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

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Outline

1. Emotions: Mood
2. Emotions: Arousal
3. Methodology: Lab and Field Experiments
4. Happiness
5. Market Reaction to Biases: Introduction

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:

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

- 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:

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

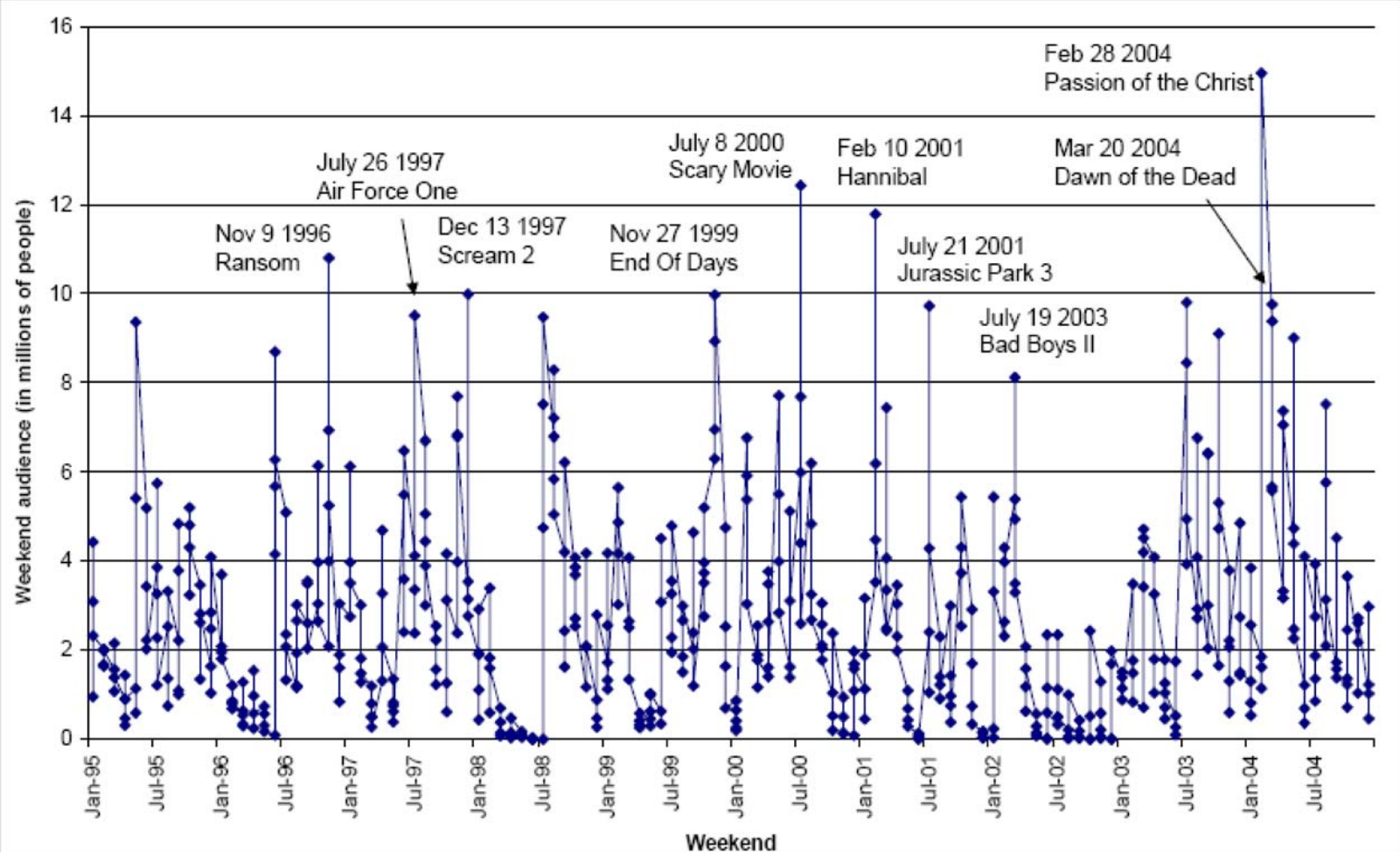
  - Psychology Experiments. Manipulate a directly, holding constant a^s out of equilibrium

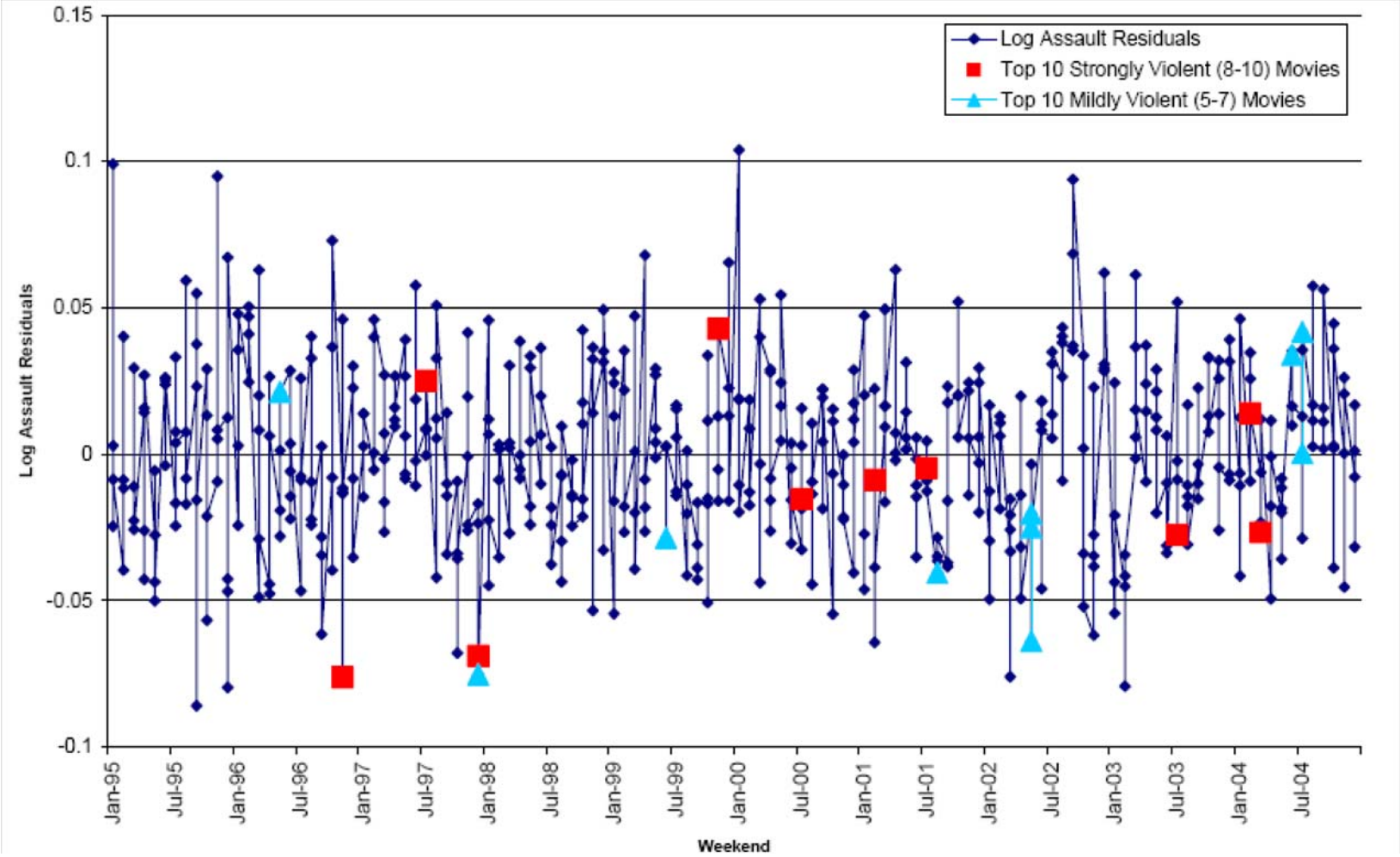
$$\beta_{lab}^v = \frac{N_y}{N_y + N_o}\alpha_y^v + (1 - \frac{N_y}{N_y + N_o})\alpha_o^v$$

- 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)
16
14
12
10
8
6
4
2
0
Nov 9 1996
Ransom
July 26 1997
Air Force One
Dec 13 1997
Scream 2
Nov 27 1999
End Of Days
July 8 2000
Scary Movie
Feb 10 2001
Hannibal
July 21 2001
Jurassic Park 3
July 19 2003
Bad Boys II
Mar 20 2004
Dawn of the Dead
Feb 28 2004
Passion of the Christ
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 (in millions of people in Day t)	-0.0050 (0.0066)	-0.0030 (0.0050)	-0.0130 (0.0049)***	-0.0192 (0.0060)***
Audience Of Mildly Violent Movies (in millions of people in Day t)	-0.0106 (0.0060)*	-0.0001 (0.0045)	-0.0109 (0.0040)***	-0.0205 (0.0052)***
Audience Of Non-Violent Movies (in millions of people in Day t)	-0.0033 (0.0060)	0.0016 (0.0046)	-0.0063 (0.0043)	-0.0060 (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 light 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

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

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

- IMDB ratings data — Share of young males among raters increases with movie violence (Figure 2) –> 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

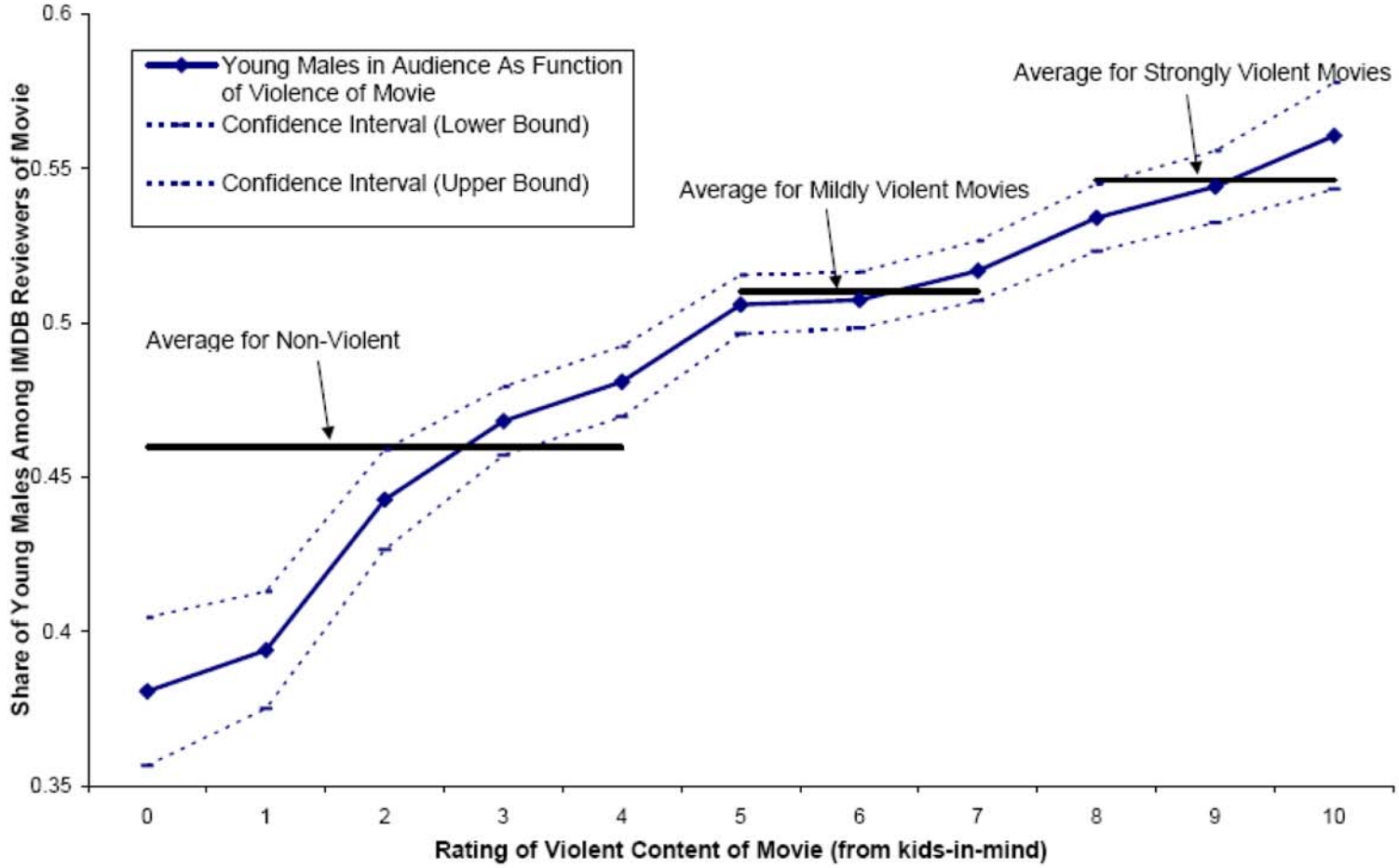
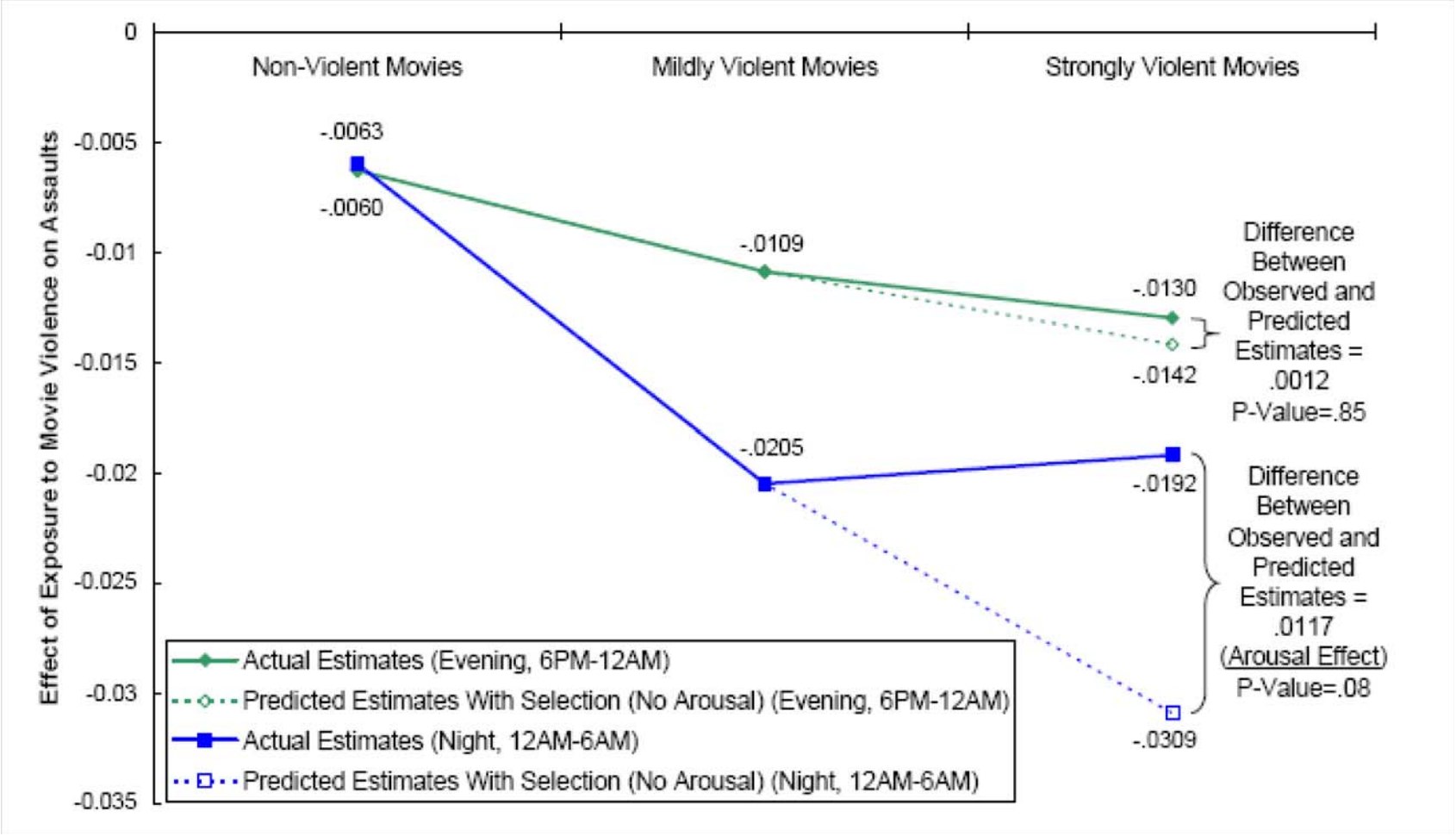


FIGURE II
Share of Young Males in Audience As Function of Movie Violence (Internet Movie Database Data)


0
-0.005
-0.01
-0.015
-0.02
-0.025
-0.03
-0.035
Effect of Exposure to Movie Violence on Assaults
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

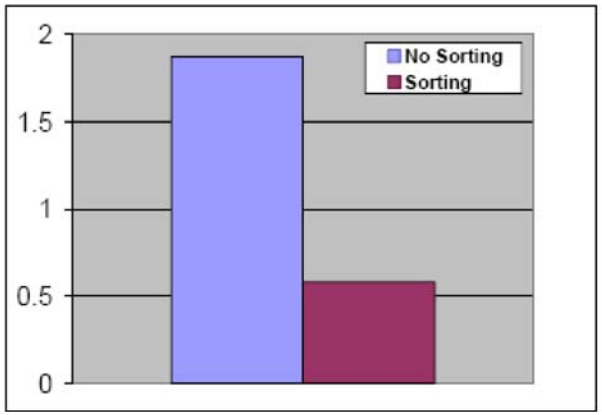
- Notice: One can integrate sorting into laboratory experiments

- **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 Happiness

- Is there a more direct way to measure utility?

- What about happiness questions?
  - 'Taken all together, how would you say things are these days, would you say that you are very happy, pretty happy, or not too happy?'
  - or 'How satisfied are you with your life as a whole?'
  - Response on 1 to 7 of 0 to 10 scale
  - Could average response measure utility?

- There are a number of issues:

1. *(Noise I)* Is the measure of happiness just noise?
2. *(Noise II)* Even if valid, there are no incentives, how affected is it by irrelevant cues?
3. *(Scale)* Happiness is measured on discrete intervals, with ceiling and floor effect
4. *(Content)* What exactly does the measure capture? Instantaneous utility? Discounted utility?

- Revealed preference approach remains heavily favored by economists (myself included)

- Still, significant progress in last 10-15 years on taking some role in economics

- *Issue 1 (Noise I).* To address,
  - Take happiness measure h
  - Does it responds to well-identified, important shifters X which affect important economic outcomes?
- **Oreopoulos (AER 2006).** Exploit binding compulsory schooling laws to study returns to education
- UK: 1947 increase in minimum schooling from 14 to 15

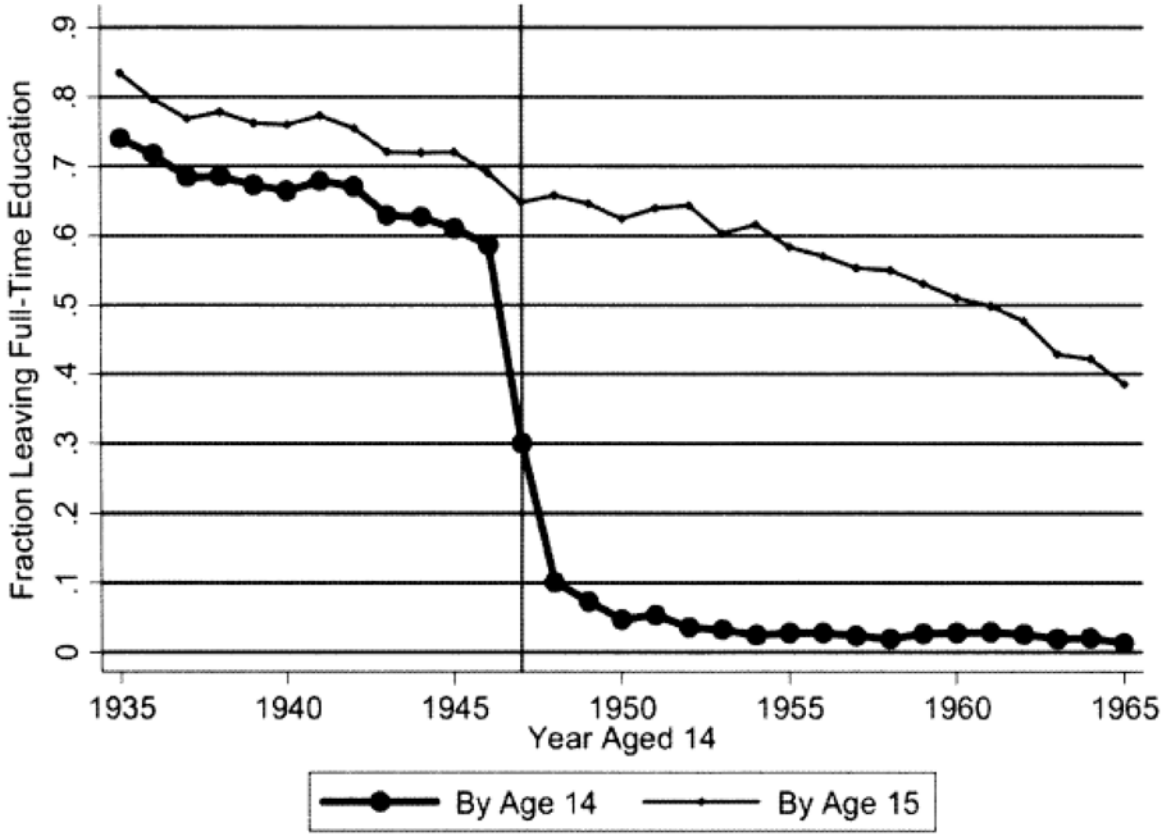


FIGURE 1. FRACTION LEFT FULL-TIME EDUCATION BY YEAR AGED 14 AND 15

- Northern Ireland: 1957 increase from 14 to 15

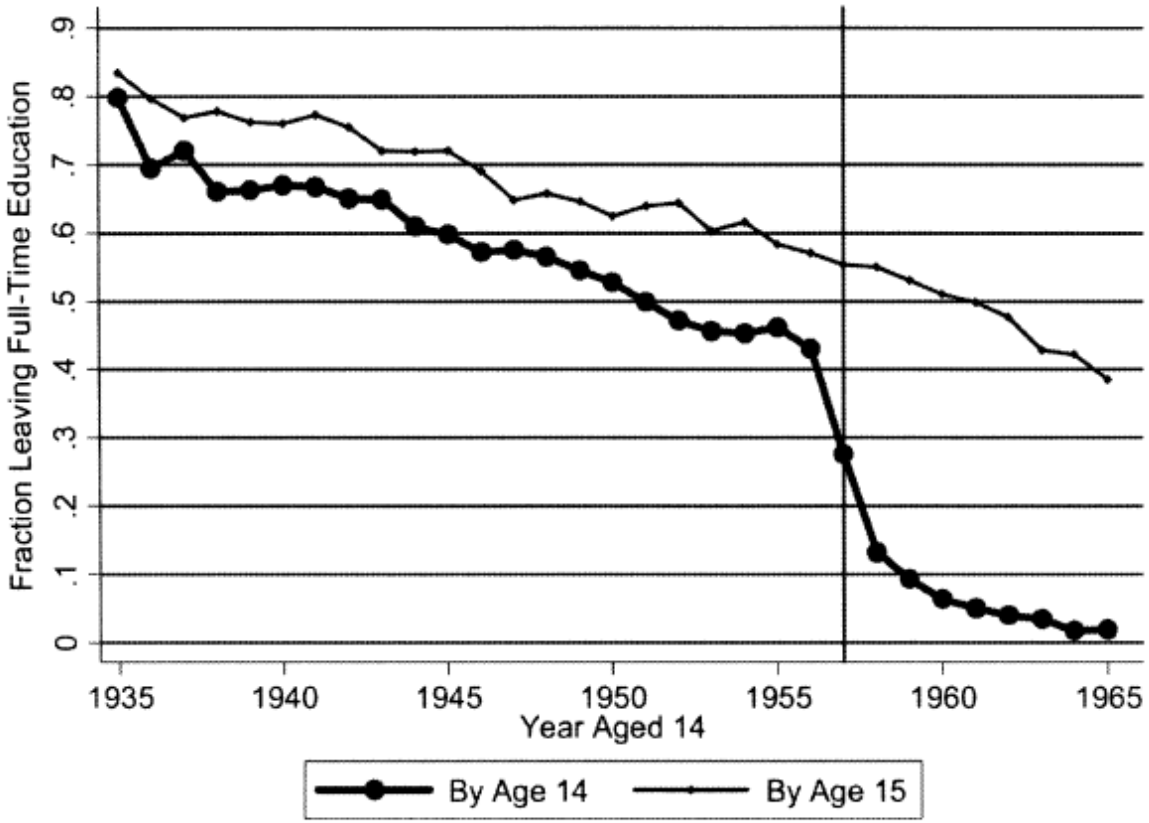


FIGURE 2. FRACTION LEFT FULL-TIME EDUCATION BY YEAR AGED 14 AND 15
(Northern Ireland)

- Clear impact on earnings: compare earnings for adults aged 32-64 as a

function of year of birth

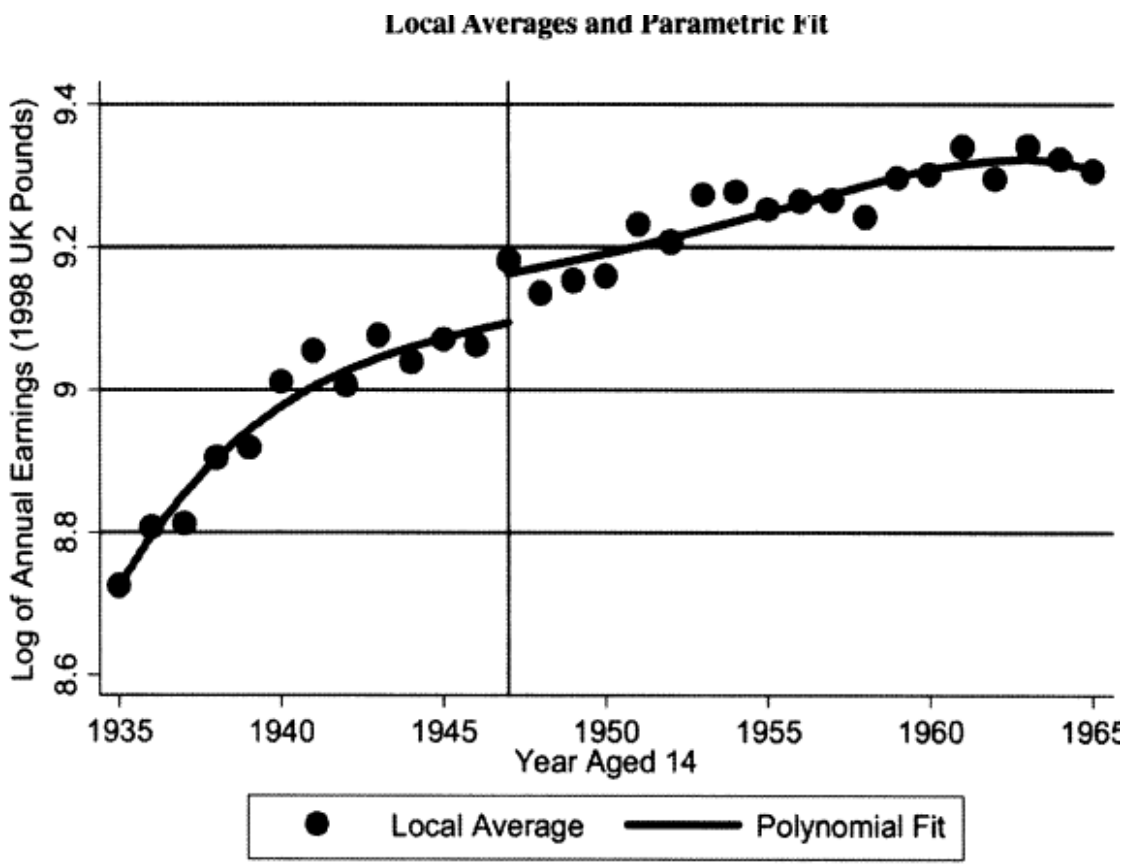


FIGURE 6. AVERAGE ANNUAL LOG EARNINGS BY YEAR AGED 14
(*Great Britain*)

- Implied returns to compulsory education: 0.148 (0.046)

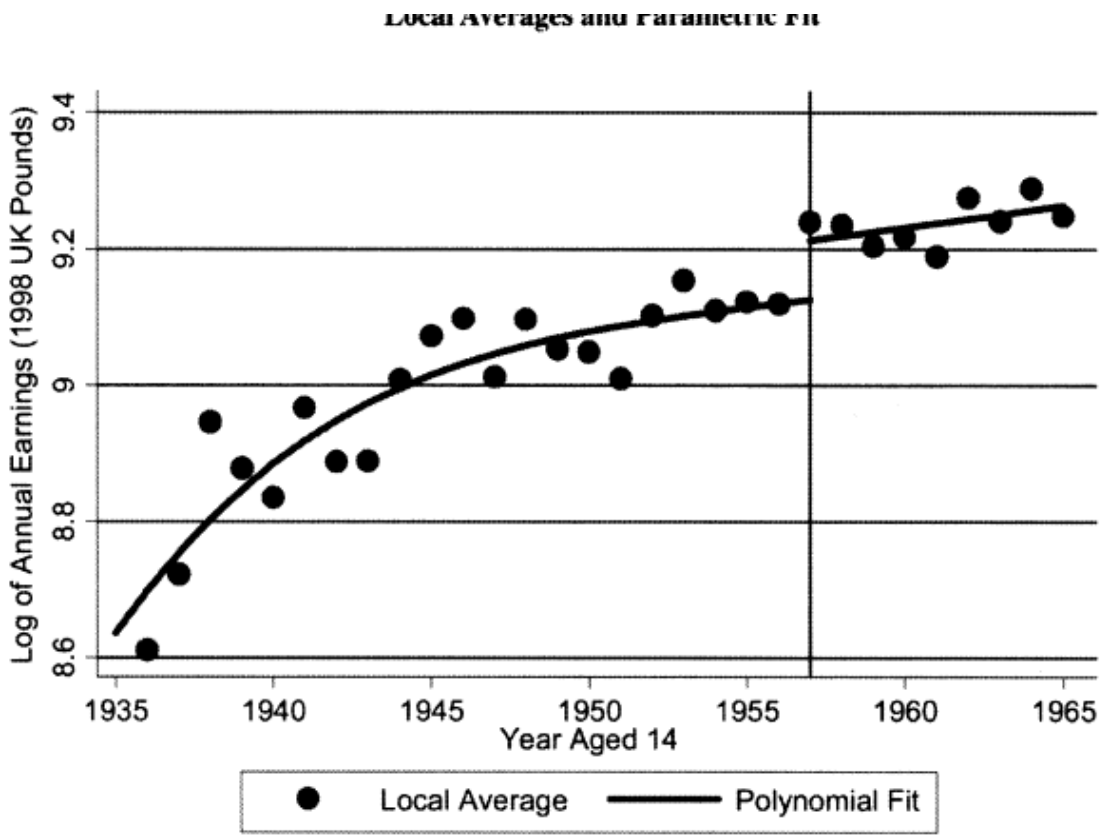


FIGURE 7. AVERAGE ANNUAL LOG EARNINGS BY YEAR AGED 14
(*Northern Ireland*)

- **Oreopoulos (JPubE 2007):** Did this affect happiness measures?
  - Eurobarometer Surveys in UK and N. Ireland, 1973-1998
  - Question on 1-4 scale

Table 4
The effect of schooling on subjective well-being least squares and IV estimates using UK and Irish changes in school-leaving age

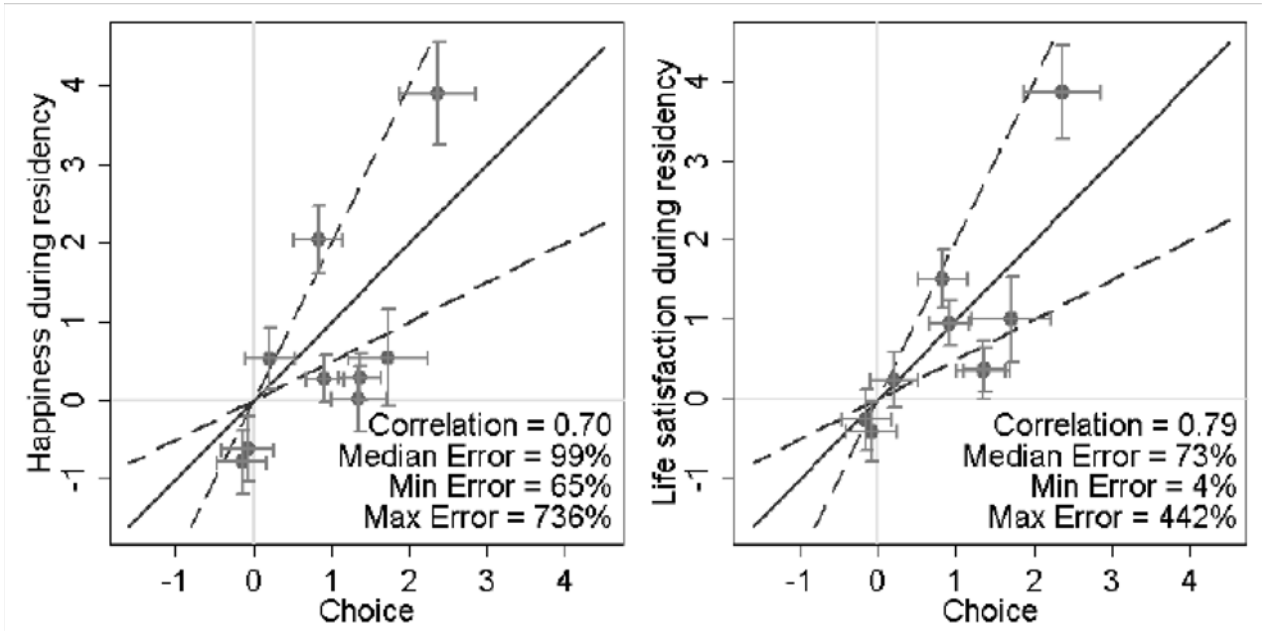
	(1)	(2)	(3)	(4)
	Mean	OLS	IV	Initial observations
Life satisfaction (1 = not at all satisfied, 4 = very satisfied)	3.14	0.073	0.059	89279
		(0.0093)***	(0.0073)***	
Satisfied with life (1 = very or fairly satisfied, 0 = not satisfied or not at all satisfied)	0.86	0.040	0.0516	89279
		(0.0046)***	(0.0033)***	
Very satisfied (1 = very satisfied)	0.325	0.027	0.0235	89279
		(0.0023)***	(0.0135)*	
Happy (1 = not so happy, 2 = fairly happy, 3 = very happy)	2.14	0.044	0.0667	24565
		(0.013)***	(0.0093)***	

Notes: All regressions include fixed effects for age, sex, birth year, and nation interacted with survey year. Data are grouped into means by age, sex, birth year, nation, and survey year. Huber–White standard errors are shown from clustering by nation. Single, double, and triple asterisks indicate significant coefficients at the 10%, 5%, and 1% levels respectively. Samples include all adults aged 18 to 65. See text for more data specifics.

- Results:
  - One year of additional (compulsory) education increases happiness somewhere between 2 and 8 percent
  - In addition, large effects on health and wealth
  - Reinforces puzzle: Why don't people stay in school longer?
- Happiness response captures real information
- Happiness answer also responds to cues (Issue 2), has scale effects (Issue 3), but valid enough to use in combination with other measures
- However, Issue 4: How would we use happiness measure as part of economic research?

- Research agenda by Dan Benjamin, Ori Heffetz, Miles Kimball, Alex Rees-Jones
  - Study Econ101a-type simple issues with happiness measures
  - Critical to know how to correctly interpret these measures
- Paper 1. **Benjamin, Heffetz, Kimball, and Rees-Jones (AER 2012)**
  - How does happiness (subjective well-being) relate to choice?
  - Compare *forecasted* happiness with choice in several hypothetical scenarios
  - Forecasts of happiness predict choice quite well, but other factors also play a role

- Paper 2. **Benjamin et al. (AER forthcoming)**
  - Medical students choosing match for residency
  - Survey to elicit ranking of medical schools for residency + Ask anticipated happiness
  - How well does happiness predict choice relative to other factors?



- Some evidence that one can also elicit intertemporal happiness

Table 4: Weight Estimates for Multi-Question Indices

	(1) Choice
Happiness during residency	4.5***
	(0.5)
Happiness in first 10 years	4.6***
	(0.8)
Happiness in rest of career	2.1**
	(0.9)
Happiness after retirement	1.2
	(0.8)

- Other important work on happiness:
  - **Luttmer (QJE 2005)**: Documents relative aspect of happiness: An increase in income of neighbors (appropriately instrumented) lower life satisfaction
  - **Stevenson and Wolfers (Brookings 2008):**
    * Debunks Easterlin paradox (income growth over time does not increase happiness)
    * Clear link over time between log income and happiness
  - **Finkelstein, Luttmer, Notowidigdo (JEEA 2014)**:
    * How does marginal utility of consumption vary with health? Needed for optimal policies
    * Observe changes in happiness for varying health

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, Voter, 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 experienced agents these conditions are more likely to be satisfied

- Implications? Study biases in the market
- Six major instances:
  - Interaction between firms and consumers (contract design, price choice)
  - Interaction between experienced and inexperienced investors (noise traders and behavioral finance)
  - Interaction between managers and investors (corporate finance)
  - Interaction between employers and employees (labor economics)
  - Interaction between politicians and voters (political economy)
  - Institutional design

6 Next Lecture

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