Econ 219B
Psychology and Economics: Applications
(Lecture 10)

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Outline

1. Menu Effects: Confusion

2. Persuasion

3. Social Pressure

4. Emotions: Mood

1 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 (2007)**
  - 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

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

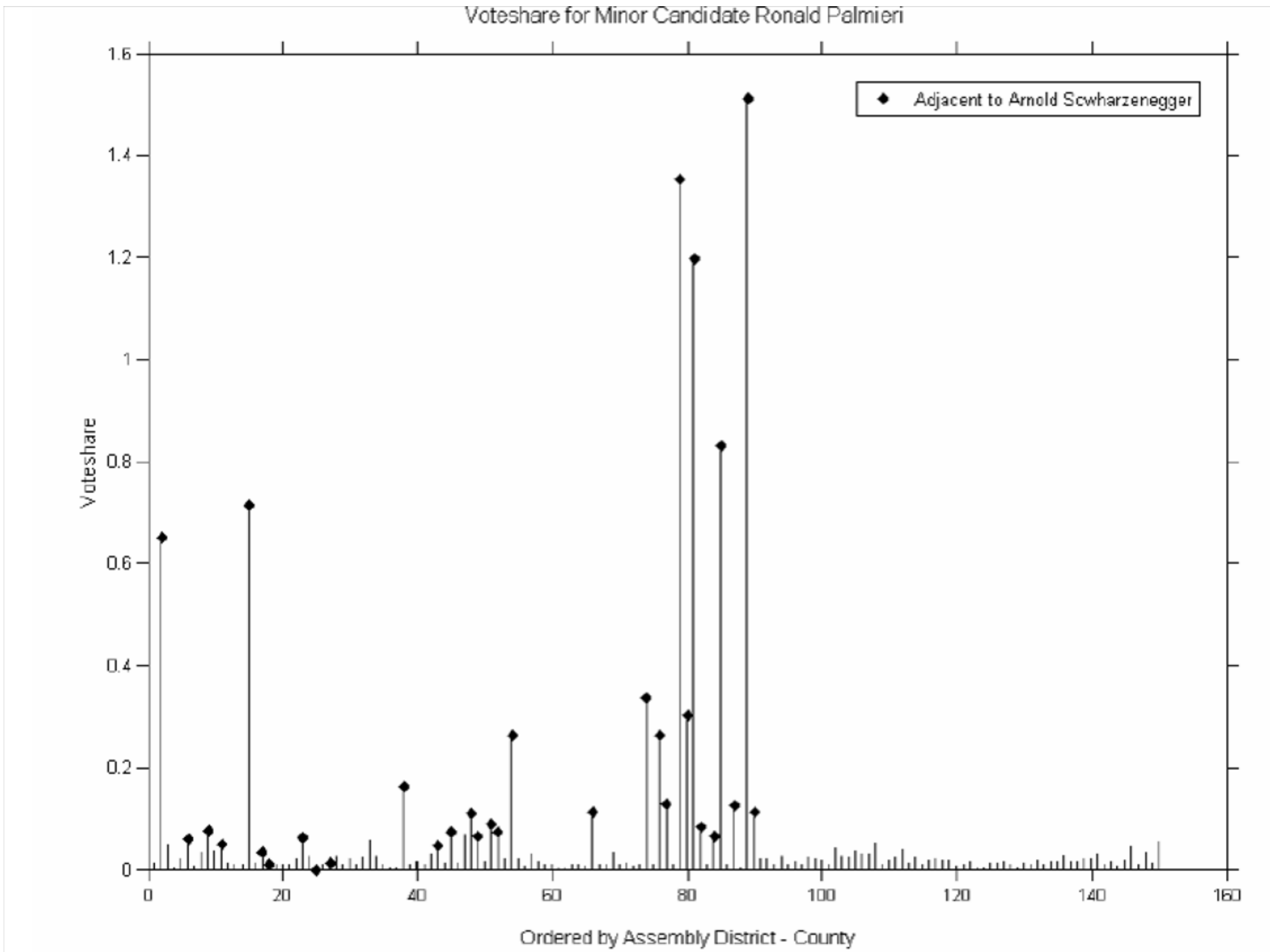
Candidates Continued / Candidatos Continúa

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]

2 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	Control	Variable t	Time Horizon	Treatment group t_T	Control group t_C	Exposure rate e_T-e_C	Persuasion rate f
	(1)	(2)	(4)	(7)	(9)	(10)	(11)	(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	Control	Variable t	Time Horizon	Treatment group t_T	Control group t_C	Exposure rate e_T-e_C	Persuasion rate f
	(1)	(2)	(4)	(7)	(9)	(10)	(11)	(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):

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

- 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

Dep. var.	Availability of Fox News via cable in 2000 (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):

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

- 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 CHANGE

	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 (0.0037)	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

- 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.*)

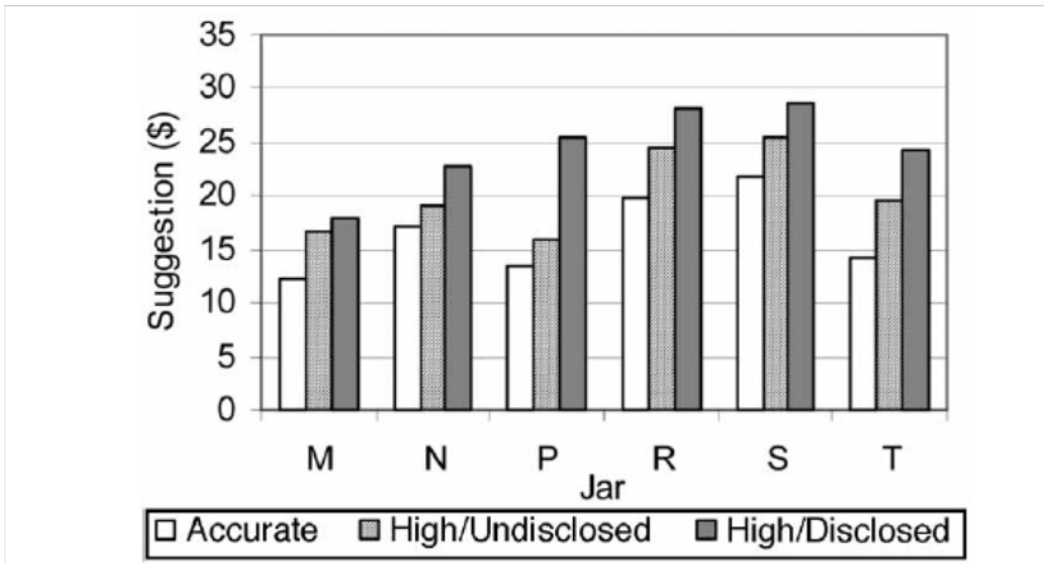
Table 1. Payoff Function for Advisors in Accurate Condition and for All Estimators

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

3 Social Pressure

- Clear example of social pressure without social learning

- *Milgram experiment*: post-WWII

- Motivation: Do Germans yield to pressure more than others?
  - Subjects: Adult males in US
  - Recruitment: experiment on punishment and memory
  - Roles:
    * teacher (subjects)
    * learner (accomplice)

- Teacher asks questions
- Teacher administers shock for each wrong answer
- Initial shock: 15V
- Increase amount up to 450V (not deadly, but very painful)
- Learner visible through glass (or audible)
- Learner visibly suffers and complains

- Results:
  - 62% subjects reach 450V
  - Subjects regret what they did ex post
  - When people asked to predict behavior, almost no one predicts escalation to 450V

- It's not the Germans (or Italians)! Most people yield to social pressure
- Furthermore, naivete' — Do not anticipate giving in to social pressure
- Social Pressure likely to be important in organization and public events

- Second classical psychology experiment: Asch (1951)
  - Subjects are shown two large white cards with lines drawn on them
    * First card has three lines of substantially differing length on them
    * Second card has only one line.
  - Subjects are asked which of the lines in the second card is closest in length to the line in the first card
- Control treatment: subjects perform the task in isolation –> 98 percent accuracy
- High social-pressure treatment: subjects choose after 4 to 8 subjects (confederates) unanimously choose the wrong answer –> Over a third of subjects give wrong answer

- Social Pressure Interpretation:
  - Avoid disagreeing with unanimous judgment of the other participants
  - Result disappears if confederates are not unanimous
- Alternative interpretation: Social learning about the rules of the experiment
- Limitation: subjects not paid for accuracy

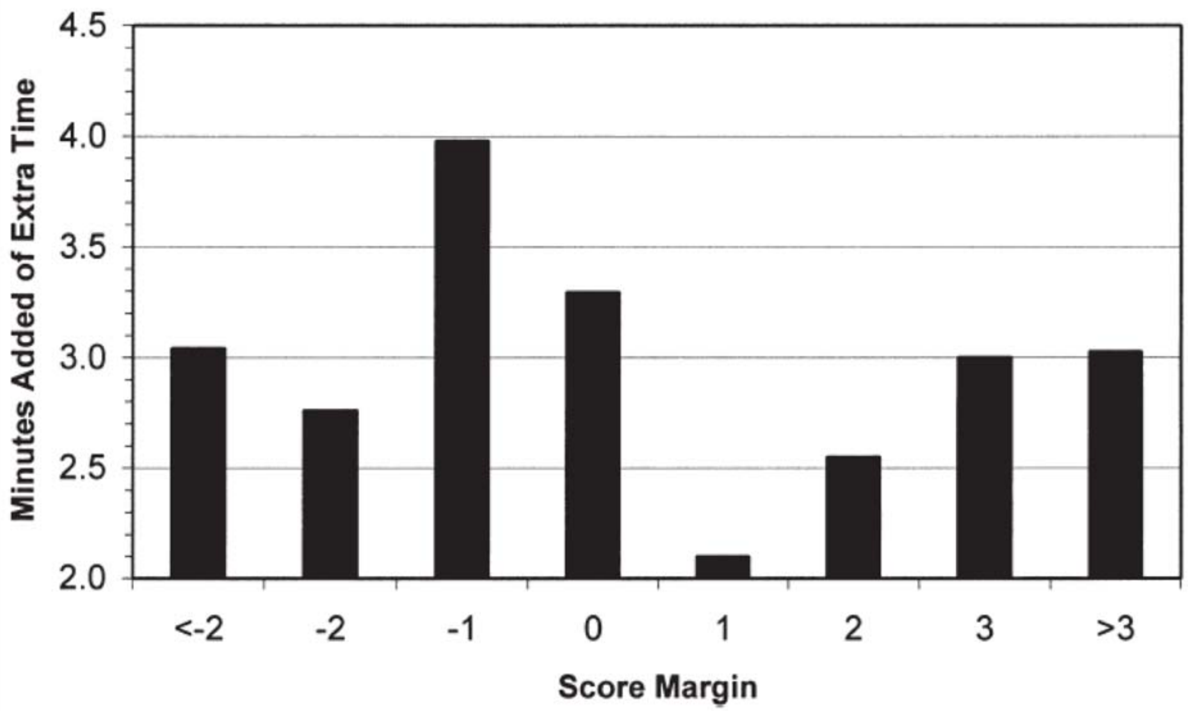
- An example of social pressure in a public event

- **Garicano, Palacios-Huerta, and Prendergast (REStat, 2006)**
  - Soccer games in Spanish league
  - Injury time at end of each game (0 to 5 min.)
  - Make up for interruptions of game
  - Injury time: last chance to change results for teams

- Social Pressure Hypothesis: Do referees provide more injury time when it benefits more the home team?
  - Yielding to social pressure of public
  - No social learning plausible
  - Note: referees professionals, are paid to be independent

- Results: Figure 1 – Clear pattern, very large effects

FIGURE 1.—INJURY TIME AWARDED BY SCORE MARGIN



Number of minutes awarded by referees as a function of the margin in favor of the home team at the end of the match. Score margin = (goals scored by home team) − (goals scored by visiting team). Note: 3.3% of the matches ended with score differences smaller than −2; 5.2%, with score differences greater than 3.

- Table 5. Response to incentives –> After 1994, 3 points for winning (1 for drawing, 0 for losing).

TABLE 5.—MARGINAL EFFECT OF INCENTIVES ON INJURY TIME

Statistic	[1]	[2]
Constant	3.50**	3.11**
	(0.14)	(0.32)
Score Difference	**−1.53****	**−1.56****
	(0.18)	**(0.18)**
Year Effect	0.81**	0.7**
	(0.18)	(0.21)
Year × Score Difference	**−0.58***	**−0.52***
	(0.23)	**(0.23)**
Yellow Cards		0.07**
		(0.02)

- Table 6. Response to social pressure: size of audience

TABLE 6.—EFFECT OF THE SIZE AND COMPOSITION OF THE CROWD ON REFEREE BI

Statistic	[1]	[2]
Constant	3.23**	2.94**
	(0.18)	(0.20)
Score Difference	**−0.93****	**−0.96****
	(0.20)	**(0.21)**
Year Effect	0.36**	0.33**
	(0.11)	(0.11)
Attendance	0.00	0.00
	(0.00)	(0.00)
Attendance × Score Difference	**−0.02****	**−0.02****
	(0.00)	**(0.00)**
Yellow Cards		0.07**
		(0.02)
Budget Home		

- P*eer effect* literature also points to social pressure

- **Falk-Ichino (JOLE, 2006):** effect of peer pressure on task performance
  - Recruit High-school students in Switzerland to perform one-time job for flat payment
  - Stuff letters into envelopes for 4 hours
  - Control group of 8 students did the task individually
  - Treatment group of 16 students worked in pairs (but each student was instructed to stuff the envelopes individually)

- Results:
  - Students in treatment group stuffed more envelopes (221 vs. 190)

– Students in treatment group coordinated the effort within group: within-pair standard-deviation of output is significantly less than the (simulated) between-pairs standard deviation

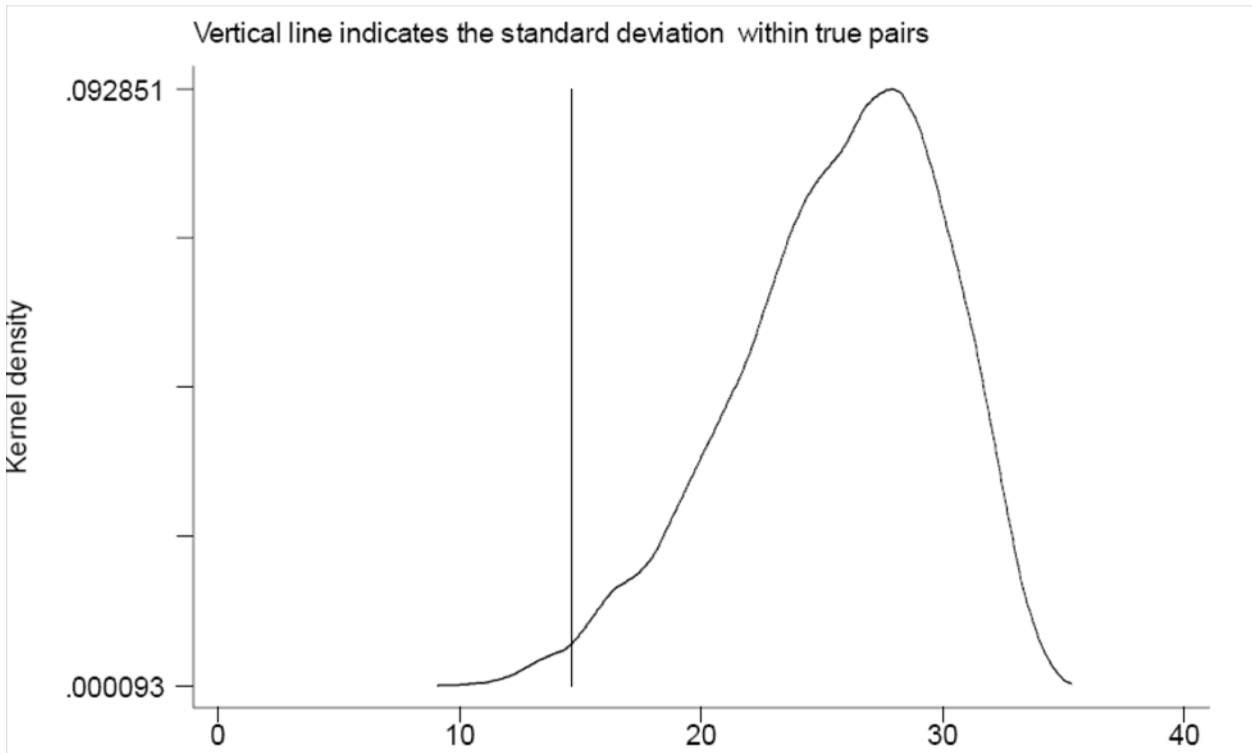


Fig. 3: St. dev. within true and hypothetical pairs in pair sample

- **Mas-Moretti (AER, forthcoming).** Evidence of response to social pressure in the workplace
  - Workplace setting –> Large retail chain
  - Very accurate measure of productivity, scanning rate
  - Social Pressure: Are others observing the employer?

- Slides courtesy of Enrico

Introduction

- We use internal scanner data from a supermarket chain to obtain a high-frequency measure of productivity of checkers
- Over a two year period, we observe each item scanned by each worker in each transaction. We define individual effort as the number of items scanned per second.
- We estimate how individual effort changes in response to changes in the average productivity of co-workers

Introduction

- Over the course of a given day, the composition of the group of co-workers varies, because workers shifts do not perfectly overlap

- Scheduling is determined two weeks prior to a shift

=> within-day timing of entry and exit of workers is predetermined

- Empirically, entry and exit of good workers appear uncorrelated with demand shocks:

  - The entry of fast workers is not concentrated in the ten minutes prior to large increases in customer volume, as would be the case if managers could anticipate demand changes

  - The exit of fast workers is not concentrated in the ten minutes prior to large declines in customer volume

  - The mix of co-workers ten minutes into the future has no effect on individual productivity in the current period.

Data

- We observe all the transactions that take place for 2 years in 6 stores. For each transaction, we observe the number of items scanned, and the length of the transaction in seconds.

- We define individual productivity as the number of items scanned per second.

- We know who is working at any moment in time, where, and whom they are facing

- Unlike much of the previous literature, our measure of productivity is precise, worker-specific and varies with high-frequency.

Institutional features

- Workers in our sample perform the same task use the same technology, and are subject to the same incentives
- Workers are unionized
- Compensation is a fixed hourly payment
- Firm gives substantial scheduling flexibility to the workers

What is the relationship between individual effort and co-worker permanent productivity?

- First we measure the *permanent* component of productivity of each worker

$$y_{itcs} = \theta_i + \Sigma_{j \neq i} \pi_j W_{jtcs} + \psi X_{itcs} + \gamma_{dhs} + \lambda_{cs} + e_{itcs.}$$

For each worker *i*, 10 minute period and store, we average the permanent productivity of all the co-workers (excluding *i*) who are active in that period: $\Delta\overline{\theta}_{-ist}$

- Second, we regress ten minutes *changes* in individual productivity on *changes* in average permanent productivity of co-workers

Finding 1: There is a positive association between changes in co-worker permanent productivity and changes in individual effort

	(1)	(2)
Δ Co-worker permanent Productivity	0.176 (0.023)	0.159 (0.023)
Controls	No	Yes

$$\Delta y_{itcs} = \beta \Delta \overline{\theta}_{-ist} + \gamma_{tds} + \psi \Delta X_{tcs} + e_{itcs}$$

i = individual
t = 10 minute time interval
c = calendar date
s = store

Finding 1: There is a positive association between changes in co-worker permanent productivity and changes in individual productivity

Entry of above average productivity worker	0.011 (0.001)	
Exit of an above average productivity worker	-0.005 (0.001)	
Shift entry of above average productivity worker		0.006 (0.002)
Shift exit of an above average productivity worker		-0.006 (0.002)
Controls	Yes	Yes

Finding 2: The magnitude of the spillover effect varies dramatically depending on the skill level

	(2)	(3)
Δ Co-worker permanent productivity	0.159 (0.023)	0.261 (0.033)
Δ Co-worker permanent prod. × Above average worker		-0.214 (0.046)
Observations	1,734,140	1,734,140
Controls	Yes	Yes

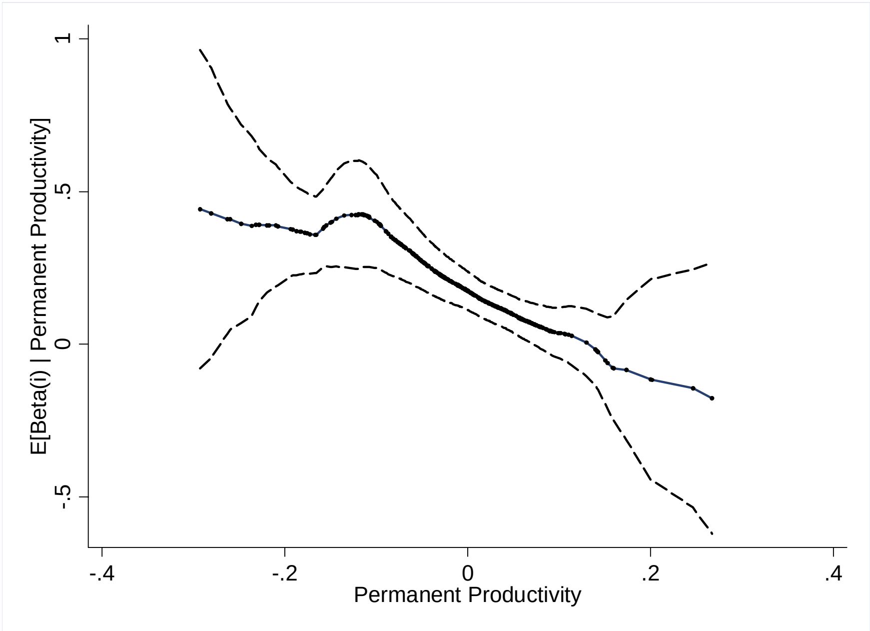
$$\Delta y_{itcs} = \beta \Delta \overline{\theta}_{-ist} + \gamma_{tds} + \psi \Delta X_{tcs} + e_{itcs}$$

Individual-specific Spillover

- Our longitudinal data allow for models with an individual-specific spillover effect, β_i:

$$\Delta y_{itcs} = \beta_i \Delta \overline{\theta}_{-icts} + \psi \Delta X_{tcs} + \gamma_{tds} + e_{itcs}$$

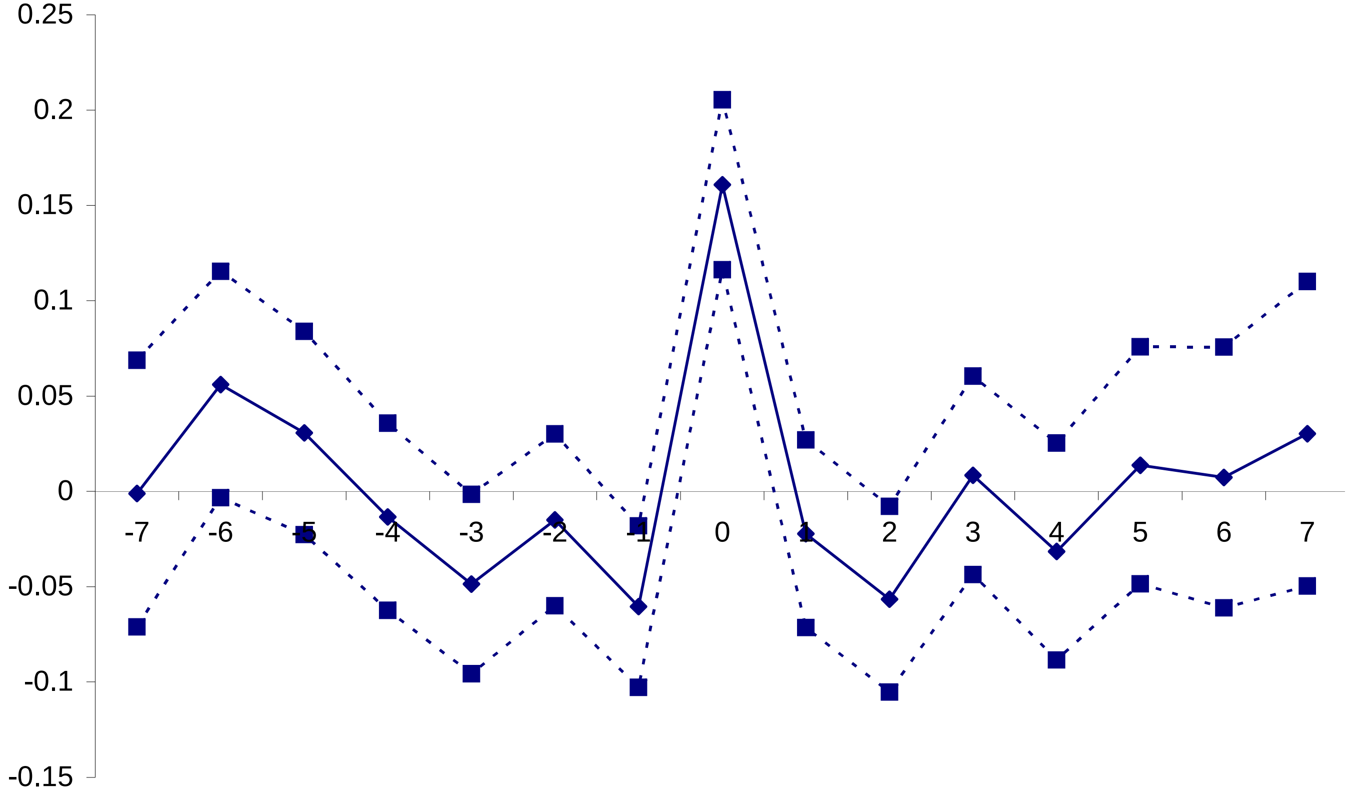
The relationship between individual permanent productivity and worker specific spillover effect



What Determines Variation in Co-Workers Quality?

- Shifts are pre-determined
- Management has no role in selecting specific workers for shifts
- We measure co-workers productivity using permanent productivity (not current)
- Our models are in first differences: We use variation within a day and within a worker

The lags and leads for the effect of changes of average co-worker productivity on reference worker productivity



$$\Delta y_{itcs} = \beta_{-7}\Delta\bar{\theta}_{-i(t-7)cs} + \beta_{-6}\Delta\bar{\theta}_{-i(t-6)cs} + \beta_{-5}\Delta\bar{\theta}_{-i(t-5)cs} + \beta_{-4}\Delta\bar{\theta}_{-i(t-4)cs} + \beta_{-3}\Delta\bar{\theta}_{-i(t-3)cs} + \beta_{-2}\Delta\bar{\theta}_{-i(t-2)cs}$$
$$+ \beta_{-1}\Delta\bar{\theta}_{-i(t-1)cs} + \beta_{0}\Delta\bar{\theta}_{-i(t)cs} + \beta_{1}\Delta\bar{\theta}_{-i(t+1)cs} + \beta_{2}\Delta\bar{\theta}_{-i(t+2)cs} + \beta_{3}\Delta\bar{\theta}_{-i(t+3)cs} + \beta_{4}\Delta\bar{\theta}_{-i(t+4)cs} + \beta_{5}\Delta\bar{\theta}_{-i(t+5)cs}$$
$$+ \beta_{6}\Delta\bar{\theta}_{-i(t+6)cs} + \beta_{7}\Delta\bar{\theta}_{-i(t+7)cs} + \boldsymbol{\zeta}\mathbf{M} + e_{itcs},$$

What explains spillovers?

- There are at least two possible explanations (Kendal and Lazear, 1992)
  - Guilt / Contagious enthusiasm
  - Social pressure ("I care what my co-workers think about me")
- We use the spatial distribution of register to help distinguish between mechanisms

  - Guilt / Contagious enthusiasm implies that the spillover generate by the entry of a new worker should be larger for those workers who can observe the entering worker

  - **Social pressure** implies that the spillover generate by the entry of a new worker should be larger for those workers who who are observed by the new worker

Finding 3

- Most of the peer effect operates through changes in workers that are able to <u>monitor</u> other workers

- As more productive workers are introduced into a shift, they influence only the co-workers that can be monitored. There is no effect on co-workers that can not be monitored.

- This finding is consistent with social pressure

Finding 3

- Moreover, the addition of a worker behind an incumbent worker, regardless of her productivity, results in increased productivity of the incumbent worker.

- The addition of a worker in front, on the other hand, *decreases* productivity of the incumbent worker.

- This finding suggests that there is still scope for free-riding, but only when the free-riding is difficult to observe by other workers.

Table 5: Models by spatial orientation and proximity

	(1)	(3)
Δ Co-worker permanent productivity behind	0.233	
	(0.019)	
Δ Co-worker permanent productivity in front	0.007	
	(0.018)	
Δ Co-worker permanent productivity behind & closer		0.162
		(0.016)
Δ Co-worker permanent productivity in front & closer		0.016
		(0.015)
Δ Co-worker permanent productivity behind & farther		0.100
		(0.018)
Δ Co-worker permanent productivity in front & farther		0.003
		(0.018)

Previous scheduling overlap

- If social pressure is the explanation, the spillover effect between two workers should also vary as a function of the amount of interactions
- If a worker does not overlap often with somebody on a given shift, she may not be as receptive to social pressure because there is not much of a repeated component to the social interaction.
- It is more difficult to exert social pressure on individuals that we meet rarely than individuals that we see every day.

Frequency of Interactions

- Suppose a shift has checkers A, B, and C. We calculate the percent of A's 10 minute intervals that have overlapped with B and C up to the time of the current shift. We do this for all checkers and all shifts.

- We then compute the average permanent productivity for checkers that are between 0% and 5% overlap, 5% and 20% overlap, and 20% to 100% overlap.

Previous scheduling overlap

	(1)
(I) Δ Co-worker permanent prod: low exposure	0.013
	(0.012)
(II) Δ Co-worker permanent prod: medium exposure	0.084
	(0.014)
(III) Δ Co-worker permanent prod: high exposure	0.075
	(0.017)
p-value: Ho: (I) = (II)	0.000
Ho: (I) = (III)	0.003
Ho: (II) = (III)	0.655
Observations	1,659,450

Conclusion

- The theoretical effect of a change in the mix of co-workers can be either positive (peer effects) or negative (free riding).

- FINDING 1
  - the net effect is on average positive

- FINDING 2
  - There is substantial heterogeneity in this effect.
  - Low productivity workers benefit from the spillover substantially more than high productivity workers.

Conclusions

- FINDING 3
  - Social pressure enforced by monitoring explains these peer effects
  - When more productive workers arrive into shifts, they induce a productivity increase only in workers that are in their line-of-vision.
  - The effect appears to decline with distance between registers

- FINDING 4
  - Optimally choosing the worker mix can lower the firm's wage bill by about $2.5 million per year
  - This does not imply that the firm is not profit maximizing

- Final Example: Effect of Social Pressure on Voting
  - Large literature of field experiments to impact voter turnout
  - Typical design: Day before (local) election reach treatment household and encourage them to vote
  - Some classical examples

Paper	Treatment (1)	Election type or question (2)	Variable t (3)	Year (4)	Place (5)	Sample size (6)	Control group t_T (7)	Treatment group t_C (8)	Exposure rate $e_T - e_C$ (9)	Persuasion rate (10)
Field Experiments										
Gerber and Green [2000]	Door-to-door canvassing	Federal elect.	Turnout	1998	New Haven	N = 14,473	0.422	0.463	0.270	0.263
	Canvassing + mail + calls	Federal elect.	Turnout	1998	New Haven	N = 14,850	0.422	0.448	0.270	0.167
Green, Gerber, and Nickerson [2003]	Door-to-door canvassing	Local elect.	Turnout	2001	6 cities	N = 18,933	0.286	0.310	0.293	0.118
Green and Gerber [2001]	Phone calls by youth vote	General elect.	Turnout	2000	4 cities	N = 4,377	0.660	0.711	0.737	0.205
	Phone calls 18–30-year-olds	General elect.	Turnout	2000	2 cities	N = 4,377	0.405	0.416	0.414	0.045

- In these experiments, typically mailings are the cheapest, but also the least effective get-out-the-vote treatment
- **Gerber, Green, and Larimer (APSR, 2008):** Add social pressure to these treatments
- Setting:
  - August 2006, Michigan
  - Primary election for statewide offices
  - Voter turnout 17.7% registered voters
- Experimental sample: 180,000 households on Voter File
- Mailing sent 11 days prior to election

- Experimental design:
  - Control households get no mail (N=100,000)
  - *Civic Duty Treatment.* ‘DO YOUR CIVIC DUTY—VOTE!”’

Civic Duty mailing

30426-2 XXX

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Dear Registered Voter:

DO YOUR CIVIC DUTY AND VOTE!

Why do so many people fail to vote? We've been talking about this problem for years, but it only seems to get worse.

The whole point of democracy is that citizens are active participants in government; that we have a voice in government. Your voice starts with your vote. On August 8, remember your rights and responsibilities as a citizen. Remember to vote.

DO YOUR CIVIC DUTY — VOTE!

- – *Hawthorne Treatment.* Information that voters turnout records are being studied

Dear Registered Voter:

YOU ARE BEING STUDIED!

Why do so many people fail to vote? We've been talking about this problem for years, but it only seems to get worse.

This year, we're trying to figure out why people do or do not vote. We'll be studying voter turnout in the August 8 primary election.

Our analysis will be based on public records, so you will not be contacted again or disturbed in any way. Anything we learn about your voting or not voting will remain confidential and will not be disclosed to anyone else.

DO YOUR CIVIC DUTY — VOTE!

- – *Self-Information Treatment.* Give information on own voting record

Dear Registered Voter:

WHO VOTES IS PUBLIC INFORMATION!

Why do so many people fail to vote? We've been talking about the problem for years, but it only seems to get worse.

This year, we're taking a different approach. We are reminding people that who votes is a matter of public record.

The chart shows your name from the list of registered voters, showing past votes, as well as an empty box which we will fill in to show whether you vote in the August 8 primary election. We intend to mail you an updated chart when we have that information.

We will leave the box blank if you do not vote.

DO YOUR CIVIC DUTY—VOTE!

OAK ST	Aug 04	Nov 04	Aug 06
9999 ROBERT WAYNE		Voted	______
9999 LAURA WAYNE	Voted	Voted	______

- – *Other-Information Treatment.* Know if neighbors voted!

Dear Registered Voter:

WHAT IF YOUR NEIGHBORS KNEW WHETHER YOU VOTED?

Why do so many people fail to vote? We've been talking about the problem for years, but it only seems to get worse. This year, we're taking a new approach. We're sending this mailing to you and your neighbors to publicize who does and does not vote.

The chart shows the names of some of your neighbors, showing which have voted in the past. After the August 8 election, we intend to mail an updated chart. You and your neighbors will all know who voted and who did not.

DO YOUR CIVIC DUTY — VOTE!

MAPLE DR	Aug 04	Nov 04	Aug 06
9995 JOSEPH JAMES SMITH	Voted	Voted	______
9995 JENNIFER KAY SMITH		Voted	______
9997 RICHARD B JACKSON		Voted	______

- Results:
  - Substantial impacts especially when neighbors get to see
  - All the results are highly statistically significant
  - Results huge given that 1/3 of recipients probably never opened the mailer
  - Impact: Obama campaign considered using this, but decided too risky

TABLE 2. Effects of Four Mail Treatments on Voter Turnout in the August 2006 Primary Election

	Experimental Group				
	Control	Civic Duty	Hawthorne	Self	Neighbors
Percentage Voting	29.7%	31.5%	32.2%	34.5%	37.8%
N of Individuals	191,243	38,218	38,204	38,218	38,201

4 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

5 Next Lecture

- Emotions: Arousal

- Methodology: Lab and Field