Econ 219B
Psychology and Economics: Applications
(Lecture 9)

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Outline

1. Social Pressure II: Charitable Giving
2. Signaling
3. Non-Standard Beliefs
4. Overconfidence
5. Law of Small Numbers
6. Projection Bias

1 Social Pressure II: Charitable Giving

- **DellaVigna, Malmendier, and List (2012)**

This Paper

- Model of giving with altruism and social pressure
  - Consumer may receive advance notice of fundraiser
  - Consumer can avoid (or seek) fundraiser at a cost
  - Consumer decides whether to give (if at home)
- Field experiment: door-to-door fundraiser
  - Control group: standard fundraiser
  - Flyer Treatment: flyer on doorknob on day before provides advance notice about hour of visit
  - Opt-Out Flyer Treatment: flyer with box “do not disturb”

Flyer Layout with and without Opt-Out

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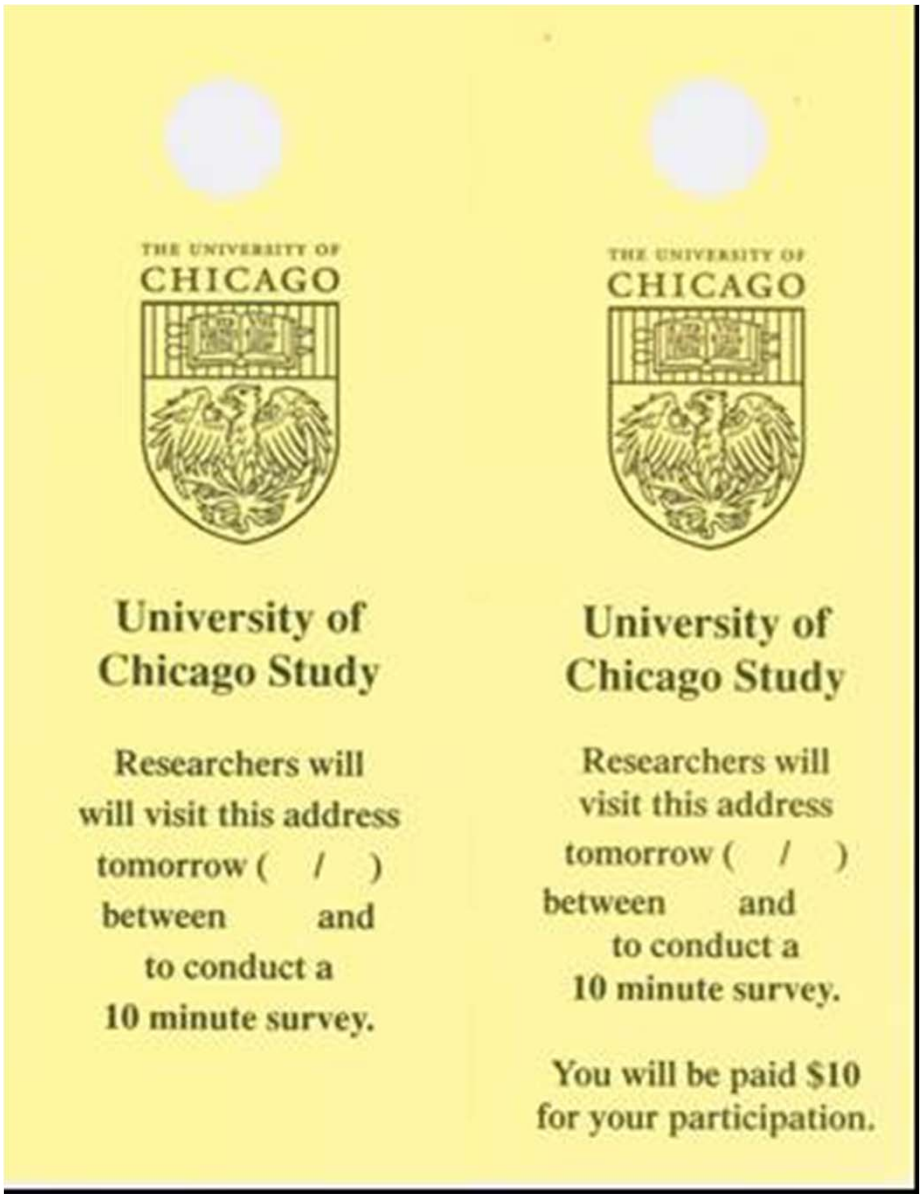
  - Flyer Treatment: flyer on doorknob on day before provides advance notice about hour of visit
  - Opt-Out Flyer Treatment: flyer with box "do not disturb"
  - Survey Treatments: Administer surveys with varying payment and duration and with or without flyers → to structurally estimate parameters.

Survey Flyers



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University of Chicago Study

Researchers will will visit this address tomorrow (/) between and to conduct a 10 minute survey.

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University of Chicago Study

Researchers will visit this address tomorrow (/) between and to conduct a 10 minute survey.

You will be paid $10 for your participation.

- **Model**

- Giving game with giver and fund-raiser. Timing:
  - *Stage 1*:
    - No Flyer: Giver at home with probability $h = h_0$
    - Flyer:
      - Giver sees flyer with probability r
      - Can alter probability of being at home h from baseline h_0 at cost $c(h)$, with $c(h_0) = 0$, $c'(h_0) = 0$, and $c''(\cdot) > 0$
  - *Stage 2*:
    - Fund-raiser visits home of giver:
      - If giver at home (w/ prob. h), in-person donation $g^* \geq 0$
      - If saw flyer (w/ prob. r), donation via mail $g_m^* \geq 0$

- Utility function of giver:

$$U(g) = u(W - g - g_m) + av(g + \theta g_m, G_{-i}) - s(g)$$

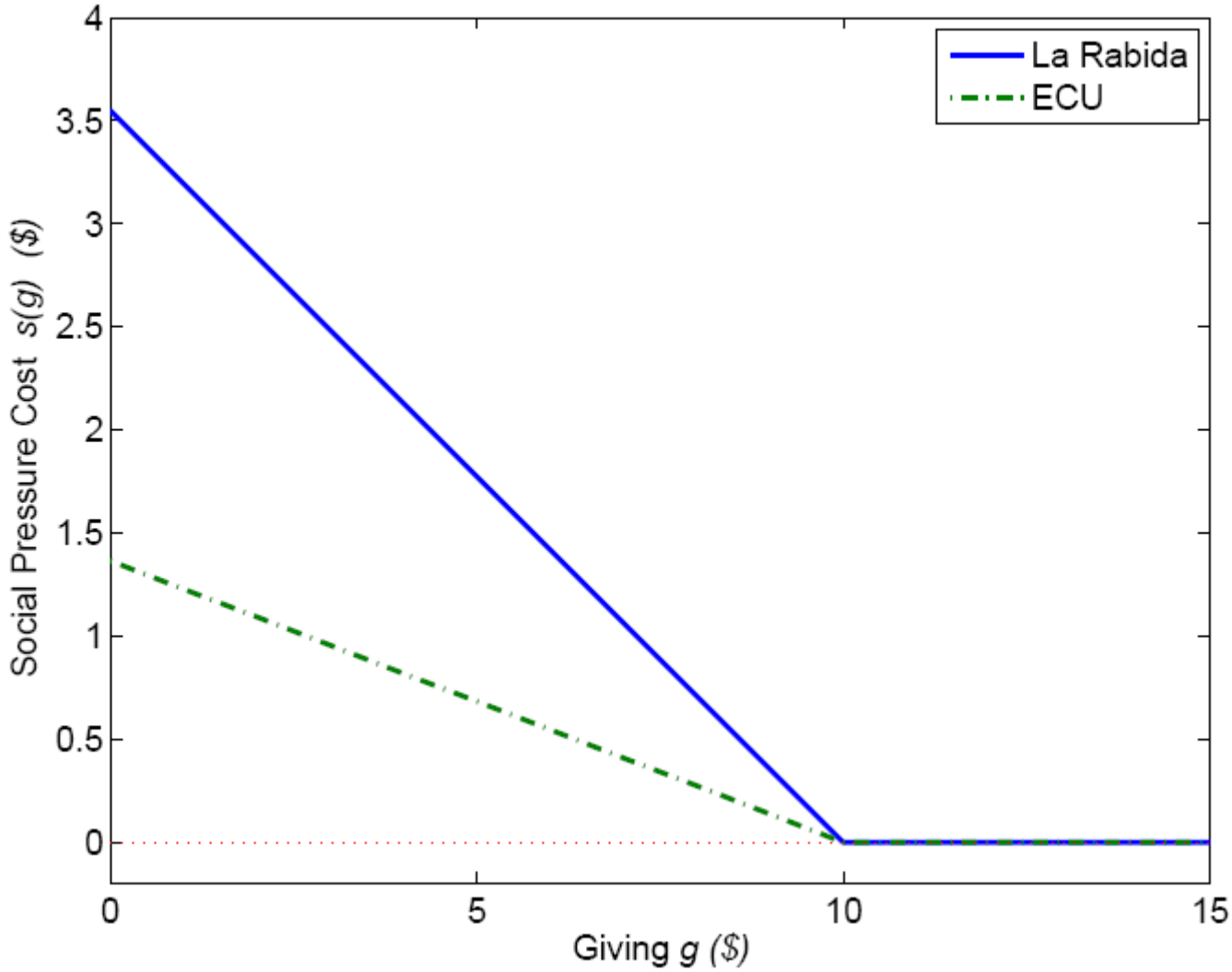
- Agent cares about:
  - Private consumption $u(W - g - g_m)$, with $u'(\cdot) > 0$ and $u''(\cdot) \leq 0$
  - Giving to charity $av(\cdot, G_{-i})$, with $v'_g(\cdot,\cdot) > 0$, $v''_{g,g}(\cdot,\cdot) < 0$, $\lim_{g\to\infty} v'_g(g,\cdot) = 0$, and $v(0, G_{-i}) = 0$.

- Two special cases for $v(g, G_{-i})$:
  - *Pure altruism* (Charness and Rabin 2002, Fehr and Gächter, 2000): $v(g, G_{-i}) = v(g + \theta g_m + G_{-i})$, a is altruism parameter
  - *Warm glow* (Andreoni, 1989 and 1990): $v(g, G_{-i}) = v(g)$, a is weight on warm glow

- Giving via mail is less attractive ($\theta < 1$): less warm glow, cost of giving,...

- Social Pressure $s(g) = S(g^s - g) \cdot \mathbf{1}_{g<g^s} \geq 0$
  - Social pressure $s = 0$ if not at home or if giving $g \geq g^s$ (socially acceptable amount)
  - Social pressure $s > 0$ for giving $g < g^s$, decreasing in g
- Captures identity (Akerlof and Kranton, 2000), social norms, or self-signalling (Bodner and Prelec, 2002; Grossman, 2007)
- Psychology evidence:
  - Tendency to conformity and obedience (Milgram, 1952 and Asch, 1957)
  - Effect stronger for face-to-face interaction

Figure. Social Pressure Cost At Estimated Parameters

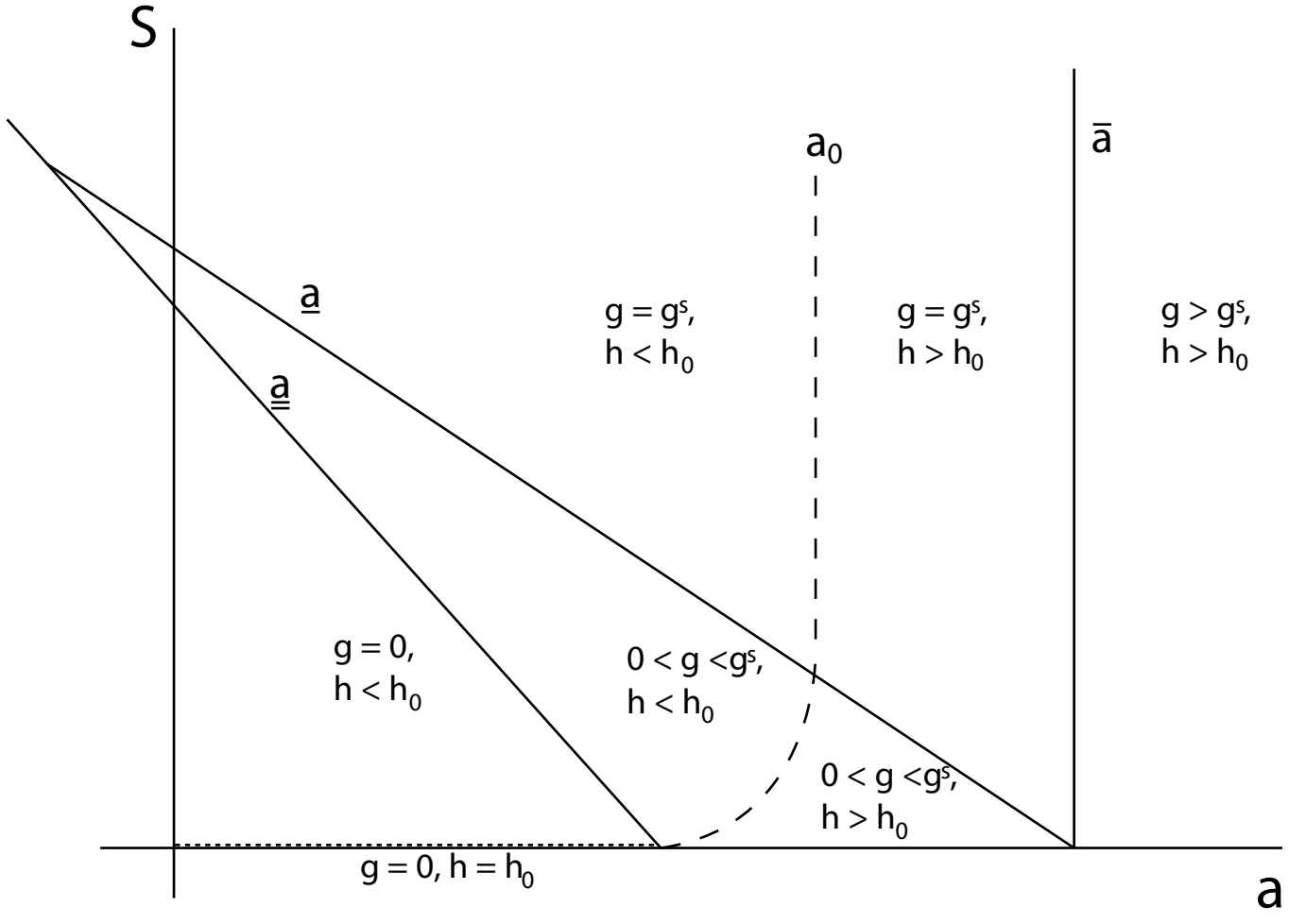


- **Second-stage Maximization (Giving)**

- **Lemma 1a. (Conditional Giving In Person).** *There is a unique optimal donation* $g^*(a, S)$ *(conditional on being at home), which is weakly increasing in* a *and takes the form: (i)* $g^*(a, S) = 0$ *for* $a \leq \underline{\underline{a}}$*; (ii)* $0 < g^*(a, S) < g^s$ *for* $\underline{\underline{a}} < a < \underline{a}$*; (iii)* $g^*(a, S) = g^s$ *for* $\underline{a} \leq a \leq \bar{a}$*; (iv)* $g^*(a, S) > g^s$ *for* $a > \bar{a}$*.*

- No giving via mail when at home

- **Lemma 1b (Conditional Giving Via Mail).** *There is a unique optimal donation via mail* $g_m^*(a)$ *(conditional on not being at home), which is weakly increasing in* a *and takes the form: (i)* $g_m^*(a) = 0$ *for* $a < a_m$*; (ii)* $g_m^*(a) > 0$ *for* $a \geq a_m$*; (iii) for all levels of* a*,* $g_m^*(a) \leq g^*(a; S)$*.*


S
a
a
a0
ā
g = gs,
h < h0
g = gs,
h > h0
g > gs,
h > h0
g = 0,
h < h0
0 < g <gs,
h < h0
0 < g <gs,
h > h0
g = 0, h = h0
a

- **First-Stage Maximization (Presence at Home)**

- Probability of being at home h:
  - **Control (NF) Treatment** $(r = 0)$: Exogenous, $h = h_0$
  - **Flyer (F) Treatment** $(r > 0)$: Choose $h \in [0, 1]$ at cost $c(h)$

- **Lemma 2 (Presence at Home).** *There is a unique optimal probability of being at home* $h^*(a, S)$
  - *For* $S = 0$ *(no social pressure),* $h^*(a, 0) = h_0$ *for* $a \leq \underline{\underline{a}}$ *and* $h^*(a, 0) > h_0$.
  - *For* $S > 0$ *(social pressure),* $h^*(a, S) < h_0$ *for* $a \leq \underline{\underline{a}}$*; there is unique* $a_0(S) \in (\underline{\underline{a}}, \bar{a})$ *such that* $h^*(a_0(S)) = h_0$.

- *Giving due to altruism* –> $h > h_0$ (Seek being at home)

- *Giving due to social pressure* –> $h < h_0$ (Avoid being at home)

- **Opt-Out (O) Treatment**
  - Flyer + Consumers can tell the charity not to disturb
  - Cost of probability of home:

$$C(h) = \begin{cases} 0 & \text{if} \quad h = 0 \\ c(h) & \text{if} \quad h > 0 \end{cases}$$

  - Still costly to remain at home, but no cost to keep charity out
  - (Notice: Never want to set $0 < h < h_0$)

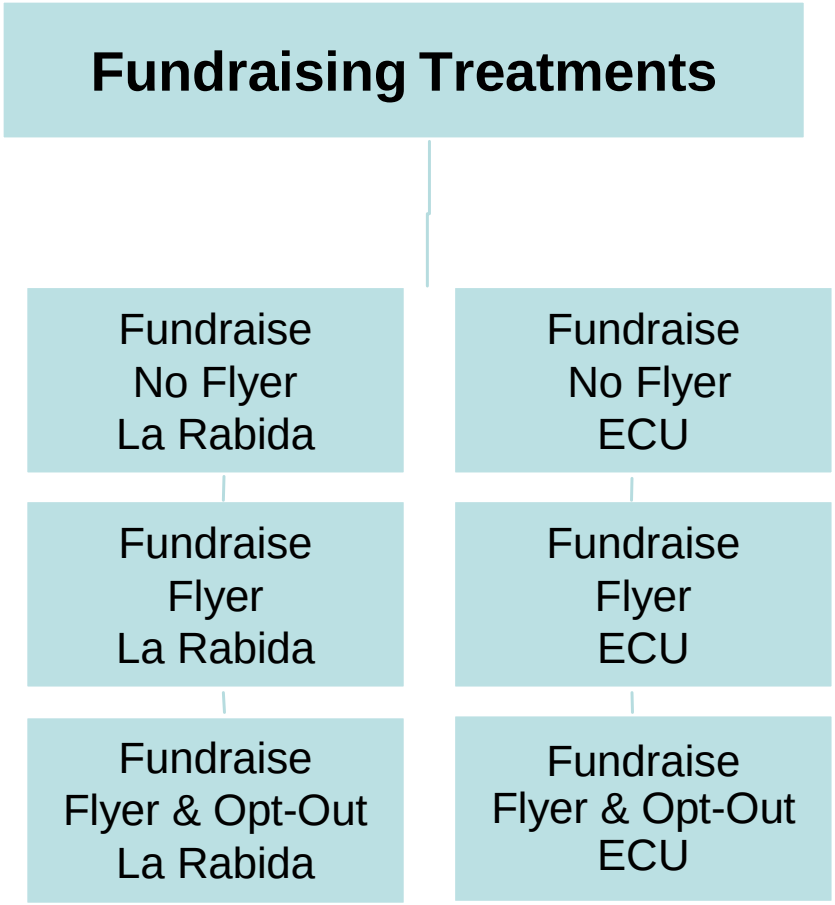
- **Lemma 3 (Opt-Out Decision).** *For $S = 0$ (no social pressure), the agent never opts out for any a. For $S > 0$ (social pressure), the agent opts out for sufficiently low altruism, $a < a_0(S)$.*

- Allow for heterogeneity in altruism a, with $a \sim F$

- Two special cases:
  - *Altruism and No Social Pressure* (*A-NoS*, $S = 0$ and $F\left(\underline{\underline{a}}\right) < 1$)
  - *Social Pressure and Limited Altruism* (*S-NoA*, $S > 0$ and $F\left(\underline{\underline{a}}\right) = 1$)

- **Proposition 1.** *The probability* $P(H)$ *of home presence is*
  - *A-NoS:* $P(H)_F = P(H)_{OO} > P(H)_{NF}$
  - *S-NoA:* $P(H)_{NF} > P(H)_F > P(H)_{OO}$

- **Proposition 2.** *The unconditional probability* $P(G)$ *of giving is*
  - *A-NoS:* $P(G)_F = P(G)_{OO} > P(G)_{NF}$
  - *S-NoA:* $P(G)_{NF} > P(G)_F > P(G)_{OO}$


Fundraising Treatments
Fundraise
No Flyer
La Rabida
Fundraise
Flyer
La Rabida
Fundraise
Flyer & Opt-Out
La Rabida
Fundraise
No Flyer
ECU
Fundraise
Flyer
ECU
Fundraise
Flyer & Opt-Out
ECU

Experimental Design

- Recruitment and Training: 48 solicitors and surveyors
  - undergraduate students at the University of Chicago, UIC, and Chicago State University
  - Interviewed, trained at UoC
  - aware of different charities but not of treatment
- Time and Place:
  - Saturdays and Sundays between April, 2008 and October, 2008
  - Hours between 10am and 5pm
  - Towns around Chicago: Burr Ridge, Flossmoor, Kenilworth, Lemont, Libertyville, Oak Brook, Orland Park, Rolling Meadows, and Roselle
- Randomization
  - within a solicitor-day observations (4h/6h shifts per day) and
  - at the street level within a town
- Different treatments in different periods ➔ randomization is conditional on solicitor and day fixed effects

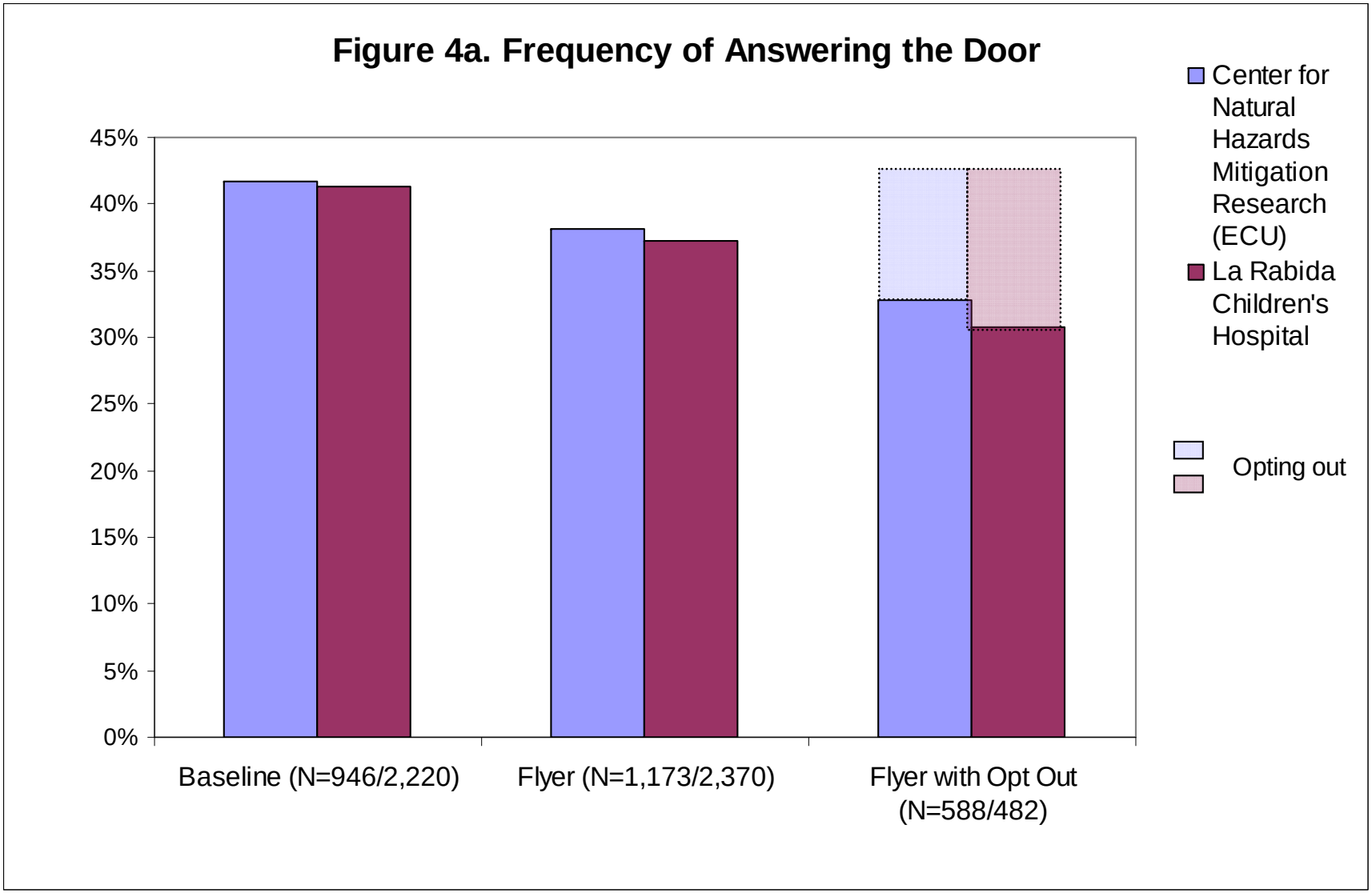


Figure 4a. Frequency of Answering the Door
45%
40%
35%
30%
25%
20%
15%
10%
5%
0%
Baseline (N=946/2,220)
Flyer (N=1,173/2,370)
Flyer with Opt Out (N=588/482)
Center for Natural Hazards Mitigation Research (ECU)
La Rabida Children's Hospital
Opting out

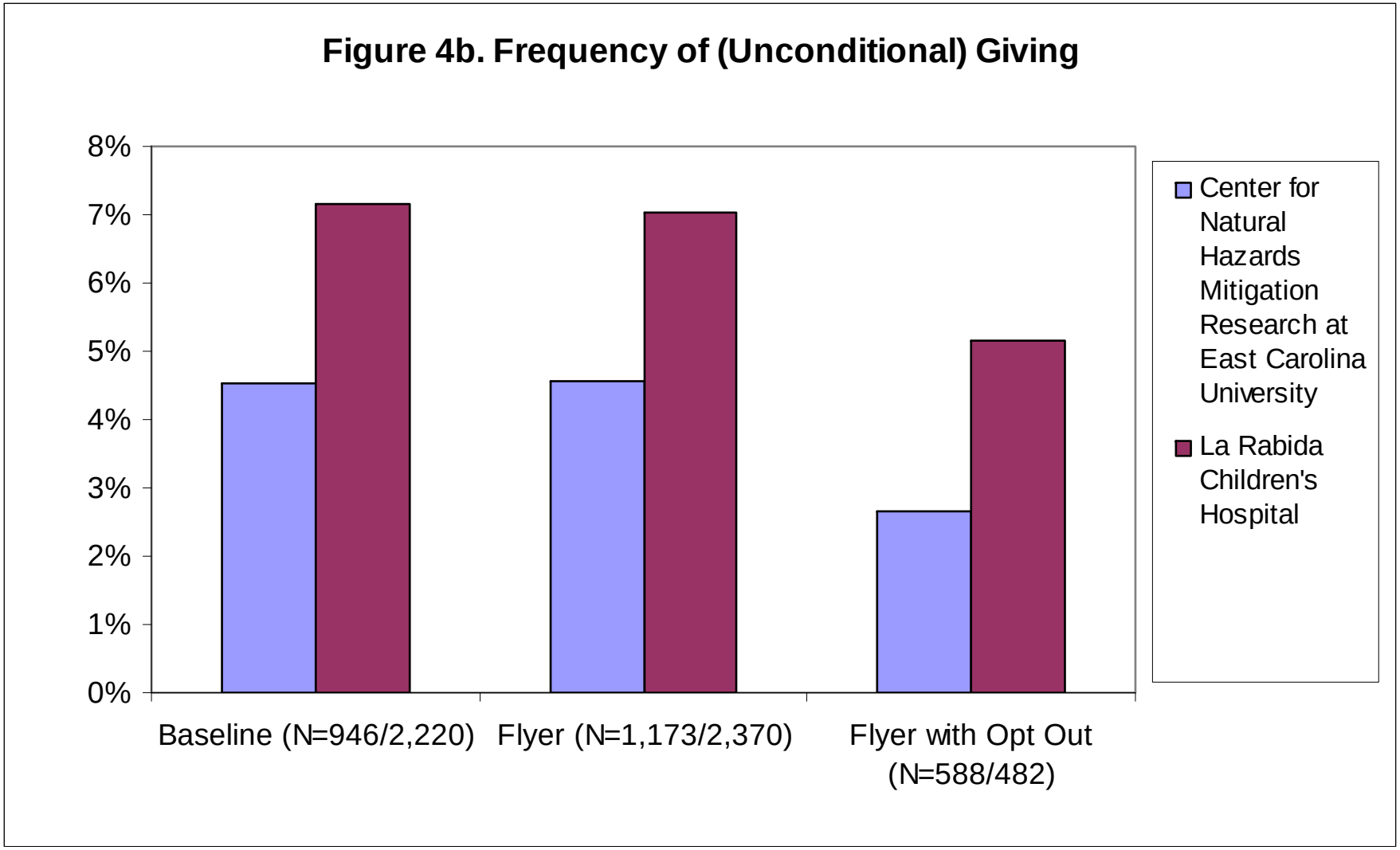


Figure 4b. Frequency of (Unconditional) Giving
8%
7%
6%
5%
4%
3%
2%
1%
0%
Baseline (N=946/2,220)
Flyer (N=1,173/2,370)
Flyer with Opt Out (N=588/482)
Center for Natural Hazards Mitigation Research at East Carolina University
La Rabida Children's Hospital

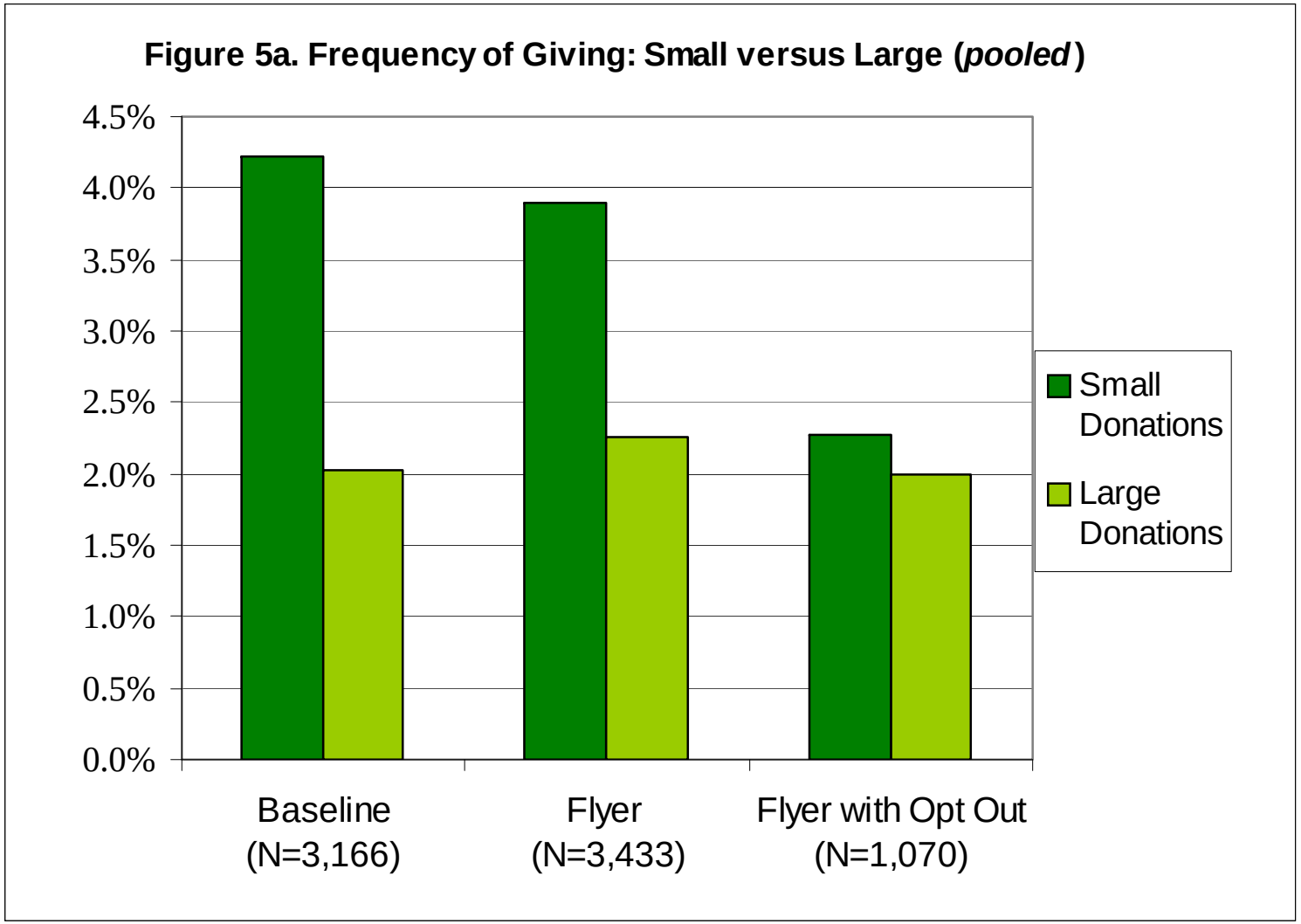
Table 2. Results for Fund-Raising Treatments

Specification:	OLS Regressions			
Dep. Var.:	Indicator for Answering the Door		Indicator for Giving	
	(1)	(2)	(3)	(4)
Flyer Treatment	-0.0388 (0.0137)***		-0.0009 (0.0062)	
Flyer with opt out Treatment	-0.0966 (0.0193)***		-0.0197 (0.0083)**	
Flyer Treatment * ECU Charity		-0.0365 (0.0313)		0.0006 (0.0094)
Flyer with opt out * ECU Charity		-0.089 (0.0271)***		-0.0183 (0.0100)*
Flyer Treatment * La Rabida Charity		-0.0396 (0.0144)***		-0.0019 (0.0078)
Flyer with opt out * La Rabida Charity		-0.106 (0.0319)***		-0.0202 (0.0132)
Indicator ECU Charity		0.0041 (0.0234)		-0.0263 (0.0085)***
Omitted Treatment	No-Flyer	No-Flyer, La Rabida	No-Flyer	No-Flyer, La Rabida
Mean of Dep. Var. for Omitted Treatment	0.4151	0.413	0.0629	0.0717
Fixed Effects for Solicitor, Date-Location, Hour, and Area Rating	X	X	X	X
N	N = 7668	N = 7668	N = 7668	N = 7668

•**Evidence by Donation Size:**

Social pressure more likely to yield small donations

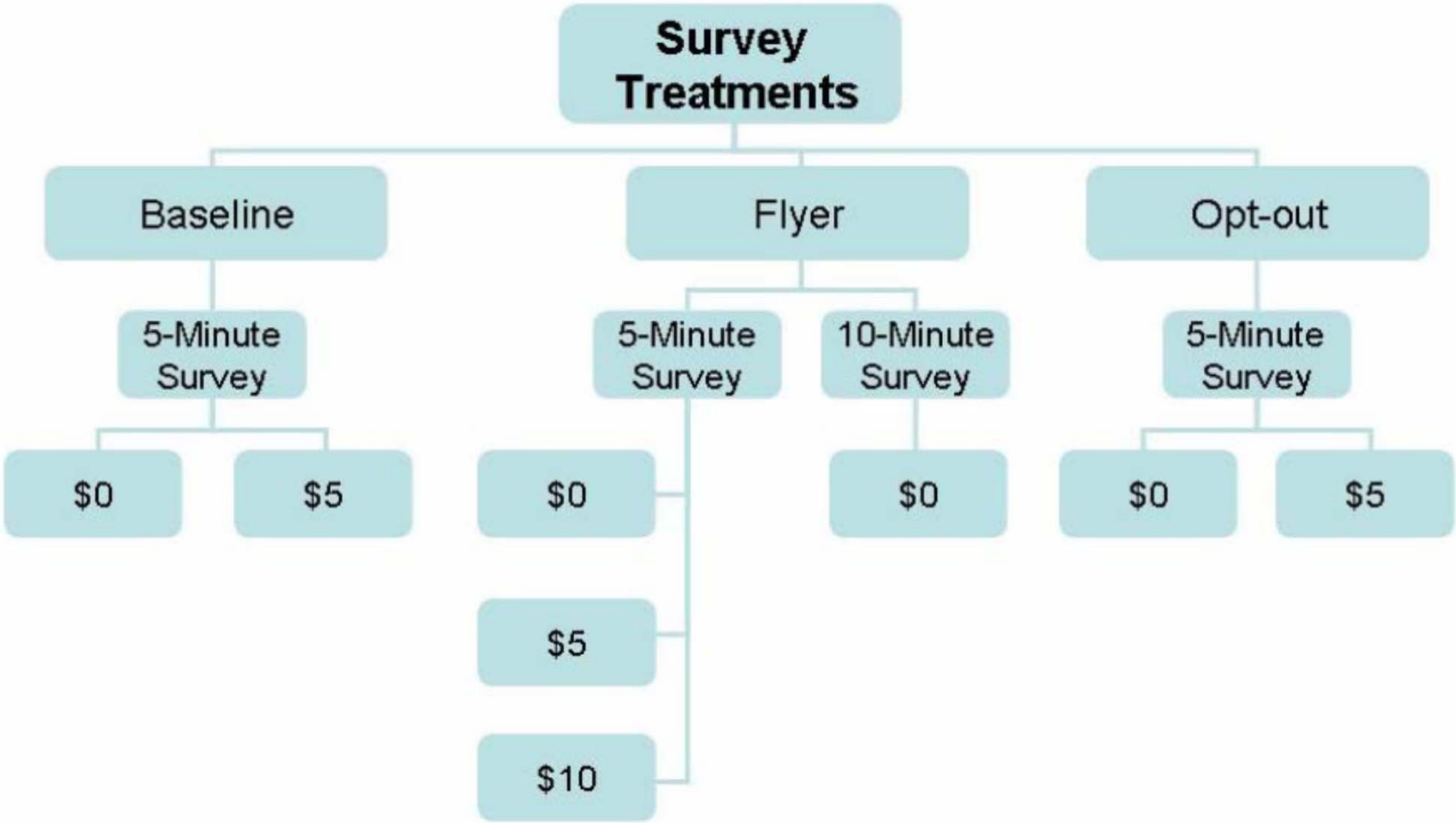
Use median donation size ($10) as cut-off point

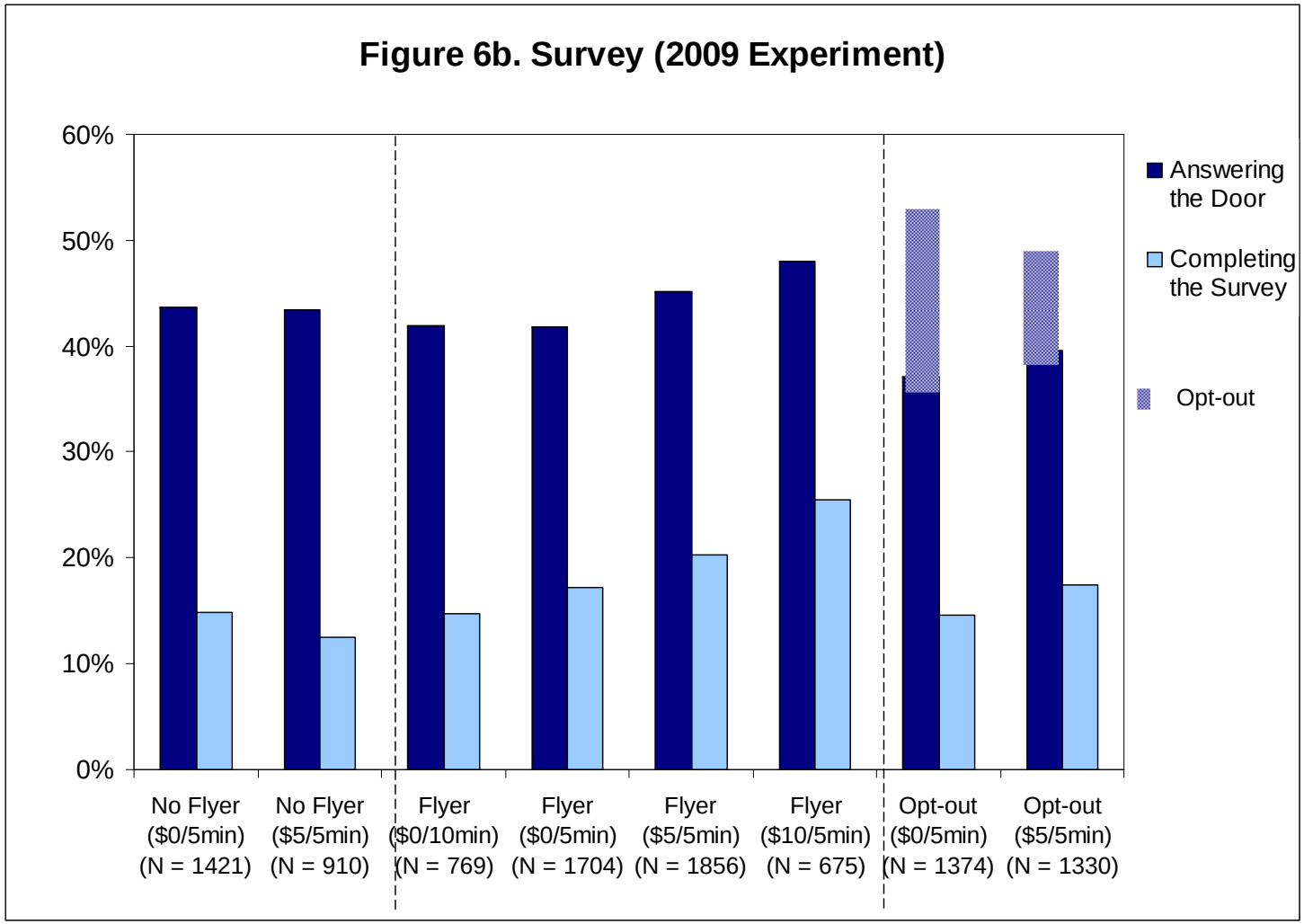


Survey Treatments

- Results of fundraiser do not easily allow the estimation of altruism and social pressure parameters
  - Unobserved cost of adjustment *c(h)*
- Solution: estimate elasticity with respect to monetary incentives
- Survey treatments with varying compensation and duration
- Treatments run in 2008 and 2009

Figure 2b. Summary of Door-to-Door Experimental Treatments Run in 2009





- **Survey Results (2009, N = 10,032)**

Higher payment (lower duration)

increases proportion at home monotonically

increases survey completion monotonically (except in NF)

- **Structural estimates (Minimum-distance estimator)**

- Minimize distance between predicted moments $m(\vartheta)$ and observed ones $\hat{m}$:

$$\min_{\vartheta} (m(\vartheta) - \hat{m})' W (m(\vartheta) - \hat{m})$$

- Moments $m(\vartheta)$:
  1. Probability of opening the door $(P(H)_j^c,\ j = F, NF, OO,\ c = LaR, Ecu)$
  2. Probability of checking opt-out box $(P(OO)_{OO}^c,\ c = LaR, Ecu)$
  3. Probability of giving at all, and giving an amount range $(P(G)_j^c,\ j = F, NF, OO,\ c = LaR, Ecu)$
  4. Probability of opening door in survey $(P(H)_j^S)$
  5. Probability of filling survey $(P(S)_j^S)$

- Weighting matrix W diagonal of inverse of variance-covariance matrix

- Parametric assumption to estimate the model:
  1. Consumption utility linear: $u(W-g) = W - g$
  2. Altruism function $av(g, G_{-i}) = a \log(G+g)$
  3. Altruism a is distributed $N(\mu, \sigma)$
  4. Acceptable donation $g^S =$ \$10 (median)
  5. Cost function $c(h) = (h - h_0)^2 / 2\eta$
  6. No mail giving ($\theta = 0$)

- Marginal utility of giving: $a/(G+g) - 1$

- Parameters ϑ:
  1. h_0^{2008} and h_0^{2009}—probability of being at home in no-flyer conditions
  2. r—probability of observing and remembering the flyer
  3. η—responsiveness of the probability of being at home to the utility of being at home
  4. μ_a^c $(c = LaR, Ecu)$—mean of the distribution F of the altruism α
  5. σ_α^c $(c = LaR, Ecu)$—standard deviation of $F(\alpha)$
  6. G—curvature of altruism/warm glow function
  7. S^c $(c = LaR, Ecu)$—social pressure associated with not giving
  8. μ^S—mean of the distribution F^S from which the utility of the survey is drawn
  9. σ^S—standard deviation of F^S
  10. S^S—social pressure associated with saying no
  11. v^S—value of an hour of time completing a survey

- Identification:
  - Prob. being at home h_0 <– Control group
  - Prob. seeing flyer r <– Share opting out
  - Utility of doing survey μ^S and σ^S <– Share completing survey
  - Value of time v^S <– Comparison of effect of \$10 payment and 5 minute duration
  - Elasticity of home presence η <– Share opening door in survey for different payments + Giving in charity
  - Altruism parameters μ^c, σ^c, G <– Given η, share giving different amounts
  - Social pressure parameters S^i and S^S <– Share opening door and giving

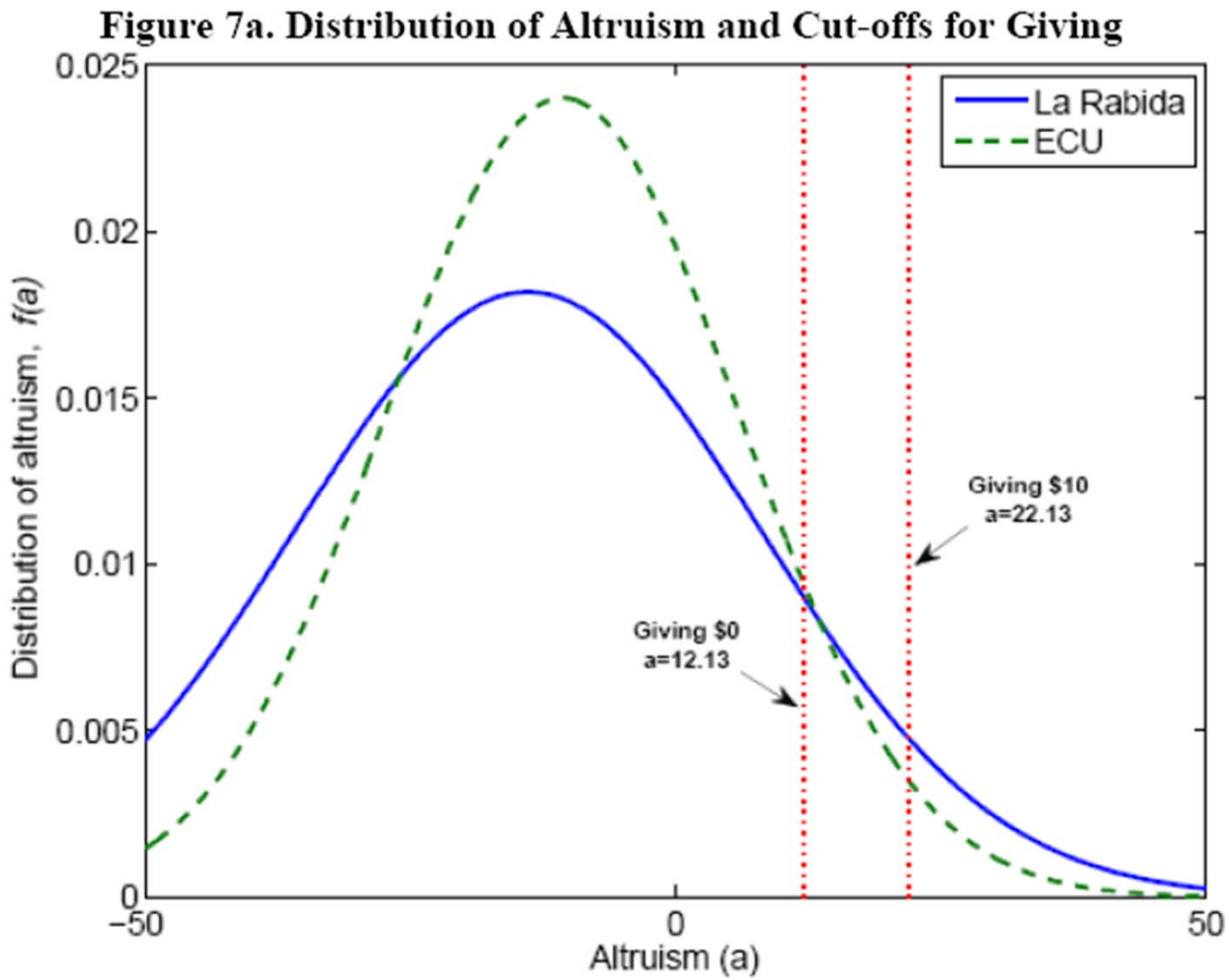
Appendix Table 1. Empirical Moments and Estimated Moments

Specification:	Minimum-Distance Estimates			
Charity	La Rabida Charity		ECU Charity	
Moments for Charity	Empirical Moments	Estimated Moments	Empirical Moments	Estimated Moments
Moments	(1)	(2)	(3)	(4)
P(Home) No Flyer	0.4130	0.4142	0.4171	0.4142
P(Home) Flyer	0.3733	0.3735	0.3806	0.3983
P(Home) Opt-Out	0.3070	0.2989	0.3281	0.2911
P(Opt Out) Opt-Out	0.1202	0.1142	0.0988	0.1179
P(Giving) No Flyer	0.0717	0.0666	0.0455	0.0422
P(Giving) Flyer	0.0699	0.0710	0.0461	0.0449
P(Giving) Opt-Out	0.0515	0.0633	0.0272	0.0390
Additional Moments (not shown)				
P(0<Giving<10), P(Giving=10), P(10<Giving<=20), P(20<Giving<=50), P(Giving>50) in Treatments NF, F, OO	X	X	X	X
N	N = 4962	N = 4962	N = 2707	N = 2707

Table 4. Minimum-Distance Estimates: Benchmark Results

	Benchmark Estimates		Estimates with Identity Weighting Matrix	
Common Parameters	(1)		(2)	
Prob. Answering Door (h) - Year 2008	0.414		0.414	
	(0.004)		(0.006)	
Prob. Answering Door (h) - Year 2009	0.449		0.445	
	(0.007)		(0.008)	
Prob. Observing Flyer (r)	0.322		0.302	
	(0.011)		(0.012)	
Elasticity of Home Presence (eta)	0.047		0.060	
	(0.014)		(0.031)	
Implied Cost of Altering Prob. Home by 10 pp.	0.106		0.083	
Survey Parameters				
Mean Utility (in $) of Doing 10-Minute Survey	-26.865		-26.936	
	(4.233)		(5.509)	
Std. Dev. of Utility of Doing Survey	30.285		30.332	
	(5.208)		(6.303)	
Value of Time of One-Hour Survey	74.580		76.761	
	(22.901)		(26.130)	
Social Pressure Cost of Saying No to Survey	4.784		3.869	
	(1.285)		(1.918)	
Charity Parameters	La Rabida	ECU	La Rabida	ECU
Mean Weight on Altruism Function (mu)	-13.910	-10.637	-13.586	-15.109
	(3.250)	(4.273)	(9.481)	(10.919)
Std. Dev. of Weight on Altruism Function	21.935	16.620	19.832	19.832
	(1.335)	(1.832)	(3.885)	(3.998)
Curvature of Altruism Function (G)	12.133		12.224	
	(5.147)		(15.518)	
Social Pressure Cost of Giving 0 in Person	3.550	1.364	3.140	1.906
	(0.615)	(0.744)	(1.674)	(1.475)

Implied distribution of altruism

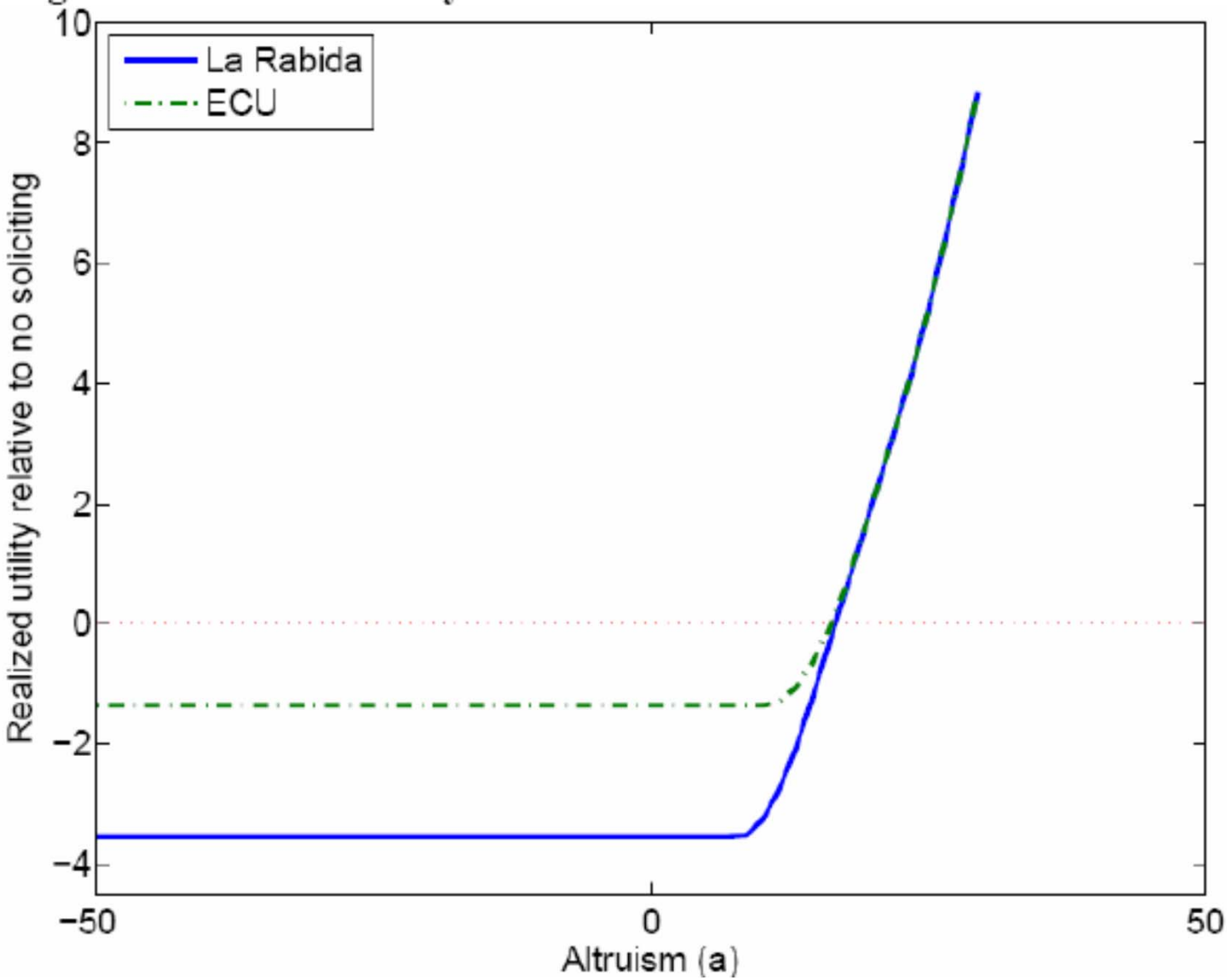


Marginal utility of giving (for $S = 0$) is $a/(G+g)-1$

Hence, give $g > 0$ if $a > G=12.13$

Welfare: Does a fund-raiser increase utility for the giver?

Figure 7b. Overall Utility of Fund-Raiser as function of Altruism



Welfare

1. Low-altruism households pay social pressure cost
2. High-altruism households get benefit
3. Since the former dominate, on net negative welfare for solicitee

Panel C. Welfare	**La Rabida Charity**	**ECU Charity**
Welfare in Standard (No-Flyer) Fund-Raiser		
Welfare per Household Contacted (in $)	-1.077 (0.160)	-0.439 (0.286)
Money Raised per Household Contacted	0.722 (0.036)	0.332 (0.046)
Money Raised per Household, Net of Salary	0.247 (0.036)	-0.143 (0.046)

- Societal welfare effect can still be positive if money used very well
  But amount of money raised small (negative for ECU)

Flyer and opt-out treatment increase solicitee welfare

Can also raise charity welfare (i.e., net fund-raising)

Panel C. Welfare	**La Rabida Charity**	**ECU Charity**
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Money Raised per Household Contacted	0.722 (0.036)	0.332 (0.046)
Money Raised per Household, Net of Salary	0.247 (0.036)	-0.143 (0.046)
Welfare in Fund-Raiser with Flier		
Welfare per Household Contacted (in $)	-0.924 (0.145)	-0.404 (0.273)
Money Raised per Household Contacted	0.859 (0.044)	0.333 (0.046)
Money Raised per Household, Net of Salary	0.248 (0.044)	-0.278 (0.046)
Welfare in Fund-Raiser with Opt-out		
Welfare per Household Contacted (in $)	-0.586 (0.085)	-0.248 (0.196)
Money Raised per Household Contacted	0.810 (0.045)	0.369 (0.055)
Money Raised per Household, Net of Salary	0.294 (0.036)	-0.147 (0.046)

2 Signaling

- **Signalling (Bodner and Prelec, 2002, Benabou and Tirole, 2004, 2006)**
  - Ego utility from thinking of self as generous
  - Individuals are unsure of (forget) their type
  - Infer type from own behavior in Bayesian way
  - Take into account signaling game in their actions
  - (Signaling can be to self or others)
- Idea:

- Individuals may behave pro-socially to signal to self (or others) that they are generous type
- Generates prediction of pro-social behavior (like other models)
- Unique prediction: behave less pro-socially if pro-social behavior is less diagnostic of generosity
- Crow-out of Intrinsic motivation (Deci 1971)

- Nice features:
  - Micro-founded: Bayesian updating, signaling
  - Ego utility very plausible

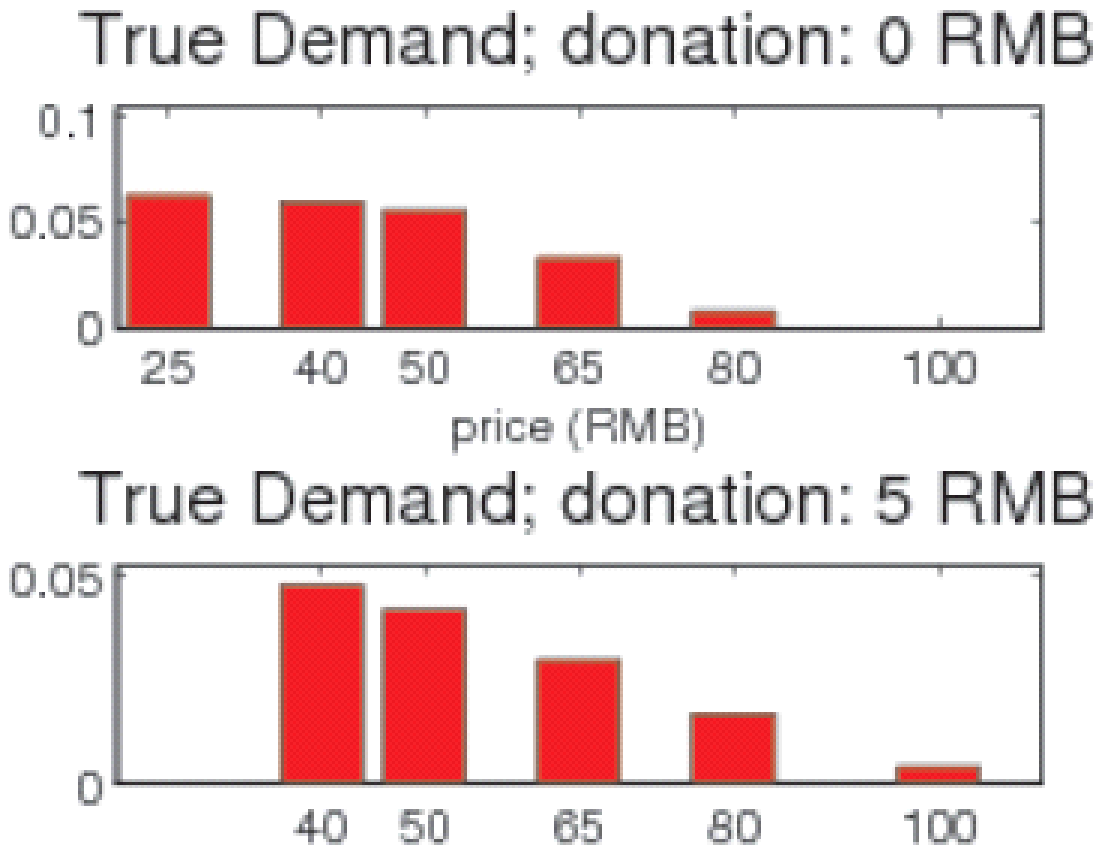
- Problems:
  - Hard to solve
  - Multiple equilibria possible
  - Hard to separate self-signaling from signaling to others

- Consider this in the context of **Dube, Luo, and Fang (2015)** paper on case-baed marketing
  - Send 30,000 SMS messages in China offering to buy movie ticket for 3-D version of *X-Men: Day of Future Past*
  - Standard price: 100 RMB
  - Randomize price discount: 0, 20, 35, 50, 60, 75 RMB
  - Cross-randomize charitable giving bundled with movie ticker purchase: "If you purchase ticket, X RMB will go to charity': 0, 5, 10, 15 RMB
  - Follow-up survey on motivation

- Sample sizes

Variable	Donation (RMB)				
discount (RMB)		**0**	**5**	**10**	**15**
	0	700	700	700	700
	20	700	1,000	1,000	1,000
	35	700	1,000	3,000	3,000
	50	700	1,000	3,000	3,000
	60	700	1,000	3,000	3,000
	75	700	-	-	-

- For low donation, monotonic effect of discount



- For high donation, non-monotonic effect of discount –> Crowd-out of motivation

- Striking result: Interpretation?

- Model adapted from Benabou-Tirole

- Part 1: Individual has consumption utility

$$V + \alpha p + \gamma a$$

  - V is utility from movie,
  - p is price of movie, α ($<$0) is price elasticity
  - a is donation, γ is (reduced-form) altruism
  - So far, standard model with altruism

- Part 2a: Ego utility on altruism:

$$\lambda_\alpha E\left(\alpha | a, p, y\right)$$

  - Individual derives utility from thinking of being altruistic (high a)
  - Weight on ego utillity is λ_a: for $\lambda_a = 0$, back to pure altruism case
  - Individual solves a signaling game to infer α given price p, discount a, and donation decision $y \in 0, 1$
  - Thus, donation ($y = 1$) has ego utility benefits, rasing $E\alpha$

- This is not enough: need Part 2b in Ego utility:

$$\lambda_\gamma E\left(\gamma | a, p, y\right)$$

  - Individual derives utility from thinking of self as stingy – or not
  - Why this term? There needs to be a signal extraction problem: giving can signal high generosity or low price elasticity
  - Unattractive part of Benabou and Tirole model

- Decision: Give $(y = 1)$ if

$$\begin{aligned} U(1) &= V + \alpha p + \gamma a + \lambda_\alpha E\left(\alpha | a, p, 1\right) + \lambda_\gamma E\left(\gamma | a, p, 1\right) \geq \\ U\left(0\right) &= \lambda_\alpha E\left(\alpha | a, p, 0\right) + \lambda_\gamma E\left(\gamma | a, p, 0\right) \end{aligned}$$

  or

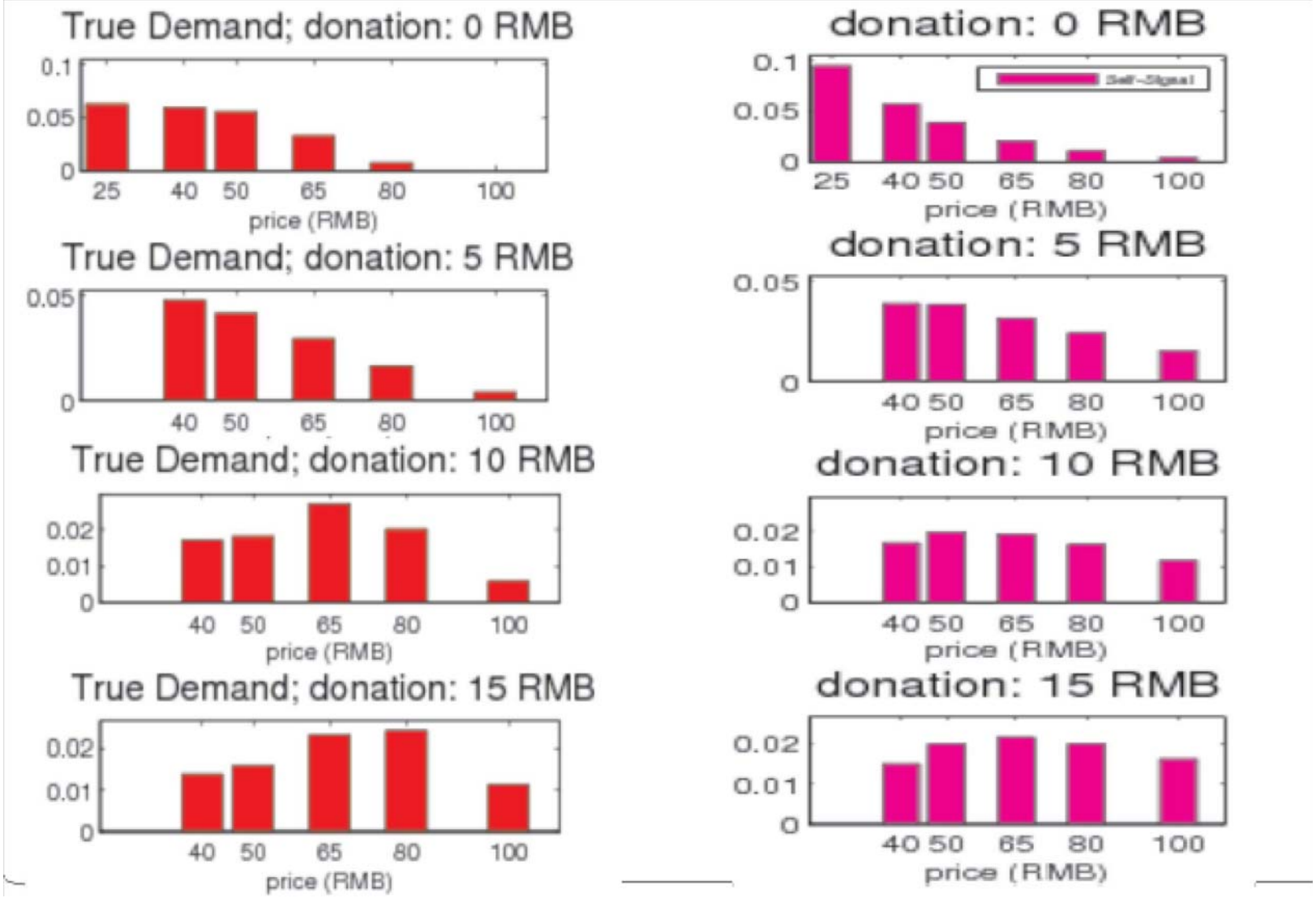
$$V + \alpha p + \gamma a + \Delta\left(a, p\right) > 0$$

  where Δ is net ego utility

- Updating on γ if purchase $(y = 1)$:

$$E\left(\gamma | \gamma > -\frac{V + \alpha p + \Delta\left(a, p\right)}{a}\right)$$

- Specify priors on parameters to derive separating equilibrium of signalling game


True Demand; donation: 0 RMB
0.1
0.05
0
25
40
50
65
80
100
price (RMB)
True Demand; donation: 5 RMB
0.05
0
40
50
65
80
100
True Demand; donation: 10 RMB
0.02
0.01
0
40
50
65
80
100
price (RMB)
True Demand; donation: 15 RMB
0.02
0.01
0
40
50
65
80
100
price (RMB)
donation: 0 RMB
0.1
0.05
0
25
40
50
65
80
100
price (RMB)
donation: 5 RMB
0.05
0
40
50
65
80
100
price (RMB)
donation: 10 RMB
0.02
0.01
0
40
50
65
80
100
price (RMB)
donation: 15 RMB
0.02
0.01
0
40
50
65
80
100
price (RMB)

- Remarkably good fit, but value of some parameters odd

- Relatedly: How much do you need ego utility on price elasticity: not obvious to interpret

$$\lambda_\gamma E\left(\gamma|a,p,y^h\right) + \lambda_\alpha E\left(\alpha|a,p,y^h\right)$$

- Relatedly: Estimation of some parameters appears problematic
  - Value V of good negative on average?

  (What if allow for not all to pay attention)
  - σ_α is at boundary

	coefficient	st. error
Donation ($\bar{\gamma}$)	-0.1411	0.1345
Price, ($\bar{\alpha}$)	-0.0183	0.0077
Intercept, ($\bar{V}$)	-0.8526	0.225
σ_γ	0.1327	0.0632
σ_α	0.0001	0.307
λ_γ	2.1948	0.7931
λ_α	-15.9831	3.452

3 Non-Standard Beliefs

- So far, focus on non-standard utility function $U\left(x_i^t|s_t\right)$ as deviations from standard model:

$$\max_{x_i^t \in X_i} \sum_{t=0}^{\infty} \delta^t \sum_{s_t \in S_t} p\left(s_t\right) U\left(x_i^t|s_t\right)$$

- Non-standard preferences
  - Self-Control Problems (β, δ)
  - Reference Dependence $(U\left(x_i^t|s_i, r\right))$
  - Social Preferences $(U\left(x_i, x_{-i}|s\right))$

- Today: Non-Standard Beliefs:

$$\max_{x_i^t \in X_i} \sum_{t=0}^{\infty} \delta^t \sum_{s_t \in S_t} \tilde{p}\left(s_t\right) U\left(x_i^t | s_t\right)$$

where $\tilde{p}\left(s_t\right)$ is the subjective distribution of states S_i for agent.

- Distribution for agent differs from actual distribution: $\tilde{p}\left(s_t\right) \neq p\left(s_t\right)$

- Three main examples:
  1. *Overconfidence*. Overestimate one's own skills (or precision of estimate): $\tilde{p}\left(good\ state_t\right) > p\left(good\ state_t\right)$
  2. *Law of Small Numbers.* Gambler's Fallacy and Overinference in updating $\tilde{p}\left(s_t | s_{t-1}\right)$
  3. *Projection Bias.* Expect future utility $\widetilde{U}\left(x_i^t | s_t\right)$ to be too close to today's

4 Overconfidence

- Overconfidence is of at least two types:
  - Overestimate one's ability (also called *overoptimism*)
  - Overestimate the precision of one's estimates (also called *overprecision*)

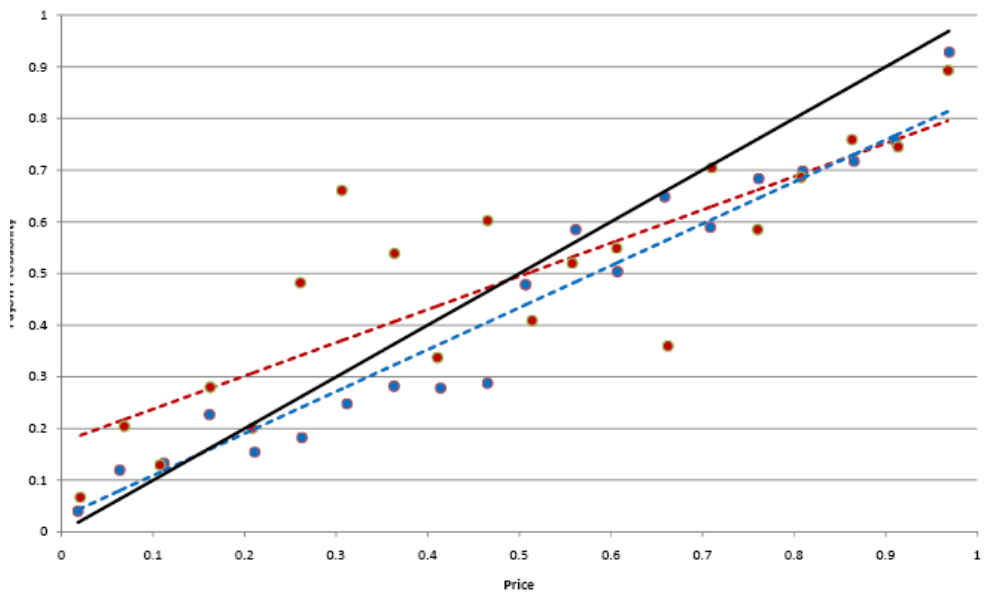
- Psychology: Evidence on overconfidence/overoptimism
  - **Svenson (1981):** 93 percent of subjects rated their driving skill as above the median, compared to the other subjects in the experiment
  - **Weinstein (1980):** Most individuals underestimate the probability of negative events such as hospitalization
  - **Buehler-Griffin-Ross (1994):** Underestimate time needed to finish a project

- Applications in the field of overconfidence/overoptimism

- **Example 1. Overconfidence about self-control by consumers ($\hat{\beta} > \beta$)**
  - Evidence on self-control supports idea of naiveté
    - Status-quo bias (Madrian-Shea, 1999)
    - Response to teaser rates (Ausubel, 1999)
    - Health-club behavior (DellaVigna-Malmendier, 2006)

- **Example 2. Overconfidence for employees: Cowgill, Wolfers, and Zitzewitz (2008)**
  - Prediction markets of Google employees (with raffle tickets for total of $10,000 per quarter in payoffs)
  - Data: years 2005-2007, 1,463 employees placed $\geq$ 1 trade

Figure 2. Prices and Probabilities in Two and Five-outcome Markets



Trades in two (red) and five-outcome (blue) markets (22,452and 42,416, respectively) are sorted into 20 bins according to price (i.e., 0-5, 5-10, etc.), and then average price and payoff probability for the bin is plotted. Dashed lines plot regression equations using OLS.

- – Securities not related to Google correctly priced on average
  - – Securities with implications for Google: Substantial overconfidence for two-outcome security, Less so for five-outcome security

Table 5. Optimistic bias in the Google markets

	Obs.	Avg price	Avg payoff	Return (SE)	
All markets	70,706	0.357	0.342	-0.015***	(0.003)
Markets with implication for Google	37,910	0.310	0.293	-0.017***	(0.004)
Two-outcome markets with implication for Google	9,023	0.509	0.492	-0.017***	(0.006)
Best outcome for Google	4,556	0.456	0.199	-0.256***	(0.063)
Worst	4,467	0.563	0.790	0.227***	(0.064)
Five-outcome markets with implication for Google	26,511	0.239	0.222	-0.017***	(0.005)
Best outcome for Google	5,592	0.244	0.270	0.027	(0.040)
2nd	5,638	0.271	0.246	-0.025	(0.066)
3rd	5,539	0.296	0.179	-0.118**	(0.053)
4th	5,199	0.206	0.178	-0.028	(0.041)
Worst	4,543	0.162	0.236	0.074	(0.056)

- Survey evidence suggests phenomenon general

- **Oyer and Schaefer, 2005; Bergman and Jenter, 2007**
  - Overconfidence of employees about own-company performance is leading explanation for provision of stock options to rank-and-file employees
  - Stock options common form of compensation: (Black and Scholes) value of options granted yearly to employees in public companies over $400 (about one percent of compensation) in 1999 (Oyer and Schaefer, 2005)
  - Incentive effects unlikely to explain the issuance: contribution of individual employee to firm value very limited
  - Overconfidence about own-company performance can make stock options an attractive compensation format for employers

- Overconfidence needs to be larger for employees than for top managers (problem set 2)
- Sorting contributes: Overconfidence plausible since workers overconfident about a company sort into it

- However, **Bergman and Jenter (2007):** employees can also purchase shares on open market, do not need to rely on the company providing them
  - Under what conditions company will still offer options to overconfident employees?
  - Also, why options and not shares in company?
  - **Bergman and Jenter (2007):** option compensation is used most intensively by company when employees more likely to be overconfident based on proxy (past returns)

- **Example 3. Overconfidence about ability by CEOs**

- **Malmendier-Tate (JF 2005 and JFE 2008)**

- Assume that CEOs overestimate their capacity to create value

- Implications for:
  - Investment decisions (MT 2005)
  - Mergers (MT 2008)
  - Equity issuance (MT 2010)

- Focus on merger implications

- Slides courtesy of Ulrike

Model

Assumptions

1. CEO acts in interest of current shareholders.
   (*No agency problem.*)

2. Efficient capital market.
   (*No asymmetric information.*)

Notation

V_A = market value of the acquiring firm
V_T = market value of the target firm
V = market value of the combined firm
$\hat{V}_A$ = acquiring CEO's valuation of his firm
$\hat{V}$ = acquiring CEO's valuation of the combined firm
c = cash used to finance the merger

Rational CEO

- Target shareholders demand share s of firm such that:

$$sV = V_T - c.$$

- CEO decides to merge if $V - (V_T - c) > V_A$ (levels).

  $\Rightarrow$ Merge if $e > 0$ (differences), where e is "synergies."

  $\Rightarrow$ First-best takeover decision.

- Post-acquisition value to current shareholders:

$$\overline{V} = V - (V_T - c) = (V_A + V_T + e - c) - (V_T - c) = V_A + e$$

$$\Rightarrow \frac{\partial \overline{V}}{\partial c} = 0 \text{ (}\textit{No financing prediction.}\text{)}$$

Overconfident CEO (I)

- CEO overestimates future returns to own firm:

$$\hat{V}_A > V_A$$

CEO overestimates returns to merger:

$$\hat{V} - V > \hat{V}_A - V_A$$

- Target shareholders demand share s of firm such that:

$$sV = V_T - c$$

CEO believes he should have to sell s such that:

$$s\hat{V} = V_T - c$$

Overconfident CEO (II)

- CEO decides to merge if

$$\hat{V} - (V_T - c) - \left[\frac{(\hat{V} - V)(V_T - c)}{V} \right] > \hat{V}_A \ (levels),$$

i.e. merges if

$$e + \hat{e} > \left[\frac{(\hat{V}_A - V_A + \hat{e})(V_T - c)}{V} \right] \ (differences),$$

where $\hat{e}$ are perceived "synergies."

Propositions

Compare

$$V(c) - (V_T - c) > V_A \quad \text{and}$$

$$\widehat{V}(c) - (V_T - c) - \frac{\left[\widehat{V}(c) - V(c)\right](V_T - c)}{V(c)} > \widehat{V}_A$$

1. Overconfident managers do some value-destroying mergers. (Rational CEOs do not.)
2. An overconfident manager does more mergers than a rational manager when internal resources are readily available
3. An overconfident manager may forgo some value-creating mergers. (Rational managers do not.)

Empirical Predictions

Rational CEO → Overconfident CEO

1. On average?
2. Overconfident CEOs do more mergers that are likely to destroy value
3. Overconfident CEOs do more mergers when they have abundant internal resources
4. The announcement effect after overconfident CEOs make bids is lower than for rational CEOs

Data

Data on private accounts

1. Hall-Liebman (1998)
   Yermack (1995)

Key: Panel data on stock and option holdings of CEOs of Forbes 500 companies 1980-1994

2. Personal information about these CEOs from
   - Dun & Bradstreet
   - Who's who in finance

Data on corporate accounts

1. CRSP/COMPUSTAT

   Cash flow, Q, stock price…

2. CRSP/SDC-merger databases

   Acquisitions

Primary Measure of Overconfidence

"Longholder"

(Malmendier and Tate 2003)

CEO holds an option until the year of expiration.

CEO displays this behavior at least once during sample period.

→ minimizes impact of CEO wealth, risk aversion, diversification

Robustness Checks:

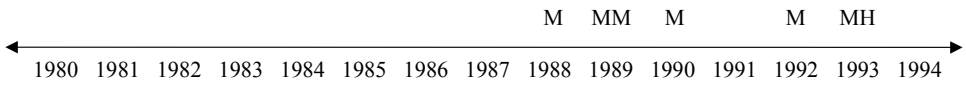
1. Require option to be at least *x*% in the money at the beginning of final year
2. Require CEO to *always* hold options to expiration
3. Compare "late exercisers" to "early exercisers"

Identification Strategy (I)

Case 1:

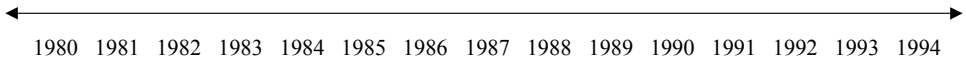
Wayne Huizenga (Cook Data Services/Blockbuster)

- CEO for all 14 years of sample
- Longholder



J Willard Marriott (Marriott International)

- CEO for all 15 years of sample
- Not a Longholder



AND

Case 2:

Colgate Palmolive

- Keith Crane CEO from 1980-1983 (Not a Longholder)
- Reuben Mark CEO from 1984-1994 (Longholder)

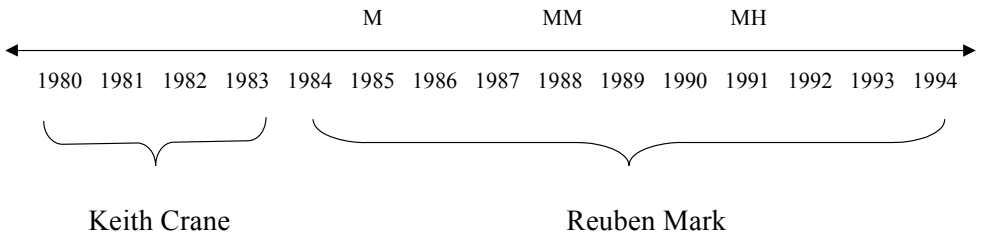


Table 4. Do Overconfident CEOs Complete More Mergers?

Longholder = holds options until last year before expiration (at least once)
Distribution: Logistic. Constant included.
Dependent Variable: Acquistion (yes or no)**; Normalization:** Capital.

	logit with controls	random effects logit	logit with fixed effects
Size	**0.8733**	**0.8600**	**0.6234**
	(1.95)*	(2.05)**	(2.60)***
Q_{t-1}	**0.7296**	**0.7316**	**0.8291**
	(2.97)***	(2.70)***	(1.11)
Cash Flow	**2.0534**	**2.1816**	**2.6724**
	(3.93)***	(3.68)***	(2.70)***
Ownership	**1.2905**	**1.3482**	**0.8208**
	(0.30)	(0.28)	(0.11)
Vested Options	**1.5059**	**0.9217**	**0.2802**
	(1.96)*	(0.19)	(2.36)**
Governance	**0.6556**	**0.7192**	**1.0428**
	(3.08)***	(2.17)**	(0.21)
Longholder	**1.5557**	**1.7006**	**2.5303**
	(2.58)***	(3.09)***	(2.67)***
Year Fixed Effects	yes	yes	yes
Observations	3690	3690	2261
Firms		327	184

Table 6. Are Overconfident CEOs Right to Hold Their Options? (I)

Returns from exercising 1 year sooner and investing in the S&P 500 index	
Percentile	Return
10th	-0.24
20th	-0.15
30th	-0.10
40th	-0.05
50th	-0.03
60th	0.03
70th	0.10
80th	0.19
90th	0.39
Mean	0.03
Standard Deviation	0.27
All exercises occur at the maximum stock price during the fiscal year	

Alternative Explanations

1. Inside Information or Signalling
   - Mergers should "cluster" in final years of option term
   - Market should react favorably on merger announcement
   - CEOs should "win" by holding

2. Stock Price Bubbles
   - Year effects already removed
   - All cross-sectional firm variation already removed
   - Lagged stock returns should explain merger activity

3. Volatile Equity

4. Finance Training

Empirical Predictions

Rational CEO	Overconfident CEO

1. On average?
2. Overconfident CEOs do more mergers that are likely to destroy value
3. Overconfident CEOs do more mergers when they have abundant internal resources
4. The announcement effect after overconfident CEOs make bids is lower than for rational CEOs

Table 8. Diversifying Mergers

Longholder = holds options until last year before expiration (at least once)
Distribution: Logistic. Constant included; **Normalization:** Capital.
Dependent Variable: Diversifying merger (yes or no).

	logit	logit with random effects	logit with fixed effects
Longholder	**1.6008**	**1.7763**	**3.1494**
	(2.40)**	(2.70)***	(2.59)***
Year Fixed Effects	yes	yes	yes
Observations	3690	3690	1577
Firms		327	128

Dependent Variable: Intra-industry merger (yes or no).

Longholder	**1.3762**	**1.4498**	**1.5067**
	(1.36)	(1.47)	(0.75)
Year Fixed Effects	yes	yes	yes
Observations	3690	3690	1227
Firms		327	100

Regressions include Cash Flow, Q_{t-1}, Size, Ownership, Vested Options, and Governance.
Industries are Fama French industry groups.

Empirical Predictions

Rational CEO

Overconfident CEO

1. On average?
2. Overconfident CEOs do more mergers that are likely to destroy value
3. Overconfident CEOs do more mergers when they have abundant internal resources
4. The announcement effect after overconfident CEOs make bids is lower than for rational CEOs

Kaplan-Zingales Index

$$KZ = -1.00 \cdot \frac{CashFlow}{Capital} + 0.28 \cdot Q + 3.14 \cdot Leverage - 39.37 \cdot \frac{Dividends}{Capital} - 1.31 \cdot \frac{Cash}{Capital}$$

- Coefficients from logit regression (Pr{financially constrained})
- High values $\longrightarrow$ Cash constrained
  - Leverage captures debt capacity
  - Deflated cash flow, cash, dividends capture cash on hand
  - Q captures market value of equity (Exclude?)

Table 9. Kaplan-Zingales Quintiles

Longholder = holds options until last year before expiration (at least once)
Distribution: Logistic. Constant included.
Dependent Variable: Acquistion (yes or no)**; Normalization:** Capital.
All regressions are logit with random effects.

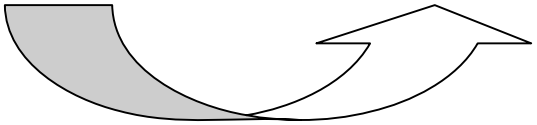
	Least Equity Dependent		---------->		Most Equity Dependent
			All Mergers		
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Longholder	**2.2861**	**1.6792**	**1.7756**	**1.9533**	**0.8858**
	(2.46)**	(1.48)	(1.54)	(1.50)	(0.33)
Year Fixed Effects	yes	yes	yes	yes	yes
Observations	718	719	719	719	718
Firms	125	156	168	165	152
			Diversifying Mergers		
	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Longholder	**2.5462**	**1.8852**	**1.7297**	**1.0075**	**1.0865**
	(1.89)*	(1.51)	(1.36)	(0.01)	(0.18)
Year Fixed Effects	yes	yes	yes	yes	yes
Observations	718	719	719	719	718
Firms	125	156	168	165	152

Regressions include Cash Flow, Q_{t-1}, Size, Ownership, Vested Options, and Governance.

Empirical Predictions

Rational CEO

Overconfident CEO



1. On average?
2. Overconfident CEOs do more mergers that are likely to destroy value
3. Overconfident CEOs do more mergers when they have abundant internal resources
4. The announcement effect after overconfident CEOs make bids is lower than for rational CEOs

Table 14. Market Response

Longholder = holds options until last year before expiration (at least once)

Dependent Variable: Cumulative abnormal returns [-1,+1]

	OLS (3)	OLS (4)	OLS (5)
Relatedness	**0.0048**	**0.0062**	**0.0043**
	(1.37)	(1.24)	(1.24)
Corporate Governance	**0.0079**	**0.0036**	**0.0073**
	(2.18)**	(0.64)	(1.98)**
Cash Financing	**0.014**	**0.0127**	**0.0145**
	(3.91)***	(2.60)***	(3.99)***
Age			**-0.0005**
			(1.46)
Boss			**0.0001**
			(0.04)
Longholder	**-0.0067**	**-0.0099**	**-0.0079**
	(1.81)*	(2.33)**	(2.00)**
Year Fixed Effects	yes	yes	yes
Industry Fixed Effects	no	yes	no
Industry*Year Fixed Effects	no	yes	no
Observations	687	687	687
R-squared	0.10	0.58	0.10

Regressions include Ownership and Vested Options.

Do Outsiders Recognize CEO Overconfidence?

Portrayal in Business Press:

1. Articles in
   - New York Times
   - Business Week
   - Financial Times
   - The Economist
   - Wall Street Journal
2. Articles published 1980-1994
3. Articles which characterize CEO as
   - Confident or optimistic
   - Not confident or not optimistic
   - Reliable, conservative, cautious, practical, steady or frugal

Table 13. Press Coverage and Diversifying Mergers

Distribution: Logistic. Constant included; **Normalization:** Capital.

Dependent Variable: Diversifying merger (yes or no).

	logit	logit with random effects	logit with fixed effects
TOTALconfident	**1.6971**	**1.7826**	**1.5077**
	(2.95)***	(3.21)***	(1.48)
Year Fixed Effects	yes	yes	yes
Observations	3647	3647	1559
Firms		326	128

Dependent Variable: Intra-industry merger (yes or no).

TOTALconfident	**1.0424**	**1.0368**	**0.8856**
	(0.20)	(0.16)	(0.31)
Year Fixed Effects	yes	yes	yes
Observations	3647	3647	1226
Firms		326	100

Regressions include Total Coverage, Cash Flow, Q_{t-1}, Size, Ownership, Vested Options, and Governance. Industries are Fama French industry groups.

- Overconfidence/Overprecision: Overestimate the precision of one's estimates

- **Alpert-Raiffa (1982).** Ask questions such as
  - 'The number of "Physicians and Surgeons" listed in the 1968 Yellow Pages of the phone directory for Boston and vicinity'
  - 'The total egg production in millions in the U.S. in 1965.'
  - 'The toll collections of the Panama Canal in fiscal 1967 in millions of dollars'

- Ask for 99 percent confidence intervals for 1,000 questions

- No. of errors: 426! (Compare to expected 20)

- (Issue: Lack of incentives)

- **Investor Overconfidence: Odean (1999)**

- Investor overconfidence/overprecision predicts excessive trading
  - investor believes signal is too accurate –> Executes trade

- Empirical test using data set from discount brokerage house

- Follow all trades of 10,000 accounts

- January 1987-December 1993

- 162,948 transactions

- Traders that overestimate value of their signal trade too much

- Substantial cost for trading too much:
  - Commission for buying 2.23 percent
  - Commission for selling 2.76 percent
  - Bid-ask spread 0.94 percent
  - Cost for ‘round-trip purchase’: 5.9 percent (!)

- Stock return on purchases must be at least 5.9 percent.
- Compute buy-and-hold returns
- Evidence: Sales outperform purchases by 2-3 percent!

TABLE 1—AVERAGE RETURNS FOLLOWING PURCHASES AND SALES

Panel A: All Transactions

	n	84 trading days later	252 trading days later	504 trading days later
Purchases	49,948	1.83	5.69	−24.00
Sales	47,535	3.19	9.00	27.32
Difference		−1.36	−3.31	−3.32
N1		(0.001)	(0.001)	(0.001)
N2		(0.001)	(0.001)	(0.002)

- Is the result weaker for individuals that trade the most? No

Panel C: The 10 Percent of Investors Who Trade the Most

	n	84 trading days later	252 trading days later	504 trading days later
Purchases	29,078	2.13	7.07	25.28
Sales	26,732	3.04	9.76	28.78
Difference		−0.91	−2.69	−3.50
N1		(0.001)	(0.001)	(0.001)
N2		(0.001)	(0.001)	(0.010)

- Huge cost to trading for individuals:
  - Transaction costs
  - Pick wrong stocks

- **Barber and Odean, 2001:** Gender difference
  - Psychology: Men more overconfident than women about financial decisions
  - Tading data: men trade 45 percent more than women –> pay a larger returns cost

- This is correlational evidence:
  - gender correlates with overconfidence + gender correlates with trading —> Overconfidence explanations
  - However: Gender may proxy for unobservables of investors that correlate with trading activity

- General issue with correlations design (Michigan and NYU schools + Heckman proponents of this)

- How to get around this?

- **D'Acunto (2013):** Use priming
  - Run experiments on lottery choices resembling investment decisions (on MTurk)
  - Control group just reads a neutral short reading
  - Treated group reads a text priming strong gender identity
  - Male priming should affect overconfidence
  - Male priming could affect overconfidence too in compensatory fashion
  - Effect on lottery choices –> More risk taking

- Overconfidence/overprecision can explain other puzzles in asset pricing:
  - short-term positive correlation of returns (momentum)
  - long-term negative correlation (long-term reversal)

- **Daniel-Hirshleifer-Subrahmanyam (1998)**

- Assume overconfidence + self-attribution bias (discount information that is inconsistent with one's priors)
  - Overconfidence –> trade excessively in response to private information
  - Long-term: public information prevails, valuation returns to fundamentals –> long-term reversal
  - Short-term: additional private information interpreted with self-attribution bias –> become even more overconfident

- Two other explanations for this: Law of small numbers + Limited attention

5 Law of Small Numbers

- Overconfidence is only one form of non-Bayesian beliefs

- **Tversky-Kahneman (1974).** Individuals follow heuristics to simplify problems:
  - *Anchoring.* –> Leads to over-precision (above)
  - *Availability.* –> Connected to limited attention (next lecture)
  - *Representativeness.* –> Today's lecture

- Individuals expect random draws to be exceedingly representative of the distribution they come from
  - HTHHTT judged more representative than HHHTTT
  - But the two are equally likely! (exchangeability)

- **Rabin (QJE, 2002). Law of Small Numbers**
  - I.i.d. signals from urn drawn with replacement
  - Subjects instead believe drawn from an urn of size $N < \infty$ without replacement
  - –> *Gambler's Fallacy:* After signal, subject expect next draw to be a different signal
  - Example: Return to mutual fund is drawn from an urn with 10 balls, 5 Up and 5 Down (with replacement)
  - Observe 'Up, Up' — Compute probability of another Up
    - Bayesian: .5
    - Law of Small Numbers: $3/8 < .5$
  - Example of representativeness: 'Up, Up, Down' more representative than 'Up, Up, Up'

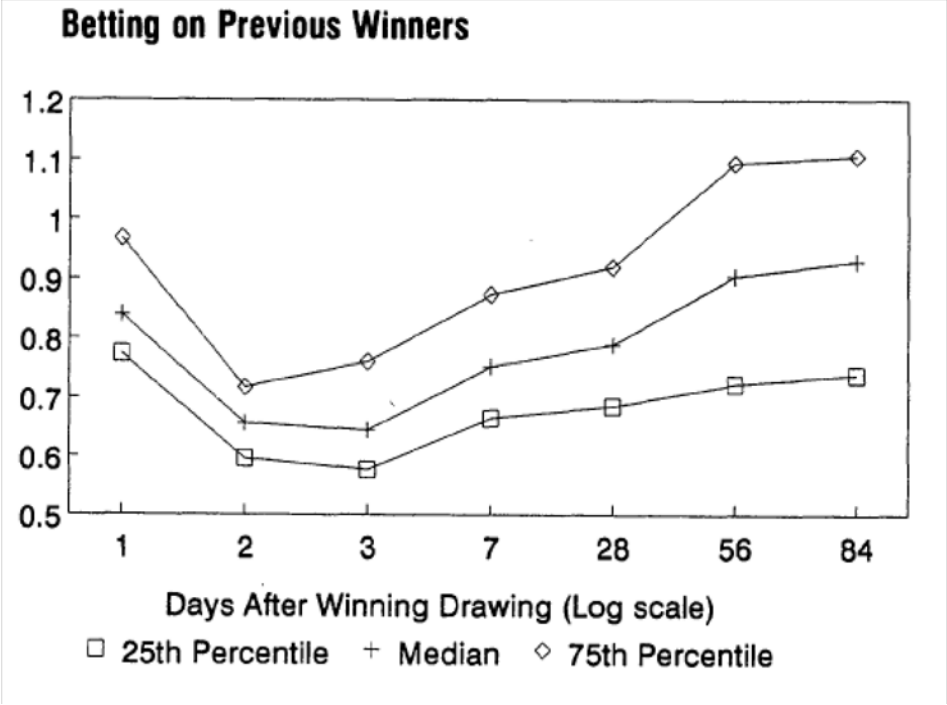
- Evidence on gambler's fallacy.

- **Clotfelter and Cook (MS, 1993)**

- Lotteries increasingly common in US ($17bn sales in 1989)

- Maryland daily-numbers lottery –> Bet on 3-digit number
  - Probability of correct guess .001
  - Payout: $500 per $1 bet (50 percent payout)

- Gambler's Fallacy –> Betters will stop betting on number just drawn
  - Examine 52 winning numbers in 1988
  - In 52 of 52 cases (!) betting volume decreases 3 days after win, relative to baseline



- – Substantial decrease in betting right after number is drawn
  - – Effect lasts about 3 months
  - – However: no cost for fallacy –> Does effect replicate with cost?

- **Terrell (JRU, 1994)**

- New Jersey's pick-three-numbers game (1988-1992)

- Pari-mutuel betting system
  - the fewer individuals bet on a number, the higher is the expected payout
  - Cost of betting on popular numbers
  - Payout ratio .52 –> Average win of $260 for 50c bet

- Issue: Do not observe betting on all numbers –> Use payout for numbers that repeat

Table 1. Average payouts to winning numbers

	Number	Mean	Standard deviation
Winners repeating within 1 week	8	349.06	91.66
Winners repeating between 1 and 2 weeks	8	349.44	81.56
Winners repeating between 2 and 3 weeks	14	307.76	58.33
Winners repeating between 3 and 8 weeks	59	301.03	70.55
Winners not repeating within 8 weeks	1622	260.11	57.98
All Winners	1714	262.79	57.99

- Strong gambler's fallacy:
  - Right after win, 34 percent decrease in betting
  - –> 34 percent payout increase
  - Effect dissipates over time

- Comparison with Maryland lottery:
  - Smaller effect (34 percent vs. 45 percent)
  - –> Incentives temper phenomenon, but only partially
- Other applications:
  - Probabilities are known, but subjects misconstrue the i.i.d. nature of the draws.
  - Example: Forecast of the gender of a third child following two boys (or two girls)

- Back to **Rabin (QJE, 2002)**.
  - Probabilities known –> Gambler's Fallacy
  - Probabilities not known –> Overinference: After signals of one type, expect next signal of *same* type

- Example:
  - Mutual fund with a manager of uncertain ability.
  - Return drawn with replacement from urn with 10 balls
    - Probability .5: fund is well managed (7 balls Up and 3 Down)
    - Probability .5: fund is poorly managed (3 Up and 7 Down)
  - Observe sequence 'Up, Up, Up' –> What is $P(Well|UUU)$?
    - Bayesian: $P(Well|UUU) = .5P(UUU|Well)/[.5P(UUU|Well) + .5P(UUU|Poor)] = .7^3/\left(.7^3 + .3^3\right) \approx .927$.

    - Law-of-Small-Number: $P(Well|UUU) = (7/10*6/9*5/8)/[(7/10*6/9*5/8) + (3/10*2/9*1/8)] \approx .972$.
    - Over-inference about the ability of the mutual-fund manager
  - Also assume:
    - Law-of-Small-Number investor believes that urn replenished after 3 periods
    - Need re-start or
  - What is Forecast of $P(U|UUU)$?
    - Bayesian: $P(U|UUU) = .927*.7 + (1-.927)*.3 \approx .671$
    - Law-of-Small-Number: $P(U|UUU) = .972*.7 + (1-.972)*.3 \approx .689$

- Over-inference despite the gambler's fallacy beliefs

- Substantial evidence of over-inference (also called extrapolation)
- Notice: Case with unknown probabilities is much more common than lottery case
- Excellent review: **Fuster, Laibson, and Mendel (JEP 2010)**
- **Benartzi (JF, 2001)**
  - Examine investment of employees in employer stock
  - Does it depend on the past performance of the stock?
- Sample:
  - S&P 500 companies with retirement program
  - Data from 11-k filing
  - 2.5 million participants, $102bn assets

Buy-and-Hold Raw Returns and Subsequent Allocations to Company Stock as a Percentage of Discretionary Contributions

This table displays equally weighted mean allocations to company stock (as a percentage of discretionary contributions) by quintile of past buy-and-hold raw returns. Company stock allocations are measured at the end of 1993. Portfolio 1 (5) includes retirement savings plans with the lowest (highest) past buy-and-hold raw returns. The table also provides the difference between the allocations of the extreme portfolios (i.e., portfolio 5 minus portfolio 1) and t-statistics. $N = 142$.

Quintiles Formed on the Basis of Buy-and-Hold Raw Returns for:	Quintile of Buy-and-Hold Returns					Observed Difference	
	(Low) 1	2	3	4	5 (High)	(5 − 1)	T-Statistic
Prior year	21.10%	23.16%	27.85%	25.99%	23.70%	2.60%	0.60
Prior 2 years	22.61	22.43	25.18	28.74	22.96	0.35	0.06
Prior 3 years	14.14	25.45	26.21	28.84	27.78	13.64	3.33
Prior 4 years	11.74	22.20	28.18	31.10	30.23	18.49	4.64
Prior 5 years	12.64	18.68	26.27	34.66	31.21	18.57	4.33
Prior 6 years	11.99	18.72	29.33	33.45	29.96	17.97	4.63
Prior 7 years	11.36	18.98	24.11	34.79	33.70	22.34	5.87
Prior 8 years	11.46	20.69	24.22	32.96	33.63	22.17	5.70
Prior 9 years	11.08	20.76	20.52	34.04	36.68	25.60	6.49
Prior 10 years	10.37	19.68	21.56	31.51	39.70	29.33	8.39

- Very large effect of past returns + Effect depends on long-term performance

- Is the effect due to inside information?

	Allocation to Company Stock					Observed Difference (5 − 1)	Threshold for Significant Difference at $\alpha = 10\%$
	(Low) 1	2	3	4	5 (High)		
Allocation to company stock as a percentage of discretionary contributions	4.59%	12.19%	19.34%	31.85%	53.90%	49.41%	
One-year returns	6.64	6.55	1.27	−1.03	0.13	−6.77	7.12
Two-year returns	43.69	40.78	38.24	43.33	31.92	−11.77	14.75
Three-year returns	59.29	70.28	68.64	79.66	56.25	−3.04	21.99
Four-year returns	101.08	114.55	109.89	149.92	103.14	2.06	36.15

- No evidence of insider information

- Over-inference pattern observed for investors of all types

- Over-inference pattern observed for investors of all types
- **Barber-Odean-Zhou (JFE, forthcoming):** Uses Individual trades data
  - Individual US investors purchase stocks with high past returns
  - Average stock that individual investors purchase outperformed the stock market in the previous three years by over 60 percent
- **Kaustia and Knupfer (JF 2008)**
  - Use Finnish data to be able to track individual investors over time
  - Examine investors that subscribe to an IPO in a 1st period, 1995-Oct. 1999
  - Return is highly idyosincratic
  - Indeed, Figure 1 shows no predictability on returns in second period: Nov. 1999-Dec. 2000

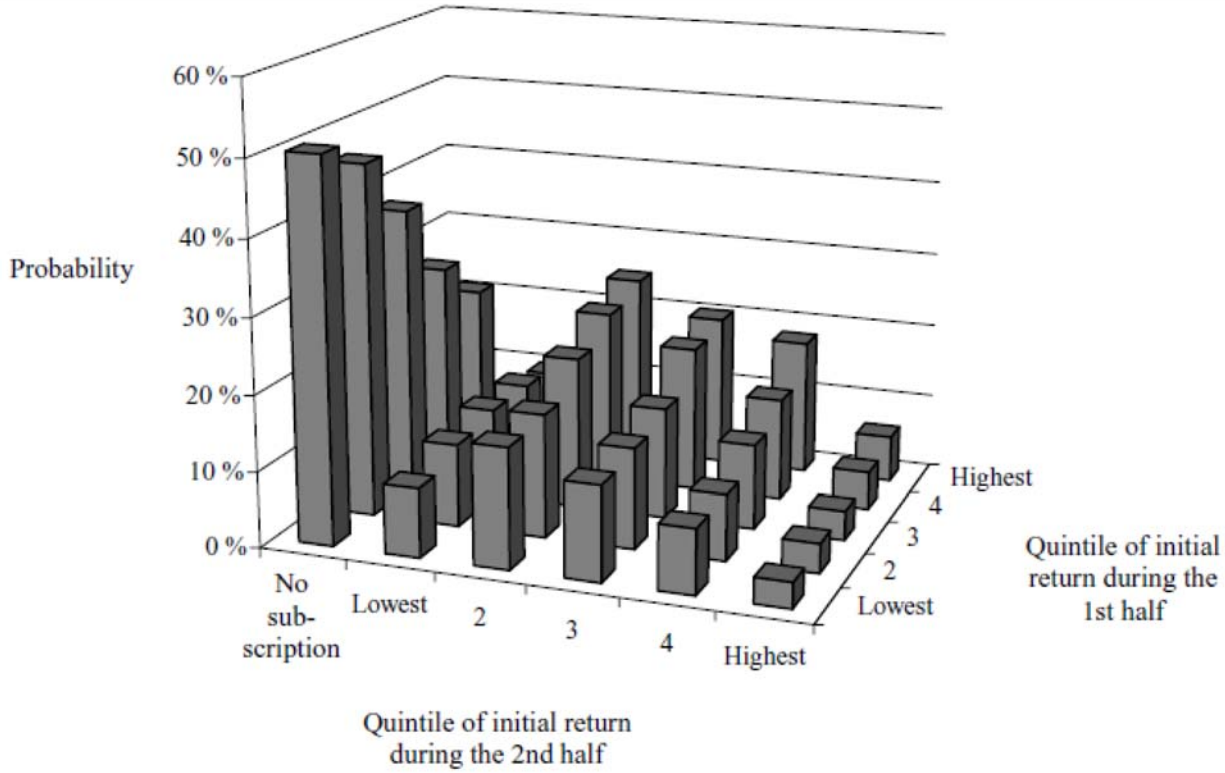


Figure 1. Transition probabilities between previous and subsequent initial return quintiles. To obtain the figure, the sample period is divided into two halves. The first half has 40 IPOs, the last occurring in October 22, 1999; the second half has 17 offerings, the last in December 20, 2000. This split is determined by placing an equal number of investor/offering pairs in both periods.

- What about probability of subscribing to IPOs in second period?

- Strong effect of personally experience returns

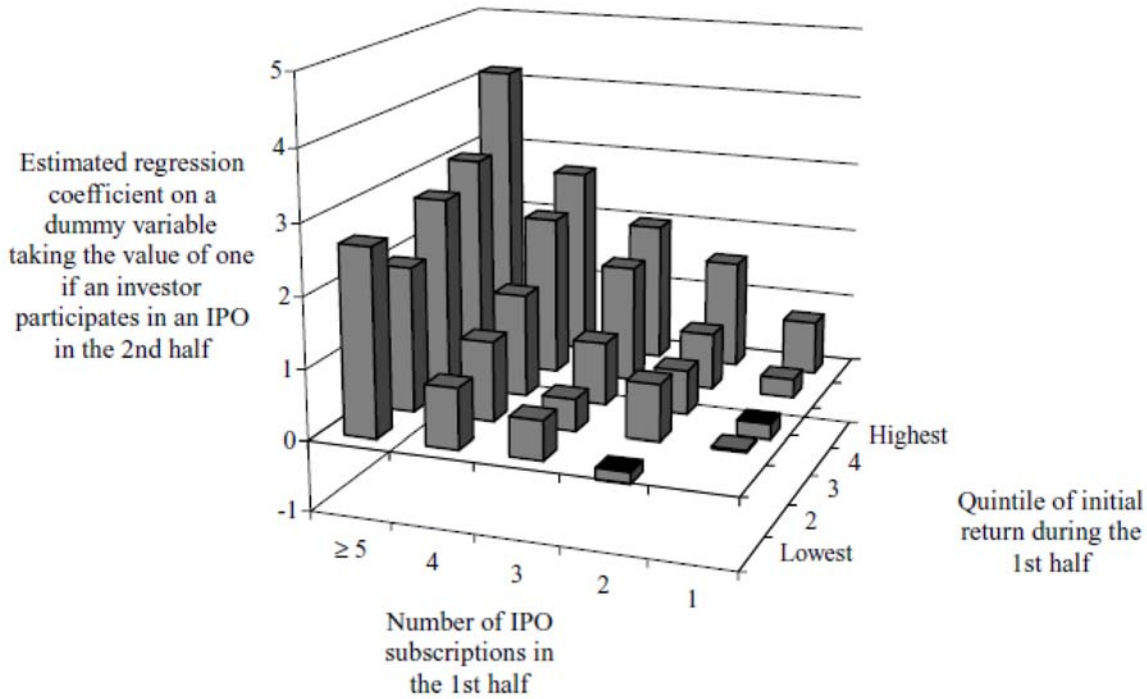


Figure 2. Likelihood of further participation by past subscription activity and past initial returns. This figure is based on a logit regression similar to that in Table II column 1, that is, the dependent variable is one if an investor participates in at least one IPO in the second half, zero otherwise (see more description in Table II header). Unlike in Table II, here previous

- This implies effect on pricing:
  - Stocks with high past returns attract individual investors
  - –> Get overpriced
  - –> Later mean-revert
- **DeBondt and Thaler (1985):**
  - Form portfolio of winners in the past 3 years
  - Form portfolio of losers in past 3 years.
  - 'Winners' underperform the 'losers' by 25 percentage points over the next three years

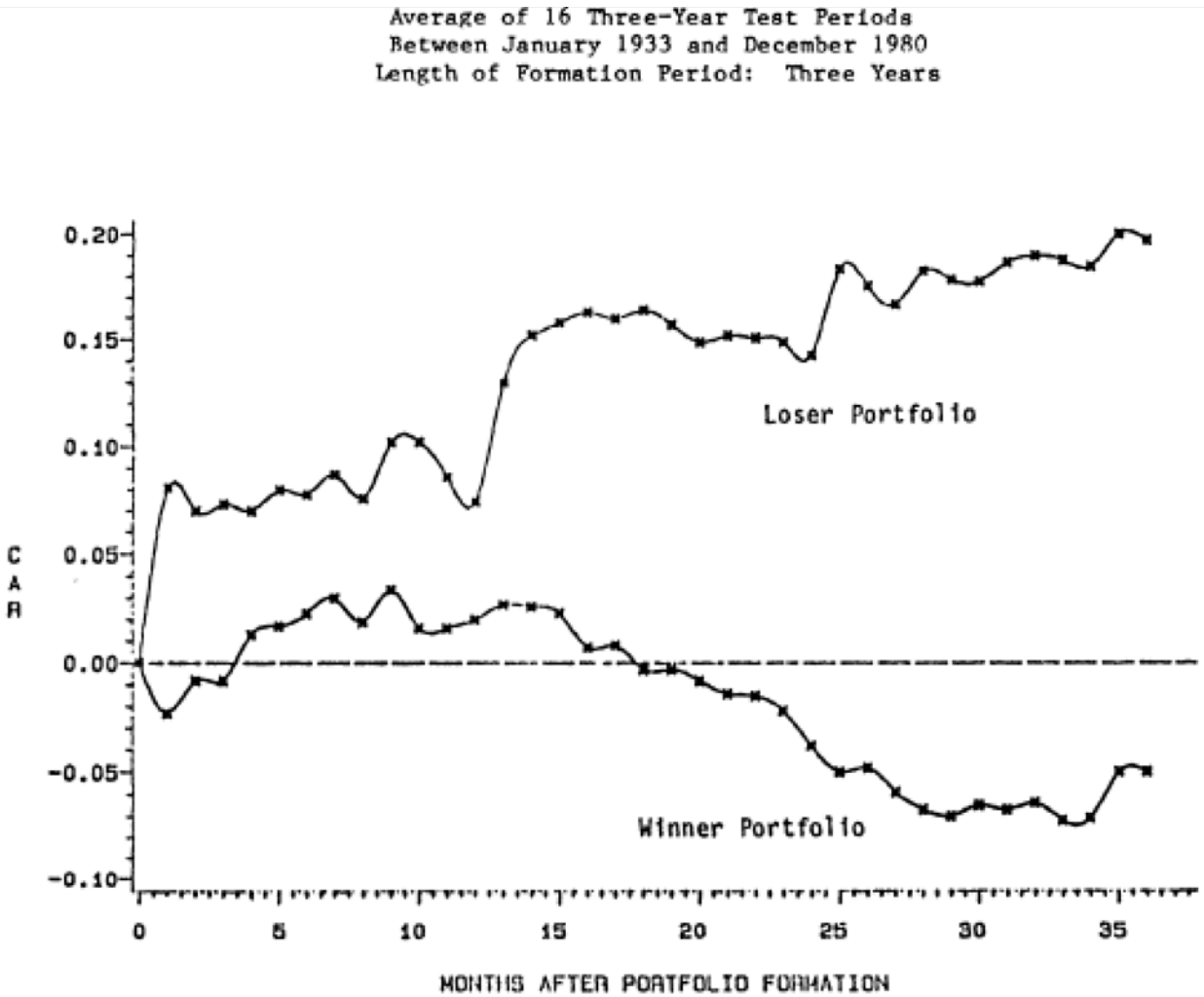


Figure 1. Cumulative Average Residuals for Winner and Loser Portfolios of 35 Stocks (1–36 months into the test period)

- **Barberis-Shleifer-Vishny (JFE, 1998)**
  - Alternative model of law of small number in financial markets.
  - Draws of dividends are i.i.d.
  - Investors believe that
    - draws come from 'mean-reverting' regime or 'trending' regime
    - 'mean-reverting' regime more likely ex ante
  - Result: If investors observe sequence of identical signals,
    - Short-Run: Expect a mean-reverting regime (the gambler's fallacy) –> Returns under-react to information –> Short-term positive correlation (momentum)
    - Long-run: Investors over-infer and expect a 'trending' regime –> Long-term negative correlation of returns

- Extrapolation also in other contexts
- **Gallagher (AEJ Applied 2014)**
  - Consider idiosincratic flood events
  - Largely uncorrelated from year to year
  - Statistical information on flood probabilities available
  - What is the effect of a recent flood?
  - Large increase in probability of insurance
- Effect is present also for communities not directly hit
- What explains the effect? Media salience is critical

Figure 2: Flood Insurance Take-up for Communities Hit by a Presidential Disa
Declaration Flood 1990-2007

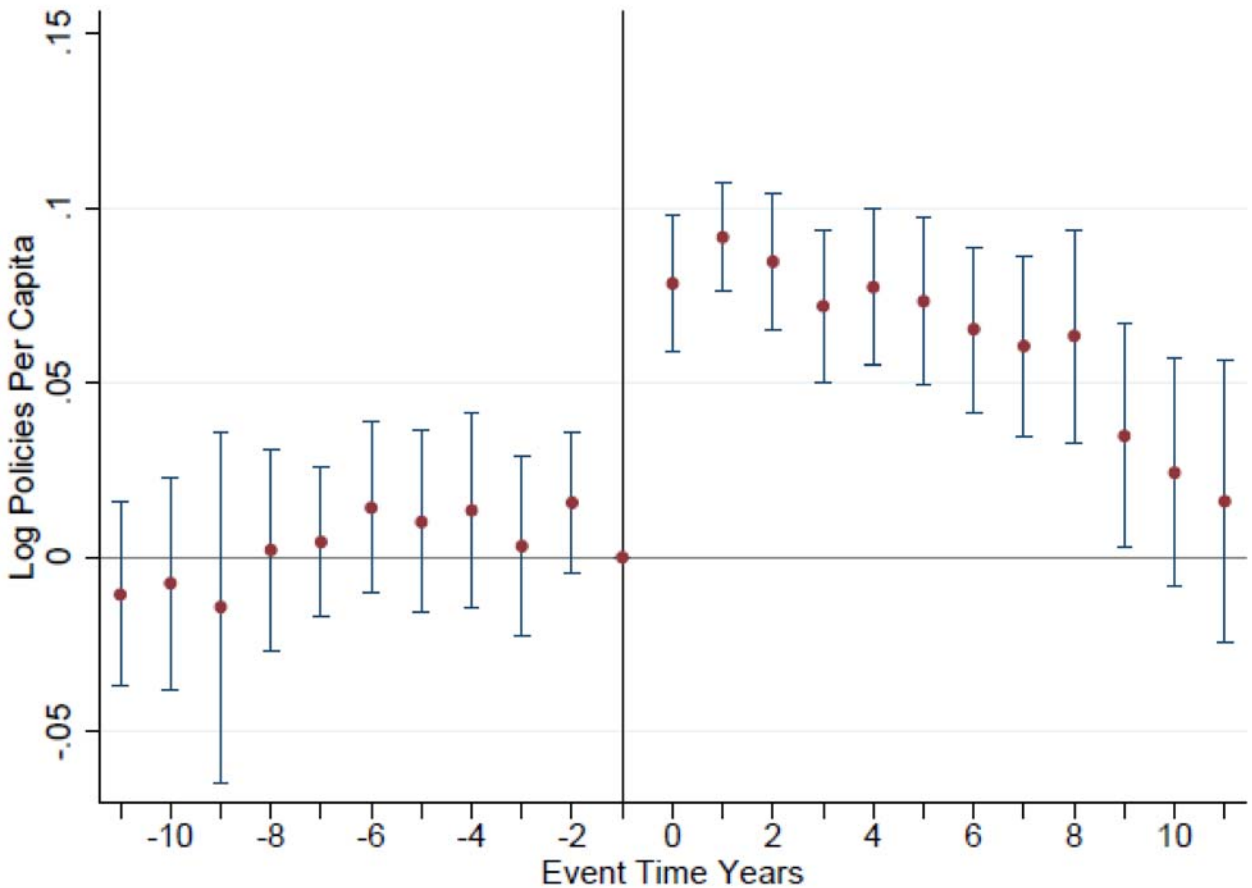


Figure 3: Flood Insurance Take-up for Hit and Non-Hit Communities within Presidential Disaster Declaration Flooded Counties 1990-2007

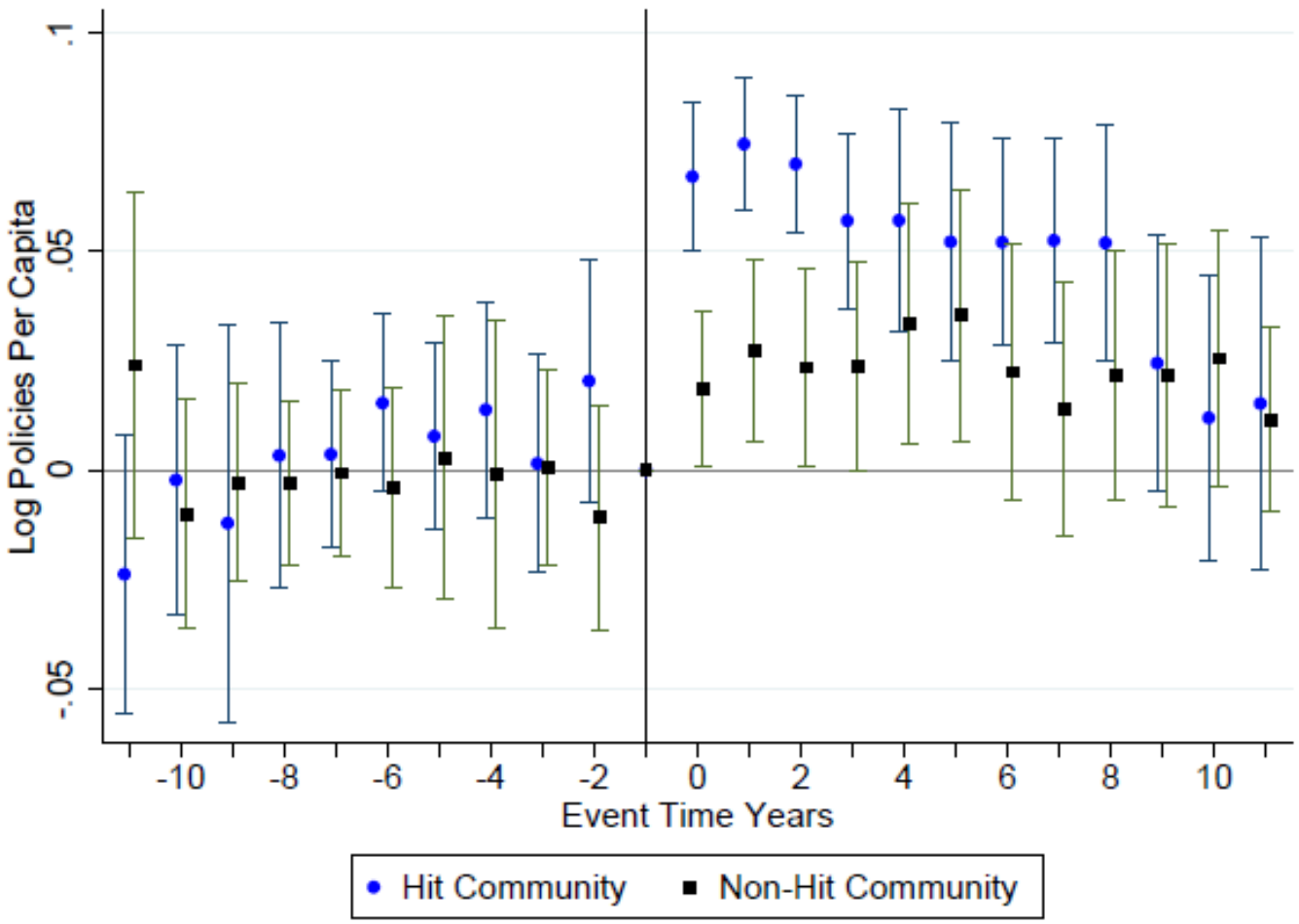
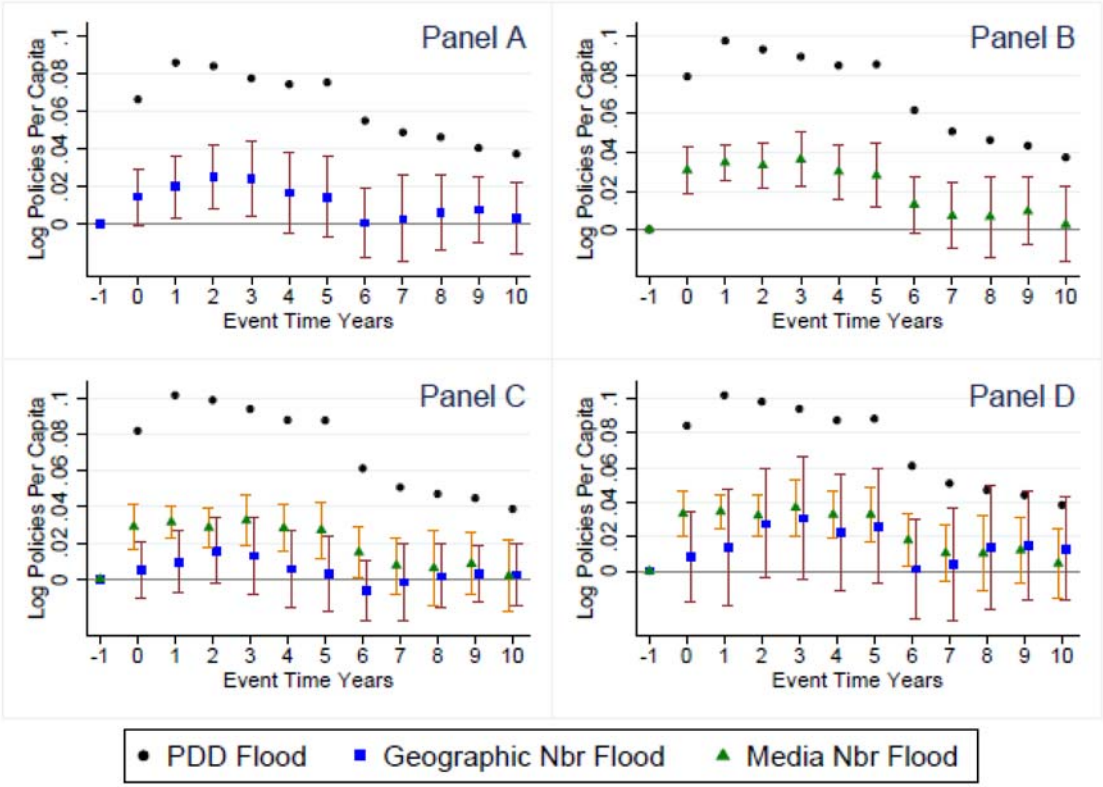


Figure 8: Flood Insurance Take-up for Geographic and Media Neighbors



Each panel contains coefficients from a distinct event study regression using a version of Equation (2) and the 1980-2007 panel. Panel A includes event time indicators for communities located in one of the five closest non-flooded counties. Panel B includes event time indicators for non-flooded communities located in the same TV media market as a flooded community. Panel C includes both geographic and media indicators. Panel D includes both geographic and media indicators, and their interaction (not displayed).

6 Projection Bias

- Beliefs systematically biased toward current state
- **Read-van Leeuwen (1998):**
  - Office workers choose a healthy snack or an unhealthy snack
  - Snack will be delivered a week later (in the late afternoon).
  - Two groups: Workers are asked
    - when plausibly hungry (in the late afternoon) –> 78 percent chose an unhealthy snack
    - when plausibly satiated (after lunch).–> 42 percent choose unhealthy snack

- **Gilbert, Pinel, Wilson, Blumberg, and Wheatly (1999):**
  - individuals under-appreciate adaptation to future circumstances –> Projection bias about future reference point
  - Subjects forecast happiness for an event
  - Compare predictions to responses after the event has occurred
  - Thirty-three current assistant professors at the University of Texas (1998) forecast that getting tenure would significantly improve their happiness (5.9 versus 3.4 on a 1-7 scale).
  - Difference in rated happiness between 47 assistant professors that were awarded tenure by the same university and 20 that were denied tenure is smaller and not significant (5.2 versus 4.7).
  - Similar results as function of election of a Democratic of Republican president, compared to the realized ex-post differences.

- *Projection bias.* (**Loewenstein, O'Donoghue, and Rabin (2003**)
  - Individual is currently in state s' with utility $u(c, s')$
  - Predict future utility in state s
  - Simple projection bias:

$$\hat{u}(c, s) = (1 - \alpha) u(c, s) + \alpha u\left(c, s'\right)$$

  - Parameter α is extent of projection bias –> $\alpha = 0$ implies rational forecast
- Notice: People misforecast utility $\hat{u}$, not state s; however, same results if the latter applies

- **Conlin-O'Donoghue-Vogelsang (2006)**
- Purchasing behavior: Cold-weather items
- Main Prediction:
  - Very cold weather
  - –> Forecast high utility for cold-weather clothes
  - –> Purchase 'too much'
  - –> Higher return probability
- Denote temperature at Order time as ω_O and temperature at Return time as ω_R
- Predictions:
  1. If $\alpha = 0$ (no proj. bias), P[R|O] is independent of ω_O and ω_R
  2. If $\alpha > 0$ (proj. bias), ∂P[R|O]$/\partial\omega_O < 0$ and ∂P[R|O]$/\partial\omega_R > 0$

- Purchase data from US Company selling outdoor apparel and gear
  - January 1995-December 1999, 12m items
  - Date of order and date of shipping + Was item returned
  - Shipping address
- Weather data from National Climatic Data Center
  - By 5-digit ZIP code, use of closest weather station
- Items:
  - Parkas/Coats/Jackets Rated Below 0F
  - Winter Boots
  - Drop mail orders, if billing and shipping address differ, >9 items ordered, multiple units same item, low price
  - No. obs. 2,200,073
- Note: Probability of return fairly high, Delay between order and receipt 4-5 days

TABLE 1

Summary Statistics by Item Categories

	Gloves/ Mittens	Winter Boots	Hats	Sports Equipment	Parkas/ Coats	Vests	Jackets	All Seven Categories
Observations	484,084	262,610	484,086	146,594	524,831	151,958	145,910	2,200,073
Number of Different Items	106	93	88	233	133	20	37	710
Percent Returned	10.9	15.6	10.8	6.6	22.2	12.8	18.0	14.4
Price of Item (dollars)	29.26	68.33	23.74	74.10	148.58	40.90	106.70	70.10
Percent of Buyer's Prior Purchases Returned	7.2	6.6	6.9	7.2	7.3	6.8	8.2	7.14
Number of Buyer's Prior Purchases	27.3	22.2	23.9	27.7	20.5	21.71	25.3	23.83
Buyer has a Prior Purchase	0.85	0.82	0.83	0.86	0.77	0.83	0.82	0.82
Days Between Order and Shipment	0.42	0.97	0.72	0.94	2.17	1.24	1.13	1.11
Days Between Order and Receipt	4.13	4.66	4.46	4.58	5.92	5.04	4.89	4.84
Ordered Through Internet	0.04	0.03	0.03	0.02	0.04	0.02	0.05	0.03
Purchased by a Female	0.71	0.66	0.71	0.70	0.66	0.72	0.66	0.69
Item Purchased with Credit Card	0.97	0.98	0.98	0.97	0.98	0.98	0.97	0.98
Items in Order	3.5	2.5	3.4	2.9	2.2	2.8	2.3	2.9
Temperature Rating					-10.11		-5.64	
WEATHER CONDITIONS								
Order-Date Temperature (°F)	40.60	39.74	41.48	37.81	43.29	44.76	46.88	41.85
Receiving-Date Temperature (°F)	39.90	38.97	40.72	36.70	42.29	43.20	45.70	40.94
Snowfall on Day Item Ordered (0.1")*	1.79	2.69	1.69	2.65	1.30	1.26	0.63	1.70
Snowfall on Day Item Received (0.1")*	1.58	2.32	1.51	2.35	1.33	1.43	0.66	1.57

- Main estimation: Probit

$$P(R|O) = \Phi\left(\alpha + \gamma_O \omega_O + \gamma_R \omega_R + BX\right)$$

TABLE 2

Probit Regression Measuring the Effect of Temperature on the Probability Cold Weather Clothing is Returned

Dependent Variable is Whether Item is Returned (=1 if item returned and 0 otherwise)

	Gloves & Mittens	Winter Boots	Hats	Sports Equipment	Parkas & Coats	Vests	Jackets	All Seven Categories
Order-Date Temperature	-0.00013**	-0.00026**	-0.00020**	-0.00011*	-0.00009	-0.00048**	-0.00014	-0.00019**
	(0.00005)	(0.00009)	(0.00005)	(0.00006)	(0.00007)	(0.00011)	(0.00013)	(0.00003)
Receiving-Date Temperature	0.00005	0.00018*	-0.00005	-0.00008	0.00007	-0.00010	0.00010	0.00003
	(0.00006)	(0.00009)	(0.00006)	(0.00007)	(0.00008)	(0.00011)	(0.00014)	(0.00003)
Price of Item	0.00075**	0.00005	0.00145**	0.00033**	0.00019**	0.00166**	0.00016	0.00023**
	(0.00024)	(0.00013)	(0.00025)	(0.00008)	(0.00004)	(0.00024)	(0.00018)	(0.00003)
Item Purchased with Credit Card	0.02042**	0.04337**	0.02876**	0.02395**	0.05893**	0.02294**	0.05312**	0.03531**
	(0.00250)	(0.00418)	(0.00244)	(0.00191)	(0.00405)	(0.00535)	(0.00568)	(0.00137)
Items in Order	-0.00157**	0.00012	-0.00035	-0.00078**	0.00196**	-0.00177**	0.00141**	-0.00028**
	(0.00022)	(0.00039)	(0.00022)	(0.00028)	(0.00033)	(0.00045)	(0.00058)	(0.00012)
Clothing Type Fixed Effects	YES	YES	YES	NO[a]	YES	YES	YES	YES
Item Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Month-Region Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Year-Region Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Observations	484,067	262,610	484,085	146,403	524,831	151,958	145,910	2,199,950
R-Squared	0.04	0.05	0.07	0.13	0.03	0.03	0.04	0.07

Table presents marginal effects on the probability that an item is returned. Standard errors are in parentheses.

* Statistically significant at the .10 level; ** Statistically significant at the .05 level.

[a] Clothing Type information was not provided for sports equipment items.

- Main finding: $\gamma_O < 0$.
  - Warmer weather on order date lowers probability of return
  - *Magnitude:*
  - This goes against standard story: If weather is warmer, less likely you will use it –> Return it more
  - Projection Bias: Very cold weather –> Mispredict future utility –> Return the item
- Second finding: $\gamma_R \approx 0$
  - Warmer weather on (predicted) return does not affect return
  - This may be due to the fact that do not observe when return decision is made

- Similar estimates for linear probability model with household fixed effects

TABLE 3

Linear Regression Measuring the Effect of Temperature on the Probability Cold Weather Clothing is Returned: With and Without Household Fixed Effects

	Household Fixed Effects	No Household Fixed Effects
Order-Date Temperature	-0.00082**	-0.00039**
	(0.00027)	(0.00013)
Receiving-Date Temperature	0.00017	0.00002
	(0.00029)	(0.00015)
Clothing Type Fixed Effects	YES	YES
Item Fixed Effects	YES	YES
Month-Region Fixed Effects	YES	YES
Year-Region Fixed Effects	YES	YES
Household Fixed Effects	YES	NO
Observations	162,580	162,580
R-Squared	0.19	0.10

- Simple structural model: Estimates of projection bias α around .3-.4

TABLE 6

Structural Estimation

	Winter Boots	Hats	Parkas & Coats	Vests	Jackets
α	0.3084**	0.4698**	0.3814**	0.0002	0.4992**
	(0.0570)	(0.00001)	(0.0352)	(0.0056)	(0.0002)

- **Busse, Pope, Pope, Silva-Risso (2013):** Evidence from car purchases and house purchases
- Projection bias:
  - Convertible looks particularly attractive on a hot day
  - 4-wheel drive attractive on snowy day
  - House with pool higher selling price on hot day
- Strong evidence in the data

Figure 5. Temperature-Convertible Residuals - Chicago. This Figure provides scatter plots for the residuals of convertible percentage of vehicles sold (Panel B of Figure 3) and residuals of mean high temperature (Panel B of Figure 4) separately for each quarter of the year.

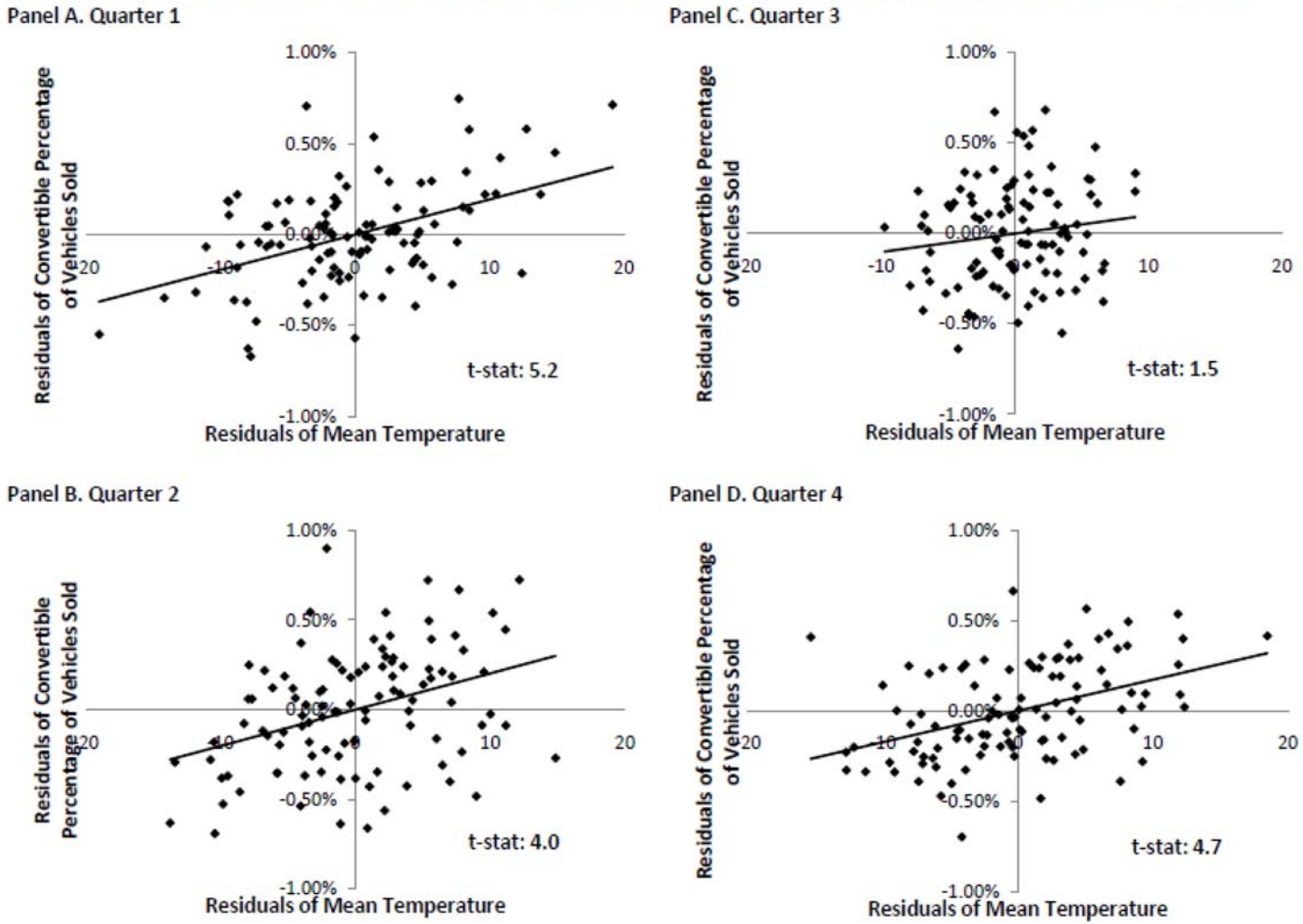


Figure 10. Snowfall and 4-Wheel Drive Sales - Event-Study Design. This Figure plots the weighted average and 95% confidence intervals for the residuals of the 4-wheel drive percentage of total vehicles sold for the twelve weeks leading up to and the twelve weeks after a snow storm event (week 0). The events were chosen to be the highest snow fall week of the year for DMAs that have above-median in weather variation.

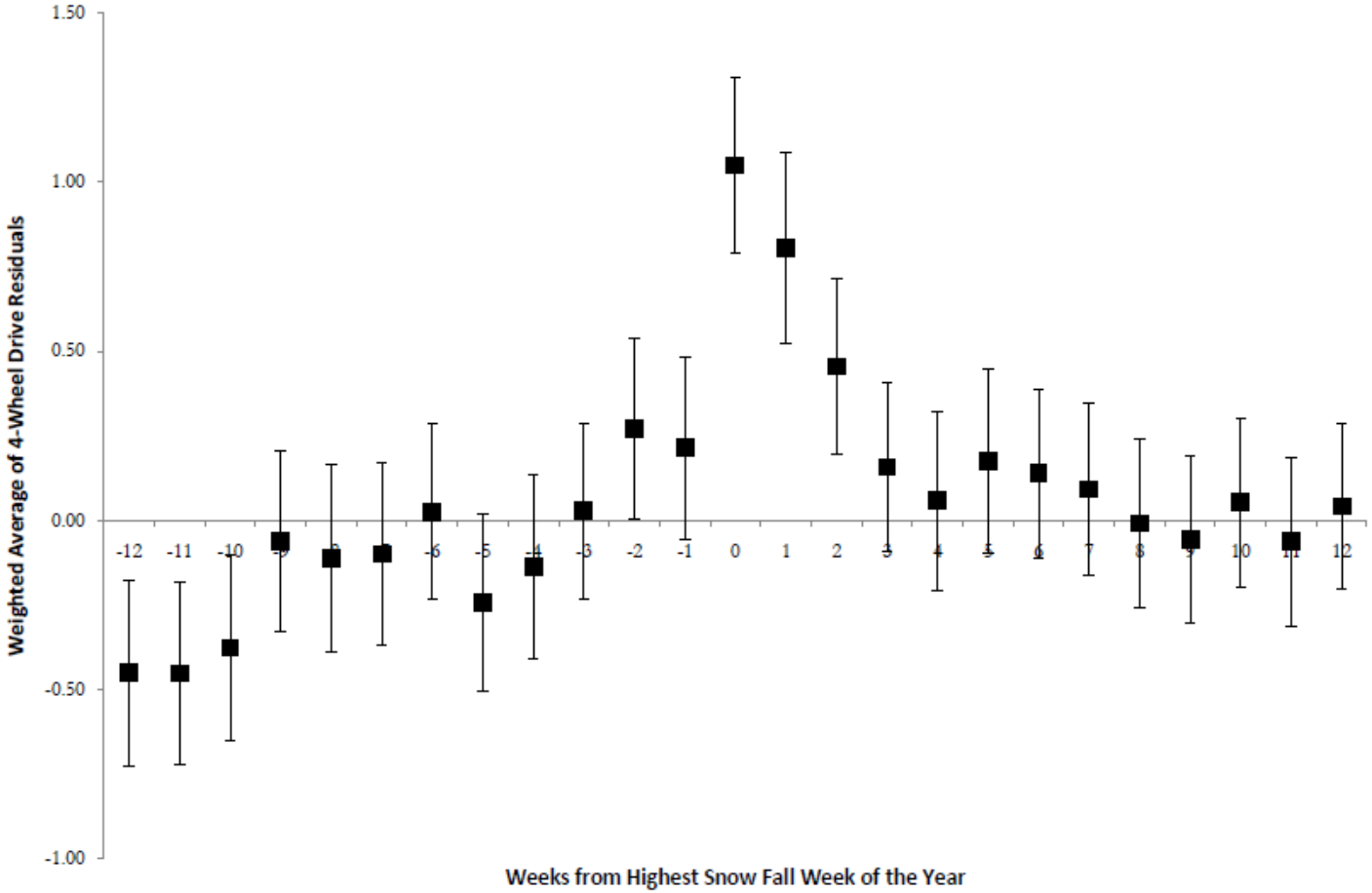
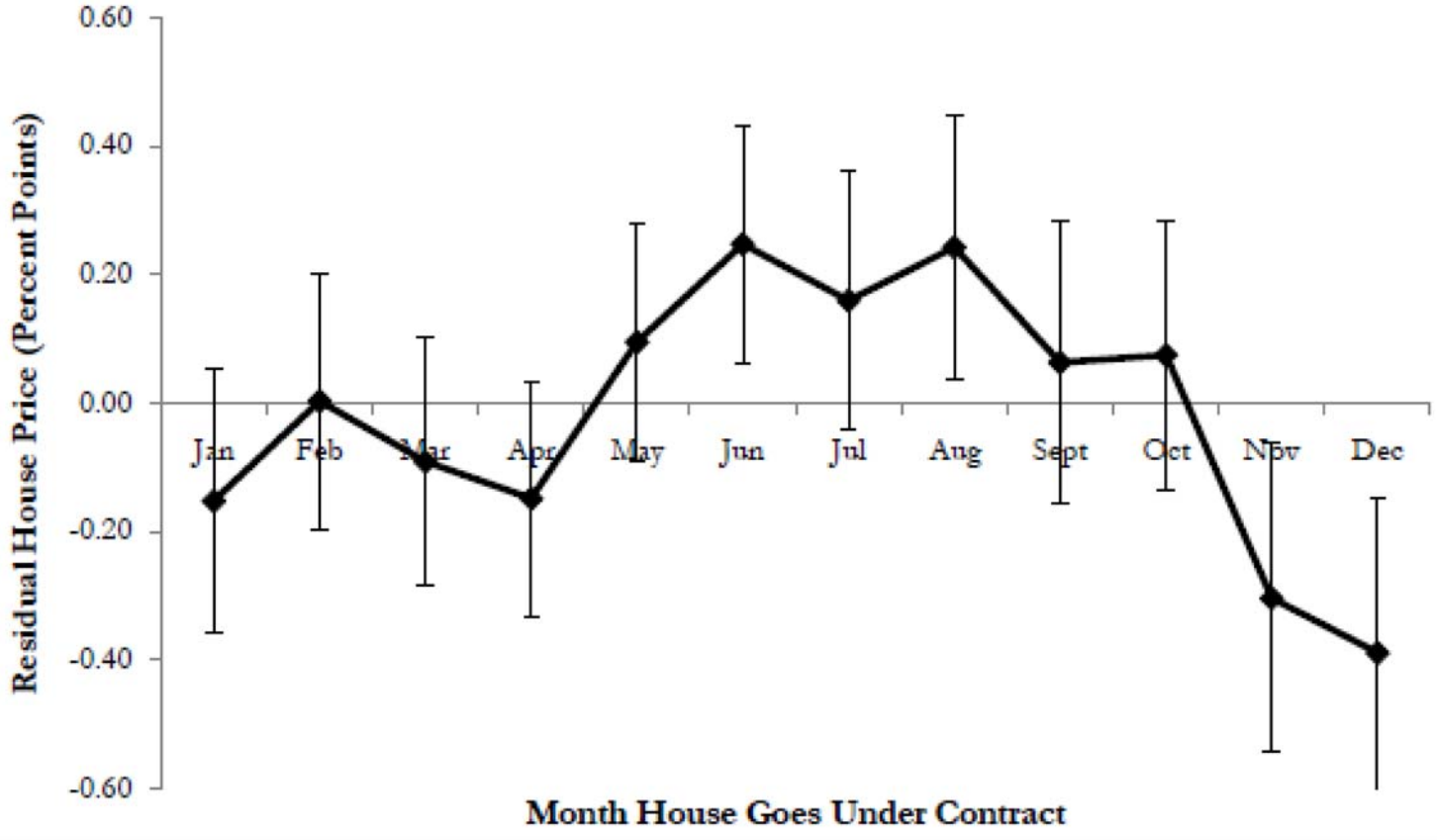


Figure 11 - Seasonal Value of a Swimming Pool. Panel A shows the average residual values for homes with swimming pools that go under contract during each month of the year. Panel B shows the estimated effect of a swimming pool on a house's residual sales price, conditional on other house characteristics, as estimated by Equation (7). 95% confidence intervals are also presented.

Panel A. Residuals by Month



7 Next Lecture

- Non-Standard Decision-Making
- Limited Attention
  - Financial Markets
  - Consumption