Econ 219B
Psychology and Economics: Applications
(Lecture 11)

Stefano DellaVigna

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Outline

1. Framing
2. Menu Effects: Introduction
3. Menu Effects: Choice Avoidance
4. Menu Effects: Preference for Familiar
5. Menu Effects: Preference for Salient
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7. Persuasion
8. Emotions: Mood
9. Menu Effects: Excess Diversification (EXTRA)

1 Framing

- Tenet of psychology: context and framing matter
- Classical example (Tversky and Kahneman, 1981 in version of Rabin and Weizsäcker, 2009): Subjects asked to consider a pair of '*concurrent decisions. [...]*
  - **Decision 1**. *Choose between: A. a sure gain of €2.40 and B. a 25% chance to gain €10.00 and a 75% chance to gain €0.00.*
  - **Decision 2**. *Choose between: C. a sure loss of €7.50 and D. a 75% chance to lose €10.00 and a 25% chance to lose €0.00.*'
  - Of 53 participants playing for money, 49 percent chooses A over B and 68 percent chooses D over C
  - 28 percent of the subjects chooses the combination of A and D
    - This lottery is a 75% chance to lose €7.60 and a 25% chance to gain €2.40

    * Dominated by combined lottery of B and C: 75% chance to lose ₤7.50 and a 25% chance to gain ₤2.50

- Separate group of 45 subjects presented same choice in broad framing (they are shown the distribution of outcomes induced by the four options)
    * None of these subjects chooses the A and D combination

- Interpret this with reference-dependent utility function with narrow framing.
  - Approximately risk-neutral over gains –> 49 percent choosing A over B
  - Risk-seeking over losses –> 68 percent choosing D over C.
  - Key point: Individuals accept the framing induced by the experimenter and do not aggregate the lotteries
- General feature of human decisions:
  - judgments are comparative
  - changes in the framing can affect a decision if they change the nature of the comparison

- Presentation format can affect preferences even aside from reference points
- **Benartzi and Thaler (JF 2002): Impact on savings plan choices:**
  - Survey 157 UCLA employees participating in a 403(b) plan
  - Ask them to rate three plans (labelled plans A, B, and C):
    - Their own portfolio
    - Average portfolio
    - Median portfolio
  - For each portfolio, employees see the 5th, 50th, and 95th percentile of the projected retirement income from the portfolio (using Financial Engines retirement calculator)
  - Revealed preferences –> expect individuals on average to prefer their own plan to the other plans

- Results:
  - Own portfolio rating (3.07)
  - Average portfolio rating (3.05)
  - Median portfolio rating (3.86)
  - 62 percent of employees give higher rating to median portfolio than to own portfolio
- Key component: Re-framing the decision in terms of ultimate outcomes affects preferences substantially
- Alternative interpretation: Employees never considered the median portfolio in their retirement savings decision –> would have chosen it had it been offered
- Survey 351 participants in a different retirement plan

  - These employees were explicitly offered a customized portfolio and actively opted out of it
  - Rate:
    * Own portfolio
    * Average portfolio
    * Customized portfolio
  - Portfolios re-framed in terms of ultimate income

- 61 percent of employees prefers customized portfolio to own portfolio
- Choice of retirement savings depends on format of the choices presented
- Open question: Why this *particular* framing effect?
- Presumably because of fees:

- Consumers put too little weight on factors that determine ultimate returns, such as fees –> Unless they are shown the ultimate projected returns

- Or consumers do not appreciate the riskiness of their investments –> Unless they are shown returns

- Framing also can focus attention on different aspects of the options
- **Duflo, Gale, Liebman, Orszag, and Saez (QJE 2006):** Field Experiment with H&R Block
  - Examine participation in IRAs for low- and middle-income households
  - Estimate impact of a match
- Field experiment:
  - Random sub-sample of H&R Block customers are offered one of 3 options:
    - No match
    - 20 percent match
    - 50 percent match

- Match refers to first \$1,000 contributed to an IRA
- Effect on take-up rate:
  - No match (2.9 percent)
  - 20 percent match (7.7 percent)
  - 50 percent match (14.0 percent)

- Match rates have substantial impact

- Framing aspect: Compare response to explicit match to response to a comparable match induced by tax credits in the Saver's Tax Credit program
  - Effective match rate for IRA contributions decreases from 100 percent to 25 percent at the $30,000 household income threshold
  - Compare IRA participation for
    - Households slightly below the threshold ($27,500-$30,000)
    - Households slight above the threshold ($30,000-$32,500)
  - Estimate difference-in-difference relative to households in the same income groups that are ineligible for program
  - Result: Difference in match rate lowers contributions by only 1.3 percentage points –> Much smaller than in H&R Block field experiment
- Why framing difference? Simplicity of H&R Block match –> Attention
- Implication: Consider behavioral factors in design of public policy

2 Menu Effects: Introduction

- Summary of Limited Attention:
  - Too little weight on opaque dimension (*Science* article, shipping cost, posted price, right digits, news to customers, indirect link, distant future)
  - Too much weight on salient dimension (*NYT* article, auction price, left digits, recent returns or volume)
- Any other examples?

- We now consider a specific context: **Choice from Menu** N (typically, **with large** N)
  - Health insurance plans
  - Savings plans
  - Politicians on a ballot
  - Stocks or mutual funds
  - Type of Contract (Ex: no. of minutes per month for cell phones)
  - Classes
  - Charities
  - ...

- We explore 4 $+1$ (non-rational) heuristics
  1. Excess Diversification (EXTRA material)
  2. Choice Avoidance
  3. Preference for Familiar
  4. Preference for Salient
  5. Confusion
- Heuristics 1-4 deal with difficulty of choice in menu
  - Related to bounded rationality: Cannot process complex choice –> Find heuristic solution
- Heuristic 5 – Random confusion in choice from menu

3 Menu Effects: Choice Avoidance

- Heuristic: Refusal to choose with choice overload

- **Choice Avoidance.** Classical Experiment (**Yiengar-Lepper, JPSP 2000**)

  – Up-scale grocery store in Palo Alto

  – Randomization across time of day of number of jams displayed for taste

    * Small number: 6 jams

    * Large number: 24 jams

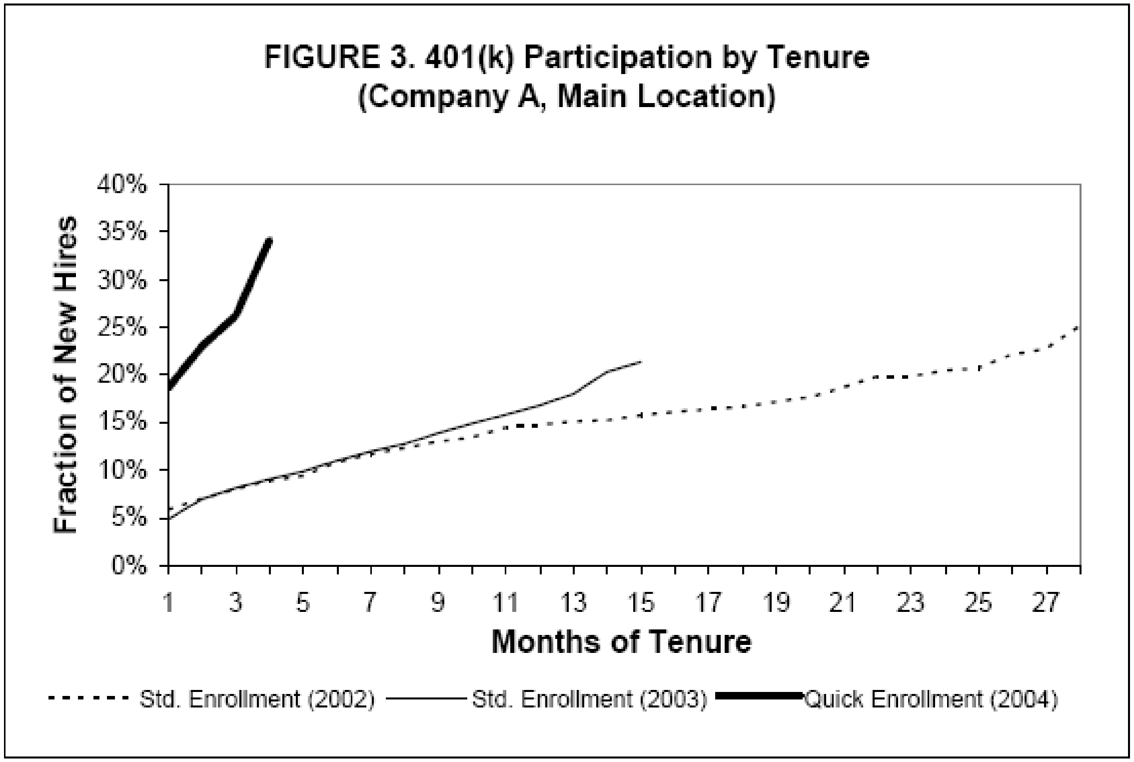
  – Results:

    * More consumers sample with Large no. of jams (145 vs. 104 customers)

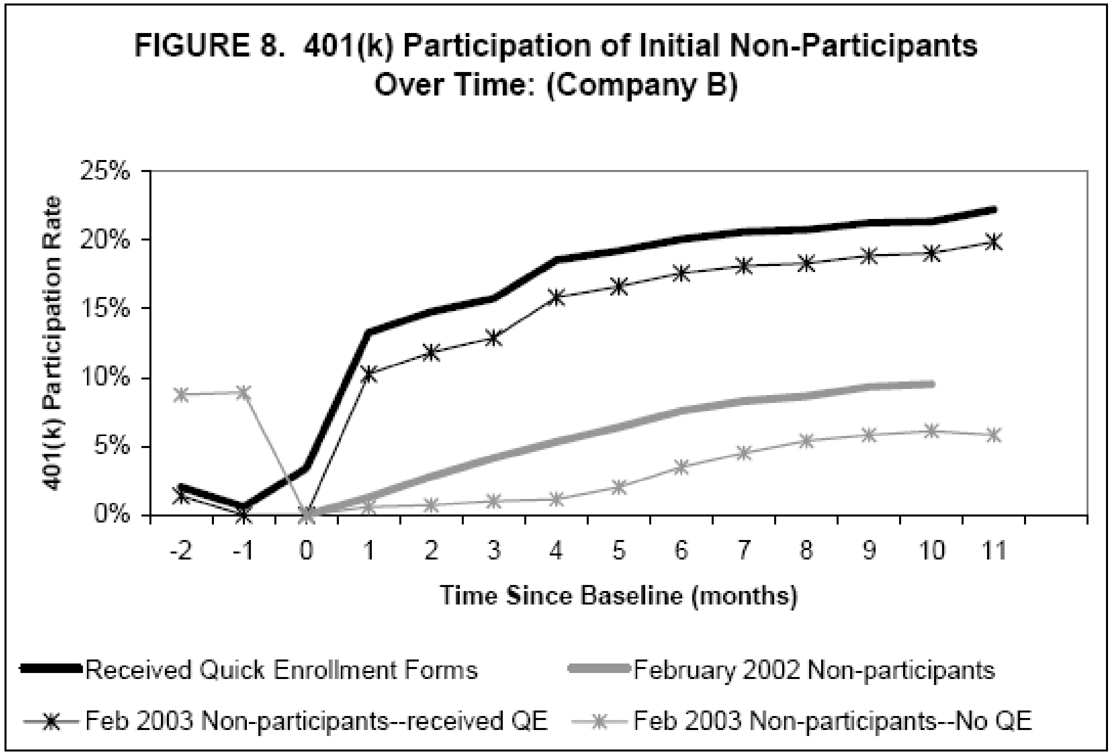
    * *Fewer* consumers buy with Large no. of jams (4 vs. 31 customers)

- Field evidence 2: **Choi-Laibson-Madrian (2006):** Natural experiment
- Introduce in company A of Quick Enrollment
  - Previously: Default no savings
  - 7/2003: Quick Enrollment Card:
    - Simplified investment choice: 1 Savings Plan
    - Deadline of 2 weeks
  - In practice: Examine from 2/2004

- Company B:
  - Previously: Default no savings
  - 1/2003: Quick Enrollment Card
- Notice: This affects
  - Simplicity of choice
  - But also cost of investing + deadline (self-control)



- 15 to 20 percentage point increase in participation – Large effect
- Increase in participation all on opt-in plan



- Very similar effect for Company B

- What is the effect due to?
- Increase may be due to a reminder effect of the card
- However, in other settings, reminders are not very powerful.
- Example: Choi-Laibson-Madrian (2005):
  - Sent a survey including 5 questions on the benefits of employer match
  - Treatment group: 345 employees that were not taking advantage of the match
  - Control group: 344 employees received the same survey except for the 5 specific questions.
  - Treatment had no significant effect on the savings rate.

- Field Evidence 2: **Bertrand, Karlan, Mullainathan, Shafir, Zinman (QJE 2010)**

- Field Experiment in South Africa
  - South African lender sends 50,000 letters with offers of credit
  - Randomization of interest rate (economic variable)
  - Randomization of psychological variables
  - Crossed Randomization: Randomize independently on each of the n dimensions
    - Plus: Use most efficiently data
    - Minus: Can easily lose control of randomization

Table 2
Summary of Randomized Interventions[a]

	(1)	(2)	(3)	(4)	(5)
Sample:	**All**	**Customers who did not take up**	**Customers who took up**	**“High attention” customer**	**“Low attention” customer**
September wave	0.395	0.394	0.401	0.398	0.393
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
October wave	0.605	0.606	0.599	0.602	0.607
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
Offer Interest	7.929	7.985	7.233	6.970	8.384
Rate	(2.42)	(2.42)	(2.31)	(2.11)	(2.43)
Small option table	0.432	0.438	0.349	0.250	0.518
	(0.50)	(0.50)	(0.48)	(0.43)	(0.50)
No comparison to	0.200	0.200	0.200	0.202	0.199
competitor	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)
comparison expressed	0.401	0.400	0.408	0.397	0.403
as a gain	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
No photo on mailing	0.202	0.202	0.206	0.198	0.204
	(0.40)	(0.40)	(0.40)	(0.40)	(0.40)
Black photo	0.477	0.477	0.476	0.488	0.472
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Coloured photo	0.071	0.071	0.071	0.072	0.071
	(0.26)	(0.26)	(0.26)	(0.26)	(0.26)
Indian photo	0.125	0.125	0.122	0.123	0.126
	(0.33)	(0.33)	(0.33)	(0.33)	(0.33)
White photo	0.124	0.124	0.125	0.120	0.127
	(0.33)	(0.33)	(0.33)	(0.32)	(0.33)
Female photo	0.399	0.398	0.411	0.398	0.399
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
Male photo	0.399	0.400	0.383	0.404	0.397
	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
Photo matches	0.534	0.535	0.531	0.537	0.533
customer's race?	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Photo matches	0.401	0.402	0.388	0.403	0.400
customer's gender?	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
Promotional lottery	0.250	0.251	0.246	0.250	0.251
	(0.43)	(0.43)	(0.43)	(0.43)	(0.43)
Suggestion call	0.003	0.003	0.005	0.003	0.003
	(0.05)	(0.05)	(0.07)	(0.05)	(0.05)
Sample	53194	49250	3944	17108	36086

- Manipulation of interest here:
  - Vary number of options of repayment presented
    - Small Table: Single Repayment option
    - Big Table 1: 4 loan sizes, 4 Repayment options, 1 interest rate
    - Big Table 2: 4 loan sizes, 4 Repayment options, 3 interest rates
    - Explicit statement that "other loan sizes and terms were available"
  - Compare Small Table to other Table sizes
  - Small Table increases Take-Up Rate by .603 percent
  - One additional point of (monthly) interest rate decreases take-up by .258

Table 3 Effect of Simplicity of Offer Description on Take-Up[a]

Dependent Variable: Take-Up Dummy			
Sample:	**All**	**High attention**	**Low attention**
	(1)	(2)	(3)
Small option table	0.603	1.146	0.407
	(0.239)	(0.674)	(0.219)
Δ interest rate equivalent	[2.337]	[3.570]	[1.887]
Interest rate	-0.258	-0.321	-0.215
	(0.049)	(0.145)	(0.044)
Risk category F.E.?	yes	yes	yes
Experimental wave F.E.?	yes	yes	yes
Sample size	53194	17108	36086

- Small-option Table increases take-up by equivalent of 2.33 pct. interest

- Strong effect of behavioral factor, compared with effect of interest rate
- Effect larger for 'High-Attention' group (borrow at least twice in the past, once within 8 months)
- Authors also consider effect of a number of other psychological variables:
  - Content of photo (large effect of female photo on male take-up)
  - Promotional lottery (no effect)
  - Deadline for loan (reduces take-up)

4 Menu Effects: Preference for Familiar

- Third Heuristic: Preference for items that are more familiar
- Choice of stocks by individual investors (**French-Poterba, AER 1991**)
  - Allocation in domestic equity: Investors in the USA: 94%
  - Explanation 1: US equity market is reasonably close to world equity market
  - BUT: Japan allocation: 98%
  - BUT: UK allocation: 82%
- Explanation 2: Preference for own-country equity may be due to costs of investments in foreign assets

- Test: Examine within-country investment: **Huberman (RFS, 2001)**
  - Geographical distribution of shareholders of Regional Bell companies
  - Companies formed by separating the Bell monopoly
  - Fraction invested in the own-state Regional Bell is 82 percent higher than the fraction invested in the next Regional Bell company

- Third, extreme case: Preference for own-company stock
  - On average, employees invest 20-30 percent of their discretionary funds in employer stocks (**Benartzi JF, 2001**)

Panel C: Company Stock Allocation as a Percentage of the Employee Contributions			
Number of plans	78	58	136
Mean: equally weighted	18	29	23
Mean: weighted by employee contributions	21	33	24
Mean: weighted by the number of active participants	21	31	24

- - Notice: This occurs despite the fact that the employees' human capital is already invested in their company
  - Also: This choice does not reflect private information about future performance
  - Companies where a higher proportion of employees invest in employer stock have lower subsequent one-year returns, compared to companies with a lower proportion of employee investment

	Allocation to Company Stock					Observed Difference
	(Low) 1	2	3	4	5 (High)	(5 − 1)
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
Two-year returns	43.69	40.78	38.24	43.33	31.92	−11.77

- Possible Explanation? Ambiguity aversion
  - **Ellsberg (1961)** paradox:
  - Investors that are ambiguity-averse prefer:
    - ∗ Investment with known distribution of returns
    - ∗ To investment with unknown distribution
  - This occurs even if the average returns are the same for the two investments, and despite the benefits of diversification.

5 Menu Effects: Preference for Salient

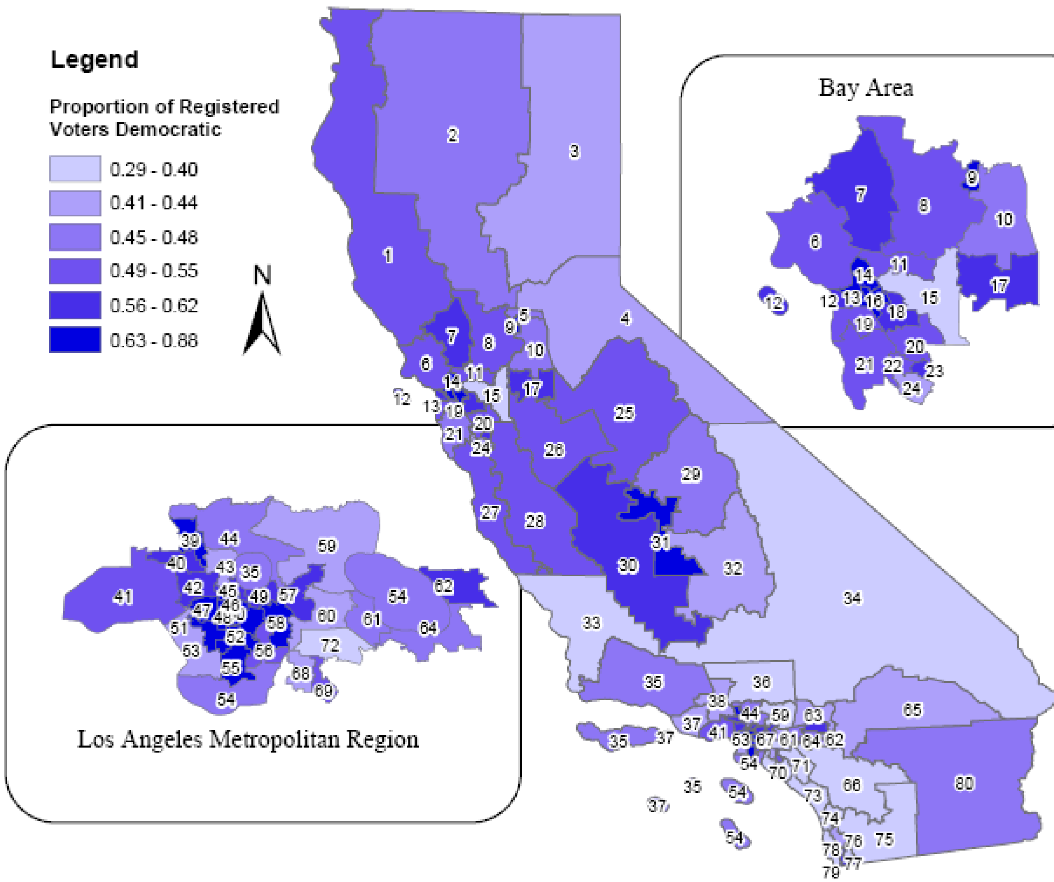
- What happens with large set of options if decision-maker uninformed?

- Possibly use of irrelevant, but salient, information to choose

- **Ho-Imai (2004).** Order of candidates on a ballot
  - Exploit randomization of ballot order in California
  - Years: 1978-2002, Data: 80 Assembly Districts

- Notice: Similar studies go back to **Bain-Hecock** (1957)

- Areas of randomization



- Use of randomized alphabet to determine first candidate on ballot

Year	Election	Randomized Alphabet
1982	Primary	S C X D Q G W R V Y U A N H L P B K J I E T O M F Z
	General	L S N D X A M W V T O F I B K Y U P E Q C J Z H R G
1983	Consolidated	L C P K I A U G Z O N B X D W H E M F V R S T Y Q J
1984	Primary	W M F B Q Y T D J U O V I K R H S N P C A E L Z G X
	General	V W I H R Q G J O M T S Y C A F U X K B P E Z N D L
1986	General	Q N H U B J E G M V L W X C K O F D Z R Y I T S P A
1988	Primary	W O K N Q A V T H J F Z L B U D Y M I R G C E S X P
	General	S W F M K J U Y A T V G O N Q B D E P L Z C I X R H
1990	Primary	E J B Y Q F K M O V X L N Z C W A P R D G T H I S U
	General	W F C L D I N J H V K O S A R E Q B T M Y U G Z X P
1992	Primary	U R F A J C D N M K P Z Y X G W O H E B I S V L Q T
	General	F Y U A J S B Z G O E Q R L I M H V N T P D K X C W
1994	Primary	K J H G A M I Q U N C Z S W V R P Y B L O T D F E X
	General	V I A E M S O K L B G N W Y D P U F Z Q J X C R H T
1996	Primary	G E F C Y P D B Z I V A U S M L H K N T O J Q R X W
	General	J Y E P A U S Q B H T R K N L X F D O G M W I Z C V
1998	Primary	L W U J X K C N D O Q A P T Z R Y F E V B H G I M S
	General	W K D N V A G P Y C Z I S T L J X Q O F H R B U M E
2000	Primary	O P C Y I H X Z V R S Q E K L G D W J U T M B F A N
	General	I T F G J S W R N M K U Y L D C Q A H X O E B V P Z
2002	Primary	W I Z C O M A Q U K X E B Y N P T R L V S J H D F G
	General	H M V P E B Q U G N D K X Z J A W Y C O S F I T R L
2003	Recall	R W Q O J M V A H B S G Z X N T C I E K U P D Y F L

Table 1: Randomized Alphabets Used for the California Statewide Elections Since 1982.

- Observe each candidate in different orders in different districts
- Compute absolute vote (Y) gain

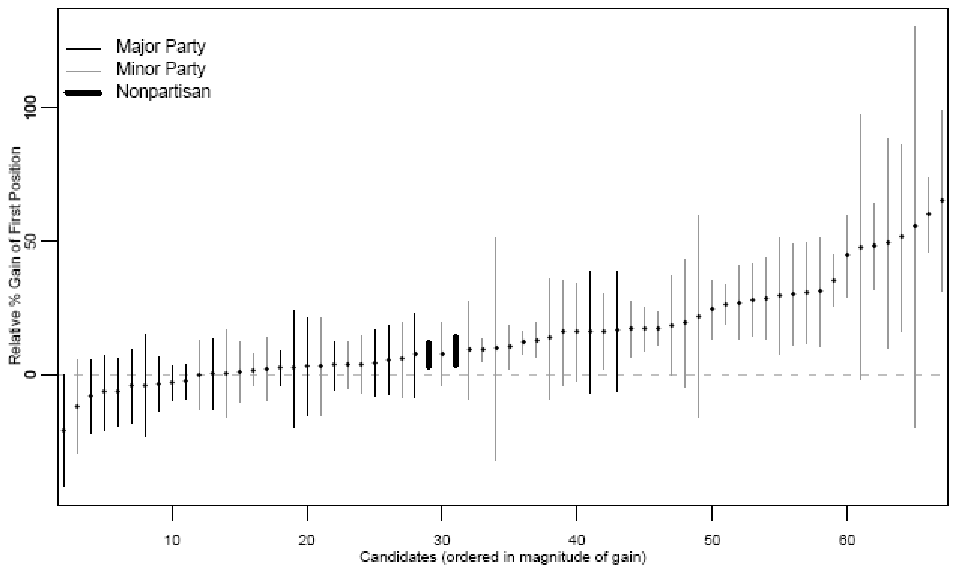
$$E\left[Y\left(i=1\right)-Y\left(i\neq 1\right)\right]$$

  and percentage vote gain

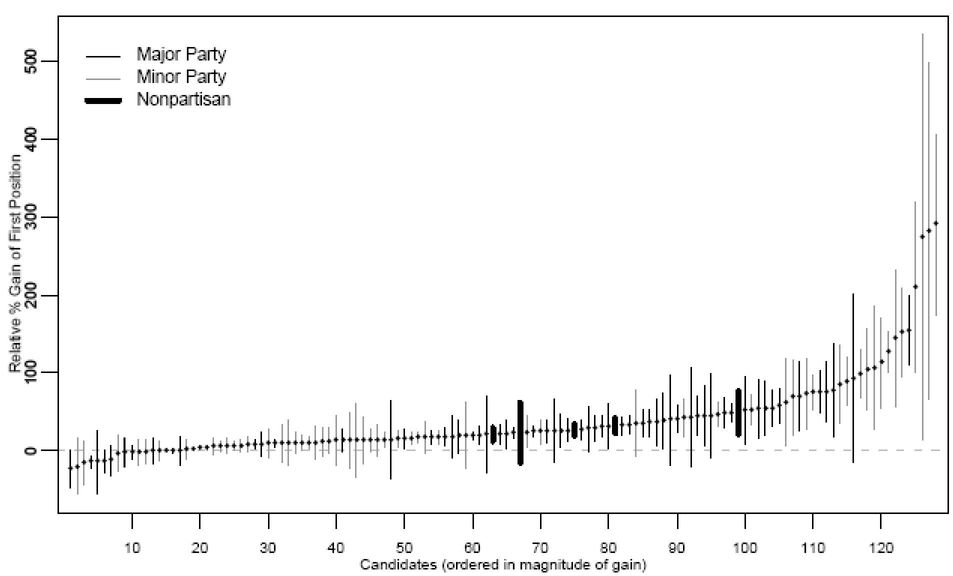
$$E\left[Y\left(i=1\right)-Y\left(i\neq 1\right)\right]/E\left[Y\left(i\neq 1\right)\right]$$

- Result:
  - Small to no effect for major candidates
  - Large effects on minor candidates

General Election 1998 & 2000



Primary Elections, 1998 & 2000



	General				Primary			
	Absolute		Relative		Absolute		Relative	
	ATE	SE	ATE	SE	ATE	SE	ATE	SE
Democratic	0.05	0.46	0.25	0.90	1.89	0.32	43.58	5.53
Republican	-0.06	0.53	-0.43	1.29	2.16	0.46	33.62	5.91
American Independent	0.16	0.02	20.83	1.39	2.33	0.15	26.76	3.55
Green	0.56	0.17	21.18	5.82	3.15	1.16	6.24	3.54
Libertarian	0.23	0.02	14.56	1.03	6.59	1.42	71.92	13.55
Natural Law	0.31	0.06	26.13	2.85	0.40	0.08	44.78	5.45
Peace and Freedom	0.28	0.03	25.49	2.15	6.31	0.53	14.75	1.43
Reform	0.26	0.07	19.57	2.23	4.11	1.56	48.45	9.66
Nonpartisan	1.95	0.30	9.21	3.31	3.44	0.78	19.42	4.05

Table 3: Party-Specific Average Causal Effects of Being Listed in First Position on Ballots Using All Races from 1978 to 2002. ATE and SE represent the average causal effects and their standard errors, respectively. For general and primary elections, the left two columns present the estimates of average absolute gains in terms of the total or party vote, respectively, while the right two columns show those of average relative gains. Each candidate-specific effect is averaged over different races to obtain the overall average effect for each party. In general elections, only minor party and nonpartisan candidates are affected by the ballot order. In primaries, however, the candidates of all parties are affected. The largest effects are found for nonpartisan candidates.

- **Barber-Odean (2008).** Investor with limited attention
  - Stocks in portfolio: Monitor continuously
  - Other stocks: Monitor extreme deviations (*salience*)
- Which stocks to purchase? High-attention (salient) stocks. On days of high attention, stocks have
  - Demand increase
  - No supply increase
  - Increase in net demand

- Heterogeneity:
  - Small investors with limited attention attracted to salient stocks
  - Institutional investors less prone to limited attention
- Market interaction: Small investors are:
  - Net buyers of high-attention stocks
  - Net sellers of low-attention stocks.
- Measure of net buying is Buy-Sell Imbalance:

$$BSI_t = 100 * \frac{\sum_i NetB\mathsf{uy}_{i,t} - \sum_i NetSell_{i,t}}{\sum_i NetB\mathsf{uy}_{i,t} + \sum_i NetSell_{i,t}}$$

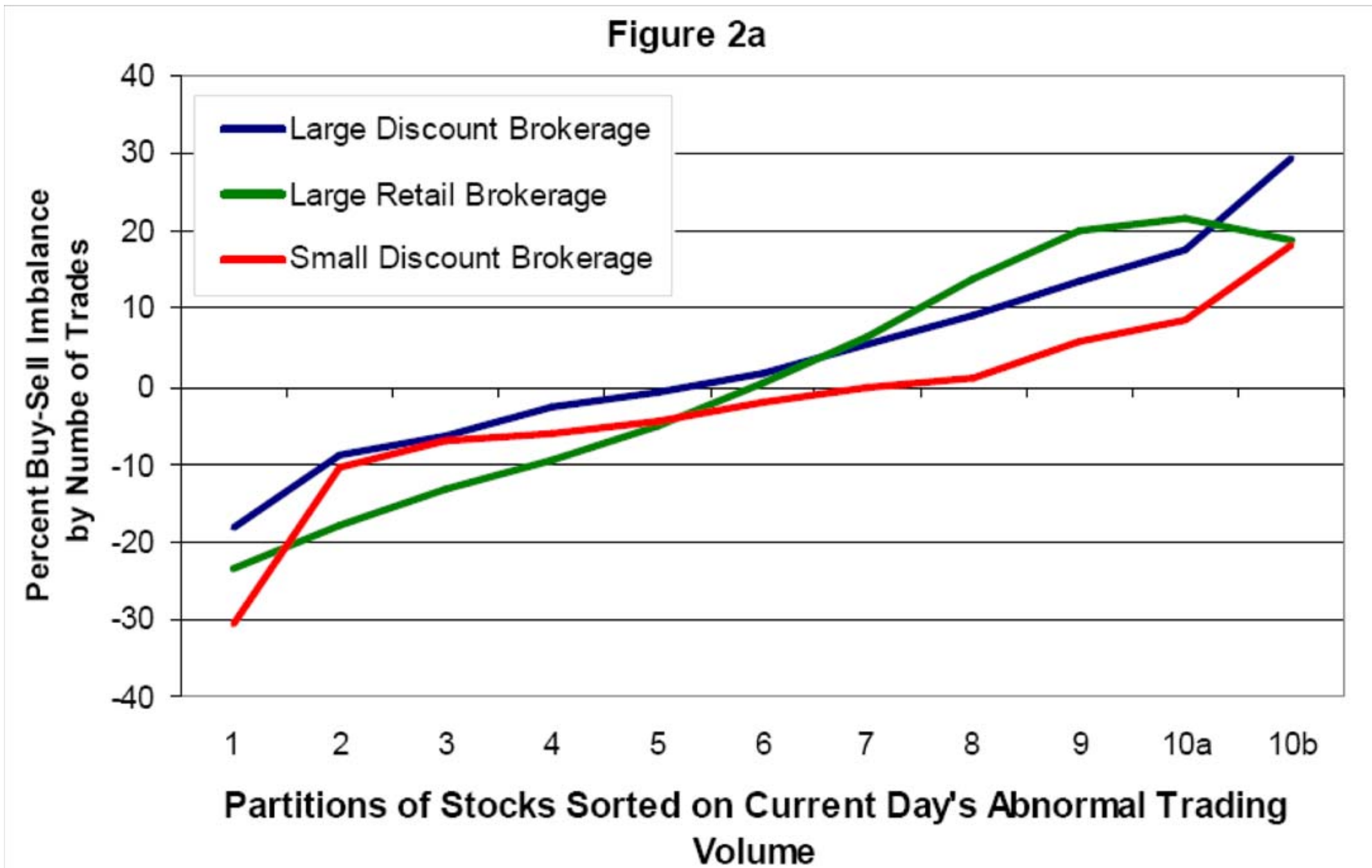
- Notice: Unlike in most financial data sets, here use of individual trading data

- In fact: No obvious prediction on prices

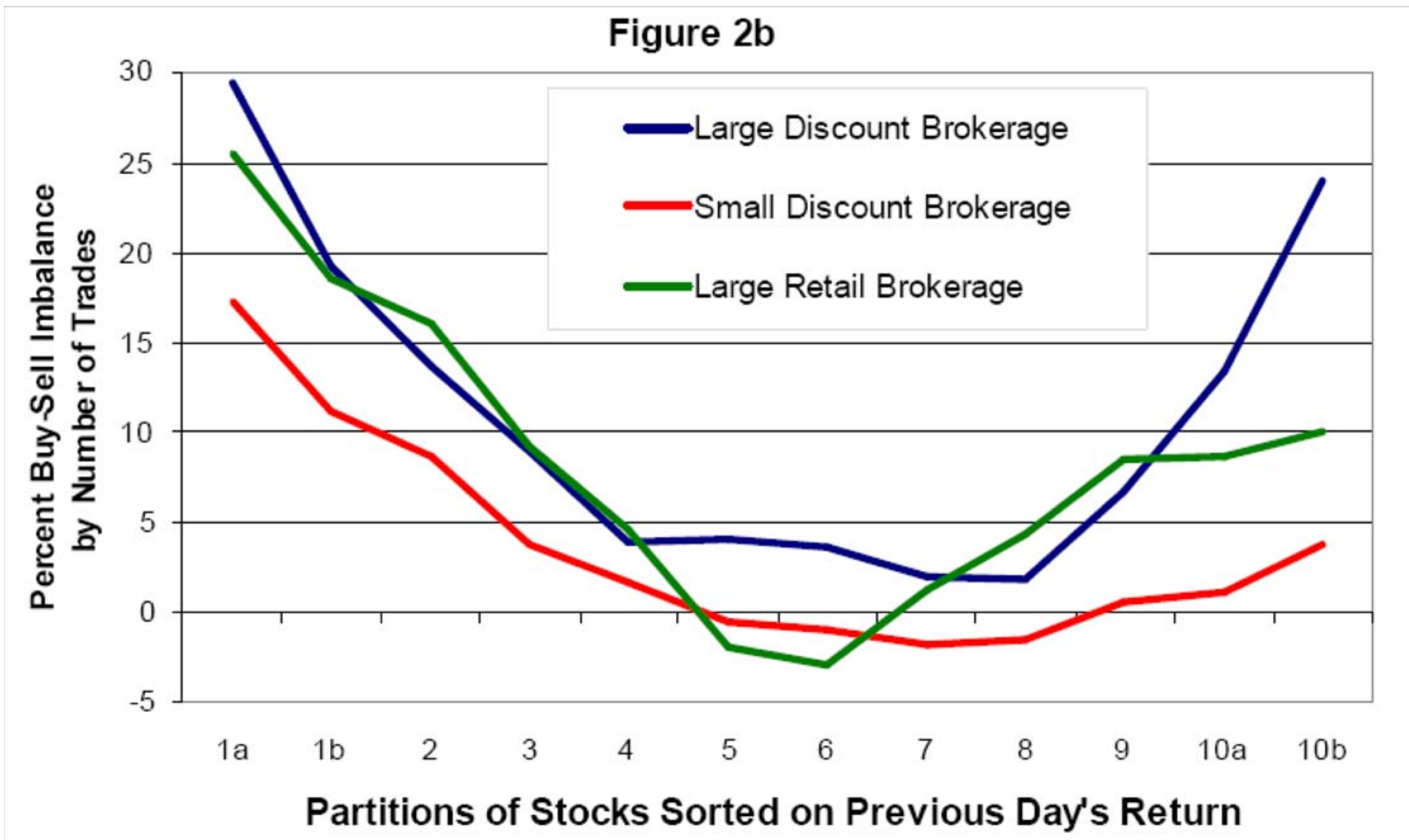
- Measures of attention:
  - same-day (abnormal) volume V_t
  - previous-day return r_{t-1}
  - stock in the news (Using Dow Jones news service)

- Use of sorting methodology
  - Sort variable (V_t, r_{t-1}) and separate into equal-sized bins (in this case, deciles)
    - Example: $V_t^1, V_t^2, V_t^3, ..., V_t^{10a}, V_t^{10b}$
    - (Finer sorting at the top to capture top 5 percent)
  - Classical approach in finance
  - Benefit: Measures variables in a non-parametric way
  - Cost: Loses some information and magnitude of variable

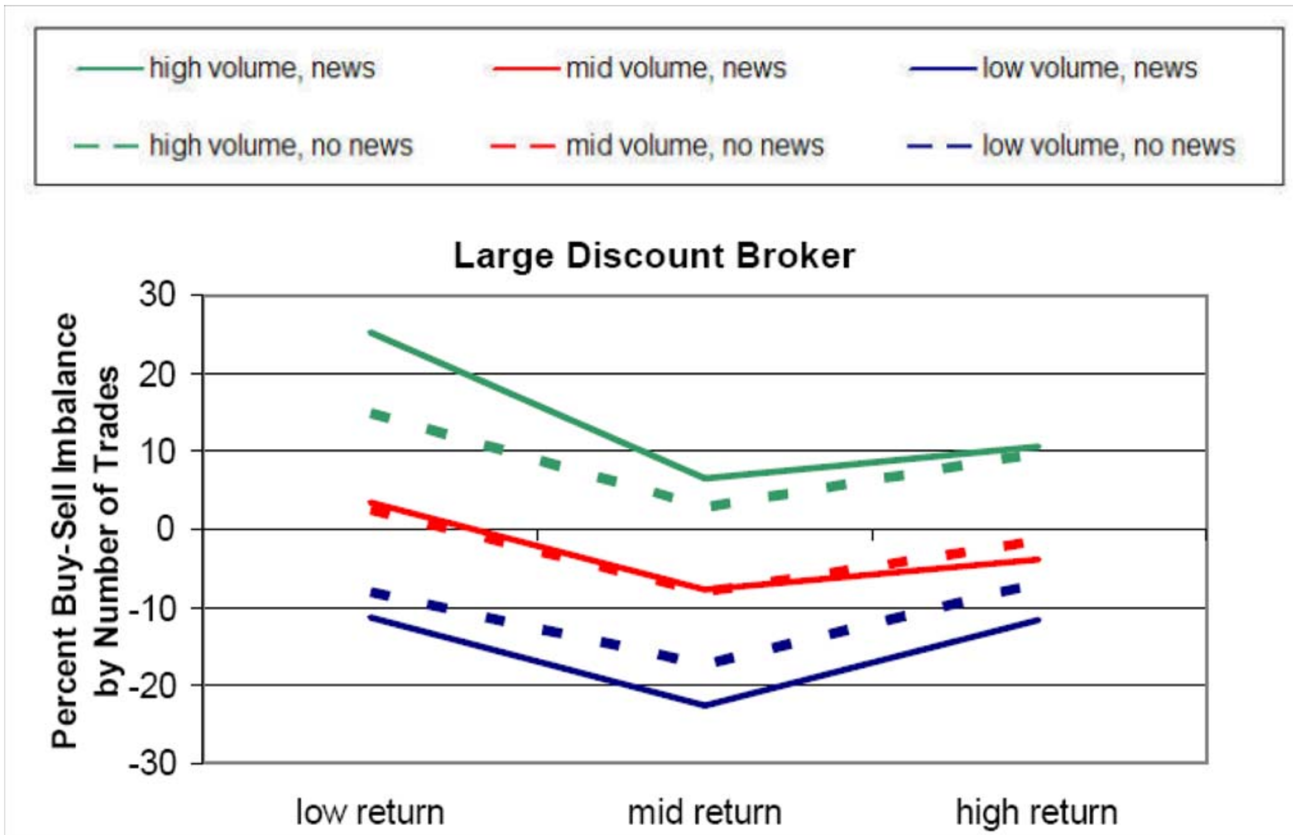
- Effect of same-day (abnormal) volume V_t monotonic (Volume captures 'attention')



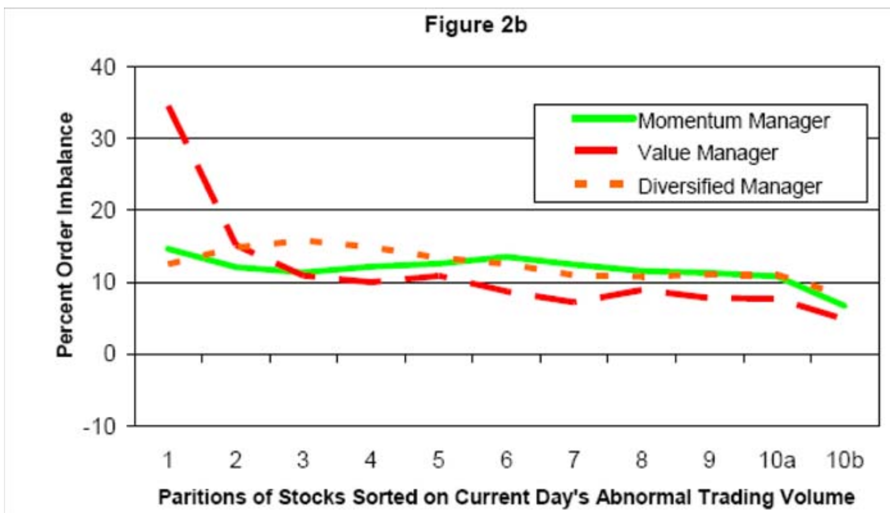
- Effect of previous-day return r_{t-1} U-shaped
  (Large returns—positive or negative—attract attention)

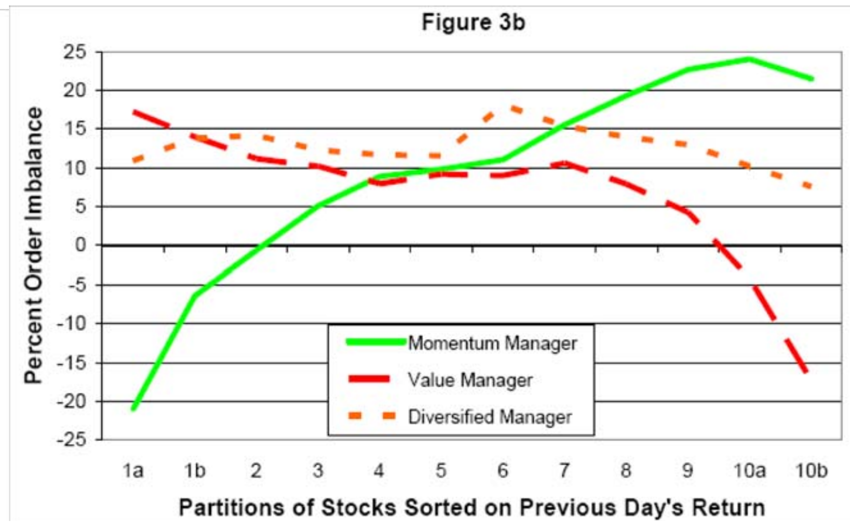


- Notice: Pattern is consistent across different data sets of investor trading
- Figures 2a and 2b are 'univariate' — Figure 3 is 'multivariate'



- Patterns are the opposite for institutional investors (Fund managers)





- Alternative interpretations of results:
- Small investors own few stocks, face short-selling constraints
- (To sell a stock you do not own you need to borrow it first, then you sell it, and then you need to buy it back at end of lending period)
- If new information about the stock:
  - buy if positive news
  - do nothing otherwise
- If no new information about the stock:
  - no trade
- Large investors are not constrained

- Study pattern for stocks that investors already own

Panel A: Buy-sell imbalance for Stocks Already Owned Sorted on Current Day's Abnormal Trading Volume.

	Large Discount Brokerage		Large Retail Brokerage		Small Discount Brokerage	
Decile	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance	Number Imbalance	Value Imbalance
1 (lowest volume)	-54.22 (1.43)	-55.64 (1.89)	-28.74 (1.42)	-33.99 (1.84)	-24.25 (6.28)	-33.22 (7.58)
2	-51.13 (0.78)	-53.20 (1.07)	-29.46 (1.09)	-34.09 (1.36)	-33.80 (3.18)	-29.67 (4.47)
3	-48.27 (0.64)	-49.69 (0.95)	-29.54 (1.04)	-31.25 (1.31)	-31.76 (1.71)	-30.05 (2.44)
4	-47.19 (0.56)	-49.51 (0.88)	-28.69 (0.94)	-32.96 (1.11)	-35.65 (1.26)	-33.93 (1.96)
5	-45.95 (0.53)	-47.59 (0.81)	-26.71 (0.90)	-31.04 (1.07)	-32.34 (1.12)	-30.01 (1.63)
6	-45.01 (0.49)	-48.65 (0.71)	-24.32 (0.90)	-29.71 (1.04)	-30.00 (0.97)	-26.50 (1.42)
7	-42.36 (0.50)	-45.85 (0.71)	-21.83 (0.84)	-30.29 (0.89)	-29.85 (0.95)	-26.21 (1.33)
8	-39.43 (0.51)	-43.75 (0.71)	-18.72 (0.81)	-27.21 (0.87)	-28.20 (0.87)	-26.23 (1.22)
9	-35.64 (0.52)	-40.68 (0.70)	-15.45 (0.78)	-21.79 (0.91)	-27.07 (0.85)	-24.99 (1.21)
10a	-33.03 (0.63)	-39.31 (0.85)	-12.27 (0.97)	-19.97 (1.12)	-26.81 (1.06)	-27.99 (1.42)
10b (highest volume)	-24.97 (0.69)	-32.82 (0.92)	-15.01 (1.04)	-20.04 (1.19)	-17.32 (0.98)	-19.38 (1.42)

6 Menu Effects: Confusion

- Previous heuristics reflect preference to avoid difficult choices or for salient options

- Confusion is simply an error in the implementation of the preferences

- Different from most behavioral phenomena which are directional biases

- How common is it?

- Application 1. **Shue-Luttmer (2009)**
  - Choice of a political candidate among those in a ballot
  - California voters in the 2003 recall elections

- Do people vote for the candidate they did not mean to vote for?

Candidates to succeed **GRAY DAVIS** as Governor if he is recalled:

Vote for One

Candidate	Occupation	Party
NATHAN WHITECLOUD WALTON	Student	Independent
MAURICE WALKER	Real Estate Appraiser	Green
CHUCK WALKER	Business Intelligence Analyst	Republican
LINGEL H. WINTERS	Consumer Business Attorney	Democratic
C.T. WEBER	Labor Official/Analyst	Peace and Freedom
JIM WEIR	Community College Teacher	Democratic
BRYAN QUINN	Businessman	Republican
MICHAEL JACKSON	Satellite Project Manager	Republican
JOHN 'JACK' MORTENSEN	Contractor/Businessman	Democratic
DARRYL L. MOBLEY	Businessman/Entrepreneur	Independent
JEFFREY L. MOCK	Business Owner	Republican
BRUCE MARGOLIN	Marijuana Legalization Attorney	Democratic
GINO MARTORANA	Restaurant Owner	Republican
PAUL MARIANO	Attorney	Democratic
ROBERT C. MANNHEIM	Retired Businessperson	Democratic
FRANK A. MACALUSO, JR.	Physician/Medical Doctor	Democratic
PAUL 'CHIP' MAILANDER		
JOEL BRITTON	Retired Meat Packer	Independent
AUDIE BOCK	Educator/Small Businesswoman	Democratic
VIK S. BAJWA	Businessman/Father/Entrepreneur	Democratic
BADI BADIOZAMANI	Entrepreneur/Author/Executive	Independent
VIP BHOLA	Attorney/Businessowner	Republican
JOHN W. BEARD	Businessman	Republican
ED BEYER	Chief Operations Officer	Republican
JOHN CHRISTOPHER BURTON	Civil Rights Lawyer	Independent
CRUZ M. BUSTAMANTE	Lieutenant Governor	Democratic
CHERYL BLY-CHESTER	Businesswoman/Environmental Engineer	Republican
B.E. SMITH	Lecturer	Independent
DAVID RONALD SAMS	Businessman/Producer/Writer	Republican
JAMIE ROSEMARY SAFFORD	Business Owner	Republican
LAWRENCE STEVEN STRAUSS	Lawyer/Businessperson/Student	Democratic
ARNOLD SCHWARZENEGGER	Actor/Businessman	Republican
GEORGE B. SCHWARTZMAN	Businessman	Independent
MIKE SCHMIER		
S. ISSA	Engineer	Republican
BOB LYNN EDWARDS	Attorney	Democratic
ERIC KOREVAAR	Scientist/Businessman	Democratic
STEPHEN L. KNAPP	Engineer	Republican
KELLY P. KIMBALL	Business Executive	Democratic
D.E. KESSINGER	Paralegal/Property Manager	Democratic
EDWARD 'ED' KENNEDY	Businessman/Educator	Democratic
TREK THUNDER KELLY	Business Executive/Artist	Independent
JERRY KUNZMAN	Chief Executive Officer	Independent
PETER V. UEBERROTH	Businessman/Olympics Advisor	Republican
BILL PRADY	Television Writer/Producer	Democratic
DARIN PRICE	University Chemistry Instructor	Natural Law
GREGORY J. PAWLIK	Realtor/Businessman	Republican
LEONARD PADILLA	Law School President	Independent
RONALD JASON PALMIERI	Gay Rights Attorney	Democratic
CHARLES 'CHUCK' PINEDA, JR.	State Hearing Officer	Democratic
HEATHER PETERS		

County of Sacramento
Statewide Special Election
October 7, 2003

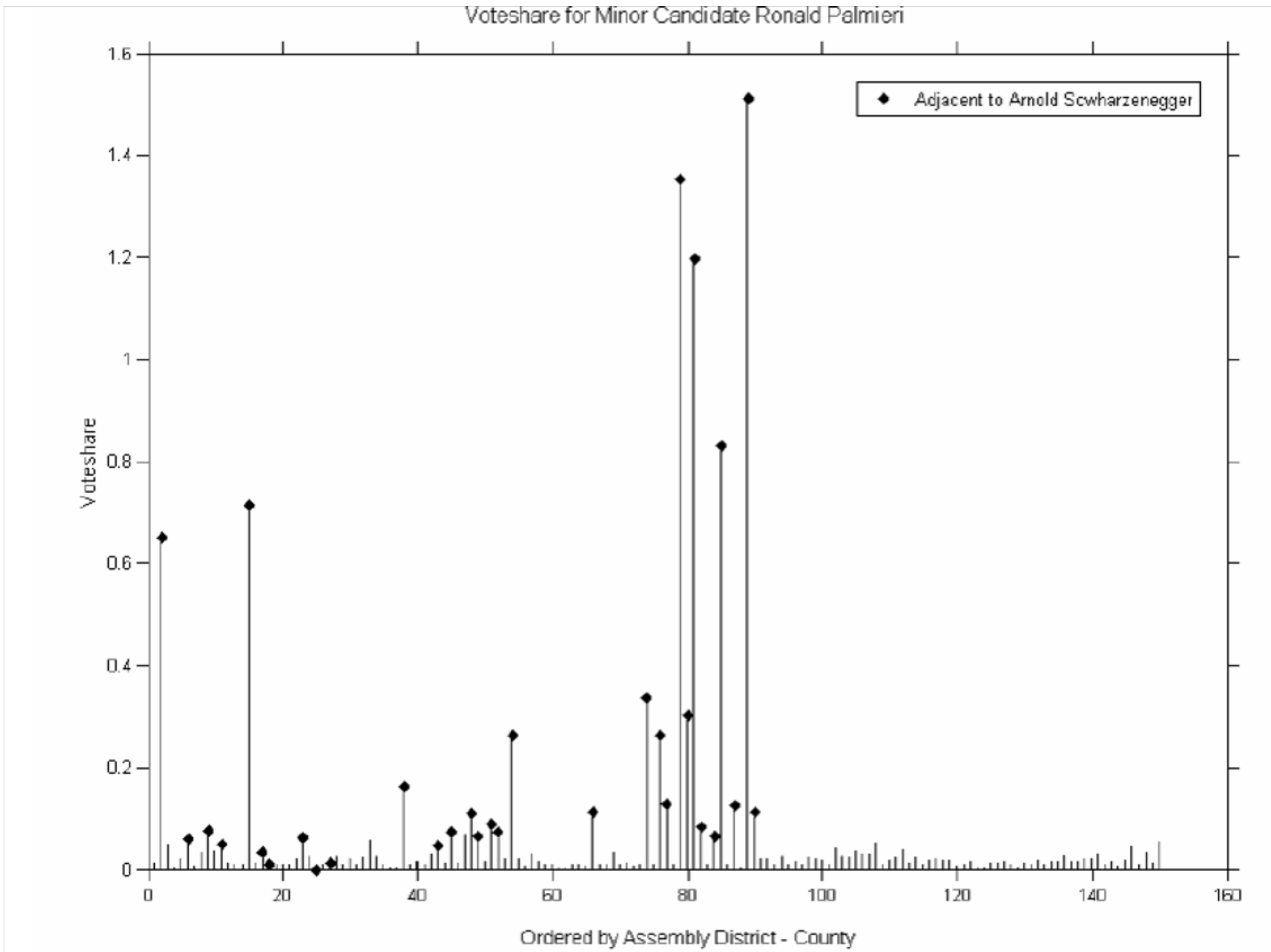
Candidates Continued / Candidatos Continúa

54	**ANGELYNE**, Independent Entertainer/Artista
55	**DOUGLAS ANDERSON**, Republican Mortgage Broker/Agente hipotecario
56	**IRIS ADAM**, Natural Law Business Analyst/Analista empresarial
57	**BROOKE ADAMS**, Independent Business Executive/Ejecutiva de empresa
58	**ALEX-ST. JAMES**, Republican Public Policy Strategist/Estratega de política pública
59	**JIM HOFFMANN**, Republican Teacher/Maestro
60	**KEN HAMIDI**, Libertarian State Tax Officer/Funcionario impositivo estatal
61	**SARA ANN HANLON**, Independent Businesswoman/Mujer de negocios
62	**IVAN A. HALL**, Green Custom Denture Manufacturer/Fabricante de dentaduras postizas a medida
63	**JOHN J. "JACK" HICKEY**, Libertarian Healthcare District Director/Director de distrito de atención de la salud
64	**RALPH A. HERNANDEZ**, Democratic District Attorney Inspector/Inspector de fiscalía
65	**C. STEPHEN HENDERSON**, Independent Teacher/Maestro
66	**ARIANNA HUFFINGTON**, Independent Author/Columnist/Mother/Escritora/columnista/madre
67	**ART BROWN**, Democratic Film Writer/Director/Guionista y director de cine
68	**JOEL BRITTON**, Independent Retired Meat Packer/Empacador de carne jubilado
69	**AUDIE BOCK**, Democratic Educator/Small Businesswoman/Educadora/propietaria de pequeña empresa
70	**VIK S. BAJWA**, Democratic Businessman/Father/Entrepreneur/Hombre de negocios/padre/empresario
71	**BADI BADIOZAMANI**, Independent Entrepreneur/Author/Executive/Empresario/escritor/ejecutivo
72	**VIP BHOLA**, Republican Attorney/Businessowner/Abogado/propietario de empresa
73	**JOHN W. BEARD**, Republican Businessman/Hombre de negocios
74	**ED BEYER**, Republican Chief Operations Officer/Funcionario principal de operaciones
75	**JOHN CHRISTOPHER BURTON**, Independent Civil Rights Lawyer/Abogado de derechos civiles
76	**CRUZ M. BUSTAMANTE**, Democratic Lieutenant Governor/Vicegobernador
77	**CHERYL BLY-CHESTER**, Republican Businesswoman/Environmental Engineer/Mujer de negocios/ingeniera ambiental
78	**B.E. SMITH**, Independent Lecturer/Conferencista

Candidate listing continues on next page /
La lista de candidatos continúa en la página siguiente ➔

1 ☐	27 ☐	53 ☐	79 ☐	105 ☐	131 ☐	157 ☐	183 ☐	209 ☐	235 ☐	261 ☐	287 ☐
2 ☐	28 ☐	54 ☐	80 ☐	106 ☐	132 ☐	158 ☐	184 ☐	210 ☐	236 ☐	262 ☐	288 ☐
3 ☐	29 ☐	55 ☐	81 ☐	107 ☐	133 ☐	159 ☐	185 ☐	211 ☐	237 ☐	263 ☐	289 ☐
4 ☐	30 ☐	56 ☐	82 ☐	108 ☐	134 ☐	160 ☐	186 ☐	212 ☐	238 ☐	264 ☐	290 ☐
5 ☐	31 ☐	57 ☐	83 ☐	109 ☐	135 ☐	161 ☐	187 ☐	213 ☐	239 ☐	265 ☐	291 ☐
6 ☐	32 ☐	58 ☐	84 ☐	110 ☐	136 ☐	162 ☐	188 ☐	214 ☐	240 ☐	266 ☐	292 ☐
7 ☐	33 ☐	59 ☐	85 ☐	111 ☐	137 ☐	163 ☐	189 ☐	215 ☐	241 ☐	267 ☐	293 ☐
8 ☐	34 ☐	60 ☐	86 ☐	112 ☐	138 ☐	164 ☐	190 ☐	216 ☐	242 ☐	268 ☐	294 ☐
9 ☐	35 ☐	61 ☐	87 ☐	113 ☐	139 ☐	165 ☐	191 ☐	217 ☐	243 ☐	269 ☐	295 ☐
10 ☐	36 ☐	62 ☐	88 ☐	114 ☐	140 ☐	166 ☐	192 ☐	218 ☐	244 ☐	270 ☐	296 ☐
11 ☐	37 ☐	63 ☐	89 ☐	115 ☐	141 ☐	167 ☐	193 ☐	219 ☐	245 ☐	271 ☐	297 ☐
12 ☐	38 ☐	64 ☐	90 ☐	116 ☐	142 ☐	168 ☐	194 ☐	220 ☐	246 ☐	272 ☐	298 ☐
13 ☐	39 ☐	65 ☐	91 ☐	117 ☐	143 ☐	169 ☐	195 ☐	221 ☐	247 ☐	273 ☐	299 ☐
14 ☐	40 ☐	66 ☐	92 ☐	118 ☐	144 ☐	170 ☐	196 ☐	222 ☐	248 ☐	274 ☐	300 ☐
15 ☐	41 ☐	67 ☐	93 ☐	119 ☐	145 ☐	171 ☐	197 ☐	223 ☐	249 ☐	275 ☐	301 ☐
16 ☐	42 ☐	68 ☐	94 ☐	120 ☐	146 ☐	172 ☐	198 ☐	224 ☐	250 ☐	276 ☐	302 ☐
17 ☐	43 ☐	69 ☐	95 ☐	121 ☐	147 ☐	173 ☐	199 ☐	225 ☐	251 ☐	277 ☐	303 ☐
18 ☐	44 ☐	70 ☐	96 ☐	122 ☐	148 ☐	174 ☐	200 ☐	226 ☐	252 ☐	278 ☐	304 ☐
19 ☐	45 ☐	71 ☐	97 ☐	123 ☐	149 ☐	175 ☐	201 ☐	227 ☐	253 ☐	279 ☐	305 ☐
20 ☐	46 ☐	72 ☐	98 ☐	124 ☐	150 ☐	176 ☐	202 ☐	228 ☐	254 ☐	280 ☐	306 ☐
21 ☐	47 ☐	73 ☐	99 ☐	125 ☐	151 ☐	177 ☐	203 ☐	229 ☐	255 ☐	281 ☐	307 ☐
22 ☐	48 ☐	74 ☐	100 ☐	126 ☐	152 ☐	178 ☐	204 ☐	230 ☐	256 ☐	282 ☐	308 ☐
23	49	75	101	127	153	179	205	231	257	283	309

- Design:
  - Exploit closeness on ballot
  - Exploit specific features of closeness
  - Exploit random variation in placement of candidates on the ballot (as in Ho-Imai)
- First evidence: Can this matter?
- If so, it should affect most minor party candidates



Voteshare for Minor Candidate Ronald Palmieri
Adjacent to Arnold Scwharzenegger
Voteshare
Ordered by Assembly District - County
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
0
20
40
60
80
100
120
140
160

- Model:
  - Share β_1 of voters meaning to vote for major candidate j vote for neighboring candidate i
  - Estimate β_1 by comparing voting for i when close to j and when far from j
  - Notice: The impact depends on vote share of j
  - Specification:

$$VoteShare_i = \beta_0 + \beta_1 * VSAdjacent_j + Controls + \varepsilon$$

  - Rich set of fixed effects, so identify off changes in order

Table 2: Primary Results

Dependent Variable: *Voteshare* = (votes / total votes)×100	**(1)**	**(2)**	**(3)**
Adjacent	0.104** (0.018)		
Adjacent* × *Schwarzenegger		0.088** (0.025)	
Adjacent* × *Bustamante		0.143** (0.025)	
Adjacent* × *McClintock		0.107* (0.045)	
Adjacent Dummy			0.037** (0.006)
Observations	1,817,904	1,817,904	1,817,904
R-Squared	0.8676	0.8676	0.8676

- Results:
  - 1 in 1,000 voters vote for adjacent candidate
  - Difference in error rate by candidate (see below)
  - Notice: Each candidate has 2.5 adjacent candidates –> Total misvoting is 1 in 400 voters

- Interpretations:
  1. Limited Attention: Candidates near major candidate get reminded in my memory
  2. Trembling Hand: Pure error
- To distinguish, go back to structure of ballot.
  - Much more likely to fill-in the bubble on right side than on left side if (2)
  - No difference if (1)

Table 3: Robustness Checks

Dependent Variable: *Voteshare* = (votes / total votes)×100	(1)	(2)	(3)	(4)	(5)	(6)
Adjacent	0.082**			0.104**	0.113**	
	(0.027)			(0.018)	(0.018)	
Adjacent Dummy	0.010					
	(0.007)					
Adjacent Dummy × CA Voteshare		0.112**				
		(0.019)				
North Adjacent			0.082**			0.082**
			(0.022)			(0.022)
South Adjacent			0.111**			0.111**
			(0.033)			(0.033)
East Adjacent			0.143**			
			(0.035)			
West Adjacent			0.038**			
			(0.011)			
Diagonally Adjacent				0.002		
				(0.003)		
Punchcard Adjacent					0.030+	
					(0.018)	
Horizontally Adjacent						0.031**
						(0.008)
Horizontally Adjacent × Confusing Side						0.123**
						(0.038)
Observations	1,817,904	1,817,904	1,817,904	1,817,904	1,817,904	1,817,904
R-Squared	0.8676	0.8676	0.8677	0.8676	0.8677	0.8677

- Effect is mostly due to Trembling hand / Confusion
- Additional results:
  - Spill-over of votes larger for more confusing voting methods (such as punch-cards)

Table 7: Interactions with Voting Technology

Dependent Variable: *Voteshare* = (votes / total votes)×100	(1)	(2)	(3)	(4)
Adjacent × punch card	0.197**	0.200**		
	(0.020)	(0.019)		
Adjacent × optical scan	0.100**	0.108**		
	(0.020)	(0.019)		
Adjacent × touch screen	0.065**	0.067**		
	(0.016)	(0.015)		

- Spill-over of votes larger for precincts with a larger share of lower-education demographics –> more likely to make errors when faced with large number of option

Table 4: Overall Effect of Precinct Demographic Ch			
Dependent Variable: *Voteshare* = (votes / total votes)×100	**(1)**	**(2)**	**(3)**
Adjacent	0.6368**	0.0544**	0.3353**
	(0.1012)	(0.0162)	(0.0467)
Adjacent* × *% HS Graduates	-0.0062**		
	(0.0013)		
Adjacent* × *% College Graduates	-0.0056**		
	(0.0010)		

- This implies (small) aggregate effect: confusion has a different prevalence among the voters of different major candidates

- **Rashes (JF, 2001)** Similar issue of confusion for investor choice
- Two companies:
  - Major telephone company MCI (Ticker MCIC)
  - Small investment company (ticker MCI)
  - Investors may confuse them
  - MCIC is much bigger –> this affects trading of company MCI

Summary Statistics

Daily return and volume information is shown for Massmutual Corporate Investors fund (MCI), MCI Communications (MCIC), and AT&T (T) for the sample period 11/21/94–11/13/97. The return for security j is expressed in percentages and defined as $\mathrm{Log}[(P_{j,t+1} + D_{j,t+1})/P_{j,t}]$, where $P_{j,t}$ and $D_{j,t}$ are the price and dividend, respectively, for security j on day t.

	Mean (Return)	*SD* (Return)	Mean (Volume)	*SD* (Volume)	Mean (Price)
MCI	0.078	0.7136	4,155	4,497	36.14
MCIC	0.087	2.3645	4.154×10^6	4.713×10^6	28.07
T	0.055	1.6440	4.810×10^6	2.837×10^6	38.64

- Check correlation of volume (Table III)
  - High correlation
  - What if two stocks have similar underlying fundamentals?
  - No correlation of MCI with another telephone company (AT&T)

Table III

Daily Volume Correlation Coefficient Matrices

This table presents the correlation of daily volumes between Massmutual Corporate Investors fund (MCI), MCI Communications (MCIC), AT&T (T) and the New York Stock Exchange Composite Index (NYSE). The pairwise Pearson product-moment correlations are shown with the standard error of these coefficients in parentheses.

	MCI	MCIC	T	NYSE
Panel A: Sample Period 11/21/94–11/13/97				
MCI	1			
MCIC	0.5592	1		
	(0.0302)			
T	0.0291	0.1566	1	
	(0.0364)	(0.0360)		
NYSE	0.1162	0.2817	0.3397	1
	(0.0362)	(0.0350)	(0.0343)	

- Predict returns of smaller company with bigger company (Table IV)
- Returns Regression:

$$r_{MCI,t} = \alpha_0 + \alpha_1 r_{MCIC,t} + \beta X_t + \varepsilon_t$$

Constant	MCIC Return	(MCIC Return) * dummy (MCIC return <0)	T Return	S&P 500 Return	S&P Smallcap Return Residual	Lehman Long Bond Index Return	R^2
Panel A: Sample Period 11/22/94–11/13/97							
0.0956				0.0372	0.1011	0.0932	0.0286
(2.6223)				(0.9370)	(1.9233)	(2.3438)	0.0247
0.0954	0.0862			0.0128	0.1068	0.0905	0.0353
(2.6243)	(2.2779)			(0.3128)	(2.0356)	(2.2818)	0.0301
0.0957	0.0851		0.0171	0.0052	0.1077	0.0907	0.0355
(2.6306)	(2.2430)		(0.4190)	(0.1166)	(2.0501)	(2.2862)	0.0290
0.0721	0.1205	−0.0722		0.0149	0.1070	0.0913	0.0360
(1.5202)	(2.0557)	(−0.7664)		(0.3630)	(2.0375)	(2.3015)	0.0296

- Results:

– Positive correlation α_1 –> The swings in volume have some impact on prices.

– Difference between reaction to positive and negative news:

$$r_{MCI,t} = \alpha_0 + \alpha_1 r_{MCIC,t} + \alpha_2 r_{MCIC,t} * \mathbf{1}\left(r_{MCIC,t} < 0\right) + \beta X_t + \varepsilon_t$$

– Negative α_2. Effect of arbitrage –> It is much easier to buy by mistake than to short a stock by mistake

- Size of confusion? Use relation in volume.

  – We would like to know the result (as in Luttmer-Shue) of

$$V_{MCI,t} = \alpha + \beta V_{MCIC,t} + \varepsilon_t$$

  – Remember: $\beta = Cov(V_{MCI,t}, V_{MCIC,t}) / Var(V_{MCIC,t})$

– We know (Table I)

$$
\begin{aligned}
.5595 &= \rho_{MCI,MCIC} = \frac{Cov(V_{MCI,t}, V_{MCIC,t})}{\sqrt{Var(V_{MCI,t})Var(V_{MCIC,t})}} = \\
&= \beta * \frac{\sqrt{Var(V_{MCIC,t})}}{\sqrt{Var(V_{MCI,t})}}
\end{aligned}
$$

– Hence, $\beta = .5595 * \sqrt{Var(V_{MCI,t})}/\sqrt{Var(V_{MCIC,t})} = .5595 * 10^{-3} = 5 * 10^{-4}$

– Hence, the error rate is approximately $5 * 10^{-4}$, that is, 1 in 2000

- Conclusion
  - Deviation from standard model: confusion.
  - Can have an aggregate impact, albeit a small one
  - Can be moderately large for error from common choice to rare choice
  - Other applications: eBay bidding on misspelled names (find cheaper items when looking for ‘shavre’ [shaver] or ‘tyo’ [toy]

7 Persuasion

- Persuasion and Social Pressure: Change in opinion/action beyond prediction of Bayesian model

- **Persuasion:** Sender attempts to convince Receiver with words/images to take an action
  - Rational persuasion through Bayesian updating
  - Non-rational persuasion, i.e.: neglect of incentives of person presenting information
  - Effect of persuasion directly on utility function (advertising/emotions)

- **Social Pressure:** Presence of Sender exerts pressure to take an action

- **DellaVigna and Gentzkow (2010)**: Overview on Persuasion:
  - Persuading consumers: Marketing
  - Persuading voters: Political Communication
  - Persuading donors: Fund-raising
  - Persuading investors: Financial releases

- First problem: How to measure when persuasion occurs?

- Treatment group *T*, control group *C*, *Persuasion Rate* is

$$f = 100 * \frac{y_T - y_C}{e_T - e_C} \frac{1}{1 - y_0},$$

  - e_i is the share of group i receiving the message,
  - y_i is the share of group i adopting the behavior of interest,
  - y_0 is the share that would adopt if there were no message

TABLE 1, PART A
PERSUASION RATES: SUMMARY OF STUDIES

Paper	Treatment (1)	Control (2)	Variable t (4)	Time Horizon (7)	Treatment group t_T (9)	Control group t_C (10)	Exposure rate e_T-e_C (11)	Persuasion rate f (12)
Persuading Consumers								
Simester et al. (2007) (NE)	17 clothing catalogs sent	12 catalogs	Share Purchasing	1 year	36.7%	33.9%	100%*	4.2%
			>= 1 item		69.1%	66.8%	100%*	6.9%
Bertrand, Karlan, Mullainathan,	Mailer with female photo	Mailer no photo	Applied for loan	1 month	9.1%	8.5%	100%*	0.7%
Shafir, and Zinman (2010) (FE)	Mailer with 4.5% interest rate	Mailer 6.5% i.r.			9.1%	8.5%	100%*	0.7%
Persuading Voters								
Gosnell (1926)	Card reminding of registration	No card	Registration	Few days	42.0%	33.0%	100.0%	13.4%
Gerber and Green (2000) (FE)	Door-to-Door GOTV Canvassing	No GOTV	Turnout	Few days	47.2%	44.8%	27.9%	15.6%
	GOTV Mailing of 1-3 Cards	No GOTV			42.8%	42.2%	100%*	1.0%
Green, Gerber, and Nickerson (2003) (FE)	Door-to-Door Canvassing	No GOTV	Turnout	Few days	31.0%	28.6%	29.3%	11.5%
Green and Gerber (2001) (FE)	Phone Calls By Youth Vote	No GOTV	Turnout	Few days	71.1%	66.0%	73.7%	20.4%
	Phone Calls 18-30 Year-Olds	No GOTV	Turnout		41.6%	40.5%	41.4%	4.5%
DellaVigna and Kaplan (2007) (NE)	Availab. of Fox News Via Cable	No F.N. via cable	Rep. Vote Share	0-4 years	56.4%	56.0%	3.7%	11.6%+
Enikolopov, Petrova, and Zhuravskaya (2010) (NE)	Availability of independent anti-Putin TV station (NTV)	No NTV	Vote Share of anti-Putin parties	3 months	17.0%	10.7%	47.0%	7.7%+
Knight and Chiang (2010) (NE)	Unsurprising Dem. Endors. (NYT)	No endors.	Support for Gore	Few weeks	75.5%	75.0%	100.0%	2.0%
	Surprising Dem. Endors. (Denver)	No endors.			55.1%	52.0%	100.0%	6.5%
Gerber, Karlan, and Bergan (2009) (FE)	Free 10-week subscription to Washington Post	No Subscr.	Dem. Vote Share (stated in survey)	2 months	67.2%	56.0%	94.0%	19.5%+
Gentzkow (2006) (NE)	Exposure to Television	No Television	Turnout	10 years	54.5%	56.5%	80.0%	4.4%
Gentzkow and Shapiro (2009) (NE)	Read Local Newspaper	No local paper	Turnout	0-4 years	70.0%	69.0%	25.0%	12.9%

TABLE 1, PART B
PERSUASION RATES: SUMMARY OF STUDIES

Paper	Treatment (1)	Control (2)	Variable t (4)	Time Horizon (7)	Treatment group t_T (9)	Control group t_C (10)	Exposure rate e_T-e_C (11)	Persuasion rate f (12)
Persuading Donors								
List and Lucking-Reiley (2002) (FE)	Fund-raiser mailer with low seed	No mailer	Share Giving Money	1-3 weeks	3.7%	0%	100%*	3.7%
	Fund-raiser mailer with high seed	No mailer			8.2%	0%	100%*	8.2%
Landry, Lange, List, Price, and Rupp (2006) (FE)	Door-To-Door Fund-raising Campaign for University Center	No visit	Share Giving Money	immediate	10.8%	0%	36.3%	29.7%
DellaVigna, List, and Malmendier (2009) (FE)	Door-To-Door Fund-raising Campaign for Out-of-State Charity	No visit	Share Giving Money	immediate	4.6%	0%	41.7%	11.0%
Falk (2007) (FE)	Fund-raiser mailer with no gift	No mailer	Share Giving Money	1-3 weeks	12.2%	0%	100%*	12.2%
	Mailer with gift (4 post-cards)	No mailer			20.6%	0%	100%*	20.6%
Persuading Investors								
Engelberg and Parsons (2009) (NE)	Coverage of Earnings News in Local Paper	No coverage	Trading of Shares of Stock in News	3 days	0.023%	0.017%	60.0%	0.010%

Notes: Calculations of persuasion rates by the authors. The list of papers indicates whether the study is a natural experiment ("NE") or a field experiment ("FE"). Columns (9) and (10) report the value of the behavior studied (Column (4)) for the Treatment and Control group. Column (11) reports the Exposure Rate, that is, the difference between the Treatment and the Control group in the share of people exposed to the Treatment. Column (12) computes the estimated persuasion rate f a 100*(tT-tC)/((eT-eC)*(1-tC)). The persuasion rate denotes the share of the audience that was not previously convinced and that is convinced by the message. The studies where the exposure rate (Column (11) is denoted by "100%*" are cases in which the data on the differential exposure rate between treatment and control is not available. In these case, we assume eT-eC=100%, which implies that the persuasion rate is a lower bound for the actual persuasion rate. In the studies on "Persuading Donors", even in cases in which an explicit control group with no mailer or no visit was not run, we assume that such a control would have yielded tC=0%, since these behaviors are very rare in absence of a fund-raiser. For studies

- Persuasion rate helps reconcile seemingly very different results, e.g. persuading voters

- More in detail: **DellaVigna-Kaplan (QJE, 2007),** Fox News natural experiment

  1. Fast expansion of Fox News in cable markets

     – October 1996: Launch of 24-hour cable channel

     – June 2000: 17 percent of US population listens regularly to Fox News (Scarborough Research, 2000)

  2. Geographical differentiation in expansion

     – Cable markets: Town-level variation in exposure to Fox News

     – 9,256 towns with variation even within a county

  3. Conservative content

     – Unique right-wing TV channel (Groseclose and Milyo, 2004)

- Empirical Results

- **Selection.** In which towns does Fox News select? (Table 3):

$$
\begin{aligned}
d_{k,2000}^{FOX} \;=\;& \alpha + \beta v_{k,1996}^{R,\text{Pres}} + \beta Contr_{k,1996}^{R} + \Gamma_{2000} X_{k,2000} + \\
& \Gamma_{00-90} X_{k,00-90} + \Gamma_C C_{k,2000} + \varepsilon_k .
\end{aligned}
$$

- Controls X
  - Cable controls (Number of channels and potential subscribers)
  - US House district or county fixed effects

- Conditional on X, Fox News availability is orthogonal to
  - political variables
  - demographic variables

TABLE III

Determinants of Fox News Availability, Linear Probability Model

	Availability of Fox News via cable in 2000				
Dep. var.	(1)	(2)	(3)	(4)	(5)
Pres. republican vote share in 1996	0.1436	0.6363	0.3902	−0.0343	−0.0442
	(0.1549)	(0.2101)***	(0.1566)**	(0.0937)	(0.1024)
Pres. log turnout in 1996	0.1101	0.0909	0.0656	0.0139	−0.0053
	(0.0557)**	(0.0348)***	(0.0278)**	(0.0124)	(0.0173)
Pres. Rep. vote share change 1998–1992					
Control variables					
Census controls: 1990 and 2000	—	X	X	X	X
Cable system controls	—	—	X	X	X
U. S. House district fixed effects	—	—	—	X	—
County fixed effects	—	—	—	—	X
F-test: Census controls = 0		F = 3.54***	F = 2.73***	F = 1.11	F = 1.28
F-test: Cable controls = 0			F = 18.08***	F = 21.09***	F = 18.61***
R^2	0.0281	0.0902	0.4093	0.6698	0.7683
N	N = 9,256	N = 9,256	N = 9,256	N = 9,256	N = 9,256

- **Baseline effect – Presidential races**
- *Effect on Presidential Republican vote share* (Table 4):

$$v_{k,2000}^{R,\mathrm{Pres}} - v_{k,1996}^{R,\mathrm{Pres}} = \alpha + \beta_F d_{k,2000}^{FOX} + \Gamma_{2000} X_{k,2000} + \Gamma_{00-90} X_{k,00-90} + \Gamma_C C_{k,2000} + \varepsilon_k.$$

- Results:
  - Significant effect of Fox News with district (Column 3) and county fixed effects (Column 4)
  - .4-.7 percentage point effect on Republican vote share in Pres. elections
  - Similar effect on Senate elections –> Effect is on ideology, not person-specific
  - Effect on turnout

TABLE IV

THE EFFECT OF FOX NEWS ON THE 2000–1996 PRESIDENTIAL VOTE SHARE CHANGI

	Republican two-party vote share change between 2000 and 1				
Dep. var.	(1)	(2)	(3)	(4)	(5)
Availability of Fox News via cable in 2000	−0.0025	0.0027	0.008	0.0042	0.0069
	(0.0037)	(0.0024)	(0.0026)***	(0.0015)***	(0.0014)***
Pres. Rep. vote share change 1988–1992					
Constant	0.0347	−0.028	−0.0255	0.0116	0.0253
	(0.0017)***	(0.0245)	(0.0236)	(0.0154)	(0.0185)
Control variables					
Census controls: 1990 and 2000	—	X	X	X	X
Cable system controls	—	—	X	X	X
U. S. House district fixed effects	—	—	—	X	—
County fixed effects	—	—	—	—	X
R^2	0.0007	0.5207	0.5573	0.7533	0.8119
N	N = 9,256	N = 9,256	N = 9,256	N = 9,256	N = 9,256

- Magnitude of effect: How do we generalize beyond Fox News?
- Estimate audience of Fox News in towns that have Fox News via cable (First stage)
  - Use Scarborough micro data on audience with Zip code of respondent
  - Fox News exposure via cable increases regular audience by 6 to 10 percentage points
  - How many people did Fox News convince?
  - Heuristic answer: Divide effect on voting (.4-.6 percentage point) by audience measure (.6 to .10)
- Result: Fox News convinced 3 to 8 percent of audience (Recall measure) or 11 to 28 percent (Diary measure)

- How do we interpret the results?

- Benchmark model:
  1. **New media source** with unknown bias β, with $\beta \sim N\left(\beta_0, \frac{1}{\gamma_\beta}\right)$
  2. Media observes (differential) quality of Republican politician, $\theta_t \sim N\left(0, \frac{1}{\gamma_\theta}\right)$, i.i.d., in periods $1, 2, ..., T$
  3. **Media broadcast:** $\psi_t = \theta_t + \beta$. Positive β implies pro-Republican media bias
  4. **Voting in period** T. Voters vote Republican if $\widehat{\theta}_T + \alpha > 0$, with α ideological preference

- Signal extraction problem. New media (Fox News) says Republican politician (George W. Bush) is great
  - Is Bush great?
  - Or is Fox News pro-Republican?
- A bit of both, the audience thinks. Updated media bias after T periods:

$$\hat{\beta}_T = \frac{\gamma_\beta \beta_0 + T\gamma_\theta \overline{\psi}_T}{\gamma_\beta + T\gamma_\theta}.$$

- Estimated quality of Republican politician:

$$\hat{\theta}_T = \frac{\gamma_\theta * 0 + W\left[\psi_T - \hat{\beta}_T\right]}{\gamma_\theta + W} = \frac{W\left[\psi_T - \hat{\beta}_T\right]}{\gamma_\theta + W}$$

- **Persuasion.** Voter with persuasion λ ($0 \leq \lambda \leq 1$) does not take into account enough media bias:

$$\hat{\theta}_T^{\lambda} = \frac{W^{\lambda}[\psi_T - (1-\lambda)\,\hat{\beta}_T]}{\gamma_\theta + W^{\lambda}}$$

- Vote share for Republican candidate. $P(\alpha + \widehat{\theta}_T^{\lambda} \geq 0) = 1 - F(-\widehat{\theta}_T^{\lambda})$

- **Proposition 1.** Three results:

  1. **Short-Run I:** *Republican media bias increases Republican vote share:* $\partial[1 - F(-\widehat{\theta}_T^{\lambda})]/\partial\beta > 0$.
  2. **Short-Run II:** *Media bias effect higher if persuasion ($\lambda > 0$).*
  3. **Long-run** *($T \to \infty$). Media bias effect $\Longleftrightarrow$ persuasion $\lambda > 0$.*

- Intuition.
  - Fox News enthusiastic of Bush
  - Audience updates beliefs: "This Bush must be really good" (**Short-Run I**)
  - Believe media more if credulous or persuadable (**Short-Run II**)
  - But: Fox News enthusiastic also of Karl Rove, Rick Lazio, Bill Frist —$>$ "They cannot be all good!"
  - Make inference that Fox News is biased, stop believing it
  - Fox News influences only individuals subject to persuasion (**Long-Run**)
- What is the evidence about persuasion bias?

- **Cain-Loewenstein-Moore (JLegalStudies, 2005).** Psychology Experiment
  - Pay subjects for precision of estimates of number of coins in a jar
  - Have to rely on the advice of second group of subjects: advisors
  - (Advisors inspect jar from close)
  - Two experimental treatments:
    - *Aligned incentives.* Advisors paid for closeness of subjects' guess
    - *Mis-Aligned incentives, Common knowledge.* Advisors paid for how high the subjects' guess is. Incentive common-knowledge
    - (*Mis-Aligned incentives, Not Common knowledge.*)

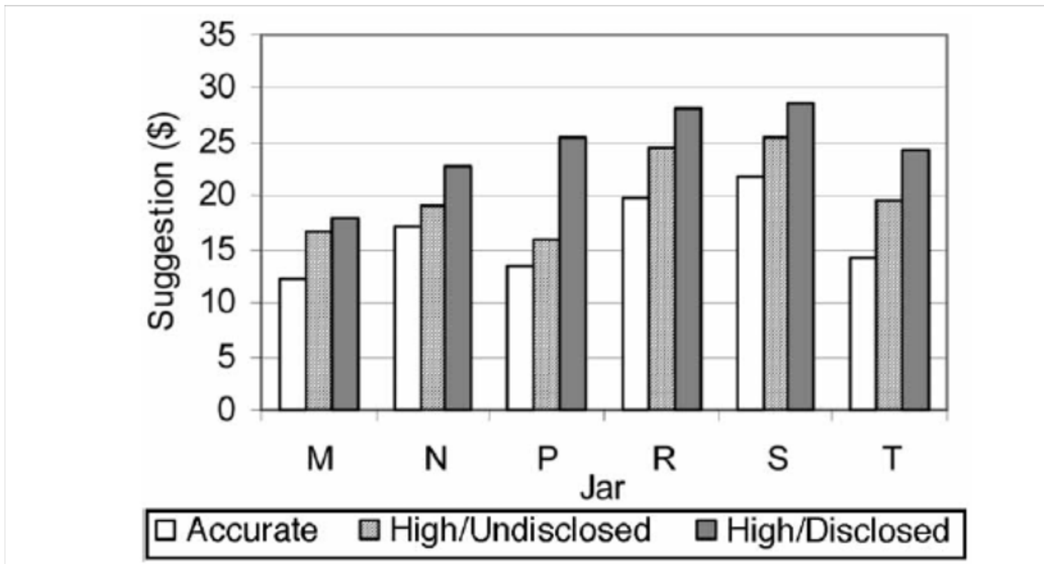
Table 1. Payoff Function for Advisors in Accurate Condition and for All Estimators

Range of Estimator's Estimate from True Value ($)	Payoff ($)
.00–.50	5.00
.51–1.00	4.50
1.01–1.50	4.00
1.51–2.00	3.50
2.01–2.50	3.00
2.51–3.00	2.50
3.01–3.50	2.00
3.51–4.00	1.50
4.01–4.50	1.00
4.51–5.00	.50

Table 2. Advisors' Payoff Function in Conflict-of-Interest Conditions

Range of Estimator's Estimate above True Value ($)	Payoff ($)
.50–1.00	1.00
1.01–1.50	1.90
1.51–2.00	2.70
2.01–2.50	3.40
2.51–3.00	4.00
3.01–3.50	4.50
3.51–4.00	4.90
4.01–4.50	5.20
4.51–5.00	5.40
5.01+	5.50

- Result 1: Advisors increase estimate in *Mis-Aligned incentives* treatment — Even more so when common knowledge



- Result 2. Estimate of subjects is higher in Treatment with *Mis-Aligned incentives*

Table 6. Estimator Estimates of Jar Values

	Accurate (N = 27)	High/Undisclosed (N = 26)	High/Disclosed (N = 27)	Significance of Advisor Incentives (p) (Accurate versus High Conditions)	Significance of Disclosure (p) (Conflict-of-Interest Conditions)
Estimator estimate	14.21 (2.20)	16.81 (3.56)	18.14 (5.00)	<.001	.19
Estimator absolute error	5.25 (1.58)	5.14 (1.31)	6.69 (2.44)	<.363	<.01

- Subjects do not take sufficiently into account incentives of information provider

- Effect even stronger when incentives are known –> Advisors feel free(er) to increase estimate

- Applications to many settings

- Application 1: **Malmendier-Shantikumar (JFE, 2007).**
  - Field evidence that small investors suffer from similar bias
  - Examine recommendations by analysts to investors
  - Substantial upward distortion in recommendations (Buy=Sell, Hold=Sell, etc)

Panel A: Entire Sample	Sample size	Percentage within category				
		Strong Sell	Sell	Hold	Buy	Strong Buy
All	121,130	1.72	2.86	36.84	32.90	25.67
Unaffiliated	112,664	1.79	2.96	37.68	32.40	25.17

- Higher distortion for analysis working in Inv. Bank affiliated with company they cover (through IPO/SEO)

- Question: Do investors discount this bias?
  - Analyze Trade Imbalance (essentially, whether trade is initiated by Buyer)
  - Assume that
    * large investors do large trades
    * small investors do small trades
  - See how small and large investors respond to recommendations
- Examine separately for affiliated and unaffiliated analysts

All Recommendations

	Large Trade	Small Trade	Difference S-L
Strong Sell	-0.103	-0.105	-0.002
	(0.040)	(0.050)	(0.064)
Sell	-0.118	-0.139	-0.021
	(0.034)	(0.046)	(0.057)
Hold	-0.091	0.007	0.099
	(0.011)	(0.014)	(0.018)
Buy	0.011	0.134	0.123
	(0.012)	(0.013)	(0.017)
Strong Buy	0.112	0.243	0.131
	(0.013)	(0.014)	(0.019)
(Strong Sell)*Affiliation	-0.196	-0.838	-0.643
	(0.255)	(0.331)	(0.418)
(Sell)*Affiliation	0.094	-0.087	-0.180
	(0.254)	(0.272)	(0.372)
(Hold)*Affiliation	-0.001	0.005	0.006
	(0.044)	(0.056)	(0.072)
(Buy)*Affiliation	-0.068	0.013	0.081
	(0.034)	(0.039)	(0.052)
(Strong Buy)*Affiliation	-0.129	-0.023	0.106
	(0.036)	(0.041)	(0.055)
Sample size	86,961	86,961	
R^2	0.0034	0.0085	

- Results:
  - Small investor takes analyst recommendations literally (buy Buys, sell Sells)
  - Large investors discount for bias (hold Buys, sell Holds)
  - Difference is particularly large for affiliated analysts
  - Small investors do not respond to affiliation information
- Strong evidence of distortion induced by incentives

8 Emotions: Mood

- Emotions play a role in several of the phenomena considered so far:
  - Self-control problems –> Temptation
  - Projection bias in food consumption –> Hunger
  - Social preferences in giving –> Empathy
  - Gneezy-List (2006) transient effect of gift –> Hot-Cold gift-exchange
- Psychology: Large literature on emotions (Loewenstein and Lerner, 2003)
  - Message 1: Emotions are very important
  - Message 1: Different emotions operate very differently: anger $\neq$ mood $\neq$

- Consider two examples of emotions:
  - Mood
  - Arousal
- Psychology: even minor mood manipulations have a substantial impact on behavior and emotions
  - On sunnier days, subjects tip more at restaurants (Rind, 1996)
  - On sunnier days, subjects express higher levels of overall happiness (Schwarz and Clore, 1983)
- Should this impact economic decisions?

- Field: Impact of mood fluctuations on stock returns:
  - Daily weather and Sport matches
  - No effect on fundamentals
  - However: If good mood leads to more optimistic expectations –> Increase in stock prices

- Evidence:
  - **Saunders (1993):** Days with higher cloud cover in New York are associated with lower aggregate US stock returns
  - **Hirshleifer and Shumway (2003)** extend to 26 countries between 1982 and 1997
    - Use weather of the city where the stock market is located
    - Negative relationship between cloud cover (de-trended from seasonal averages) and aggregate stock returns in 18 of the 26 cities

	OLS Regression			Logit Model		
Location	Observations	β_{iC}	t-Statistic	γ_{iC}	χ^2	P-Value
Amsterdam	3984	-0.007	-1.07	-0.024	2.76	0.0963
Athens	2436	0.012	0.71	-0.014	0.53	0.4649
Buenos Aires	2565	-0.030	-0.98	-0.019	1.60	0.2054
Bangkok	3617	0.009	0.45	-0.014	0.24	0.6259
Brussels	3997	-0.018*	-3.25	-0.036*	6.75	0.0094
Copenhagen	4042	-0.002	-0.30	-0.002	0.02	0.8999
Dublin	3963	-0.000	-0.02	-0.025	2.13	0.1445
Helsinki	2725	-0.016	-1.67	-0.034*	4.01	0.0452
Istanbul	2500	0.007	0.32	-0.001	0.00	0.9488
Johannesburg	3999	0.004	0.47	-0.012	0.67	0.4124
Kuala Lumpur	3863	0.014	0.26	-0.109	1.99	0.1586
London	4003	-0.010	-1.52	-0.019	1.41	0.2355
Madrid	3760	-0.011	-1.60	-0.015	1.41	0.2353
Manila	2878	0.018	0.83	0.003	0.02	0.9023
Melbourne	3674	-0.013	-1.45	-0.008	0.26	0.6116
Milan	3961	-0.014*	-2.03	-0.021	3.69	0.0549
New York	4013	-0.007	-1.28	-0.035*	8.64	0.0033
Oslo	3877	-0.018	-1.92	-0.025	3.31	0.0688
Paris	3879	-0.009	-1.27	-0.027*	3.93	0.0474
Rio de Janeiro	2988	-0.057	-1.93	-0.016	0.96	0.3267
Santiago	2636	0.000	0.05	-0.012	0.73	0.3935
Singapore	3890	0.008	0.37	-0.002	0.00	0.9588
Stockholm	3653	-0.014	-1.54	-0.025	2.89	0.0889
Taipei	3784	-0.016	-0.97	-0.013	0.66	0.4164
Vienna	3907	-0.013*	-2.14	-0.026*	4.11	0.0425
Zurich	3851	-0.007	-1.28	-0.012	0.89	0.3465
All Cities (naive)	92445	-0.011*	-4.42	-0.019*	41.30	0.0001
All Cities (PCSE)	92445	-0.010*	-3.97	-	-	-

- – Magnitude:
  - Days with completely covered skies have daily stock returns .11 percent lower than days with sunny skies
  - Five percent of a standard deviation
  - Small magnitude, but not negligible
- After controlling for cloud cover, other weather variables such as rain and snow are unrelated to returns

- Additional evidence (**Edmans-Garcia-Norli, 2007**): International soccer matches (39 countries, 1973-2004)

Panel A. Abnormal Raw Returns

All games	638	0.016	0.27	524	−0.212	−3.27
Elimination games	177	0.046	0.43	138	−0.384	−3.24
World Cup elimination games	76	0.090	0.53	56	−0.494	−2.71
Continental cups elimination games	101	0.013	0.09	82	−0.309	−1.99
Group games	243	0.052	0.53	198	−0.168	−1.47
World Cup group games	115	0.007	0.05	81	−0.380	−2.23
Continental cups group games	128	0.092	0.67	117	−0.022	−0.14
Close qualifying games	218	−0.049	−0.52	188	−0.131	−1.29
World Cup close qualifying games	137	−0.095	−0.78	122	−0.132	−1.05
European Championship close qualifying games	81	0.029	0.19	66	−0.130	−0.75

- Results:
  - Compared to a day with no match, a loss lowers daily returns (significantly) by .21 percent. (Surprisingly, a win has essentially no effect)
  - More important matches, such as World Cup elimination games, have larger effects
  - Effect does not appear to depend on whether the loss was expected or not
  - International matches in other sports have a consistent, though smaller, effect (24 countries)

	Wins			Losses		
	N	β_W	t-val	N	β_L	t-val
			Panel A. Abnormal Returns			
All games	903	−0.013	−0.39	645	−0.084	−2.21
Cricket	153	−0.057	−0.73	88	−0.187	−1.85
Rugby	403	−0.086	−1.73	307	−0.095	−1.74
Ice hockey	238	0.105	1.57	148	0.083	1.02
Basketball	111	0.071	0.74	102	−0.208	−2.11

- Interpretations:
  - Mood impacts risk aversion or perception of volatility
  - Mood is projected to economic fundamentals

- **Simonsohn (2007):** Subtle role of mood
  - Weather on the day of campus visit to a prestigious university (CMU)
  - Students visiting on days with more cloud cover are significantly *more* likely to enroll
  - Higher cloud cover induces the students to focus more on academic attributes versus social attributes of the school
  - Support from laboratory experiment

Table 2. Regressions of enrollment and admission decisions on cloudcover (OLS)

	(1)	(2)	(3)	(4)	(5)
Dependent variable (1-yes, 0-no)	Enrollment	Enrollment	Enrollment	Enrollment	Admission
	Baseline	Adds other weather variables	Adds Average weather conditions	Predicts with weather from two days *prior* to visit	Same as (3) but with *admission* decision as dependent variable
Intercept	0.342***	0.180	-0.013	0.407***	0.538**
	(0.055)	*(0.164)*	*(0.353)*	*(0.137)*	*(0.210)*
Cloud Cover on day of visit *(0-clear skies to 10-overcast)*	0.018**	0.027**	0.032***	--	0.004
	(0.008)	*(0.011)*	*(0.012)*	--	*(0.008)*
Cloud Cover two days prior to visit	--	--	--	0.001	--
	--	--	--	*(0.009)*	--
Maximum Temperature (max)	--	0.004	0.003	0.000	0.000
	--	*(0.004)*	*(0.004)*	*(0.004)*	*(0.003)*
Minimum Temperature (min)	--	-0.002	-0.005	0.001	-0.002
	--	*(0.004)*	*(0.005)*	*(0.004)*	*(0.003)*
Wind Speed	--	-0.004	-0.005	0.002	-0.003
	--	*(0.003)*	*(0.004)*	*(0.004)*	*(0.002)*
Rain precipitation (in inches)	--	-0.056	-0.024	-0.076	0.026
	--	*(0.091)*	*(0.119)*	*(0.144)*	*(0.078)*
Snow precipitation (in inches)	--	0.008	0.009	0.002	0.007
	--	*(0.008)*	*(0.009)*	*(0.008)*	*(0.006)*
Average weather conditions for calendar date (DF=6)	No	No	Yes	No	Yes
Month dummies	No	No	Yes	No	Yes
Number of Observations	562	562	562	562	1284
R-square	0.0096	0.0146	0.0573	0.0018	0.0279

9 Menu Effects: Excess Diversification

- First heuristic: **Excess Diversification or 1/n Heuristics**
  - Facing a menu of choices, if possible allocate
  - (Notice: Not possible for example for health insurance plan)
- Example: Experiment of Simonson (1990)
  - Subjects have to pick one snack out of six (cannot pick >1) in 3 different weeks
  - Sequential choice: only 9 percent picks three different snacks
  - Simultaneous choice ex ante: 64 percent chooses three different snacks

- **Benartzi-Thaler (AER, 2001)**
- Study 401(k) plan choices
- Data:
  - 1996 plan assets for 162 companies
  - Aggregate allocations, no individual data
- Average of 6.8 plan options per company
- Lacking individual data, cannot estimate if allocation is truly 1/n
- Proxy: Is there more investment in stocks where more stocks are offered?

- They estimate the relationship

$$\%Invested\ In\ Equity = \alpha + .36\ (.04) * \%Equity\ Options + \beta X$$

TABLE 7—THE RELATIVE NUMBER OF EQUITY-TYPE INVESTMENT OPTIONS AND ASSET ALLOCATION: A REGRESSION ANALYSIS (DEPENDENT VARIABLE: THE PERCENTAGE OF PLAN ASSETS INVESTED IN EQUITIES)

WLS regression model	Intercept	Relative number of equity options	Indicator whether the plan offers company stock	Log of the plan assets in thousands	Adjusted R^2
Panel A: No Industry Indicators ($N = 162$)					
1	22.09	63.14			34.61 percent
	(4.94)	(9.28)			
2	29.72	36.75	15.05		43.45 percent
	(6.73)	(4.49)	(5.10)		
3	10.57	36.77	14.78	1.40	44.16 percent
	(0.89)	(4.52)	(5.03)	(1.74)	
Panel B: Including Industry Indicators Based on 2-Digit SIC Codes ($N = 142$)					
4		58.68			55.12 percent
		(8.29)			
5		43.90	12.93		58.91 percent
		(5.39)	(3.26)		
6		47.07	9.09	4.13	61.79 percent
		(5.93)	(2.25)	(2.96)	

Notes: The initial sample consists of the June 1996 MMD sample of 401(k) plans. Eight plans with less than four investment options were excluded, resulting in a sample of 162 plans. When we include industry indicators, the sample is further reduced to 142 plans due to missing industry information. The table reports WLS regression estimates with plan assets as weights (t-statistics are in parentheses).

- For every ten percent additional offering in stocks, the percent invested in stocks increases by 3.6 percent
- Notice: availability of company stocks is a key determinant of holdings in stocks
- Issues of endogeneity:
  - Companies offer more stock when more demand for it
  - Partial response: Industry controls
- Additional evidence based on a survey
  - Ask people to allocate between Fund A and Fund B
  - Vary Fund A and B to see if people respond in allocation

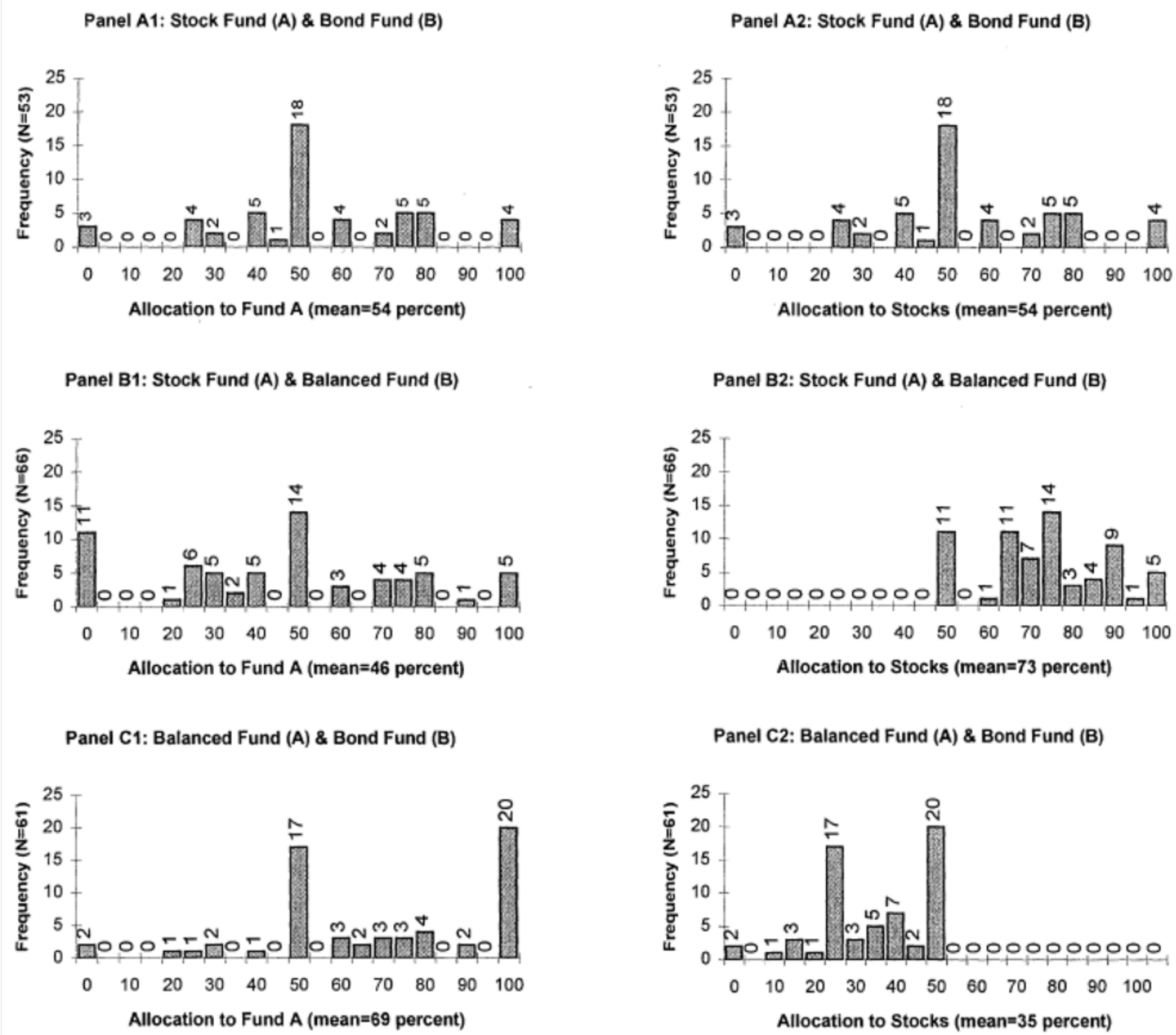
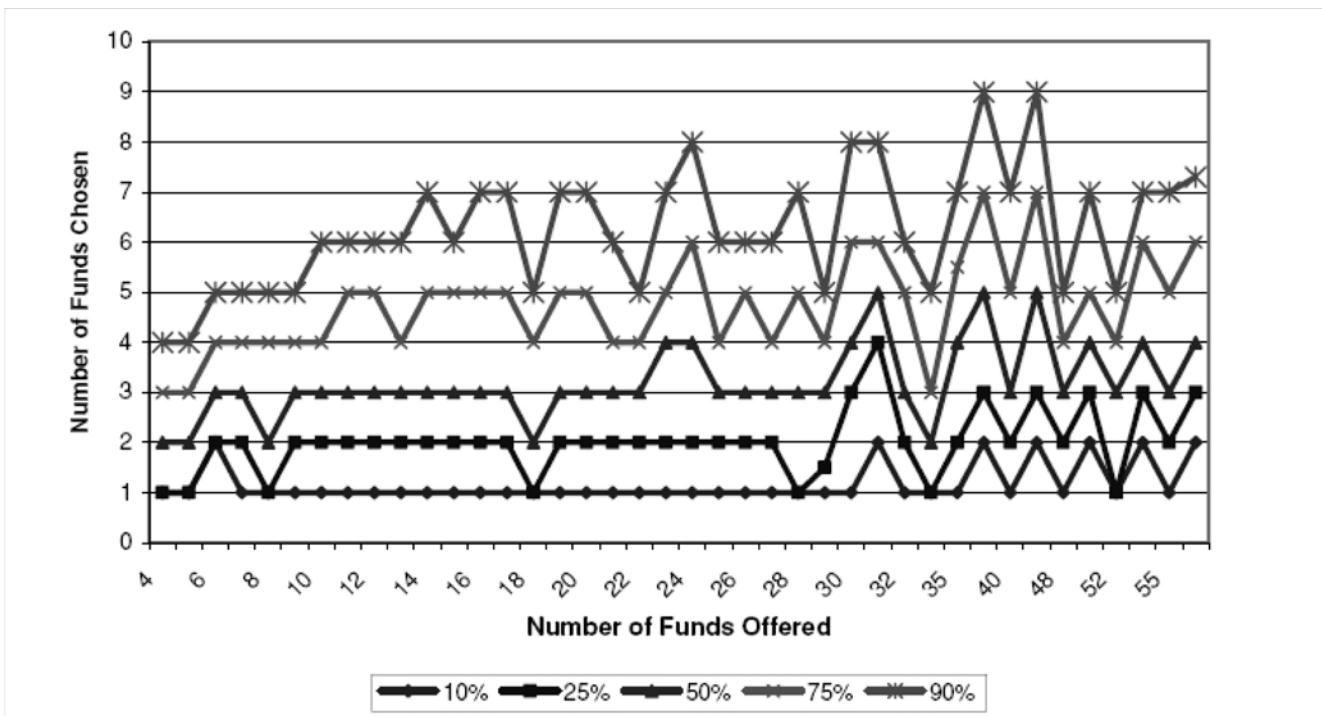


FIGURE 1. VERBAL SAVINGS QUESTIONNAIRE: HISTOGRAMS OF THE ALLOCATION TO FUND A AND THE RESULTING ALLOCATION TO STOCKS

- People respond to changes in content of Fund A and B, but incompletely
- Issues:
  - Not for real payoff
  - Low response rate (12%)
  - People dislike extreme in responses

- **Huberman-Jiang (JF, 2006)**
- Data:
  - Vanguard data to test BT (2001)
  - Data on individual choices of participants
  - Half a million 401(k) participants
  - 647 Defined Contribution plans in year 2001
  - Average participation rate 71 percent
- Summary Statistics:
  - 3.48 plans choices on average
  - 13.66 plans available on average

- **Finding 1**. People do not literally do 1/n, definitely not for n large
  - Flat relationship between $\#Chosen$ and $\#Offered$ for $\#Offered >$ 10
  - BT (2001): could not estimate this + $\#Offered$ rarely above 15



- Regressions specification:

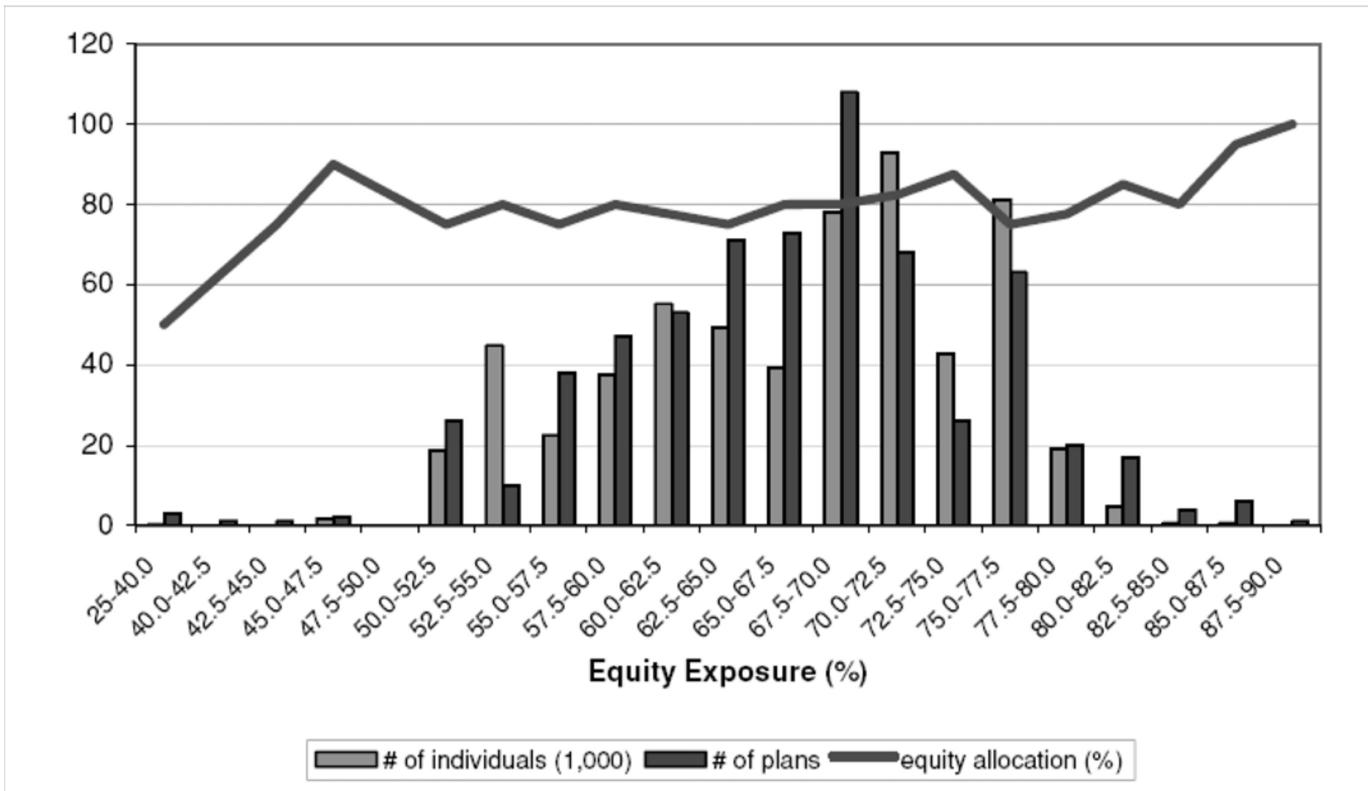
$$\#Chosen = \alpha + \beta * \#Offered + \beta X$$

	All Participants			
	NCHOSEN			
	(1)		(2)	
	COEF × 100	SE × 100	COEF × 100	SE × 100
NCHOICE	0.95	0.70	1.03	0.70
CONTRIBUTION	10.54*	0.56	—	—
COMP	−0.02	2.30	33.05*	2.87
WEALTH	1.20*	0.51	3.90*	0.55
FEMALE	14.51*	1.97	14.84*	1.95
AGE	−1.66*	0.10	−1.35*	0.09
TENURE	0.88*	0.26	0.95*	0.26
MATCH	0.00	0.24	0.00	0.23
COMPSTK	70.67*	12.72	67.16*	12.68
DB	−6.31	15.35	−6.06	15.21
WEB	1.17	0.71	1.39	0.71
NEMPLOY	−10.28*	4.79	−9.25*	4.73
Intercept	1036.95	284.44	664.25	290.06
No. of individuals and plans	572,157	641	572,157	641
R^2	0.075		0.060	

- **Finding 2.** Employees do 1/n on the *chosen* funds if
  - number n is small
  - $1/n$ is round number

No. of Funds Chosen (1)	New Entrants (%) (2)	$\underline{H}$ (3)	$\bar{H}$ (4)	$Freq_1$ (%) (5)	$Freq_1/\max_{j\neq 1}(Freq_j)$ (6)
1	38.6	1.0000	1.0000	–	–
2	17.5	0.5000	0.5050	64.0	12.81*
3	15.6	0.3333	0.3356	17.9	1.78*
4	13.2	0.2500	0.2513	37.4	8.89*
5	7.3	0.2000	0.2008	26.6	8.19*
6	3.5	0.1667	0.1672	1.3	0.25
7	1.8	0.1429	0.1433	1.0	0.19
8	1.1	0.1250	0.1253	3.9	1.14
9	0.6	0.1111	0.1114	5.1	1.20
10	0.4	0.1000	0.1002	53.3	13.50*

- **Finding 3.** Equity choice (most similar to BT (2001))
- In aggregate very mild relationship between $\%Equity$ and $\%EquityOffered$



- Split by $\#Offered$:
  1. For $\#Offered \leq 10$, BT finding replicates:

$$\%Equity = \alpha + .292 * \%EquityOffered$$
$$(.063)$$

  2. For $\#Offered > 10$, no effect:

$$\%Equity = \alpha + .058 * \%EquityOffered$$
$$(.068)$$

	(1)		(2)		(3)		(4)	
	All *NFunds*				$NFunds \leq 10$		$NFunds > 10$	
	COEF	SE	COEF	SE	COEF	SE	COEF	SE
Panel A: Full Sample—Uniform Sensitivity								
%EQOffered	0.175	0.274	0.177*	0.088	0.292*	0.107	0.058	0.09
R^2	0.000		0.061		0.063		0.068	

- Psychologically plausible:
  - Small menu set guides choices –> Approximate $1/n$ in weaker form
  - Larger menu set does not
- BT-HJ debate: Interesting case
  - Heated debate at beginning
  - At the end, reasonable convergence: we really understand better the phenomenon
  - Convergence largely due to better data

10 Next Lecture

- Emotions: Arousal
- Methodology: Lab and Field