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

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Outline

1. Reference Dependence: Housing II
2. Reference Dependence: Tax Elusion
3. Reference Dependence: Goals
4. Reference Dependence: Mergers
5. Reference Dependence: Non-Bunching Papers
6. Reference Dependence: Labor Supply
7. Reference Dependence: Employment and Effort
8. Reference Dependence: Domestic Violence

Section 1

Reference Dependence: Housing II

Formalize Intuition

- Return to Housing case, formalize intuition.
  - Seller chooses price P at sale
  - Higher Price P
    - lowers probability of sale $p(P)$ (hence $p'(P) < 0$)
    - increases utility of sale $U(P)$
  - If no sale, utility is $\bar{U} < U(P)$ (for all relevant P)

Model

- Maximization problem:

$$\max_{P} p(P)U(P) + (1 - p(P))\bar{U}$$

- F.o.c. implies

$$MG = p(P^*)U'(P^*) = -p'(P^*)(U(P^*) - \bar{U}) = MC$$

- Interpretation: Marginal Gain of increasing price equals Marginal Cost
- S.o.c are

$$2p'(P^*)U'(P^*) + p(P^*)U''(P^*) + p''(P^*)(U(P^*) - \bar{U}) < 0$$

- Need $p''(P^*)(U(P^*) - \bar{U}) < 0$ or not too positive

Model

- Reference-dependent preferences with reference price P_0 (with pure gain-loss utility):

$$v(P|P_0) = \begin{cases} P + \eta(P - P_0) & \text{if } P \geq P_0; \\ P + \eta\lambda(P - P_0) & \text{if } P < P_0, \end{cases}$$

  - Can write as

$$\begin{aligned} p(P)(1+\eta) &= -p'(P)(P + \eta(P - P_0) - \bar{U}) \text{ if } P \geq P_0 \\ p(P)(1+\eta\lambda) &= -p'(P)(P + \eta\lambda(P - P_0) - \bar{U}) \text{ if } P < P_0 \end{aligned}$$

  - Plot Effect on MG and MC of loss aversion

- Compare $P^*_{\lambda=1}$ (equilibrium with no loss aversion) and $P^*_{\lambda>1}$ (equilibrium with loss aversion)

Cases

- Case 1. Loss Aversion λ increase price $(P^*_{\lambda=1} < P_0)$

- Case 2. Loss Aversion λ induces bunching at $P = P_0$ $(P^*_{\lambda=1} < P_0)$

Cases

- Case 3. Loss Aversion has no effect ($P^*_{\lambda=1} > P_0$)

- General predictions. When aggregate prices are low:
  - High prices P relative to fundamentals
  - Bunching at purchase price P_0
  - Lower probability of sale $p(P)$, longer waiting on market
- Important to tie housing evidence to model
- Would be great to redo with data from recent recession

Section 2

Reference Dependence: Tax Elusion

Alex Rees-Jones (2014)

- Preparation of tax returns
  - Can lower taxes due expending effort (finding receipts/elusion)
  - Important setting with clear reference point: 0 taxes due
  - Pre-manipulation balance due b^{PM}
  - Denote by s the tax dollars sheltered
- Slides courtesy of Alex
- Other relevant paper: **Engstrom, P., Nordblom, K., Ohlsson, H., & Persson, A. (AEJ: Policy, 2016)**
  - Similar evidence, but focus on claiming deductions

Simple example with smooth utility

Consider a model abstracting from income effects:

$$\max_{s \in \mathbb{R}^+} \quad \underbrace{(w - b^{PM} + s)}_{\text{linear utility over money}} \quad - \quad \underbrace{c(s)}_{\text{cost of sheltering}}$$

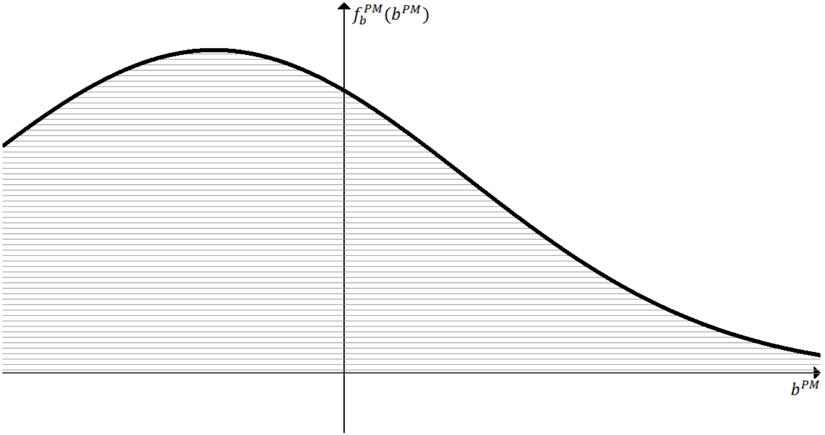
Optimal sheltering is determined by the first-order condition:

$$1 - c'(s^*) = 0$$

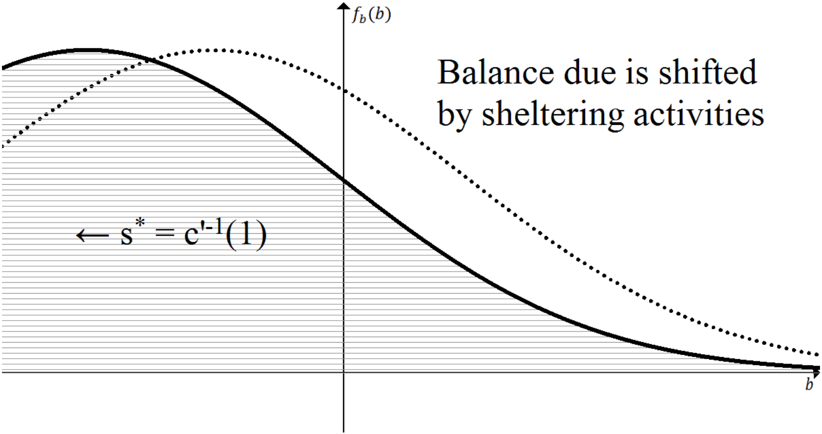
Optimal sheltering solution: $s^* = c'^{-1}(1)$.

$\rightarrow$ Distribution of balance due, $b \equiv b^{PM} - s^*$, is a horizontal shift of the distribution of b^{PM}.

PDF of pre-manipulation balance due



PDF of final balance due after sheltering



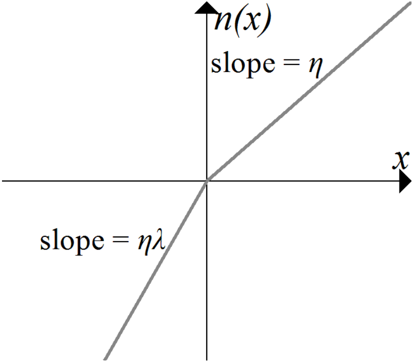
Loss-averse case

$$\max_{s \in \mathbb{R}^+} \quad \underbrace{m(-b^{PM} + s)}_{\text{utility over money}} \quad - \quad \underbrace{c(s)}_{\text{cost of sheltering}}$$

Loss-averse utility specification:

$$\underbrace{(w - b^{PM} + s)}_{\text{consumption utility}} + \underbrace{n(-b^{PM} + s - r)}_{\text{gain-loss utility}}$$

$$n(x) = \begin{cases} \eta x & \text{if } x \geq 0 \\ \eta \lambda x & \text{if } x < 0 \end{cases}$$



Optimal loss-averse sheltering

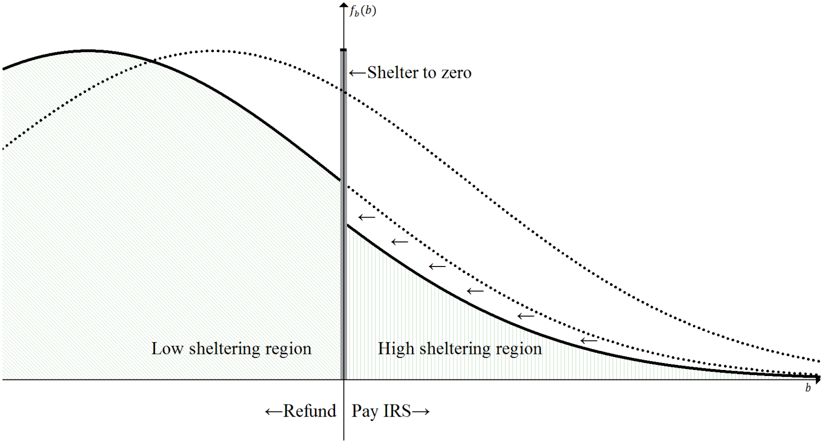
This model generates an optimal sheltering solution with different behavior across three regions:

$$s^*(b^{PM}) = \begin{cases} s^H & \text{if } b^{PM} > s^H - r \\ b^{PM} + r & \text{if } b^{PM} \in \left[s^L - r, s^H - r\right] \\ s^L & \text{if } b^{PM} < s^L - r \end{cases}$$

where $s^H \equiv c'^{-1}(1 + \eta\lambda)$ and $s^L \equiv c'^{-1}(1 + \eta)$.

- Sufficiently large $b^{PM} \rightarrow$ high amount of sheltering.
- Sufficiently small $b^{PM} \rightarrow$ low amount of sheltering.
- For an intermediate range, sheltering chosen to offset b^{PM}.

PDF of final balance due after loss-averse sheltering



Revenue effect of loss framing: $s^H - s^L$.

Data description

Dataset: 1979-1990 SOI Panel of Individual Returns.

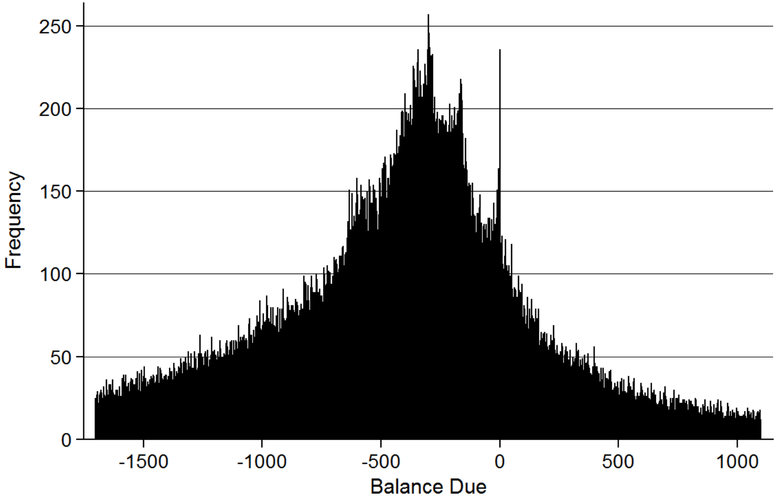
- Contains most information from Form 1040 and some related schedules.
- Randomized by SSNs.

Exclude observations filed from outside of the 50 states + DC, drawn from outside the sampling frame, observations before 1979.

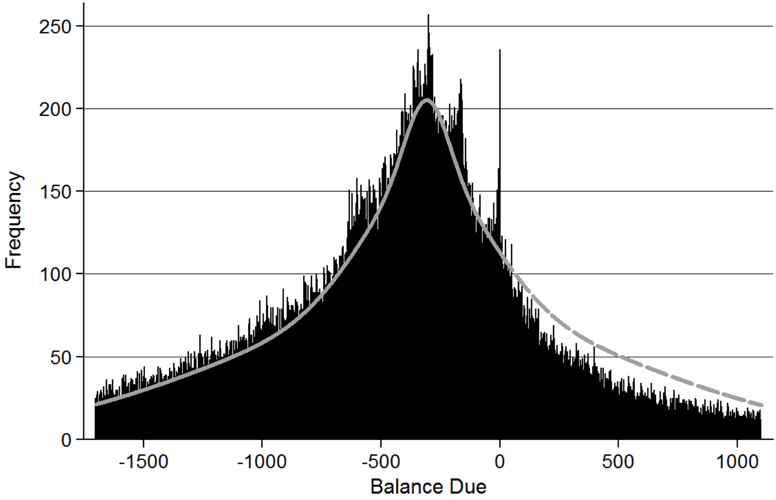
Exclude individuals with zero pre-credit tax due, individuals with zero tax prepayments.

Primary sample: $\approx 229k$ tax returns, $\approx 53k$ tax filers.

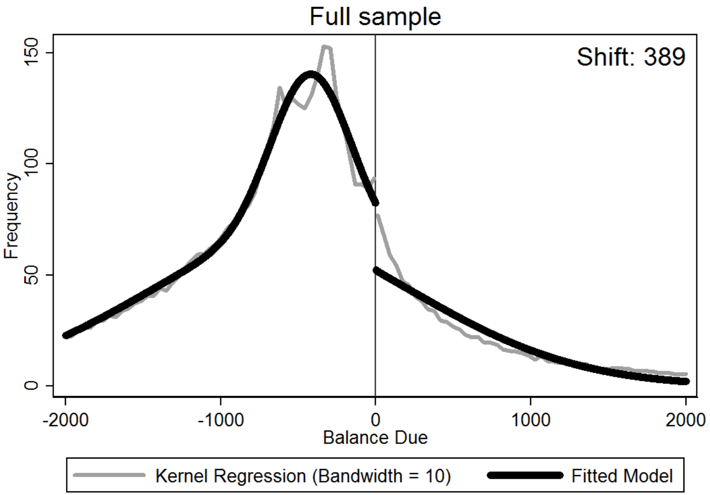
First look: distribution of nominal balance due



First look: distribution of nominal balance due

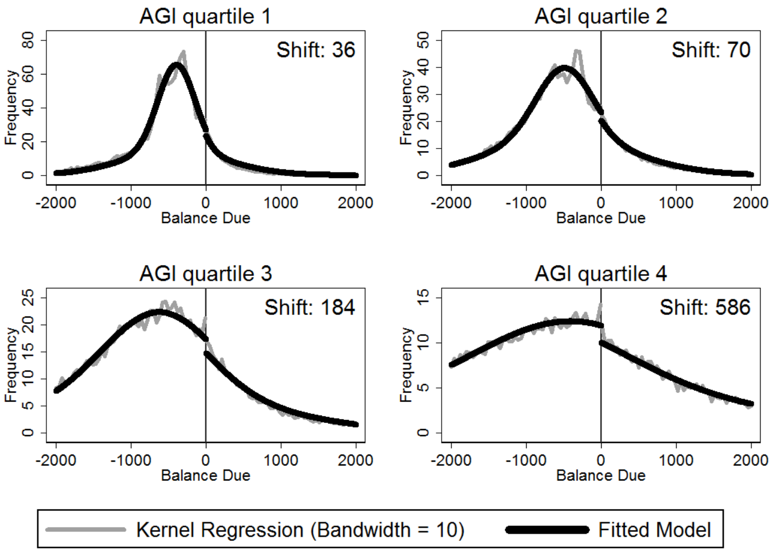


Fit of predicted distributions



Estimate table

Fit of predicted distributions



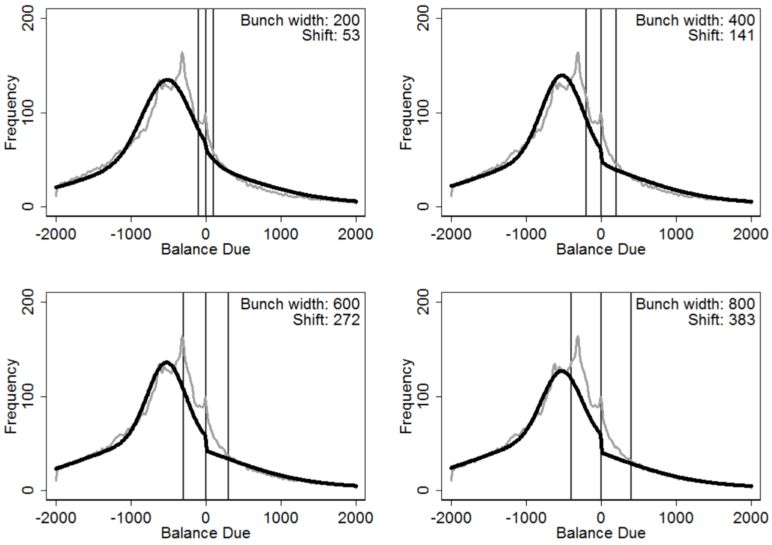
Rationalizing differences in magnitudes

What drives the differences in the bunching and shifting estimates?

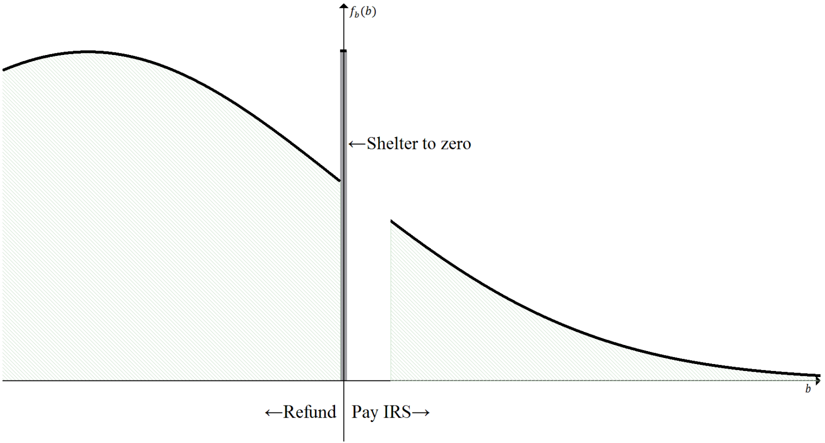
Primary explanation: assumption that sheltering can be manipulated to-the-dollar.

- Possible for some types of sheltering: e.g. direct evasion, choosing amount to give to charity, targeted capital losses.
- Not possible for many types of sheltering.
- Excess mass at zero will “leave out” individuals without finely manipulable sheltering technologies.
- Potential solution: permit diffuse bunching “near” zero.

Fit of predicted distributions



Distribution with fixed cost in loss domain



Back

Section 3

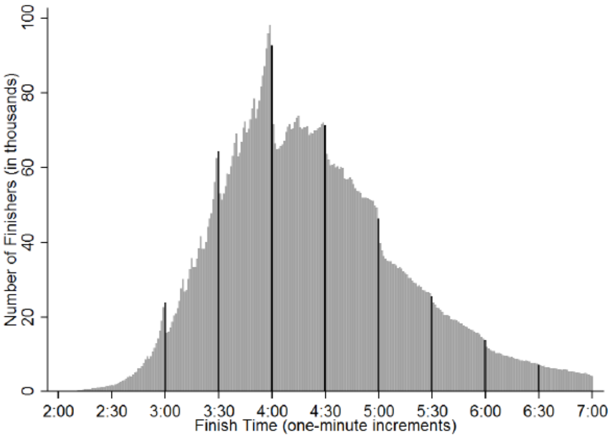
Reference Dependence: Goal Setting

Allen, Dechow, Pope, Wu (*MS* 2016)

- Reference point can be a goal
- Marathon running: Round numbers as goals
- Similar identification considering discontinuities in finishing times around round numbers

Distribution of Finishing Times

Figure 2: Distribution of marathon finishing times ($n = 9,378,546$)



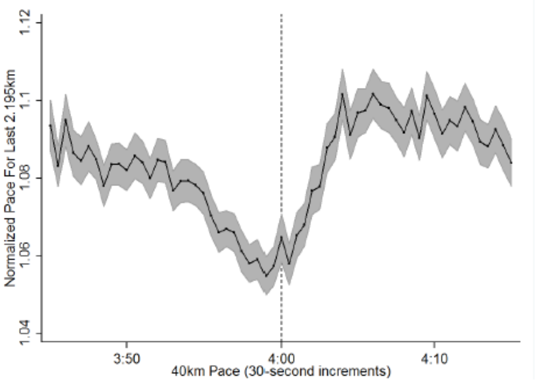
NOTE: The dark bars highlight the density in the minute bin just prior to each 30 minute threshold.

Intuition

- Channel of effects: Speeding up if behind and can still make goal

Figure 8: Normalized pace for last 2.195 kilometers as a function of 40 kilometer pace

(a) Runners on 3:45 to 4:15 pace through 40 kilometers



Summary

- Evidence strongly consistent with model
  - Missing distribution to the right
  - Some bunching
- Hard to back out loss aversion given unobservable cost of effort

Section 4

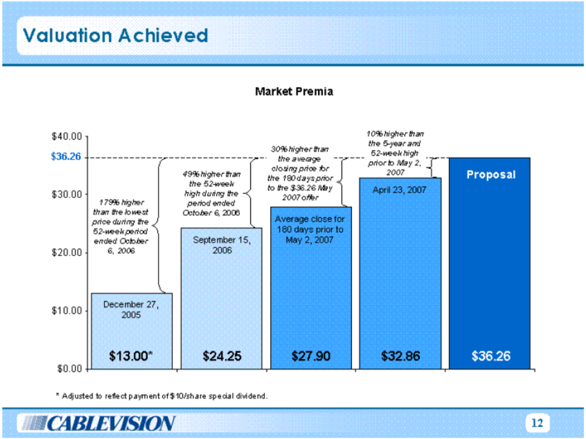
Reference Dependence: Mergers

Baker, Pan, Wurgler (*JFE* 2012)

- On the appearance, very different set-up:
    - Firm A (Acquirer)
    - Firm T (Target)
- After negotiation, Firm A announces a price P for merger with Firm T
    - Price P typically at a 20-50 percent premium over current price
    - About 70 percent of mergers go through at price proposed
    - Comparison price for P often used is highest price in previous 52 weeks, P_{52}

Example: How Cablevision (Target) trumpets deal

Figure 1. Slide from Cablevision Presentation to Shareholders, October 24, 2007. The management of Cablevision recommended acceptance of a $36.26 per share cash bid from the Dolan family. The slide compares this bid price to various recent prices including 52-week highs.



Model

- Assume that Firm T chooses price P, and A decides accept reject
- As a function of price P, probability $p(P)$ that deal is accepted (depends on perception of values of synergy of A)
- If deal rejected, go back to outside value $\bar{U}$
- Then maximization problem is same as for housing sale:

$$\max_P p(P)U(P) + (1 - p(P))\bar{U}$$

- Can assume T reference-dependent with respect to P_{52} :

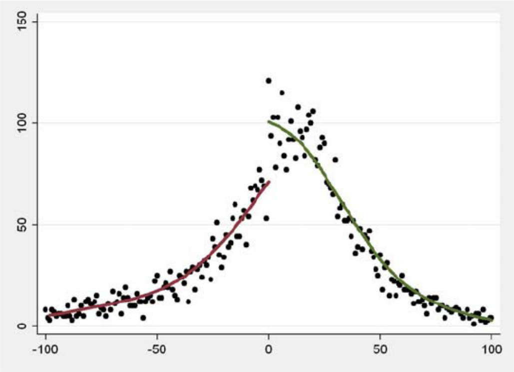
$$v(P|P_0) = \begin{cases} P + \eta(P - P_{52}) & \text{if } P \geq P_{52}; \\ P + \eta\lambda(P - P_{52}) & \text{if } P < P_{52} \end{cases}$$

Predictions and Tests

- Obtain same predictions as in housing market
- (This neglects possible reference dependence of A)
- Baker, Pan, and Wurgler (2009): Test reference dependence in mergers
  - Test 1: Is there bunching around P_{52}? (GM did not do this)
  - Test 2: Is there effect of P_{52} on price offered?
  - Test 3: Is there effect on probability of acceptance?
  - Test 4: What do investors think? Use returns at announcement

Test 1: Offer price P around P_{52}

- Some bunching, shift in left tail of distribution, as predicted



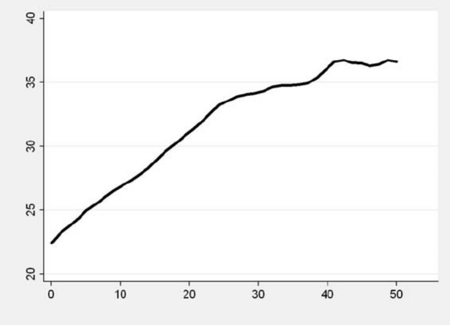
Test 1: Offer price P around P_{52}

- Notice that this does not tell us how the missing left tail occurs:
  - Firms in left tail raise price to P_{52}?
  - Firms in left tail wait for merger until 12 months after past peak, so P_{52} is higher?
  - Preliminary negotiations break down for firms in left tail
- Would be useful to compare characteristics of firms to right and left of P_{52}

Test 2: Kernel regression of P

- Kernel regression of price offered P (Renormalized by price 30 days before, P_{-30}, to avoid heterosked.) on P_{52} :

$$100 * \frac{P - P_{-30}}{P_{-30}} = \alpha + \beta \left[100 * \frac{P_{52} - P_{-30}}{P_{-30}} \right] + \varepsilon$$



Test 4: What do investors think?

- Test 3: Probability of final acquisition is higher when offer price is above P_{52} (Skip)

- Test 4: What do investors think of the effect of P_{52}?
    - Holding constant current price, investors should think that the higher P_{52}, the more expensive the Target is to acquire
    - Standard methodology to examine this:
        - 3-day stock returns around merger announcement: $CAR_{t-1,t+1}$
        - This assumes investor rationality
        - Notice that merger announcements are typically kept top secret until last minute $\rightarrow$ On announcement day, often big impact

Test 4: What do investors think?

- Regression (Columns 3 and 5):

$$CAR_{t-1,t+1} = \alpha + \beta \frac{P}{P_{-30}} + \varepsilon$$

where P/P_{-30} is instrumented with P_{52}/P_{-30}

Table 8. Mergers and Acquisitions: Market Reaction. Ordinary and two-stage least squares regressions of the 3-day CAR of the bidder on the offer premium.

$$r_{t-1\to t+1} = a + b\frac{Offer_{it}}{P_{i,t-30}} + e_{it}$$

$$\left(\frac{Offer_{it}}{P_{i,t-30}} - 1\right)\cdot 100 = a + b_1 \min\left(\left(\frac{52WeekHigh_{i,t-30}}{P_{i,t-30}} - 1\right)\cdot 100, 25\right) + b_2 \max\left(0, \min\left(\left(\frac{52WeekHigh_{i,t-30}}{P_{i,t-30}} - 1.25\right)\cdot 100, 50\right)\right) + b_3 \max\left(\left(\frac{52WeekHigh_{i,t-30}}{P_{i,t-30}} - 1.75\right)\cdot 100, 0\right) + e_{it}$$

where r is the market-adjusted return of the bidder for the three-day period centered on the announcement date, *Offer* is the offer price from Thomson, P is the target stock price from CRSP, and *52WeekHigh* is the high stock price over the 365 calendar days ending 30 days prior to the announcement date. The first, second, and fourth columns use ordinary least squares. The third and the fifth columns instrument for the offer premium using *52WeekHigh*. Robust t-statistics with standard errors clustered by month are in parentheses.

	OLS	*OLS*	*IV*	*OLS*	*IV*
	1	**2**	**3**	**4**	**5**
Offer Premium:					
b	-0.0186***	-0.0204***	-0.215***	-0.0443***	-0.253***
	(-2.64)	(-2.74)	(-3.48)	(-4.21)	(-4.39)

- Results very supportive of reference dependence hypothesis – Also alternative anchoring story

Section 5

Reference Dependence: Non-Bunching

Previous Papers: Bunching Assumption

- Previous papers had bunching implication
  - Some papers test for bunching (mergers, tax evasion, marathon running)
  - Some papers do not test it... but should! (housing)
- For bunching test, need
  - Reference point r obvious enough to people AND researcher (house purchase price, zero taxes, round number goal)
  - Effort can be altered to get to reference point

Next Set of Papers: No Bunching

- Next set of papers, these conditions do not apply:
  - Reference point r not an exact number (labor supply, effort and crime, job search)
  - Choice is not about effort (domestic violence, insurance)
- Identification in these papers typically relies on variants of:
  - Loss aversion induces higher marginal utility of income to left of reference point
  - Identify comparing when to the left of reference point, versus to the right
  - Still need some model about reference point (more later on this)

Section 6

Reference Dependence: Labor Supply

Framework

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

$$U(Y) - c(h) = wh - \frac{\theta h^2}{2}$$

Framework

- (Assumption that each day is orthogonal to other days – see below)
- Reference dependence: Threshold T of earnings agent wants to achieve
- Loss aversion for outcomes below threshold:

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

  with $\lambda > 1$ loss aversion coefficient

- Reference-dependent agent maximizes

$$\begin{array}{lll} wh + \eta (wh - T) - \frac{\theta h^2}{2} & \text{if} & h \geq T/w \\ wh + \eta\lambda (wh - T) - \frac{\theta h^2}{2} & \text{if} & h < T/w \end{array}$$

Framework

- Derivative with respect to h:

$$\begin{array}{lll} (1+\eta)w-\theta h & \text{if} & h \geq T/w \\ (1+\eta\lambda)w-\theta h & \text{if} & h < T/w \end{array}$$

1. Case 1 ($(1+\eta\lambda)w-\theta T/w<0$).
    - Optimum at $h^* = (1+\eta\lambda)w/\theta < T/w$

Framework

2. Case 2 ($(1+\eta\lambda)w - \theta T/w > 0 > (1+\eta)w - \theta T/w$)
    - Optimum at $h^* = T/w$

3. Case 3 ($(1+\eta)w - \theta T/w > 0$)
    - Optimum at $h^* = (1+\eta)\, w/\theta > T/w$

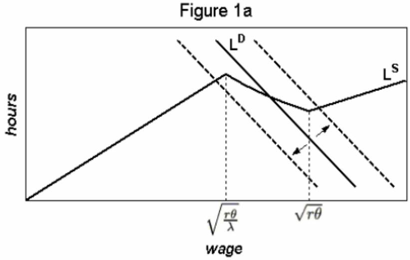
Standard theory $(\lambda = 1)$

- Interior maximum: $h^* = (1+\eta)\, w/\theta$ (Cases 1 or 3)
- Labor supply

- Combine with labor demand: $h^* = a - bw$, with $a > 0, b > 0$.

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: On low-demand days (low w) need to work harder to achieve reference point $T \rightarrow$ Work harder $\rightarrow$ Opposite to standard theory

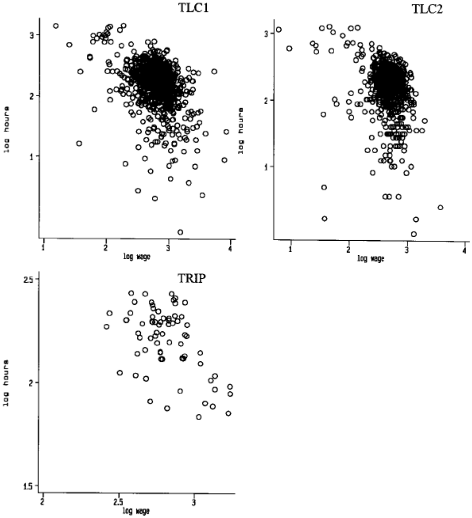
Camerer, Babcock, Loewenstein, and Thaler (QJE 1997)

- 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

Framework

- Analysis in paper neglects wealth effects: Higher wage today $\rightarrow$ Higher lifetime income
- Justification:
  - Correlation of wages across days close to zero
  - Each day can be considered in isolation
  - $\rightarrow$Wealth effects of wage changes are very small
- Test:
  - Assume variation across days driven by Δa (labor demand shifter)
  - Do hours worked h and w co-vary positively (standard model) or negatively?

Raw evidence



Model

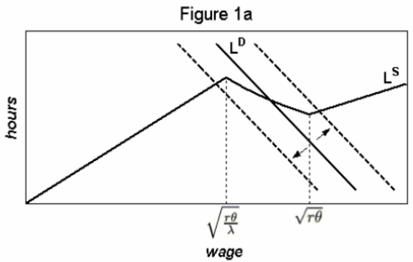
- Estimate:

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

- 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

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 are 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

Econometric Issue 1: Use IV

- 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)

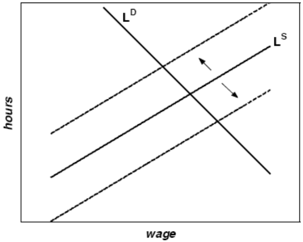
	First-stage regressions				
Median	.316	.026	−.385	−.276	1.292
	(.225)	(.188)	(.394)	(.467)	(4.281)
25th percentile	.323	.287	.693	.469	−.373
	(.160)	(.126)	(.241)	(.332)	(3.516)
75th percentile	.399	.289	.614	.688	.479
	(.171)	(.149)	(.242)	(.292)	(1.699)
Adjusted R^2	.374	.642	.056	.206	.019
P-value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

Farber (JPE, 2005)

- Re-Estimate Labor Supply of Cab Drivers on new data
- Address Econometric Issue 1 (Division Bias)
- 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

Model

- Key specification: Hazard model that does not suffer from division bias
  - 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 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.

Results

- Positive, but not significant effect of $Y_{i,t}$ on probability of stopping:
  - 10 percent increase in Y (\$15) $\rightarrow$ 1.6 percent increase in stopping prob. (.225 pctg. pts. increase in stopping prob. out of average 14 pctg. pts.) $\rightarrow$ 0.16 elasticity
  - Cannot reject large effect: 10 pct. increase in Y increase stopping prob. by 6 percent $\rightarrow$ 0.6 elasticity
- 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

Still, Supply or Demand?

- Farber (2005) cannot address the Econometric Issue 2: Is it Supply or Demand that Varies

- **Fehr and Goette (AER 2007).** 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.

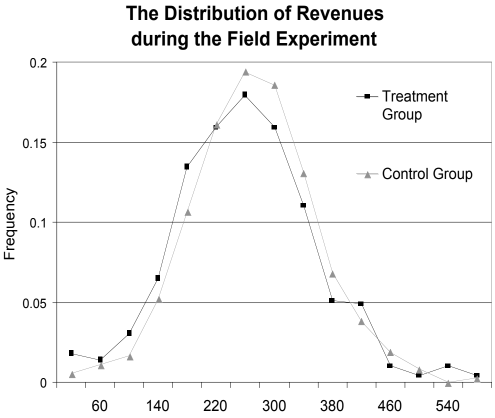
Results for Hours

- 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.**

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)

Farber (2008)

- **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

Farber (2008)

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

Crawford and Meng (AER 2011)

- Re-estimates on Farber (2005) data 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)
- Perhaps, reconciling Camerer et al. (1997) and Farber (2005)
  - $w > w^e$: hours binding $\rightarrow$ hours explain stopping
  - $w < w^e$: income binding $\rightarrow$ income explains stopping

Crawford and Meng (2011)

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

Variable	(1) Pooled data	$w^a > w^e$	$w^a \le w^e$	(2) Pooled data	$w^a > w^e$	$w^a \le w^e$	(3) Pooled data	$w^a > w^e$	$w^a \le w^e$
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

Farber (QJE 2015)

- Finally data set with large K and large T
  - $K = 62,000$ drivers
  - $T = 5 * 365$ (2009 to 2013)
  - 100+ million trips!
  - Electronic record of all information (except tips)
- Inexplicably, most of analysis uses discredited OLS specification
- We focus on hazard model (Table 7) as in Farber (2005)
  - P(stopping) for $300-$349 compared to $200-$224 is $0.059 - 0.015 = 0.044$ higher out of average of 0.14
  - Thus, 31% increase in stopping for a 51% increase in income $->$ elasticity of 0.6!
  - Within the confidence interval of Farber (2005) and clearly sizable

Farber (2015)

TABLE VII

Marginal Effects of Income and Hours on Probability of Ending Shift (Linear Probability Model)

Income ($)	(1) Day shift	(2) Night shift	Hours	(3) Day shift	(4) Night shift
100–149	0.0001	−0.0045	3–5	0.0020	−0.0049
	(0.0003)	(0.0003)		(0.0004)	(0.0003)
150–199	0.0044	−0.0077	6	0.0001	0.0007
	(0.0006)	(0.0005)		(0.0007)	(0.0006)
200–224	0.0157	−0.0062	7	0.0034	0.0223
	(0.0010)	(0.0007)		(0.0011)	(0.0010)
225–249	0.0264	−0.0046	8	0.0281	0.0536
	(0.0013)	(0.0008)		(0.0017)	(0.0016)
250–274	0.0389	−0.0042	9	0.0750	0.0897
	(0.0017)	(0.0011)		(0.0025)	(0.0022)
275–299	0.0506	−0.0033	10	0.1210	0.1603
	(0.0020)	(0.0013)		(0.0035)	(0.0031)
300–349	0.0596	−0.0027	11	0.1236	0.2563
	(0.0024)	(0.0017)		(0.0050)	(0.0051)
350–399	0.0607	0.0011	12	0.1004	0.2573
	(0.0028)	(0.0024)		(0.0078)	(0.0142)
$\geq$ 400	0.0702	0.0101	$\geq$ 13	0.1093	0.2406
	(0.0034)	(0.0035)		(0.0050)	(0.0063)

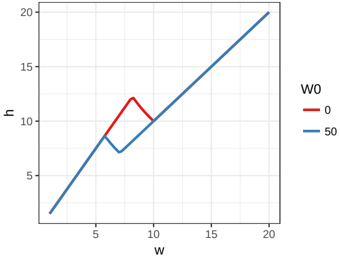
Thakral and To (2017)

- Uses same data as Farber (2015) – in fact, uses replication data set on QJE site
- Re-estimates hazard model as in Farber (2005)
- Estimate separately the impact of earnings early, versus late, in spell
- Model:
  - allow for extra earnings W_0
    - extra earning are partially integrated in reference point
  - Utility function $U(h; T, \eta, \lambda, \theta, w, w_0)$is now

$$\begin{array}{ll} W_0 + wh - \frac{\theta h^2}{2} + \eta\left(wh + W_0 - (T + \alpha W_0)\right) & \text{if} \quad wh + W_0 \geq T + \alpha \\ W_0 + wh - \frac{\theta h^2}{2} + \eta\lambda\left(wh + W_0 - (T + \alpha W_0)\right) & \text{if} \quad wh + W_0 < T + \alpha \end{array}$$

Thakral and To (2017)

- Special case 1: Reference point fully reflects extra earnings ($\alpha = 1$):
  - W_0 cancels out from expression above –> no effect
  - Intuition: extra income already expected, no impact on gain/loss
- Special case 2: Reference point not affected by extra earnings ($\alpha = 0$):
  - In this case can rewrite solution above replace T with $T - W_0$



Thakral and To (2017)

Table 3: Stopping model estimates: Income effect at 8.5 hours—Subsamples

	(1) Night weekday	(2) Medallion owners	(3) Top decile experience
Panel A			
Income effect	0.3564	0.5421	0.4625
	(0.0473)	(0.1548)	(0.0805)
Panel B			
Income in hour 2	0.0725	-0.1175	-0.0130
	(0.0742)	(0.2351)	(0.1236)
Income in hour 4	0.0077	0.0282	0.3062
	(0.0717)	(0.2269)	(0.1284)
Income in hour 6	0.2645	0.2363	0.3309
	(0.0732)	(0.2389)	(0.1267)
Income in hour 8	0.3270	0.5714	0.5580
	(0.0752)	(0.2246)	(0.1335)

- Estimates in Panel B are
  - increases in pp in P(stop) for \$10 $\triangle Y$ in that hour, equal to 5% higher income overall
  - Mean stopping probability is 13.6%
- \$10 $\triangle Y$ in hour 2 $->$ $\triangle P(stop) = 0.07\%$ $->$ $\eta_{Stop,Y} = 0.1$
- \$10 $\triangle Y$ in hour 8 $->$ $\triangle P(stop) = 0.32\%$ $->$ $\eta_{Stop,Y} = 0.46$

Thakral and To (2017)

- Findings provide evidence on speed of formation of reference point:
- Income earned early during the day is already incorporated into reference point T −> Does not impact stopping
  - Income earned late in the shift not incorporated −> Affect stopping
- Provides evidence of backward looking reference points
- Can also be interpreted as forard-looking (KR) delayed expectations

Section 7

Reference Dependence: Employment and Effort

Mas (2006): Police Performance

- 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 $\rightarrow$ If undecided, arbitration
  - 9 percent of police labor contracts decided with final offer arbitration

Framework

- pay is $w \cdot (1 + r)$
- 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 $r_e \leq r_a \leq r_u \rightarrow$ Then

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

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 $\rightarrow$ Lower r_e and increase utility $(U' < 0)$

Union's problem

- Maximize:

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

  - Notice: $V' > 0$

- First order condition for union:

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

- To simplify, assume $U\left(x\right)=-bx$ and $V\left(x\right)=bx$
- This implies $V\left(w\left(1+r_e^*\right)\right)-V\left(w\left(1+r_u^*\right)\right)=$ $-U\left(w\left(1+r_e^*\right)\right)-U\left(w\left(1+r_u^*\right)\right)$, so

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

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

Prediction

- 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)

Summary Statistics

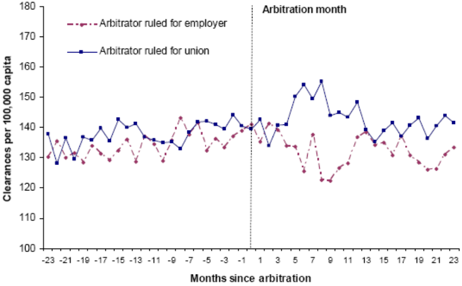
- Compare summary statistics of cases when employer and when police wins
- Estimated $\hat{P} = .344 \neq 1/2 \rightarrow$ Unions more risk-averse than employers
- No systematic difference between Union and Employer cases except for r_e

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 per 100,000 capita	120.31	122.28	118.57	3.71
	[106.65]	[108.76]	[104.35]	(9.46)

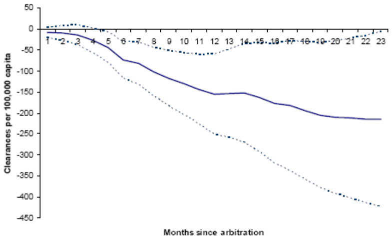
Effects on Performance

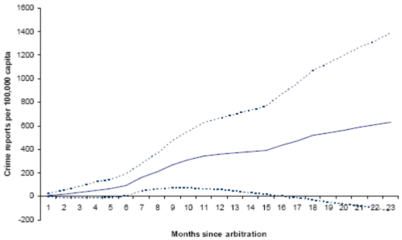
- Graphical evidence of effect of ruling on crime clearance rate



- 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

Effects on Performance





Effects on Performance

- 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

- 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	26.86	24.68	7.75	4.87	19.19	19.86
× Employer win	(25.29)	(14.68)	(7.85)	(4.70)	(18.17)	(11.19)
Post-arbitration	7.64	6.68	7.07	2.49	0.170	4.40
× Union win	(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	-31.81		-20.43		-11.35	
(Yes = 1)	(84.42)		(27.57)		(59.50)	
Fixed-effects?		Yes		Yes		Yes
Mean of the	444.03	519.42	95.49	98.26	348.45	421.28
dependent variable	[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 $\bar{r}_a - (r_e + r_u)/2$

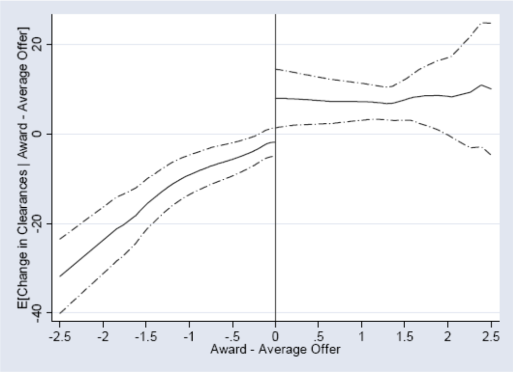


Figure V
Estimated expected change in clearances conditional on the deviation of the award from the average of the offers

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.

Reference Dependence Model

- 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

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

where

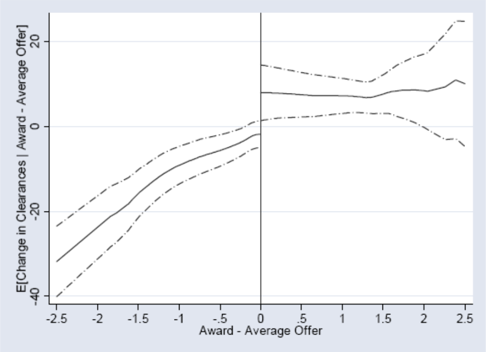
$$U(w) = \begin{cases} w - \hat{w} & \text{if} \quad w \geq \hat{w} \\ \lambda (w - \hat{w}) & \text{if} \quad w < \hat{w} \end{cases}$$

Reference Dependence Model

- Reduced form of reciprocity model where altruism towards the city is a function of how nice the city was to the policemen $(\bar{U} + U(w))$
- 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)

Results

- Compare to observed pattern



- Close to predictions of model

Section 8

Reference Dependence: Domestic Violence

Introduction

- Consider a man in conflicted relationship with the spouse
- What is the effect of an event such as the local (American) 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

Introduction

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

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

Similarly, the utility from a loss is

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

- Implication:

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

  - The more a win is expected, the more a loss is painful $\rightarrow$ the more likely it is to trigger violence
  - The (positive) effect of a gain is higher the more unexpected

Testing the Predictions

- **Card and Dahl (QJE 2011)** 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)

Testing the Predictions

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 increases 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 function of very negative utility)
- Other findings:
  - Effect is larger for more important games
  - Effect disappears within a few hours of game end $\rightarrow$ Emotions are transient
  - No effect on violence of females on males

Section 9

Next Lecture

Next Lecture

- More Reference-Dependence:
  - Insurance
  - Finance
  - Job Search
  - KR vs. backward looking ref. points
  - Endowment Effect
  - Effort