# Econ 219B
# Psychology and Economics: Applications
# (Lecture 9)

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# Outline

# Section 1

## Social Signaling

# Social Signaling

- **Benabou and Tirole (2003):**

$$U = u(x_s) + \alpha u(x_o) + \lambda_\alpha E(\alpha | x_s)$$

- Individuals have an altruism weight $\alpha$
  - Individuals 'forget' their altruism $\alpha$
  - They infer $\alpha$ from their own behavior in a signaling game
  - They care about the inferred $\alpha$ with social signaling weight $\lambda_\alpha$
  - Behave generously to convince one self (and others)
- Can explain:
  - People behave generously when observed, less so when no one sees (dictator with exit)
  - Small donations to signal generosity to others
  - Can generate crowd out of generosity with incentives

# Example

- Consider this in the context of **Dube, Luo, and Fang (2015)** paper on case-based marketing
  - Send 30,000 SMS messages in China offering to buy movie ticket for 3-D version of *X-Men: Days of Future Past*
  - Standard price: 100 RMB
  - Randomize price discount: 0, 20, 35, 50, 60, 75 RMB
  - Cross-randomize charitable giving bundled with movie ticker purchase: "If you purchase ticket, X RMB will go to charity': 0, 5, 10, 15 RMB
  - Follow-up survey on motivation

# Sample sizes

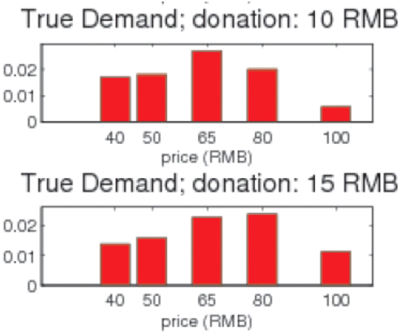
| Variable | Donation (RMB) | | | | |
|---|---|---|---|---|---|
| discount (RMB) | | 0 | 5 | 10 | 15 |
| | 0 | 700 | 700 | 700 | 700 |
| | 20 | 700 | 1,000 | 1,000 | 1,000 |
| | 35 | 700 | 1,000 | 3,000 | 3,000 |
| | 50 | 700 | 1,000 | 3,000 | 3,000 |
| | 60 | 700 | 1,000 | 3,000 | 3,000 |
| | 75 | 700 | - | - | - |

# Results: Low Donation

- For low donation, monotonic effect of discount

# Results: High Donation

- For high donation, non-monotonic effect of discount $\rightarrow$ Crowd-out of motivation



# Striking result: Interpretation?

- Model adapted from Benabou-Tirole
- Part 1: Individual has consumption utility

$$V + \alpha p + \gamma a$$

  - $V$ is utility from movie,
  - $p$ is price of movie, $\alpha$ ($<0$) is price elasticity
  - $a$ is donation, $\gamma$ is (reduced-form) altruism
  - So far, standard model with altruism

# Striking result: Interpretation?

- Part 2a: Ego utility on altruism:

$$\lambda_\gamma E\left(\gamma|a, p, y\right)$$

  - Individual derives utility from thinking of being altruistic (high $a$)
  - Weight on ego utillity is $\lambda_\gamma$: for $\lambda_\gamma = 0$, back to pure altruism case
  - Individual solves a signaling game to infer $\gamma$ given price $p$, discount $a$, and donation decision $y \in 0, 1$
  - Thus, donation ($y = 1$) has ego utility benefits, rasing $E\gamma$

# Striking result: Interpretation?

- This is not enough: need Part 2b in Ego utility:

$$\lambda_\alpha E\left(a \middle| a, p, y\right)$$

  - Individual derives utility from thinking of self as stingy – or not
  - Why this term? There needs to be a signal extraction problem: giving can signal high generosity or low price elasticity
  - More questionable assumption

- Decision: Give ($y = 1$) if

$$\begin{aligned} U(1) &= V + \alpha p + \gamma a + \lambda_\alpha E\left(\alpha | a, p, 1\right) + \lambda_\gamma E\left(\gamma | a, p, 1\right) \geq \\ U\left(0\right) &= \lambda_\alpha E\left(\alpha | a, p, 0\right) + \lambda_\gamma E\left(\gamma | a, p, 0\right) \end{aligned}$$

  or

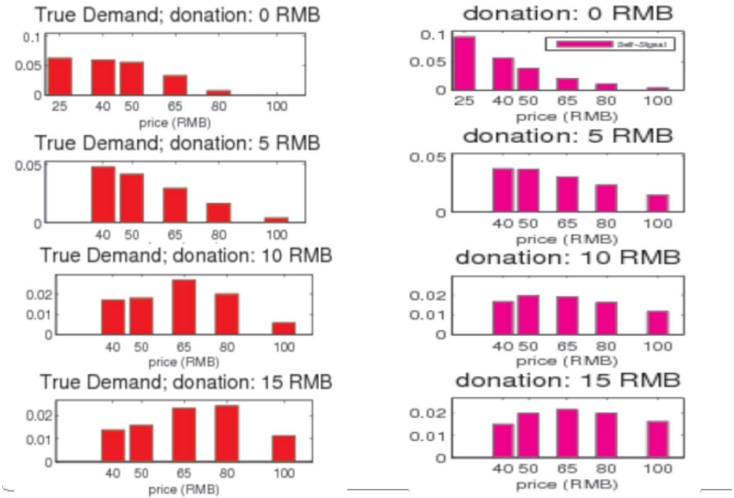
$$V + \alpha p + \gamma a + \Delta\left(a, p\right) > 0$$

  where $\Delta$ is net ego utility
- Updating on $\gamma$ if purchase ($y = 1$):

$$E\left(\gamma | \gamma > -\frac{V + \alpha p + \Delta\left(a, p\right)}{a}\right)$$

- Specify priors on parameters to derive separating equilibrium of signaling game

# True Demand vs. Model



# Parameter Values

- Remarkably good fit, but value of some parameters odd
  - Relatedly: How much do you need ego utility on price elasticity: not obvious to interpret

    $$\lambda_\gamma E\left(\gamma|a, p, y^h\right) + \lambda_\alpha E\left(\alpha|a, p, y^h\right)$$

  - Relatedly: Estimation of some parameters appears problematic
    - Value V of good negative on average?

      (What if allow for not all to pay attention)
    - $\sigma_\alpha$ is at boundary

| | coefficient | st. error |
|---|---|---|
| Donation ($\bar{\gamma}$) | -0.1411 | 0.1345 |
| Price, ($\alpha$) | -0.0183 | 0.0077 |
| Intercept, ($\bar{V}$) | -0.8526 | 0.225 |
| $\sigma_\gamma$ | 0.1327 | 0.0632 |
| $\sigma_\alpha$ | 0.0001 | 0.307 |
| $\lambda_\gamma$ | 2.1948 | 0.7931 |
| $\lambda_\alpha$ | -15.9831 | 3.452 |

# Other Work

- **Karing (2018)**: Introduce social signal for health choice
  - Bracelet for mothers to wear (in Sierra Leone) when child reached 3rd vaccination
  - Compare to control group that got object of similar private value, but with no signaling capacity
  - Does this motivate additional vaccination?
- **Birke (2018):** Study of precise predictions of crowd-out with effort task
  - Consider pro-social behavior, like coding for GitHub
  - Introduce a private incentive, say a payment for coding 1,000 lines
  - Standard model has bunching at threshold
  - Social signaling has anti-bunching instead, as people signal that they are not motivated by love of money, but more by pro-social mission

# Section 2

## Social Norms

# Social Norms

- Utility is
$$U = u(x_s) - \gamma (x_s - \bar{x})^2$$
where $\bar{x}$ is a prescribed social norm
- The individual pays a disutility cost from deviating from norm
  - E.g., equal sharing in dictator game (Krupka and Weber, 2013)
  - E.g., a behavior prescribed by one's identity (Akerlof and Kranton, 2003)
- Can explain:
  - People are generous in some settings, not others, if social norms prescribes so
- Drawback:
  - Need to explain where social norm comes from

# Krupka and Weber (2013)

- **Krupka and Weber (JEEA 2013)**
- Consider social preference experiments with moral wriggle-room
  - dictator games with exit
  - avoidance of information
- Can observed behavior in these experiments be explained with a social norm term $\gamma (x_s - \bar{x})^2$?
- Elicit social norm by asking how acceptable each action is
  - More precisely, to incentivize reporting, ask subjects to predict how socially acceptable other forecasters will find an action
  - Pay for accuracy in prediction
  - Then transform this measure with scaling into a measure of acceptability of an action

# Elicitation of Social Norms

TABLE 1. Elicited norms ($N(a_k)$) for bully versus standard dictator environments (data from Experiment 1).

| Action (final wealth) | Standard ($n = 107$) (Initial wealth: \$10, \$0) Action | Mean | $--$ | $-$ | $+$ | $++$ | Bully ($n = 92$) (Initial wealth: \$5, \$5) Action | Mean | $--$ | $-$ | $+$ | $++$ | *Rank-sum test (z)* |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| \$10, \$0 | "Give \$0" | **−0.80** | 82% | 10% | 3% | 5% | "Take \$5" | **−0.90** | 91% | 5% | 0% | 3% | *1.85** |
| \$9, \$1 | "Give \$1" | **−0.64** | 61% | 31% | 3% | 6% | "Take \$4" | **−0.83** | 82% | 14% | 1% | 3% | *3.13**** |
| \$8, \$2 | "Give \$2" | **−0.44** | 35% | 51% | 10% | 4% | "Take \$3" | **−0.67** | 55% | 40% | 3% | 1% | *3.27**** |
| \$7, \$3 | "Give \$3" | **−0.16** | 8% | 62% | 26% | 4% | "Take \$2" | **−0.38** | 28% | 53% | 16% | 2% | *3.34**** |
| \$6, \$4 | "Give \$4" | **0.14** | 3% | 30% | 61% | 7% | "Take \$1" | **−0.09** | 12% | 46% | 36% | 7% | *3.42**** |
| \$5, \$5 | "Give \$5" | **0.87** | 0% | 3% | 14% | 83% | "Give \$0" / "Take \$0" | **0.93** | 0% | 0% | 11% | 89% | *1.26* |
| \$4, \$6 | "Give \$6" | **0.57** | 0% | 7% | 50% | 43% | "Give \$1" | **0.48** | 4% | 12% | 40% | 43% | *0.72* |
| \$3, \$7 | "Give \$7" | **0.42** | 1% | 22% | 39% | 37% | "Give \$2" | **0.31** | 7% | 23% | 38% | 33% | *1.12* |
| \$2, \$8 | "Give \$8" | **0.32** | 6% | 31% | 23% | 40% | "Give \$3" | **0.20** | 14% | 27% | 23% | 36% | *1.08* |
| \$1, \$9 | "Give \$9" | **0.22** | 17% | 24% | 19% | 40% | "Give \$4" | **0.10** | 27% | 16% | 21% | 31% | *0.99* |
| \$0, \$10 | "Give \$10" | **0.18** | 26% | 13% | 18% | 43% | "Give \$5" | **0.04** | 36% | 10% | 16% | 38% | *1.13* |

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; all two-tailed.
Responses are: "very socially inappropriate" (−−), "somewhat socially inappropriate" (−), "somewhat socially appropriate" (+), "very socially appropriate" (++); modal response are shaded. To construct the mean ratings, we converted responses into numerical scores ("very socially inappropriate" = −1, "somewhat socially inappropriate" = −1/3, "somewhat socially appropriate" = 1/3, "very socially appropriate" = 1).

- Example for standard dictator game versus dictator game with different framing ("bully" game)
- Derive summary measure of acceptability, $s(a)$, for each action $a$

# Elicitation of Social Norms

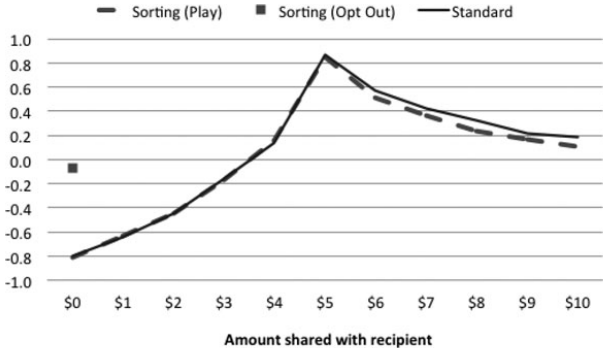



FIGURE 3. Mean ratings of social appropriateness from standard versus sorting treatments (data from Experiment 1).

- In dictator game with sorting, sorting out is much more acceptable than not giving

# Fitting Behavior

- How well can predict behavior with simple model:

$$U(a) = u(x_s) + \gamma s(a)$$

TABLE 3. Conditional (fixed-effect) logit estimation of choice determinants across experiments (includes mean appropriateness ratings from Experiment 1 as an explanatory variable).

| Behavioral data (experimental treatment) | Experiment 2 (Standard vs. Bully) (1) | (2) | Lazear et al. (2012) (Standard vs. Sorting) (3) | (4) | List (2007) (Standard vs. Take $1) (5) | (6) | Data from all three experiments (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Monetary payoff ($\beta$) | 0.656*** | 0.630*** | 0.811*** | 0.810*** | 1.456*** | 1.312*** | 0.750*** | 0.808*** |
| | (0.132) | (0.138) | (0.075) | (0.075) | (0.408) | (0.401) | (0.060) | (0.105) |
| Appropriateness rating ($\gamma$) | 1.858*** | 1.556*** | 2.304*** | 2.283*** | 1.941** | 1.982** | 1.856*** | 2.192*** |
| | (0.410) | (0.521) | (0.287) | (0.312) | (0.921) | (0.843) | (0.204) | (0.326) |
| Appropriateness rating X non-standard treatment | | 0.374 | | 0.062 | | −0.629 | | |
| | | (0.326) | | (0.331) | | (0.593) | | |
| Monetary payoff X Lazear et al., experiment | | | | | | | | −0.094 |
| | | | | | | | | (0.127) |
| Appropriateness rating X Lazear et al., experiment | | | | | | | | −0.125 |
| | | | | | | | | (0.470) |
| Monetary payoff X List experiment | | | | | | | | 0.426 |
| | | | | | | | | (0.391) |
| Appropriateness rating X List experiment | | | | | | | | −1.029 |
| | | | | | | | | (1.038) |
| $2\gamma/\beta$ | *5.66**** | *4.94**** | *5.68**** | *5.64**** | *2.67**** | *3.02**** | *4.95**** | *5.43**** |
| | *(0.49)* | *(0.98)* | *(0.39)* | *(0.48)* | *(0.98)* | *(0.90)* | *(0.29)* | *(0.30)* |
| Log-likelihood | −208.5 | −207.7 | −308.8 | −308.7 | −126.8 | −126.1 | −672.3 | −649.8 |
| Obs. | 1,166 | 1,166 | 2,105 | 2,015 | 816 | 816 | 4,087 | 4,087 |
| (subjects) | (106) | (106) | (183) | (183) | (70) | (70) | (359) | (359) |

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$; all two-tailed.
Bootstrapped standard errors are in parentheses. The variable "appropriateness rating" converts subject responses in Experiment 1 to numerical scores ("very socially inappropriate" = –1, "somewhat socially inappropriate" = –1/3, "somewhat socially appropriate" = 1/3, "very socially appropriate" = 1).

# Explaining Dictator Game with Sorting

- Good fit of observed behavior in dictator game with sorting

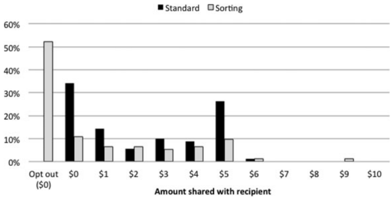



FIGURE 2(a). Distributions of amounts shared in standard versus sorting treatments (data from Experiments 1 and 2 of Lazear, Malmendier, and Weber 2012).

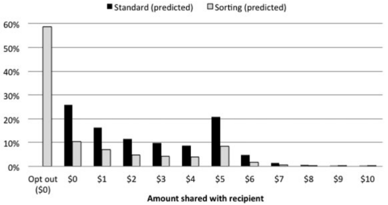



FIGURE 2(b). Predicted distributions of amounts shared in standard versus sorting treatments (based on coefficients in Table 3, Model 3).

# Field Evidence on Social Norms

- Field evidence on social norms relies typically on public/private design
- Identify setting where it is clear what is the signal to be sent:
  - Example 1: Student wants to signal that she is cool (eg., not hard-working), see "acting white" literature
  - Example 2: Student wants to signal that she is smart (and hard-working)
  - Example 3: Single professional woman wants to signal that she is not too ambitious
- Offer a choice and randomize whether the choice is private, or publicly observed by peers
- When choice is public, signaling component is turned on –> Estimate impact on choice
- Series of papers by Leonardo Bursztyn

# Social Norms in Education

- **Bursztyn and Jensen (QJE 2015)**
- Experiment in 4 Los Angeles public high schools
  - 11th graders, low income, 96% Hispanic
- N=560 students in non-honors classes, N=265 in honors classes
- Offer free SAT prep course (normally costs $200)
  - *"[Company Name] is offering a free online test preparation course for the SAT that is intended to improve your chances of being accepted and receiving financial aid at a college you like."*
  - Public condition: "*Your decision to sign up for the course will be kept completely private from everyone, except the other students in the room*"
  - Private condition: "*Your decision to sign up for the course will be kept completely private from everyone, including the other students in the room*"
- Randomization within classroom

# Social Norms in Education

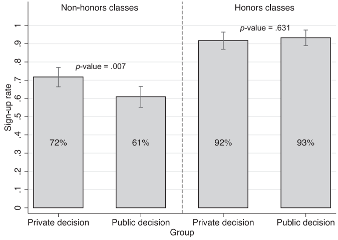



FIGURE IV

Sign-up Rates for Private versus Public Decisions, NonHonors versus Honors Classes

- Results:
  - Take up is higher in honors class, as expected
  - Public (vs private) has slight positive effect for honors class (ceiling effect)
  - Public (vs private) has strong negative effect for non-honors class
- Interpretation: students do not like to signal to peers in non-honors class that they want to go to college, uncool

# Social Norms and Gender Roles

- Evidence from speed dating (eg, Fisman, Kamenica, Simonsohn, Yiengar 2006) suggest that
  - women value professional ambition and achievements in men
  - men instead are conflicted about professional ambition and achievements in women
- Does this impact signals sent by single men versus single women?
- **Bursztyn, Fujiwara, and Pallais (AER 2017)**
- Setting is prestigious MBA
- Questionnaire during session with career center on 1st day
  - Randomize whether mention that answers will be discussed
  - "*The information on this survey will help the career center get to know you and help it find the right fit for your first-year internship. [...] This information will be shared with your career advisor and* **[your/anonymized]** *answers will be discussed during the [name of the career class].*"

# Social Norms and Gender Roles

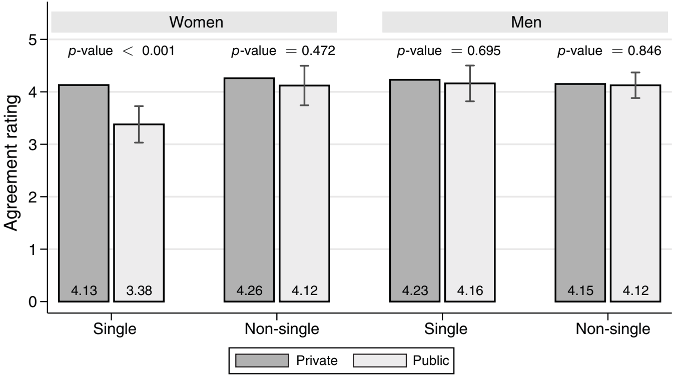



FIGURE 6. PROFESSIONAL AMBITION (*Primary Experiment*)

- Single women in public distort their stated ambition, at a real cost

# Section 3

# Non-Standard Beliefs

# So far: Non-Standard Preferences

- So far, focus on non-standard utility function $U\left(x_i^t|s_t\right)$ as deviations from standard model:

$$\max_{x_i^t \in X_i} \sum_{t=0}^{\infty} \delta^t \sum_{s_t \in S_t} p\left(s_t\right) U\left(x_i^t|s_t\right)$$

- Non-standard preferences
  - Self-Control Problems $(\beta, \delta)$
  - Reference Dependence $\left(U\left(x_i^t|s_i, r\right)\right)$
  - Social Preferences $\left(U\left(x_i, x_{-i}|s\right)\right)$

# Today: Non-Standard Beliefs

$$\max_{x_i^t \in X_i} \sum_{t=0}^{\infty} \delta^t \sum_{s_t \in S_t} \tilde{p}(s_t) U(x_i^t | s_t)$$

where $\tilde{p}(s_t)$ is the subjective distribution of states $S_i$ for agent.

- Distribution for agent differs from actual distribution: $\tilde{p}(s_t) \neq p(s_t)$

# Today: Non-Standard Beliefs

$$\max_{x_i^t \in X_i} \sum_{t=0}^{\infty} \delta^t \sum_{s_t \in S_t} \tilde{p}(s_t) U(x_i^t | s_t)$$

where $\tilde{p}(s_t)$ is the subjective distribution of states $S_i$ for agent.

- Distribution for agent differs from actual distribution: $\tilde{p}(s_t) \neq p(s_t)$
- Three main examples:
  1. *Overconfidence.* Overestimate one's own skills (or precision of estimate): $\tilde{p}(good\ \ state_t) > p(good\ \ state_t)$
  2. *Law of Small Numbers.* Gambler's Fallacy and Overinference in updating $\tilde{p}(s_t | s_{t-1})$
  3. *Projection Bias.* Expect future utility $\tilde{U}(x_i^t | s_t)$ to be too close to today's

# Section 4

## Overconfidence

# Background

- Overconfidence is of at least two types:
  - Overestimate one's ability (also called *overoptimism*)
  - Overestimate the precision of one's estimates (also called *overprecision*)
- Psychology: Evidence on overconfidence/overoptimism
  - **Svenson (1981):** 93 percent of subjects rated their driving skill as above the median, compared to the other subjects in the experiment
  - **Weinstein (1980):** Most individuals underestimate the probability of negative events such as hospitalization
  - **Buehler-Griffin-Ross (1994):** Underestimate time needed to finish a project

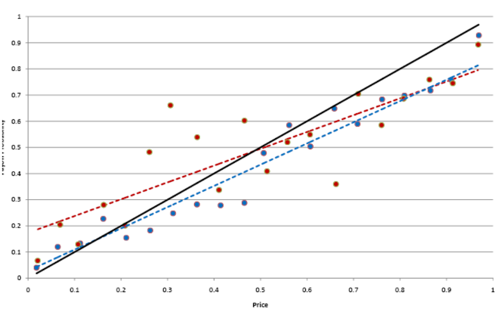
# Applications: Self-Control

- Applications in the field of overconfidence/overoptimism
- **Example 1. Overconfidence about self-control by consumers ($\hat{\beta} > \beta$)**
  - Evidence on self-control supports idea of naiveté
    - Status-quo bias (Madrian-Shea, 1999)
    - Response to teaser rates (Ausubel, 1999)
    - Health-club behavior (DellaVigna-Malmendier, 2006)

# Applications: Overconfidence

- **Example 2. Overconfidence for employees: Cowgill and Zitzewitz (REStud 2015)**
  - Prediction markets of Google employees (with raffle tickets for total of \$10,000 per quarter in payoffs)
  - Data: years 2005-2007, 1,463 employees placed $\geq 1$ trade

**Figure 2. Prices and Probabilities in Two and Five-outcome Markets**




Trades in two (red) and five-outcome (blue) markets (22,452and 42,416, respectively) are sorted into 20 bins according to price (i.e., 0-5, 5-10, etc.), and then average price and payoff probability for the bin is plotted. Dashed lines plot regression equations using OLS.

# Applications: Overconfidence

- Securities not related to Google correctly priced on average
- Securities with implications for Google: Substantial overconfidence for two-outcome security, Less so for five-outcome security

**Table 5. Optimistic bias in the Google markets**

| | Obs. | Avg price | Avg payoff | Return (SE) | |
|---|---|---|---|---|---|
| All markets | 70,706 | 0.357 | 0.342 | -0.015*** | (0.003) |
| Markets with implication for Google | 37,910 | 0.310 | 0.293 | -0.017*** | (0.004) |
| Two-outcome markets with implication for Google | 9,023 | 0.509 | 0.492 | -0.017*** | (0.006) |
| Best outcome for Google | 4,556 | 0.456 | 0.199 | -0.256*** | (0.063) |
| Worst | 4,467 | 0.563 | 0.790 | 0.227*** | (0.064) |
| Five-outcome markets with implication for Google | 26,511 | 0.239 | 0.222 | -0.017*** | (0.005) |
| Best outcome for Google | 5,592 | 0.244 | 0.270 | 0.027 | (0.040) |
| 2nd | 5,638 | 0.271 | 0.246 | -0.025 | (0.066) |
| 3rd | 5,539 | 0.296 | 0.179 | -0.118** | (0.053) |
| 4th | 5,199 | 0.206 | 0.178 | -0.028 | (0.041) |
| Worst | 4,543 | 0.162 | 0.236 | 0.074 | (0.056) |

# Overconfidence: A general phenomenon

- Survey evidence suggests phenomenon general
- **Oyer and Schaefer, 2005; Bergman and Jenter, 2007**
  - Overconfidence of employees about own-company performance is leading explanation for provision of stock options to rank-and-file employees
  - Stock options common form of compensation: (Black and Scholes) value of options granted yearly to employees in public companies over $400 (about one percent of compensation) in 1999 (Oyer and Schaefer, 2005)
  - Incentive effects unlikely to explain the issuance: contribution of individual employee to firm value very limited
  - Overconfidence about own-company performance can make stock options an attractive compensation format for employers
  - Overconfidence needs to be larger for employees than for top managers (problem set 2)
  - Sorting contributes: Overconfidence plausible since workers overconfident about a company sort into it

# However...

- However, **Bergman and Jenter (2007):** employees can also purchase shares on open market, do not need to rely on the company providing them
  - Under what conditions company will still offer options to overconfident employees?
  - Also, why options and not shares in company?
  - **Bergman and Jenter (2007):** option compensation is used most intensively by company when employees more likely to be overconfident based on proxy (past returns)

# Overconfidence by CEOs

- **Example 3. Overconfidence about ability by CEOs**

- **Malmendier-Tate (JF 2005 and JFE 2008)**
- Assume that CEOs overestimate their capacity to create value
- Implications for:
  - Investment decisions (MT 2005)
  - Mergers (MT 2008)
  - Equity issuance (MT 2010)
- Focus on merger implications
- Slides courtesy of Ulrike

# Model

## Assumptions

1. CEO acts in interest of current shareholders.
   (*No agency problem.*)

2. Efficient capital market.
   (*No asymmetric information.*)

## Notation

$V_A$ = market value of the acquiring firm
$V_T$ = market value of the target firm
$V$ = market value of the combined firm
$\hat{V}_A$ = acquiring CEO's valuation of his firm
$\hat{V}$ = acquiring CEO's valuation of the combined firm
$c$ = cash used to finance the merger

## Rational CEO

- Target shareholders demand share $s$ of firm such that:

$$sV = V_T - c.$$

- CEO decides to merge if $V - \left(V_T - c\right) > V_A$ (levels).

  $\Rightarrow$ Merge if $e > 0$ (differences), where $e$ is "synergies."

  $\Rightarrow$ First-best takeover decision.

- Post-acquisition value to current shareholders:

$$\overline{V} = V - (V_T - c) = (V_A + V_T + e - c) - (V_T - c) = V_A + e$$

$$\Rightarrow \frac{\partial \overline{V}}{\partial c} = 0 \text{ (\textit{No financing prediction}.)}$$

# Overconfident CEO (I)

- CEO overestimates future returns to own firm:

$$\hat{V}_A > V_A$$

CEO overestimates returns to merger:

$$\hat{V} - V > \hat{V}_A - V_A$$

- Target shareholders demand share $s$ of firm such that:

$$sV = V_T - c$$

CEO believes he should have to sell $s$ such that:

$$s\hat{V} = V_T - c$$

# Overconfident CEO (II)

- CEO decides to merge if

$$\hat{V} - (V_T - c) - \left[ \frac{(\hat{V} - V)(V_T - c)}{V} \right] > \hat{V}_A \text{ } (\textit{levels}),$$

i.e. merges if

$$e + \hat{e} > \left[ \frac{(\hat{V}_A - V_A + \hat{e})(V_T - c)}{V} \right] (\textit{differences}),$$

where $\hat{e}$ are perceived "synergies."

# Propositions

Compare

$V(c) - (V_T - c) > V_A$ and

$\widehat{V}(c) - (V_T - c) - \frac{[\widehat{V}(c) - V(c)](V_T - c)}{V(c)} > \widehat{V}_A$

1. Overconfident managers do some value-destroying mergers. (Rational CEOs do not.)
2. An overconfident manager does more mergers than a rational manager when internal resources are readily available
3. An overconfident manager may forgo some value-creating mergers. (Rational managers do not.)

# Empirical Predictions

Rational CEO

Overconfident CEO

1. On average?
2. Overconfident CEOs do more mergers that are likely to destroy value
3. Overconfident CEOs do more mergers when they have abundant internal resources
4. The announcement effect after overconfident CEOs make bids is lower than for rational CEOs

# Data

| Data on private accounts | Data on corporate accounts |
| --- | --- |
| 1. Hall-Liebman (1998)<br>Yermack (1995)<br><br>Key: Panel data on stock and option holdings of CEOs of Forbes 500 companies 1980-1994<br><br>2. Personal information about these CEOs from<br>- Dun & Bradstreet<br>- Who's who in finance | 1. CRSP/COMPUSTAT<br><br>Cash flow, Q, stock price…<br><br>2. CRSP/SDC-merger databases<br><br>Acquisitions |

# Primary Measure of Overconfidence
## "Longholder"

(Malmendier and Tate 2003)

CEO holds an option until the year of expiration.

CEO displays this behavior at least once during sample period.

→ minimizes impact of CEO wealth, risk aversion, diversification

Robustness Checks:

1. Require option to be at least *x*% in the money at the beginning of final year
2. Require CEO to *always* hold options to expiration
3. Compare "late exercisers" to "early exercisers"

# Empirical Specification

$$\Pr\{Y_{it} = 1 \mid X, O_{it}\} = G(\beta_1 + \beta_2 \bullet O_{it} + X^T \boldsymbol{\gamma})$$

with $i$ company, $t$ year, $Y$ acquisition (yes or no), $O$ overconfidence, $X$ controls

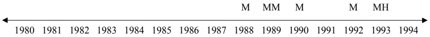
→ $H_0$: $\beta_2 = 0$ (overconfidence does not matter)
→ $H_1$: $\beta_2 > 0$ (overconfidence does matter)

# Identification Strategy (I)

<u>Case 1:</u>

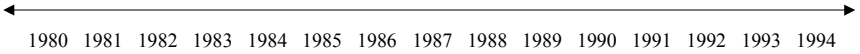
Wayne Huizenga (Cook Data Services/Blockbuster)

- CEO for all 14 years of sample
- Longholder




J Willard Marriott (Marriott International)

- CEO for all 15 years of sample
- Not a Longholder

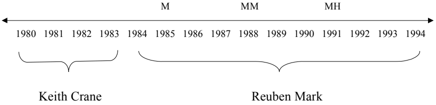



**AND**

<u>Case 2:</u>

Colgate Palmolive

- Keith Crane CEO from 1980-1983 (Not a Longholder)
- Reuben Mark CEO from 1984-1994 (Longholder)



# Table 4. Do Overconfident CEOs Complete More Mergers?

**Longholder** = holds options until last year before expiration (at least once)

**Distribution:** Logistic. Constant included.

**Dependent Variable:** Acquistion (yes or no); **Normalization:** Capital.

| | logit with controls | random effects logit | logit with fixed effects |
|---|---|---|---|
| Size | **0.8733** | **0.8600** | **0.6234** |
| | (1.95)* | (2.05)** | (2.60)*** |
| $Q_{t-1}$ | **0.7296** | **0.7316** | **0.8291** |
| | (2.97)*** | (2.70)*** | (1.11) |
| Cash Flow | **2.0534** | **2.1816** | **2.6724** |
| | (3.93)*** | (3.68)*** | (2.70)*** |
| Ownership | **1.2905** | **1.3482** | **0.8208** |
| | (0.30) | (0.28) | (0.11) |
| Vested Options | **1.5059** | **0.9217** | **0.2802** |
| | (1.96)* | (0.19) | (2.36)** |
| Governance | **0.6556** | **0.7192** | **1.0428** |
| | (3.08)*** | (2.17)** | (0.21) |
| Longholder | **1.5557** | **1.7006** | **2.5303** |
| | (2.58)*** | (3.09)*** | (2.67)*** |
| Year Fixed Effects | yes | yes | yes |
| Observations | 3690 | 3690 | 2261 |
| Firms | | 327 | 184 |

# Table 6. Are Overconfident CEOs Right to Hold Their Options? (I)

| Returns from exercising 1 year sooner and investing in the S&P 500 index | |
|---|---|
| Percentile | Return |
| 10th | -0.24 |
| 20th | -0.15 |
| 30th | -0.10 |
| 40th | -0.05 |
| 50th | -0.03 |
| 60th | 0.03 |
| 70th | 0.10 |
| 80th | 0.19 |
| 90th | 0.39 |
| Mean | 0.03 |
| Standard Deviation | 0.27 |

All exercises occur at the maximum stock price during the fiscal year

# Empirical Predictions

Rational CEO

Overconfident CEO

1. On average?
2. Overconfident CEOs do more mergers that are likely to destroy value
3. Overconfident CEOs do more mergers when they have abundant internal resources
4. The announcement effect after overconfident CEOs make bids is lower than for rational CEOs

# Table 8. Diversifying Mergers

**Longholder** = holds options until last year before expiration (at least once)

**Distribution:** Logistic. Constant included; **Normalization:** Capital.

**Dependent Variable:** Diversifying merger (yes or no).

| | logit | logit with random effects | logit with fixed effects |
|---|---|---|---|
| Longholder | **1.6008** | **1.7763** | **3.1494** |
| | (2.40)** | (2.70)*** | (2.59)*** |
| Year Fixed Effects | yes | yes | yes |
| Observations | 3690 | 3690 | 1577 |
| Firms | | 327 | 128 |

**Dependent Variable:** Intra-industry merger (yes or no).

| | | | |
|---|---|---|---|
| Longholder | **1.3762** | **1.4498** | **1.5067** |
| | (1.36) | (1.47) | (0.75) |
| Year Fixed Effects | yes | yes | yes |
| Observations | 3690 | 3690 | 1227 |
| Firms | | 327 | 100 |

Regressions include Cash Flow, $Q_{t-1}$, Size, Ownership, Vested Options, and Governance.
Industries are Fama French industry groups.

# Empirical Predictions

Rational CEO → Overconfident CEO

1. On average?
2. Overconfident CEOs do more mergers that are likely to destroy value
3. Overconfident CEOs do more mergers when they have abundant internal resources
4. The announcement effect after overconfident CEOs make bids is lower than for rational CEOs

# Kaplan-Zingales Index

$$KZ = -1.00 \cdot \frac{CashFlow}{Capital} + 0.28 \cdot Q + 3.14 \cdot Leverage - 39.37 \cdot \frac{Dividends}{Capital} - 1.31 \cdot \frac{Cash}{Capital}$$

- Coefficients from logit regression (Pr{financially constrained})
- High values $\longrightarrow$ Cash constrained
  - Leverage captures debt capacity
  - Deflated cash flow, cash, dividends capture cash on hand
  - Q captures market value of equity (Exclude?)

# Table 9. Kaplan-Zingales Quintiles

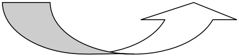
**Longholder** = holds options until last year before expiration (at least once)
**Distribution:** Logistic. Constant included.
**Dependent Variable:** Acquistion (yes or no)**; Normalization:** Capital.
All regressions are logit with random effects.

| | Least Equity Dependent | | --------------------------------> | | Most Equity Dependent |
|---|---|---|---|---|---|
| | | | All Mergers | | |
| | Quintile 1 | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 |
| Longholder | **2.2861** | **1.6792** | **1.7756** | **1.9533** | **0.8858** |
| | (2.46)** | (1.48) | (1.54) | (1.50) | (0.33) |
| Year Fixed Effects | yes | yes | yes | yes | yes |
| Observations | 718 | 719 | 719 | 719 | 718 |
| Firms | 125 | 156 | 168 | 165 | 152 |
| | | | Diversifying Mergers | | |
| | Quintile 1 | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 |
| Longholder | **2.5462** | **1.8852** | **1.7297** | **1.0075** | **1.0865** |
| | (1.89)* | (1.51) | (1.36) | (0.01) | (0.18) |
| Year Fixed Effects | yes | yes | yes | yes | yes |
| Observations | 718 | 719 | 719 | 719 | 718 |
| Firms | 125 | 156 | 168 | 165 | 152 |

Regressions include Cash Flow, $Q_{t-1}$, Size, Ownership, Vested Options, and Governance.

# Empirical Predictions

Rational CEO | Overconfident CEO



1. On average?
2. Overconfident CEOs do more mergers that are likely to destroy value
3. Overconfident CEOs do more mergers when they have abundant internal resources
4. The announcement effect after overconfident CEOs make bids is lower than for rational CEOs

# Empirical Specification

$$CAR_i \;=\; \beta_1 \;+\; \beta_2 \bullet O_i \;+\; X'\boldsymbol{\gamma} \;+\; \varepsilon_i$$

| | | | | |
|---|---|---|---|---|
| with | $i$ | company | $O$ | overconfidence |
| | | | $X$ | controls |

$$CAR_i = \sum_{t=-1}^{1} \left( r_{it} - E[r_{it}] \right)$$

where $E[r_{it}]$ is daily S&P 500 returns ($\alpha$=0; $\beta$=1)

# Table 14. Market Response

**Longholder** = holds options until last year before expiration
(at least once)

**Dependent Variable:** Cumulative abnormal returns [-1,+1]

| | OLS (3) | OLS (4) | OLS (5) |
|---|---|---|---|
| Relatedness | **0.0048** | **0.0062** | **0.0043** |
| | (1.37) | (1.24) | (1.24) |
| Corporate Governance | **0.0079** | **0.0036** | **0.0073** |
| | (2.18)** | (0.64) | (1.98)** |
| Cash Financing | **0.014** | **0.0127** | **0.0145** |
| | (3.91)*** | (2.60)*** | (3.99)*** |
| Age | | | **-0.0005** |
| | | | (1.46) |
| Boss | | | **0.0001** |
| | | | (0.04) |
| Longholder | **-0.0067** | **-0.0099** | **-0.0079** |
| | (1.81)* | (2.33)** | (2.00)** |
| Year Fixed Effects | yes | yes | yes |
| Industry Fixed Effects | no | yes | no |
| Industry*Year Fixed Effects | no | yes | no |
| Observations | 687 | 687 | 687 |
| R-squared | 0.10 | 0.58 | 0.10 |

Regressions include Ownership and Vested Options.

# Do Outsiders Recognize CEO Overconfidence?

**Portrayal in Business Press**:

1. Articles in
   - New York Times
   - Business Week
   - Financial Times
   - The Economist
   - Wall Street Journal
2. Articles published 1980-1994
3. Articles which characterize CEO as
   - Confident or optimistic
   - Not confident or not optimistic
   - Reliable, conservative, cautious, practical, steady or frugal

# Table 13. Press Coverage and Diversifying Mergers

**Distribution:** Logistic. Constant included; **Normalization:** Capital.

**Dependent Variable:** Diversifying merger (yes or no).

| | logit | logit with random effects | logit with fixed effects |
|---|---|---|---|
| TOTALconfident | **1.6971** | **1.7826** | **1.5077** |
| | (2.95)*** | (3.21)*** | (1.48) |
| Year Fixed Effects | yes | yes | yes |
| Observations | 3647 | 3647 | 1559 |
| Firms | | 326 | 128 |

**Dependent Variable:** Intra-industry merger (yes or no).

| | logit | logit with random effects | logit with fixed effects |
|---|---|---|---|
| TOTALconfident | **1.0424** | **1.0368** | **0.8856** |
| | (0.20) | (0.16) | (0.31) |
| Year Fixed Effects | yes | yes | yes |
| Observations | 3647 | 3647 | 1226 |
| Firms | | 326 | 100 |

Regressions include Total Coverage, Cash Flow, $Q_{t-1}$, Size, Ownership, Vested Options, and Governance. Industries are Fama French industry groups.

# Overprecision

- Overconfidence/Overprecision: Overestimate the precision of one's estimates
- **Alpert-Raiffa (1982).** Ask questions such as
  - 'The number of "Physicians and Surgeons" listed in the 1968 Yellow Pages of the phone directory for Boston and vicinity'
  - 'The total egg production in millions in the U.S. in 1965.'
  - 'The toll collections of the Panama Canal in fiscal 1967 in millions of dollars'
- Ask for 99 percent confidence intervals for 1,000 questions
- No. of errors: 426! (Compare to expected 20)
- (Issue: Lack of incentives)

# Investor Overconfidence: Odean (1999)

- Investor overconfidence/overprecision predicts excessive trading
  - Investor believes signal is too accurate $\rightarrow$ Executes trade
- Empirical test using data set from discount brokerage house
- Follow all trades of 10,000 accounts
- January 1987-December 1993
- 162,948 transactions

# Overtrading?

- Traders that overestimate value of their signal trade too much
- Substantial cost for trading too much:
  - Commission for buying 2.23 percent
  - Commission for selling 2.76 percent
  - Bid-ask spread 0.94 percent
  - Cost for 'round-trip purchase': 5.9 percent (!)

# Compare Returns

- Stock return on purchases must be at least 5.9 percent.
- Compute buy-and-hold returns
- Evidence: Sales outperform purchases by 2-3 percent!

TABLE 1—AVERAGE RETURNS FOLLOWING PURCHASES AND SALES

| Panel A: All Transactions | *n* | 84 trading days later | 252 trading days later | 504 trading days later |
|---|---|---|---|---|
| Purchases | 49,948 | 1.83 | 5.69 | −24.00 |
| Sales | 47,535 | 3.19 | 9.00 | 27.32 |
| Difference | | −1.36 | −3.31 | −3.32 |
| N1 | | (0.001) | (0.001) | (0.001) |
| N2 | | (0.001) | (0.001) | (0.002) |

# Distribution of Results

- Is the result weaker for individuals that trade the most? No

Panel C: The 10 Percent of Investors Who Trade the Most

| | $n$ | 84 trading days later | 252 trading days later | 504 trading days later |
|---|---|---|---|---|
| Purchases | 29,078 | 2.13 | 7.07 | 25.28 |
| Sales | 26,732 | 3.04 | 9.76 | 28.78 |
| Difference | | −0.91 | −2.69 | −3.50 |
| N1 | | (0.001) | (0.001) | (0.001) |
| N2 | | (0.001) | (0.001) | (0.010) |

- Huge cost to trading for individuals:
  - Transaction costs
  - Pick wrong stocks

# Related to Other Asset Pricing Puzzles

- Overconfidence/overprecision can explain other puzzles:
  - short-term positive correlation of returns (momentum)
  - long-term negative correlation (long-term reversal)
- **Daniel-Hirshleifer-Subrahmanyam (1998)**
- Assume overconfidence + self-attribution bias (discount information that is inconsistent with one's priors)
  - Overconfidence → trade excessively in response to private information
  - Long-term: public information prevails, valuation returns to fundamentals → long-term reversal
  - Short-term: additional private information interpreted with self-attribution bias → become even more overconfident
- Two other explanations for this: Law of small numbers + Limited attention

# Section 5

# Law of Small Numbers

# Introduction

- Overconfidence is only one form of non-Bayesian beliefs
- **Tversky-Kahneman (1974).** Individuals follow heuristics to simplify problems:
  - *Anchoring.* $\rightarrow$ Leads to over-precision (above)
  - *Availability.* $\rightarrow$ Connected to limited attention (next lecture)
  - *Representativeness.* $\rightarrow$ Today's lecture
- Individuals expect random draws to be exceedingly representative of the distribution they come from
  - HTHHTT judged more representative than HHHTTT
  - But the two are equally likely! (exchangeability)

# Rabin (QJE, 2002). Law of Small Numbers

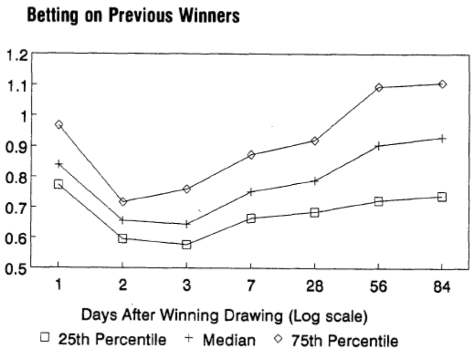
- I.i.d. signals from urn drawn with replacement
  - Subjects instead believe drawn from an urn of size $N < \infty$ without replacement
  - $\rightarrow$ *Gambler's Fallacy:* After signal, subject expect next draw to be a different signal
  - Example: Return to mutual fund is drawn from an urn with 10 balls, 5 Up and 5 Down (with replacement)
  - Observe 'Up, Up' — Compute probability of another Up
    - Bayesian: .5
    - Law of Small Numbers: $3/8 < .5$
  - Example of representativeness: 'Up, Up, Down' more representative than 'Up, Up, Up'

# Clotfelter and Cook (MS, 1993)

- Evidence on gambler's fallacy.

- Lotteries increasingly common in US ($17bn sales in 1989)
- Maryland daily-numbers lottery → Bet on 3-digit number
  - Probability of correct guess .001
  - Payout: $500 per $1 bet (50 percent payout)
- Gambler's Fallacy → Betters will stop betting on number just drawn
  - Examine 52 winning numbers in 1988
  - In 52 of 52 cases (!) betting volume decreases 3 days after win, relative to baseline

# Results




- Substantial decrease in betting right after number is drawn
  - Effect lasts about 3 months
- However: no cost for fallacy → Does effect replicate with cost?

# Terrell (JRU, 1994)

- New Jersey's pick-three-numbers game (1988-1992)
- Pari-mutuel betting system
  - the fewer individuals bet on a number, the higher is the expected payout
  - Cost of betting on popular numbers
  - Payout ratio .52 $\rightarrow$ Average win of $260 for 50c bet
- Issue: Do not observe betting on all numbers $\rightarrow$ Use payout for numbers that repeat

# Results

*Table 1.* Average payouts to winning numbers

| | Number | Mean | Standard deviation |
|---|---|---|---|
| Winners repeating within 1 week | 8 | 349.06 | 91.66 |
| Winners repeating between 1 and 2 weeks | 8 | 349.44 | 81.56 |
| Winners repeating between 2 and 3 weeks | 14 | 307.76 | 58.33 |
| Winners repeating between 3 and 8 weeks | 59 | 301.03 | 70.55 |
| Winners not repeating within 8 weeks | 1622 | 260.11 | 57.98 |
| All Winners | 1714 | 262.79 | 57.99 |

- Strong gambler's fallacy:
  - Right after win, 34 percent decrease in betting
  - $\rightarrow$ 34 percent payout increase
  - Effect dissipates over time

# Summary

- Comparison with Maryland lottery:
  - Smaller effect (34 percent vs. 45 percent)
  - $\rightarrow$ Incentives temper phenomenon, but only partially
- Other applications:
  - Probabilities are known, but subjects misconstrue the i.i.d. nature of the draws.
  - Example: Forecast of the gender of a third child following two boys (or two girls)

# Back to Rabin (QJE, 2002)

- Probabilities known $\rightarrow$ Gambler's Fallacy
- Probabilities not known $\rightarrow$ Overinference: After signals of one type, expect next signal of *same* type

- Example:
    - Mutual fund with a manager of uncertain ability.
    - Return drawn with replacement from urn with 10 balls
        - Probability .5: fund is well managed (7 balls Up and 3 Down)
        - Probability .5: fund is poorly managed (3 Up and 7 Down)

- Observe sequence 'Up, Up, Up' $\rightarrow$ What is $P(Well|UUU)$?
    - Bayesian:
      $P(Well|UUU) = .5P(UUU|Well)/[.5P(UUU|Well) + .5P(UUU|Poor)] = .7^3/\left(.7^3 + .3^3\right) \approx .927.$
    - Law-of-Small-Number: $P(Well|UUU) = (7/10*6/9*5/8)/[(7/10*6/9*5/8)+(3/10*2/9*1/8)] \approx .972.$
    - Over-inference about the ability of the mutual-fund manager
- Also assume:
    - Law-of-Small-Number investor believes that urn replenished after 3 periods
    - Need re-start to avoid contradiction
- What is Forecast of $P(U|UUU)$?
    - Bayesian: $P(U|UUU) = .927 * .7 + (1 - .927) * .3 \approx .671$
    - Law-of-Small-Number:
      $P(U|UUU) = .972 * .7 + (1 - .972) * .3 \approx .689$
- Over-inference despite the gambler's fallacy beliefs

# Conclusion

- Substantial evidence of over-inference (also called extrapolation)
- Notice: Case with unknown probabilities is much more common than lottery case
- Excellent review: **Fuster, Laibson, and Mendel (JEP 2010)**

# Application: Benartzi (JF, 2001)

- Examine investment of employees in employer stock
  - Does it depend on the past performance of the stock?
- Sample:
  - S&P 500 companies with retirement program
  - Data from 11-k filing
  - 2.5 million participants, $102bn assets

**Buy-and-Hold Raw Returns and Subsequent Allocations to Company Stock as a Percentage of Discretionary Contributions**

This table displays equally weighted mean allocations to company stock (as a percentage of discretionary contributions) by quintile of past buy-and-hold raw returns. Company stock allocations are measured at the end of 1993. Portfolio 1 (5) includes retirement savings plans with the lowest (highest) past buy-and-hold raw returns. The table also provides the difference between the allocations of the extreme portfolios (i.e., portfolio 5 minus portfolio 1) and $t$-statistics. $N = 142$.

| Quintiles Formed on the Basis of Buy-and-Hold Raw Returns for: | Quintile of Buy-and-Hold Returns (Low) 1 | 2 | 3 | 4 | 5 (High) | Observed Difference (5 − 1) | $T$-Statistic |
|---|---|---|---|---|---|---|---|
| Prior year | 21.10% | 23.16% | 27.85% | 25.99% | 23.70% | 2.60% | 0.60 |
| Prior 2 years | 22.61 | 22.43 | 25.18 | 28.74 | 22.96 | 0.35 | 0.06 |
| Prior 3 years | 14.14 | 25.45 | 26.21 | 28.84 | 27.78 | 13.64 | 3.33 |
| Prior 4 years | 11.74 | 22.20 | 28.18 | 31.10 | 30.23 | 18.49 | 4.64 |
| Prior 5 years | 12.64 | 18.68 | 26.27 | 34.66 | 31.21 | 18.57 | 4.33 |
| Prior 6 years | 11.99 | 18.72 | 29.33 | 33.45 | 29.96 | 17.97 | 4.63 |
| Prior 7 years | 11.36 | 18.98 | 24.11 | 34.79 | 33.70 | 22.34 | 5.87 |
| Prior 8 years | 11.46 | 20.69 | 24.22 | 32.96 | 33.63 | 22.17 | 5.70 |
| Prior 9 years | 11.08 | 20.76 | 20.52 | 34.04 | 36.68 | 25.60 | 6.49 |
| Prior 10 years | 10.37 | 19.68 | 21.56 | 31.51 | 39.70 | 29.33 | 8.39 |

- Very large effect of past returns + Effect depends on long-term performance

# Inside Information?

- Is the effect due to inside information?

| | Allocation to Company Stock | | | | | Observed Difference | Threshold for Significant Difference at |
|---|---|---|---|---|---|---|---|
| | (Low) 1 | 2 | 3 | 4 | 5 (High) | (5 − 1) | $\alpha = 10\%$ |
| Allocation to company stock as a percentage of discretionary contributions | 4.59% | 12.19% | 19.34% | 31.85% | 53.90% | 49.41% | |
| One-year returns | 6.64 | 6.55 | 1.27 | −1.03 | 0.13 | −6.77 | 7.12 |
| Two-year returns | 43.69 | 40.78 | 38.24 | 43.33 | 31.92 | −11.77 | 14.75 |
| Three-year returns | 59.29 | 70.28 | 68.64 | 79.66 | 56.25 | −3.04 | 21.99 |
| Four-year returns | 101.08 | 114.55 | 109.89 | 149.92 | 103.14 | 2.06 | 36.15 |

- No evidence.
- Over-inference pattern observed for investors of all types

# Additional Examples of Over-Inference

- **Barber-Odean-Zhou (JFE, 2009):** Uses Individual trades data
  - Individual US investors purchase stocks with high past returns
  - Average stock that individual investors purchase outperformed the stock market in the previous three years by over 60 percent
- **Kaustia and Knupfer (JF 2008)**
  - Use Finnish data to be able to track individual investors over time
  - Examine investors that subscribe to an IPO in a 1st period, 1995-Oct. 1999
  - Return is highly idyosincratic
  - Indeed, Figure 1 shows no predictability on returns in second period: Nov. 1999-Dec. 2000

# Results: Returns

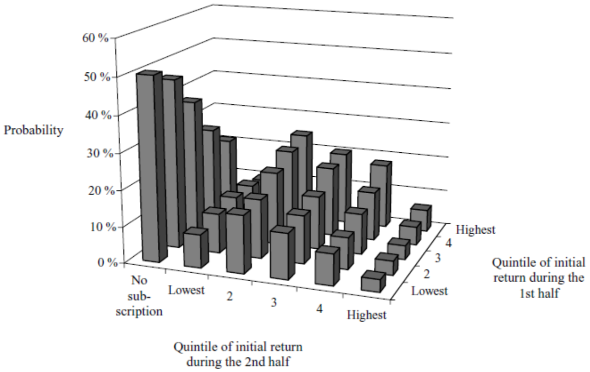



**Figure 1. Transition probabilities between previous and subsequent initial return quintiles.** To obtain the figure, the sample period is divided into two halves. The first half has 40 IPOs, the last occurring in October 22, 1999; the second half has 17 offerings, the last in December 20, 2000. This split is determined by placing an equal number of investor/offering pairs in both periods.

- What about probability of subscribing to IPOs in second period?

# Results: Further Participation

- Strong effect of personally experienced returns

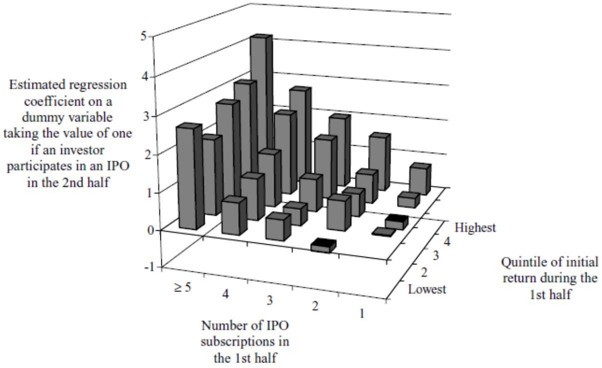



**Figure 2. Likelihood of further participation by past subscription activity and past initial returns.** This figure is based on a logit regression similar to that in Table II column 1, that is, the dependent variable is one if an investor participates in at least one IPO in the second half, zero otherwise (see more description in Table II header). Unlike in Table II, here previous

# Implications

- This implies effect on pricing:
  - Stocks with high past returns attract individual investors
  - $\rightarrow$ Get overpriced
  - $\rightarrow$ Later mean-revert

# DeBondt and Thaler (1985)

- Form portfolio of winners in the past 3 years
- Form portfolio of losers in past 3 years.
- 'Winners' underperform the 'losers' by 25 percentage points over the next three years

Average of 16 Three-Year Test Periods
Between January 1933 and December 1980
Length of Formation Period: Three Years

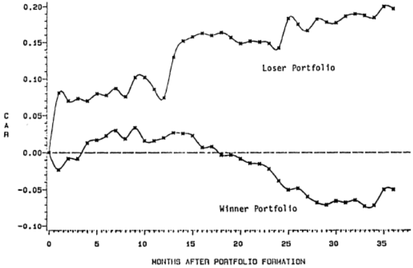



**Figure 1.** Cumulative Average Residuals for Winner and Loser Portfolios of 35 Stocks (1-36 months into the test period)

# Barberis, Shleifer, and Vishny (JFE, 1998)

- Alternative model of law of small number in financial markets.
  - Draws of dividends are i.i.d.
  - Investors believe that
    - draws come from 'mean-reverting' regime or 'trending' regime
    - 'mean-reverting' regime more likely ex ante
  - Result: If investors observe sequence of identical signals,
    - Short-Run: Expect a mean-reverting regime (the gambler's fallacy) $\rightarrow$ Returns under-react to information $\rightarrow$ Short-term positive correlation (momentum)
    - Long-run: Investors over-infer and expect a 'trending' regime $\rightarrow$ Long-term negative correlation of returns

# Extrapolation in other contexts

- **Gallagher (AEJ Applied 2014)**
  - Consider idiosincratic flood events
  - Largely uncorrelated from year to year
  - Statistical information on flood probabilities available
  - What is the effect of a recent flood?
  - Large increase in probability of insurance
- Effect is present also for communities not directly hit
- What explains the effect? Media salience is critical

Figure 2: Flood Insurance Take-up for Communities Hit by a Presidential Disa
Declaration Flood 1990-2007

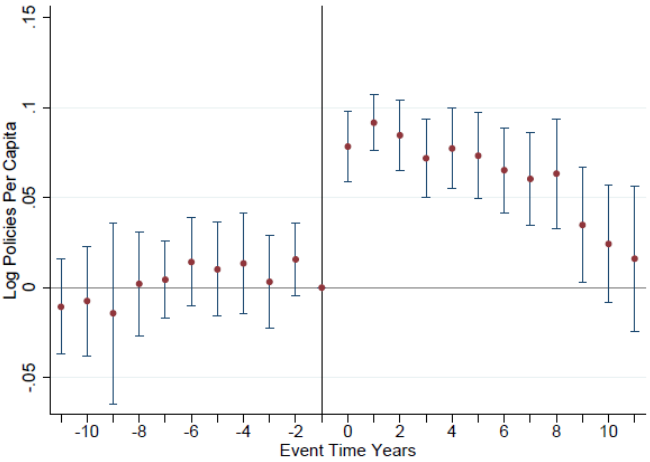


Figure 3: Flood Insurance Take-up for Hit and Non-Hit Communities within Presidential Disaster Declaration Flooded Counties 1990-2007

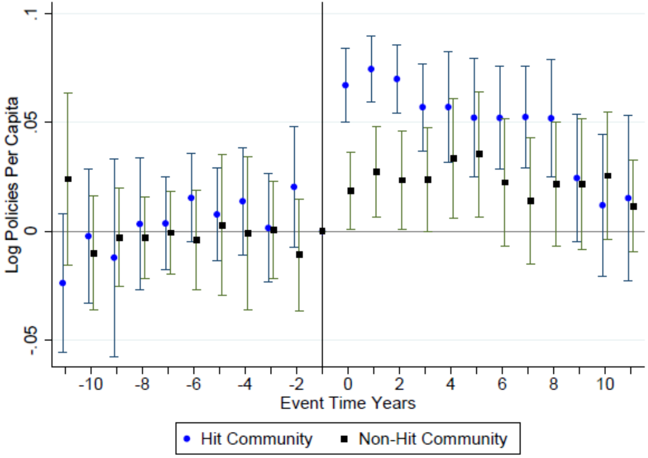
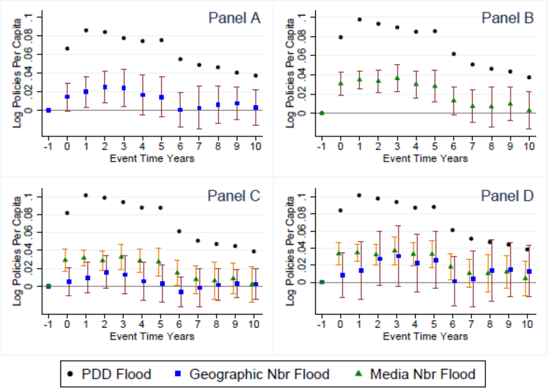


Figure 8: Flood Insurance Take-up for Geographic and Media Neighbors




Each panel contains coefficients from a distinct event study regression using a version of Equation (2) and the 1980-2007 panel. Panel A includes event time indicators for communities located in one of the five closest non-flooded counties. Panel B includes event time indicators for non-flooded communities located in the same TV media market as a flooded community. Panel C includes both geographic and media indicators. Panel D includes both geographic and media indicators, and their interaction (not displayed).

# Section 6

## Projection Bias

# Introduction

- Beliefs systematically biased toward current state

- **Read-van Leeuwen (1998):**
  - Office workers choose a healthy snack or an unhealthy snack
  - Snack will be delivered a week later (in the late afternoon).
  - Two groups: Workers are asked
    - when plausibly hungry (in the late afternoon) $\rightarrow$ 78 percent chose an unhealthy snack
    - when plausibly satiated (after lunch) $\rightarrow$ 42 percent choose unhealthy snack

# Gilbert, Pinel, Wilson, Blumberg, and Wheatly (1999)

- Individuals under-appreciate adaptation to future circumstances $\rightarrow$ Projection bias about future reference point
- Subjects forecast happiness for an event
- Compare predictions to responses after the event has occurred
- Thirty-three current assistant professors at the University of Texas (1998) forecast that getting tenure would significantly improve their happiness (5.9 versus 3.4 on a 1-7 scale).
- Difference in rated happiness between 47 assistant professors that were awarded tenure by the same university and 20 that were denied tenure is smaller and not significant (5.2 versus 4.7).
- Similar results as function of election of a Democratic of Republican president, compared to the realized ex-post differences.

# Model

- *Projection bias.* (**Loewenstein, O'Donoghue, and Rabin (2003)**)
  - Individual is currently in state $s'$ with utility $u(c, s')$
  - Predict future utility in state $s$
  - Simple projection bias:

$$\hat{u}(c, s) = (1 - \alpha) u(c, s) + \alpha u(c, s')$$

  - Parameter $\alpha$ is extent of projection bias $\rightarrow$ $\alpha = 0$ implies rational forecast
- Notice: People misforecast utility $\hat{u}$, not state $s$; however, same results if the latter applies

# Conlin-O'Donoghue-Vogelsang (AER 2006)

- Purchasing behavior: Cold-weather items
- Main Prediction:
  - Very cold weather
  - $\rightarrow$ Forecast high utility for cold-weather clothes
  - $\rightarrow$ Purchase 'too much'
  - $\rightarrow$ Higher return probability
- Denote temperature at Order time as $\omega_O$ and temperature at Return time as $\omega_R$
- Predictions:
  1. If $\alpha = 0$ (no proj. bias), P[R|O] is independent of $\omega_O$ and $\omega_R$
  2. If $\alpha > 0$ (proj. bias), $\partial P[R|O]/\partial\omega_O < 0$ and $\partial P[R|O]/\partial\omega_R > 0$

# Data

- Purchase data from US Company selling outdoor apparel and gear
  - January 1995-December 1999, 12m items
  - Date of order and date of shipping + Was item returned?
  - Shipping address
- Weather data from National Climatic Data Center
  - By 5-digit ZIP code, use of closest weather station
- Items:
  - Parkas/Coats/Jackets Rated Below 0F
  - Winter Boots
  - Drop mail orders, if billing and shipping address differ, >9 items ordered, multiple units same item, low price
  - No. obs.: 2,200,073
- Note: Probability of return fairly high, Delay between order and receipt 4-5 days

# Main estimation: Probit

$$P(R|O) = \Phi\left(\alpha + \gamma_O \omega_O + \gamma_R \omega_R + BX\right)$$

Probit Regression Measuring the Effect of Temperature on the Probability Cold Weather Clothing is Returned

Dependent Variable is Whether Item is Returned (=1 if item returned and 0 otherwise)

| | Gloves & Mittens | Winter Boots | Hats | Sports Equipment | Parkas & Coats | Vests | Jackets | All Seven Categories |
|---|---|---|---|---|---|---|---|---|
| Order-Date Temperature | -0.00013** | -0.00026** | -0.00020** | -0.00011* | -0.00009 | -0.00048** | -0.00014 | -0.00019** |
| | (0.00005) | (0.00009) | (0.00005) | (0.00006) | (0.00007) | (0.00011) | (0.00013) | (0.00003) |
| Receiving-Date Temperature | 0.00005 | 0.00018* | -0.00005 | -0.00008 | 0.00007 | -0.00010 | 0.00010 | 0.00003 |
| | (0.00006) | (0.00009) | (0.00006) | (0.00007) | (0.00008) | (0.00011) | (0.00014) | (0.00003) |
| Price of Item | 0.00075** | 0.00005 | 0.00145** | 0.00033** | 0.00019** | 0.00166** | 0.00016 | 0.00023** |
| | (0.00024) | (0.00013) | (0.00025) | (0.00008) | (0.00004) | (0.00024) | (0.00018) | (0.00003) |
| Item Purchased with Credit Card | 0.02042** | 0.04337** | 0.02876** | 0.02395** | 0.05893** | 0.02294** | 0.05312** | 0.03531** |
| | (0.00250) | (0.00418) | (0.00244) | (0.00191) | (0.00405) | (0.00535) | (0.00568) | (0.00137) |
| Items in Order | -0.00157** | 0.00012 | -0.00035 | -0.00078** | 0.00196** | -0.00177** | 0.00141** | -0.00028** |
| | (0.00022) | (0.00039) | (0.00022) | (0.00028) | (0.00033) | (0.00045) | (0.00058) | (0.00012) |
| Clothing Type Fixed Effects | YES | YES | YES | NO[a] | YES | YES | YES | YES |
| Item Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES |
| Month-Region Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES |
| Year-Region Fixed Effects | YES | YES | YES | YES | YES | YES | YES | YES |
| Observations | 484,067 | 262,610 | 484,085 | 146,403 | 524,831 | 151,958 | 145,910 | 2,199,950 |
| R-Squared | 0.04 | 0.05 | 0.07 | 0.13 | 0.03 | 0.03 | 0.04 | 0.07 |

Table presents marginal effects on the probability that an item is returned. Standard errors are in parentheses.

* Statistically significant at the .10 level; ** Statistically significant at the .05 level.

[a] Clothing Type information was not provided for sports equipment items.

# Model Robustness Checks

- Similar estimates for linear probability model with household fixed effects

TABLE 3
Linear Regression Measuring the Effect of Temperature on the Probability Cold Weather Clothing is Returned: With and Without Household Fixed Effects

| | Household Fixed Effects | No Household Fixed Effects |
|---|---|---|
| Order-Date Temperature | -0.00082** | -0.00039** |
| | (0.00027) | (0.00013) |
| Receiving-Date Temperature | 0.00017 | 0.00002 |
| | (0.00029) | (0.00015) |
| Clothing Type Fixed Effects | YES | YES |
| Item Fixed Effects | YES | YES |
| Month-Region Fixed Effects | YES | YES |
| Year-Region Fixed Effects | YES | YES |
| Household Fixed Effects | YES | NO |
| Observations | 162,580 | 162,580 |
| R-Squared | 0.19 | 0.10 |

- Simple structural model: Estimates of projection bias $\alpha$ around .3-.4

TABLE 6
Structural Estimation

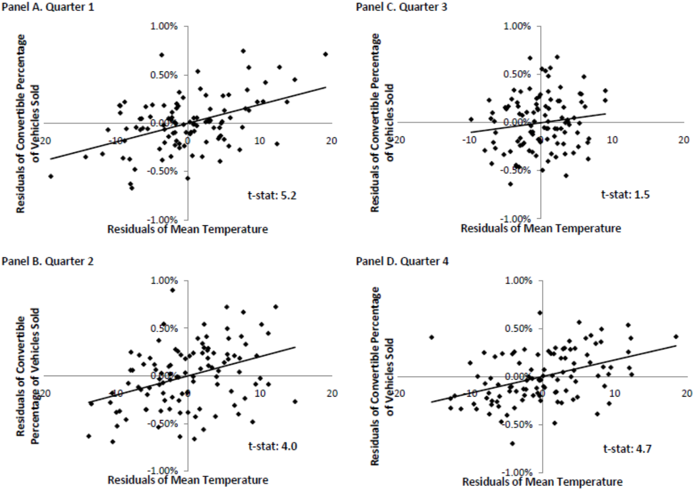
| | Winter Boots | Hats | Parkas & Coats | Vests | Jackets |
|---|---|---|---|---|---|
| $\alpha$ | 0.3084** | 0.4698** | 0.3814** | 0.0002 | 0.4992** |
| | (0.0570) | (0.00001) | (0.0352) | (0.0056) | (0.0002) |

# Car and Home Purchases

- **Busse, Pope, Pope, Silva-Risso (2013):** Evidence from car purchases and house purchases
- Projection bias:
  - Convertible looks particularly attractive on a hot day
  - 4-wheel drive attractive on snowy day
  - House with pool higher selling price on hot day
- Strong evidence in the data

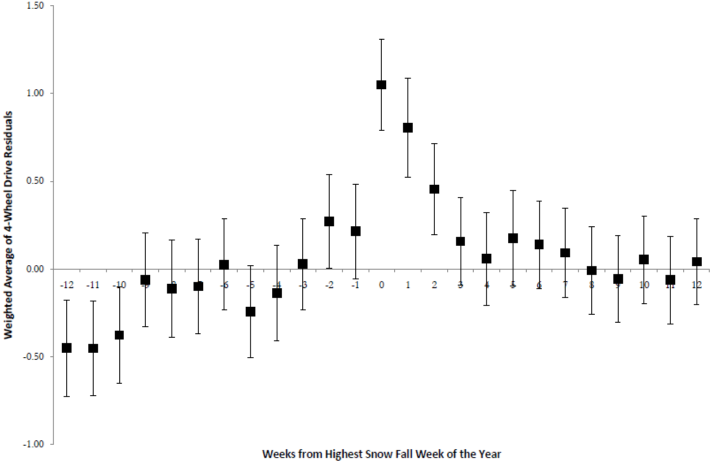
# Temperature and Convertibles

**Figure 5. Temperature-Convertible Residuals - Chicago.** This Figure provides scatter plots for the residuals of convertible percentage of vehicles sold (Panel B of Figure 3) and residuals of mean high temperature (Panel B of Figure 4) separately for each quarter of the year.



# Snow and 4-Wheel Drive

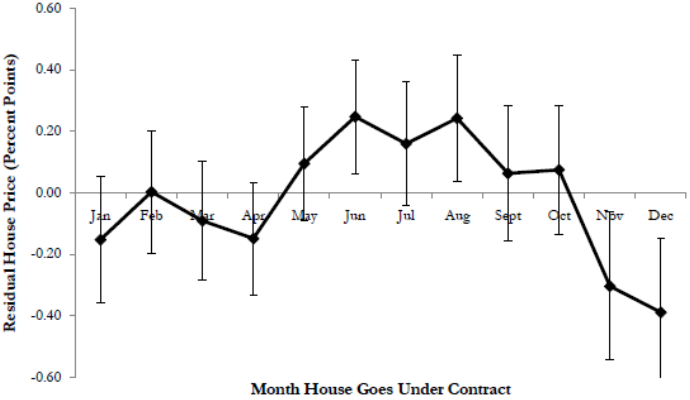
**Figure 10. Snowfall and 4-Wheel Drive Sales - Event-Study Design.** This Figure plots the weighted average and 95% confidence intervals for the residuals of the 4-wheel drive percentage of total vehicles sold for the twelve weeks leading up to and the twelve weeks after a snow storm event (week 0). The events were chosen to be the highest snow fall week of the year for DMAs that have above-median in weather variation.



# Seasonal Value of a Pool

**Figure 11 - Seasonal Value of a Swimming Pool.** Panel A shows the average residual values for homes with swimming pools that go under contract during each month of the year. Panel B shows the estimated effect of a swimming pool on a house's residual sales price, conditional on other house characteristics, as estimated by Equation (7). 95% confidence intervals are also presented.

**Panel A. Residuals by Month**



# Insurance Purchases

- **Chang, Huang, and Wang (RES 2018):** Evidence from insurance purchases
- Purchase of health insurance in China:
  - Day-to-day variation in perceived health due to swings in (substantial) air pollution in China
  - May affect demand for health insurance
  - Since 180 days waiting period, should have no rational impact
- Consider impact on
  - health insurance take up and
  - cancellations during 10-day period

# Variation in Pollution

- Significant daily variation in pollution level, with documented health effects

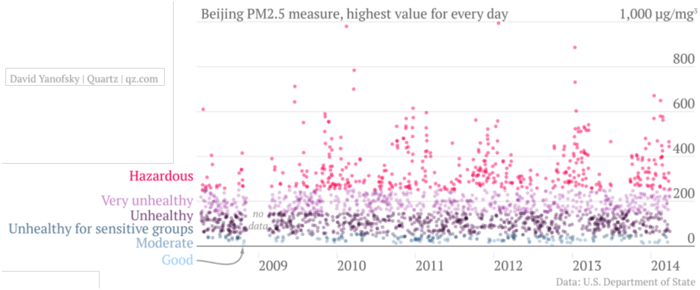



Figure 2. Daily PM2.5 levels as measured by the U.S. Embassy in Beijing.

- Estimate impact on number of insurance contracts sold

# Impact on Purchases

**Table II**
**The Effect of Pollution on Insurance Sales**

Dependent Variable: Log(Number of Contracts Sold)

| Insurance Type | Health | | | Other |
|---|---|---|---|---|
| $AQI_{PM2.5}$ | 0.00072** | | 0.00067** | -0.00018 |
| | (0.00018) | | (0.00019) | (0.00022) |
| $AQI_{PM2.5}$ 50-100 | | 0.0116 | | |
| | | (0.0715) | | |
| $AQI_{PM2.5}$ 100-150 | | 0.1147 | | |
| | | (0.0759) | | |
| $AQI_{PM2.5}$ 150-200 | | 0.1681* | | |
| | | (0.0800) | | |
| $AQI_{PM2.5}$ 200-300 | | 0.1680+ | | |
| | | (0.0861) | | |
| $AQI_{PM2.5}$ 300+ | | 0.2340* | | |
| | | (0.0936) | | |
| Other City $AQI_{PM2.5}$ | | | 0.00010 | |
| | | | (0.00022) | |
| Adjusted R-squared | 0.481 | 0.481 | 0.478 | 0.427 |
| Observations | 2,573 | 2,573 | 2,489 | 2,573 |

# Impact on Cancellations

**Table III**
**The Effect of Pollution on cancellations**

| Dependent Variable: Indicator equal to 1 if contract is canceled | | | | |
|---|---|---|---|---|
| % of Contracts canceled | 2.90% | 2.90% | 2.79% | 2.90% |
| *Relative AQI* | -0.00110** | | | |
| | (0.00043) | | | |
| *Order-date AQI* | | 0.00085+ | 0.00092+ | 0.00002 |
| | | (0.00045) | (0.00049) | (0.00053) |
| *CoP AQI* | | -0.00252** | | |
| | | (0.00094) | | |
| $\sum_{\tau=1}^{11} \beta_{AQI,\tau}$ | | | -0.00268** | |
| | | | (see notes) | |
| *1(CoP AQI<Order-date AQI)* | | | | 0.2008* |
| | | | | (0.0881) |
| Log(Term Length) | -0.507** | -0.570** | -0.563** | -0.571** |
| | (0.018) | (0.018) | (0.018) | (0.018) |
| Log(Age) | 0.402** | 0.402** | 0.372** | 0.403** |
| | (0.034) | (0.034) | (0.035) | (0.034) |
| Self | 1.203** | 1.201** | 1.160** | 1.201** |
| | (0.080) | (0.080) | (0.081) | (0.079) |
| Female | 0.118** | 0.119* | 0.100+ | 0.116* |
| | (0.057) | (0.057) | (0.058) | (0.057) |
| Adj. R-squared | 0.059 | 0.059 | 0.060 | 0.059 |
| Observations | 411,525 | 411,525 | 381,146 | 411,525 |

# Section 7

## Next Lecture

# Next Lecture

- Non-Standard Decision-Making
- Limited Attention
  - Financial Markets
  - Consumption