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

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Outline

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

1 Reference Dependence: Labor Supply

- 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:

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

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

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

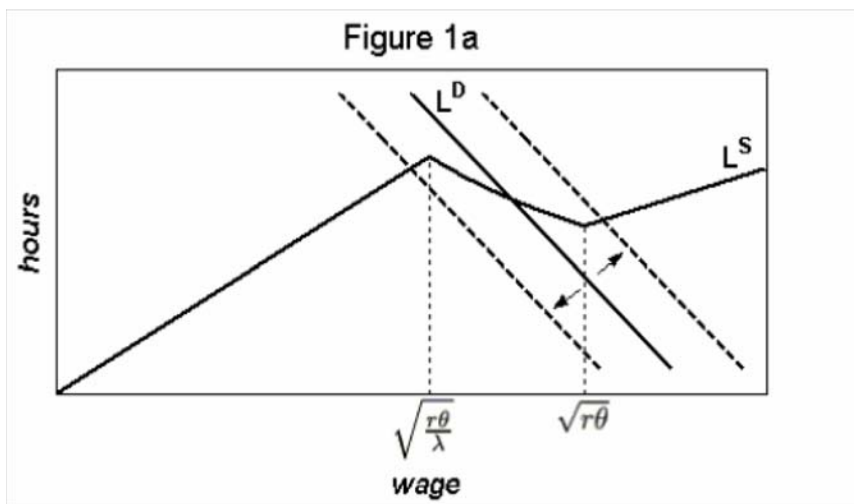
and

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

- 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)

Camerer, Babcock, Loewenstein, and Thaler (QJE 1997)

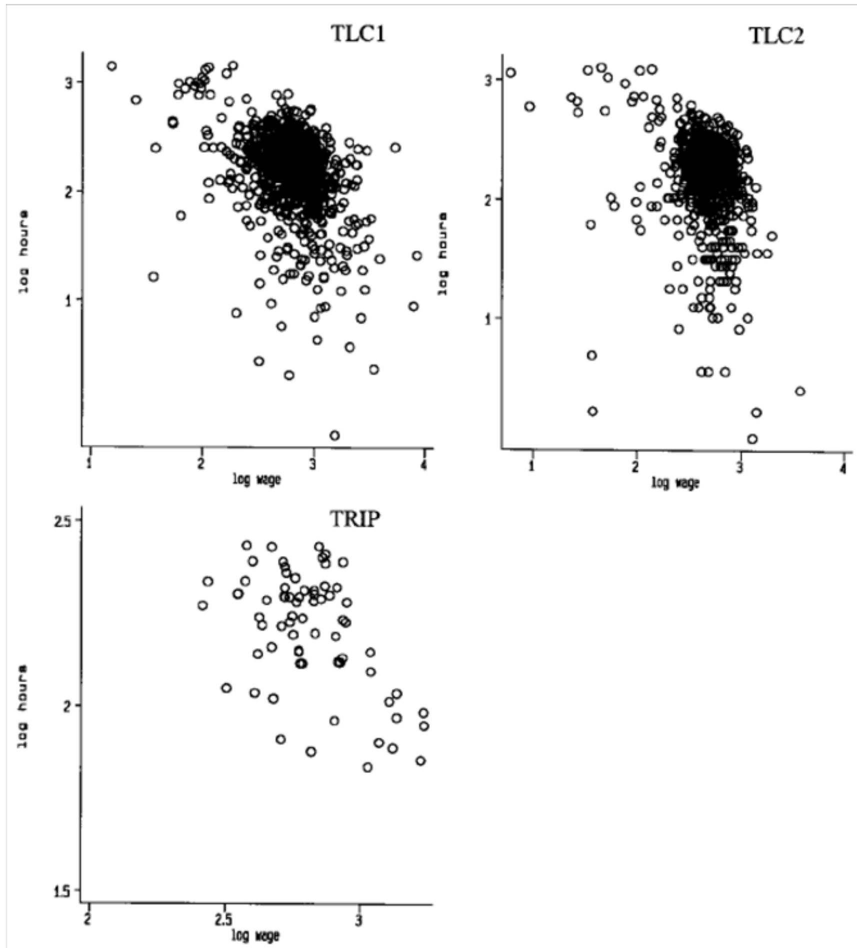
- Data on daily labor supply of New York City cab drivers
  - 70 Trip sheets, 13 drivers (TRIP data)
  - 1044 summaries of trip sheets, 484 drivers, dates: 10/29-11/5, 1990 (TLC1)
  - 712 summaries of trip sheets, 11/1-11/3, 1988 (TLC2)
- Notice data feature: Many drivers, few days in sample

- 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.

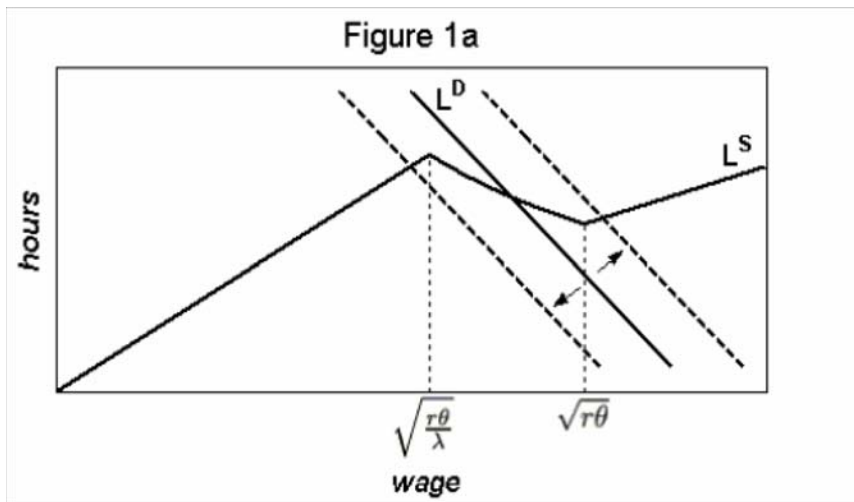
  - $\hat{\beta} = -.355$ (s.e. .051) – TLC2

- 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

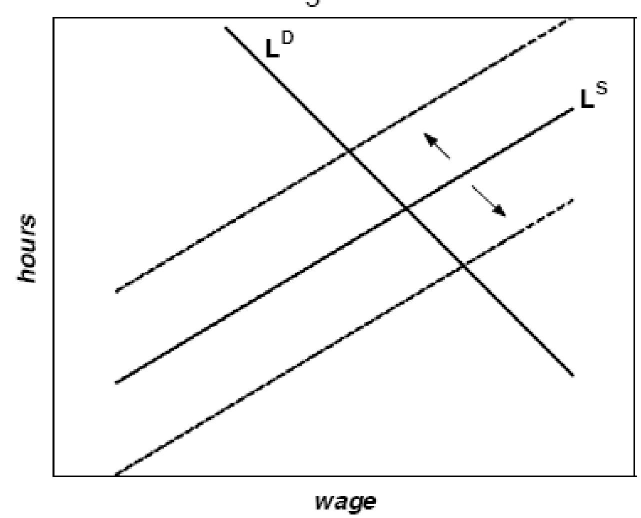
Sample	TRIP		TLC1		TLC2
Log hourly wage	−.319	.005	−1.313	−.926	−.975
	(.298)	(.273)	(.236)	(.259)	(.478)
High temperature	−.000	−.001	.002	.002	−.022
	(.002)	(.002)	(.002)	(.002)	(.007)

- 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

- 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) $w^a \le w^e$	(2) Pooled data	(2) $w^a > w^e$	(2) $w^a \le w^e$	(3) Pooled data	(3) $w^a > w^e$	(3) $w^a \le w^e$
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

- **Oettinger (1999)** estimates labor supply of stadium vendors

- Finds that more stadium vendors show up at work on days with predicted higher audience

  - Clean identification

  - BUT: Does not allow to distinguish between standard model and reference-dependence

  - With *daily* targets, reference-dependent workers will respond the same way

  - *Not* a test of reference dependence

  - (Would not be true with *weekly* targets)

2 Reference Dependence: Disposition Effect

- **Odean (JF, 1998)**

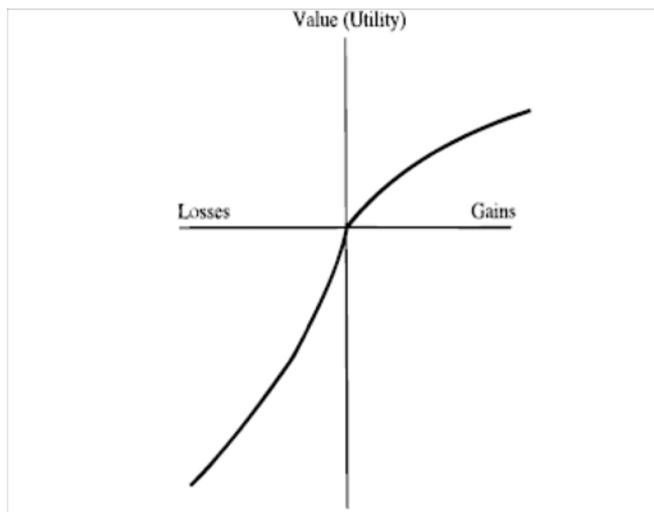
- Do investors sell winning stocks more than losing stocks?

- Tax advantage to sell losers

  – Can post a deduction to capital gains taxation

  – Stronger incentives to do so in December, so can post for current tax year

- Prospect theory intuition:
  - Evaluate stocks regularly
  - Reference point: price of purchase
  - Convexity over losses —> 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

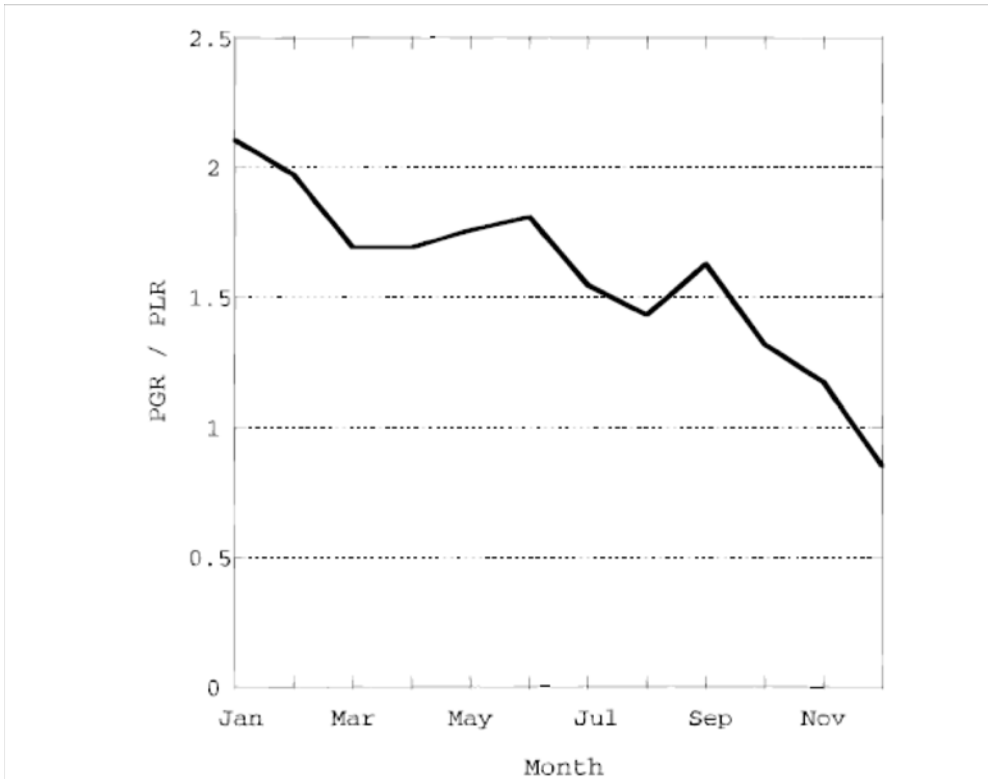
PGR and PLR for the Entire Data Set

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:

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

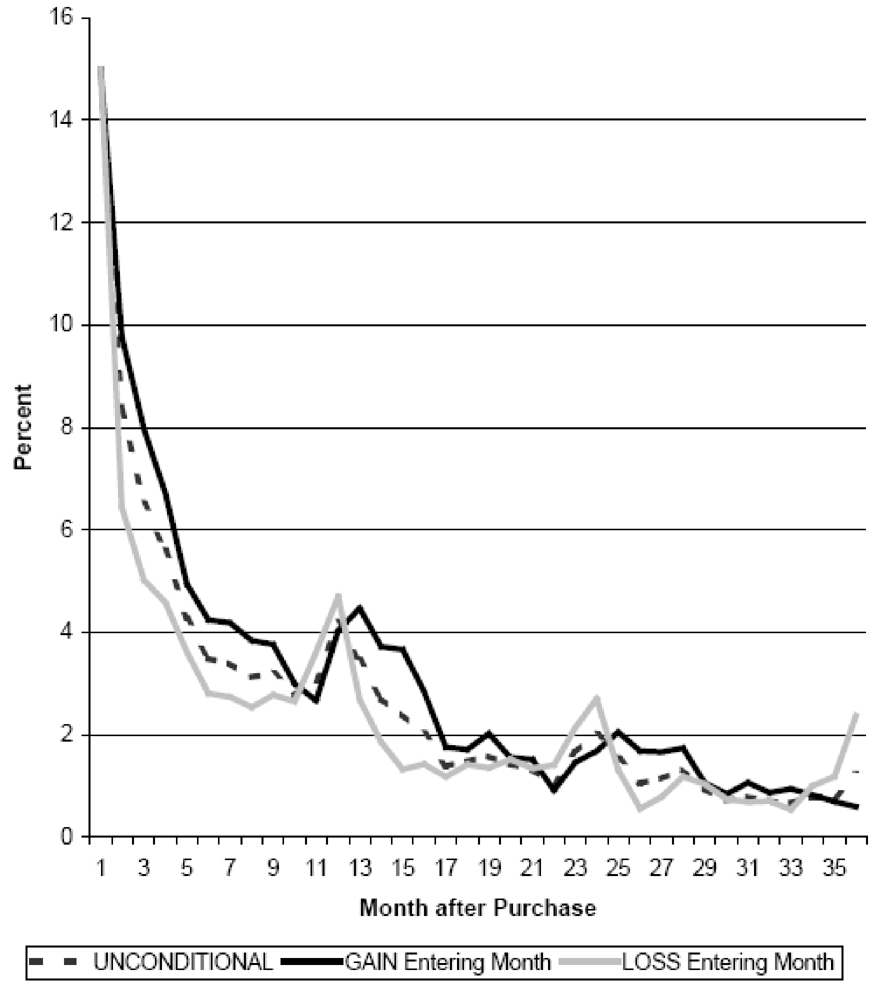
- Regression only applies to shares not already sold

- α_t is baseline hazard at month t

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

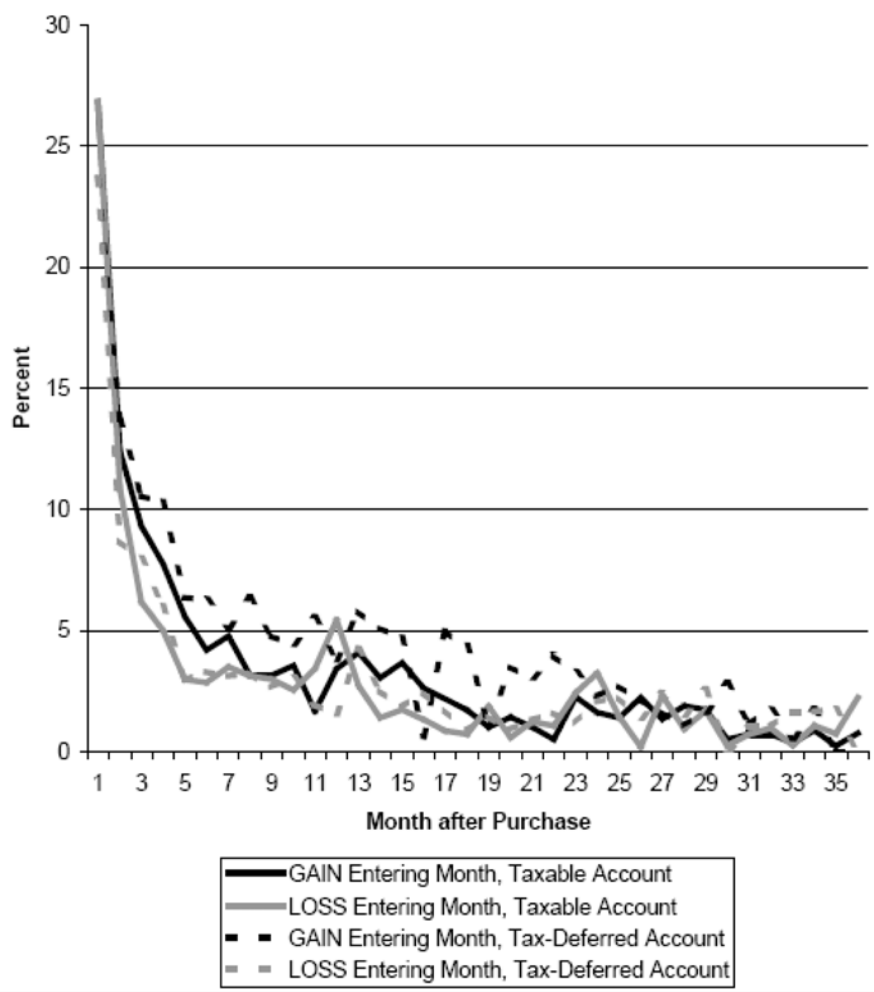
- Difference is small for tax-deferred accounts

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.

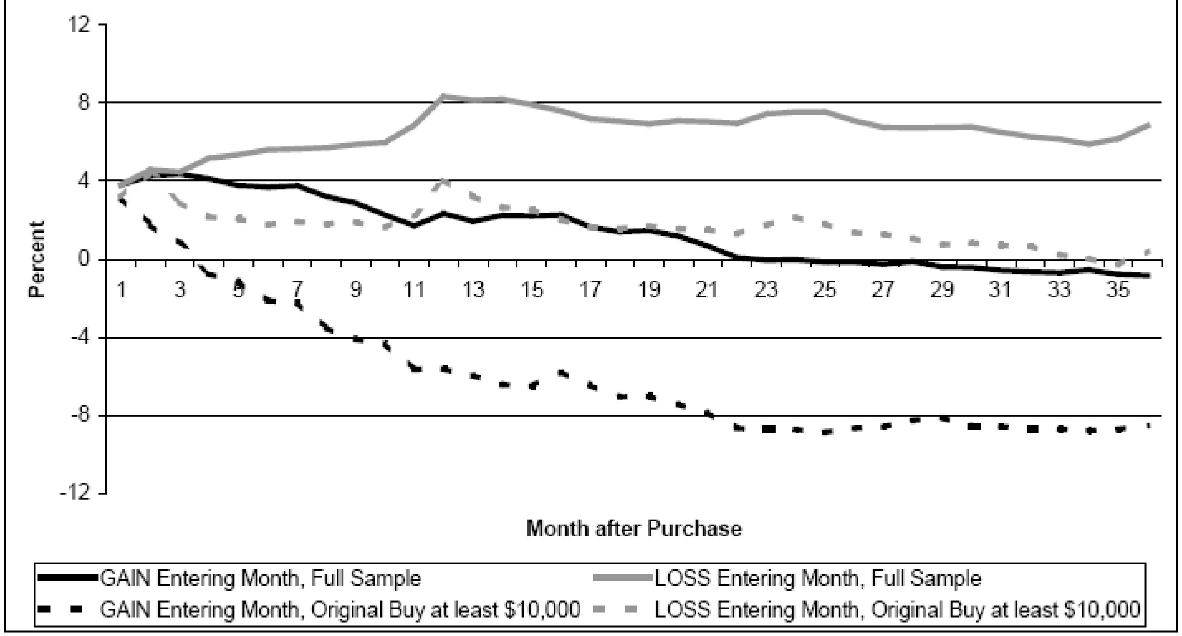


Figure 4: Cumulative Probability of Having Sold Stock in Taxable Account *Relative* to Tax-Deferred Account

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

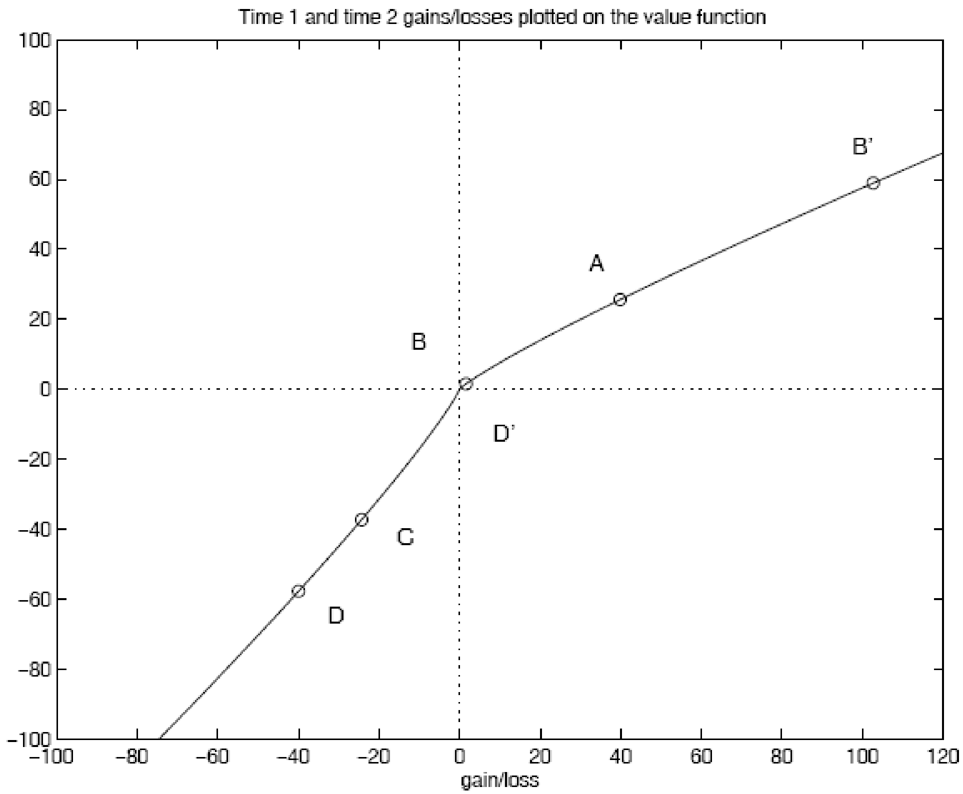
  - utility is $v\left(W_T - W_0 R_f\right)$

- 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.

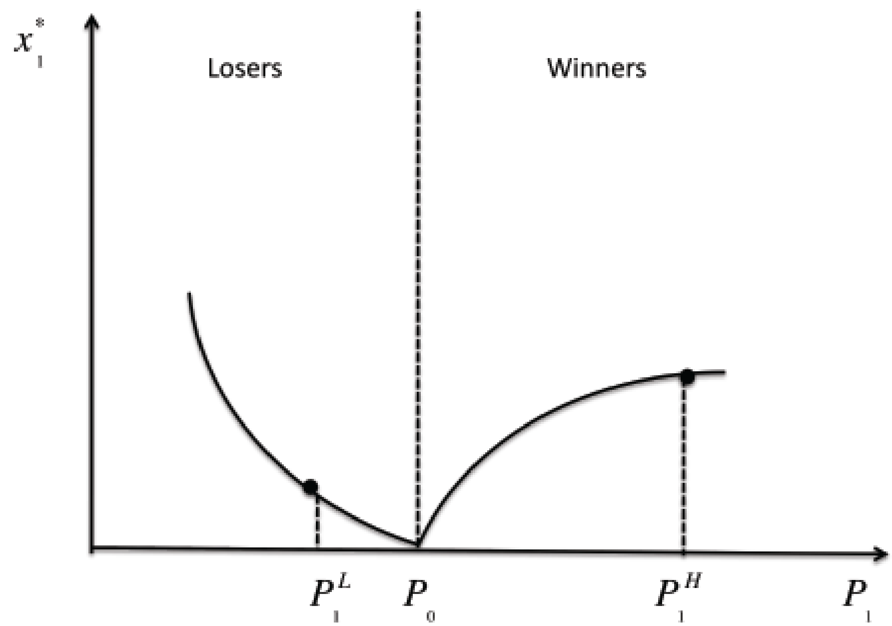
μ	$T = 2$	$T = 4$	$T = 6$	$T = 12$
1.03	-	-	-	.55/.50
1.04	-	-	.54/.52	.54/.52
1.05	-	-	.54/.52	.59/.45
1.06	-	.70/.25	.54/.52	.58/.47
1.07	-	.70/.25	.54/.52	.57/.49
1.08	-	.70/.25	**.48/.58**	**.47/.60**
1.09	-	**.43/.70**	**.48/.58**	**.46/.61**
1.10	**0.0/1.0**	**.43/.70**	**.48/.58**	**.36/.69**
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

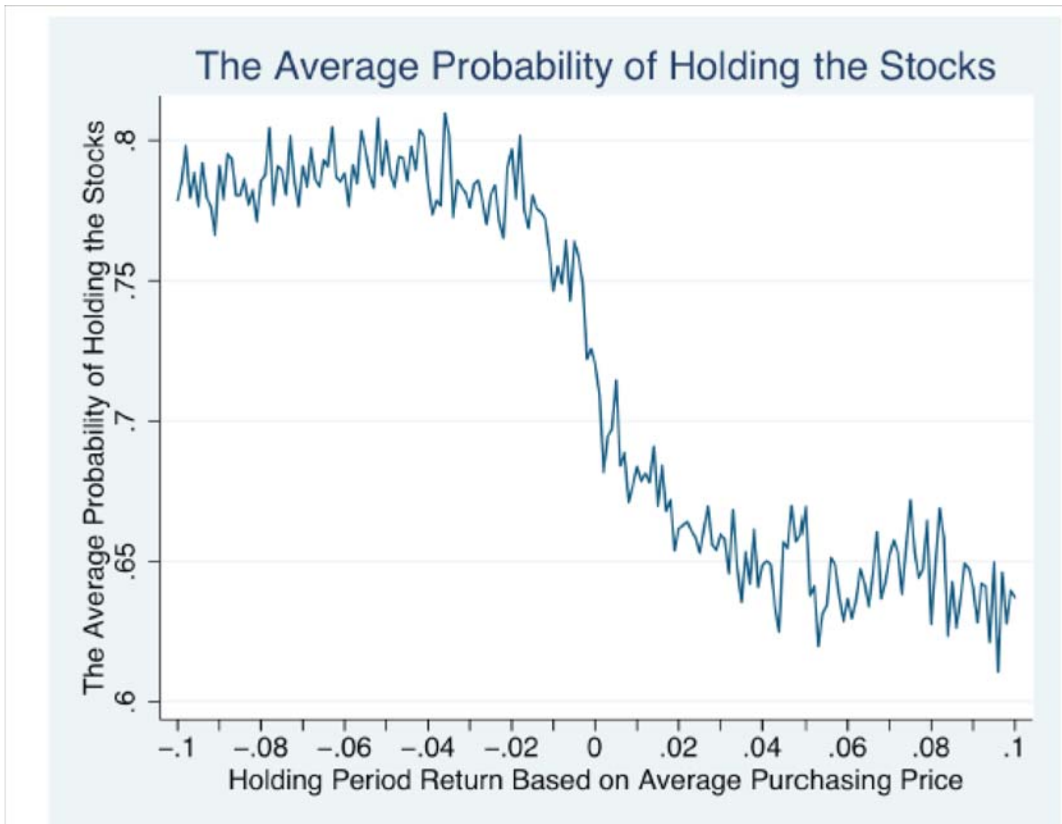


- Some novel predictions of this model:
  - Stocks near buying price are more likely to be sold
  - Disposition effect should hold when away from ref. point

- **Meng (2009)** elaborates on this point
  - Model of two-period portfolio holding
  - Loss Aversion with respect to (potentially stochastic) reference point
  - Derives optimal holding of risk asset x as function of past returns



- Empirical test: We should see a drop in propensity to hold a stock when return is near the reference point



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

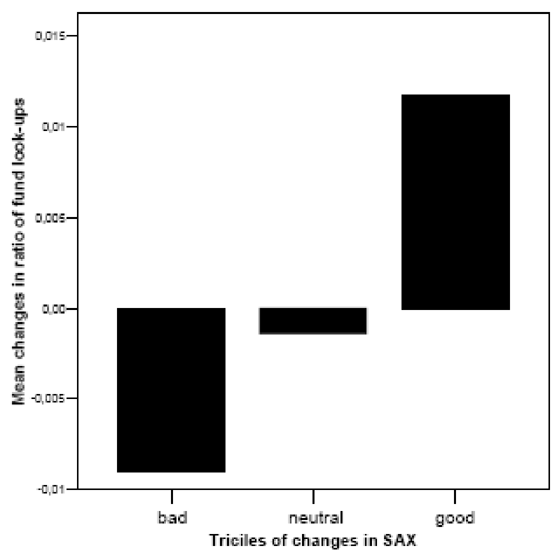
- Alternative assumption: Investors evaluate utility **only** when selling
  - Loss from selling a loser $>$ Gain of selling winner
  - Sell winners, hoping in option value
  - Would induce bunching at exactly purchase price

- Key question: When is utility evaluated?

- **Karlsson, Loewenstein, and Seppi (JRU 2009): Ostrich Effect**
  - Investors do not want to evaluate their investments at a loss
  - Stock market down –> Fewer logins into investment account

Figure 4b: Changes in the SAX and ratio of fund look-ups to logins to personal banking page by investors at a large Swedish bank

The sample period is June 30, 2003 through October 7, 2003.



3 Reference Dependence: Equity Premium

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

- Now consider reference dependence and market-wide returns

- **Benartzi and Thaler (1995)**

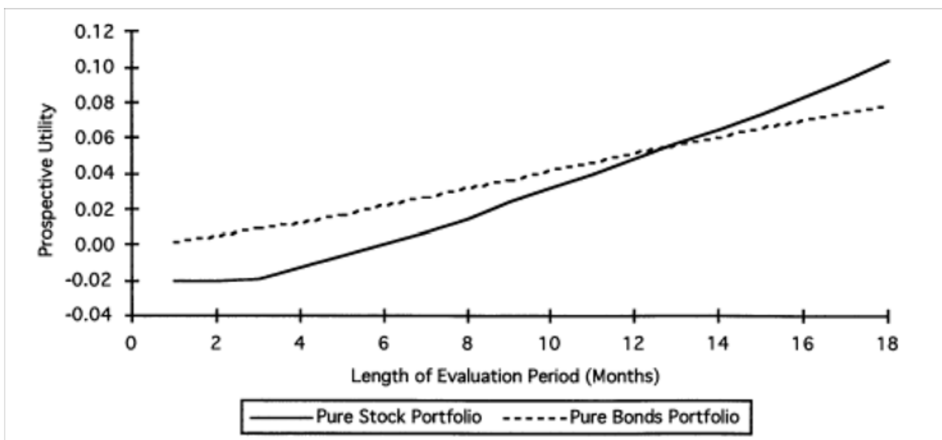
- Equity premium (Mehra and Prescott, 1985)
  - Stocks not so risky
  - Do not covary much with GDP growth
  - BUT equity premium 3.9% over bond returns (US, 1871-1993)

- Need very high risk aversion: $RRA \geq 20$

- Benartzi and Thaler: Loss aversion + narrow framing solve puzzle
  - Loss aversion from (nominal) losses—> Deter from stocks
  - Narrow framing: Evaluate returns from stocks every n months

- More frequent evaluation—>Losses more likely –> Fewer stock holdings

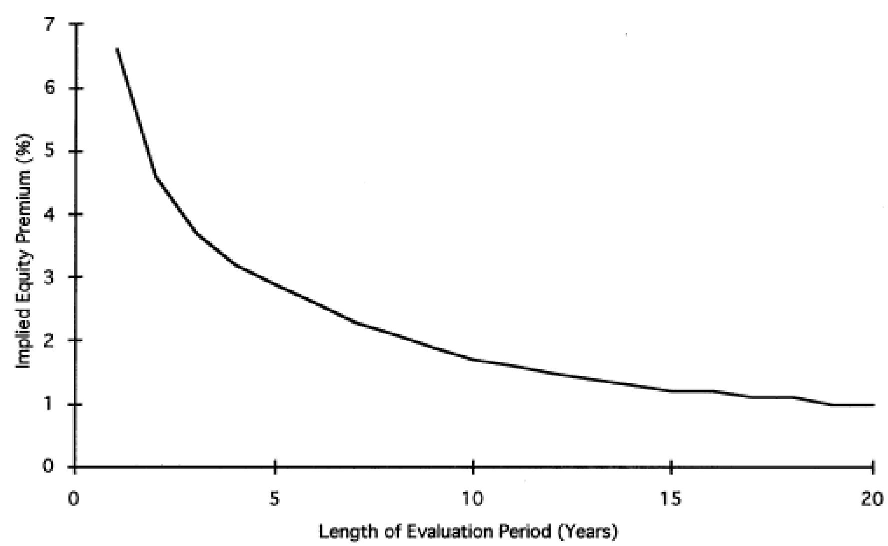
- Calibrate model with λ (loss aversion) 2.25 and full prospect theory specification –>Horizon n at which investors are indifferent between stocks and bonds



- 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)

4 Reference Dependence: Domestic Violence

- Consider a man in conflictual relationship with the spouse

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

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

- Model the utility u as

$$\begin{array}{ll} 1-p & \text{if Team wins} \\ \lambda\,(0-p) & \text{if Team loses} \end{array}$$

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

- Implications:
  - Losses have a larger impact than gains
  - The (negative) effect of a loss is higher the more unexpected (higher p)
  - The (positive) effect of a gain is higher the more unexpected (lower p)

- Card and Dahl (2009) test these predictions using a data set of:
  - Domestic violence (NIBRS)
  - Football matches by State
  - Expected win probability from Las Vegas predicted point spread
- Separate matches into
  - Predicted win (+3 points of spread)
  - Predicted close
  - Predicted loss (-3 points)

Table 4. Emotional Shocks from Football Games and Male-on-Female Intimate Partner Violence Occurring at Home, Poisson Regressions.

	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

- Other findings:
  - Effect is larger for more important games
  - Effect disappears within a few hours of game end –> Emotions are transient
  - No effect on violence of females on males

5 Reference Dependence: Employment and Effort

- Back to labor markets: Do reference points affect performance?

- **Mas (QJE 2006)** examines police performance

- Exploits quasi-random variation in pay due to arbitration

- Background

  – 60 days for negotiation of police contract –> If undecided, arbitration

  – 9 percent of police labor contracts decided with final offer arbitration

- Framework:
  - pay is $w * (1 + r)$
  - union proposes r_u, employer proposes r_e, arbitrator prefers r_a
  - arbitrator chooses r_e if $|r_e - r_a| \leq |r_u - r_a|$
  - $P(r_e, r_u)$ is probability that arbitrator chooses r_e
  - Distribution of r_a is common knowledge (cdf F)
  - Assume $r_e \leq r_a \leq r_u$ –> Then

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

- Nash Equilibrium:
  - If r_a is certain, Hotelling game: convergence of r_e and r_u to r_a
  - Employer's problem:

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

  - Notice: $U' < 0$
  - First order condition (assume $r_u \geq r_e$):

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

  - $r_e^* = r_u^*$ cannot be solution –> Lower r_e and increase utility ($U' < 0$)

- Union's problem: maximizes

$$\max_{r_u} PV\left(w\left(1+r_e^*\right)\right)+\left(1-P\right)V\left(w\left(1+r_u\right)\right)$$

- Notice: $V' > 0$

- First order condition for union:

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

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

- This implies $V\left(w\left(1+r_e^*\right)\right)-V\left(w\left(1+r_u^*\right)\right)=-U\left(w\left(1+r_e^*\right)\right)-U\left(w\left(1+r_u^*\right)\right)$ ->

$$-bP^*w=-\left(1-P^*\right)bw$$

- Result: $P^* = 1/2$

- Prediction (i) in Mas (2006): "*If disputing parties are equally risk-averse, the winner in arbitration is determined by a coin toss.*"

- Therefore, as-if random assignment of winner

- Use to study impact of pay on police effort

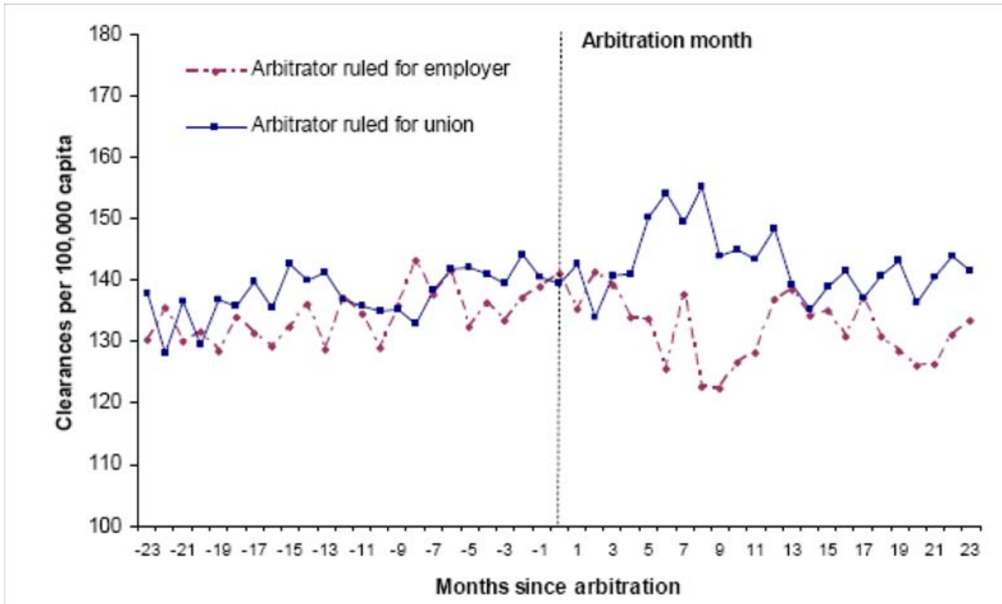
- Data:
  - 383 arbitration cases in New Jersey, 1978-1995
  - Observe offers submitted r_e, r_u, and ruling $\bar{r}_a$
  - Match to UCR crime clearance data (=number of crimes solved by arrest)

- Compare summary statistics of cases when employer and when police wins
- Estimated $\hat{P} = .344 \neq 1/2$ –>Unions more risk-averse than employers
- No systematic difference between Union and Employer cases except for r_e

Table I
Sample characteristics in the -12 to +12 month event time window

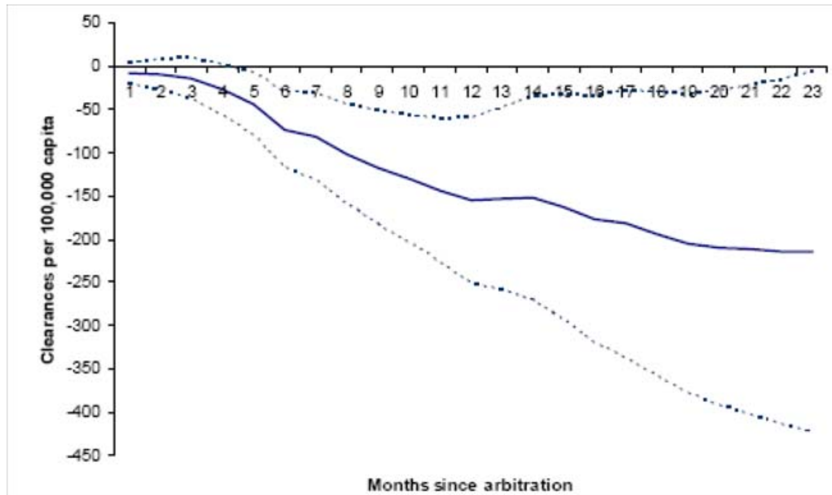
	(1) Full-sample	(2) Pre-arbitration: Employer wins	(3) Pre-arbitration: Employer loses	(4) Pre-arbitration: Employer win-Employer loss
Arbitrator rules for employer	0.344			
Final Offer: Employer	6.11	6.44	5.94	0.50
	[1.65]	[1.54]	[1.68]	(0.18)
Final Offer: Union	7.65	7.87	7.54	0.32
	[1.71]	[2.03]	[1.51]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

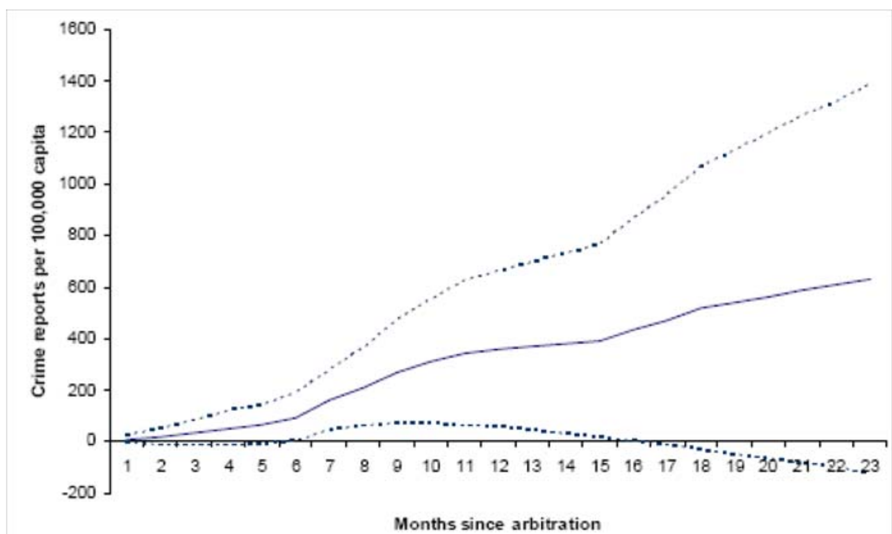
- Graphical evidence of effect of ruling on crime clearance rate



- Significant effect on clearance rate for one year after ruling

- Estimate of the cumulated difference between Employer and Union cities on clearance rates and crime


Clearances per 100,000 capita
Months since arbitration
50
0
-50
-100
-150
-200
-250
-300
-350
-400
-450
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23


Crime reports per 100,000 capita
Months since arbitration
1600
1400
1200
1000
800
600
400
200
0
-200
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23

- Arbitration leads to an average increase of 15 clearances out of 100,000 each month

Table II
Event study estimates of the effect of arbitration rulings on clearances; -12 to +12 month event time window

	All clearances			Violent crime clearances			Property crime clearances		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	118.57	141.25		63.16	75.10		55.42	66.15	
	(5.12)	(9.94)		(3.13)	(6.86)		(2.88)	(4.55)	
Post-arbitration × Employer win	-6.79	-8.48	-9.75	-2.54	-3.10	-3.77	-4.26	-5.39	-4.45
	(2.62)	(2.20)	(2.70)	(1.75)	(1.35)	(1.78)	(1.62)	(2.25)	(1.87)
Post-arbitration × Union win	4.99	7.92	5.96	4.17	5.62	5.31	0.819	2.31	2.19
	(2.09)	(2.91)	(2.65)	(1.53)	(1.95)	(1.42)	(1.24)	(1.58)	(1.37)
Row 3 – Row 2	11.78	16.40	15.71	6.71	8.71	9.08	5.08	7.69	6.40
	(3.35)	(3.65)	(3.75)	(2.32)	(2.37)	(2.26)	(2.04)	(2.75)	(2.30)
Employer Win (Yes = 1)	3.71	-2.81		2.14	-5.73		1.57	2.92	
	(9.46)	(14.92)		(6.11)	(9.53)		(4.93)	(7.51)	
Fixed-effects?			Yes			Yes			Yes
Weighted sample?		Yes	Yes		Yes	Yes		Yes	Yes
Augmented sample?			Yes			Yes			Yes
Mean of the Dependent variable	120.31	120.31	130.82	64.79	64.79	72.15	55.51	55.51	58.63
	[106.65]	[106.65]	[370.58]	[71.28]	[71.28]	[294.78]	[58.72]	[58.72]	[180.55]
Sample Size	9,538	9,538	59,137	9,538	9,538	59,135	9,538	9,538	59,136
R^2	0.0008	0.005	0.63	0.0007	0.0078	0.59	0.001	0.0015	0.55

- Effects on crime rate more imprecise

Table IV
Event study estimates of the effect of arbitration rulings on crime; -12 to +12 month event time window

	All crime		Violent crime		Property crime	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	612.18		150.26		461.81	
	(63.98)		(23.23)		(42.00)	
Post-arbitration × Employer win	26.86	24.68	7.75	4.87	19.19	19.86
	(25.29)	(14.68)	(7.85)	(4.70)	(18.17)	(11.19)
Post-arbitration × Union win	7.64	6.68	7.07	2.49	0.170	4.40
	(16.24)	(11.42)	(5.46)	(4.46)	(11.68)	(7.87)
Row 3 – Row 2	-19.21	-18.01	-0.68	-2.38	-19.02	-15.46
	(30.06)	(19.12)	(9.56)	(6.63)	(21.60)	(13.96)
Employer Win (Yes = 1)	-31.81		-20.43		-11.35	
	(84.42)		(27.57)		(59.50)	
Fixed-effects?		Yes		Yes		Yes
Mean of the dependent variable	444.03	519.42	95.49	98.26	348.45	421.28
	[364.23]	[2037.4]	[103.16]	[363.76]	[292.10]	[1865.8]
Sample size	9,528	59,060	9,529	59,085	9,537	59,119
R^2	0.001	0.54	0.007	0.76	0.0003	0.42

- Do reference points matter?
- Plot impact on clearances rates (12,-12) as a function of $\bar{r}_a - (r_e + r_u)/2$

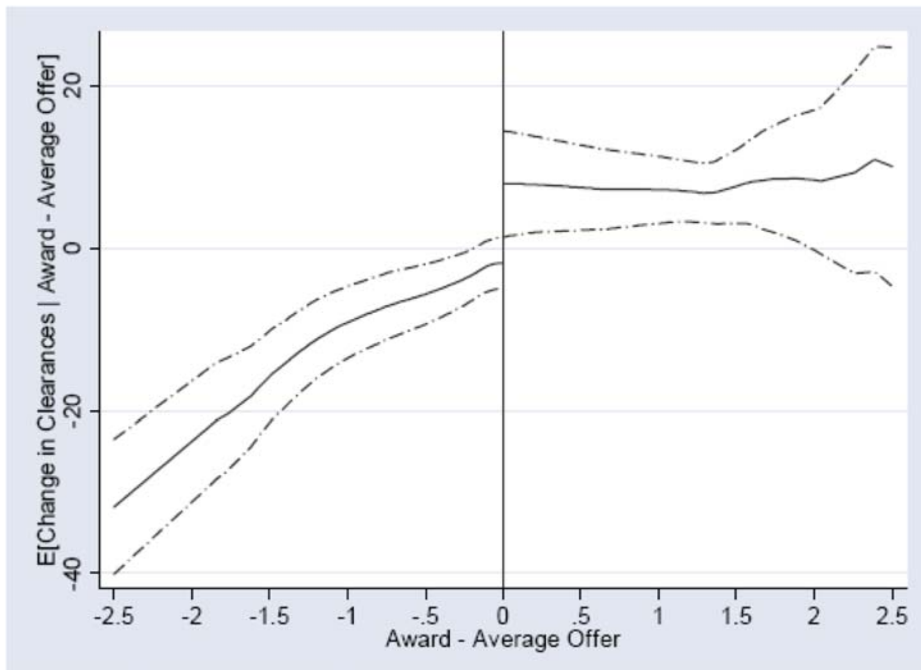


Figure V
Estimated expected change in clearances conditional on the deviation of the award from the average of the offers

- Effect of loss is larger than effect of gain

Table VII
Heterogeneous effects of arbitration decisions on clearances by loss size, award, and deviation from the expected offer; -12 to +12 month event time window

	(1)	(2)	(3)	(4)	(5) Police lose	(6) Police win
Post-Arbitration	5.72	-8.17	12.99	-7.42	4.97	7.30
	(2.31)	(9.58)	(8.45)	(4.76)	(3.14)	(4.17)
Post-Arbitration × Award		1.23	-1.00			
		(1.16)	(0.98)			
Post-Arbitration × Loss size	-10.31		-10.93		-0.20	
	(1.59)		(1.89)		(4.54)	
Post-Arbitration × Union win				13.38		
				(5.32)		
Post-Arbitration × (expected award-award)					-17.72	2.82
					(7.94)	(4.13)
Post-Arbitration × p(loss size)^				Included		
Sample Size	59,137	59,137	59,137	59,137	52,857	55,879
R^2	0.63	0.63	0.63	0.63	0.60	0.62

Standard errors, clustered on the intersection of arbitration window and city, are in parentheses. Standard deviations are in brackets. Observations are municipality × month cells. The sample is weighted by population size in 1976. The dependant variable is clearances per 100,000 capita. Loss size is defined as the union demand (percent increase on previous wage) less the arbitrator award. Amongst cities that underwent arbitration, the mean loss size is 0.489 with a standard deviation of 0.953. The expected award is the mathematical expectation of the award given the union and employer offers and the predicted probability of an employer win. The predicted probability of an employer win is estimated with a probit model using as predictors year of arbitration dummies, the average of the final offers, log population, and the length of the contract. See text for details. The samples in models (1)-(4) consist of the 12 months before to the 12 months after arbitration, for jurisdictions that underwent arbitration, as well as all jurisdictions that never underwent arbitration for all months between 1976 and 1996. The sample in model (5) consists of cities where the union lost in arbitration and the comparison group of non-arbitrating cities. The sample in model (6) consists of cities where the union won in arbitration and the comparison group of non-arbitrating cities. All models include month × year effects (252), arbitration window effects (383), and city effects (452). Author's calculation based on NJ PERC arbitration cases matched to monthly municipal clearance rates at the jurisdiction level from FBI Uniform Crime Reports.

- Column (3): Effect of a gain relative to $(r_e + r_u)/2$ is not significant; effect of a loss is

- Columns (5) and (6): Predict expected award $\hat{r}_a$ using covariates, then compute $\bar{r}_a - \hat{r}_a$

  - $\bar{r}_a - \hat{r}_a$ does not matter if union wins

  - $\bar{r}_a - \hat{r}_a$ matters a lot if union loses

- Assume policeman maximizes

$$\max_e \left[\bar{U} + U\left(w\right)\right] e - \theta \frac{e^2}{2}$$

where

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

- F.o.c.:

$$\bar{U} + U(w) - \theta e = 0$$

Then

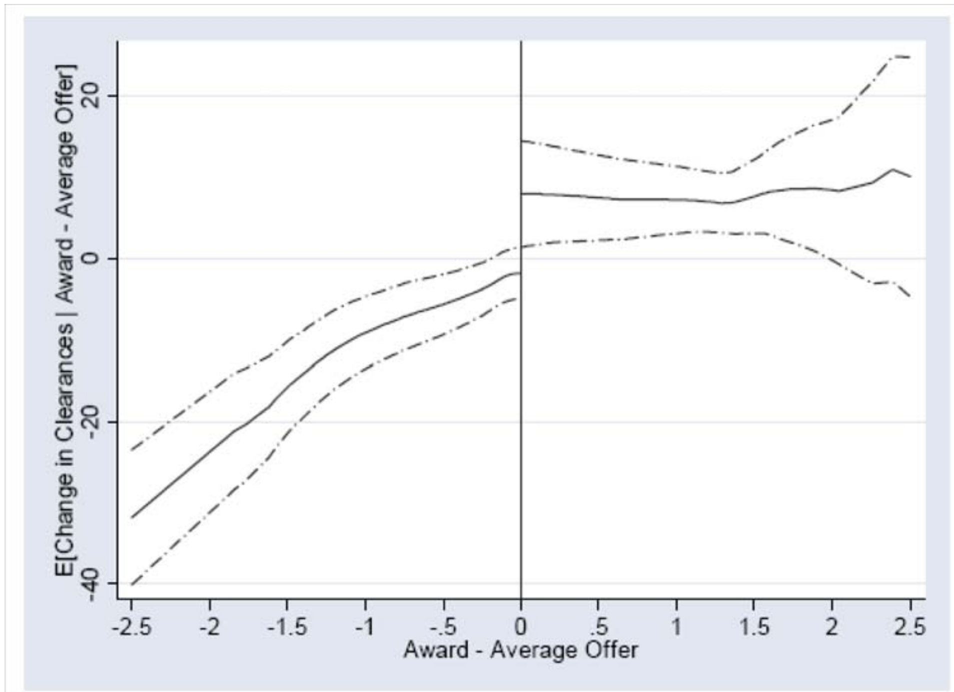
$$e^*(w) = \frac{\bar{U}}{\theta} + \frac{1}{\theta} U(w)$$

- It implies that we would estimate

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

with $\beta > 0$ (also *in* standard model) and $\gamma > 0$ (not in standard model)

- Compare to observed pattern



- Close to predictions of model

6 Next Lecture

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