Econ 219B
Psychology and Economics: Applications
(Lecture 12)

Stefano DellaVigna

April 21, 2010

Outline

1. Social Pressure II
2. Emotions: Mood
3. Emotions: Arousal
4. Methodology: Lab and Field
5. Market Reaction to Biases: Introduction
6. Market Reaction to Biases: Pricing
7. Market Reaction to Biases: Employers
8. Market Reaction to Biases: Political Economy

1 Social Pressure II

- **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

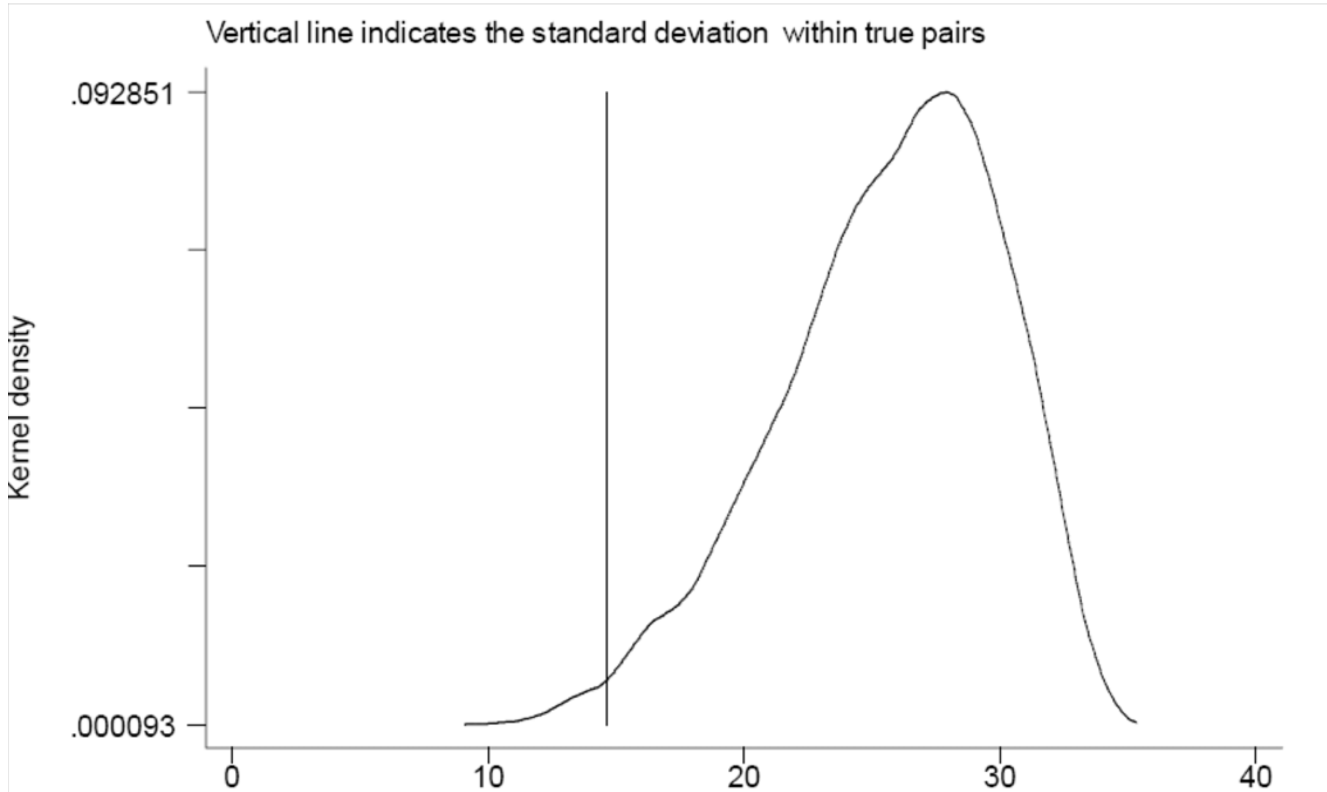


Fig. 3: St. dev. within true and hypothetical pairs in pair sample

- **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: $\Delta\bar{\theta}_{-ist}$

- 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

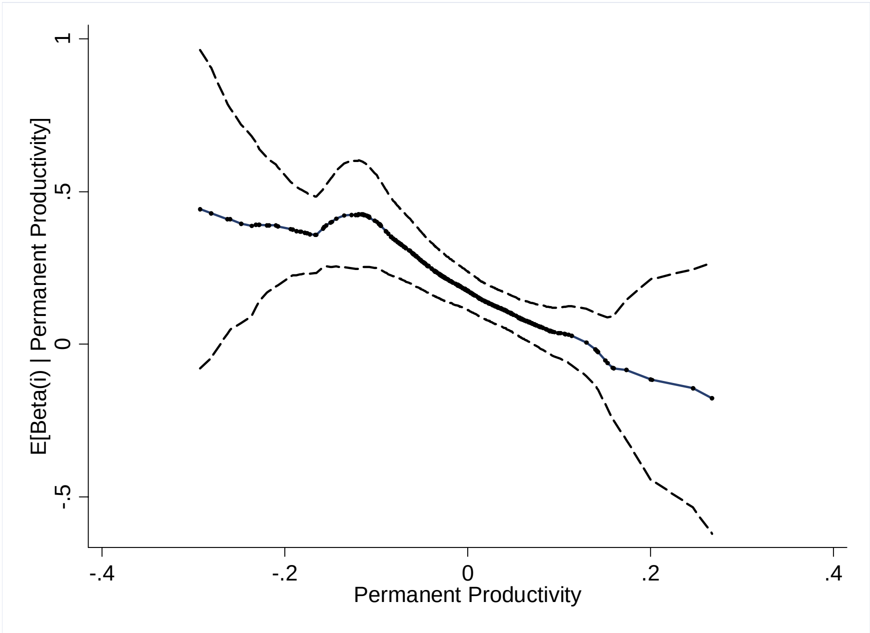
$$\Delta y_{itcs} = \beta \Delta \overline{\theta}_{-ist} + \gamma_{tds} + \psi \Delta X_{tcs} + e_{itcs}$$

Individual-specific Spillover

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

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

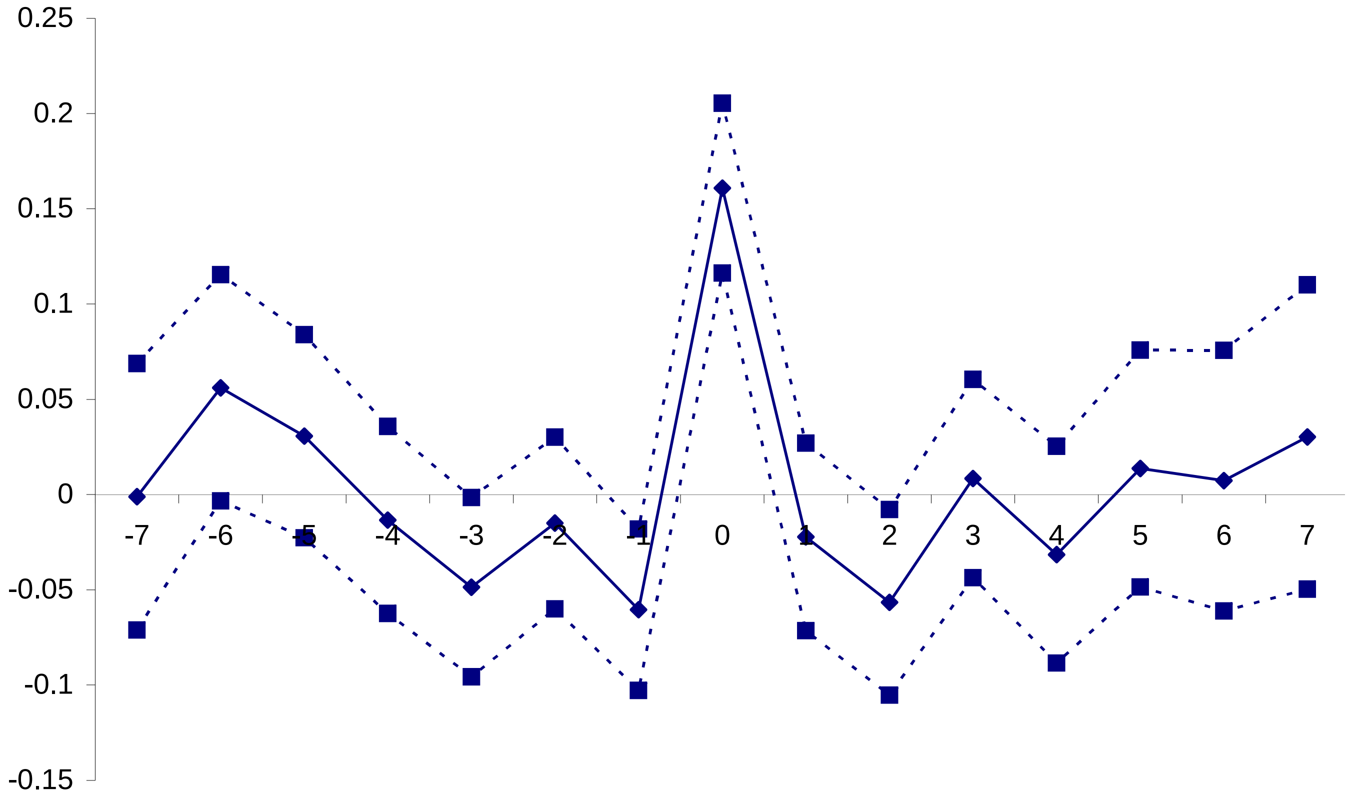
The relationship between individual permanent productivity and worker specific spillover effect



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

2 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

3 Emotions: Arousal

- Separate impact of emotions: Arousal

- **Ariely-Loewenstein (2005):** Sexual arousal

  - Control group: Students

  - Treatment group: Students that are sexually aroused

  - Subjects in treatment group report a substantially higher willingness to engage in behavior that may lead to date rape

  - (Projection bias)

- **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 (2007)**: 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 –> 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:

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

- First point — Estimate of net effect
  - Direct effect: Increase in violent movie exposure –> α_i^v
  - Indirect effect: Decrease in Social Activity –> σ_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:

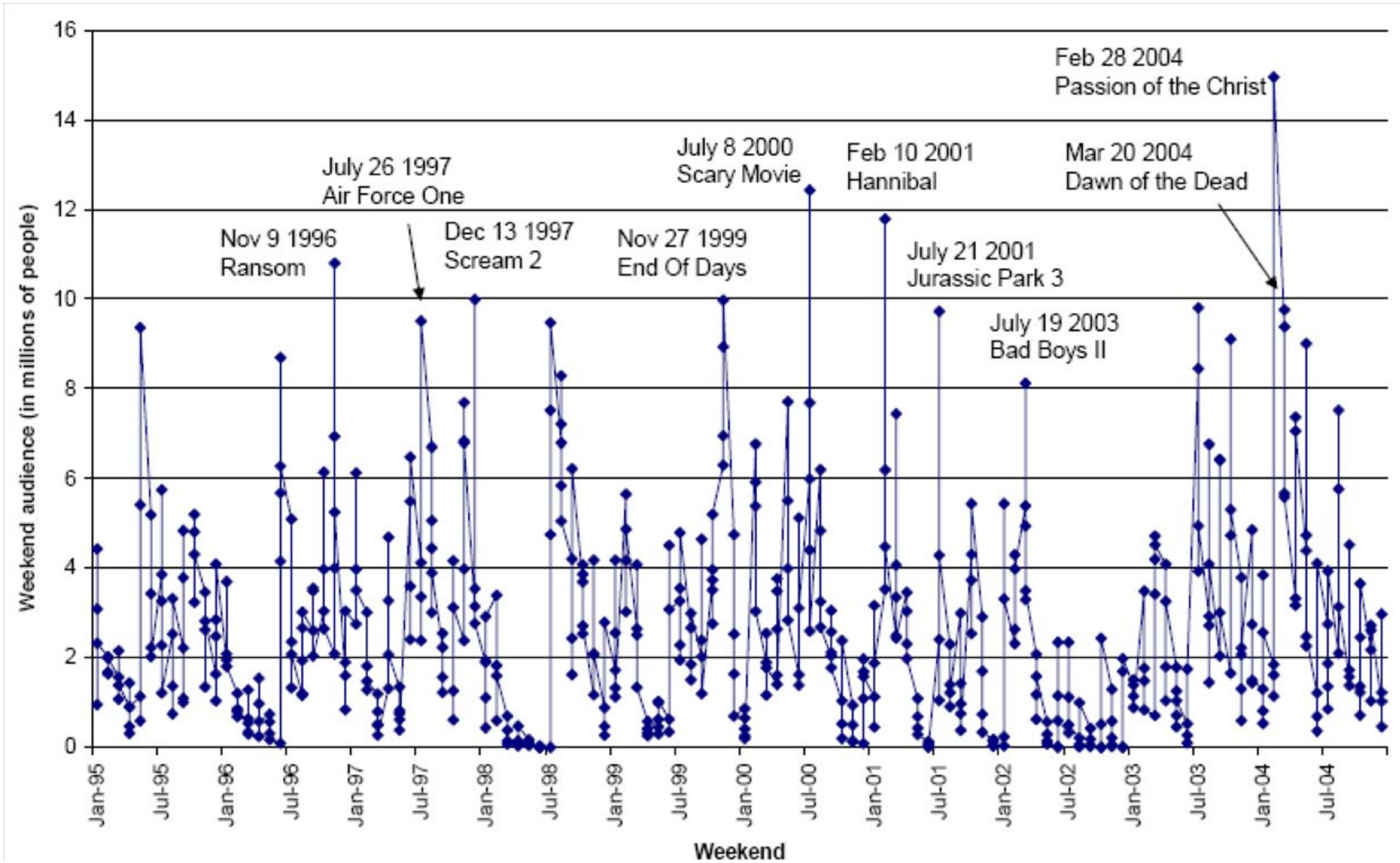
$$\beta^v = x^v(\alpha_y^v - \sigma_y) + (1 - x^v)(\alpha_o^v - \sigma_o)$$

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

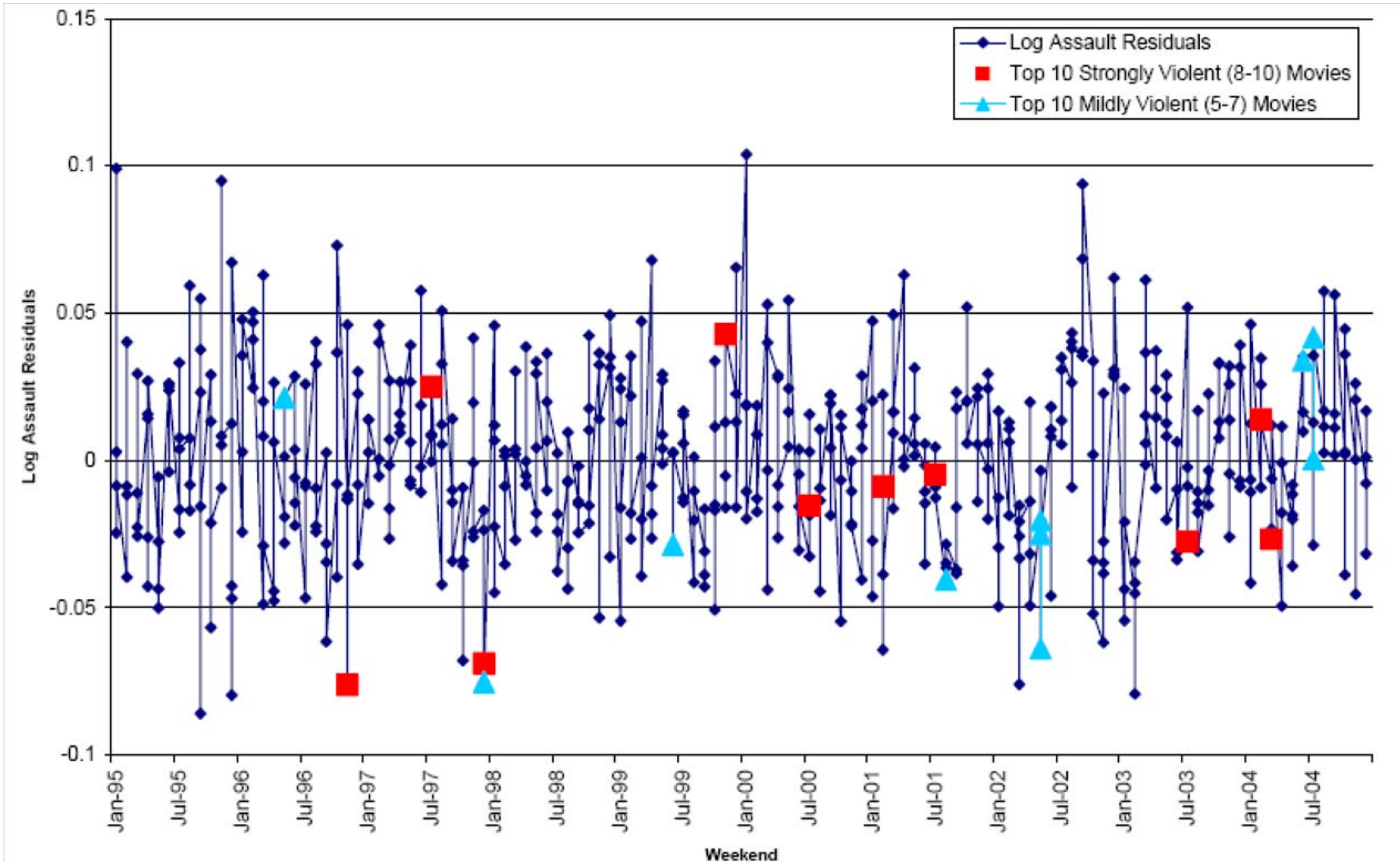
$$\beta_{lab}^v = \frac{N_y}{N_y + N_o}\alpha_y^v + (1 - \frac{N_y}{N_y + N_o})\alpha_o^v$$

- 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

- **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)



Feb 28 2004
Passion of the Christ
July 8 2000
Scary Movie
Feb 10 2001
Hannibal
Mar 20 2004
Dawn of the Dead
July 26 1997
Air Force One
Dec 13 1997
Scream 2
Nov 9 1996
Ransom
Nov 27 1999
End Of Days
July 21 2001
Jurassic Park 3
July 19 2003
Bad Boys II
Weekend audience (in millions of people)
16
14
12
10
8
6
4
2
0
Jan-95
Jul-95
Jan-96
Jul-96
Jan-97
Jul-97
Jan-98
Jul-98
Jan-99
Jul-99
Jan-00
Jul-00
Jan-01
Jul-01
Jan-02
Jul-02
Jan-03
Jul-03
Jan-04
Jul-04
Weekend



Log Assault Residuals
Top 10 Strongly Violent (8-10) Movies
Top 10 Mildly Violent (5-7) Movies
0.15
0.1
0.05
0
-0.05
-0.1
Log Assault Residuals
Jan-95
Jul-95
Jan-96
Jul-96
Jan-97
Jul-97
Jan-98
Jul-98
Jan-99
Jul-99
Jan-00
Jul-00
Jan-01
Jul-01
Jan-02
Jul-02
Jan-03
Jul-03
Jan-04
Jul-04
Weekend

- **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

- **Additional Results:**

  - No Medium-Run Effects.

    * No effect on Monday and Tuesday of weekend exposure

    * No effect one, two, or three weeks later

  - Placebo:

    * No effect on crime the week after

    * No effect if randomly draw year and reassign dates

  - Similar result for DVD-VHS Rentals

- **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 –> 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 linght of Lab-Field debate

- **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 –> Can estimate direct effect of violent movies if can control for selection

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

  - 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) –> 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 1: Can provide benchmark for size of arousal effect

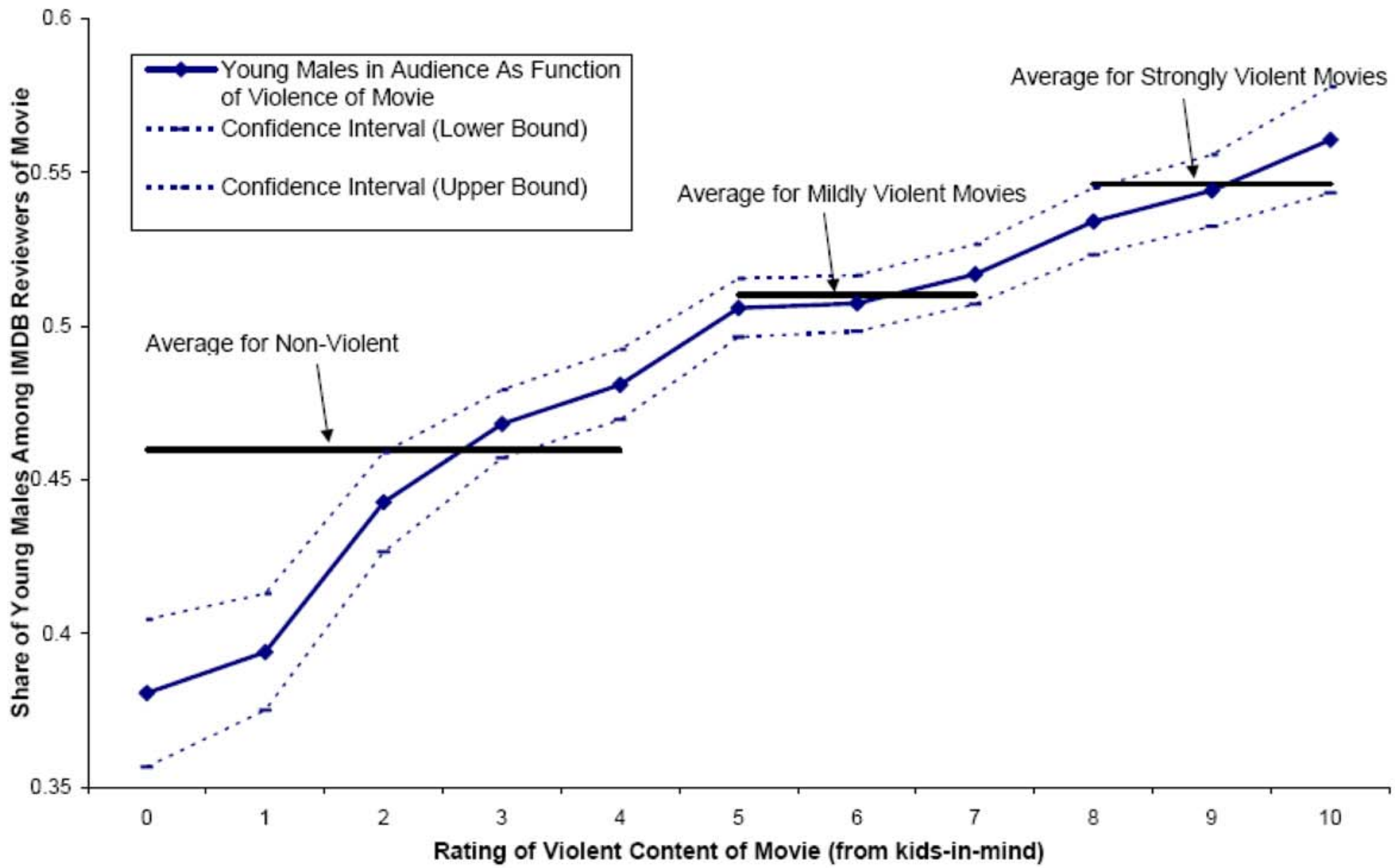
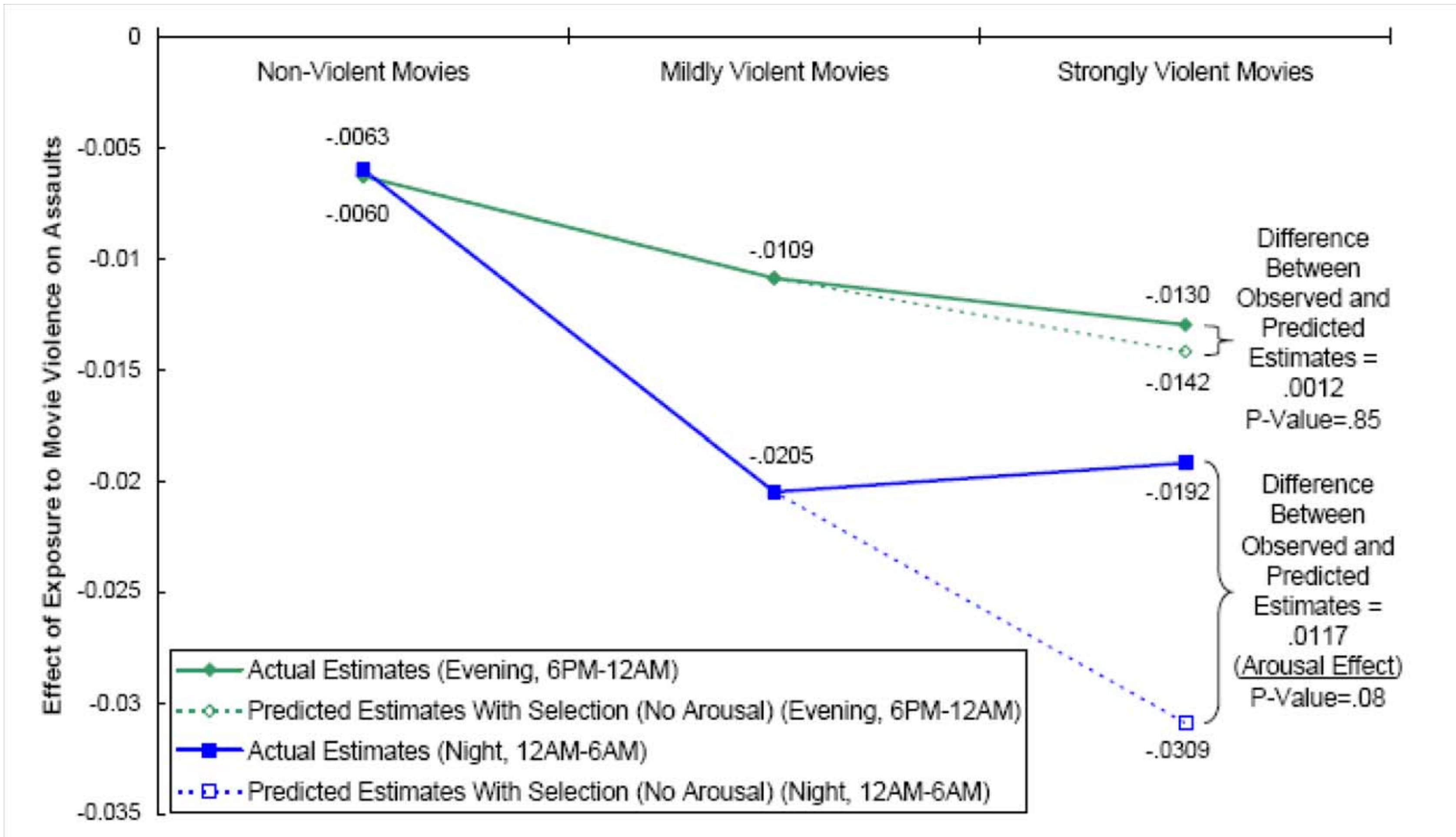


FIGURE II
Share of Young Males in Audience As Function of Movie Violence (Internet Movie Database Data)



Effect of Exposure to Movie Violence on Assaults
0
-0.005
-0.01
-0.015
-0.02
-0.025
-0.03
-0.035
Non-Violent Movies
Mildly Violent Movies
Strongly Violent Movies
-.0063
-.0060
-.0109
-.0130
-.0142
-.0205
-.0192
-.0309
Difference Between Observed and Predicted Estimates = .0012 P-Value=.85
Difference Between Observed and Predicted Estimates = .0117 (Arousal Effect) P-Value=.08
Actual Estimates (Evening, 6PM-12AM)
Predicted Estimates With Selection (No Arousal) (Evening, 6PM-12AM)
Actual Estimates (Night, 12AM-6AM)
Predicted Estimates With Selection (No Arousal) (Night, 12AM-6AM)

- 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

- This leaves a number of open questions

- Example: Peer Effects through the media.
  - To what extent do we imitate role models in the media?
  - Ongoing work: Movies with Car races –> Dangerous driving –> Car accidents?
  - Can measure exact duration of car chases and intensity
  - Is imitation higher for characters of same race and gender?

4 Methodology: Lab and Field

- What do we learn about the relationship between lab experiments and field evidence?

- Contentious topic recently since **List-Levitt (JEP, 2007)**

- To simplify, define field evidence as:

  – Natural Experiments

  – Field Experiments

- Let us start from **Dahl-DellaVigna** example

- **Difference 1.** Differences in comparison group

  - *Lab Experiment*: Activity in control group exogenously assigned

  - *Natural Experiment*: Activity in control group chosen to max utility

  - Notice: *Field Experiments* are (usually) like lab experiments

- Implication: Parameters estimated very different

- Write down model: what parameter are you estimating?

- **Difference 2. Self-Selection**
  - *Lab Experiment*: Subjects are group of students unaware of nature of task –> No selection
  - *Natural Experiment*: People self-select into a setting
  - *Field Experiments:* Can have self-selection too

- Different purposes:
  - Often useful to control for self-selection and impose a treatment
  - However, can lose external validity –> Put people in a situation they normally would not be in

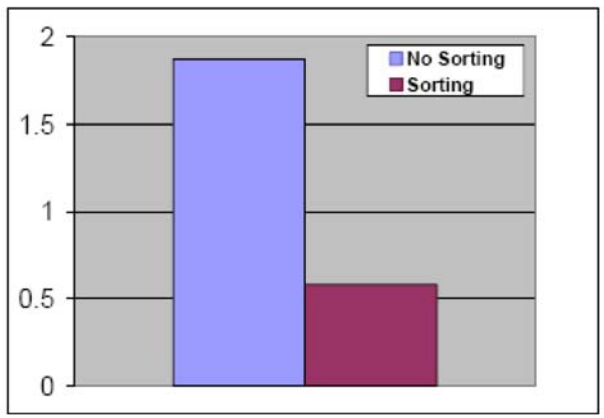
- Example: Social preferences
  - I give $10 if confronted with fund-raiser asking for money
  - However: I do all possible to avoid this interaction
  - –> Without sorting: Frequent giving
  - –> With sorting: No giving

- Notice: One can integrate sorting into laboratory experiments

- **Lazear-Malmendier-Weber (2006)** (similar to **Dana-Cain-Dawes, 2007**)
  - Control: Standard dictator game (share $10)
  - Treatment: Dictator game with sorting: Can opt out and get $10

- Large difference in results

Panel A. Average Amount Shared
The amount is denoted in Euros. The left bar indicates the average amount in the treatment without a sorting option; the right bar the average amount in the treatment with a sorting option. Non-participation in the treatment with sorting is included as sharing zero.



- 28 of 39 subjects sort out

- **Difference 3.** Differences in context

- Example 1: Dahl-DellaVigna
  - Laboratory experiments on movie violence: 15-min, clips (to save time)
  - Field: Full-length movies

- Example 2: Dictator experiment
  - Laboratory: Have been given $10 – Give it to anonymous subject
  - Field: Have earned money – Give some of it to someone

- Example 3: Prisoner Dilemma experiment
  - Framed as 'Community Game' –> Low defection
  - Framed as 'Wall-Street Game' –> High defection

- Tension for laboratory experiments: Resemble field at cost of losing experimental controls

- **Difference 4.** Demand effects in the laboratory
  - Subjects generate the effect that they think experimenter is looking for
  - Social preference!
- Example: Dictator game
  - I was given $10 and asked how much to give —> Inference: Should give some away
- Field evidence does not have this feature
- However:
  - This is genuine phenomenon also in field (Obedience)
  - Trade-off between demand effects and loss of control in the field

- Related: Anonymity
  - Situations are rarely double-blind even in experiments
  - If subjects worry about experimenter, this affects behavior
- Again: Same issue also in the field
- Advantage of lab: Can control for this by running double-blind sessions

- **Difference 5.** Differences in Stakes
  - Laboratory: Small stakes
  - Field: Large stakes
- Examples:
  - Dictator Games for \$10 vs. \$100+ of charitable giving
  - Aggressive hockey play in Violence epxeriments vs. violent crime
- However:
  - Evidence not consistent that large stakes change behavior
  - In field, many repeated interactions, all with small stakes

5 Market Reaction to Biases: Introduction

- So far, we focused on consumer deviations from standard model

- Who exhibits these deviations?

  1. **Self-control and naivete'.** Consumers (health clubs, food, credit cards, smoking), Employees (retirement saving, benefit take-up), Students (homework)

  2. **Reference dependence.** Workers (labor supply, increasing wages), (inexperienced) traders (sport cards), Investors, Consumers (insurance), House owners

  3. **Social preferences.** Consumers (giving to charities), Employees (effort, strikes)

4. **Biased Beliefs.** Individual investors, CEOs, Consumers (purchases, betting)

5. **Inattention.** Individual investors, Consumers (eBay bidding, taxation)

6. **Menu Effects.** Individual investors, Consumers (loans, 410(k) plans)

7. **Social Pressure and Persuasion.** Voters, Employees (productivity), Individual investors (and analysts)

8. **Emotions.** Individual investors, Consumers

- What is missing from picture?

- Experienced agents
- Firms
- Broadly speaking, market interactions with ‘rational’ agents

- Market interactions
  - Everyone ‘born’ with biases
  - But: Effect of biases lower if:
    - learning with plenty of feedback
    - advice, access to consulting
    - specialization

    * Competition 'drives out of market' (BUT: See last lecture)

- For which agents are these conditions more likely to be satisfied?

- Firms

- In particular, firms more likely to be aware of biases

- Implications? Study biases in the market

- Six major instances:
  - Interaction between firms and consumers (contract design, price choice — today)
  - Interaction between experienced and inexperienced investors (noise traders and behavioral finance — today or next week)
  - Interaction between managers and investors (corporate finance — next week)
  - Interaction between employers and employees (labor economics — briefly next week)
  - Interaction between politicians and voters (political economy — next week)
  - Institutional design (next week)

6 Market Reaction to Biases: Pricing

- Consider now the case in which consumers purchasing products have biases

- Firm maximize profits

- Do consumer biases affect profit-maximizing contract design?

- How is consumer welfare affected by firm response?

- Analyze first the case of consumers with $\left(\beta, \hat{\beta}, \delta\right)$ preferences

6.1 Self-Control I

MARKET (I). INVESTMENT GOODS

- Monopoly
- Two-part tariff: L (lump-sum fee), p (per-unit price)
- Cost: set-up cost K, per-unit cost a

Consumption of investment good

Payoffs relative to best alternative activity:

- Cost c at $t = 1$, stochastic
  - non-monetary cost
  - experience good, distribution $F(c)$
- Benefit $b > 0$ at $t = 2$, deterministic

FIRM BEHAVIOR. Profit-maximization

$$\max_{L,p} \delta \left\{ L - K + F(\beta\delta b - p)(p - a) \right\}$$

$$\text{s.t. } \beta\delta \left\{ -L + \int_{-\infty}^{\hat{\beta}\delta b - p} (\delta b - p - c)\, dF(c) \right\} \geq \beta\delta\overline{u}$$

- Notice the difference between β and $\hat{\beta}$
- Substitute for L to maximize

$$\max_{L,p} \delta \left\{ \int_{-\infty}^{\hat{\beta}\delta b - p} (\delta b - p - c)\, dF(c) + F(\beta\delta b - p)(p - a) - K - \beta\delta\overline{u} \right\}$$

Solution for the per-unit price p^*:

$$\begin{aligned} p^* &= a && \text{[exponentials]} \\ &-\left(1-\hat{\beta}\right)\delta b \frac{f\left(\hat{\beta}\delta b - p^*\right)}{f\left(\beta\delta b - p^*\right)} && \text{[sophisticates]} \\ &-\frac{F\left(\hat{\beta}\delta b - p^*\right) - F\left(\beta\delta b - p^*\right)}{f\left(\beta\delta b - p^*\right)} && \text{[naives]} \end{aligned}$$

Features of the equilibrium

1. *Exponential agents* $(\beta = \hat{\beta} = 1)$.
   Align incentives of consumers with cost of firm
   $\Longrightarrow$ marginal cost pricing: $p^* = a$.

$$
\begin{aligned}
p^* \;=\;& a && \text{[exponentials]} \\
& - \left(1 - \hat{\beta}\right) \delta b \frac{f\left(\hat{\beta}\delta b - p^*\right)}{f\left(\beta\delta b - p^*\right)} && \text{[sophisticates]} \\
& - \frac{F\left(\hat{\beta}\delta b - p^*\right) - F\left(\beta\delta b - p^*\right)}{f\left(\beta\delta b - p^*\right)} && \text{[naives]}
\end{aligned}
$$

2. *Hyperbolic agents.* Time inconsistency $\Longrightarrow$ below-marginal cost pricing: $p^* < a$.

   (a) *Sophisticates* ($\beta = \hat{\beta} < 1$): commitment.

   (b) *Naives* ($\beta < \hat{\beta} = 1$): overestimation of consumption.

MARKET (II). LEISURE GOODS

Payoffs of consumption at $t = 1$:

- Benefit at $t = 1$, stochastic
- Cost at $t = 2$, deterministic

$\Longrightarrow$ Use the previous setting: $-c$ is "current benefit", $b < 0$ is "future cost."

Results:

1. *Exponential agents.*

   Marginal cost pricing: $p^* = a$, $L^* = K$ (PC).

2. *Hyperbolic agents* tend to overconsume. $\Longrightarrow$

   Above-marginal cost pricing: $p^* > a$. Initial bonus $L^* < K$ (PC).

EXTENSIONS

- *Perfect Competition.* Can write maximization problem as

$$\max_{L,p} - L + \int_{-\infty}^{\hat{\beta}\delta b - p} (\delta b - p - c) \, dF(c)$$
$$\text{s.t. } \delta \{L - K + F(\beta\delta b - p)(p - a)\} = 0$$

  – Implies the same solution for p^*.

- *Heterogeneity.* Simple case of heterogeneity:

  – Share μ of fully naive consumers ($\beta < \hat{\beta} = 1$)

  – Share $1 - \mu$ of exponential consumers ($\beta = \hat{\beta} = 1$)

  – At $t = 0$ these consumers pool on same contract, given no immediate payoffs

- Maximization (with Monopoly):

$$\max_{L,p} \delta \left\{ L - K + \left[\mu F \left(\beta\delta b - p \right) + (1-\mu)\left(\delta b - p\right) \right] (p - a) \right\}$$

$$\text{s.t.} \quad - L + \int_{-\infty}^{\delta b - p} \left(\delta b - p - c \right) dF(c) \geq \overline{u}$$

- Solution:

$$\begin{aligned} p^* &= a \\ &\quad - \mu \frac{F\left(\delta b - p\right) - F\left(\beta\delta b - p\right)}{\mu f\left(\beta\delta b - p\right) + (1-\mu) f\left(\delta b - p\right)} \end{aligned}$$

- The higher the fraction of naives μ, the higher the underpricing of p

EMPIRICAL PREDICTIONS

Two predictions for time-inconsistent consumers:

1. Investment goods (Proposition 1):
   (a) Below-marginal cost pricing
   (b) Initial fee (Perfect Competition)
2. Leisure goods (Corollary 1)
   (a) Above-marginal cost pricing
   (b) Initial bonus or low initial fee (Perfect Competition)

FIELD EVIDENCE ON CONTRACTS

- US Health club industry ($11.6bn revenue in 2000)
  - monthly and annual contracts
  - Estimated marginal cost: $3-$6 + congestion cost
  - Below-marginal cost pricing despite small transaction costs and price discrimination
- Vacation time-sharing industry ($7.5bn sales in 2000)
  - high initial fee: $11,000 (RCI)
  - minimal fee per week of holiday: $140 (RCI)

- Credit card industry ($500bn outstanding debt in 1998)
  - Resale value of credit card debt: 20% premium (Ausubel, 1991)
  - No initial fee, bonus (car / luggage insurance)
  - Above-marginal-cost pricing of borrowing

- Gambling industry: Las Vegas hotels and restaurants:
  - Price rooms and meals below cost, at bonus
  - High price on gambling

WELFARE EFFECTS

Result 1. Self-control problems + Sophistication $\Rightarrow$ First best

- Consumption if $c \leq \beta\delta b - p^*$
- Exponential agent:
  - $p^* = a$
  - consume if $c \leq \delta b - p^* = \delta b - a$
- Sophisticated time-inconsistent agent:
  - $p^* = a - (1 - \beta)\delta b$
  - consume if $c \leq \beta\delta b - p^* = \delta b - a$
- Perfect commitment device
- Market interaction maximizes joint surplus of consumer and firm

Result 2. Self-control + Partial naiveté $\Rightarrow$ Real effect of time inconsistency

- $p^* = a - [F(\delta b - p^*) - F(\beta\delta b - p^*)]/f(\beta\delta b - p^*)$

- Firm sets p^* so as to accentuate overconfidence

- Two welfare effects:
  - Inefficiency: $\text{Surplus}_{\text{naive}} \leq \text{Surplus}_{\text{soph.}}$
  - Transfer (under monopoly) from consumer to firm

- Profits are increasing in naivete' $\hat{\beta}$ (monopoly)

- $\text{Welfare}_{\text{naive}} \leq \text{Welfare}_{\text{soph.}}$

- Large welfare effects of non-rational expectations

6.2 Self-Control II

- Kfir and Spiegler (2004), Contracting with Diversely Naive Agents.

- Extend DellaVigna and Malmendier (2004):

  - incorporate heterogeneity in naiveté

  - allow more flexible functional form in time inconsistency

  - different formulation of naiveté

- Setup:
  1. Actions:
     - Action $a \in [0, 1]$ taken at time 2
     - At time 1 utility function is $u(a)$
     - At time 2 utility function is $v(a)$
  2. Beliefs: At time 1 believe:
     - Utility is $u(a)$ with probability θ
     - Utility is $v(a)$ with probability $1 - \theta$
     - Heterogeneity: Distribution of types θ
  3. Transfers:
     - Consumer pays firm $t(a)$
     - Restrictive assumption: no cost to firm of providing a

- Therefore:
  - Time inconsistency ($\beta < 1$) –> Difference between u and v
  - Naiveté ($\hat{\beta} > \beta$) –> $\theta > 0$
  - Partial naiveté here modelled as stochastic rather than deterministic
  - Flexibility in capturing time inconsistency (self-control, reference dependence, emotions)

- Main result:
- **Proposition 1.** There are two types of contracts:
  1. Perfect commitment device for sufficiently sophisticated agents ($\theta < \underline{\theta}$)
  2. Exploitative contracts for sufficiently naive agents ($\theta > \underline{\theta}$)

- Commitment device contract:
  - Implement $a_\theta = \max_a u(a)$
  - Transfer:
    * $t(a_\theta) = \max_a u(a)$
    * $t(a) = \infty$ for other actions

  - Result here is like in DM: Implement first best

- Exploitative contract:
  - Agent has negative utility:

$$u\left(a_{\theta}^{v}\right) - t\left(a_{\theta}^{v}\right) < 0$$

  - Maximize overestimation of agents:

$$a_{\theta}^{u} = \arg\max\left(u\left(a\right) - v\left(a\right)\right)$$

6.3 Bounded Rationality

- Gabaix and Laibson (2003), *Competition and Consumer Confusion*
- Non-standard feature of consumers:
  - Limited ability to deal with complex products
  - imperfect knowledge of utility from consuming complex goods
- Firms are aware of bounded rationality of consumers
  $\longrightarrow$ design products & prices to take advantage of bounded rationality of consumers

Example: Checking account. Value depends on

- interest rates
- fees for dozens of financial services (overdrafts, more than x checks per months, low average balance, etc.)
- bank locations
- bank hours
- ATM locations
- web-based banking services
- linked products (e.g. investment services)

Given such complexity, consumers do not know the exact value of products they buy.

Model

- Consumers receive noisy, *unbiased* signals about product value.
  - Agent a chooses from n goods.
  - True utility from good i:

$$Q_i - p_i$$

  - Utility signal

$$U_{ia} = Q_i - p_i + \sigma_i \varepsilon_{ia}$$

    σ_i is complexity of product i.

    ε_{ia} is zero mean, iid across consumers and goods, with density f and cumulative distribution F.

    (Suppress consumer-specific subscript a;
    $U_i \equiv U_{ia}$ and $\varepsilon_i \equiv \varepsilon_{ia}$.)

- Consumer decision rule: Picks the one good with highest signal U_i from $(U_i)_{i=1}^n$.

Market equilibrium with exogenous complexity. Bertrand competition with

- Q_i : quality of a good,

  σ_i : complexity of a good,

  c_i : production cost

  p_i : price

- Simplification: Q_i, σ_i, c_i identical across firms. (*Problem: How should consumers choose if all goods are known to be identical?*)

- Firms maximize profit $\pi_i = (p_i - c_i)\, D_i$

- Symmetry reduces demand to

$$D_i = \int f(\varepsilon_i)\, F\left(\frac{p_j - p_i + \sigma\varepsilon_i}{\sigma}\right)^{n-1} d\varepsilon_i$$

Example of demand curves

Gaussian noise $\varepsilon \sim N\,(0{,}1)$, 2 firms

Demand curve faced by firm 1:

$$
\begin{aligned}
D_1 &= P\left(Q - p_1 + \sigma\varepsilon_1 > Q - p_2 + \sigma\varepsilon_2\right) \\
&= P\left(p_2 - p_1 > \sigma\sqrt{2}\eta\right) \text{ with } \eta = \left(\varepsilon_2 - \varepsilon_1\right)/\sqrt{2}\ \mathrm{N(0,1)} \\
&= \Phi\left(\frac{p_2 - p_1}{\sigma\sqrt{2}}\right)
\end{aligned}
$$

Usual Bertrand case $(\sigma = 0)$: infinitely elastic demand at $p_1 = p_2$

$$
D_1 \in \left\{ \begin{array}{ccc} 1 & \text{if} & p_1 < p_2 \\ [0,1] & \text{if} & p_1 = p_2 \\ 0 & \text{if} & p_1 > p_2 \end{array} \right\}
$$

Complexity case ($\sigma > 0$) : Smooth demand curve, no infinite drop at $p_1 = p_2$. At $p_1 = p_2 = p$ demand is $1/2$.

$$\max_{p_1} \Phi\left(\frac{p_2 - p_1}{\sigma\sqrt{2}}\right)[p_1 - c_1]$$

$$f.o.c. : -\frac{1}{\sigma\sqrt{2}}\phi\left(\frac{p_2 - p_1}{\sigma\sqrt{2}}\right)[p_1 - c_1] + \Phi\left(\frac{p_2 - p_1}{\sigma\sqrt{2}}\right) = 0$$

Intuition for non-zero mark-ups: Lower elasticity increases firm mark-ups and profits. Mark-up proportional to complexity σ.

Endogenous complexity

- Consider Normal case –> For $\sigma \to \infty$

$$\max_{p_1} \Phi\left(\frac{p_2 - p_1}{\sigma\sqrt{2}}\right)[p_1 - c_1] \to \max_{p_1} \frac{1}{2}[p_1 - c_1]$$

Set $\sigma \to \infty$ and obtain infinite profits by letting $p_1 \to \infty$

(Choices are random, Charge as much as possible)

- Gabaix and Laibson: Concave returns of complexity $Q_i(\sigma_i)$

  Firms increase complexity, unless "clearly superior" products in model with heterogenous products.

In a nutshell: market does not help to overcome bounded rationality. Competition may not help either

- More work on Behavioral IO:
- **Heidhus-Koszegi (2006, 2007)**
  - Incorporate reference dependence into firm pricing
  - Assume reference point rational exp. equilibrium (**Koszegi-Rabin**)
  - Results on
    * Price compression (consumers hate to pay price higher than reference point)
    * But also: Stochastic sales
- **Gabaix-Laibson (1996)**
  - Consumers pay attention to certain attributes, but not others (Shrouded attributes)

  - Form of limited attention
  - Firms charge higher prices on shrouded attributes (add-ons)
  - Similar to result in **DellaVigna-Malmendier (2004)**: Charge more on items consumers do not expect to purchase

- **Ellison (2006):** Early, very concise literature overview

- Future work: *Empirical Behavioral IO*
  - Document non-standard behavior
  - Estimate structurally
  - Document firm response to non-standard feature

7 Market Reaction to Biases: Employers

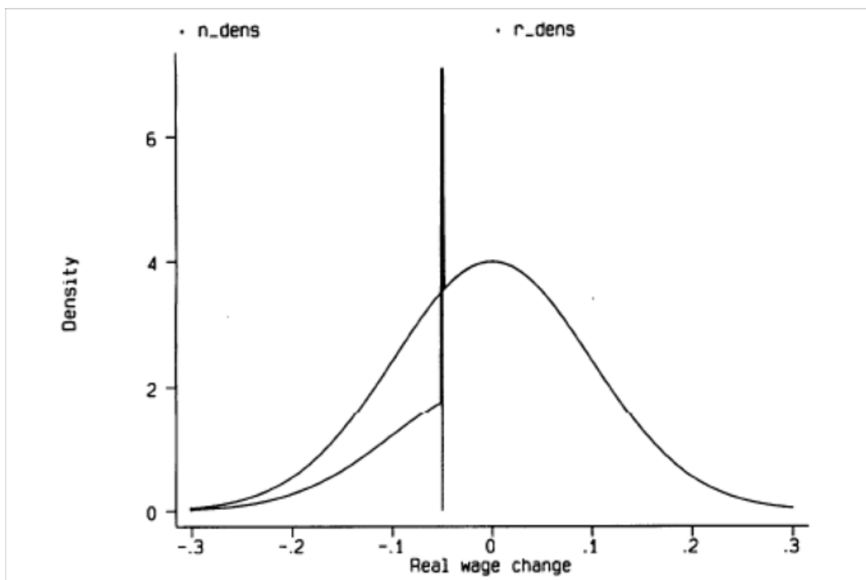
- Employee dislike for nominal wage cuts
- **Kahneman, Knetsch and Thaler (1986)**: Telephone surveys in Canada in 1984 and 1985 –> Ask questions on fairness

Question 4A. A company is making a small profit. It is located in a community experiencing a recession with substantial unemployment but no inflation. There are many workers anxious to work at the company. The company decides to decrease wages and salaries 7% this year.
($N = 125$) Acceptable 38% Unfair 62%

Question 4B. ...with substantial unemployment and inflation of 12%...The company decides to increase salaries only 5% this year.
($N = 129$) Acceptable 78% Unfair 22%

- A real and nominal wage cut is not fair (Question 4A)
- A real (but not nominal) wage cut is fair (Question 4B)

- If this is true, expect employers to minimize cases of $w_t - w_{t-1} < 0$
- **Card and Hyslop, 1997**: Examine discontinuity around 0 of nominal wage changes
- Prediction of theory:



- Data sources:
  - 1979-1993 CPS.
    * Rolling 2-year panel
    * Restrict to paid by the hour and to same 2-digit industry in the two years
    * Restrict to non-minimum wage workers
  - PSID 4-year panels 1976-79 and 1985-88
- Use Log Wage changes: $\log w_t - \log w_{t-1}$
- Issue with measurement error and heaping at $\log w_t - \log w_{t-1} = 0$
- Construct counterfactual density of LogWage changes
  - Assume symmetry
  - Positive log wage changes would not be affected

- Plots using kernel estimates of density (local smoother)
- Compare the actual distribution and the predicted one
- Evidence from the CPS year-by-year
- Problem more severe in years with lower inflation

- Large effect of nominal rigidities
- Effect on firings?

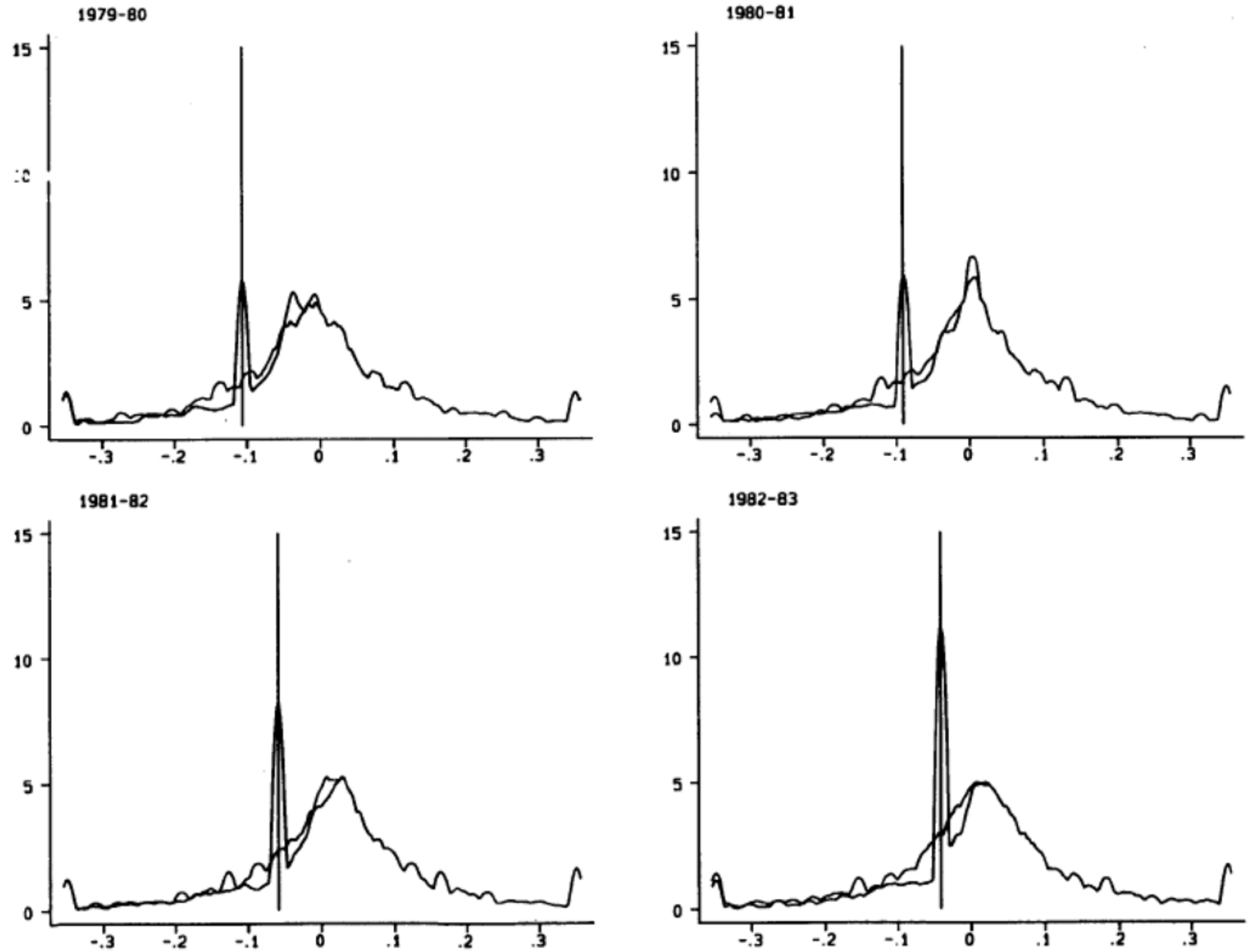


Figure 4: Smoothed (Kernel) Estimates of Actual and Counterfactual Densities of Real Wage Changes, CPS Samples from 1979-80 to 1982-83

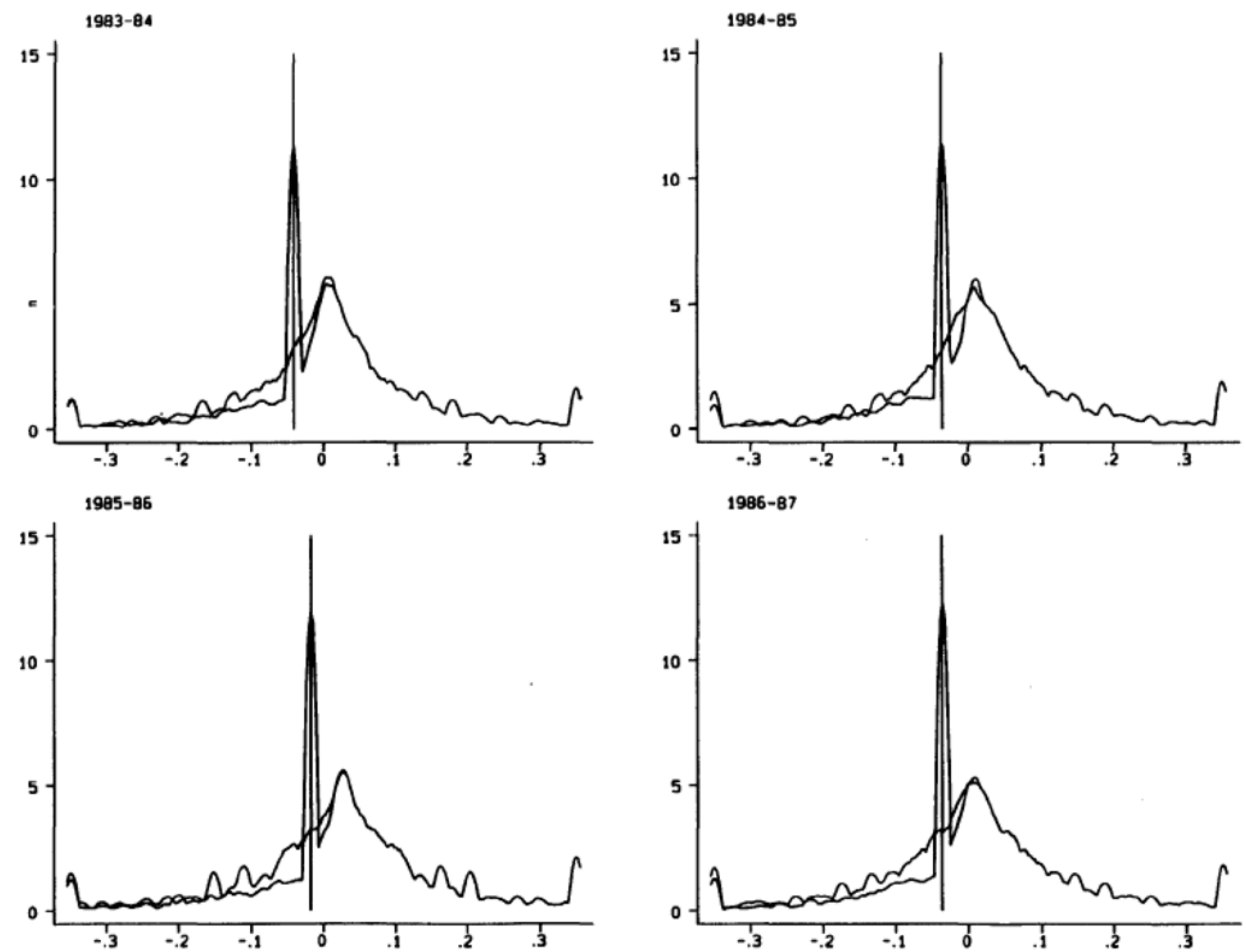


Figure 4 (Continued): Smoothed (Kernel) Estimates of Actual and Counterfactual Densities of Real Wage Changes, CPS Samples from 1983-84 to 1986-87

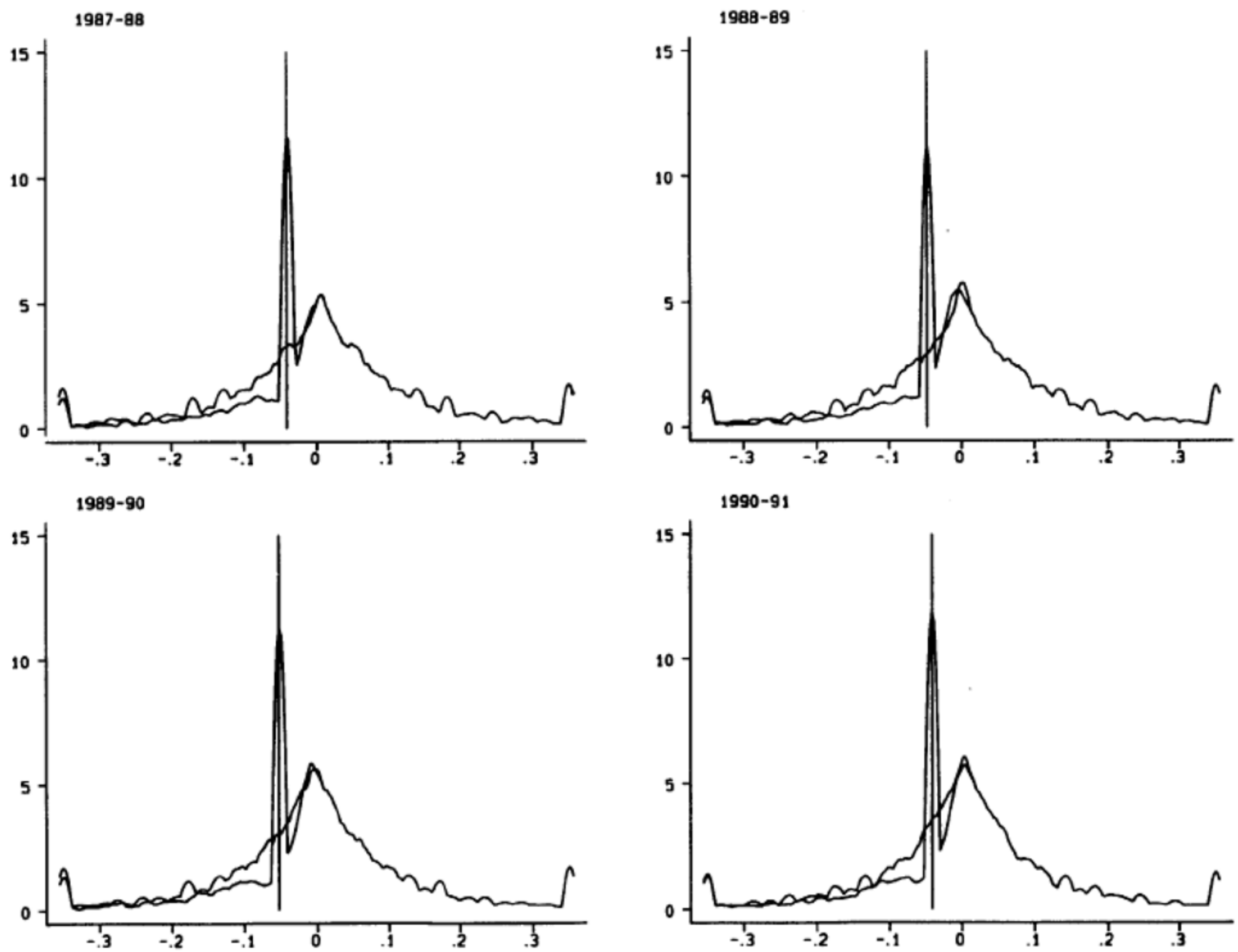


Figure 4 (Continued): Smoothed (Kernel) Estimates of Actual and Counterfactual Densities of Real Wage Changes, CPS Samples from 1987-88 to 1990-91

8 Market Reaction to Biases: Political Economy

- Interaction between:
  - (Smart) Politicians:
    * Personal beliefs and party affiliation
    * May pursue voters/consumers welfare maximization
    * BUT also: strong incentives to be reelected
  - Voters (with biases):
    * Low (zero) incentives to vote
    * Limited information through media
    * Likely to display biases
- **Behavioral political economy**

- Examples of voter biases:
  - Effect of candidate order (Ho and Imai)
  - Imperfect signal extraction (Wolfers, 2004) –> Voters more likely to vote an incumbent if the local economy does well even if... it's just due to changes in oil prices
  - Susceptible to persuasion (DellaVigna and Kaplan, 2007)
  - More? Short memory about past performance?
- **Eisensee and Stromberg (2007)**: Limited attention of voters

- Setting:
  - Natural Disasters occurring throughout the World
  - US Ambassadors in country can decide to give Aid
  - Decision to give Aid affected by
    * Gravity of disaster
    * Political returns to Aid decision
- Idea: Returns to aid are lower when American public is distracted by a major news event

- Main Measure of Major News: median amount of Minutes in Evening TV News captured by top-3 news items (Vanderbilt Data Set)

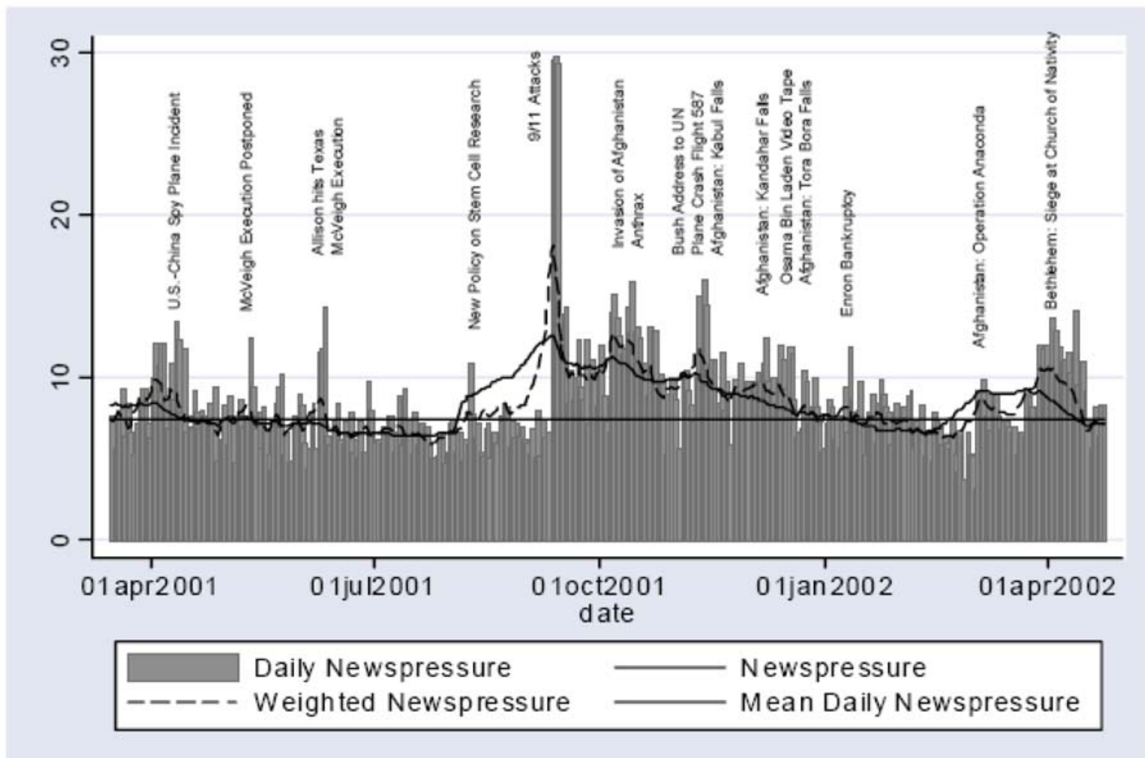


FIGURE IV
News Pressure (Minutes) during 405 Days, 15 March 2001 – 23 Apr 2002, by Day

- Dates with largest news pressure

TABLE III

DATES OF TWO LARGEST *daily news pressure* AND MAIN STORY, BY YEAR

Year	Date	Main News Story
2003	14 Aug	*New York City Blackout*
	22 Mar	*Invasion of Iraq: Day 3*
2002	11 Sep	*9/11 Commemoration*
	24 Oct	*Sniper Shooting in Washington: Arrest of Suspects*
2001	13 Sep	*9/11 Attack on America: Day 3*
	12 Sep	*9/11 Attack on America: Day 2*
2000	26 Nov	*Gore vs. Bush: Florida Recount - Certification by Katherine Harris*
	8 Dec	*Gore vs. Bush: Florida Recount - Supreme Court Ruling*
1999	1 Apr	*Kosovo Crisis: U.S. Soldiers Captured*
	18 Jul	*Crash of Plane Carrying John F. Kennedy, Junior*
1998	16 Dec	*U.S. Missile Attack on Iraq*
	18 Dec	*Clinton Impeachment*
1997	23 Dec	*Oklahoma City Bombing: Trial*
	31 Aug	*Princess Diana's Death*
1996	18 Jul	*TWA Flight 800 Explosion*
	27 Jul	*Olympic Games Bombing in Atlanta*
1995	3 Oct	*O.J. Simpson Trial: The Verdict*
	22 Apr	*Oklahoma City Bombing*
1994	17 Jan	*California Earthquake*
	18 Jun	*O.J. Simpson Arrested*
1993	17 Jan	*U.S. Missile Attack on Iraq*
	20 Apr	*Waco, Texas: Cult Standoff Ends in Fire*
1992	16 Jul	*Perot Quits 1992 Presidential Campaign*
	1 May	*Los Angeles Riots*

- 5,000 natural Disasters in 143 countries between 1968 and 2002 (CRED)
  - 20 percent receive USAID from Office of Foreign Disaster Assistance (first agency to provide relief)
  - 10 percent covered in major broadcast news
  - OFDA relief given if (and only if) Ambassador (or chief of Mission) in country does Disaster Declaration
  - Ambassador can allocate up to $50,000 immediately
- Estimate

$$\mathrm{Re}\,lief = \alpha News + \beta X + \varepsilon$$

- Below: $News$ about the Disaster is instrumented with:
  - Average News Pressure over 40 days after disaster
  - Olympics

TABLE IV

EFFECT OF THE PRESSURE FOR NEWS TIME ON DISASTER *News* AND *Relief*

	Dependent variable: *News*				Dependent variable: *Relief*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
News Pressure	-0.0162	-0.0163	-0.0177	-0.0142	-0.0117	-0.0119	-0.0094	-0.0078
	(0.0041)***	(0.0041)***	(0.0057)***	(0.0037)***	(0.0045)***	(0.0045)***	(0.0058)	(0.0040)**
Olympics	-0.1078	-0.1079	-0.0871	-0.111	-0.1231	-0.1232	-0.1071	-0.1098
	(0.0470)**	(0.0470)**	(-0.0628)	(0.0413)***	(0.0521)**	(0.0521)**	(0.0763)	(0.0479)**
World Series	-0.1133				-0.1324			
	(-0.1065)				(0.1031)			
log Killed			0.0605				0.0582	
			(0.0040)***				(0.0044)***	
log Affected			0.0123				0.0376	
			(0.0024)***				(0.0024)***	
imputed log Killed				0.0491				0.0442
				(0.0034)***				(0.0037)***
imputed log Affected				0.0151				0.0394
				(0.0020)***				(0.0020)***
Observations	5212	5212	2926	5212	5212	5212	2926	5212
R-squared	0.1799	0.1797	0.3624	0.2875	0.1991	0.1989	0.4115	0.3726

Linear probability OLS regressions. All regressions include year, month, country and disaster type fixed effects. Regressions with imputed values ((4) and (8)) also include fixed effects for the interaction of missing values and disaster type. Robust standard errors in parentheses:* significant at 10%; ** significant at 5%; *** significant at 1%.

- First-Stage: 2 s.d increase in News Pressure (2.4 extra minutes) decrease
  - probability of coverage in news by 4 ptg. points (40 percent)
  - probability of relief by 3 ptg. points (15 percent)

- Is there a spurious correlation between instruments and type of disaster?

- No correlation with severity of disaster

TABLE V

CORRELATIONS BETWEEN INSTRUMENTS AND THE SEVERITY OF DISASTERS

	Dependent variable	
	News Pressure	*Olympics*
log Killed	-0.0082	0.0003
	(0.0113)	(0.0010)
log *Affected*	0.0005	-0.0006
	(0.0068)	(0.0006)
p-value: F-test of joint insignificance	0.75	0.62
Observations	5212	5212
R-squared	0.3110	0.2035

OLS regressions with the instruments *News Pressure* and *Olympics* as dependent variables, and including year, month, country and disaster type fixed effects. Robust standard errors in parentheses:* significant at 10%; ** significant at 5%; *** significant at 1%. The F-test tests the joint significance of log *Killed* and log *Affected* in the regression.

- OLS and IV Regressions of Reliefs on presence in the News
- (Instrumented) availability in the news at the margin has huge effect: Almost one-on-one effect of being in the news on aid

TABLE VI

DEPENDENT VARIABLE: *Relief*

	OLS					IV		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
News	0.2886	0.158	0.1309	0.2323	0.2611	0.8237	0.6341	0.6769
	(0.0200)***	(0.0232)***	(0.0178)***	(0.0328)***	(0.0569)***	(0.2528)***	(0.3341)*	(0.2554)***
News*abs(Pr(news)-0.5)				-0.4922	-0.302			
				(0.1059)***	(0.0840)***			
abs(Pr(news)-0.5)				0.5374	0.2959			
				(0.0943)***	(0.0831)***			
log Killed		0.0486					0.0198	
		(0.0046)***					-0.0208	
log Affected		0.0358					0.0299	
		(0.0024)***					(0.0048)***	
imputed log Killed			0.0378	0.0546	0.0307			0.0109
			(0.0038)***	(0.0049)***	(0.0046)***			-0.0132
imputed log Affected			0.0375	0.0445	0.0345			0.0292
			(0.0020)***	(0.0023)***	(0.0026)***			(0.0045)***
F-stat, instruments, 1st stage						11.0	6.1	11.1
Over-id restrictions, χ^2_{df} (p-value)						0.51_1(0.47)		0.64_1 (0.42)
Observations	5212	2926	5212	5212	5027	5212	2926	5212
R-squared	0.2443	0.4225	0.3800	0.3860				

All regressions include year, month, country, and disaster type fixed effects. Regressions with imputed values ((3), (4) and (5)) also include fixed effects for the interaction of missing values and disaster type. Robust standard errors in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%.

- Second example: Theory/History paper, **Glaeser (2005)** on Political Economy of Hatred
- Idea: Hatred has demand side and supply side
  - Demand side:
    - Voters are susceptible to hatred (experiments: ultimatum game)
    - Media can mediate hatred
  - Supply side:
    - Politicians maximize chances of reelection
    - Set up a hatred media campaign toward a group for electoral gain
    - In particular, may target non-median voter

- Idea:
  - Group hatred can occur, but does not tend to occur naturally
  - Group hatred can be due to political incentives
  - Example 1: *African Americans in South, 1865-1970*
    - No hatred before Civil War
    - Conservative politicians foment it to lower demand for redistribution
    - Diffuse stories of violence by Blacks
  - Example 2: *Hatred of Jews in Europe, 1930s*
    - No hatred before 1920
    - Jews disproportionately left-wing
    - Right-wing Hitler made up Protocol of Elders of Zion

9 Next Lecture

- More Market Response to Biases

  - Investors: Behavioral Finance

  - Managers: Corporate Decisions

  - Welfare Response to Biases

- Methodology of Field Psychology and Economics

- Concluding Remarks