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

Stefano DellaVigna

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Outline

1. Methodology: Effect of Experience

2. Reference Dependence: Labor Supply – A Model

3. Reference Dependence: Labor Supply – The Evidence

4. Reference Dependence: Insurance

1 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) –> 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

   – Behavioral IO –> DellaVigna-Malmendier (2004) and Gabaix-Laibson (2006)

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 –> Less Endowment Effect

  - Effect applies across goods

  - Interpretations:

    - Loss aversion can be un-learnt

    - Experience leads to update reference point –> Expect to trade

- **Case 2. Nash Eq. in Zero-Sum Games.**

- Palacios-Huerta-Volij (2006): Soccer players practice –> Better Nash play

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

$1\backslash 2$	A	B
A	.60	.95
B	.90	.70

- 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

		Equilibrium	Professional Soccer Players	College Students: Soccer Experience	College Students: No Soccer Experience
I. Aggregate Data					
Row Player frequencies	*L*	0.363	0.333	0.392	0.401
	R	0.636	0.667	0.608	0.599
Column Player frequencies	*L*	0.454	0.462	0.419	0.397
	R	0.545	0.538	0.581	0.603
Row Player Win percentage		0.7909	0.7947	0.7927	0.7877
(std. deviation)		(0.0074)			
II. Number of Individual Rejections of Minimax Model at 5 (10) percent					
Row Player (All Cards)		1 (2)	0 (1)	1 (3)	2 (3)
Column Player (All Cards)		1 (2)	1 (2)	2 (2)	3 (10)
Both Players (All Cards)		1 (2)	1 (1)	1 (3)	3 (9)
All Cards		4 (8)	4 (7)	9 (12)	12 (20)

- Surprisingly close on average

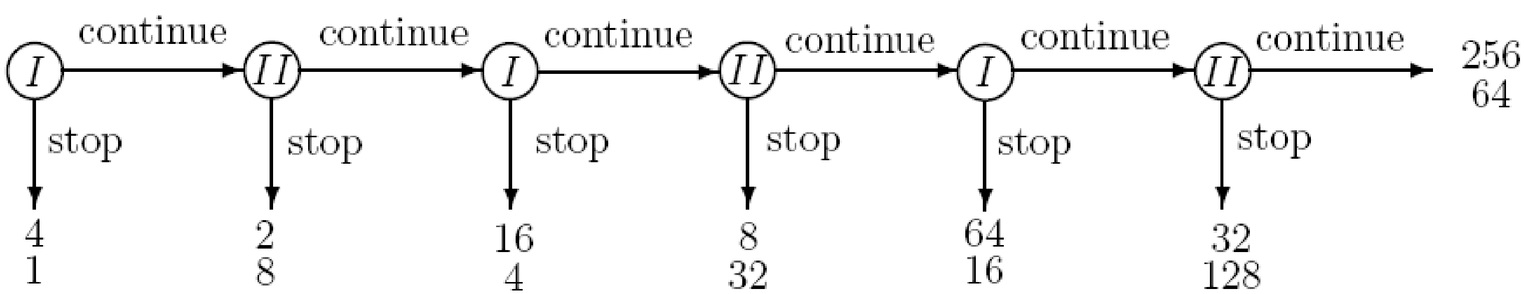
- More deviations for students –> Experience helps (though people surprisingly good)

- 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

- **Case 3. Backward Induction.** Palacios-Huerta-Volij (2007)

- Play in centipede game



- – Optimal strategy (by backward induction) –> Exit immediately

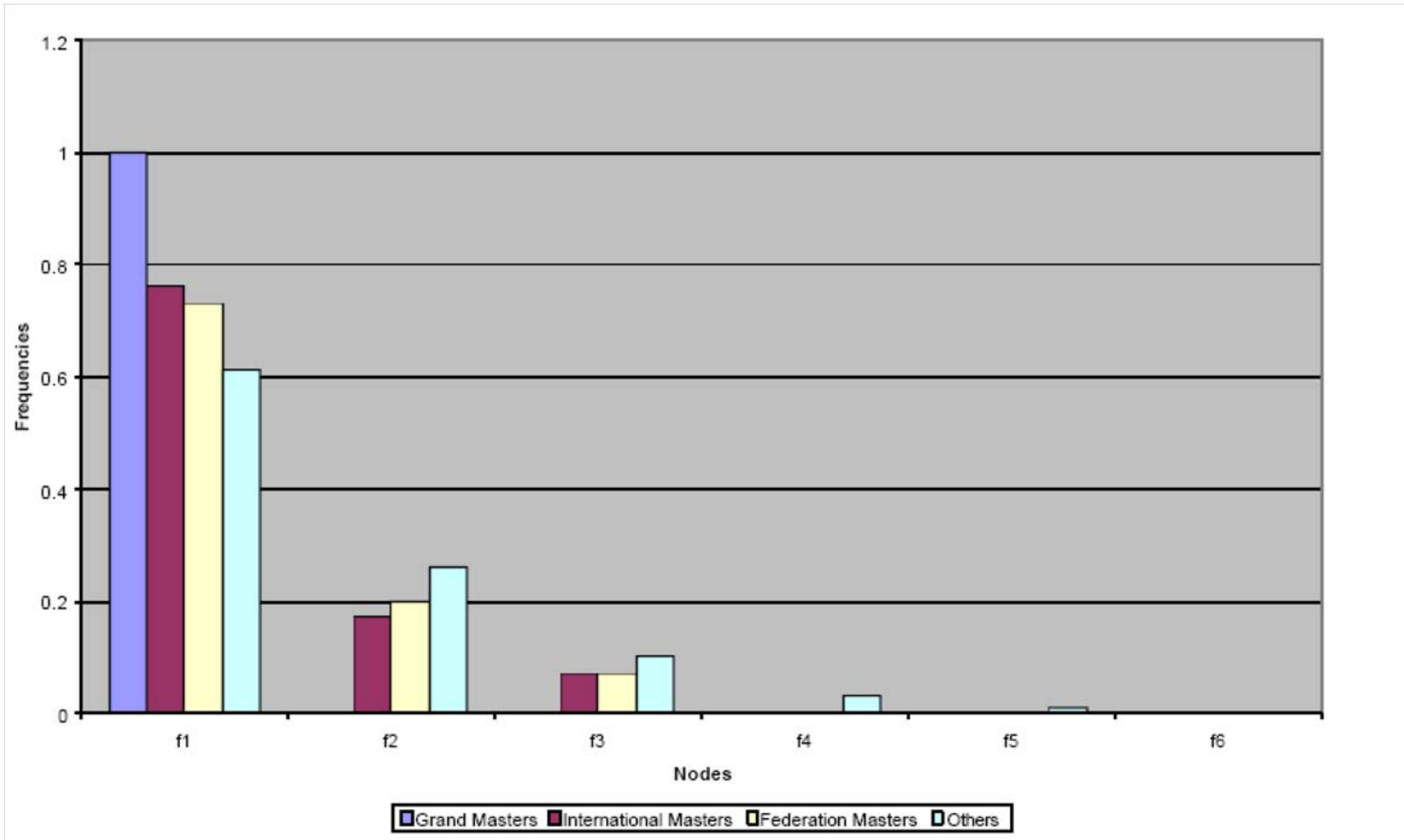
  – Continue if:

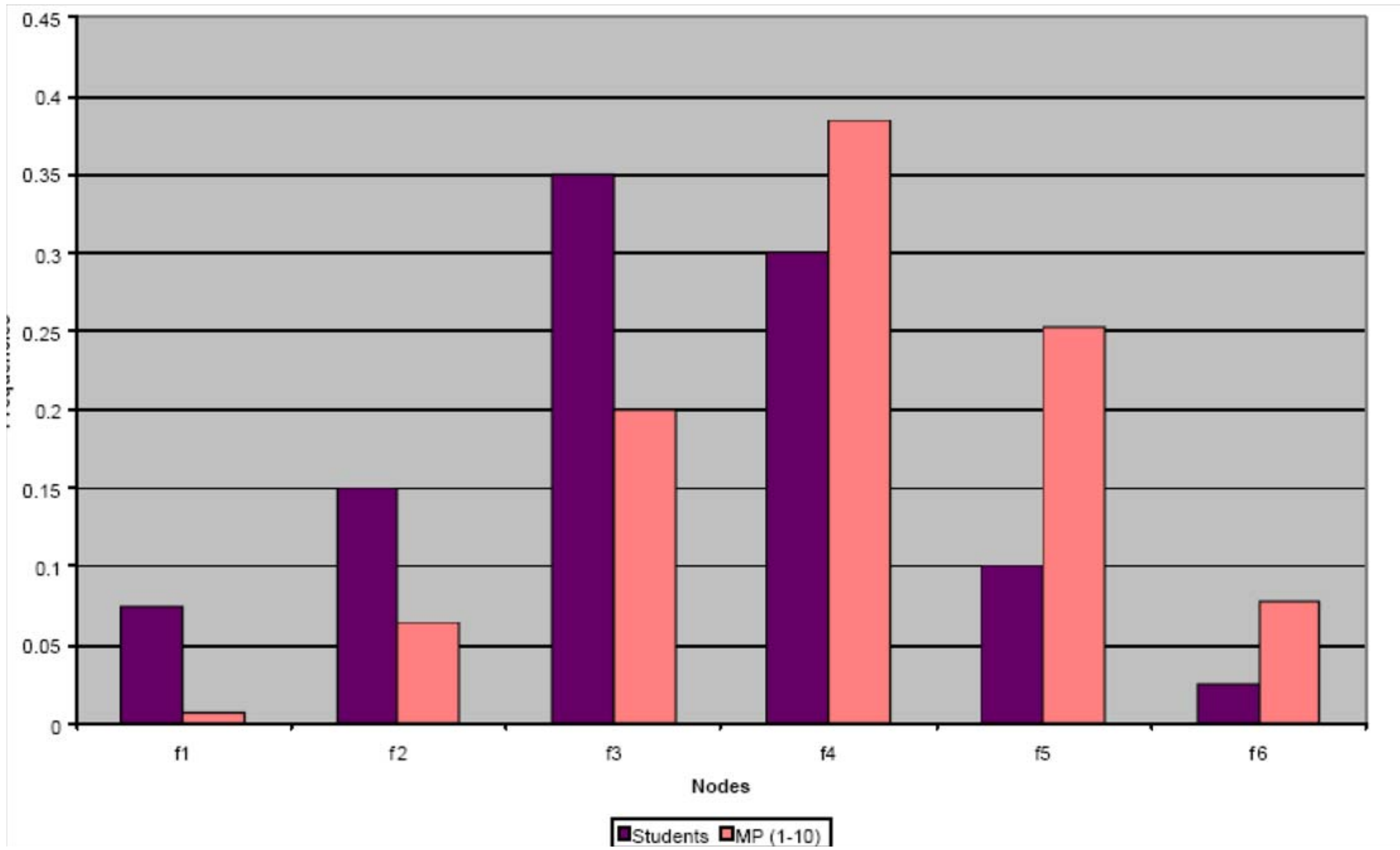
    * No induction

    * 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




0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
f1
f2
f3
f4
f5
f6
Nodes
Students
MP (1-10)

- Interpretations:
  - Cognition: Better at backward induction
  - Preferences More selfish
- Open questions:
  - Who earned the hhigher payoffs? almost surely the students
  - What would happen if you mix groups and people know it?

- **Case 4. Myopic Loss Aversion.**

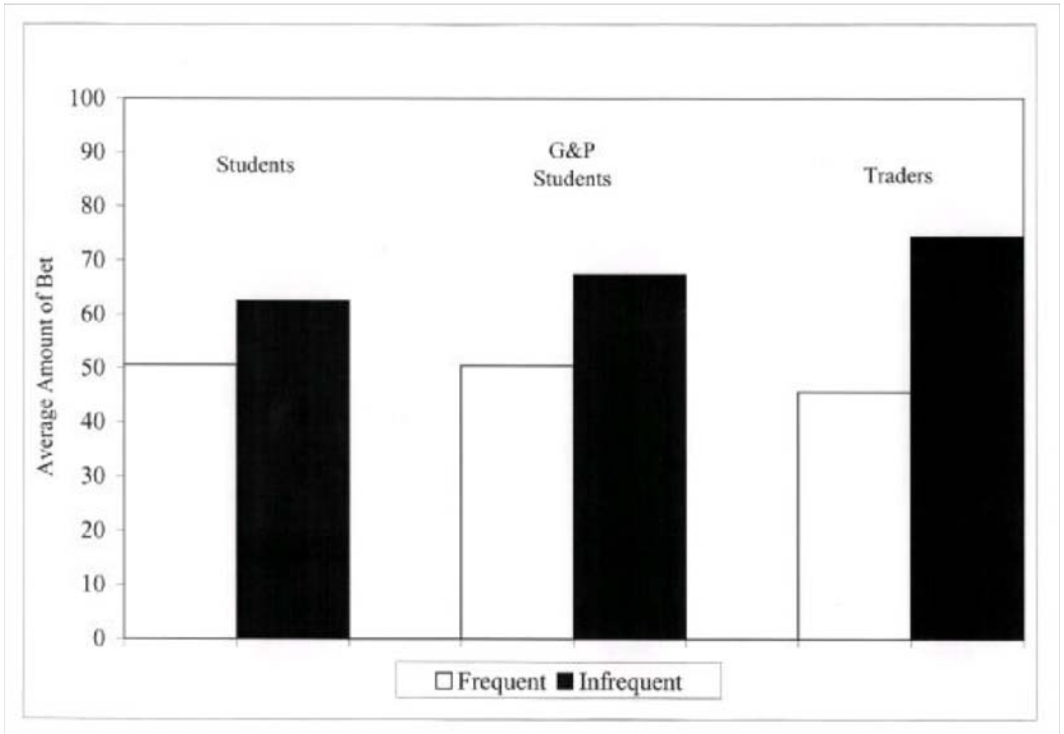
- Lottery: 2/3 chance to win 2.5X, 1/3 chance to lose X
  - Treatment F (Frequent): Make choice 9 times
  - Treatment I (Infrequent): Make choice 3 times in blocks of 3

- Standard theory: Essentially no difference between F and I

- Prospect Theory with Narrow Framing: More risk-taking when lotteries are chosen together —> Lower probability of a loss

- Gneezy-Potters (*QJE*, 1997): Strong evidence of myopic loss aversion with student population

- Haigh and List (2004): Replicate with
  - Students
  - Professional Traders –> *More* Myopic Loss Aversion



- Summary: Effect of Experience?
  - Can go either way
  - Open question

2 Reference Dependence: Labor Supply – A Model

- Camerer et al. (1997), Farber (2004, 2008), Meng (2008), Fehr and Goette (2007), Oettinger (1999)

- 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:

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

with $\lambda > 1$ loss aversion coefficient

- Referent-dependent agent maximizes

$$\begin{array}{ll} wh - T - \frac{\theta h^2}{2} & \text{if} \quad h \geq T/w \\ \lambda\left(wh - T\right) - \frac{\theta h^2}{2} & \text{if} \quad h < T/w \end{array}$$

- Derivative with respect to h:

$$\begin{array}{ll} w - \theta h & \text{if} \quad h \geq T/w \\ \lambda w - \theta h & \text{if} \quad h < T/w \end{array}$$

- 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

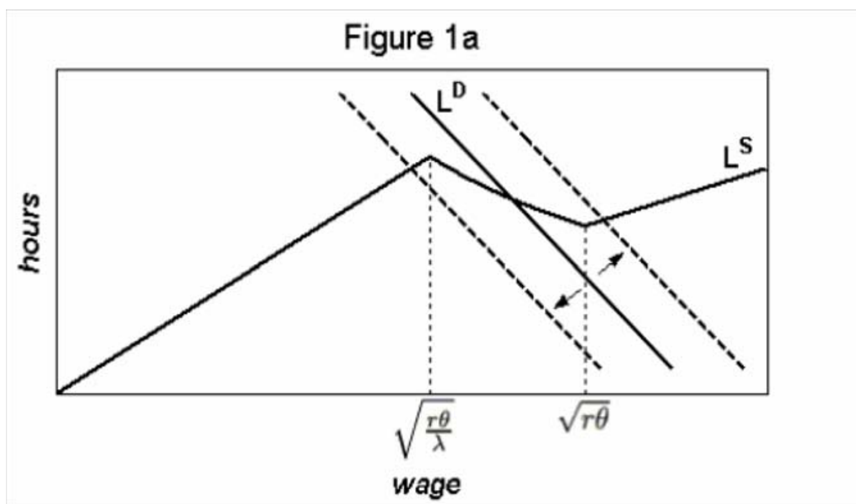
$$h^* = \frac{a}{b\theta + 1}$$

- Comparative statics with respect to a (labor demand shock): $a \uparrow$ –> $h^* \uparrow$ and $w^* \uparrow$

- On low-demand days (low w) work less hard –> 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):
  - $a \uparrow$ –> $h^* \uparrow$ and $w^* \uparrow$ (Cases 1 or 3)
  - $a \uparrow$ –> $h^* \downarrow$ and $w^* \uparrow$ (Case 2)

- Case 2: On low-demand days (low w) need to work harder to achieve reference point T −> Work harder

- Opposite prediction to standard theory

- (Neglected negligible wealth effects)

3 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 $->$ Higher lifetime income

- Justification:

  - Correlation of wages across days close to zero

  - Each day can be considered in isolation

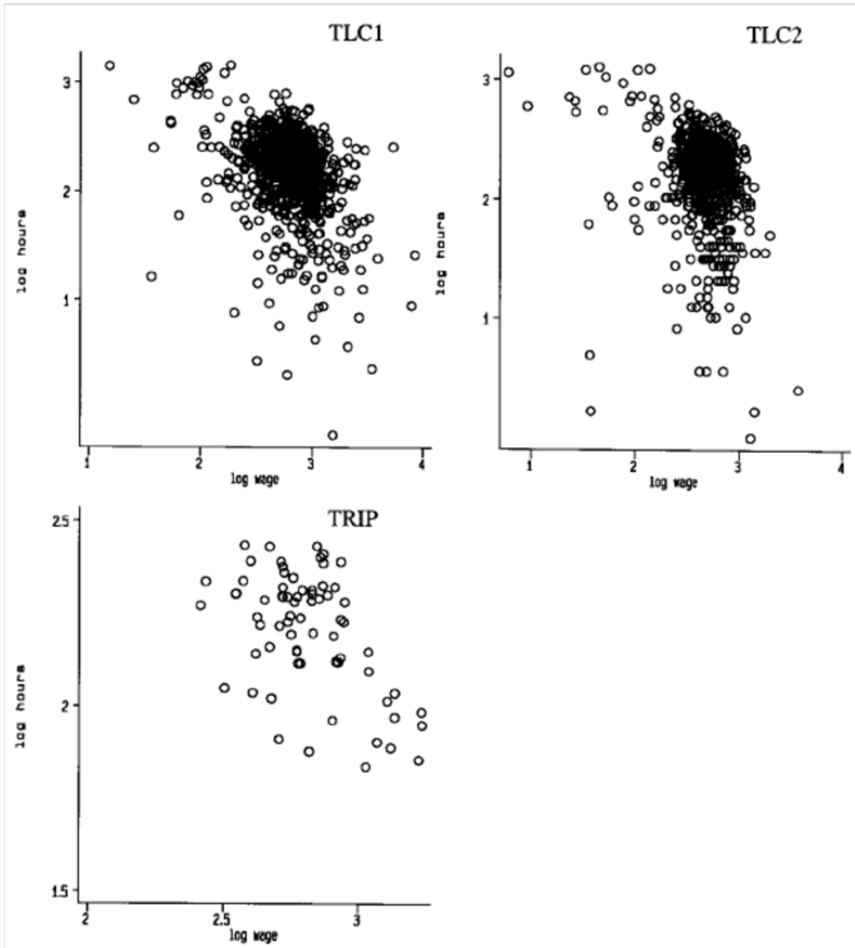
  - $->$ Wealth effects of wage changes are very small

- Test:

  - Assume variation across days driven by Δa (labor demand shifter)

  - Do hours worked h and w co-vary negatively (standard model) or positively?

- Raw evidence



- Estimated Equation:

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

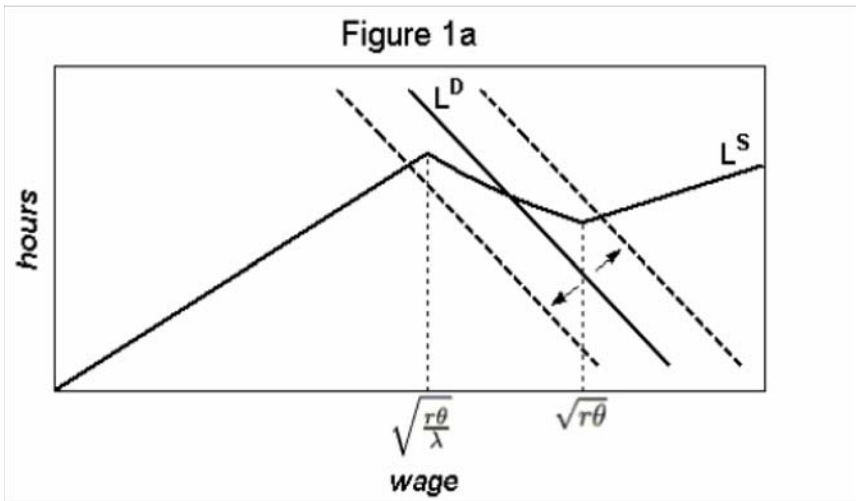
- Estimates of $\hat{\beta}$:
  - $\hat{\beta} = -.186$ (s.e. 129) – TRIP with driver f.e.
  - $\hat{\beta} = -.618$ (s.e. .051) – TLC1 with driver f.e.
  - $\hat{\beta} = -.355$ (s.e. .051) – TLC2

- Estimate is not consistent with prediction of standard model

- Indirect support for income targeting

- 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: $\tilde{h}_{i,t} = h_{i,t} * \phi_{i,t}$. Then,

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

  becomes

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

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

- Response: instrument wage using other workers' wage on same day

- IV Estimates:

TABLE III
IV Log Hours Worked Equations

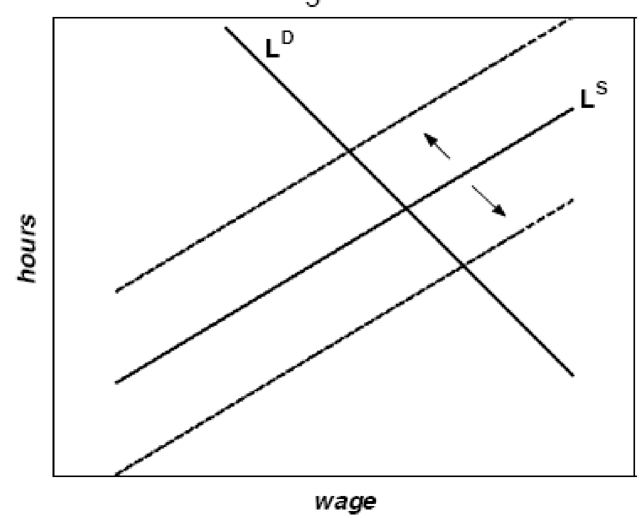
Sample	TRIP		TLC1		TLC2
Log hourly wage	−.319	.005	−1.313	−.926	−.975
	(.298)	(.273)	(.236)	(.259)	(.478)
High temperature	−.000	−.001	.002	.002	−.022
	(.002)	(.002)	(.002)	(.002)	(.007)

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

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

- Econometric issue 2. Are the authors really capturing demand shocks or supply shocks?
  - Assume θ (disutility of effort) varies across days.
  - Even in standard model we expect negative correlation of $h_{i,t}$ and $w_{i,t}$

Figure 1b



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

  – 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:

  - 244 trip sheets, 13 drivers, 6/1999-5/2000

  - 349 trip sheets, 10 drivers, 6/2000-5/2001

  - Daily summary not available (unlike in Camerer et al.)

  - Notice: Few drivers, many days in sample

- First, replication of Camerer et al. (1997)

TABLE 3
LABOR SUPPLY FUNCTION ESTIMATES: OLS REGRESSION OF LOG HOURS

Variable	(1)	(2)	(3)
Constant	4.012	3.924	3.778
	(.349)	(.379)	(.381)
Log(wage)	−.688	−.685	−.637
	(.111)	(.114)	(.115)
Day shift	...	.011	.134
		(.040)	(.062)
Minimum temperature	...	.126	.024
< 30		(.053)	(.058)
Maximum temperature	...	.041	.055
≥ 80		(.055)	(.064)
Rainfall	...	−.022	−.054
		(.073)	(.071)
Snowfall	...	−.096	−.093
		(.036)	(.035)
Driver effects	no	no	yes
Day-of-week effects	no	yes	yes
R^2	.063	.098	.198

- 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 ($\beta > 0$)?

TABLE 5

HAZARD OF STOPPING AFTER TRIP: NORMALIZED PROBIT ESTIMATES

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

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

- 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.) –> .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
DRIVER-SPECIFIC HAZARD OF STOPPING AFTER TRIP: NORMALIZED PROBIT ESTIMATES

	DRIVER					
VARIABLE	4	10	16	18	20	21
Hours	.073	.056	.043	.010	.195	.198
	(.060)	(.047)	(.015)	(.007)	(.045)	(.030)
Income÷100	.178	.039	.064	.048	−.160	−.002
	(.167)	(.059)	(.041)	(.020)	(.123)	(.150)
Number of shifts	40	45	70	72	46	46
Number of trips	884	912	1,754	2,023	1,125	882
Log likelihood	−124.1	−116.0	−221.1	−260.6	−123.4	−116.9

- 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* = „wage“). Earnings wr_{it}
  - Messengers can freely choose the number of shifts and whether they want to do a delivery, when offered by the dispatcher.

  ➢ suitable setting to test for intertemporal substitution.

- Highly volatile earnings
  - Demand varies strongly between days

  ➢ Familiar with changes in intertemporal incentives.

Experiment 1

- **The Temporary Wage Increase**
  - Messengers were randomly assigned to one of two treatment groups, A or B.
    - *N*=22 messengers in each group

  - Commission rate *w* was increased by 25 percent during four weeks
    - Group A: September 2000 (Control Group: B)
    - Group B: November 2000 (Control Group: A)

- **Intertemporal Substitution**
  - Wage increase has no (or tiny) income effect.
  - Prediction with time-separable prefernces, *t*= a day:
    - ➢ Work more shifts
    - ➢ Work harder to obtain higher revenues

  - Comparison between TG and CG during the experiment.
    - Comparison of TG over time confuses two effects.

Results for Hours

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

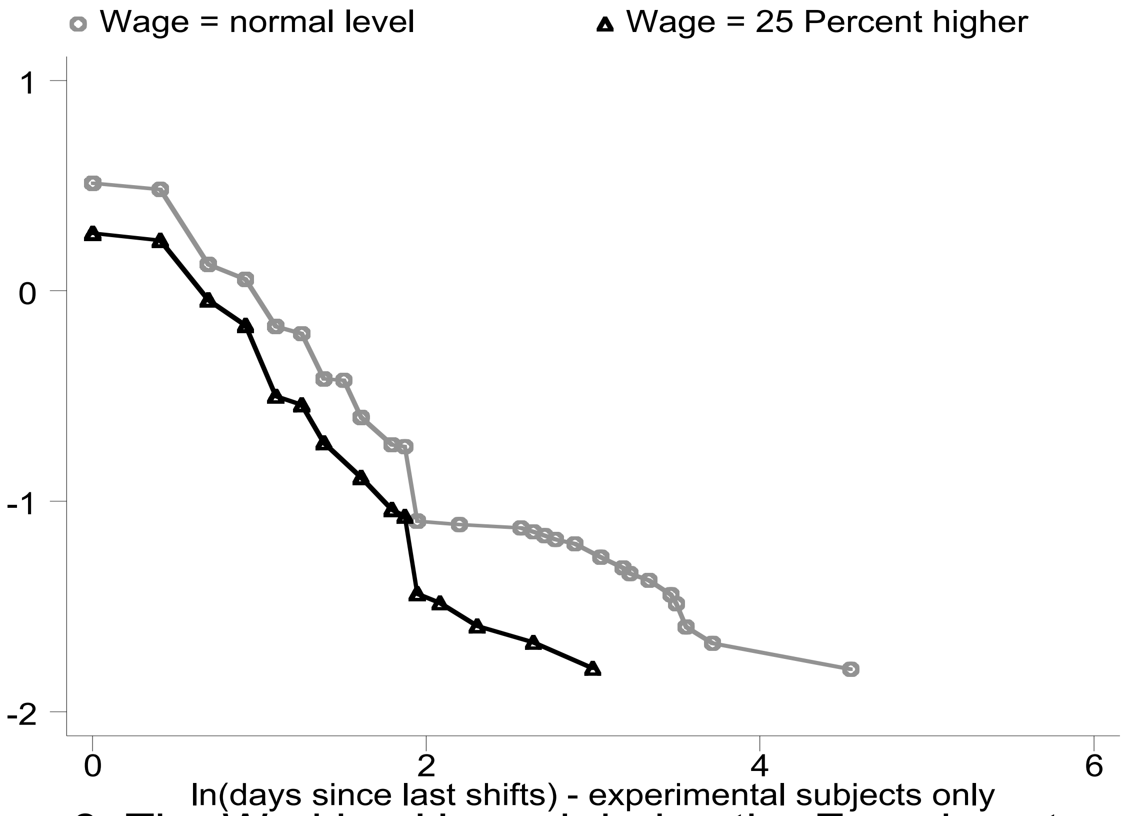
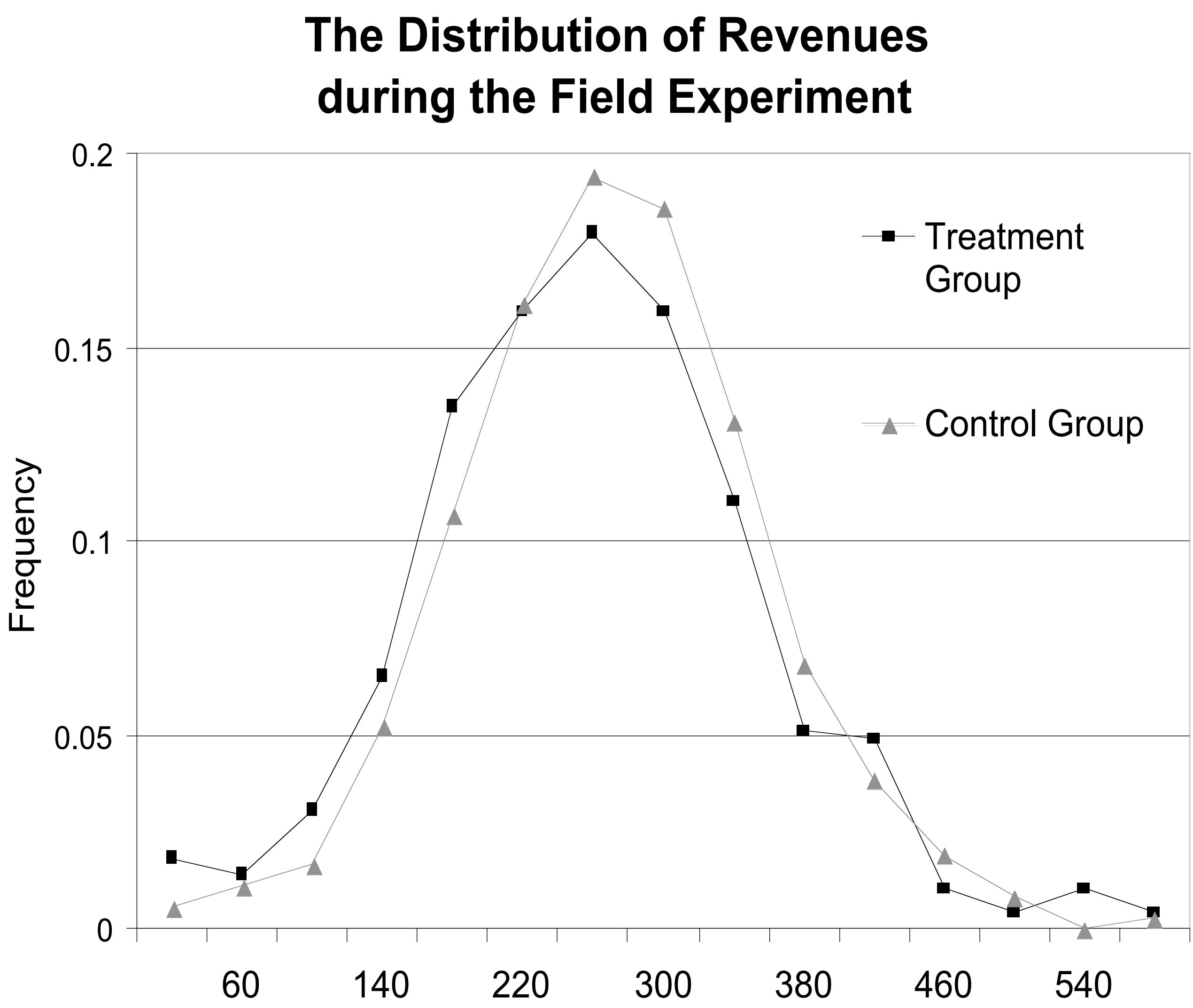


Figure 6: The Working Hazard during the Experiment

Results for Effort: Revenues per shift

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



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

Results for Effort, cont.

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

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

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

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 explanantions**

  - 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 δ

  – Estimate (stochastic) reference point T

- Same data as Farber (2005)

- Results:

  – significant loss aversion δ

  – however, large variation in T mitigates effect of loss-aversion

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

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

- Most recent paper: **Meng (2008)**

- 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 (2006) data for:

  - Wage above average (income likely to bind)

  - Wages below average (hours likely to bind)

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

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

- Results:
  - $w > w^e$: income binding –> income explains stopping
  - $w < w^e$: hours binding –> 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)

4 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

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

* 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

Available Deductible	Full Sample
1000	$615.82 (292.59)
500	+99.91 (45.82)
250	+86.59 (39.71)
100	+133.22 (61.09)

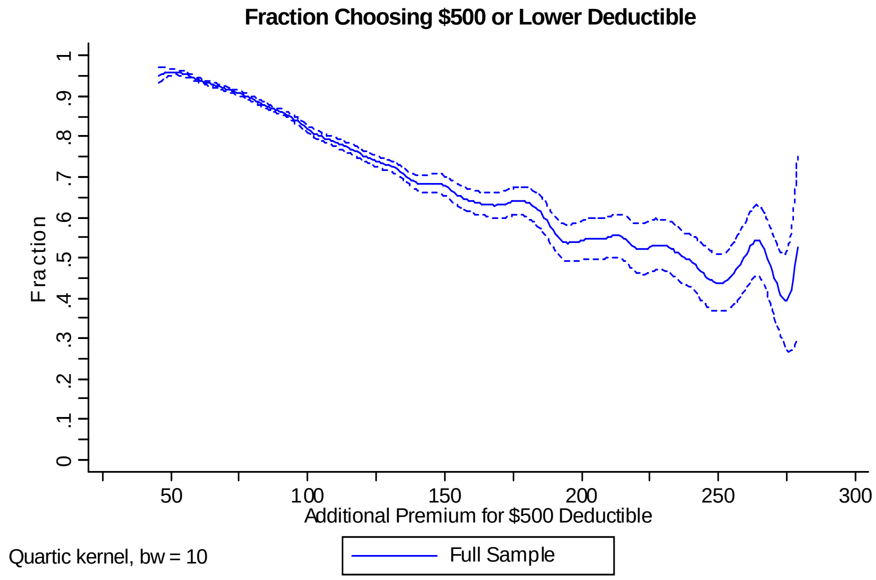
* Means with standard deviations in parentheses

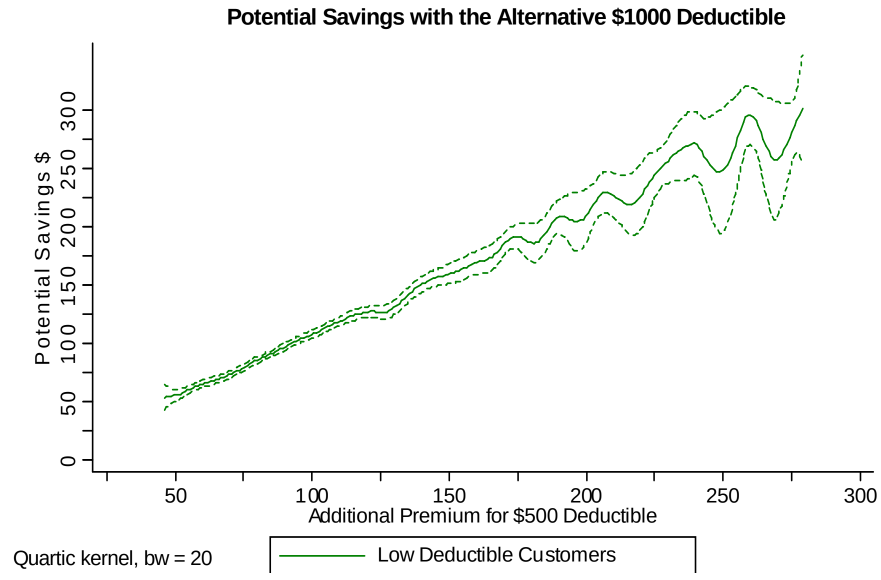
Risk Neutral Claim Rates?

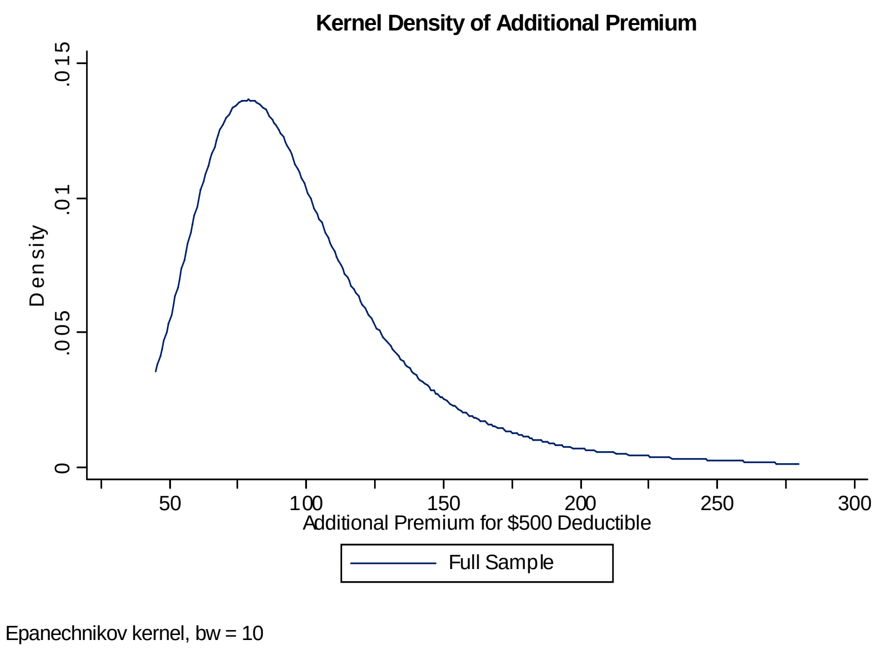
100/500 = 20%

87/250 = 35%

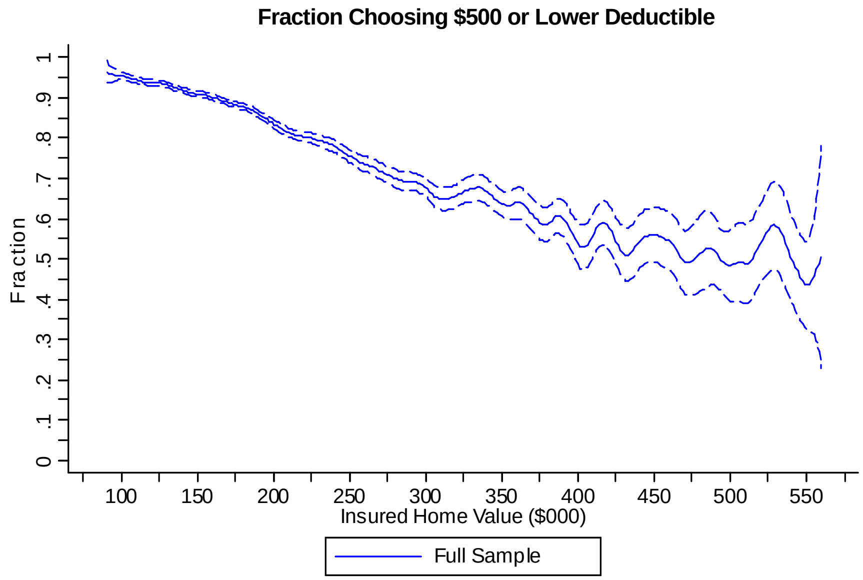
133/150 = 89%



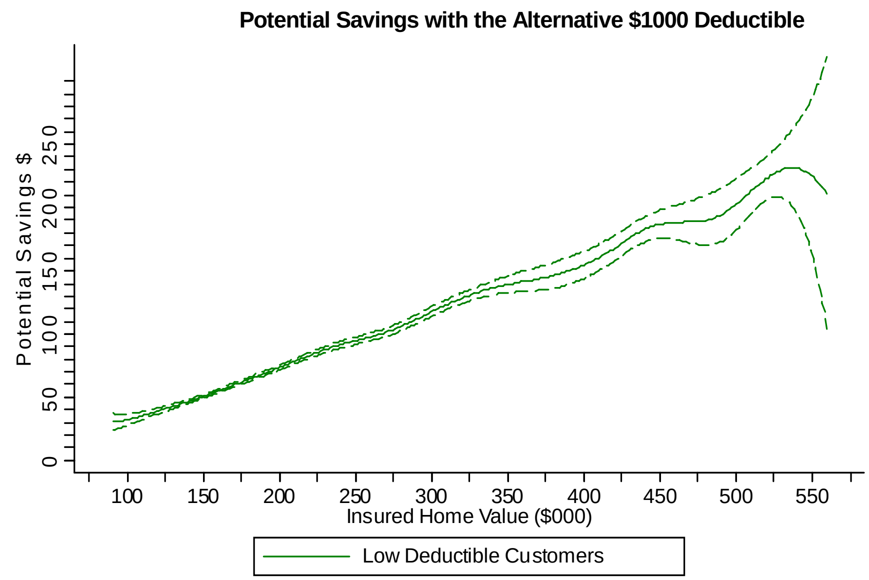




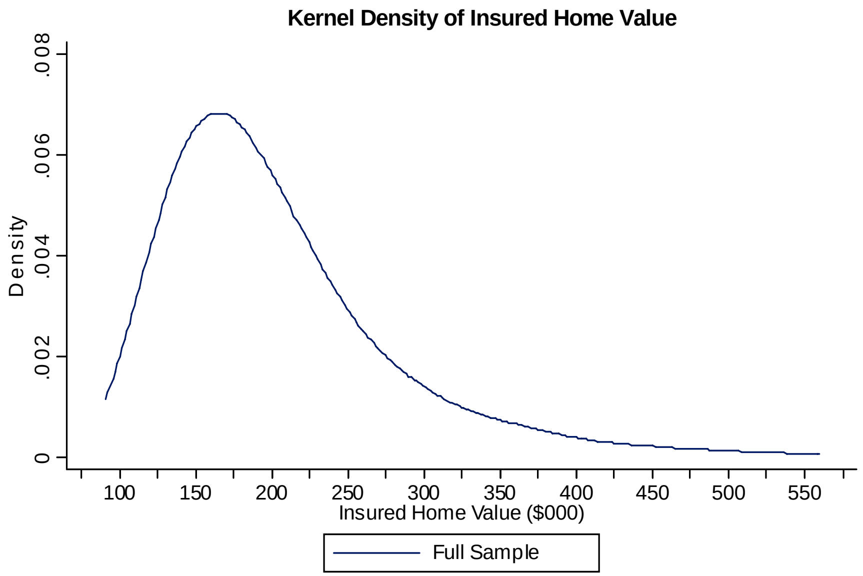
What if the x-axis were insured home value?



Quartic kernel, bw = 25



Quartic kernel, bw = 50



Epanechnikov kernel, bw = 25

Potential Savings with 1000 Ded

Claim rate?

Value of lower deductible?

Additional premium?

Potential savings?

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

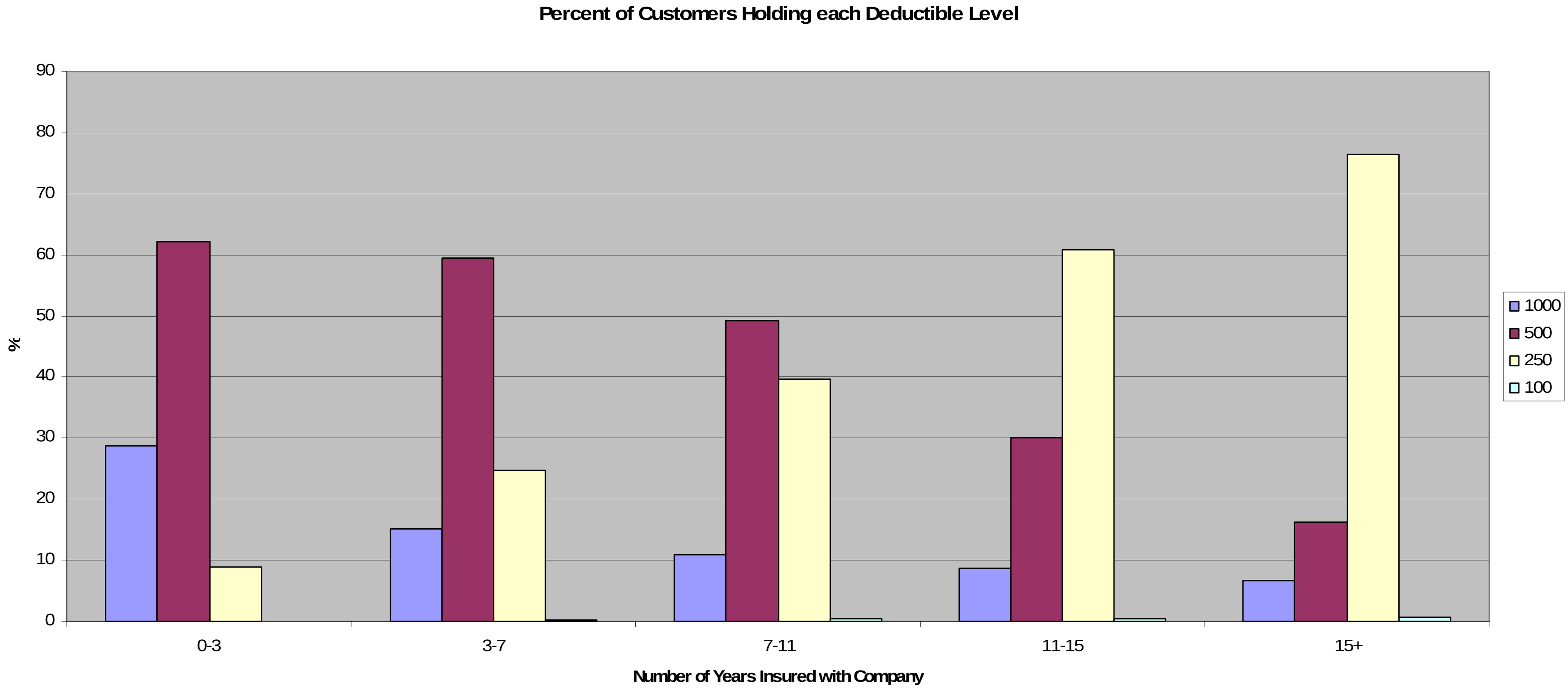
Average forgone expected savings for all low-deductible customers: $99.88

* Means with standard errors in parentheses

Back of the Envelope

- BOE 1: Buy house at 30, retire at 65, 3% interest rate $\Rightarrow$ \$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 $\Rightarrow$ \$4.8 billion per year

Consumer Inertia?



Look Only at New Customers

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

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

What level of wealth? Chetty (2005)

- 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)
- π = 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:

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

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

Chosen Deductible	Measure of Lifetime Wealth (W): (Insured Home Value)		
	W	min ρ	max ρ
$1,000	256,900	- infinity	794
N = 2,474 (39.5%)	{113,565}		(9.242)
$500	190,317	397	1,055
N = 3,424 (54.6%)	{64,634}	(3.679)	(8.794)
$250	166,007	780	2,467
N = 367 (5.9%)	{57,613}	(20.380)	(59.130)

Interpreting Magnitude

- 50-50 gamble:
  Lose $1,000/ Gain $10 million
  - 99.8% of low-ded customers would reject
  - Rabin (2000), Rabin & Thaler (2001)
- Labor-supply calibrations, consumption-savings behavior $\Rightarrow \rho < 10$
  - 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)
- π = 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

- Slovic et al (1982)
  - 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):

$$v(-P_L) - v(-P_H) < w(\pi)[v(-D_H) - v(-D_L)]$$

- 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 to 6 times EV

Parameter values

- Kahneman and Tversky (1992)
  - λ = 2.25
  - β = 0.88
- Weighting function

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

  - γ = 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

Chosen Deductible	Predicted Deductible Choice from Prospect Theory NLIB Specification: $\lambda = 2.25$, $\gamma = 0.69$, $\beta = 0.88$				Predicted Deductible Choice from EU(W) CRRA Utility: $\rho = 10$, W = Insured Home Value			
	1000	500	250	100	1000	500	250	100
$1,000 N = 2,474 (39.5%)	**87.39%**	11.88%	0.73%	0.00%	**100.00%**	0.00%	0.00%	0.00%
$500 N = 3,424 (54.6%)	18.78%	**59.43%**	21.79%	0.00%	100.00%	**0.00%**	0.00%	0.00%
$250 N = 367 (5.9%)	3.00%	44.41%	**52.59%**	0.00%	100.00%	0.00%	**0.00%**	0.00%
$100 N = 3 (0.1%)	33.33%	66.67%	0.00%	**0.00%**	100.00%	0.00%	0.00%	**0.00%**

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
- Mehra & Prescott (1985), Benartzi & Thaler (1995)

Alternative Explanations

- Misestimated probabilities
  - ≈ 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

5 Next Lecture

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