Econ 219B
Psychology and Economics: Applications
(Lecture 6)

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Outline

1. Reference Dependence: Insurance
2. Reference Dependence: Job Search
3. Methodology: Bunching-Based Evidence of Reference Dependence
4. Reference Dependence: Tax Elusion
5. Reference Dependence: Goals
6. Reference Dependence: Endowment Effect (EXTRA)
7. Methodology: Effect of Experience (EXTRA)

1 Reference Dependence: Insurance

- Much of the laboratory evidence on prospect theory is on risk taking

- Field evidence considered so far (mostly) does not involve risk:
  - House Sale
  - Merger Offer

- Field evidence on risk taking?

- **Sydnor (AEJ Applied, 2010)** on deductible choice in the life insurance industry

- Menu Choice as identification strategy as in DellaVigna and Malmendier (2006)

- Slides courtesy of Justin Sydnor

Dataset

- 50,000 Homeowners-Insurance Policies
  - 12% were new customers
- Single western state
- One recent year (post 2000)
- Observe
  - Policy characteristics including deductible
    - 1000, 500, 250, 100
  - Full available deductible-premium menu
  - Claims filed and payouts by company

Features of Contracts

- Standard homeowners-insurance policies (no renters, condominiums)
- Contracts differ only by deductible
- Deductible is *per claim*
- No experience rating
  - Though underwriting practices not clear
- Sold through agents
  - Paid commission
  - No “default” deductible
- Regulated state

Premium-Deductible Menu

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

* Means with standard deviations in parentheses

Risk Neutral Claim Rates?

100/500 = 20%

87/250 = 35%

133/150 = 89%

Potential Savings with 1000 Ded

Claim rate?

Value of lower deductible?

Additional premium?

Potential savings?

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

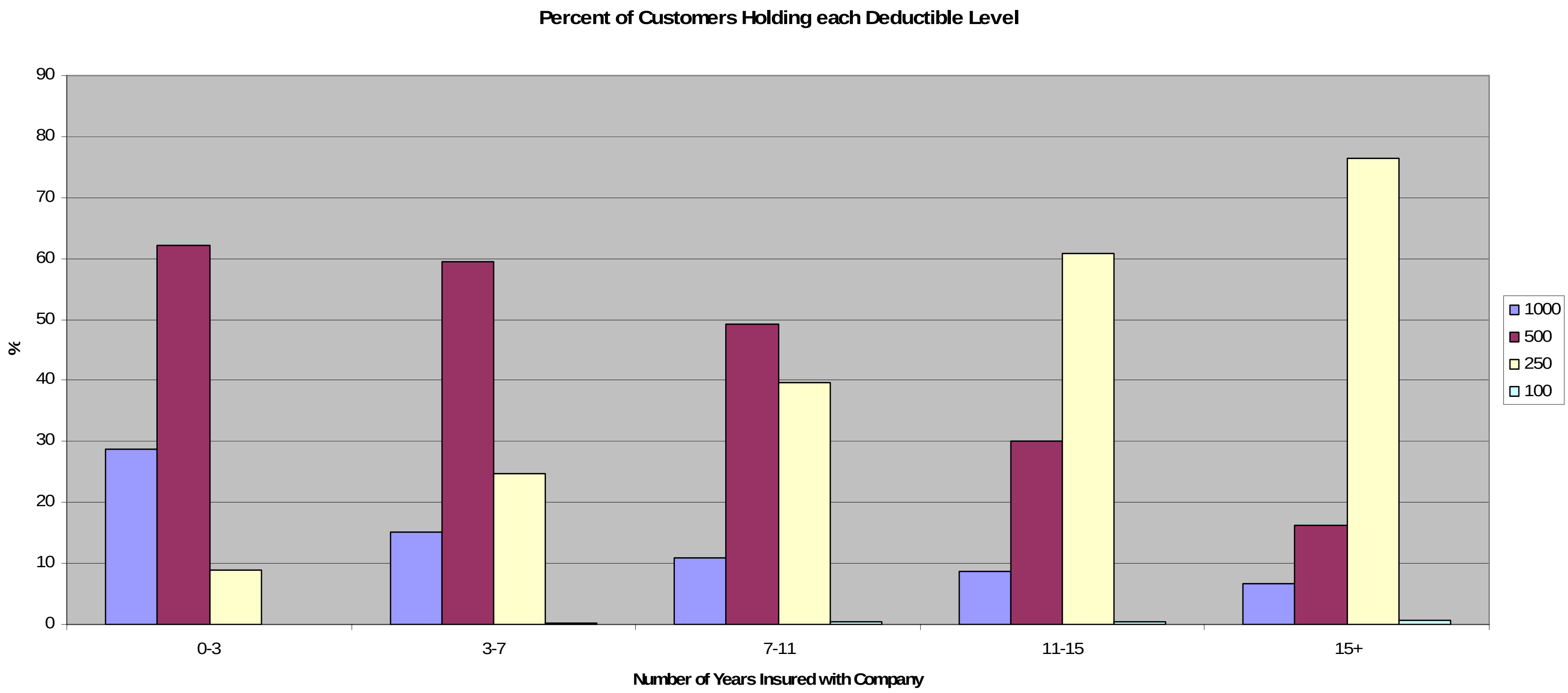
Average forgone expected savings for all low-deductible customers: $99.88

* Means with standard errors in parentheses

Back of the Envelope

- BOE 1: Buy house at 30, retire at 65, 3% interest rate $\Rightarrow$ \$6,300 expected
  - With 5% Poisson claim rate, only 0.06% chance of losing money
- BOE 2: (Very partial equilibrium) 80% of 60 million homeowners could expect to save \$100 a year with “high” deductibles $\Rightarrow$ \$4.8 billion per year

Consumer Inertia?



Look Only at New Customers

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

Average forgone expected savings for all low-deductible customers: $81.42

Model of Deductible Choice

- Choice between (P_L, D_L) and (P_H, D_H)
- π = probability of loss
  - Simple case: only one loss
- EU of contract:
  - $U(P,D,\pi) = \pi u(w-P-D) + (1-\pi)u(w-P)$

Bounding Risk Aversion

Assume CRRA form for u:

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

Indifferent between contracts iff:

$$\pi\frac{(w-P_L-D_L)^{(1-\rho)}}{(1-\rho)}+(1-\pi)\frac{(w-P_L)^{(1-\rho)}}{(1-\rho)}=\pi\frac{(w-P_H-D_H)^{(1-\rho)}}{(1-\rho)}+(1-\pi)\frac{(w-P_H)^{(1-\rho)}}{(1-\rho)}$$

CRRA Bounds

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

Wrong level of wealth?

- Lifetime wealth inappropriate if borrowing constraints.
- \$94 for \$500 insurance, 4% claim rate
  - W = \$1 million $\Rightarrow \rho = 2{,}013$
  - W = \$100k $\Rightarrow \rho = 199$
  - W = \$25k $\Rightarrow \rho = 48$

Model of Deductible Choice

- Choice between (P_L, D_L) and (P_H, D_H)
- π = probability of loss
- EU of contract:
  - $U(P,D,\pi) = \pi u(w-P-D) + (1-\pi)u(w-P)$
- PT value:
  - $V(P,D,\pi) = v(-P) + w(\pi)v(-D)$
- Prefer (P_L, D_L) to (P_H, D_H)
  - $v(-P_L) - v(-P_H) < w(\pi)[v(-D_H) - v(-D_L)]$

No loss aversion in buying

- Novemsky and Kahneman (2005)
  (Also Kahneman, Knetsch & Thaler (1991))
  - Endowment effect experiments
  - Coefficient of loss aversion = 1 for “transaction money”
- Köszegi and Rabin (forthcoming QJE, 2005)
  - Expected payments
- Marginal value of deductible payment > premium payment (2 times)

So we have:

- Prefer (P_L, D_L) to (P_H, D_H):

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

- Which leads to:

$$P_L^{\beta} - P_H^{\beta} < w(\pi)\lambda[D_H^{\beta} - D_L^{\beta}]$$

- Linear value function:

$$WTP = \Delta P = \underbrace{\boxed{w(\pi)\lambda}}_{= \text{ 4 to 6 times EV}}\Delta D$$

Choices: Observed vs. Model

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

Alternative Explanations

- Misestimated probabilities
  - ≈ 20% for single-digit CRRA
  - Older (age) new customers just as likely
- Liquidity constraints
- Sales agent effects
  - Hard sell?
  - Not giving menu? ($500?, data patterns)
  - Misleading about claim rates?
- Menu effects

- **Barseghyan, Molinari, O'Donoghue, and Teitelbaum (AER 2013)**
  - Micro data for same person on 4,170 households for 2005 or 2006 on
    - home insurance
    - auto collision insurance
    - auto comprehensive insurance

- Estimate a model of reference-dependent preferences with Koszegi-Rabin reference points
  - Separate role of loss aversion, curvature of value function, and probability weighting

- Key to identification: variation in probability of claim:
  - * home insurance –> 0.084
    * auto collision insurance –> 0.069
    * auto comprehensive insurance –> 0.021

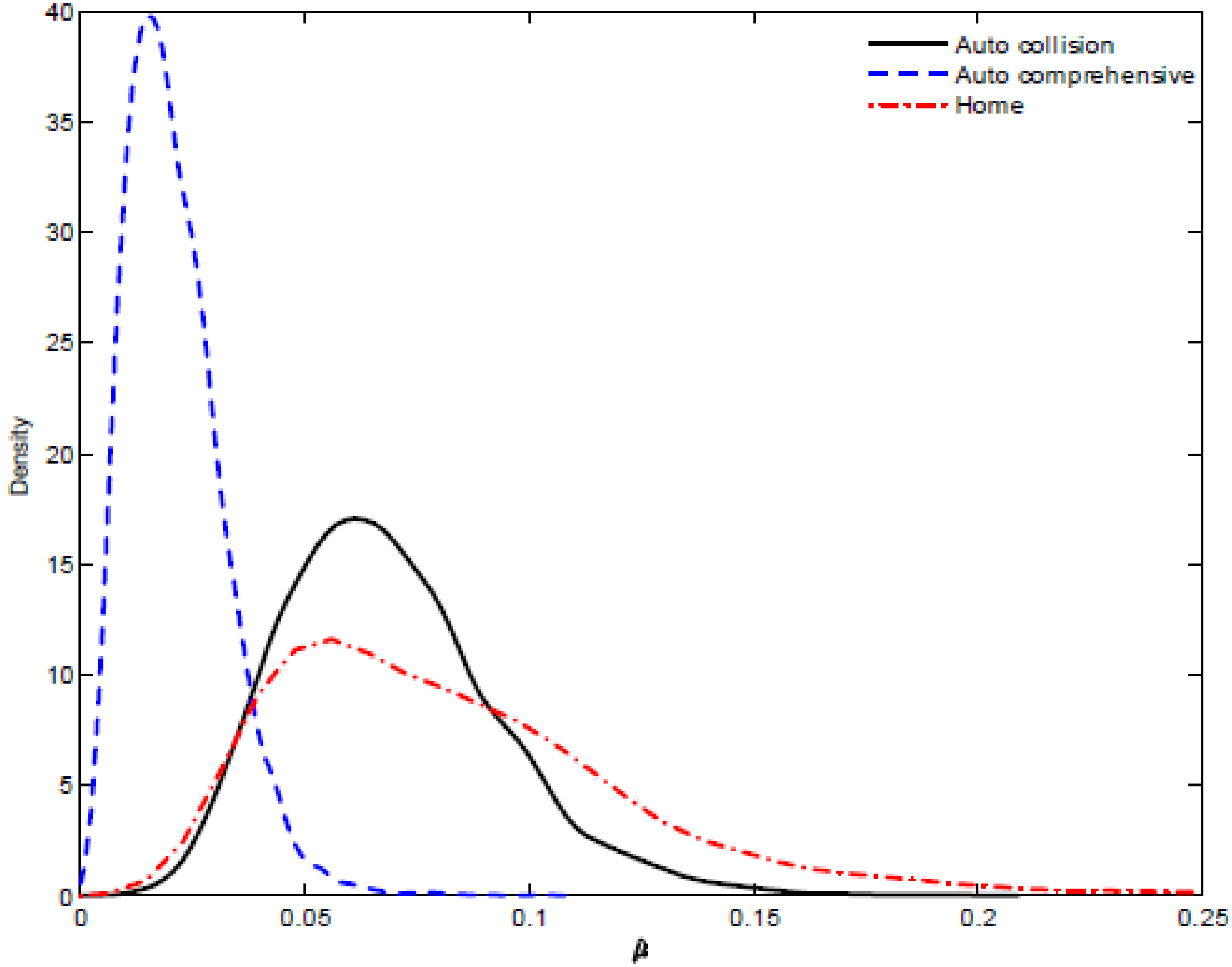


Figure 1: Empirical Density Functions for Predicted Claim Probabilities

- This allows for better identification of probability weighting function

- Main result: Strong evidence from probability weighting, implausible to obtain with standard risk aversion

- Share of probability weighting function

- With probability weighting, realistic demand for low-deductible insurance

- [**Next year write model**]

- Follow-up work: distinguish probability weighting from probability distortion

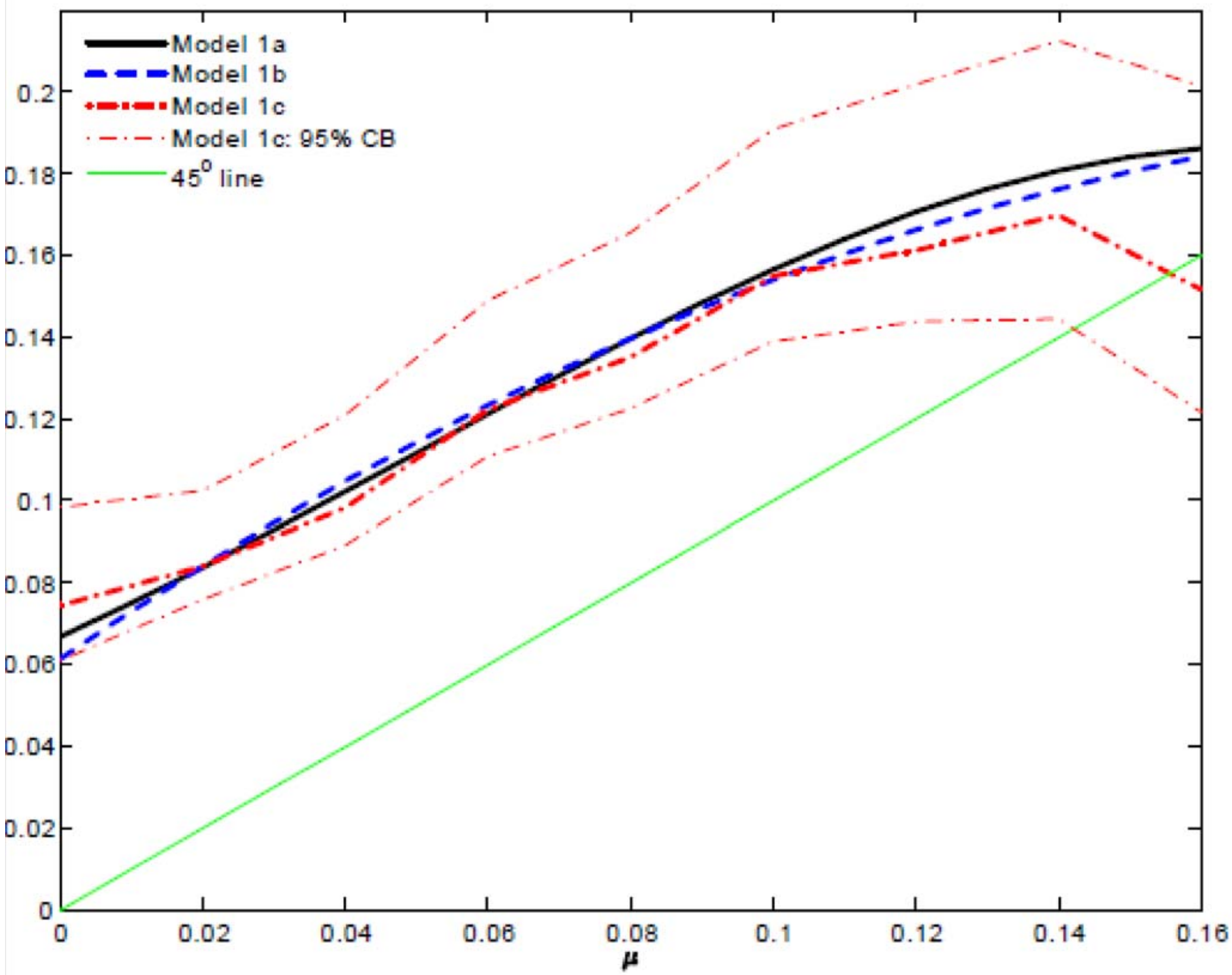


Figure 2: Estimated $\Omega(\mu)$ – Model 1

Table 6: Economic Significance

	(1)	(2)	(3)	(4)	(5)
Standard risk aversion	**r=0**	**r=0.00064**	**r=0**	**r=0.00064**	**r=0.0129**
Probability distortions?	**No**	**No**	**Yes**	**Yes**	**No**
μ	**WTP**	**WTP**	**WTP**	**WTP**	**WTP**
0.020	10.00	14.12	41.73	57.20	33.76
0.050	25.00	34.80	55.60	75.28	75.49
0.075	37.50	51.60	67.30	90.19	104.86
0.100	50.00	68.03	77.95	103.51	130.76
0.125	62.50	84.11	86.41	113.92	154.00

Notes: WTP denotes—for a household with claim rate μ, the utility function in equation (2), and the specified utility parameters—the household's maximum willingness to pay to reduce its deductible from $1000 to $500 when the premium for coverage with a $1000 deductible is $200. Columns (3) and (4) use the probability distortion estimates from Model 1a.

2 Reference Dependence: Job Search

- **DellaVigna, Lindner, Reizer, Schmieder (2014)**

- Insert slides

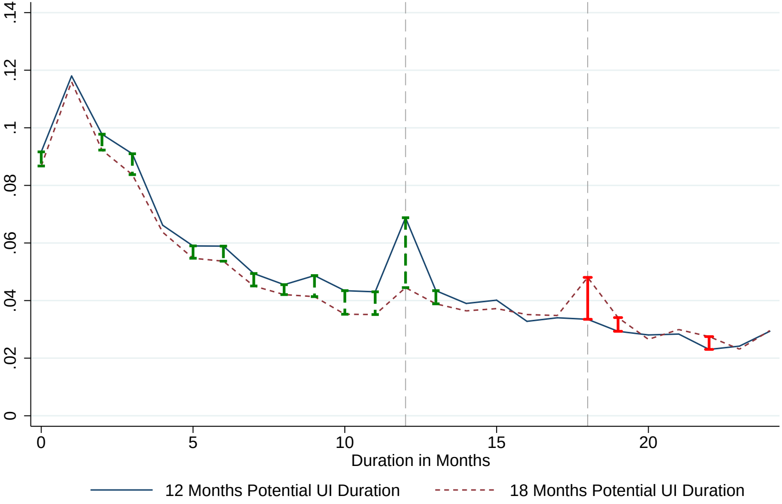
Introduction

- Large literature on understanding path of hazard rate from unemployment with different models.
- **Typical finding**: There is a **spike** in the hazard rate at the **exhaustion point** of unemployment benefits.

⇒ Such a spike is **not easily explained** in the standard (McCall / Mortensen) model of job search.

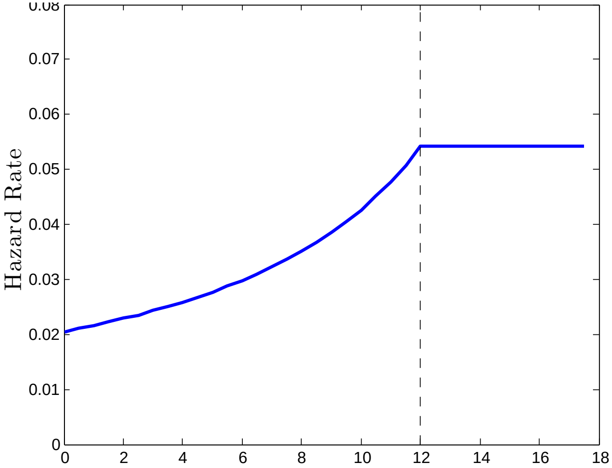
⇒ To explain this path, one needs unobserved heterogeneity of a special kind, and/or storeable offers

Germany - Spike in Exit Hazard



Source: Schmieder, von Wachter, Bender (2012)

Simulation of Standard model



Predicted path of the hazard rate for a standard model with expiration of benefit at period 25

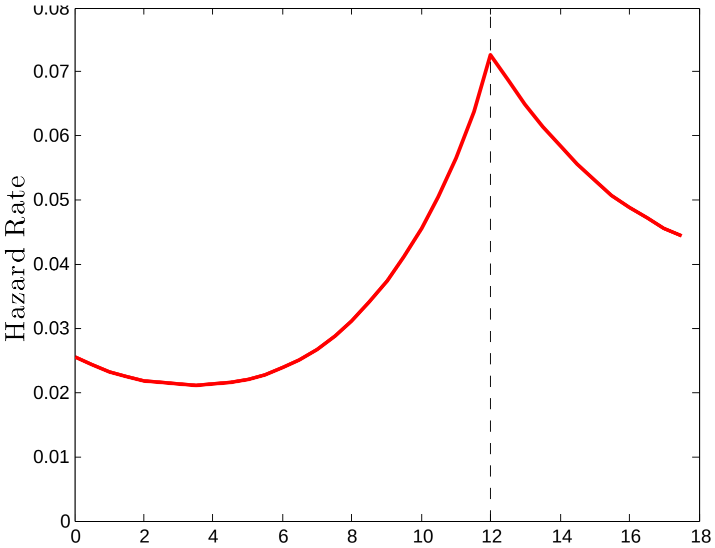
Alternative Explanation for Spike

- We propose an alternative model of job search with **reference-dependent preferences**
- This model **naturally accommodates the observed hazard path** without extra assumptions
- Building on Kahneman and Tversky (1979) and following, we assume that unemployed workers have a **reference-dependent utility of consumption**
  - [For today: Assume hand-to-mouth workers: consumption=income]
- Critically, the **reference point** is the **average of recent consumption**

Preview

- This **Reference Dependence (RD) model generates** a spike in the exit **hazard**:
    - **Initially** the worker works very hard because of the **high disutility of being unemployed** given the **loss relative to the previous earnings**
    - then the worker **gets used to the lower UI benefits** and searches less hard
    - then the workers **anticipates the exhaustion of benefits** and works harder
    - finally, the workers **gets used to the lower UA benefits** again

Simulation of the RD model



Model

- We integrate a **reference dependent utility** function into the standard McCall / Mortensen model of job search.
- The model is set in **discrete time** and models the job search behavior of an unemployed worker throughout the spell of unemployment.
- In each period individuals optimally choose:
  - a **search** intensity s_t, normalized to be the probability of receiving an offer in period t
  - a **reservation wage** w_t^*, such that all jobs above w_t^* are accepted.
- Search intensity comes at a per period cost of $c(s_t)$, which is increasing and convex.

Utility Function

- Individuals receive unemployment benefits b_t when they are unemployed
- Flow utility from these benefits also depends on a reference point r_t such that:

$$u_t(b_t, r_t) = \begin{cases} v(b_t) + \eta(v(b_t) - v(r_t)) & \text{if} \quad b_t \geq r_t \\ v(b_t) + \eta\lambda(v(b_t) - v(r_t)) & \text{if} \quad b_t < r_t \end{cases}$$

  - η signifies the relative importance of the reference-dependence
  - $\lambda > 1$ parameterizes loss aversion
- This builds on Kahneman and Tversky (1979) and is in the spirit of Koszegi and Rabin (2006)

Reference Point

- Unlike in Koszegi and Rabin (2006), but like in habit formation literature, reference point is backward-looking
- The reference point in period t is simply the **average income** earned over the $N \geq 1$ periods **directly preceding period** t:

$$r_t = \frac{1}{N} \sum_{k=t-N}^{t-1} b_k$$

- Consider a drop in UI benefits by db,
  - In the short term, there will be a sharp drop in the flow utility of about $\Delta u_{short} \approx db \times v'(b_t)(1 + \eta\lambda)$
  - However over time the reference point will adjust to the new consumption level
  - The long term drop in flow utility is: $\Delta u \approx db \times v'(b_t)$

Value Function of Unemployed

- An unemployed workers value function is given as:

$$V_t^U(b_t, r_t) = \max_{s_t, w_t^*} \Big\{ u_t(b_t, r_t) - c(s_t) + (1 - s_t)\delta V_{t+1}^U(b_{t+1}, r_{t+1}) + s_t\delta \int_{w_t^*}^{\infty} V_{t+1}^E(w, r_{t+1}) dF(w) \Big\}$$

- Value function when employed in statedy-state:

$$V_t^E(w_t, r_t) = \frac{u_t(w_t, r_t)}{1 - \delta}$$

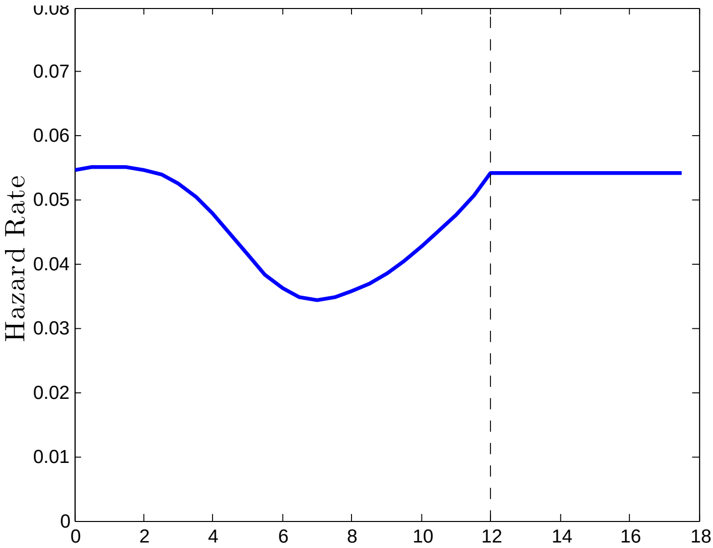
- We assume that there is a point $\bar{T}$ after which the environment becomes stationary.
  - Solve for optimal s_t and w_t^* using backward induction.

Standard vs. RD Model

- In order **to give the standard model** a fighting **chance** we have to incorporate **heterogeneity**.
- In this case the standard model can generate a spike at exhaustion due to **selection over the spell**.
  - Suppose there is a group of individuals with a very elastic cost function but low exit rate initially.
  - At the exhaustion point these workers increases their search intensity dramatically and quickly exit. Hazard first increases and then falls again after this high elasticity group has exited.
- From the existence of the spike alone it is thus hard to tell apart the Standard and the RD model.

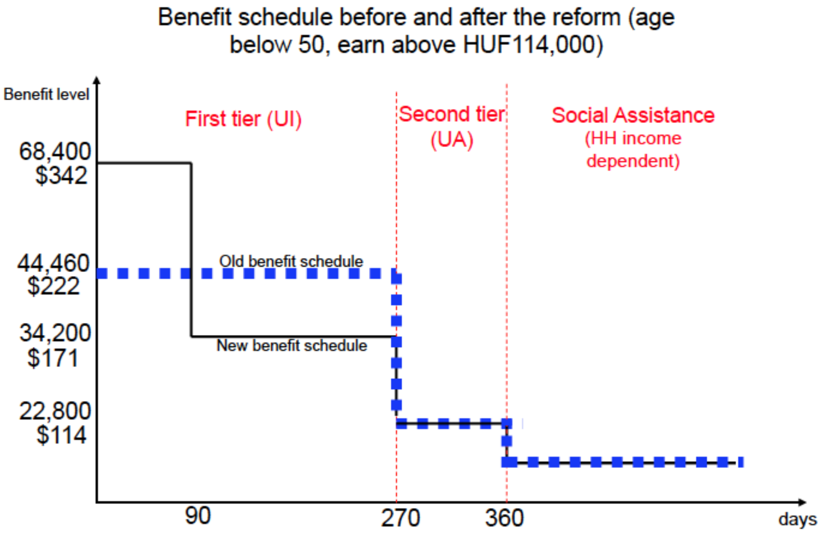
$\Rightarrow$ Need a reform where the two models yield different predictions!

Standard model with heterogenity



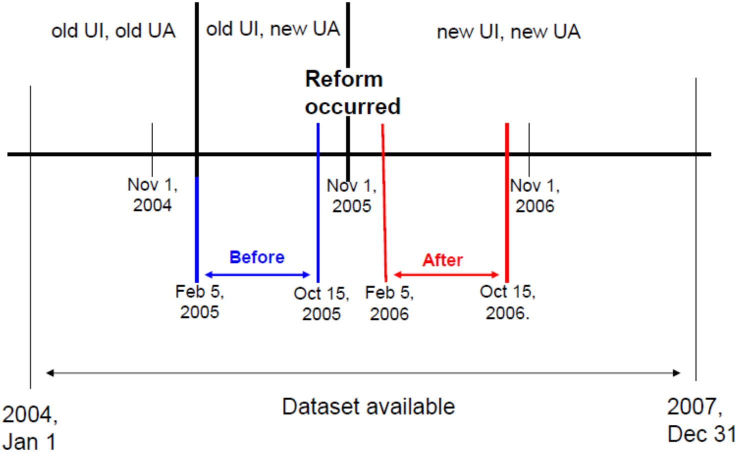
Unemployment Insurance in Hungary

- We analyze a reform of the UI system in Hungary.
  - Focus on people at the maximum benefit level (benefits are fixed replacement rate up to maximum, most interesting variation at the maximum).
- Prior to November 2005, system similar to US:
  - Constant benefits for 270 days, then fall to second tier (unemployment assistance UA).
- After November 2005, benefits were increased in first 90 days and lowered between 90 and 270 days.
- Total amount of benefits is the same if unemployed for 270 or more days.



Eligible for 270 days, base salary is higher than 114,000HUF

Define before and after



Predictions

- The reform changes the benefit schedule to be more front loaded.
  - Similar to a lump sum payment, in that sense it should be less distortionary.
  - Both standard and RD model would predict a reduction in unemployment durations, but shape of hazards different.
- The **drop** in UI benefits at the 270 day point in the **Before** period is much **larger** than in the **After** period, but after 270 days benefit levels are the same.
  - Standard model: predict that hazard rates are the same after 270 days in both periods.
  - RD Model: predict that after 270 days hazard rate is higher in the Before period, since reference point needs time to adjust.

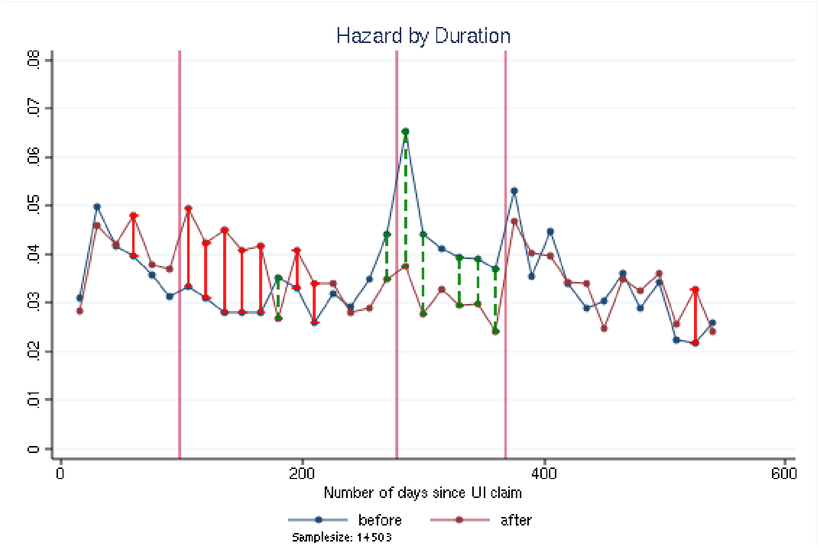
Empirical Design

- To get a non-parameteric estimate of the shift of the hazard function in the Before and After period we estimate:

$$I(Dur_i = t | Dur_i \geq t) = \gamma_{0,x} + \gamma_{1,x} After_i + X_i \beta + \varepsilon_{ai},$$

  where we estimate this for $t = 1 \ldots T = 40$, where each t is a 2 week interval
    - Since $h(t) = f(Dur_i = t | Dur_i \geqq t)$ is the hazard function, we thus have estimates of the level and shift in $h(t)$ at the threshold.
- We control flexibly for obervables X_i where the observables can have a different impact at each point t.

Hazard rates before and after



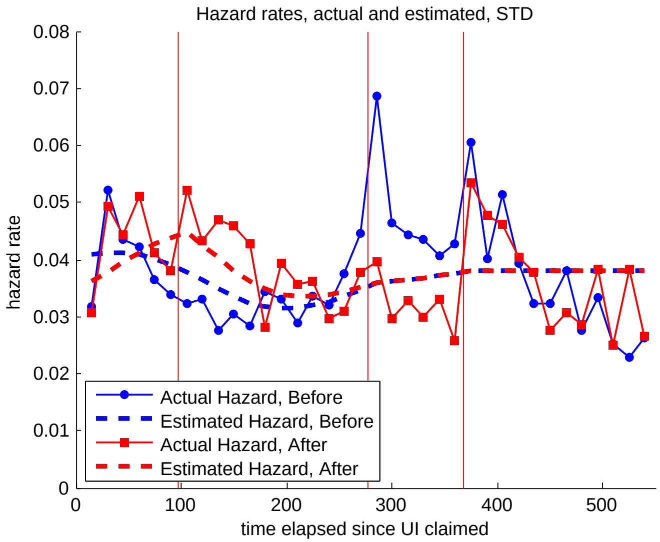
Estimation

- We estimate our search model (Standard and Reference Dependent) using a minimum distance estimator.
- We try to match the estimated hazard rates in the pre- and post period.
    - Moments: estimated hazard rates in 36 periods Before and After.
- Parameters to estimate:
    - λ size of gain loss component in utility function ($\lambda = 0$ implies the standard model).
    - N adjustment time for reference period.
    - $c(.) = k_j \frac{s^{1+\gamma}}{1+\gamma}$
- There are two types with different k_j: k_h and k_l. We estimate k_h and k_l and the proportion of high cost types.

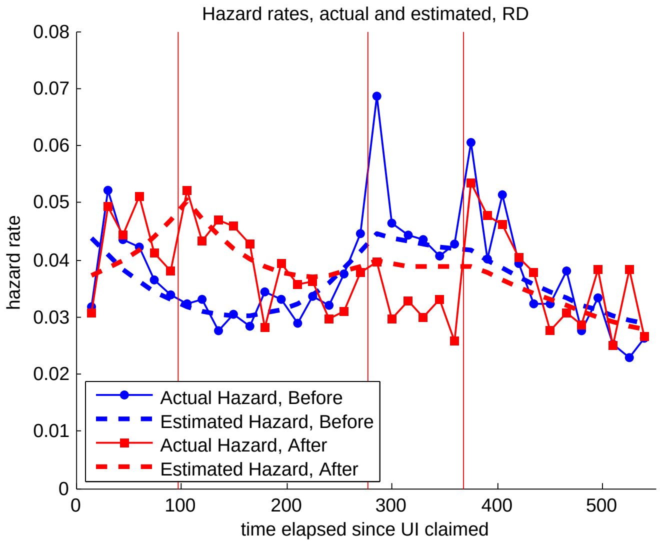
Parameter Estimates

	RD model	Standard model
high cost constant	52,653	50,562
	(1277)	(1061)
low cost constant	50,080	32,567
	(511)	(1036)
exponent of the power function	0.054	0.098
	(0.006)	(0.018)
probability of being a high type (at job loss)	0.99	0.53
	(0.02)	(0.05)
loss aversion	1	
	(0.07)	
Speed of adjestment (in 15 days)	16	
	(1.14)	
SSE	0.0034	0.0051

Simulation of Standard Model



Simulation of RD Model



3 Methodology: Bunching-Based Evidence of Reference Dependence

- How does one identify reference-dependence?
- Some Cases: Key role for *diminishing sensitivity* and *probability weighting*
  - Disposition effect: Diminishing sensitivity –> more prone to sell winners (part of effect)
  - Insurance: Prob. weighting –> propensity to get low deductible
- Most Cases: Key role for *loss aversion*
  - Housing: Below purchase price –> Post higher listing price
  - Mergers: Below 52 high –> Ask higher merger price
  - Job Search: Below previous earnings –> Search harder

- Labor Supply: Below earnings target –> Work harder
- Domestic Violence: Below expected score –> More aggression
- Work effort: Below expected pay –> Less effort for employer

- Common element for several papers in second group:
  - Cost of effort $c(e)$
  - Return of effort e, reference point r

- Individual maximizes

$$\begin{aligned} \max_e e + \eta [e - r] - c(e) \text{ for } e &\geq r \\ \max_e e + \eta\lambda [e - r] - c(e) \text{ for } e &< r \end{aligned}$$

  - Discontinuity in marginal utility –> Bunching at $e^* = r$
  - Older literature does not purse this, new literature does

- Bunching is much harder to explain with alternative models

4 Reference Dependence: Tax Elusion

- **Alex Rees-Jones (2014)**
- Slides courtesy of Alex

Decision environment

Consider the decisions made in the process of filing tax returns.

Some tax-relevant behaviors are predetermined.

- E.g., withholding, labor supply.

But, conditional on predetermined behavior, the taxpayer can:

1. Work to claim tax shelters for past behavior.
2. Pursue additional tax shelters.

Sheltering reduces current tax payment, at a cost:

- Evasion: e.g., income underreporting.
  - Costs: expected future penalties, accounting effort, stigma, etc.
- Avoidance: e.g., legal pursuit of credits, deductions.
  - Costs: effort and attention.

Model of sheltering decisions

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

- b^{PM} —"pre-manipulation" balance due, with PDF f_b^{PM}.
  - Determined by past labor supply decisions, tax payments, and many other factors.
  - **Primary assumption:** f_b^{PM} is continuous.
- s — tax dollars sheltered.
  - Assumes that sheltering can be precisely targeted.
- $c(\cdot)$ — increasing, convex, and twice continuously differentiable cost of sheltering.

Simple example with smooth utility

Consider a model abstracting from income effects:

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

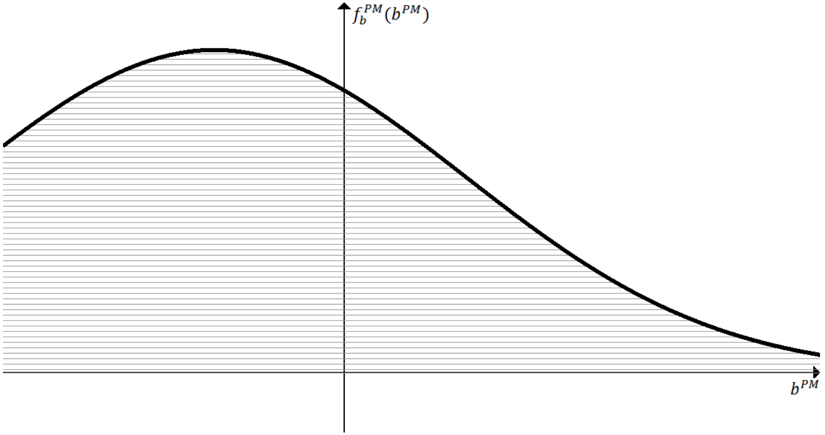
Optimal sheltering is determined by the first-order condition:

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

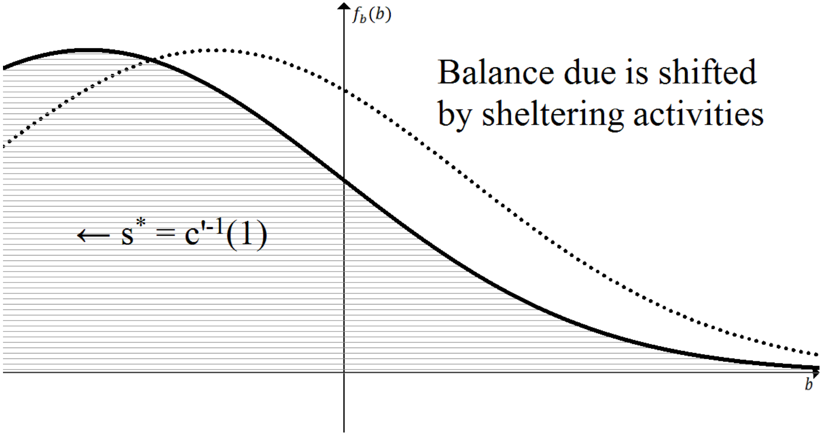
Optimal sheltering solution: $s^* = c'^{-1}(1)$.

→ 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



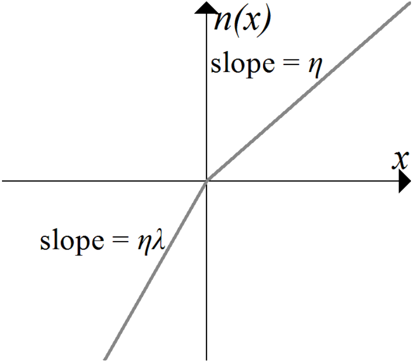
Loss-averse case

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

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

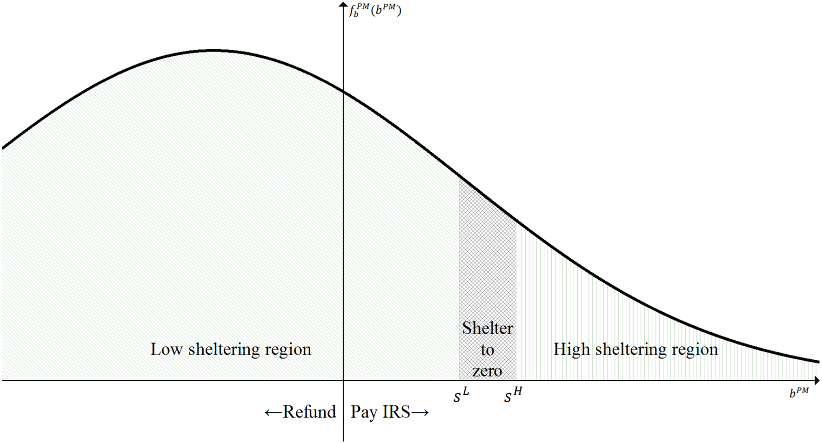
This model generates an optimal sheltering solution with different behavior across three regions:

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

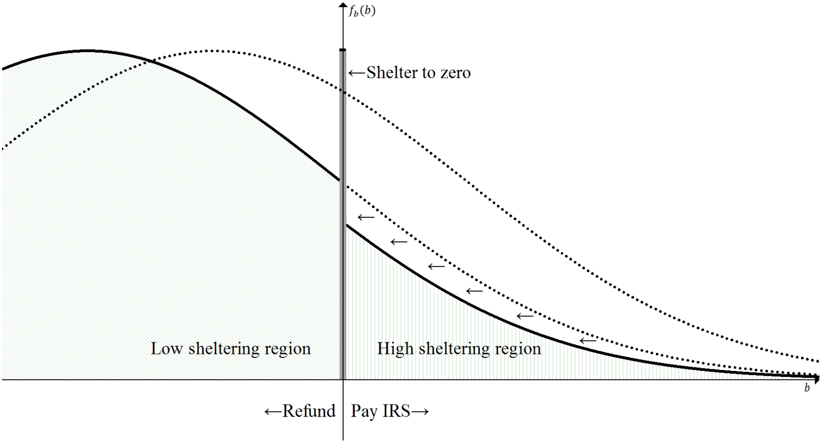
where $s^H \equiv c'^{-1}(1 + \eta\lambda)$ and $s^L \equiv c'^{-1}(1 + \eta)$.

- 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 pre-manipulation balance due



PDF of final balance due after loss-averse sheltering



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

Goals of empirical analysis

We will now test these two predictions in IRS tax records, and quantify the revenue effect each implies.

Bunching prediction: Excess mass at gain/loss threshold.

Shifting prediction: Dist. of losses shifted relative to gains.

Need to address potential confounds:

- Nonrefundable credits
- Extremely accurate tax forecasting
- Fixed costs in the loss domain
- Interactions with tax preparers
- Avoidance of underwitholding penalties
- Liquidity constraints

Data description

Dataset: 1979-1990 SOI Panel of Individual Returns.

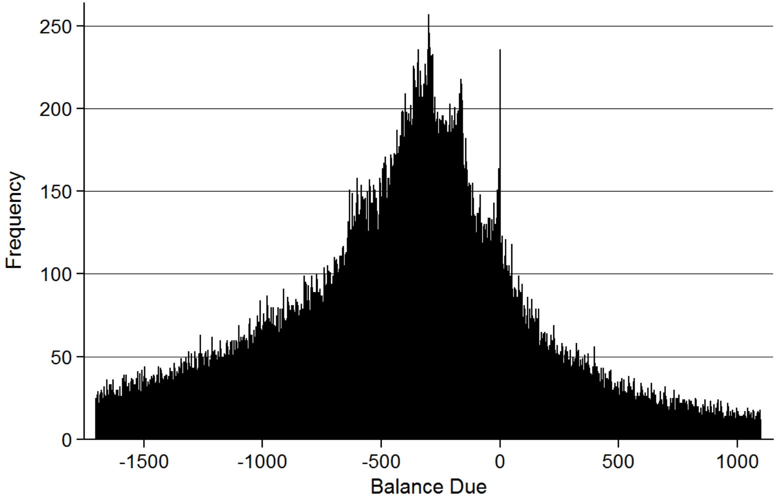
- Contains most information from Form 1040 and some related schedules.
- Randomized by SSNs.

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

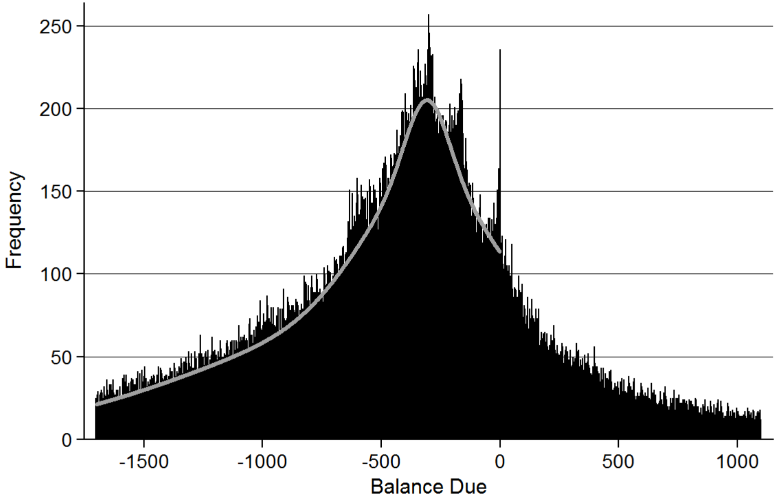
Exclude individuals with zero pre-credit tax due, individuals with zero tax prepayments.

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

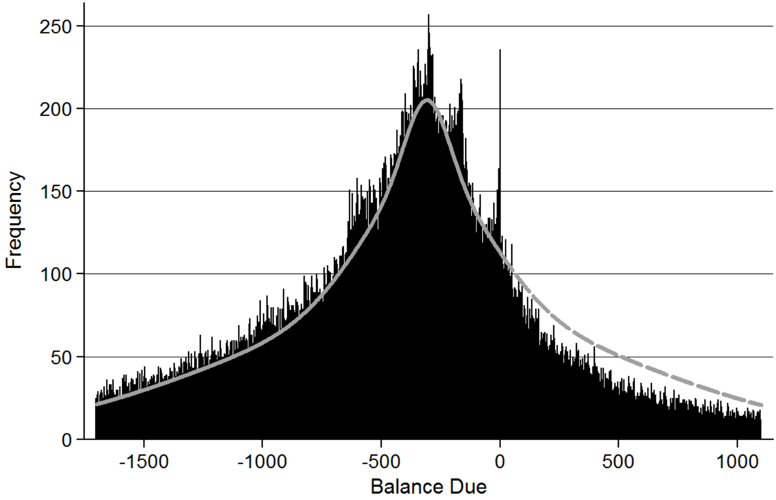
First look: distribution of nominal balance due



First look: distribution of nominal balance due



First look: distribution of nominal balance due



Quantifying excess mass

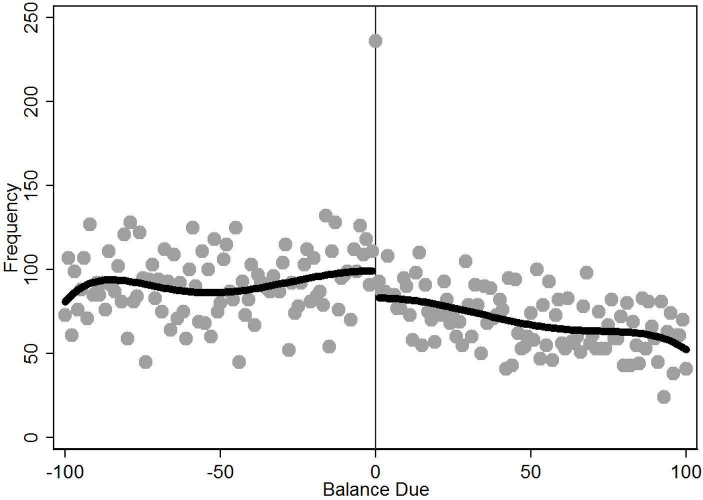
Approach motivated by Chetty, Friedman, Olsen, and Pistaferri (2011), who studied bunching behavior in an alternate setting.

$$C_j = \alpha + \left[\sum_{i=1}^{7} \beta_i \cdot b_j^i \right] + \gamma \cdot I(b_j = 0) + \delta \cdot I(b_j > 0) + \epsilon_j$$

Fits the histogram local to the referent with a 7th-order polynomial.

- All values expressed in 1990 dollars.

Distribution of balance due near gain/loss threshold



	(1) All AGI groups	(2) 1st AGI quartile	(3) 2nd AGI quartile	(4) 3rd AGI quartile	(5) 4th AGI quartile
γ: I(balance due $= 0$)	136.43***	46.57***	26.79***	21.06***	42.01***
	(18.46)	(8.25)	(6.95)	(5.66)	(4.15)
δ : I(balance due > 0)	-16.26*	-3.50	-4.20	-3.42	-5.14**
	(9.41)	(4.21)	(3.54)	(2.89)	(2.12)
α : Constant	99.57***	33.43***	27.21***	21.94***	16.99***
	(5.45)	(2.44)	(2.05)	(1.67)	(1.23)
Balance-due polynomial	X	X	X	X	X
N: Bins in histogram	201	201	201	201	201
Observations	16348	5725	4553	3602	2468
R^2	0.490	0.479	0.259	0.209	0.489

Notes: Standard errors in parentheses. Similar estimates generated with bootstrapped standard errors. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Table with bootstrapped SEs

Results robust to alternative orders of the polynomial.

- Similar or stronger significance patterns for polynomials of order one through ten.
- BIC selects 2nd-order polynomial, yields similar results.

These estimates can be used to bound $s^H - s^L$.

Estimates of shifting in loss domain

The estimates we've focused on thus far have been based on the bunching prediction.

Now we will assess the shifting prediction.

- Complementary approach: estimates $(s^H - s^L)$ from a different feature of the data.
- Different strengths and weaknesses.

Pros: uses more of the data, less danger that individuals near zero are non-representative.

Cons: will rely more on functional form restrictions, more susceptible to systematic differences in unobserved variables.

Excluding data at gain/loss threshold, loss-averse sheltering implies:

$$f_b(x) = \begin{cases} f_b^{PM}(x+\kappa) & \text{if } x < r \\ f_b^{PM}(x+\kappa+\tilde{s}) & \text{if } x > r \end{cases}$$

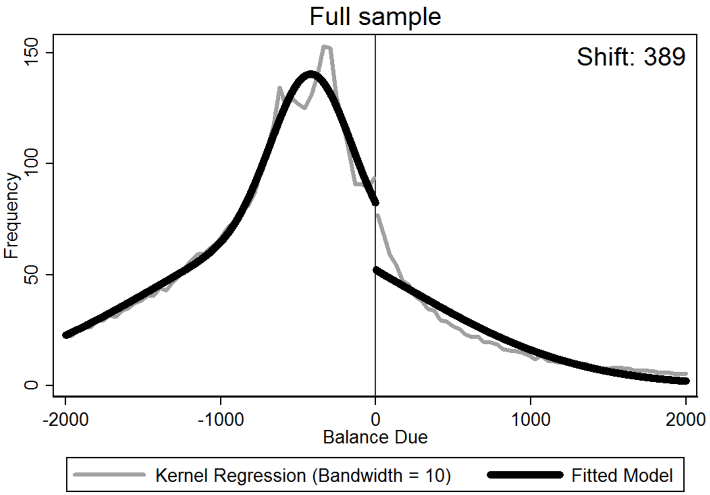
$$\kappa \equiv s^L,\ \tilde{s} \equiv s^H - s^L$$

Empirical approach: Use NLLS to fit a mixture of normal distributions to the histogram, directly modeling shift.

$$C_j = Obs \cdot \left[\sum_{i=1}^{2} \frac{p_i}{\sigma_i} \phi \left(\frac{b_j + \tilde{s} \cdot I(b > 0) - \mu}{\sigma_i} \right) \right] + \epsilon_j$$

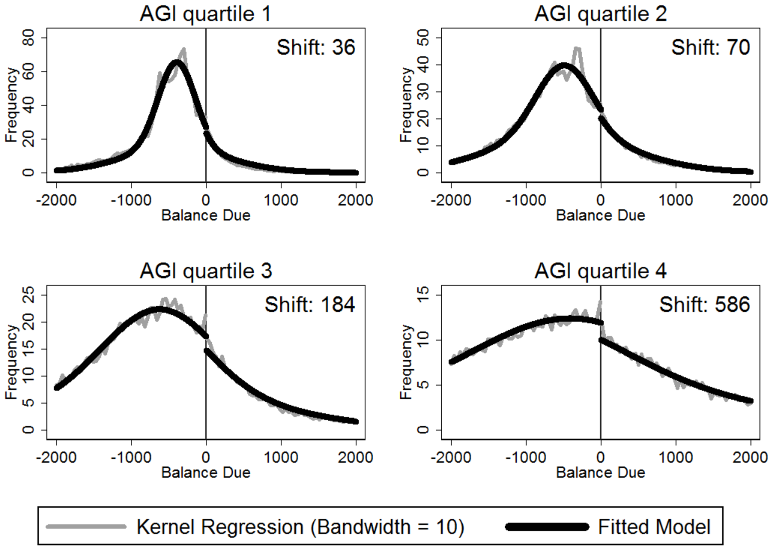
- Common mean assumed to preserve symmetry.
- Similar estimates generated by fitting skew-normal distribution, but fit is worse.

Fit of predicted distributions



Estimate table

Fit of predicted distributions



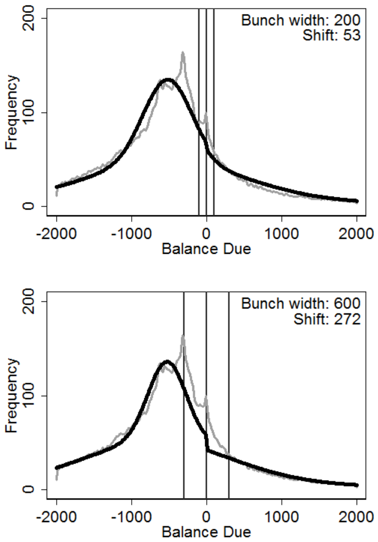
Rationalizing differences in magnitudes

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



Sheltering-relevant behaviors at zero balance due

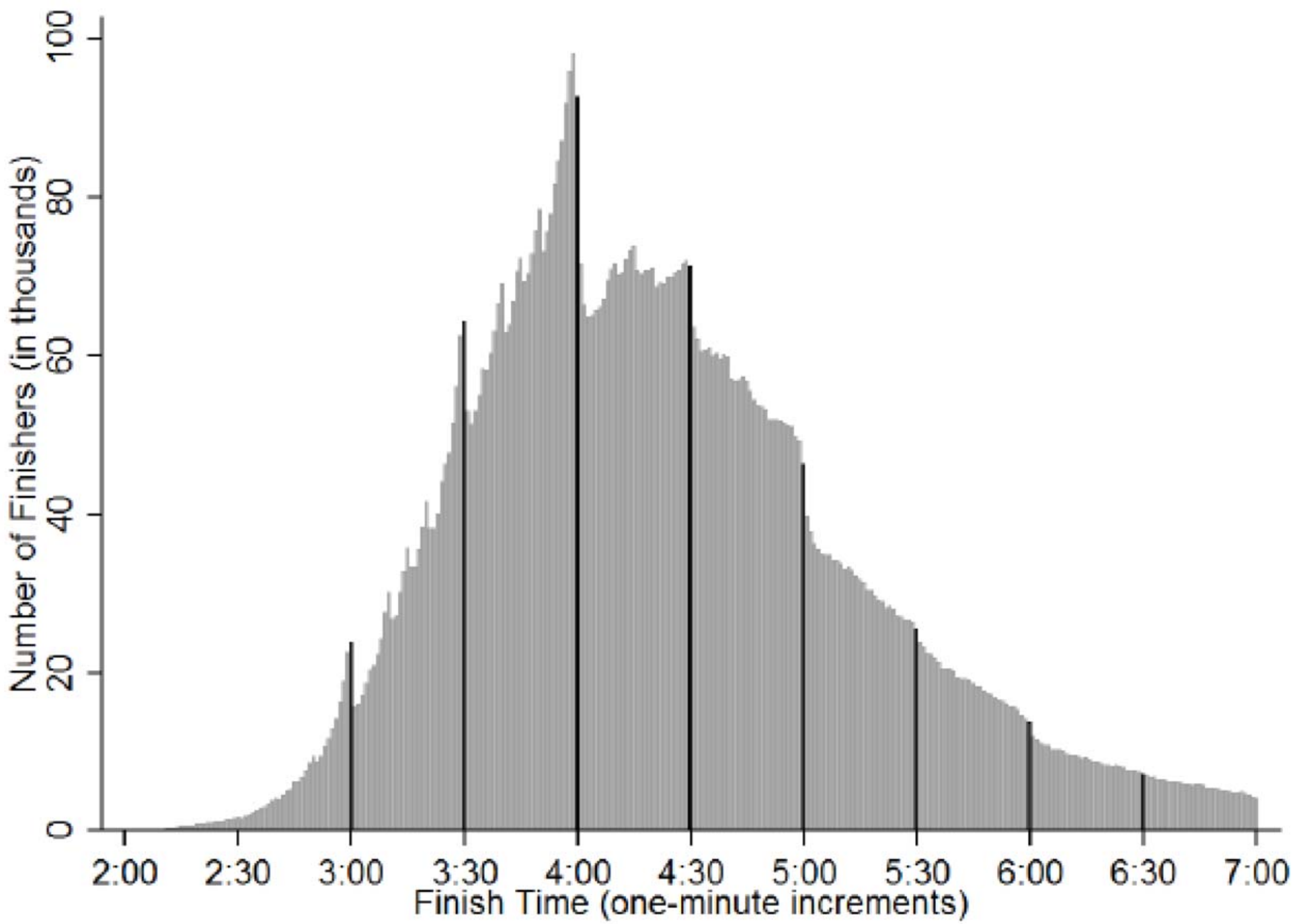
	(1)	(2)	(3)	(4)	(5)	(6)
	Adjustments		*Itemized Deduction*		*Credits*	
	> 0	Amount	> 0	Amount	> 0	Amount
Balance due $= 0$	0.09***	1138.38*	0.01	2015.49*	0.01	535.50
	(0.03)	(619.59)	(0.03)	(1112.42)	(0.03)	(493.06)
Balance due > 0	0.05***	259.35***	-0.00	429.42***	-0.01***	27.97
	(0.00)	(76.24)	(0.00)	(99.31)	(0.00)	(29.76)
Filing-year fixed effects	X	X	X	X	X	X
Balance-due polynomial	X	X	X	X	X	X
Lagged-AGI polynomial	X	X	X	X	X	X
N	148325	33935	148325	62441	148325	54223

Notes: OLS regressions with standard errors clustered at the individual level. Monetary quantities expressed in 1990 dollars. Xs indicate the presence of filing-year fixed effects, a third-order polynomial in lagged AGI, or a third-order polynomial in balance due interacted with I(balance due > 0) to allow for discontinuity at zero. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Reference Dependence: Goal Setting

- **Allen, Dechow, Pope, Wu (2014)**
- Reference point can be a goal
- Marathon running: Round numbers as goals
- Similar identification considering discontinuities in finishing times around round numbers

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

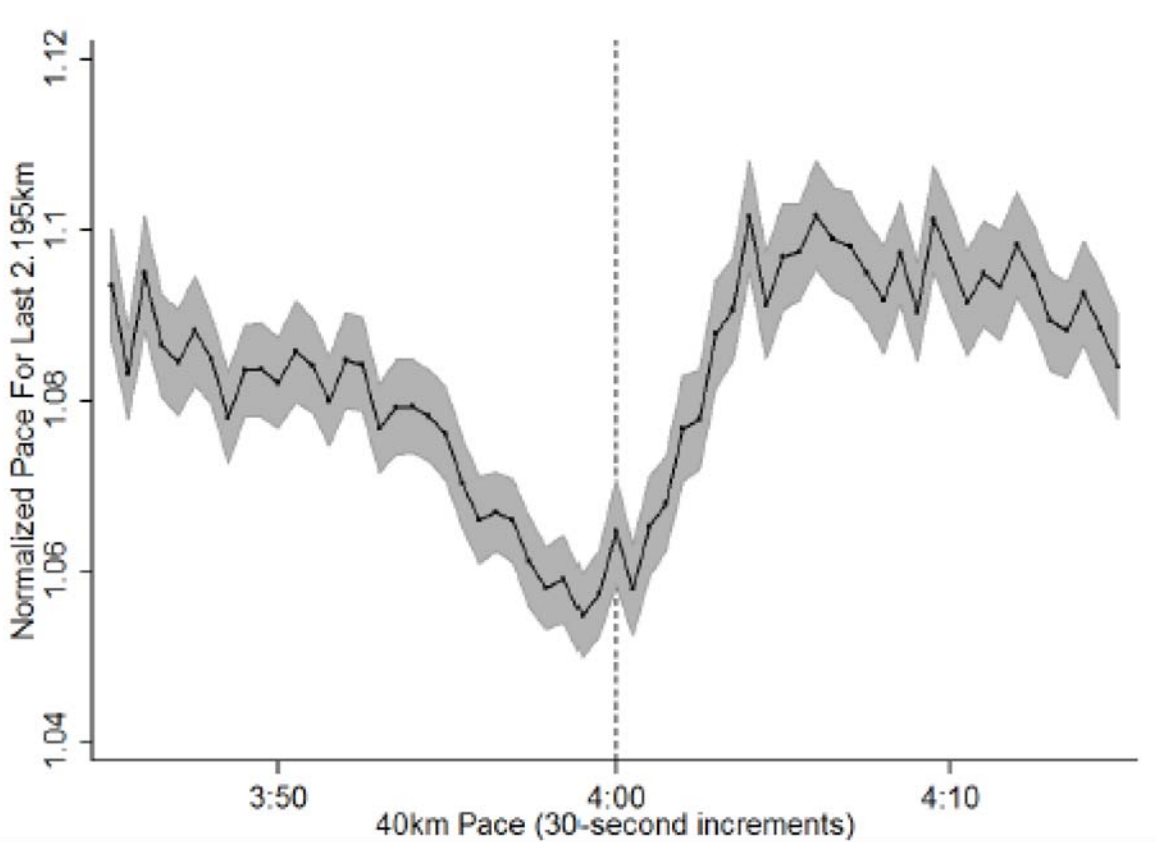


NOTE: The dark bars highlight the density in the minute bin just prior to each 30 minute threshold.

- 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



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

6 Reference Dependence: Endowment Effect

- Plott and Zeiler (AER 2005) replicating Kahneman, Knetsch, and Thaler (JPE 1990)
  - Half of the subjects are given a mug and asked for WTA
  - Half of the subjects are shown a mug and asked for WTP
  - Finding: $WTA \simeq 2 * WTP$

Table 2: Individual Subject Data and Summary Statistics from KKT Replication

Treatment	Individual Responses (in U.S. dollars)	Mean	Median	Std. Dev.
WTP (n = 29)	0, 0, 0, 0, 0.50, 0.50, 0.50, 0.50, 0.50, 1, 1, 1, 1, 1, 1.50 2, 2, 2, 2, 2, 2.50, 2.50, 2.50, 3, 3, 3.50, 4.50, 5, 5	1.74	1.50	1.46
WTA (n = 29)	0, 1.50, 2, 2, 2.50, 2.50, 3, 3.50, 3.50, 3.50, 3.50, 3.50, 4, 4.50 4.50, 5.50, 5.50, 5.50, 6, 6, 6, 6.50, 7, 7, 7, 7.50, 7.50, 7.50, 8.50	4.72	4.50	2.17

- How do we interpret it? Use reference-dependence in piece-wise linear form
  - Assume only gain-loss utility, and assume piece-wise linear formulation (1)+(3)
  - Two components of utility: utility of owning the object $u(m)$ and (linear) utility of money p
  - Assumption: No loss-aversion over money
  - WTA: Given mug –> $r = \{mug\}$, so selling mug is a loss
  - WTP: Not given mug –> $r = \{\varnothing\}$, so getting mug is a gain
  - Assume $u\{\varnothing\} = 0$

- This implies:
  - WTA: Status-Quo $\sim$ Selling Mug

$$\begin{aligned} u\{mug\} - u\{mug\} &= \lambda\left[u\left\{\varnothing\right\} - u\{mug\}\right] + p_{WTA} \text{ or} \\ p_{WTA} &= \lambda u\{mug\} \end{aligned}$$

  - WTP: Status-Quo $\sim$ Buying Mug

$$\begin{aligned} u\left\{\varnothing\right\} - u\left\{\varnothing\right\} &= u\{mug\} - u\left\{\varnothing\right\} - p_{WTP} \text{ or} \\ p_{WTP} &= u\{mug\} \end{aligned}$$

  - It follows that

$$p_{WTA} = \lambda u\{mug\} = \lambda p_{WTP}$$

  - If loss-aversion over money,

$$p_{WTA} = \lambda^2 p_{WTP}$$

- Result $WTA \simeq 2 * WTP$ is consistent with loss-aversion $\lambda \simeq 2$
- Plott and Zeiler (*AER* 2005): The result disappears with
  - appropriate training
  - practice rounds
  - incentive-compatible procedure
  - anonymity

Pooled Data	WTP (n = 36)		6.62	6.00	4.20
	WTA (n = 38)		5.56	5.00	3.58

- What interpretation?

- Interpretation 1. Endowment effect and loss-aversion interpretation are wrong

  - Subjects feel bad selling a 'gift'

  - Not enough training

- Interpretation 2. In Plott-Zeiler (2005) experiment, subjects did *not* perceive the reference point to be the endowment

- Koszegi-Rabin: *Assume* reference point $(.5,\ \{mug\};\ .5,\ \{\varnothing\})$ in both cases

  - WTA:

$$\left[\begin{array}{c} .5 * [u\{mug\} - u\{mug\}] \\ +.5 * [u\{mug\} - u\{\varnothing\}] \end{array}\right] = \left[\begin{array}{c} .5 * \lambda [u\{\varnothing\} - u\{mug\}] \\ +.5 * [u\{\varnothing\} - u\{\varnothing\}] \end{array}\right] + p_{WTA}$$

  - WTP:

$$\left[\begin{array}{c} .5 * \lambda [u\{\varnothing\} - u\{mug\}] \\ +.5 * [u\{\varnothing\} - u\{\varnothing\}] \end{array}\right] = \left[\begin{array}{c} .5 * [u\{mug\} - u\{mug\}] \\ +.5 * [u\{mug\} - u\{\varnothing\}] \end{array}\right] - p_{WTP}$$

  - This implies no endowment effect:

$$p_{WTA} = p_{WTP}$$

- Notice: Open question, with active follow-up literature
  - Plott-Zeiler (*AER* 2007): Similar experiment with different outcome variable: Rate of subjects switching
  - Isoni, Loomes, and Sugden (*AER* 2010):
    * In Plott-Zeiler data, there is endowment effect for lotteries in training rounds on lotteries!
    * New experiments: for lotteries, mean WTA is larger than the mean WTP by a factor of between 1.02 and 2.19
- Rejoinder paper(s)?

- List (*QJE* 2003) – Further test of endowment effect and role of experience
- Protocol:
  - Get people to fill survey
  - Hand them memorabilia card A (B) as thank-you gift
  - After survey, show them memorabilia card B (A)
  - "Do you want to switch?"
  - "Are you going to keep the object?"
  - Experiments I, II with different object
- Prediction of Endowment effect: too little trade

- Experiment I with Sport Cards – Table II

TABLE II

SUMMARY TRADING STATISTICS FOR EXPERIMENT I: SPORTSCARD SHOW

Variable	Percent traded	p-value for Fisher's exact test
Pooled sample (n = 148)		
Good A for Good B	32.8	<0.001
Good B for Good A	34.6	
Dealers (n = 74)		
Good A for Good B	45.7	0.194
Good B for Good A	43.6	
Nondealers (n = 74)		
Good A for Good B	20.0	<0.001
Good B for Good A	25.6	

a. Good A is a Cal Ripken, Jr. game ticket stub, circa 1996. Good B is a Nolan Ryan certificate, circa 1990.
b. Fisher's exact test has a null hypothesis of no endowment effect.

- Experiment II with Pins – Table V

TABLE V

SUMMARY TRADING STATISTICS FOR EXPERIMENT II: PIN TRADING STATION

Variable	Percent traded	p-value for Fisher's exact test
Pooled sample (n = 80)		
Good C for Good D	25.0	<0.001
Good D for Good C	32.5	
Inexperienced consumers (<7 trades monthly; n = 60)	25.0	<0.001
Experienced consumers (≥7 trades monthly; n = 20)	40.0	0.26
Inexperienced consumers (<5 trades monthly; n = 50)	18.0	<0.001
Experienced consumers (≥5 trades monthly; n = 30)	46.7	0.30

- **Finding 1.** Strong endowment effect for inexperienced dealers
- How to reconcile with Plott-Zeiler?
  - Not training? No, nothing difficult about switching cards)
  - Not practice? No, people used to exchanging cards)
  - Not incentive compatibility? No
  - Is it anonymity? Unlikely
  - Gift? Possible
- **Finding 2.** Substantial experience lowers the endowment effect to zero
  - Getting rid of loss aversion?
  - Expecting to trade cards again? (Koszegi-Rabin, 2005)

- Objection 1: Is it experience or is it just sorting?
- Experiment III with follow-up of experiment I – Table IX

TABLE IX
SUMMARY STATISTICS FOR EXPERIMENT III: FOLLOW-UP SPORTSCARD SHOW

	Increased number of trades	Stable number of trades	Decreased number of trades
No trade in Experiment I; trade in Experiment III	13	1	2
No trade in Experiment I; no trade in Experiment III	8	7	11
Trade in Experiment I; Trade in Experiment III	4	0	0
Trade in Experiment I; No trade in Experiment III	2	0	5
N	27	8	18

a. Columns denote changes in subjects' trading experience over the year; rows denote subjects' behavior in the two field trading experiments.
b. Fifty-three subjects participated in both Experiment I and the follow-up experiment.

- Objection 2. Are inexperienced people indifferent between different cards?
- People do not know own preferences – Table XI

TABLE XI
SELECTED CHARACTERISTICS OF TUCSON SPORTSCARD PARTICIPANTS

	Dealers		Nondealers	
	WTA mean (std. dev.)	WTP mean (std. dev.)	WTA mean (std. dev.)	WTP mean (std. dev.)
Bid or offer	8.15	6.27	18.53	3.32
	(9.66)	(6.90)	(19.96)	(3.02)
Trading experience	16.67	15.78	4.00	3.73
	(19.88)	(13.71)	(5.72)	(3.46)
Years of market experience	10.23	10.57	5.97	5.60
	(5.61)	(8.13)	(5.87)	(6.70)

- Objection 3. What are people learning about?
- Getting rid of loss-aversion?
- Learning better value of cards?
- If do not know value, adopt salesman technique
- Is learning localized or do people generalize the learning to other goods?

- List (*EMA*, 2004): Field experiment similar to experiment I in List (2003)
- Sports traders but objects are mugs and chocolate
- Trading in four groups:
  1. Mug: "Switch to Chocolate?"
  2. Chocolate: "Switch to Mug?"
  3. Neither: "Choose Mug or Chocolate?"
  4. Both: "Switch to Mug or Chocolate?"

	Preferred Exchange	p-Value for Fisher's Exact Test
Panel D. Trading Rates		
Pooled nondealers (n = 129)	.18 (.38)	< .01
Inexperienced consumers (< 6 trades monthly; n = 74)	.08 (.27)	< .01
Experienced consumers (≥ 6 trades monthly; n = 55)	.31 (.47)	< .01
Intense consumers (≥ 12 trades monthly; n = 16)	.56 (.51)	.64
Pooled dealers (n = 62)	.48 (.50)	.80

- Large endowment effect for inexperienced card dealers
- No endowment effect for experienced card dealers!
- Learning (or reference point formation) generalizes beyond original domain
- More recent evidence: Ericson and Fuster (QJE 2011)

7 Methodology: Effect of Experience

- Effect of experience is debated topic
- Does Experience eliminate behavioral biases?
- Argument for 'irrelevance' of Psychology and Economics
- Opportunities for learning:
  - Getting feedback from expert agents
  - Learning from past (own) experiences
  - Incentives for agents to provide advice
- This will drive away 'biases'

- However, four arguments to contrary:

  1. Feedback is often infrequent (house purchases) and noisy (financial investments) –> Slow convergence

  2. Feedback can exacerbate biases for non-standard agents:

     – Ego-utility (Koszegi, 2001): Do not want to learn

     – Learn on the wrong parameter

     – See Haigh and List (2004) below

3. No incentives for Experienced agents to provide advice

   – Exploit naives instead

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

4. No learning on preferences:

   – Social Preferences or Self-control are non un-learnt

   – Preference features as much as taste for Italian red cars (undeniable)

- Empirically, four instances:

- **Case 1. Endowment Effect**. List (2003 and 2004)

  - Trading experience –> Less Endowment Effect

  - Effect applies across goods

  - Interpretations:

    * Loss aversion can be un-learnt

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

- **Case 2. Nash Eq. in Zero-Sum Games.**
- Palacios-Huerta-Volij (*EMA* 2008): Soccer players practice –> Better Nash play
- Idea: Penalty kicks are practice for zero-sum game play

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

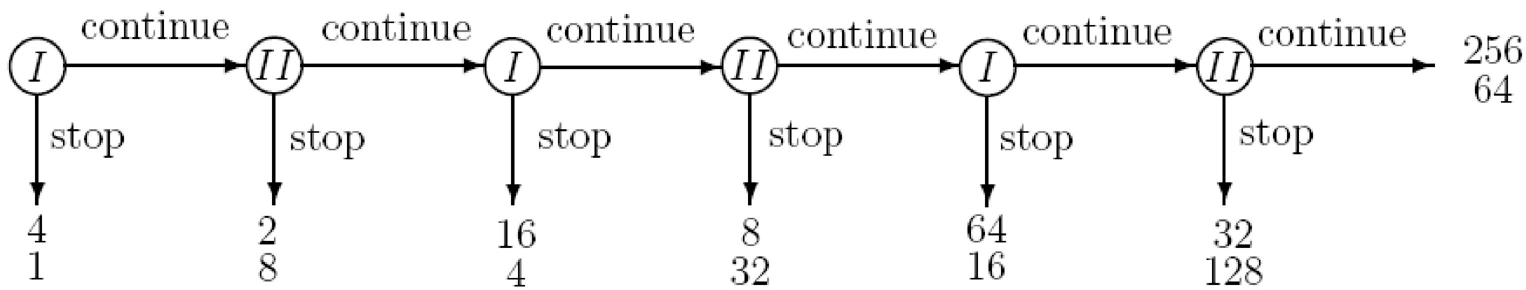
- How close are players to the Nash mixed strategies?
- Compare professional (2nd League) players and college students – 150 repetitions

Table E - Summary Statistics in Penalty Kick's Experiment

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

- Surprisingly close on average
- More deviations for students –> Experience helps (though people surprisingly good)
- However: Levitt-List-Reley (*EMA* 2010): Replicate in the US
  - Soccer and Poker players, 150 repetition
  - No better at Nash Play than students
- Maybe hard to test given that even students are remarkably good

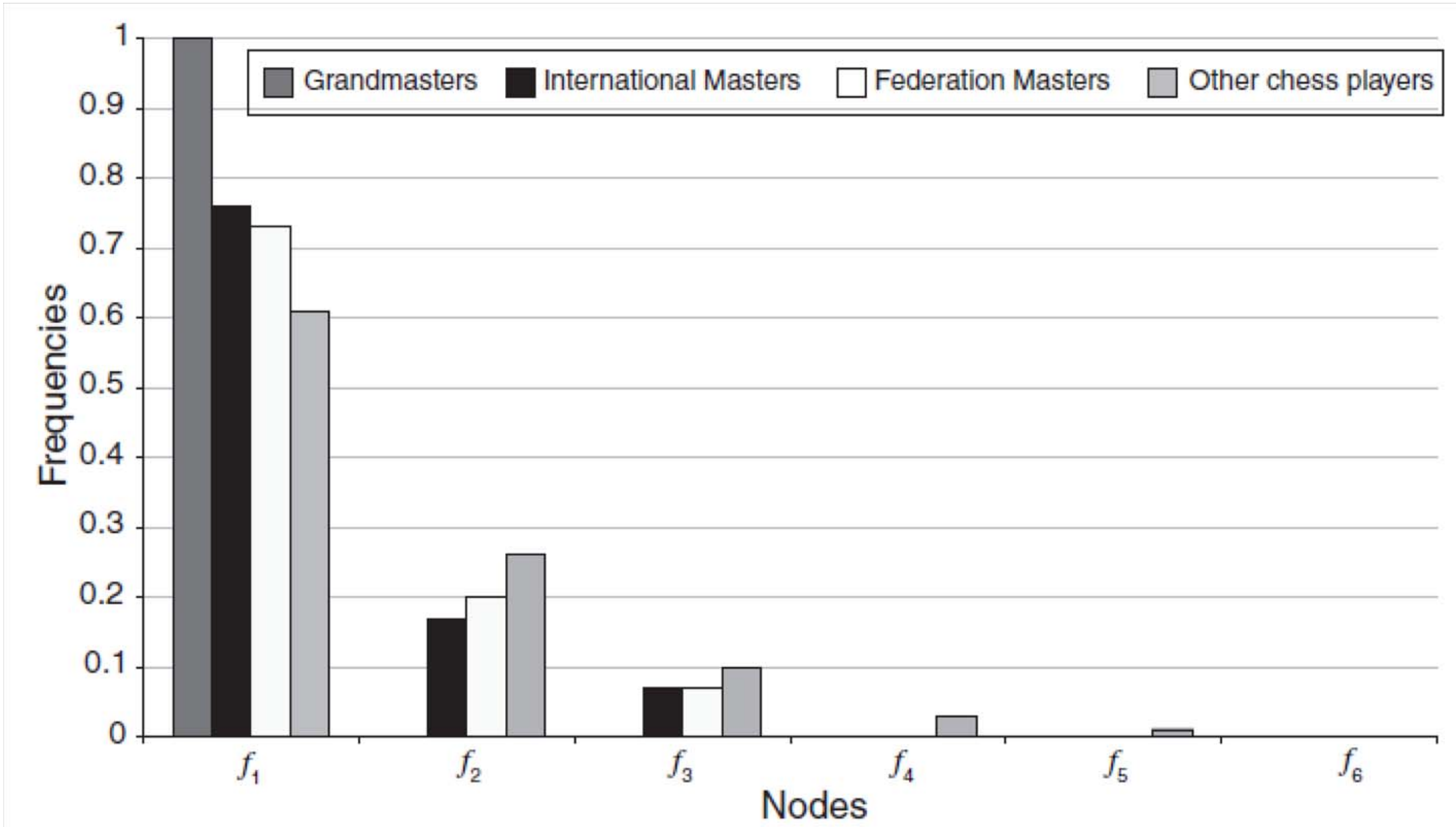
- **Case 3. Backward Induction.** Palacios-Huerta-Volij (*AER* 2009)



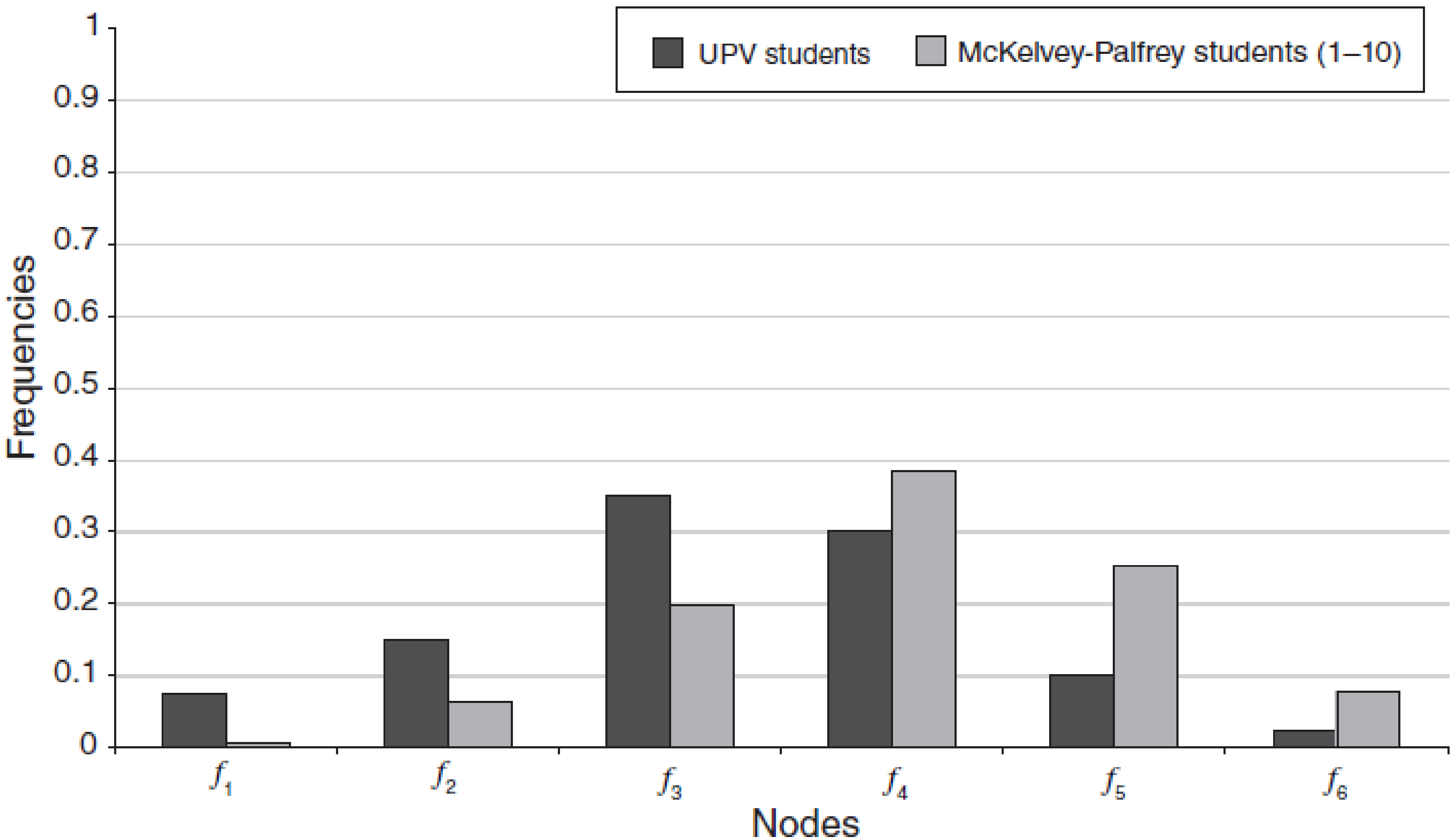
- Play in centipede game
  - Optimal strategy (by backward induction) –> Exit immediately
  - Continue if
    - No induction
    - Higher altruism
- Test of backward induction: Take Chess players

- 211 pairs of chess players at Chess Tournament
- Randomly matched, anonymity
- 40 college students
- Games with SMS messages

- Results:
  - Chess Players end sooner
  - More so the more experience



Grandmasters
International Masters
Federation Masters
Other chess players
Frequencies
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
f_1
f_2
f_3
f_4
f_5
f_6
Nodes


UPV students
McKelvey-Palfrey students (1–10)
Frequencies
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
f_1
f_2
f_3
f_4
f_5
f_6
Nodes

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

- Laboratory experiment (added after the initial study)
  - Recruit students and chess players (not masters) in Bilbao
  - Create 2*2 combinations, with composition common knowledge

TABLE 5—PROPORTION OF OBSERVATIONS AND IMPLIED STOP PROBABILITIES AT EACH TERMINAL NODE

	Session	N	f_1	f_2	f_3	f_4	f_5	f_6	f_7
Panel A: Proportion of observations f_i									
I. Students versus students	1	100	0.04	0.15	0.40	0.27	0.13	0.01	0
	2	100	0.02	0.18	0.28	0.33	0.14	0.04	0.01
	Total 1–2	200	0.030	0.165	0.340	0.300	0.135	0.025	0.005
II. Students versus chess players	3	100	0.28	0.36	0.19	0.11	0.06	0	0
	4	100	0.32	0.37	0.22	0.07	0.02	0	0
	Total 3–4	200	0.300	0.365	0.205	0.090	0.040	0	0
III. Chess players versus students	5	100	0.37	0.26	0.22	0.09	0.06	0	0
	6	100	0.38	0.29	0.17	0.10	0.06	0	0
	Total 5–6	200	0.375	0.275	0.195	0.095	0.060	0	0
IV. Chess players versus chess players	7	100	0.69	0.19	0.11	0.01	0	0	0
	8	100	0.76	0.16	0.07	0.01	0	0	0
	Total 7–8	200	0.725	0.175	0.090	0.010	0	0	0

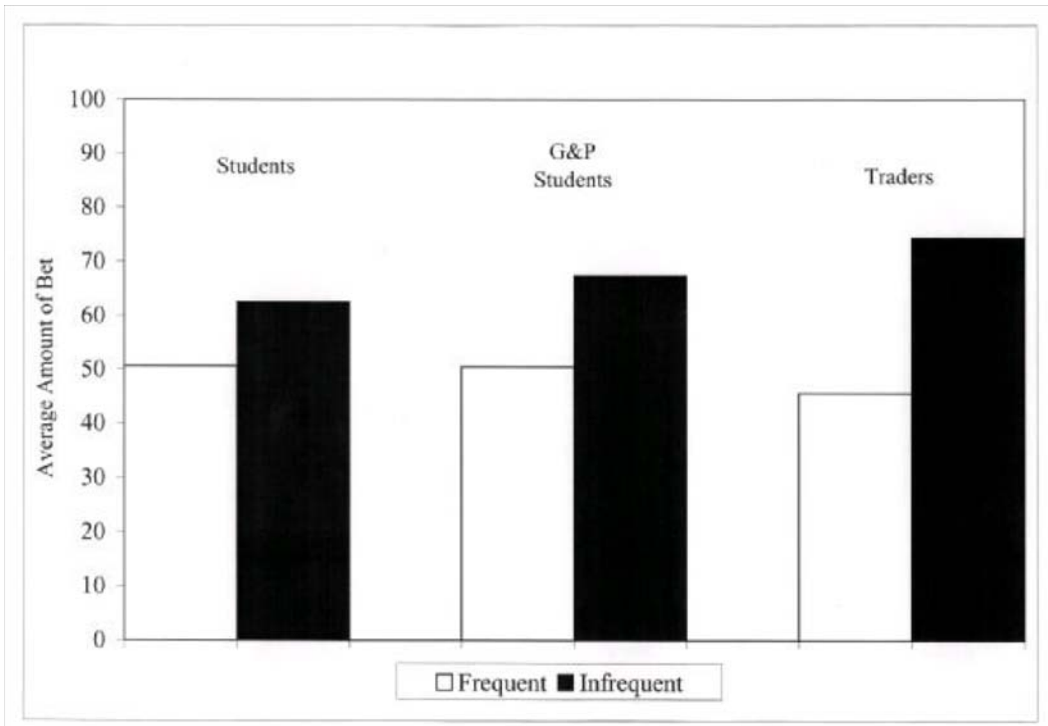
- Mixed groups exhibit very different behavior
- Possibility 1: Social preferences I
  - Students care less about chess players than about other students
  - Chess players care more about students than about other chess players
  - Part 2 is very unlikely
- Possibility 2: Social Preferences II
  - Belief that students are more reciprocal
- Possibility 3: Knowledge of rationality matters
  - It is common knowledge that chess players stop early, and that students stop late

- Where exactly does this belief come from?

- Would be useful to compute whether strategies employed are profit-maximizing against opponent strategies

- **Case 4. Myopic Loss Aversion.**
- Lottery: 2/3 chance to win 2.5X, 1/3 chance to lose X
  - Treatment F (Frequent): Make choice 9 times
  - Treatment I (Infrequent): Make choice 3 times in blocks of 3
- Standard theory: Essentially no difference between F and I
- Prospect Theory with Narrow Framing: More risk-taking when lotteries are chosen together —> Lower probability of a loss
- Gneezy-Potters (*QJE*, 1997): Strong evidence of myopic loss aversion with student population

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



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