Econ 219B
Psychology and Economics: Applications (Lecture 3)

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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

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

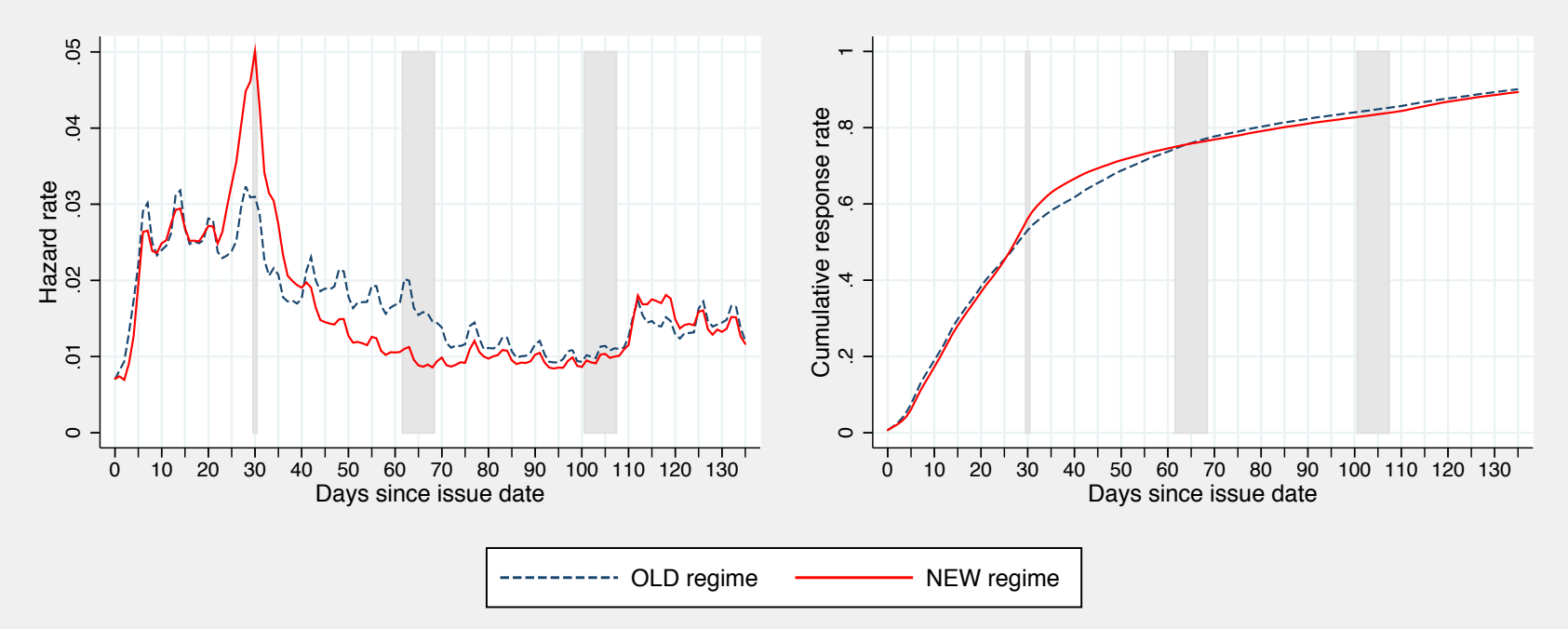
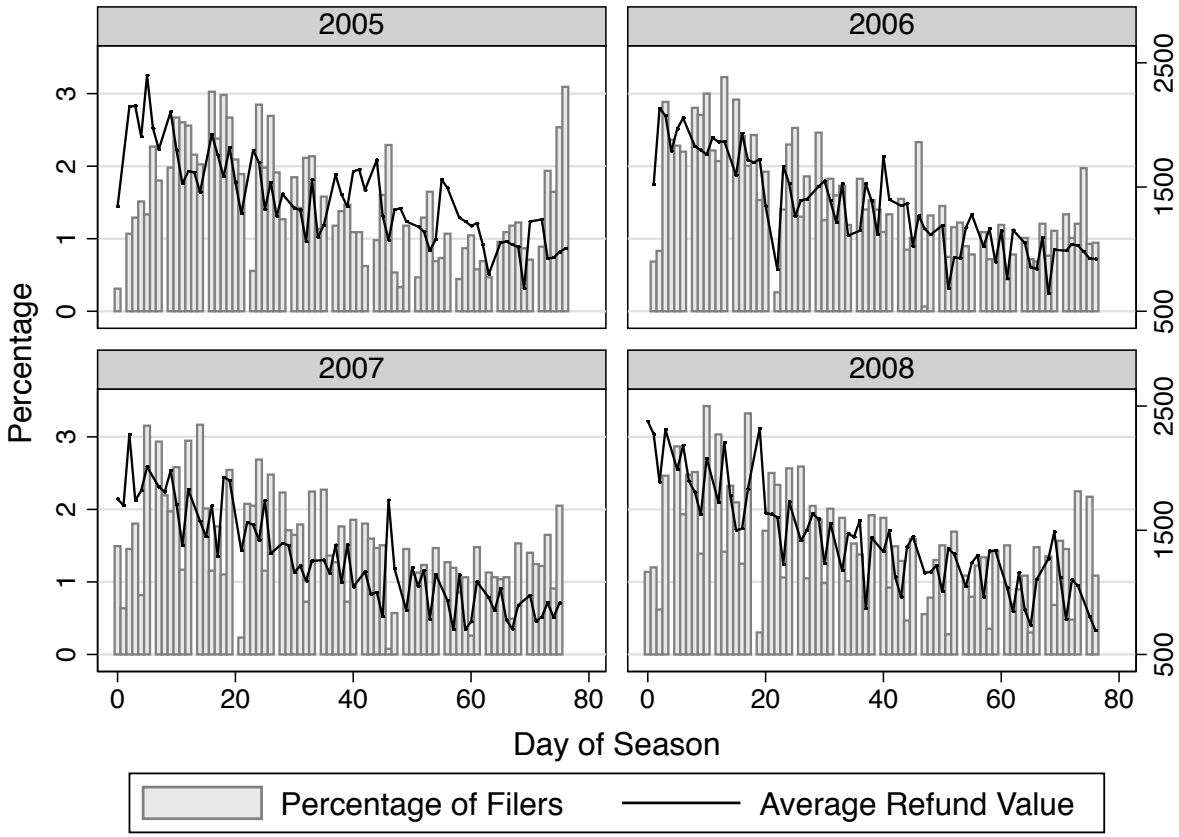


Figure 1: Hazard Rates and Cumulative Response Rates in OLD vs. NEW Regimes. Note: All tickets have a first deadline at day 30, second deadline at days 62-68, and third deadline at days 101-107, indicated by the shaded areas (the latter two deadlines are a range because they depend on ticket-issuance 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



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)**
  - 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-identiability).** Suppose the agent is sophisticated $(\hat{\beta} = \beta)$. For every non-decreasing sequence of stopping probabilities $0 < p1 \leq p2...pT < 1$, every (β, δ) 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.

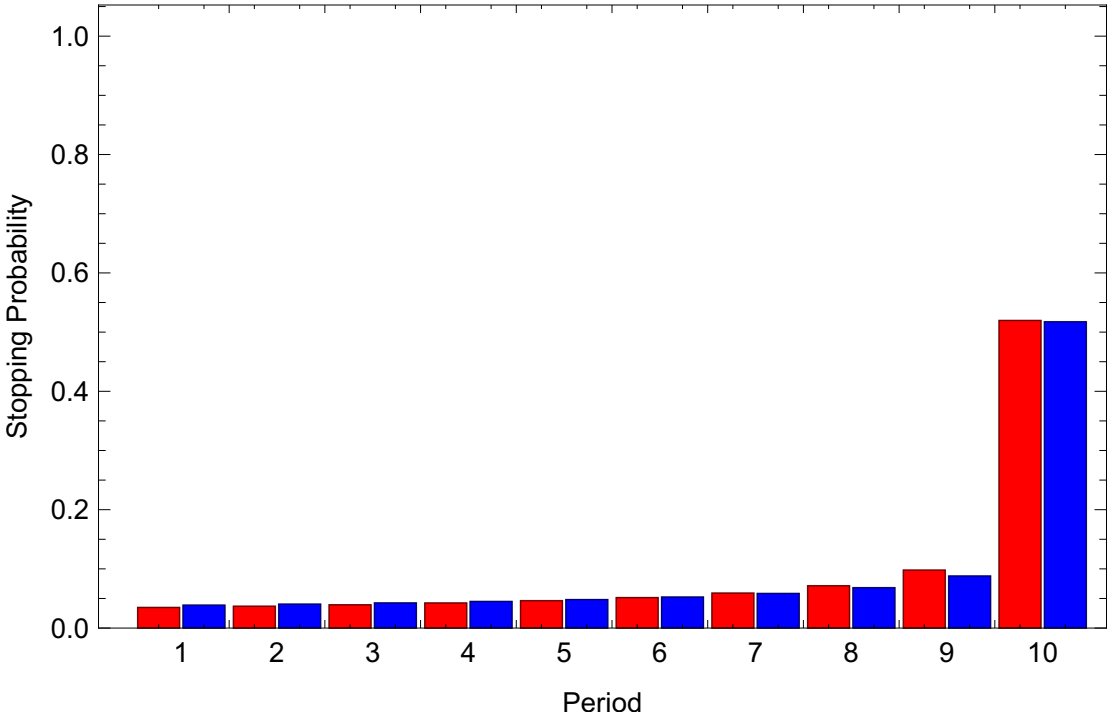


Figure 1: Observed Task Completion Times. The above graphs illustrates the observed stopping times. In both cases $\delta = 1$, and the penalty for not doing the task is -5. The red bar plot shows the distribution of task completion times of a time-consistent agent whose cost of completing the task are 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 $\mu = 0, \eta = 2.3$.

Parametric Family	*Sq. Distance Minimzation*		*Likelihood Maximization*	
	β	Distance	β	Log-Likelihood
Normal Sophisticate	0.819	0.0026777	0.818	1.59188
Normal Naive	0.817	0.00231803	0.816	1.59187
Extreme Value Sophisticate	0.57	0.0402888	0.5705	1.59638
Extreme Value Naive	0.561	0.0396802	0.562	1.59627
Logistic Sophisticate	0.7605	0.00331235	0.7595	1.59189
Logistic Naive	0.7565	0.00267175	0.7555	1.59188

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 1: SUMMARY OF MARKET EXPERIMENTS

MARKET EXPERIMENT	MARKET CELL	NUMBER OF SOLICITATIONS MAILED	EFFECTIVE RESPONSE RATE	PERCENT GOLD CARDS	AVERAGE CREDIT LIMIT
MKT EXP I	A: 4.9% Intro Rate 6 months	100,000	1.073%	83.97%	$6,446
MKT EXP I	B: 5.9% Intro Rate 6 months	100,000	0.903%	80.18%	$6,207
MKT EXP I	C: 6.9% Intro Rate 6 months	100,000	0.687%	80.06%	$5,973
MKT EXP I	D: 7.9% Intro Rate 6 months	100,000	0.645%	76.74%	$5,827
MKT EXP I	E: 6.9% Intro Rate 9 months	100,000	0.992%	81.15%	$6,279
MKT EXP I	F: 7.9% Intro Rate 12 months	100,000	0.944%	82.31%	$6,296

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_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): $T_s\left(r_0' - r_0^0\right) b_0$
  - approx. saving in post-teaser rates ($21/12 - T_s$ years): $(21/12 - T_s)\left(r_1^{'} - r_1\right) b_1$
- 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,

$$R\left(NB^i\right) = R\left(NB^{St}\right) + R'_{NB}\left(NB^i - NB^{St}\right)$$

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%)
    - $NB^{Pre} - NB^{St} \approx 6/12 * 2\% * \$2,000 = \$20$
    - $R\left(NB^{Pre}\right) - R\left(NB^{St}\right) = 386$ out of 100,000

Model

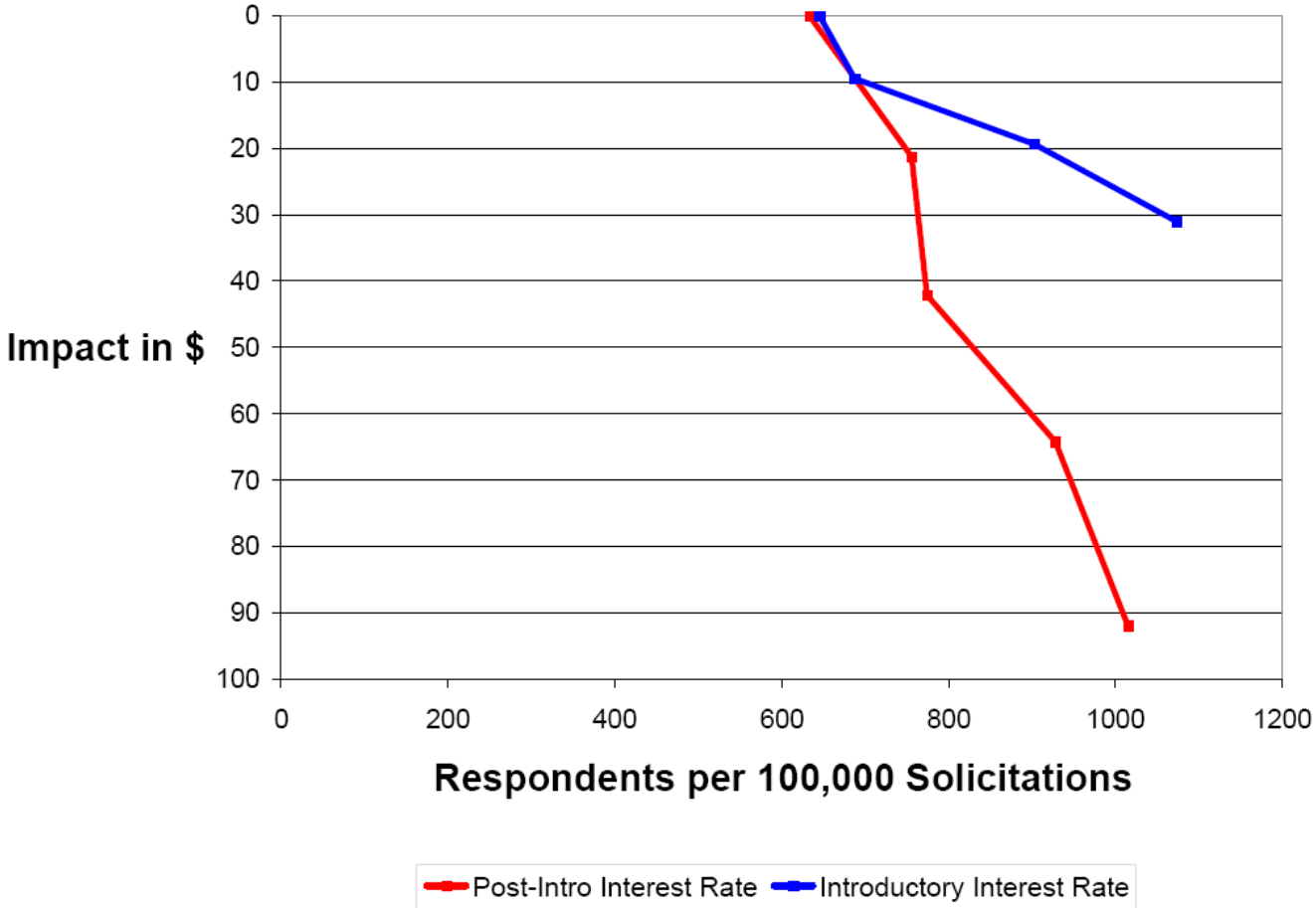
- Compare cards *Post* and *St* that differ only in interest rate r_1 (post-teaser)
- Assume $b_1^{Post} = b_1^{St} = b_1$ (Post-teaser balance) $\approx \$1,000$
- Difference in attractiveness:

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

  - 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 $R(NB^{Pre}) - R(NB^{St}) >> R(NB^{Post}) - R(NB^{St})$

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)
  - $\rightarrow$ Underestimate post-teaser borrowing: $\hat{b}_1 < b_1$ and $\hat{b}_0 = b_0$
- Compare cards:

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

and

$$\widehat{NB}^{Post} - \widehat{NB}^{St} = (21/12 - T_s) \left(r_1^{Post} - r_1^{St}\right) \hat{b}_1$$

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

Section 3

Leisure Goods: Consumption and Savings

Introduction

- Laibson (1997) to Laibson, Repetto, and Tobacman (2007)
- 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

Description and Name	$\overline{m}_{J_m}$	se($\overline{m}_{J_m}$)
% Borrowing on Visa: *"% Visa"*	0.678	0.015
Mean (Borrowing$_t$ / mean(Income$_t$)): *"mean Visa"*	0.117	0.009
Consumption-Income Comovement: *"CY"*	0.231	0.112
Average weighted $\frac{wealth}{income}$: *"wealth"*	2.60	0.13

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:

$$y_t = f^W(t) + u_t + \nu_t^W \tag{3}$$

- During retirement:

$$y_t = f^R(t) + \nu_t^R \tag{4}$$

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 γZ.
- 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:

$$\max_{I_t^X, I_t^Z} \quad u(C_t, Z_t, n_t) + \beta\delta E_t V_{t,t+1}(\Lambda_{t+1})$$
$$s.t. \text{ Budget constraints}$$

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

- Functional Equation:

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

- Solve for eq strategies using backwards induction

- Simulate behavior

- Calculate descriptive moments of consumer behavior

4 Estimation

Estimate parameter vector θ 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.
- Pakes and Pollard (1989) prove asymptotic consistency and normality.
- Specification tests: $q(\hat{\theta}) \sim \chi^2(N - \#parameters)$

- Two steps of estimation: of MSM (Method of Simulated Moments)
  1. Estimate ('calibrate') auxiliary parameters
     - Interest rate
     - Mortality
     - Income shocks
  2. Estimate main parameters (β, δ) 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

	(1) Hyperbolic	(2) Exponential	(3) Hyperbolic Optimal Wts	(4) Exponential Optimal Wts	(5) Data
Parameter estimates $\hat{\theta}$					
$\hat{\beta}$	0.7031	1.0000	0.7150	1.0000	-
s.e. (i)	(0.1093)	-	(0.0948)	-	-
s.e. (ii)	(0.1090)	-	-	-	-
s.e. (iii)	(0.0170)	-	-	-	-
s.e. (iv)	(0.0150)	-	-	-	-
$\hat{\delta}$	0.9580	0.8459	0.9603	0.9419	-
s.e. (i)	(0.0068)	(0.0249)	(0.0081)	(0.0132)	-
s.e. (ii)	(0.0068)	(0.0247)	-	-	-
s.e. (iii)	(0.0010)	(0.0062)	-	-	-
s.e. (iv)	(0.0009)	(0.0056)	-	-	-
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					
$q(\hat{\theta},\hat{\chi})$	67.2	436	2.48	34.4	-
$\xi(\hat{\theta},\hat{\chi})$	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 4

ROBUSTNESS

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Benchmark	$\gamma = 3.38\%$	$\gamma = 6.59\%$	$r^{CC} = 10\%$	$r^{CC} = 13\%$	$\rho = 1$	$\rho = 3$
Hyperbolic							
Parameter Estimates $\hat{\theta}$							
$\hat{\beta}$	0.7031	0.5071	0.8024	0.7235	0.6732	0.8186	0.5776
s.e. (i)	(0.1093)	(0.0441)	(0.0614)	(0.1053)	(0.1167)	(0.0959)	(0.1339)
$\hat{\delta}$	0.9580	0.9731	0.9425	0.9567	0.9595	0.9610	0.9545
s.e. (i)	(0.0068)	(0.0188)	(0.0093)	(0.0071)	(0.0045)	(0.0037)	(0.0096)
Goodness-of-fit							
$q(\hat{\theta}, \hat{\chi})$	67.2	108.4	49.7	64.1	70.7	63.0	67.7
$\xi(\hat{\theta}, \hat{\chi})$	3.01	16.79	5.27	12.09	10.97	7.97	1.85
p-value	0.222	0.0002	0.0717	0.0024	0.0041	0.0186	0.3965
Exponential							
Parameter Estimates $\hat{\theta}$							
$\hat{\beta}$	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
s.e. (i)	-	-	-	-	-	-	-
$\hat{\delta}$	0.8459	0.8459	0.8459	0.8520	0.8354	0.8924	0.7841
s.e. (i)	(0.0249)	(0.0249)	(0.0250)	(0.0267)	(0.0262)	(0.0204)	(0.0357)
Goodness-of-fit							
$q(\hat{\theta}, \hat{\chi})$	435.6	435.6	435.6	434.7	436.6	438.1	435.5
$\xi(\hat{\theta}, \hat{\chi})$	217	217	263	177	339	349	310
p-value	<1e-10	<1e-10	<1e-10	<1e-10	<1e-10	<1e-10	<1e-10

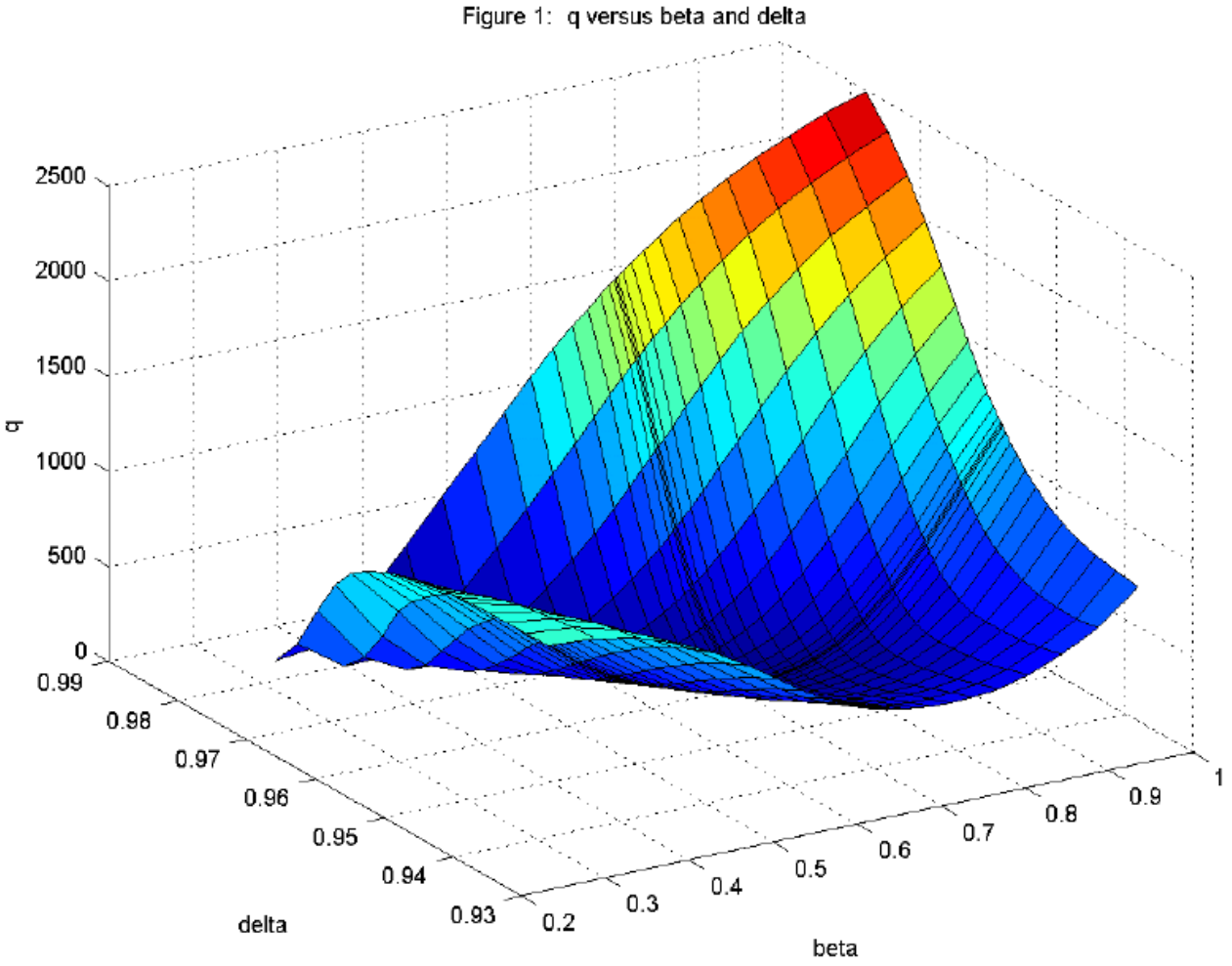


Figure 1: This figure plots the MSM objective function with respect to beta and delta under the paper's benchmark assumptions. The objective, q, equals a weighted sum of squared deviations of the empirical moments from the moments predicted by the model. Lower values of q represent a better fit of the model, and the (beta,delta) pair that minimizes q is the MSM estimator.

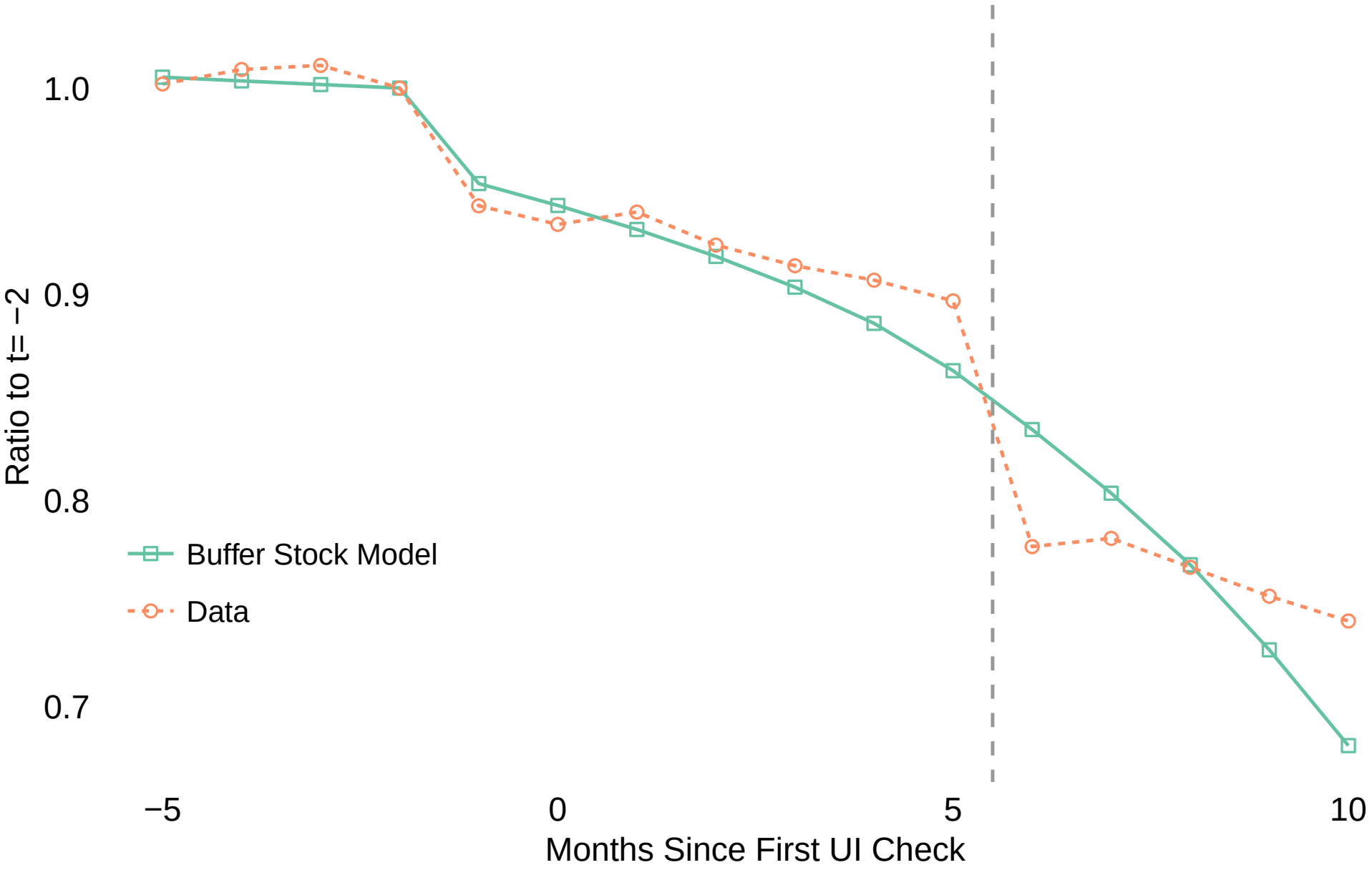
Section 4

Leisure Goods: Consumption and UI Benefits

Introduction

- Literature on Consumption –> 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



Build: Who

- 186,000 households receiving UI in their Chase checking account
- September 2013 through June 2016 (receive UI after Jan 2014)
- 20 states Map
- Chase bank account spending and income (more on next slide)
  - Chase credit card spending

Build: Spending & Employment History

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%. ▸ Diary of Consumer Payment Choice

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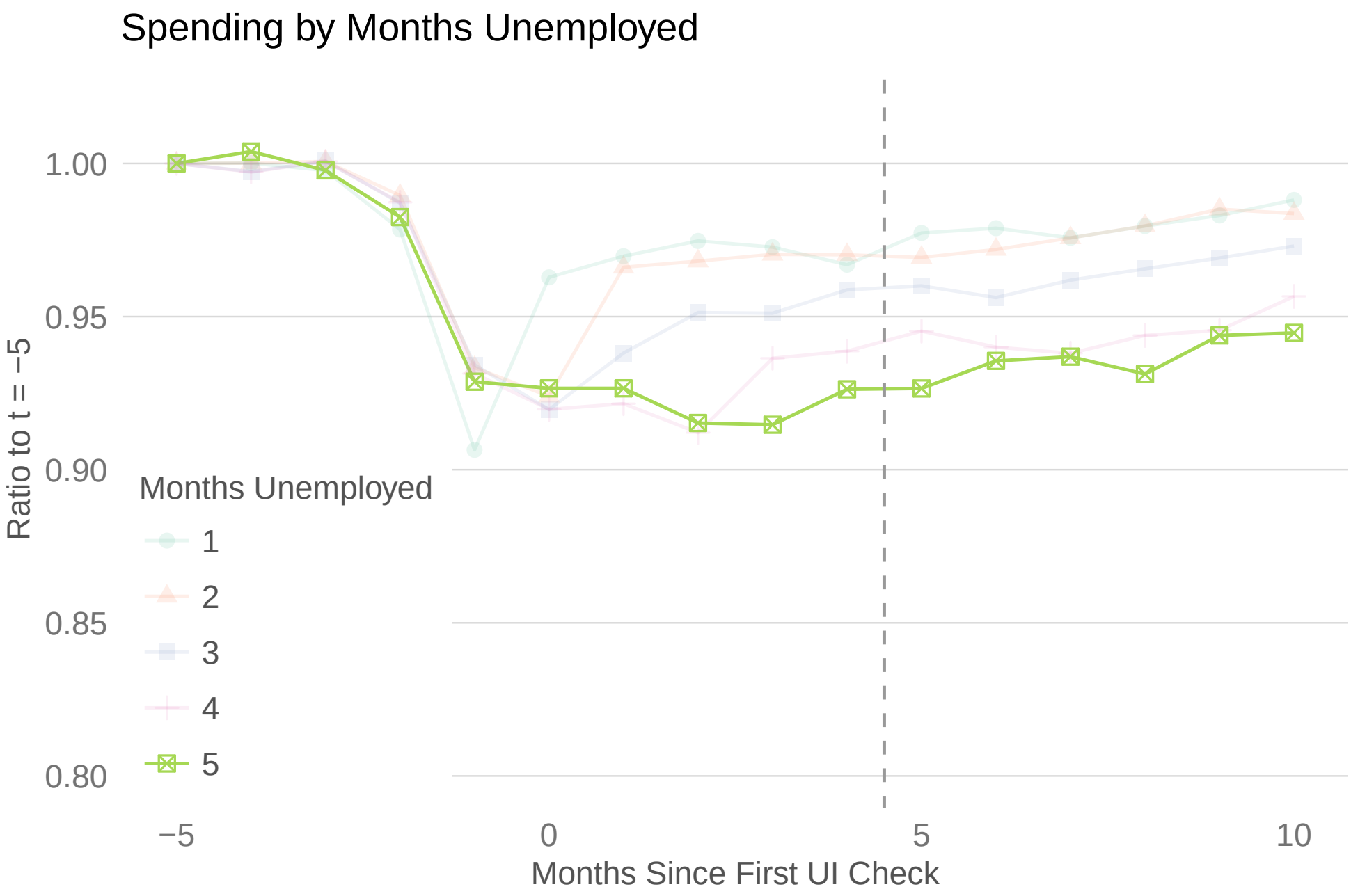
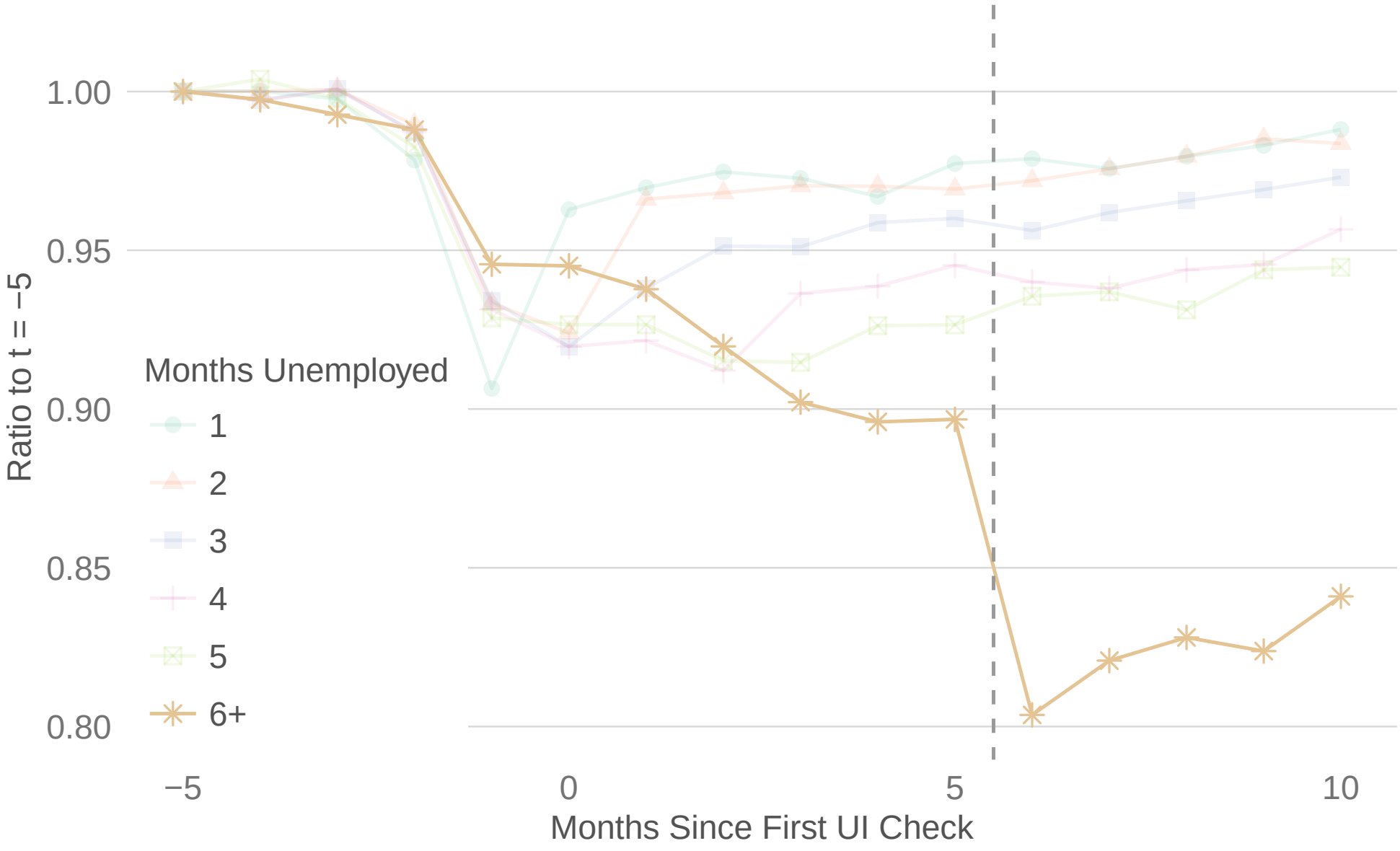
- Durables, Debt, & Transfers
  - 27%. Examples: Home Improvement, Mortgage, Credit Card, Transfer to Savings Account.
- Uncategorized
  - 29%. Paper Checks, Ambiguous Electronic Transfers.

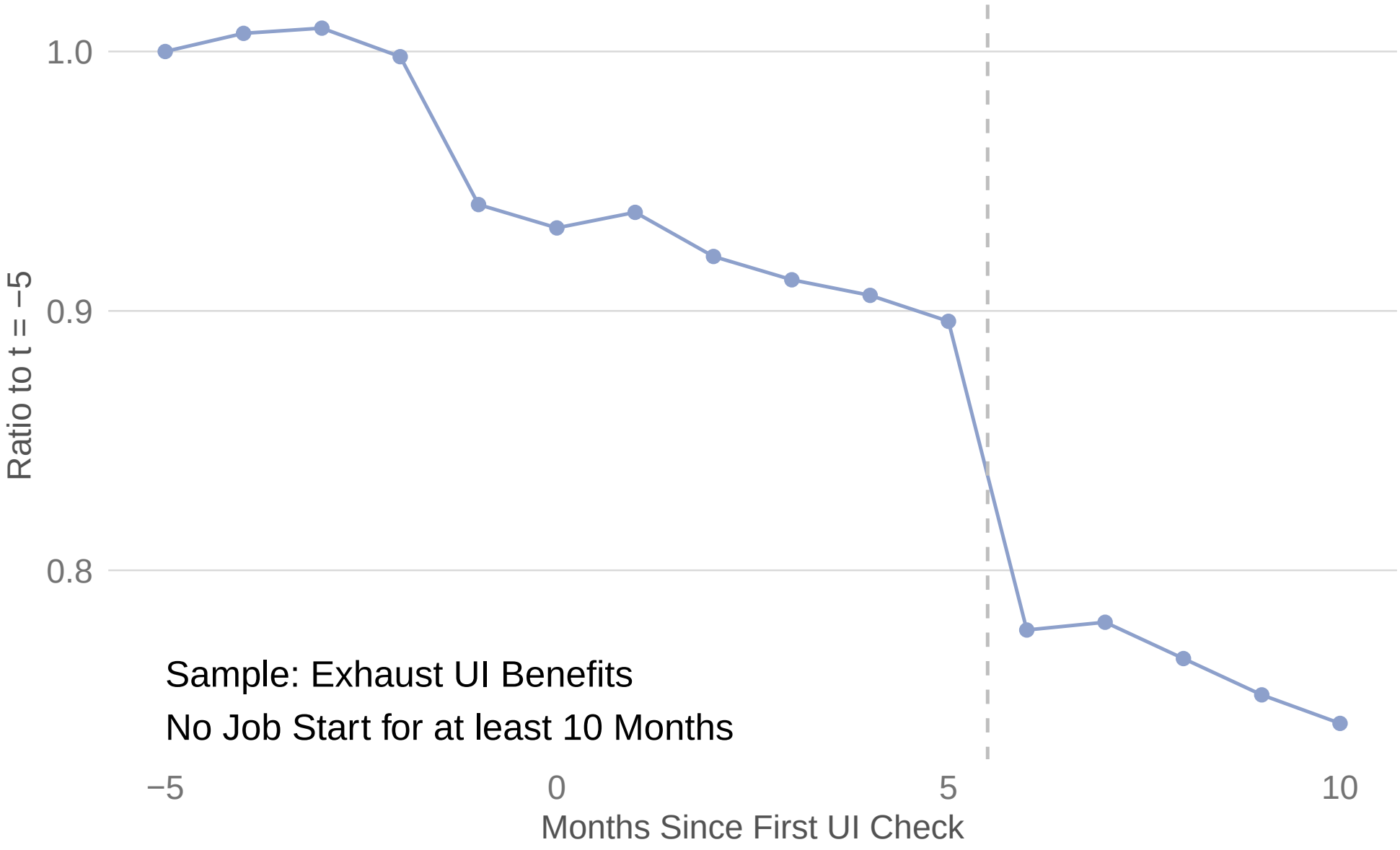
Inflows (Direct Deposit of Payroll) $\rightarrow$ *Employment History*


Spending by Months Unemployed
1.00
0.95
0.90
0.85
0.80
Ratio to t = −5
Months Unemployed
1
2
3
4
5
−5
0
5
10
Months Since First UI Check

Spending by Months Unemployed

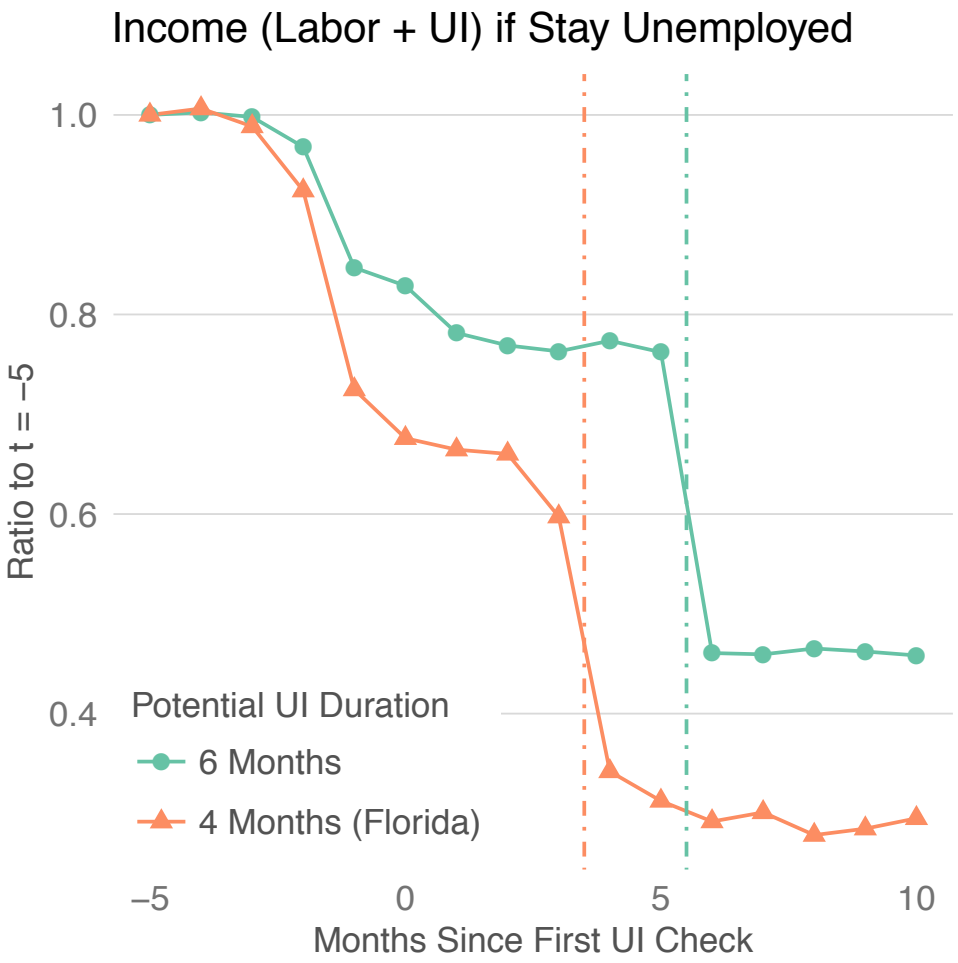


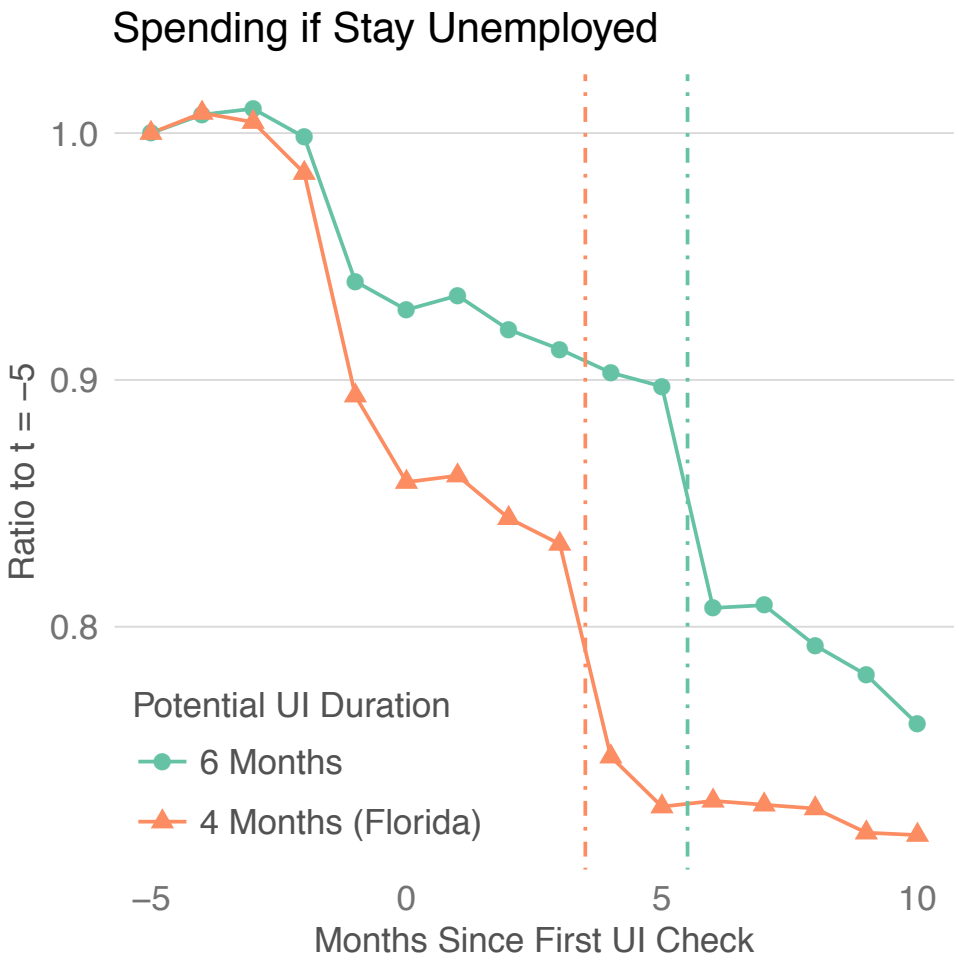
Spending If Stay Unemployed



Income | Income by Duration | Standard Errors | Equation | Ex Post Exhaustees

Stingy UI Benefits: Florida





▸ All UI Recipients

Exhaustion: Is Consumption Really Dropping?

	Pre-Exhaust	Post-Exhaust	Δ%
Large % Drop			
Discount Stores	$58	$47	-19%
Groceries	$294	$247	-16%
Restaurants	$164	$138	-16%
Drug Stores	$35	$30	-15%
Medical Copay	$29	$25	-14%
Entertainment	$27	$23	-13%
Auto Repair	$36	$32	-13%
Small % Change			
Auto Loan	$76	$71	-7%
Mortgage	$148	$142	-4%
Insurance	$159	$155	-3%

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.

▸ Robustness ▸ MPC at Onset ▸ Constructing Job Finding ▸ Job-Finding Hazard

Income Decrease: New Test for Models of Consumption

MPC from predictable income decrease as an "identified moment"
[Nakamura and Steinsson 2018]

	Tax rebate MPC	Income decline MPC
PIH	X	X
Liquidity constraints	✓	X
Behavioral/myopia	✓	✓

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

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

$$\text{subject to } c_t + a_{t+1} = Ra_t + z_t \qquad a_t \geq -L$$

- 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 Π

Model: Environment

Parameter	Value	Source
Calibrated to JPMCI Data		
	1.00 Employed	
Income z_t	0.82 Unemp $<$ 6 Months	Bank
	0.53 Unemp $\geq$ 6 Months	
Initial Assets a_0	0.66	Bank with SCF
Calibrated to External Data		
Separation Rate	0.0325	BLS
Interest Rate R	1.0025	Cagetti 03
Risk Aversion γ	2	Carroll 97
Job Search Convexity ξ	1.5	Schmieder & von Wachter 18
Estimated to match empirical path of consumption and job-finding		
Discount Factor δ	0.991	
Borrowing Limit L	4.3	
Job Search Cost k	27	

Spending in Data and Representative Agent Model

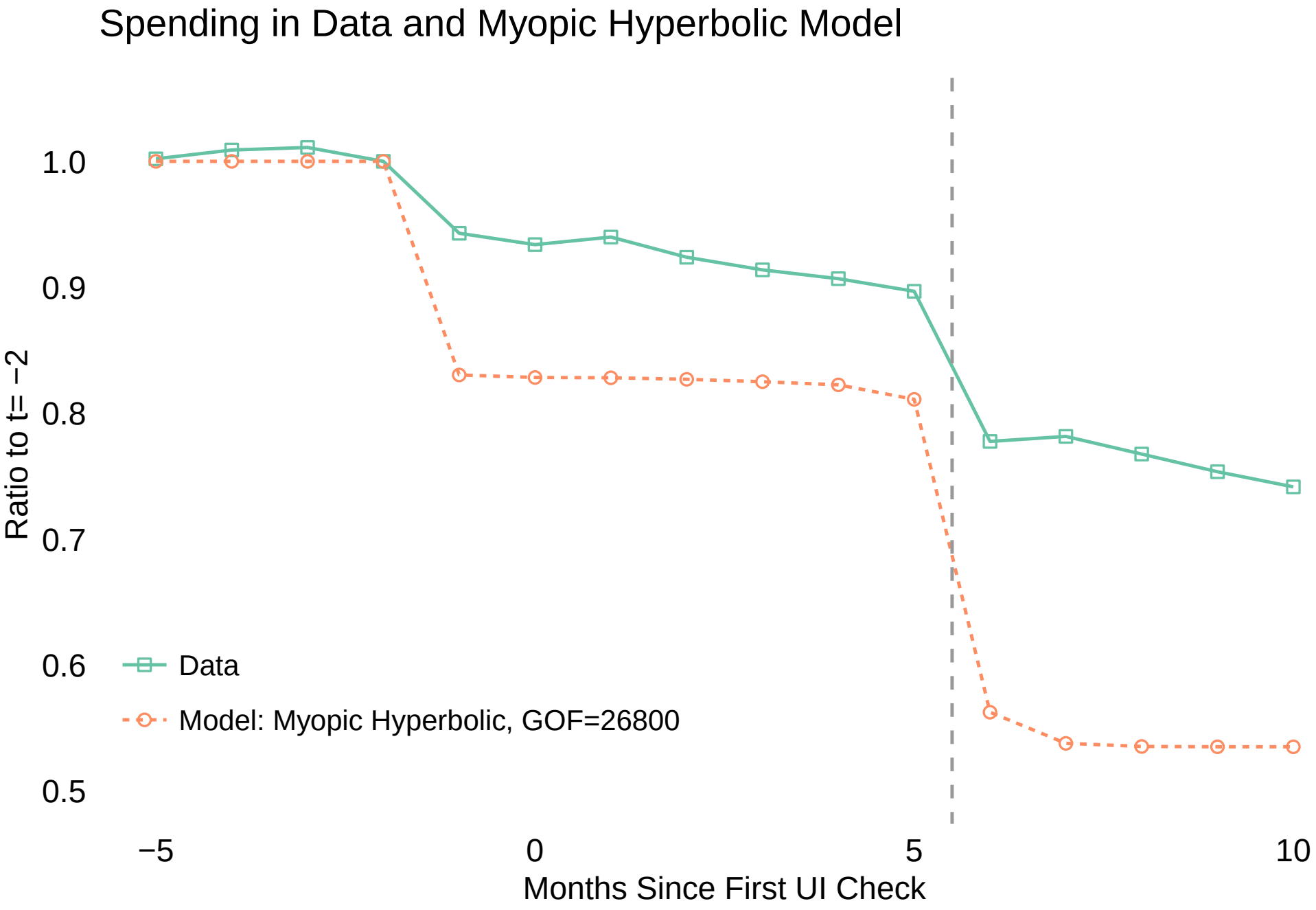
Search

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

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

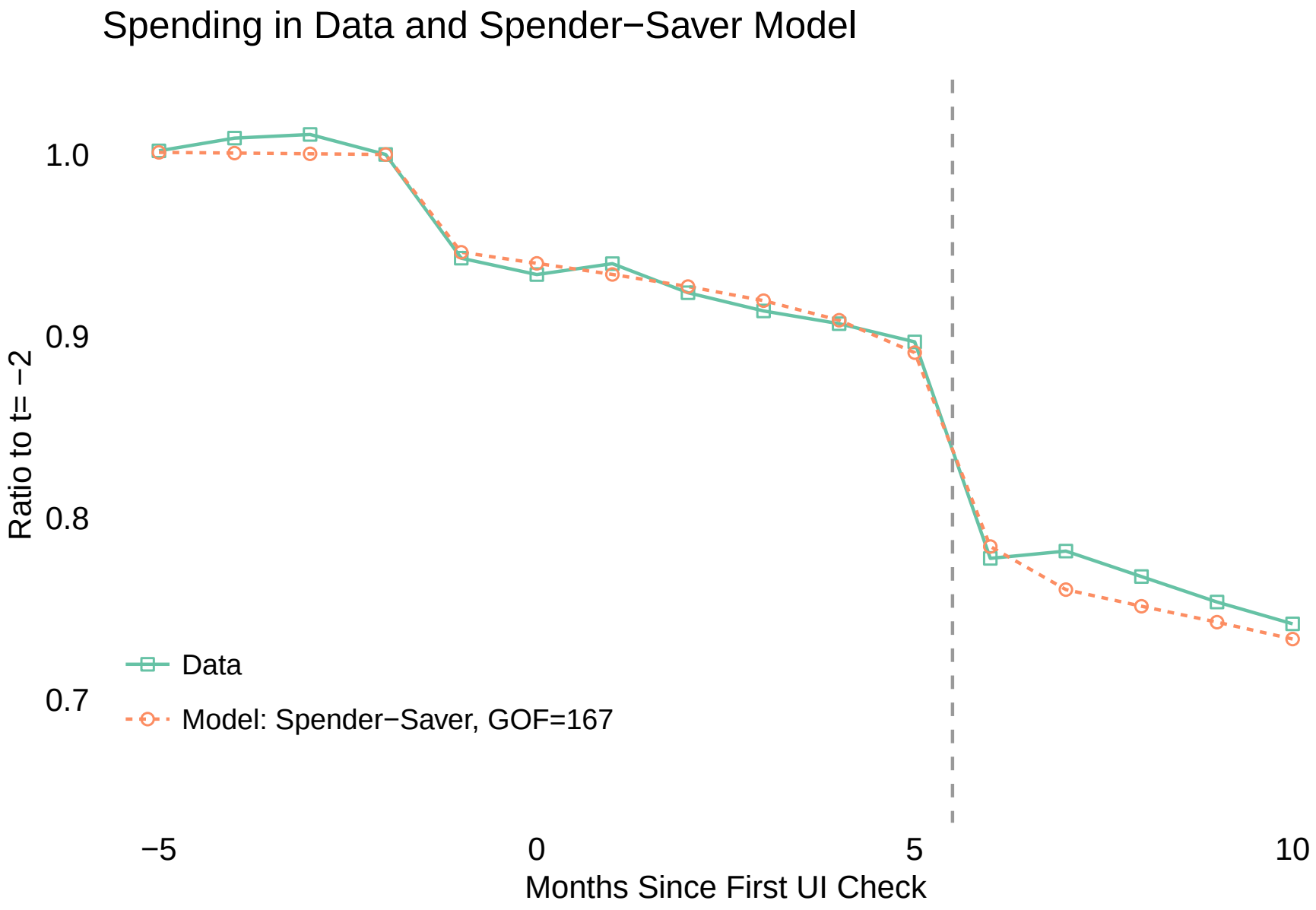
- low-β helps to qualitatively match the observed path


Spending in Data and Myopic Hyperbolic Model
1.0
0.9
0.8
0.7
0.6
0.5
Ratio to t= −2
Data
Model: Myopic Hyperbolic, GOF=26800
−5
0
5
10
Months Since First UI Check

Spender-Saver Model (following Campbell and Mankiw 89)

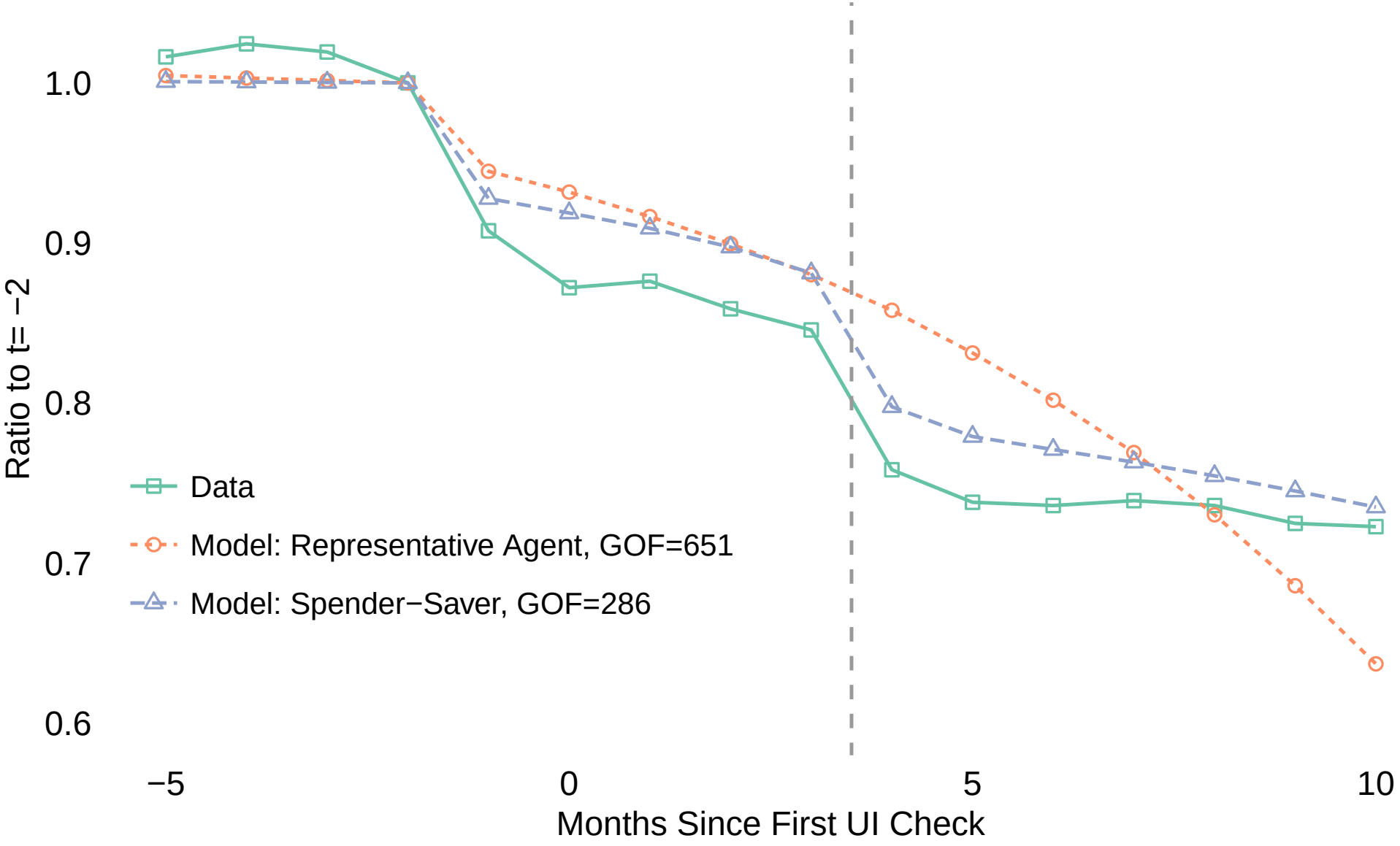
Model	Borrowing limit	Discount factor	Population share
Buffer stock	$L = 0$	$\delta = 0.995$	36%
Permanent income	natural limit	$\delta = 0.995$	46%
$\beta\delta$ "Hand-to-mouth"	$L = 0$	$\delta = 0.995$, $\beta = 0.5$	18%

- Alternatives to present ~~bias~~ focus
  - Exponential discounting with $\delta = 0.35$
  - Mechanically set $c = y$ (Campbell and Mankiw 1989)



Search Out-of-Sample Test

Spending in Data and in Models,
Out of Sample Test With Low−Benefit State Florida

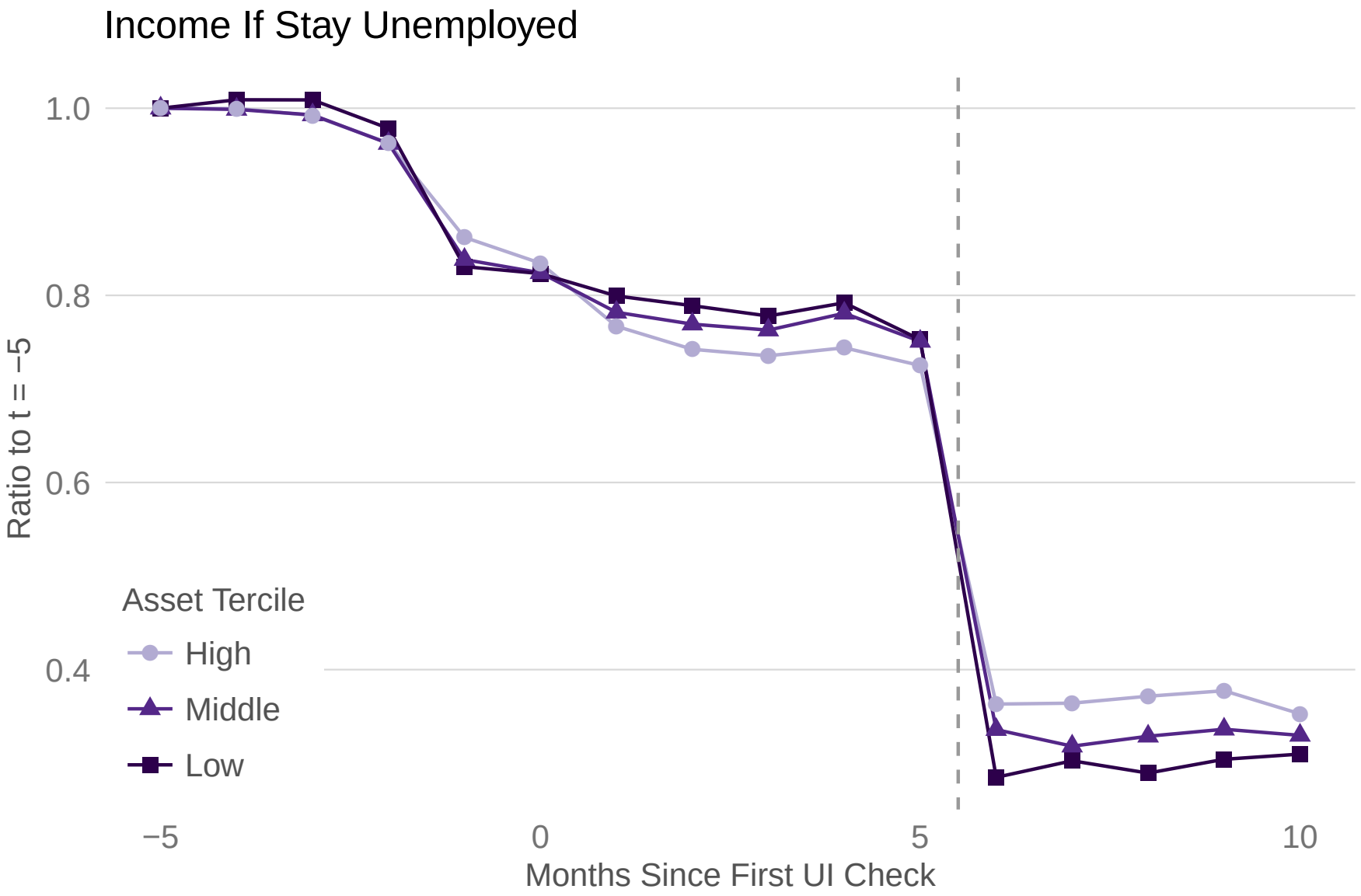


Normative Implications

	Gains from Alternative UI Policy (as a % of Lifetime Utility, $\gamma = 2$)		
	UI Benefits	UI Durations	Ratio
	$\uparrow$ 1.7%	$\uparrow$ 1 Month	
	(1)	(2)	(2)/(1)
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

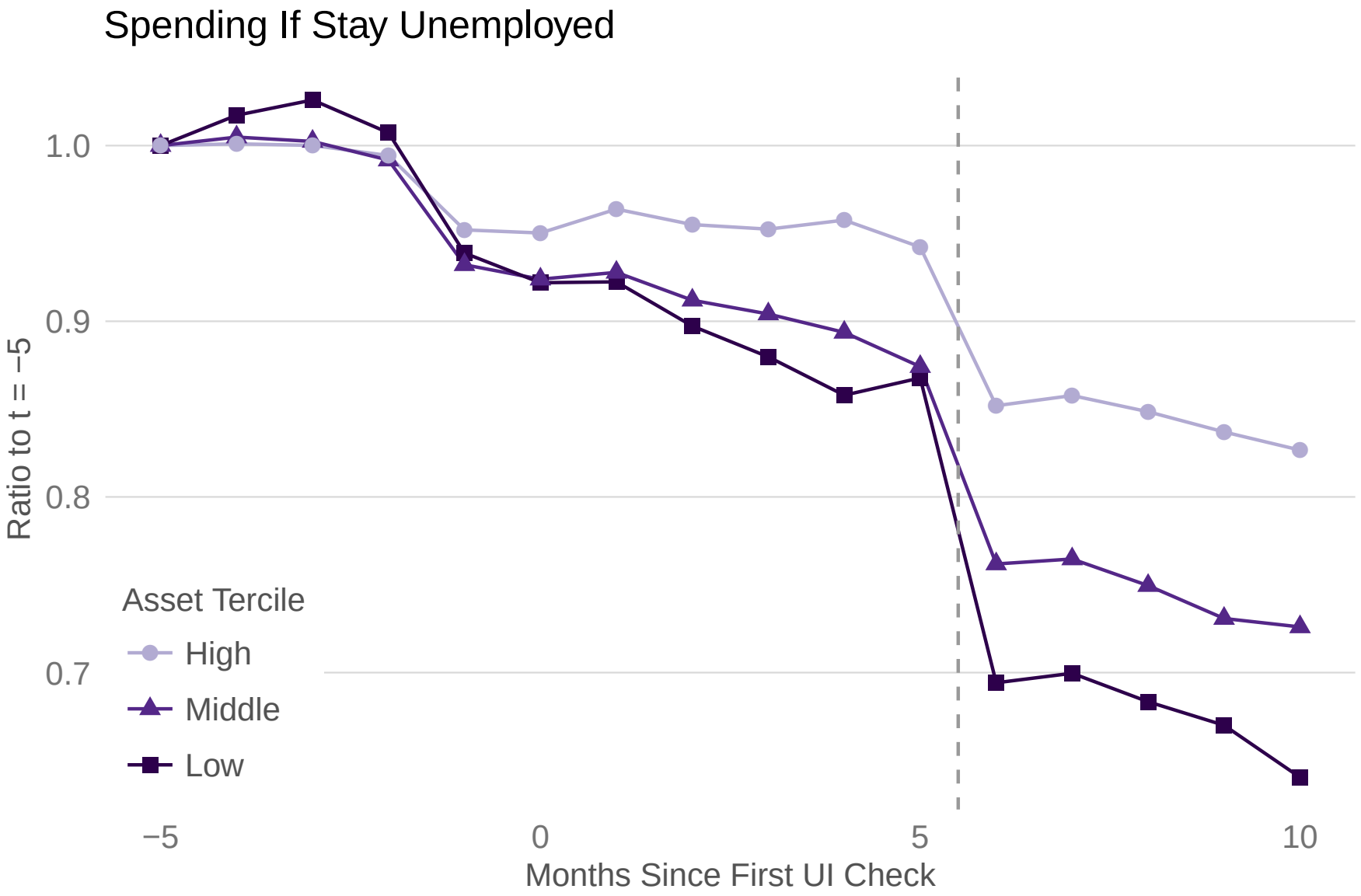
Moral Hazard

Onset: Heterogeneity By Total Liquid Assets



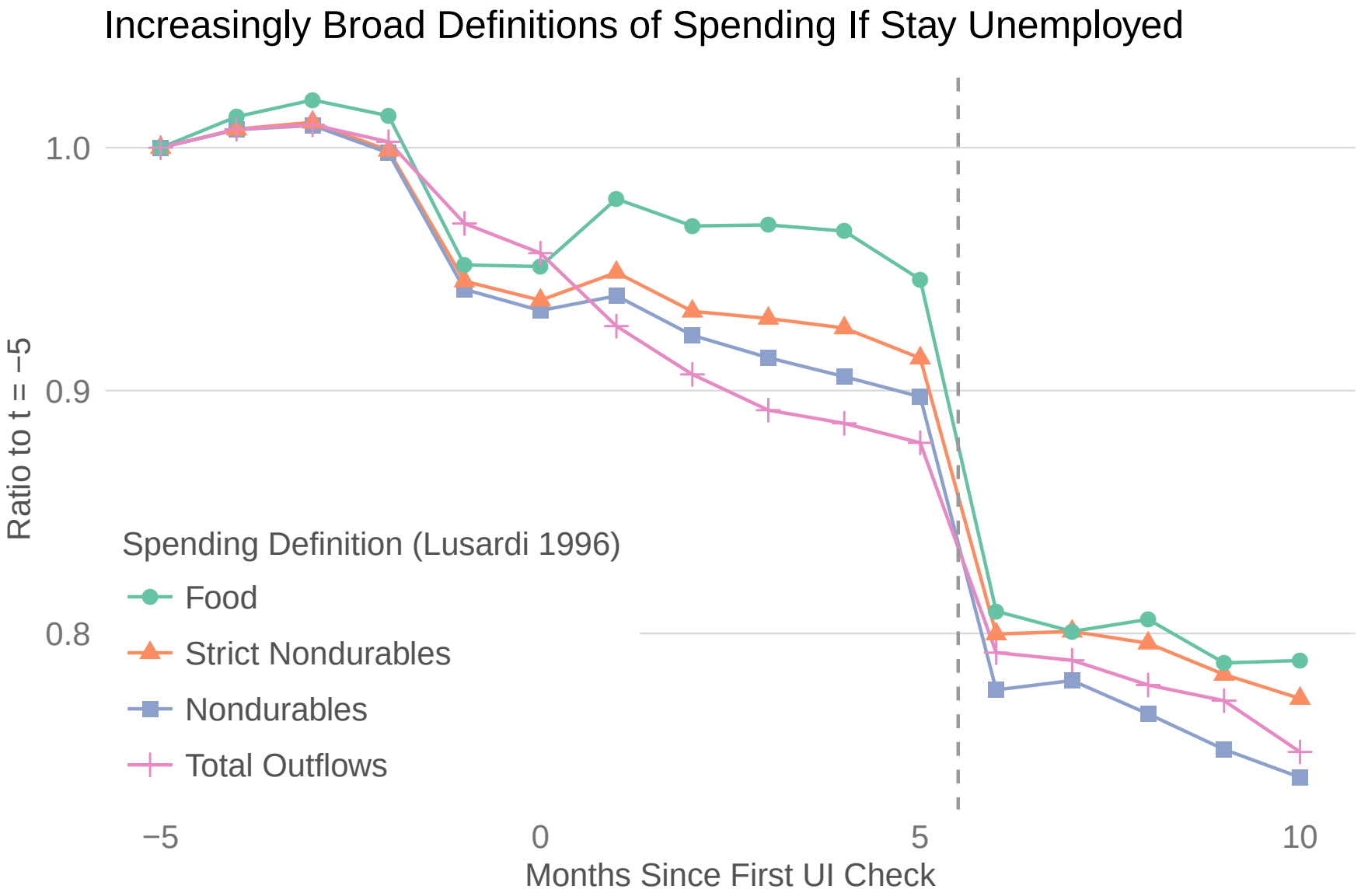
Back

Onset: Heterogeneity By Total Liquid Assets



Back

Exhaustion: Is Consumption Really Dropping?



Back

Figure 1a

Job Finding vs. Unemployment Exit Hazards: 20 Week UI

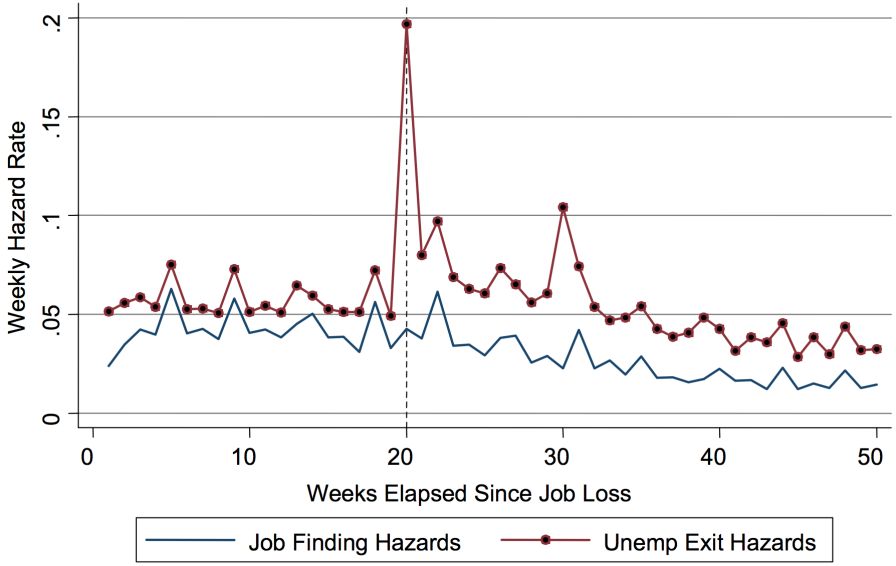
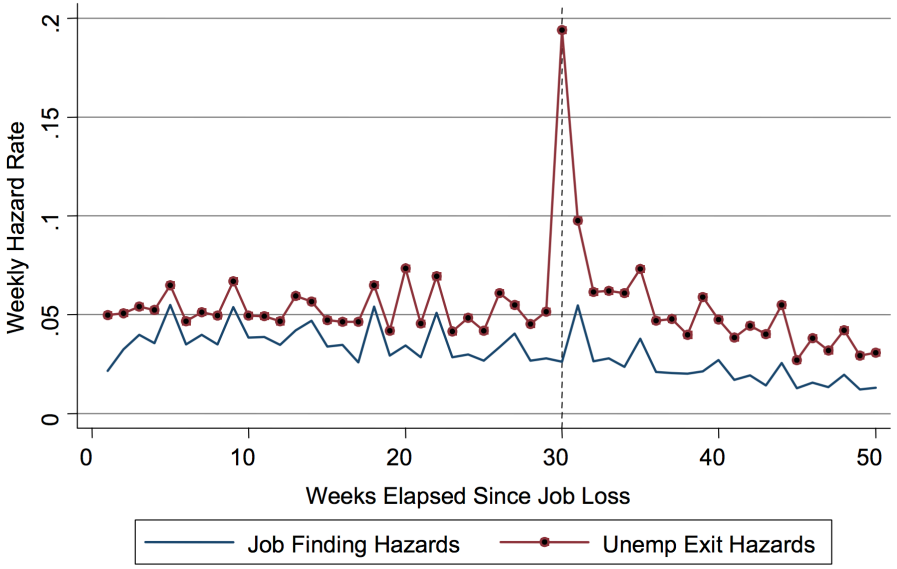
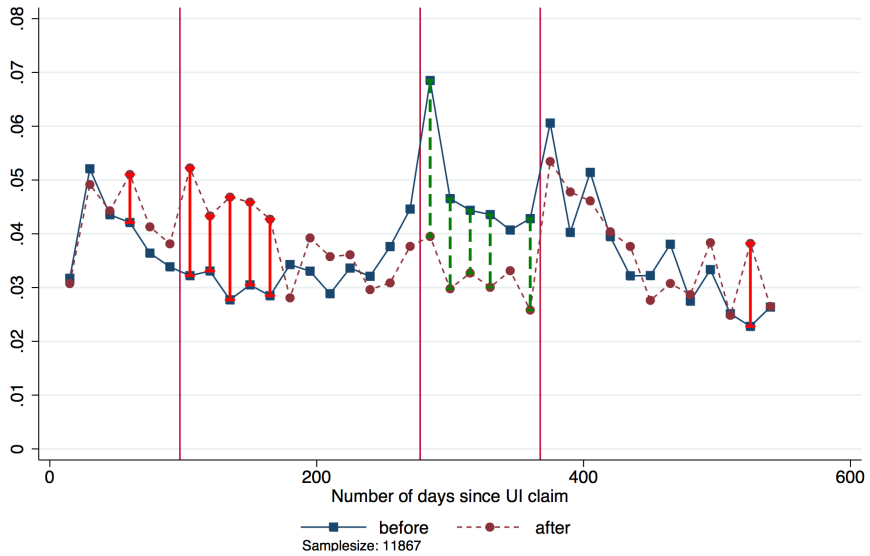


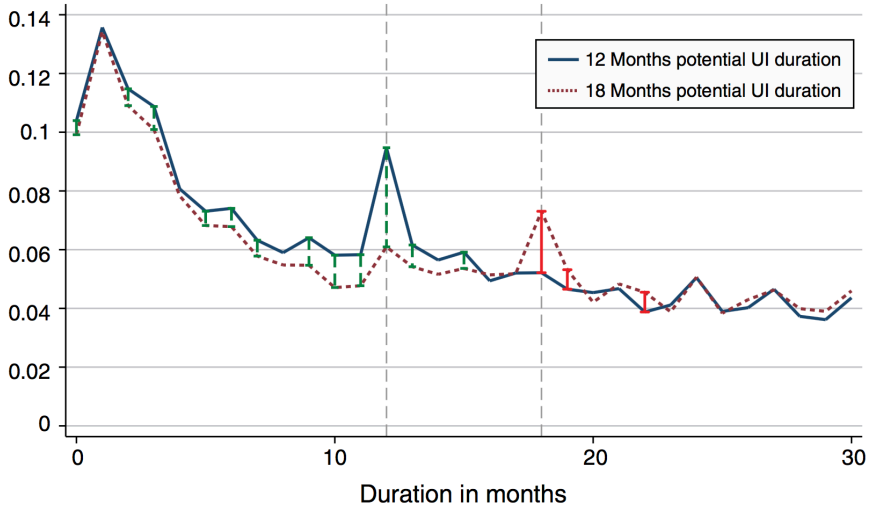
Figure 1b

Job Finding vs. Unemployment Exit Hazards: 30 Week UI



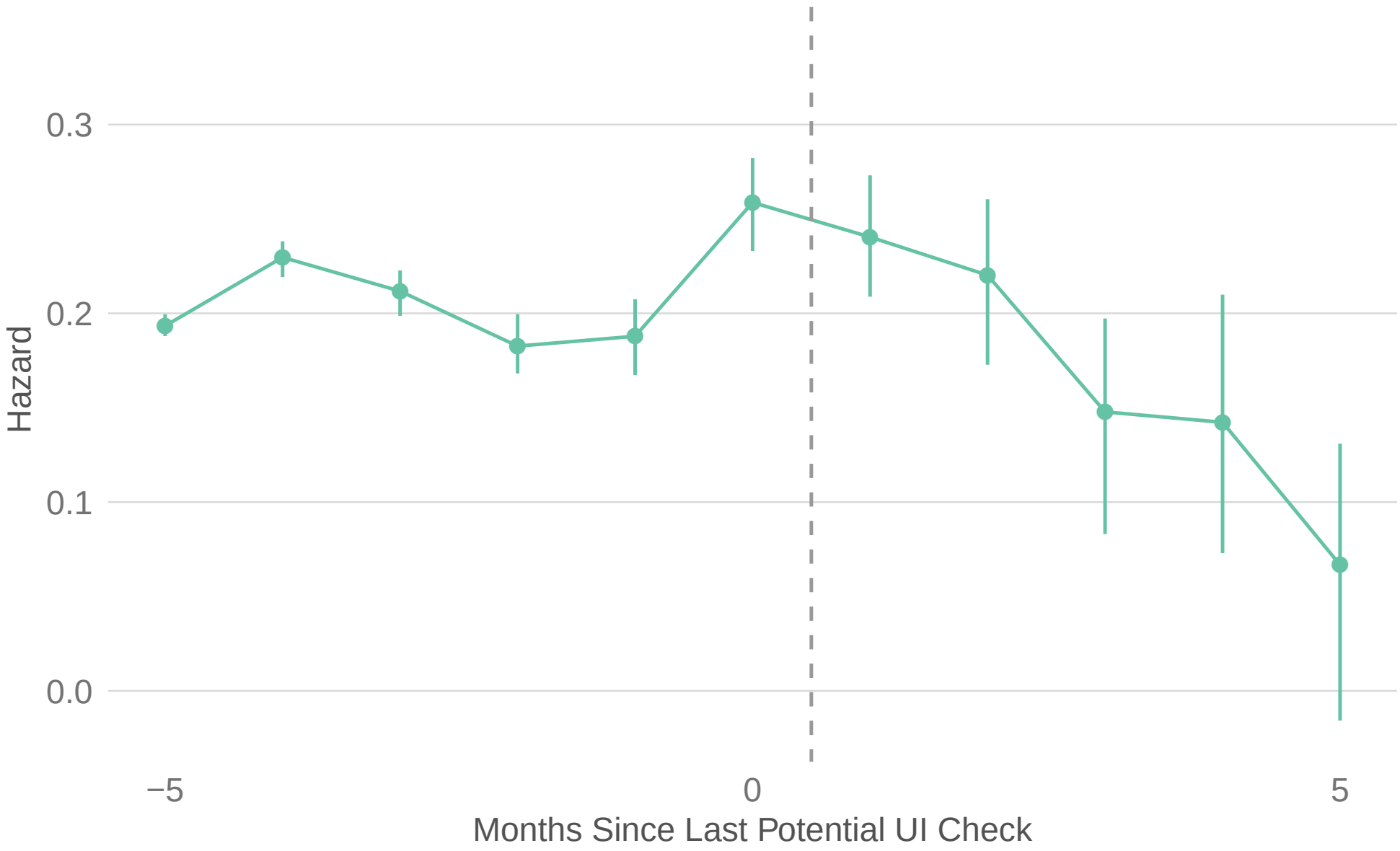


Panel A. Unemployment exit hazard



▸ Card, Chetty, and Weber (2007) 20 Week
▸ Card, Chetty, and Weber (2007) 30 Week
▸ DellaVigna et al. (2017)
▸ Schmieder, von Wachter, and Bender (2016)
▸ Back

Calculated Job−Finding Hazard



Back | False Positives | False Negatives | UI | Europe | U.S. | FL | NJ

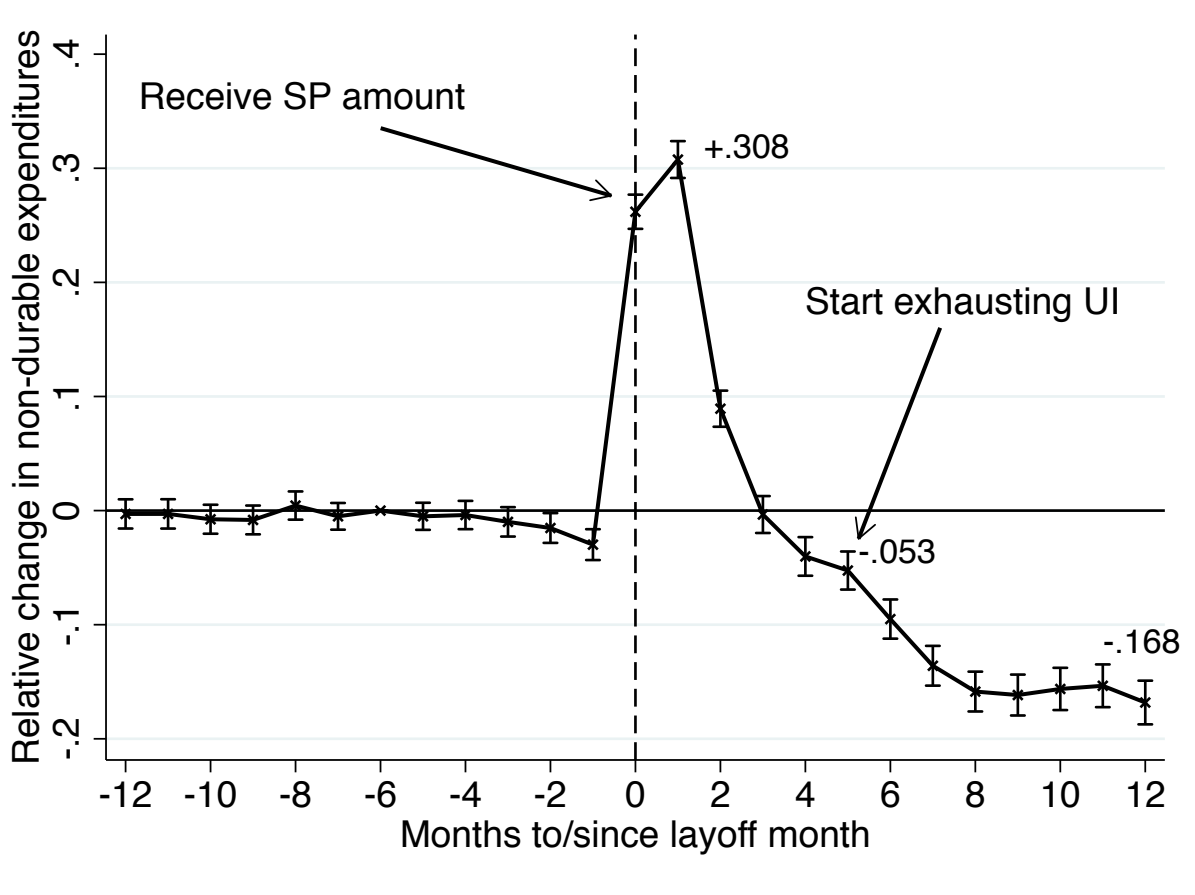
Introduction

- 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 ($\simeq$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

Other key data matched to App data (also de-identified)

- 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

$\Rightarrow$ matched expenditure-employment data for about $400,000$ workers

Expenditure data coverage

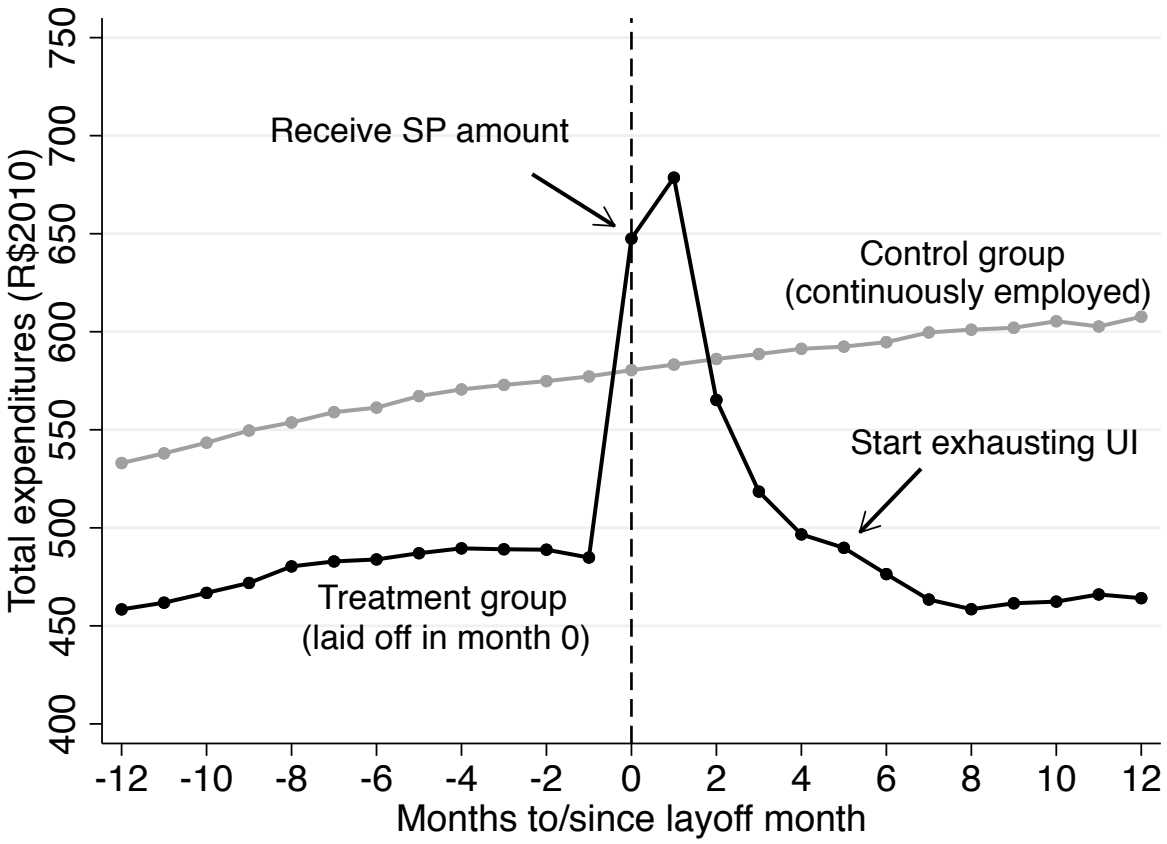
- VAT receipts: many expenditure categories, all means of payment
- VAT only levied on goods: data cannot cover VAT-excluded items (e.g., services, housing costs)
- Among purchases taxed by the VAT: only those with SSN provided
- Average monthly expenditures prior to layoff $\simeq$ 30% of average wages $\Rightarrow$ 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

Figure: Laid-off vs. fired workers (no benefits)

- Immediate and persistent drop in consumption for fired workers
- Mitigate concerns about receipt reporting changes after displacement

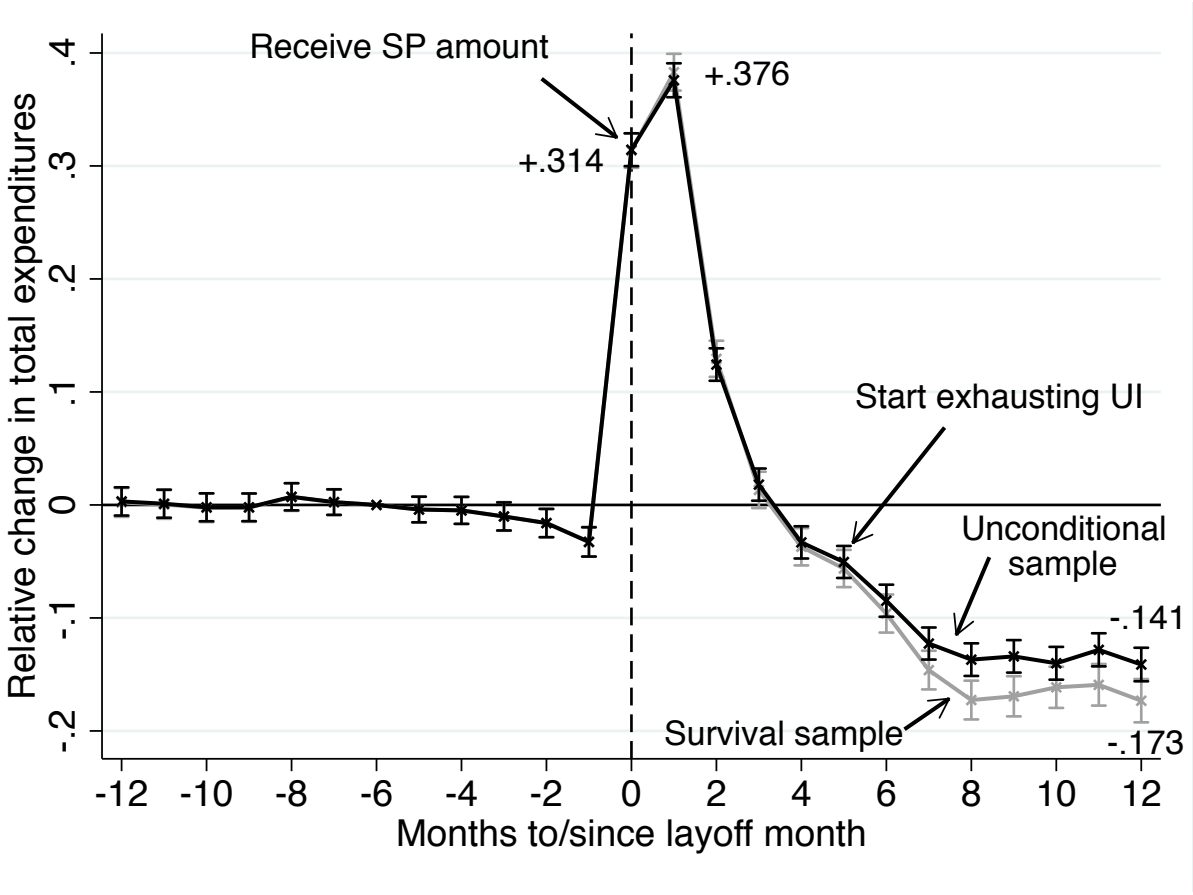
Outline

Figure: Treatment vs. control (raw data; unconditional sample)



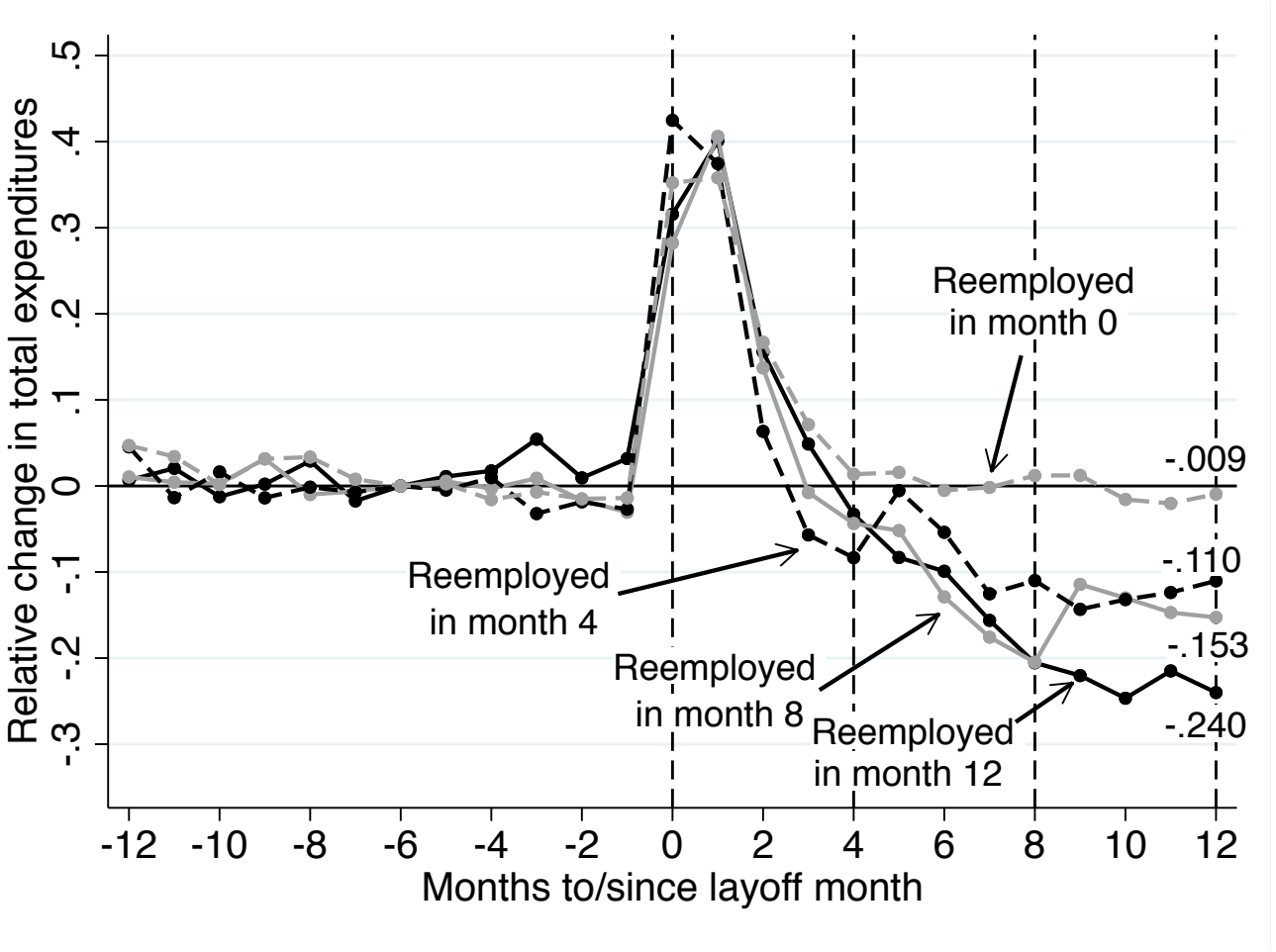
Treatment: displaced in month 0 (77,862 layoff events)
Control: workers continuously employed for 25 months (220,160 placebo events)
Note: raw data (netting out month fixed effects)

Figure: DD estimates (unconditional and survival samples)



Specification: $y_{ikt} = \alpha_i + \alpha_k + \alpha_t + \delta_k \cdot \mathit{Treatment}_i + \varepsilon_{ikt}$ 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 $\widehat{\delta_k}$ divided by level in reference month (% change)

Figure: DD estimates (reemployed in months 0, 4, 8, 12)



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%) ▸ PME

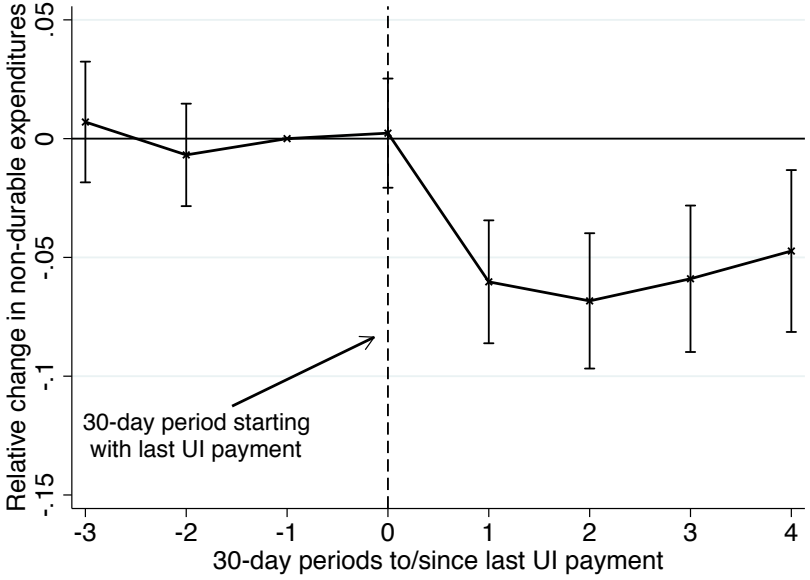
Outline

Event analysis around UI exhaustion

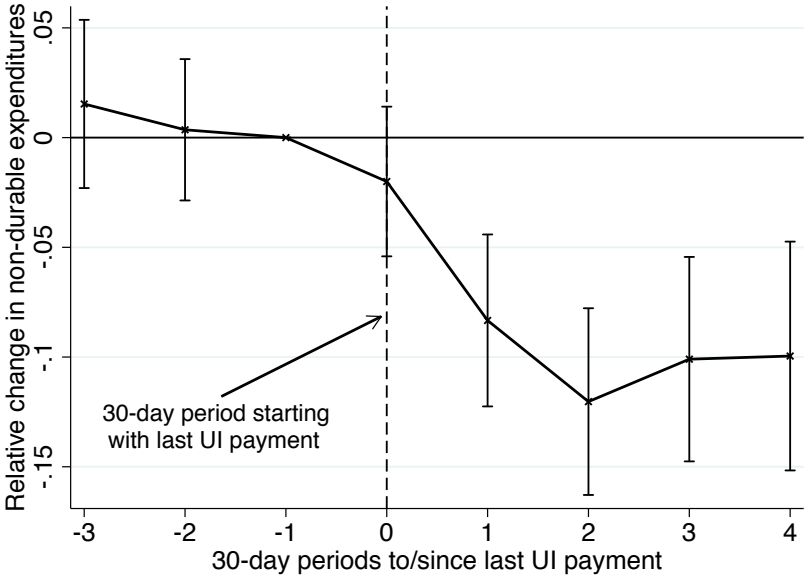
- Make consumption profile around UI exhaustion clearer
- Useful to discriminate between models
  - Sensitivity of consumption to expected drop in income at UI exhaustion cannot be due to liquidity constraint (Ganong and Noel, 2018)
- Sample: workers laid off in years with UI data (2011-2012)
  - All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

Relative change in consumption around UI exhaustion



(a) All UI exhaustees

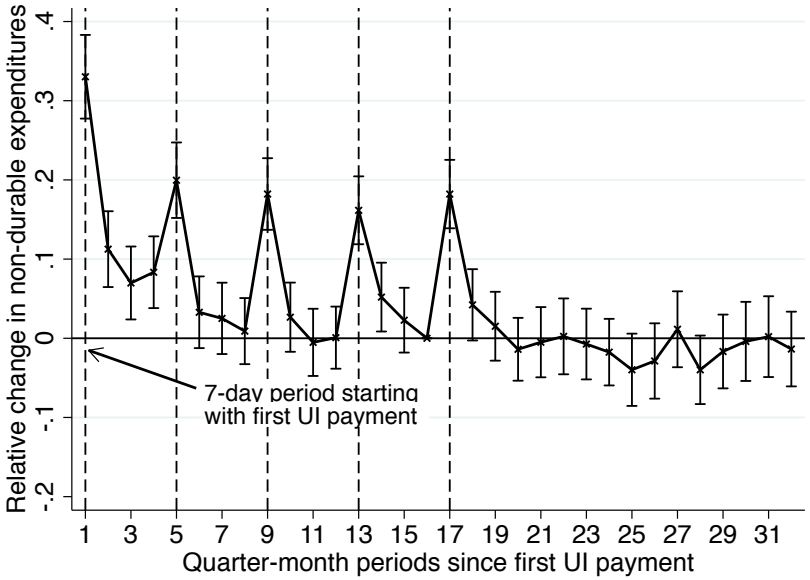


(b) UI exhaustees who remain without a formal job until the end of the window

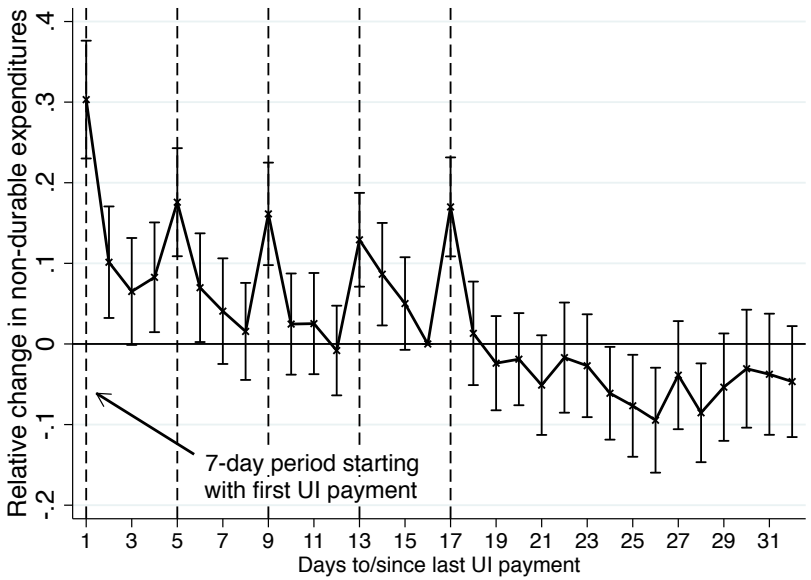
Takeaways:
(i) Lack of smoothing in anticipation of expected drop in income at UI exhaustion;
(ii) Despite 10% drop for those who remained without a formal job ▸ median

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 ▸ graph

Outline

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

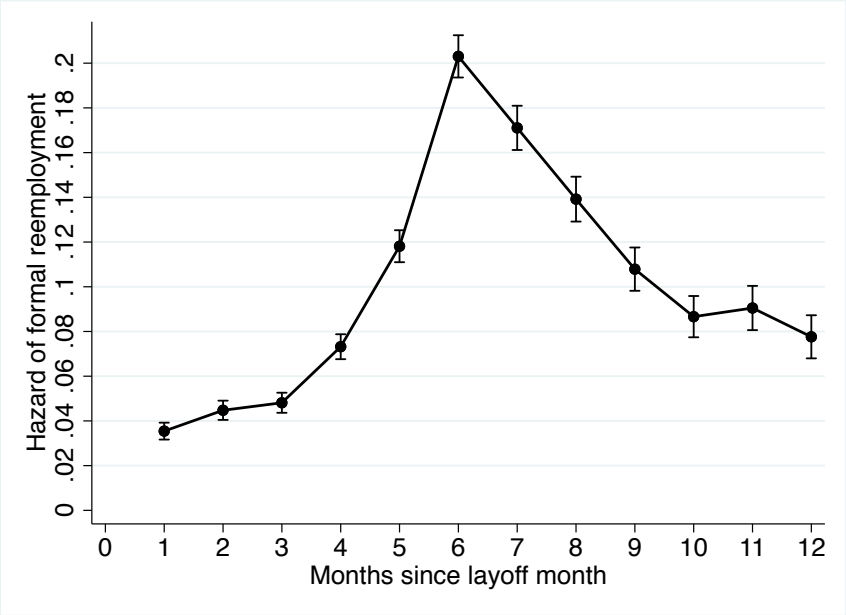
⇒ Show this concretely by estimating dynamic model of job search and consumption (DellaVigna et al., 2017; Ganong and Noel, 2018)

- 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

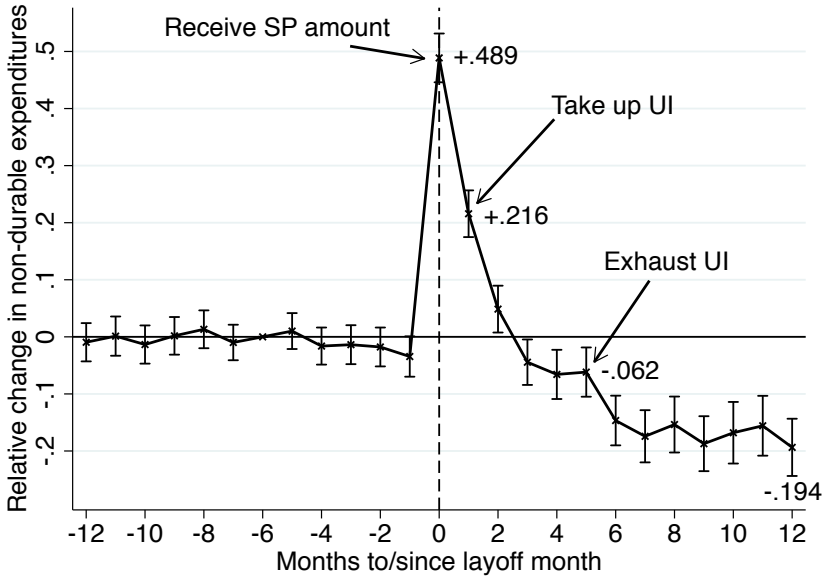
Other mechanisms

- 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 $\psi_i(h_{i,t}) = \kappa_i \cdot h_{i,t}^{1+\gamma}/(1+\gamma)$

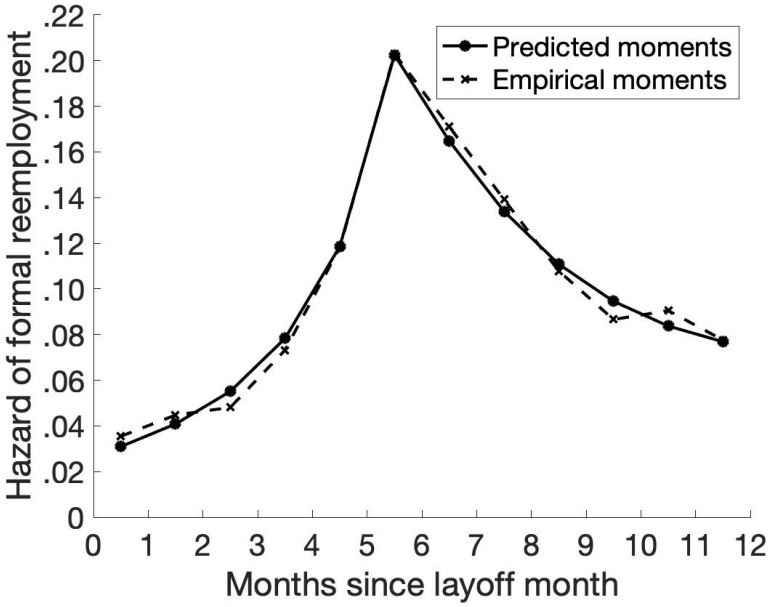
Model

- Choose consumption subject to: $c_{i,t} = a_{i,t} + y_{i,t} - \frac{a_{i,t+1}}{1+r}$ and $a_{i,t} > \overline{a}$
  - 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 $\phi(l_{i,t}) = \chi \cdot l_{i,t}^{1+\lambda}/(1+\lambda)$
  - Assumptions for asset accumulation: $a_{i,0} = 0$, $r = 0$, $\overline{a} = 0$
- 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

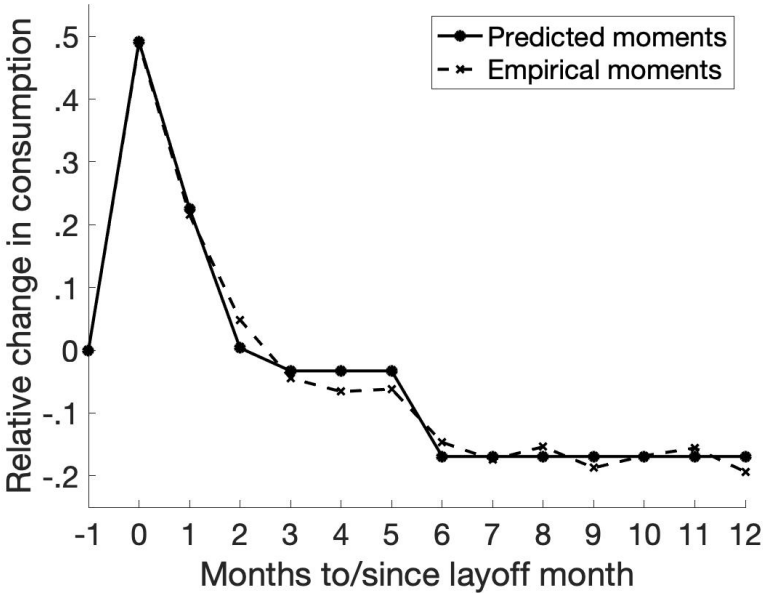
Estimation

- Parameters calibrated to averages in estimation sample (w^e, w^r, b, f)
- Vector of 8 free parameters $\xi = (\kappa_1, \kappa_2, s_1, \gamma, , \omega, \chi, \lambda, \delta$ or $\beta)$
  - Model 1 (myopia): δ-discounting with δ free
  - Model 2 ("naive" present bias): $\beta\delta$-discounting with β free ($\delta = .995$)
- For given ξ, 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

Model fit for myopia model



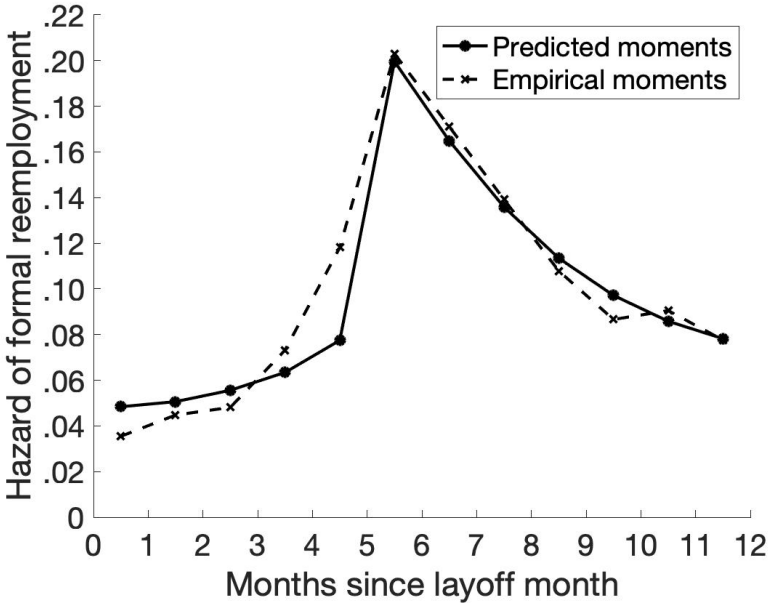
(a) Hazard of formal reemployment



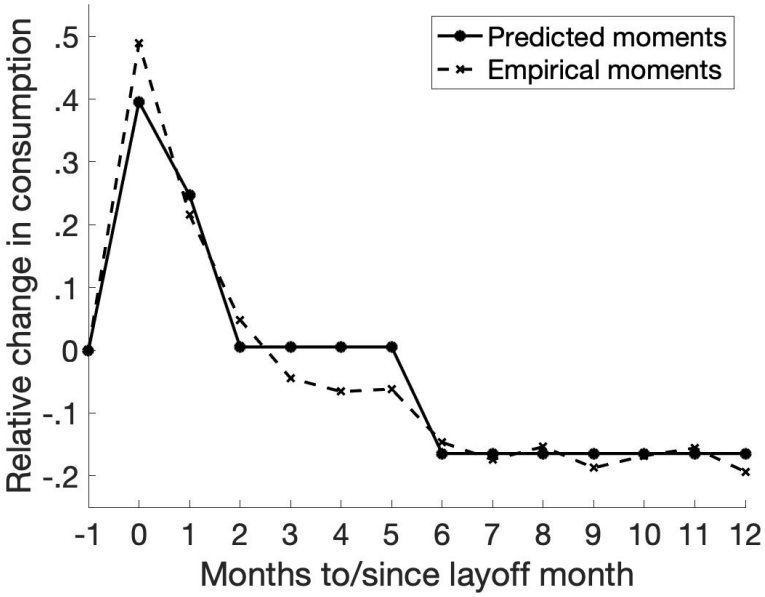
(b) Relative change in consumption

Fits the data well, but the estimated $\hat{\delta} = 0.82$ at monthly level!

Model fit for present-bias model



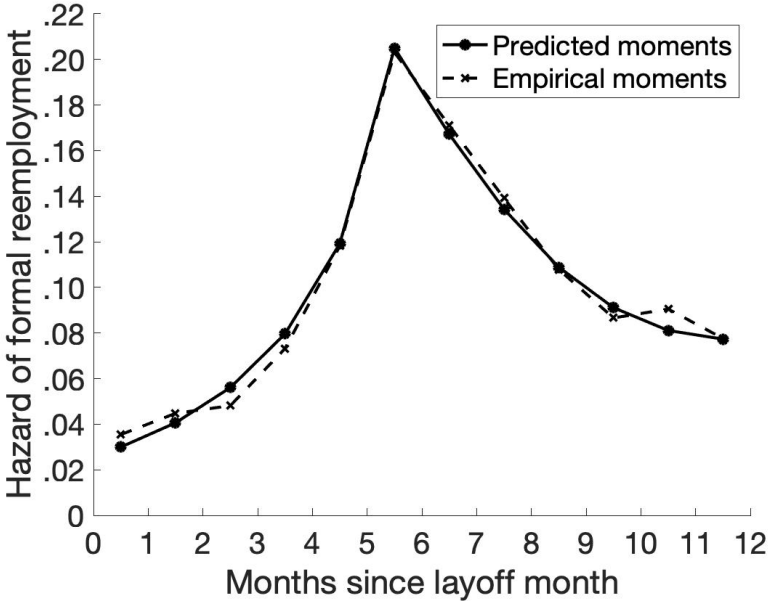
(a) Hazard of formal reemployment



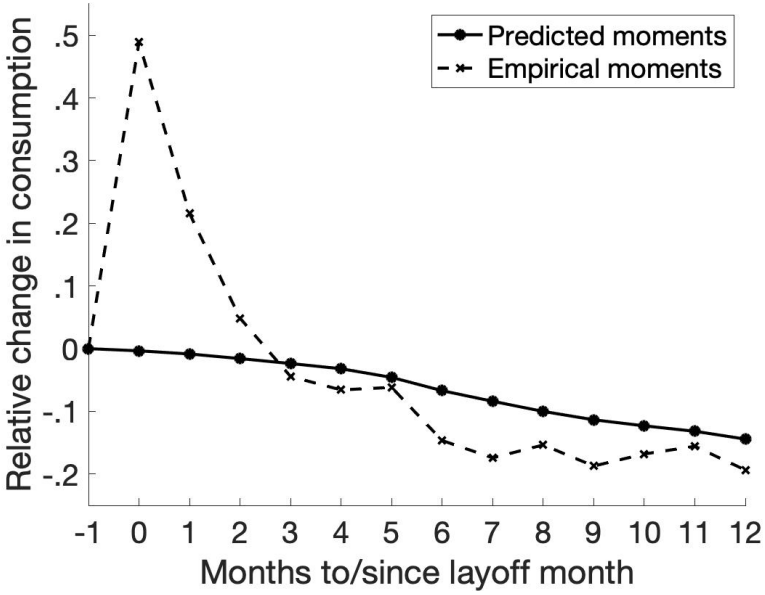
(b) Relative change in consumption

Fits the data well, and the estimated $\hat{\beta} = 0.71$ in line with literature

"Benchmark model" ($\delta = .995$, $\beta = 1$)



(a) Hazard of formal reemployment

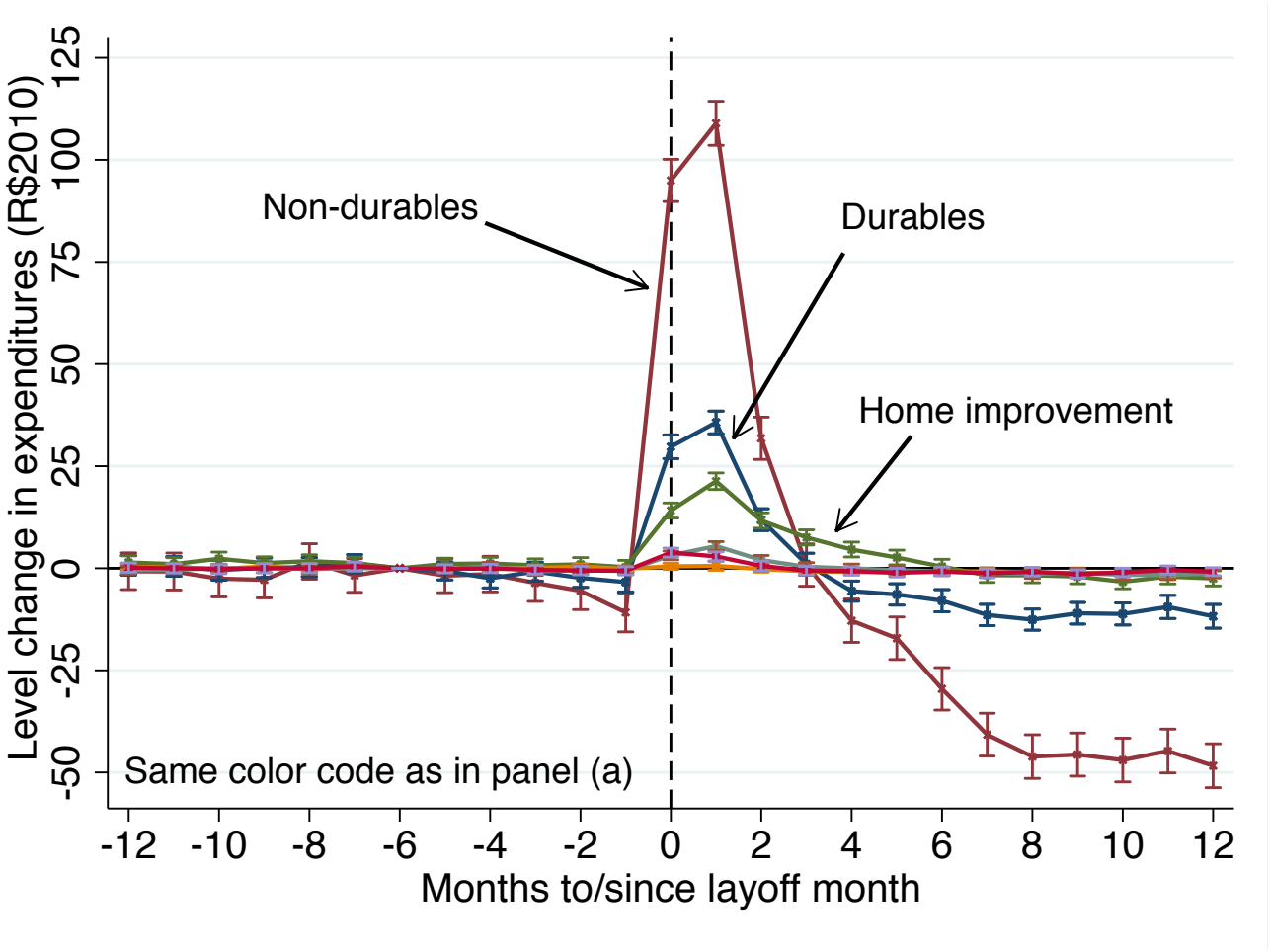


(b) Relative change in consumption

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

parameters

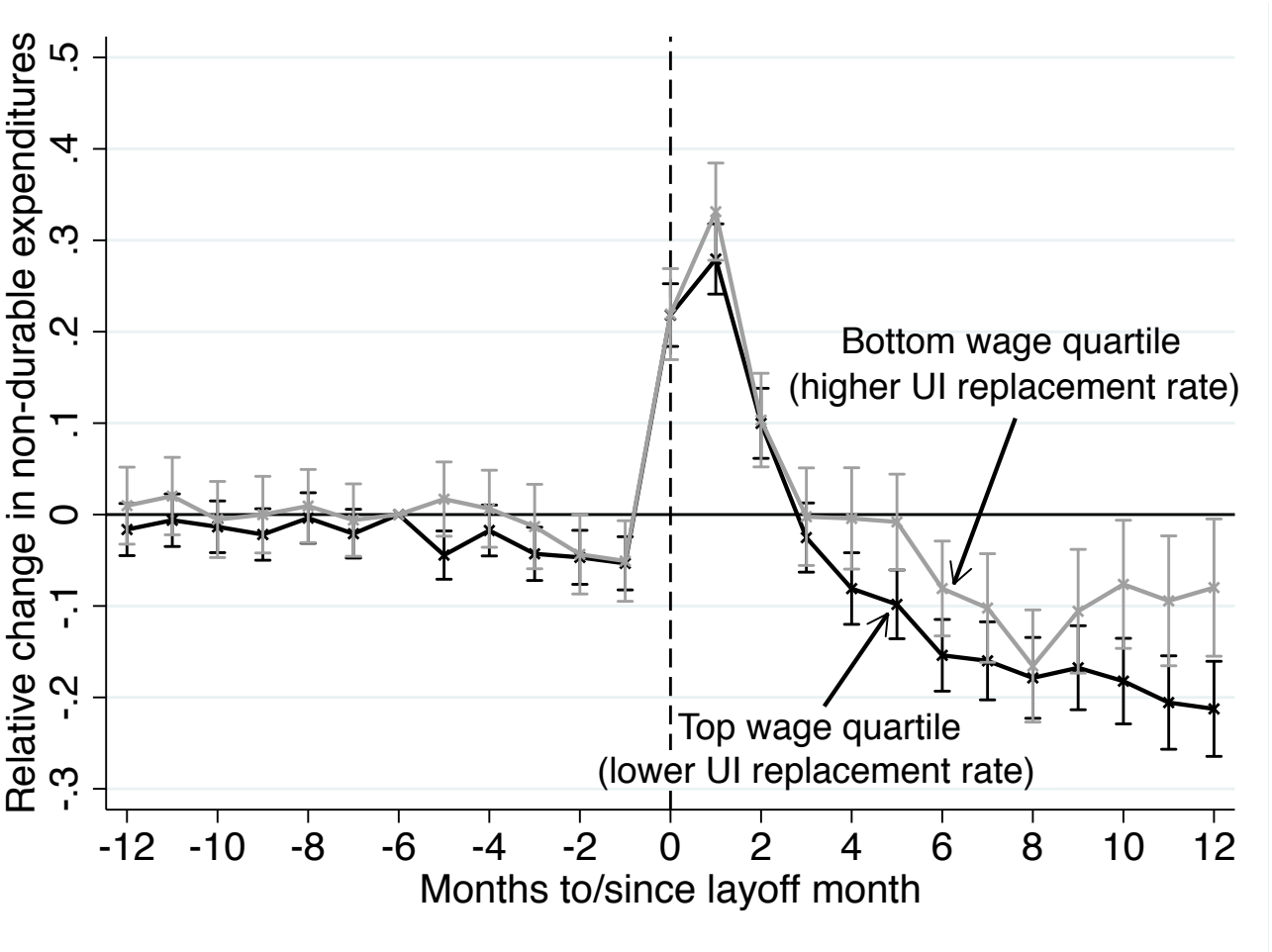
Figure: DD estimates by category (in levels)



Takeaway: (i) overall effect mostly driven by non-durables

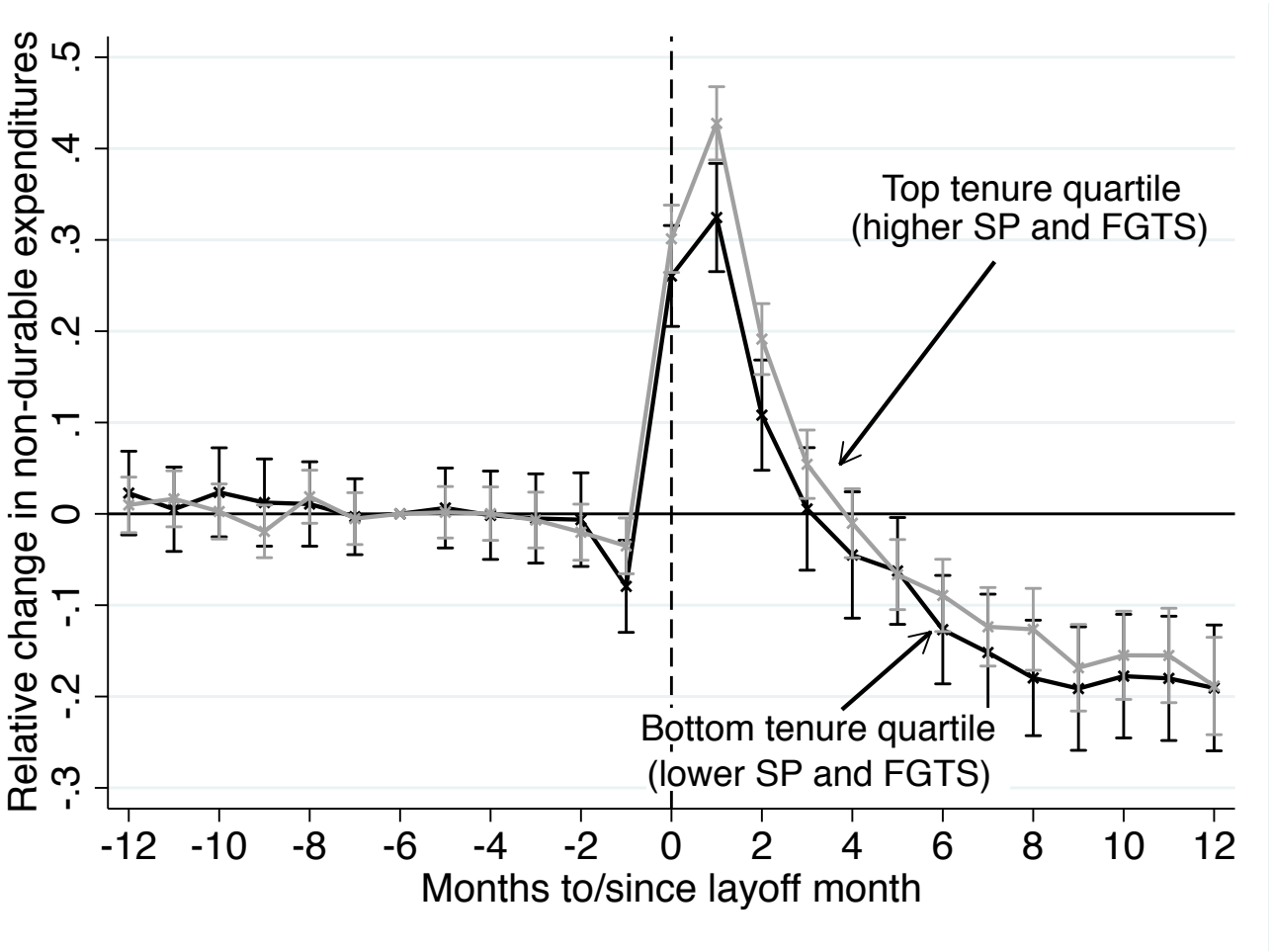
back

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 back

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)

back

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 VI
Impact on Change in Savings Held at Bank
OLS, Probit

INTENT TO TREAT EFFECT

	OLS				Probit			
Length	6 months		12 months		12 months			
Dependent Variable:	Change in Total Balance	Change in Total Balance	Change in Total Balance	Change in Total Balance	Binary Outcome = 1 if Change in Balance > 0%	Binary Outcome = 1 if Change in Balance > 0%	Binary Outcome = 1 if Change in Balance > 20%	Binary Outcome = 1 if Change in Balance > 20%
Sample	All	Commitment & Marketing Only	All	Commitment & Marketing Only	All	Commitment & Marketing Only	All	Commitment & Marketing Only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Commitment Treatment	234.678*	49.828	411.466*	287.575	0.102***	0.056**	0.101***	0.064***
	(101.748)	(156.027)	(244.021)	(228.523)	(3.82)	(0.026)	(0.022)	(0.021)
Marketing Treatment	184.851		123.891		0.048		0.041	
	(146.982)		(153.440)		(1.56)		(0.027)	
Constant	40.626	225.476*	65.183	189.074**				
	(61.676)	(133.405)	(124.215)	(90.072)				
Observations	1777	1308	1777	1308	1777	1308	1777	1308
R-squared	0.00	0.00	0.00	0.00				

Robust standard errors in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable in the first two column is the change in total savings held at the Green Bank after six months. Column (1) regresses chnage 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 x%. 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 remain at zero were coded as zero for the outcome variables for columns (5) through (8). Exchange rate is 50 pesos 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

			Indifferent between 200 pesos in 6 months and X in 7 months			
			Patient X<250	Somewhat Impatient 250<X<300	Most Impatient 300<X	Total
Indifferent between 200 pesos now and X in one month	Patient	X<250	606 34.4%	126 7.2%	73 4.1%	805 45.7%
	Somewhat Impatient	250<X<300	206 11.7%	146 8.3%	59 3.3%	411 23.3%
	Most Impatient	300<X	154 8.7%	93 5.3%	299 17%	546 31%
	Total		966 54.8%	365 20.7%	431 24.5%	1,762 100%

"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

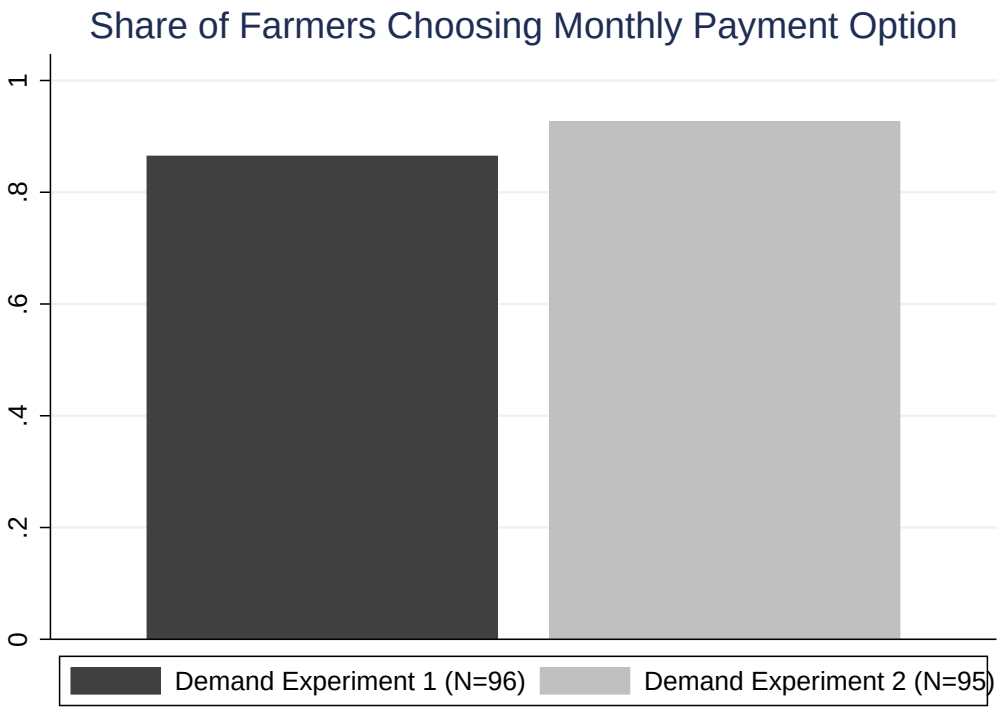
	(1) All	(2) All	(3) Female	(4) Male
Time inconsistent	0.125*	0.005	0.158*	0.046
	(0.067)	(0.080)	(0.085)	(0.098)
Impatient, Now versus 1 Month	-0.030	-0.039	-0.036	-0.041
	(0.050)	(0.050)	(0.062)	(0.075)
Patient, Now versus 1 Month	0.076	0.070	0.035	0.119
	(0.072)	(0.072)	(0.089)	(0.110)
Impatient, 6 months versus 7 Months	0.097	0.108*	0.124	0.078
	(0.065)	(0.065)	(0.087)	(0.091)
Patient, 6 months versus 7 Months	0.015	0.022	0.057	-0.021
	(0.064)	(0.064)	(0.081)	(0.093)

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



Results

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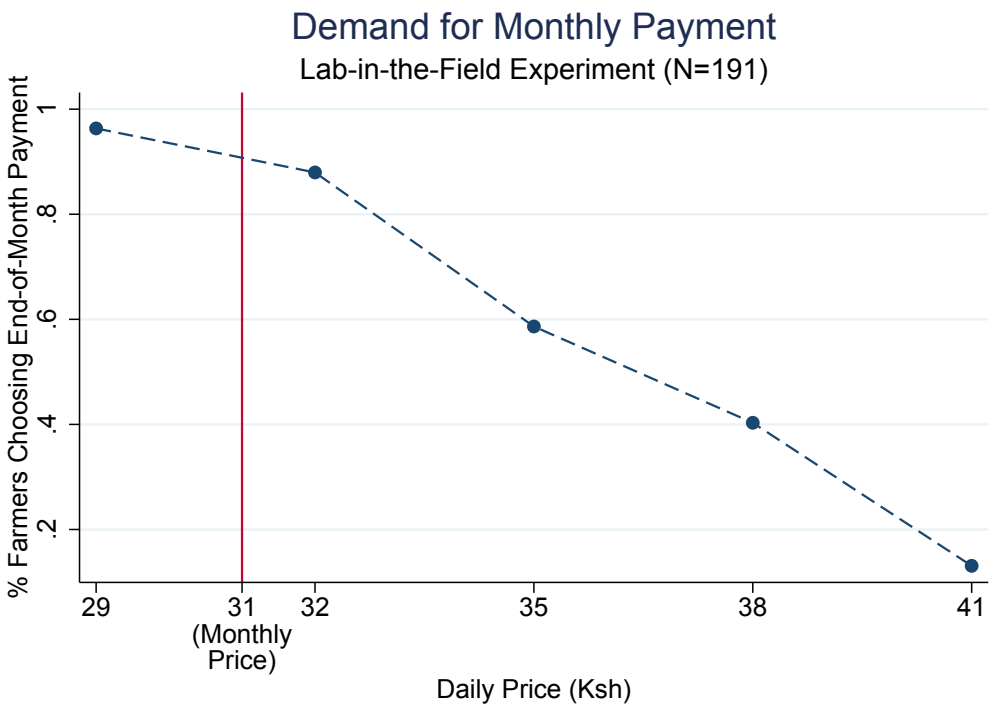


- Interesting parallel with US case: Demand for refunds at tax return time

Section 6

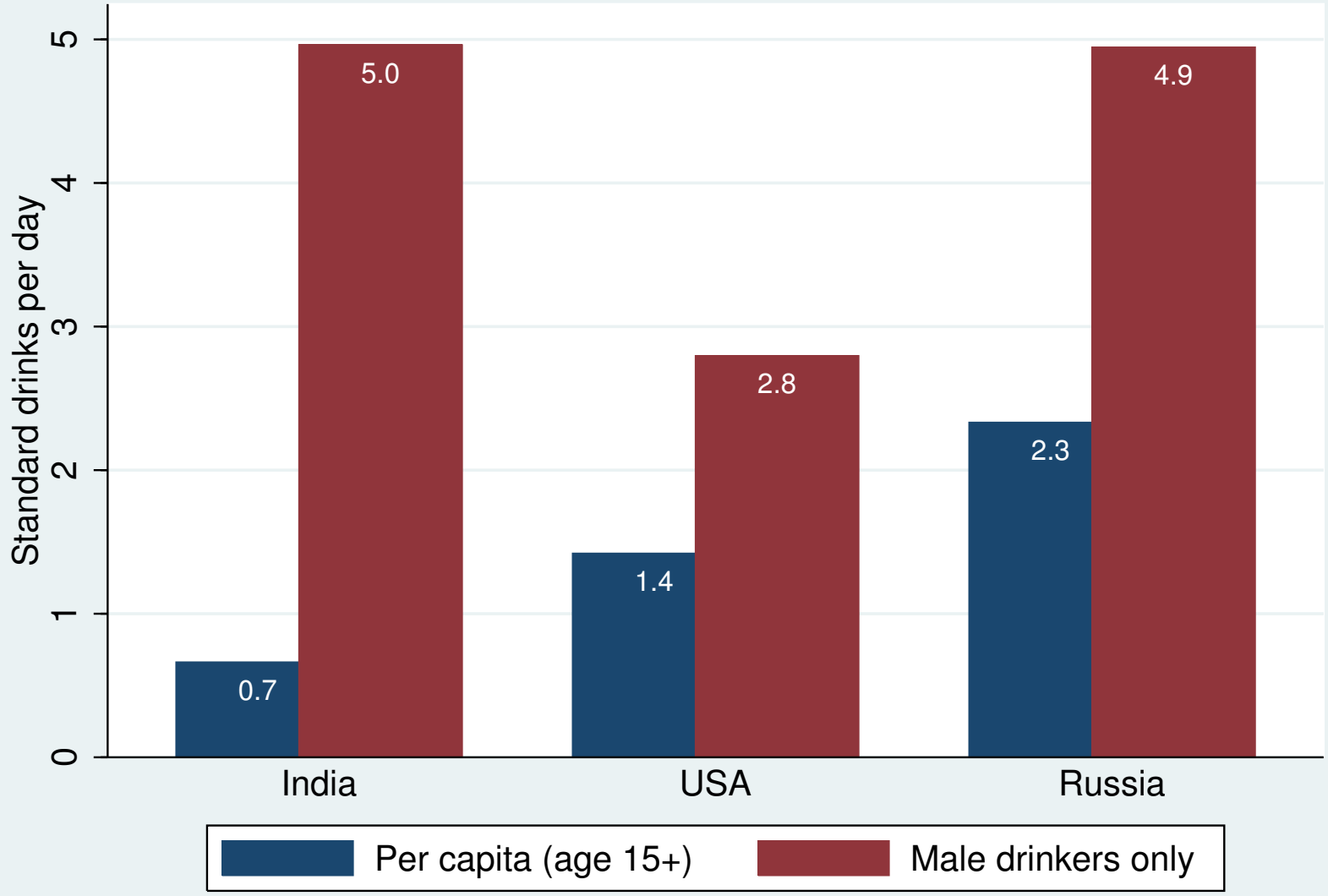
Leisure Goods: Drinking

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



Source: WHO (2014), WHO (2001), own calculation.

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.

SELECTION TABLE

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

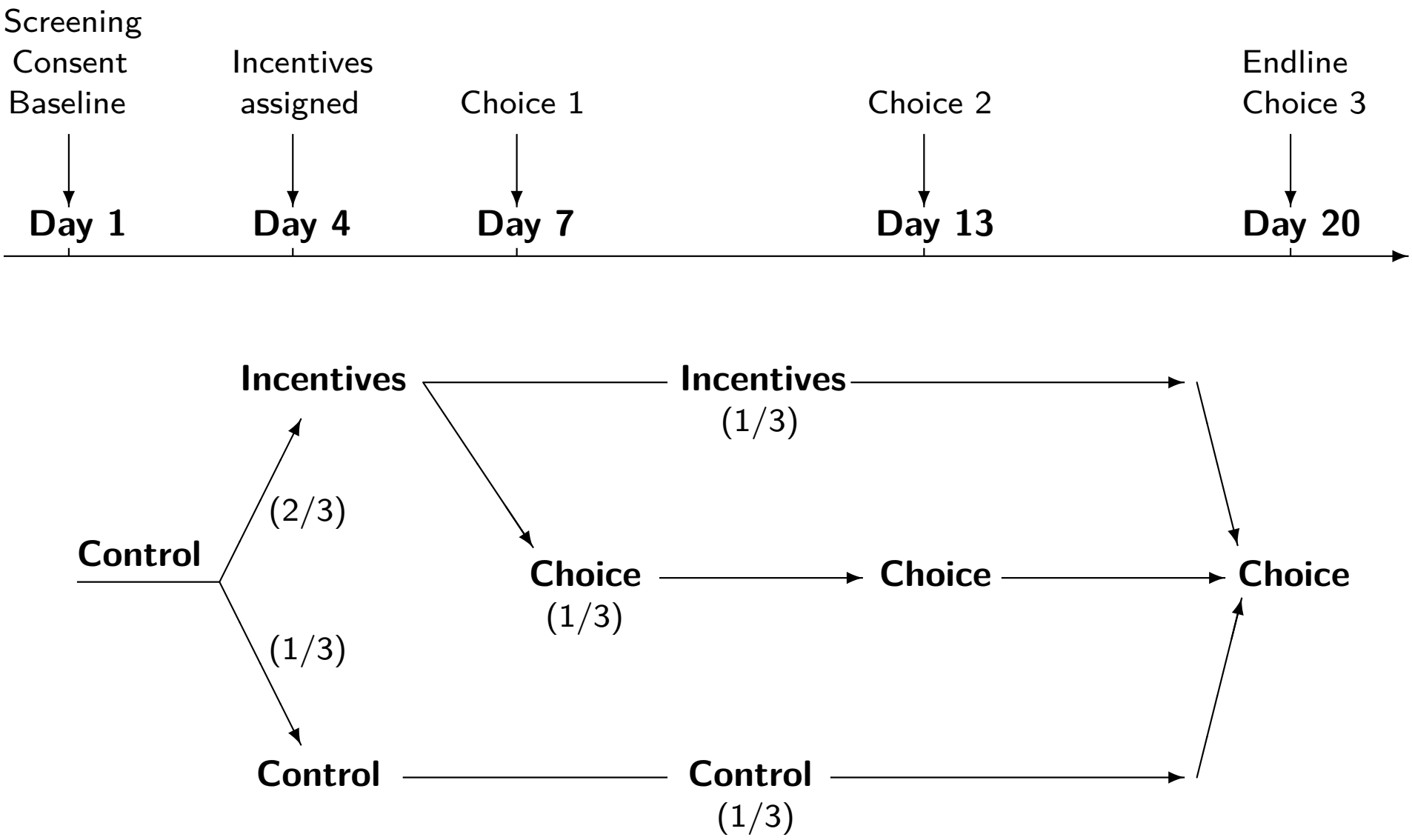
- Paid Rs. 60 if BAC > 0
- Paid Rs. 120 if BAC $= 0$

(III) **Choice Group**

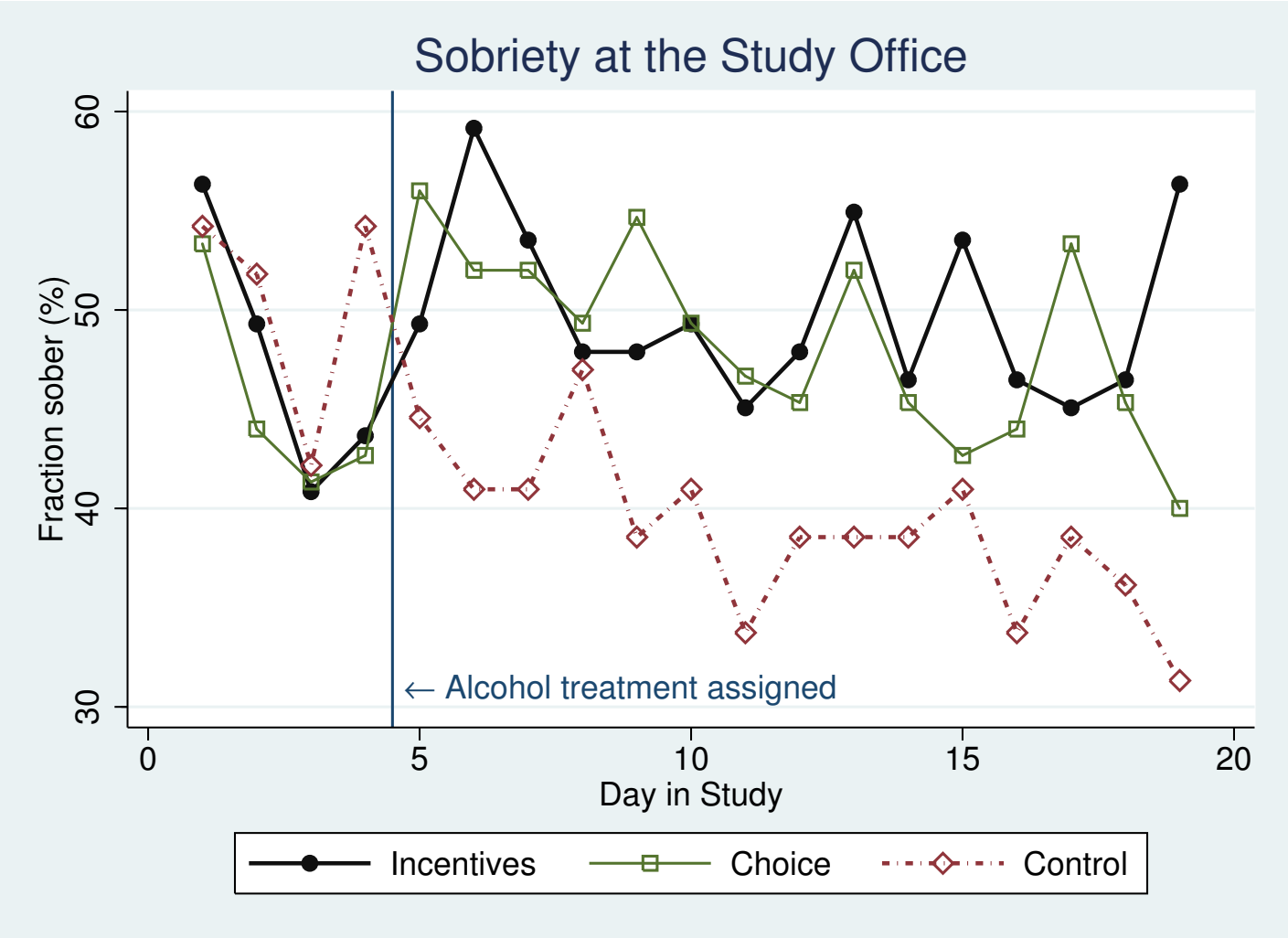
- Choice between incentives and unconditional payments

▸ BALANCE TABLES

Experimental design



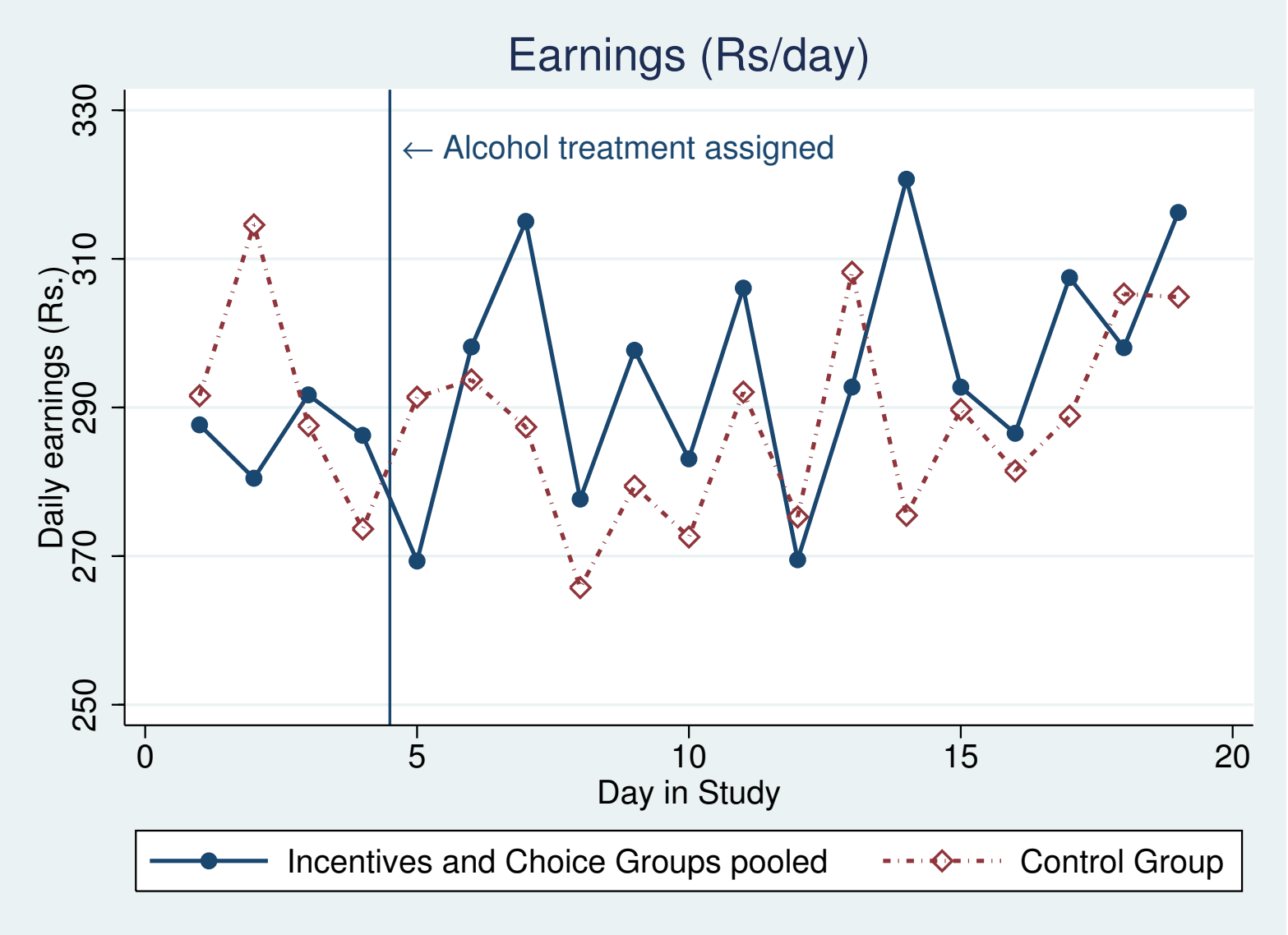
Financial incentives significantly increased daytime sobriety.



▸ ATTENDANCE IN THE INCENTIVE GROUP IS LOWER.

...but reported overall drinking did not fall by much.

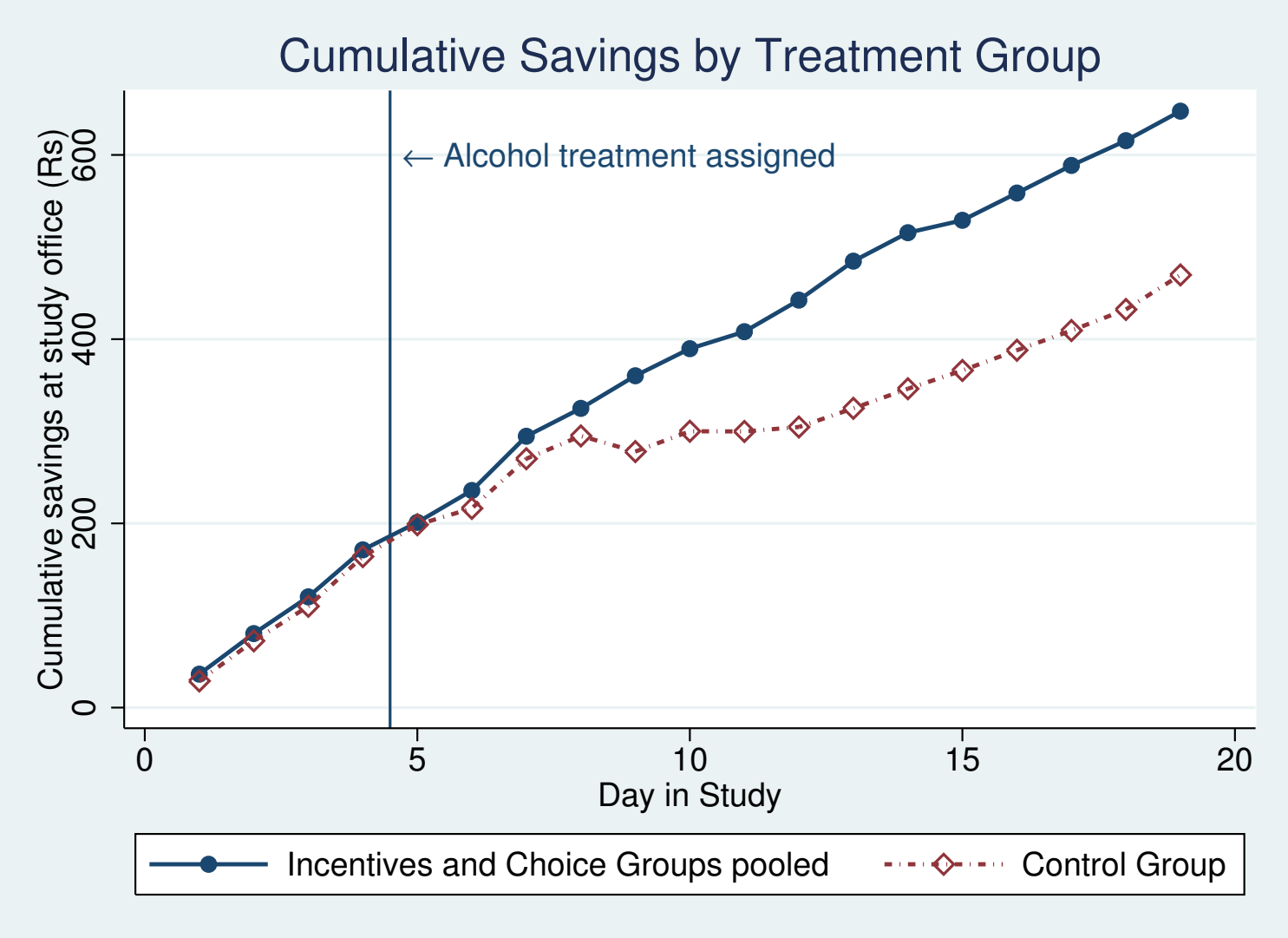
No significant effects on earnings



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.



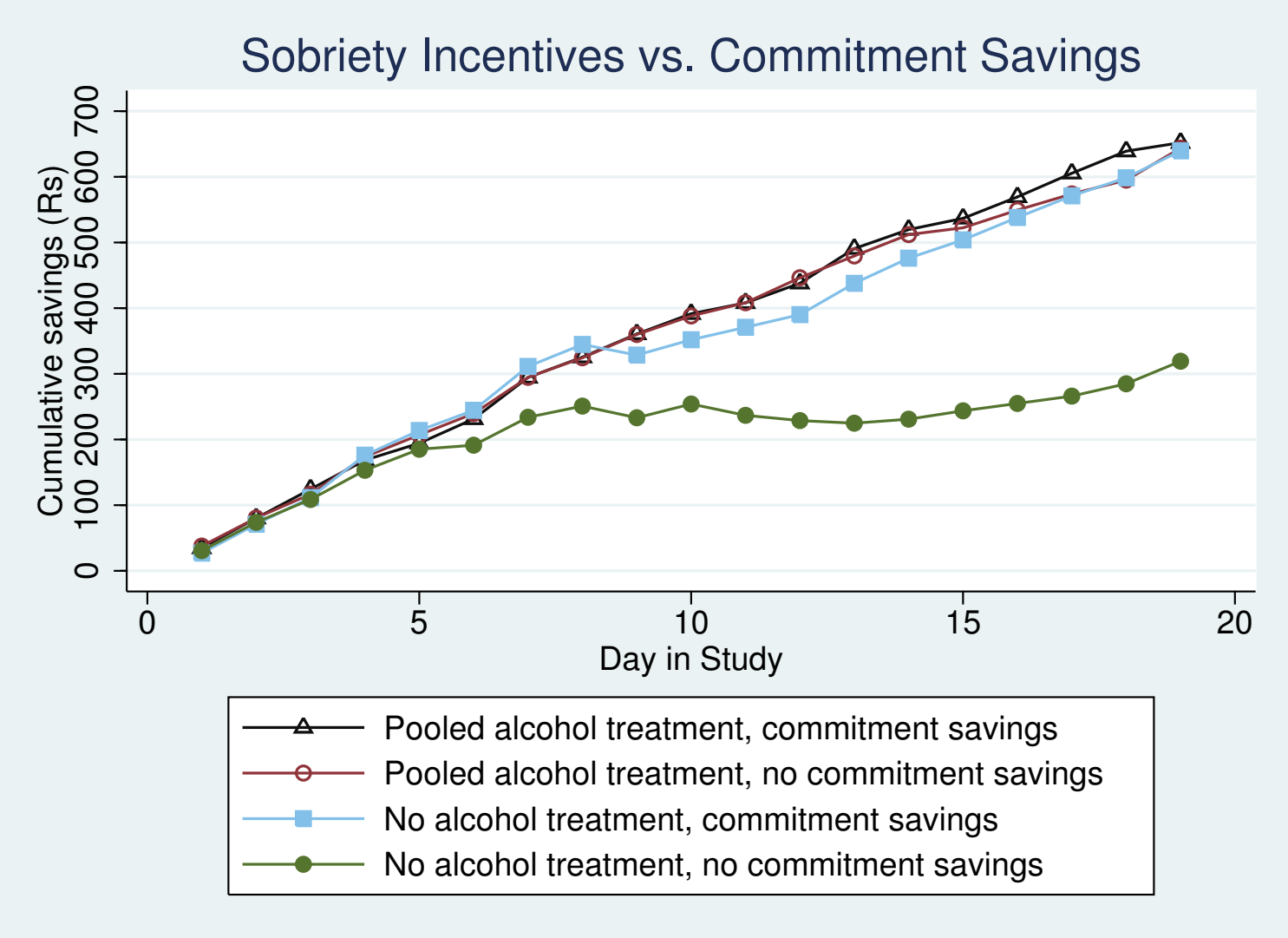
▸ DEPOSITS ▸ WITHDRAWALS

Incentives for sobriety increased savings.

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

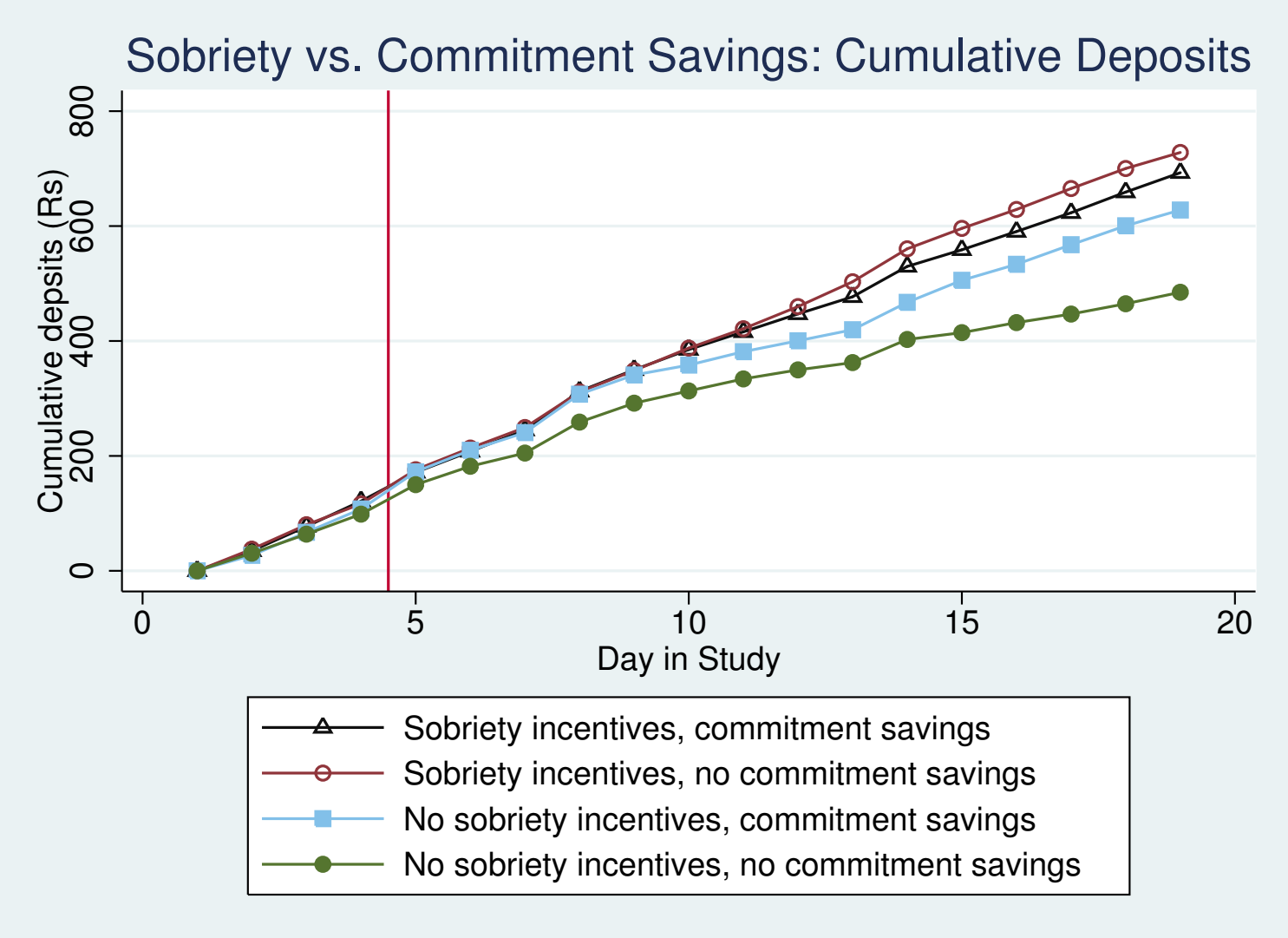
Standard errors in parentheses, clustered by individual.

Interaction between sobriety and commitment savings



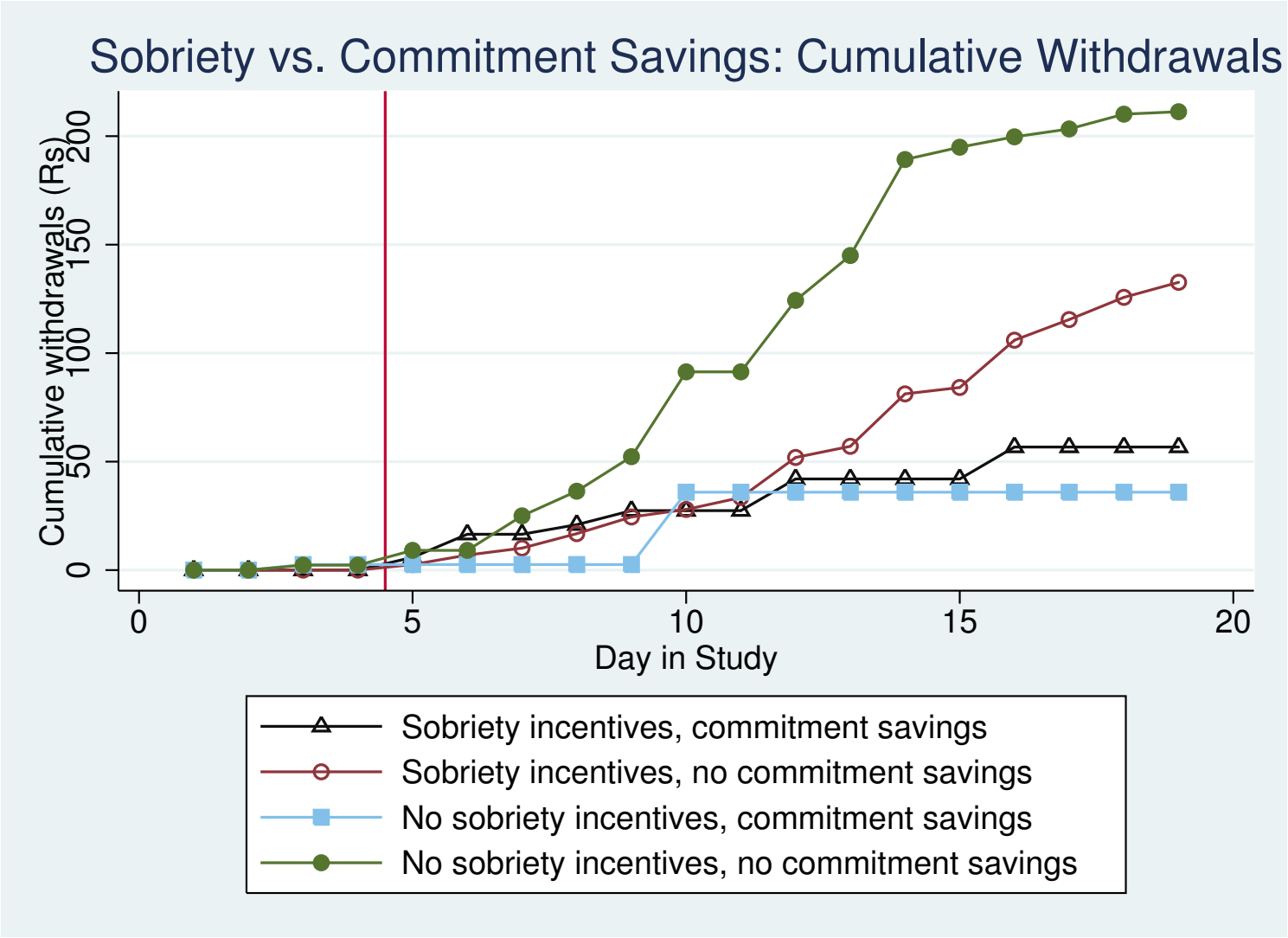
WITHDRAWALS DEPOSITS

Sobriety incentives vs. commitment savings: deposits



BACK TO SAVINGS SECTION

Sobriety incentives vs. commitment savings: withdrawals



BACK TO SAVINGS SECTION

Eliciting willingness to pay for incentives

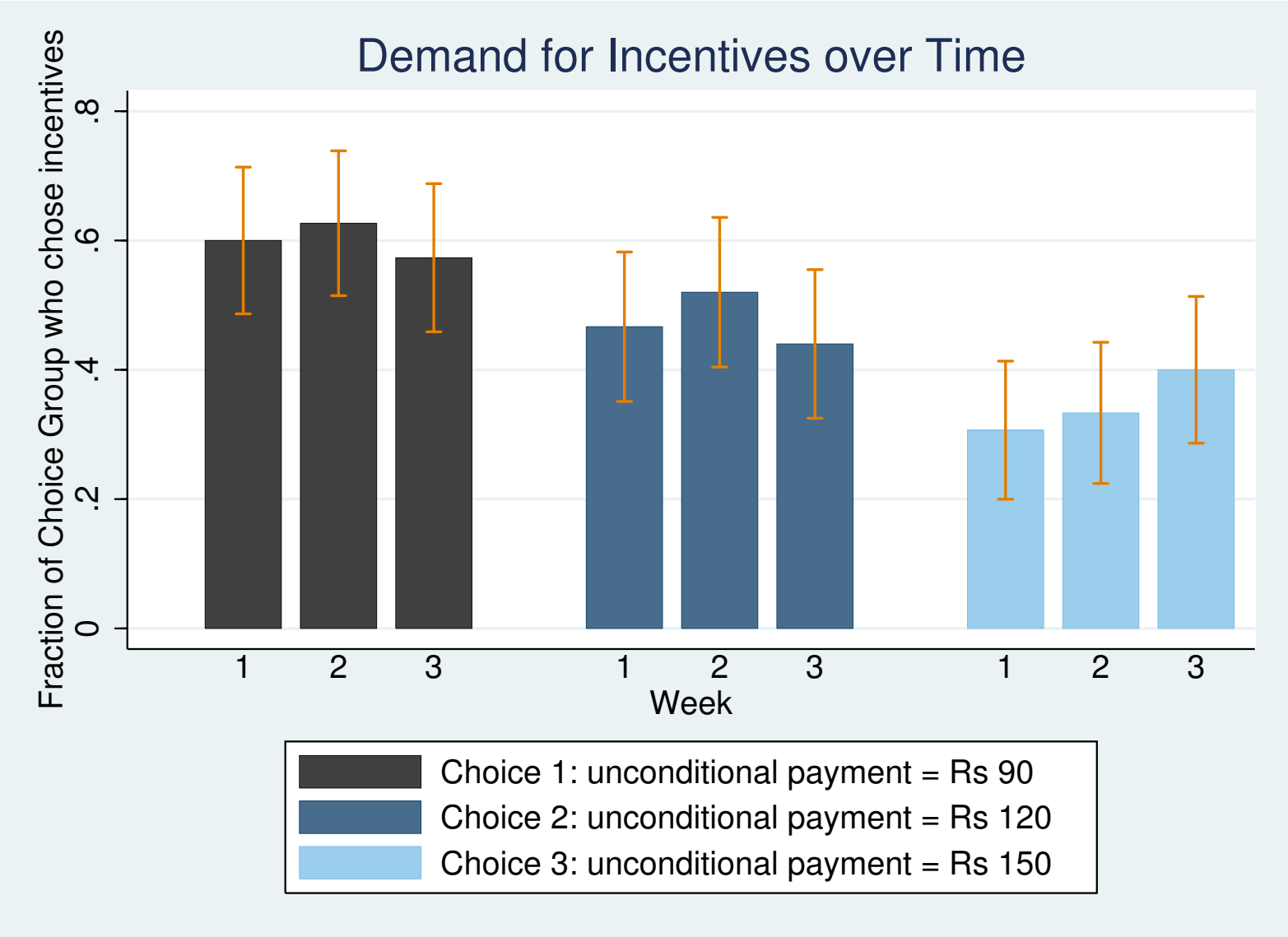
- Choice Group chooses between:
  - Incentives for sobriety
  - Unconditional payments
- Choice sessions on days 7, 13, 20, each for subsequent week
  - Elicit preferences for set of 3 choices
  - Then randomly select one choice to be implemented (RLIS)

Demand for incentives

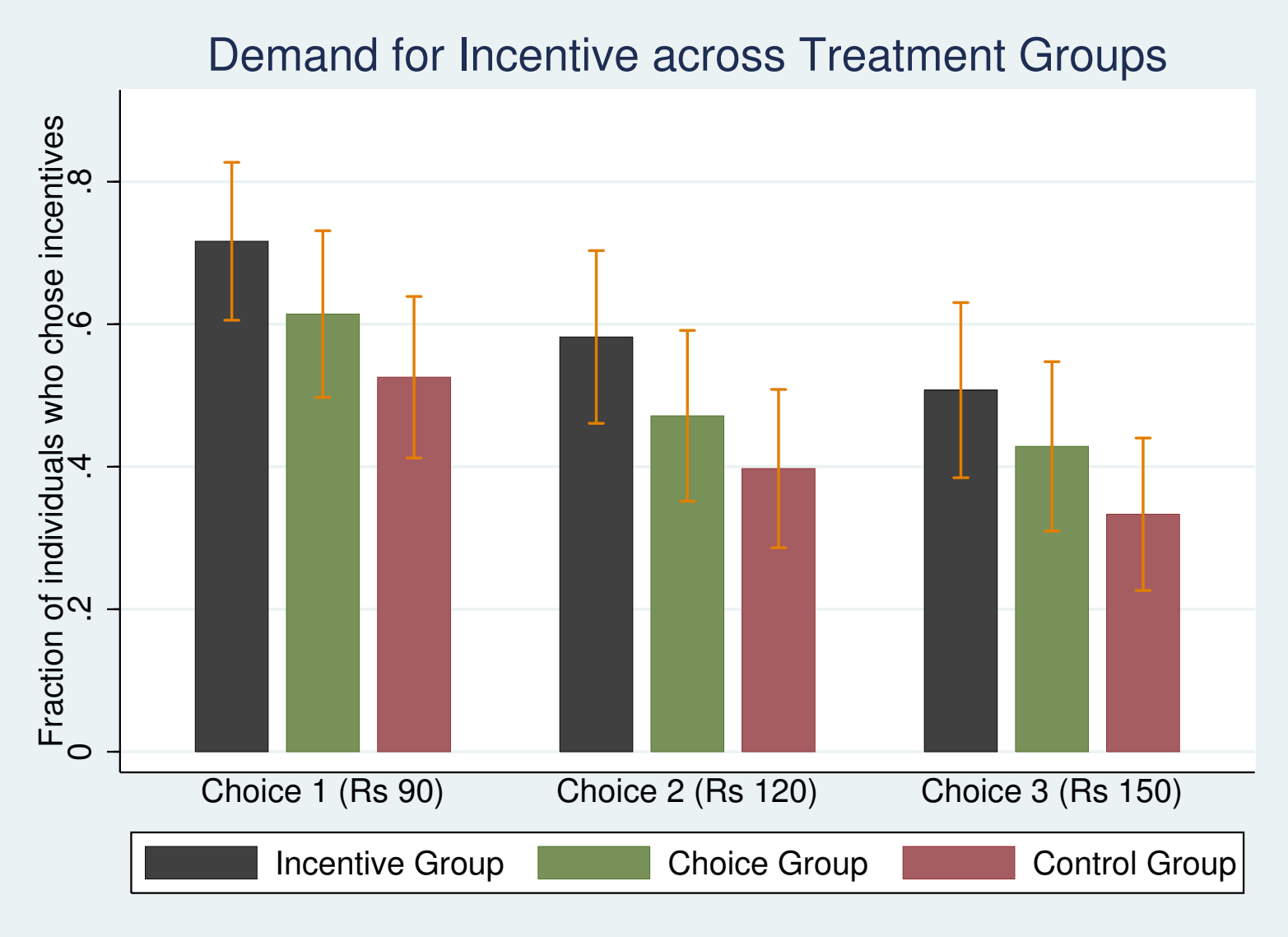
- **Option A:** incentives for sobriety
  - Same payment structure as Incentive Group
  - Rs. 60 if BAC > 0, Rs. 120 if BAC $= 0$
- **Option B:** payment of Rs. Y regardless of BAC

	Option A		**Option B**
	BAC > 0	BAC $= 0$	regardless of BAC
(1)	Rs. 60	Rs. 120	Rs. 90
(2)	Rs. 60	Rs. 120	Rs. 120
(3)	Rs. 60	Rs. 120	Rs. 150

Demand for commitment persists over time.



Exposure to incentives increases demand for incentives.



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 $\rightarrow$ Smoking gun for time inconsistency
   - Time inconsistency can be from present bias+ sophistication
   - OR from hot/cold states or intra-family bargaining

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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)

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   - 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

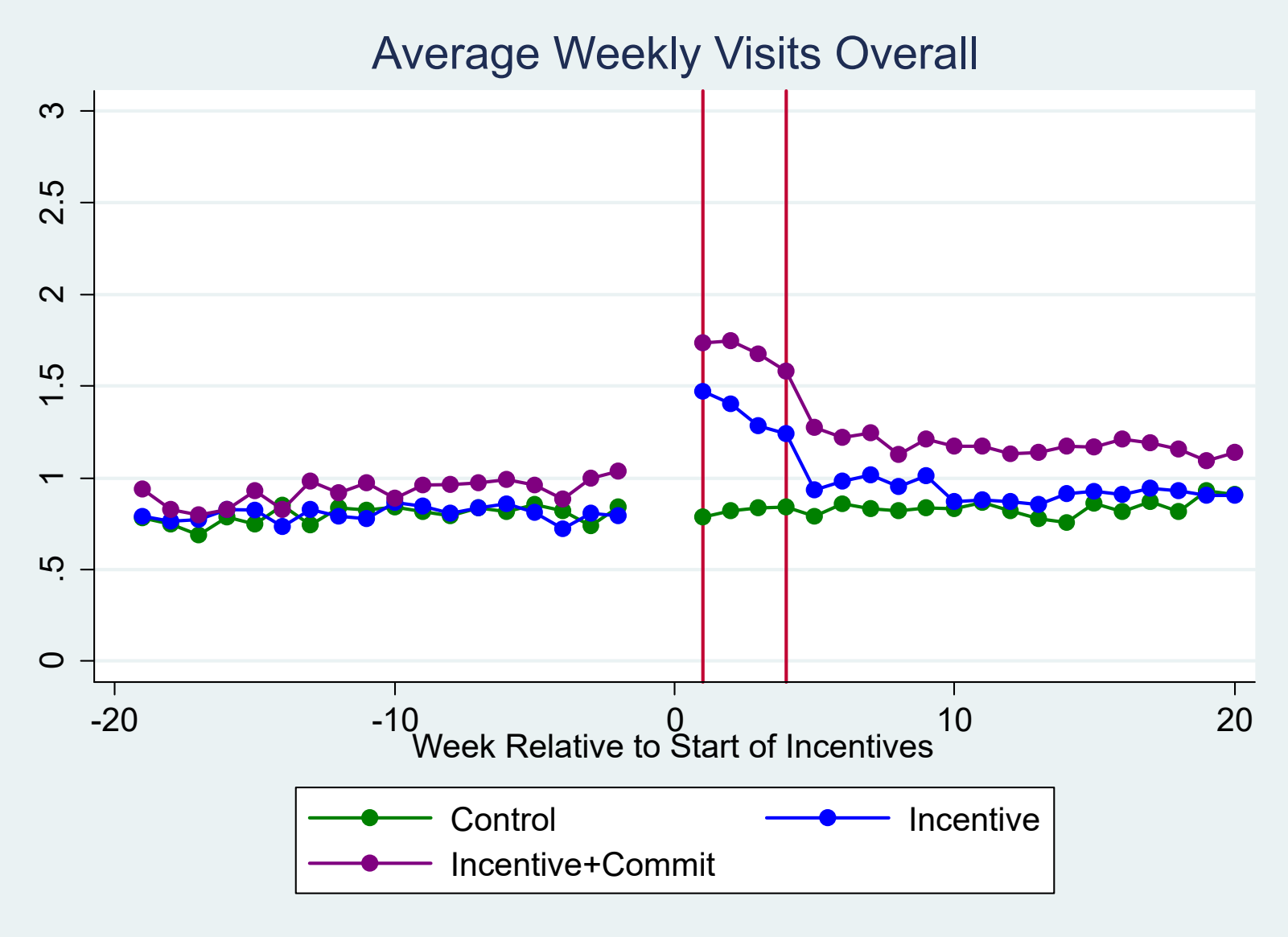
Representative studies: Investment Goods

- *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



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

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  - Result 1. Commitment device take-up 24%
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- *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

Beshears et al., 2011

- Result 1. Commitment device take-up quite high – up to 56%

	21%	22%	23%
10% penalty	0.28	0.39	0.58
20% penalty		0.45	0.61
No withdrawal		0.56	0.60

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

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*)

Assumption:	Everyone that did not take the test continues smoking		Drop if did not take the test		Everyone that was found but refused to take the test still smokes	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. With baseline covariates						
CARES treatment	0.035**	0.035*	0.057**	0.055*	0.054**	0.054**
	(0.018)	(0.018)	(0.028)	(0.028)	(0.027)	(0.027)

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