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

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Outline

1. Emotions: Mood
2. Emotions: Arousal
3. Methodology: Lab and Field
4. Methodology: Human Subjects Approval
5. Market Reaction to Biases: Introduction
6. Market Reaction to Biases: Pricing
7. Methodology: Markets and Non-Standard Behavior
8. Market Reaction to Biases: Corporate Decisions

1 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

2 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 (2009)**: Field evidence — Exploit timing of release of blockbuster violent movies

- **Model.** Consumer chooses between strongly violent movie a^v, mildly violent movie a^m, non-violent movie a^n, or alternative social activity a^s
  - Utility depends on quality of movies –> Demand functions $P(a^j)$

- Heterogeneity:
  - High taste for violence (Young): N_y consumers
  - Low taste for violence (Old): N_o consumers
  - Aggregate demand for group i: $N_i P(a_i^j)$

- Production function of violence V (not part of utility fct.) depends on a^v, a^m, a^n, and a_s:

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

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

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

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

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

- First point — Estimate of net effect
  - Direct effect: Increase in violent movie exposure –> α^v_i
  - 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:

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

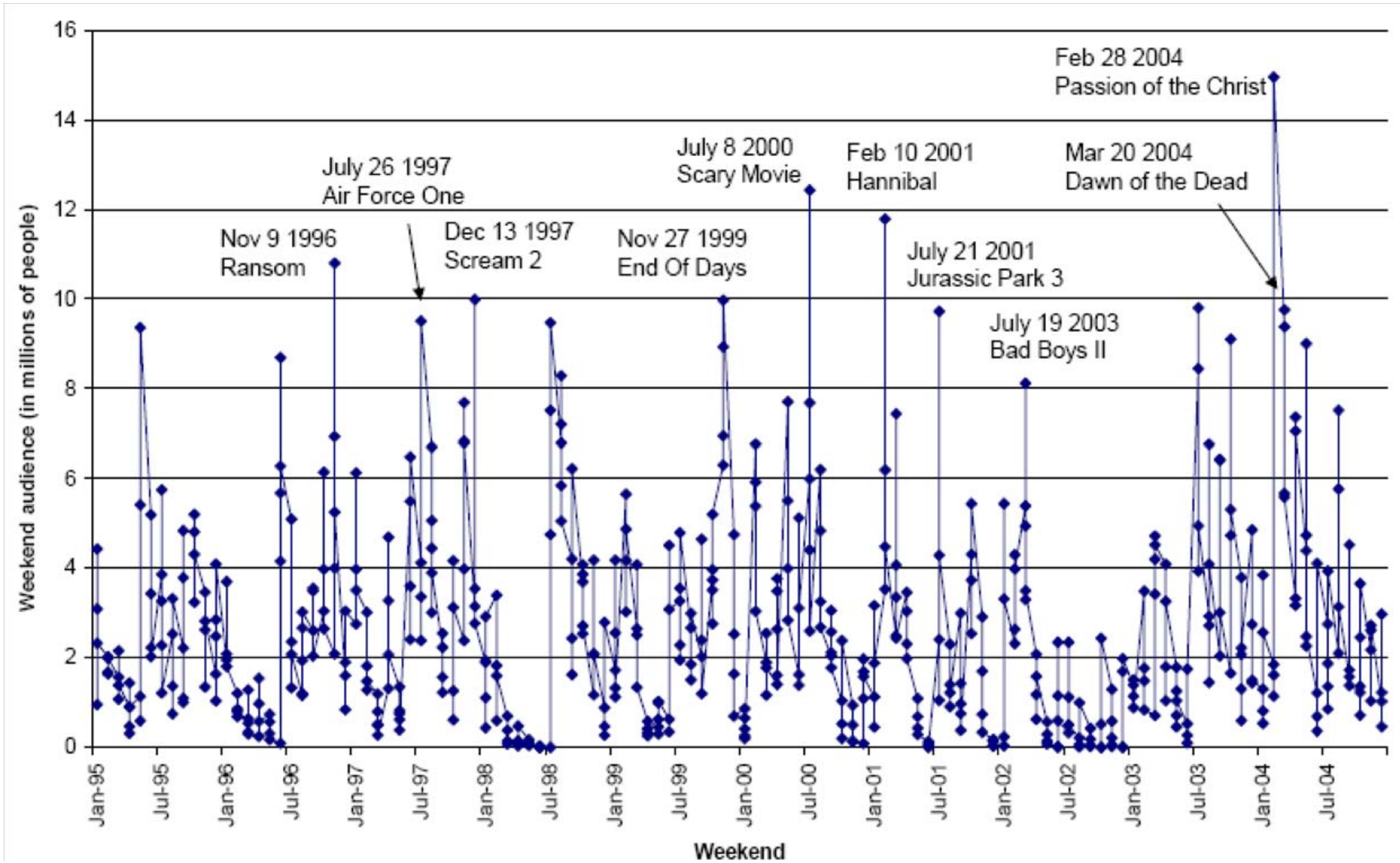
  - Psychology Experiments. Manipulate a directly, holding constant a^s out of equilibrium

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

- 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)



Weekend audience (in millions of people)
16
14
12
10
8
6
4
2
0
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
Jan-95
Jul-95
Jan-96
Jul-96
Jan-97
Jul-97
Jan-98
Jul-98
Jan-99
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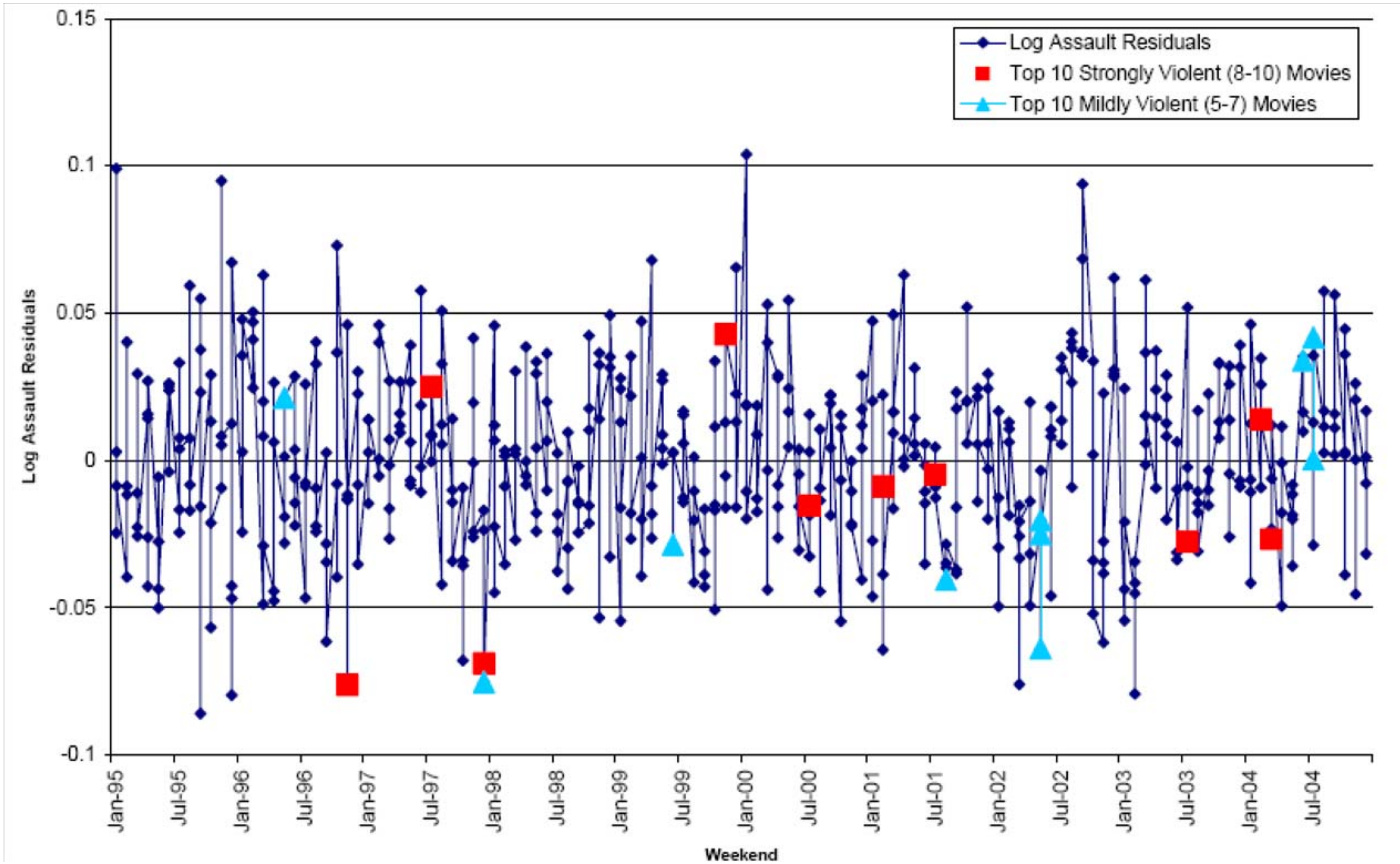
Jul-03
Jan-04
Jul-04
Weekend



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

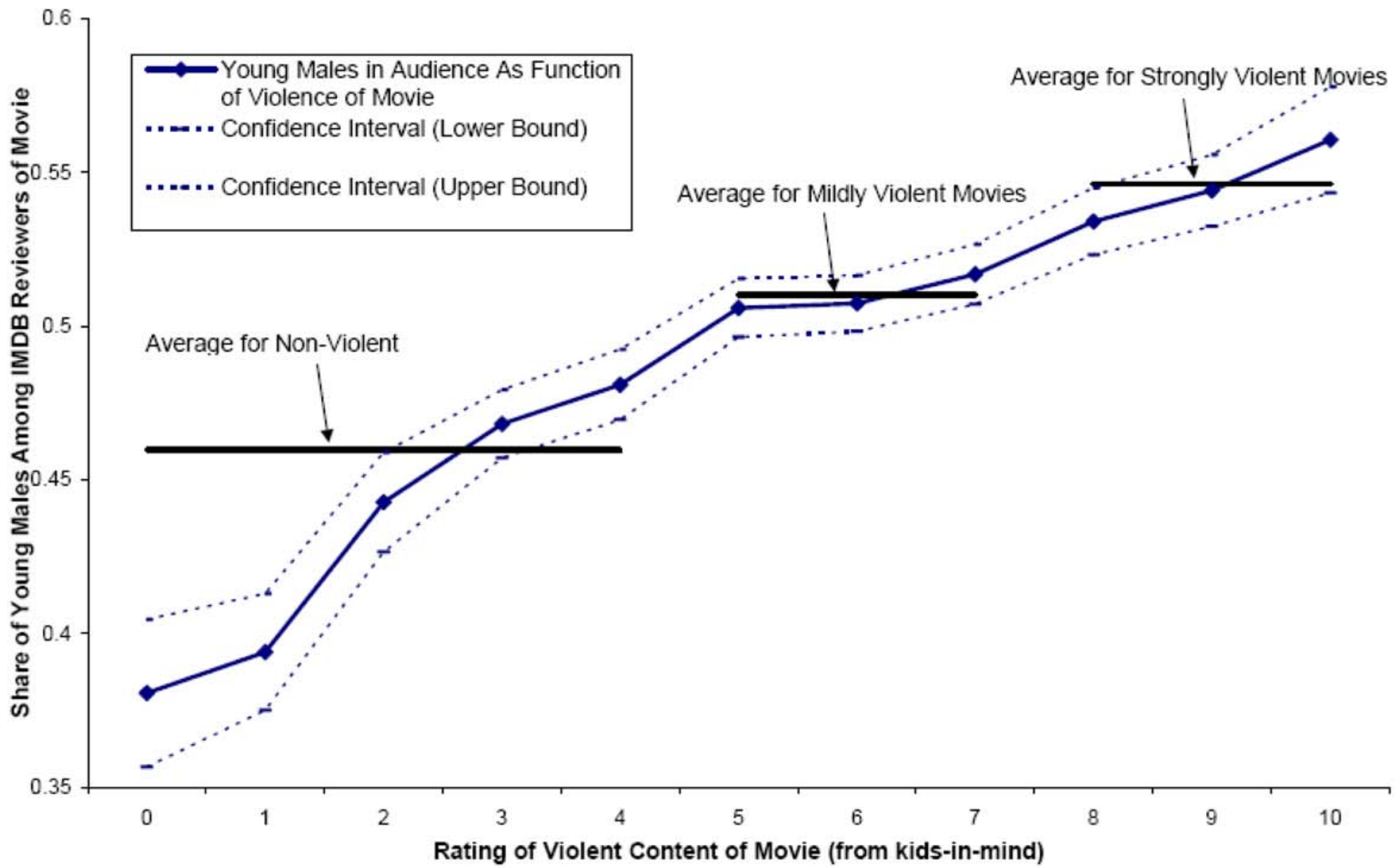
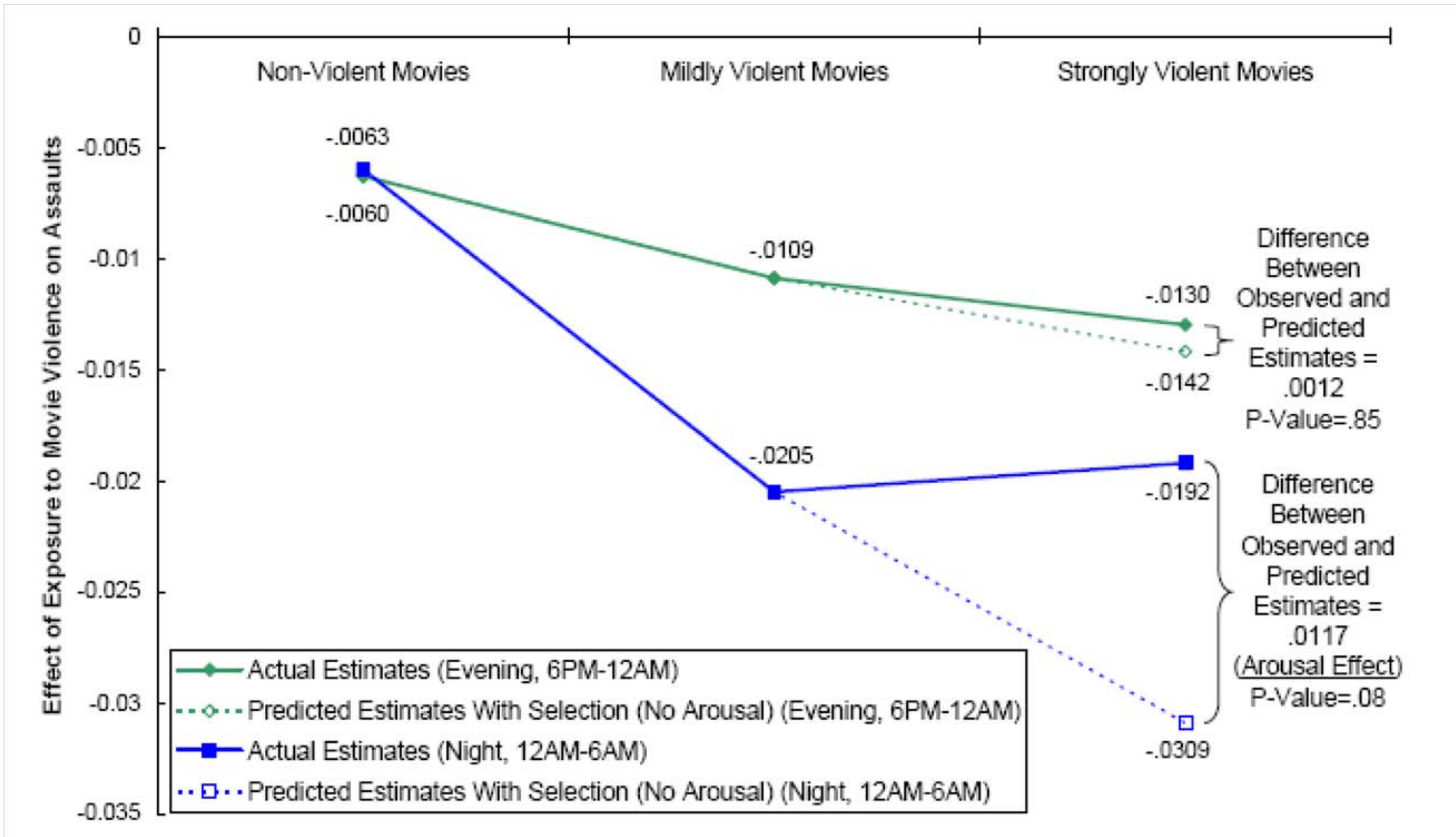


FIGURE II
Share of Young Males in Audience As Function of Movie Violence (Internet Movie Database Data)



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?

3 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

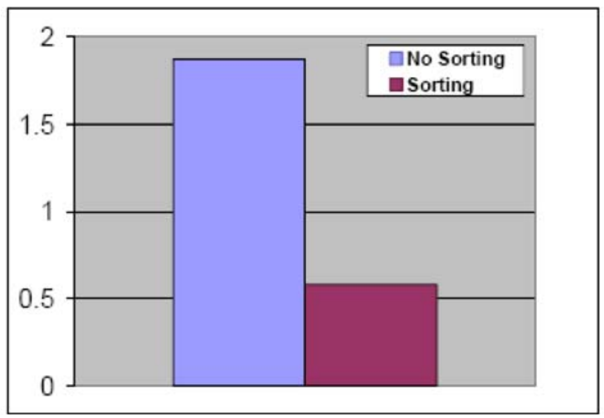
- Notice: One can integrate sorting into laboratory experiments

- **Lazear-Malmendier-Weber (2012)** (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 experiments vs. violent crime

- However:
  - Evidence not consistent that large stakes change behavior
  - In field, many repeated interactions, all with small stakes

4 Human Subjects Approval

Dan Acland's notes

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?

- **DellaVigna and Malmendier (2004).** 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

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

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

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

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

Solution for the per-unit price p^*:

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

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):

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

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

- Solution:

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

- 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 (RES 2006),** 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 $a_\theta = \mathsf{max}_a\, u(a)$
  - Transfer:
    - $t(a_\theta) = \mathsf{max}_a\, u(a)$
    - $t(a) = \infty$ 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 $\varepsilon \sim N\left(0{,}1\right)$, 2 firms

Demand curve faced by firm 1:

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

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 (2006)**

  - 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, concise literature overview

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

7 Methodology: Markets and Non-Standard Behavior

- Why don't market forces eliminate non-standard behavior?
- Common Chicago-type objection
- **Argument 1.** Experience reduces non-standard behavior.
  - Experience appears to mitigate the endowment effect (List, 2003 and 2004).
  - Experience improves ability to perform backward induction (Palacios-Huerta and Volji, 2007 and 2008)
  - BUT: Maybe experience does not really help (Levitt, List, and Reiley, 2008)

- What does experience imply in general?
  * Feedback is often infrequent (such as in house purchases) or noisy (such as in financial investments) –>not enough room for experience
  * Experience can exacerbate a bias if individuals are not Bayesian learners (Haigh and List 2004)
  * Not all non-standard features should be mitigated by experience. Example: social preferences
  * Debiasing by experienced agents can be a substitute for direct experience. However, as Gabaix and Laibson (2006) show, experienced agents such as firms typically have little or no incentive to debias individuals

- *Curse of Debiasing* (Gabaix-Laibson 2006)
  - Credit Card A teaser fees on $1000 balance:
    - $0 for six months
    - $100 fee for next six months
  - Cost of borrowing to company $100 –> Firm makes 0 profit in Perfectly Competitive market
  - Naive consumer:
    - Believes no borrowing after 6 months
    - Instead keeps borrowing
    - Expects cost of card to be $0, instead pays $100

- Can Credit Card B debias consumers and profit from it?
  - Advertisement to consumers: 'You will borrow after 6 months!'
  - Offer rate of
    - $50 for six months
    - $50 for next six months
- What do consumers (now sophisticated) do?
  - Stay with Card A
    - Borrow for 6 months at $0
    - Then switch to another company
- No debiasing in equilibrium

- System of transfers:
  - Firms take advantage of naive consumers
  - Sophisticated consumers benefit from naive consumers
- Related: Suppose Credit Card B can identify naive consumer
  - What should it do?
  - If debias, then lose consumer
  - Rather, take advantage of consumer

- **Argument 2.** Even if experience or debiasing do not eliminate the biases, the biases will not affect aggregate market outcomes
  - Arbitrage –> Rational investors set prices
  - However, limits to arbitrage (DeLong et al., 1991) –> individuals with non-standard features affect stock prices
  - In addition, in most settings, there is no arbitrage!
    * Example: Procrastination of savings for retirement
    * (Keep in mind SMRT plan though)
  - Behavioral IO: Non-standard features can have a disproportionate impact on market outcomes
    * Firms focus pricing on the biases
    * **Lee and Malmendier (2011)** on overbidding in eBay auctions

Table V. Disproportionate Influence of Overbidders

		Observations	(Percent)
Auction-level sample			
Does the auction end up overbid?	No	78	56.52%
	Yes	60	**43.48%**
Total		138	100.00%
Bidder-level sample			
Does the bidder ever overbid?	No	670	83.02%
	Yes	137	**16.98%**
Total		807	100.00%
Bid-level sample			
Is the bid an over-bid?	No	2,101	89.29%
	Yes	252	**10.71%**
Total		2,353	100.00%

Overbidding is defined using the final price.

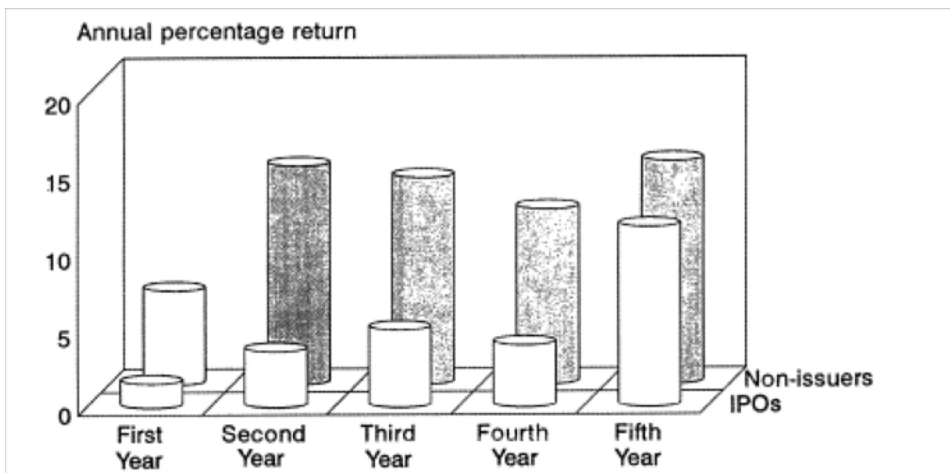
- Bidders with bias have *disproportionate* impact
- Opposite of Chicago intuition

8 Market Reaction to Biases: Corporate Decisions

- **Baker, Ruback, and Wurgler (2005)**
- Behavioral corporate finance:
  - biased investors (overvalue or undervalue company)
  - smart managers
  - (Converse: biased (overconfident) managers and rational investors)
- Firm has to decide how to finance investment project:
  1. internal funds (cash flow/retained earnings)
  2. bonds
  3. stocks

- Fluctuation of equity prices due to noise traders
- Managers believe that the market is inefficient
  - Issue equity when stock price exceeds perceived fundamental value
  - Delay equity issue when stock price below perceived fundamental value
- Consistent with
  - Survey Evidence of 392 CFO's (Graham and Harvey 2001): 67% say under/overvaluation is a factor in issuance decision
  - Insider trading
- Go over quickly two examples

- **Long-run performance of equity issuers**
  - Market Timing prediction: Companies issuing equity underperform later
  - Loughran-Ritter (1995): Compare matching samples of
    * companies doing IPOs
    * companies not doing IPOs but have similar market cap.



- Similar finding with SEOs

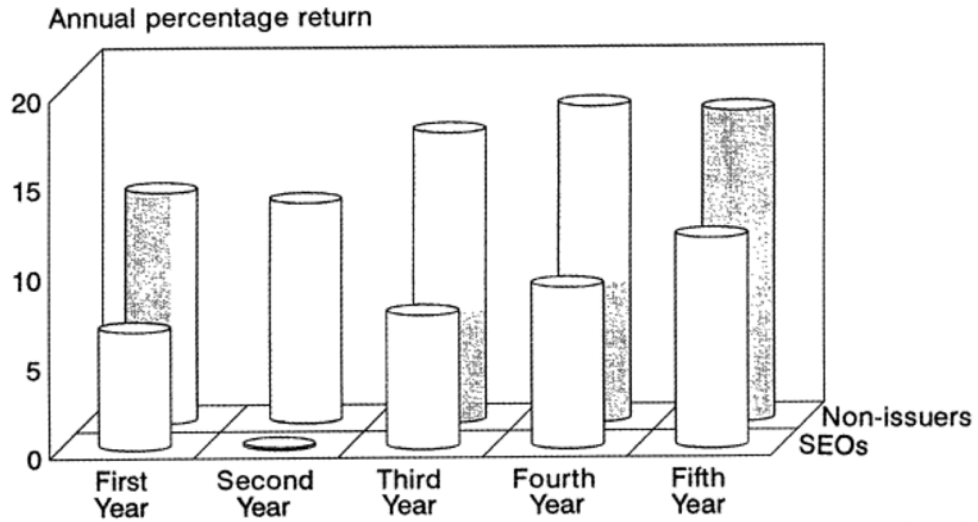


Figure 2. The average annual raw returns for 4,753 initial public offerings (IPOs), and their matching nonissuing firms (top), and the average annual raw returns for 3,702 seasoned equity offerings (SEOs), and their matching nonissuing firms (bottom), during the five years after the issue. The equity issues are from 1970 to 1990. Using the first closing postissue market price, the equally weighted average buy-and-hold return for the year after the issue is calculated for the issuing firms and for their matching firms (firms with the same market capitalization that have not issued equity during the prior five years). On each anniversary of the issue date, the equally weighted average buy-and-hold return during the next year for all of the surviving issuers and their matching firms is calculated. For matching firms that get delisted (or issue equity) while the issuer is still trading, the proceeds from the sale on the delisting date are reinvested in a new matching firm for the remainder of that year (or until the issuer is delisted). The numbers graphed above are reported in Table III.

9 Next Lecture

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