# Econ 219B Psychology and Economics: Applications (Lecture 8)

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#### Outline

1. Social Preferences: Charitable Giving

2. Non-Standard Beliefs

3. Overconfidence

4. Law of Small Numbers

5. Projection Bias

#### 1 Social Preferences: Charitable Giving

- Andreoni (2004). Excellent survey of the theory and evidence
- Stylized facts:
  - US Giving very large: 1.5 to 2.1 percent GDP!
  - Most giving by individuals (Table 1)

Table 1			
Sources of Private Philanthropy, 2002			
Source of gifts	Billions	Percent	
	of dollars	of total	
Individuals	183.7	76.3	
Foundations	26.9	11.2	
Bequests	18.1	7.5	
Corporations	12.2	5.1	
Total for all Sources	240.9	100	
Source: Giving USA, 2003			

#### Giving fairly constant over time (Figure 1)

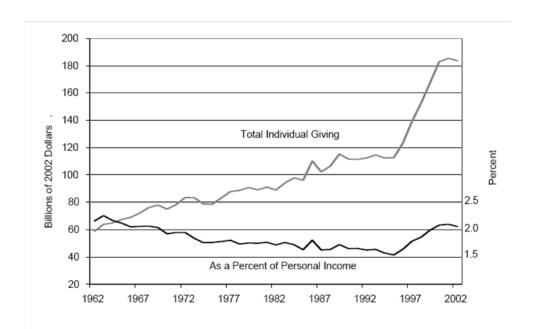


Figure 1: Trends in Individual Giving. Source: Giving USA 2003.

- Giving by income, age, and education (Table 2 no controls)
  - Giving as percent of income fairly stable
  - Increase for very rich (tax incentives matter here)

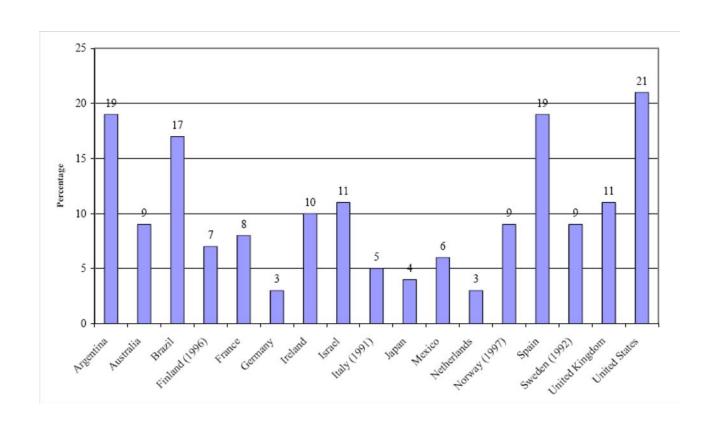
Table 2				
Private philanthropy by income, age, and education of the giver, 1995				
	Percent of	Average	Percent of	
	households	amount given by	household	
	who give	those who give	income	
All contributing households	68.5	1,081	2.2	
Household Income				
under \$10,000	47.3	324	4.8	
10,000-19,000	51.1	439	2.9	
20,000-29,999	64.9	594	2.3	
30,000-39,999	71.8	755	2.2	
40,000-49,999	75.3	573	1.3	
50,000-59,999	85.5	1,040	1.9	
60,000-74,999	78.5	1,360	2.0	
75,000-99,999	79.7	1,688	2.0	
100,000 or above	88.6	3,558	3.0	

- Giving to whom? (Table 3)
  - Mostly for religion
  - Also: human services, education, health
  - Very little international donations

Table 3				
Private Philantropy by Type of Charitable Organization, 1995.				
	Percent	Average amount	Percent of total	
	of Households	given by	household	
Type of Charity	who give	those who give	contributions	
Arts, culture and humanities	9.4	221	2.6	
Education	20.3	335	9.0	
Environment	11.5	110	1.6	
Health	27.3	218	8.1	
Human Services	25.1	285	9.5	
International	3.1	293	1.1	
Private and	6.1	196	1.4	
community foundations				
Public or Societal benefit	10.3	127	1.7	
Recreation	7.0	161	1.4	
Religious	48.0	946	59.4	
Youth Development	20.9	140	3.8	
Other	2.1	160	0.3	

Source: Author's calculations, data from Independent Sector, Giving and Volunteering, 1995.

- Compare to giving in other countries (Figure 2)
  - In US non-profits depend more on Charitable contributions



- Charitable giving important phenomenon How do we understand it?
- Model 1. Social preferences: Giving because caring for welfare of others
- Problem (i): Amounts given off relative to lab experiments
- Problem (ii): Model predicts crowding out of giving:
  - If government spends on income of needy group, corresponding oneon-one decrease in giving
  - Evidence of crowding out: Limited crowd-out
- Problem (iii): Model predicts giving to one highest-value charity—Instead we observe dispersion across charities
- Problem (iv): In-person or phone requests for giving raise much more than impersonal requests (mail)

- Model 2. Andreoni (1994): Warm-Glow or Impure altruism.
  - Agent gets utility v(g) directly from giving
  - Utility v(g) sharply concave
- Can explain (i), (ii), and (iii) See Problem Set 3
- Does not directly explain (iv) Can assume though that warm-glow is triggered more by in-person giving

- **Model 3.** Giving is due to social pressure
  - Pay a disutility cost S if do not give when asked
  - No disutility cost if can avoid to meet the solicitor
- Can explain (i), (ii), and (iii): Give small amounts to charities, mostly because asked
- Can also explain (iv): Give more in higher social pressure environments
- Key prediction differentiating Models 2 and 3:
  - Model 2: Agent seeks giving occasions to get warm glow
  - Modle 3: Agents avoids giving occasions to avoid social pressure
- DellaVigna, List, and Malmendier (2008): Test prediction

- 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

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  - Flyer Treatment: flyer on doorknob on day before provides advance notice about hour of visit

# **Flyer Layout**



Fundraising
Campaign for
La Rabida
Children's Hospital

Fundraisers will visit
this address
tomorrow ( / )
between and
to raise funds for
La Rabida
Children's Hospital.

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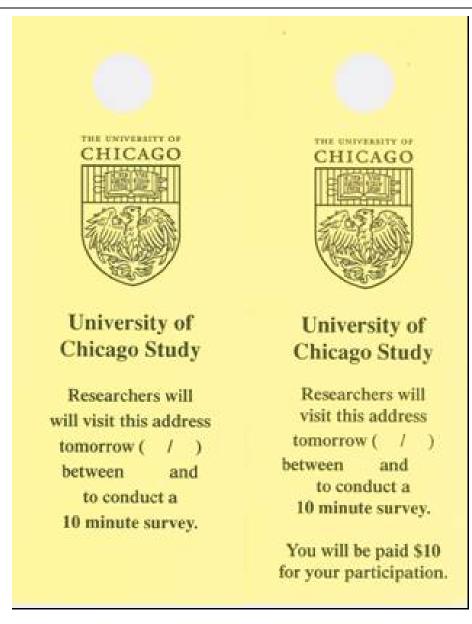
#### Flyer Layout with and without Opt-Out



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  - Survey Treatments: Administer surveys with varying payment and duration and with or without flyers → to structurally estimate parameters.

## **Survey Flyers**



- 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"
  - Survey Treatments: Administer surveys with varying payment and duration and with or without flyers → to structurally estimate parameters.
- Structural estimates of parameters of model

#### Model

- Giving game with giver and fund-raiser. Timing:
  - *Stage 1*:
    - \* No-Flyer case: Giver at home with prob.  $h=h_0$
    - \* Flyer case:
      - $\cdot$  Giver reads notice 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 not home (w/ prob. 1-h) -> Donation g=0
      - · If giver at home (w/ prob. h) -> Choose donation  $g^* \geq 0$

• Utility function of giver:

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

- Agent cares about:
  - Private consumption u(W-g), with  $u'(\cdot) > 0$  and  $u''(\cdot) \leq 0$
  - Giving to charity  $av\left(g,G_{-i}\right)$ , with  $v_g'(\cdot,\cdot)>0$ ,  $v_{g,g}''(\cdot,\cdot)<0$ ,  $\lim_{g\to\infty}v'\left(g,\cdot\right)$ 0, and  $v\geq0$ .
- Two special cases for  $v(g, G_{-i})$ :
  - Pure altruism (Charness and Rabin 2002, Fehr and Gächter, 2000):  $v\left(g,G_{-i}\right)=v\left(g+G_{-i}\right),\ a$  is altruism parameter
  - Warm glow (Andreoni, 1989 and 1990):  $v(g, G_{-i}) = v(g)$ , a is weight on warm glow

- Social Pressure  $s(g) = S(g^s g) \cdot \mathbf{1}_{g < g^s} \ge 0$ 
  - No disutility for not giving while not at home
  - Disutility for giving  $g < g^s$  (socially acceptable level) when face-to-face with fund-raiser
  - Disutility is decreasing in amount given g for  $g < g^s$
- 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

- Second-stage Maximization (Giving)
- Lemma 1. (Conditional Giving). 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  $a \leq \underline{a}$ ; (ii)  $0 < g^*(a,S) < g^s$  for  $\underline{a} < a < \underline{a}$ ; (iii)  $g^*(a,S) = g^s$  for  $\underline{a} \leq a \leq \overline{a}$ ; (iv)  $g^*(a,S) > g^s$  for  $a > \overline{a}$ .
- Figure 1:
  - Giving above  $\bar{a} \equiv u'(W-g^s)/v'(g^s,G_{-i})$  only due to altruism
  - Giving below  $\bar{a}$  due to social pressure

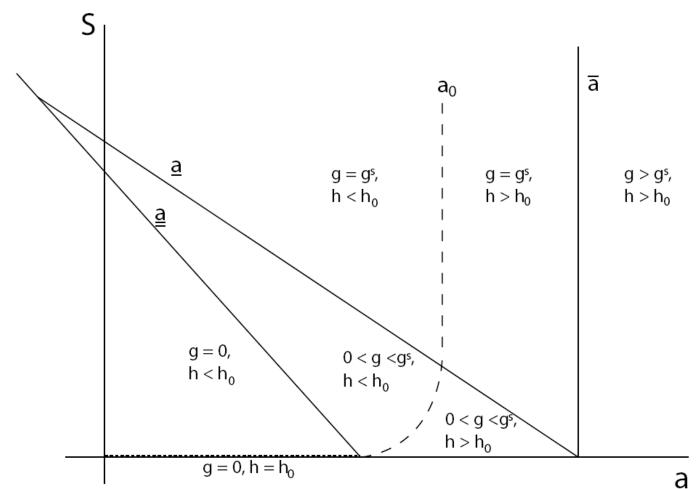


Figure 1. Giving g and Probability of Home Presence h as Function of Parameters

**Notes:** The Figure indicates the different regions for giving (no giving–g=0, small giving–0<g<g $^s$ , giving equal to  $g^s$ , and large giving–g>g $^s$ ) and for probability of being at home (avoidance of solicitor--h<h $_0$ , seeking solicitor--h> h $_0$ ). The regions are a function of the altruism parameter a and of the social pressure parameter 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  $h^*(a,0)>h_0$  and strictly increasing in a for  $a>\underline{a}$ .
  - For S>0 (social pressure),  $h^*(a,S)< h_0$  for  $a\leq \underline{\underline{a}}$  and strictly increasing in a for  $a>\underline{\underline{a}}$ ; there is a unique  $a_0(S)\in (\underline{\underline{a}},\overline{a})$  such that  $h^*(a_0(S))=h_0$ . Moreover,  $a_0(S)$  is increasing in S.
- 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:

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

- 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:  $P(G)_{NF} > P(G)_{F} > P(G)_{OO}$

- **Proposition 3.** The conditional probability P(G|H) of giving given home presence satisfies min  $(P(G|H)_F, P(G|H)_{OO}) \ge P(G|H)_{NF}$
- Separate analysis of small and large giving:
  - $P\left(G^{LO}\right)$  is probability of giving  $g \leq g^s$   $P\left(G^{HI}\right)$  is probability of giving  $g > g^s$

#### Proposition 4.

- (i)  $P(G^{HI})_F = P(G^{HI})_{OO} \ge P(G^{HI})_{NF}$  (with strict inequality if  $F(\bar{a}) < 1$ ).
- (ii) If no social pressure,  $P(G^{LO})_F = P(G^{LO})_{OO}$
- (iii) If social pressure (and  $F(a_0)-F(\underline{a})>0$ )  $P(G^{LO})_F>P(G^{LO})_{CO}$
- Intuition: Large donations are driven by altruism, small donation by social pressure (and some altruism)

## **Experimental Design**

- Fund-raising for two charities:
  - La Rabida Children's Hospital in Chicago
  - East Carolina Hazard Center (ECU)
  - Ask survey respondents to rank 5 charities:
    - La Rabida Rank 3.95 (out of 5)
    - Donate Life Rank 3.79
    - Seattle Children's Hospital Rank 3.47
    - Chicago Historical Society Rank 2.96
    - ECU Rank 2.54
  - Similar ranking when ask preferred charity for a \$1 donations "an anonymous sponsor has pledged to give":
     147 out of 255 prefer La Rabida
  - Two charities: La Rabida (Best shot for altruism), ECU (Low likely altruism)

## **Experimental Design**

- Door-to-Door Fund-raising
  - Chosen because easier to provide notice of future drive
  - How Common? Use survey to ask respondents
    - Did people "come to your door to raise money for a charity" in past 12 months?
      - 73 percent of 177 respondents had door-to-door visit
      - Compare to 84 percent for phone, 95 percent for mail
    - Did you give at least once in past 12 months?
      - 40 percent for door-to-door
      - Compare to 27 percent for phone, 53 percent for mail
    - How much did you give in past 12 months?
      - \$26 for door-to-door (\$26 if not capped at \$1,000)
      - \$59 for phone (\$89 if not capped), \$114 by mail (\$897 if not capped)
  - Summary: Common method, Small amounts given

## **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
  - assigned to multiple treatments (→ fixed effects)
  - aware of different charities but not of treatment
- Time and Place:
  - Saturdays and Sundays between April 27, 2008 and October 18, 2008
  - Hours between 10am and 5pm
  - Towns around Chicago: Burr Ridge, Flossmoor,
     Kenilworth, Lemont, Libertyville, Oak Brook, Orland
     Park, Rolling Meadows, and Roselle

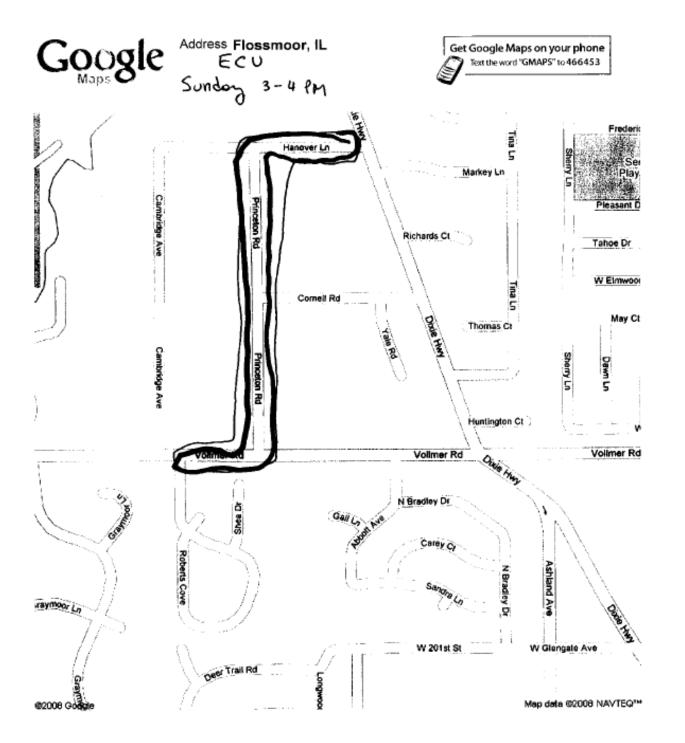
#### **Script For Solicitor**

- (If a minor answers the door, please ask to speak to a parent. Never enter a house.)
- Hi, my name is \_\_\_\_\_\_\_. I am a student volunteering for the University of Chicago visiting Chicago area households today on behalf of La Rabida Children's Hospital [the East Carolina University Center for Natural Hazards Research].
- (Hand brochure to the resident.)
- La Rabida is one of Illinois' foremost children's hospitals, dedicated to caring for **children with chronic illnesses**, **disabilities**, **or who have been abused or neglected**. La Rabida's mission is to provide **family-centered care that goes beyond a child's medical needs** to help them experience as normal a childhood as possible **regardless of a family's ability to pay**. La Rabida is a non-profit organization.

[The ECU Center provides support and coordination for research on natural hazard risks, such as hurricanes, tornadoes, and flooding. The ECU Center's mission is to reduce the loss of life and property damages due to severe weather events through research, outreach, and public education work.]

#### **Script For Solicitor** (continued)

- To help La Rabida [the ECU Center] fulfill its mission, we are collecting contributions for La Rabida Children's hospital [the ECU Center for Natural Hazards Research] today.
- Would you like to make a contribution today?
- (If you receive a contribution, please write a receipt that includes their name and contribution amount.)
- [AFTER they decide whether or not to give]: If I may ask you one quick question did you see our flyer on your door yesterday? [Record answer in log]
- If you have questions regarding La Rabida [the ECU Center] or want additional information, there is a phone number and web site address provided in this brochure.
- Thank you.



#### ECU

#### Sunday April 27th 3-4pm

#### REMEMBER THAT THE HOUSE NUMBERS MIGHT NOT BE IN ORDER!!

Number	Street	Comments
1844	Princeton Rd	
1841	Princeton Rd	
1840	Princeton Rd	
1820	Princeton Rd	
1825	Princeton Rd	
1816	Princeton Rd	
1802	Princeton Rd	
1751	Princeton Rd	
1740	Princeton Rd	
1730	Princeton Rd	
1656	Princeton Rd	
1650	Princeton Rd	
1639	Princeton Rd	
1644	Princeton Rd	
1632	Princeton Rd	
1635	Princeton Rd	
1842	Hanover Rd	
1843	Hanover Rd	
1832	Hanover Rd	
1827	Hanover Rd	
1811	Hanover Rd	Red brick at the end of road
1910	Hanover Rd	
1911	Hanover Rd	
1936	Vollner Rd	
1930	Vollner Rd	

1/25		
House Number: 163		
Exact Time Approached:	3:21	Princedon
☐ Check if flyer still on door	☐ Check if flyer ON GROUND	RA
☐ Check if "Do Not Disturb"	box is CHECKED	0 .
Check if NO ANSWER		N ol
Respondent Sex	DM DF	
Respondent Age (est.)		
	☐ White ☐ AA ☐ Hispanic ☐ East Asian	
Respondent Race	☐ South Asian ☐ Other:	
Amount donated	\$	
Did respondent see FLYER?	☐ Yes ☐ No ☐ Forgot to ask	
Did respondent see 1 B 1 B 1.		
Comments		
. 1.0		
House Number: 13	<u> </u>	
Exact Time Approached:	3 \ 7 3	
☐ Check if flyer still on door		
☐ Check if "Do Not Disturb"	box is CHECKED	
☐ Check if NO ANSWER		
Respondent Sex	DM DF	
Respondent Age (est.)	73.	
	☐ White ☐ AA ☐ Hispanic ☐ East Asian	
Respondent Race	☐ South Asian ☐ Other:	
Amount donated	\$ 0	
Did respondent see FLYER?	☐ Yes ☐ No ☐ Forgot to ask	
- I I I I I I I I I I I I I I I I I I I		
Comments	This sind the last. Asked who	
	This is a	
	- 1100 LOV 144	

## Randomization

- Randomization
  - within a solicitor-day observations (4h/6h shifts per day) and
  - at the street level within a town
- Treatment sample is unbalanced
  - overweighted flyer/non-flyer treatments
    - Baseline: 3,166
    - Flyer: 3,433 (760 indicate only visit in next 2 weeks no difference)
    - Flyer with Opt-Out: 1,070
  - overweighted La Rabida relative to ECU
    - ECU: 2,707
    - La Rabida: 4,962
- Different treatments in different periods → randomization is conditional on solicitor and day fixed effects.

#### **Fundraising Treatments**

Fundraise No Flyer La Rabida

Fundraise Flyer La Rabida

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

Fundraise Flyer ECU

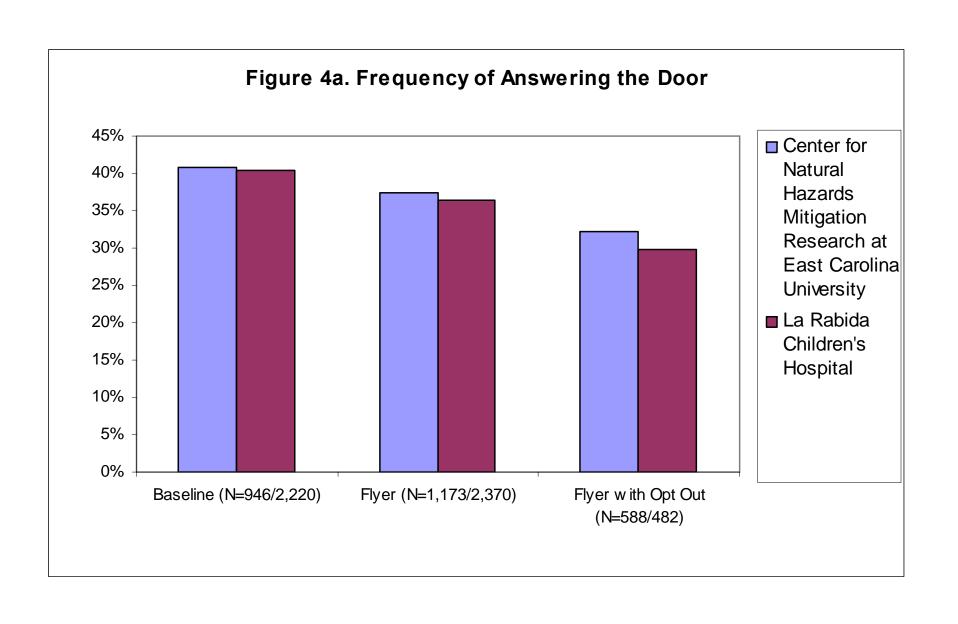
Fundraise Flyer & Opt-Out ECU

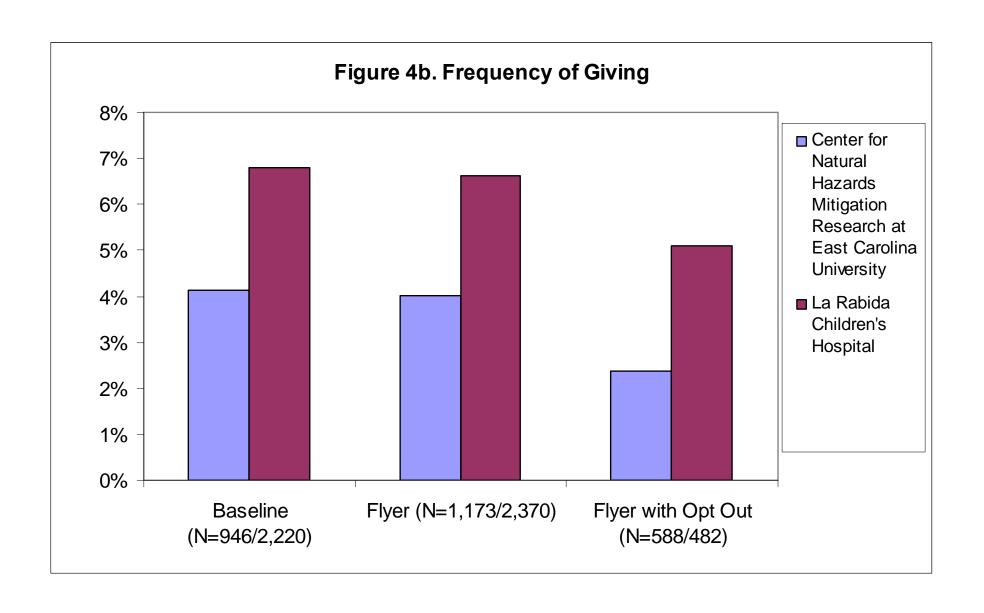
## **Estimation Strategy**

• Estimate treatment effects conditioning on solicitor, town, and day fixed effects

$$y_{i,j,t,h} = \alpha + \Gamma T_{i,j,t,h} + \eta_i + \varphi_j + \lambda_t + BX_{i,j,t,h} + \varepsilon_{i,j,t,h}$$

- Obtain estimate for baseline treatment from same regression without any controls.
- Estimate impact for
  - Probability of answering door
  - Probability of giving
  - (Implied Conditional probability of giving)
  - Probability of large versus small giving





**Table 2. Results for Fund-Raising Treatments** 

Specification:	OLS Regressions										
Dep. Var.:	Indicator fo	or Answerin	g the Door	Indicator for Giving							
Sample:	Pooled	ECU	La Rabida	Pooled	ECU	La Rabida					
	(1)	(2)	(3)	(4)	(5)	(6)					
Flyer Treatment	-0.038 (0.0139)***	-0.0323 (0.0324)	-0.0397 (0.0150)**	-0.0013 (0.0062)	0.0034 (0.0070)	-0.0014 (0.0080)					
Flyer with opt out Treatment	-0.0946 (0.0193)***	-0.0902 (0.0276)***	-0.1019 (0.0313)***	-0.0174 (0.0079)**	-0.0173 (0.0099)*	-0.0155 (0.0135)					
Mean of Dep. Var. for Baseline Group Control Variables:	0.409	0.4228	0.4032	0.0629	0.0507	0.068					
Solicitor-Date Fixed Effects	X	X	Χ	Х	Χ	X					
N	N = 7669	N = 2707	N = 4962	N = 7669	N = 2707	N = 4962					

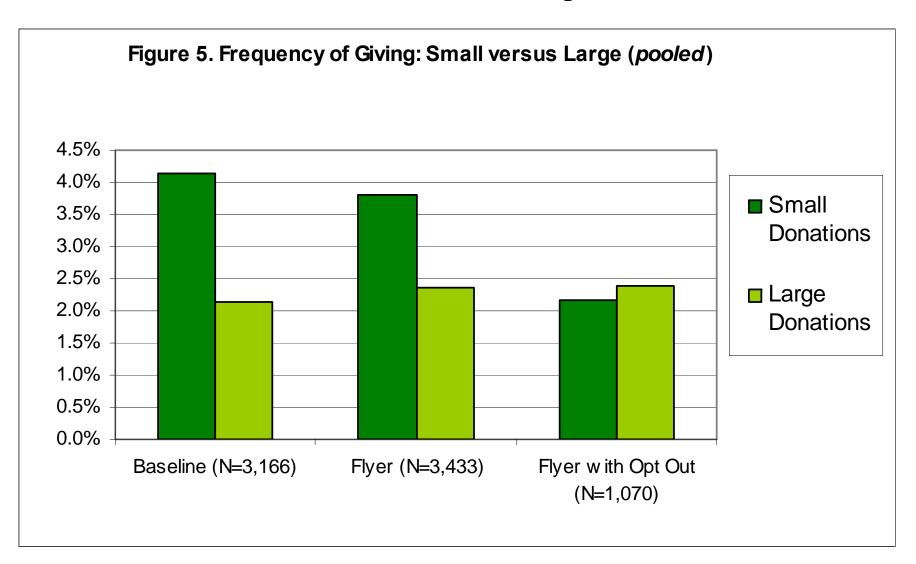
**Notes:** Estimates for a linear probability model, with standard errors clustered by solicitor-date in parenthesis. The omitted treatment is the Baseline No-Flyer fund-rasigin treatment. The regressions include controls for solicitor-date fixed effects, as well as a 0-10 rating \* significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

# Interpretation of results

- Result 1:  $P(H)_{NF} > P(H)_F > P(H)_{OO}$ 
  - Proposition 1: Support for social pressure
- Result 2:  $P(G)_F = P(G)_{NF}$ 
  - Proposition 2: Consistent with heterogeneous population with both social pressure and altruism
  - Reconcile with Result 1? Social pressure reduces presence at home even among non-givers
- Result 3:  $P(G)_F > P(G)_{OO}$ 
  - Proposition 2: Support for social pressure
- Result 4:  $P(G/H)_F > P(G/H)_{NF}$ 
  - Proposition 3: Consistent with any model
- Further Test: Proposition 4 on small versus large donations

#### •Separate by Donation Size:

Social pressure more likely to yield small donations Use median donation size (\$10) as cut-off point



**Table 2. Results for Fund-Raising Treatments** 

Specification:							
Dep. Var.:	Indicator 1	for Giving	Indicator for Giving				
	Small	Large	Prior to	Post			
	Amount	Amount	Crisis	Crisis			
	(≤ \$10)	(> \$10)	(9/1/2008)	(9/1/2008)			
Sample:	Poo	oled	Pod	oled			
	(7)	(8)	(9)	(10)			
Flyer Treatment	-0.0034	0.0021	-0.0043	0.0182			
-	(0.0052)	(0.0035)	(0.0071)	(0.0097)*			
Flyer with opt out	-0.0197	0.0023	-0.019	-0.0075			
Treatment	(0.0076)**	(0.0051)	(0.0100)*	(0.0121)			
Mean of Dep. Var.							
for Baseline Group	0.0414	0.0215	0.0677	0.0267			
<b>Control Variables:</b>							
Solicitor-Date							
Fixed Effects	X	X	X	X			
N	N = 7669	N = 7669	N = 6115	N = 1554			

**Notes:** Estimates for a linear probability model, with standard errors clustered by solicitor-date in parenthesis. The omitted treatment is the Baseline No-Flyer fund-rasigin treatment. The regressions include controls for solicitor-date fixed effects, as well as a 0-10 rating of home values in the block.

<sup>\*</sup> significant at 10%; \*\*

# **Summary of Results**

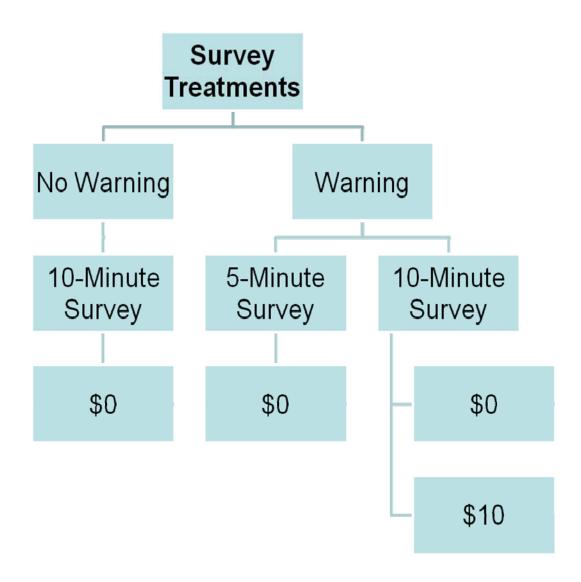
- 1. Flyer reduces the share of households at home by 10% (simple flyer) to 25% (flyer with opt-out box)
- 2. Simple flyer does not affect giving
- 3. Flyer with opt-out box reduces giving by 30%
- 4. Reduction in giving exclusively for small donations (donations < \$10)
- 5. Overall reduction of level of giving after financial crisis
- 6. Reduction in giving larger for women

### • Interpretation:

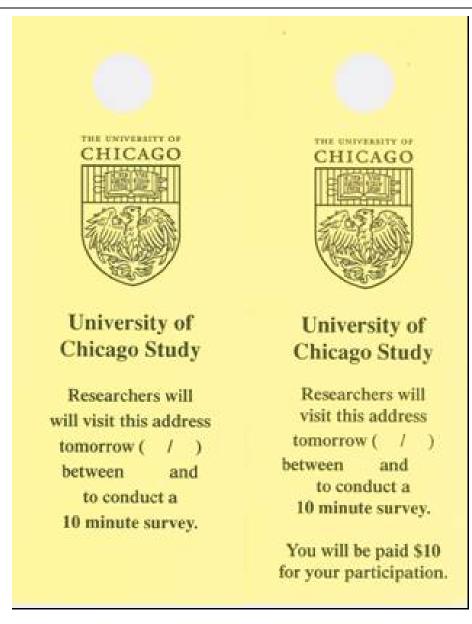
- Results 1, 3-4 point to social pressure
- Result 2 points to altruism

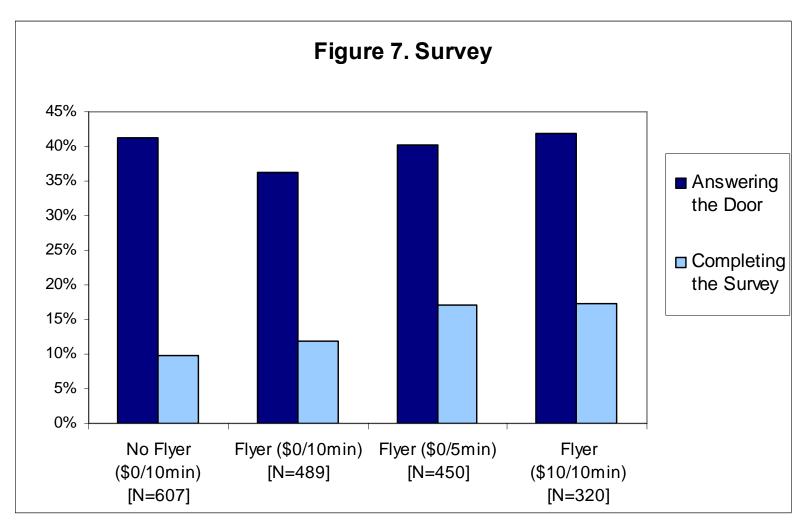
# **Survey Treatments**

- Results of fundraiser do not allow us to estimate underlying 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



# **Survey Flyers**





#### •Survey Results:

Higher payment (lower duration) increases proportion at home by 10% (insig.) increases survey completion by 70% (significant)

**Table 4. Results for Survey Treatments** 

Specification:	OLS Regressions									
Dependent Variable:	Indicator for Answering the Door	Indicator f	ing Survey Post Crisis (9/1/2008)							
	(1)	(2)	(3)	(4)						
Flyer (\$0/10min) Treatment Flyer (\$0/5min) Treatment Flyer (\$10/10min) Treatment	-0.0514 (0.0385) -0.0107 (0.0328) 0.0044 (0.0416)	-0.0041 (0.0262) 0.0716 (0.0229)*** 0.0752 (0.0278)**	-0.0109 (0.0303) 0.0882 (0.0301)*** 0.0934 (0.0364)**	0.0234 (0.0353) 0.0333 (0.0250) 0.0329 (0.0290)						
Mean of Dep. Var. for No Flyer (\$0/10min) Control Variables: Randomization Fixed Effects	0.4135 X	0.0972 X	0.109 X	0.0576 X						
N	N = 1866	N = 1866	N = 1378	N = 488						

**Notes:** Estimates for a linear probability model, with standard errors clustered by solicitor-date in parenthesis. The omitted treatment is the Baseline No-Flyer \$0-10 minutes survey. The regressions include controls for solicitor-date fixed effects, as well as a 0-10 rating of home values in the block.

<sup>\*</sup> significant at 10%; \*\* significant at 5%; \*\*\* significant at 1%

## **Conclusions**

- Test of welfare effects of giving in context of door-todoor fundraiser
- Flyer with information about upcoming fundraiser
  - Reduces the share of households at home by 10-25%
  - Reduces the share of households giving by 30% only if optout box is included (otherwise no effect)
  - Reduction in giving only in small donations (<\$10)</li>
- Evidence of social pressure and some evidence of altruism
- Implication: giving not necessarily welfare-enhancing
- Revisit tax-advantaged status of contributions for highpressure fund-raising

#### 2 Non-Standard Beliefs

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

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

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

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  $\tilde{p}(s_t)$  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):  $\tilde{p} (good\ state_t) > p (good\ state_t)$
  - 2. Law of Small Numbers. Gambler's Fallacy and Overinference in updating  $\tilde{p}(s_t|s_{t-1})$
  - 3. Projection Bias. Expect future utility  $\tilde{U}\left(x_i^t|s_t\right)$  to be too close to today's

#### 3 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

- Economic experiment: Camerer and Lovallo (AER, 1999)
  - Experimental design:
    - \* Initial endowment: \$10
    - \* Simultaneous entry decision: enter -> play game or stay out -> payoff 0
    - \* Parameter c for entry payoffs:
      - $\cdot$  Top c entrants share \$50
      - · Bottom n-c entrants get -\$10

TABLE 1—RANK-BASED PAYOFFS								
	Payoff for successful entrar as a function of "c"							
Rank	2	4	6	8				
1	33	20	14	11				
2	17	15	12	10				
3		10	10	8				
4		5	7	7				
5			5	6				
6			2	4				
7				3				
8				2				

- -n = 12, 14, 16 subjects
  - Within-subject variation in games played if entry: chance or skill (trivia, puzzles)
  - Only feedback: Total number of entrants
  - Paid at the end of game for one randomly-determined round (no feed-back on performance)

TABLE 3—DESCRIPTION OF EXPERIMENTS

Experiment #	Sample	n	Selection procedure	Rank order
1	Chicago, undergraduates	12	random	R/S
2	Chicago, undergraduates	14	random	S/R
3	Wharton, undergraduates	16	random	R/S
4	Wharton, undergraduates	16	random	S/R
5	Wharton, undergraduates	16	self-selection	R/S
6	Wharton, undergraduates	16	self-selection	S/R
7	Chicago, M.B.A.'s	14	self-selection	R/S
8	Wharton, M.B.A.'s	14	self-selection	S/R

- Optimal decision for risk-neutral players in chance game
  - Assume e players enter and n-e stay out
  - Probability of being in top group p = c/e (with  $c \ge e$ )
  - average payoff of entry is

$$\pi_E = p \frac{50}{c} - (1-p) \cdot 10 = \frac{c \cdot 50}{e} - \frac{e-c}{e} \cdot 10 = \frac{50-10(e-c)}{e}$$

- average payoff of exit  $\pi_E=0$
- Enter is Best Response if  $50 10 \, (e c) \geq 0$  or  $e \leq 5 + c$
- Asymmetric Nash Equilibria:  $e_C^*=c+{
  m 4}$  or  $e_C^*=c+{
  m 5}$  players enter
- Group profits should be 10 (if  $e^* = c + 4$ ) or 0 (if  $e^* = c + 5$ )
- $\bullet$  Games of skill –> If overconfidence, overestimate chance of winning p –> Too much entry  $e_S^*$

- Luck: Higher profits than in Nash eq. -> Too little entry (Risk av.?)
- Skill: Lower profits (but still >0), Profits<0 with selection (Exp. 5-8)

	Rounds													
Experiment #	n	1	2	3	4	5	6	7	8	9	10	11	12	Total
1	12	50	50	20	30	40	30	20	50	30	40	20	40	420
2	14	0	-10	10	20	-10	10	20	10	0	0	30	20	100
3	16	10	50	20	40	10	20	30	40	20	40	30	20	330
4.	16	0	10	10	20	10	-10	0	10	20	10	0	20	100
5	16	20	10	10	10	0	0	30	20	-10	0	0	0	90
6	16	30	20	10	0	-10	30	20	10	10	30	10	20	180
7	14	10	20	40	20	30	40	-30	40	10	0	0	20	200
8	14	20	10	0	30	30	0	10	10	20	10	20	40	200

Profit for skill-rank condition														
		Rounds												
Experiment #	n	1	2	3	4	5	6	7	8	9	10	11	12	Total
1	12	50	0	20	10	30	10	20	10	40	10	10	30	240
2	14	0	-10	10	20	-10	10	20	10	0	0	30	20	100
3	16	10	20	10	20	0	10	20	10	10	30	20	10	180
4	16	0	0	20	20	10	-30	10	-10	-10	10	-20	0	0
5	16	-30	-20	-20	-10	-40	-10	-30	0	-30	-10	-20	0	-220
6	16	10	-40	-20	-30	-10	-30	-10	-20	-20	-10	0	0	-180
7	14	-40	-10	-10	0	-20	-10	-40	0	0	0	-10	0	-140
8	14	10	-10	-10	-10	-20	-20	-20	0	-20	10	-20	-20	-130

- Overconfidence about own performance *relative* to others
  - Overconfidence about own ability?
  - Or underestimation of entry of others?
- Forecasts of people about entry of others:
  - forecast 0.3 entrants too high in chance game;
  - forecast 0.5 entrants too low in skill game;
  - (some underestimation of entry of others)

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 about ability by CEOs
- Malmendier-Tate (JF 2005, JFE forthcoming, and 2007)
- Assume that CEOs overestimate their capacity to create value
- Consider implications for:
  - Investment decisions (MT 2005)
  - Mergers (MT forthcoming)
  - Equity issuance (MT 2007)
- 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."
  - ⇒ First-best takeover decision.
- Post-acquisition value to current shareholders:

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

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

## **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

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

i.e. merges if

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

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

## **Propositions**

#### Compare

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

- 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 valuecreating mergers. (Rational managers do not.)

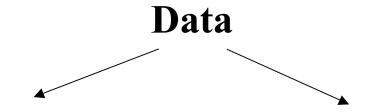
## **Empirical Predictions**

#### 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 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"

## **Empirical Specification**

$$Pr\{Y_{it} = 1 \mid X, O_{it}\} = G(\beta_1 + \beta_2 \cdot O_{it} + X^T \gamma)$$

```
with i company O overconfidence t year X controls Y acquisition (yes or no)
```

 $\rightarrow$  H<sub>0</sub>:  $\beta_2 = 0$  (overconfidence does not matter)

 $\rightarrow$  H<sub>1</sub>:  $\beta_2 > 0$  (overconfidence does matter)

## **Identification Strategy (I)**

#### Case 1:

Wayne Huizenga (Cook Data Services/Blockbuster)

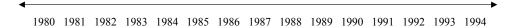
- CEO for all 14 years of sample
- Longholder

```
M MM M M MH

1980 1981 1982 1983 1984 1985 1986 1987 1988 1989 1990 1991 1992 1993 1994
```

J Willard Marriott (Marriott International)

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

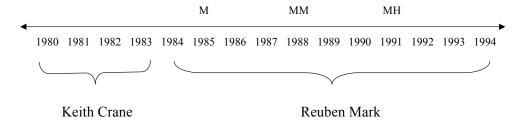


#### **AND**

#### 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				
<u>Percentile</u>	<u>Return</u>			
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 p	orice 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 (2.40)**	<b>1.7763</b> (2.70)***	<b>3.1494</b> (2.59)***
Year Fixed Effects Observations Firms	yes 3690	yes 3690 327	yes 1577 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 <sub>t-1</sub>, 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 → 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

<b>Longholder</b> = holds	•	•	oiration (at least	once)			
<b>Distribution:</b> Logistic	<ul><li>c. Constant inclu</li></ul>	ded.					
Dependent Variable	: Acquistion (yes	or no); Norma	<b>lization:</b> Capital.				
All regressions are lo	git with random e	effects.					
	Least Equity				Most Equity		
	Dependent			>	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 C	ash Flow, Q <sub>t-1</sub> , Size	e, Ownership, Ves	sted 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

## **Empirical Specification**

$$CAR_i = \beta_1 + \beta_2 \cdot O_i + X'\gamma + \varepsilon_i$$

with *i* company

O overconfidence

X controls

$$CAR_{i} = \sum_{t=-1}^{1} (r_{it} - E[r_{it}])$$

where  $E[r_{it}]$  is daily S&P 500 returns ( $\alpha$ =0;  $\beta$ =1)

# Table 14. Market Response

Longholder = holds options until last year before expiration								
(at least once)								
Dependent Variable: Cumul	lative abnor	mal returns [-1	,+1]					
	OLS	OLS	OLS					
	(3)	(4)	(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	logit with fixed
		random effects	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<sub>1</sub>, Size, Ownership, Vested Options, and Governance. Industries are Fama French industry groups.

#### **Conclusions**

- Overconfident managers are more acquisitive.
- Much of this acquisitiveness is in the form of diversifying mergers.
- Overconfidence has largest impact if CEO has abundant internal resources.
- The market reacts more negatively to the mergers of overconfident CEOs

- 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

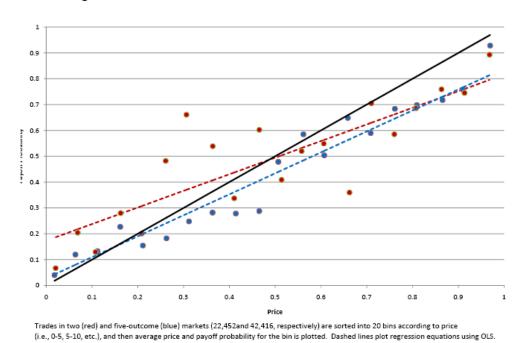


Figure 2. Prices and Probabilities in Two and Five-outcome Markets

- 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

- 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)

- 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 98 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	Panel A: All Transactions							
	n	84 trading	252 trading	504 trading				
		days later	days later	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

	n	84 trading	252 trading	504 trading
		days later	days later	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)

- 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

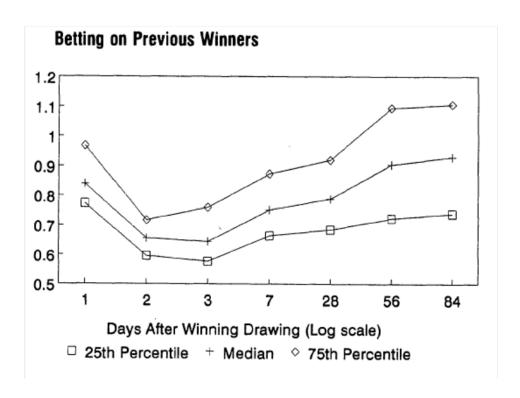
#### 4 Law of Small Numbers

- 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:  $P(Well|UUU) = .5P(UUU|Well)/[.5P(UUU|Well)+ .5P(UUU|Poor)] = .7^3/(.7^3 + .3^3) \approx .927.$

- \* 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 get into negative probabilities...
- What is Forecast of P(U|UUU)?
  - \* Bayesian:  $P(U|UUU) = .927 * .7 + (1 .927) * .3 \approx .671$
  - \* Law-of-Small-Number:  $P\left(U|UUU\right) = .972*.7 + (1-.972)*.3 \approx .689$
- Over-inference despite gambler's fallacy beliefs

- Substantial evidence of over-inference (also called extrapolation)
- Notice: Case with unknown probabilities is much more common than lottery case

#### • 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	Q	uintile of	Observed Difference				
Raw Returns for:	(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?

		Allocati	Observed Difference	Threshold for Significant Difference at			
	(Low) 1	2	3	4	5 (High)	(5-1)	$\alpha = 10\%$
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
- 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
- This implies effect on pricing: Stocks with high past returns get overpriced
   Later mean-revert
- DeBondt and Thaler (1985):
  - Compare winners in the past 3 years to losers in past 3 years.
  - 'Winners' underperform the 'losers' by 25 percentage points over the next three years

### 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

# 5 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
  - $\ast$  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  $u\left(c,s'\right)$
  - Predict future utility in state s
  - Simple projection bias:

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

- Parameter  $\alpha$  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
- Additional Prediction:
  - Cold weather at return -> Fewer returns

- Focus on Probability[Return|Order]
- $\bullet$  Denote temperature at Order time as  $\omega_O$  and temperature at Return time as  $\omega_R$
- Predictions:
  - 1. If  $\alpha=0$  (no proj. bias), P[R|O] is independent of  $\omega_O$  and  $\omega_R$
  - 2. If  $\alpha>0$  (proj. bias),  $\partial P[R|O]/\partial\omega_O<0$  and  $\partial P[R|O]/\partial\omega_R>0$
- Notice: Do not observe date of return decision

- 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

- Summary Stats:
  - Probability of return fairly high
  - Prices of items substantial
  - Delay between order and receipt 4-5 days

TABLE 1 Summary Statistics by Item Categories

Gloves/ Winter Hats Sports Parkas/ Vests Jackets All Seve							
Mittens	I	111113		Coats	7 0313	Juckets	Categories
484,084	262,610	484,086	146,594	524,831	151,958	145,910	2,200,073
106	93	88	233	133	20	37	710
10.9	15.6	10.8	6.6	22.2	12.8	18.0	14.4
29.26	68.33	23.74	74.10	148.58	40.90	106.70	70.10
7.2	6.6	6.9	7.2	7.3	6.8	8.2	7.14
27.3	22.2	23.9	27.7	20.5	21.71	25.3	23.83
0.85	0.82	0.83	0.86	0.77	0.83	0.82	0.82
0.42	0.97	0.72	0.94	2.17	1.24	1.13	1.11
4.13	4.66	4.46	4.58	5.92	5.04	4.89	4.84
0.04	0.03	0.03	0.02	0.04	0.02	0.05	0.03
0.71	0.66	0.71	0.70	0.66	0.72	0.66	0.69
0.97	0.98	0.98	0.97	0.98	0.98	0.97	0.98
3.5	2.5	3.4	2.9	2.2	2.8	2.3	2.9
				-10.11		-5.64	
40.60	39.74	41.48	37.81	43.29	44.76	46.88	41.85
39.90	38.97	40.72	36.70	42.29	43.20	45.70	40.94
1.79	2.69	1.69	2.65	1.30	1.26	0.63	1.70
1.58	2.32	1.51	2.35	1.33	1.43	0.66	1.57
	484,084 106 10.9 29.26 7.2 27.3 0.85 0.42 4.13 0.04 0.71 0.97 3.5 40.60 39.90 1.79	Mittens         Boots           484,084         262,610           106         93           10.9         15.6           29.26         68.33           7.2         6.6           27.3         22.2           0.85         0.82           0.42         0.97           4.13         4.66           0.04         0.03           0.71         0.66           0.97         0.98           3.5         2.5           40.60         39.74           39.90         38.97           1.79         2.69	Mittens         Boots           484,084         262,610         484,086           106         93         88           10.9         15.6         10.8           29.26         68.33         23.74           7.2         6.6         6.9           27.3         22.2         23.9           0.85         0.82         0.83           0.42         0.97         0.72           4.13         4.66         4.46           0.04         0.03         0.03           0.71         0.98         0.98           3.5         2.5         3.4           40.60         39.74         41.48           39.90         38.97         40.72           1.79         2.69         1.69	Mittens         Boots         Equipment           484,084         262,610         484,086         146,594           106         93         88         233           10.9         15.6         10.8         6.6           29.26         68.33         23.74         74.10           7.2         6.6         6.9         7.2           27.3         22.2         23.9         27.7           0.85         0.82         0.83         0.86           0.42         0.97         0.72         0.94           4.13         4.66         4.46         4.58           0.04         0.03         0.03         0.02           0.71         0.66         0.71         0.70           0.97         0.98         0.98         0.97           3.5         2.5         3.4         2.9           40.60         39.74         41.48         37.81           39.90         38.97         40.72         36.70           1.79         2.69         1.69         2.65	Mittens         Boots         Equipment         Coats           484,084         262,610         484,086         146,594         524,831           106         93         88         233         133           10.9         15.6         10.8         6.6         22.2           29.26         68.33         23.74         74.10         148.58           7.2         6.6         6.9         7.2         7.3           27.3         22.2         23.9         27.7         20.5           0.85         0.82         0.83         0.86         0.77           0.42         0.97         0.72         0.94         2.17           4.13         4.66         4.46         4.58         5.92           0.04         0.03         0.03         0.02         0.04           0.71         0.66         0.71         0.70         0.66           0.97         0.98         0.98         0.97         0.98           3.5         2.5         3.4         2.9         2.2           -10.11         40.60         39.74         41.48         37.81         43.29           39.90         38.97         40.72 <td< td=""><td>Mittens         Boots         Equipment         Coats           484,084         262,610         484,086         146,594         524,831         151,958           106         93         88         233         133         20           10.9         15.6         10.8         6.6         22.2         12.8           29.26         68.33         23.74         74.10         148.58         40.90           7.2         6.6         6.9         7.2         7.3         6.8           27.3         22.2         23.9         27.7         20.5         21.71           0.85         0.82         0.83         0.86         0.77         0.83           0.42         0.97         0.72         0.94         2.17         1.24           4.13         4.66         4.46         4.58         5.92         5.04           0.04         0.03         0.03         0.02         0.04         0.02           0.71         0.66         0.71         0.70         0.66         0.72           0.97         0.98         0.99         0.98         0.98           3.5         2.5         3.4         2.9         2.2         2</td><td>Mittens         Boots         Equipment         Coats           484,084         262,610         484,086         146,594         524,831         151,958         145,910           106         93         88         233         133         20         37           10.9         15.6         10.8         6.6         22.2         12.8         18.0           29.26         68.33         23.74         74.10         148.58         40.90         106.70           7.2         6.6         6.9         7.2         7.3         6.8         8.2           27.3         22.2         23.9         27.7         20.5         21.71         25.3           0.85         0.82         0.83         0.86         0.77         0.83         0.82           0.42         0.97         0.72         0.94         2.17         1.24         1.13           4.13         4.66         4.46         4.58         5.92         5.04         4.89           0.04         0.03         0.03         0.02         0.04         0.02         0.05           0.71         0.66         0.71         0.70         0.66         0.72         0.66</td></td<>	Mittens         Boots         Equipment         Coats           484,084         262,610         484,086         146,594         524,831         151,958           106         93         88         233         133         20           10.9         15.6         10.8         6.6         22.2         12.8           29.26         68.33         23.74         74.10         148.58         40.90           7.2         6.6         6.9         7.2         7.3         6.8           27.3         22.2         23.9         27.7         20.5         21.71           0.85         0.82         0.83         0.86         0.77         0.83           0.42         0.97         0.72         0.94         2.17         1.24           4.13         4.66         4.46         4.58         5.92         5.04           0.04         0.03         0.03         0.02         0.04         0.02           0.71         0.66         0.71         0.70         0.66         0.72           0.97         0.98         0.99         0.98         0.98           3.5         2.5         3.4         2.9         2.2         2	Mittens         Boots         Equipment         Coats           484,084         262,610         484,086         146,594         524,831         151,958         145,910           106         93         88         233         133         20         37           10.9         15.6         10.8         6.6         22.2         12.8         18.0           29.26         68.33         23.74         74.10         148.58         40.90         106.70           7.2         6.6         6.9         7.2         7.3         6.8         8.2           27.3         22.2         23.9         27.7         20.5         21.71         25.3           0.85         0.82         0.83         0.86         0.77         0.83         0.82           0.42         0.97         0.72         0.94         2.17         1.24         1.13           4.13         4.66         4.46         4.58         5.92         5.04         4.89           0.04         0.03         0.03         0.02         0.04         0.02         0.05           0.71         0.66         0.71         0.70         0.66         0.72         0.66

#### • Main estimation: Probit

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

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 &	Winter	Hats	Sports	Parkas &	Vests	Jackets	All Seven
	Mittens	Boots		Equipment	Coats			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 Item Fixed Effects Month-Region Fixed Effects	YES	YES	YES	NOª	YES	YES	YES	YES
	YES	YES	YES	YES	YES	YES	YES	YES
	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.

<sup>\*</sup> Statistically significant at the .10 level; \*\* Statistically significant at the .05 level.

<sup>&</sup>lt;sup>a</sup> 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 nto observe when return decision is made

- Similar estimates for linear probability model with household fixed effects
- (Restrict sample to multiple orders by households)

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** (0.00027)	-0.00039** (0.00013)
Receiving-Date Temperature	0.00017 (0.00029)	0.00002 (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

 $\bullet$  Simple structural model of projection bias: Estimates of projection bias  $\alpha$  around .3-.4

	TABLE 6 Structural Estimation				
	Winter Boots	Hats	Parkas & Coats	Vests	Jackets
			ı		1
	ı	1	1	1	
α	0.3084** (0.0570)	0.4698** (0.00001)	0.3814** (0.0352)	0.0002 (0.0056)	0.4992** (0.0002)

• Other applications?

- Also, Levy (2009): addiction model with present bias and projecion bias
  - Test for projection bias: Effect of higher variance of future prices
    - \* Standard model: Higher variance lowers current consumption because getting addicted becomes more costly
    - \* Projection bias: Do not realize link between current smoking and future addiction —> Higher variance can increase smoking
  - Data: Positive correlation of variance of prices with current smoking
     Supports projection bias
- Parametric estimate: projection bias  $\alpha \approx .4$

## 6 Next Lecture

• Non-Standard Decision-Making (next 3 lectures)

• Limited Attention (next lecture)