen t and claims data, SNAP applications and enrollmen t data, and SNAP b enets data.

BDT pro vided DHS with the crossw alk b et w en these de-iden tied study IDs and their unique
Medicaid recipien t ID. DHS then attac hed information on SNAP applications, SNAP enrollmen t,
SNAP b enets, and Medicaid enrollmen t and claims. F or the SNAP data, DHS sen t the data to
BDT who remo v ed all p ersonally-iden tifying information (i.e. full name, so cial securit y n um b er,
full address, and Medicaid recipien t ID) and transmitted the de-iden tied data to us via a secure
FTP pro cess. F or the Medicaid enrollmen t and claims les, DHS remo v ed the same iden tifying
information and directly transmitted the data to us.
Figure A3: Experimental Design

Study Population
(N = 31,188)
Age 60+, on Medicaid and not on SNAP

Control
(N = 10,630)
No intervention

Info & Assistance Treatment
(N = 10,629)
Mail information on SNAP eligibility and provide application assistance over the phone

Info Only Treatment
(N = 10,629)
Mail information on SNAP eligibility.

Standard (N = 7,927)
Marketing (N = 2,657)
Standard Follow-Up Postcard
Marketing Follow-Up Postcard
Application Assistance
Application Assistance

Standard (N = 2,657)
Marketing Follow-Up Postcard
Application Assistance

Standard (N = 2,657)
Marketing Follow-Up Postcard
Framing Follow-Up Postcard

Standard, No Postcard (N = 2,658)

Notes: Figure shows experimental design. Grey arms are the ones included in the main analyses.
Table 2: Behavioral Responses to “Information Only” and “Information Plus Assistance”

<table>
<thead>
<tr>
<th></th>
<th>Control</th>
<th>Information Only</th>
<th>Information Plus Assistance</th>
<th>P Value of Difference (Column 2 vs 3)</th>
</tr>
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<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
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<tr>
<td>SNAP Enrollees</td>
<td>0.058</td>
<td>0.105</td>
<td>0.176</td>
<td>[0.000]</td>
</tr>
<tr>
<td></td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[0.000]</td>
</tr>
<tr>
<td>SNAP Applicants</td>
<td>0.077</td>
<td>0.147</td>
<td>0.238</td>
<td>[0.000]</td>
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<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>[0.000]</td>
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<tr>
<td>SNAP Rejections among Applicants</td>
<td>0.233</td>
<td>0.266</td>
<td>0.255</td>
<td>[0.119]</td>
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<tr>
<td></td>
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<tr>
<td></td>
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<td></td>
<td>[0.557]</td>
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<tr>
<td>Callers</td>
<td>0.000</td>
<td>0.267</td>
<td>0.301</td>
<td>[0.000]</td>
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<td></td>
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<td>Adjusted Callers</td>
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<td>0.289</td>
<td>0.301</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>[1.156]</td>
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<tr>
<td>SNAP Applicants among Non-Callers</td>
<td>0.077</td>
<td>0.086</td>
<td>0.081</td>
<td>[0.063]</td>
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<tr>
<td></td>
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<tr>
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<td>SNAP Applicants among Callers</td>
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<td>0.313</td>
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<tr>
<td>SNAP Enrollees among Non-Callers</td>
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<td>0.061</td>
<td>0.059</td>
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<tr>
<td>SNAP Enrollees among Callers</td>
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<td></td>
<td></td>
<td>[0.000]</td>
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<tr>
<td>Observations (N)</td>
<td>10,630</td>
<td>5,314</td>
<td>10,629</td>
<td></td>
</tr>
</tbody>
</table>
NOTE: 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. 95 percent confidence intervals on these estimates are shown in the dashed light gray lines.
"Information only" increases enrollment less but may be more cost-effective

- 9-month enrollment: 6% (control), 11% (info only); 18% (info plus assistance)
- Applications increase proportionally - no change in approval rate
- Cost per additional enrollee: ~$20 (info only); $60 (info + assistance)

Reminder postcard
- Info only without reminder postcard has about 20% lower applications and enrollment
- Suggestive of inattention?
Targeting results

- Both interventions decrease targeting in a similar manner:
- Marginal applicants and enrollees are "less needy" than average enrollees
  - Lower benefits (progressive benefit formula)
  - Better health
- Note: do not observe "ground truth" (i.e. what social planner would like to target on):
  - marginal utility of consumption?
  - Compare to Alatas et al.
"Calibrating" model

- Results consistent with misperceptions
  - Impact of reminder postcard
  - Given empirical rejection rate of applications and resulting expected benefits from applying, and estimates of time cost of applying, absent misperception of acceptance rate need implausibly high non-time cost of applying to rationalize (e.g. $3,000)
  - Alternatively, if assume zero non-time cost, estimate substantial misperceptions for marginal individual (higher for low income / high benefit individuals by construction)
Given our estimates of misperceptions, we can calculate the MVPF of the interventions.

Estimates suggest MVPF would be worse if targeting were worse.

- but this is because the higher need individuals have higher misperceptions (to rationalize non take up of higher benefits)

Key point is that whether improved targeting improves social welfare depends not just on need (marginal utility of consumption) but also on misperception.

- Implicit assumption in prior work that those in greater need had greater failures of rationality
- Needs empirical examination
Areas for future work

- Attractive features of this area
  - Rich, interesting and inconclusive theory
  - Relative paucity of empirical evidence
  - Positive and normative questions

- Fertile ground for research
  - Impact of reducing barriers to takeup on takeup, screening, and welfare
    - Policy question: should we have auto enrollment?
  - Recertifications
  - Estimating optimal level of hassles

- Normative analysis:
  - What we really want is the joint distribution of fiscal externalities and behavioral frictions
  - Now that we know this, we might have designed a different RCT!
Methodological Comment

- Feasibility of RCTs in this space
  - Letters are cheap (e.g. EITC)
  - Partners interested in improving or demonstrating their efficacy (BDT)
- Yet implementing and expositing compelling quasi-experimental design in this space very valuable
  - Often have larger samples (important for power to examine heterogeneity of effects)
- Key advantage of RCT is can design / choose your variation