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

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Outline

1. Social Pressure II
2. Emotions: Mood
3. Emotions: Arousal
4. Methodology: Lab and Field
5. Market Reaction to Biases: Introduction

# 1 Social Pressure II

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

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

- Results:
  - Students in treatment group stuffed more envelopes (221 vs. 190)
  - Students in treatment group coordinated the effort within group: within-pair standard-deviation of output is significantly less than the (simulated) between-pairs standard deviation

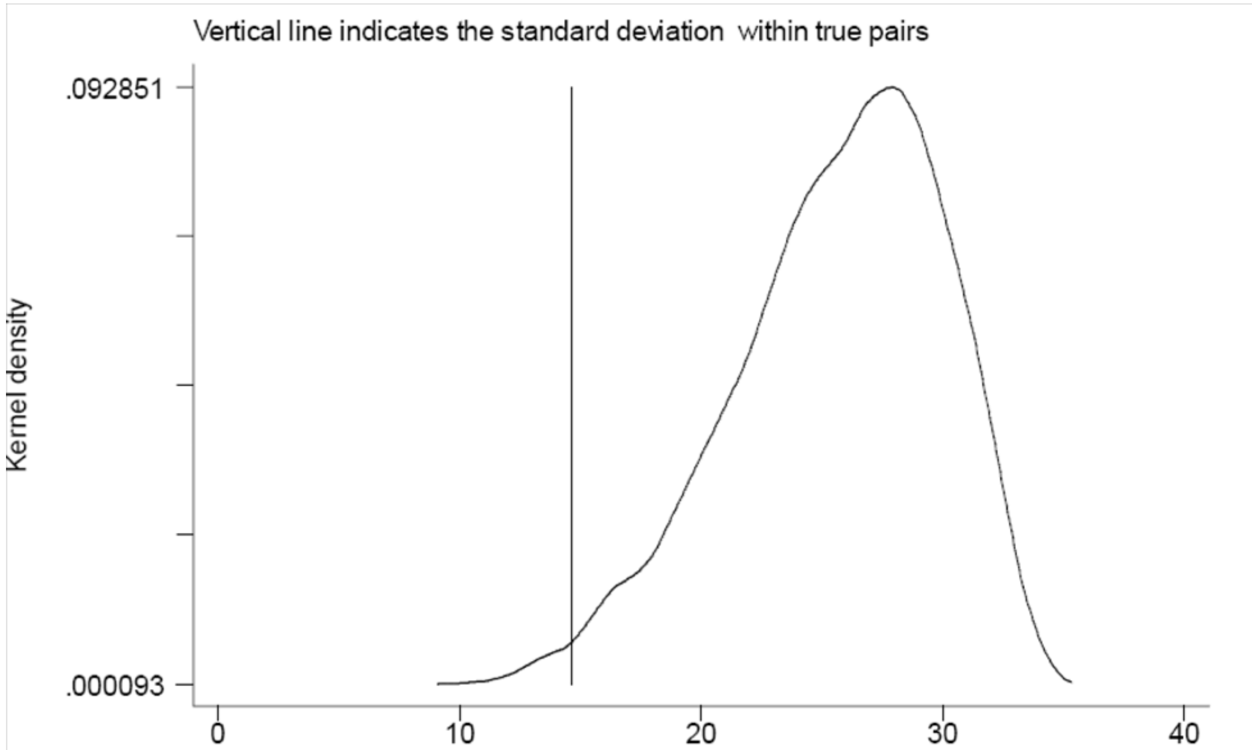



Fig. 3: St. dev. within true and hypothetical pairs in pair sample

- **Mas-Moretti (AER, forthcoming).** Evidence of response to social pressure in the workplace

  - Workplace setting –> Large retail chain

  - Very accurate measure of productivity, scanning rate

  - Social Pressure: Are others observing the employer?

- Slides courtesy of Enrico

# Introduction

- We use internal scanner data from a supermarket chain to obtain a high-frequency measure of productivity of checkers

- Over a two year period, we observe each item scanned by each worker in each transaction. We define individual effort as the number of items scanned per second.

- We estimate how individual effort changes in response to changes in the average productivity of co-workers

# Introduction

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

- Scheduling is determined two weeks prior to a shift

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

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

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

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

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

## Preview of results

(1) The introduction of a high-productivity worker into the checkout stand is associated with a significant *increase* in incumbent worker effort

(2) Spillovers depend on workers' ability to monitor one another and frequency of interactions

(a) A given worker's effort is positively related to the speed of workers who face him, but not the speed of workers whom he faces

(b) Workers respond more to the presence of co-workers with whom they frequently overlap

=> Social pressure is the mechanism that generate peer effects

# Preview of results

(3) The magnitude of the spillover varies depending on the skill level of the relevant worker: it is large for slow workers, and is small for fast workers

=> The optimal mix of workers is the one that maximizes skill diversity in a shift

(4) By optimally arranging the mix of workers, this firm could generate the same amount of sales with 124,000 fewer hours of work each year. This is *not* inconsistent with profit maximization.

# Why are spillovers important?

- What is the true benefit of hiring a high productivity worker?
- What is the optimal workplace organization? Can we increase output by simply re-arranging the mix of workers in each shift?
- Getting inside the black-box of productivity spillovers
- What motivates workers in jobs with fixed-pay?

# Literature on Peer Effects in School

- Our question is methodologically similar to the question addressed in the literature on peer effects in education.
- Should we minimize or maximize variance of students?
- Empirical Evidence
  - Sacerdote (2001)
  - Hanushek et al. (2000)
  - Vigdor and Nechyba (2004)
  - Graham (2005)
- Methodological issues
  - Graham, Imbens and Ridder, 2006
  - Imbens and Ridder, 2005

# 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<br>(0.023) | 0.159<br>(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<br>(0.001) | |
| Exit of an above average productivity worker | -0.005<br>(0.001) | |
| Shift entry of above average productivity worker | | 0.006<br>(0.002) |
| Shift exit of an above average productivity worker | | -0.006<br>(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<br>(0.023) | 0.261<br>(0.033) |
| Δ Co-worker permanent prod. × Above average worker | | -0.214<br>(0.046) |
| Observations | 1,734,140 | 1,734,140 |
| Controls | Yes | Yes |

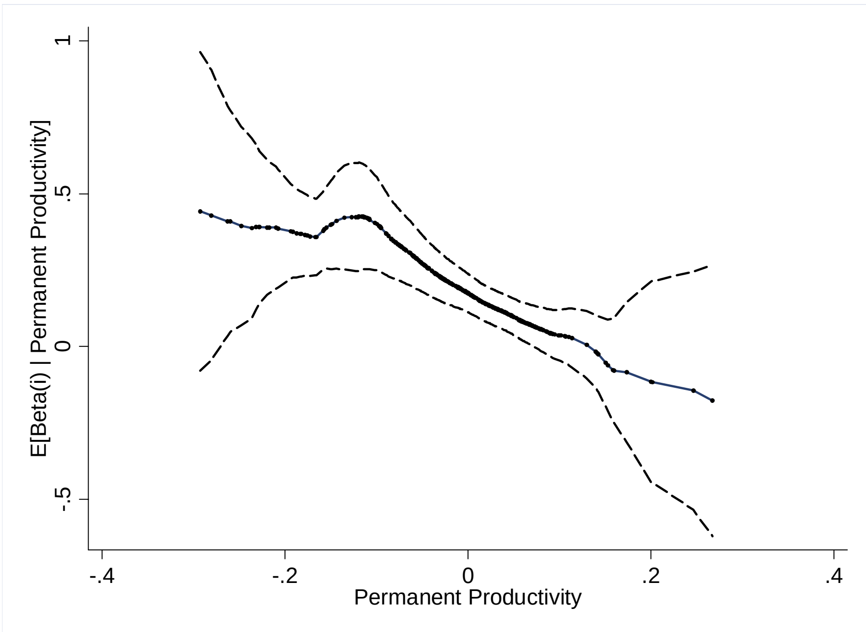
$$\Delta y_{itcs} = \beta \Delta \overline{\theta}_{-ist} + \gamma_{tds} + \psi \Delta X_{tcs} + e_{itcs}$$

# Individual-specific Spillover

- Our longitudinal data allow for models with an individual-specific spillover effect, $\beta_i$:

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

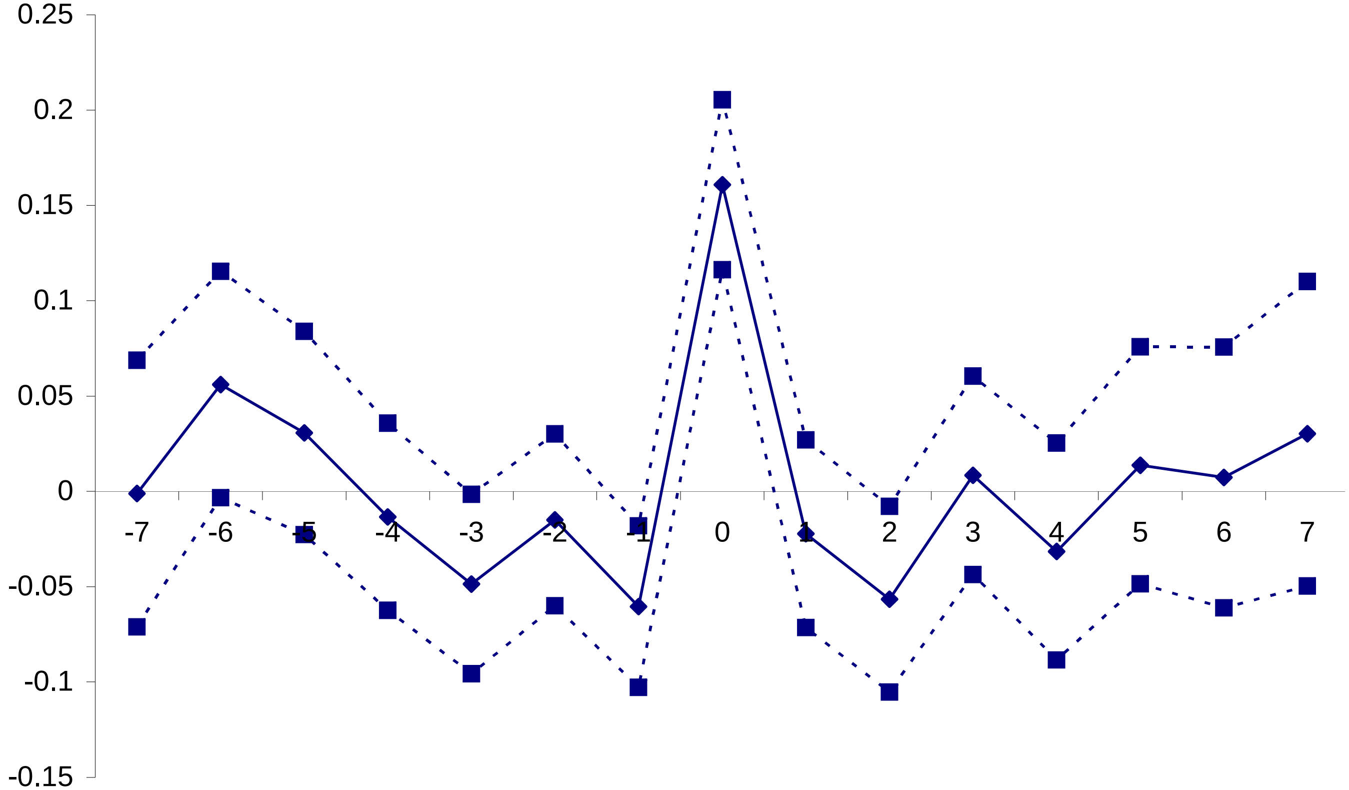
The relationship between individual permanent productivity and worker specific spillover effect



## 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




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

# 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 monitor 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<br>(0.019) | |
| Δ Co-worker permanent productivity in front | 0.007<br>(0.018) | |
| Δ Co-worker permanent productivity behind & closer | | 0.162<br>(0.016) |
| Δ Co-worker permanent productivity in front & closer | | 0.016<br>(0.015) |
| Δ Co-worker permanent productivity behind & farther | | 0.100<br>(0.018) |
| Δ Co-worker permanent productivity in front & farther | | 0.003<br>(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 | $\beta_{iC}$ | $t$-Statistic | $\gamma_{iC}$ | $\chi^2$ | 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 | $\beta_W$ | $t$-val | N | $\beta_L$ | $t$-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

## Table 12. Examples of Studies of Media Effects on Violence in Psychology

| Paper | Exposure to violence (Type of movie) (1) | Control Group (2) | Subjects (3) | Measure of Violence $t$ (6) | Treatment Group $t_T$ (7) | Control Group $t_C$ (8) |
|---|---|---|---|---|---|---|
| **Laboratory Experiments** | | | | | | |
| **Lovaas (1961)** | 5-min. Extract from "Rassling Match" -- cartoon violence | 5-min. Non-Violent Clip from "Bear Facts" | Children of Nursery Sch. | Time Spent Playing with Aggressive Doll (hits other doll) | 98.2 | 58.6 |
| **Bandura et al. (1963)** | 10-min. Scenes of Aggression of Doll | No Movie | Children of Nursery Sch. | Aggression toward Doll | 91.5 | 54.3 |
| **Geen and O'Neal (1969)** | 7-min. Prizefight Scene from "Champion" + 2 min. White Noise | 7-min. Scenes Non-violent Sport + 2 min. White Noise | College Students | Intensity Electric Shock Inflicted on Other Subject | 22.2 | 10.3 |
| **Bushman (1995)** | 15-min. Violent Scenes from "Karate Kid III" | 15-min. non-violent scenes from "Gorillas in The Mist" | College Students | Level of Noise Inflicted On Other Subject For Slow Answer | 4.6 | 3.9 |
| **Josephson (1987)** | 14-min. Scenes of Killing of Police Officer and SWAT team | 14-min. Scenes Motorcross Bike-Racing Team | Grades 2-3, Boys | Aggression in 9 Min. of Floor Hockey Game | 6.6 | 3.6 |
| **Leyens et al. (1975)** | Showing of 5 Violent Movies On 5 Consecutive Days | 5 Non-Violent Movies On 5 Consecutive Days | Juvenile Detention | Physical Aggression In Evening After Movie | 4.0 | 0.2 |
| | | | | Physical Aggression At Noon Day After Movie | 2.1 | 1.5 |
| **Surveys** | | | | | | |
| **Johnson et al. (2002)** | High (Self-reported) Television Viewing at Age 14 (>=3 hrs./day) | Low TV Viewing at Age 14 (<1 hrs./day) | Random Sample | % Committing Assaults Causing Injury, at Age 16-22 | 25.3% | 5.7% |

**Notes:** Calculations of effects on violence are by the authors based on data from the papers cited. Columns (7) and (8) report the level of violence in the Treatment and Control group. The difference is always significant at the 5% level, except for the second comparison in the Geen and O"Neal (1969) paper and the second comparison in Leyens et al. (1975).

Figure 1a. Weekend Theater Audience of Strongly Violent Movies

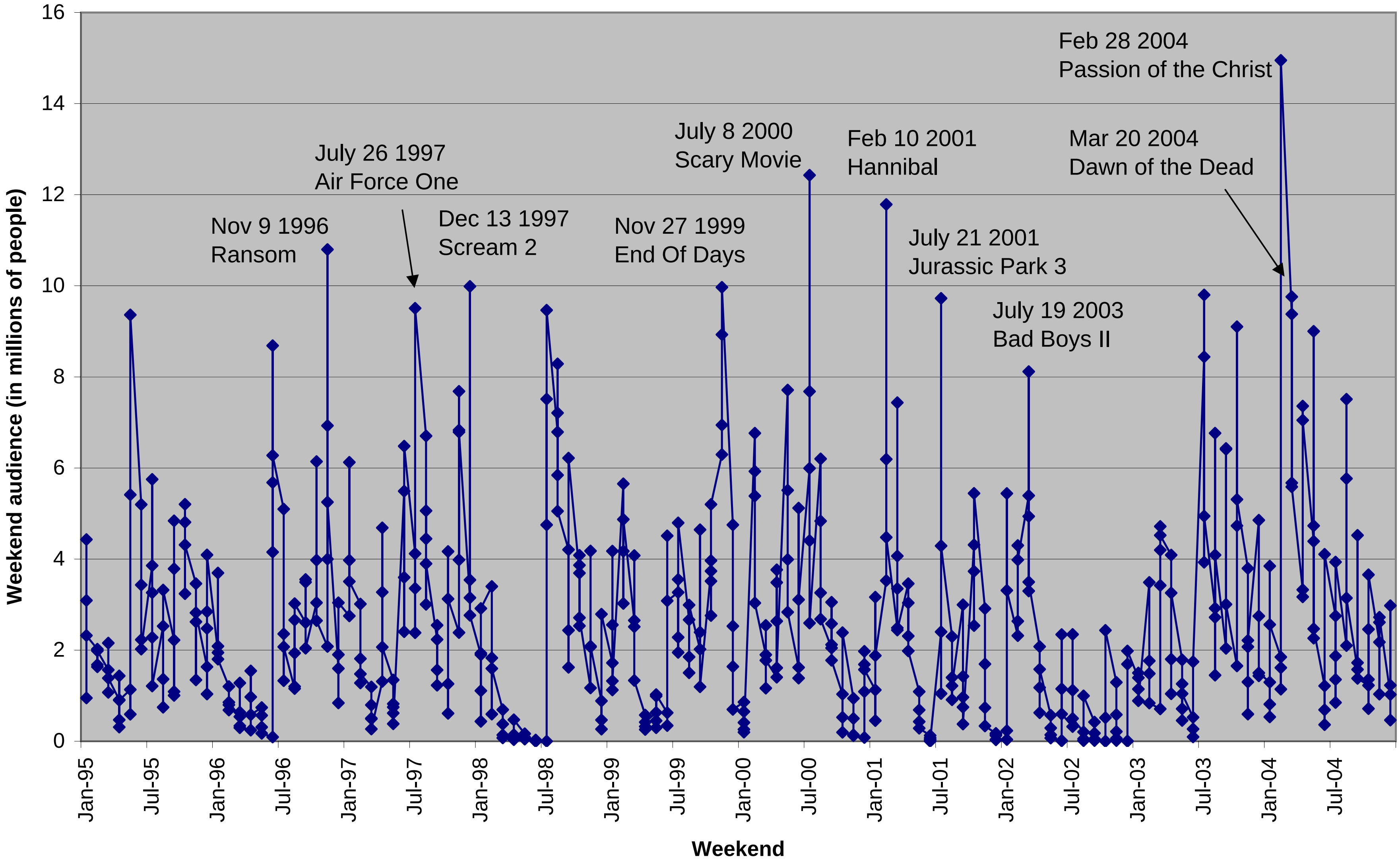
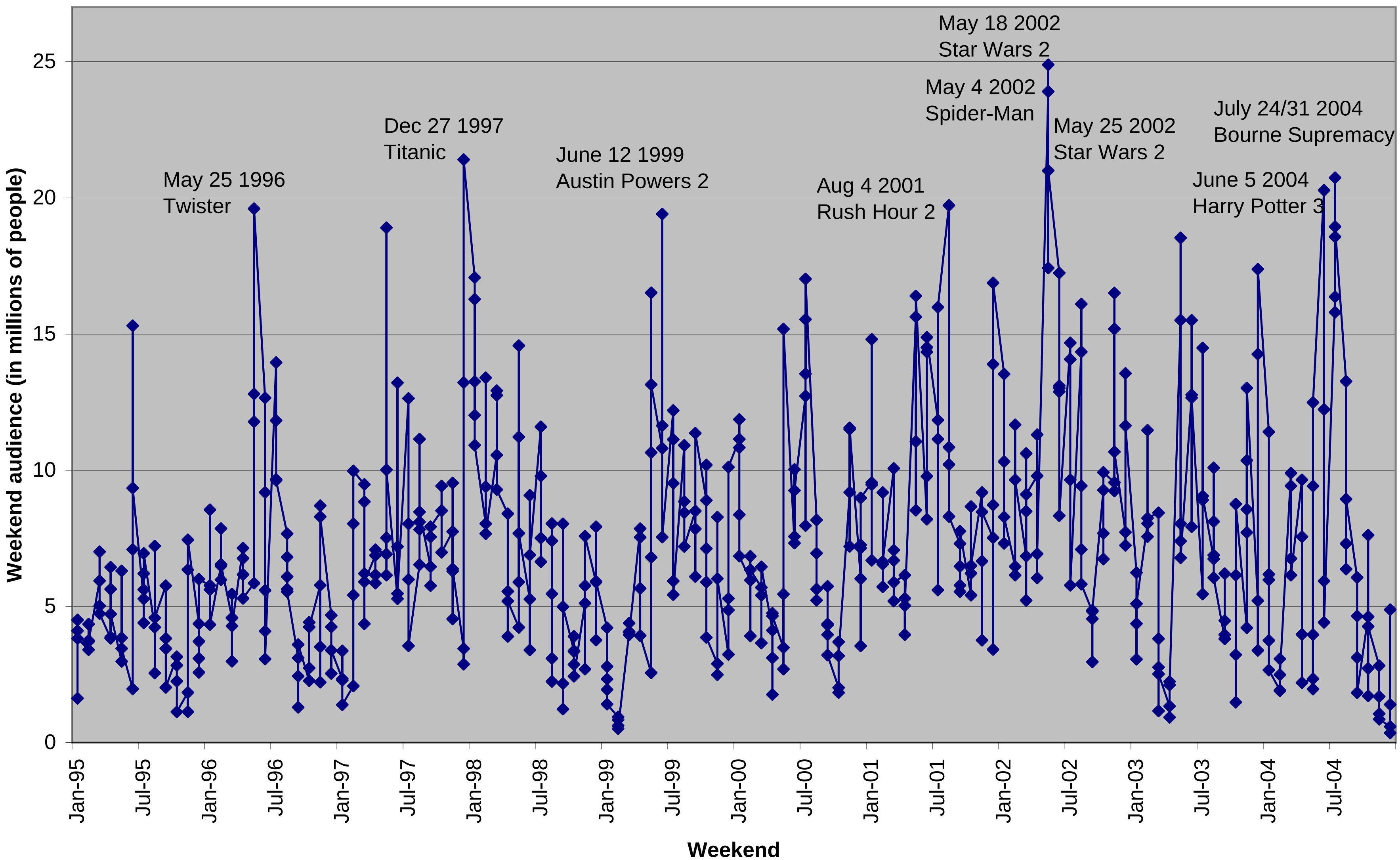


**Figure 1b. Weekend Theater Audience of Mildly Violent Movies**



- **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 $\beta^v$:

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

- First point — Estimate of net effect
  - Direct effect: Increase in violent movie exposure –> $\alpha_i^v$
  - Indirect effect: Decrease in Social Activity –> $\sigma_i$

- 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 $\beta^v$:

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

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

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

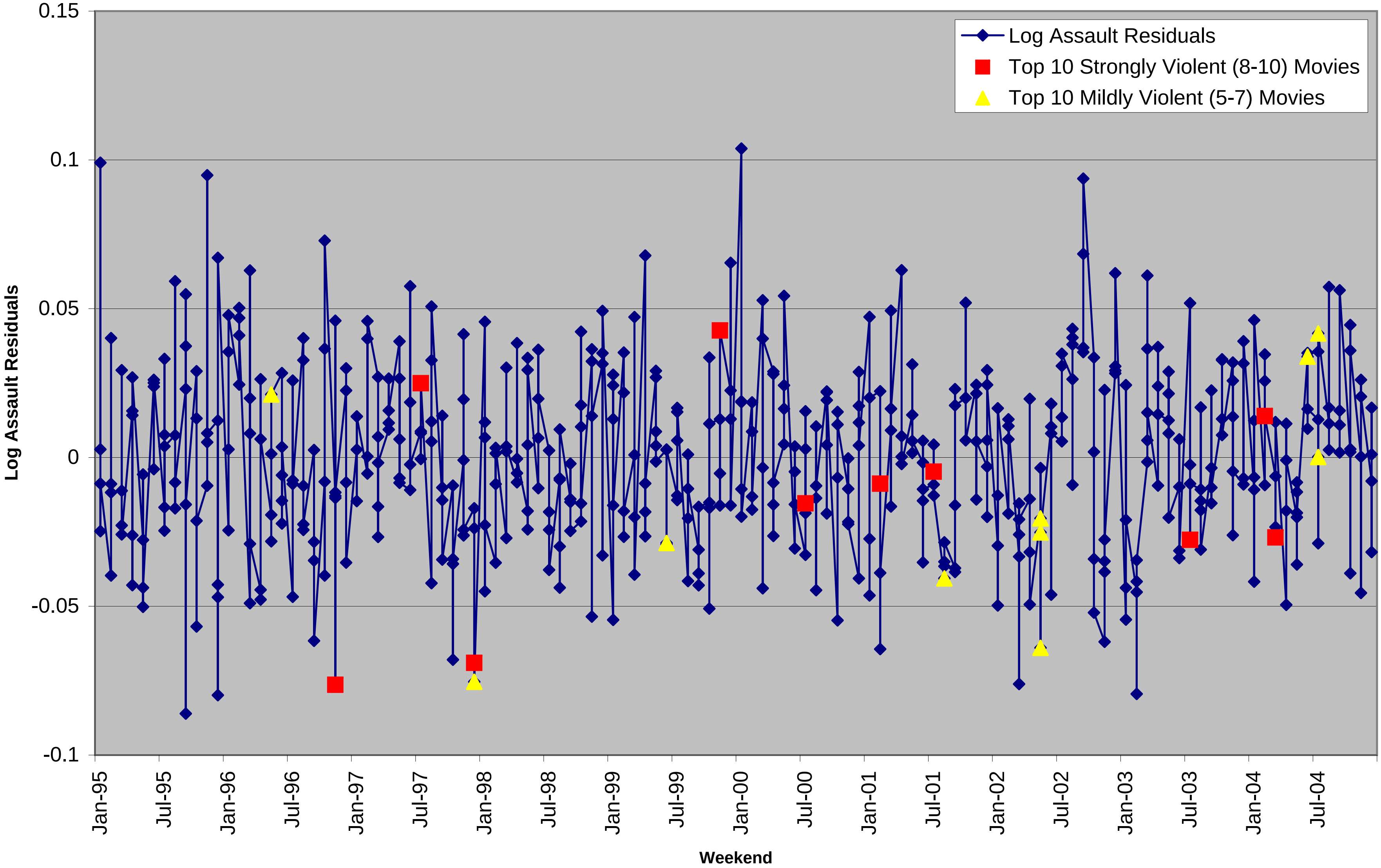
- Two differences:
  - 'Shut down' alternative activity, and hence $\sigma_i$ does not appear
  - Weights representative of (student) population, not of population that selects into violent movies

- **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)

Figure 1d. Residuals of Regression of Log Assault on Seasonality Controls



- **Regression Specification.** (Table 2)

$$\log V_t = \beta^v A_t^v + \beta^m A_t^m + \beta^n A_t^n + \Gamma X_t + \varepsilon_t$$

  - Coefficient $\beta^v$ is percent increase in assault for one million people watching strongly violent movies day $t$ ($A_t^v$) (Similarly $\beta^m$ and $\beta^n$)
  - Cluster standard errors by week
  - –> Effect of exposure to violent movies is negative. Puzzle?
  - Third factor (weather? TV?) affecting assaults and movie audience
    - Control for weather and TV audience (Column 6)
    - Instrument movie audience based on next-week weekend audience (details in paper)

- Effect of violent movies more negative (and significant) (Column 7)

## Table 2. The Effect of Movie Violence on Same-Day Assaults

| Specification: | OLS Regressions | | | | | | IV Regr. |
|---|---|---|---|---|---|---|---|
| Dep. Var.: | Log (Number of Assaults in Day t) | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| **Audience Of Strongly Violent Movies** | 0.0324 | 0.0005 | -0.0061 | -0.0051 | -0.0072 | -0.0091 | -0.0106 |
| **(in millions of people in Day t)** | (0.0053)*** | (0.0053) | (0.0033)* | (0.0033) | (0.0033)** | (0.0026)*** | (0.0031)*** |
| **Audience Of Mildly Violent Movies** | 0.0246 | 0.0017 | -0.0084 | -0.0042 | -0.0056 | -0.0079 | -0.0102 |
| **(in millions of people in Day t)** | (0.0030)*** | (0.0029) | (0.0020)*** | (0.0026) | (0.0027)** | (0.0022)*** | (0.0028)*** |
| **Audience Of Non-Violent Movies** | 0.0082 | -0.0164 | -0.0062 | -0.0023 | -0.0029 | -0.0035 | -0.005 |
| **(in millions of people in Day t)** | (0.0029)*** | (0.0030)*** | (0.0021)*** | (0.0024) | (0.0026) | (0.0024) | (0.0029)* |
| **Control Variables:** | | | | | | | |
| **Year Indicators** | X | X | X | X | X | X | X |
| **Day-of-Week Indicators** | | X | X | X | X | X | X |
| **Month Indicators** | | | X | X | X | X | X |
| **Day-of-Year Indicators** | | | | X | X | X | X |
| **Holiday Indicators** | | | | | X | X | X |
| **Weather Controls** | | | | | | X | X |
| **F-Test on Additional Controls** | F=1934.02 | F=1334.31 | F=88.56 | F=13.37 | F=15.05 | F=18.58 | |
| **Audience Instrumented With Predicted Audience Using Next** | | | | | | | X |
| **$R^2$** | 0.9344 | 0.9711 | 0.9846 | 0.9904 | 0.9912 | 0.9931 | . |
| **N** | N = 1563 | N = 1563 | N = 1563 | N = 1563 | N = 1563 | N = 1563 | N = 1563 |

- **Time of Day Results.** (Table 3)
  - 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)
  - Effect larger for more violent movies in evening, but not in night
  - Smaller, not significant impact of non-violent movies

## Table 3. 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** | -0.005 | -0.003 | -0.013 | -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 | -0.006 |
| **(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 |
| **Predicted Audience Using Next Week's Audience** | X | X | X | X |
| **N** | N = 1563 | N = 1563 | N = 1563 | N = 1562 |

- **Medium-Run Effects.** (Table 4)
  - Limitation: Cannot estimate long-term effects
  - Can estimate medium-term effects after one week of exposure
    * Are effects due to intertemporal substitution of crime between days?
    * Evidence of imitation of violent behavior in next days?
  - Results:
    * No effect on Monday and Tuesday of weekend exposure (Columns 1-2)
    * No effect one, two, or three weeks later (Columns 3-8)

## Table 4. Medium-Run Effect of Movie Violence

| Specification: | | | | | | |
|---|---|---|---|---|---|---|
| Dep. Var.: | Log (Number of Assaults in Day t in Time Window) | | | | | |
| | (3) | (4) | (5) | (6) | (7) | (8) |
| **Audience Of Strongly Violent Movies** | -0.0127 | -0.0081 | -0.0142 | -0.0209 | -0.0136 | -0.0199 |
| **(in millions of people in day t)** | (0.0045)*** | (0.0060) | (0.0051)*** | (0.0067)*** | (0.0051)*** | (0.0063)*** |
| **Audience Of Mildly Violent Movies** | -0.0061 | -0.0087 | -0.0096 | -0.0194 | -0.0114 | -0.0199 |
| **(in millions of people in day t)** | (0.0031)** | (0.0043)** | (0.0042)** | (0.0056)*** | (0.0041)*** | (0.0052)*** |
| **Audience Of Non-Violent Movies** | -0.0027 | 0.003 | -0.005 | -0.0079 | -0.007 | -0.0076 |
| **(in millions of people in day t)** | (0.0033) | (0.0050) | (0.0046) | (0.0061) | (0.0044) | (0.0056) |
| **Lagged Audience Of Strongly Violent Movies** | 0.0046 | -0.0017 | -0.0028 | 0.002 | 0.0017 | -0.0065 |
| **(in millions of people in day t)** | (0.0042) | (0.0054) | (0.0047) | (0.0062) | (0.0044) | (0.0056) |
| **Lagged Audience Of Mildly Violent Movies** | -0.0018 | 0.0001 | -0.0061 | -0.0056 | 0.0002 | -0.0105 |
| **(in millions of people in day t)** | (0.0026) | (0.0037) | (0.0037) | (0.0049) | (0.0031) | (0.0045)** |
| **Lagged Audience Of Non-Violent Movies** | -0.0007 | 0.0031 | -0.006 | 0.0012 | 0.0011 | -0.0049 |
| **(in millions of people in day t)** | (0.0028) | (0.0041) | (0.0042) | (0.0055) | (0.0036) | (0.0048) |
| **Lag Specification** | Lag: 7 Days Before | | Lag: 14 Days Before | | Lag: 21 Days Before | |
| **Time of Day** | 6PM-12AM | 12AM-6AM next day | 6PM-12AM | 12AM-6AM next day | 6PM-12AM | 12AM-6AM next day |
| **Control Variables:** | | | | | | |
| **Full Set of Controls** | X | X | X | X | X | X |
| **Audience Instrumented With Predicted Audience Using Following Week's Audience** | No | No | X | X | X | X |
| **N** | N = 1559 | N = 1558 | N = 1556 | N = 1555 | N = 1553 | N = 1552 |

- **Robustness Checks.** (Appendix Table 2)

- **Individual Movie Violence Level.** (Figure 3)
  - No single violence level responsible for results

- **2-Hour Time Blocks.** (Figure 4)
  - Negative effect concentrated between 8PM and 6AM

- **Alternative Movie Violence Measure Using MPAA Rating.** (App. Table 3)
  - Strong Violence if "Violence"/"Violent" with “Bloody", “Brutal", “Disturbing”, “Graphic", “Grisly", “Gruesome”, or “Strong" in Rating
  - Mild Violence if "Violence"/"Violent"
  - Similar, but weaker effects

- **Placebos** (Table 5)
  - No effect in placebo specifications

- **Findings**:
  1. Violent movies lower same-day violent crime in the evening
  2. Violent movies lower violent crime in the night after exposure
  3. Strongly violent movies have somewhat larger negative effects compared to mildly violent movies in the evening, but *not* after exposure
  4. Nighttime hours have larger negative effects compared to evening hours –> Compositional effect
  5. No lagged effect of exposure in weeks following movie attendance –> No intertemporal substitution

- Interpretations for Findings 1-3

- **Finding 1. Lower Crime in the Evening**
- *Voluntary incapacitation* since no crime in movie theater
- Effect increases in movie violence due to self-selection
- Magnitude of findings: too large?
  - Assume incapacitate for half of time block
  - Estimate $\beta^j = -0.5x^j\sigma_y$ –> If criminals were not over-represented, $\beta^v_{equal} = -0.5 * (1/300) \approx -0.0017$
  - Self-selection of criminals:
    * $0.0130/0.0017 = 7.6$ times in strongly violent movies
    * $0.0109/0.0017 = 6.4$ times in mildly violent movies

- Compare selection to observed selection on ‘violent’ demographics

- Consumer Expenditure Survey time diary for period 1995-2004

  – Estimate regression at daily level (Friday-Sunday) (Table 7)

$$share_t^{CEX} = \alpha + \beta^v \frac{A_t^v}{Pop_t} + \beta^m \frac{A_t^m}{Pop_t} + \beta^n \frac{A_t^n}{Pop_t} + \Gamma X_t + \varepsilon_t$$

  – Younger people more likely to watch violent movies (Columns 3-4):

    * $2.094/0.9469 = 2.2$ times over-sampled in strongly violent movies

    * $1.4642/0.7736 = 1.9$ times over-sampled in mildly violent movies

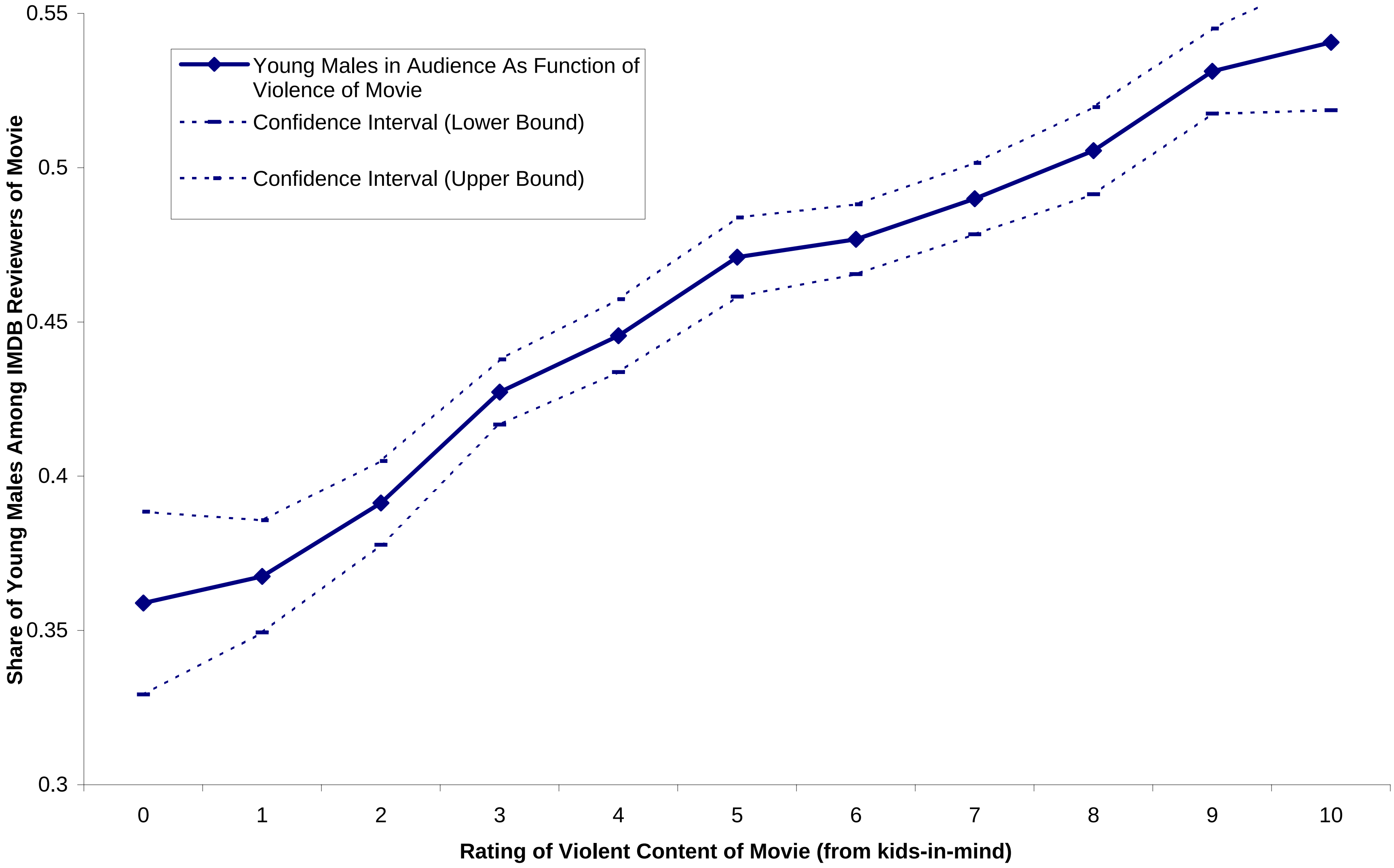
  – Stronger (though noisier) findings for young single males (Columns 4-5)

  – Observed magnitudes of incapacitation plausible

- **Finding 2. Lower Crime in the Night**
  - Movie attendance –> substitute away from more dangerous activities
  - Not trivial: Movie theater could have been meeting point for criminals
  - Is alcohol part of explanation? (Table 8)
    * Larger negative effect on assaults involving alcohol consumption (Columns 1-4)
    * Larger negative effect for assaults in bar and night clubs (though imprecise estimates) (Columns 5-6)
    * Some evidence from CEX data

- **Finding 3. Non-monotonicity in Violent Content**
  - Night hours: $\hat{\beta}^v = -0.0192$ versus $\hat{\beta}^m = -0.0205$
  - Pattern consistent with arousal ($\alpha^v > \alpha^m$). For strongly violent movies:
    - $*$ Substitution effect lowers crime
    - $*$ Arousal effect increases crime
  - BUT: Is selection of potential criminals linear?
  - Linear selection with IMDB data (Figure 5) — Share of young males among raters of movies online

**Figure 5. Share of Young Males in Audience As Function of Violence (Internet Movie Database Data)**



- **Additional Evidence on Selection**
  - Test 1: Movies highly attended by violent demographics (young males) should have larger effect – Use data on demographics of audience from IMDB (see text)
  - Test 2: Movies that do not attract violent demographics do not lower crime
    - High-Profanity movies and High-Sexual-Content movies (Table 11)
    - Conditional on movie violence:
      - No additional selection of young into these movies (CEX data)
      - No effect on violent crime
  - Strong support for selection

- **Magnitudes and Psychology Experiments**

- Differences from laboratory evidence (Levitt-List, 2006): 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

- Question 1. Peer Effects through the media.
  - To what extent do we imitate role models in the media?
  - Example 1: Movies with Car races –> Dangerous driving –> Car accidents
  - Example 2: Smoking in Movies –> Increased purchase of cigarettes
  - Is imitation higher for characters of same race and gender?

- Question 2. Psychology of Arousal
  - Does glamorized violence affect behavior differently?

# 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

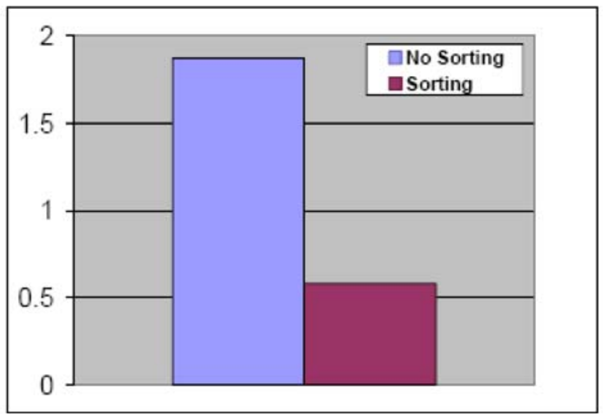
- Notice: One can integrate sorting into laboratory experiments

- **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

- Model:
  - Pure altruism is minority of subjects
  - Social pressure – Pay a utility cost $k$ if say no (but no cost if sort out)
  - Self- or Other-Signalling – Like to signal that one is good type

- What captures better charitable giving in the field? Sorting or no sorting?

- Depends on situation: Fund-raiser visit can be announced or unannounced

- Can take this to a Field Experiment: **DellaVigna-List-Malmendier** (in planning)
  - Control group $C$: Door-to-Door Fund-raiser
  - Treatment group $T$: Day before, hang flyer on door-knob indicating hour of visit

- Outcomes:
  - Share opening the door: $d$
  - Share giving: $g$

- Predictions:
  - Opposite for the two main models
  - Altruism: $d_T > d_C$ and $g_T > g_C$
  - Social pressure: $d_T < d_C$ and $g_T < g_C$

- Also: Vary Quality of charity:
  - La Rabida Children's Hospital (high altruism)
  - East Carolina Center for Hazard Migration (low altruism)
  - Organ donation card (?)

- Interpretations:
  - Information on flyer affecting giving?
    * Treatment $T2w$: Flyer announces a visit in next 2 weeks
    * Visit will be unannounced, but information like in $T$ treatment
  - Social pressure or self-signalling?
    * Treatment $Too$ (opt-out): Flyer specifies option 'Please do not disturb'
    * Yes if social pressure, no if signalling

- Finally, magnitudes:
  - Assume $g_T = .1 < g_C = .15$
  - What does this imply about social pressure?
  - Calibrate against magnitude in other treatments
    * Survey Control Group $CS$: Ask to complete survey on charitable giving
    * Survey Treatment Group $TS$: Survey with flyer that announces visit
    * Vary payment for survey ($0 vs. $10) and length (5 min. vs. 10 min.)
  - Estimate elasticity with respect to money and value of time

- **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), workers (retirement saving, benefit take-up), students (homework)

  2. **Reference dependence.** Workers (labor supply, increasing wages), (inexperienced) traders (sport cards), financial investors, consumers (insurance), house owners

  3. **Social preferences.** Consumers (giving to charities)

4. **Inattention.** Individual investors, Consumers (eBay bidding)

5. **Menu Effects.** Individual investors, Consumers (loans)

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

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

- 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’

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

- Firms

- In particular, firms are 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 and next week)
  - Interaction between experienced and inexperienced investors (noise traders and behavioral finance — 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 — in two weeks)
  - Institutional design (in two weeks)

# 6 Next Lecture

- Market Response to Biases: Pricing
- Market Response to Biases: Asset Pricing
- Market Response to Biases: Corporate Finance
- Market Response to Biases: Employers
- Market Response to Biases: Political Economy
- Next week: Empirical Problem Set Handed Out