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

Stefano DellaVigna

April 11, 2012

Outline

1. Emotions: Arousal
2. Methodology: Lab and Field
3. Methodology: Human Subjects Approval
4. Market Reaction to Biases: Introduction
5. Market Reaction to Biases: Corporate Decisions
6. Market Reaction to Biases: Employers

1 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:

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

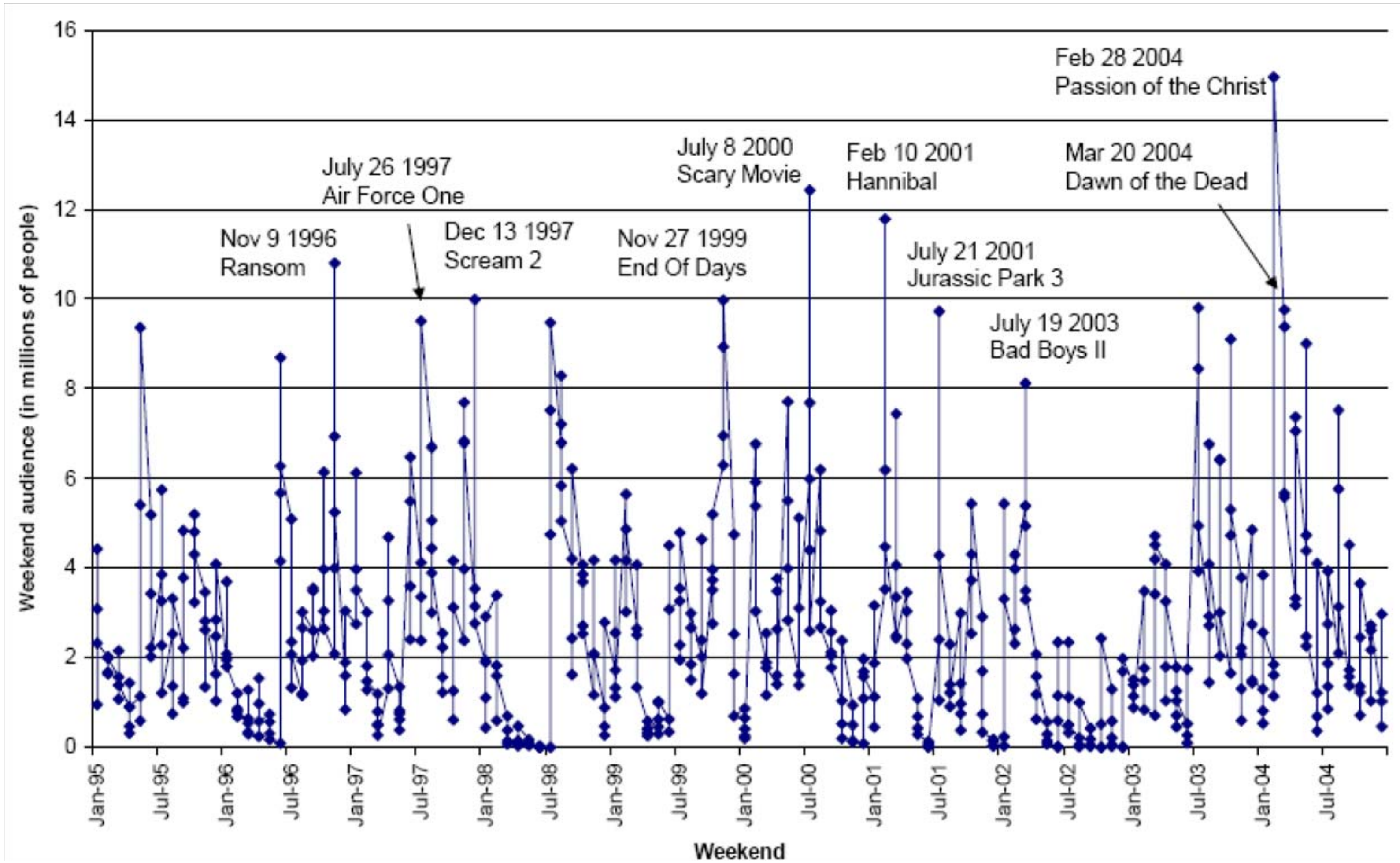
  - Psychology Experiments. Manipulate a directly, holding constant a^s out of equilibrium

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

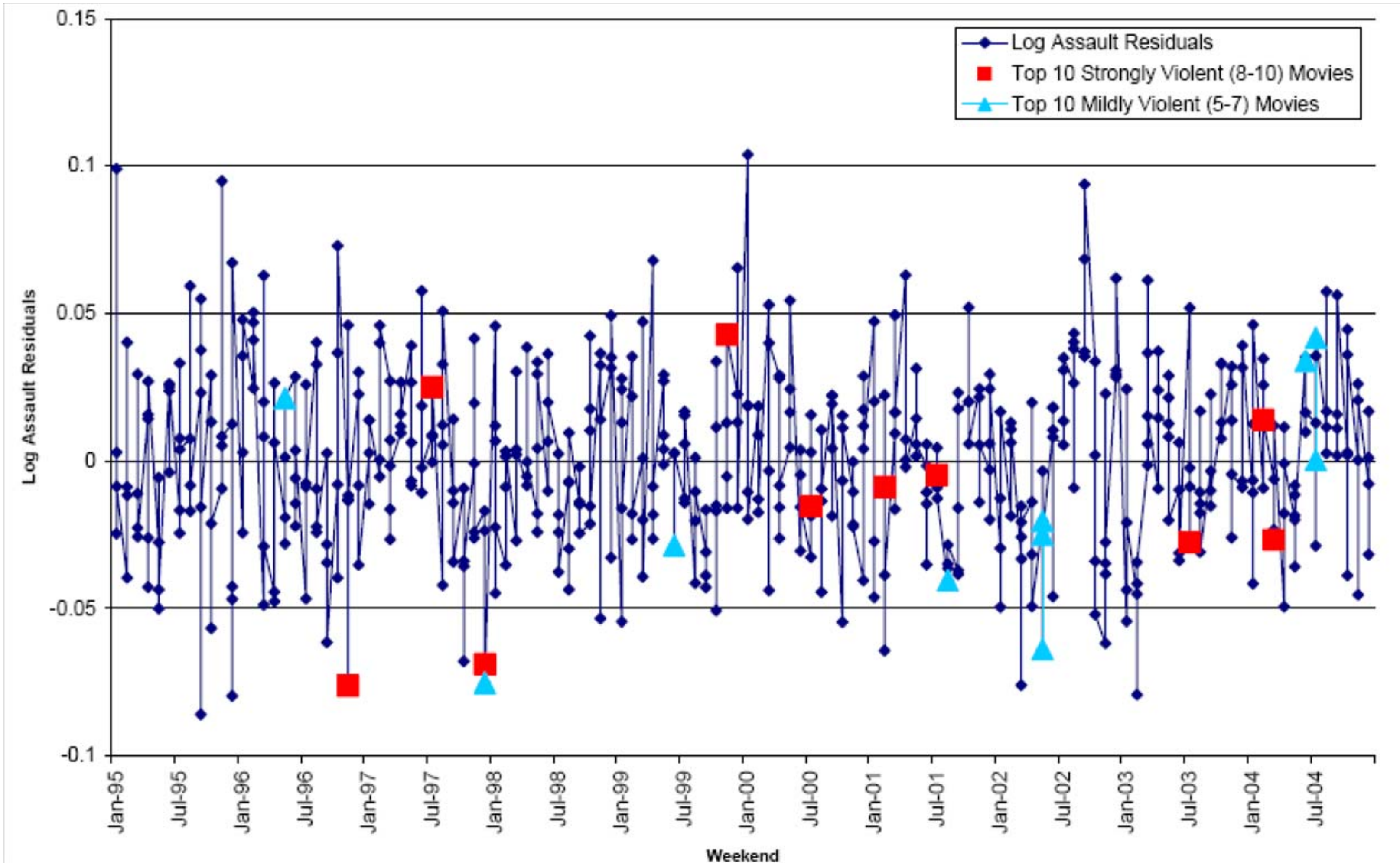
- Two differences:
  - 'Shut down' alternative activity, and hence σ_i does not appear
  - Weights representative of (student) population, not of population that selects into violent movies

- **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)



Weekend audience (in millions of people)
Weekend
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
0
2
4
6
8
10
12
14
16
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



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

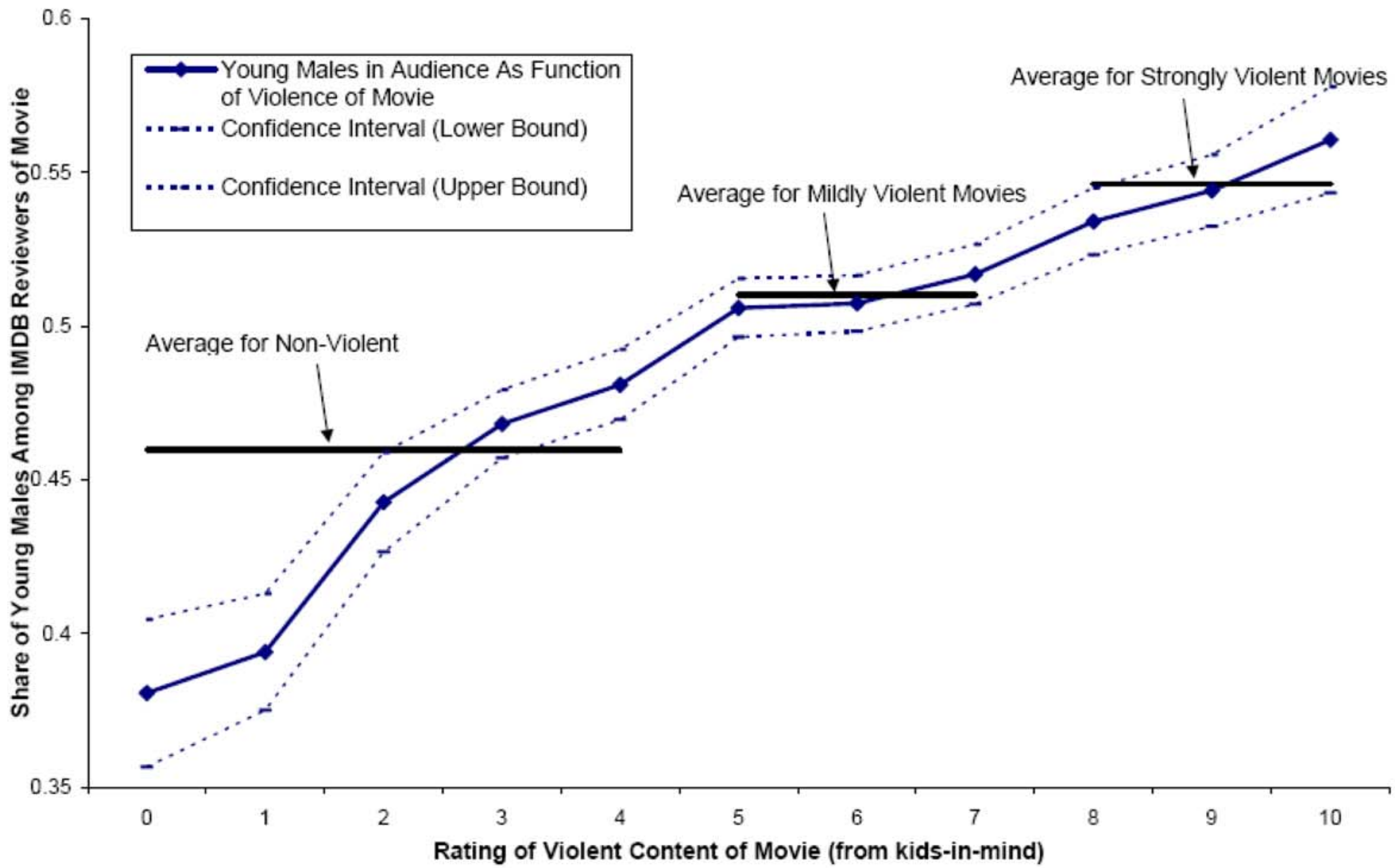
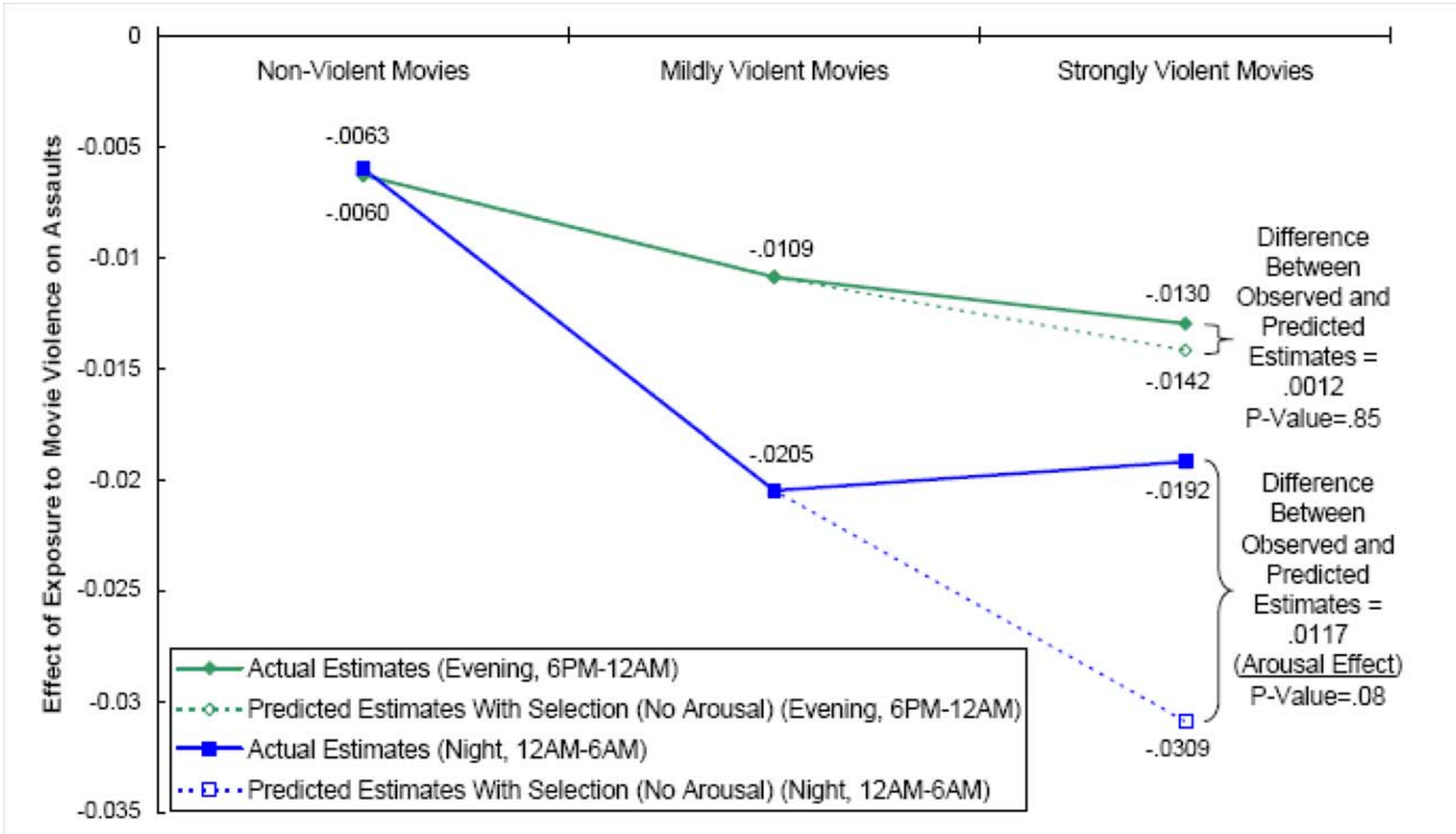


FIGURE II

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?

2 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

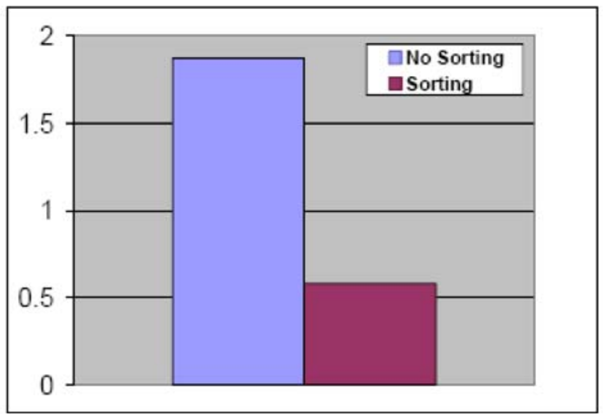
- Notice: One can integrate sorting into laboratory experiments

- **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 experiments vs. violent crime

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

3 Human Subjects Approval

Dan Acland's notes

4 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)

5 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

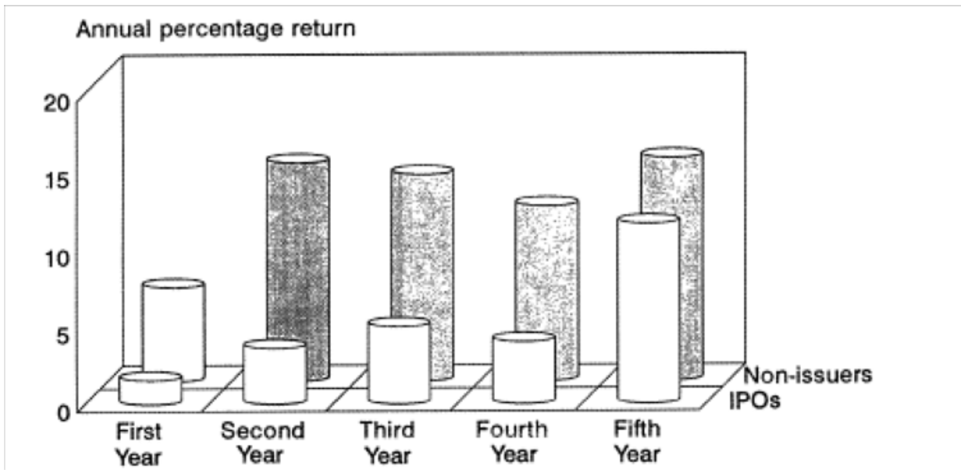
- Fluctuation of equity prices due to noise traders

- 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

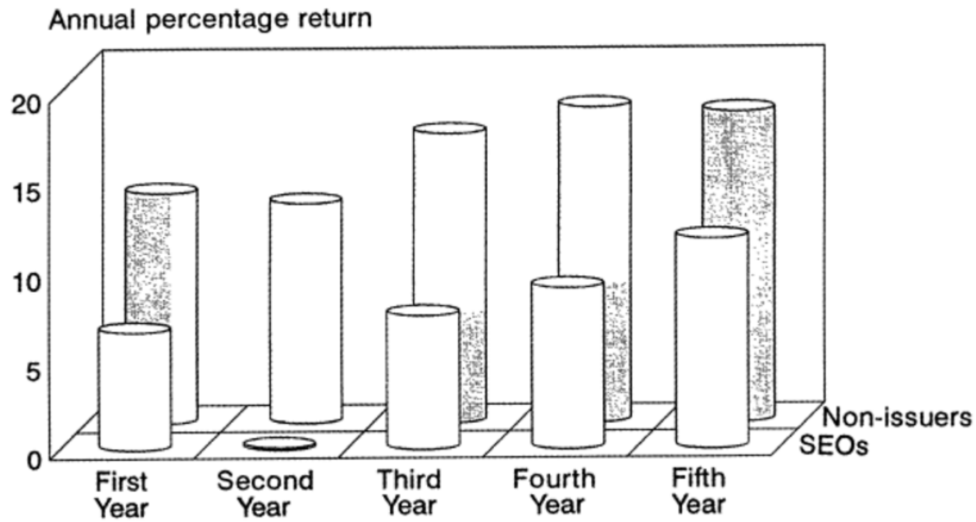


Figure 2. The average annual raw returns for 4,753 initial public offerings (IPOs), and their matching nonissuing firms (top), and the average annual raw returns for 3,702 seasoned equity offerings (SEOs), and their matching nonissuing firms (bottom), during the five years after the issue. The equity 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.

6 Market Reaction to Biases: Employers

- **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.

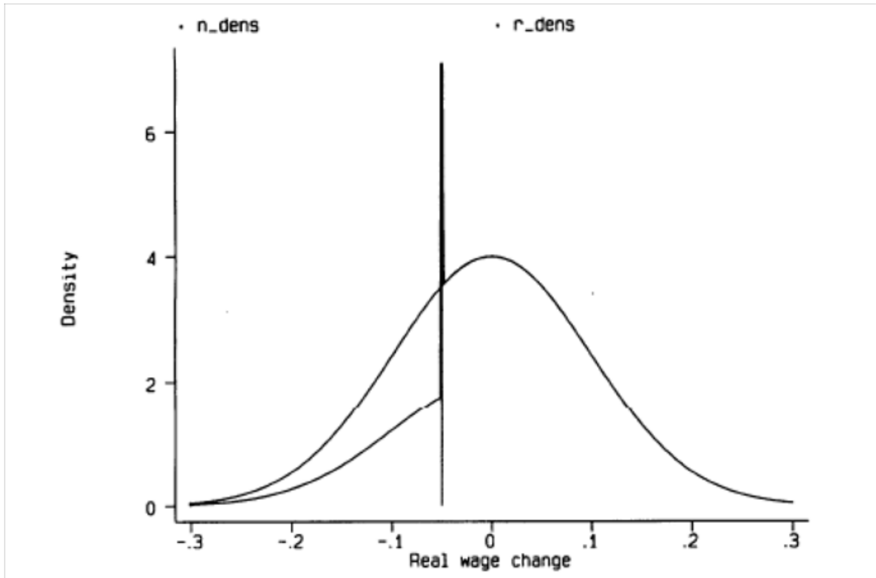
($N = 125$) Acceptable 38% Unfair 62%

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?

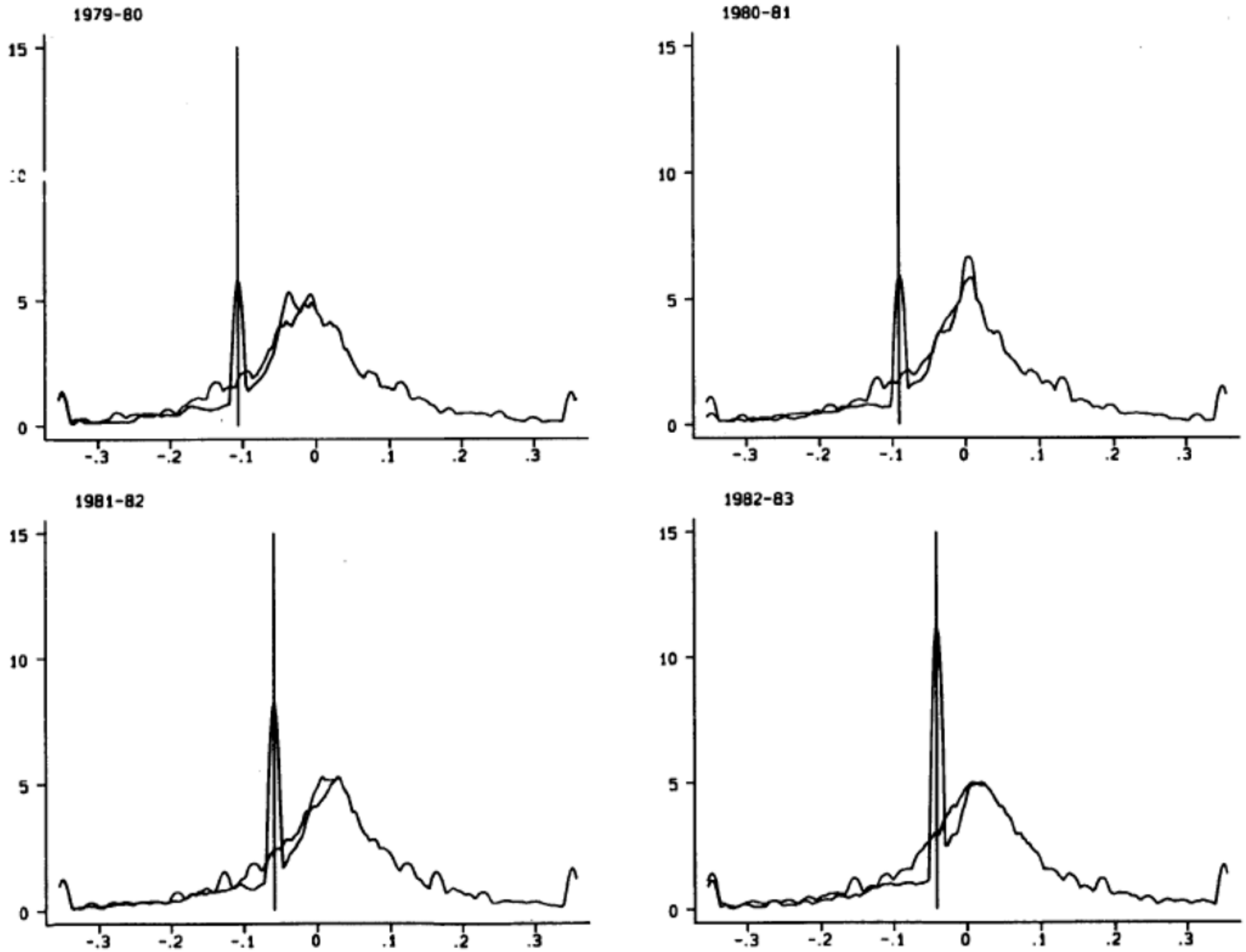


Figure 4: Smoothed (Kernel) Estimates of Actual and Counterfactual Densities of Real Wage Changes, CPS Samples from 1979-80 to 1982-83

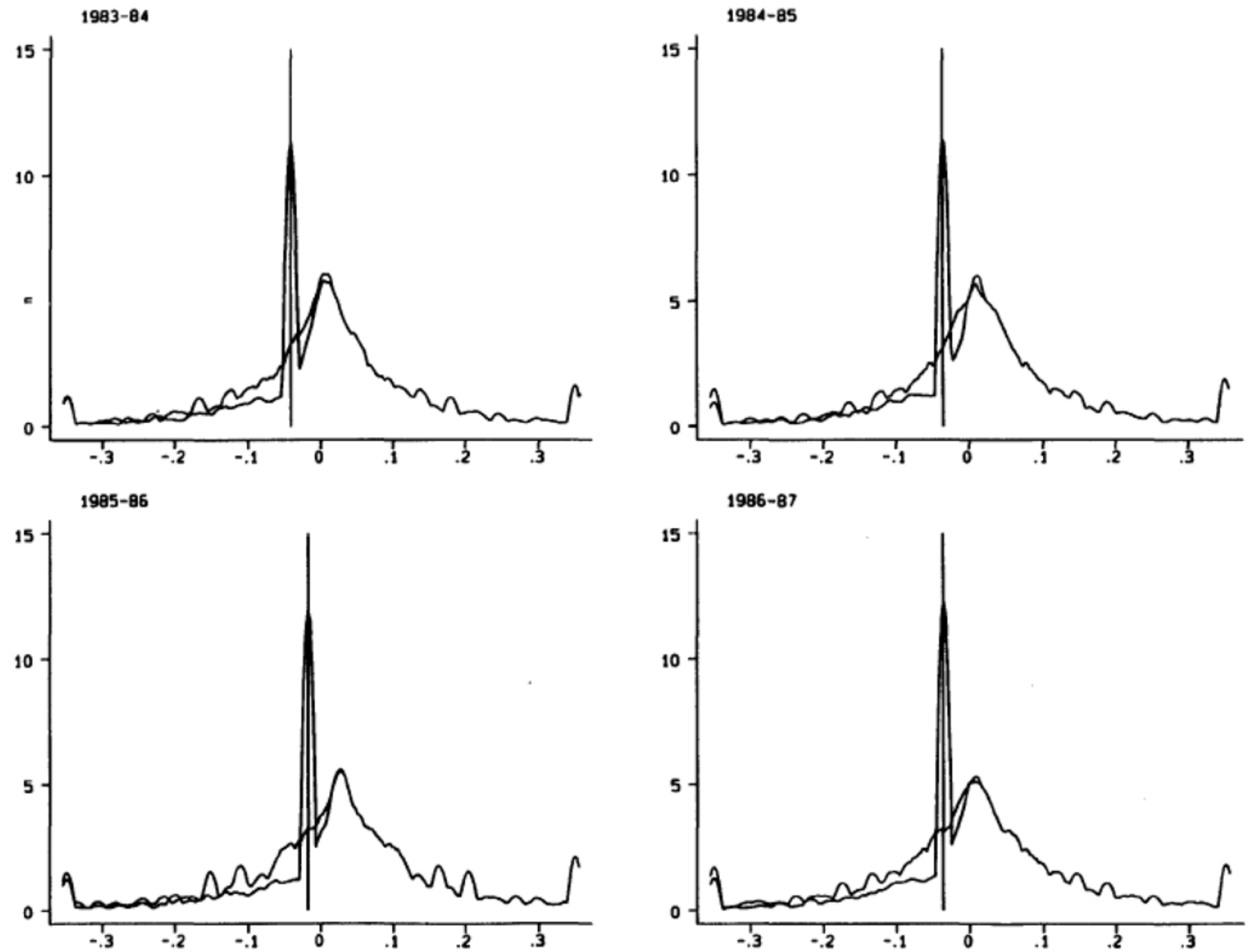


Figure 4 (Continued): Smoothed (Kernel) Estimates of Actual and Counterfactual Densities of Real Wage Changes, CPS Samples from 1983-84 to 1986-87

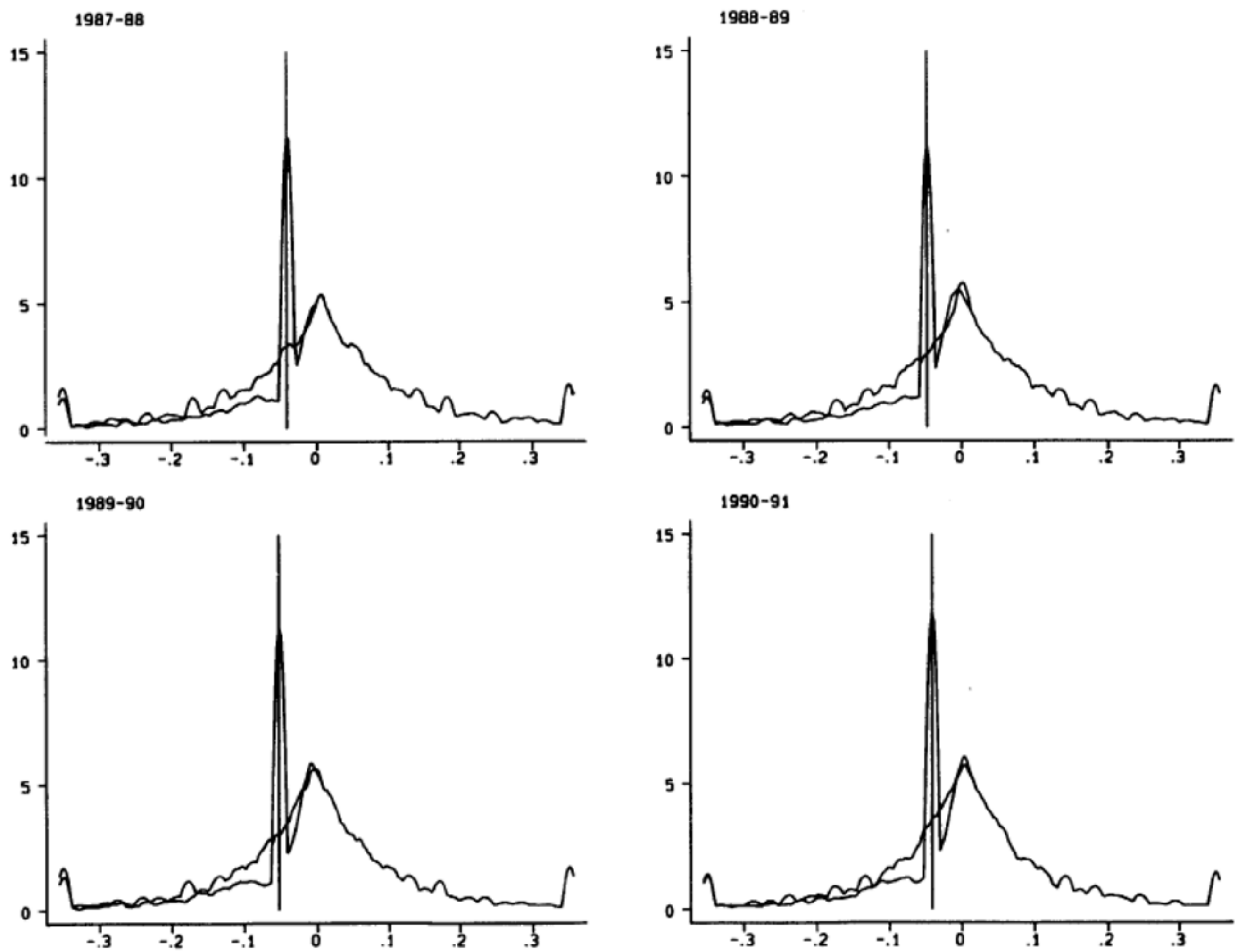


Figure 4 (Continued): Smoothed (Kernel) Estimates of Actual and Counterfactual Densities of Real Wage Changes, CPS Samples from 1987-88 to 1990-91

7 Next Lecture

- More Market Response to Biases
  - Firms: Behavioral IO
  - Investors: Behavioral Finance