Econ 219A
Psychology and Economics: Foundations
(Stefano's Lecture 3)

Stefano DellaVigna

November 25, 2009

Outline

1. Reference Dependence: Disposition Effect II
2. Reference Dependence: Labor Supply
3. Reference Dependence: Domestic Violence
4. Social Preferences: Introduction
5. Social Preferences: Gift Exchange in the Field

1 Reference Dependence: Disposition Effect II

- Disposition Effect is very solid empirical finding. Explanation?

- **Barberis and Xiang (2006).** Model asset prices with full prospect theory (loss aversion+concavity+convexity), except for prob. weighting

- Under what conditions prospect theory generates disposition effect?

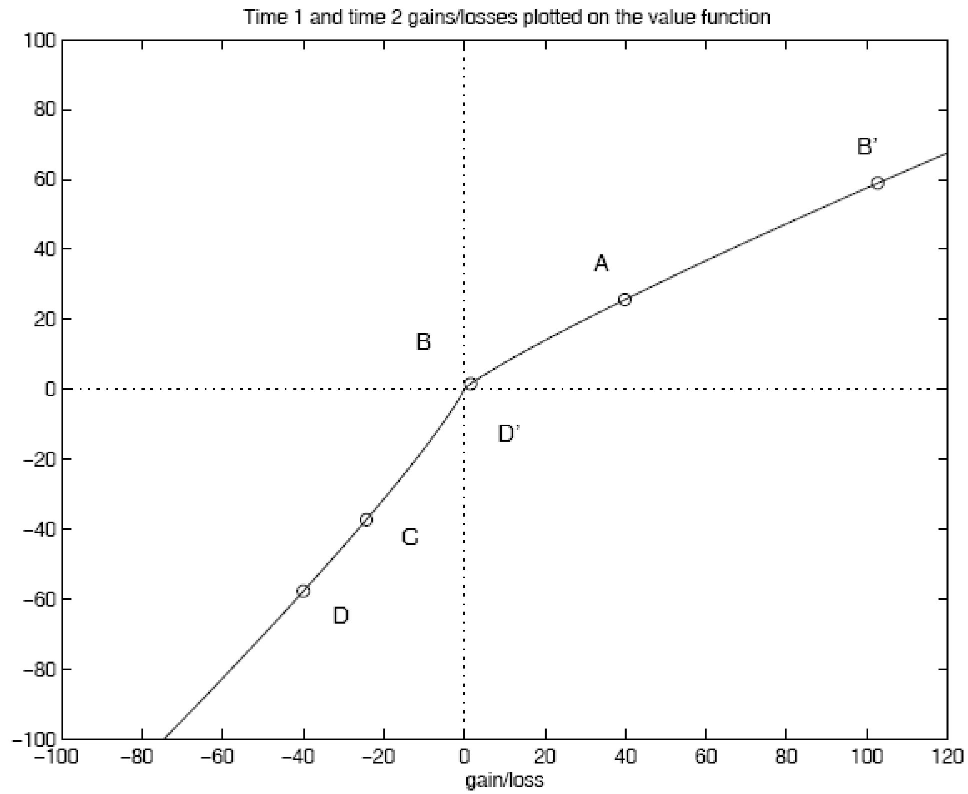
- Setup:
  - Individuals can invest in risky asset or riskless asset with return R_f
  - Can trade in $t = 0, 1, ..., T$ periods
  - Utility is evaluated only at end point, after T periods
  - Reference point is initial wealth W_0
  - utility is $v\left(W_T - W_0 R_f\right)$

- 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

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

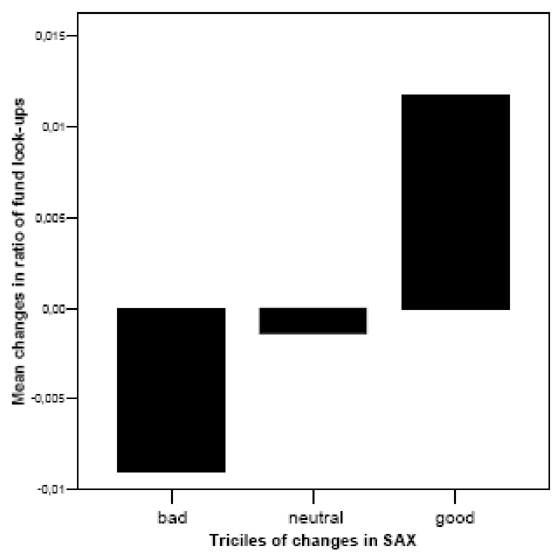
- Alternative assumption: Investors evaluate utility **only** when selling
  - Loss from selling a loser $>$ Gain of selling winner
  - Sell winners, hoping in option value
  - Would induce bunching at exactly purchase price

- Key question: When is utility evaluated?

- **Karlsson, Loewenstein, and Seppi: 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.



2 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)**

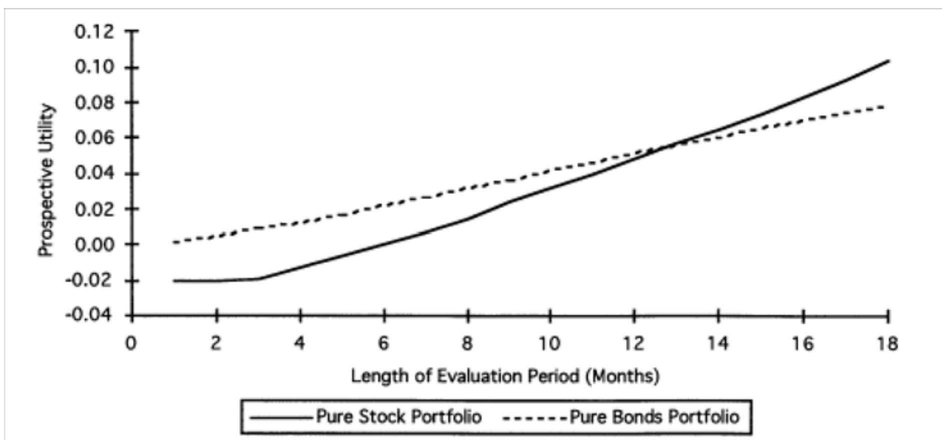
- Equity premium (Mehra and Prescott, 1985)
  - Stocks not so risky
  - Do not covary much with GDP growth
  - BUT equity premium 3.9% over bond returns (US, 1871-1993)

- 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

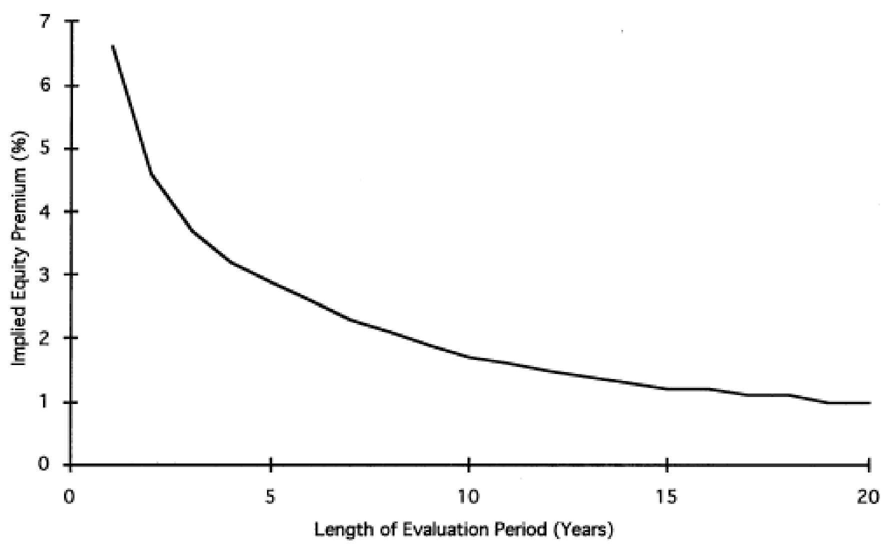
- Calibrate model with λ (loss aversion) 2.25 and full prospect theory specification –>Horizon n at which investors are indifferent between stocks and bonds



- 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)

3 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

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

- 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

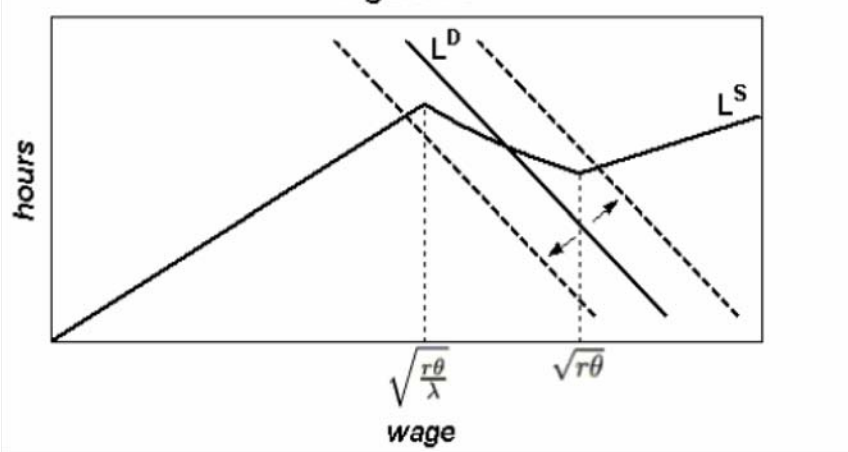
$$h^* = \frac{a}{b\theta + 1}$$

- 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 $a > 0, b > 0$.

Figure 1a



- 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)

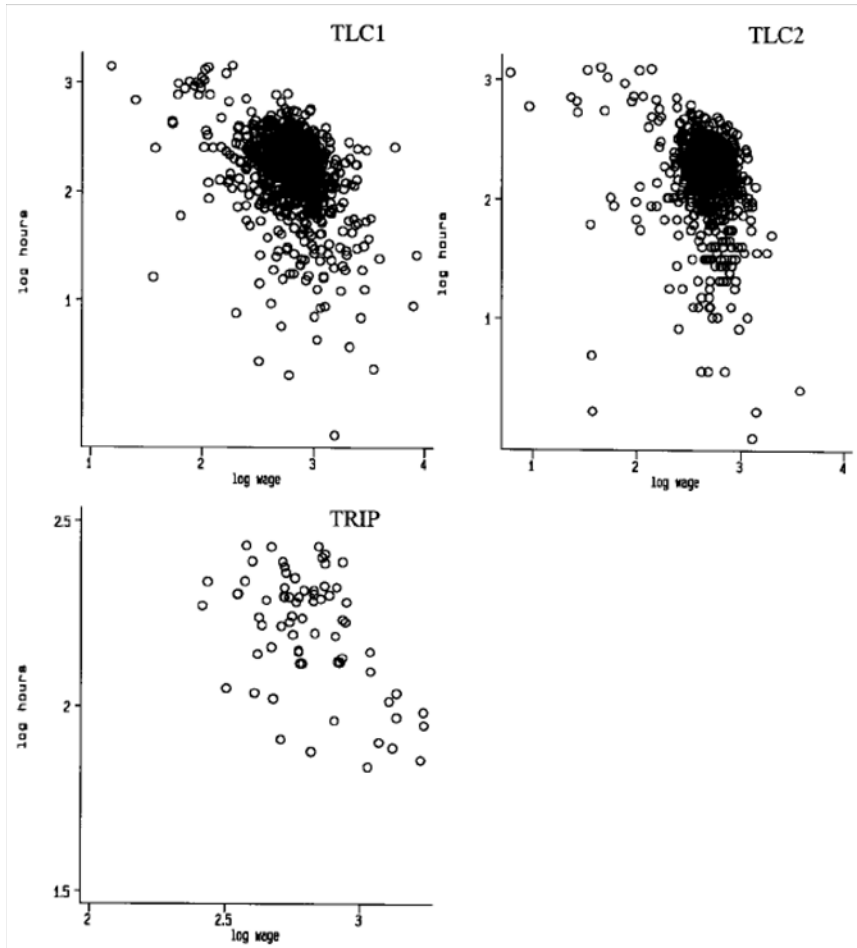
- **Camerer, Babcock, Loewenstein, and Thaler (1997)**

- 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:

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

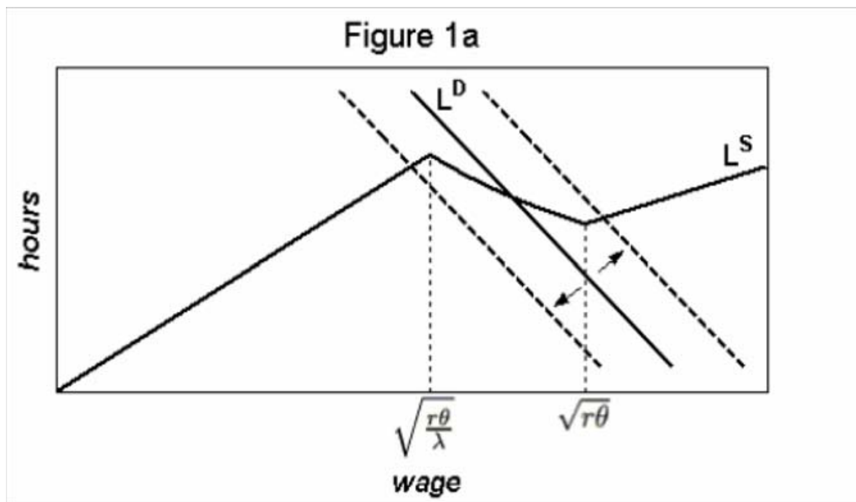
- Estimates of $\hat{\beta}$:
  - $\hat{\beta} = -.186$ (s.e. 129) – TRIP with driver f.e.
  - $\hat{\beta} = -.618$ (s.e. .051) – TLC1 with driver f.e.
  - $\hat{\beta} = -.355$ (s.e. .051) – TLC2

- 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

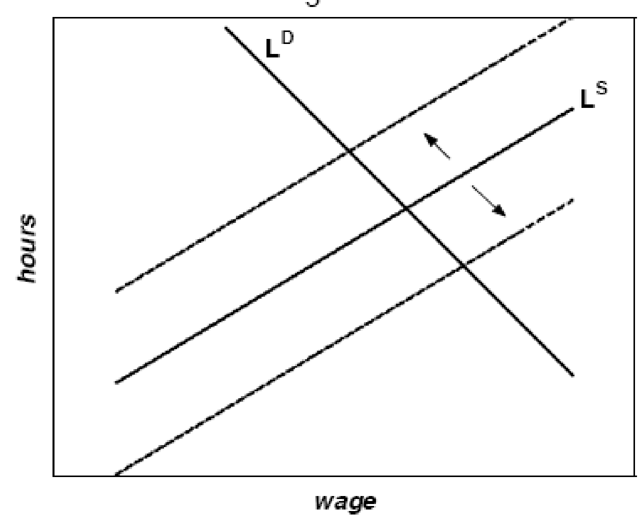
Sample	TRIP		TLC1		TLC2
Log hourly wage	−.319	.005	−1.313	−.926	−.975
	(.298)	(.273)	(.236)	(.259)	(.478)
High temperature	−.000	−.001	.002	.002	−.022
	(.002)	(.002)	(.002)	(.002)	(.007)

- 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.

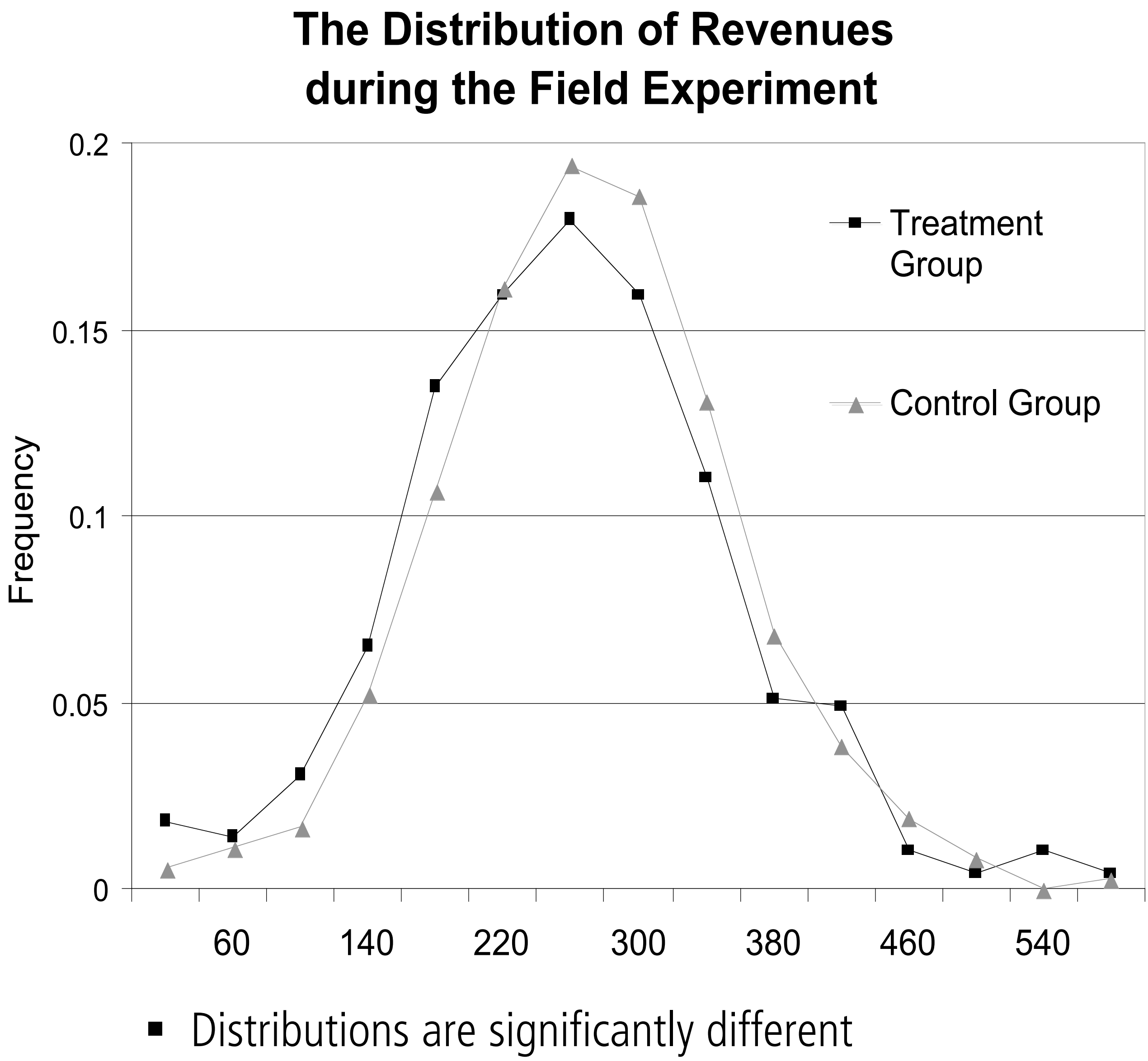
Results for Hours

- 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: **Crawford and 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 2: Marginal Effects on the Probability of Stopping: Linear Probits with Split Samples

		(1)			(2)		
	Evaluation Point for Marginal Effect	Pooled data	First hour's earning > expected	First hour's earning < expected	Pooled data	First hour's earning> expected	First hour's earning < expected
Cumulative total hours	8.0	0.022** (0.011)	0.040*** (0.016)	-0.001 (0.010)	.014** (0.008)	.045*** (0.023)	-.006 (0.010)
Cumulative Income/100	1.5	0.029 (0.027)	-0.008 (0.040)	0.071** (0.027)	.011 (0.020)	-.033 (0.052)	.065** (0.035)
Cumulative waiting hours	2.5	0.005 (0.013)	-0.014 (0.016)	0.036*** (0.010)	.002 (0.008)	-.009 (0.019)	.027** (0.013)
Cumulative Break hours	0.5	-0.001 (0.010)	-0.011 (0.013)	0.019 (0.011)	-.005 (0.007)	-.019 (0.019)	.012 (0.011)

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

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

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

– 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)
<u>Coefficient Estimates</u>					
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 Social Preferences: Introduction

- Laboratory data from ultimatum, dictator, and trust games
  —> Clear evidence of social preferences

- **Fehr-Schmidt (QJE, 1999)** and **Charness-Rabin (QJE, 2002)**

- Simplified model of preferences of B when interacting with A:

$$\begin{aligned} U_B(\pi_A, \pi_B) &\equiv \rho\pi_A + (1-\rho)\pi_B \text{ when } \pi_B \geq \pi_A. \\ U_B(\pi_A, \pi_B) &\equiv \sigma\pi_A + (1-\sigma)\pi_B \text{ when } \pi_B \leq \pi_A. \end{aligned}$$

- Captures:
  - baseline altruism (if $\rho > 0$ and $\sigma > 0$)
  - differentially so if ahead or behind ($\rho > \sigma$)

- Example: Dictator Game. Have \$10 and have to decide how to share

- **Forsythe et al. (GEB, 1994)**: sixty percent of subjects transfers a positive amount.

- Transfer \$5 if

$$\begin{aligned}\rho 5 + (1-\rho)5 &= 5 \geq \rho 0 + (1-\rho)10 \text{ –>} \rho \geq 1/2 \text{ and} \\ \sigma 5 + (1-\sigma)5 &\geq \sigma 10 + (1-\sigma)0 \text{ –> } \sigma \leq 1/2\end{aligned}$$

- Transfer \$5 if $\rho \geq .5 \geq \sigma$

- Taking this to field data? Hard

- **Charitable giving.**

- Qualitative Patterns consistent overall with social preferences:

  - 240.9 billion dollars donated to charities in 2002 (Andreoni, 2006)

  - 2 percent of GDP

- Quantitative patterns, however: Hard to fit with models of social preferences from the lab

- Issue 1:
  - Person B with disposable income M_B meets needy person A with income $M_A < M_B$
  - Person B decides on donation D
  - Assume parameters $\rho \geq .5 \geq \sigma$
  - This implies $\pi_A^* = \pi_B^*$ -> $M_B - D^* = M_A + D^*$ -> $D^* = (M_B - M_A)/2$
  - Wealthy person transfers half of wealth difference!
  - Clearly counterfactual

- Issue 2.

  - Lab: Person A and B.

  - Field: Millions of needy people. Public good problem

- Issue 3.

  - Lab: Forced interaction.

  - Field: Sorting – can get around, or look for, occasions to give

- In addition to payoff-based social preferences, intentions likely to matter

- ρ and σ higher when B treated nicely by A

- Positive reciprocity and negative reciprocity

- More evidence of the latter in experiments

- Other field applications we do not analyze

  1. Pricing. When are price increases acceptable?

     - **Kahneman, Knetsch and Thaler (1986)**

     - Survey evidence

     - Effect on price setting

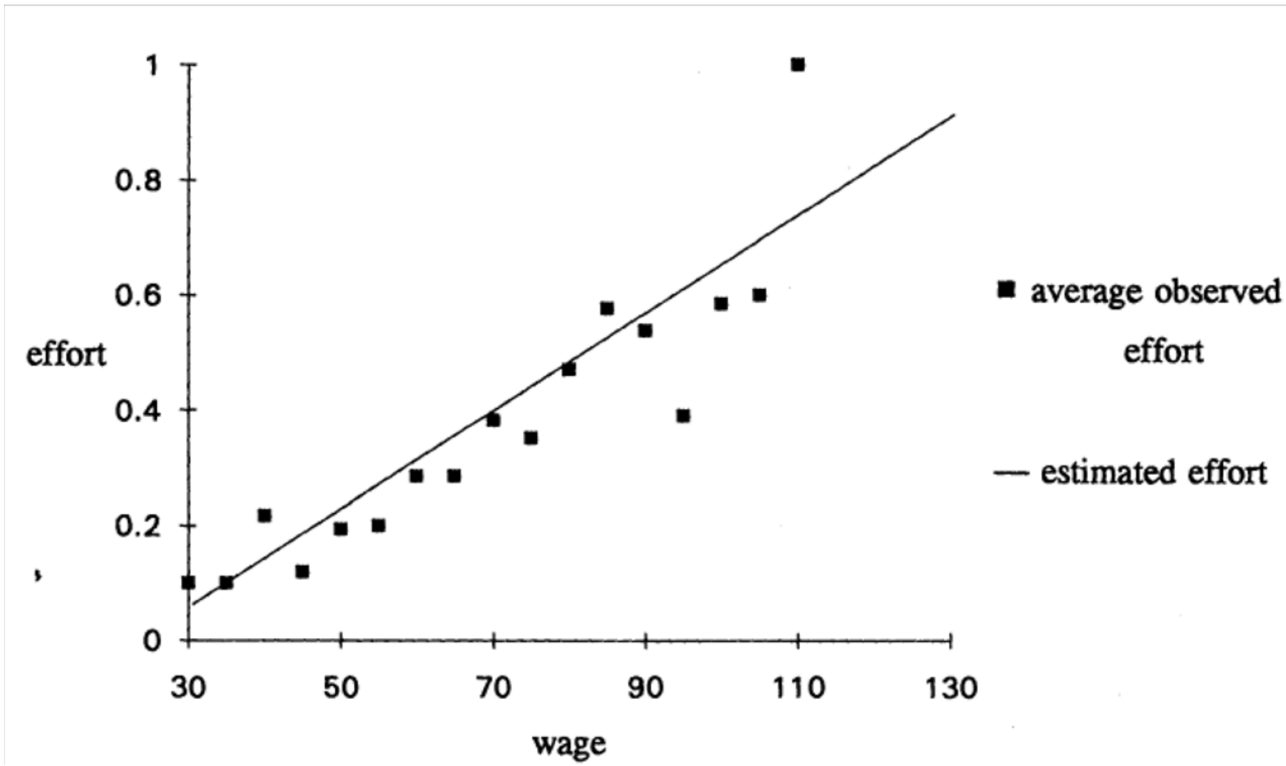
  2. Wage setting. Fairness toward other workers –> Wage compression

6 Social Preferences: Gift Exchange in the Field

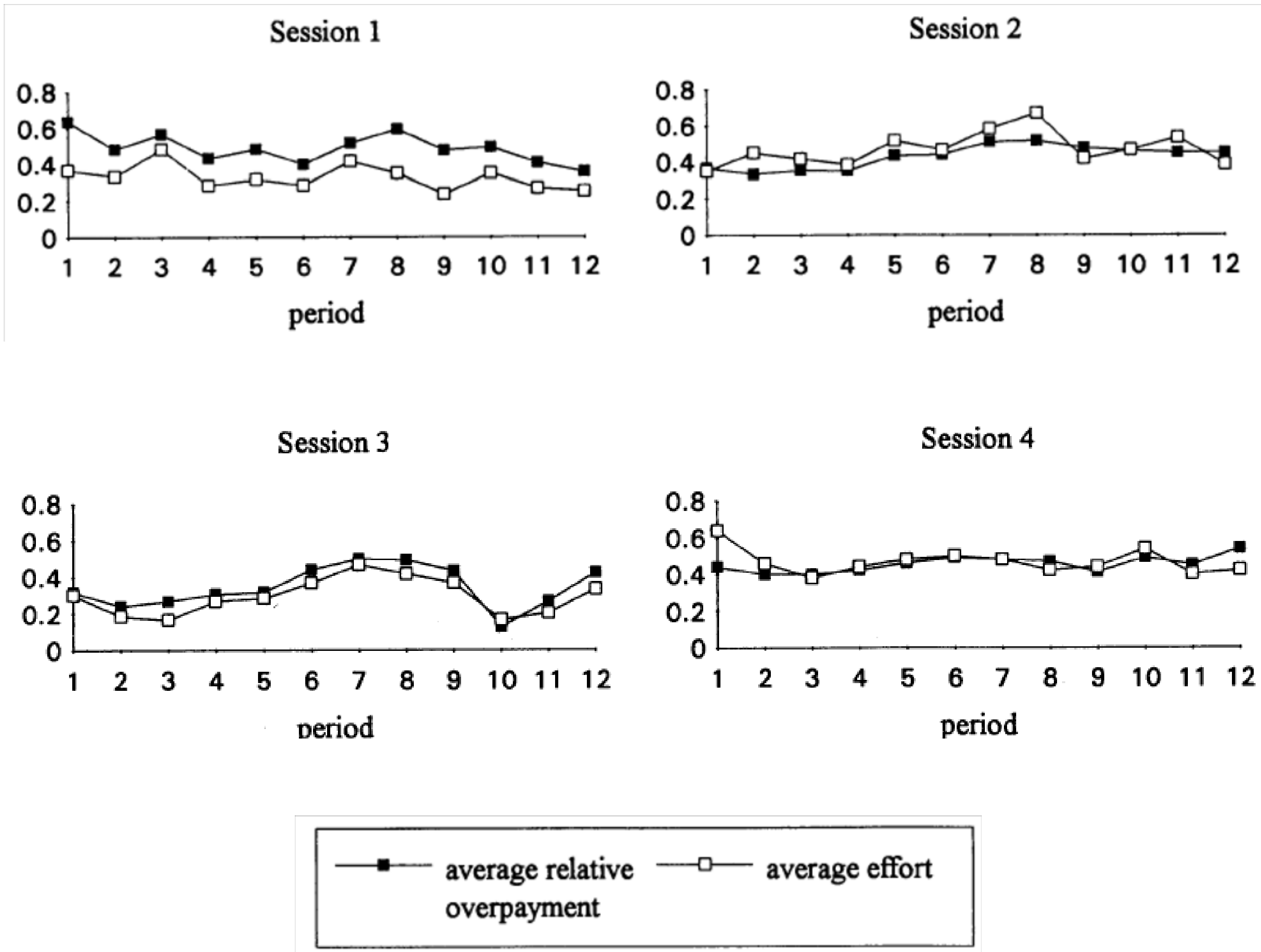
- Laboratory evidence: **Fehr-Kirchsteiger-Riedl (QJE, 1993).**
  - 5 firms bidding for 9 workers
  - Workers are first paid $w \in \{0, 5, 10, ...\}$ and then exert effort $e \in [.1, 1]$
  - Firm payoff is $(126 - w)\, e$
  - Worker payoff is $w - 26 - c(e)$, with $c(e)$ convex (but small)

- Standard model: $w^* = 30$ (to satisfy IR), $e^*(w) = .1$ for all w

- Findings: effort e increasing in w and $Ew = 72$



- These findings are stable over time


Session 1
Session 2
Session 3
Session 4
0.8
0.6
0.4
0.2
0
1 2 3 4 5 6 7 8 9 10 11 12
period
average relative overpayment
average effort

- Where evidence of gift exchange in the field?

- **Falk (EMA, 2008)** — field experiment in fund-raising
  - 9,846 solicitation letters in Zurich (Switzerland) for Christmas
  - Target: Schools for street children in Dhaka (Bangladesh)
  - 1/3 no gift, 1/3 small gift 1/3 large gift
  - Gift consists in postcards drawn by kids

Appendix: An example of the included postcards

- Short-Run effect: Donations within 3 months

TABLE 1: DONATION PATTERNS IN ALL TREATMENT CONDITIONS

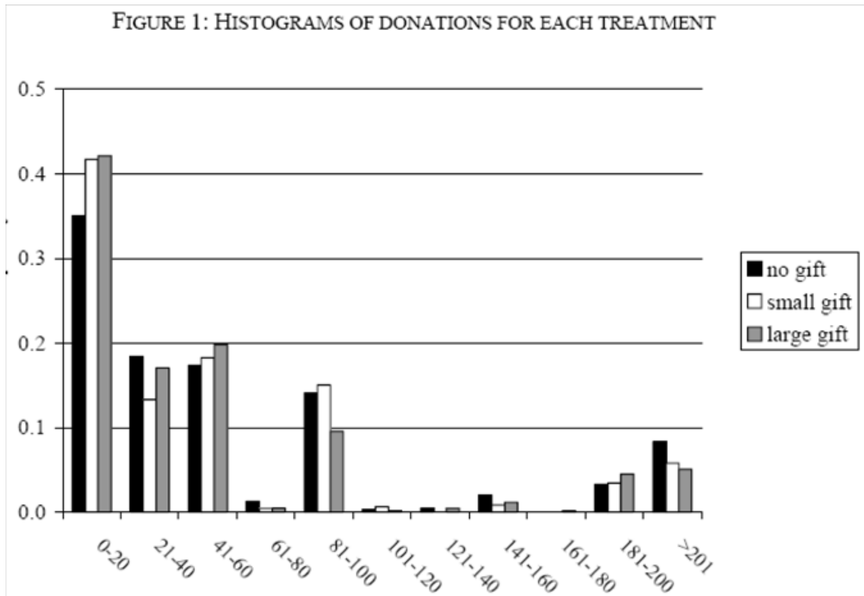
	No gift	Small gift	Large gift
Number of solicitation letters	3,262	3,237	3,347
Number of donations	397	465	691
Relative frequency of donations	0.12	0.14	0.21

- Large gift leads to doubling of donation probability

- Effect does not depend on previous donation pattern (donation in previous mailing)

- Note: High donation levels, not typical for US

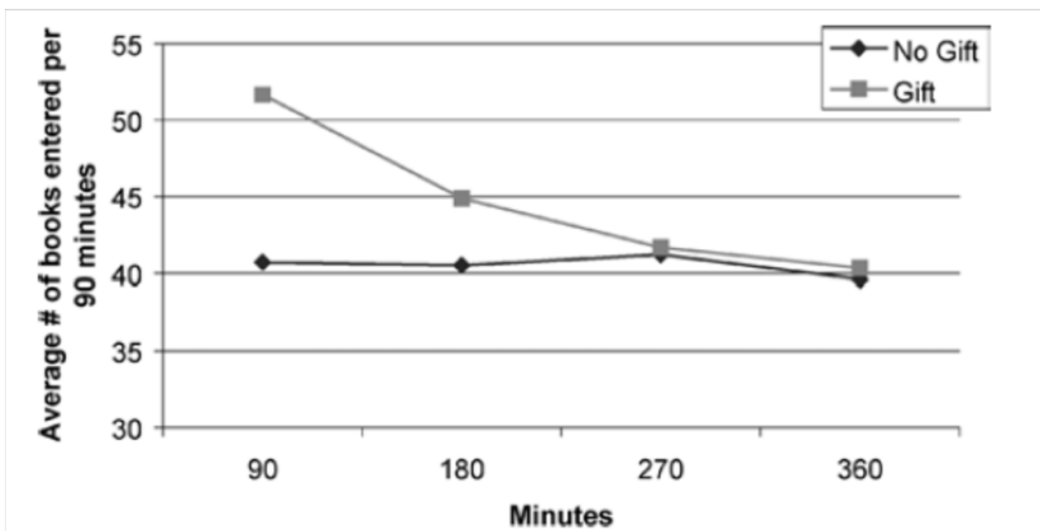
- Small decrease in average donation, conditional on donation (Marginal donors adversely selected, as in 401(k) Active choice paper)



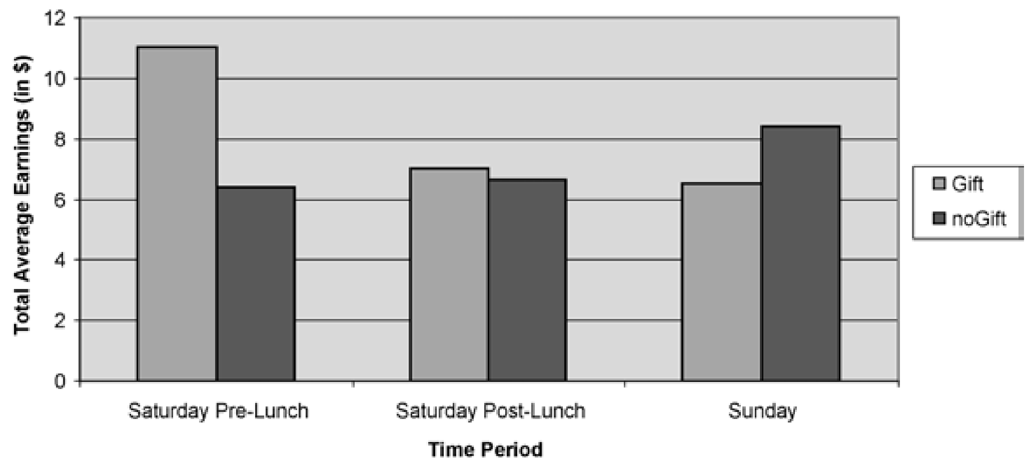
- Limited intertemporal substitution. February 2002 mailing with no gift. Percent donation is 9.6 (control), 8.9 (small gift), and 8.6 (large gift) (differences not significant)

- **Gneezy-List (EMA, 2006)** $->$ Evidence from labor markets

- *Field experiment 1.* Students hired for one-time six-hour (typing) library job for \$12/hour
  - No Gift group paid \$12 ($N = 10$)
  - Gift group paid \$20 ($N = 9$)



- *Field experiment 2.* Door-to-Door fund-raising in NC for one-time weekend for \$10/hour
  - Control group paid \$10 ($N = 10$)
  - Treatment group paid \$20 ($N = 13$)



- Note: Group coming back on Sunday is subset only (4+9)

- Evidence of reciprocity, though short-lived

- Issue: These papers test only for positive reciprocity

- Laboratory evidence: negative reciprocity stronger than positive reciprocity

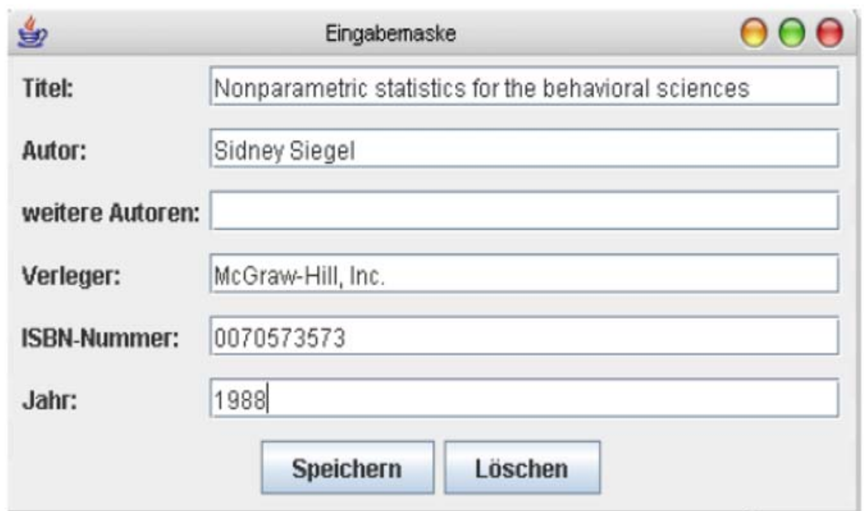
- More difficult to test for negative reciprocity

- Can say that pay is random and see what happens to (randomly) lower paid people

- **Kube-Marechal-Puppe (2007).**

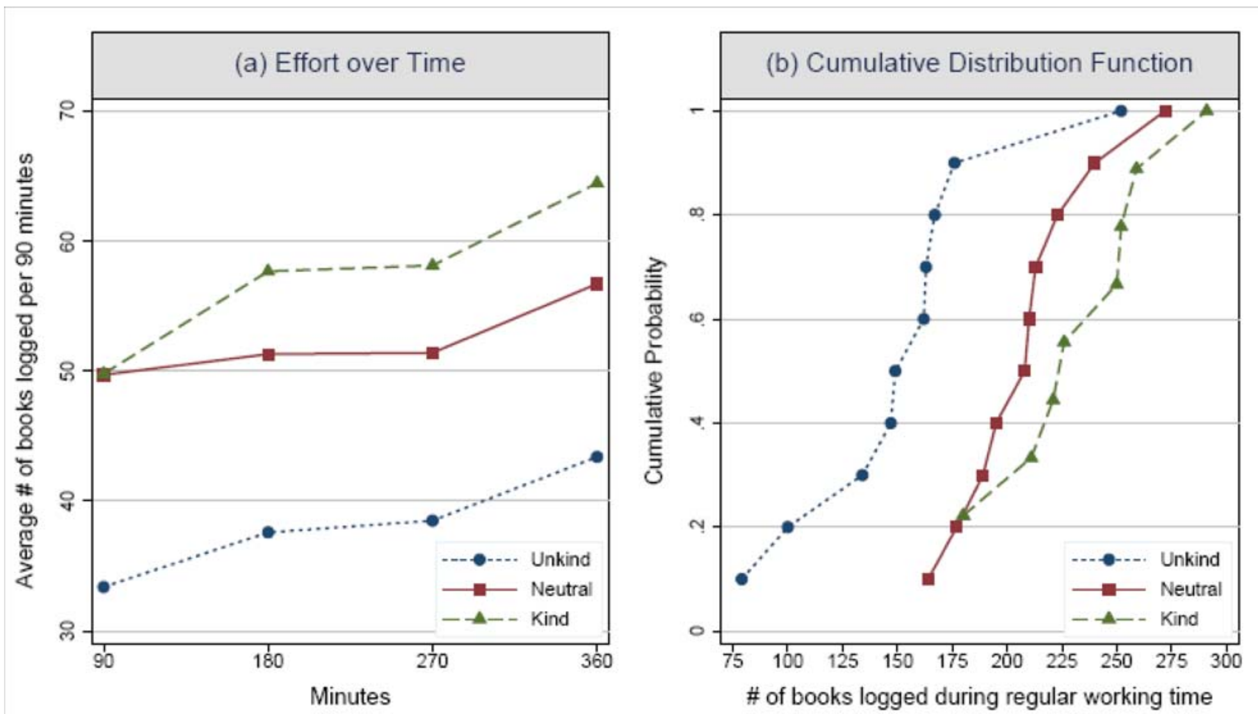
- Field Experiment: Hire job applicants to catalog books for 6 hours

Figure 2: Screenshot: Computer Application



- Announced Wage: '*Presumably*' 15 Euros/hour
  - Control ($n = 10$). 15 Euros/hour
  - Treatment 1 (Negative Reciprocity, $n = 10$). 10 Euros/hour (No one quits)
  - Treatment 2 (Positive Reciprocity, $n = 9$). 20 Euros/hour
- Offer to work one additional hour for 15 Euros/hour

- Result 1: Substantial effect of pay cut
- Result 2: Smaller effect of pay increase
- Result 3: No decrease over time



- Notice: No effect on quality of effort (no. of books incorrectly classified)

- Finding consistent with experimental results:

  - Positive reciprocity weaker than negative reciprocity

- Final result: No. of subjects that accept to do one more hour for 15 Euro:

  - 3 in Control, 2 in Pos. Rec., 7 in Neg. Rec.

  - Positive Reciprocity does not extend to volunteering for one more hour

- **Kube-Marechal-Puppe (2008).**

- Field Experiment 2: Hire job applicants to catalog books for 6 hours

- Announced Wage: 12 Euros/hour for 3 hours=36

  - Control ($n = 17$). 36 Euros

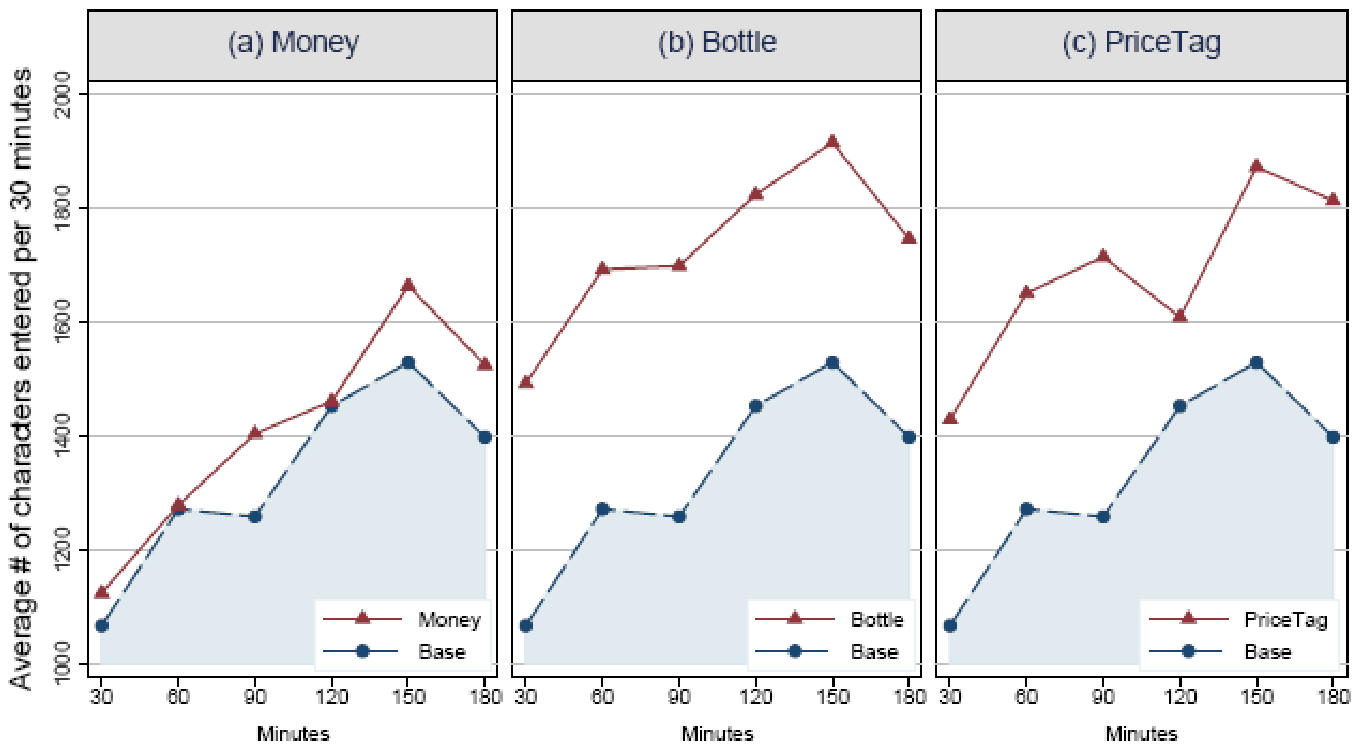
  - Treatment 1 (Positive Reciprocity, Cash, $n = 16$). $36 + 7 = 43$ Euros

  - Treatment 2 (Positive Reciprocity, Gift, $n = 15$). 36 Euros plus Gift of Thermos

  - Treatment 3 – Same as Tr. 2, but Price Tag for Thermos

- What is the effect of cash versus in-kind gift?

- Result 1: Small effect of 20% pay increase
- Result 2: Large effect of Thermos –> High elasticity, can pay for itself
- Result 3: No decrease over time



- Explanation 1. Thermos perceived more valuable
  - –> But Treatment 3 with price tag does not support this
  - Additional Experiment:
    - At end of (unrelated) lab experiment, ask choice for 7 Euro or Thermos
    - 159 out of 172 subjects prefer 7 Euro
- Explanation 2. Subjects perceive the thermos gift as more kind, and respond with more effort
- Survey: Ask which is kinder? Thermos rated higher in kindness than 7 Euro

- **List (JPE, 2006).** Test of social preferences from sellers to buyers

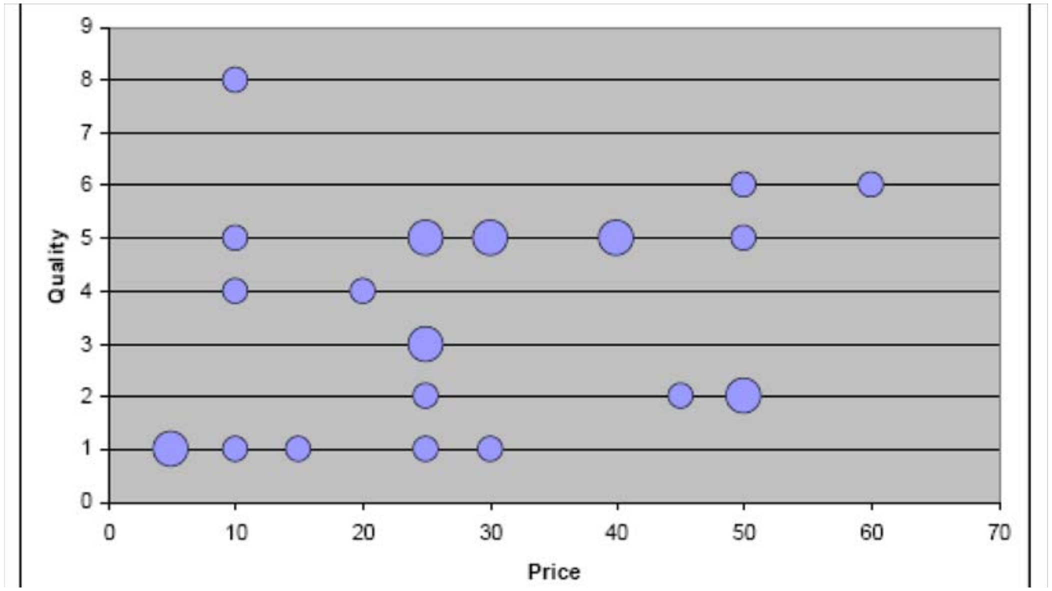
- Context: sports card fairs –> Buyers buying a particular (unrated) card from dealers

- Compare effect of laboratory versus field setting

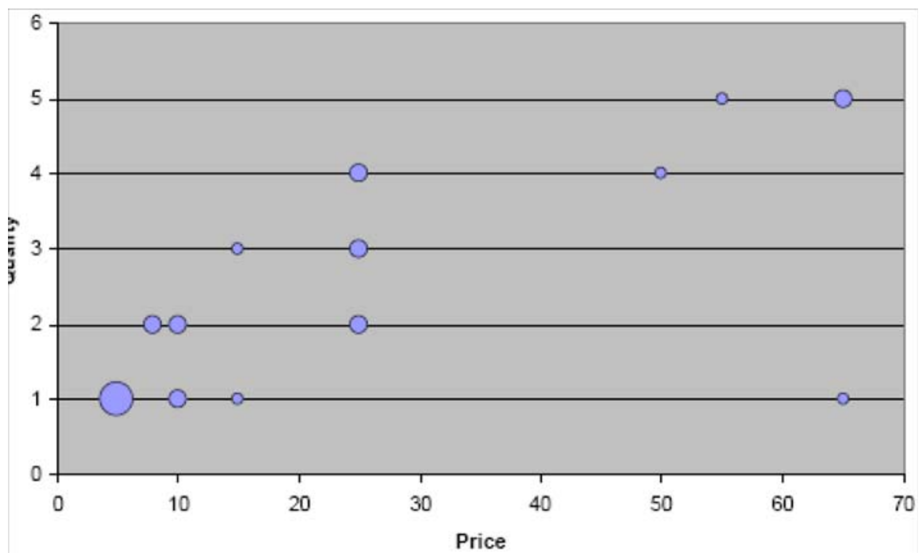
- *Treatment I-R.* Clever dual version to the **Fehr-Kirchsteiger-Riedl (1993)** payoffs
  - Laboratory setting, abstract words
  - Buyer pay $p \in \{5, 10, ...\}$ and dealer sells card of quality $q \in [.1, 1]$
  - Buyer payoff is $(80 - p)\, q$
  - Dealer payoff is $p - c\,(q)$, with $c\,(q)$ convex (but small)

- Standard model: $p^* = 5$ (to satisfy IR), $q^*\,(p) = 0.1$ for all p

- Effect: Substantial reciprocity
  - Buyers offer prices $p > 0$
  - Dealers respond with increasing quality to higher prices

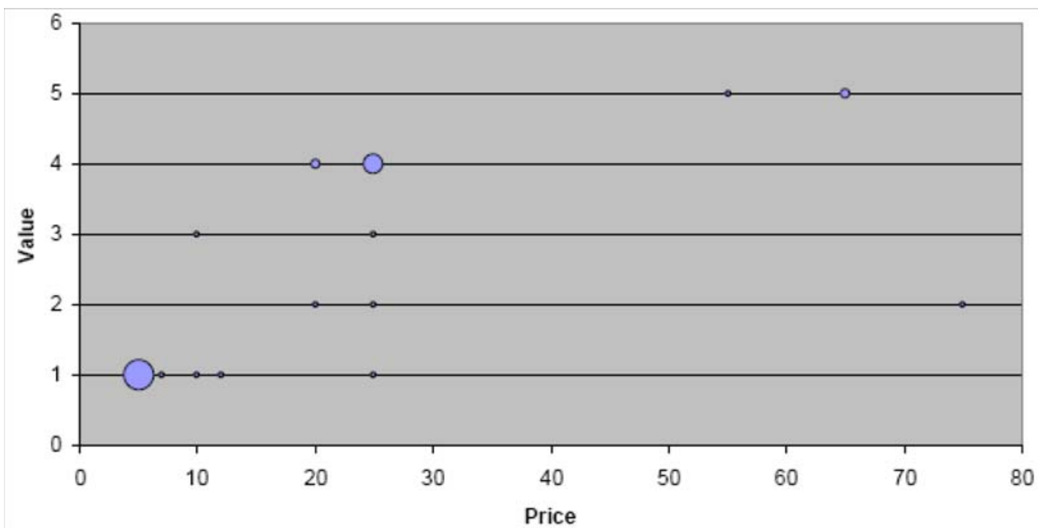


- *Treatment I-RF.* Similar result (with more instances of $p = 5$) when payoffs changed to
  - Buyer payoff is $v(q) - p$
  - Dealer payoff is $p - c(q)$, with $c(q)$ convex (but small)
  - $v(q)$ estimated value of card to buyer, $c(q)$ estimate cost of card to dealer

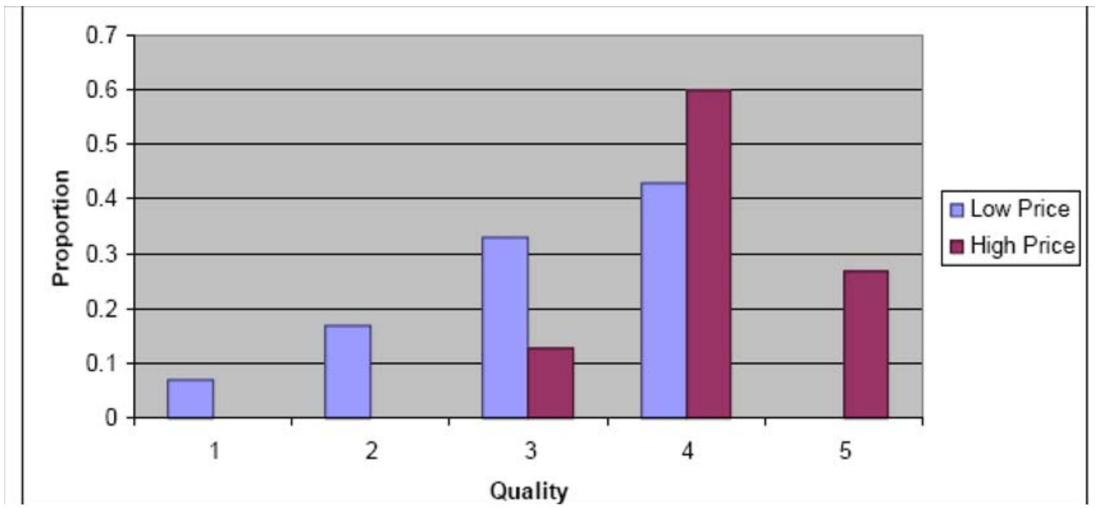


- *Treatment II-C.* Same as Treatment I-RF, except that use context (C) of Sports Card

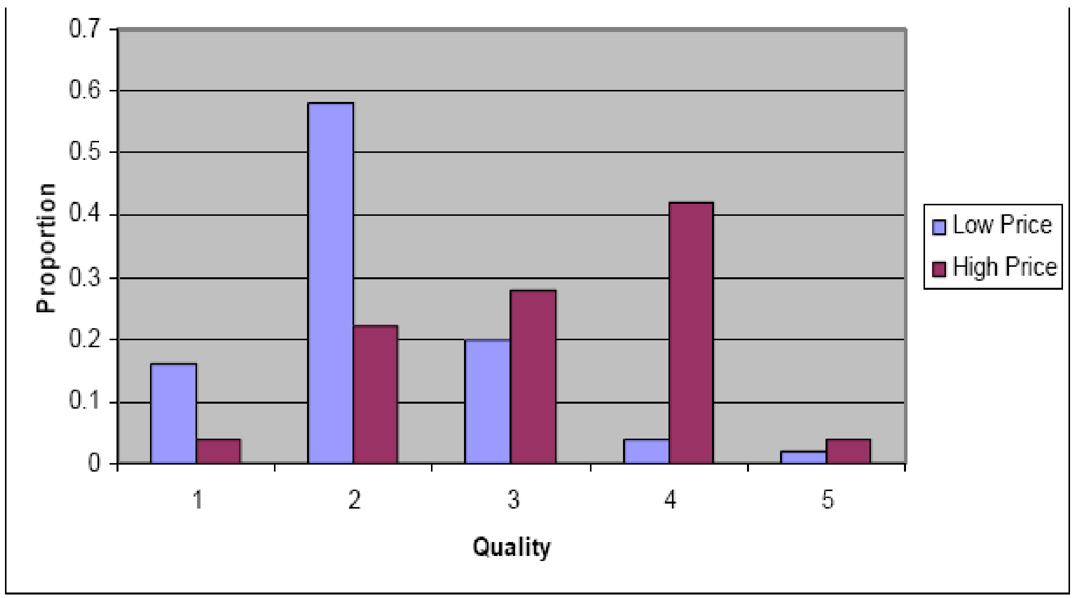
- Relatively similar results



- *Treatment II-M* –> Laboratory, real payoff (for dealer) but...
  - takes place with face-to-face purchasing
  - Group 1: Buyer offers \$20 for card of quality PSA 9
  - Group 2: Buyer offers \$65 for card of quality PSA 10
  - Substantial "gift exchange"



- *Treatment III* −> In field setting, for real payoffs (for dealer)
  - Group 1: Buyer offers \$20 for card of quality PSA 9
  - Group 2: Buyer offers \$65 for card of quality PSA 10
  - Lower quality provided, though still "gift exchange"



- However, “gift exchange” behavior depends on who the dealer is
  - Local dealer (frequent interaction): Strong “gift exchange”
  - Non-Local dealer (frequent interaction): No “gift exchange”

- This appears to be just rational behavior

- *Treatment IV.* –> Test a ticket market before (*IV-NG*) and after (*IV-AG* and *IV-G*) introduction of certification
  - No “gift exchange” in absence of certification(*IV-NG*)
  - “gift exchange” only for local dealers

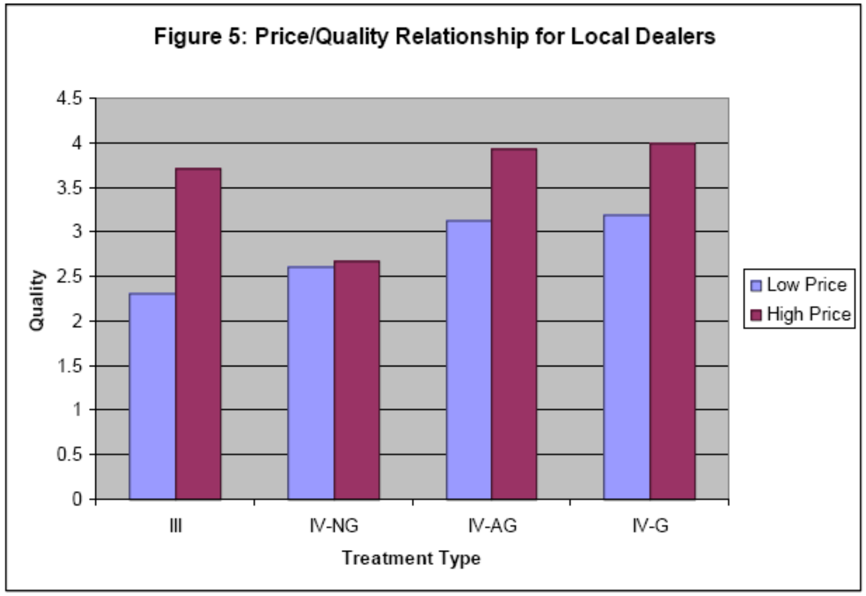


Figure 5: Price/Quality Relationship for Local Dealers
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Quality
III
IV-NG
IV-AG
IV-G
Treatment Type
Low Price
High Price

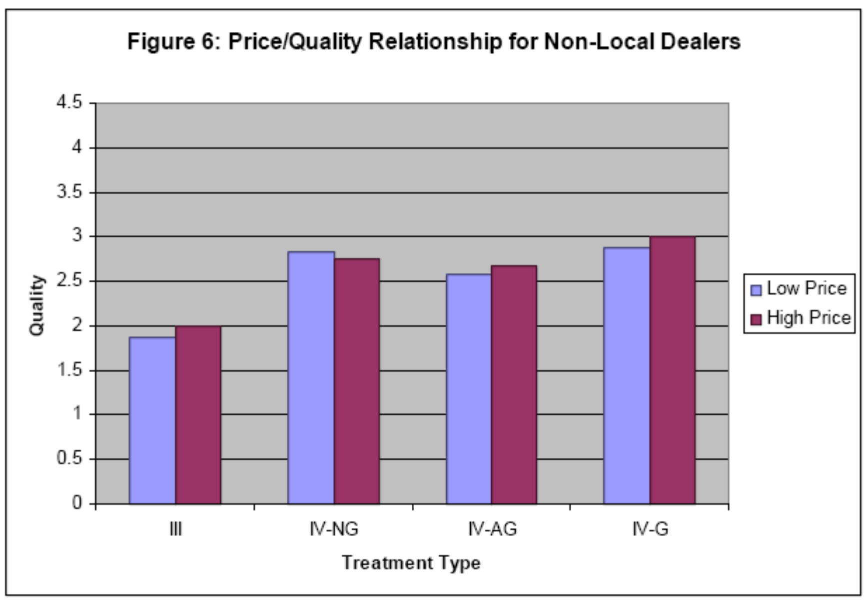


Figure 6: Price/Quality Relationship for Non-Local Dealers
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
Quality
III
IV-NG
IV-AG
IV-G
Treatment Type
Low Price
High Price

Table 1. Experimental Design

Treatment I	**Treatment I-R** *Replicate lab studies* $n = 25$	**Treatment I-RF** *Extend to field values* $n = 25$	**Treatment I-RF1** *Extend to one-shot environment* $n = 27$
Treatment II	**Treatment II-C** *Adds market context* $n = 32$	**Treatment II-M$20** *Adds market interaction* $n = 30$	**Treatment II-M$65** *Adds market interaction* $n = 30$
Treatment III	**Treatment III$20** *Naturally occurring sportscards* $n = 50$	**Treatment III$65** *Naturally occurring sportscards* $n = 50$	
Treatment IV	**Treatment IV-NG** *Naturally occurring tickets before grading was available* $n = 60$	**Treatment IV-AG** *Naturally occurring tickets post-grading announcement* $n = 54$	**Treatment IV-G** *Naturally occurring tickets when grading service is available* $n = 36$

Notes: Each cell represents one (or two, in the case of Treatment IV) unique treatment. For example, Treatment I-R in row 1, column 1, denotes that 25 dealer and 25 nondealer observations were gathered to replicate the laboratory gift exchange studies in the literature.

Table 3: Marginal Effects Estimates for the Sellers' Quality[a,b]

	Treatment Type									
Variable	**I-R**	**I-RF**	**I-RF1**	**II-C**	**II-M**	**III**	**IV-NG**	**IV-AG**	**IV-G**	**IV-P**
Price	0.05*	0.05^	0.10^	0.06^	0.02^	0.02^	-0.001	0.02^	0.02	0.02^
	(1.8)	(3.3)	(5.0)	(4.2)	(4.4)	(6.6)	(0.01)	(2.1)	(1.1)	(2.6)
Constant	0.6	-0.4	-0.8	-0.6	1.6^	0.6^	1.7^	1.6^	1.8^	1.7^
	(0.7)	(0.7)	(1.7)	(1.7)	(6.2)	(3.1)	(8.0)	(5.8)	(3.3)	(7.3)
θ	---	\$0.72^	\$1.3^	\$0.77^	0.45^	\$0.21^	\$0.01	\$0.17	\$0.23	\$0.21^
		(3.6)	(5.5)	(4.2)	(2.1)	(5.0)	(0.3)	(1.1)	(1.1)	(2.3)
Person Random Effects	YES	YES	NO	NO	YES	YES	YES	YES	YES	YES
N	25	25	27	32	60	100	60	54	36	90

[a]Dependent variable is the sellers' product quality given to the buyer. IV-P pools IV-AG and IV-G data. θ is the monetary gift exchange estimate, computed as $\partial v(q)/\partial P$.
[b]t-ratios (in absolute value) are beneath marginal effect estimates.
^ Significant at the .05 level.
* Significant at the .10 level.

Table 4: Marginal Effects Estimates for the Sellers' Quality Split by Dealer Type[a,b,c]

	Treatment Type								
Variable	**III_L**	**III_N**	**IV-NG_L**	**IV-NG_N**	**IV-AG_L**	**IV-AG_N**	**IV-G_L**	**IVG_N**	**IV-P_L**
Price	0.03^	0.004	0.002	-0.005	0.04^	0.003	0.04^	0.003	0.04^
	(8.6)	(0.7)	(0.2)	(0.5)	(2.1)	(0.3)	(2.7)	(0.1)	(4.8)
Constant	0.6^	0.6^	1.6^	1.8^	1.7^	1.5^	1.8^	1.8*	1.8^
	(4.1)	(4.6)	(5.0)	(5.2)	(5.2)	(4.6)	(5.0)	(1.7)	(10.0)
θ	\$0.31^	\$0.01	\$0.02	-\$0.006	\$0.32	\$0.02	\$0.42	\$0.03	\$0.35^
	(5.2)	(0.5)	(0.4)	(0.5)	(1.4)	(0.6)	(1.5)	(0.1)	(2.1)
Person Random Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	70	30	36	24	30	24	20	16	50

- Conclusion on gift exchange and social preferences
  - Reciprocation and gift exchange are present in field-type setting (Falk)
  - They disappear fast (Gneezy-List)...
  - ...Or maybe not (Kube et al.)
  - They are stronger on the negative than on the positive side (Kube et al.)
  - Not all individuals display them – not dealers, for example (List)
  - Laboratory settings may (or may not) matter for the inferences we derive

7 Next Lecture

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