Econ 219A
Psychology and Economics: Foundations (Lecture 5)

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Outline

1. Reference Dependence: Labor Supply

2. Reference Dependence: Disposition Effect

3. Reference Dependence: Equity Premium

4. Reference Dependence: Domestic Violence

5. Reference Dependence: Employment and Effort
1 Reference Dependence: Labor Supply


- Daily labor supply by cab drivers, bike messengers, and stadium vendors

- 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

$$U(Y) - c(h) = wh - \frac{\theta h^2}{2}$$
• (Key assumption that each day is orthogonal to other days – see below)

• Model with reference dependence:

• Threshold $T$ of earnings agent wants to achieve

• Loss aversion for outcomes below threshold:

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

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

\[ wh - T - \frac{\theta h^2}{2} \quad \text{if} \quad h \geq T/w \]
\[ \lambda (wh - T) - \frac{\theta h^2}{2} \quad \text{if} \quad h < T/w \]

• Derivative with respect to \( h \):

\[ w - \theta h \quad \text{if} \quad h \geq T/w \]
\[ \lambda w - \theta h \quad \text{if} \quad h < T/w \]
• Three cases.

1. Case 1 \((\lambda w - \theta T/w < 0)\).
   
   – Optimum at \(h^* = \frac{\lambda w}{\theta} < \frac{T}{w}\)
2. Case 2 ($\lambda w - \theta T/w > 0 > w - \theta T/w$).
   
   - Optimum at $h^* = T/w$
3. Case 3 \((w - \theta T/w > 0)\).

- Optimum at \(h^* = w/\theta > T/w\)
• **Standard theory** \((\lambda = 1)\).

• Interior maximum: \(h^* = w/\theta\) (Cases 1 or 3)

• Labor supply

• Combine with labor demand: \(h^* = a - bw\), with \(a > 0, b > 0\).
• Optimum:

\[ L^S = \frac{w^*}{\theta} = a - bw^* = L^D \]

or

\[ w^* = \frac{a}{b + 1/\theta} \]

and

\[ h^* = \frac{a}{b\theta + 1} \]

• Comparative statics with respect to \( a \) (labor demand shock): \( a \uparrow \Rightarrow h^* \uparrow \) and \( w^* \uparrow \)

• On low-demand days (low \( w \)) work less hard \( \Rightarrow \) Save effort for high-demand days
• 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: Optimum:

\[ L^S = \frac{T}{w^*} = a - bw^* = L^D \]

and

\[ w^* = \frac{a + \sqrt{a^2 + 4Tb}}{2b} \]

• Comparative statics with respect to \( a \) (labor demand shock):
  - \( a \uparrow \rightarrow h^* \uparrow \) and \( w^* \uparrow \) (Cases 1 or 3)
  - \( a \uparrow \rightarrow h^* \downarrow \) and \( w^* \uparrow \) (Case 2)
• Case 2: On low-demand days (low $w$) need to work harder to achieve reference point $T \rightarrow$ Work harder

• Opposite prediction to standard theory

• (Neglected negligible wealth effects)
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
• 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 negatively (standard model) or positively?
- Raw evidence
• Estimated Equation:

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

• Estimates of \( \hat{\beta} \):
  
  - \( \hat{\beta} = -0.186 \) (s.e. 129) – TRIP with driver f.e.
  
  - \( \hat{\beta} = -0.618 \) (s.e. 0.051) – TLC1 with driver f.e.
  
  - \( \hat{\beta} = -0.355 \) (s.e. 0.051) – TLC2

• Estimate is not consistent with prediction of standard model

• Indirect support for income targeting
- Issues with paper:

- 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 is not directly observed – Computed at $Y_{i,t}/h_{i,t}$

• Assume $h_{i,t}$ measured with noise: $\tilde{h}_{i,t} = h_{i,t} \cdot \phi_{i,t}$. Then,

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

becomes

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

• Downward bias in estimate of $\hat{\beta}$

• Response: instrument wage using other workers’ wage on same day
- **IV Estimates:**

<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>-.313</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)
• 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 being due to $a$ rather than $\theta$
  
  – No direct way to address this issue
• Farber (JPE, 2005)

• Re-Estimate Labor Supply of Cab Drivers on new data

• Address Econometric Issue 1

• Data:
  
  
  
  – Daily summary not available (unlike in Camerer et al.)
  
  – Notice: Few drivers, many days in sample
First, replication of Camerer et al. (1997)

Farber (2005) however cannot replicate the IV specification (too few drivers on a given day)

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>4.012</td>
<td>3.924</td>
<td>3.778</td>
</tr>
<tr>
<td></td>
<td>(.349)</td>
<td>(.379)</td>
<td>(.381)</td>
</tr>
<tr>
<td>Log(wage)</td>
<td>-.688</td>
<td>-.685</td>
<td>-.637</td>
</tr>
<tr>
<td></td>
<td>(.111)</td>
<td>(.114)</td>
<td>(.115)</td>
</tr>
<tr>
<td>Day shift</td>
<td>...</td>
<td>.011</td>
<td>.134</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.040)</td>
<td>(.062)</td>
</tr>
<tr>
<td>Minimum temperature &lt; 30</td>
<td>...</td>
<td>.126</td>
<td>.024</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.053)</td>
<td>(.058)</td>
</tr>
<tr>
<td>Maximum temperature ≥ 80</td>
<td>...</td>
<td>.041</td>
<td>.055</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.055)</td>
<td>(.064)</td>
</tr>
<tr>
<td>Rainfall</td>
<td>...</td>
<td>-.022</td>
<td>-.054</td>
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<tr>
<td></td>
<td></td>
<td>(.073)</td>
<td>(.071)</td>
</tr>
<tr>
<td>Snowfall</td>
<td>...</td>
<td>-.096</td>
<td>-.093</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.036)</td>
<td>(.035)</td>
</tr>
<tr>
<td>Driver effects</td>
<td>no</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Day-of-week effects</td>
<td>no</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>.063</td>
<td>.098</td>
<td>.198</td>
</tr>
</tbody>
</table>
• Key specification: Estimate hazard model that does not suffer from division bias

• Estimate at driver-hour level

• 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 past earned income $Y_{i,t}$ increase probability of stopping ($\beta > 0$)?
• 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.) $\Rightarrow$ .16 elasticity

### TABLE 5

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

**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.
– Cannot reject large effect: 10 pct. increase in $Y$ increase stopping prob. by 6 percent

• 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
- Final step in Farber (2005): Re-analysis of Camerer et al. (1997) data with hazard model
  - Use only TRIP data (small part of sample)
  - No significant evidence of effect of past income $Y$
  - However: Cannot reject large positive effect

<table>
<thead>
<tr>
<th>TABLE 7</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRIVER-SPECIFIC HAZARD OF STOPPING AFTER TRIP: NORMALIZED PROBIT ESTIMATES</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>VARIABLE</th>
<th>Driver 4</th>
<th>Driver 10</th>
<th>Driver 16</th>
<th>Driver 18</th>
<th>Driver 20</th>
<th>Driver 21</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hours</td>
<td>.073</td>
<td>.056</td>
<td>.043</td>
<td>.010</td>
<td>.195</td>
<td>.198</td>
</tr>
<tr>
<td></td>
<td>(.060)</td>
<td>(.047)</td>
<td>(.015)</td>
<td>(.007)</td>
<td>(.045)</td>
<td>(.030)</td>
</tr>
<tr>
<td>Income+100</td>
<td>.178</td>
<td>.089</td>
<td>.064</td>
<td>.048</td>
<td>-.160</td>
<td>-.002</td>
</tr>
<tr>
<td></td>
<td>(.167)</td>
<td>(.059)</td>
<td>(.041)</td>
<td>(.020)</td>
<td>(.123)</td>
<td>(.150)</td>
</tr>
<tr>
<td>Number of shifts</td>
<td>40</td>
<td>45</td>
<td>70</td>
<td>72</td>
<td>46</td>
<td>46</td>
</tr>
<tr>
<td>Number of trips</td>
<td>884</td>
<td>912</td>
<td>1,754</td>
<td>2,023</td>
<td>1,125</td>
<td>882</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-124.1</td>
<td>-116.0</td>
<td>-221.1</td>
<td>-260.6</td>
<td>-123.4</td>
<td>-116.9</td>
</tr>
</tbody>
</table>
• Farber (2005) cannot address the Econometric Issue 2: Is it Supply or Demand that Varies

• **Fehr and Goette (2002)**. 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.
Corrections for Selectivity

- Comparison TG vs. CG without controls
  - Revenues 6 % lower (s.e.: 2.5%)

- Controls for daily fixed effects, experience profile, workload during week, gender
  - Revenues are 7.3 % lower (s.e.: 2 %)

- + messenger fixed effects
  - Revenues are 5.8 % lower (s.e.: 2%)

- Distinguishing between fixed and sign-up shifts
  - Revenues are 6.8 percent lower on fixed shifts (s.e.: 2 %)
  - Revenues are 9.4 percent lower on sign-up shifts (s.e.: 5 %)

- Conclusion: Messengers put in less effort
  - Not due to selectivity.
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)
Concluding Remarks

- **Our evidence does not show that intertemporal substitution in unimportant.**
  - Messenger work more shifts during Experiment 1
  - But they also put in less effort during each shift.

- **Consistent with two competing explanations**
  - Preferences to spread out workload
    - But fails to explain results in Experiment 2
  - Daily income target and Loss Aversion
    - Consistent with Experiment 1 and Experiment 2
    - Measure of Loss Aversion from Experiment 2 predicts reduction in effort in Experiment 1
    - Weakly loss averse subjects behave consistently with simplest standard economic model.
    - Consistent with results from many other studies.
• Other work:

• **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
- $\delta$ is loss-aversion parameter

- Reference point: mean $\theta$ and variance $\sigma^2$

<table>
<thead>
<tr>
<th>Parameter</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta$ (contprob)</td>
<td>-0.691</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td>(0.243)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\hat{\theta}$ (mean ref inc)</td>
<td>159.02</td>
<td>206.71</td>
<td>250.86</td>
<td>---</td>
</tr>
<tr>
<td></td>
<td>(4.99)</td>
<td>(7.99)</td>
<td>(16.47)</td>
<td></td>
</tr>
<tr>
<td>$\hat{\delta}$ (cont increment)</td>
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<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>
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<tr>
<td>$\hat{\sigma}^2$ (ref inc var)</td>
<td>3199.4</td>
<td>10440.0</td>
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<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>
</tbody>
</table>

| Driver $\theta_i$ (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  |
• Most recent paper: Crawford and Meng (AER 2011)

• Re-estimates the Farber paper 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)
<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>$w^g &gt; w^f$</td>
<td>$w^g \leq w^f$</td>
</tr>
<tr>
<td>Total hours</td>
<td>.013</td>
<td>.016</td>
<td>.016</td>
</tr>
<tr>
<td>Waiting hours</td>
<td>(.009)***</td>
<td>(.007)**</td>
<td>(.003)**</td>
</tr>
<tr>
<td>Break hours</td>
<td>(.003)**</td>
<td>(.001)**</td>
<td>(.008)</td>
</tr>
<tr>
<td>Income/100</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>
<td>-</td>
<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>
• 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
• Oettinger (1999) estimates labor supply of stadium vendors

• Finds that more stadium vendors show up at work on days with predicted higher audience
  – Clean identification
  – BUT: Does not allow to distinguish between standard model and reference-dependence
  – With daily targets, reference-dependent workers will respond the same way
  – *Not* a test of reference dependence
  – (Would not be true with weekly targets)
2 Reference Dependence: Disposition Effect

- Odean (JF, 1998)

- Do investors sell winning stocks more than losing stocks?

- Tax advantage to sell losers
  - Can post a deduction to capital gains taxation
  - Stronger incentives to do so in December, so can post for current tax year
Prospect theory intuition:

- Evaluate stocks regularly
- Reference point: price of purchase
- Convexity over losses $\rightarrow$ gamble, hold on stock
- Concavity over gains $\rightarrow$ risk aversion, sell stock
• Individual trade data from Discount brokerage house (1987-1993)

• Rare data set —> Most financial data sets carry only aggregate information

• Share of realized gains:

\[ PGR = \frac{\text{Realized Gains}}{\text{Realized Gains} + \text{Paper Gains}} \]

• Share of realized losses:

\[ PLR = \frac{\text{Realized Losses}}{\text{Realized Losses} + \text{Paper Losses}} \]

• These measures control for the availability of shares at a gain or at a loss
• Notes on construction of measure:

- Use only stocks purchased after 1987
- Observations are counted on all _days_ in which a sale or purchase occurs
- On those days the paper gains and losses are counted
- Reference point is _average_ purchase price
- PGR and PLR ratios are computed using data over all observations.
- Example:

\[
PGR = \frac{13,883}{13,883 + 79,658}
\]
● Result: \( PGR > PLR \) for all months, except December

<table>
<thead>
<tr>
<th></th>
<th>Entire Year</th>
<th>December</th>
<th>Jan.–Nov.</th>
</tr>
</thead>
<tbody>
<tr>
<td>PLR</td>
<td>0.098</td>
<td>0.128</td>
<td>0.094</td>
</tr>
<tr>
<td>PGR</td>
<td>0.148</td>
<td>0.108</td>
<td>0.152</td>
</tr>
<tr>
<td>Difference in proportions</td>
<td>−0.050</td>
<td>0.020</td>
<td>−0.058</td>
</tr>
<tr>
<td>( t )-statistic</td>
<td>−35</td>
<td>4.3</td>
<td>−38</td>
</tr>
</tbody>
</table>

● Strong support for disposition effect
• Effect monotonically decreasing across the year

• Tax reasons are also at play
• Robustness: Across years and across types of investors

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Entire year PLR</td>
<td>0.126</td>
<td>0.072</td>
<td>0.079</td>
<td>0.296</td>
</tr>
<tr>
<td>Entire year PGR</td>
<td>0.201</td>
<td>0.115</td>
<td>0.119</td>
<td>0.452</td>
</tr>
<tr>
<td>Difference in proportions</td>
<td>−0.075</td>
<td>−0.043</td>
<td>−0.040</td>
<td>−0.156</td>
</tr>
<tr>
<td>t-statistic</td>
<td>−30</td>
<td>−25</td>
<td>−29</td>
<td>−22</td>
</tr>
</tbody>
</table>

• Alternative Explanation 1: **Rebalancing** → Sell winners that appreciated
  
  – Remove partial sales

<table>
<thead>
<tr>
<th></th>
<th>Entire Year</th>
<th>December</th>
</tr>
</thead>
<tbody>
<tr>
<td>PLR</td>
<td>0.155</td>
<td>0.197</td>
</tr>
<tr>
<td>PGR</td>
<td>0.233</td>
<td>0.162</td>
</tr>
<tr>
<td>Difference in proportions</td>
<td>−0.078</td>
<td>0.035</td>
</tr>
<tr>
<td>t-statistic</td>
<td>−32</td>
<td>4.6</td>
</tr>
</tbody>
</table>
Alternative Explanation 2: **Ex-Post Return** \(\rightarrow\) Losers outperform winners ex post

- Table VI: Winners sold outperform losers that could have been sold

<table>
<thead>
<tr>
<th></th>
<th>Performance over Next 84 Trading Days</th>
<th>Performance over Next 252 Trading Days</th>
<th>Performance over Next 504 Trading Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average excess return on winning stocks sold</td>
<td>0.0047</td>
<td>0.0235</td>
<td>0.0645</td>
</tr>
<tr>
<td>Average excess return on paper losses</td>
<td>-0.0056</td>
<td>-0.0106</td>
<td>0.0287</td>
</tr>
<tr>
<td>Difference in excess returns ((p\text{-values}))</td>
<td>0.0103 ((0.002))</td>
<td>0.0341 ((0.001))</td>
<td>0.0358 ((0.014))</td>
</tr>
</tbody>
</table>
• Alternative Explanation 3: **Transaction costs** $\rightarrow$ Losers more costly to trade (lower prices)
  
  – Compute equivalent of $PGR$ and $PLR$ for additional purchases of stock
  
  – This story implies $PGP > PLP$
  
  – Prospect Theory implies $PGP < PLP$ (invest in losses)

• Evidence:

$$PGP = \frac{Gains \text{ Purchased}}{Gains \text{ Purchased} + Paper \text{ Gains}} = .094$$

$$< PLP = \frac{Losses \text{ Purchased}}{Losses \text{ Purchased} + Paper \text{ Losses}} = .135.$$
• Alternative Explanation 4: **Belief in Mean Reversion** –> Believe that losers outperform winners

  – Behavioral explanation: Losers do not outperform winners

  – Predicts that people will buy new losers –> Not true

• How big of a cost? Assume $1000 winner and $1000 loser

  – Winner compared to loser has about $850 in capital gain –> $130 in taxes at 15% marginal tax rate

  – Cost 1: Delaying by one year the $130 tax ded. –> $10

  – Cost 2: Winners overperform by about 3% per year –> $34
• Are results robust to time period and methodology?

• **Ivkovich, Poterba, and Weissbenner (2006)**

• Data
  
  – 78,000 individual investors in Large discount brokerage, 1991-1996
  
  – Compare taxable accounts and tax-deferred plans (IRAs)
  
  – Disposition effect should be stronger for tax-deferred plans
• Methodology: Do hazard regressions of probability of buying an selling monthly, instead of $PGR$ and $PLR$

• For each month $t$, estimate linear probability model:

$$SELL_{i,t} = \alpha_t + \beta_{1,t}I(Gain)_{i,t-1} + \beta_{2,t}I(Loss)_{i,t-1} + \varepsilon_{i,t}$$

• Regression only applies to shares not already sold

• $\alpha_t$ is baseline hazard at month $t$

• Pattern of $\beta$s always consistent with disposition effect, except in December

• Difference is small for tax-deferred accounts
Figure 1: Hazard Rate of Having Sold Stock in Taxable Accounts, Full Sample

Note: Sample is January purchases of stock 1991-96 in taxable accounts. The hazard rate for stock purchases unconditional on the stock’s price performance, as well as conditional on whether the stock has an accrued capital gain or loss entering the month, is displayed.
Figure 2: Hazard Rate of Having Sold Stock in Taxable and Tax-Deferred Accounts, Original Buy at least $10,000

Notes: Sample is January purchases of stock of at least $10,000 from 1991-96. The hazard rate for stock purchases conditional on whether the stock has an accrued capital gain or loss entering the month is displayed for taxable and tax-deferred accounts.
Different hazards between taxable and tax-deferred accounts $\rightarrow$ Taxes

Disposition Effect very solid finding. Explanation?
• **Barberis and Xiang (JF 2009).** Model asset prices with full prospect theory (loss aversion+concavity+convexity), except for prob. weighting

• Under what conditions prospect theory generates disposition effect?

• Setup:
  
  – Individuals can invest in risky asset or riskless asset with return $R_f$
  – Can trade in $t = 0, 1, \ldots, T$ periods
  – Utility is evaluated only at end point, after $T$ periods
  – Reference point is initial wealth $W_0$
  – utility is $v \left( W_T - W_0 R_f \right)$
Calibrated model: Prospect theory may not generate disposition effect!

Table 2: For a given \((\mu, T)\) pair, we construct an artificial dataset of how 10,000 investors with prospect theory preferences, each of whom owns \(N_g\) stocks, each of which has an annual gross expected return \(\mu\), would trade those stocks over \(T\) periods. For each \((\mu, T)\) pair, we use the artificial dataset to compute PGR and PLR, where PGR is the proportion of gains realized by all investors over the entire trading period, and PLR is the proportion of losses realized. The table reports "PGR/PLR" for each \((\mu, T)\) pair. Boldface type identifies cases where the disposition effect fails (PGR < PLR). A hyphen indicates that the expected return is so low that the investor does not buy any stock at all.

<table>
<thead>
<tr>
<th>(\mu)</th>
<th>(T = 2)</th>
<th>(T = 4)</th>
<th>(T = 6)</th>
<th>(T = 12)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.03</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>.55/.50</td>
</tr>
<tr>
<td>1.04</td>
<td>-</td>
<td>-</td>
<td>.54/.52</td>
<td>.54/.52</td>
</tr>
<tr>
<td>1.05</td>
<td>-</td>
<td>-</td>
<td>.54/.52</td>
<td>.59/.45</td>
</tr>
<tr>
<td>1.06</td>
<td>-</td>
<td>.70/.25</td>
<td>.54/.52</td>
<td>.58/.47</td>
</tr>
<tr>
<td>1.07</td>
<td>-</td>
<td>.70/.25</td>
<td>.54/.52</td>
<td>.57/.49</td>
</tr>
<tr>
<td>1.08</td>
<td>-</td>
<td>.70/.25</td>
<td>.48/.58</td>
<td>.47/.60</td>
</tr>
<tr>
<td>1.09</td>
<td>-</td>
<td>.43/.70</td>
<td>.48/.58</td>
<td>.46/.61</td>
</tr>
<tr>
<td>1.10</td>
<td>0.0/1.0</td>
<td>.43/.70</td>
<td>.48/.58</td>
<td>.36/.69</td>
</tr>
<tr>
<td>1.11</td>
<td>0.0/1.0</td>
<td>.43/.70</td>
<td>.49/.58</td>
<td>.37/.68</td>
</tr>
<tr>
<td>1.12</td>
<td>0.0/1.0</td>
<td>.28/.77</td>
<td>.23/.81</td>
<td>.40/.66</td>
</tr>
<tr>
<td>1.13</td>
<td>0.0/1.0</td>
<td>.28/.77</td>
<td>.24/.83</td>
<td>.25/.78</td>
</tr>
</tbody>
</table>
• Intuition:
  – Previous analysis of reference-dependence and disposition effect focused on concavity and convexity of utility function
  – Neglect of kink at reference point (loss aversion)
  – Loss aversion induces high risk-aversion around the kink → Two effects
    1. Agents purchase risky stock only if it has high expected return
    2. Agents sell if price of stock is around reference point
  – Now, assume that returns are high enough and one invests:
    * on gain side, likely to be far from reference point → do not sell, despite (moderate) concavity
    * on loss side, likely to be close to reference point → may lead to more sales (due to local risk aversion), despite (moderate) convexity
Some novel predictions of this model:

- Stocks near buying price are more likely to be sold
- Disposition effect should hold when away from ref. point
• **Meng (2009)** elaborates on this point
  
  – Model of two-period portfolio holding
  – Loss Aversion with respect to (potentially stochastic) reference point
  – Derives optimal holding of risk asset \( x \) as function of past returns
• Empirical test: We should see a drop in propensity to hold a stock when return is near the reference point
• Barberis-Xiong assumes that utility is evaluated every $T$ period for all stocks.

• Alternative assumption: Investors evaluate utility **only** when selling:
  
  – Loss from selling a loser $>\,$ Gain of selling winner
  
  – Sell winners, hoping in option value
  
  – Would induce bunching at exactly purchase price

• Key question: When is utility evaluated?
• Karlsson, Loewenstein, and Seppi (JRU 2009): Ostrich Effect
  – Investors do not want to evaluate their investments at a loss
  – Stock market down $\rightarrow$ Fewer logins into investment account

Figure 4b: Changes in the SAX and ratio of fund look-ups to logins to personal banking page by investors at a large Swedish bank
The sample period is June 30, 2003 through October 7, 2003.
3 Reference Dependence: Equity Premium

- Disposition Effect is about cross-sectional returns and trading behavior →
  Compare winners to losers

- Now consider reference dependence and market-wide returns

- Benartzi and Thaler (1995)

- Equity premium (Mehra and Prescott, 1985)
  - Stocks not so risky
  - Do not covary much with GDP growth
  - BUT equity premium 3.9% over bond returns (US, 1871-1993)

- Need very high risk aversion: $RRA \geq 20$
• Benartzi and Thaler: Loss aversion + narrow framing solve puzzle
  – Loss aversion from (nominal) losses—> Deter from stocks
  – Narrow framing: Evaluate returns from stocks every $n$ months

• More frequent evaluation—>Losses more likely —> Fewer stock holdings

• Calibrate model with $\lambda$ (loss aversion) 2.25 and full prospect theory specification —> Horizon $n$ at which investors are indifferent between stocks and bonds
• If evaluate every year, indifferent between stocks and bonds

• (Similar results with piecewise linear utility)

• Alternative way to see results: Equity premium implied as function on $n$
• Barberis, Huang, and Santos (2001)

• Piecewise linear utility, $\lambda = 2.25$

• Narrow framing at aggregate stock level

• Range of implications for asset pricing

• Barberis and Huang (2001)

• Narrowly frame at individual stock level (or mutual fund)
4 Reference Dependence: Domestic Violence

- Consider a man in conflictual relationship with the spouse

- What is the effect of an event such as the local football team losing or winning a game?

- With probability $h$ the man loses control and becomes violent
  - Assume $h = h(u)$ with $h' < 0$ and $u$ the underlying utility
  - Denote by $p$ the probability that the team wins
– Model the utility $u$ as

$$
1 - p \quad \text{if Team wins} \\
\lambda (0 - p) \quad \text{if Team loses}
$$

– That is, the reference point $R$ is the expected probability or winning the match $p$

• Implications:

– Losses have a larger impact than gains

– The (negative) effect of a loss is higher the more unexpected (higher $p$)

– The (positive) effect of a gain is higher the more unexpected (lower $p$)
• Card and Dahl (2009) test these predictions using a data set of:
  – Domestic violence (NIBRS)
  – Football matches by State
  – Expected win probability from Las Vegas predicted point spread

• Separate matches into
  – Predicted win (+3 points of spread)
  – Predicted close
  – Predicted loss (-3 points)
Table 4. Emotional Shocks from Football Games and Male-on-Female Intimate Partner Violence Occurring at Home, Poisson Regressions.

<table>
<thead>
<tr>
<th>Coefficient Estimates</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loss * Predicted Win (<em>Upset Loss</em>)</td>
<td>.083</td>
<td>.077</td>
<td>.080</td>
<td>.074</td>
<td>.076</td>
</tr>
<tr>
<td></td>
<td>(.026)</td>
<td>(.027)</td>
<td>(.027)</td>
<td>(.028)</td>
<td>(.028)</td>
</tr>
<tr>
<td>Loss * Predicted Close (<em>Close Loss</em>)</td>
<td>.031</td>
<td>.034</td>
<td>.036</td>
<td>.024</td>
<td>.026</td>
</tr>
<tr>
<td></td>
<td>(.023)</td>
<td>(.024)</td>
<td>(.024)</td>
<td>(.025)</td>
<td>(.025)</td>
</tr>
<tr>
<td>Win * Predicted Loss (<em>Upset Win</em>)</td>
<td>-.002</td>
<td>.011</td>
<td>.021</td>
<td>.013</td>
<td>.011</td>
</tr>
<tr>
<td></td>
<td>(.027)</td>
<td>(.027)</td>
<td>(.028)</td>
<td>(.029)</td>
<td>(.029)</td>
</tr>
<tr>
<td>Predicted Win</td>
<td>-.004</td>
<td>-.019</td>
<td>-.015</td>
<td>.000</td>
<td>-.068</td>
</tr>
<tr>
<td></td>
<td>(.022)</td>
<td>(.032)</td>
<td>(.032)</td>
<td>(.033)</td>
<td>(.044)</td>
</tr>
<tr>
<td>Predicted Close</td>
<td>-.012</td>
<td>-.017</td>
<td>-.016</td>
<td>-.007</td>
<td>-.074</td>
</tr>
<tr>
<td></td>
<td>(.023)</td>
<td>(.032)</td>
<td>(.032)</td>
<td>(.034)</td>
<td>(.044)</td>
</tr>
<tr>
<td>Predicted Loss</td>
<td>-.000</td>
<td>-.004</td>
<td>-.011</td>
<td>.006</td>
<td>-.057</td>
</tr>
<tr>
<td></td>
<td>(.022)</td>
<td>(.031)</td>
<td>(.031)</td>
<td>(.033)</td>
<td>(.042)</td>
</tr>
<tr>
<td>Non-game Day</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Nielsen Rating</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>---</td>
<td>.009</td>
</tr>
<tr>
<td></td>
<td>(.004)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Municipality fixed effects</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Year, week, &amp; holiday dummies</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Weather variables</td>
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<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Nielsen Data Sub-sample</td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Number of Municipalities</td>
<td>765</td>
<td>765</td>
<td>765</td>
<td>749</td>
<td>749</td>
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<tr>
<td>Observations</td>
<td>77,520</td>
<td>77,520</td>
<td>77,520</td>
<td>71,798</td>
<td>71,798</td>
</tr>
</tbody>
</table>
• Findings:
  1. Unexpected loss increase domestic violence
  2. No effect of expected loss
  3. No effect of unexpected win, if anything increases violence

• Findings 1-2 consistent with ref. dep. and 3 partially consistent

• Other findings:
  – Effect is larger for more important games
  – Effect disappears within a few hours of game end → Emotions are transient
  – No effect on violence of females on males
5 Reference Dependence: Employment and Effort

- Back to 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 $w \times (1 + r)$

- 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 $r_e \leq r_a \leq r_u$ \implies 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^* \text{ cannot be solution} \Rightarrow \text{Lower } r_e \text{ and increase utility } (U' < 0)
- Union’s problem: maximizes
  \[
  \max_{r_u} PV (w (1 + r_u^*)) + (1 - P) V (w (1 + r_u))
  \]
- Notice: \( V' > 0 \)
- First order condition for union:
  \[
  \frac{P'}{2} [V (w (1 + r_u^*)) - V (w (1 + r_u^*)))] + (1 - P) V' (w (1 + r_u^*)) w = 0
  \]
- To simplify, assume \( U (x) = -bx \) and \( V (x) = bx \)
- This implies
  \[
  V (w (1 + r_u^*)) - V (w (1 + r_u^*)) = -U (w (1 + r_u^*)) - U (w (1 + r_u^*)) \rightarrow
  -bP^* w = -(1 - P^*) bw
  \]
- Result: \( P^* = 1/2 \)

- 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)
- 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>
<thead>
<tr>
<th>Table I</th>
<th>Sample characteristics in the -12 to +12 month event time window</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Full-sample</td>
</tr>
<tr>
<td>Arbitrator rules for employer</td>
<td>0.344</td>
</tr>
<tr>
<td>Final Offer: Employer</td>
<td>6.11 [1.65]</td>
</tr>
<tr>
<td>Final Offer: Union</td>
<td>7.85 [1.71]</td>
</tr>
<tr>
<td>Contract length</td>
<td>2.09 [0.66]</td>
</tr>
<tr>
<td>Size of bargaining unit</td>
<td>42.58 [97.34]</td>
</tr>
<tr>
<td>Arbitration year</td>
<td>85.56 [4.75]</td>
</tr>
<tr>
<td>Clearances per 100,000 capita</td>
<td>120.31 [106.65]</td>
</tr>
</tbody>
</table>
• 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
Arbitration leads to an average increase of 15 clearances out of 100,000 each month.
- Effects on crime rate more imprecise

<table>
<thead>
<tr>
<th></th>
<th>All crime</th>
<th>Violent crime</th>
<th>Property crime</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constant</strong></td>
<td>612.18</td>
<td>150.26</td>
<td>461.81</td>
</tr>
<tr>
<td></td>
<td>(63.98)</td>
<td>(23.23)</td>
<td>(42.00)</td>
</tr>
<tr>
<td><strong>Post-arbitration</strong></td>
<td>26.86</td>
<td>24.68</td>
<td>7.75</td>
</tr>
<tr>
<td>× Employer win</td>
<td>(25.29)</td>
<td>(14.68)</td>
<td>(7.85)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(18.17)</td>
</tr>
<tr>
<td><strong>Post-arbitration</strong></td>
<td>7.64</td>
<td>6.68</td>
<td>7.07</td>
</tr>
<tr>
<td>× Union win</td>
<td>(16.24)</td>
<td>(11.42)</td>
<td>(5.46)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(4.46)</td>
</tr>
<tr>
<td><strong>Row 3 – Row 2</strong></td>
<td>-19.21</td>
<td>-18.01</td>
<td>-0.68</td>
</tr>
<tr>
<td></td>
<td>(30.06)</td>
<td>(19.12)</td>
<td>(9.56)</td>
</tr>
<tr>
<td><strong>Employer Win</strong></td>
<td>-31.81</td>
<td>-20.43</td>
<td>-11.35</td>
</tr>
<tr>
<td>(Yes = 1)</td>
<td>(84.42)</td>
<td>(27.57)</td>
<td>(39.50)</td>
</tr>
</tbody>
</table>

| Fixed-effects?            | Yes       | Yes           | Yes            |
| Mean of the dependent variable | 444.03   | 519.42        | 95.49          |
|                           | [364.23]  | [2037.4]      | [103.16]       |
| Sample size               | 9,528     | 59,060        | 9,529          |
| $R^2$                     | 0.001     | 0.54          | 0.007          |
|                           |           |               | 0.76           |
|                           |           |               | 0.0003         |
|                           |           |               | 0.42           |
• Do reference points matter?

• Plot impact on clearances rates (12,-12) as a function of $\bar{r}_a - (r_e + r_u)/2$
- Effect of loss is larger than effect of gain

### Table VII

<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>-0.20</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.59)</td>
<td>(1.89)</td>
<td></td>
<td>(4.54)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Post-Arbitration × Union win</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>13.38</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(5.32)</td>
<td></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>(7.94)</td>
<td>(4.13)</td>
</tr>
<tr>
<td>Post-Arbitration × p(loss size)^α</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>R²</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>
</tr>
</tbody>
</table>

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 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. 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 1998. 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 (232), arbitration window effects (383), and city effects (432). Author's calculation based on NJ PERC arbitration cases matched to monthly municipal clearance rates at the jurisdiction level from FBI Uniform Crime Reports.
• 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

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

- 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 \textit{in} standard model) and \( \gamma > 0 \) (not in standard model)
• Compare to observed pattern

• Close to predictions of model
6 Next Lecture

- Social Preferences
  - Gift Exchange
  - Workplace
  - From Lab to Field