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

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Outline

1. Reference Dependence: Domestic Violence
2. Reference Dependence: Labor Supply
3. Reference Dependence: Disposition Effect
4. Reference Dependence: Equity Premium
5. Reference Dependence: Insurance

1 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 ex-ante expectation that the team wins
  - Denote by $u(W)$ and $u(L)$ the consumption utility of a loss

- Using a Koszegi-Rabin specification, then ex-post the utility from a win is

$$\begin{aligned} U\left(W|p\right) &= u(W) \text{ [consumption utility]} \\ &\quad + p\left[0\right] + \left(1-p\right)\eta\left[u\left(W\right) - u\left(L\right)\right] \text{ [gain-loss utility]} \end{aligned}$$

- Similarly, the utility from a loss is

$$U\left(L|p\right) = u(W) + \left(1-p\right)\left[0\right] - \lambda p \eta \left[u\left(W\right) - u\left(L\right)\right]$$

- Implication:

$$\partial U\left(L|p\right)/\partial p = -\lambda\eta\left[u\left(W\right) - u\left(L\right)\right] < 0$$

  - The more a win is expected, the more a loss is painful –> the more likely it is to trigger violence

  - The (positive) effect of a gain is higher the more unexpected (lower p)

- Card and Dahl (QJE 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.

	Intimate Partner Violence, Male on Female, at Home				
			Baseline Model		
	(1)	(2)	(3)	(4)	(5)
Coefficient Estimates					
Loss * Predicted Win (*Upset Loss*)	.083	.077	.080	.074	.076
	(.026)	(.027)	(.027)	(.028)	(.028)
Loss * Predicted Close (*Close Loss*)	.031	.034	.036	.024	.026
	(.023)	(.024)	(.024)	(.025)	(.025)
Win * Predicted Loss (*Upset Win*)	-.002	.011	.021	.013	.011
	(.027)	(.027)	(.028)	(.029)	(.029)
Predicted Win	-.004	-.019	-.015	.000	-.068
	(.022)	(.032)	(.032)	(.033)	(.044)
Predicted Close	-.012	-.017	-.016	-.007	-.074
	(.023)	(.032)	(.032)	(.034)	(.044)
Predicted Loss	-.000	-.004	-.011	.006	-.057
	(.022)	(.031)	(.031)	(.033)	(.042)
Non-game Day	---	---	---	---	---
Nielsen Rating					.009
					(.004)
Municipality fixed effects	X	X	X	X	X
Year, week, & holiday dummies		X	X	X	X
Weather variables			X	X	X
Nielsen Data Sub-sample				X	X
Log likelihood	-42,890	-42,799	-42,784	-39,430	-39,428
Number of Municipalities	765	765	765	749	749
Observations	77,520	77,520	77,520	71,798	71,798

- 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 (given that violence is a funciton is very negative utility)

- 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

2 Reference Dependence: Labor Supply

- Camerer et al. (1997), Farber (2004, 2008), Crawford and 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:

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

with $\lambda > 1$ loss aversion coefficient

- Referent-dependent agent maximizes

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

- Derivative with respect to h:

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

- 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

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

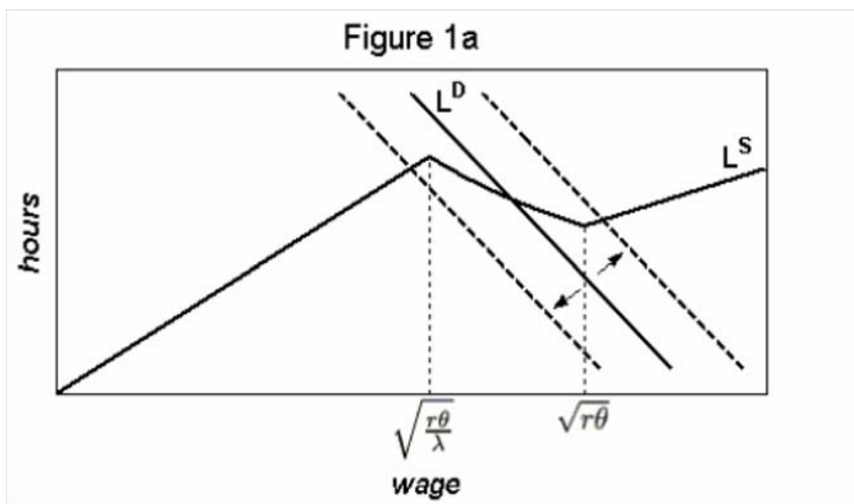
and

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

- 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)

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 $->$ Higher lifetime income

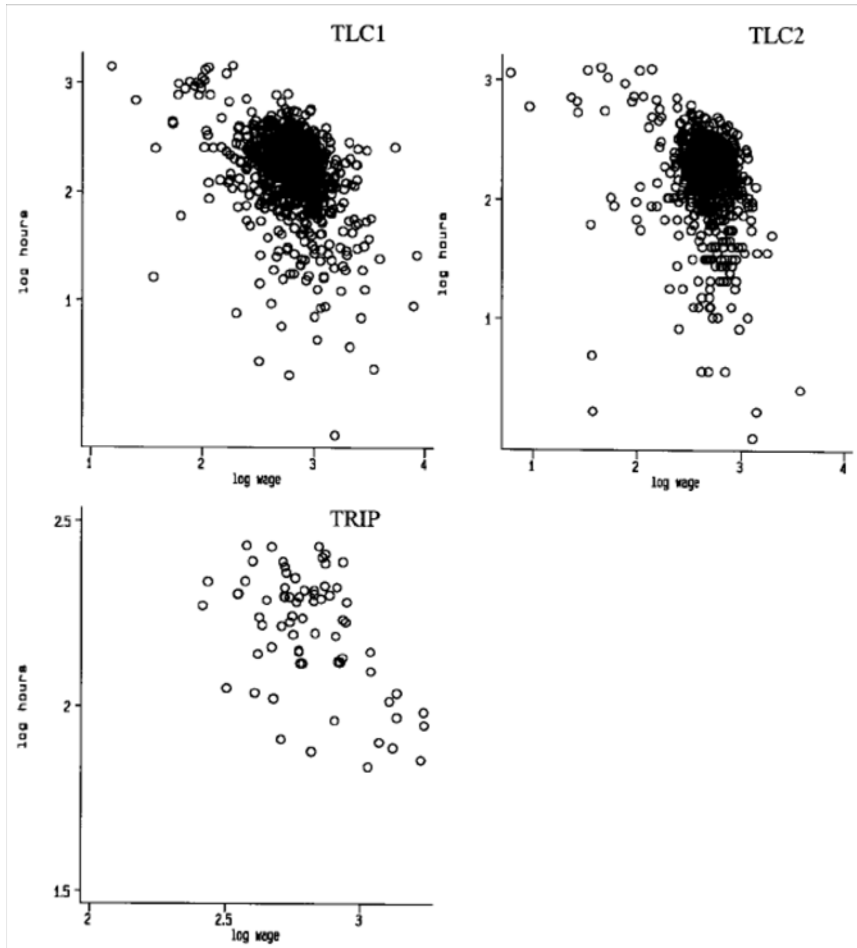
- Justification:

  - 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



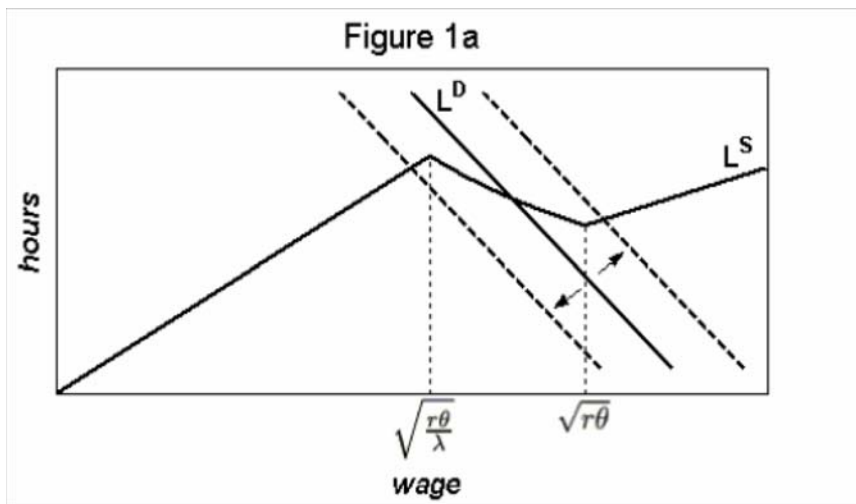
- Estimated Equation:

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

- 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)

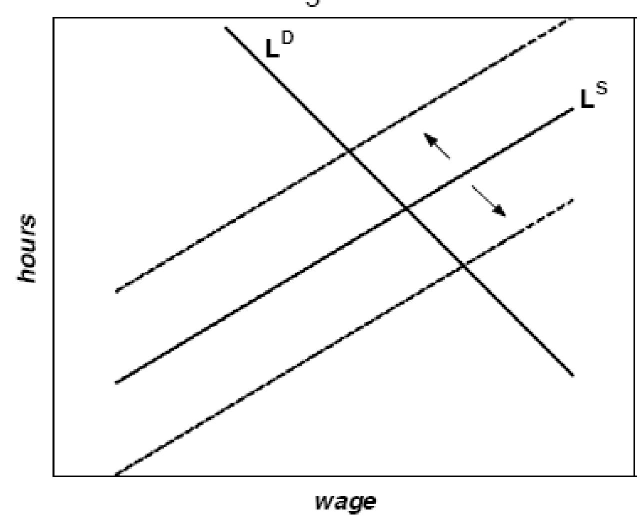
	First-stage regressions				
Median	.316	.026	−.385	−.276	1.292
	(.225)	(.188)	(.394)	(.467)	(4.281)
25th percentile	.323	.287	.693	.469	−.373
	(.160)	(.126)	(.241)	(.332)	(3.516)
75th percentile	.399	.289	.614	.688	.479
	(.171)	(.149)	(.242)	(.292)	(1.699)
Adjusted R^2	.374	.642	.056	.206	.019
P-value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

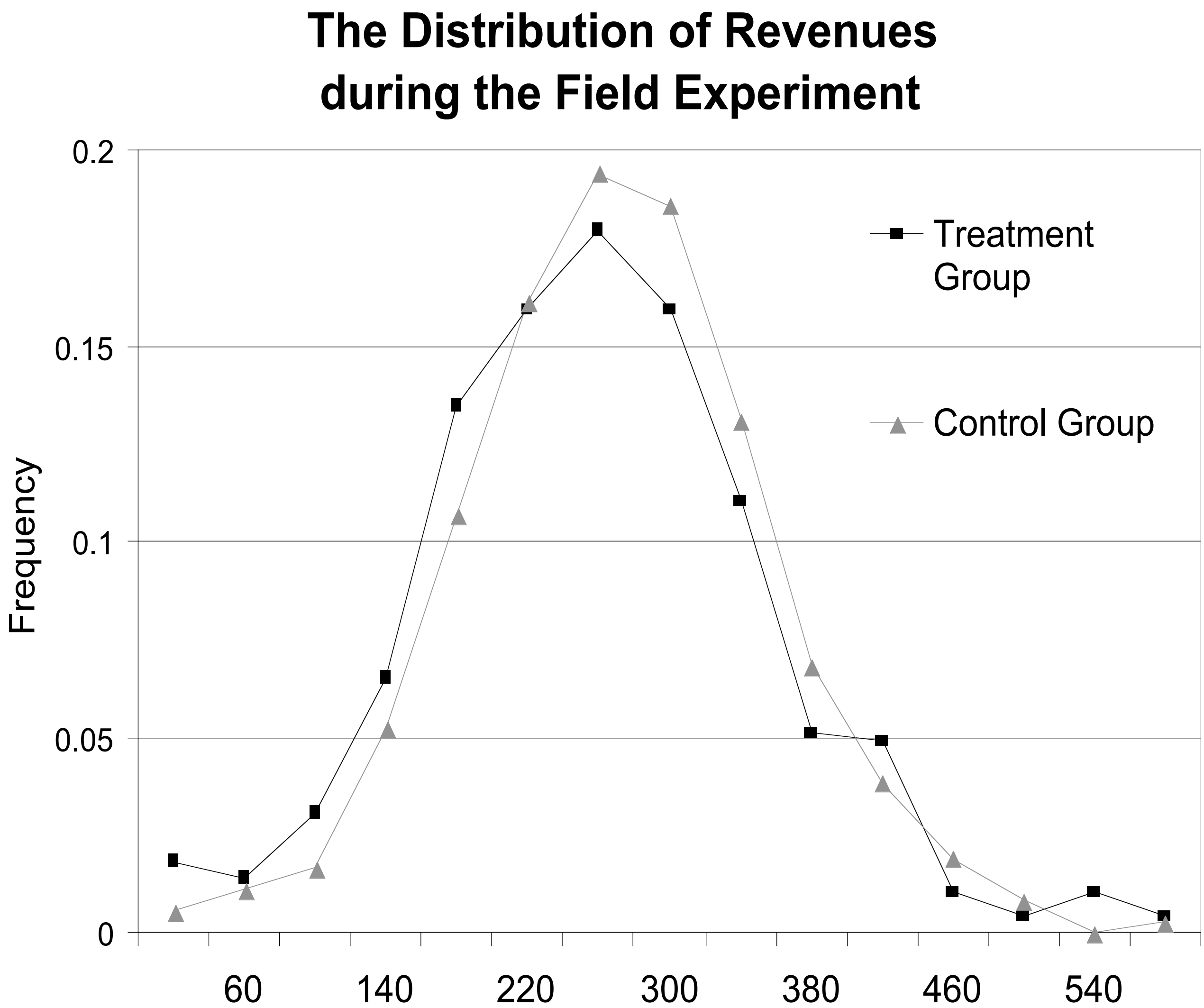
Results for Hours

- 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 (AER 2008)** goes beyond Farber (JPE, 2005) and attempts to estimate model of labor supply with loss-aversion
  - Estimate loss-aversion δ
  - Estimate (stochastic) reference point T

- Same data as Farber (2005)

- Results:
  - significant loss aversion δ
  - however, large variation in T mitigates effect of loss-aversion

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: **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 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

- Perhaps, reconciling Camerer et al. (1997) and Farber (2005)
  - $w > w^e$: hours binding –> hours explain stopping
  - $w < w^e$: income binding –> income explains stopping

3 Reference Dependence: Disposition Effect

- **Odean (JF, 1998)**

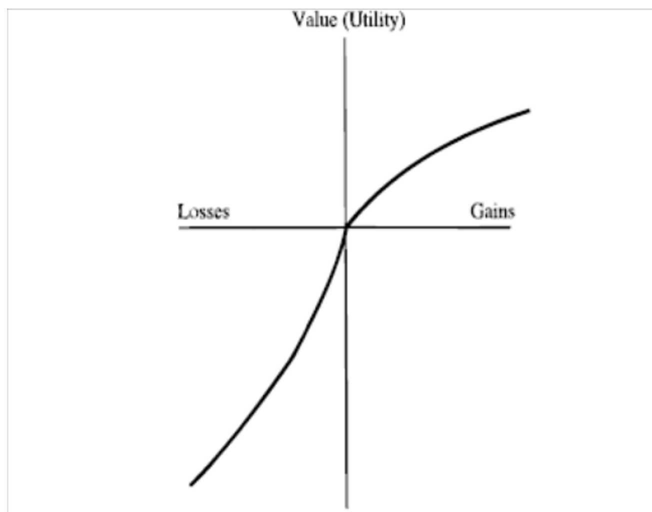
- Do investors sell winning stocks more than losing stocks?

- 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 —> gamble, hold on stock
  - Concavity over gains —> 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:

$$PGR = \frac{\text{Realized Gains}}{\text{Realized Gains+Paper Gains}}$$

- Share of realized losses:

$$PLR = \frac{\text{Realized Losses}}{\text{Realized Losses+Paper Losses}}$$

- 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 I

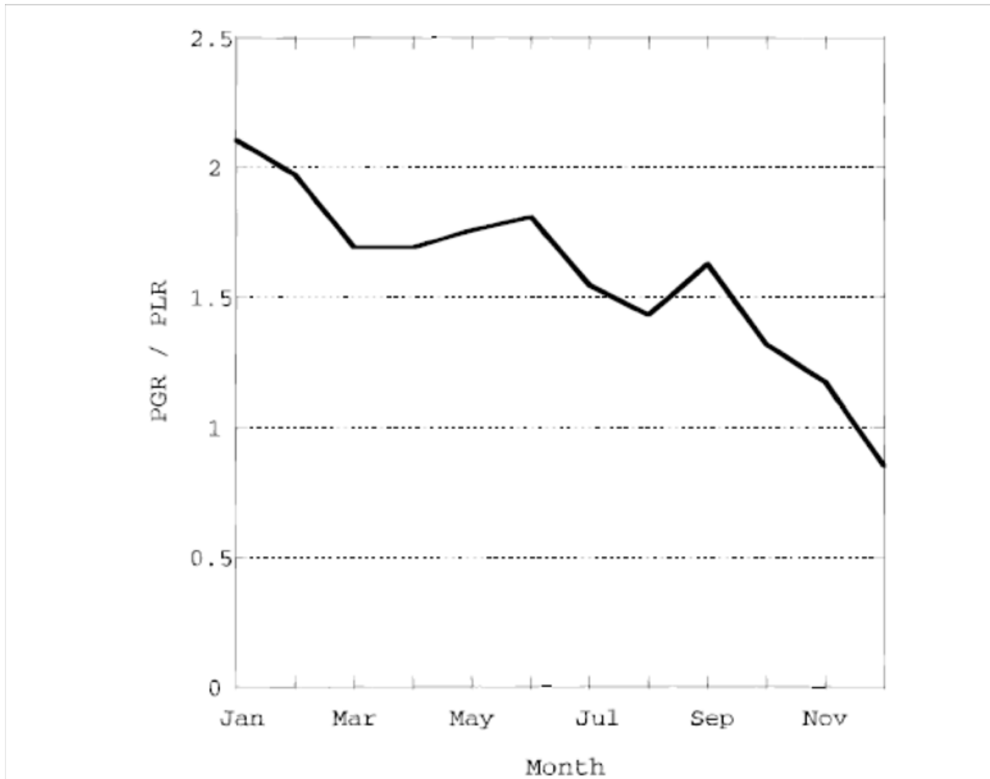
PGR and PLR for the Entire Data Set

This table compares the aggregate Proportion of Gains Realized (PGR) to the aggregate Proportion of Losses Realized (PLR), where PGR is the number of realized gains divided by the number of realized gains plus the number of paper (unrealized) gains, and PLR is the number of realized losses divided by the number of realized losses plus the number of paper (unrealized) losses. Realized gains, paper gains, losses, and paper losses are aggregated over time (1987–1993) and across all accounts in the data set. PGR and PLR are reported for the entire year, for December only, and for January through November. For the entire year there are 13,883 realized gains, 79,658 paper gains, 11,930 realized losses, and 110,348 paper losses. For December there are 866 realized gains, 7,131 paper gains, 1,555 realized losses, and 10,604 paper losses. The t-statistics test the null hypotheses that the differences in proportions are equal to zero assuming that all realized gains, paper gains, realized losses, and paper losses result from independent decisions.

	Entire Year	December	Jan.–Nov.
PLR	0.098	0.128	0.094
PGR	0.148	0.108	0.152
Difference in proportions	−0.050	0.020	−0.058
t-statistic	−35	4.3	−38

- 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

	1987–1990	1991–1993	Frequent Traders	Infrequent Traders
Entire year PLR	0.126	0.072	0.079	0.296
Entire year PGR	0.201	0.115	0.119	0.452
Difference in proportions	−0.075	−0.043	−0.040	−0.156
t-statistic	−30	−25	−29	−22

- Alternative Explanation 1: **Rebalancing** –> Sell winners that appreciated
  - Remove partial sales

	Entire Year	December
PLR	0.155	0.197
PGR	0.233	0.162
Difference in proportions	−0.078	0.035
t-statistic	−32	4.6

- Alternative Explanation 2: **Ex-Post Return** –> Losers outperform winners ex post
  - Table VI: Winners sold outperform losers that could have been sold

	Performance over Next 84 Trading Days	Performance over Next 252 Trading Days	Performance over Next 504 Trading Days
Average excess return on winning stocks sold	0.0047	0.0235	0.0645
Average excess return on paper losses	−0.0056	−0.0106	0.0287
Difference in excess returns	0.0103	0.0341	0.0358
(p-values)	(0.002)	(0.001)	(0.014)

- Alternative Explanation 3: **Transaction costs** –> 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:

$$\begin{aligned} PGP &= \frac{Gains\ Purchased}{Gains\ Purchased + Paper\ Gains} = .094 \\ &< PLP = \frac{Losses\ Purchased}{Losses\ Purchased + Paper\ Losses} = .135. \end{aligned}$$

- 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:

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

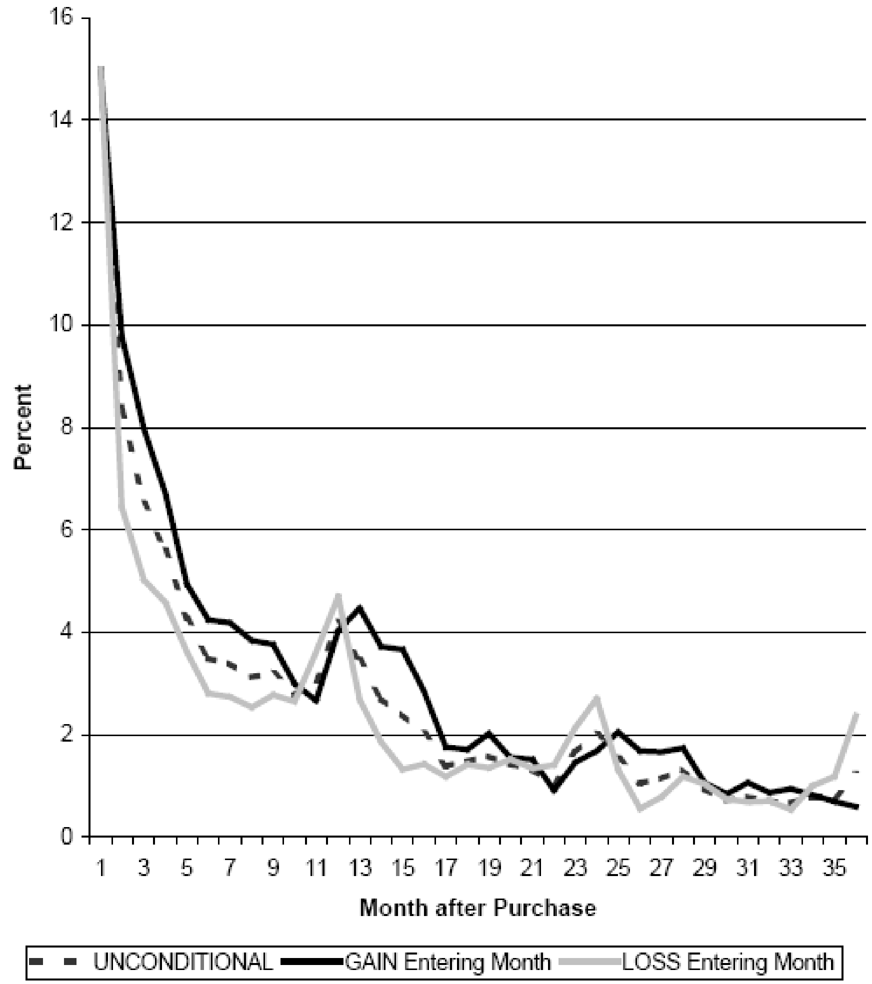
- Regression only applies to shares not already sold

- α_t is baseline hazard at month t

- Pattern of βs always consistent with disposition effect, except in December

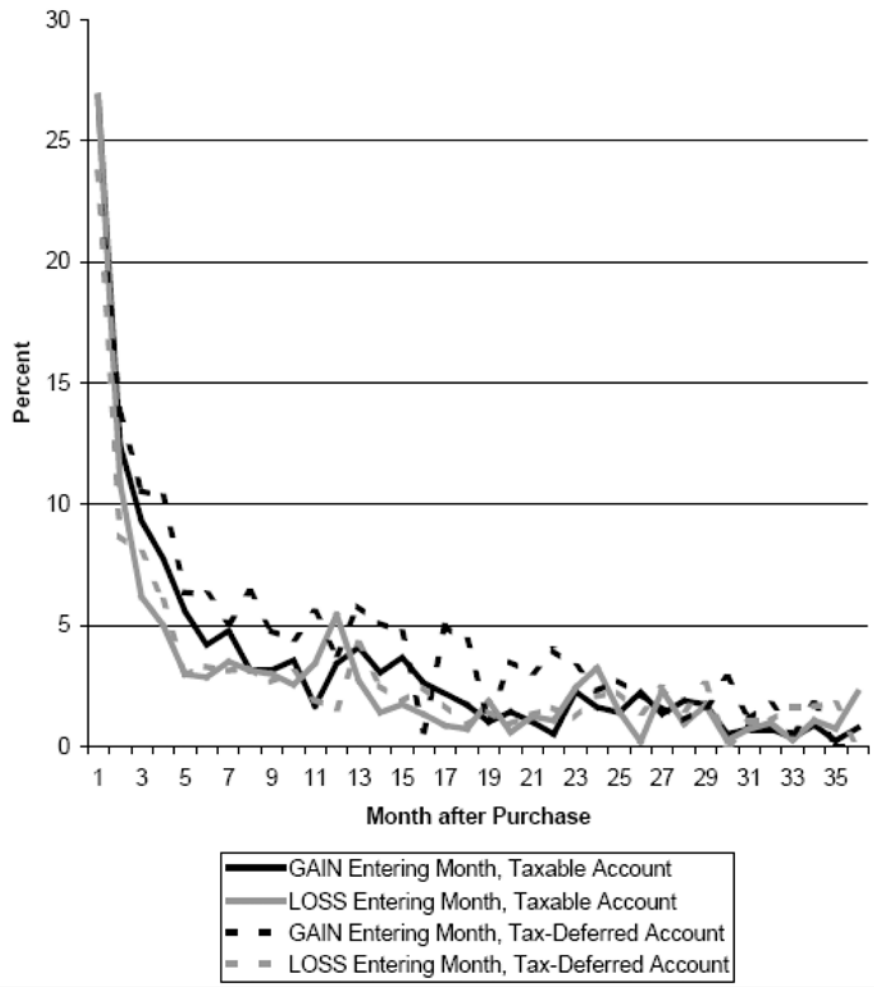
- Difference is small for tax-deferred accounts

Figure 1: Hazard Rate of Having Sold Stock in Taxable Accounts, Full Sample



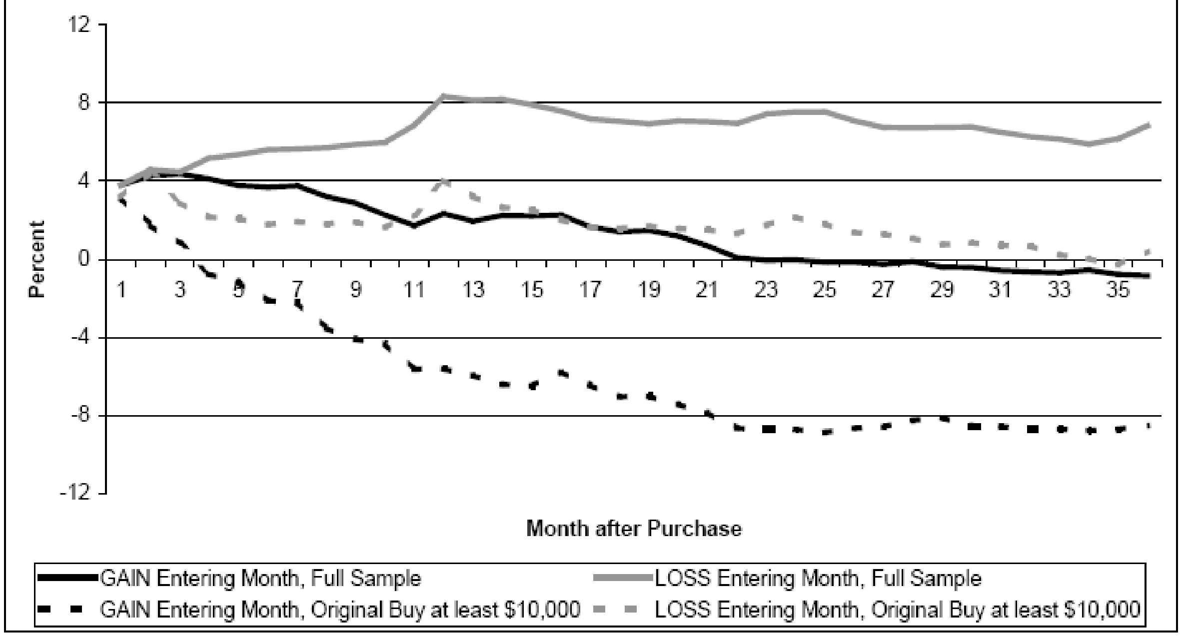
Notes: Sample is January purchases of stock 1991-96 in taxable accounts. The hazard rate for stock purchases unconditional on the stock's price performance, as well as conditional on whether the stock has an accrued capital gain or loss entering the month, is displayed.

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.

Figure 4: Cumulative Probability of Having Sold Stock in Taxable Account *Relative* to Tax-Deferred Account



Notes: Sample is January purchases of stock 1991-96. If h(t) denotes the hazard rate in month t, the probability that the stock is sold by the end of month t is $[\,1 - (\,\Pi_{s=1,t}\,(1\text{-}h(s))\,)\,]$. Figure 4 displays cumulative probability of sale in a taxable account less that in a tax-deferred account for each month.

- – Different hazards between taxable and tax-deferred accounts –>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 $t = 0, 1, ..., T$ periods

  – Utility is evaluated only at end point, after T periods

  – Reference point is initial wealth W_0

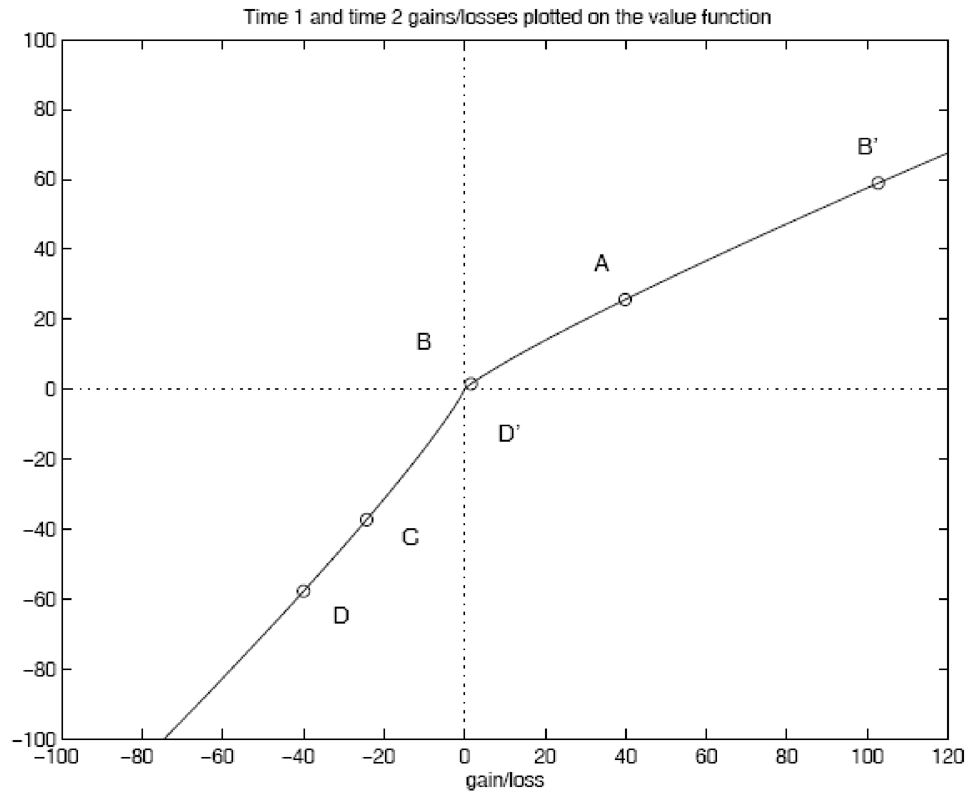
  – utility is $v\left(W_T - W_0 R_f\right)$

- Calibrated model: Prospect theory may not generate disposition effect!

Table 2: For a given (μ, T) pair, we construct an artificial dataset of how 10,000 investors with prospect theory preferences, each of whom owns N_S stocks, each of which has an annual gross expected return μ, would trade those stocks over T periods. For each (μ, T) pair, we use the artifical 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 (μ, 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.

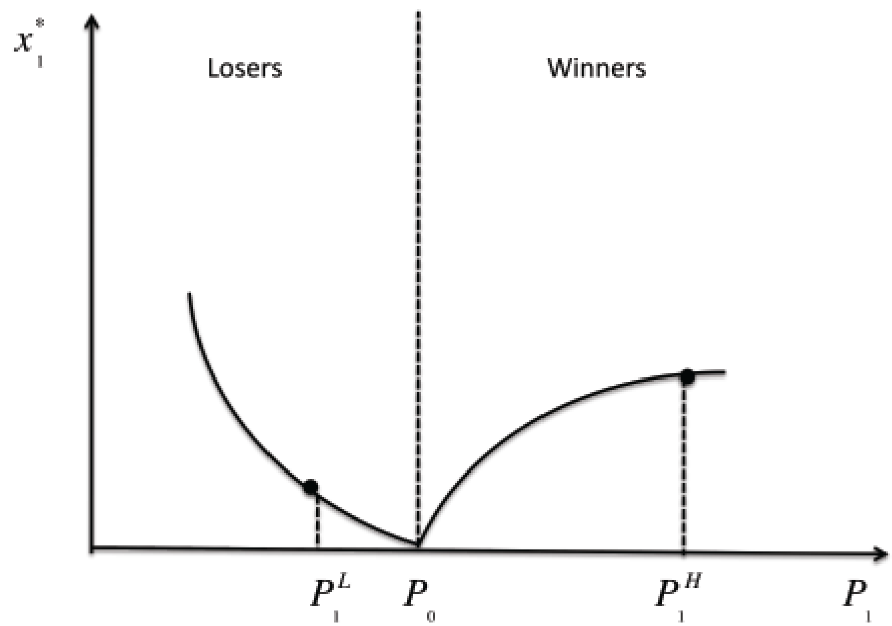
μ	$T = 2$	$T = 4$	$T = 6$	$T = 12$
1.03	-	-	-	.55/.50
1.04	-	-	.54/.52	.54/.52
1.05	-	-	.54/.52	.59/.45
1.06	-	.70/.25	.54/.52	.58/.47
1.07	-	.70/.25	.54/.52	.57/.49
1.08	-	.70/.25	**.48/.58**	**.47/.60**
1.09	-	**.43/.70**	**.48/.58**	**.46/.61**
1.10	**0.0/1.0**	**.43/.70**	**.48/.58**	**.36/.69**
1.11	**0.0/1.0**	**.43/.70**	**.49/.58**	**.37/.68**
1.12	**0.0/1.0**	**.28/.77**	**.23/.81**	**.40/.66**
1.13	**0.0/1.0**	**.28/.77**	**.24/.83**	**.25/.78**

- 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, all else constant
  - Disposition effect should hold when away from ref. point

- **Meng (2010)** elaborates on this point
  - Model of two-period portfolio holding
  - Loss Aversion with respect to (potentially stochastic) reference point
  - Derives optimal value of holding of risk asset x as function of past returns

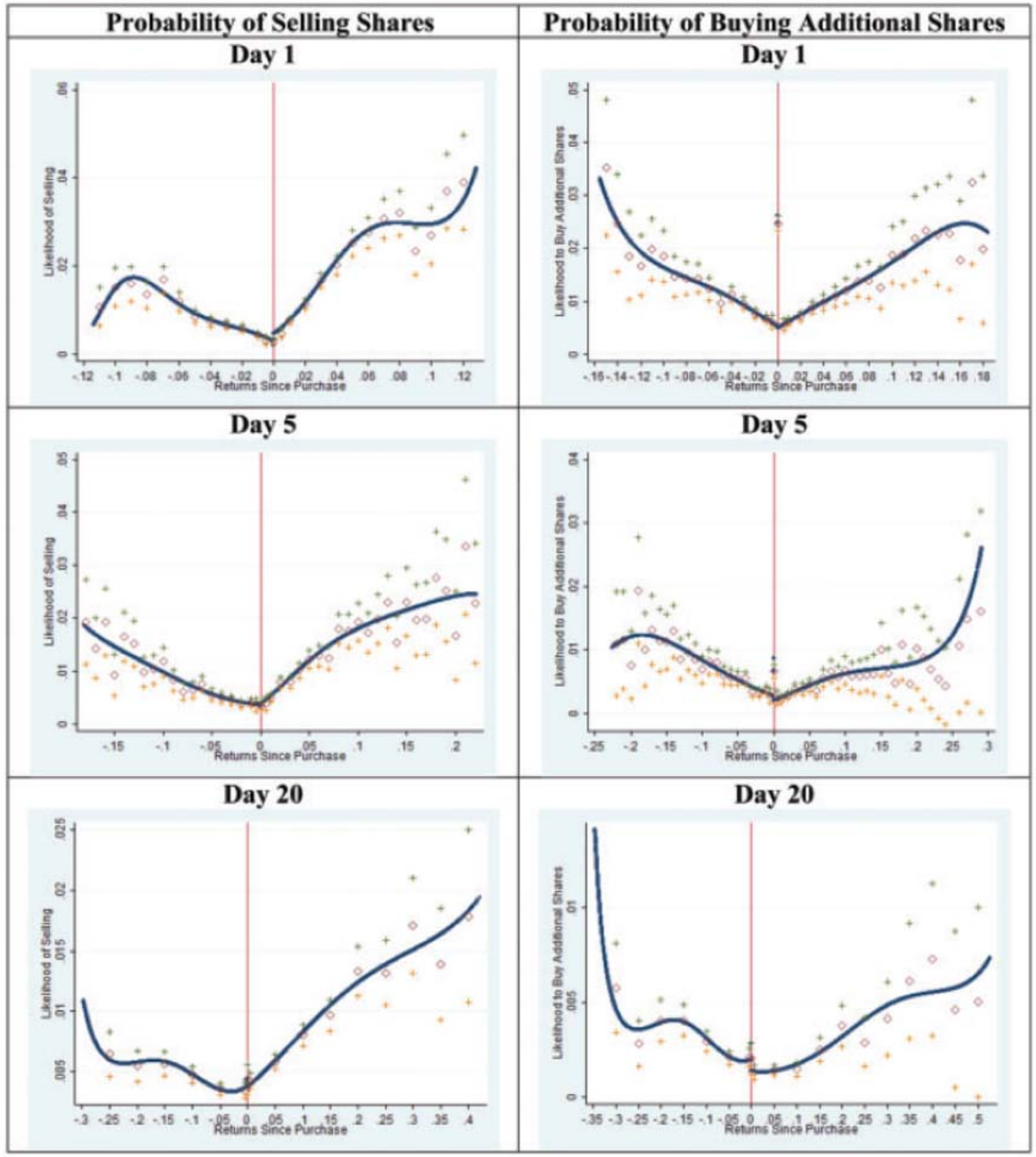


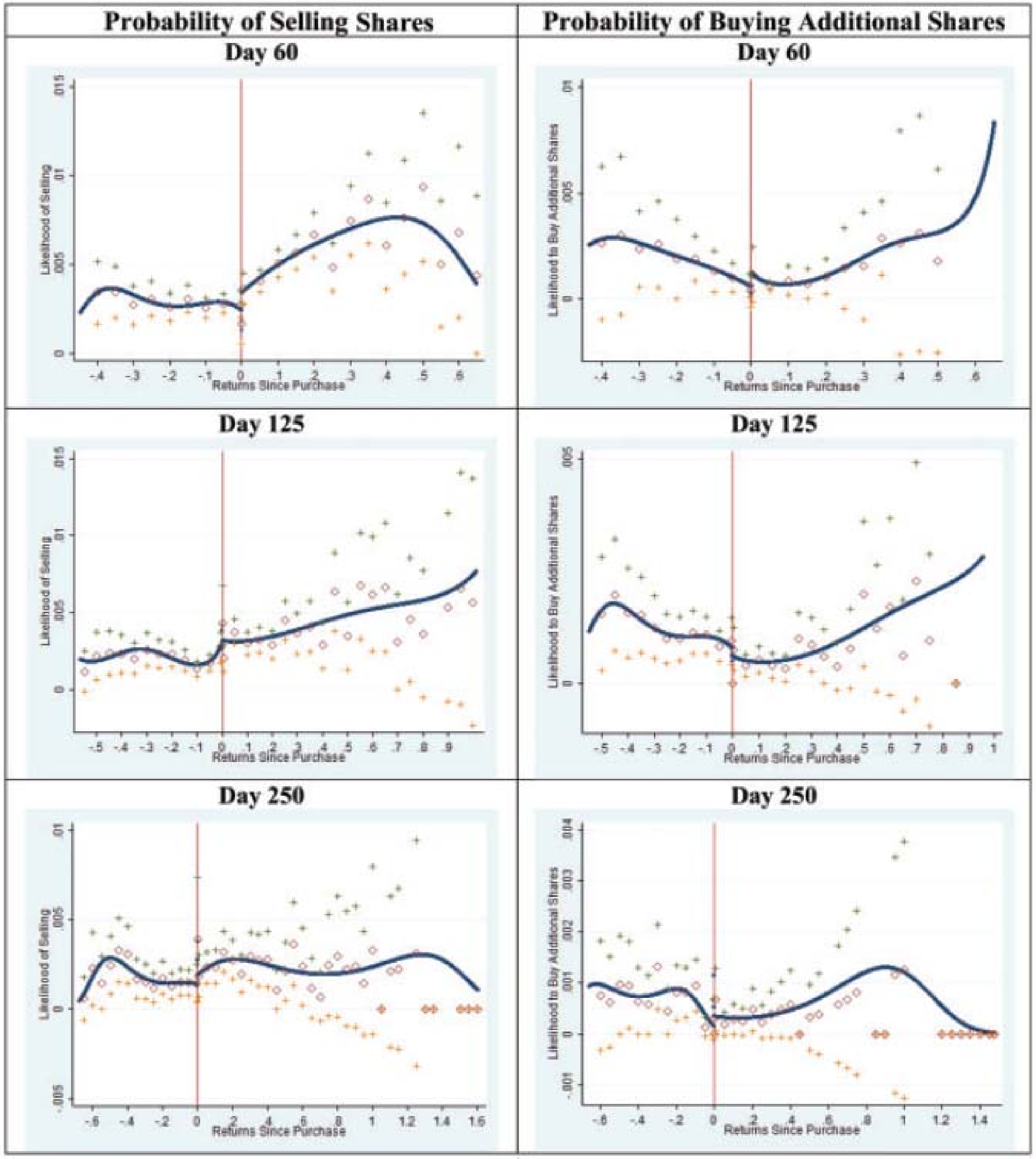
- Empirical test: When the return is near the purchase price we should see
  - More selling
  - Less buying

- —> The selling hazard should be an *inverse V-shaped* function of price

- —> The buying hazard should be a *V-shaped* function of price

- **Ben-David and Hirshleifer (RFS 2012)** plot the hazards above, that is,
  - $P(Sell\ at/t|holding\ at\ t)$
  - $P(B\text{uy}\ more\ at/t|holding\ at\ t)$


Probability of Selling Shares
Probability of Buying Additional Shares
Day 1
Day 1
Likelihood of Selling
Likelihood to Buy Additional Shares
Returns Since Purchase
Returns Since Purchase
Day 5
Day 5
Likelihood of Selling
Likelihood to Buy Additional Shares
Returns Since Purchase
Returns Since Purchase
Day 20
Day 20
Likelihood of Selling
Likelihood to Buy Additional Shares
Returns Since Purchase
Returns Since Purchase


Probability of Selling Shares
Probability of Buying Additional Shares
Day 60
Day 60
Likelihood of Selling
Likelihood to Buy Additional Shares
Returns Since Purchase
Day 125
Day 125
Day 250
Day 250

- Results
  - Strinkingy, no evidence of the pattern predicted by prospect theory at any horizon.
  - Strong rejection of prospect theory model with purchase price as reference point.
  - Could reference point be expected return (that is, $P_0 * (1 + r)$)? BUT No visible inverse V-shaped pattern for positive return
- Back to the drawing board!

- Barberis-Xiong assumes that utility is evaluated every T period for all stocks

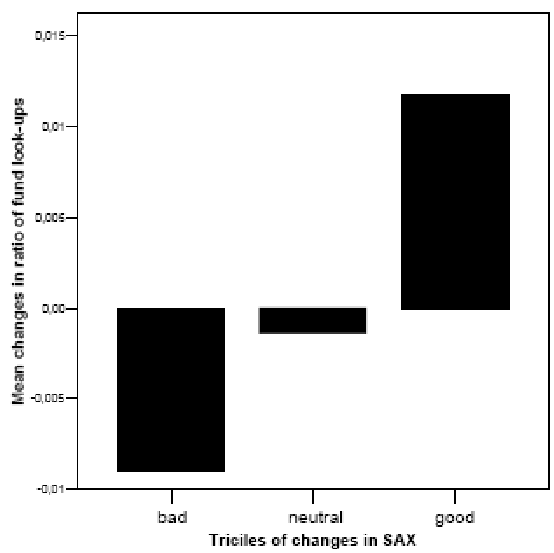
- Alternative assumption: Investors evaluate utility **only** when selling
  - Loss from selling a loser $>$ Gain of selling winner
  - Sell winners, hoping in option value
  - Would induce bunching at exactly purchase price

- 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 –> 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.



4 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)**

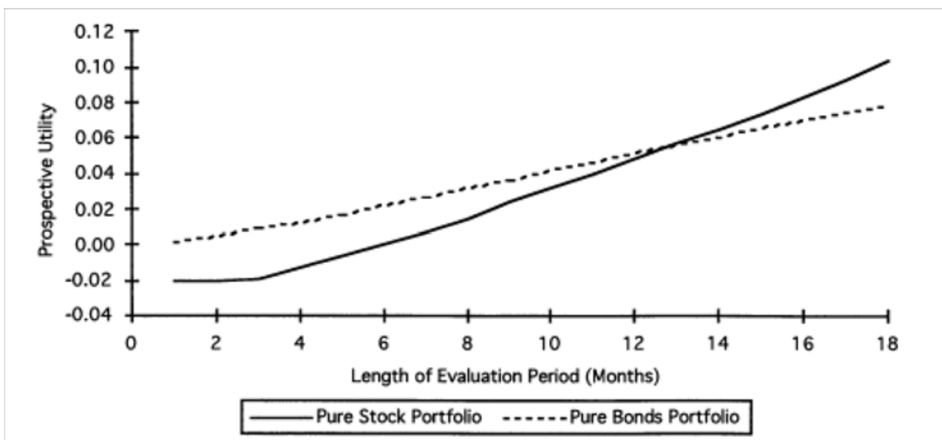
- Equity premium (Mehra and Prescott, 1985)
  - Stocks not so risky
  - Do not covary much with GDP growth
  - BUT equity premium 3.9% over bond returns (US, 1871-1993)

- 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

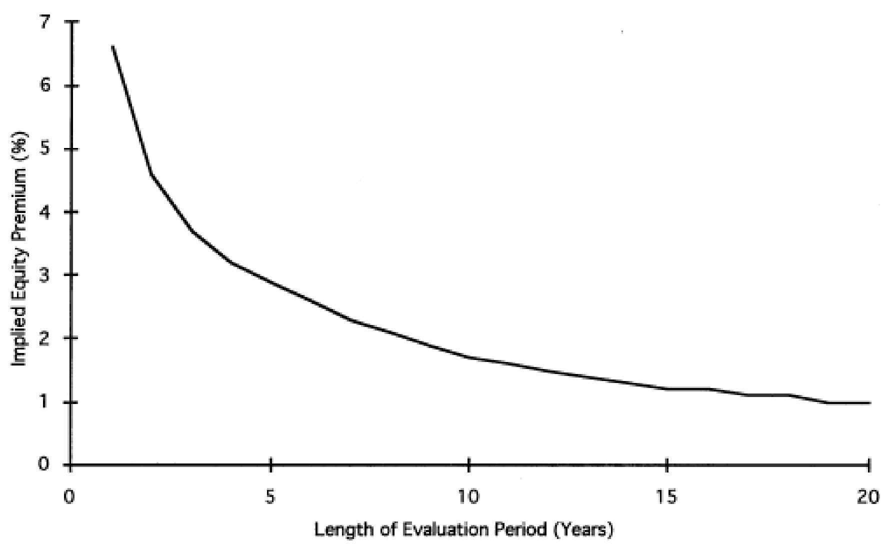
- Calibrate model with λ (loss aversion) 2.25 and full prospect theory specification –>Horizon n at which investors are indifferent between stocks and bonds



- 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)

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
  - House Sale
  - Merger Offer

- Field evidence on risk taking?

- Sydnor (2010) 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.

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%

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)

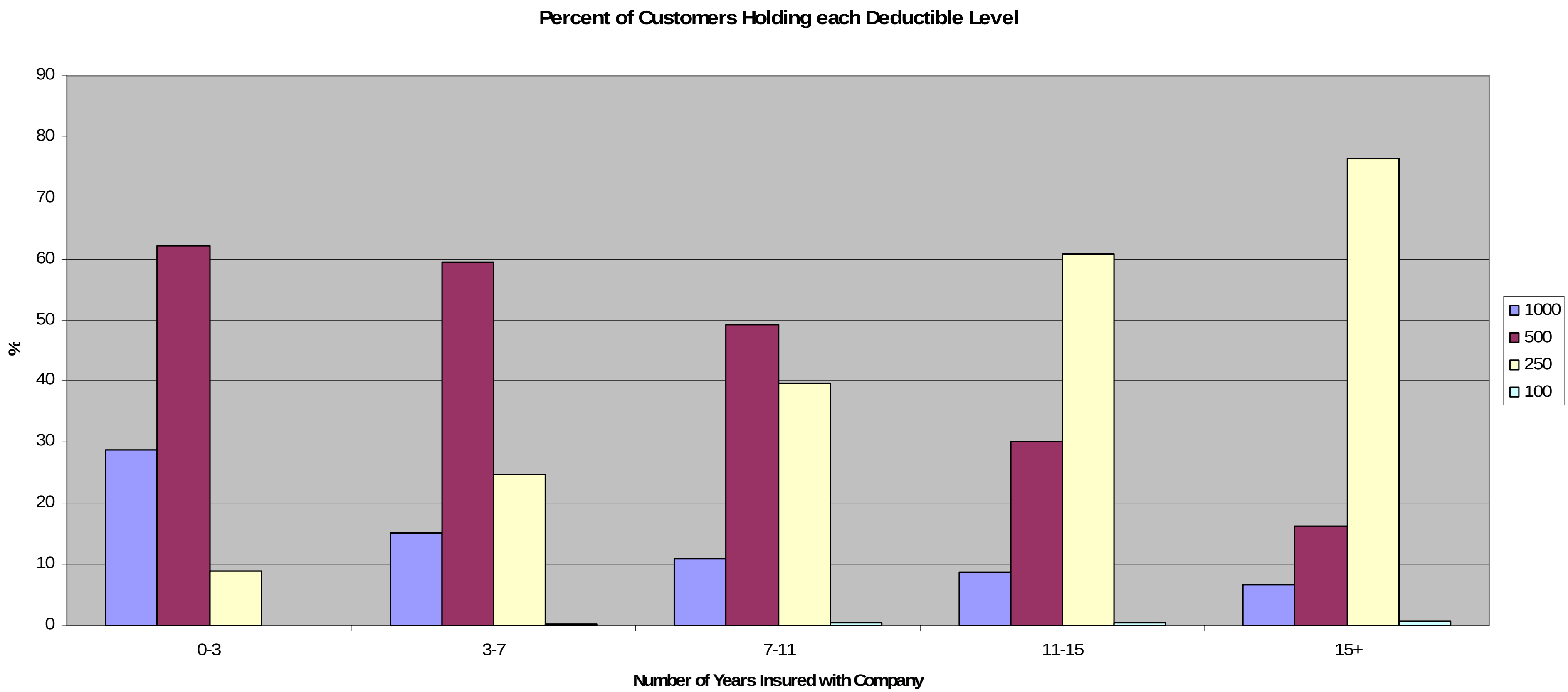
Average forgone expected savings for all low-deductible customers: $99.88

* 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:

$$\max_{c_t} U(c_1, c_2, \ldots, c_T),$$

$$s.t.\ c_1 + c_2 + \ldots + c_T = y_1 + y_2 + \ldots y_T.$$

- (Indirect) utility of wealth maximization

$$\max_{w} u(w),$$

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

$$s.t.\ c_1 + c_2 + \ldots + c_T = y_1 + y_2 + \ldots + y_T = w$$

$\Rightarrow$ *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)

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 $\Rightarrow \rho = 48$

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

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

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%**

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

- More recent evidence: Barseghyan, Molinari, O'Donoghue, and Teitelbaum (2011)
  - Micro data on car and home insurance for same person
  - Estimate a model of reference-dependent preferences with Koszegi-Rabin reference points
  - Strong evidence of probability weighting

6 Next Lecture

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