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
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.

Valuation Achieved

Market Premia

- 179% higher than the lowest price during the 62-week period ended October 6, 2006
- 49% higher than the 52-week high during the period ended October 6, 2006
- 30% higher than the average closing price for the 180 days prior to the $36.26 offer
- 10% higher than the 6-year and 62-week high prior to May 2, 2007

- 13.00*
- $24.25
- $27.90
- $32.86
- $36.26

* Adjusted to reflect payment of $10/share special dividend.
Model

- Assume that Firm T chooses price $P$, and A decides accept or 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 → On announcement day, often big impact
Test 4: What do investors think?

- Regression (Columns 3 and 5):

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

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

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
Does reference dependence affect work/leisure decision?

- **Framework:**
  - effort $h$ (no. of hours)
  - hourly wage $w$
  - Returns of effort: $Y = w \times h$
  - 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:

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

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

$$wh + \eta (wh - T) - \frac{\theta h^2}{2} \quad \text{if } h \geq T/w$$

$$wh + \eta \lambda (wh - T) - \frac{\theta h^2}{2} \quad \text{if } h < T/w$$
Framework

- Derivative with respect to $h$:

\[
(1 + \eta)w - \theta h \quad \text{if} \quad h \geq T/w \\
(1 + \eta \lambda)w - \theta h \quad \text{if} \quad h < T/w
\]

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: \(h^* = (1 + \eta) \frac{w}{\theta}\) (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 \(a > 0\), \(b > 0\)

- 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
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
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 $\Delta a$ (labor demand shifter)
- Do hours worked $h$ and $w$ co-vary positively (standard model) or negatively?
Raw evidence
Model

- Estimate:
  \[ \log(h_{i,t}) = \alpha + \beta \log\left(\frac{Y_{i,t}}{h_{i,t}}\right) + X_{i,t} \Gamma + \varepsilon_{i,t} \]

- Estimates of \( \hat{\beta} \):
  - \( \hat{\beta} = -0.186 \text{ (s.e. 129)} \) – TRIP with driver f.e.
  - \( \hat{\beta} = -0.618 \text{ (s.e. 0.051)} \) – TLC1 with driver f.e.
  - \( \hat{\beta} = -0.355 \text{ (s.e. 0.051)} \) – 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: $\tilde{h}_{i,t} = h_{i,t} \ast \phi_{i,t}$. Then,

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

becomes

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

- 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**

<table>
<thead>
<tr>
<th>Sample</th>
<th>TRIP</th>
<th>TLC1</th>
<th>TLC2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log hourly wage</td>
<td>-.319</td>
<td>-.1313</td>
<td>-.926</td>
</tr>
<tr>
<td></td>
<td>(.298)</td>
<td>(.236)</td>
<td>(.259)</td>
</tr>
<tr>
<td>High temperature</td>
<td>-.000</td>
<td>.002</td>
<td>.002</td>
</tr>
<tr>
<td></td>
<td>(.002)</td>
<td>(.002)</td>
<td>(.002)</td>
</tr>
</tbody>
</table>

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

  **First-stage regressions**

<table>
<thead>
<tr>
<th></th>
<th>TRIP</th>
<th>TLC1</th>
<th>TLC2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median</td>
<td>.316</td>
<td>-.385</td>
<td>-.276</td>
</tr>
<tr>
<td></td>
<td>(.225)</td>
<td>(.394)</td>
<td>(.467)</td>
</tr>
<tr>
<td>25th percentile</td>
<td>.323</td>
<td>.693</td>
<td>.469</td>
</tr>
<tr>
<td></td>
<td>(.160)</td>
<td>(.241)</td>
<td>(.332)</td>
</tr>
<tr>
<td>75th percentile</td>
<td>.399</td>
<td>.614</td>
<td>.688</td>
</tr>
<tr>
<td></td>
<td>(.171)</td>
<td>(.242)</td>
<td>(.292)</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>.374</td>
<td>.056</td>
<td>.206</td>
</tr>
<tr>
<td>P-value for F-test of instruments for wage</td>
<td>.000</td>
<td>.000</td>
<td>.020</td>
</tr>
</tbody>
</table>
Econometric issue 2

Are the authors really capturing demand shocks or supply shocks?

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

Camerer et al. argue for plausibility of shocks due to $a$ rather than $\theta$
Farber (JPE, 2005)

- Re-Estimate Labor Supply of Cab Drivers on new data
- Address Econometric Issue 1 (Division Bias)
- Data:
  - 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 $t$:
    \[ Stop_{i,t} = \Phi(\alpha + \beta_Y Y_{i,t} + \beta_h h_{i,t} + \Gamma X_{i,t}) \]
  - 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

<table>
<thead>
<tr>
<th>Variable</th>
<th>$X^\circ$</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total hours</td>
<td>8.0</td>
<td>0.013</td>
<td>0.037</td>
<td>0.011</td>
<td>0.010</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.009)</td>
<td>(0.012)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Waiting hours</td>
<td>2.5</td>
<td>0.010</td>
<td>-0.005</td>
<td>0.014</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.010)</td>
<td>(0.012)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Break hours</td>
<td>0.5</td>
<td>0.066</td>
<td>-0.015</td>
<td>-0.003</td>
<td>-0.001</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.008)</td>
<td>(0.011)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Shift income $\times 100$</td>
<td>1.5</td>
<td>0.063</td>
<td>0.036</td>
<td>0.014</td>
<td>0.016</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.022)</td>
<td>(0.030)</td>
<td>(0.015)</td>
<td>(0.016)</td>
<td>(0.015)</td>
</tr>
</tbody>
</table>

- Driver (21)
- Day of week (7)
- Hour of day (19)
- Log likelihood

Note: The sample includes 15,486 trips in 184 shifts for 21 drivers. Probit estimates are normalized to reflect the marginal effect at $X^\circ$ on the probability of stopping. The normalized probit estimate is $\beta = \Phi'(\beta) \cdot X^\circ$, where $\Phi'$ is the standard normal density. The values of $X^\circ$ 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 estimation point is after 5:30 driving hours, 2.5 waiting hours, and 0.5 break hour in a day in the city. 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) → 1.6 percent increase in stopping prob. (.225 pctg. pts. increase in stopping prob. out of average 14 pctg. pts.) → 0.16 elasticity
  - Cannot reject large effect: 10 pct. increase in $Y$ increase stopping prob. by 6 percent → 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 $r_{it}$ ($w = \text{"wage"}$). 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 preferences, $t= a$ 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 ($\chi^2(1) = 4.57, p<0.05$)
- 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

The Distribution of Revenues during the Field Experiment

- 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 \( \delta \)
  - Estimate (stochastic) reference point \( T \)
- Same data as Farber (2005)
- Results:
  - significant loss aversion \( \delta \)
  - however, large variation in \( T \) mitigates effect of loss-aversion
Farber (2008)

<table>
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<tr>
<th>Parameter</th>
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<th>(4)</th>
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<td>$\beta$ (contprob)</td>
<td>-0.691</td>
<td>---</td>
<td>---</td>
<td>---</td>
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<tr>
<td></td>
<td>(0.243)</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>$\hat{\theta}$ (mean ref inc)</td>
<td>159.02</td>
<td>206.71</td>
<td>250.86</td>
<td>---</td>
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<tr>
<td></td>
<td>(4.99)</td>
<td>(7.98)</td>
<td>(16.47)</td>
<td></td>
</tr>
<tr>
<td>$\delta$ (cont increment)</td>
<td>3.40</td>
<td>5.35</td>
<td>4.85</td>
<td>5.38</td>
</tr>
<tr>
<td></td>
<td>(0.279)</td>
<td>(0.573)</td>
<td>(0.711)</td>
<td>(0.545)</td>
</tr>
<tr>
<td>$\sigma^2$ (ref inc var)</td>
<td>3199.4</td>
<td>10440.0</td>
<td>15944.3</td>
<td>8236.2</td>
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<tr>
<td></td>
<td>(294.0)</td>
<td>(1660.7)</td>
<td>(3652.1)</td>
<td>(1222.2)</td>
</tr>
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Driver $\hat{\theta}$, (15) | No | No | No | Yes

Vals in Cont Prob

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<td>Driver FE's (14)</td>
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<td>Yes</td>
<td>Yes</td>
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<td>Accum Hours (7)</td>
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<td>Yes</td>
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<td>Weather (4)</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Day Shift and End (2)</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Location (1)</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Day-of-Week (6)</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Hour-of-Day (18)</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Log(L) | -1867.8 | -1631.6 | -1572.8 | -1606.0
Number Parms | 4 | 43 | 57 | 57

- $\delta$ is loss-aversion parameter
- Reference point: mean $\theta$ and variance $\sigma^2$
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

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pooled data</td>
<td>$W^a &gt; W^e$</td>
<td>$W^a \leq W^e$</td>
</tr>
<tr>
<td>Total hours</td>
<td>.013</td>
<td>.005</td>
<td>.016</td>
</tr>
<tr>
<td></td>
<td>(.009)*</td>
<td>(.009)</td>
<td>(.007)**</td>
</tr>
<tr>
<td>Waiting hours</td>
<td>.010</td>
<td>.007</td>
<td>.016</td>
</tr>
<tr>
<td></td>
<td>(.003)**</td>
<td>(.007)</td>
<td>(.001)**</td>
</tr>
<tr>
<td>Break hours</td>
<td>.006</td>
<td>.005</td>
<td>.004</td>
</tr>
<tr>
<td></td>
<td>(.003)**</td>
<td>(.001)**</td>
<td>(.008)</td>
</tr>
<tr>
<td>Income/100</td>
<td>.053</td>
<td>.076</td>
<td>.055</td>
</tr>
<tr>
<td></td>
<td>(.000)**</td>
<td>(.007)**</td>
<td>(.007)**</td>
</tr>
<tr>
<td>Min temp&lt;30</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Max temp&gt;80</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Hourly rain</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Daily snow</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Location dummies</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Driver dummies</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Day of week</td>
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<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Hour of day</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-2039.2</td>
<td>-1148.4</td>
<td>-882.6</td>
</tr>
<tr>
<td>Pseudo R2</td>
<td>0.1516</td>
<td>0.1555</td>
<td>0.1533</td>
</tr>
<tr>
<td>Observation</td>
<td>13461</td>
<td>7936</td>
<td>5525</td>
</tr>
</tbody>
</table>
Farber (QJE 2015)

- Finally data set with large $K$ and large $T$
  - $K = 62,000$ drivers
  - $T = 5 \times 365$ (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)
  - $P(\text{stopping})$ 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 $\rightarrow$ 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)

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

Notes. Based on estimates of two linear probability models for the probability of stopping: day shifts (columns (1) and (3)) and night shifts (columns (2) and (4)). The base category for income is $0–99 and the base category for hours is 0–2. Both models additionally include sets of fixed effects for driver, hour of the day by day of the week (168), week of the year (52), and year (5) as well as indicators for the period subsequent to the September 4, 2012, fare increase and major holiday. Robust standard errors clustered by driver are in parentheses. See text for information on sample size and composition.
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

\[
\begin{align*}
W_0 + wh - \frac{\theta h^2}{2} + \eta (wh + W_0 - (T + \alpha W_0)) & \quad \text{if } wh + W_0 \geq T + \alpha W_0 \\
W_0 + wh - \frac{\theta h^2}{2} + \eta \lambda (wh + W_0 - (T + \alpha W_0)) & \quad \text{if } wh + W_0 < T + \alpha W_0
\end{align*}
\]
Thakral and To (2017)

- Special case 1: Reference point fully reflects extra earnings ($\alpha = 1$):
  - $W_0$ cancels out from expression above $\rightarrow$ 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 $T - W_0$
Table 3: Stopping model estimates: Income effect at 8.5 hours—Subsamples

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

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 $\rightarrow \triangle P(stop) = 0.07\% \rightarrow \eta_{Stop,Y} = 0.1$
- $10 \triangle Y$ in hour 8 $\rightarrow \triangle P(stop) = 0.32\% \rightarrow \eta_{Stop,Y} = 0.46$
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 $T \rightarrow$ Does not impact stopping
    - Income earned late in the shift not incorporated $\rightarrow$ 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 → If undecided, arbitration
  - 9 percent of police labor contracts decided with final offer arbitration
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 $r_e \leq r_a \leq r_u$ → Then

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

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

- Employer’s problem:

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

- Notice: $U' < 0$

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

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

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

- **Maximize:**

  \[
  \max_{r_u} PV (w (1 + r_e^*)) + (1 - P) V (w (1 + r_u))
  \]

- **Notice:** \( V' > 0 \)

- **First order condition for union:**

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

- To simplify, assume \( U (x) = -bx \) and \( V (x) = bx \)

- This implies \( V (w (1 + r_e^*)) - V (w (1 + r_u^*)) = -U (w (1 + r_e^*)) - U (w (1 + r_u^*)) \), so

  \[-bP^* w = -(1 - P^*) bw\]

- **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

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

[Graphs showing changes in clearance rates and crime reports over time after arbitration.]
Effects on Performance

- Union win $\rightarrow$ 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 | (2.62) | (2.20) | (2.70) | (1.75) | (1.35) | (1.78) | (1.62) | (2.25) | (1.87) |
| Post-arbitration $\times$ Employer win | 4.99 | 7.92 | 5.96 | 4.17 | 5.62 | 5.31 | 0.819 | 2.31 | 2.19 | (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 (Yes = 1) | 3.71 | -2.81 | 2.14 | -5.73 | 1.57 | 2.92 | (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 Dependent variable 120.31 120.31 130.82 64.79 64.79 72.15 55.51 55.51 58.63
[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

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5) Police lose</th>
<th>(6) Police win</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(2.31)</td>
<td>(9.58)</td>
<td>(8.45)</td>
<td>(4.76)</td>
<td>(3.14)</td>
<td>(4.17)</td>
</tr>
<tr>
<td>Post-Arbitration × Award</td>
<td>1.23</td>
<td>-1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.16)</td>
<td>(0.98)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-Arbitration × Loss size</td>
<td>-10.31</td>
<td>-10.93</td>
<td></td>
<td></td>
<td>-0.20</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.59)</td>
<td>(1.89)</td>
<td></td>
<td></td>
<td></td>
<td>(4.54)</td>
</tr>
<tr>
<td>Post-Arbitration × Union win</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>13.38</td>
<td>(5.32)</td>
</tr>
<tr>
<td>Post-Arbitration × (expected award-award)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-17.72</td>
<td>2.82</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(7.94)</td>
</tr>
<tr>
<td>Post-Arbitration × p(loss size)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Included</td>
<td></td>
</tr>
<tr>
<td>Sample Size</td>
<td>59,137</td>
<td>59,137</td>
<td>59,137</td>
<td>59,137</td>
<td>52,857</td>
<td>55,879</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.63</td>
<td>0.63</td>
<td>0.63</td>
<td>0.63</td>
<td>0.60</td>
<td>0.62</td>
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</tbody>
</table>

Standard errors, clustered on the intersection of arbitration window and city, are in parentheses. Standard deviations are in brackets. Observations are municipality x month cells. The sample is weighted by population size in 1976. The dependent variable is clearances per 100,000 capita. Loss size is defined as the union demand (percent increase on previous wage) less the arbitrator award. Among 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 average award 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 won 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

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

- F.o.c.:

\[ \tilde{U} + U(w) - \theta e = 0 \]

Then

\[ e^*(w) = \frac{\tilde{U}}{\theta} + \frac{1}{\theta} U(w) \]

- It implies that we would estimate

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

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
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
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
## Dependent Variable Equals 1 if Putt was Made
### Logit Estimation

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<thead>
<tr>
<th></th>
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<tbody>
<tr>
<td>Putt for Birdie or Eagle</td>
<td>-.020**</td>
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<tr>
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<tr>
<td>Putt for Eagle</td>
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<tr>
<td></td>
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<td><strong>Putt for Birdie</strong></td>
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<td><strong>-.019</strong>**</td>
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<td>Putt for Bogey</td>
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<td>(.001)</td>
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<td>Observations</td>
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<td>2,525,161</td>
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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
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.

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

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

- $\eta$ is weight on **gain-loss utility**
- $\lambda$ 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

  \[ V^U_t(A_t) = \max_{s_t \in [0,1]; A_{t+1}} u(c_t | r_t) - c(s_t) + \delta \left[ s_t V^E_{t+1}(A_{t+1}) + (1 - s_t) V^U_{t+1}(A_{t+1}) \right] \]

- Value function when **employed**: \[ V^E_{t+1}(A_{t+1}) = \max_{c_{t+1}} u(c_{t+1} | r_{t+1}) + \delta V^E_{t+2}(A_{t+2}). \]

- Solution for **optimal search**: \[ c'(s_t^*) = \delta \left[ V^E_{t+1}(A_{t+1}) - V^U_{t+1}(A_{t+1}) \right] \]

- 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-dependent** model **without heterogeneity**?
Example: Hazards under Two Models

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<th>Benefit</th>
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Periods

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<th>Reference-Dependent Model</th>
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Example: Hazards under Two Models

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<th>Hazard Rate, Standard Model</th>
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<table>
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<tr>
<th>Hazard Rate, Ref.-Dep. Model</th>
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<table>
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<th>Periods</th>
<th>Hazard Rate</th>
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<td>T</td>
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<td>0.08</td>
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</tbody>
</table>
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

Reference-Dependent Job Search
Evidence from Hungary

UI Benefits in Hungary

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.
Define before and after

old UI, old UA  |  old UI, new UA  |  new UI, new UA

Reform occurred

Nov 1, 2004  |  Nov 1, 2005  |  Nov 1, 2006

Before    |   Reform occurred   |   After


2004, Jan 1  |  Dataset available  |  2007, Dec 31
Hazard rates before and after

Hazard by Duration

Survival Rate
Reemployment Wages

Reference-Dependent Job Search
Interrupted Time Series Analysis
Structural Estimation

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

\[ \min_{\xi} (m(\xi) - \hat{m})' W (m(\xi) - \hat{m}) \]

- \( \hat{m} \) - 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 \( c(s) = kj \frac{s^{1+\gamma}}{1+\gamma} \)
Estimation Method

Parameters $\xi$ to estimate:

- $\lambda$ loss component in utility function
- $N$ speed of adjustment of reference point
- 15-day discount factor $\delta$ (fixed at $\delta = 0.995$ for hand-to-mouth case)
- Cost of effort curvature $\gamma$
- 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)
- Reemployment wage fixed at the empirical median

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)

[Diagram showing hazard rates over days elapsed since UI claimed, with actual and estimated hazard rates differentiated.]

Reference-Dependent Job Search
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 $\delta$ and $\beta, \delta$
Standard model (Optimal Consumption)

- Standard model with 3 cost types and estimated $\delta$ performs no better than with hand-to-mouth assumption
Reference-dependent model with estimated $\delta$ performs well

BUT: estimated $\delta = .9$ (bi-weekly) – not realistic

Estimated $\hat{\beta} = 0.58$ with $\delta = 0.995$, reasonable

Noticed: maintained naiveté
## Benchmark Estimates (Optimal Consumption)

<table>
<thead>
<tr>
<th>Parameters of Utility function</th>
<th>(1) Standard Delta</th>
<th>(2) RefD. Delta</th>
<th>(3) Standard Beta</th>
<th>(4) RefD. Beta</th>
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</thead>
<tbody>
<tr>
<td>Discounting:</td>
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<td></td>
<td></td>
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<tr>
<td>Delta</td>
<td>log(b)</td>
<td>log(b)</td>
<td>log(b)</td>
<td>log(b)</td>
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<tr>
<td>Beta</td>
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<td>4.69</td>
<td>(0.58)</td>
<td>(0.62)</td>
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<td>Gain utility $\eta$</td>
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<td>Adjustment speed of reference</td>
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<td>(11)</td>
<td>(11.2)</td>
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<td>$\delta$</td>
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<th>Model Fit</th>
<th>Goodness of fit</th>
<th>Number of cost-types</th>
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<tr>
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<td>183.5</td>
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</table>
Goodness of fit by Impatience

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

- Key prediction of different models on search effort

Search Effort, Standard model

Search Effort, Reference Dependence

⇒ 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

![Graph showing unfilled duration vs. number of minutes per day for the last 7 days (weekly recall).]

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
More Reference-Dependence:

- Insurance
- Finance
- KR vs. backward looking ref. points
- Endowment Effect
- Effort