Outline

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

Investment Goods: Delay with Deadline
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

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
Heidhues and Strack (2019)

Assume \((\beta, \hat{\beta}, \delta)\) preferences, and i.i.d. cost shocks each period.

Negative result: Cannot infer time preferences from any observed task completion.

Theorem 2 (Non-identifiability). Suppose the agent is sophisticated \((\hat{\beta} = \beta)\). For every non-decreasing sequence of stopping probabilities \(0 < p_1 \leq p_2 \ldots p_T < 1\), every \((\beta, \delta)\) and every penalty \(y\), there exists a distribution \(F\) that rationalizes the agent’s stopping probabilities as the (unique) outcome of a perception perfect equilibrium.

For any discount rate, can find a cost of effort function that rationalizes that delay.

Positive result: With more variation (observing continuation payoffs), identification is possible.
Figure 1: Observed Task Completion Times. The above graphs illustrates the observed stopping times. In both cases $\delta = 1$, and the penalty for not doing the task is $-5$. The red bar plot shows the distribution of task completion times of a time-consistent agent whose cost of completing the task are drawn from a log-normal distribution, whose underlying normal distribution has mean $\mu = 1$ and variance $\eta = 1$. The blue bar plot that of a sophisticated time-inconsistent agent with $\beta = 0.7$ whose cost are drawn from a log-normal distribution with parameters $\mu = 0, \eta = 2.3$. independently of our work, Heffetz, O’Donoghue and Schneider observe that substantially different values of $\beta$ can explain the parking-ticket payment behavior in New York City, which they analyze in Heffetz et al. (2016). They illustrate this supposing that the cost for paying the parking ticket is drawn from the small parametric family of distributions that has a mass point at zero and admit a constant density on an interval above zero. Their real-world data nicely demonstrates the practical importance of the identification challenge we illustrate in Example 1 with synthetic data. We are very grateful to these authors for sharing their example with us during private communication.
parametric family

<table>
<thead>
<tr>
<th>Parametric Family</th>
<th>Sq. Distance Minimization</th>
<th>Likelihood Maximization</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>β</td>
<td>Distance</td>
</tr>
<tr>
<td>Normal Sophisticate</td>
<td>0.819</td>
<td>0.0026777</td>
</tr>
<tr>
<td>Normal Naive</td>
<td>0.817</td>
<td>0.00231803</td>
</tr>
<tr>
<td>Extreme Value Sophisticate</td>
<td>0.57</td>
<td>0.0402888</td>
</tr>
<tr>
<td>Extreme Value Naive</td>
<td>0.561</td>
<td>0.0396802</td>
</tr>
<tr>
<td>Logistic Sophisticate</td>
<td>0.7605</td>
<td>0.00331235</td>
</tr>
<tr>
<td>Logistic Naive</td>
<td>0.7565</td>
<td>0.00267175</td>
</tr>
</tbody>
</table>

Table 1: Parameter estimates of β and squared distance and log-likelihood.
Section 2

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)
Design

- Part of the randomization – Incredible sample sizes. How much would this cost to run? Millions

<table>
<thead>
<tr>
<th>TABLE 1: SUMMARY OF MARKET EXPERIMENTS</th>
</tr>
</thead>
<tbody>
<tr>
<td>MARKET EXPERIMENT</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>MKT EXP I</td>
</tr>
<tr>
<td>MKT EXP I</td>
</tr>
<tr>
<td>MKT EXP I</td>
</tr>
<tr>
<td>MKT EXP I</td>
</tr>
<tr>
<td>MKT EXP I</td>
</tr>
<tr>
<td>MKT EXP I</td>
</tr>
</tbody>
</table>
Design

- 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 \((r_0^0, r_1^0, T^0_s)\). 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:
  \[
  R(NB^{Pre}) - R(NB^{St}) = R'_{NB} T_s (r_0^{Pre} - r_0^{St}) b_0
  \]

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

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

- Post-Teaser Offer (Card B in Exp. III): (6.9% followed by 14%)
  - $NB^{Post} - NB^{St} \approx 15/12 \times 2\% \times$ $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)
  - Underestimate post-teaser borrowing: \( \hat{b}_1 < b_1 \) and \( \hat{b}_0 = b_0 \)
- Compare cards:

\[
NB^{Pre} - NB^{St} = T_s (r_0^{Pre} - r_0^{St}) b_0
\]

and

\[
\hat{NB}^{Post} - \hat{NB}^{St} = (21/12 - T_s) (r_1^{Post} - r_1^{St}) \hat{b}_1
\]

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

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>$\bar{m}_{j_m}$</th>
<th>$se(\bar{m}_{j_m})$</th>
</tr>
</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$_t$)): &quot;mean Visa&quot;</td>
<td>0.117</td>
<td>0.009</td>
</tr>
<tr>
<td>Consumption-Income Comovement: &quot;CY&quot;</td>
<td>0.231</td>
<td>0.112</td>
</tr>
<tr>
<td>Average weighted $\frac{wealth}{income}$: “wealth”</td>
<td>2.60</td>
<td>0.13</td>
</tr>
</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:

  $$y_t = f^W(t) + u_t + \nu^W_t$$  \hspace{1cm} (3)

- During retirement:

  $$y_t = f^R(t) + \nu^R_t$$  \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:

\[
\max_{I^X_t, I^Z_t} u(C_t, Z_t, n_t) + \beta \delta E_t V_{t+1}(\Lambda_{t+1})
\]

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 $= \Omega$

- $m_s (\theta) = \text{analogous simulated moments}$

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

- 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 \((\hat{\beta}, \hat{\delta})\) 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 3
BENCHMARK STRUCTURAL ESTIMATION RESULTS

<table>
<thead>
<tr>
<th>Parameter estimates $\hat{\theta}$</th>
<th>(1) Hyperbolic</th>
<th>(2) Exponential</th>
<th>(3) Hyperbolic Optimal Wts</th>
<th>(4) Exponential Optimal Wts</th>
<th>(5) Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\hat{\beta}$</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>
<tr>
<td>s.e. (iii)</td>
<td>(0.0170)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>s.e. (iv)</td>
<td>(0.0150)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$\hat{\delta}$</td>
<td>0.9580</td>
<td>0.8459</td>
<td>0.9603</td>
<td>0.9419</td>
<td>-</td>
</tr>
<tr>
<td>s.e. (i)</td>
<td>(0.0068)</td>
<td>(0.0249)</td>
<td>(0.0081)</td>
<td>(0.0132)</td>
<td>-</td>
</tr>
<tr>
<td>s.e. (ii)</td>
<td>(0.0068)</td>
<td>(0.0247)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>s.e. (iii)</td>
<td>(0.0010)</td>
<td>(0.0062)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>s.e. (iv)</td>
<td>(0.0009)</td>
<td>(0.0056)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Second-stage moments

| % Visa | 0.634 | 0.669 | 0.613 | 0.284 | 0.678 |
| mean Visa | 0.167 | 0.150 | 0.159 | 0.049 | 0.117 |
| CY | 0.314 | 0.293 | 0.269 | 0.074 | 0.231 |
| wealth | 2.69 | -0.05 | 3.22 | 2.81 | 2.60 |

Goodness-of-fit

| $q(\hat{\theta}, \hat{\delta})$ | 67.2 | 436 | 2.48 | 34.4 | - |
| $\xi(\hat{\theta}, \hat{\delta})$ | 3.01 | 217 | 8.91 | 258.7 | - |
| p-value | 0.222 | <1e-10 | 0.0116 | <2e-7 | - |

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>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</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>Parameter Estimates $\hat{\theta}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<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>
</tr>
<tr>
<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>
</tr>
<tr>
<td>$\hat{\delta}$</td>
<td>0.9580</td>
<td>0.9731</td>
<td>0.9425</td>
<td>0.9567</td>
<td>0.9595</td>
<td>0.9610</td>
<td>0.9545</td>
</tr>
<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>
</tr>
<tr>
<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>67.2</td>
<td>108.4</td>
<td>49.7</td>
<td>64.1</td>
<td>70.7</td>
<td>63.0</td>
<td>67.7</td>
</tr>
<tr>
<td>$\xi(\hat{\theta}, \hat{\delta})$</td>
<td>3.01</td>
<td>16.79</td>
<td>5.27</td>
<td>12.09</td>
<td>10.97</td>
<td>7.97</td>
<td>1.85</td>
</tr>
<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>
<td>0.3965</td>
</tr>
<tr>
<td><strong>Exponential</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Parameter Estimates $\hat{\theta}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<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>
<td>0.8924</td>
<td>0.7841</td>
</tr>
<tr>
<td>s.e. (i)</td>
<td>(0.0249)</td>
<td>(0.0249)</td>
<td>(0.0250)</td>
<td>(0.0267)</td>
<td>(0.0262)</td>
<td>(0.0204)</td>
<td>(0.0357)</td>
</tr>
<tr>
<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>
</tr>
<tr>
<td>$\xi(\hat{\theta}, \hat{\delta})$</td>
<td>217</td>
<td>217</td>
<td>263</td>
<td>177</td>
<td>339</td>
<td>349</td>
<td>310</td>
</tr>
<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>
</tr>
</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 4

Leisure Goods: Consumption and UI Benefits
Introduction

- Literature on Consumption $\rightarrow$ Hard to find detailed micro data
- Two major recent break-throughs in the literature examine response to UI
  - Ganong and Noel (2019): US data from Chase banking data
  - Gerard and Naritomi (2020): Brazil data from tax evasion data
- Start with Ganong and Noel (2019)
Spending in Data and Buffer Stock Model

- Ratio to $t = -2$
- Months Since First UI Check
- Buffer Stock Model
- Data

Graph showing the ratio of spending compared to a base period ($t = -2$) over months since the first UI check, with a comparison between the buffer stock model and the data.
186,000 households receiving UI in their Chase checking account

September 2013 through June 2016 (receive UI after Jan 2014)

20 states

Chase bank account spending and income (more on next slide)
  - Chase credit card spending
Outflows $\rightarrow$ Consumption [Lusardi 96]

- Strict Nondurables
  - 21% of Spend. Examples: Groceries, Restaurants, Fuel, Utilities, Haircuts.
- Other Nondurables
  - 6%. Examples: Clothing, Specialty Retail, Medical Copays, Drug Stores.
- Cash + Misc Nondurables. 15%.

Durables, Debt, & Transfers
- 27%. Examples: Home Improvement, Mortgage, Credit Card, Transfer to Savings Account.

Uncategorized
- 29%. Paper Checks, Ambiguous Electronic Transfers.

Inflows (Direct Deposit of Payroll) $\rightarrow$ Employment History
Spending If Stay Unemployed

Sample: Exhaust UI Benefits
No Job Start for at least 10 Months

Ratio to $t = -5$

Spending If Stay Unemployed

Income

Income by Duration

Standard Errors

Equation

Ex Post Exhaustees
Stingy UI Benefits: Florida

Income (Labor + UI) if Stay Unemployed

Spending if Stay Unemployed

Potential UI Duration

- 6 Months
- 4 Months (Florida)

Ratio to $t = -5$

Months Since First UI Check

All UI Recipients
Exhaustion: Is Consumption Really Dropping?

<table>
<thead>
<tr>
<th>Large % Drop</th>
<th>Pre-Exhaust</th>
<th>Post-Exhaust</th>
<th>Δ%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount Stores</td>
<td>$58</td>
<td>$47</td>
<td>-19%</td>
</tr>
<tr>
<td>Groceries</td>
<td>$294</td>
<td>$247</td>
<td>-16%</td>
</tr>
<tr>
<td>Restaurants</td>
<td>$164</td>
<td>$138</td>
<td>-16%</td>
</tr>
<tr>
<td>Drug Stores</td>
<td>$35</td>
<td>$30</td>
<td>-15%</td>
</tr>
<tr>
<td>Medical Copay</td>
<td>$29</td>
<td>$25</td>
<td>-14%</td>
</tr>
<tr>
<td>Entertainment</td>
<td>$27</td>
<td>$23</td>
<td>-13%</td>
</tr>
<tr>
<td>Auto Repair</td>
<td>$36</td>
<td>$32</td>
<td>-13%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Small % Change</th>
<th>Pre-Exhaust</th>
<th>Post-Exhaust</th>
<th>Δ%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto Loan</td>
<td>$76</td>
<td>$71</td>
<td>-7%</td>
</tr>
<tr>
<td>Mortgage</td>
<td>$148</td>
<td>$142</td>
<td>-4%</td>
</tr>
<tr>
<td>Insurance</td>
<td>$159</td>
<td>$155</td>
<td>-3%</td>
</tr>
</tbody>
</table>

Drop by Spending Group
Drop by Months Nonemployed
Consumption Tracks UI Benefits

1. Spike when UI payments begin. Generous New Jersey.

2. Drop at exhaustion. Stingy Florida.

3. Categories which drop most are nondurables.
MPC from predictable income decrease as an “identified moment” [Nakamura and Steinsson 2018]

<table>
<thead>
<tr>
<th></th>
<th>Tax rebate MPC</th>
<th>Income decline MPC</th>
</tr>
</thead>
<tbody>
<tr>
<td>PIH</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Liquidity constraints</td>
<td>✓</td>
<td>X</td>
</tr>
<tr>
<td>Behavioral/myopia</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

UI exhaustion + bank account data is particularly useful predictable decline

1. Nearly everyone is unemployed at least once
2. Everyone has saving technology by construction
3. No change in time budget ⇒ rules out home production
   [Bernheim, Skinner, Weinberg 01, Aguiar and Hurst 2005]
Model: Setup

Monthly frequency

\[
\max_{\{c_t, s_t\}} E \sum_{n=0}^{T-t} \delta^n [u(c_{t+n}) - \psi(s_{t+n})]
\]

subject to \( c_t + a_{t+1} = R a_t + z_t \quad a_t \geq -L \)

- CRRA utility \( u(c) = \frac{c^{1-\gamma}}{1-\gamma} \)
- Isoelastic search \( \psi(s) = k \frac{s^{1+\xi}}{1+\xi} \)
- Income \( z \)
  - Employed
  - Receive UI Benefits
  - Exhaust UI Benefits
- Markov process \( \Pi \)
## Model: Environment

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Calibrated to JPMCI Data</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employed Income $z_t$</td>
<td>1.00</td>
<td>Employed</td>
</tr>
<tr>
<td>Unemployed for &lt; 6 Months</td>
<td>0.82</td>
<td>Bank</td>
</tr>
<tr>
<td>Unemployed for ≥ 6 Months</td>
<td>0.53</td>
<td></td>
</tr>
<tr>
<td>Initial Assets $a_0$</td>
<td>0.66</td>
<td>Bank with SCF</td>
</tr>
<tr>
<td><strong>Calibrated to External Data</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Separation Rate</td>
<td>0.0325</td>
<td>BLS</td>
</tr>
<tr>
<td>Interest Rate $R$</td>
<td>1.0025</td>
<td>Cagetti 03</td>
</tr>
<tr>
<td>Risk Aversion $\gamma$</td>
<td>2</td>
<td>Carroll 97</td>
</tr>
<tr>
<td>Job Search Convexity $\xi$</td>
<td>1.5</td>
<td>Schmieder &amp; von Wachter 18</td>
</tr>
<tr>
<td>Estimated to match empirical path of consumption and job-finding</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discount Factor $\delta$</td>
<td>0.991</td>
<td></td>
</tr>
<tr>
<td>Borrowing Limit $L$</td>
<td>4.3</td>
<td></td>
</tr>
<tr>
<td>Job Search Cost $k$</td>
<td>27</td>
<td></td>
</tr>
</tbody>
</table>
Spending in Data and Representative Agent Model

- Data
- Model: Representative Agent, GOF=460
Can Alternative Behavioral Models Explain the Drop?

- Second class of candidate models
  - Behavioral alternatives
  - Break assumption of rational forward-looking households with exponential discount rates
- Ex: Laibson (97) hyperbolic discounting

\[
\max_{\{c_t, s_t\}} u(c_t) - \psi(s_t) + \mathbb{E} \left[ \beta \sum_{n=1}^{T-t} \delta^n (u(c_{t+n}) - \psi(s_{t+n})) \right]
\]

- low-$\beta$ helps to qualitatively match the observed path
Spending in Data and Myopic Hyperbolic Model

Ratio to $t = -2$

Data
Model: Myopic Hyperbolic, GOF=26800

Months Since First UI Check

Ratio to $t = -2$

Data
Model: Myopic Hyperbolic, GOF=26800
Spender-Saver Model (following Campbell and Mankiw 89)

<table>
<thead>
<tr>
<th>Model</th>
<th>Borrowing limit</th>
<th>Discount factor</th>
<th>Population share</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buffer stock</td>
<td>$L = 0$</td>
<td>$\delta = 0.995$</td>
<td>36%</td>
</tr>
<tr>
<td>Permanent income</td>
<td>natural limit</td>
<td>$\delta = 0.995$</td>
<td>46%</td>
</tr>
<tr>
<td>$\beta \delta$ “Hand-to-mouth”</td>
<td>$L = 0$</td>
<td>$\delta = 0.995$, $\beta = 0.5$</td>
<td>18%</td>
</tr>
</tbody>
</table>

- Alternatives to present bias focus
  - Exponential discounting with $\delta = 0.35$
  - Mechanically set $c = y$ (Campbell and Mankiw 1989)
Spending in Data and Spender–Saver Model

Ratio to t=−2

Data

Model: Spender–Saver, GOF=167

Search Out-of-Sample Test 28
Spending in Data and in Models, Out of Sample Test With Low–Benefit State Florida

- **Data**
- **Model: Representative Agent, GOF=651**
- **Model: Spender–Saver, GOF=286**

Ratio to $t=-2$ vs. Months Since First UI Check
## Normative Implications

### Gains from Alternative UI Policy
(as a % of Lifetime Utility, $\gamma = 2$

<table>
<thead>
<tr>
<th></th>
<th>UI Benefits</th>
<th>UI Durations</th>
<th>Ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>↑ 1.7%</td>
<td>↑ 1 Month</td>
<td></td>
</tr>
<tr>
<td><strong>(1)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>(2)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>(2)/(1)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Generalized Baily-Chetty
- **Gruber (1997)**: 0.019%
- **JPMCI**: 0.020% 0.083% 4.13

#### Structural Model Simulation
- **Buffer Stock**: 0.036% 0.092% 2.55
- **Spender-Saver**: 0.024% 0.059% 2.51

---

Moral Hazard
Onset: Heterogeneity By Total Liquid Assets

Income If Stay Unemployed

Ratio to t = -5

Months Since First UI Check

Asset Tercile

- High
- Middle
- Low

Back 46
Onset: Heterogeneity By Total Liquid Assets

Spending If Stay Unemployed

Months Since First UI Check

Ratio to $t = -5$

Asset Tercile
- High
- Middle
- Low

Back
Increasingly Broad Definitions of Spending If Stay Unemployed

Spending Definition (Lusardi 1996)
- Food
- Strict Nondurables
- Nondurables
- Total Outflows
Introduction

- Gerard and Naritomi (2020):
  - Brazil data
  - UI severance, in addition to UI benefits
  - Tax evasion data
This paper contributes to filling both gaps

- Study consumption profile of displaced workers in São Paulo, Brazil
  - Relevant setting: large economy and sizable informal sector
  - Interesting laboratory: workers eligible for both UI and lump-sum schemes upon layoff, with some variation in benefits across workers

- Combine high-frequency longitudinal data on consumption and formal employment from administrative records (∼400,000 workers)
  - New source of consumption data: VAT receipts linked to individual ids
  - Cover wide range of expenditure categories before and after layoff
Figure: DD estimates - Non-durables (survival sample)

- Large spike at layoff despite long-term loss
- Results not driven by durables, so refer to consumption profile
- Long-term loss comparable to findings from richer countries
- Also, fail to smooth consumption in anticipation of drop in income at UI exhaustion (as in Ganong and Noel, 2018) despite lots of liquidity at layoff
Outline

1 Background and Data
2 Consumption profile around dismissal event
3 Consumption profile around UI exhaustion
4 Models of behavior and policy implications
5 Conclusion
RAIS: matched employee-employer data for all formal employees
  ▶ Wage, hiring and separation month, reason for separation (2005-2014)
  ▶ Education, gender, race, age, location and sector of establishment

UI registry: universe of UI payments
  ▶ Date and amount (2009-2012)

No data on lump-sum schemes but can calculate statutory amounts
workers eligible for using employment history in RAIS
  ▶ Moreover, small survey of UI applicants indicates:
    i. Overall firms appear to mostly comply with their obligations in SP
    ii. Most workers withdraw amount in FGTS accounts

⇒ matched expenditure-employment data for about 400,000 workers
Expenditure data coverage

- VAT receipts: many expenditure categories, all means of payment
- VAT only levied on goods: data cannot cover VAT-excluded items (e.g., services, housing costs)
- Among purchases taxed by the VAT: only those with SSN provided
- Average monthly expenditures prior to layoff $\approx 30\%$ of average wages
  $\Rightarrow$ suggests quite good coverage of what data could cover
- Yet, incomplete so rely on “constant-coverage” assumption
  - Show that holds in cross-section of income for formal employees
Immediate and persistent drop in consumption for fired workers

Mitigate concerns about receipt reporting changes after displacement
Outline

1 Background and Data
2 Consumption profile around dismissal event
3 Consumption profile around UI exhaustion
4 Models of behavior and policy implications
5 Conclusion
Figure: Treatment vs. control (raw data; unconditional sample)

Control group (continuously employed)  Treatment group (laid off in month 0)

Start exhausting UI
Receive SP amount

Total expenditures (R$2010)

-12 -10 -8 -6 -4 -2 0 2 4 6 8 10 12

Months to/since layoff month

Treatment: displaced in month 0 (77,862 layoff events)
Control: workers continuously employed for 25 months (220,160 placebo events)
Note: raw data (netting out month fixed effects)
Figure: DD estimates (unconditional and survival samples)

Specification:  \( y_{ikt} = \alpha_i + \alpha_k + \alpha_t + \delta_k \cdot Treatment_i + \varepsilon_{ikt} \) for worker \( i \) observed \( k \) months before/after event in month \( t \) (s.e. clustered by individual)
All samples reweighed to match distribution (wage, SP amount, expenditures pre-layoff) in overall treatment group. Report \( \hat{\delta}_k \) divided by level in reference month (% change)
Takeaway: (i) all groups have spike at layoff (so pattern not due composition effect or complementarity with leisure), (ii) expenditures increase at reemployment (5%-10%) event, (iii) but long-term loss unless reemployed immediately (wage loss 10.8%).
Outline

1 Background and Data
2 Consumption smoothing around dismissal event
3 Consumption smoothing around UI exhaustion
4 Models of behavior and policy implications
5 Conclusion
Event analysis around UI exhaustion

- Make consumption profile around UI exhaustion clearer
- Useful to discriminate between models
  - Sensitivity of consumption to expected drop in income at UI exhaustion cannot be due to liquidity constraint (Ganong and Noel, 2018)
- Sample: workers laid off in years with UI data (2011-2012)
  - All outcomes de-trended using control group

1 Event analysis aggregating data by 30-day periods around last UI pay
  - Lack of smoothing in anticipation of drop in income at UI exhaustion
  - Despite 10% drop for those who remained without a formal job
  - Also, non-durable spendings increase by 20% in first week after each UI pay date within a month, including after last UI pay date

2 RD analysis for causal effect of potential UI duration
  - Potential UI duration increases from 4 to 5 months at tenure > 24 mo.
  - Any impact on consumption around timing of 5th UI payment!
Takeaways:
(i) Lack of smoothing in anticipation of expected drop in income at UI exhaustion;
(ii) Despite 10% drop for those who remained without a formal job

(a) All UI exhaustees
(b) UI exhaustees who remain without a formal job until the end of the window
Sensitivity to cash-on-hand around UI payday

**Figure:** Relative change in non-durable expenditures between UI payments

(a) All UI exhaustees

(b) UI exhaustees who remain without a formal job until the end of the window

Takeaways: (i) expenditures very sensitive to timing of payment (but here, not clear that non-durable expenditures = consumption), (ii) lack of smoothing in anticipation of UI exhaustion; (iii) same pattern around paydays for formal employees
Outline

1. Background and Data
2. Data
3. Consumption smoothing around dismissal event
4. Consumption smoothing around UI exhaustion
5. Models of behavior and policy implications
6. Conclusion
Possible mechanism

Liquidity constraint and present bias (DellaVigna and Passerman, 2005)

- Simple way to generate high propensity to consume out of liquidity and low propensity to save in anticipation of negative shock

⇒ Show this concretely by estimating dynamic model of job search and consumption (DellaVigna et al., 2017; Ganong and Noel, 2018)

- Mechanism supported by survey of UI applicants
  - 60% say they would not want to get all UI benefits in lump-sum fashion at layoff (“control expenditures” or “not spend it all at once”)

- Mechanism also provides policy rationale for the existence of forced savings accounts, such as the one that exists in Brazil
Other mechanisms

- Liquidity constraint and...
  - Biased beliefs about reemployment probabilities (Spinnewijn, 2015)
  - Inattention to, or underestimation of, income drop at UI exhaustion
  - Near-rationality (Kueng, 2018)
  - Lumpy consumption needs (Campbell & Hercowitz, 2018)

- ... would not generate both high propensity to consume out of liquidity and low propensity to save in anticipation of negative shock

- Complementarity or substitution of spending with leisure (Aguiar and Hurst, 2005) would also not be consistent with main results.

- Saving constraints (kinship taxation, no savings technology) would explain our findings, but do not seem to be an issue in this context
Target empirical moments

(a) Hazard of formal reemployment

(b) Change in non-durable expenditures

For simplicity, estimation sample restricted to displaced workers eligible for 5 monthly UI payments, and who took up UI in their 1st month of eligibility.
Model

- Partial-equilibrium job-search model with borrowing constraint
- Discrete time, layoff from formal job with wage $w^e$ in period $t = 0$
- When formally-reemployed: new job with wage $w^r < w^e$ until $T$
- When non-formally-employed: choose search effort $h_{i,t}$ (reemployment probability) at cost $\psi_i(h_{i,t}) = \kappa_i \cdot \frac{h_{i,t}^{1+\gamma}}{(1 + \gamma)}$
Choose consumption subject to: \( c_{i,t} = a_{i,t} + y_{i,t} - \frac{a_{i,t+1}}{1+r} \) and \( a_{i,t} > \bar{a} \)

- Income \( y_{i,t} \) from SP (\( f \)), UI (\( b_t \)), and reemployment wage (\( w^r \))
- Also fixed spousal income (\( w^e \)) with the couple pooling all resources
- Also choice of “informal” earnings at cost \( \phi(l_{i,t}) = \chi \cdot \frac{l_{i,t}^{1+\lambda}}{(1 + \lambda)} \)
- Assumptions for asset accumulation: \( a_{i,0} = 0, r = 0, \bar{a} = 0 \)

Assume relative change in non-durable expenditures in data capture relative change in consumption in model

- But possible demand for lump-sum (Casaburi and Macchiavelo, 2018) separate from purpose captured in model (repay debt, buy durables)
- So allow share \( \omega \in [0, 1] \) of lump-sum \( f \) used for consumption
Parameters calibrated to averages in estimation sample \((w^e, w^r, b, f)\)

Vector of 8 free parameters \(\xi = (\kappa_1, \kappa_2, s_1, \gamma, \omega, \chi, \lambda, \delta \text{ or } \beta)\)

- Model 1 (myopia): \(\delta\)-discounting with \(\delta\) free
- Model 2 (“naive” present bias): \(\beta\delta\)-discounting with \(\beta\) free (\(\delta = .995\))

For given \(\xi\), model is solved by backwards induction

Indirect inference: choose \(\hat{\xi}\) to minimize \((m(\xi) - \hat{m})' V (m(\xi) - \hat{m})\)

- Vector of moments \(m\)
- Diagonal matrix \(V\) with inverse of variance of moments on diagonal

Utility function: \(u(c) = \log(c)\)

Parameters estimated jointly but identification intuitive
Fits the data well, but the estimated $\hat{\delta} = 0.82$ at monthly level!
Model fit for present-bias model

(a) Hazard of formal reemployment
(b) Relative change in consumption

Fits the data well, and the estimated $\hat{\beta} = 0.71$ in line with literature
“Benchmark model” \((\delta = .995, \beta = 1)\)

Takeaways: (i) possible to match reemployment, (ii) but not consumption patterns

(a) Hazard of formal reemployment

(b) Relative change in consumption

params
Figure: DD estimates by category (in levels)

Takeaway: (i) overall effect mostly driven by non-durables
Figure: Using variation in UI replacement rates from variation in wages (controlling for tenure; survival sample)

Takeaway: steeper drop at UI exhaustion if higher UI benefit level (but same tenure); long-term loss smaller for low-wage workers
Figure: Using variation in SP and FGTS from variation in tenure (controlling for wages; survival sample)

Takeaway: spike larger for workers with higher lump-sum at layoff (but same wage)
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 → 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
### TABLE VI

<table>
<thead>
<tr>
<th>Sample</th>
<th>OLS</th>
<th>Probit</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>6 months</td>
<td>12 months</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Commitment Treatment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
</tr>
<tr>
<td>Commitment Treatment</td>
<td>234.678*</td>
<td>49.828</td>
<td>411.466*</td>
<td>287.575</td>
<td>0.102***</td>
<td>0.056**</td>
<td>0.101***</td>
<td>0.064***</td>
</tr>
<tr>
<td>(101.748)</td>
<td>(156.027)</td>
<td>(244.021)</td>
<td>(228.523)</td>
<td>(3.82)</td>
<td>(0.028)</td>
<td>(0.022)</td>
<td>(0.021)</td>
<td></td>
</tr>
<tr>
<td>Marketing Treatment</td>
<td>184.851</td>
<td>123.891</td>
<td>153.440</td>
<td>85.183</td>
<td>0.047*</td>
<td>0.041</td>
<td>0.041</td>
<td>0.027</td>
</tr>
<tr>
<td>(146.962)</td>
<td>(133.405)</td>
<td>(124.215)</td>
<td>(90.072)</td>
<td>(1.56)</td>
<td>(0.06)</td>
<td>(0.02)</td>
<td>(0.027)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>40.625</td>
<td>225.476*</td>
<td>55.183</td>
<td>189.074**</td>
<td>0.102***</td>
<td>0.056**</td>
<td>0.101***</td>
<td>0.064***</td>
</tr>
<tr>
<td>(61.676)</td>
<td>(133.405)</td>
<td>(124.215)</td>
<td>(90.072)</td>
<td>(1.56)</td>
<td>(0.06)</td>
<td>(0.02)</td>
<td>(0.027)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>1777</td>
<td>1308</td>
<td>1308</td>
<td>1308</td>
<td>1777</td>
<td>1308</td>
<td>1777</td>
<td>1308</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 in 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 savings balances equal to zero. 24 of them had positive savings after 12 months. These individuals were coded as “1,” and those that remain 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

TABLE 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>Indifferent between 200 Pesos in 6 months and X in 7 months</th>
</tr>
</thead>
<tbody>
<tr>
<td>X&lt;250</td>
<td>X&lt;250</td>
</tr>
<tr>
<td>Patient</td>
<td>Somewhat Impatient</td>
</tr>
<tr>
<td>---------</td>
<td>-------------------</td>
</tr>
<tr>
<td>X=250</td>
<td>606</td>
</tr>
<tr>
<td>34.4%</td>
<td>7.2%</td>
</tr>
<tr>
<td>250&lt;X&lt;300</td>
<td>206</td>
</tr>
<tr>
<td>11.7%</td>
<td>8.3%</td>
</tr>
<tr>
<td>300&lt;X</td>
<td>154</td>
</tr>
<tr>
<td>8.7%</td>
<td>5.3%</td>
</tr>
<tr>
<td>Total</td>
<td>966</td>
</tr>
<tr>
<td>54.8%</td>
<td>20.7%</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>
<thead>
<tr>
<th>TABLE V</th>
<th>Determinants of SEED Takeup</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Probit</td>
</tr>
<tr>
<td></td>
<td>(1) All</td>
</tr>
<tr>
<td></td>
<td>(2) All</td>
</tr>
<tr>
<td></td>
<td>(3) Female</td>
</tr>
<tr>
<td></td>
<td>(4) Male</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>
<td></td>
<td>(0.072)</td>
</tr>
<tr>
<td>Impatient, 6 months versus 7 Months</td>
<td>0.097</td>
</tr>
<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>
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

![Graph showing the share of farmers choosing monthly payment option](image-url)


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
Schilbach (2019)

Schilbach (AER, 2019)
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

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
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

- Day 1: Screening, Consent, Baseline
- Day 4: Incentives assigned
- Day 7: Choice 1
- Day 13: Choice 2
- Day 20: Endline Choice 3

Control: (2/3) Incentives, (1/3) Control
Choice: (1/3) Incentives, (1/3) Control, (1/3) Control
Financial incentives significantly increased daytime sobriety.
...but reported overall drinking did not fall by much.
No significant effects on earnings

Earnings (Rs/day)

Alcohol treatment assigned

Incentives and Choice Groups pooled

Control Group
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>
<tr>
<td>Observations</td>
<td>3,435</td>
<td>3,435</td>
<td>3,435</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.006</td>
<td>0.113</td>
<td>0.129</td>
</tr>
<tr>
<td>Baseline survey controls</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Phase 1 controls</td>
<td>NO</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Control mean</td>
<td>20.42</td>
<td>20.42</td>
<td>20.42</td>
</tr>
</tbody>
</table>

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

Sobriety Incentives vs. Commitment Savings

Cumulative savings (Rs)

Day in Study

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

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
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>Option A</th>
<th>Option B</th>
</tr>
</thead>
<tbody>
<tr>
<td>BAC &gt; 0</td>
<td>BAC = 0</td>
</tr>
<tr>
<td>(1) Rs. 60</td>
<td>Rs. 120</td>
</tr>
<tr>
<td>(2) Rs. 60</td>
<td>Rs. 120</td>
</tr>
<tr>
<td>(3) Rs. 60</td>
<td>Rs. 120</td>
</tr>
<tr>
<td></td>
<td>Rs. 90</td>
</tr>
<tr>
<td></td>
<td>Rs. 120</td>
</tr>
<tr>
<td></td>
<td>Rs. 150</td>
</tr>
</tbody>
</table>
Demand for commitment persists over time.

### Demand for Incentives over Time

<table>
<thead>
<tr>
<th>Week</th>
<th>Choice 1</th>
<th>Choice 2</th>
<th>Choice 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.6</td>
<td>0.6</td>
<td>0.4</td>
</tr>
<tr>
<td>2</td>
<td>0.6</td>
<td>0.6</td>
<td>0.4</td>
</tr>
<tr>
<td>3</td>
<td>0.6</td>
<td>0.6</td>
<td>0.4</td>
</tr>
</tbody>
</table>

**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

Fraction of individuals who chose incentives
Choice 1 (Rs 90) Choice 2 (Rs 120) Choice 3 (Rs 150)
Incentive Group Choice Group Control Group

Incentive Group | Choice Group | Control Group
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
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)
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
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
Average Weekly Visits Overall

Stefano DellaVigna
Econ 219B : Applications (Lecture 3)
February 5, 2020 123 / 132
**Representative studies: Leisure Goods**

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

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>0.45</td>
<td></td>
<td>0.61</td>
</tr>
<tr>
<td>No withdrawal</td>
<td></td>
<td>0.56</td>
<td>0.60</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

- 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
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
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>
<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>Panel A. With baseline covariates</td>
<td>(1) 0.035** 0.035* 0.018</td>
<td>(2) 0.057** 0.055* 0.028</td>
<td>(3) 0.054** 0.054** 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, 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