Outline

1. Investment Goods: Work Effort
2. Investment Goods: Delay with Deadline
3. Leisure Goods: Credit Card Borrowing
4. Leisure Goods: Consumption and Savings
5. Leisure Goods: Commitment and Savings
7. Methodology: Commitment Field Experiments
Section 1

Investment Goods: Work Effort
"Self-Control at Work"

Kaur, Kremer, and Mullainathan, “Self Control at Work.” *JPE* 2015

- Setting: workers in India who are paid a piece rate $w$ in a weekly paycheck.
- Since effort at work is immediate and benefits delayed, effort at work is an investment good.
- $\left(\beta, \hat{\beta}, \delta\right)$ model, with $\delta = 1$.
- Consider effort at work $e$, which costs $-c(e)$, with $c' > 0$, $c'' > 0$.
- Assume for special case $c(e) = \gamma e^2 / 2$.
Model

- Two states:
  - high output $y_H$ with probability $e \rightarrow$ pay $w_H$
  - low output $y_L$ with probability $1 - e \rightarrow$ pay $w_L$
  - Notice: this is only local approximation, for $e \in [0, 1]$

- Pay at $t = 2$

- If working at $t = 1$, maximize

  $$\max_{e_1} \beta \left[ e_1 w_H + (1 - e_1) w_L \right] - c(e_1)$$

- f.o.c.

  $$\beta \left[ w_H - w_L \right] - c'(e_1^*) = 0$$

- Effort $e_1^*$ increases in $w_H - w_L$ and in $\beta$
Model

- Special case:
  \[ e_1^* = \frac{\beta [w_H - w_L]}{\gamma} \]

- If working at \( t = 2 \) (same period as paydate), optimal effort \( e_2^* \) solves
  \[ \max_{e_2} [e_2 w_H + (1 - e_2) w_L] - c(e_2) \]
  and thus (for the special case)
  \[ e_2^* = \frac{w_H - w_L}{\gamma} \]

- **Prediction 1.** Effort is higher near payday for \( \beta < 1 \) (independent of \( \hat{\beta} \))

- From \( t = 0 \) perspective, (perceived) utility \( V_0 \) from working at \( t = 1 \) is
  \[ V_0 = e_1^* w_H + (1 - e_1^*) w_L - c(e_1^*) \]
Model

Effect of altering $w_L$ on $t = 0$ (expected) welfare $V_0$ is

$$\frac{dV_0}{dw_L} = (1 - e_1^*) + \frac{de_1^*}{dw_L} \left[ [w_H - w_L] - c'(e_1^*) \right] =$$

$$= (1 - e_1^*) + \frac{de_1^*}{dw_L} \left[ (1 - \hat{\beta}) [w_H - w_L] \right]$$

First term is direct effect on pay: lowering $w_L$ lowers pay and thus welfare

The second term is the effect on incentive, which is zero for $\beta = \hat{\beta} = 1$, by the envelope theorem – but envelope theorem does not apply for $\hat{\beta} < 1$. Indeed, second term is negative

Notice that it is $\hat{\beta}$ which matters, since this is the value function from the $t = 0$ perspective
Model

- Special case for $\hat{\beta} = \beta$:

$$\frac{dV_0}{dw_L} = 1 - \frac{\beta [w_H - w_L]}{\gamma} - \frac{\beta (1 - \beta) [w_H - w_L]}{\gamma}$$

- Second term becomes large as $\beta$ goes below 1 and is highest at $\beta = 1/2$
- If large enough, individual wants commitment device, prefers $w_L$ low

Prediction 2. Individual with $\beta < 1$ may prefer commitment device (low $w_L$)

Prediction 3. If there are both types with $\beta = 1$ and $\beta < 1$, demand for commitment should be associated with a payday cycle
Experiment

- Field experiment in India
  - Randomization of pay date (Tu, Th, Sa) to test proposition 1 unconfounded with day-of-week effects
  - Randomization of availability of commitment device: get paid $w/2$ instead of $w$ if miss production target
  - Randomization of whether choice is made evening before, or morning of
Figure 1
Incentive Contracts

- Control contract
- Dominated contract
Predictions

- **Prediction 1.** Evidence of pay cycle in effort

![Figure 2](image-url)

*Figure 2*

**Production over the Pay Cycle**
Predictions

- **Prediction 2.** Quite significant take-up of commitment contract
## Results

### Table 4

<table>
<thead>
<tr>
<th>Treatment Effects of Contract Assignment on Worker Production</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable:</strong> Production</td>
</tr>
<tr>
<td>-----------------------------------</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>Assignment to choice</td>
</tr>
<tr>
<td>Assignment to evening choice</td>
</tr>
<tr>
<td>Assignment to morning choice</td>
</tr>
<tr>
<td>Assignment to low target</td>
</tr>
<tr>
<td>Assignment to medium target</td>
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<td>Assignment to high target</td>
</tr>
<tr>
<td>Worker fixed effects</td>
</tr>
<tr>
<td>Seat fixed effects</td>
</tr>
<tr>
<td>Date fixed effects</td>
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<tr>
<td>Lag production controls</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R2</td>
</tr>
<tr>
<td>Dependent variable mean</td>
</tr>
<tr>
<td>Proportion choosing a positive target</td>
</tr>
<tr>
<td>Proportion choosing a positive target (target=1 when absent)</td>
</tr>
</tbody>
</table>
Predictions

**Prediction 3.** Correlation between payday effect and take-up of commitment, as well as with productivity effect

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Target level chosen</th>
<th>Positive target indicator</th>
</tr>
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<tbody>
<tr>
<td>High payday production impact</td>
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<tr>
<td></td>
<td>353</td>
<td>0.138</td>
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<tr>
<td></td>
<td>(129)***</td>
<td>(0.044)***</td>
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<td>Yes</td>
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<td>Date fixed effects</td>
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<tr>
<td>Lag production controls</td>
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<tr>
<td>Observations</td>
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<tr>
<td>Dependent variable mean</td>
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Table 5
Heterogeneity in Take-up of Dominated Contracts: Correlation with Payday Impact
## Results

### Table 6: Heterogeneity in Contract Treatment Effects: Correlation with Payday Impact

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Production (1)</th>
<th>Production (2)</th>
<th>Production (3)</th>
<th>Attendance (4)</th>
<th>Attendance (5)</th>
<th>Attendance (6)</th>
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<tbody>
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<td>-146</td>
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<td>-0.016</td>
<td>-0.028</td>
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<tr>
<td></td>
<td>(60)*</td>
<td>(74)</td>
<td>(84)*</td>
<td>(0.009)</td>
<td>(0.010)</td>
<td>(0.011)**</td>
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<tr>
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<td>735</td>
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<td>0.091</td>
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<tr>
<td>High payday production impact</td>
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<td>(144)***</td>
<td>(0.019)***</td>
<td>(0.022)***</td>
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<td>Assignment to choice *</td>
<td></td>
<td>401</td>
<td>0.064</td>
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</tr>
<tr>
<td>Payday</td>
<td></td>
<td>(179)**</td>
<td></td>
<td>(0.024)***</td>
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<tr>
<td>Assignment to choice * Payday *</td>
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<tr>
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<td>(288)***</td>
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<td>(0.041)***</td>
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<td>(71)**</td>
<td>(86)</td>
<td>(96)</td>
<td>(0.010)</td>
<td>(0.012)*</td>
<td>(0.013)*</td>
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<td>Assignment to a target *</td>
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<td>673</td>
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<td>Seat fixed effects</td>
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<td>0.11</td>
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<td>5355</td>
<td>0.875</td>
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</table>
Summary

- Evidence very consistent with model of self-control problems and (at least partial) sophistication
- Discount factor is not $\beta - \delta$, but smoother decay (true hyperbolic)
- Significant demand of commitment device – different than some of other settings, see later
- Correlation with underlying measure of self-control
- Great evidence in important setting
Related: Exercise for Diabetics

Aggarwal, Dizon-Ross, and Zucker (2019)

- Setting: 3,200 diabetics in India who need to get more exercise
- Control group is just monitored with a fitbit
- Incentive group receives a payment if make $\geq 10,000$ steps
- Further, randomize timing of payment
  - Daily (most immediate, at 1am)
  - Weekly (at end of week)
  - Monthly (after a whole month)
- Also, randomize threshold payment ($4+/5+$ days with 10k steps per week) – not focusing on that here
Results

- Result 1: Incentives for walking are effective at increasing exercise
- Result 2: Timing of payments does not matter

![Graphs showing the results of the study](image)

(a) Probability Exceeded Step Target
(b) Average Daily Steps

Figure 13: Payment frequency does not significantly impact walking.
Results

Result 3: Timing of payments does not matter even considering within a payment scheme, varying distance from payoff.

(a) Weekly Payment Cycle

(b) Monthly Payment Cycle

Figure 14: The probability of exceeding the step target is stable over the payment cycle.

What explains difference from Kaur et al? Open question.
Section 2

Investment Goods: Delay with Deadline
Setting

- Consider as individual that has to do an unpleasant task, with a fixed deadline
- Examples:
  - Paying a traffic fine (Heffetz, O’Donoghue, and Schneider, 2016)
  - Filing taxes (Martinez, Meier, and Sprenger, 2017; Benzarti, 2016)
  - Finding a job by the deadline (job search papers)
- What can we infer from spike at deadline?
Paying a Traffic fine with multiple deadlines

Figure 1: Hazard Rates and Cumulative Response Rates in OLD vs. NEW Regimes. Note: All tickets have a first deadline at day 30, second deadline at days 62-68, and third deadline at days 101-107, indicated by the shaded areas (the latter two deadlines are a range because they depend on ticket-issuance day of the week). First notification letter is received around day 40 (OLD) vs. day 20 (NEW). Based on 3,355,094 (OLD) and 3,020,357 (NEW) observations; see details in Section 3.
Filing Taxes by April 15

Figure 1: Filing Times and Refund Values

Notes: 2005-2008 percentage of filers on each day of tax season (gray bars) and average refund value for filers on each day (black line).

Figure 1: Filing Times and Refund Values
Inference

- What can we learn from extent of last-minute completion?
- If there is a lot of last-minute completion, does that indicate procrastination?
- Or could it indicate a particular distribution of the cost of doing the action?
- Heffetz, O’Donoghue, and Schneider, 2016:
  - Use multiple traffic fines
  - There are types that delay more on multiple traffic ticket infractions
- Martinez, Meier, and Sprenger (2017)
  - Structural estimation of time preference parameters using also variation in amount of tax refund and delay in refund
Inference

- Heidhues and Strack (2019)
  - Negative result: Cannot infer time preferences from any observed task completion
  - For any discount rate, can find a cost of effort function that rationalizes that delay
  - Positive result: With more variation (different incentives/delay), identification is possible.
Section 3

Leisure Goods: Credit Card Borrowing
Ausubel, “Adverse Selection in Credit Card Market”

- Joint-venture: company-researcher
- Field Experiment: Randomized mailing of two million solicitations!
- Follow borrowing behavior for 21 months
- Variation of:
  - pre-teaser interest rate $r_0$: 4.9% to 7.9%
  - post-teaser interest rate $r_1$: Standard - 4% to Standard +4%
  - Duration of teaser period $T_s$ (measured in years)
Part of the randomization – Incredible sample sizes. How much would this cost to run? Millions

<table>
<thead>
<tr>
<th>MARKET EXPERIMENT</th>
<th>MARKET CELL</th>
<th>NUMBER OF SOLICITATIONS MAILED</th>
<th>EFFECTIVE RESPONSE RATE</th>
<th>PERCENT GOLD CARDS</th>
<th>AVERAGE CREDIT LIMIT</th>
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<tbody>
<tr>
<td>MKT EXP I</td>
<td>A: 4.9% Intro Rate 6 months</td>
<td>100,000</td>
<td>1.073%</td>
<td>83.97%</td>
<td>$6,446</td>
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<tr>
<td>MKT EXP I</td>
<td>B: 5.9% Intro Rate 6 months</td>
<td>100,000</td>
<td>0.903%</td>
<td>80.18%</td>
<td>$6,207</td>
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<tr>
<td>MKT EXP I</td>
<td>C: 6.9% Intro Rate 6 months</td>
<td>100,000</td>
<td>0.687%</td>
<td>80.06%</td>
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<td>MKT EXP I</td>
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<td>MKT EXP I</td>
<td>E: 6.9% Intro Rate 9 months</td>
<td>100,000</td>
<td>0.992%</td>
<td>81.15%</td>
<td>$6,279</td>
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<td>MKT EXP I</td>
<td>F: 7.9% Intro Rate 12 months</td>
<td>100,000</td>
<td>0.944%</td>
<td>82.31%</td>
<td>$6,296</td>
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</table>
Another set of experiments:

| MKT EXP III | A: Post-Intro Rate Standard - 4% | 100,000 | 1.015% | 82.96% | $5,666 |
| MKT EXP III | B: Post-Intro Rate Standard - 2% | 100,000 | 0.928% | 77.69% | $5,346 |
| MKT EXP III | C: Post-Intro Rate Standard + 0% | 100,000 | 0.774% | 76.87% | $5,167 |
| MKT EXP III | D: Post-Intro Rate Standard + 2% | 100,000 | 0.756% | 76.98% | $5,265 |
| MKT EXP III | E: Post-Intro Rate Standard + 4% | 100,000 | 0.633% | 73.62% | $5,095 |
Model

Setting:
- Individual has initial credit card \((r_0^0, r_1^0, T_s^0)\). Balances: \(b_0\) pre-teaser, \(b_1\) post-teaser
- Credit card offers: \((r_0', r_1', T_s')\)

Decision to take-up new credit card:
- switching cost \(k > 0\)
- approx. saving in pre-teaser rates \((T_s\) years\): \(T_s (r_0' - r_0^0) b_0\)
- approx. saving in post-teaser rates \((21/12 - T_s\) years\): \((21/12 - T_s) (r_1' - r_1) b_1\)

Net benefit of switching:

\[
NB' = -k + T_s \left( r_0' - r_0^0 \right) b_0 + (21/12 - T_s) \left( r_1' - r_1^0 \right) b_1
\]
Model

- Switch if $NB + \varepsilon > 0$
- Take-up rate $R$ is function of attractiveness $NB$:

$$R = R(NB), \quad R' > 0$$

- Compare take-up rate of card $i$, $R^i$, to take-up rate of Standard Card $St$, $R^{St}$
  - Standard Card (6.9% followed by 16%) (Card C above)
- Assume $R$ (approximately) linear in a neighborhood of $NB^{St}$, that is,

$$R(NB^i) = R(NB^{St}) + R'_{NB} (NB^i - NB^{St})$$
Model

- Compare cards $Pre$ and $St$ that differ only in interest rate $r_0$ (pre-teaser)
- Assume $b_0^{Pre} = b_0^{St} = b_0$ (Pre-teaser balance) $\approx$ $2,000$
- Difference in attractiveness:

$$R\left(NB^{Pre}\right) - R\left(NB^{St}\right) = R'_{NB} T_s \left(r_0^{Pre} - r_0^{St}\right) b_0$$

- Pre-Teaser Offer (Card A): (4.9% followed by 16%)
  - $NB^{Pre} - NB^{St} \approx 6/12 \times 2\% \times 2,000 = 20$
  - $R\left(NB^{Pre}\right) - R\left(NB^{St}\right) = 386$ out of $100,000$
Model

- Compare cards Post and St that differ only in interest rate $r_1$ (post-teaser)
- Assume $b_1^{Post} = b_1^{St} = b_1$ (Post-teaser balance) $\approx$ $1,000$
- Difference in attractiveness:

  $$R(NB^{Post}) - R(NB^{St}) = R'_{NB} (21/12 - T_s) \left( r_1^{Post} - r_1^{St} \right) b_1$$

- Post-Teaser Offer (Card B in Exp. III): (6.9% followed by 14%)
  - $NB^{Post} - NB^{St} \approx 15/12 * 2% * $1000 = $25$
  - $R(NB^{Post}) - R(NB^{St}) = 154$ out of $100,000$

- Puzzle:
  - $NB^{Post} - NB^{St} > NB^{Pre} - NB^{St}$
  - But $R(NB^{Pre}) - R(NB^{St}) \gg R(NB^{Post}) - R(NB^{St})$
Results

- Plot $NB$ and $R(NB)$ for different offers
- Compare offers varying in $r_0$ (flat line) and in $r_1$ (steep line)
Results

- People underrespond to post-teaser interest rate.
- Most likely explanation: Present Bias + Naivete
  - Naives overestimate switching to another card (procrastination)
  - $\hat{b}_1 < b_1$ and $\hat{b}_0 = b_0$
- Compare cards:

\[
NB_{\text{Pre}} - NB_{\text{St}} = T_s \left(r_{0\text{Pre}} - r_{0\text{St}}\right) b_0
\]

and

\[
\hat{NB}_{\text{Post}} - \hat{NB}_{\text{St}} = \left(\frac{21}{12} - T_s\right) \left(r_{1\text{Post}} - r_{1\text{St}}\right) \hat{b}_1
\]

- Calibration: $\hat{b}_1 \approx (1/3) b_1 \rightarrow$ Underestimation of borrowing by a factor of 3
Section 4

Leisure Goods: Consumption and Savings
Leisure Goods: Consumption and Savings

Introduction

- Leisure Good: Temptation to overconsume at present
- Stylized facts:
  - Low liquid wealth accumulation
  - Extensive credit card borrowing (SCF, Fed, Gross and Souleles 2000)
  - Consumption-income excess comovement (Hall and Mishkin, 1982)
  - Substantial illiquid wealth (housing + 401(k)s)
## Table 1
SECOND-STAGE MOMENTS

<table>
<thead>
<tr>
<th>Description and Name</th>
<th>$\bar{m}$</th>
<th>se($\bar{m}$)</th>
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</thead>
<tbody>
<tr>
<td>% Borrowing on Visa: “% Visa”</td>
<td>0.678</td>
<td>0.015</td>
</tr>
<tr>
<td>Mean (Borrowing$_t$ / mean(Income$_t$)): “mean Visa”</td>
<td>0.117</td>
<td>0.009</td>
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<tr>
<td>Consumption-Income Comovement: “CY”</td>
<td>0.231</td>
<td>0.112</td>
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<tr>
<td>Average weighted $\frac{wealth}{income}$: “wealth”</td>
<td>2.60</td>
<td>0.13</td>
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</tbody>
</table>

Source: Authors’ calculations based on data from the Survey of Consumer Finances, the Federal Reserve, and the Panel Study on Income Dynamics. Calculations pertain to households with heads who have high school diplomas but not college degrees. The variables are defined as follows: % Visa is the fraction of U.S. households borrowing and paying interest on credit cards (SCF 1995 and 1998); mean Visa is the average amount of credit card debt as a fraction of the mean income for the age group (SCF 1995 and 1998, weighted by Fed aggregates); CY is the marginal propensity to consume out of anticipated changes in income (PSID 1978-92); and wealth is the weighted average wealth-to-income ratio for households with heads aged 50-59 (SCF 1983-1998).
Reduced-form evidence here not sufficient

Life-cycle consumption model (Gourinchas and Parker, 2004)

Assume realistic features:
- borrowing constraints
- illiquid assets
- bequests...

David Laibson’s slides to follow
3.1 Demographics

- Mortality, Retirement (PSID), Dependents (PSID), HS educational group

3.2 Income from transfers and wages

- $Y_t =$ after-tax labor and bequest income plus govt transfers (assumed exog., calibrated from PSID)

- $y_t \equiv \ln(Y_t)$. During working life:

  $$y_t = f_W(t) + u_t + \nu_t^W$$  \hspace{1cm} (3)

- During retirement:

  $$y_t = f_R(t) + \nu_t^R$$  \hspace{1cm} (4)
3.3 Liquid assets and non-collateralized debt

- $X_t + Y_t$ represents liquid asset holdings at the beginning of period $t$.

- Credit limit: $X_t \geq -\lambda \cdot \bar{Y}_t$

- $\lambda = .30$, so average credit limit is approximately $8,000$ (SCF).
3.4 Illiquid assets

- $Z_t$ represents illiquid asset holdings at age $t$.
- $Z$ bounded below by zero.
- $Z$ generates consumption flows each period of $\gamma Z$.
- Conceive of $Z$ as having some of the properties of home equity.
- Disallow withdrawals from $Z$; $Z$ is perfectly illiquid.
- $Z$ stylized to preserve computational tractability.
3.7 Computation

- Dynamic problem:
  \[
  \max_{I^X_t, I^Z_t} u(C_t, Z_t, n_t) + \beta \delta E_t V_{t+1}(\Lambda_{t+1}) \\
  \text{s.t. Budget constraints}
  \]

- \( \Lambda_t = (X_t + Y_t, Z_t, u_t) \) (state variables)

- Functional Equation:
  \[
  V_{t-1,t}(\Lambda_t) = \\
  \{ s_t[u(C_t, Z_t, n_t) + \delta E_t V_{t+1}(\Lambda_{t+1})] + (1-s_t)E_t B(\Lambda_t) \}
  \]

- Solve for eq strategies using backwards induction

- Simulate behavior

- Calculate descriptive moments of consumer behavior
4 Estimation

Estimate parameter vector $\theta$ and evaluate models wrt data.

- $m_e = N$ empirical moments, VCV matrix $= \Omega$

- $m_s(\theta) =$ analogous simulated moments

- $q(\theta) \equiv (m_s(\theta) - m_e) \Omega^{-1} (m_s(\theta) - m_e)'$, a scalar-valued loss function

- Minimize loss function: $\hat{\theta} = \arg \min_\theta q(\theta)$

- $\hat{\theta}$ is the MSM estimator.


- Specification tests: $q(\hat{\theta}) \sim \chi^2(N - \#\text{parameters})$
Two steps of estimation: of MSM (Method of Simulated Moments)

1. Estimate (‘calibrate’) auxiliary parameters
   - Interest rate
   - Mortality
   - Income shocks

2. Estimate main parameters ($\beta, \delta$) using Method of Simulated Moments
   - Simulate model (cannot solve analytically)
   - Choose parameters ($\hat{\beta}, \hat{\delta}$) that minimize distance of simulated moments to estimated moments
   - Take into account uncertainty in estimates of 1st stage
<table>
<thead>
<tr>
<th>Parameter estimates $\hat{\theta}$</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$</td>
<td>0.7031</td>
<td>1.0000</td>
<td>0.7150</td>
<td>1.0000</td>
<td>-</td>
</tr>
<tr>
<td>s.e. (i)</td>
<td>0.1093</td>
<td>-</td>
<td>(0.0948)</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>s.e. (ii)</td>
<td>0.1090</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
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<td>s.e. (iii)</td>
<td>0.0170</td>
<td>-</td>
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<td>s.e. (iv)</td>
<td>0.0150</td>
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<td>-</td>
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<td>-</td>
</tr>
<tr>
<td>$\delta$</td>
<td>0.9580</td>
<td>0.8459</td>
<td>0.9603</td>
<td>0.9419</td>
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</tr>
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<td>s.e. (i)</td>
<td>0.0068</td>
<td>(0.0249)</td>
<td>(0.0081)</td>
<td>(0.0132)</td>
<td>-</td>
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<tr>
<td>s.e. (ii)</td>
<td>0.0068</td>
<td>(0.0247)</td>
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<td>-</td>
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<td>s.e. (iii)</td>
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<td>(0.0062)</td>
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<tr>
<td>s.e. (iv)</td>
<td>0.0009</td>
<td>(0.0056)</td>
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</table>

Second-stage moments

<table>
<thead>
<tr>
<th>% Visa</th>
<th>0.634</th>
<th>0.669</th>
<th>0.613</th>
<th>0.284</th>
<th>0.678</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean Visa</td>
<td>0.167</td>
<td>0.150</td>
<td>0.159</td>
<td>0.049</td>
<td>0.117</td>
</tr>
<tr>
<td>CY</td>
<td>0.314</td>
<td>0.293</td>
<td>0.269</td>
<td>0.074</td>
<td>0.231</td>
</tr>
<tr>
<td>wealth</td>
<td>2.69</td>
<td>-0.05</td>
<td>3.22</td>
<td>2.81</td>
<td>2.60</td>
</tr>
</tbody>
</table>

Goodness-of-fit

<table>
<thead>
<tr>
<th>$q(\hat{\theta}, \hat{\delta})$</th>
<th>67.2</th>
<th>436</th>
<th>2.48</th>
<th>34.4</th>
<th>-</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\xi(\hat{\theta}, \hat{\delta})$</td>
<td>3.01</td>
<td>217</td>
<td>8.91</td>
<td>258.7</td>
<td>-</td>
</tr>
<tr>
<td>p-value</td>
<td>0.222</td>
<td>&lt;1e-10</td>
<td>0.0116</td>
<td>&lt;2e-7</td>
<td>-</td>
</tr>
</tbody>
</table>

Source: Authors’ calculations.
Note on standard errors: (i) includes both the first stage correction and the simulation correction, (ii) includes just the first stage correction, (iii) includes just the simulation correction, and (iv) includes neither correction.
<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
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<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Benchmark</td>
<td>$\gamma = 3.38%$</td>
<td>$\gamma = 6.59%$</td>
<td>$r^{CC} = 10%$</td>
<td>$r^{CC} = 13%$</td>
<td>$\rho = 1$</td>
<td>$\rho = 3$</td>
</tr>
<tr>
<td><strong>Hyperbolic</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Parameter Estimates</strong> $\hat{\theta}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>$\hat{\beta}$</td>
<td>0.7031</td>
<td>0.5071</td>
<td>0.8024</td>
<td>0.7235</td>
<td>0.6732</td>
<td>0.8186</td>
<td>0.5776</td>
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<td>s.e. (i)</td>
<td>(0.1093)</td>
<td>(0.0441)</td>
<td>(0.0614)</td>
<td>(0.1053)</td>
<td>(0.1167)</td>
<td>(0.0959)</td>
<td>(0.1339)</td>
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<tr>
<td>$\hat{\delta}$</td>
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<td>0.9731</td>
<td>0.9425</td>
<td>0.9567</td>
<td>0.9595</td>
<td>0.9610</td>
<td>0.9545</td>
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<tr>
<td>s.e. (i)</td>
<td>(0.0068)</td>
<td>(0.0188)</td>
<td>(0.0093)</td>
<td>(0.0071)</td>
<td>(0.0045)</td>
<td>(0.0037)</td>
<td>(0.0096)</td>
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<tr>
<td><strong>Goodness-of-fit</strong></td>
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<td></td>
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<tr>
<td>$q(\hat{\theta}, \hat{\delta})$</td>
<td>67.2</td>
<td>108.4</td>
<td>49.7</td>
<td>64.1</td>
<td>70.7</td>
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<td>67.7</td>
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<tr>
<td>$\xi(\hat{\theta}, \hat{\delta})$</td>
<td>3.01</td>
<td>16.79</td>
<td>5.27</td>
<td>12.09</td>
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<tr>
<td>$p$-value</td>
<td>0.222</td>
<td>0.0002</td>
<td>0.0717</td>
<td>0.0024</td>
<td>0.0041</td>
<td>0.0186</td>
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<td><strong>Exponential</strong></td>
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<td><strong>Parameter Estimates</strong> $\hat{\theta}$</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{\beta}$</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
<td>1.0000</td>
</tr>
<tr>
<td>s.e. (i)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\hat{\delta}$</td>
<td>0.8459</td>
<td>0.8459</td>
<td>0.8459</td>
<td>0.8520</td>
<td>0.8354</td>
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<td>s.e. (i)</td>
<td>(0.0249)</td>
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<td>(0.0262)</td>
<td>(0.0204)</td>
<td>(0.0357)</td>
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<td><strong>Goodness-of-fit</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$q(\hat{\theta}, \hat{\delta})$</td>
<td>435.6</td>
<td>435.6</td>
<td>435.6</td>
<td>434.7</td>
<td>436.6</td>
<td>438.1</td>
<td>435.5</td>
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<td>217</td>
<td>263</td>
<td>177</td>
<td>339</td>
<td>349</td>
<td>310</td>
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<tr>
<td>$p$-value</td>
<td>&lt;1e-10</td>
<td>&lt;1e-10</td>
<td>&lt;1e-10</td>
<td>&lt;1e-10</td>
<td>&lt;1e-10</td>
<td>&lt;1e-10</td>
<td>&lt;1e-10</td>
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</tbody>
</table>
Figure 1: This figure plots the MSM objective function with respect to beta and delta under the paper's benchmark assumptions. The objective, $q$, equals a weighted sum of squared deviations of the empirical moments from the moments predicted by the model. Lower values of $q$ represent a better fit of the model, and the (beta,delta) pair that minimizes $q$ is the MSM estimator.
Section 5

Leisure Goods: Commitment and Savings
Ashraf, Karlan, and Yin (2005), *QJE*

- **Different Methodology:** Commitment Device Field Experiment
- **Different Setting:** Philippines
- **Three treatments:**
  - *SEED Treatment* ($N=842$): Encourage to save, Offer commitment device (account with savings goal)
  - *Marketing Treatment* ($N=466$): Encourage to save, Offer no commitment
  - *Control Treatment* ($N=469$)
Results

- **Result 1. Take-up of commitment device** (in SEED Treatment):
  - Out of 842 treated people, 202 take up SEED \( \rightarrow \) Take up of 24%
  - 167 also got lock-up box (did not observe savings there)

- **Result 2. Effect of Availability of Commitment on Total Savings** (including funds in non-committed account)
  - Compare SEED to Marketing (Include all 842 people, Intent-to-Treat)
  - Share of people with increased Balances: 5.6 percentage
    (33.3 percent in SEED and 27.7 in Marketing)
  - Share of people with increased Balances by at least 20 percent: 6.4 percentage points
  - Total Balances: 287 Pesos after 6 months (not significant)
  - To compute Treatment-on-The-Treated, divide by 202/842
## Results

<table>
<thead>
<tr>
<th>Sample</th>
<th>Length</th>
<th>Intent TO TREAT EFFECT</th>
<th>OLS</th>
<th>Probit</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>6 months</td>
<td>All</td>
<td>12 months</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Commitment Treatment</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>234.678*</td>
<td>49.828</td>
<td>411.466*</td>
<td>287.575</td>
</tr>
<tr>
<td>(101.748)</td>
<td>(156.027)</td>
<td></td>
<td>(244.021)</td>
<td>(228.523)</td>
</tr>
<tr>
<td>Marketing Treatment</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All</td>
<td>184.851</td>
<td>123.891</td>
<td>153.440</td>
<td></td>
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<tr>
<td>(146.962)</td>
<td></td>
<td>(153.440)</td>
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<tr>
<td>Constant</td>
<td></td>
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<tr>
<td>All</td>
<td>40.626</td>
<td>225.476*</td>
<td>65.183</td>
<td>189.074**</td>
</tr>
<tr>
<td>(61.676)</td>
<td>(133.405)</td>
<td>(124.215)</td>
<td>(90.072)</td>
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<tr>
<td>Observations</td>
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</tr>
<tr>
<td>1777</td>
<td>1308</td>
<td>1777</td>
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<tr>
<td>R-squared</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses. * significant at 10%, ** significant at 5%, *** significant at 1%. The dependent variable in the first two columns is the change in total savings held at the Green Bank after six months. Column (1) regresses change in total savings balances on indicators for assignment to the commitment and marketing-treatment groups. The omitted group indicator in this regression corresponds to the control group. Column (2) shows the regression restricting the sample to commitment and marketing-treatment groups. Columns (3) and (4) repeat this regression, using change in savings balances after 12 months as a dependent variable. The dependent variable in columns (5)-8 is a binary variable equal to 1 if balances increased by 5%. 154 clients had pre-intervention a savings balance equal to zero. 24 of them had positive savings after 12 months. These individuals were coded as “one,” and those that remained at zero were coded as zero for the outcome variables for columns (5) through (8). Exchange rate is 50 pages for US $1.00.
Results

- Survey response to hyperbolic-discounting-type question:
  - Preference between 200 Pesos now and in 1 month
  - Preference between 200 Pesos in 6 months and in 7 months
  - On average, evidence of hyperbolic-discounting-type preferences

 Tếtable III
Tabulations of Responses to Hypothetical Time Preference Questions

<table>
<thead>
<tr>
<th>Indifferent between 200 pesos now and X in one month</th>
<th>X&lt;250</th>
<th>250&lt;X&lt;300</th>
<th>300&lt;X</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient</td>
<td>606</td>
<td>126</td>
<td>73</td>
<td>805</td>
</tr>
<tr>
<td>Somewhat Impatient</td>
<td>206</td>
<td>146</td>
<td>59</td>
<td>411</td>
</tr>
<tr>
<td>Most Impatient</td>
<td>154</td>
<td>93</td>
<td>299</td>
<td>546</td>
</tr>
<tr>
<td>Total</td>
<td>966</td>
<td>365</td>
<td>431</td>
<td>1,762</td>
</tr>
</tbody>
</table>

"Hyperbolic": More patient over future tradeoffs than current tradeoffs
"Patient Now, Impatient Later": Less patient over future tradeoffs than current tradeoffs.
Time inconsistent (direction of inconsistency depends on answer to open-ended question).
Results: Selection

- **Result 3. Who takes up the Commitment device?**
- Correlate survey response with commitment take-up (see also Fehr-Goette paper)
- Evidence of correlation for women, not for men

| TABLE V
Determinants of SEED Takeup | Probit |
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>All</td>
</tr>
<tr>
<td>Time inconsistent</td>
<td>0.125*</td>
</tr>
<tr>
<td></td>
<td>(0.067)</td>
</tr>
<tr>
<td>Impatient, Now versus 1 Month</td>
<td>-0.030</td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
</tr>
<tr>
<td>Patient, Now versus 1 Month</td>
<td>0.076</td>
</tr>
<tr>
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<td>(0.072)</td>
</tr>
<tr>
<td>Impatient, 6 months versus 7 Months</td>
<td>0.097</td>
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<tr>
<td></td>
<td>(0.065)</td>
</tr>
<tr>
<td>Patient, 6 months versus 7 Months</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
</tr>
</tbody>
</table>
Casaburi and Macchiavello (2019), *AER*

- Another Commitment Device Field Experiment
- Setting: Kenya, dairy sector
- Farmers get partly paid daily for milk, partly paid monthly by intermediary
- Preference for *infrequent payments*
- Offer farmers choice of:
  - *Daily payments with a bonus*
  - *Monthly payment*
- Daily payment is preferable giving discounting
Results

- **Result. Take-up of commitment device:** Strong preferences for infrequent payment

![Chart showing share of farmers choosing monthly payment option](chart.png)
Results

- **Result. Take-up of commitment device:** Strong preferences for infrequent payment

  ![Demand for Monthly Payment](image)

- **Interesting parallel with US case:** Demand for refunds at tax return time
Section 6

Leisure Goods: Drinking
Consider population with high levels of drinking while working

- Offer incentives to not drink during work hours
- Examine impact on
  - Drinking during work hours
  - Drinking after work hours
  - Earnings
  - Savings with (and without) savings commitment

Frank’s slides follow
Heavily concentrated alcohol consumption in India

<table>
<thead>
<tr>
<th>Country</th>
<th>Per capita (age 15+)</th>
<th>Male drinkers only</th>
</tr>
</thead>
<tbody>
<tr>
<td>India</td>
<td>0.7</td>
<td>5.0</td>
</tr>
<tr>
<td>USA</td>
<td>1.4</td>
<td>2.8</td>
</tr>
<tr>
<td>Russia</td>
<td>2.3</td>
<td>4.9</td>
</tr>
</tbody>
</table>

Study sample

- Cycle-rickshaw peddlers in Chennai
  - 35 years old, 5 years of education
  - 80% are married, 2 children
  - Average daily labor incomes of about Rs. 300 ($5)

- Alcohol consumption
  - Individuals drink (almost) every day, usually alone.
  - A third of labor incomes spent on hard liquor (>80 proof)
  - Individuals drink over 5 standard drinks per day.
  - High levels of intoxication, often during the day
  - 80% say they would be better off if all liquor stores closed.
Experimental design

• 229 individuals paid to visit study office for 20 days
• Daily visits any time between 6 pm and 10 pm
• Measure blood-alcohol content (BAC) using breathalyzer test
• Short survey
  • Labor market outcomes
  • Alcohol consumption
  • Expenditure patterns
• Opportunity to save money at study office
Introduction Background Design Alcohol Impact Commitment Outlook

Financial incentives for sobriety: three treatment groups

(I) **Control Group**: unconditional payments
   - Paid Rs. 90 regardless of BAC

(II) **Incentive Group**: monetary incentives to show up sober
   - Paid Rs. 60 if BAC > 0
   - Paid Rs. 120 if BAC = 0

(III) **Choice Group**
   - Choice between incentives and unconditional payments
Experimental design

- Screening
- Consent
- Baseline

Day 1

- Incentives assigned

Day 4

- Choice 1

Day 7

- Choice 2

Day 13

- Endline
- Choice 3

Day 20

- Incentives (2/3)

Control (2/3)

Choice (1/3)

Control (1/3)

Choice (1/3)

Control (1/3)

Choice (1/3)

Choice (1/3)
Financial incentives significantly increased daytime sobriety.

ATTENDANCE IN THE INCENTIVE GROUP IS LOWER.
...but reported overall drinking did not fall by much.
No significant effects on earnings
Measuring the impact of increased sobriety on savings

- All subjects got personalized savings box at study office.
  - Could save up to Rs. 200 per day.
  - Paid out entire amount plus matching contribution on day 20.

- Cross-randomized matching contribution to benchmark effects
  - 10% vs. 20% of amount saved

- Cross-randomized commitment savings feature
  - Allowed to withdraw any day between 6 pm and 10 pm
  - Not allowed to withdraw until day 20
Incentives for sobriety increased savings.
Incentives for sobriety increased savings.

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Rs/day</th>
<th>(2) Rs/day</th>
<th>(3) Rs/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pooled alcohol treatment</td>
<td>12.45**</td>
<td>13.41***</td>
<td>11.55**</td>
</tr>
<tr>
<td></td>
<td>(6.262)</td>
<td>(5.018)</td>
<td>(4.792)</td>
</tr>
<tr>
<td>High matching contribution</td>
<td>9.29</td>
<td>10.11**</td>
<td>11.65**</td>
</tr>
<tr>
<td></td>
<td>(6.532)</td>
<td>(4.873)</td>
<td>(4.619)</td>
</tr>
<tr>
<td>Commitment savings</td>
<td>7.59</td>
<td>2.88</td>
<td>2.86</td>
</tr>
<tr>
<td></td>
<td>(6.539)</td>
<td>(5.074)</td>
<td>(4.820)</td>
</tr>
<tr>
<td>Daily study payment (Rs)</td>
<td></td>
<td></td>
<td>0.35***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.050)</td>
</tr>
</tbody>
</table>

Observations: 3,435 3,435 3,435
R-squared: 0.006 0.113 0.129
Baseline survey controls: NO YES YES
Phase 1 controls: NO YES YES
Control mean: 20.42 20.42 20.42

Standard errors in parentheses, clustered by individual.
Interaction between sobriety and commitment savings

Sobriety Incentives vs. Commitment Savings

- Pooled alcohol treatment, commitment savings
- Pooled alcohol treatment, no commitment savings
- No alcohol treatment, commitment savings
- No alcohol treatment, no commitment savings

Cumulative savings (Rs)
Day in Study
WITHDRAWALS
DEPOSITS
39 / 53
Sobriety incentives vs. commitment savings: deposits

Sobriety vs. Commitment Savings: Cumulative Deposits

- Sobriety incentives, commitment savings
- Sobriety incentives, no commitment savings
- No sobriety incentives, commitment savings
- No sobriety incentives, no commitment savings
Appendix

Sobriety incentives vs. commitment savings: withdrawals

Sobriety vs. Commitment Savings: Cumulative Withdrawals

- Sobriety incentives, commitment savings
- Sobriety incentives, no commitment savings
- No sobriety incentives, commitment savings
- No sobriety incentives, no commitment savings
Eliciting willingness to pay for incentives

- Choice Group chooses between:
  - Incentives for sobriety
  - Unconditional payments

- Choice sessions on days 7, 13, 20, each for subsequent week
  - Elicit preferences for set of 3 choices
  - Then randomly select one choice to be implemented (RLIS)
Demand for incentives

- **Option A**: incentives for sobriety
  - Same payment structure as Incentive Group
  - Rs. 60 if BAC > 0, Rs. 120 if BAC = 0

- **Option B**: payment of Rs. \( Y \) regardless of BAC

<table>
<thead>
<tr>
<th></th>
<th>Option A</th>
<th>Option B</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>BAC &gt; 0</td>
<td>BAC = 0</td>
</tr>
<tr>
<td>(1)</td>
<td>Rs. 60</td>
<td>Rs. 120</td>
</tr>
<tr>
<td>(2)</td>
<td>Rs. 60</td>
<td>Rs. 120</td>
</tr>
<tr>
<td>(3)</td>
<td>Rs. 60</td>
<td>Rs. 120</td>
</tr>
</tbody>
</table>
Demand for commitment persists over time.

Demand for Incentives over Time

- **Choice 1:** unconditional payment = Rs 90
- **Choice 2:** unconditional payment = Rs 120
- **Choice 3:** unconditional payment = Rs 150
Exposure to incentives increases demand for incentives.

Demand for Incentive across Treatment Groups

<table>
<thead>
<tr>
<th>Choice</th>
<th>Incentive Group</th>
<th>Choice Group</th>
<th>Control Group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Choice 1 (Rs 90)</td>
<td>Dark Green</td>
<td>Red</td>
<td>Black</td>
</tr>
<tr>
<td>Choice 2 (Rs 120)</td>
<td>Dark Green</td>
<td>Red</td>
<td>Black</td>
</tr>
<tr>
<td>Choice 3 (Rs 150)</td>
<td>Dark Green</td>
<td>Red</td>
<td>Black</td>
</tr>
</tbody>
</table>

Fraction of individuals who chose incentives

0.0 0.2 0.4 0.6 0.8
Unique Features

- Unique feature 1: Effect of commitment device on drinking on another patience-related activity: savings
  - How do we interpret the effect?
    - Effect on withdrawing – mechanical given drunkenness
    - Effect on deposits – sophistication?
  - Would be great to know if sobriety incentives increases or lowers demand for savings commitment device (not in design)
- Unique feature 2: Exceptional demand for commitment device by for drinking
  - 1/3 population even when very expensive
  - Other existing studies – Demand typically goes to near zero
Section 7

Methodology: Commitment Field Experiments
Growing literature on field experiments offering commitment devices

Recipe for typical device:
- Random assignment into Treatment (T) and Control (C)
- Group T: Offered commitment option (action that imposes constraints)
- Group C: No option
- Observe take-up of commitment in T
- Observe outcome (e.g., saving, smoking, eating) in C and T
Three sets of results

1. **Take-up.** What share in T uses commitment device?
   - Standard agent would not choose additional constraints → Smoking gun for time inconsistency
   - Time inconsistency can be from present bias + sophistication
   - OR from hot/cold states or intra-family bargaining

2. **Effect on outcome.** Compare outcomes in T and C
   - Notice: Compare everybody in T to everybody in C
   - Cannot focus on those that took up the commitment in T, since do not know who they compare to in C
   - Treatment on Treated: rescale by dividing by take-up (assumption of no effect on non-takers)

3. **Who Takes Up?** Document who in T takes up commitment
   - Correlation with measured time preferences, previous behavior, etc.
   - This is not causal evidence, but still interesting
Methodology: Commitment Field Experiments

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   - Correlation with measured time preferences, previous behavior, etc.
   - This is not causal evidence, but still interesting
Representative studies: Investment Goods

- **Homework Completion** (Ariely-Wertenbroch *PS*)
  - Deadlines are penalties for delivering homework late
  - Result 1. Very large take-up rate (65 percent)
  - Result 2. Large effect on quality of homework and delay (in exp. 2)
Representative studies: Investment Goods

- Health-club attendance (Royer, Stehr, and Sydnor, AEJ Applied 2014)
  - First pay a treatment group to go to the gym
  - Then offer half of this treated group commitment device to keep going
  - Commitment device is money deposited into an account. Money forfeited if do not attend at least once every 14 days for 4 months
  - Result 1: Low demand for commitment: 13% take-up, with average sum of $63
  - Result 2: Some effect on attendance
Health-club attendance

Average Weekly Visits Overall

Week Relative to Start of Incentives

Control
Incentive
Incentive+Commit

0 0.5 1 1.5 2 2.5 3
-20 -10 0 10 20

Methodology: Commitment Field Experiments

Stefano DellaVigna
Econ 219B: Applications (Lecture 3)
February 5, 2019
Representative studies: Leisure Goods

- Consumption/Savings (Ashraf-Karlan-Yin)
  - Result 1. Commitment device take-up 24%
  - Result 2. Significant effect on overall savings
Representative studies: Leisure Goods

- Consumption/Savings (Ashraf-Karlan-Yin)
  - Result 1. Commitment device take-up 24%
  - Result 2. Significant effect on overall savings

- Consumption/Savings (Beshears, Choi, Laibson, Madrian, Mekong, 2011)
  - RAND panel respondents, 495 subjects, given $50, $100, or $500
  - Choice between
    - Liquid account (r=22% yearly)
    - Commitment account (set a goal) with r of 21%, 22%, or 23%
    - Penalty for early withdrawal
    - (Notice: only group with r=21% is a commitment device design)
    - Can choose share into each account
Result 1. Commitment device take-up quite high – up to 56%

<table>
<thead>
<tr>
<th>Penalty</th>
<th>21%</th>
<th>22%</th>
<th>23%</th>
</tr>
</thead>
<tbody>
<tr>
<td>10% penalty</td>
<td>0.28</td>
<td>0.39</td>
<td>0.58</td>
</tr>
<tr>
<td>20% penalty</td>
<td></td>
<td>0.45</td>
<td>0.61</td>
</tr>
<tr>
<td>No withdrawal</td>
<td></td>
<td></td>
<td>0.56</td>
</tr>
</tbody>
</table>
Representative studies: Leisure Goods

- *Retirement Savings* (SMRT plan, Thaler and Benartzi, 2007 – last lecture)
  - Result 1. Take-up rate 80% when offered in person
  - Result 2. Huge effects on 401(k) contribution rates
Representative studies: Leisure Goods

- **Retirement Savings** (SMRT plan, Thaler and Benartzi, 2007 – last lecture)
  - Result 1. Take-up rate 80% when offered in person
  - Result 2. Huge effects on 401(k) contribution rates

- **Online gaming** (Chow, 2010 and Acland and Chow, 2010)
  - Offer online interface that one can use to limit play of online games
  - Result 1. Take-up rate relatively high initially, but declines to 5-10%
  - Result 2. Suggestive effects on time spent playing
Methodology: Commitment Field Experiments

Representative studies: Leisure Goods

- **Smoking** (Gine, Karlan, and Zinman, 2010)
  - Offer urine test for smoking in 6 months
  - Can deposit money into account – forfeited if fail test at month 6
  - Result 1. Low take-up: 11% of 781 offered product
  - Result 1. Conditional on take-up, average deposit of 57 pesos (4 weeks worth of cigarettes)
  - Result 2: At 6 months, increase of 4-5 percentage point in chance of making urine test
Representative studies: Leisure Goods

- Smoking (Gine, Karlan, and Zinman, 2010), continued
  - Result 2: At 12 months, similar increase at surprise test

**Table 5—Impact of CARES on Passing Urine Test One Year Later**

*OLS, intent-to-treat estimates*

<table>
<thead>
<tr>
<th>Assumption:</th>
<th>Everyone that did not take the test continues smoking</th>
<th>Drop if did not take the test</th>
<th>Everyone that was found but refused to take the test still smokes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td><strong>Panel A. With baseline covariates</strong></td>
<td>0.035** 0.035*</td>
<td>0.057** 0.055*</td>
<td>0.054** 0.054**</td>
</tr>
<tr>
<td>CARES treatment</td>
<td>(0.018)  (0.018)</td>
<td>(0.028)  (0.028)</td>
<td>(0.027)  (0.027)</td>
</tr>
</tbody>
</table>
Representative studies: Leisure Goods

- Why often low-take up? At least 3 possibilities:
  - Self-control not prevalent
  - Self-control prevalent, but naivete’ is strong
  - Demand for commitment outweighed by costs of commitment in terms of loss of flexibility

- Important to have designs to separate explanations

- See also Laibson (2018) Ely lecture

- Also, Morrison, Sydnor, Taubinsky (2019): demand for commitment can reflect just a mistake
Representative studies: Leisure Goods

- Alternative design of the commitment device field experiments: 2*2 Design (Chow, 2010)
  - Offer *everyone* the commitment device
  - Then randomly assign whether commitment device is actually offered
  - Therefore groups are 2 (wanted comm./did not) * (got comm./did not)
Representative studies: Leisure Goods

- Alternative design of the commitment device field experiments: 2*2 Design (Chow, 2010)
  - Offer everyone the commitment device
  - Then randomly assign whether commitment device is actually offered
  - Therefore groups are 2 (wanted comm./did not) * (got comm./did not)

- Advantage of this design
  - More power on demand for commitment since everybody (not just 1/2 of subjects) is asked
  - Can estimate effect of commitment both on the subjects that demand it, and the ones who do not (but who may end up using it)
  - See also Chassang, Padro-i-Miguel, Snowberg, (AER 2012)
Section 8

Next Lecture
Next Lecture

- Present Bias
  - Laboratory Experiments
  - Errors in Applying Present Bias
- Then Reference-Dependent Preferences
  - Housing
  - Bunching-based Evidence