Econ 219B
Psychology and Economics: Applications (Lecture 5)

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Outline

1. Reference Dependence: Mergers
2. Reference Dependence: Non-Bunching Papers
3. Reference Dependence: Labor Supply
4. Reference Dependence: Employment and Effort
5. Reference Dependence: Golf
6. Reference Dependence: Job Search

Section 1

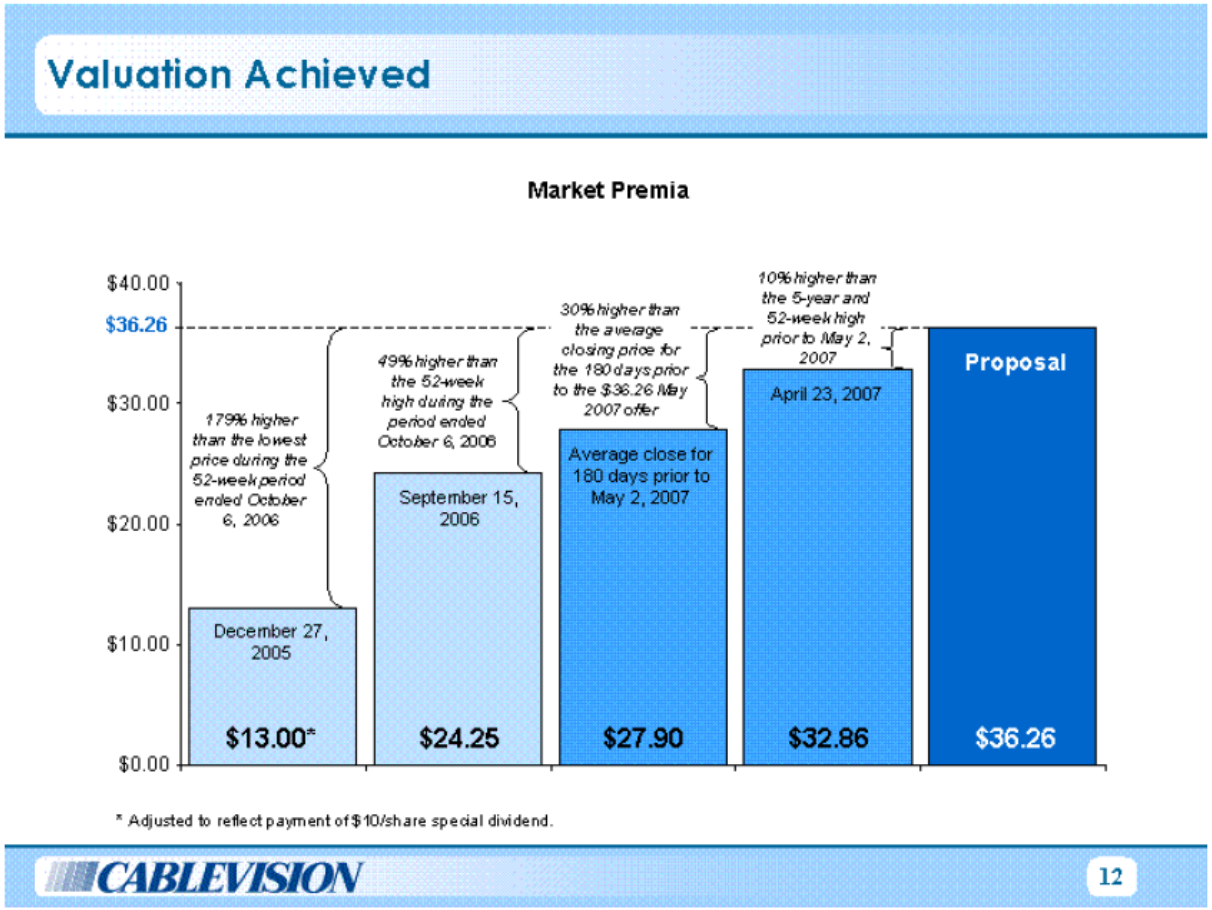
Reference Dependence: Mergers

Baker, Pan, Wurgler (*JFE* 2012)

- On the appearance, very different set-up:
  - Firm A (Acquirer)
  - Firm T (Target)
- After negotiation, Firm A announces a price P for merger with Firm T
  - Price P typically at a 20-50 percent premium over current price
  - About 70 percent of mergers go through at price proposed
  - Comparison price for P often used is highest price in previous 52 weeks, P_{52}

Example: How Cablevision (Target) trumpets deal

Figure 1. Slide from Cablevision Presentation to Shareholders, October 24, 2007. The management of Cablevision recommended acceptance of a $36.26 per share cash bid from the Dolan family. The slide compares this bid price to various recent prices including 52-week highs.



Model

- Assume that Firm T chooses price P, and A decides accept reject
- As a function of price P, probability $p(P)$ that deal is accepted (depends on perception of values of synergy of A)
- If deal rejected, go back to outside value $\bar{U}$
- Then maximization problem is same as for housing sale:

$$\max_P p(P)U(P) + (1 - p(P))\bar{U}$$

- Can assume T reference-dependent with respect to P_{52} :

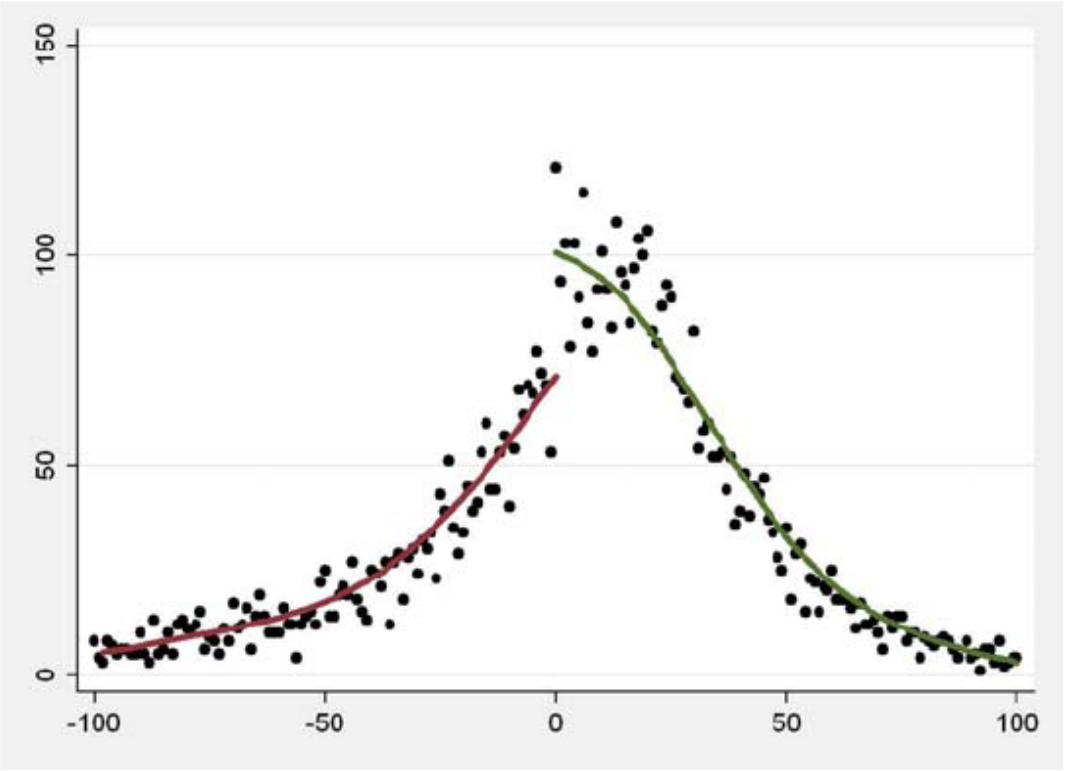
$$v(P|P_0) = \begin{cases} P + \eta(P - P_{52}) & \text{if } P \geq P_{52}; \\ P + \eta\lambda(P - P_{52}) & \text{if } P < P_{52} \end{cases}$$

Predictions and Tests

- Obtain same predictions as in housing market
- (This neglects possible reference dependence of A)
- Baker, Pan, and Wurgler (2009): Test reference dependence in mergers
  - Test 1: Is there bunching around P_{52}? (GM did not do this)
  - Test 2: Is there effect of P_{52} on price offered?
  - Test 3: Is there effect on probability of acceptance?
  - Test 4: What do investors think? Use returns at announcement

Test 1: Offer price P around P_{52}

- Some bunching, shift in left tail of distribution, as predicted



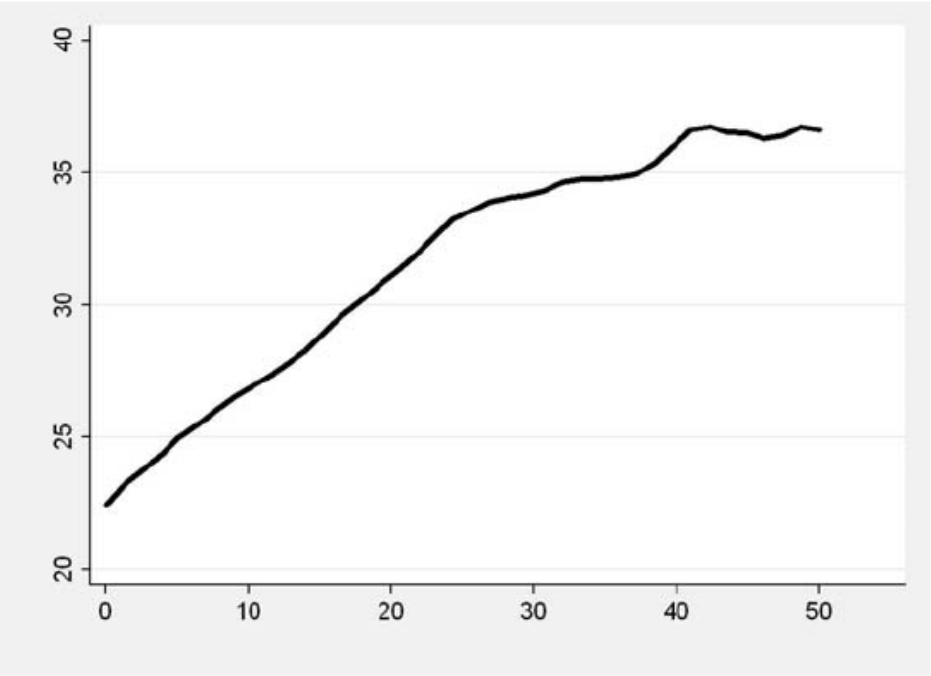
Test 1: Offer price P around P_{52}

- Notice that this does not tell us how the missing left tail occurs:
  - Firms in left tail raise price to P_{52}?
  - Firms in left tail wait for merger until 12 months after past peak, so P_{52} is higher?
  - Preliminary negotiations break down for firms in left tail
- Would be useful to compare characteristics of firms to right and left of P_{52}

Test 2: Kernel regression of P

- Kernel regression of price offered P (Renormalized by price 30 days before, P_{-30}, to avoid heterosked.) on P_{52} :

$$100 * \frac{P - P_{-30}}{P_{-30}} = \alpha + \beta \left[100 * \frac{P_{52} - P_{-30}}{P_{-30}} \right] + \varepsilon$$



Test 4: What do investors think?

- Test 3: Probability of final acquisition is higher when offer price is above P_{52} (Skip)

- Test 4: What do investors think of the effect of P_{52}?
  - Holding constant current price, investors should think that the higher P_{52}, the more expensive the Target is to acquire
  - Standard methodology to examine this:
    - 3-day stock returns around merger announcement: $CAR_{t-1,t+1}$
    - This assumes investor rationality
    - Notice that merger announcements are typically kept top secret until last minute $\rightarrow$ On announcement day, often big impact

Test 4: What do investors think?

- Regression (Columns 3 and 5):

$$CAR_{t-1,t+1} = \alpha + \beta \frac{P}{P_{-30}} + \varepsilon$$

where P/P_{-30} is instrumented with P_{52}/P_{-30}

Table 8. Mergers and Acquisitions: Market Reaction. Ordinary and two-stage least squares regressions of the 3-day CAR of the bidder on the offer premium.

$$r_{t-1\to t+1} = a + b\frac{Offer_{it}}{P_{i,t-30}} + e_{it}$$

$$\left(\frac{Offer_{it}}{P_{i,t-30}} - 1\right)\cdot 100 = a + b_1 \min\left(\left(\frac{52WeekHigh_{i,t-30}}{P_{i,t-30}} - 1\right)\cdot 100, 25\right) + b_2 \max\left(0, \min\left(\left(\frac{52WeekHigh_{i,t-30}}{P_{i,t-30}} - 1.25\right)\cdot 100, 50\right)\right) + b_3 \max\left(\left(\frac{52WeekHigh_{i,t-30}}{P_{i,t-30}} - 1.75\right)\cdot 100, 0\right) + e_{it}$$

where r is the market-adjusted return of the bidder for the three-day period centered on the announcement date, *Offer* is the offer price from Thomson, P is the target stock price from CRSP, and *52WeekHigh* is the high stock price over the 365 calendar days ending 30 days prior to the announcement date. The first, second, and fourth columns use ordinary least squares. The third and the fifth columns instrument for the offer premium using *52WeekHigh*. Robust t-statistics with standard errors clustered by month are in parentheses.

	OLS	*OLS*	*IV*	*OLS*	*IV*
	1	**2**	**3**	**4**	**5**
Offer Premium:					
b	-0.0186***	-0.0204***	-0.215***	-0.0443***	-0.253***
	(-2.64)	(-2.74)	(-3.48)	(-4.21)	(-4.39)

- Results very supportive of reference dependence hypothesis – Also alternative anchoring story

Section 2

Reference Dependence: Non-Bunching

Previous Papers: Bunching Assumption

- Previous papers had bunching implication
  - Some papers test for bunching (mergers, tax evasion, marathon running)
  - Some papers do not test it... but should! (housing)
- For bunching test, need
  - Reference point r obvious enough to people AND researcher (house purchase price, zero taxes, round number goal)
  - Effort can be altered to get to reference point

Next Set of Papers: No Bunching

- Next set of papers, these conditions do not apply:
  - Reference point r not an exact number (labor supply, effort and crime, job search)
  - Choice is not about effort (domestic violence, insurance)
- Identification in these papers typically relies on variants of:
  - Loss aversion induces higher marginal utility of income to left of reference point
  - Identify comparing when to the left of reference point, versus to the right
  - Still need some model about reference point (more later on this)

Section 3

Reference Dependence: Labor Supply

Framework

Does reference dependence affect work/leisure decision?

- Framework:
  - effort h (no. of hours)
  - hourly wage w
  - Returns of effort: $Y = w * h$
  - Linear utility $U(Y) = Y$
  - Cost of effort $c(h) = \theta h^2/2$ convex within a day
- Standard model: Agents maximize

$$U(Y) - c(h) = wh - \frac{\theta h^2}{2}$$

Framework

- (Assumption that each day is orthogonal to other days – see below)
- Reference dependence: Threshold T of earnings agent wants to achieve
- Loss aversion for outcomes below threshold:

$$U = \begin{cases} wh + \eta (wh - T) & \text{if} \quad wh \geq T \\ wh + \eta\lambda (wh - T) & \text{if} \quad wh < T \end{cases}$$

  with $\lambda > 1$ loss aversion coefficient
- Reference-dependent agent maximizes

$$\begin{array}{lll} wh + \eta (wh - T) - \frac{\theta h^2}{2} & \text{if} & h \geq T/w \\ wh + \eta\lambda (wh - T) - \frac{\theta h^2}{2} & \text{if} & h < T/w \end{array}$$

Framework

- Derivative with respect to h:

$$\begin{array}{lll} (1+\eta)w - \theta h & \text{if} & h \geq T/w \\ (1+\eta\lambda)w - \theta h & \text{if} & h < T/w \end{array}$$

1. Case 1 ($(1+\eta\lambda)w - \theta T/w < 0$).
   - Optimum at $h^* = (1+\eta\lambda)w/\theta < T/w$

Framework

2. Case 2 $((1+\eta\lambda)w - \theta T/w > 0 > (1+\eta)w - \theta T/w)$
   - Optimum at $h^* = T/w$

3. Case 3 $((1+\eta)w - \theta T/w > 0)$
   - Optimum at $h^* = (1+\eta)\, w/\theta > T/w$

Standard theory ($\lambda = 1$)

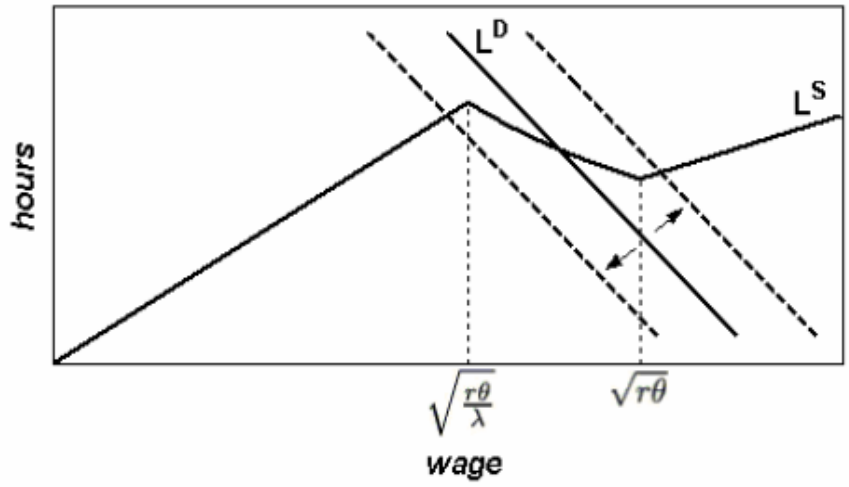
- Interior maximum: $h^* = (1 + \eta)\, w/\theta$ (Cases 1 or 3)
- Labor supply

- Combine with labor demand: $h^* = a - bw$, with $a > 0, b > 0$.

Model with reference dependence ($\lambda > 1$)

- Case 1 or 3 still exist
- BUT: Case 2. Kink at $h^* = T/w$ for $\lambda > 1$
- Combine Labor supply with labor demand: $h^* = a - bw$, with $a > 0, b > 0$

Figure 1a



- Case 2: On low-demand days (low w) need to work harder to achieve reference point $T \rightarrow$ Work harder $\rightarrow$ Opposite to standard theory

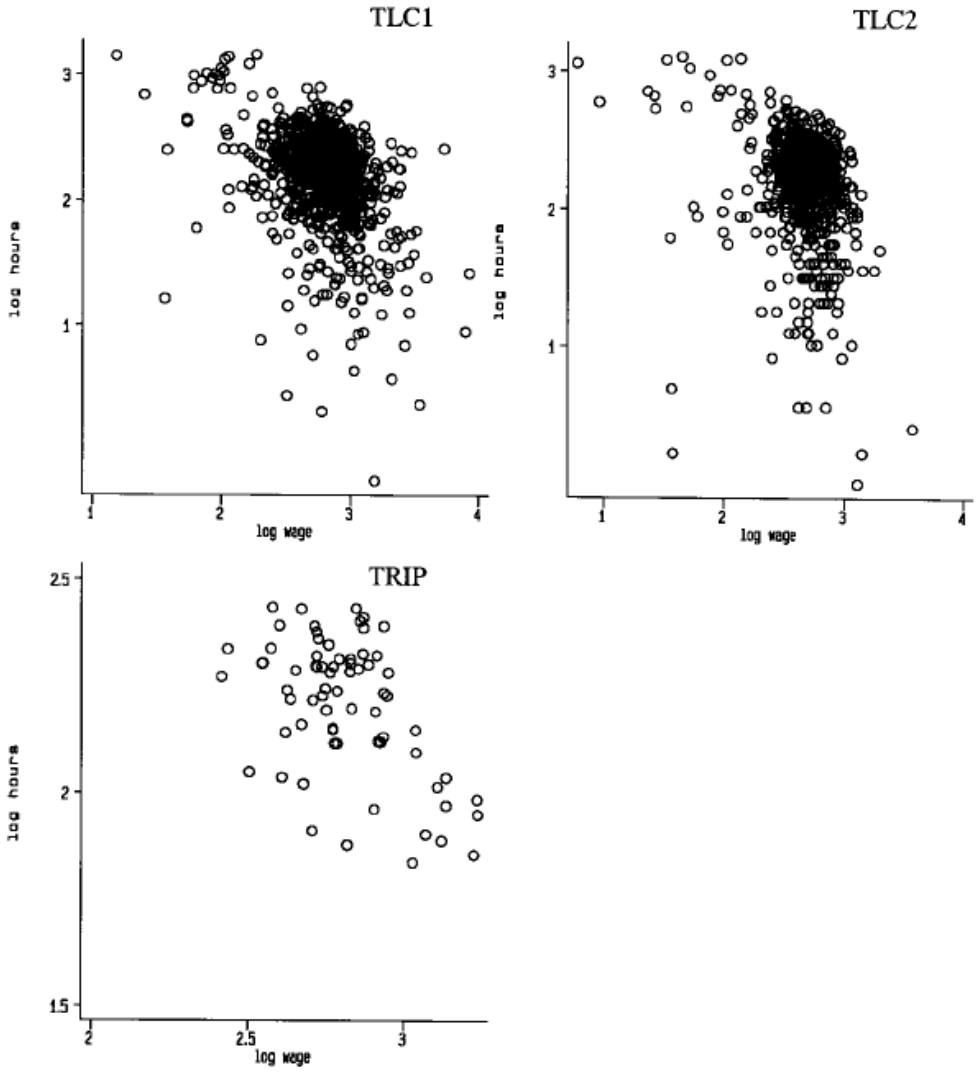
Camerer, Babcock, Loewenstein, and Thaler (QJE 1997)

- Data on daily labor supply of New York City cab drivers
  - 70 Trip sheets, 13 drivers (TRIP data)
  - 1044 summaries of trip sheets, 484 drivers, dates: 10/29-11/5, 1990 (TLC1)
  - 712 summaries of trip sheets, 11/1-11/3, 1988 (TLC2)
- Notice data feature: Many drivers, few days in sample

Framework

- Analysis in paper neglects wealth effects: Higher wage today $\rightarrow$ Higher lifetime income
- Justification:
  - Correlation of wages across days close to zero
  - Each day can be considered in isolation
  - $\rightarrow$Wealth effects of wage changes are very small
- Test:
  - Assume variation across days driven by Δa (labor demand shifter)
  - Do hours worked h and w co-vary positively (standard model) or negatively?

Raw evidence



Model

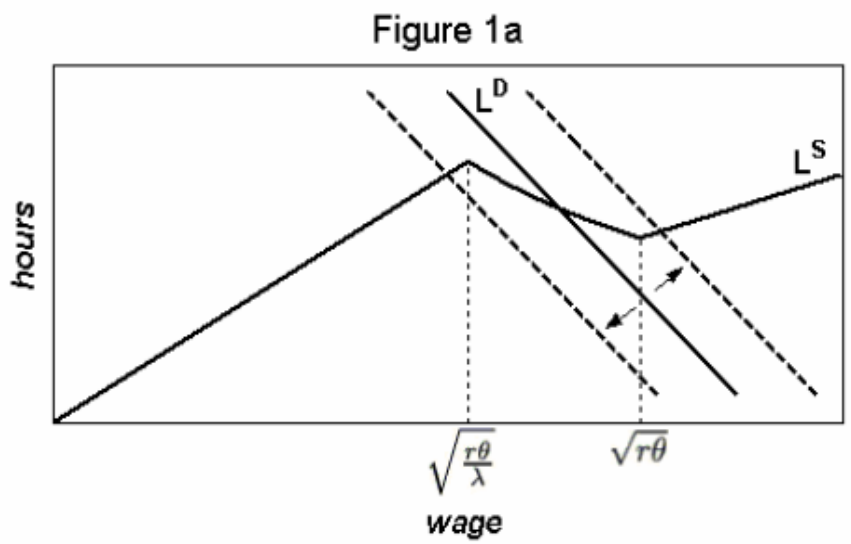
- Estimate:

$$\log(h_{i,t}) = \alpha + \beta \log(Y_{i,t}/h_{i,t}) + X_{i,t}\Gamma + \varepsilon_{i,t}.$$

- Estimates of $\hat{\beta}$:
- $\hat{\beta} = -.186$ (s.e. 129) – TRIP with driver f.e.
  - $\hat{\beta} = -.618$ (s.e. .051) – TLC1 with driver f.e.
  - $\hat{\beta} = -.355$ (s.e. .051) – TLC2
- Estimate is not consistent with prediction of standard model
- Indirect support for income targeting

Economic Issue 1

Reference-dependent model does not predict (log-) linear, negative relation



- What happens if reference income is stochastic? (Koszegi-Rabin, 2006)

Econometric Issue 1

Division bias in regressing hours on log wages

- Wages are not directly observed – Computed at $Y_{i,t}/h_{i,t}$
- Assume $h_{i,t}$ measured with noise: $\tilde{h}_{i,t} = h_{i,t} * \phi_{i,t}$. Then,

$$\log\left(\tilde{h}_{i,t}\right) = \alpha + \beta \log\left(Y_{i,t}/\tilde{h}_{i,t}\right) + \varepsilon_{i,t}.$$

becomes

$$\log\left(h_{i,t}\right) + \log\left(\phi_{i,t}\right) = \alpha + \beta\left[\log(Y_{i,t}) - \log(h_{i,t})\right] - \beta \log(\phi_{i,t}) + \varepsilon_{i,t}.$$

- Downward bias in estimate of $\hat{\beta}$
- Response: instrument wage using other workers' wage on same day

Econometric Issue 1: Use IV

- IV Estimates:

TABLE III
IV LOG HOURS WORKED EQUATIONS

Sample	TRIP		TLC1		TLC2
Log hourly wage	−.319	.005	−1.313	−.926	−.975
	(.298)	(.273)	(.236)	(.259)	(.478)
High temperature	−.000	−.001	.002	.002	−.022
	(.002)	(.002)	(.002)	(.002)	(.007)

- Notice: First stage not very strong (and few days in sample)

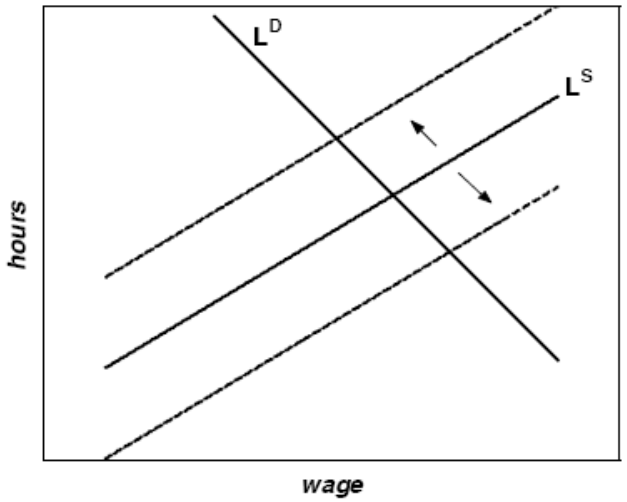
	First-stage regressions				
Median	.316	.026	−.385	−.276	1.292
	(.225)	(.188)	(.394)	(.467)	(4.281)
25th percentile	.323	.287	.693	.469	−.373
	(.160)	(.126)	(.241)	(.332)	(3.516)
75th percentile	.399	.289	.614	.688	.479
	(.171)	(.149)	(.242)	(.292)	(1.699)
Adjusted R^2	.374	.642	.056	.206	.019
P-value for F-test of instruments for wage	.000	.004	.000	.000	.020

Econometric issue 2

Are the authors really capturing demand shocks or supply shocks?

- Assume θ (disutility of effort) varies across days.
- Even in standard model we expect negative correlation of $h_{i,t}$ and $w_{i,t}$

Figure 1b



- Camerer et al. argue for plausibility of shocks due to a rather than θ

Farber (JPE, 2005)

- Re-Estimate Labor Supply of Cab Drivers on new data
- Address Econometric Issue 1 (Division Bias)
- Data:
  - 244 trip sheets, 13 drivers, 6/1999-5/2000
  - 349 trip sheets, 10 drivers, 6/2000-5/2001
  - Daily summary not available (unlike in Camerer et al.)
  - Notice: Few drivers, many days in sample

Model

- Key specification: Hazard model that does not suffer from division bias
  - Dependent variable is dummy $Stop_{i,t} = 1$ if driver i stops at hour t:

$$Stop_{i,t} = \Phi\left(\alpha + \beta_Y Y_{i,t} + \beta_h h_{i,t} + \Gamma X_{i,t}\right)$$

  - Control for hours worked so far $(h_{i,t})$ and other controls $X_{i,t}$
- Does a higher earned income $Y_{i,t}$ increase probability of stopping $(\beta > 0)$?

TABLE 5
HAZARD OF STOPPING AFTER TRIP: NORMALIZED PROBIT ESTIMATES

Variable	X^*	(1)	(2)	(3)	(4)	(5)
Total hours	8.0	.013	.037	.011	.010	.010
		(.009)	(.012)	(.005)	(.005)	(.005)
Waiting hours	2.5	.010	−.005	.001	.004	.004
		(.010)	(.012)	(.006)	(.006)	(.005)
Break hours	.5	.006	−.015	−.003	−.001	−.002
		(.008)	(.011)	(.005)	(.005)	(.005)
Shift income ÷ 100	1.5	.053	.036	.014	.016	.011
		(.022)	(.030)	(.015)	(.016)	(.015)
Driver (21)		no	yes	yes	yes	yes
Day of week (7)		no	no	yes	yes	yes
Hour of day (19)	2:00 p.m.	no	no	yes	yes	yes
Log likelihood		−2,039.2	−1,965.0	−1,789.5	−1,784.7	−1,767.6

NOTE.—The sample includes 13,461 trips in 584 shifts for 21 drivers. Probit estimates are normalized to reflect the marginal effect at X^* of X on the probability of stopping. The normalized probit estimate is $\beta \cdot \phi(X^*\beta)$, where $\phi(\cdot)$ is the standard normal density. The values of X^* chosen for the fixed effects are equally weighted for each day of the week and for each driver. The hours from 5:00 a.m. to 10:00 a.m. have a common fixed effect. The evaluation point is after 5.5 driving hours, 2.5 waiting hours, and 0.5 break hour in a dry hour on a day with moderate temperatures in midtown Manhattan at 2:00 p.m. Robust standard errors accounting for clustering by shift are reported in parentheses.

Results

- Positive, but not significant effect of $Y_{i,t}$ on probability of stopping:
  - 10 percent increase in Y (\$15) $\rightarrow$ 1.6 percent increase in stopping prob. (.225 pctg. pts. increase in stopping prob. out of average 14 pctg. pts.) $\rightarrow$ 0.16 elasticity
  - Cannot reject large effect: 10 pct. increase in Y increase stopping prob. by 6 percent $\rightarrow$ 0.6 elasticity
- Qualitatively consistent with income targeting
- Also notice:
  - Failure to reject standard model is not the same as rejecting alternative model (reference dependence)
  - Alternative model is not spelled out

Still, Supply or Demand?

- Farber (2005) cannot address the Econometric Issue 2: Is it Supply or Demand that Varies
- **Fehr and Goette (AER 2007).** Experiments on Bike Messengers
- Use explicit randomization to deal with Econometric Issues 1 and 2
- Combination of:
  - *Experiment 1.* Field Experiment shifting wage and
  - *Experiment 2.* Lab Experiment (relate to evidence on loss aversion)...
  - ... on the same subjects
- Slides courtesy of Lorenz Goette

The Experimental Setup in this Study

Bicycle Messengers in Zurich, Switzerland

- Data: Delivery records of Veloblitz and Flash Delivery Services, 1999 - 2000.
  - Contains large number of details on every package delivered.

  ➢ Observe hours (shifts) and effort (revenues per shift).

- Work at the messenger service
  - Messengers are paid a commission rate w of their revenues r_{it}. (w = „wage“). Earnings wr_{it}
  - Messengers can freely choose the number of shifts and whether they want to do a delivery, when offered by the dispatcher.

  ➢ suitable setting to test for intertemporal substitution.

- Highly volatile earnings
  - Demand varies strongly between days

  ➢ Familiar with changes in intertemporal incentives.

Experiment 1

- **The Temporary Wage Increase**
  - Messengers were randomly assigned to one of two treatment groups, A or B.
    - N=22 messengers in each group
  - Commission rate w was increased by 25 percent during four weeks
    - Group A: September 2000 (Control Group: B)
    - Group B: November 2000 (Control Group: A)

- **Intertemporal Substitution**
  - Wage increase has no (or tiny) income effect.
  - Prediction with time-separable prefernces, t= a day:
    - Work more shifts
    - Work harder to obtain higher revenues
  - Comparison between TG and CG during the experiment.
    - Comparison of TG over time confuses two effects.

Results for Hours

- Treatment group works 12 shifts, Control Group works 9 shifts during the four weeks.
- Treatment Group works significantly more shifts ($X^2(1) = 4.57, p<0.05$)
- Implied Elasticity: 0.8

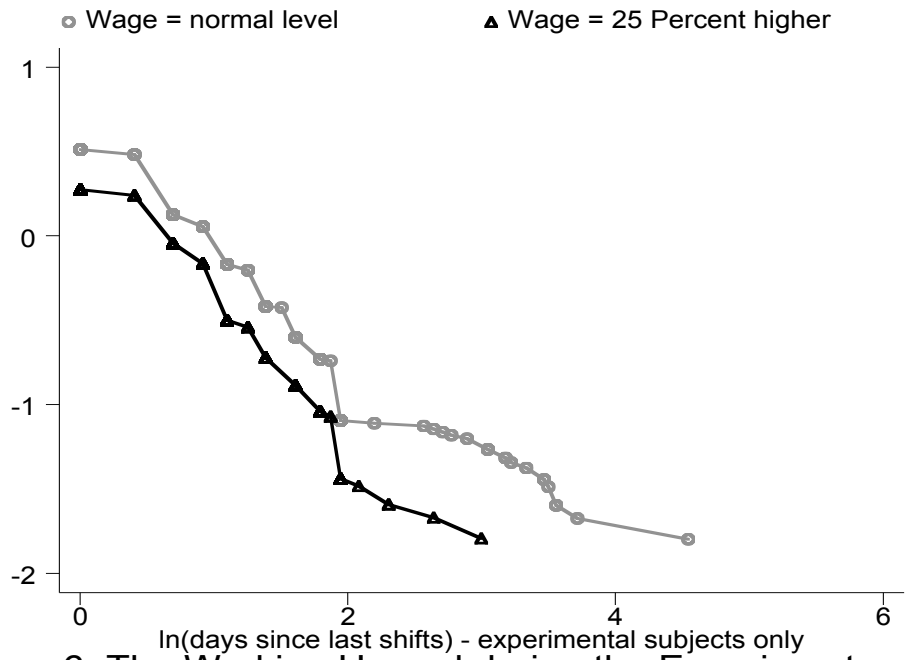
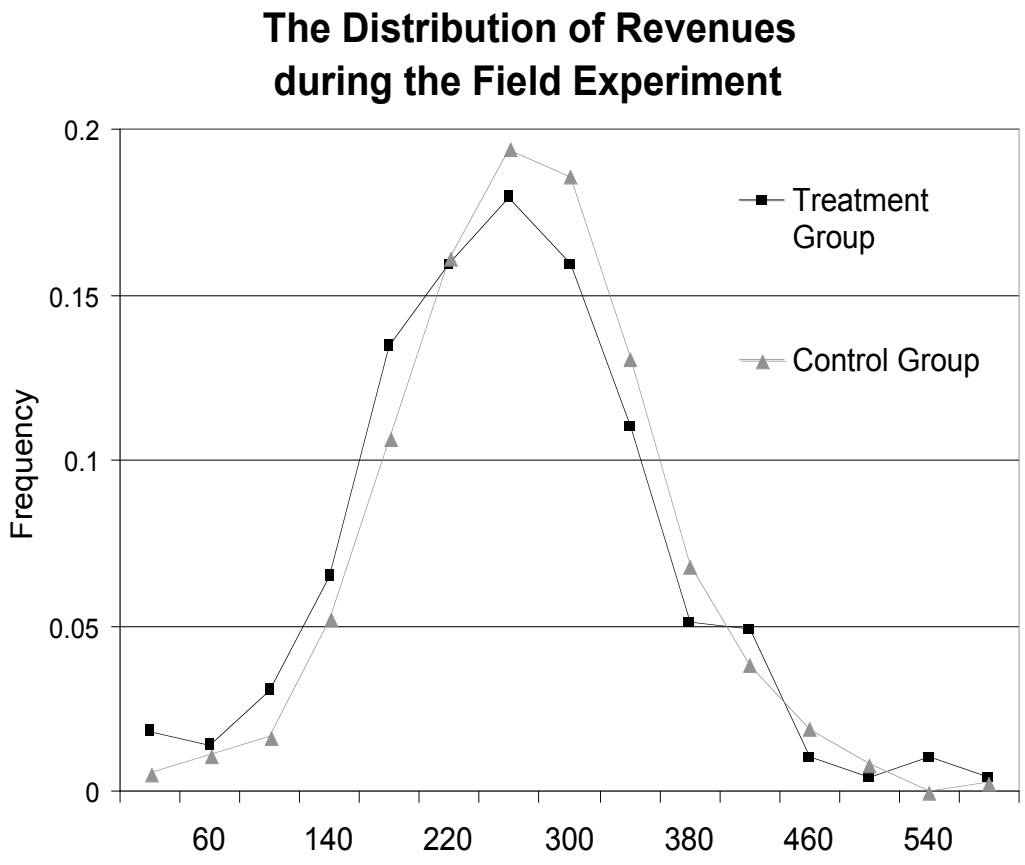


Figure 6: The Working Hazard during the Experiment

Results for Effort: Revenues per shift

- Treatment Group has lower revenues than Control Group: - 6 percent. ($t = 2.338$, $p < 0.05$)
- Implied *negative* Elasticity: -0.25



- Distributions are significantly different (KS test; $p < 0.05$);

Results for Effort, cont.

- **Important caveat**
  - Do lower revenues relative to control group reflect lower effort or something else?

- **Potential Problem: Selectivity**
  - Example: Experiment induces TG to work on bad days.
  - More generally: Experiment induces TG to work on days with unfavorable states
    - If unfavorable states raise marginal disutility of work, TG may have lower revenues during field experiment than CG.

- **Correction for Selectivity**
  - Observables that affect marginal disutility of work.
    - Conditioning on experience profile, messenger fixed effects, daily fixed effects, dummies for previous work **leave result unchanged.**
  - Unobservables that affect marginal disutility of work?
    - Implies that reduction in revenues only stems from sign-up shifts in addition to fixed shifts.
    - **Significantly lower revenues on fixed shifts, not even different from sign-up shifts.**

Measuring Loss Aversion

- **A potential explanation for the results**
  - Messengers have a daily income target in mind
  - They are loss averse around it
  - Wage increase makes it easier to reach income target

  ➢ That's why they put in less effort per shift

- **Experiment 2: Measuring Loss Aversion**
  - Lottery A: Win CHF 8, lose CHF 5 with probability 0.5.
    - 46 % accept the lottery
  - Lottery C: Win CHF 5, lose zero with probability 0.5; or take CHF 2 for sure
    - 72 % accept the lottery
  - Large Literature: Rejection is related to loss aversion.

- **Exploit individual differences in Loss Aversion**
  - Behavior in lotteries used as proxy for loss aversion.

  ➢ Does the proxy predict reduction in effort during experimental wage increase?

Measuring Loss Aversion

- **Does measure of Loss Aversion predict reduction in effort?**
  - Strongly loss averse messengers reduce effort substantially: Revenues are 11 % lower (s.e.: 3 %)
  - Weakly loss averse messenger do not reduce effort noticeably: Revenues are 4 % lower (s.e. 8 %).
  - No difference in the number of shifts worked.

➢ **Strongly loss averse messengers put in less effort while on higher commission rate**

  - Supports model with daily income target

➢ **Others kept working at normal pace, consistent with standard economic model**

  - Shows that not everybody is prone to this judgment bias (but many are)

Farber (2008)

- **Farber (AER 2008)** goes beyond Farber (JPE, 2005) and attempts to estimate model of labor supply with loss-aversion
  - Estimate loss-aversion δ
  - Estimate (stochastic) reference point T
- Same data as Farber (2005)
- Results:
  - significant loss aversion δ
  - however, large variation in T mitigates effect of loss-aversion

Farber (2008)

Parameter	(1)	(2)	(3)	(4)
$\hat{\beta}$ (contprob)	-0.691	---	---	---
	(0.243)			
$\hat{\theta}$ (mean ref inc)	159.02	206.71	250.86	---
	(4.99)	(7.98)	(16.47)	
$\hat{\delta}$ (cont increment)	3.40	5.35	4.85	5.38
	(0.279)	(0.573)	(0.711)	(0.545)
$\hat{\sigma}^2$ (ref inc var)	3199.4	10440.0	15944.3	8236.2
	(294.0)	(1660.7)	(3652.1)	(1222.2)
Driver $\hat{\theta}_i$ (15)	No	No	No	Yes
Vars in Cont Prob				
Driver FE's (14)	No	No	Yes	No
Accum Hours (7)	No	Yes	Yes	Yes
Weather (4)	No	Yes	Yes	Yes
Day Shift and End (2)	No	Yes	Yes	Yes
Location (1)	No	Yes	Yes	Yes
Day-of-Week (6)	No	Yes	Yes	Yes
Hour-of-Day (18)	No	Yes	Yes	Yes
Log(L)	-1867.8	-1631.6	-1572.8	-1606.0
Number Parms	4	43	57	57

- δ is loss-aversion parameter
- Reference point: mean θ and variance σ^2

Crawford and Meng (AER 2011)

- Re-estimates on Farber (2005) data allowing for two dimensions of reference dependence:
  - Hours (loss if work more hours than $\bar{h}$)
  - Income (loss if earn less than $\bar{Y}$)
- Re-estimates Farber (2005) data for:
  - Wage above average (income likely to bind)
  - Wages below average (hours likely to bind)
- Perhaps, reconciling Camerer et al. (1997) and Farber (2005)
  - $w > w^e$: hours binding $\rightarrow$ hours explain stopping
  - $w < w^e$: income binding $\rightarrow$ income explains stopping

Crawford and Meng (2011)

Table 1: Probability of Stopping: Probit Model with Linear Effect

Variable	(1)			(2)			(3)		
	Pooled data	$w^a > w^e$	$w^a \leq w^e$	Pooled data	$w^a > w^e$	$w^a \leq w^e$	Pooled data	$w^a > w^e$	$w^a \leq w^e$
Total hours	.013	.005	.016	.010	.003	.011	.009	.002	.011
	(.009)*	(.009)	(.007)**	(.003)**	(.004)	(.008)**	(.006)*	(.005)	(.002)**
Waiting hours	.010	.007	.016	.001	.001	.002	.003	.003	.005
	(.003)**	(.007)	(.001)**	(.009)	(.012)	(.004)	(.010)	(.012)	(.003)**
Break hours	.006	.005	.004	-.003	-.006	-.003	-.002	-.004	-.002
	(.003)**	(.001)**	(.008)	(.006)	(.009)	(.004)	(.007)	(.009)	(.001)
Income/100	.053	.076	.055	.013	.045	.009	.010	.042	.002
	(.000)**	(.007)**	(.007)**	(.010)	(.019)**	(.024)	(.005)**	(.019)**	(.011)
Min temp<30	-	-	-	-	-	-	Yes	Yes	Yes
Max temp>80	-	-	-	-	-	-	Yes	Yes	Yes
Hourly rain	-	-	-	-	-	-	Yes	Yes	Yes
Daily snow	-	-	-	-	-	-	Yes	Yes	Yes
Location dummies	-	-	-	-	-	-	Yes	Yes	Yes
Driver dummies	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Day of week	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Hour of day	-	-	-	Yes	Yes	Yes	Yes	Yes	Yes
Log likelihood	-2039.2	-1148.4	-882.6	-1789.5	-1003.8	-753.4	-1767.5	-9878.0	-740.0
Pseudo R2	0.1516	0.1555	0.1533	0.2555	0.2618	0.2773	0.2647	0.2735	0.2901
Observation	13461	7936	5525	13461	7936	5525	13461	7936	5525

Farber (QJE 2015)

- Finally data set with large K and large T
  - $K = 62,000$ drivers
  - $T = 5 * 365$ (2009 to 2013)
  - 100+ million trips!
  - Electronic record of all information (except tips)
- Inexplicably, most of analysis uses discredited OLS specification
- We focus on hazard model (Table 7) as in Farber (2005)
  - P(stopping) for \$300-\$349 compared to \$200-\$224 is $0.059 - 0.015 = 0.044$ higher out of average of 0.14
  - Thus, 31% increase in stopping for a 51% increase in income –> elasticity of 0.6!
  - Within the confidence interval of Farber (2005) and clearly sizable

Farber (2015)

TABLE VII

MARGINAL EFFECTS OF INCOME AND HOURS ON PROBABILITY OF ENDING SHIFT (LINEAR PROBABILITY MODEL)

Income ($)	(1) Day shift	(2) Night shift	Hours	(3) Day shift	(4) Night shift
100–149	0.0001	−0.0045	3–5	0.0020	−0.0049
	(0.0003)	(0.0003)		(0.0004)	(0.0003)
150–199	0.0044	−0.0077	6	0.0001	0.0007
	(0.0006)	(0.0005)		(0.0007)	(0.0006)
200–224	0.0157	−0.0062	7	0.0034	0.0223
	(0.0010)	(0.0007)		(0.0011)	(0.0010)
225–249	0.0264	−0.0046	8	0.0281	0.0536
	(0.0013)	(0.0008)		(0.0017)	(0.0016)
250–274	0.0389	−0.0042	9	0.0750	0.0897
	(0.0017)	(0.0011)		(0.0025)	(0.0022)
275–299	0.0506	−0.0033	10	0.1210	0.1603
	(0.0020)	(0.0013)		(0.0035)	(0.0031)
300–349	0.0596	−0.0027	11	0.1236	0.2563
	(0.0024)	(0.0017)		(0.0050)	(0.0051)
350–399	0.0607	0.0011	12	0.1004	0.2573
	(0.0028)	(0.0024)		(0.0078)	(0.0142)
$\geq$ 400	0.0702	0.0101	$\geq$ 13	0.1093	0.2406
	(0.0034)	(0.0035)		(0.0050)	(0.0063)

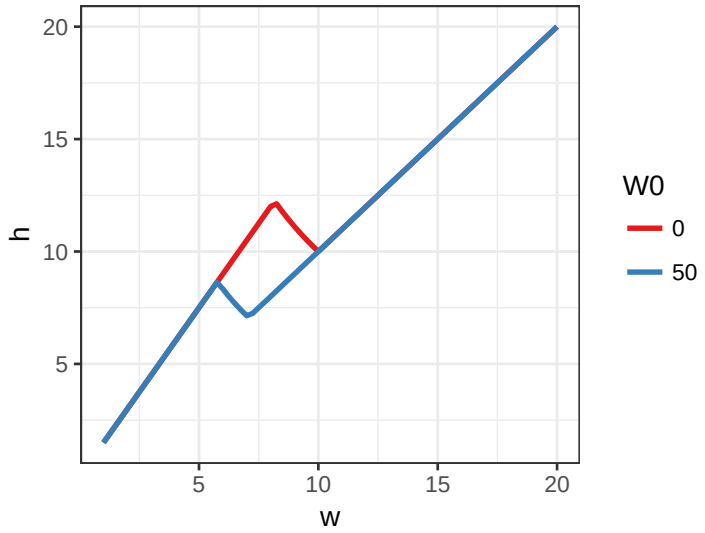
Thakral and To (2017)

- Uses same data as Farber (2015) – in fact, uses replication data set, also same data as Haggag and Paci (*AEJ*)
- Re-estimates hazard model as in Farber (2005)
- Estimate separately the impact of earnings early, versus late, in spell
- Model:
  - allow for extra earnings W_0
    - extra earning are partially integrated in reference point
  - Utility function $U(h; T, \eta, \lambda, \theta, w, w_0)$is now

$$\begin{array}{lll} W_0 + wh - \frac{\theta h^2}{2} + \eta\left(wh + W_0 - (T + \alpha W_0)\right) & \text{if} & wh + W_0 \geq T + \alpha \\ W_0 + wh - \frac{\theta h^2}{2} + \eta\lambda\left(wh + W_0 - (T + \alpha W_0)\right) & \text{if} & wh + W_0 < T + \alpha \end{array}$$

Thakral and To (2017)

- Special case 1: Reference point fully reflects extra earnings ($\alpha = 1$):
  - W_0 cancels out from expression above –> no effect
  - Intuition: extra income already expected, no impact on gain/loss
- Special case 2: Reference point not affected by extra earnings ($\alpha = 0$):
  - In this case can rewrite solution above replace T with $T - W_0$



Thakral and To (2017)

Table 3: Stopping model estimates: Income effect at 8.5 hours—Subsamples

	(1) Night weekday	(2) Medallion owners	(3) Top decile experience
Panel A			
Income effect	0.3564	0.5421	0.4625
	(0.0473)	(0.1548)	(0.0805)
Panel B			
Income in hour 2	0.0725	-0.1175	-0.0130
	(0.0742)	(0.2351)	(0.1236)
Income in hour 4	0.0077	0.0282	0.3062
	(0.0717)	(0.2269)	(0.1284)
Income in hour 6	0.2645	0.2363	0.3309
	(0.0732)	(0.2389)	(0.1267)
Income in hour 8	0.3270	0.5714	0.5580
	(0.0752)	(0.2246)	(0.1335)

- Estimates in Panel B are
  - increases in pp in P(stop) for \$10 $\triangle Y$ in that hour, equal to 5% higher income overall
  - Mean stopping probability is 13.6%
- \$10 $\triangle Y$ in hour 2 –> $\triangle P(stop) = 0.07\%$ –> $\eta_{Stop,Y} = 0.1$
- \$10 $\triangle Y$ in hour 8 –> $\triangle P(stop) = 0.32\%$ –> $\eta_{Stop,Y} = 0.46$

Thakral and To (2017)

- Findings provide evidence on speed of formation of reference point:
- Income earned early during the day is already incorporated into reference point T –> Does not impact stopping
  - Income earned late in the shift not incorporated –> Affect stopping
- Provides evidence of backward looking reference points
- Can also be interpreted as forward-looking (KR) delayed expectations

Section 4

Reference Dependence: Employment and Effort

Mas (2006): Police Performance

- More on labor markets: Do reference points affect performance?

- **Mas (QJE 2006)** examines police performance
- Exploits quasi-random variation in pay due to arbitration
- Background
  - 60 days for negotiation of police contract $\rightarrow$ If undecided, arbitration
  - 9 percent of police labor contracts decided with final offer arbitration

Framework

- pay is $w \cdot (1 + r)$
- union proposes r_u, employer proposes r_e, arbitrator prefers r_a
- arbitrator chooses r_e if $|r_e - r_a| \leq |r_u - r_a|$
- $P(r_e, r_u)$ is probability that arbitrator chooses r_e
- Distribution of r_a is common knowledge (cdf F)
- Assume $r_e \leq r_a \leq r_u \rightarrow$ Then

$$P = P(r_a - r_e \leq r_u - r_a) = P(r_a \leq (r_u + r_e)/2) = F(\frac{r_u + r_e}{2})$$

Nash Equilibrium

If r_a is certain, Hotelling game: convergence of r_e and r_u to r_a

- Employer's problem:

$$\max_{r_e} PU\left(w\left(1+r_e\right)\right)+\left(1-P\right)U\left(w\left(1+r_u^*\right)\right)$$

  - Notice: $U' < 0$

- First order condition (assume $r_u \geq r_e$):

$$\frac{P'}{2}\left[U\left(w\left(1+r_e^*\right)\right)-U\left(w\left(1+r_u^*\right)\right)\right]+PU'\left(w\left(1+r_e^*\right)\right)w=0$$

- $r_e^* = r_u^*$ cannot be solution $\rightarrow$ Lower r_e and increase utility ($U' < 0$)

Union's problem

- Maximize:

$$\max_{r_u} PV\left(w\left(1+r_e^*\right)\right)+\left(1-P\right)V\left(w\left(1+r_u\right)\right)$$

  - Notice: $V' > 0$
- First order condition for union:

$$\frac{P'}{2}\left[V\left(w\left(1+r_e^*\right)\right)-V\left(w\left(1+r_u^*\right)\right)\right]+\left(1-P\right)V'\left(w\left(1+r_u^*\right)\right)w=0$$

- To simplify, assume $U(x) = -bx$ and $V(x) = bx$
- This implies $V\left(w\left(1+r_e^*\right)\right)-V\left(w\left(1+r_u^*\right)\right) = -U\left(w\left(1+r_e^*\right)\right)-U\left(w\left(1+r_u^*\right)\right)$, so

$$-bP^*w=-\left(1-P^*\right)bw$$

- Result: $P^* = 1/2$

Prediction

- Prediction (i) in Mas (2006): "*If disputing parties are equally risk-averse, the winner in arbitration is determined by a coin toss.*"
- Therefore, as-if random assignment of winner
- Use to study impact of pay on police effort
- Data:
  - 383 arbitration cases in New Jersey, 1978-1995
  - Observe offers submitted r_e, r_u, and ruling $\bar{r}_a$
  - Match to UCR crime clearance data (=number of crimes solved by arrest)

Summary Statistics

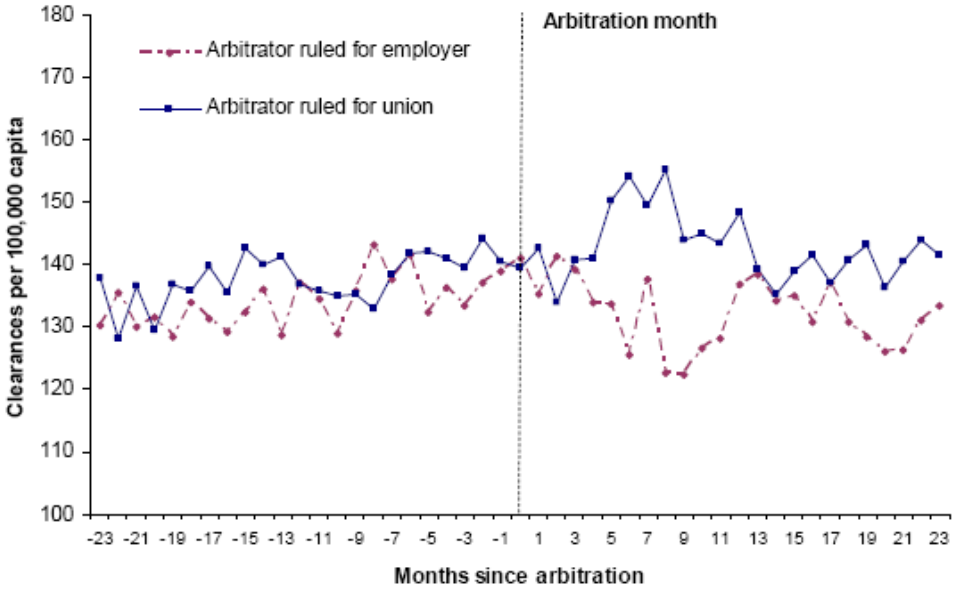
- Compare summary statistics of cases when employer and when police wins
- Estimated $\hat{P} = .344 \neq 1/2 \rightarrow$ Unions more risk-averse than employers
- No systematic difference between Union and Employer cases except for r_e

Table I
Sample characteristics in the -12 to +12 month event time window

	(1) Full-sample	(2) Pre-arbitration: Employer wins	(3) Pre-arbitration: Employer loses	(4) Pre-arbitration: Employer win-Employer loss
Arbitrator rules for employer	0.344			
Final Offer: Employer	6.11	6.44	5.94	0.50
	[1.65]	[1.54]	[1.68]	(0.18)
Final Offer: Union	7.65	7.87	7.54	0.32
	[1.71]	[2.03]	[1.51]	(0.18)
Population	21,345	22,893	20,534	2,358
	[33,463]	[34,561]	[32,915]	(3,598)
Contract length	2.09	2.09	2.09	0.007
	[0.66]	[0.64]	[0.66]	(0.071)
Size of bargaining unit	42.58	41.36	43.22	-1.86
	[97.34]	[53.33]	[113.84]	(15.66)
Arbitration year	85.56	85.85	85.41	0.436
	[4.75]	[5.10]	[4.56]	(0.510)
Clearances per 100,000 capita	120.31	122.28	118.57	3.71
	[106.65]	[108.76]	[104.35]	(9.46)

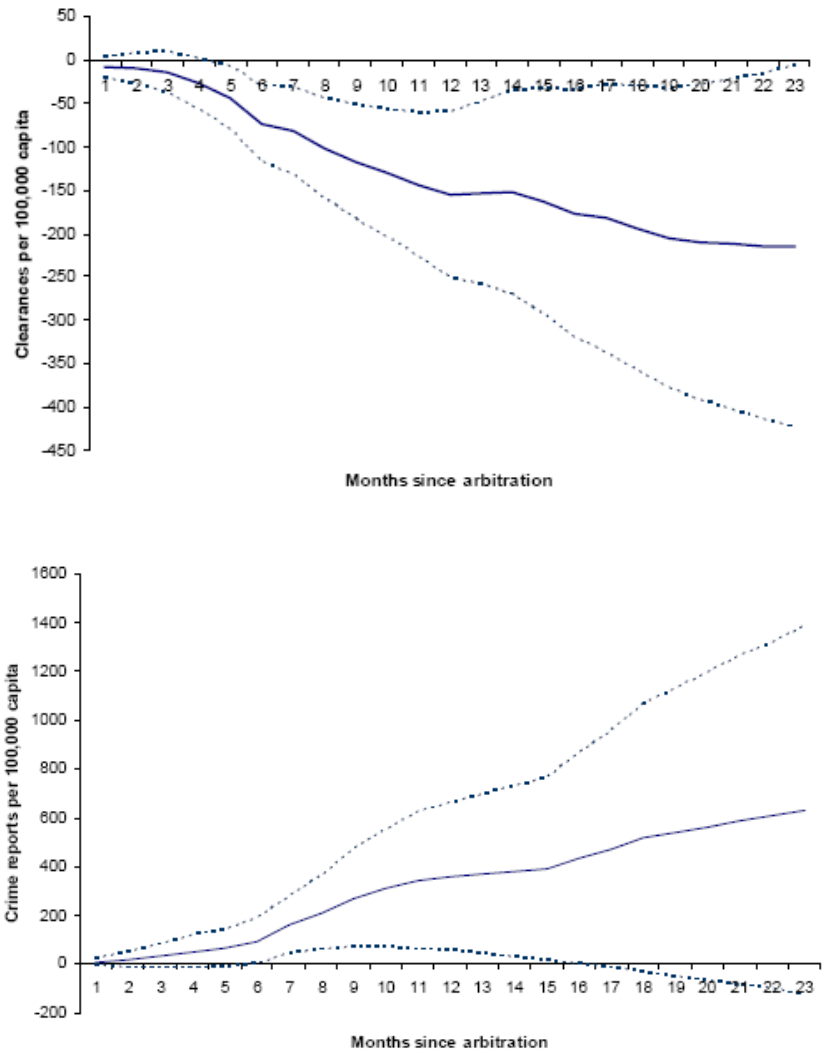
Effects on Performance

- Graphical evidence of effect of ruling on crime clearance rate



- Significant effect on clearance rate for one year after ruling
- Estimate of the cumulated difference between Employer and Union cities on clearance rates and crime

Effects on Performance



Effects on Performance

- Unoin win –> 15 more clearances out of 100,000 each month

Table II
Event study estimates of the effect of arbitration rulings on clearances; -12 to +12 month event time window

	All clearances			Violent crime clearances			Property crime clearances		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	118.57	141.25		63.16	75.10		55.42	66.15	
	(5.12)	(9.94)		(3.13)	(6.86)		(2.88)	(4.55)	
Post-arbitration	-6.79	-8.48	-9.75	-2.54	-3.10	-3.77	-4.26	-5.39	-4.45
× Employer win	(2.62)	(2.20)	(2.70)	(1.75)	(1.35)	(1.78)	(1.62)	(2.25)	(1.87)
Post-arbitration	4.99	7.92	5.96	4.17	5.62	5.31	0.819	2.31	2.19
× Union win	(2.09)	(2.91)	(2.65)	(1.53)	(1.95)	(1.42)	(1.24)	(1.58)	(1.37)
Row 3 – Row 2	11.78	16.40	15.71	6.71	8.71	9.08	5.08	7.69	6.40
	(3.35)	(3.65)	(3.75)	(2.32)	(2.37)	(2.26)	(2.04)	(2.75)	(2.30)
Employer Win	3.71	-2.81		2.14	-5.73		1.57	2.92	
(Yes = 1)	(9.46)	(14.92)		(6.11)	(9.53)		(4.93)	(7.51)	
Fixed-effects?			Yes			Yes			Yes
Weighted sample?		Yes	Yes		Yes	Yes		Yes	Yes
Augmented sample?			Yes			Yes			Yes
Mean of the	120.31	120.31	130.82	64.79	64.79	72.15	55.51	55.51	58.63
Dependent variable	[106.65]	[106.65]	[370.58]	[71.28]	[71.28]	[294.78]	[58.72]	[58.72]	[180.55]
Sample Size	9,538	9,538	59,137	9,538	9,538	59,135	9,538	9,538	59,136
R^2	0.0008	0.005	0.63	0.0007	0.0078	0.59	0.001	0.0015	0.55

Do reference points matter?

- Plot impact on clearances rates (12,-12) as a function of $\bar{r}_a - (r_e + r_u)/2$

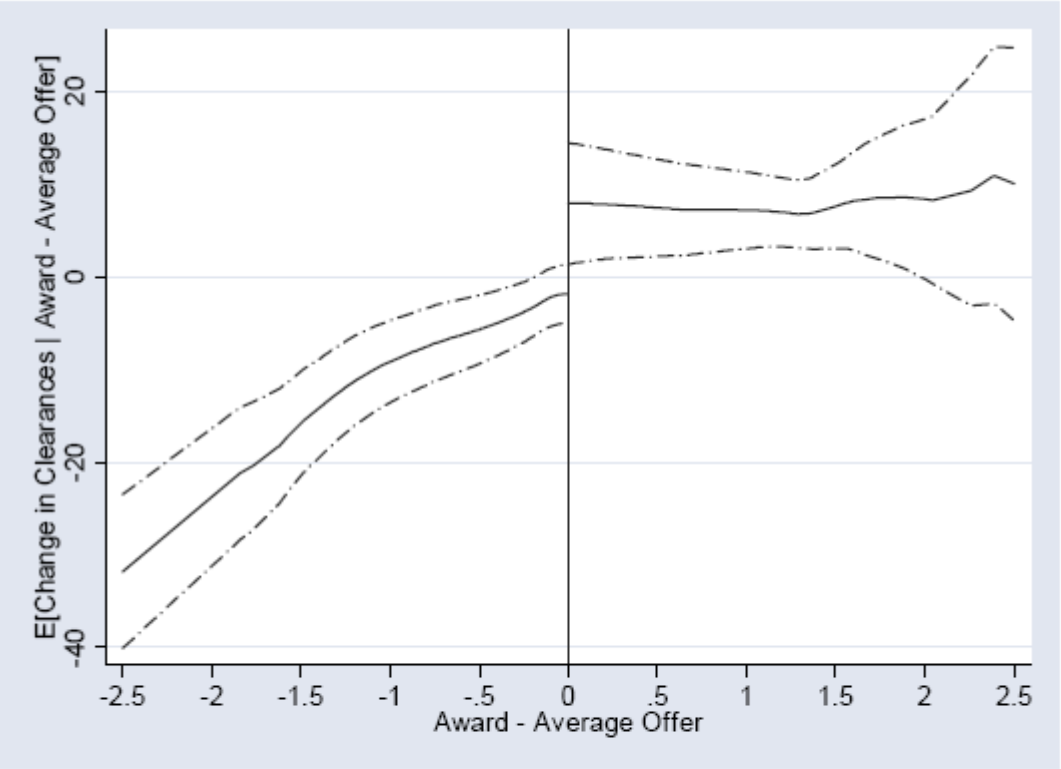


Figure V
Estimated expected change in clearances conditional on the deviation of the award from the average of the offers

Effect of loss is larger than effect of gain

Table VII
Heterogeneous effects of arbitration decisions on clearances by loss size, award, and deviation from the expected offer; -12 to +12 month event time window

	(1)	(2)	(3)	(4)	(5) Police lose	(6) Police win
Post-Arbitration	5.72	-8.17	12.99	-7.42	4.97	7.30
	(2.31)	(9.58)	(8.45)	(4.76)	(3.14)	(4.17)
Post-Arbitration × Award		1.23	-1.00			
		(1.16)	(0.98)			
Post-Arbitration × Loss size	-10.31		-10.93		-0.20	
	(1.59)		(1.89)		(4.54)	
Post-Arbitration × Union win				13.38		
				(5.32)		
Post-Arbitration × (expected award-award)					-17.72	2.82
					(7.94)	(4.13)
Post-Arbitration × p(loss size)^				Included		
Sample Size	59,137	59,137	59,137	59,137	52,857	55,879
R^2	0.63	0.63	0.63	0.63	0.60	0.62

Standard errors, clustered on the intersection of arbitration window and city, are in parentheses. Standard deviations are in brackets. Observations are municipality × month cells. The sample is weighted by population size in 1976. The dependant variable is clearances per 100,000 capita. Loss size is defined as the union demand (percent increase on previous wage) less the arbitrator award. Amongst cities that underwent arbitration, the mean loss size is 0.489 with a standard deviation of 0.953. The expected award is the mathematical expectation of the award given the union and employer offers and the predicted probability of an employer win. The predicted probability of an employer win is estimated with a probit model using as predictors year of arbitration dummies, the average of the final offers, log population, and the length of the contract. See text for details. The samples in models (1)-(4) consist of the 12 months before to the 12 months after arbitration, for jurisdictions that underwent arbitration, as well as all jurisdictions that never underwent arbitration for all months between 1976 and 1996. The sample in model (5) consists of cities where the union lost in arbitration and the comparison group of non-arbitrating cities. The sample in model (6) consists of cities where the union won in arbitration and the comparison group of non-arbitrating cities. All models include month × year effects (252), arbitration window effects (383), and city effects (452). Author's calculation based on NJ PERC arbitration cases matched to monthly municipal clearance rates at the jurisdiction level from FBI Uniform Crime Reports.

Reference Dependence Model

- Column (3): Effect of a gain relative to $(r_e + r_u)/2$ is not significant; effect of a loss is
- Columns (5) and (6): Predict expected award $\hat{r}_a$ using covariates, then compute $\bar{r}_a - \hat{r}_a$
  - $\bar{r}_a - \hat{r}_a$ does not matter if union wins
  - $\bar{r}_a - \hat{r}_a$ matters a lot if union loses
- Assume policeman maximizes

$$\max_e \left[\bar{U} + U(w)\right] e - \theta \frac{e^2}{2}$$

where

$$U(w) = \begin{cases} w + \eta(w - \hat{w}) & \text{if} \quad w \geq \hat{w} \\ w + \eta\lambda(w - \hat{w}) & \text{if} \quad w < \hat{w} \end{cases}$$

Reference Dependence Model

- Reduced form of reciprocity model where altruism towards the city is a function of how nice the city was to the policemen $(\bar{U} + U(w))$
- F.o.c.:

$$\bar{U} + U(w) - \theta e = 0$$

Then

$$e^*(w) = \frac{\bar{U}}{\theta} + \frac{1}{\theta} U(w)$$

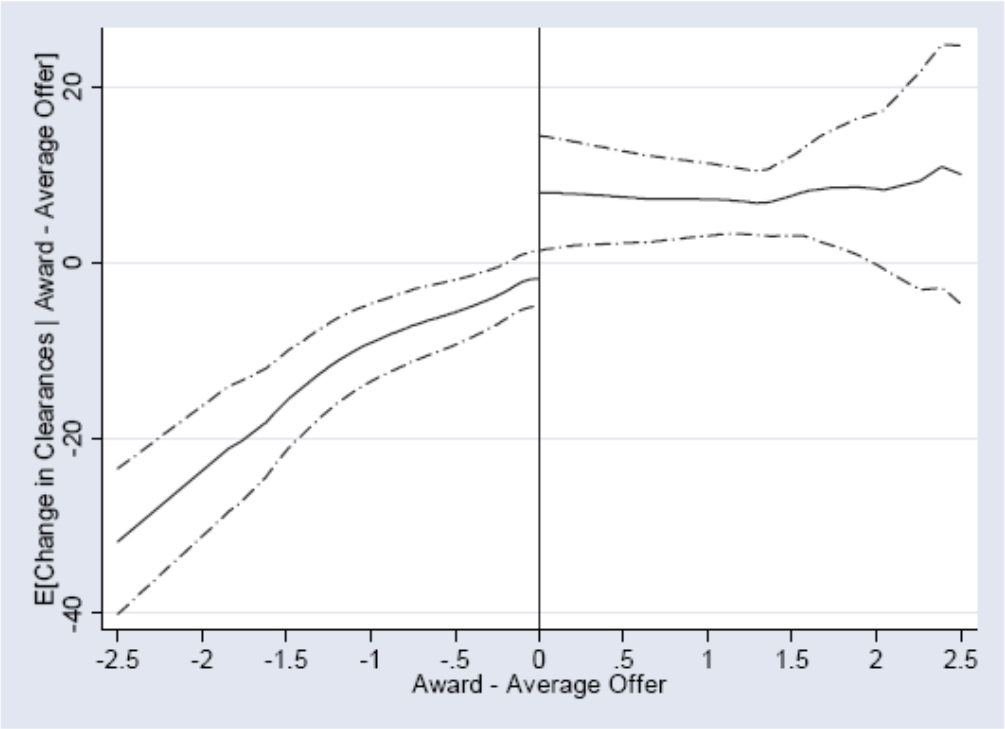
- It implies that we would estimate

$$Clearances = \alpha + \beta(\bar{r}_a - \hat{r}_a) + \gamma(\bar{r}_a - \hat{r}_a) 1(\bar{r}_a - \hat{r}_a < 0) + \varepsilon$$

with $\beta > 0$ (also *in* standard model) and $\gamma > 0$ (not in standard model)

Results

- Compare to observed pattern



- Close to predictions of model

Section 5

Reference Dependence: Golf

Pope and Schweitzer (AER 2011)

- Last example applying the effort framework: golf
- To win golf tournament, only thing that matters is total sum of strokes
- Yet, each hole has a "suggested" number of strokes ("par value")
- That works as a reference point
- **Pope and Schweitzer (AER 2011)**

Is Tiger Woods Loss Averse (Pope & Schweitzer, AER, 2011)

Golf

Start at the tee, end by putting on the green

Total # of strokes determines the winner

Par values of 3, 4, or 5

Eagle, birdie, par, bogey, and double bogey

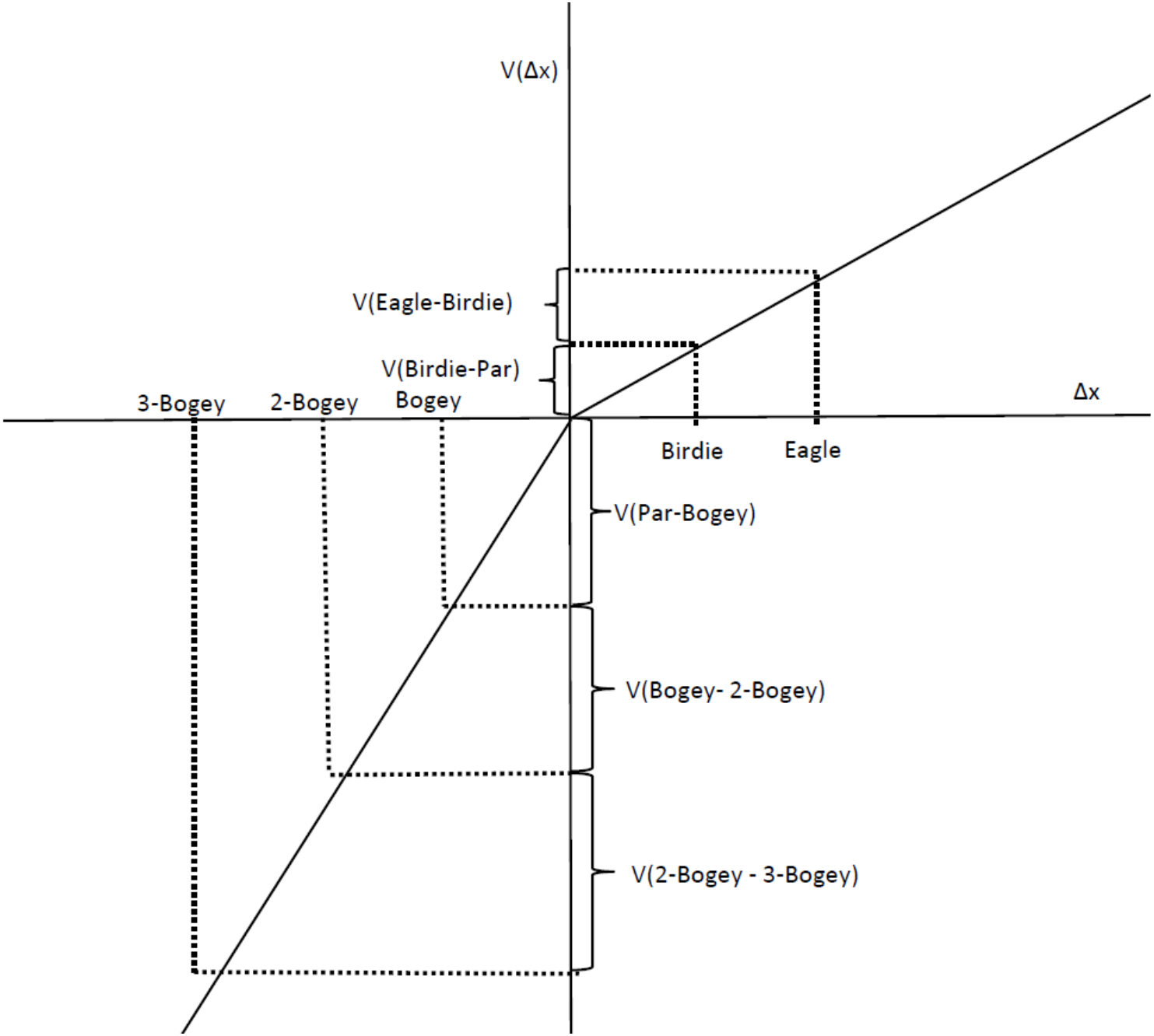
PGA TOUR

40-50 tournaments per/year

~150 golfers per tournament

4 rounds of 18 holes

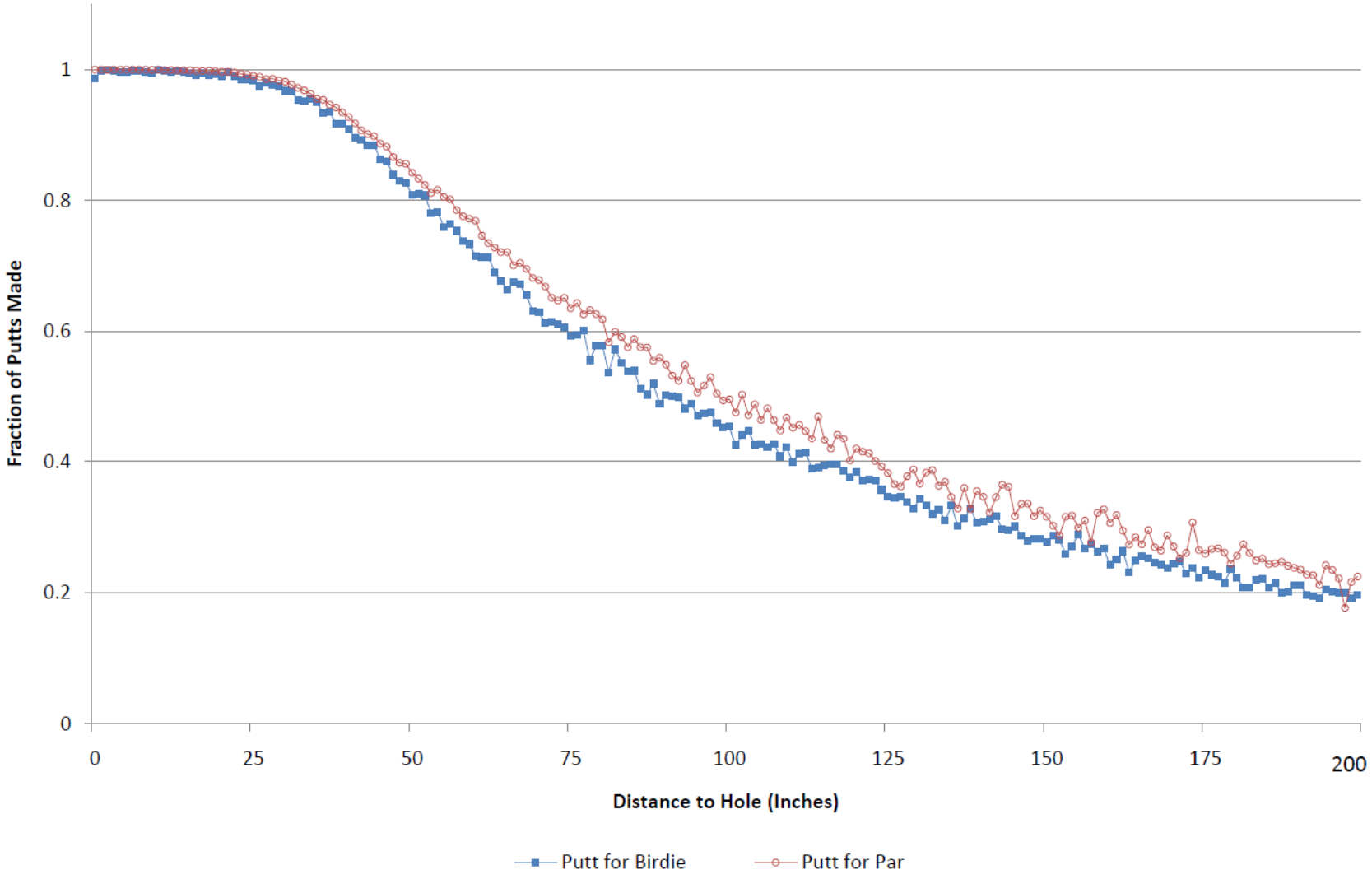
~$5M total purse – very convex


V(Δx)
V(Eagle-Birdie)
V(Birdie-Par)
3-Bogey
2-Bogey
Bogey
Δx
Birdie
Eagle
V(Par-Bogey)
V(Bogey- 2-Bogey)
V(2-Bogey - 3-Bogey)

Data

- PGA Tour ShotLinks data from 2004 to 2009
- 239 Tournaments, 421 golfers (with more than 1,000 putts each), ~2.5 million putts
- X, y, and z coordinates for every ball placement within a centimeter on the green
- Focus on putts attempted for eagle, birdie, par, bogey, or double bogey

"A 10-footer for par feels more important than one for birdie. The reality is, that's ridiculous. I can't explain it in any way other than that it's subconscious. And pars are O.K. – Bogeys aren't." **- Paul Goydos**


Fraction of Putts Made
1
0.8
0.6
0.4
0.2
0
0
25
50
75
100
125
150
175
200
Distance to Hole (Inches)
Putt for Birdie
Putt for Par

	Dependent Variable Equals 1 if Putt was Made Logit Estimation	
	(1)	(2)
Putt for Birdie or Eagle	-.020**	
	(.001)	
Putt for Eagle		-.024**
		(.002)
Putt for Birdie		**-.019****
		(.001)
Putt for Bogey		.009**
		(.001)
Putt for Double Bogey		-.006**
		(.002)
Putt Distance: 7th-Order Polynomial	X	X
Psuedo R-Squared	0.550	0.550
Observations	2,525,161	2,525,161

Section 6

Reference Dependence: Job Search

DellaVigna, Lindner, Reizer, Schmieder (QJE 2017)

- Job Search in Hungary
- Example where identification is not from comparing gains from losses
- Identification comes from
  - how much at a loss relative to reference point
  - reference point adapts over time
  - aim to identify reference point adaptation

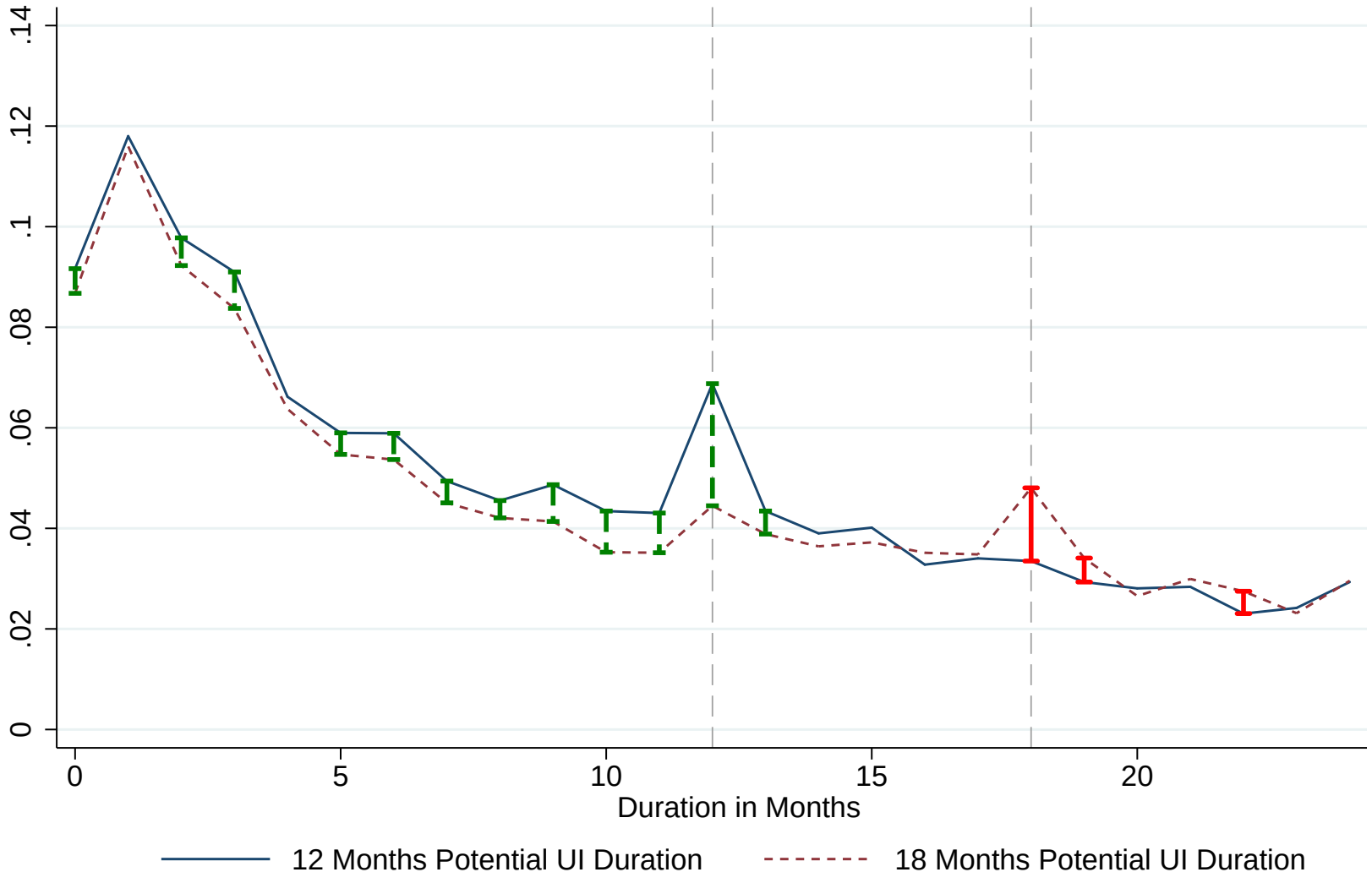
Introduction

- Large literature on understanding path of hazard rate from unemployment with different models.
- **Typical finding**: There is a **spike** in the hazard rate at the **exhaustion point** of unemployment benefits.

$\Rightarrow$ Such a spike is **not easily explained** in the standard (McCall / Mortensen) model of job search.

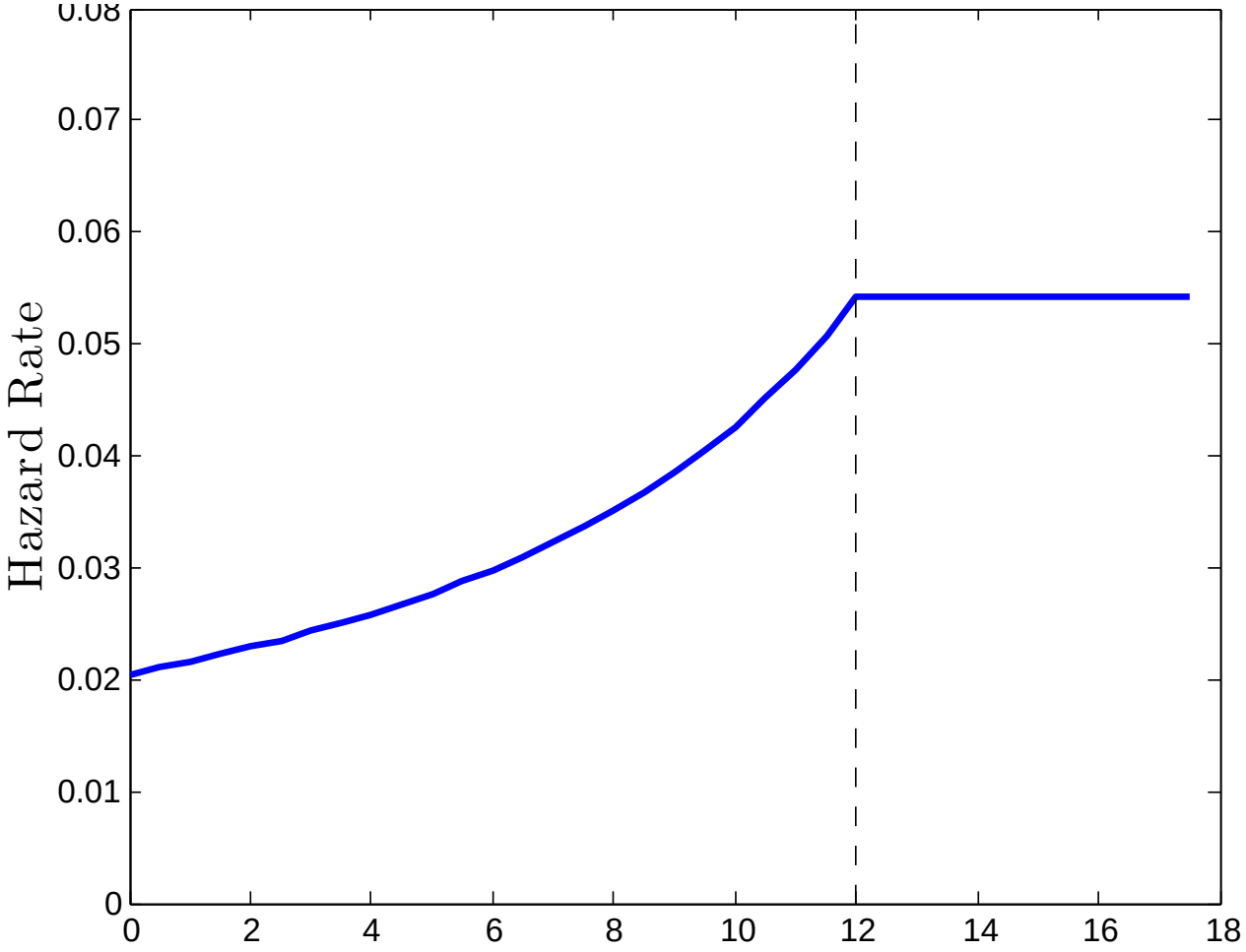
$\Rightarrow$ To explain this path, one needs unobserved heterogeneity of a special kind, and/or storeable offers

Germany - Spike in Exit Hazard



Source: Schmieder, von Wachter, Bender (2012)

Simulation of Standard model



Predicted path of the hazard rate for a standard model with expiration of benefit at period 25

Model - Set-up

- We integrate **reference dependence** into standard McCall / Mortensen **discrete time** model of job search
- Job Search:
  - Search intensity comes at per-period **cost** of $c(s_t)$, which is **increasing** and **convex**
  - With probability s_t, a job is found with salary w
  - Once an individual finds a job the job is kept forever
- Optimal consumption-savings choice
  - Individuals choose optimal consumption c_t (hand-to-mouth $c_t = y_t$ as special case)
- Individuals are **forward looking** and have rational expectations

Utility Function

- Utility function $v(c)$
- **Flow utility** $u_t(c_t|r_t)$ depends on **reference point** r_t:

$$u_t(c_t|r_t) = \begin{cases} v(c_t) + \eta(v(c_t) - v(r_t)) & \text{if} \quad c_t \geq r_t \\ v(c_t) + \eta\lambda(v(c_t) - v(r_t)) & \text{if} \quad c_t < r_t \end{cases}$$

  - η is weight on **gain-loss utility**
  - λ indicates **loss aversion**
  - Standard model is **nested** for $\eta = 0$
- Builds on Kahneman and Tversky (1979) and Kőszegi and Rabin (2006)
  - Note: No probability weighting or diminishing sensitivity

Reference Point

- Unlike in Kőszegi and Rabin (2006), but like in Bowman, Minehart, and Rabin (1999), **reference point is backward-looking**
- The reference point in period t is the **average income** earned over the N periods **preceding period** t and **the period t income:**

$$r_t = \frac{1}{N+1} \sum_{k=t-N}^{t} y_k$$

Key Equations

- An **unemployed** worker's value function is

$$V_t^U(A_t) = \max_{s_t \in [0,1]; A_{t+1}} u\left(c_t | r_t\right) - c\left(s_t\right) + \delta\left[s_t V_{t+1}^E(A_{t+1}) + \left(1 - s_t\right) V_{t+1}^U(A_{t+1})\right]$$

- Value function when **employed**:

$$V_{t+1}^E(A_{t+1}) = \max_{c_{t+1}} u\left(c_{t+1} | r_{t+1}\right) + \delta V_{t+2}^E(A_{t+2}).$$

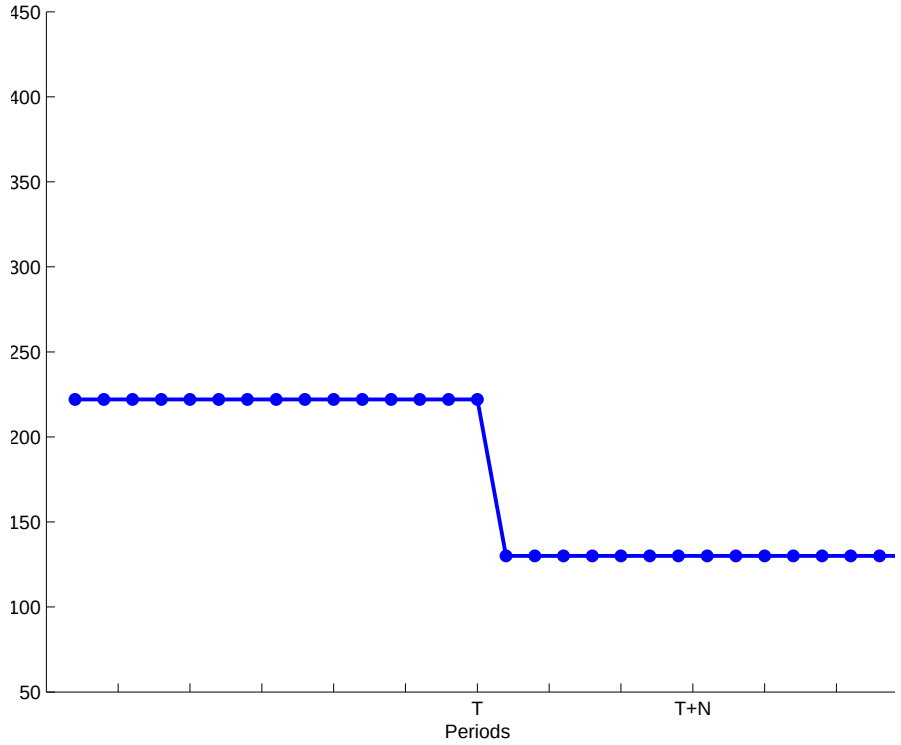
- Solution for **optimal search**:

$$c'\left(s_t^*\right) = \delta\left[V_{t+1}^E\left(A_{t+1}\right) - V_{t+1}^U\left(A_{t+1}\right)\right]$$

- Solve for s_t^* and c_t^* using backward induction

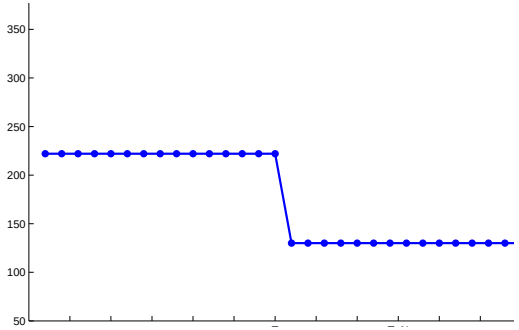
How does the model work?

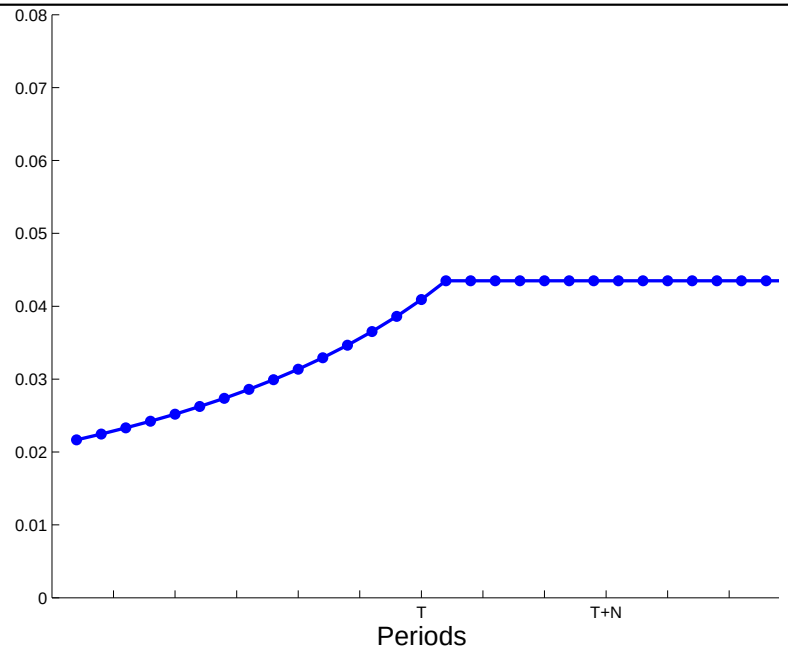
- Consider a **step-wise** benefit schedule



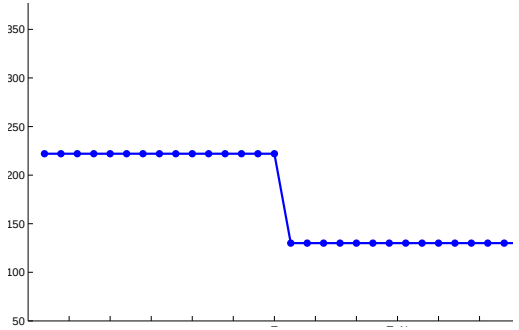
- What are the **predictions** of the **standard** vs. **reference-depedent** model **without heterogeneity**?

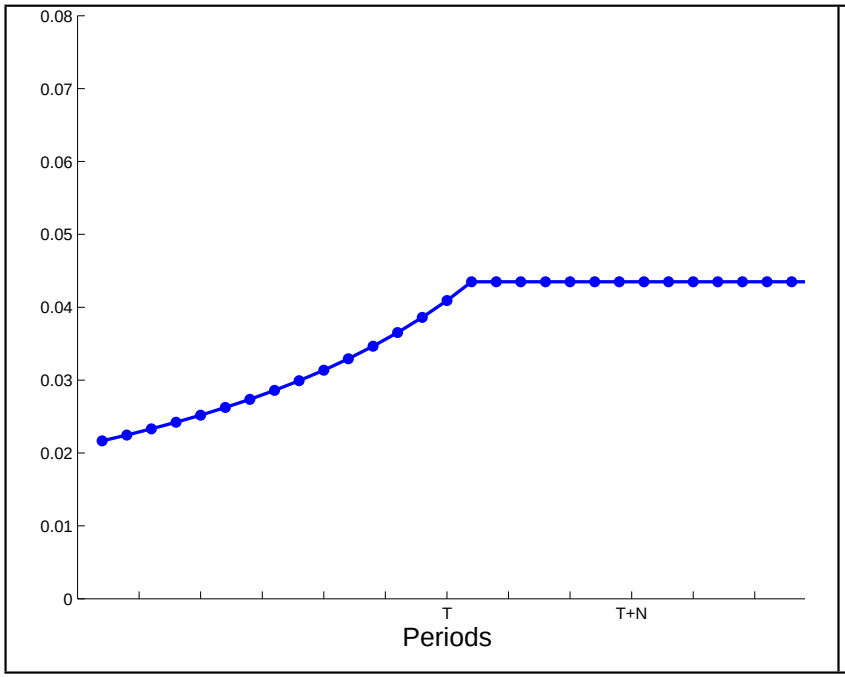
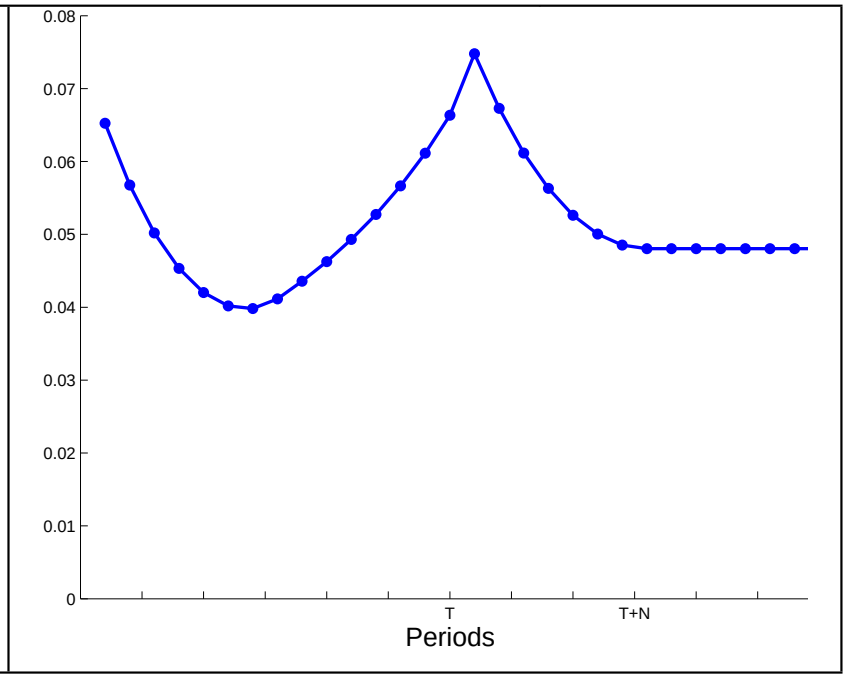
Example: Hazards under Two Models



Hazard Rate, Standard Model	Hazard Rate, Ref.-Dep. Model
	

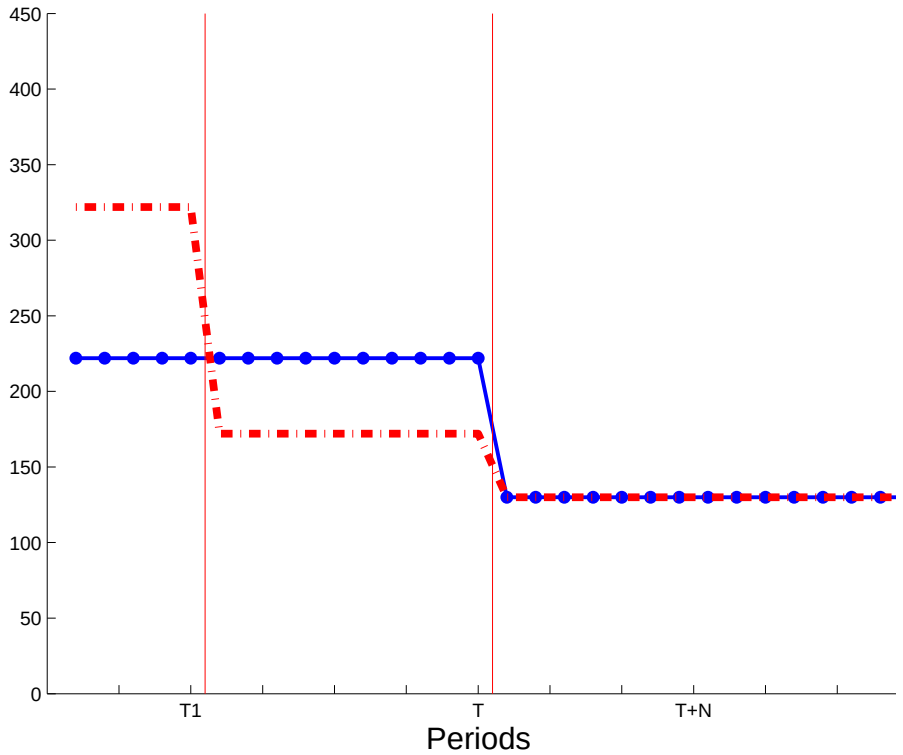
Example: Hazards under Two Models



Hazard Rate, Standard Model	Hazard Rate, Ref.-Dep. Model
	

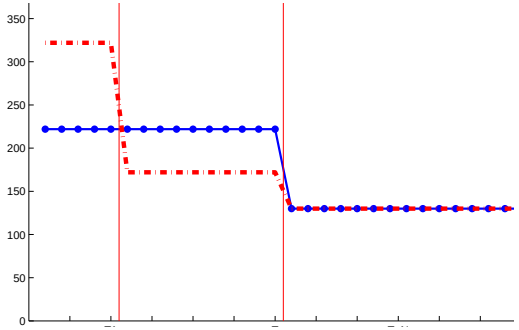
Example: Hazards under Two Models

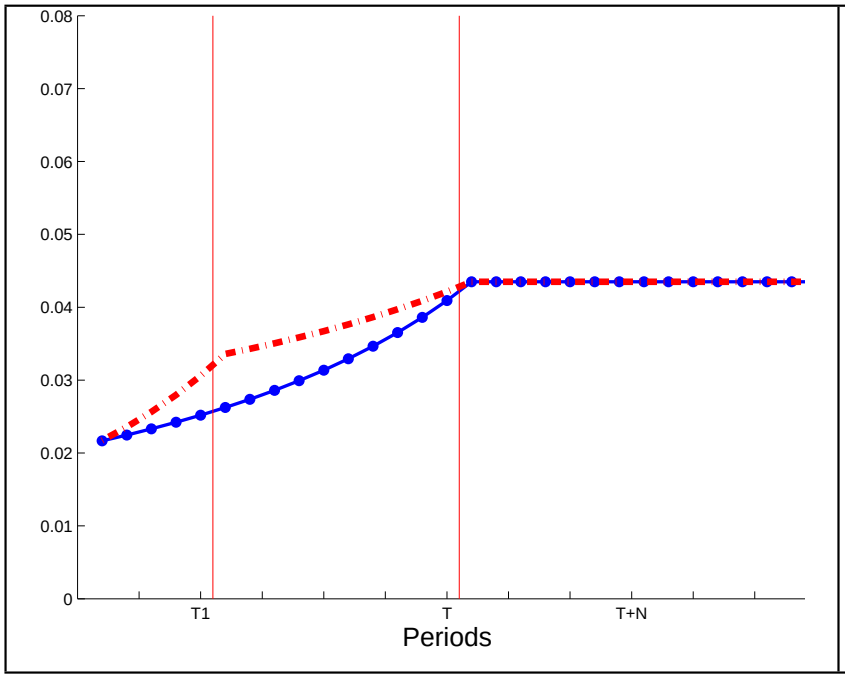
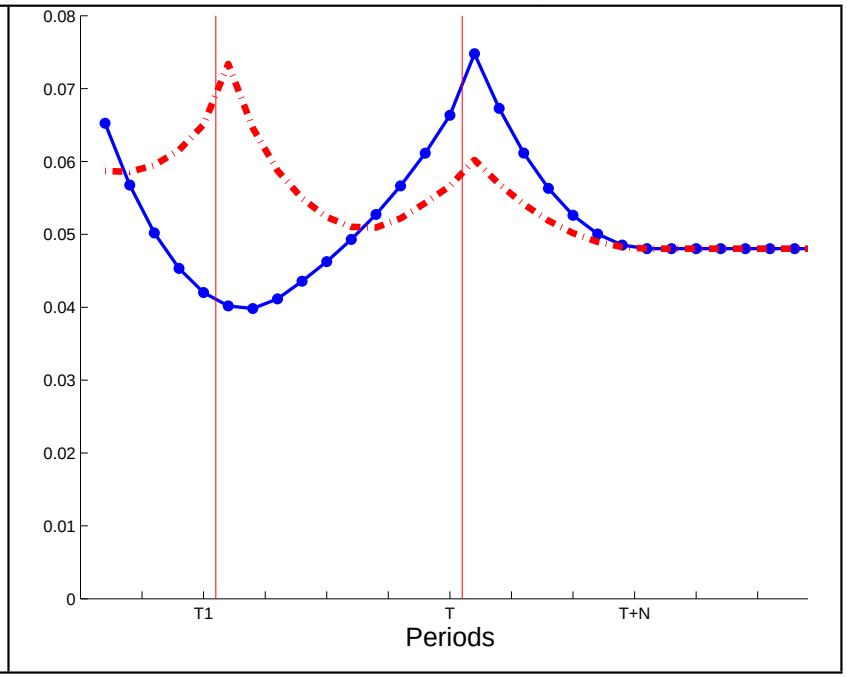
- Consider the introduction of an additional step-down after T_1 periods, such that total benefits paid until T are identical:



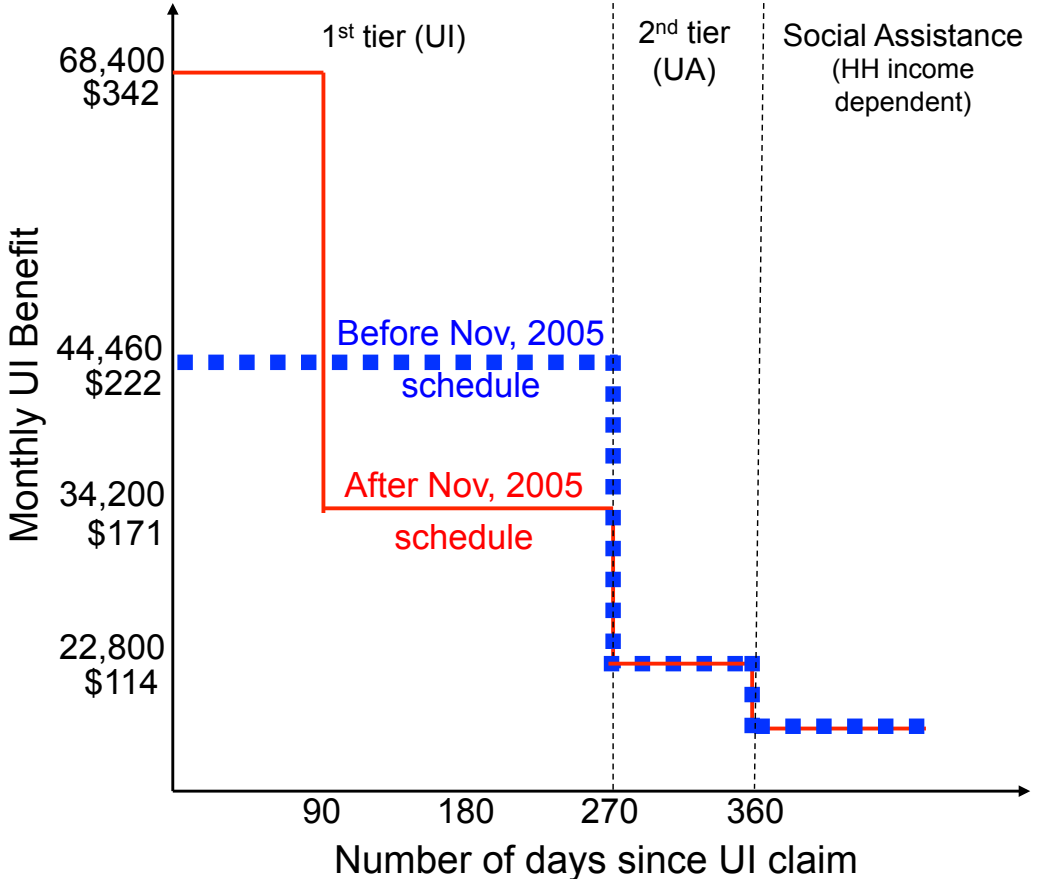
- What are the predictions of the standard vs. ref.-dep. model?

Example: Hazards under Two Models



Hazard Rate, Standard Model	Hazard Rate, Ref.-Dep. Model
	

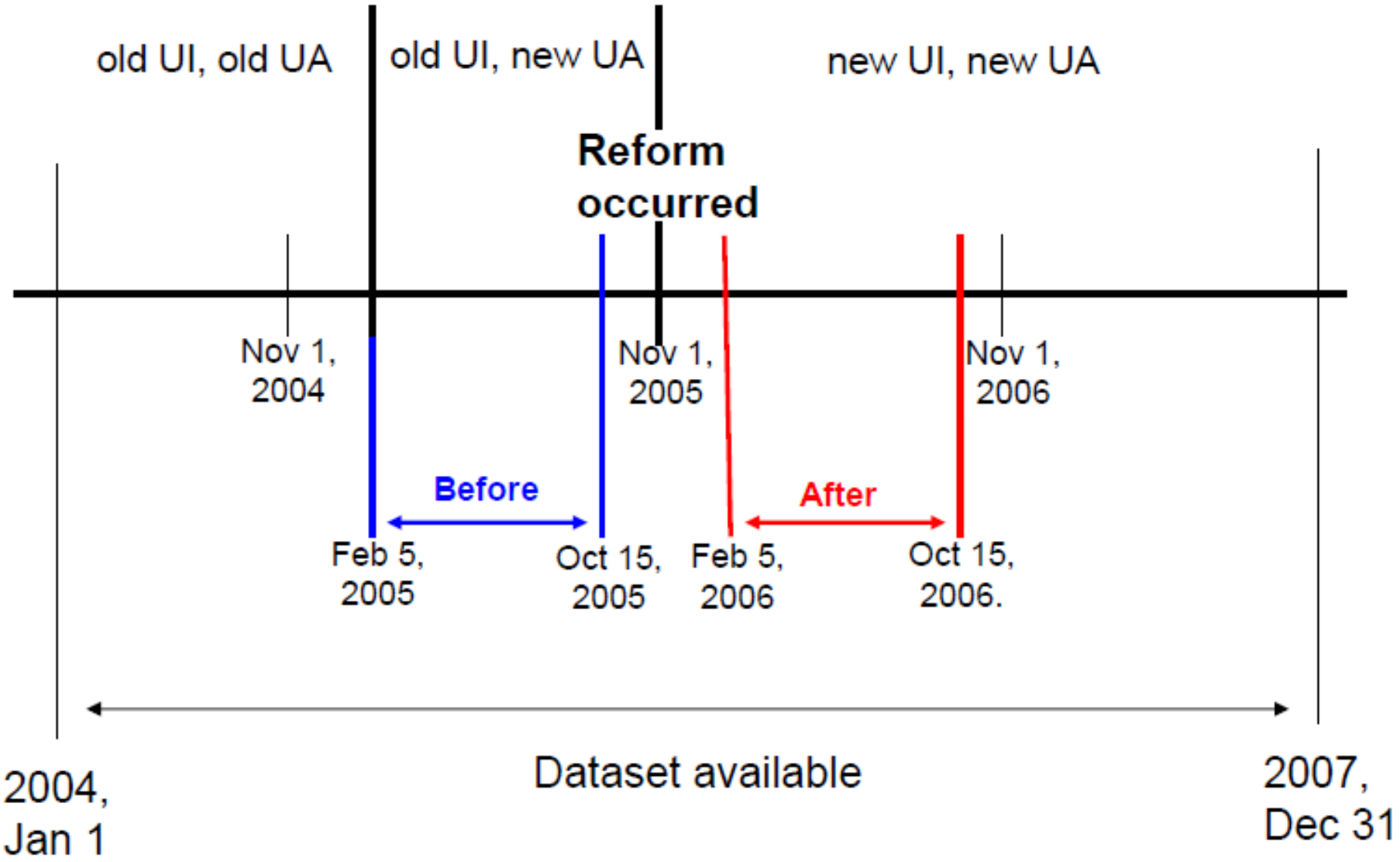
Benefit schedule before and after the reform



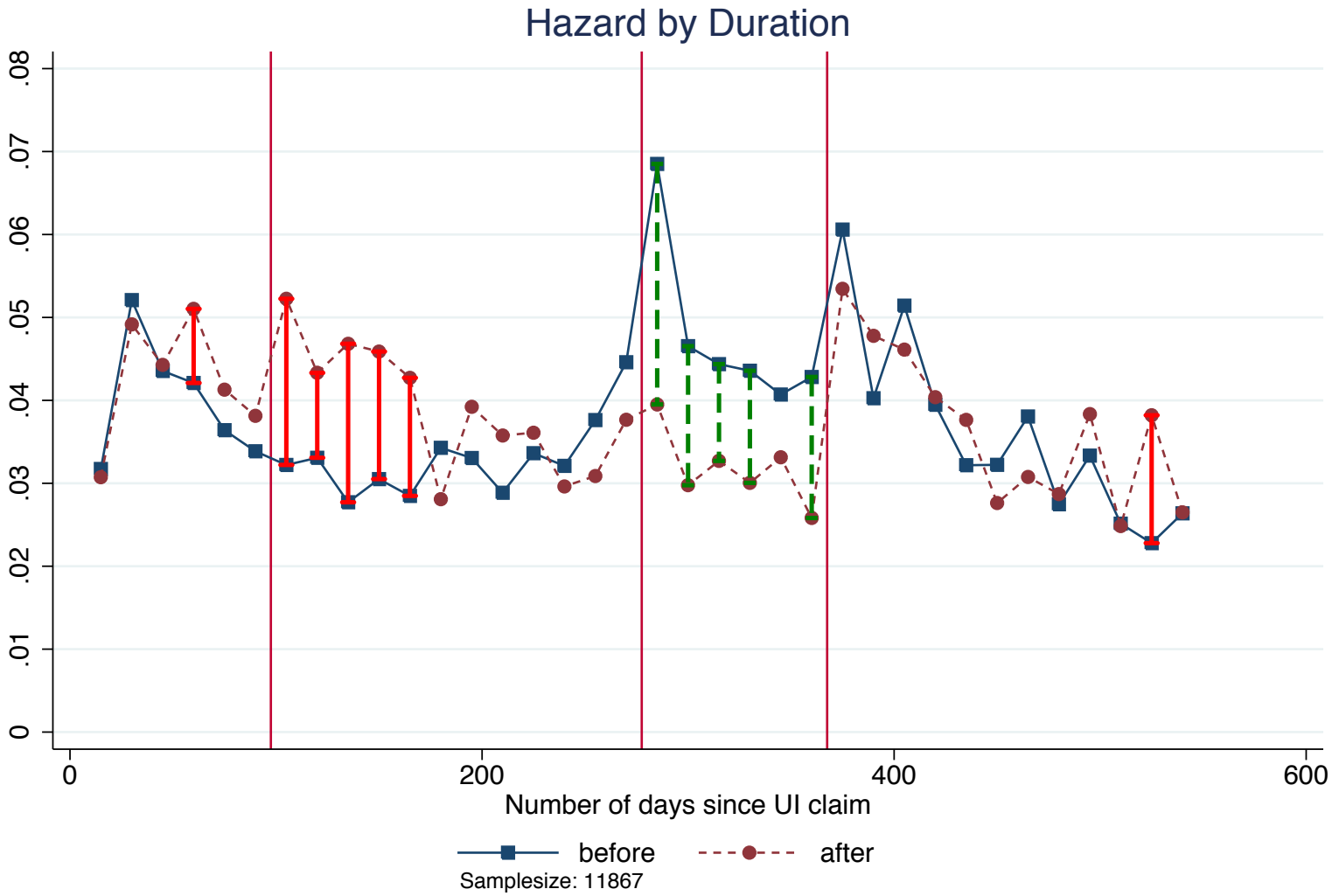
Note: Eligible for 270 days in the first tier, base salary is higher than 114,000HUF ($570), younger than 50.

→ Benefit-Schedule Macro Context Institutional Context

Define before and after

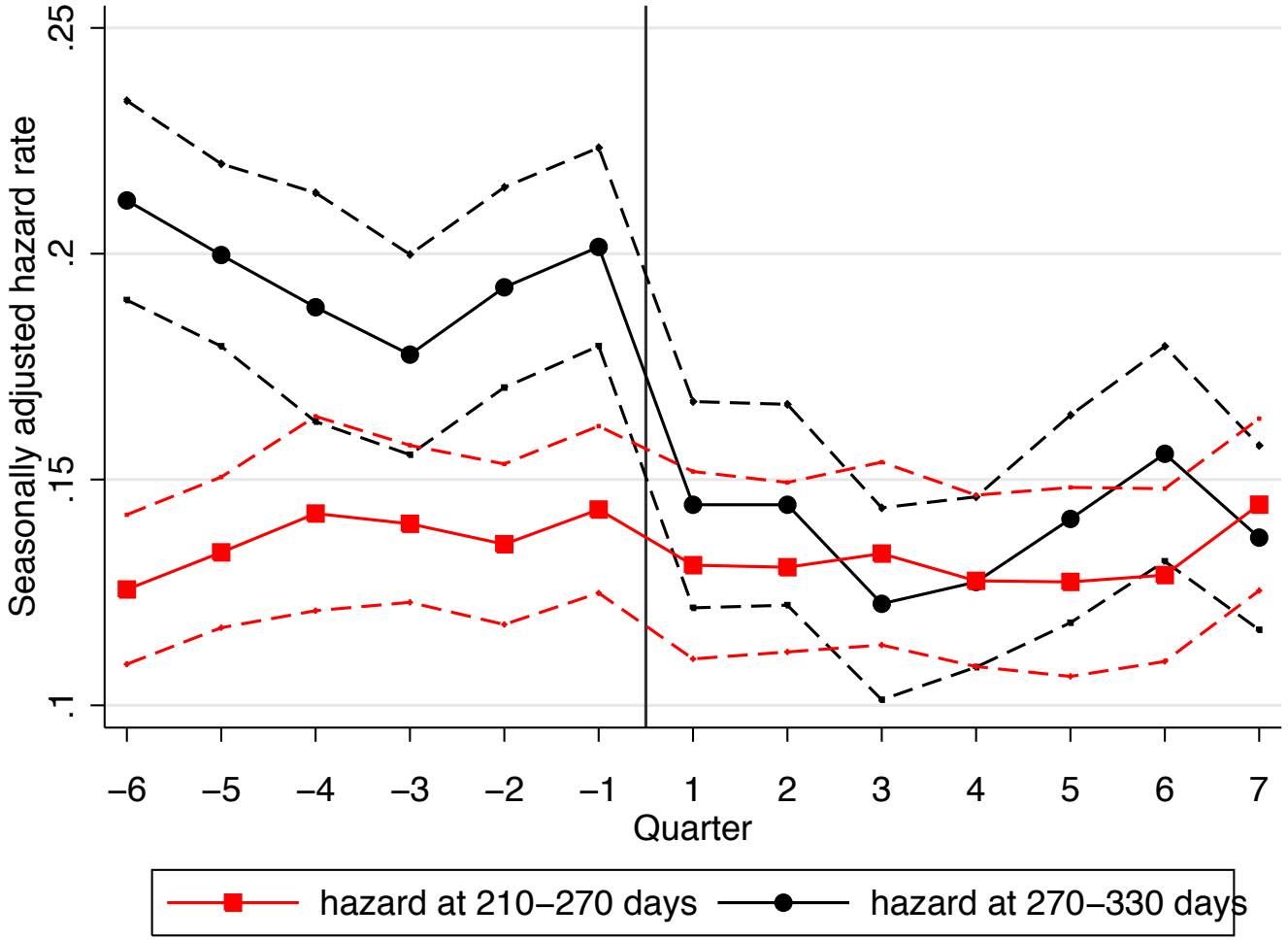


Hazard rates before and after



Survival Rate | Reemployment Wages

Interrupted Time Series Analysis



Before Placebo Test | After Placebo Test

Structural Estimation

- We estimate model using **minimum distance** estimator:

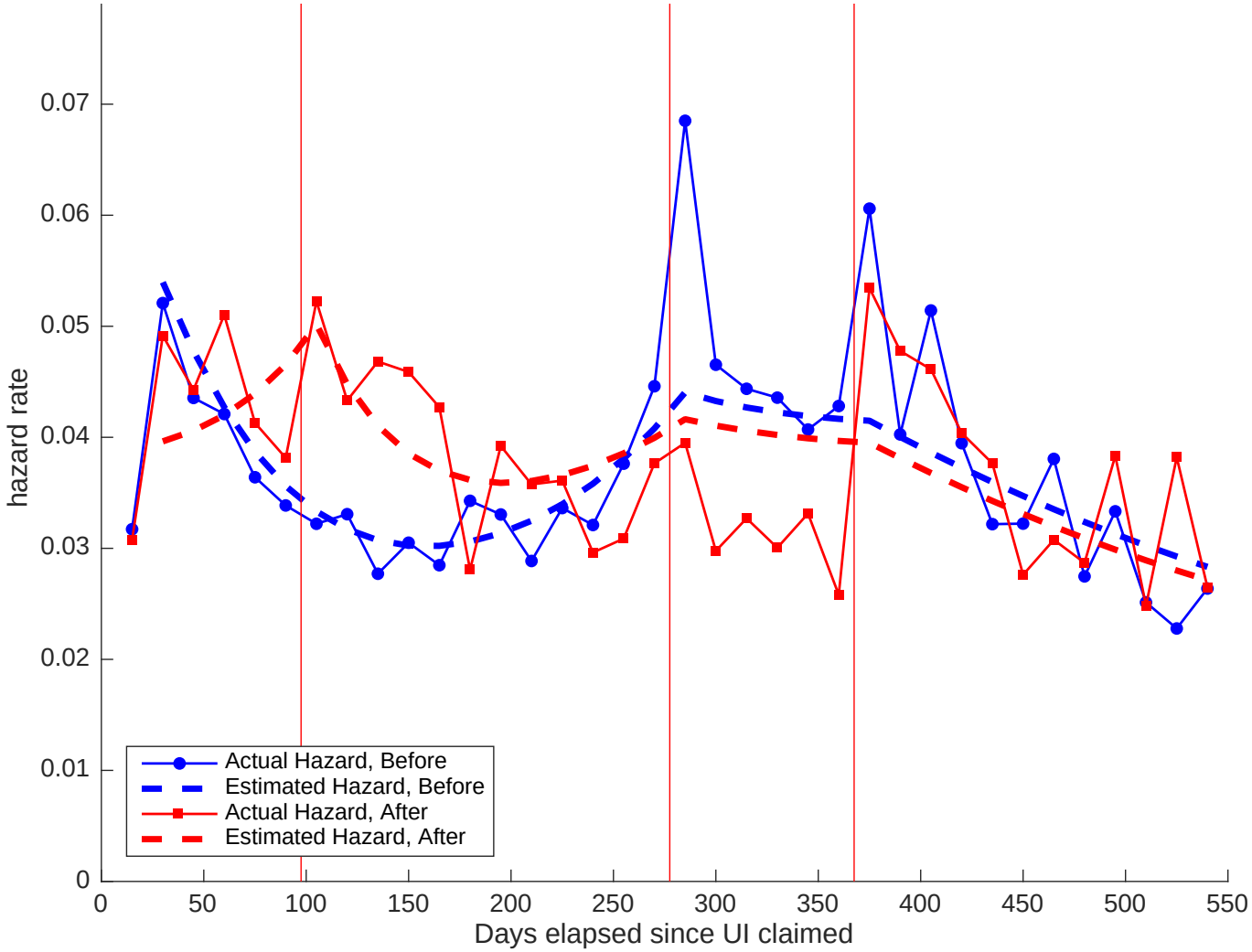
$$\min_{\xi} \left(m\left(\xi\right) - \hat{m}\right)' W \left(m\left(\xi\right) - \hat{m}\right)$$

- $\hat{m}$ - Empirical Moments (without controls)
  - 35 15-day pre-reform hazard rates
  - 35 15-day pre-reform hazard rates
- W is the inverse of diagonal of variance-covariance matrix
- Further assumptions about utility maximization:
  - Log utility: $v(c) = log(c)$
  - Assets $A_0 = 0$, Borrowing limit $L = 0$, Interest rate $R = 1$
  - Cost of effort $c(s) = k_j \frac{s^{1+\gamma}}{1+\gamma}$

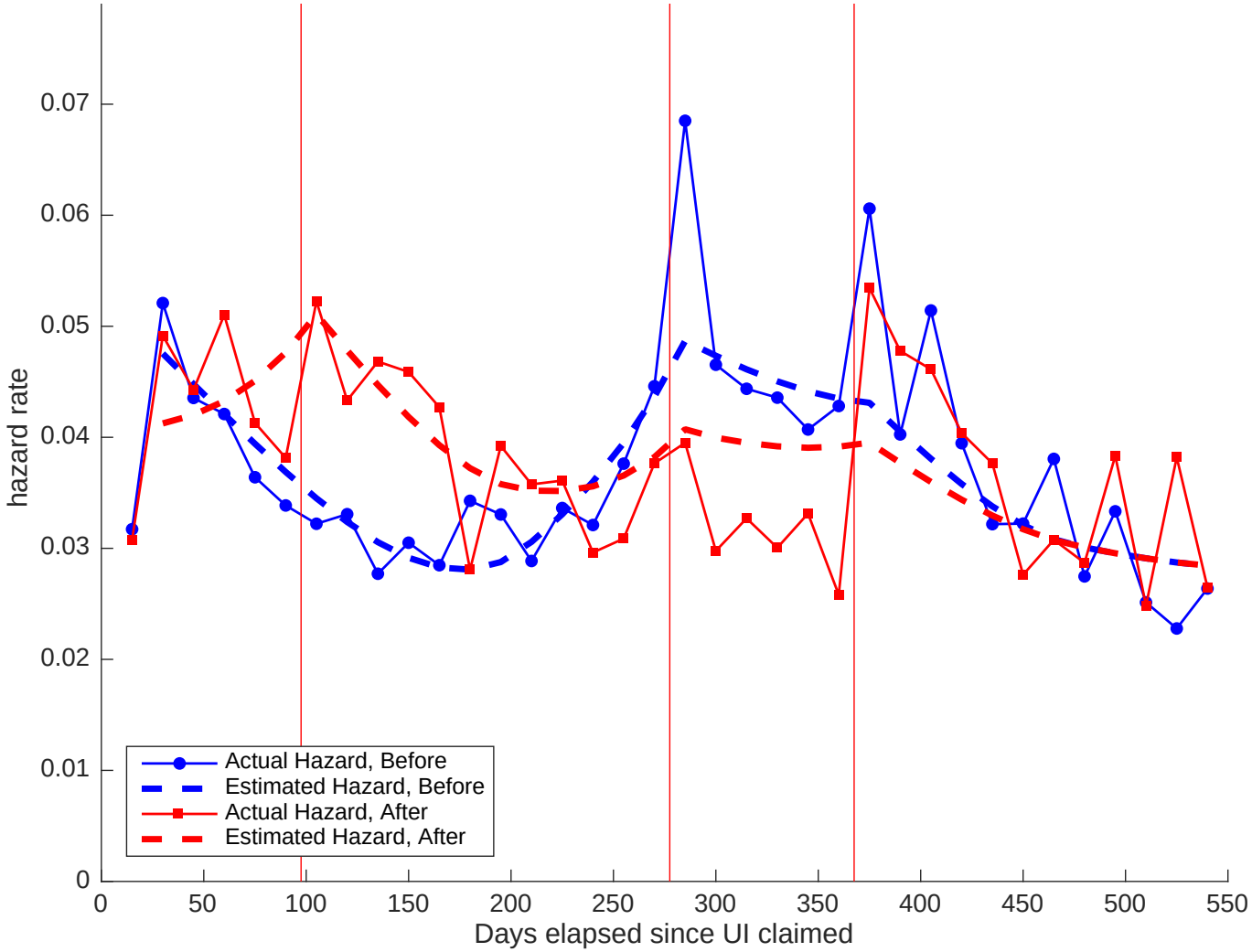
Estimation Method

- Parameters ξ to estimate:
  - λ loss component in utility function
  - N speed of adjustment of reference point
  - 15-day discount factor δ (fixed at $\delta = 0.995$ for hand-to-mouth case)
  - Cost of effort curvature γ
  - Unobserved Heterogeneity: k_h, k_m and k_l cost types, and their proportions (only one type for ref. dep. model)
- Fixed parameters:
  - Gain-loss utility weight $\eta = 0$ (standard model), $\eta = 1$ (ref.-dep. model) Link
  - Reemployment wage fixed at the empirical median Link
- Start with hand-to-mouth estimates ($c_t = y_t$)

Standard Model, 3 types (Hand-to-Mouth)



Ref.-Dep. Model, 1 types (Hand-to-Mouth)



Incorporating Consumption-Savings

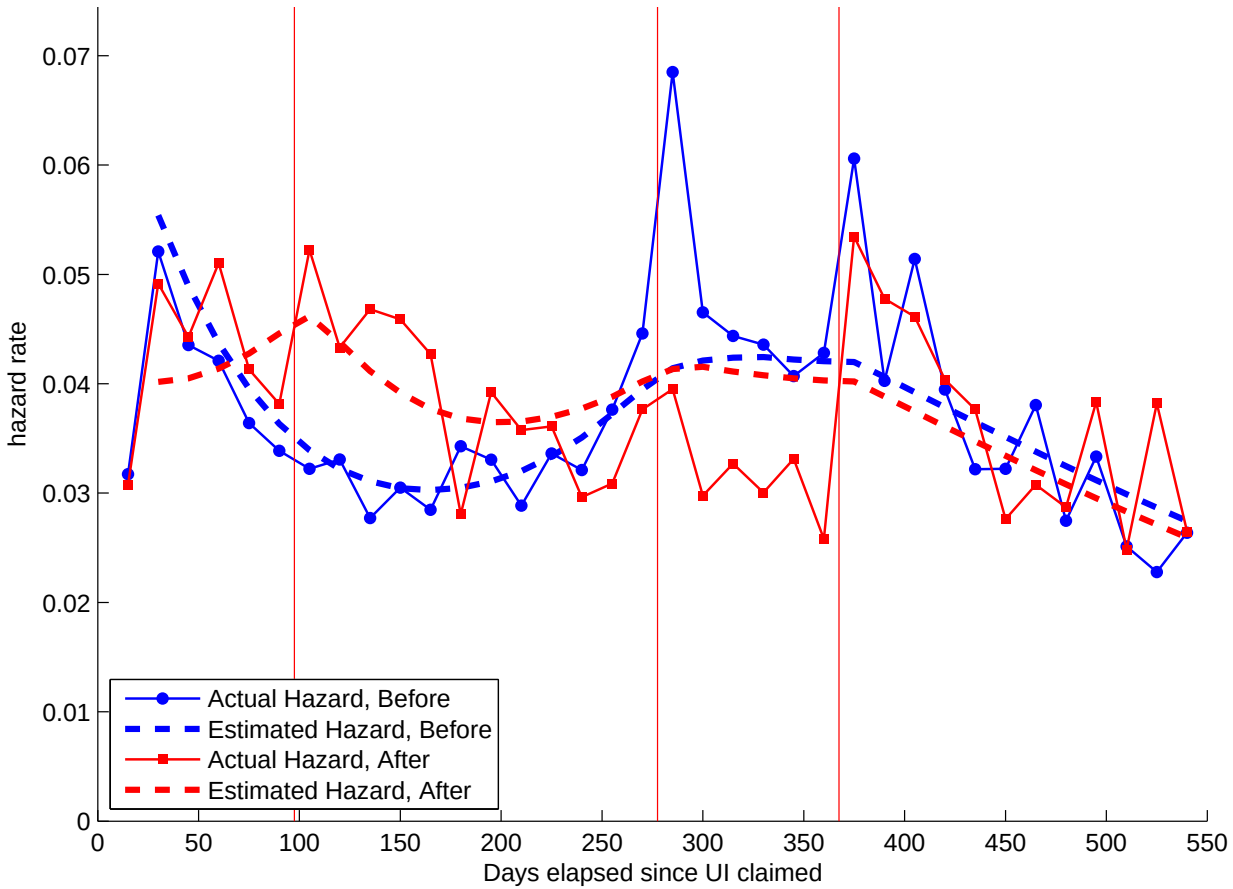
Previous results have key weakness

- Reference-dependent workers are aware of painful loss utility at benefit decrease
- Should save in anticipation
- Ruled out by hand-to-mouth assumption

Introduce optimal consumption:

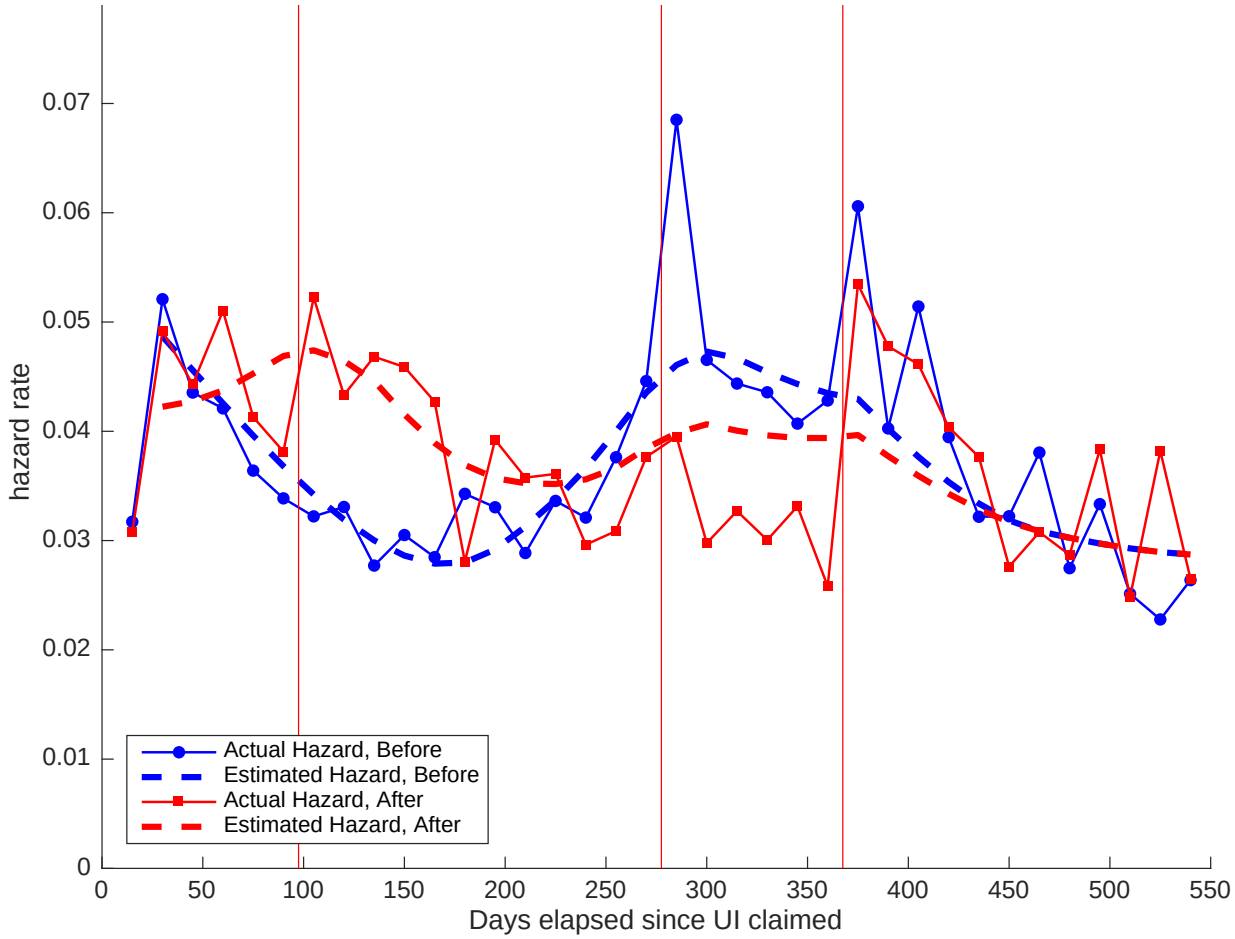
- In each period t individuals choose search effort s_t^* and consumption c_t^*
- Estimate also degree of patience δ and β, δ

Standard model (Optimal Consumption)



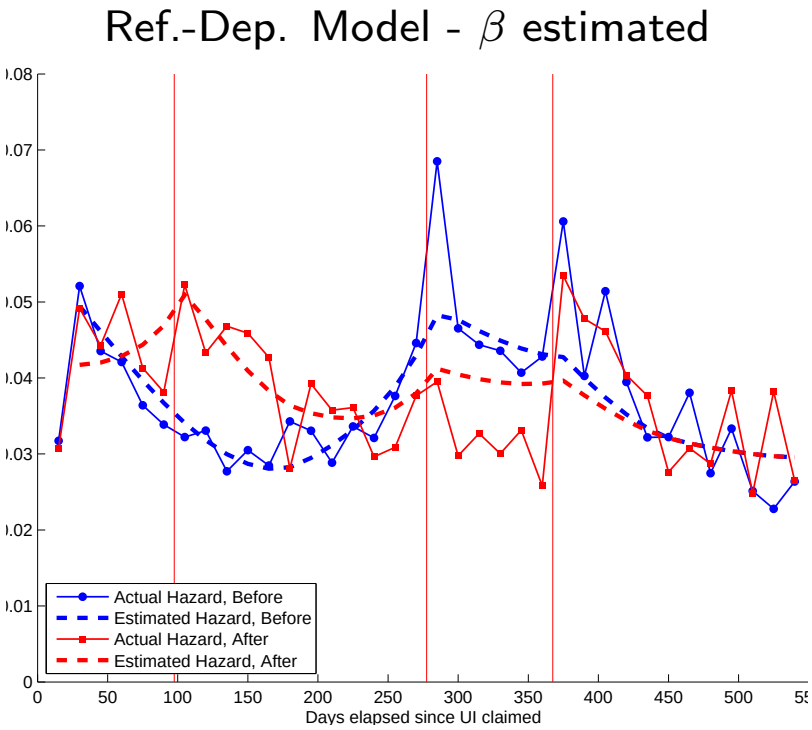
- Standard model with 3 cost types and estimated δ performs no better than with hand-to-mouth assumption

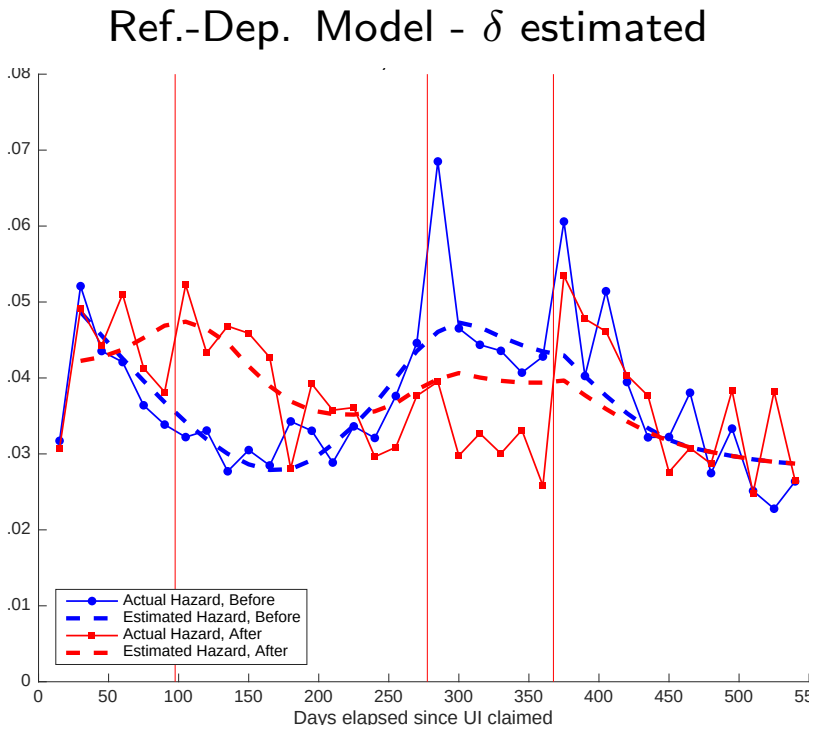
Ref.-Dep. model (Optimal Consumption)



- Reference-dependent model with estimated δ performs well
- BUT: estimated $\delta = .9$ (bi-weekly) – not realistic

Ref.-Dep. model - Discount Factor Estimated





- The reference-dependent model with β, δ performs about equally well - Laibson (1997), O'Donoghue and Rabin (1999), Paserman (2008), Cockx, Ghirelli and van der Linden (2014)
- Estimated $\hat{\beta} = 0.58$ with $\delta = .995$, reasonable
- Noticed: maintained naiveté

Benchmark Estimates (Optimal Consumption)

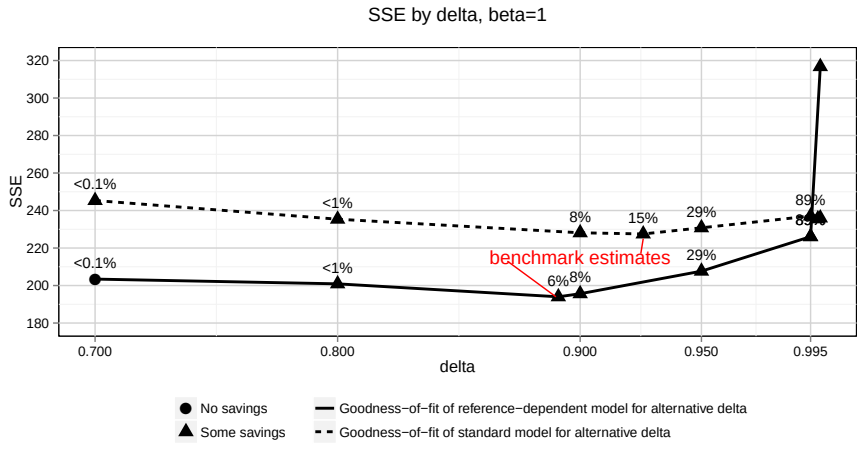
Structural estimation of Standard and Ref.-Dep. models - Optimal Consumption

	(1)	(2)	(3)	(4)
	Standard	RefD.	Standard	RefD.
Discounting:	Delta	Delta	Beta	Beta
Parameters of Utility function				
Utility function $\nu(.)$	log(b)	log(b)	log(b)	log(b)
Loss aversion λ		4.92		4.69
		(0.58)		(0.62)
Gain utility η		1		1
Adjustment speed of reference		184		167.5
point N in days		(11)		(11.2)
δ	0.93	0.89	0.995	0.995
	(0.01)	(0.02)		
	1	1	0.92	0.58
β			(0.01)	(0.19)
Parameters of Search Cost Function				
Elasticity of search cost γ	0.4	0.81	0.07	0.4
	(0.04)	(0.16)	(0.01)	(0.2)
Model Fit				
Goodness of fit	227.5	194.0	229.0	183.5
Number of cost-types	3	1	3	1

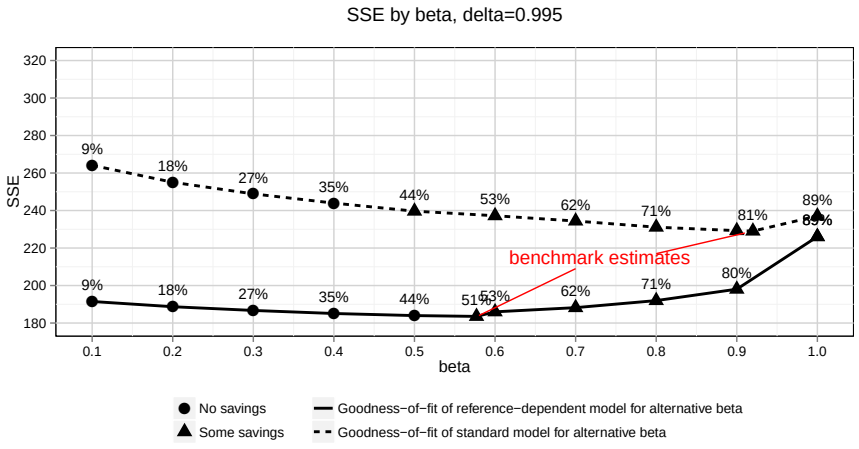
Goodness of fit by Impatience

- Extra dividend of optimal consumption: Estimate patience
  - Unemployed workers estimated to be very impatient
  - Impatience too high in δ model, but realistic with β, δ model
    $\Rightarrow$ Evidence supporting present-bias

Ref.Dep. Model - SSE by (by-weekly)δ



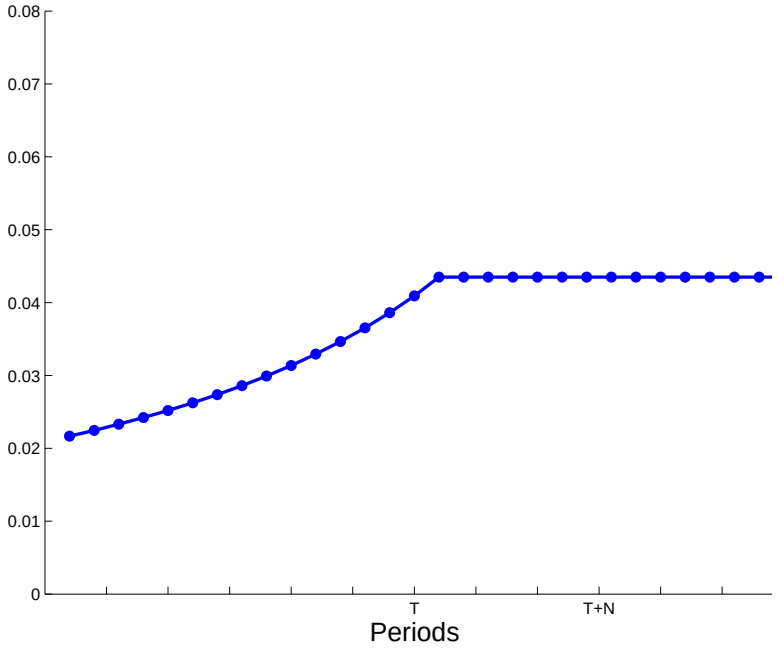
Ref.-Dep. Model - SSE by β



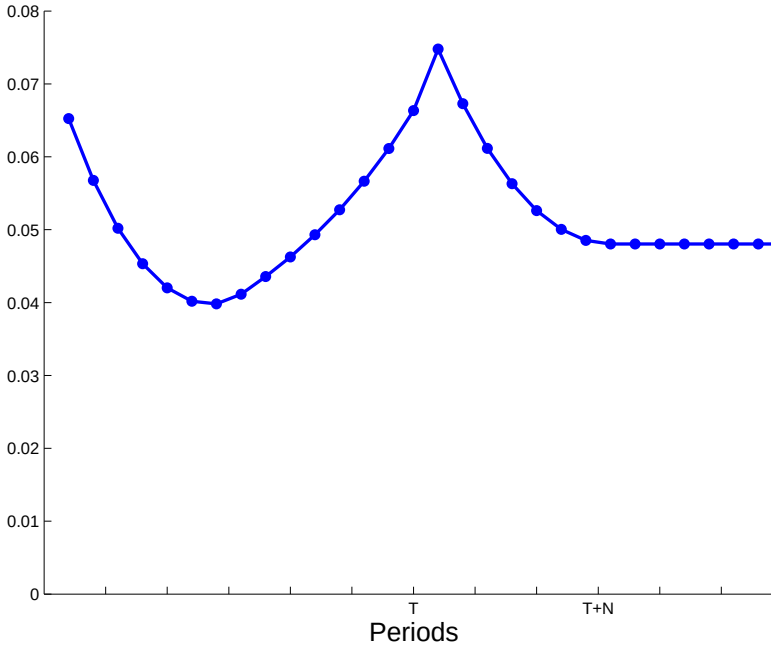
Ongoing Work: Survey

- Key prediction of different models on **search effort**

Search Effort, Standard model



Search Effort, Reference Dependence



$\Rightarrow$ Ideally we would have individual level **panel data** on search effort

Ongoing Work: Survey

- Build on Krueger and Mueller (2011, 2014):
  - Large **web based survey** among UI recipients in NJ
  - 5% participation rate
  - No benefit expiration in their sample

Source: Authors' calculations based on the survey data and on administrative data from LWD.

Ongoing Work: Survey

- Conduct SMS-based survey in 2017 in Germany with IAB
- Twice-a-week 'How many hours did you spend on search effort yesterday?'
  - Follow around 10,000 UI recipients over 4 months.
  - Use discontinuity in benefit duration (6/8/10 months) to get control group
  - Examine in particular search effort around benefit expiration
- Advantages of SMS messages:
  - Very easy to reply / low cost to respondent.
  - A lot of control, easy to send reminders etc.

Section 7

Next Lecture

Next Lecture

- More Reference-Dependence:
  - Insurance
  - Finance
  - KR vs. backward looking ref. points
  - Endowment Effect
  - Effort