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

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Outline

1. Reference Dependence: Endowment Effect II

2. Methodology: Effect of Experience


5. Reference Dependence: Insurance
1 Reference Dependence: Endowment Effect II

• List (EMA, 2004): Field experiment similar to experiment I in List (2003)
  
  – Sports traders but objects are mugs and chocolate

  – Trading in four groups:
    
    1. Mug: "Switch to Chocolate?"
    
    2. Chocolate: "Switch to Mug?"
    
    3. Neither: "Choose Mug or Chocolate?"
    
    4. Both: "Switch to Mug or Chocolate?"
**Large endowment effect for inexperienced card dealers**

**No endowment effect for experienced card dealers!**

**Learning (or reference point formation) generalizes beyond original domain**

<table>
<thead>
<tr>
<th>Panel D. Trading Rates</th>
<th>Preferred Exchange</th>
<th>p-Value for Fisher's Exact Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pooled nondealers ($n = 129$)</td>
<td>.18 (.38)</td>
<td>&lt; .01</td>
</tr>
<tr>
<td>Inexperienced consumers ($&lt; 6$ trades monthly; $n = 74$)</td>
<td>.08 (.27)</td>
<td>&lt; .01</td>
</tr>
<tr>
<td>Experienced consumers ($\geq 6$ trades monthly; $n = 55$)</td>
<td>.31 (.47)</td>
<td>&lt; .01</td>
</tr>
<tr>
<td>Intense consumers ($\geq 12$ trades monthly; $n = 16$)</td>
<td>.56 (.51)</td>
<td>.64</td>
</tr>
<tr>
<td>Pooled dealers ($n = 62$)</td>
<td>.48 (.50)</td>
<td>.80</td>
</tr>
</tbody>
</table>
2 Methodology: Effect of Experience

- Effect of experience is debated topic
- Does Experience eliminate behavioral biases?
- Argument for ‘irrelevance’ of Psychology and Economics
  - Opportunities for learning:
    - Getting feedback from expert agents
    - Learning from past (own) experiences
    - Incentives for agents to provide advice
- This will drive away ‘biases’
• However, four arguments to contrary:

1. Feedback is often infrequent (house purchases) and noisy (financial investments) $\rightarrow$ Slow convergence

2. Feedback can exacerbate biases for non-standard agents:
   - Ego-utility (Koszegi, 2001): Do not want to learn
   - Learn on the wrong parameter
   - See Haigh and List (2004) below
3. No incentives for Experienced agents to provide advice
   - Exploit naives instead

4. No learning on preferences:
   - Social Preferences or Self-control are non un-learnt
   - Preference features as much as taste for Italian red cars (undeniable)
• Empirically, four instances:

• **Case 1. Endowment Effect.** List (2003 and 2004)
  
  – Trading experience $\rightarrow$ Less Endowment Effect
  
  – Effect applies across goods
  
  – Interpretations:
    
    * Loss aversion can be un-learnt
  
    * Experience leads to update reference point $\rightarrow$ Expect to trade
• Case 2. Nash Eq. in Zero-Sum Games.


• Idea: Penalty kicks are practice for zero-sum game play

\[ \begin{array}{c|cc}
1 & A & B \\
\hline
A & .60 & .95 \\
B & .90 & .70 \\
\end{array} \]

• How close are players to the Nash mixed strategies?

• Compare professional (2nd League) players and college students – 150 repetitions
**Table E - Summary Statistics in Penalty Kick’s Experiment**

<table>
<thead>
<tr>
<th></th>
<th>Equilibrium</th>
<th>Professional Soccer Players</th>
<th>College Soccer Experience</th>
<th>No Soccer Experience</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>I. Aggregate Data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Row Player frequencies</td>
<td>$L$</td>
<td>0.363</td>
<td>0.333</td>
<td>0.392</td>
</tr>
<tr>
<td></td>
<td>$R$</td>
<td>0.636</td>
<td>0.667</td>
<td>0.608</td>
</tr>
<tr>
<td>Column Player frequencies</td>
<td>$L$</td>
<td>0.454</td>
<td>0.462</td>
<td>0.419</td>
</tr>
<tr>
<td></td>
<td>$R$</td>
<td>0.545</td>
<td>0.538</td>
<td>0.581</td>
</tr>
<tr>
<td>Row Player Win percentage</td>
<td>Equilibrium</td>
<td>0.7909</td>
<td>0.7947</td>
<td>0.7927</td>
</tr>
<tr>
<td></td>
<td>(std. deviation)</td>
<td>(0.0074)</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>II. Number of Individual Rejections of Minimax Model at 5 (10) percent</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Row Player (All Cards)</td>
<td>1 (2)</td>
<td>0 (1)</td>
<td>1 (3)</td>
<td>2 (3)</td>
</tr>
<tr>
<td>Column Player (All Cards)</td>
<td>1 (2)</td>
<td>1 (2)</td>
<td>2 (2)</td>
<td>3 (10)</td>
</tr>
<tr>
<td>Both Players (All Cards)</td>
<td>1 (2)</td>
<td>1 (1)</td>
<td>1 (3)</td>
<td>3 (9)</td>
</tr>
<tr>
<td>All Cards</td>
<td>4 (8)</td>
<td>4 (7)</td>
<td>9 (12)</td>
<td>12 (20)</td>
</tr>
</tbody>
</table>

- Surprisingly close on average
• More deviations for students \(\rightarrow\) Experience helps (though people surprisingly good)

• However: Levitt-List-Reley (2007): Replicate in the US
  – Soccer and Poker players, 150 repetition
  – No better at Nash Play than students

• Maybe hard to test given that even students are remarkably good

• Play in centipede game

```
  continue  continue  continue  continue  continue  continue  continue  256
II       I       II       I       II       I       II
stop     stop     stop     stop     stop     stop     stop
4        2        16       8        64       32
1        8        4        32       16       128
```

• – Optimal strategy (by backward induction) → Exit immediately

  – Continue if:
    * No induction
* Higher altruism

- Test of backward induction: Take Chess players
  - 211 pairs of chess players at Chess Tournament
  - Randomly matched, anonymity
  - 40 college students
  - Games with SMS messages

- Results:
  - Chess Players end sooner
- More so the more experience
• Interpretations:
  – Cognition: Better at backward induction
  – Preferences: More selfish

• Open questions:
  – Who earned the higher payoffs? Almost surely the students
  – What would happen if you mix groups and people know it?
• Case 4. Myopic Loss Aversion.

• Haigh and List (2004): Professional Traders $\rightarrow$ More Myopic Loss Aversion (See Next Lecture)

• Summary: Effect of Experience?
  – Can go either way
  – Open question
3 Reference Dependence: Labor Supply – A Model


- 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: $Y = w \cdot h$
  
  – Linear utility $U(Y) = Y$
  
  – Cost of effort $c(h) = \frac{\theta h^2}{2}$ 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 \(h^* = \lambda w/\theta < T/w\)
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:

\[ L^S = w^*/\theta = a - bw^* = L^D \]

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:

\[ L^S = T/w^* = a - bw^* = L^D \]

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)
4 Reference Dependence: Labor Supply – The Evidence

- Camerer, Babcock, Loewenstein, and Thaler (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. .051) – TLC1 with driver f.e.
- \( \hat{\beta} = -0.355 \) (s.e. .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: $\tilde{h}_{i,t} = h_{i,t} \times \phi_{i,t}$. Then,

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

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

• 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>-.131</td>
<td>-.926</td>
</tr>
<tr>
<td></td>
<td>(.298) (.273) (.236) (.259) (.478)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High temperature</td>
<td>-.000</td>
<td>-.001</td>
<td>.002</td>
</tr>
<tr>
<td></td>
<td>(.002) (.002) (.002) (.002) (.007)</td>
<td></td>
<td></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)

<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</td>
<td>...</td>
<td>.126</td>
<td>.024</td>
</tr>
<tr>
<td>&lt; 30</td>
<td></td>
<td>(.053)</td>
<td>(.058)</td>
</tr>
<tr>
<td>Maximum temperature</td>
<td>...</td>
<td>.041</td>
<td>.055</td>
</tr>
<tr>
<td>≥ 80</td>
<td></td>
<td>(.055)</td>
<td>(.064)</td>
</tr>
<tr>
<td>Rainfall</td>
<td>...</td>
<td>-.022</td>
<td>-.054</td>
</tr>
<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>

• Farber (2005) however cannot replicate the IV specification (too few drivers on a given day)
• 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
– 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 7](image.png)

<table>
<thead>
<tr>
<th>Variable</th>
<th>4</th>
<th>10</th>
<th>16</th>
<th>18</th>
<th>20</th>
<th>21</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hours</td>
<td>0.073</td>
<td>0.056</td>
<td>0.043</td>
<td>0.010</td>
<td>0.195</td>
<td>0.198</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.047)</td>
<td>(0.015)</td>
<td>(0.007)</td>
<td>(0.045)</td>
<td>(0.050)</td>
</tr>
<tr>
<td>Income + 100</td>
<td>0.178</td>
<td>0.089</td>
<td>0.064</td>
<td>0.048</td>
<td>-0.160</td>
<td>-0.002</td>
</tr>
<tr>
<td></td>
<td>(0.167)</td>
<td>(0.059)</td>
<td>(0.041)</td>
<td>(0.020)</td>
<td>(0.123)</td>
<td>(0.150)</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 ($X^2(1) = 4.57, p<0.05$)
- Implied Elasticity: 0.8
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 (2006)** 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 \( \sigma^2 \)

\begin{center}
\begin{tabular}{lcccc}
Parameter & (1) & (2) & (3) & (4) \\
\hline
\( \beta \) (contprob) & -0.691 & --- & --- & --- \\
 & (0.243) & & & \\
\( \hat{\theta} \) (mean ref inc) & 159.02 & 206.71 & 250.86 & --- \\
 & (4.99) & (7.99) & (16.47) & \\
\( \hat{\delta} \) (cont increment) & 3.40 & 5.35 & 4.85 & 5.38 \\
 & (0.279) & (0.573) & (0.711) & (0.545) \\
\( \hat{\sigma}^2 \) (ref inc var) & 3199.4 & 10440.0 & 15944.3 & 8236.2 \\
 & (294.0) & (1660.7) & (3652.1) & (1222.2) \\
\hline
Driver \( \theta \), (15) & No & No & No & Yes \\
\hline
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 \\
\hline
Log(L) & -1867.8 & -1631.6 & -1572.8 & -1606.0 \\
NumberParms & 4 & 43 & 57 & 57 \\
\end{tabular}
\end{center}
• Most recent paper: **Meng (2008)**

• Re-estimates the Farber paper allowing for two dimensions of reference dependence:
  
  – Hours (loss if work more house than $\bar{h}$)

  – Income (loss if earn less than $\bar{Y}$)

• Re-estimates Farber (2006) 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>Pooled data</th>
<th>$w^g &gt; w^f$</th>
<th>$w^g \leq w^f$</th>
<th>(2)</th>
<th>Pooled data</th>
<th>$w^g &gt; w^f$</th>
<th>$w^g \leq w^f$</th>
<th>(3)</th>
<th>Pooled data</th>
<th>$w^g &gt; w^f$</th>
<th>$w^g \leq w^f$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total hours</td>
<td>.013</td>
<td>(.009)*</td>
<td>.005</td>
<td>.016</td>
<td>.010</td>
<td>(.007)**</td>
<td>.001</td>
<td>.001</td>
<td>.003</td>
<td>(.003)**</td>
<td>.011</td>
<td>.009</td>
</tr>
<tr>
<td>Waiting hours</td>
<td>.010</td>
<td>.007</td>
<td>.016</td>
<td>.001</td>
<td>.001</td>
<td>.001</td>
<td>.002</td>
<td>.003</td>
<td>.003</td>
<td>.003</td>
<td>.005</td>
<td>.005</td>
</tr>
<tr>
<td>Break hours</td>
<td>.006</td>
<td>.005</td>
<td>.004</td>
<td>-.003</td>
<td>-.006</td>
<td>-.003</td>
<td>-.002</td>
<td>-.004</td>
<td>-.002</td>
<td>-.004</td>
<td>-.002</td>
<td>-.003**</td>
</tr>
<tr>
<td>Income/100</td>
<td>.053</td>
<td>.076</td>
<td>.055</td>
<td>.013</td>
<td>.045</td>
<td>.009</td>
<td>.010</td>
<td>.042</td>
<td>.002</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Min temp&lt;30</td>
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<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Max temp&gt;80</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hourly rain</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
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<td>-</td>
<td>-</td>
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<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Daily snow</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Location dummies</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Driver dummies</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day of week</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hour of day</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</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>
<td>-1789.5</td>
<td>-1003.8</td>
<td>-753.4</td>
<td>-1767.5</td>
<td>-9878.0</td>
<td>-740.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pseudo R2</td>
<td>0.1516</td>
<td>0.1555</td>
<td>0.1533</td>
<td>0.2555</td>
<td>0.2618</td>
<td>0.2773</td>
<td>0.2647</td>
<td>0.2735</td>
<td>0.2901</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observation</td>
<td>13461</td>
<td>7936</td>
<td>5525</td>
<td>13461</td>
<td>7936</td>
<td>5525</td>
<td>13461</td>
<td>7936</td>
<td>5525</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Probability of Stopping: Probit Model with Linear Effect
• Results:
  
  – $w > w^e$: income binding $\rightarrow$ income explains stopping
  
  – $w < w^e$: hours binding $\rightarrow$ hours explain stopping

• Perhaps, reconciling Camerer et al. (1997) and Farber (2005)
• 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)
5 Reference Dependence: Insurance

- Much of the laboratory evidence on prospect theory is on risk taking.

- Field evidence considered so far (mostly) does not involve risk:
  - Trading behavior – Endowment Effect
  - Daily Labor Supply

- Field evidence on risk taking?

- Sydnor (2006) on deductible choice in the life insurance industry

- Uses Menu Choice as identification strategy as in DellaVigna and Malmendier (2006)

- Slides courtesy of Justin Sydnor
Dataset

- 50,000 Homeowners-Insurance Policies
  - 12% were new customers
- Single western state
- One recent year (post 2000)
- Observe
  - Policy characteristics including deductible
    - 1000, 500, 250, 100
  - Full available deductible-premium menu
  - Claims filed and payouts by company
Features of Contracts

- Standard homeowners-insurance policies (no renters, condominiums)
- Contracts differ only by deductible
- Deductible is *per claim*
- No experience rating
  - Though underwriting practices not clear
- Sold through agents
  - Paid commission
  - No “default” deductible
- Regulated state
## Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Full Sample</th>
<th>1000</th>
<th>500</th>
<th>250</th>
<th>100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Insured home value</td>
<td>206,917</td>
<td>266,461</td>
<td>205,026</td>
<td>180,895</td>
<td>164,485</td>
</tr>
<tr>
<td></td>
<td>(91,178)</td>
<td>(127,773)</td>
<td>(81,834)</td>
<td>(65,089)</td>
<td>(53,808)</td>
</tr>
<tr>
<td>Number of years insured by the company</td>
<td>8.4</td>
<td>5.1</td>
<td>5.8</td>
<td>13.5</td>
<td>12.8</td>
</tr>
<tr>
<td></td>
<td>(7.1)</td>
<td>(5.6)</td>
<td>(5.2)</td>
<td>(7.0)</td>
<td>(6.7)</td>
</tr>
<tr>
<td>Average age of H.H. members</td>
<td>53.7</td>
<td>50.1</td>
<td>50.5</td>
<td>59.8</td>
<td>66.6</td>
</tr>
<tr>
<td></td>
<td>(15.8)</td>
<td>(14.5)</td>
<td>(14.9)</td>
<td>(15.9)</td>
<td>(15.5)</td>
</tr>
<tr>
<td>Number of paid claims in sample year (claim rate)</td>
<td>0.042</td>
<td>0.025</td>
<td>0.043</td>
<td>0.049</td>
<td>0.047</td>
</tr>
<tr>
<td></td>
<td>(0.22)</td>
<td>(0.17)</td>
<td>(0.22)</td>
<td>(0.23)</td>
<td>(0.21)</td>
</tr>
<tr>
<td>Yearly premium paid</td>
<td>719.80</td>
<td>798.60</td>
<td>715.60</td>
<td>687.19</td>
<td>709.78</td>
</tr>
<tr>
<td></td>
<td>(312.76)</td>
<td>(405.78)</td>
<td>(300.39)</td>
<td>(267.82)</td>
<td>(269.34)</td>
</tr>
<tr>
<td>N</td>
<td>49,992</td>
<td>8,525</td>
<td>23,782</td>
<td>17,536</td>
<td>149</td>
</tr>
<tr>
<td>Percent of sample</td>
<td>100%</td>
<td>17.05%</td>
<td>47.57%</td>
<td>35.08%</td>
<td>0.30%</td>
</tr>
</tbody>
</table>

* Means with standard errors in parentheses.
Deductible Pricing

- $X_i$ = matrix of policy characteristics
- $f(X_i)$ = "base premium"
  - Approx. linear in home value
- Premium for deductible $D$
  - $P_i^D = \delta_D f(X_i)$
- Premium differences
  - $\Delta P_i = \Delta \delta f(X_i)$
- $\Rightarrow$ Premium differences depend on base premiums (insured home value).
## Premium-Deductible Menu

<table>
<thead>
<tr>
<th>Available Deductible</th>
<th>Full Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>$615.82</td>
</tr>
<tr>
<td></td>
<td>(292.59)</td>
</tr>
<tr>
<td>500</td>
<td>+99.91</td>
</tr>
<tr>
<td></td>
<td>(45.82)</td>
</tr>
<tr>
<td>250</td>
<td>+86.59</td>
</tr>
<tr>
<td></td>
<td>(39.71)</td>
</tr>
<tr>
<td>100</td>
<td>+133.22</td>
</tr>
<tr>
<td></td>
<td>(61.09)</td>
</tr>
</tbody>
</table>

**Risk Neutral Claim Rates?**

- \( \frac{100}{500} = 20\% \)
- \( \frac{87}{250} = 35\% \)
- \( \frac{133}{150} = 89\% \)

* Means with standard deviations in parentheses
The curves in the upper graphs are fan locally-weighted kernel regressions using a quartic kernel. The dashed lines give 95% confidence intervals calculated using a bootstrap procedure with 200 repetitions. The range for additional premium covers 98% of the available data.

The graph in the upper left gives the fraction that chose either the $250 or $500 deductibles versus the additional premium an individual faced to move from a $1000 to the $500 deductible. The graph in the upper right represents the average expected savings from switching to the $1000 deductible for customers facing a given premium difference. The potential savings is calculated at the individual level and then the kernel regressions are run. Because they filed no claims, for most customers this measure is simply the premium reductions they would have seen with the $1000 deductible. For the roughly 4% of customers who filed claims the potential savings is typically negative.

Kernel Density of Additional Premium

Epanechnikov kernel, bw = 10

Potential Savings with the Alternative $1000 Deductible

Quartic kernel, bw = 20

Low Deductible Customers

What if the x-axis were insured home value?
The graph in the upper left gives the fraction that chose either the $250 or $500 deductibles as a function of the insured home value.

The graph in the upper right represents the average expected savings from switching to the $1000 deductible for customers who chose one of the lower deductibles. The potential savings is calculated at the individual level and then the kernel regressions are run. Because they filed no claims, for most customers this measure is simply the premium reductions they would have seen with the $1000 deductible. For the roughly 4% of customers who filed claims the potential savings is typically negative.

The curves in the upper graphs are fan locally-weighted kernel regressions using a quartic kernel. The dashed lines give 95% confidence intervals calculated using a bootstrap procedure with 200 repetitions.

The range for insured home value covers 99% of the available data.

The right figure shows the potential savings with the alternative $1000 deductible for low deductible customers.

Kernel Density of Insured Home Value

Quartic kernel, bw = 25

Epanechnikov kernel, bw = 25
## Potential Savings with 1000 Ded

### Claim rate?

#### Value of lower deductible?

#### Additional premium?

#### Potential savings?

<table>
<thead>
<tr>
<th>Chosen Deductible</th>
<th>Number of claims per policy</th>
<th>Increase in out-of-pocket payments per claim with a $1000 deductible</th>
<th>Increase in out-of-pocket payments per policy with a $1000 deductible</th>
<th>Reduction in yearly premium per policy with $1000 deductible</th>
<th>Savings per policy with $1000 deductible</th>
</tr>
</thead>
<tbody>
<tr>
<td>$500</td>
<td>0.043</td>
<td>469.86</td>
<td>19.93</td>
<td>99.85</td>
<td>79.93</td>
</tr>
<tr>
<td>N=23,782 (47.6%)</td>
<td>(.0014)</td>
<td>(2.91)</td>
<td>(0.67)</td>
<td>(0.26)</td>
<td>(0.71)</td>
</tr>
<tr>
<td>$250</td>
<td>0.049</td>
<td>651.61</td>
<td>31.98</td>
<td>158.93</td>
<td>126.95</td>
</tr>
<tr>
<td>N=17,536 (35.1%)</td>
<td>(.0018)</td>
<td>(6.59)</td>
<td>(1.20)</td>
<td>(0.45)</td>
<td>(1.28)</td>
</tr>
</tbody>
</table>

Average forgone expected savings for all low-deductible customers: $99.88

* Means with standard errors in parentheses
Back of the Envelope

- **BOE 1:** Buy house at 30, retire at 65, 3% interest rate ⇒ $6,300 expected
  - With 5% Poisson claim rate, only 0.06% chance of losing money

- **BOE 2:** (Very partial equilibrium) 80% of 60 million homeowners could expect to save $100 a year with “high” deductibles ⇒ $4.8 billion per year
Consumer Inertia?

Percent of Customers Holding each Deductible Level

Number of Years Insured with Company

- 0-3
- 3-7
- 7-11
- 11-15
- 15+

Deductible Levels:
- 1000
- 500
- 250
- 100
#### Look Only at New Customers

<table>
<thead>
<tr>
<th>Chosen Deductible</th>
<th>Number of claims per policy</th>
<th>Increase in out-of-pocket payments per claim with a $1000 deductible</th>
<th>Increase in out-of-pocket payments per policy with a $1000 deductible</th>
<th>Reduction in yearly premium per policy with $1000 deductible</th>
<th>Savings per policy with $1000 deductible</th>
</tr>
</thead>
<tbody>
<tr>
<td>$500</td>
<td>0.037</td>
<td>475.05</td>
<td>17.16</td>
<td>94.53</td>
<td>77.37</td>
</tr>
<tr>
<td>N = 3,424 (54.6%)</td>
<td>(.0035)</td>
<td>(7.96)</td>
<td>(1.66)</td>
<td>(0.55)</td>
<td>(1.74)</td>
</tr>
<tr>
<td>$250</td>
<td>0.057</td>
<td>641.20</td>
<td>35.68</td>
<td>154.90</td>
<td>119.21</td>
</tr>
<tr>
<td>N = 367 (5.9%)</td>
<td>(.0127)</td>
<td>(43.78)</td>
<td>(8.05)</td>
<td>(2.73)</td>
<td>(8.43)</td>
</tr>
</tbody>
</table>

Average forgone expected savings for all low-deductible customers: $81.42
Risk Aversion?

- Simple Standard Model
  - Expected utility of wealth maximization
  - Free borrowing and savings
  - Rational expectations
  - Static, single-period insurance decision
  - No other variation in lifetime wealth

- Consumption maximization:

\[
\max_{c_t} U(c_1, c_2, ..., c_T),
\]

\[
s.t. \ c_1 + c_2 + ... + c_T = y_1 + y_2 + ... y_T.
\]

- (Indirect) utility of wealth maximization

\[
\max_w u(w),
\]

where \( u(w) = \max_{c_t} U(c_1, c_2, ..., c_T), \)

\[
s.t. \ c_1 + c_2 + ... + c_T = y_1 + y_2 + ... + y_T = w
\]

\( \Rightarrow w \) is lifetime wealth
Model of Deductible Choice

- Choice between \((P_L, D_L)\) and \((P_H, D_H)\)
- \(\pi = \) probability of loss
  - Simple case: only one loss
- EU of contract:
  - \(U(P, D, \pi) = \pi u(w-P-D) + (1- \pi)u(w-P)\)
Bounding Risk Aversion

Assume CRRA form for $u$:

$$u(x) = \frac{x^{(1-\rho)}}{(1-\rho)} \quad \text{for } \rho \neq 1, \quad \text{and} \quad u(x) = \ln(x) \quad \text{for } \rho = 1$$

Indifferent between contracts iff:

$$\pi \frac{(w - P_L - D_L)^{(1-\rho)}}{(1-\rho)} + (1 - \pi) \frac{(w - P_L)^{(1-\rho)}}{(1-\rho)} = \pi \frac{(w - P_H - D_H)^{(1-\rho)}}{(1-\rho)} + (1 - \pi) \frac{(w - P_H)^{(1-\rho)}}{(1-\rho)}$$
Getting the bounds

- Search algorithm at individual level
  - New customers
- Claim rates: Poisson regressions
  - Cap at 5 possible claims for the year
- Lifetime wealth:
  - Conservative: $1 million (40 years at $25k)
  - More conservative: Insured Home Value
## CRRA Bounds

<table>
<thead>
<tr>
<th>Chosen Deductible</th>
<th>Measure of Lifetime Wealth (W): (Insured Home Value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>W</td>
</tr>
<tr>
<td>$1,000$</td>
<td>256,900</td>
</tr>
<tr>
<td>[N = 2,474 (39.5%)]</td>
<td>{113,565}</td>
</tr>
<tr>
<td>$500$</td>
<td>190,317</td>
</tr>
<tr>
<td>[N = 3,424 (54.6%)]</td>
<td>{64,634}</td>
</tr>
<tr>
<td>$250$</td>
<td>166,007</td>
</tr>
<tr>
<td>[N = 367 (5.9%)]</td>
<td>{57,613}</td>
</tr>
</tbody>
</table>
Interpreting Magnitude

- 50-50 gamble:
  Lose $1,000/ Gain $10 million
  - 99.8% of low-ded customers would reject

- Labor-supply calibrations, consumption-savings behavior ⇒ ρ < 10
  - Gourinchas and Parker (2002) -- 0.5 to 1.4
  - Chetty (2005) -- < 2
Wrong level of wealth?

- Lifetime wealth inappropriate if borrowing constraints.
- $94 for $500 insurance, 4% claim rate
  - $W = $1 million $\Rightarrow \rho = 2,013$
  - $W = $100k $\Rightarrow \rho = 199$
  - $W = $25k $\Rightarrow \rho = 48$
Prospect Theory

- Kahneman & Tversky (1979, 1992)
- Reference dependence
  - Not final wealth states
- Value function
  - Loss Aversion
  - Concave over gains, convex over losses
- Non-linear probability weighting
Model of Deductible Choice

- Choice between \((P_L,D_L)\) and \((P_H,D_H)\)
- \(\pi\) = probability of loss
- EU of contract:
  - \(U(P,D,\pi) = \pi u(w-P-D) + (1- \pi)u(w-P)\)
- PT value:
  - \(V(P,D,\pi) = v(-P) + w(\pi)v(-D)\)
- Prefer \((P_L,D_L)\) to \((P_H,D_H)\)
  - \(v(-P_L) - v(-P_H) < w(\pi)[v(-D_H) - v(-D_L)]\)
Loss Aversion and Insurance

  - Choice A
    - 25% chance of $200 loss [80%]
    - Sure loss of $50 [20%]
  - Choice B
    - 25% chance of $200 loss [35%]
    - Insurance costing $50 [65%]
No loss aversion in buying

- Novemsky and Kahneman (2005)  
  (Also Kahneman, Knetsch & Thaler (1991))
  - Endowment effect experiments
  - Coefficient of loss aversion = 1 for “transaction money”

- Köszegi and Rabin (forthcoming QJE, 2005)
  - Expected payments

- Marginal value of deductible payment > premium payment (2 times)
So we have:

- Prefer \((P_L, D_L)\) to \((P_H, D_H)\):
  \[
  \nu(-P_L) - \nu(-P_H) < w(\pi)[\nu(-D_H) - \nu(-D_L)]
  \]

- Which leads to:
  \[
  P_L^\beta - P_H^\beta < w(\pi) \lambda [D_H^\beta - D_L^\beta]
  \]

- Linear value function:
  \[
  WTP = \Delta P = \boxed{w(\pi) \lambda \Delta D}
  \]
  \[
  = 4 \text{ to } 6 \text{ times EV}
  \]
Parameter values

- Kahneman and Tversky (1992)
  - $\lambda = 2.25$
  - $\beta = 0.88$

- Weighting function

$$w(\pi) = \frac{\pi^\gamma}{(\pi^\gamma + (1 - \pi)^\gamma)^{\gamma}}$$

- $\gamma = 0.69$
WTP from Model

- Typical new customer with $500 ded
  - Premium with $1000 ded = $572
  - Premium with $500 ded = +$94.53
  - 4% claim rate
- Model predicts WTP = $107
- Would model predict $250 instead?
  - WTP = $166. Cost = $177, so no.
## Choices: Observed vs. Model

<table>
<thead>
<tr>
<th>Chosen Deductible</th>
<th>Predicted Deductible Choice from Prospect Theory NLIB Specification: ( \lambda = 2.25, \gamma = 0.69, \beta = 0.88 )</th>
<th>Predicted Deductible Choice from EU(W) CRRA Utility: ( \rho = 10, W = \text{Insured Home Value} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1000</td>
<td>500</td>
</tr>
<tr>
<td>$1,000</td>
<td>87.39%</td>
<td>11.88%</td>
</tr>
<tr>
<td>N = 2,474 (39.5%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$500</td>
<td>18.78%</td>
<td>59.43%</td>
</tr>
<tr>
<td>N = 3,424 (54.6%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$250</td>
<td>3.00%</td>
<td>44.41%</td>
</tr>
<tr>
<td>N = 367 (5.9%)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$100</td>
<td>33.33%</td>
<td>66.67%</td>
</tr>
<tr>
<td>N = 3 (0.1%)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Conclusions

- (Extreme) aversion to moderate risks is an empirical reality in an important market
- Seemingly anomalous in Standard Model where risk aversion = DMU
- Fits with existing parameter estimates of leading psychology-based alternative model of decision making
Alternative Explanations

- Misestimated probabilities
  - $\approx 20\%$ for single-digit CRRA
  - Older (age) new customers just as likely
- Liquidity constraints
- Sales agent effects
  - Hard sell?
  - Not giving menu? ($500\?, data patterns)
  - Misleading about claim rates?
- Menu effects
6 Next Lecture

- Reference Dependence
  - Housing
  - Finance
  - Pay Setting and Effort