Econ 219b
Psychology and Economics: Applications
(Lecture 15)

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Outline

1. Overconfidence: Excess Market Entry

2. Social Preferences: Introduction

3. Charitable Contributions: Survey

4. Charitable Contributions: Field Experiments

5. Some Advice

6. Course Evaluation

1 Overconfidence: Excess Market Entry

- Camerer and Lovallo (AER, 1999)

- Enterpreneurs choose

  - new business with stochastic outcome $\mathbf{x} = (x_1, ..., x_n)$

  - riskless activity y

- Standard model: Choose business if $\sum_{i=1}^{N} p_i x_i > y$

- Overconfidence: Choose business if $\sum_{i=1}^{N} \tilde{p}_i x_i > y$

- The higher the overconfidence, the higher the incidence of business failure

- Experimental design:
  - Initial endowment: \$10
  - $n = 12, 14, 16$ subjects
  - Simultaneous entry decision:
    - enter –> accept risk
    - stay out –> payoff 0
  - Parameter c for entry payoffs:
    - Top c entrants share \$50
    - Bottom $n - c$ entrants get $-$\$10
  - Within-subject variation in games played if entry:
    - chance
    - skill (trivia, puzzles)

- Optimal decision for risk-neutral players in chance game

- Asymmetric Nash equilibria:
  - $c+4$ enter
  - $n-(c+4)$ stay out
  - Probability of being in top group p
  - Probability $p = c/(c+5)$
  - average payoff of entry is

$$\begin{aligned} p\frac{50}{c} - (1-p)\,10 &= \\ \frac{1}{c+5}50 - \frac{5}{c+5}10 &= 0 \end{aligned}$$

  - average payoff of exit is 0
  - predicted average profit of entry 0

- In game of skill, similar equilibria

- Enter until zero profits

- Overconfidence about winning probability $(\tilde{p} > p)$. Enter until

$$\tilde{p}\frac{50}{c} - (1 - \tilde{p})\,10 = 0$$

- In reality, profits

$$p\frac{50}{c} - (1 - p)\,10 < 0$$

- Compare profits in games of luck and games of skill

- Table 4:

- Games of luck: Substantial profits (more than in Nash eq.)
- Games of skill:
  * lower profits (but still >0)
  * negative profits in cases with recruitement on skill

In their game, N players choose simultaneously, and without communicating, whether to enter a market or not. The market "capacity" is a preannounced number, c. If players stay out they earn a payment K. If the total number of entrants is E, the entrants each earn $K + rK(c - E)$ (with $rK > 0$). The optimal behavior is simple: Players want to enter only if the number of expected entrants (including themselves) is less than the capacity c. If they do enter, players prefer the number of entrants to be as small as possible. The interesting questions are whether the right number of players enter (is E around c?), whether E changes with c, and how players figure out whether to enter or not.

Kahneman (1988) was surprised to see that the number of entrants, E, was typically in the range $[c - 2, c + 2]$ even though subjects could not communicate or coordinate their decisions in any explicit way. "To a psychologist," he wrote, "it looks like magic." Rapoport (1995) replicated the results using Ph.D. students playing for much larger stakes. He also found that subjects entered a bit too frequently at first, but gradually E converged very close to c. E and c were highly correlated across trials. Extensions by James Sundali et al. (1995) and Rapoport et al. (1998a) replicated the earlier findings. Rapoport et al. (1998b) introduced probabilistic payoffs and showed that deviations from equilibrium entry could be parsimoniously explained by nonlinear transformations of entry probabilities.

Our experiments extend this paradigm in four ways: Payoffs depend on a subject's rank (relative to other entrants); ranks depend on either a chance device, or on a subject's skill; subjects in some experiments are told in advance that the experiment depends on skill (and hence, more skilled subjects presumably self-select into the experiment); and subjects forecast the number of entrants in each period.

Skill-dependent payoffs are the crucial new design feature. The early experiments capture an important aspect of entry—tacit coordination among potential entrants to avoid excess entry—but all entrants earned the same amount. In naturally occurring settings, some entrants win and others lose, due at least partly to differences in managerial skill (see Kenneth R. MacCrimmon and Donald A. Wehrung, 1986). Besides being more realistic, differences in payoffs based on skill allow the possibility that overconfidence will lead to excess entry.

TABLE 1—RANK-BASED PAYOFFS

	Payoff for successful entrants 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

Table 1 shows how payoffs depend on a subject's rank and on the market capacity c. The top c entrants share \$50 proportionally, with higher-ranking entrants earning more. All entrants ranking below the top c lose \$10. For example, if the market capacity $c = 2$, then the highest-ranked entrant receives \$33, the second highest-ranked entrant receives \$17, and any lower-ranked entrant loses \$10. (Subjects are staked \$10 initially.) Notice that if the number of entrants is exactly $c + 5$, then the total payoff to all entering subjects ("industry profit") is zero; if there are more than $c + 5$ entrants, the average entrant loses money.

Actual ranks are assigned in two different ways: Each subject is ranked by a random drawing, and also ranked according to his relative performance on a skill or trivia task. Skill ranks are determined by how many questions subjects answer correctly on a sample of 10 logic puzzles (sessions 1–2) or trivia questions about sports or current events (sessions 3–8). It is important to stress that subjects' ranks were not determined until the end of the experiment, *after* they made all their entry decisions in both the skill and random conditions.

Here are the steps in each experimental session:

1. Before the experiment, subjects were recruited using either standard recruiting instructions or "self-selection" instructions.

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

round. This design was chosen to model initial entry behavior by firms that do not learn much about their competitive advantage until after they incur substantial nonsalvageable fixed costs. The question of how post-entry feedback about performance impacts subsequent behavior is interesting, of course—it is certainly likely that overconfidence would be diminished if subjects were given a separate skill test and told their ranks after each round. But it is natural to begin by establishing whether overconfidence is present in the first place, before turning to the question of what forces make it go away.

The procedures described above were used in eight sessions. Table 3 summarizes differences in treatment variables across sessions.[4] In half of the experimental sessions the random-rank condition rounds were conducted first; in the other half the skill-rank rounds were first. Four sessions involved self-selected subjects (who knew trivia skill would help) and four sessions did not.

A. *Equilibrium Predictions*

Assuming risk neutrality, there are many pure-strategy Nash equilibria in which $c + 4$ or $c + 5$ subjects enter (the fifth subject is indifferent since he or she expects to earn zero from entering). Since the pure-strategy equilibria are necessarily asymmetric, it is hard to see how they might arise without communication or some coordinating device, like history, sequential moves, or public labels distinguishing subjects. There is also a unique symmetric mixed-strategy equilibrium in which (risk-neutral) players enter with a probability close to $(c + 5)/N$ (see Lovallo and Camerer, 1996).

Relaxing the assumption of risk neutrality, there is no way to determine the equilibrium number of entrants without measuring or making specific assumptions about subjects' risk preferences.[5] The random-rank condition gives an empirical estimate of observed equilibrium without having to impose any a priori assumption about risk preferences. Since subjects participate in both random- and skill-rank conditions, their decisions in the random-rank condition act as a within-subject control for risk preferences. The *difference* in the number of entrants in the random and skill conditions is the primary measure of interest.

III. Results

A. *Does Overconfidence About Skill Increase Entry?*

Table 4 lists the total amount of money earned by subjects (''industry profit'') per

[4] Business students, especially M.B.A.'s, are an appropriate sample because many go on to start businesses or participate in corporate entry decisions (e.g., entrepreneurship is the fifth most popular major among Wharton M.B.A.'s).

[5] An alternative is to try to induce risk neutrality (or some other specific degree of risk aversion) by paying subjects in units of probability (see Joyce E. Berg et al., 1986). We chose to use the random-rank condition because the probability procedure does not induce risk neutrality reliably (see Reinhard Selten et al., 1995; cf., Vesna Prasnikar, 1996), and the random-rank condition is equally theoretically valid, and simpler.

TABLE 4—INDUSTRY PROFIT BY ROUND

		Profit for random-rank condition												
		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

round in each experimental session, by rank condition. Recall that if c subjects enter, total industry profit is \$50. If $c + 5$ enter, total profits are 0.

The main question is whether there is more entry (and lower industry profit) when people are betting on their own relative skill rather than on a random device. The answer is "Yes": In the majority of the random-rank rounds (74/96 or 77 percent) industry profit is strictly positive[6] and total profit is negative only six times (6 percent). Average industry profit across rounds is \$16.87. In contrast, in the skill-rank rounds industry profit is strictly positive in only 37 rounds (40 percent) and negative in 41 (42 percent). Average profit across the skill-rank rounds is −\$1.56. The difference in average profits between the conditions is \$18.43, which is about two extra entrants per round in the skill conditions (about a third of the number expected to *not* enter).

A powerful statistical test of significance exploits the yoked design by comparing industry profit in each pair of skill-rank and random-rank periods in exactly the same periods of experimental sessions t and $t + 1$ (for $t = 1, 3, 5, 7$). In this comparison, each pair of periods has exactly the same location in experimental time and the same value of c, and differ only in whether ranks were due to skill or chance. (Fixed effects of periods, self-selection, and subject pool are all controlled for by this comparison.) A matched-pair t-test using these comparisons yields $t = -7.43$ (dof $= 95, p < 0.0001$). Industry profits under skill-based entry are clearly lower.

The next question is whether reference group neglect produces a larger skill-random entry differential in the experiments with self-selected subjects. The answer appears to be "Yes." In sessions without self-selection (1–4), the average per-period industry profit is \$19.79 and \$10.83 for the random and skill

[6] This is also consistent with tacit collusion among risk-neutral players, since having exactly c entrants is the collusive solution (but is not a Nash equilibrium), or with some degree of risk aversion or (more likely) loss aversion.

TABLE 5—AVERAGE DIFFERENCE IN EXPECTED PROFITS PER ENTRANT BETWEEN RANDOM AND SKILL CONDITIONS

Measure	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5	Experiment 6	Experiment 7	Experiment 8	Total
$\Pi_r - \Pi_s$	1.635	0.477	−1.19	0.24	1.62	2.49	3.16	1.80	1.31
	(1.98)	(1.41)	(1.72)	(2.41)	(1.32)	(1.27)	(1.61)	(1.20)	(2.04)
# of S's with	10/12	10/13	3/11	7/14	12/13	12/13	13/13	11/12	78/101
$\Pi_r - \Pi_s < 0$	(83)	(77)	(27)	(50)	(92)	(92)	(100)	(92)	(77)
(percent)									
# of S's with	0/12	0/13	0/12	2/15	12/15	15/16	12/14	11/14	52/111
$\Pi_s < 0$	(0)	(0)	(0)	(13)	(80)	(94)	(86)	(79)	(47)
(percent)									

conditions, respectively—a difference of \$9.14, or about one extra entrant in the skill-based rounds. In sessions with self-selection (5–8) profit is \$13.96 in the random condition and −\$13.13 in the skill condition, which results in an entry differential of \$27.10—about three times as large as in the sessions without self-selection. Furthermore, in the experiments with self-selection, industry profits are positive in only 3 of the 48 skill-rank periods, compared with 34 of 48 in the non-self-selected sessions. A matched-pairs test comparing the skill-random profit differentials for matched periods between sessions 1–4 and 5–8 strongly rejects the hypothesis that differentials are the same in sessions with and without self-selection ($t(94) = -4.08$, $p < 0.001$). Reference group neglect clearly makes the overconfidence effect stronger.

B. *Expected Earnings Differences in Skill and Random Rounds*

The matched-pairs tests illustrate the effect of overconfidence on entry and demonstrate that self-selection makes the effect stronger. But these tests do not carefully control for all alternative explanations.[7] For example, the blind spots hypothesis suggests that excessive entry in the skill conditions may be due to players underforecasting how many others will enter.

To test this hypothesis, we use subject j's forecast F_{ijt} to compute the profit that subject j expects the average entrant to earn in round t of experiment i. If the capacity is c_{it} in that particular period, then the "expected average profit"—the amount of profit subject j thinks the average entrant will earn—is $(50-10*(F_{ijt} - c_{it}))/F_{ijt}$, which we denote by $E_j(\Pi_{ijt})$. This method effectively separates the blind spots hypothesis from the overconfidence hypothesis. Suppose, for example, that in skill conditions subjects are more apt to enter because they think fewer people will enter, not because they feel they are more skilled. Then their $E_j(\Pi_{ijt})$ values will be larger in the skill condition. Including $E_j(\Pi_{ijt})$ in an entry regression will then wipe out the effect spuriously attributed to skill.

If entering subjects are more overconfident in the skill rounds, then their expected average profits $E(\Pi_{ijt})$ will be smaller than in random rounds because the skilled subjects expect to earn more than the average entrant and, hence, are willing to enter even when the expected average profit is low. To test this prediction, Table 5 reports the difference between expected average profits in random rounds (denoted Π_r) and the same statistic in skill rounds (Π_s), using only the rounds in which a subject entered. The table shows three different measures for each session: The mean difference $\Pi_r - \Pi_s$ averaged across entering subjects, the number and percentage of subjects who have a negative mean (i.e., who expect less average profit in skill periods), and the number and percentage of subjects whose expected aver-

[7] Gender could be confounded with self-selection, too, since women may be less likely to volunteer for tasks which reward expertise in sports trivia (and are usually found to be less overconfident than men, in general). We controlled for this by only recruiting male subjects in sessions 3–8. Thus, the logit analysis of sessions 3–8 effectively controls for gender.

- (Relative) overconfidence. About what?
  - Own ability
  - Underestimate 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)

- Open questions:

  - Are people overconfident in general?

  - Without ex-ante selection, more entry but no *excess* entry

  - Perhaps on average people are unbiased, but:

    * sorting

    * overconfident people sort into risky projects and become...

    * ...traders (Odean)

    * ...enterpreneurs (Camerer-Lovallo)

    * ...CEOs (Malmendier-Tate)

  - If overconfidence on average, why so little investment in stocks?

2 Social Preferences: Introduction

- 219A. Emphasis on social preferences

- In the field?

  1. Pricing. When are price increases acceptable?

     – Kahneman, Knetsch and Thaler (1986)

     – Survey evidence

     – Effect on price setting

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

     – Charness and Kuhn (2004).

     – Classical gift exchange

– Type 1 and Type 2 worker, differently productive

– Workers do not know type of others, Firm knows

– Public treatment: workers observe own pay and pay of other

– Result: No effect of pay of others on own effort

3. Charitable Contributions.

   – Contributions of money and time

   – Survey by Andreoni (2004)

- Charitable contributions is only setting with field evidence

Table 1: Effort Costs and Revenues

Effort Level	Cost to Worker	Revenue produced by Type 1 Worker	Revenue produced by Type 2 Worker
Zero (0)	0	0	0
Low (1)	.10	1.90	2.80
Medium (2)	.30	2.50	4.20
High (3)	.60	2.70	5.40

Table 3: Effects of Wages on Workers' Effort, Public-wage Regime

A. Type 1 Workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own wage	.783 (.060)	.784 (.058)	.767 (.064)				
Own wage =1				.723 (.072)	.720 (.071)	.652 (.080)	.510 (.093)
Own wage =2				1.603 (.107)	1.580 (.123)	1.498 (.124)	1.412 (.131)
Own wage =3				2.099 (.254)	2.107 (.261)	1.982 (.265)	1.967 (.276)
Own wage =4				2.341 (.270)	2.376 (.262)	2.171 (.286)	2.224 (.215)
Co-worker's wage		-.007 (.035)		-.030 (.036)			
Own wage less than Co-Worker's			-.057 (.090)		-.023 (.091)	-.041 (.092)	-.077 (.076)
Period effects?	No	No	No	No	No	Yes	Yes
Worker effects?	No	No	No	No	No	No	Yes
R squared	.340	.340	.341	.346	.345	.376	.628

B. Type 2 Workers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own wage	.608 (.056)	.615 (.059)	.617 (.053)				
Own wage =1				.301 (.136)	.286 (.088)	.233 (.095)	.196 (.098)
Own wage =2				0.978 (.200)	.958 (.098)	.892 (.108)	.837 (.119)
Own wage =3				1.759 (.184)	1.772 (.159)	1.721 (.167)	1.667 (.171)
Own wage =4				2.103 (.214)	2.135 (.217)	2.041 (.224)	2.142 (.166)
Co-worker's wage		-.073 (.057)		-.029 (.079)			
Own wage less than Co-Worker's			.131 (.207)		.117 (.183)	.088 (.189)	.103 (.168)
Period effects?	No	No	No	No	No	Yes	Yes
Worker effects?	No	No	No	No	No	No	Yes
R squared	.283	.286	.283	.294	.295	.319	.588

Robust standard errors, adjusted for clustering on 47 individual workers, in parentheses. Sample Size for all Regressions is 825.

3 Charitable Contributions: Survey

- Andreoni (2004). Excellent survey of the theory and evidence on:
  - charitable contributions
  - contributions of time (short)
  - fundraising industry

- Stylized facts:
  - US Giving very large: 1.5 to 2.1 percent GDP!
  - Most giving by individuals (Table 1)
  - Slight trend to decrease in generosity (Figure 1)

- Giving by income, age, and education (Table 2 – no controls)
  * Giving as percent of income fairly stable
  * Increase for very rich

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

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

over 183 billion dollars to charity, or 76% of the total dollars donated. The second biggest source, foundations, was responsible for 11.2% of all donations.

Table 1
Sources of Private Philanthropy, 2002

Source of gifts	Billions of dollars	Percent 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

The trends in giving over the last 30 years can be seen in Figure 1. Total giving has been on a steady rise, with temporary jumps coming in 1986, along with a pronounced rise starting in 1996 trough 2001. When measured as a percent of income, however, giving seems much more stable. Since 1968 giving has varied from 1.5% to 2.1% of income. In the most recent years, however, giving has risen from 1.5% of income in 1995 to 2.1% in 2001. This rise coincided with a run up on stock-market wealth, which is the likely explanation for the latest increase in giving. Notice, however, that this latest rise in giving counteracts a longer trend of slowly falling generosity. The peak of giving in 2001 matches the former peak set back in 1963. Table 2 presents details on the characteristics of individual givers. The data, from the Independent Sector in 1995, show that 68.5% of all households gave to charity and that the average gift among those giving was $1081. Table 2 shows that the more income a household has, the more likely the household is to give to charity, and the more it gives when it does donate. This table also reveals an interesting pattern typically found in charitable statistics. Those with the lowest incomes give over 4% of income to charity. As incomes grow to about $50,000, gifts fall to 1.3% of income, but then rise again to 3.0% for the highest incomes. What could cause this "u-shaped" giving pattern? One explanation is that those with low incomes may be young people who know their wages will be rising, hence they feel they can afford more giving now. It may also be due to the composition of the types of charities people give to, since lower income people tend to give significantly more to religious causes. Hence, it will be important to account for all the factors that may explain giving before offering explanations for the averages seen in these tables.

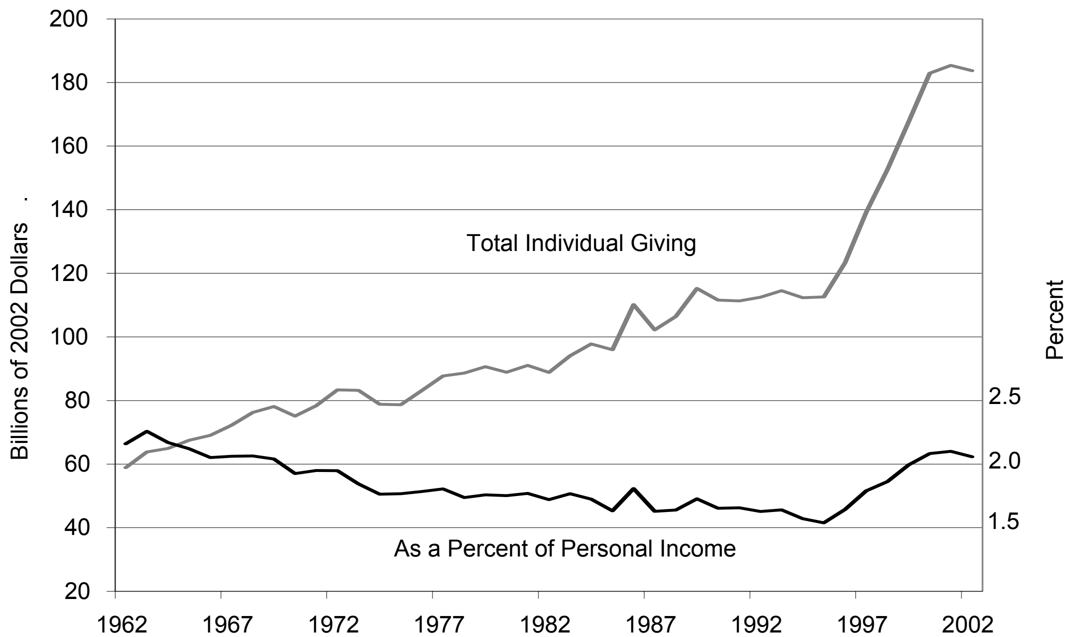


Figure 1: Trends in Individual Giving.
Source: Giving USA 2003.

Table 2 also illustrates that giving varies significantly with the age and educational attainment of the givers. As people get older they are typically more likely to give to charity and to give a greater fraction of their incomes. Likewise, those with more education give more often, give more dollars, and generally give a higher fraction of income. Note that the table does not show a smooth acceleration of giving with age. Again, age, education, and income all vary with each grouping in the table and will have to be considered jointly.

In 1997 over 45,000 charitable, religious and other non-profit organizations filed with the US government (see Bilodeau and Steinberg in this volume). Table 3 attempts to categorize these charities by the types of services they provide. This reveals that, among all types, households are most likely to give to religious organizations and to give them the most money—48% of all households give to religion and 59% of all charitable dollars go to religion.

Table 2
Private philanthropy by income, age, and education of the giver, 1995

	Percent of households who give	Average amount given by those who give	Percent of household 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
Age of Giver			
18–24 years	57.1	266	0.6
25–34 years	66.9	793	1.7
35–44 years	68.5	1,398	2.6
45–54 years	78.5	979	1.8
55–64 years	71.7	2,015	3.6
65–74 years	73.0	1,023	2.9
75 years and above	58.6	902	3.1
Highest Education of Giver			
Not a high school graduate	46.6	318	1.2
High school graduate	67.2	800	1.9
Some college	74.1	1,037	2.1
College graduate or more	82.3	1,830	2.9

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

Table 3
Private Philantropy by Type of Charitable Organization, 1995.

Type of Charity	Percent of Households who give	Average amount given by those who give	Percent of total household 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 community foundations	6.1	196	1.4
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.

2.2. International Statistics

A difficult aspect of comparing data from across countries is the varied sources of information and the inconsistent definitions of charitable giving and non-profit organizations. Using data from Johns Hopkins Comparative Nonprofit Sector Project[6], we can nonetheless attempt to gain some perspective on the differing size of the charitable sectors of various economies.

Figure 2 shows reports of cash revenues of non-profits from philanthropy. The experience varies widely around the globe. The US, however, stands out as being the most reliant on private donations, at 21 percent of all revenues. With the exception of Spain, European countries are much lower, varying from 3 to 11 percent. The South American countries of Argentina and Brazil rely heavily on philanthropy (about 18 percent), while Mexico does not (6 percent).

[6] See their web-site, http://www.jhu.edu/~cnp/.

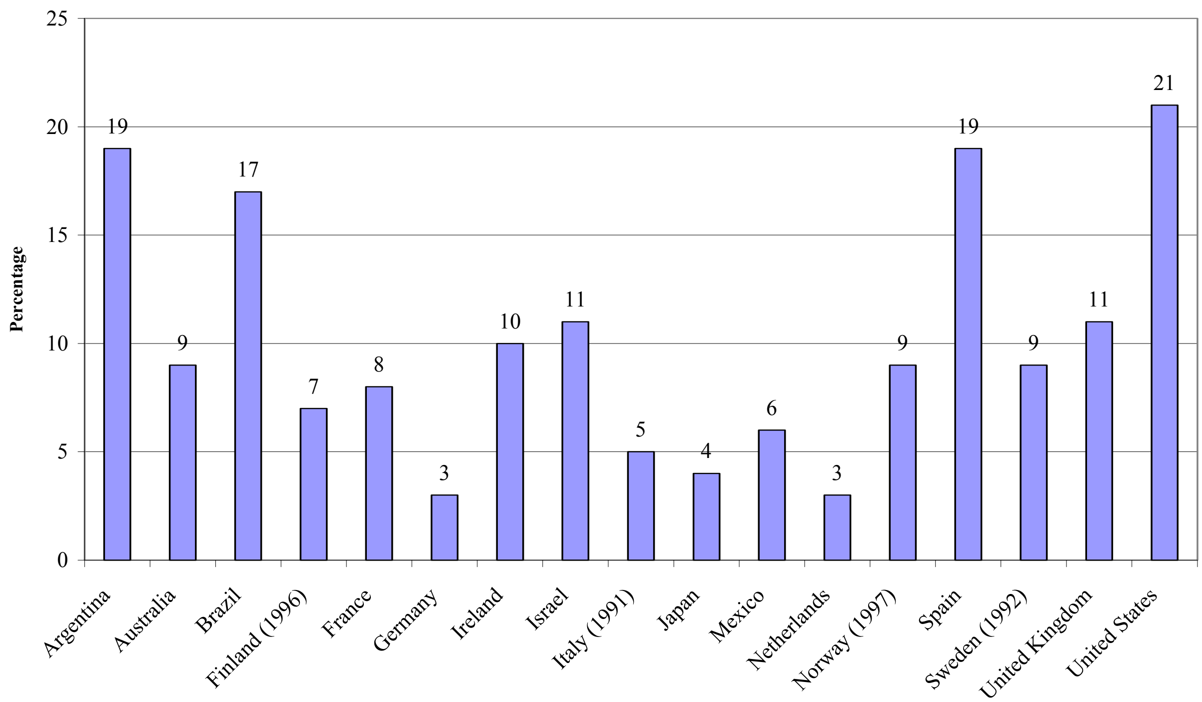


Figure 2: Percentage of Cash Revenues of the Nonprofit Sector Received from Philanthropy: 1995.

Figure 3 provides a different perspective by looking at the total expenditures of the non-profit sector. Here the US falls closer to the middle of the pack, at 7.5 percent of GDP. The Netherlands and Israel have the largest non-profit sectors, while Mexico and Brazil have the smallest.

- (Very) stylized model

- 2-person economy:

  - Mark has income M_M and consumes c_M

  - Wendy has income M_W and consumes c_W

  - One good: c, with price $p = 1$

- Utility functions: $u(c)$, with $u' > 0$, $u'' < 0$

- Wendy is altruistic: she maximizes $u(c_W) + \alpha u(c_M)$ with $\alpha > 0$

- Mark simply maximizes $u(c_M)$

- Wendy can give a donation of income D to Mark.

- Mark maximizes

$$\max_{c_M} u(c_M)$$
$$s.t.\ c_M \leq M_M + D$$

- Solution: $c_M^* = M_M + D$

- Wendy maximizes

$$\max_{c_M, D} u(c_W) + \alpha u\left(M_M + D\right)$$
$$s.t.\ c_W \leq M_W - D$$

or

$$\max_{D} u(M_W - D) + \alpha u\left(M_M + D\right)$$

- First order condition:

$$-u'(M_W - D^*) + \alpha u'\left(M_M + D^*\right) = 0$$

- Second order conditions:

$$u''(M_W - D^*) + \alpha u''\left(M_M + D^*\right) < 0$$

- Assume $\alpha = 1$.
  - Solution?
  - $u'(M_W - D) = u'(M_M + D^*)$
  - $M_W - D^* = M_M + D^*$ or $D^* = (M_W - M_M)/2$
  - Transfer money so as to equate incomes
  - $D < 0$ (negative donation!) if $M_M > M_W$

- Corrected maximization:

$$\max_D u(M_W - D) + \alpha u(M_M + D)$$
$$s.t. D \geq 0$$

- Solution ($\alpha = 1$):

$$D^* = \begin{cases} (M_W - M_M)/2 & \text{if } M_W - M_M > 0 \\ 0 & \text{otherwise} \end{cases}$$

- Allow $\alpha \leq 1$. Assume interior solution. $(D^* > 0)$

- Comparative statics 1 (altruism):

$$\frac{\partial D^*}{\partial \alpha} = -\frac{u'(M_M + D^*)}{u''(M_W - D^*) + \alpha u''(M_M + D^*)} > 0$$

- Comparative statics 2 (income of donor):

$$\frac{\partial D^*}{\partial M_W} = -\frac{-u''(M_W + D^*)}{u''(M_W - D^*) + \alpha u''(M_M + D^*)} > 0$$

- Comparative statics 3 (income of recipient):

$$\frac{\partial D^*}{\partial M_M} = -\frac{\alpha u''(M_M + D^*)}{u''(M_W - D^*) + \alpha u''(M_M + D^*)} < 0$$

- Reality check for these comparative statics
- Richer people donate more (as total). Good.
- BUT: Do poorer people receive more? Not obvious
- Donate to person with highest marginal utility in more general model
- Table 3: Very little international donations –> Limited donations to poorest countries

- Additional prediction of model – Crowding out
- If government spends on income of Mark, Wendy will donate less.

- What is the evidence of crowding out?

- Mixed evidence – open question

- Some open questions for field data work:

- Why do people donate?
  - Altruism?
  - Warm glow? What does it mean?
  - Social pressure?
  - Emotional connection?

- How sensitive are donors to features of charities?
  - Expense ratio
  - Marginal utility of recipient
  - (Psychological) Distance of donor from recipient

  - Previous donations (see below)
  - Gifts (see below)

- Non-profits are willing to run field experiments (they do them anyway)

4 Charitable Contributions: Field Experiments

- Sarah

The Effect of Seed Money and Refunds on Charitable Giving

John A. List and David Lucking-Reiley

&

Charitable Giving as a Gift Exchange

Armin Falk

Presented by

Sarah Rosen Frank

May 5, 2004

Seed Money and Refunds

- Field experiment to test two theories about capital campaigns
  - Seed money will increase donations
  - Offering refunds if threshold not reached will increase donations
- University capital campaign
  - Need $3,000 to buy computer for new center
- Solicited contributions from 3,000 people
  - Three groups: told that 10%, 33%, or 67% of necessary funds were already raised
  - Refund policy

Seed Money

- Untested truism in fundraising industry that at least 30% of necessary funds must be first raised in 'silent' campaign
- Andreoni (1998) models public good provision or capital campaign as simultaneous play Nash equilibrium game

$$G = G_{-i} + g_i = \sum_{j \neq i} g_j + g_i$$

$$\max_{x_i, g_i} u_i(x_i, g_i + G_{-i})$$

$$\max_{x_i, g_i} u_i(x_i, G)$$

Capital campaign: Non-convexity at the threshold $\overline{G}$

If $g_{\max}^{o} \leq \overline{G} \leq G^*$

then there will be exactly two Nash equilibrium: one at G=0 and another at G=G*

Exogenous amount t selected so that most generous person just willing to bring public good up to threshold value by acting alone.

$$g_i = \overline{G} - t_i$$

“The crux of the model is that the charity will choose leaders so that when they turn to the general contributions stage they have omitted zero as a Nash equilibrium”

Effect of Seed Money

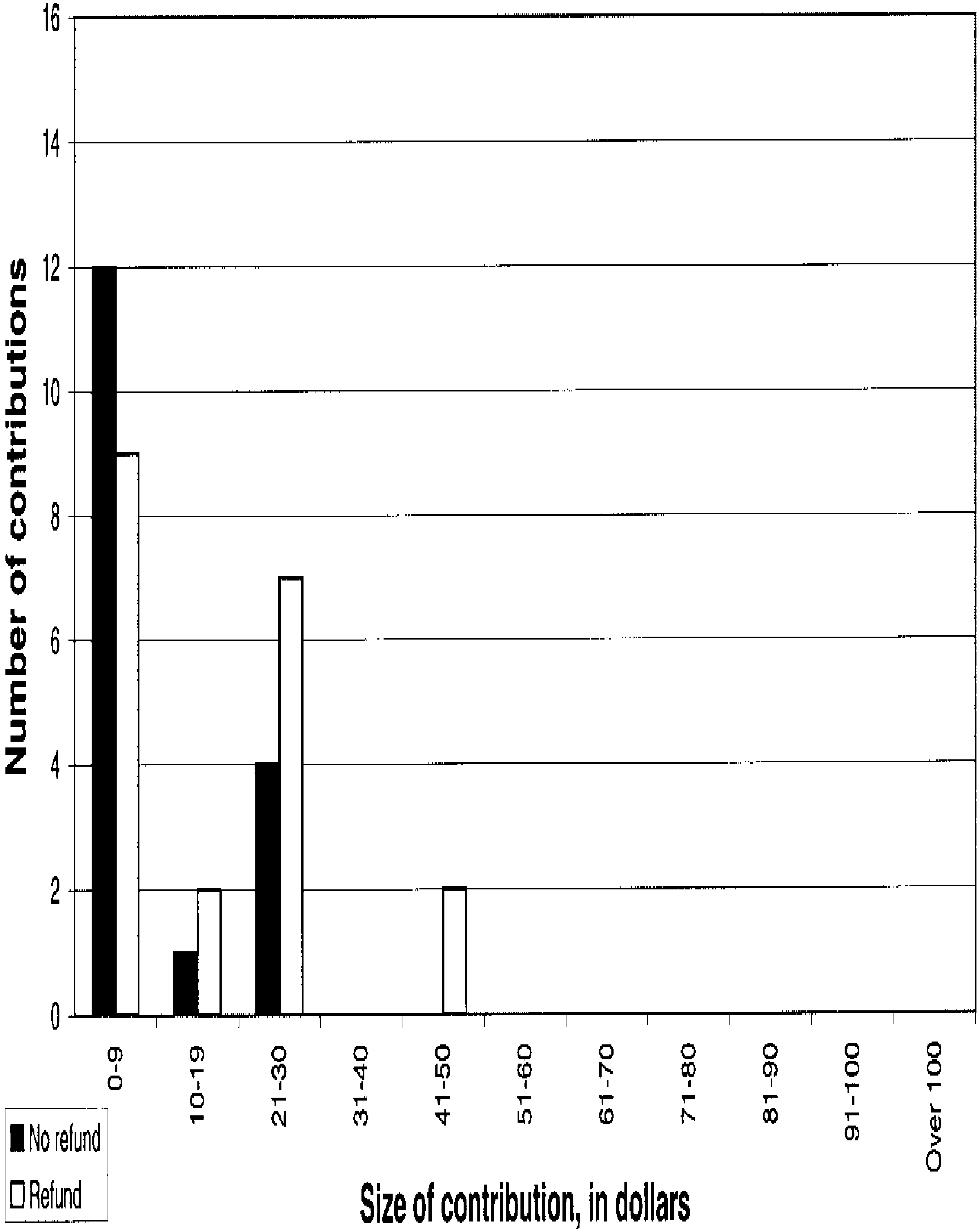
As seed money increases:

- Participation rate increases monotonically
- Size of gift increases monotonically

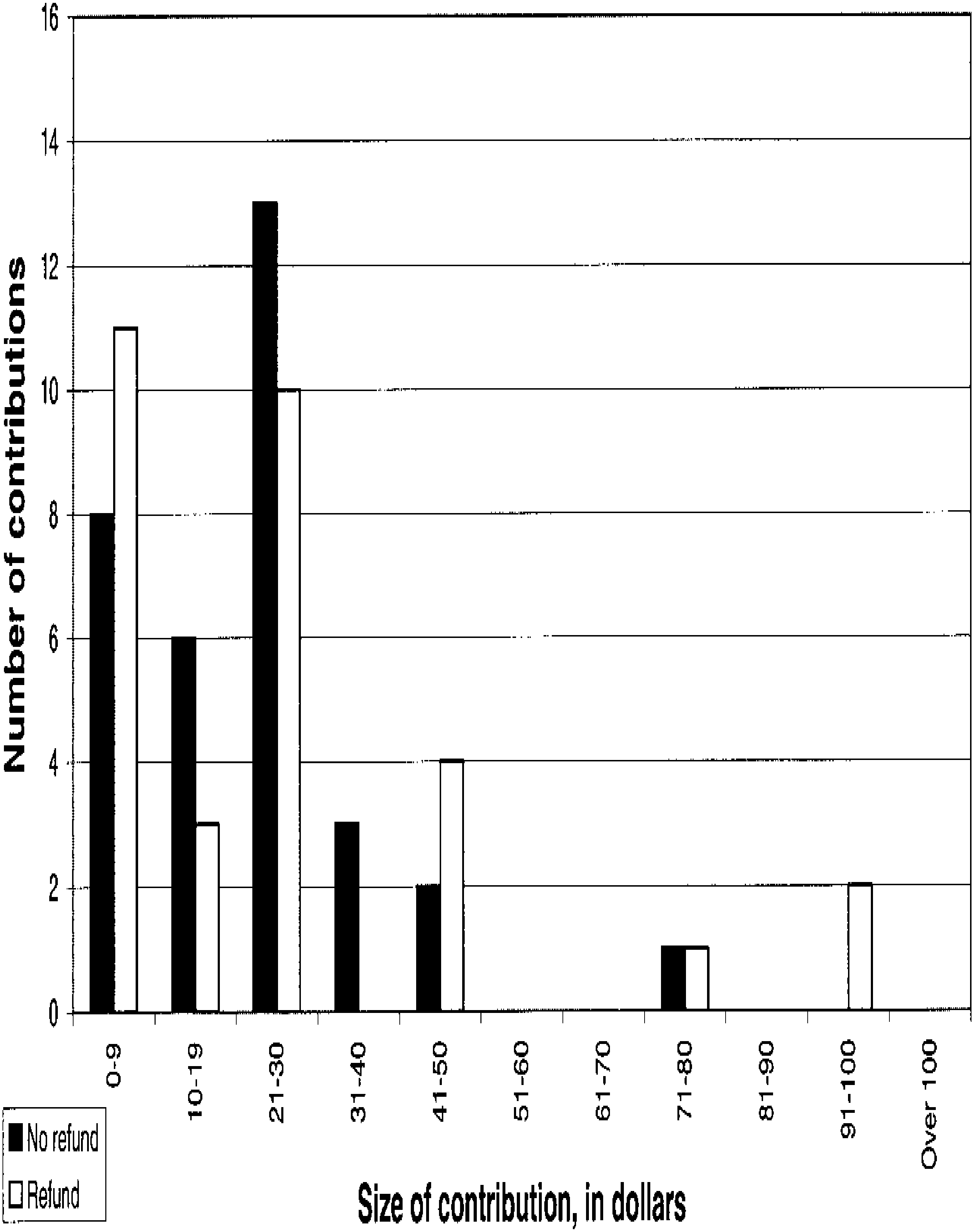
	10	10R	33
Number of solicitations mailed	500	500	500
Seed money (%)	10%	10%	33%
Seed money ($)	$300	$300	$1,000
Refund offered?	no	yes	no
Number of contributions	17	20	33
Participation rate	3.4%	4.0%	6.6%
Total contributions	$202	$379	$805
Mean amount given	$11.88	$18.95	$24.39
Standard error of mean amount	$2.27	$3.13	$2.50

	33R	67	67R
Number of solicitations mailed	500	500	500
Seed money (%)	33%	67%	67%
Seed money ($)	$1,000	$2,000	$2,000
Refund offered?	yes	no	yes
Number of contributions	31	42	40
Participation rate	6.2%	8.4%	8.0%
Total contributions	$863	$1,485	$1,775
Mean amount given	$27.84	$35.36	$44.38
Standard error of mean amount	$4.59	$2.26	$6.19

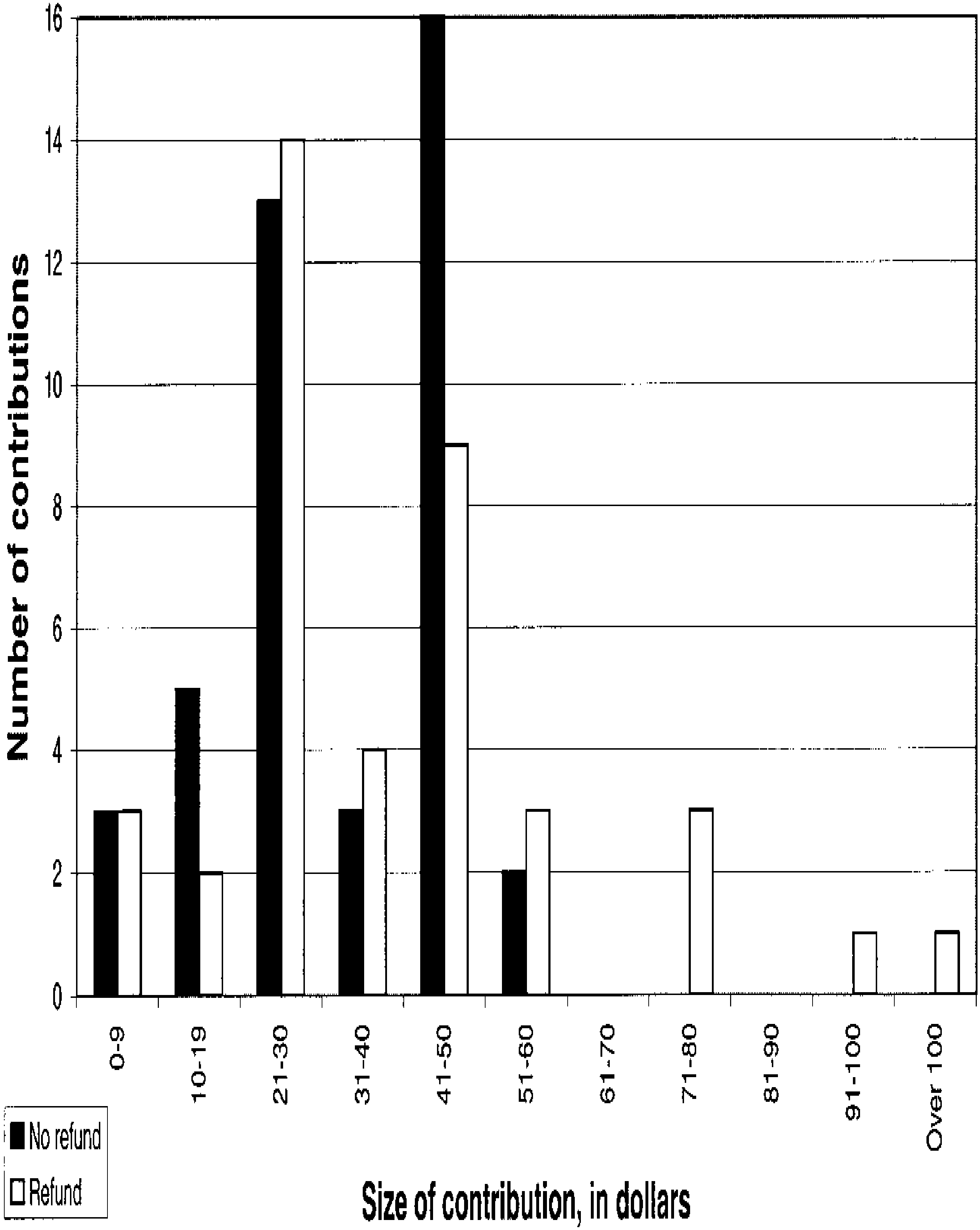
Contributions with 10 percent seed money



Contributions with 33 percent seed money



Contributions with 67 percent seed money



Seed money conclusions

- Andreoni’s (1998) main prediction is borne out in data: seed money increases donations
- Puzzles:
  - Predicted discrete jump
  - Does not predict increasing gift size
  - Seed money should be irrelevant with refund

Alternative theories

- Vesterlund models seed contributions as signals of quality to later donors
- Seed might signal “right amount to give”
- Want to be part of winning campaign

Refund

- Offer refund if threshold not met
- Does not increase participation rate
- Does increase gift size

Refund conclusions

- Supports Bagnoli and Lipman's predictions
- Effect smaller than seed money
- Does not move funding from inefficient to efficient level
- Not clear if the charity earns more or less

Charitable Giving as a Gift Exchange
Armin Falk

- Field experiment using large charitable organization and mailing in Zurich
- 9,846 solicitation letters mailed out
  - Three groups: no gift, small gift, large gift
- Test reciprocity: “reciprocally motivated people reward kind behavior and sanction unkind behavior, even if costly to them”

Donation patterns

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

Results

- Gifts do not effect previous donors differently
- Non-gift donations somewhat higher than gift donations, but not “overwhelmingly strong”
- Some evidence of inter-temporal substitution, but not significant

Alternate conclusions

- Could just make mailing stand out from others
- Could deepen connection with the impoverished children
- Operating out of guilt

Treatment differences in the frequency of donations

Dependent variable: Frequency of donation

	Model 1	*Model 2*
Small gift dummy	0.022***	0.021***
	(0.008)	(0.008)
Large gift dummy	0.085***	0.081***
	(0.009)	(0.009)
		0.047
Small gift x last year		(0.036)
		0.047
Large gift x last year		(0.036)
		0.243***
Last year		(0.024)
Constant	0.122***	0.092***
	(0.006)	(0.005)
n	9846	9846
Prob. > F	0.0000	0.0000
R-squared	0.0098	0.0671

Note: The estimation procedure is an OLS-regression with robust standard errors (in parentheses).

*** indicates significance on the 1-percent level.

5 Some advice

- How to complete a dissertation and be (approximately) happy

  1. Know yourself, and put yourself to work
     - Do you procrastinate?
     - Are you afraid of undirected research?
     - Not enough intuition?
     - Not enough technicality?
     - Work in team with a classmate!

  2. Economics is about techniques, and about ideas.
     - Are second-price, affiliated combinatorial auctions not your bread?

– Do you find it hard to derive asymptotic distribution of MSM estimators?

– I do as well!

– But... anyone can have ideas (Levitt)!

– Start from new idea, not from previous papers

3. But...

   – No excuse not to know the techniques.

   – It will be much easier to learn and use them once you have an interesting problem at hand

4. What are good ideas?

   – 1% of GDP (Glaeser)

   – new questions (better) or unknown answers

– think about topics you care about (comparative advantage!)

– think about socially important topics, if you can

5. Look for occasions to learn:

   – Attend seminars

   – Attend job market talks

   – Do not read too much literature

   – Discuss ideas with peers, over lunch, with yourself

   – Be curious!

6. Above all, do not get discouraged!

– Unproductive periods are a fact of life

– Ideas keep getting better over time with exercise

– Keep up the exercise!