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

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Outline

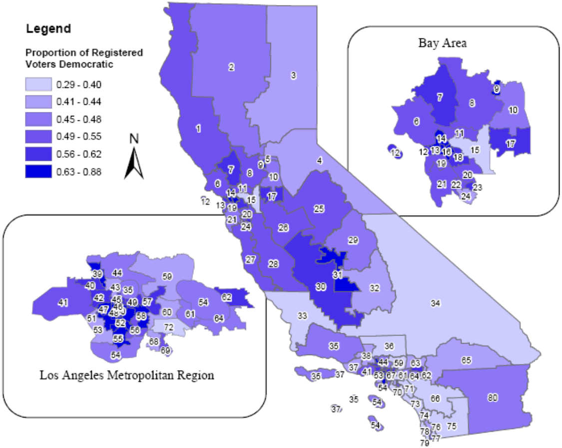
1. Menu Effects: Preference for Salient
2. Menu Effects: Confusion
3. Choice of Dominated Options
4. Mental Accounting
5. Persuasion
6. Emotions: Mood
7. Emotions: Arousal

Section 1

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.

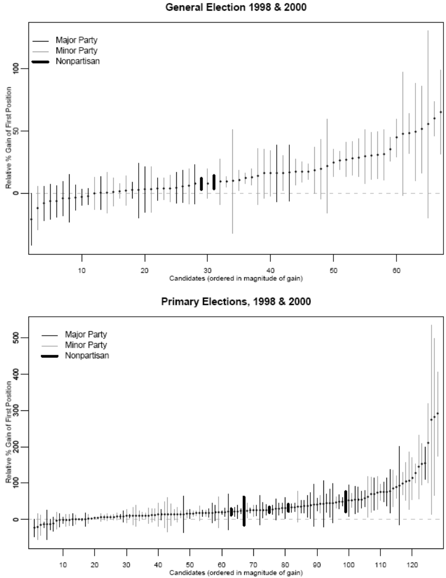
- Observe each candidate in different orders in different districts
- Compute absolute vote (Y) gain

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

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
Major Party
Minor Party
Nonpartisan
Relative % Gain of First Position
0
50
100
10
20
30
40
50
60
Candidates (ordered in magnitude of gain)
Primary Elections, 1998 & 2000
Major Party
Minor Party
Nonpartisan
Relative % Gain of First Position
0
100
200
300
400
500
10
20
30
40
50
60
70
80
90
100
110
120
Candidates (ordered in magnitude of gain)

	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.

Investors with Limited Attention

- **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
- 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:

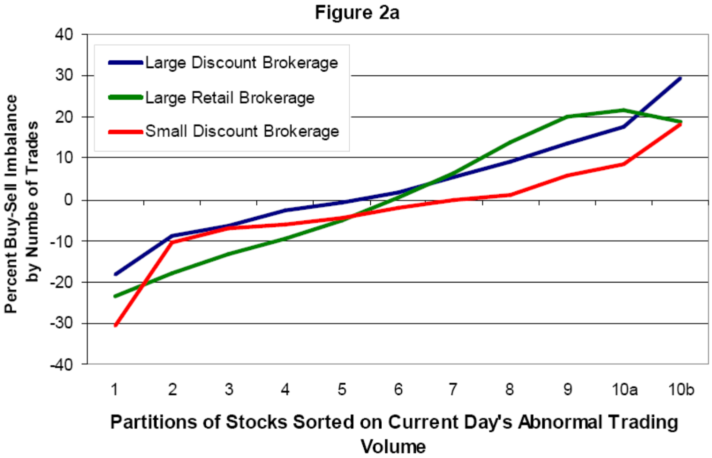
$$BSI_t = 100 * \frac{\sum_i NetB\text{uy}_{i,t} - \sum_i NetSell_{i,t}}{\sum_i NetB\text{uy}_{i,t} + \sum_i NetSell_{i,t}}$$

Methodology: Bins

- 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: $V_t^1, V_t^2, V_t^3, \ldots, V_t^{10a}, V_t^{10b}$
    - (Finer sorting at the top to capture top 5 percent)

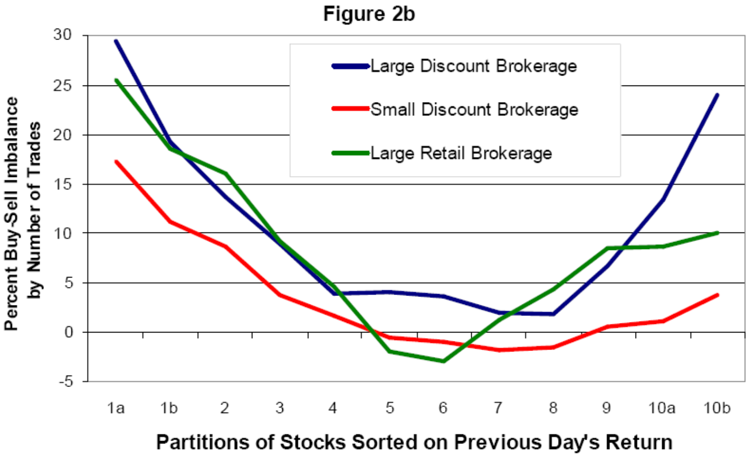
Results: Abnormal Volume

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



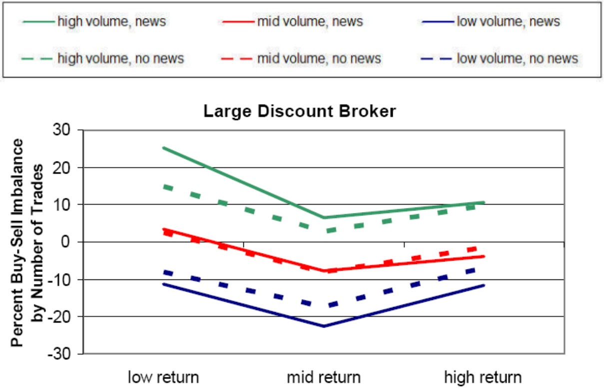
Results: Previous Returns

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



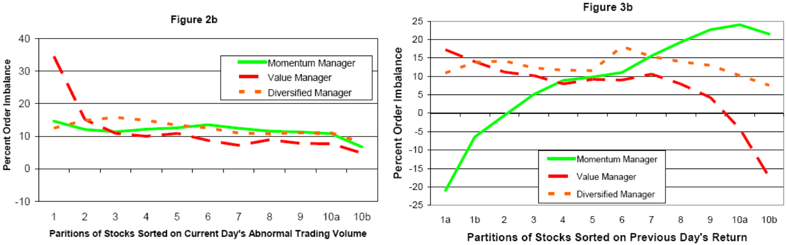
Results: Robustness

- Notice: Pattern is consistent across different data sets of investor trading
- Figures 2a and 2b a



Comparison

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



Section 2

Menu Effects: Confusion

Confusion in Voting

- 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?

Sample Ballots

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

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

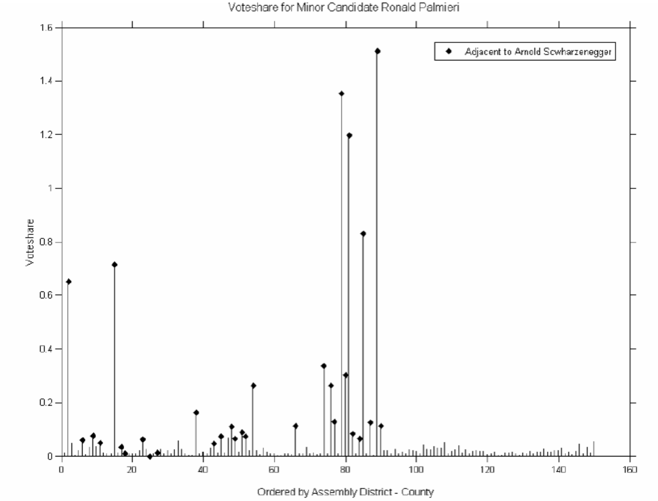
Candidate listing continues on next page /
La lista de candidatos continúa en la página siguiente →

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

- 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

Vote Share for Minor Candidate



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

Results

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

- 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

Possible 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)

Investigate Interpretations

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

Interpretation and Additional Results

- Effect is mostly due to Trembling hand / Confusion

Additional results:

1. 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)		

Additional Results

2. Spill-over of votes larger for precincts with a larger share of lower-education demographics $\rightarrow$ more likely to make errors when faced with large number of options

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

Confusion in Investor Choice

- **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 $\text{Log}[(P_{j,t+1} + D_{j,t+1})/P_{j,t}]$, 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

Correlation of Volume

- 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

- 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: Correlation

- Positive correlation $\alpha_1 \rightarrow$ 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 $\rightarrow$ 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: $\beta = Cov(V_{MCI,t}, V_{MCIC,t})/Var(V_{MCIC,t})$

Results: Error Rate

- 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

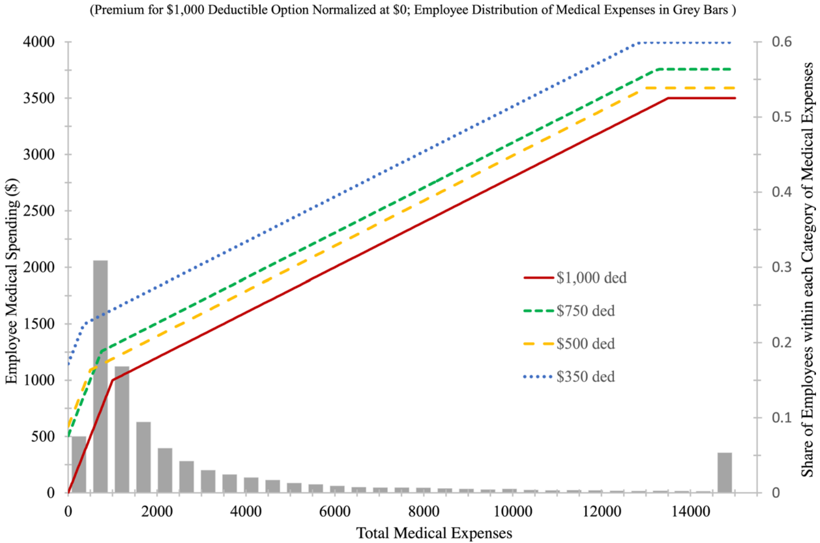
Section 3

Choice of Dominated Options

Dominated Choice

- An especially strong case of non-standard decision making is the choice of a dominated option
- **Bhargava, Loewenstein, and Sydnor (QJE 2017)**
- Examine choice of health plans for employees of a large company
- Plans are such that the high-deductible plans tend to dominate the low-deductible plans

Bhargava, Loewenstein, Sydnor



Bhargava, Loewenstein, Sydnor

- Large costs of picking the wrong plan

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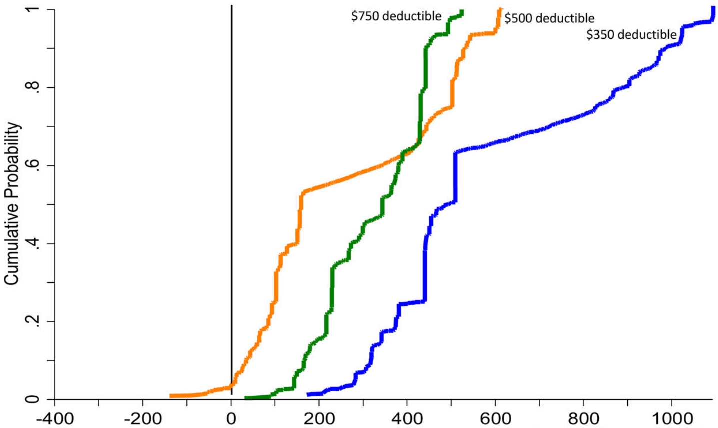
Panel A. Switch to equivalent plan with the $1,000 deductible

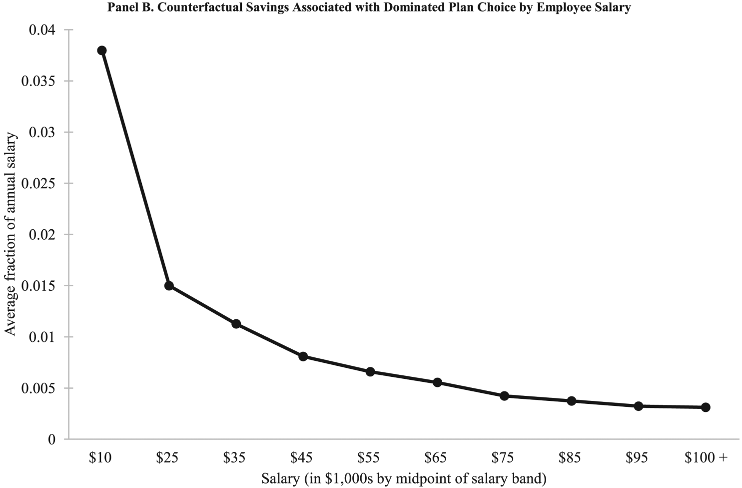


Bhargava, Loewenstein, Sydnor

- Incidence of errors is much larger for low-income people

Bhargava, Loewenstein, Sydnor

- Large costs of picking the wrong plan for the poor



Other papers

- Are behavioral biases disproportionately hurting the poor (Mullainathan and Shafir)?
- Key variables in determining implications of behavioral economics for redistribution and inequality
- Two forces:
  - Poor are likely less educated –> More bias
  - Poor have lower cost of time –> Can in principle search harder
- In literature:
  - Bhargava et al. (2017): first force clearly dominates
  - Lacetera, Pope, and Sydnor: also similar results for limited attention to odometer, much smaller magnitude
  - Madrian and Shea (2001) – default effects larger for lower income
  - Other papers?
- Incidence of behavioral biases is key emerging theme

Section 4

Mental Accounting

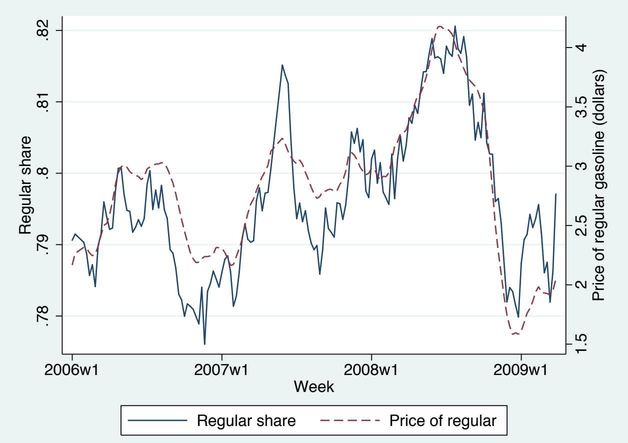
Introduction

- **Thaler (1981)**: Mental Accounting is tendency of individuals to form special accounts for different expenditures, and keep inflows and outflow separated across accounts
  - Example: $200/wk food budget and $100/wk entertaiment budget
- Deviates from standard model with just one budget
- Why use mental accounting?
  - Self control problems
  - Simplicity
- What is the evidence for this?
- Until recently, quite weak. Rare compoment in Thaler agenda without too much support

Gas Prices

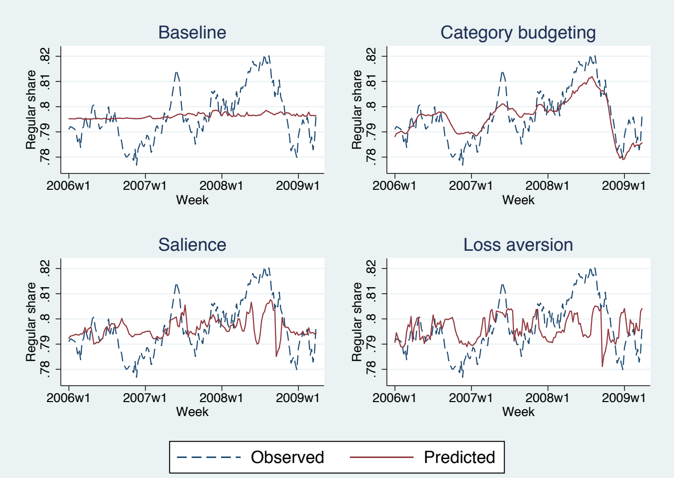
- **Hastings and Shapiro (QJE 2013)**
  - Assume a mental account for gasoline
  - Choice at the pump for regular gas, or premium (usually 10c more expensive)
  - *Mental accounting*: Price of gasoline goes up –> switch to regular gasoline (from premium) to try to stay more in account
  - Notice: *Proportional thinking* makes opposite prediction
  - *Standard model*:
    - Makes same prediction based on income effect, but much smaller impact
    - Can also look at 2009 when price of gasoline went down

Gas Prices, Data



- Gas price and purchase of regular gasoline clearly move together
- Notice: Also true in 2009 when income effects go the other way

Gas Prices, Model Fit



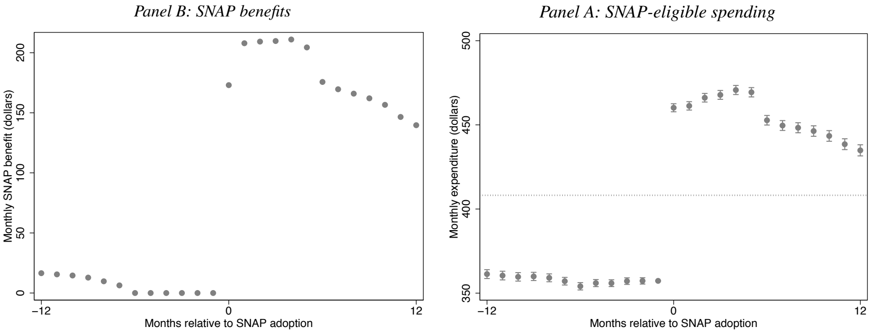
- Simple mental accounting model does good job of fit

Food Stamps

- **Hastings and Shapiro (AER forthcoming)**
- What happens when food stamps come in?
  - Large majority of individuals spend more on food than food stamp amount
  - *Standard model*: Increase in food expenditure should equal the marginal propensity to consume on food from income shocks (about 0.1)
  - *Mental accounting*: MPCF from food stamps will be high, since same account
- Use data from a retailer where can observe is spend with food stamps
  - Three empirical strategies:

1. Individuals enter food stamp program
2. Exit from program most likely after 6, 12, 18... months
3. Legislative changes in food stamp magnitude

Food Stamps

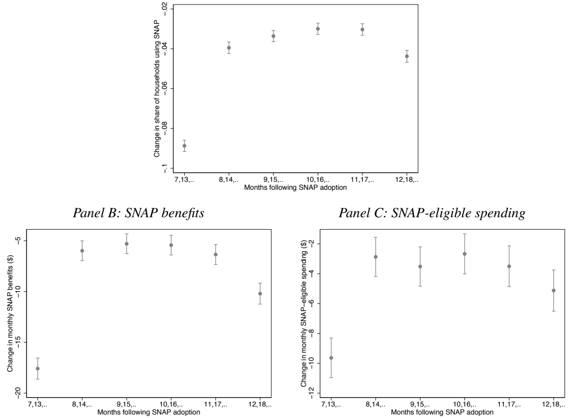


- Strategy 1: Identify entry into SNAP as 6 months of SNAP spending, after 6 months of no SNAP
- MPC of about 0.5/0.6

Food Stamps

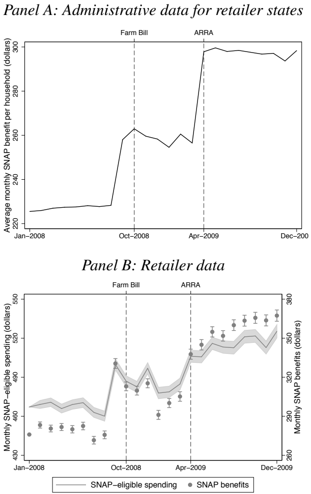
Figure 6: Participation, benefits, and spending over the six-month SNAP clock

Panel A: SNAP use



- Strategy 2: Identify exit from SNAP every 6 months
- MPC of about 0.5/0.6

Food Stamps



- Strategy 3: Identify from legislative changes in levels of benefits

Food Stamps

Table 1: Estimated marginal propensities to consume

	(1) SNAP-eligible spending	(2) SNAP-eligible spending	(3) SNAP-eligible spending	(4) SNAP-ineligible spending
MPC out of				
SNAP benefits	0.5891	0.5495	0.5884	0.0230
	(0.0074)	(0.0360)	(0.0073)	(0.0043)
cash	-0.0019	-0.0013	-0.0020	0.0421
	(0.0494)	(0.0494)	(0.0494)	(0.0688)
p-value for equality of MPCs	0.0000	0.0000	0.0000	0.7764
Instruments:				
Change in price of regular gasoline	Yes	Yes	Yes	Yes
$\times$(Household average gallons per month)				
SNAP adoption	Yes	No	Yes	Yes
First month of SNAP clock	No	Yes	Yes	Yes
Number of household-months	2005392	2005392	2005392	2005392
Number of households	24456	24456	24456	24456

- Estimated MPCF stable across the three strategies around 0.6
- Estimated MPCF from other income skocks (gas prices) much smaller

Section 5

Persuasion

Introduction

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

Overview on Persuasion

- **DellaVigna and Gentzkow (2010)**:
  - 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	75.5%	75.0%	100.0%	2.0%
	Surprising Dem. Endors. (Denver)	No endors.		weeks	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

- 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):

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

- 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

Fox News Availability

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):

$$v^{R,\text{ Pres}}_{k,2000} - v^{R,\text{ Pres}}_{k,1996} = \alpha + \beta_F d^{FOX}_{k,2000} + \Gamma_{2000} X_{k,2000} + \Gamma_{00-90} X_{k,00-90} + \Gamma_C C_{k,2000} + \varepsilon_k.$$

- 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 $\rightarrow$ Effect is on ideology, not person-specific
  - Effect on turnout

Presidential Vote Share

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

Dep. var.	Republican two-party vote share change between 2000 and 1				
	(1)	(2)	(3)	(4)	(5)
Availability of Fox News via cable in 2000	−0.0025 (0.0037)	0.0027 (0.0024)	0.008 (0.0026)***	0.0042 (0.0015)***	0.0069 (0.0014)***
Pres. Rep. vote share change 1988–1992					
Constant	0.0347 (0.0017)***	−0.028 (0.0245)	−0.0255 (0.0236)	0.0116 (0.0154)	0.0253 (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

Generalizing the Effect

- 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)

Interpretation

- 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 $1, 2, \ldots, T$
  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:

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

- 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* $\lambda > 0$.

Evidence for 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.*)

Payoffs

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

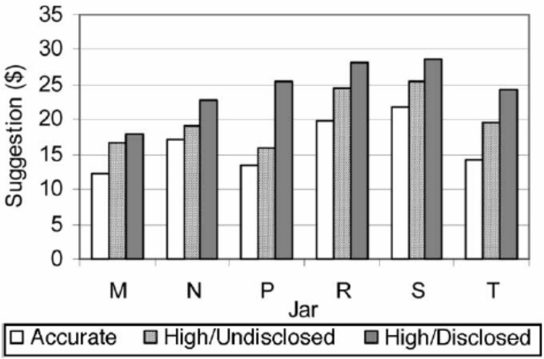
Range of Estimator's Estimate from True Value ($)	Payoff ($)
.00–.50	5.00
.51–1.00	4.50
1.01–1.50	4.00
1.51–2.00	3.50
2.01–2.50	3.00
2.51–3.00	2.50
3.01–3.50	2.00
3.51–4.00	1.50
4.01–4.50	1.00
4.51–5.00	.50

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 $\rightarrow$ Advisors feel free(er) to increase estimate

- Applications to many settings

Application: Small Investors

- Application 1: **Malmendier-Shanthikumar (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

- 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

Analyst Recommendations

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

- 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

Section 6

Emotions: Mood

Emotions Matter

- Emotions play a role in several of the phenomena considered so far:
  - Self-control problems $\rightarrow$ Temptation
  - Projection bias in food consumption $\rightarrow$ Hunger
  - Social preferences in giving $\rightarrow$ Empathy
  - Gneezy-List (2006) transient effect of gift $\rightarrow$ 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 $\neq$ joy

- 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 Evidence

- 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 $\rightarrow$ 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

Weather and Stock Returns

	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	-	-	-

Weather and Stock Returns

- 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
- **Edmans-Garcia-Norli, 2007**: Evidence from international soccer matches (39 countries, 1973-2004)
- Interpretations:
  - Mood impacts risk aversion or perception of volatility
  - Mood is projected to economic fundamentals

College Enrollment

- **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

Enrollment and Weather

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

Section 7

Emotions: Arousal

Separate impact of emotions: Arousal

- **Josephson (1987):** Arousal due to violent content
  - Control group exposed to non-violent clip
  - Treatment group exposed to violent clip
  - Treatment group more likely to display more aggressive behavior, such as aggressive play during a hockey game
  - Impact not due to imitation (violent movie did not involve sport scenes)
- Consistent finding from large set of experiments (Table 11)
- **Dahl-DellaVigna (2009)**: Field evidence — Exploit timing of release of blockbuster violent movies

Model

- Consumer chooses between strongly violent movie a^v, mildly violent movie a^m, non-violent movie a^n, or alternative social activity a^s
  - Utility depends on quality of movies $\rightarrow$ Demand functions $P(a^j)$
- Heterogeneity:
  - High taste for violence (Young): N_y consumers
  - Low taste for violence (Old): N_o consumers
  - Aggregate demand for group i: $N_i P(a_i^j)$
- Production function of violence V (not part of utility fct.) depends on a^v, a^m, a^n, and a_s:

$$\ln V = \sum_{i=y,o} [\sum_{j=v,m,n} \alpha_i^j N_i P(a_i^j) + \sigma_i N_i (1 - P(a_i^v) - P(a_i^m) - P(a_i^n))]$$

- Estimate (A^j is total attendance to movie of type j)

$$\ln V = \beta_0 + \beta^v A^v + \beta^m A^m + \beta^n A^n + \varepsilon$$

- Estimated impact of exposure to violent movies β^v:

$$\beta^v = x^v(\alpha^v_y - \sigma_y) + (1 - x^v)(\alpha^v_o - \sigma_o)$$

- First point — Estimate of net effect
  - Direct effect: Increase in violent movie exposure $\rightarrow \alpha^v_i$
  - Indirect effect: Decrease in Social Activity $\rightarrow \sigma_i$
- Second point — Estimate on self-selected population:
  - Estimate parameters for group actually attending movies
  - Young over-represented: $x^v > N^y / (N^y + N^o)$

- Comparison with Psychology experiments
  - Natural Experiment. Estimated impact of exposure to violent movies β^v:

$$\beta^v = x^v(\alpha_y^v - \sigma_y) + (1 - x^v)(\alpha_o^v - \sigma_o)$$

  - Psychology Experiments. Manipulate a directly, holding constant a^s out of equilibrium

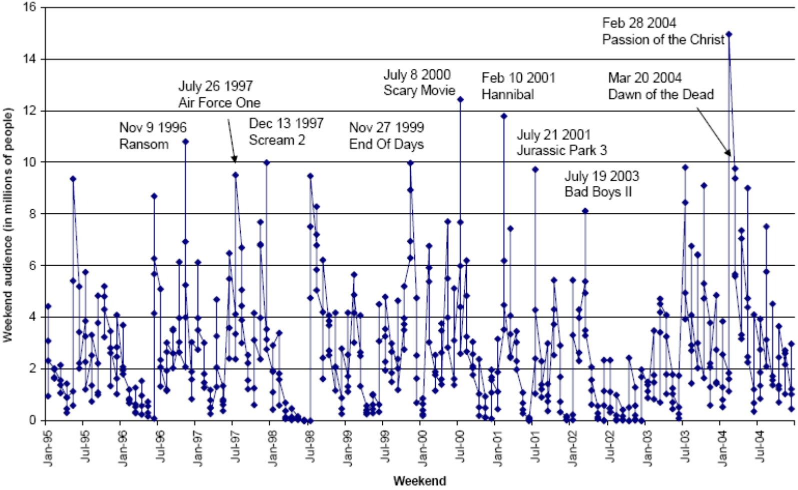
$$\beta_{lab}^v = \frac{N_y}{N_y + N_o}\alpha_y^v + (1 - \frac{N_y}{N_y + N_o})\alpha_o^v$$

- Two differences:
  - 'Shut down' alternative activity, and hence σ_i does not appear
  - Weights representative of (student) population, not of population that selects into violent movies

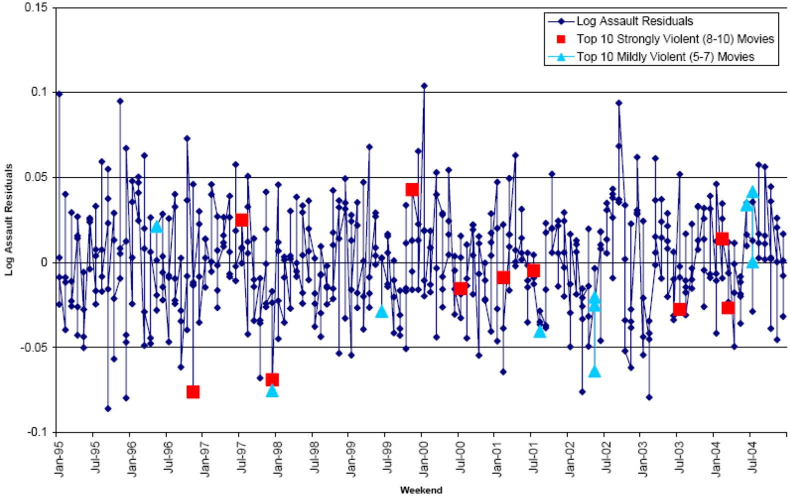
Data

- **Movie data**
  - Revenue data: Weekend (top 50) and Day (top 10) from *The Numbers*
  - Violence Ratings from 0 to 10 from *Kids In Mind* (Appendix Table 1)
  - Strong Violence Measure A_t^v: Audience with violence 8-10 (Figure 1a)
  - Mild Violence Measure A_t^m: Audience with violence 5-7 (Figure 1b)
- **Assault data**
  - Source: National Incident-Based Reporting System (NIBRS)
  - All incidents of aggravated assault, simple assault, and intimidation from 1995 to 2004
  - Sample: Agencies with no missing data on crime for > 7 days
  - Sample: 1995-2004, days in weekend (Friday, Saturday, Sunday)

Movie Attendance



Log Assault Residuals



Regression and Results

- **Regression Specification.** (Table 3)

$$\log V_t = \beta^v A_t^v + \beta^m A_t^m + \beta^n A_t^n + \Gamma X_t + \varepsilon_t$$

  - Coefficient β^v is percent increase in assault for one million people watching strongly violent movies day t (A_t^v) (Similarly β^m and β^n)
  - Cluster standard errors by week

- **Results.**
  - No effect of movie exposure in morning or afternoon (Columns 1-2)
  - Negative effect in the evening (Column 3)
  - Stronger negative effect the night after (Column 4)

TABLE III
THE EFFECT OF MOVIE VIOLENCE ON SAME-DAY ASSAULTS BY TIME OF DAY
Panel A. Benchmark Results

Specification:	Instrumental Variable Regressions			
Dep. Var.:	Log (Number of Assaults in Day t in Time Window)			
	(1)	(2)	(3)	(4)
Audience Of Strongly Violent Movies	-0.0050	-0.0030	-0.0130	-0.0192
(in millions of people in Day t)	(0.0066)	(0.0050)	(0.0049)***	(0.0060)***
Audience Of Mildly Violent Movies	-0.0106	-0.0001	-0.0109	-0.0205
(in millions of people in Day t)	(0.0060)*	(0.0045)	(0.0040)***	(0.0052)***
Audience Of Non-Violent Movies	-0.0033	0.0016	-0.0063	-0.0060
(in millions of people in Day t)	(0.0060)	(0.0046)	(0.0043)	(0.0054)
Time of Day	6AM-12PM	12PM-6PM	6PM-12AM	12AM-6AM next day
Control Variables:				
Full Set of Controls	X	X	X	X
Audience Instrumented With Predicted Audience Using Next Week's Audience	X	X	X	X
N	N = 1563	N = 1563	N = 1563	N = 1562

Summary of Findings

1. Violent movies lower same-day violent crime in the evening (incapacitation)
2. Violent movies lower violent crime in the night after exposure (less consumption of alcohol in bars)
3. No lagged effect of exposure in weeks following movie attendance $\rightarrow$ No intertemporal substitution
4. Strongly violent movies have slightly *smaller* impact compared to mildly violent movies in the night after exposure

- Interpret Finding 4 in light of Lab-Field debate

Interpretation

- **Finding 4. Non-monotonicity in Violent Content**
  - Night hours: $\hat{\beta}^{v} = -0.0192$ versus $\hat{\beta}^{m} = -0.0205$
  - Odd if more violent movies attract more potential criminals
  - Model above $\rightarrow$ Can estimate direct effect of violent movies if can control for selection

$$\alpha^{v} - \alpha = \beta^{v} - \left(\beta^{n} + \frac{x^{v} - x^{n}}{x^{m} - x^{n}} \left(\beta_{m} - \beta_{n} \right) \right)$$

  - Do not observe selection of criminals x^{j}, but observe selection of correlated demographics (young males)

- IMDB ratings data — Share of young males among raters increases with movie violence (Figure 2) $\rightarrow$ Use as estimate of x^j
  - Compute $\widehat{\alpha^v - \alpha} = .011$ ($p = .08$), about one third of total effect
  - Pattern consistent with arousal induced by strongly violent movies ($\alpha^v > \alpha^m$)

- Bottom-line 1: Can reconcile with laboratory estimates
- Bottom-line 2: Can provide benchmark for size of arousal effect

Share of Young Males vs. Movie Violence

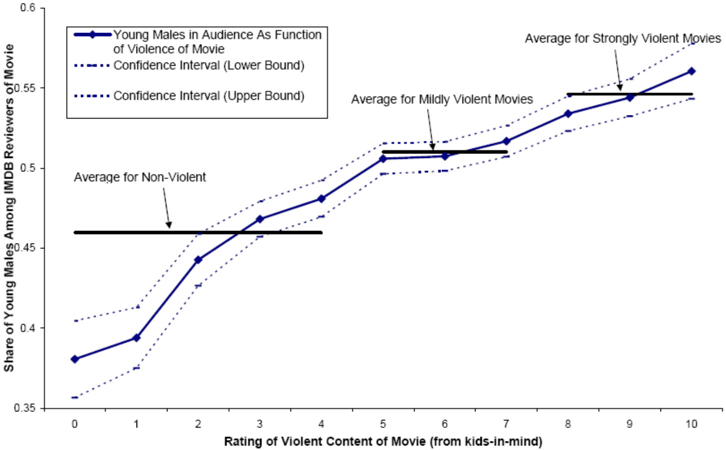
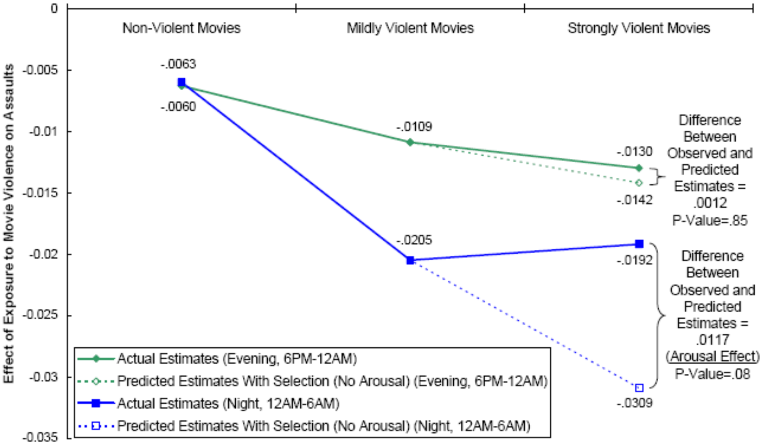


FIGURE II
Share of Young Males in Audience As Function of Movie Violence (Internet Movie Database Data)

The Arousal Effect



Lab vs. Field

- Differences from laboratory evidence (Levitt-List, 2007): Exposure to violent movies is
  - Less dangerous than alternative activity ($\alpha^v < \sigma$) (Natural Experiment)
  - More dangerous than non-violent movies ($\alpha^v > \alpha^n$) (Laboratory Experiments and indirect evidence above)
- Both types of evidence are valid for different policy evaluations
  - Laboratory: Banning exposure to unexpected violence
  - Field: Banning temporarily violent movies

Section 8

Next Lecture

Next Lecture

- Market Response to Biases
  - Employees: Behavioral Labor
  - Investors: Behavioral Finance
  - Voters: Behavioral Political Economy