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

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Outline

1. Law of Small Numbers
2. Projection Bias
3. Non-Standard Decision-Making
4. Attention: Introduction
5. Attention: Simple Model
6. Attention: eBay Auctions
7. Attention: Taxes

8. Attention: Financial Markets

9. Methodology: Portfolio Methodology
1 Law of Small Numbers

Back to Rabin (QJE, 2002).

- Probabilities known → Gambler’s Fallacy
  - Probabilities not known → 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’ → What is $P(Well|UUU)$?
    - Bayesian: $P(Well|UUU) = .5P(UUU|Well)/[.5P(UUU|Well) + .5P(UUU|Poor)] = .7^3/ (.7^3 + .3^3) \approx .927.$
* Law-of-Small-Number: \( P(\text{Well}|UUU) = \frac{7/10 \times 6/9 \times 5/8}{[(7/10 \times 6/9 \times 5/8) + (3/10 \times 2/9 \times 1/8)]} \approx 0.972. \)
* 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 or get into negative probabilities...
  – What is Forecast of \( P(U|UUU) \)?
    * Bayesian: \( P(U|UUU) = 0.927 \times 0.7 + (1 - 0.927) \times 0.3 \approx 0.671 \)
    * Law-of-Small-Number: \( P(U|UUU) = 0.972 \times 0.7 + (1 - 0.972) \times 0.3 \approx 0.689 \)
* Over-inference despite gambler’s fallacy beliefs
• Substantial evidence of over-inference (also called extrapolation)
• Notice: Case with unknown probabilities is much more common than lottery case

**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
• Very large effect of past returns + Effect depends on long-term performance
- Is the effect due to inside information?

<table>
<thead>
<tr>
<th>Allocation to Company Stock</th>
<th>Observed Difference (5 - 1)</th>
<th>Threshold for Significant Difference at $\alpha = 10%$</th>
</tr>
</thead>
<tbody>
<tr>
<td>(Low) 1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.59%</td>
<td>-6.77</td>
<td>7.12</td>
</tr>
<tr>
<td>43.69</td>
<td>-11.77</td>
<td>14.75</td>
</tr>
<tr>
<td>59.29</td>
<td>-3.04</td>
<td>21.99</td>
</tr>
<tr>
<td>101.08</td>
<td>2.06</td>
<td>36.15</td>
</tr>
</tbody>
</table>

- No evidence of insider information
• Over-inference pattern observed for investors of all types

• **Barber-Odean-Zhou (JFE, forthcoming):** 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

• This implies effect on pricing: Stocks with high past returns get overpriced
  –> Later mean-revert

• **DeBondt and Thaler (1985):**
  – Compare winners in the past 3 years to losers in past 3 years.
  – ‘Winners’ underperform the ‘losers’ by 25 percentage points over the next three years
Barberis-Shleifer-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)
    --> Returns under-react to information --> Short-term positive correlation (momentum)
  * Long-run: Investors over-infer and expect a ‘trending’ regime --> Long-term negative correlation of returns
2 Projection Bias

- 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.
• **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 (2006)

• Purchasing behavior: Cold-weather items

• Main Prediction:
  – Very cold weather
  – → Forecast high utility for cold-weather clothes
  – → Purchase ‘too much’
  – → Higher return probability

• Additional Prediction:
  – Cold weather at return → Fewer returns
• Focus on Probability[Return|Order]
• 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 $\partial P[R|O]/\partial \omega_R > 0$
• Notice: Do not observe date of return decision
• 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
• Summary Stats:
  – Probability of return fairly high
  – Prices of items substantial
  – Delay between order and receipt 4-5 days
TABLE 1
Summary Statistics by Item Categories

<table>
<thead>
<tr>
<th></th>
<th>Gloves/ Mitten</th>
<th>Winter Boots</th>
<th>Hats Equipment</th>
<th>Sports Equipment</th>
<th>Parkas/ Coats</th>
<th>Vests</th>
<th>Jackets</th>
<th>All Seven Categories</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>484,084</td>
<td>262,610</td>
<td>484,086</td>
<td>146,594</td>
<td>524,831</td>
<td>151,958</td>
<td>145,910</td>
<td>2,200,073</td>
</tr>
<tr>
<td>Number of Different Items</td>
<td>106</td>
<td>93</td>
<td>88</td>
<td>233</td>
<td>133</td>
<td>20</td>
<td>37</td>
<td>710</td>
</tr>
<tr>
<td>Percent Returned</td>
<td>10.9</td>
<td>15.6</td>
<td>10.8</td>
<td>6.6</td>
<td>22.2</td>
<td>12.8</td>
<td>18.0</td>
<td>14.4</td>
</tr>
<tr>
<td>Price of Item (dollars)</td>
<td>29.26</td>
<td>68.33</td>
<td>23.74</td>
<td>74.10</td>
<td>148.58</td>
<td>40.90</td>
<td>106.70</td>
<td>70.10</td>
</tr>
<tr>
<td>Percent of Buyer’s Prior Purchases Returned</td>
<td>7.2</td>
<td>6.6</td>
<td>6.9</td>
<td>7.2</td>
<td>7.3</td>
<td>6.8</td>
<td>8.2</td>
<td>7.14</td>
</tr>
<tr>
<td>Number of Buyer’s Prior Purchases</td>
<td>27.3</td>
<td>22.2</td>
<td>23.9</td>
<td>27.7</td>
<td>20.5</td>
<td>21.71</td>
<td>25.3</td>
<td>23.83</td>
</tr>
<tr>
<td>Buyer has a Prior Purchase</td>
<td>0.85</td>
<td>0.82</td>
<td>0.83</td>
<td>0.86</td>
<td>0.77</td>
<td>0.83</td>
<td>0.82</td>
<td>0.82</td>
</tr>
<tr>
<td>Days Between Order and Shipment</td>
<td>0.42</td>
<td>0.97</td>
<td>0.72</td>
<td>0.94</td>
<td>2.17</td>
<td>1.24</td>
<td>1.13</td>
<td>1.11</td>
</tr>
<tr>
<td>Days Between Order and Receipt</td>
<td>4.13</td>
<td>4.66</td>
<td>4.46</td>
<td>4.58</td>
<td>5.92</td>
<td>5.04</td>
<td>4.89</td>
<td>4.84</td>
</tr>
<tr>
<td>Ordered Through Internet</td>
<td>0.04</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.04</td>
<td>0.02</td>
<td>0.05</td>
<td>0.03</td>
</tr>
<tr>
<td>Purchased by a Female</td>
<td>0.71</td>
<td>0.66</td>
<td>0.71</td>
<td>0.70</td>
<td>0.66</td>
<td>0.72</td>
<td>0.66</td>
<td>0.69</td>
</tr>
<tr>
<td>Item Purchased with Credit Card</td>
<td>0.97</td>
<td>0.98</td>
<td>0.98</td>
<td>0.97</td>
<td>0.98</td>
<td>0.98</td>
<td>0.97</td>
<td>0.98</td>
</tr>
<tr>
<td>Items in Order</td>
<td>3.5</td>
<td>2.5</td>
<td>3.4</td>
<td>2.9</td>
<td>2.2</td>
<td>2.8</td>
<td>2.3</td>
<td>2.9</td>
</tr>
<tr>
<td>Temperature Rating</td>
<td>-10.11</td>
<td>-10.11</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-5.64</td>
</tr>
</tbody>
</table>

WEATHER CONDITIONS
 Order-Date Temperature (°F)    | 40.60          | 39.74        | 41.48          | 37.81             | 43.29         | 44.76 | 46.88   | 41.85                |
 Receiving-Date Temperature (°F) | 39.90          | 38.97        | 40.72          | 36.70             | 42.29         | 43.20 | 45.70   | 40.94                |
 Snowfall on Day Item Ordered (0.1") | 1.79           | 2.69         | 1.69           | 2.65              | 1.30          | 1.26  | 0.63    | 1.70                 |
 Snowfall on Day Item Received (0.1") | 1.58           | 2.32         | 1.51           | 2.35              | 1.33          | 1.43  | 0.66    | 1.57                 |
Main estimation: Probit

\[ P(R|O) = \Phi (\alpha + \gamma_O \omega_O + \gamma_R \omega_R + BX) \]

<table>
<thead>
<tr>
<th>Probit Regression Measuring the Effect of Temperature on the Probability Cold Weather Clothing is Returned</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable is Whether Item is Returned (=1 if item returned and 0 otherwise)</td>
</tr>
<tr>
<td>Gloves &amp; Mittens</td>
</tr>
<tr>
<td>-------------------</td>
</tr>
<tr>
<td>Order-Date Temperature</td>
</tr>
<tr>
<td>Receiving-Date Temperature</td>
</tr>
<tr>
<td>Price of Item</td>
</tr>
<tr>
<td>Item Purchased with Credit Card</td>
</tr>
<tr>
<td>Items in Order</td>
</tr>
<tr>
<td>Clothing Type Fixed Effects</td>
</tr>
<tr>
<td>Item Fixed Effects</td>
</tr>
<tr>
<td>Month-Region Fixed Effects</td>
</tr>
<tr>
<td>Year-Region Fixed Effects</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R-Squared</td>
</tr>
</tbody>
</table>

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.

* Clothing Type information was not provided for sports equipment items.
• Main finding: $\gamma_O < 0$.
  
  – Warmer weather on order date lowers probability of return
  
  – **Magnitude:**
  
  – This goes against standard story: If weather is warmer, less likely you will use it $\rightarrow$ Return it more
  
  – Projection Bias: Very cold weather $\rightarrow$ Mispredict future utility $\rightarrow$ Return the item

• Second finding: $\gamma_R \approx 0$

  – Warmer weather on (predicted) return does not affect return
  
  – This may be due to the fact that do not observe when return decision is made
• Similar estimates for linear probability model with household fixed effects
• (Restrict sample to multiple orders by households)

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

<table>
<thead>
<tr>
<th></th>
<th>Household Fixed Effects</th>
<th>No Household Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td>Order-Date Temperature</td>
<td>0.00002*</td>
<td>0.00039**</td>
</tr>
<tr>
<td></td>
<td>(0.00027)</td>
<td>(0.00013)</td>
</tr>
<tr>
<td>Receiving-Date Temperature</td>
<td>0.00017</td>
<td>0.00002</td>
</tr>
<tr>
<td></td>
<td>(0.00029)</td>
<td>(0.00015)</td>
</tr>
<tr>
<td>Clothing Type Fixed Effects</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Item Fixed Effects</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Month-Region Fixed Effects</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Year-Region Fixed Effects</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Household Fixed Effects</td>
<td>YES</td>
<td>NO</td>
</tr>
<tr>
<td>Observations</td>
<td>162.580</td>
<td>162.580</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.19</td>
<td>0.10</td>
</tr>
</tbody>
</table>
• Simple structural model of projection bias: Estimates of projection bias $\alpha$ around .3-.4

<table>
<thead>
<tr>
<th></th>
<th>Winter Boots</th>
<th>Hats</th>
<th>Parkas &amp; Coats</th>
<th>Vests</th>
<th>Jackets</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha$</td>
<td>0.3064***</td>
<td>0.4698**</td>
<td>0.3814**</td>
<td>0.0002</td>
<td>0.4092**</td>
</tr>
<tr>
<td></td>
<td>(0.0570)</td>
<td>(0.00001)</td>
<td>(0.0352)</td>
<td>(0.0956)</td>
<td>(0.0002)</td>
</tr>
</tbody>
</table>

• Other applications?
• Also, **Levy (2009):** addiction model with present bias and projection bias
  – Test for projection bias: Effect of higher variance of future prices
    * Standard model: Higher variance lowers current consumption because getting addicted becomes more costly
    * Projection bias: Do not realize link between current smoking and future addiction $\rightarrow$ Higher variance can increase smoking
  – Data: Positive correlation of variance of prices with current smoking $\rightarrow$ Supports projection bias

• Parametric estimate: projection bias $\alpha \approx .4$
3 Non-Standard Decision-Making

• First part of class: Non-standard preferences $U(x|s)$:
  – Over time (present-bias)
  – Over risk (reference-dependence)
  – Over social interactions (social preferences)

• And Non-Standard Beliefs $p(s)$
  – About skill (overconfidence)
  – Updating (law of small numbers)
  – About preferences (projection bias)
• Now, third category: non-standard decision-making
• Standard $U(x|s)$ and $p(s) \rightarrow$ Still, non-standard decisions
• Five sub-categories
  – Limited attention
  – Framing
  – Menu effects
  – Persuasion and social pressure
  – Emotions
• This in turn often leads to non-standard beliefs $\tilde{p}(s)$
4 Attention: Introduction

- Attention as limited resource
- Psychology Experiments: Dichotic listening (Broadbent, 1958)
  - Hear two messages:
    * in left ear
    * in right ear
  - Instructed to attend to message in one year
  - Asked about message in other ear → Cannot remember it
  - More important: Asked to rehearse a number (or note) in their head
    → Remember much less the message
- Attention clearly finite
• How to optimize given limited resources?
  – Satisficing choice (Simon, 1955 –> Conlisk, JEL 1996)
  – Heuristics for solving complex problems (Gabaix-Laibson, 2002; Gabaix et al., 2003)

• In a world with a plethora of stimuli, which ones do agents attend to?
• Psychology: Salient stimuli (Fiske-Taylor, 1991) –> Not very helpful
• Probably, no general rule – Inattention along many dimensions
• Does this apply to high-stakes items?
• Event of economic importance: **Huberman-Regev (JF, 2001)**
• Timeline:
  – October-November 1997: Company EntreMed has very positive early results on a cure for cancer
• In a world with unlimited arbitrage...

• In reality...
Figure 5: ENMD Closing Prices and Trading Volume 10/1/97-12/30/98
• At least two interpretations:
  1. Limited attention initially + Catch up later
  2. Full incorporation initially + Overreaction later
• Persistence for 6 months suggests (1) more plausible
• Other interpretations:
  – Focal point
  – non-Bayesian inference
5 Attention: Simple Model

• Simple model

• Consider good with value $V$ (inclusive of price), sum of two components:
  \[ V = v + o \]
  1. Visible component $v$
  2. Opaque component $o$

• Inattention
  – Consumer perceives the value $\hat{V} = v + (1 - \theta) o$
  – Degree of inattention $\theta$, with $\theta = 0$ standard case
  – Interpretation: each individual sees $o$, but processes it only partially, to the degree $\theta$

• Alternative model:
- share \( \theta \) on individuals are inattentive, \( 1 - \theta \) attentive \( \rightarrow \)
- Models differ where not just mean, but also max/min matter (Ex.: auctions)

- **Inattention \( \theta \) is function of:**
  - Salience \( s \in [0, 1] \) of \( o \), with \( \theta'_s < 0 \) and \( \theta (1, N) = 0 \)
  - Number of competing stimuli \( N \): \( \theta = \theta (s, N) \), with \( \theta'_N > 0 \) (Broadbent)

- **Consumer demand** \( D[\hat{V}] \), with \( D'[x] > 0 \) for all \( x \)
Model suggests three strategies to identify the inattention parameter $\theta$:

1. Compute response of $\hat{V}$ to change in $o$ - compare $\partial \hat{V} / \partial o = (1 - \theta)$ to $\partial \hat{V} / \partial v = 1$ (Hossain-Morgan (2006) and Chetty-Looney-Kroft (2007))

2. Examine the response of $\hat{V}$ to an increase in the salience $s$, $\partial \hat{V} / \partial s = -\theta'_s o$ : differs from zero? (Chetty et al. (2007))

3. Vary competing stimuli $N$, $\partial \hat{V} / \partial N = -\theta'_N o$ : differs from zero? (DellaVigna-Pollet (forthcoming) and Hirshleifer-Lim-Teoh (2007))

Common trick: identify a piece of opaque information $o$ — Hardest part
Two caveats:

- Measuring salience of information is subjective — psychology experiments do not provide a general criterion

- Inattention can be rational or not.

  * Can rephrase as rational model with information costs

  * However, opaque information is publicly available at a zero or small cost (for example, earnings announcements news)

  * Rational interpretation less plausible
6 Attention: eBay Auctions

- Two different papers using eBay data:
  - **Hossain-Morgan (2006).** *Inattention to shipping cost*
  - **Lee-Malmendier (2006).** *Inattention to posted price* —> See Lecture 13

- Both shipping cost and posted price are not salient in an ongoing auction
  - the current price is salient

- Two different ways to identify a phenomenon:
  - **Hossain-Morgan (2006).** *Field Experiment with shipping costs*
  - **Lee-Malmendier (2006).** *Menu Choice*
• **Hossain-Morgan (2006)**

• Setting:
  
  – $v$ is value of the object
  
  – $o$ negative of the shipping cost: $o = -c$
  
  – Inattentive bidders bid value net of the (perceived) shipping cost: $b^* = v - (1 - \theta) c$ (2nd price auction)
  
  – Revenue $R$ raised by the seller: $R = b^* + c = v + \theta c$. 
  
  – Hence, $1$ increase in the shipping cost $c$ increases revenue by $\theta$ dollars
  
  – Full attention ($\theta = 0$): increases in shipping cost have no effect on revenue
Field experiment selling CD and XBoxs on eBay

- Treatment ‘LowSC’ [A]: reserve price \( r = \$4 \) and shipping cost \( c = \$0 \)
- Treatment ‘HighSC’ [B]: reserve price \( r = \$0.01 \) and shipping cost \( c = \$3.99 \)
- Same total reserve price \( r_{TOT} = r + c = \$4 \)
- Measure effect on total revenue \( R \), probability of sale \( p \)

Predictions:

- Standard model: \( \partial R / \partial c = 0 = \partial p / \partial c \rightarrow R_A = R_B \)
- Inattention: \( \partial R / \partial c = \theta \rightarrow R_A < R_B \)
• Similar strategy to Ausubel (1999)

• Strong effect: $R_B - R_A = 2.61 \rightarrow \text{lnattention } \theta = 2.61/4 = .65$

<table>
<thead>
<tr>
<th>CD Title</th>
<th>Revenues under Treatment A</th>
<th>Revenues under Treatment B</th>
<th>B - A</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Music</td>
<td>5.50</td>
<td>7.24</td>
<td>1.74</td>
<td>32%</td>
</tr>
<tr>
<td>Oops! I Did it Again</td>
<td>6.50</td>
<td>7.74</td>
<td>1.24</td>
<td>19%</td>
</tr>
<tr>
<td>Serendipity</td>
<td>8.50</td>
<td>10.49</td>
<td>1.99</td>
<td>23%</td>
</tr>
<tr>
<td>O Brother Where Art Thou?</td>
<td>12.50</td>
<td>11.99</td>
<td>-0.51</td>
<td>-4%</td>
</tr>
<tr>
<td>Greatest Hits - Tim McGraw</td>
<td>11.00</td>
<td>15.99</td>
<td>4.99</td>
<td>45%</td>
</tr>
<tr>
<td>A Day Without Rain</td>
<td>13.50</td>
<td>14.99</td>
<td>1.49</td>
<td>11%</td>
</tr>
<tr>
<td>Automatic for the People</td>
<td>0.00</td>
<td>9.99</td>
<td>9.99</td>
<td></td>
</tr>
<tr>
<td>Everyday</td>
<td>7.28</td>
<td>9.49</td>
<td>2.21</td>
<td>30%</td>
</tr>
<tr>
<td>Joshua Tree</td>
<td>6.07</td>
<td>8.25</td>
<td>2.18</td>
<td>36%</td>
</tr>
<tr>
<td>Unplugged in New York</td>
<td>4.50</td>
<td>5.24</td>
<td>0.74</td>
<td>16%</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>7.54</strong></td>
<td><strong>10.14</strong></td>
<td><strong>2.61</strong></td>
<td><strong>35%</strong></td>
</tr>
<tr>
<td><strong>Average excluding unsold</strong></td>
<td><strong>8.37</strong></td>
<td><strong>10.16</strong></td>
<td><strong>1.79</strong></td>
<td><strong>21%</strong></td>
</tr>
</tbody>
</table>
• Smaller effect for XBox: $R_B - R_A = 0.71 \implies \text{Inattention } \theta = 0.71/4 = 0.18$

• Pooling data across treatments: $R_B > R_A$ in 16 out of 20 cases $\implies$ Significant difference

<table>
<thead>
<tr>
<th>Xbox Game Title</th>
<th>Revenues under Treatment A</th>
<th>Revenues under Treatment B</th>
<th>B - A</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Halo</td>
<td>34.05</td>
<td>41.24</td>
<td>7.19</td>
<td>21%</td>
</tr>
<tr>
<td>Wreckless</td>
<td>44.01</td>
<td>33.99</td>
<td>-10.02</td>
<td>-23%</td>
</tr>
<tr>
<td>Circus Maximus</td>
<td>40.99</td>
<td>39.99</td>
<td>-1.00</td>
<td>-2%</td>
</tr>
<tr>
<td>Max Payne</td>
<td>36.01</td>
<td>36.99</td>
<td>0.98</td>
<td>3%</td>
</tr>
<tr>
<td>Geena Onimusha</td>
<td>41.00</td>
<td>32.99</td>
<td>-8.01</td>
<td>-20%</td>
</tr>
<tr>
<td>Project Gotham Racing</td>
<td>37.00</td>
<td>38.12</td>
<td>1.12</td>
<td>3%</td>
</tr>
<tr>
<td>NBA 2K2</td>
<td>42.12</td>
<td>42.99</td>
<td>0.87</td>
<td>2%</td>
</tr>
<tr>
<td>NFL 2K2</td>
<td>26.00</td>
<td>33.99</td>
<td>7.99</td>
<td>31%</td>
</tr>
<tr>
<td>NHL 2002</td>
<td>36.00</td>
<td>37.00</td>
<td>1.00</td>
<td>3%</td>
</tr>
<tr>
<td>WWF Raw</td>
<td>33.99</td>
<td>40.99</td>
<td>7.00</td>
<td>21%</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>37.12</strong></td>
<td><strong>37.83</strong></td>
<td><strong>0.71</strong></td>
<td><strong>2%</strong></td>
</tr>
</tbody>
</table>
• Similar treatment with high reserve price:
  – Treatment ‘LowSC’ [C]: reserve price $r = 6$ and shipping cost $c = 2$
  – Treatment ‘HighSC’ [D]: reserve price $r = 2$ and shipping cost $c = 6$

• No significant effect for CDs (perhaps reserve price too high?): \( R_D - R_C = -0.29 \rightarrow \text{Inattention } \theta = -0.29/4 = -0.07 \)

• Large, significant effect for XBoxs: \( R_D - R_C = 4.11 \rightarrow \text{Inattention } \theta = 4.11/4 = 1.05 \)

• Overall, strong evidence of partial disregard of shipping cost: \( \hat{\theta} \approx 0.5 \)

• Inattention or rational search costs
<table>
<thead>
<tr>
<th>CD Title</th>
<th>Revenues under Treatment C</th>
<th>Revenues under Treatment D</th>
<th>D - C</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Music</td>
<td>9.00</td>
<td>8.00</td>
<td>-1.00</td>
<td>-11%</td>
</tr>
<tr>
<td>Ooops! I Did it Again</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Serendipity</td>
<td>12.50</td>
<td>13.50</td>
<td>1.00</td>
<td>8%</td>
</tr>
<tr>
<td>O Brother Where Art Thou?</td>
<td>11.52</td>
<td>11.00</td>
<td>-0.52</td>
<td>-5%</td>
</tr>
<tr>
<td>Greatest Hits - Tim McGraw</td>
<td>18.00</td>
<td>17.00</td>
<td>-1.00</td>
<td>-6%</td>
</tr>
<tr>
<td>A Day Without Rain</td>
<td>15.50</td>
<td>16.00</td>
<td>0.50</td>
<td>3%</td>
</tr>
<tr>
<td>Automatic for the People</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td></td>
</tr>
<tr>
<td>Everyday</td>
<td>10.50</td>
<td>13.50</td>
<td>3.00</td>
<td>29%</td>
</tr>
<tr>
<td>Joshua Tree</td>
<td>8.00</td>
<td>11.10</td>
<td>3.10</td>
<td>39%</td>
</tr>
<tr>
<td>Unplugged in New York</td>
<td>8.00</td>
<td>0.00</td>
<td>-8.00</td>
<td>-100%</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>9.30</strong></td>
<td><strong>9.01</strong></td>
<td><strong>-0.29</strong></td>
<td><strong>-3%</strong></td>
</tr>
<tr>
<td><strong>Average excluding unsold</strong></td>
<td><strong>12.15</strong></td>
<td><strong>12.87</strong></td>
<td><strong>0.73</strong></td>
<td><strong>6%</strong></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Game Title</th>
<th>Revenues under Treatment C</th>
<th>Revenues under Treatment D</th>
<th>D - C</th>
<th>Percent Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Halo</td>
<td>40.01</td>
<td>43.00</td>
<td>2.99</td>
<td>7%</td>
</tr>
<tr>
<td>Wreckless</td>
<td>35.00</td>
<td>36.00</td>
<td>1.00</td>
<td>3%</td>
</tr>
<tr>
<td>Circus Maximus</td>
<td>39.00</td>
<td>42.53</td>
<td>3.53</td>
<td>9%</td>
</tr>
<tr>
<td>Max Payne</td>
<td>37.50</td>
<td>42.00</td>
<td>4.50</td>
<td>12%</td>
</tr>
<tr>
<td>Genma Onimusha</td>
<td>36.00</td>
<td>37.00</td>
<td>1.00</td>
<td>3%</td>
</tr>
<tr>
<td>Project Gotham Racing</td>
<td>35.02</td>
<td>40.01</td>
<td>4.99</td>
<td>14%</td>
</tr>
<tr>
<td>NBA 2K2</td>
<td>41.00</td>
<td>45.00</td>
<td>4.00</td>
<td>10%</td>
</tr>
<tr>
<td>NFL 2K2</td>
<td>33.00</td>
<td>40.10</td>
<td>7.10</td>
<td>22%</td>
</tr>
<tr>
<td>NHL 2002</td>
<td>36.00</td>
<td>41.00</td>
<td>5.00</td>
<td>14%</td>
</tr>
<tr>
<td>WWF Raw</td>
<td>37.00</td>
<td>44.00</td>
<td>7.00</td>
<td>19%</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>36.95</strong></td>
<td><strong>41.06</strong></td>
<td><strong>4.11</strong></td>
<td><strong>11%</strong></td>
</tr>
</tbody>
</table>
7 Attention: Taxes

- **Chetty et al. (2007):** Taxes not featured in price likely to be ignored
- Use data on the demand for items in a grocery store.
- Demand $D$ is a function of:
  - visible part of the value $v$, including the price $p$
  - less visible part $o$ (state tax $-tp$)
  - $D = D [v - (1 - \theta) tp]$
- Variation: Make tax fully salient ($s = 1$)
- Linearization: change in log-demand

$$
\Delta \log D = \log D [v - tp] - \log D [v - (1 - \theta) tp] = \\
= -\theta tp * D' [v - (1 - \theta) tp] / D [v - (1 - \theta) tp] \\
= -\theta t * \eta_{D,p}
$$
- $\eta_{D,p}$ is the price elasticity of demand
- $\Delta \log D = 0$ for fully attentive consumers ($\theta = 0$)
- This implies $\theta = -\Delta \log D / (t \ast \eta_{D,p})$
• Chetty et al. (2007) Part I: field experiment
  – Three-week period: price tags of certain items make salient after-tax price (in addition to pre-tax price).
• Compare sales $D$ to:
  – previous-week sales for the same item
  – sales for items for which tax was not made salient
  – sales in control stores
  – Hence, D-D-D design (pre-post, by-item, by-store)

• Result: average quantity sold decreases (significantly) by 2.20 units relative to a baseline level of 25, an 8.8 percent decline
## TABLE 3
### DDD Analysis of Means: Weekly Quantity by Category

<table>
<thead>
<tr>
<th>Period</th>
<th>Control Categories</th>
<th>Treated Categories</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>TREATMENT STORE</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>26.48</td>
<td>25.17</td>
<td>-1.31</td>
</tr>
<tr>
<td>(2005:1-2006:6)</td>
<td>(0.22)</td>
<td>(0.37)</td>
<td>(0.43)</td>
</tr>
<tr>
<td></td>
<td>[5510]</td>
<td>[754]</td>
<td>[8284]</td>
</tr>
<tr>
<td>Experiment</td>
<td>27.32</td>
<td>23.87</td>
<td>-3.45</td>
</tr>
<tr>
<td>(2006:8-2006:10)</td>
<td>(0.87)</td>
<td>(1.02)</td>
<td>(0.64)</td>
</tr>
<tr>
<td></td>
<td>[285]</td>
<td>[39]</td>
<td>[324]</td>
</tr>
<tr>
<td>Difference over time</td>
<td>0.84</td>
<td>-1.30</td>
<td>DD_{TS} = -2.14</td>
</tr>
<tr>
<td></td>
<td>(0.75)</td>
<td>(0.92)</td>
<td>(0.64)</td>
</tr>
<tr>
<td></td>
<td>[5795]</td>
<td>[793]</td>
<td>[8588]</td>
</tr>
<tr>
<td><strong>CONTROL STORES</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>30.57</td>
<td>27.94</td>
<td>-2.63</td>
</tr>
<tr>
<td>(2005:1-2006:6)</td>
<td>(0.24)</td>
<td>(0.30)</td>
<td>(0.32)</td>
</tr>
<tr>
<td></td>
<td>[11020]</td>
<td>[1500]</td>
<td>[12528]</td>
</tr>
<tr>
<td>Experiment</td>
<td>30.76</td>
<td>28.19</td>
<td>-2.57</td>
</tr>
<tr>
<td>(2006:8-2006:10)</td>
<td>(0.72)</td>
<td>(1.06)</td>
<td>(1.09)</td>
</tr>
<tr>
<td></td>
<td>[570]</td>
<td>[78]</td>
<td>[648]</td>
</tr>
<tr>
<td>Difference over time</td>
<td>0.19</td>
<td>0.25</td>
<td>DD_{CS} = 0.06</td>
</tr>
<tr>
<td></td>
<td>(0.64)</td>
<td>(0.92)</td>
<td>(0.90)</td>
</tr>
<tr>
<td></td>
<td>[11590]</td>
<td>[1588]</td>
<td>[13178]</td>
</tr>
<tr>
<td>DDD Estimate</td>
<td>-2.20</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.58)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[19764]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Each cell shows mean number of units sold per category per week, for various subsets of the sample. Standard errors (clustered by week) in parentheses, number of observations in square.
• Compute inattention:
  – Estimates of price elasticity $\eta_{D,p}$: $-1.59$
  – Tax is $0.07375$
  – $\hat{\theta} = -(-0.088)/(-1.59 \times 0.07375) \approx 0.75$

• Additional check of randomization: Generate placebo changes over time in sales

• Compare to observed differences

• Use Log Revenue and Log Quantity
• Non-parametric p-value of about 5 percent
• Chetty et al. (2007) Part II: Panel Variation
  – Compare more and less salient tax on beer consumption
  – Excise tax included in the price
  – Sales tax is added at the register
  – Panel identification: across States and over time
  – Indeed, elasticity to excise taxes substantially larger \( \rightarrow \) estimate of the inattention parameter of \( \hat{\theta} = .94 \)

• Substantial consumer inattention to non-transparent taxes
TABLE 7
Effect of Excise and Sales Taxes on Beer Consumption

<table>
<thead>
<tr>
<th></th>
<th>Baseline (1)</th>
<th>Bus Cycle (2)</th>
<th>Bus Cycle Lags (3)</th>
<th>Alc Regulations (4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔLog(1+Excise Tax Rate)</td>
<td>-0.87</td>
<td>-0.91</td>
<td>-0.86</td>
<td>-0.89</td>
</tr>
<tr>
<td></td>
<td>(0.17)**</td>
<td>(0.17)**</td>
<td>(0.17)**</td>
<td>(0.17)**</td>
</tr>
<tr>
<td>ΔLog(1+Sales Tax Rate)</td>
<td>-0.20</td>
<td>-0.00</td>
<td>0.03</td>
<td>-0.02</td>
</tr>
<tr>
<td></td>
<td>(0.30)</td>
<td>(0.30)</td>
<td>(0.30)</td>
<td>(0.30)</td>
</tr>
<tr>
<td>ΔLog(Population)</td>
<td>0.03</td>
<td>-0.07</td>
<td>0.05</td>
<td>-0.07</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.19)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>ΔLog(Income per Capita)</td>
<td>0.22</td>
<td>0.18</td>
<td>0.22</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.05)**</td>
<td>(0.05)**</td>
<td>(0.05)**</td>
<td></td>
</tr>
<tr>
<td>ΔLog(Unemployment Rate)</td>
<td>-0.01</td>
<td>-0.01</td>
<td>-0.01</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.01)**</td>
<td>(0.01)</td>
<td>(0.01)**</td>
<td></td>
</tr>
<tr>
<td>Lag Bus. Cycle Controls</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alcohol Regulation Controls</td>
<td>x</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td>x</td>
<td>x</td>
<td>x</td>
<td>x</td>
</tr>
<tr>
<td>F-Test for Equality of Tax Variables (Prob&gt;F)</td>
<td>0.05</td>
<td>0.01</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Sample Size</td>
<td>1607</td>
<td>1487</td>
<td>1440</td>
<td>1487</td>
</tr>
</tbody>
</table>

Notes: Standard errors, clustered by state, in parentheses: * significant at 10%; ** significant at 5%; *** significant at 1%. All specifications include year fixed effects and log state population. Column 2 controls for log state personal income per capita and log state unemployment rate (unavailable in some states in the early 1970s). Column 3 adds one year lags of personal income per capita and unemployment rate variables. Column 4 controls for changes in alcohol policy by including three separate indicators for whether the state implemented per se drunk driving standards, administrative license revocation laws, or zero tolerance youth drunk driving laws, and the change in the minimum drinking age (measured in years).
8 Attention: Financial Markets I

- Is inattention limited to consumers?
- Finance: examine response of asset prices to release of quarterly earnings news
- Setting:
  - Announcement a time $t$
  - $v$ is known information about cash-flows of the company
  - $o$ is new information in earnings announcement
  - Day $t - 1$: company price is $P_{t-1} = v$
  - Day $t$:
    * company value is $v + o$
* Inattentive investors: asset price $P_t$ responds only partially to the new information: $P_t = v + (1 - \theta) o$.

- Day $t + 60$: Over time, price incorporates full value: $P_{t+60} = v + o$

- Implication about returns:
  - Short-run stock return $r_{SR}$ equals $r_{SR} = (1 - \theta) o/v$
  - Long-run stock return $r_{LR}$, instead, equals $r_{LR} = o/v$
  - Measure of investor attention: $(\partial r_{SR}/\partial o)/(\partial r_{LR}/\partial o) = (1 - \theta) \rightarrow$ Test: Is this smaller than 1?
  - (Similar results after allowing for uncertainty and arbitrage, as long as limits to arbitrage — see final lectures)

- Indeed: Post-earnings announcement drift (Bernard-Thomas, 1989): Stock price keeps moving after initial signal

- Inattention leads to delayed absorption of information.
• DellaVigna-Pollet (forthcoming)
  – Estimate \( (\partial r_{SR}/\partial o)/(\partial r_{LR}/\partial o) \) using the response of returns \( r \) to
    the earnings surprise \( o \)
  – \( r_{SR} \): returns in 2 days surrounding an announcement
  – \( r_{LR} \): returns over 75 trading days from an announcement
• Measure earnings news \( o_t \):
  \[
  o_t = \frac{e_t - \hat{e}_t}{p_{t-1}}
  \]
  – Difference between earnings announcement \( e_t \) and consensus earnings
    forecast by analysts in 30 previous days
  – Divide by (lagged) price \( p_{t-1} \) to renormalize
• Next step: estimate \( \partial r_{SR}/\partial o \)
• Problem: Response of stock returns \( r \) to information \( o \) is highly non-linear
• How to evaluate derivative?
9 Methodology: Portfolio Methodology

- Economists’ approach:
– Make assumptions about functional form –> Arctan for example
– Do non-parametric estimate –> kernel regressions
• Finance: Use of quantiles and portfolios (explained in the context of DellaVigna-Pollet (forthcoming))
• First methodology: *Quantiles*
  – Sort data using underlying variable (in this case earnings surprise $o_t$)
  – Divide data into $n$ equal-spaced quantiles: $n = 10$ (deciles), $n = 5$ (quintiles), etc
  – Evaluate difference in returns between top quantiles and bottom quantiles: $Er_n - Er_1$
• This paper:
  – Quantiles 7-11. Divide all positive surprises
  – Quantiles 6. Zero surprise (15-20 percent of sample)
  – Quantiles 1-5. Divide all negative surprise

• Notice: Use of quantiles "linearizes" the function
• Delayed response $r_{LR} - r_{SR}$ (post-earnings announcement drift)
• Inattention:
  – To compute $\partial r_{SR}/\partial o$, use $Er_{SR}^{11} - Er_{SR}^{1} = 0.0659$ (on non-Fridays)
  – To compute $\partial r_{LR}/\partial o$, use $Er_{LR}^{11} - Er_{LR}^{1} = 0.1210$ (on non-Fridays)
  – Implied investor inattention: $(\partial r_{SR}/\partial o)/(\partial r_{LR}/\partial o) = (1 - \theta) = 0.544 \rightarrow \text{Inattention } \theta = 0.456$

• Is inattention larger when more distraction?

• Weekend as proxy of investor distraction.
  – Announcements made on Friday: $(\partial r_{SR}/\partial o)/(\partial r_{LR}/\partial o)$ is 41 percent $\rightarrow \hat{\theta} \approx 0.59$

• Second methodology: Portfolios
  – Instead of using individual data, pool all data for a given time period $t$ into a ‘portfolio’
  – Compute average return $r_{t}^{P}$ for portfolio $t$ over time
Control for Fama-French ‘factors’:

* Market return $r^m_t$
* Size $r^S_t$
* Book-to-Market $r^{BM}_t$
* Momentum $r^M_t$
* (Download all of these from Kenneth French’s website)

Regression:

$$r^P_t = \alpha + BRF_{t}^{Factors} + \varepsilon_t$$

Test: Is $\alpha$ significantly different from zero?

Example in DellaVigna-Pollet (forthcoming)

Each month $t$ portfolio formed as follows: $(r^{11}_F - r^1_F) - (r^{11}_{Non-F} - r^1_{Non-F})$

Use returns $r_{Drift}$ (3-75)
• Differential drift between Fridays and non-Fridays

• Test for significance

\[
\hat{\alpha} = 0.0384 \text{ implies monthly returns of 3.84 percent of pursuing this strategy}
\]
10 Attention: Financial Markets II

- Cohen-Frazzini (forthcoming) – Inattention to subtle links
- Suppose that you are an investor following company A
- Are you missing more subtle news about Company A?
- Example: Huberman and Regev (2001) – Missing the Science article
- Cohen-Frazzini (forthcoming) – Missing the news about your main customer
- Example:
  - Coastcoast Co. is leading manufacturer of golf club heads
  - Callaway Golf Co. is leading retail company for golf equipment
  - What happens after shock to Callaway Co.?
Figure 1: Coastcast Corporation and Callaway Golf Corporation

This figure plots the stock prices of Coastcast Corporation (ticker = PAR) and Callaway Golf Corporation (ticker = ELY) between May and August 2001. Prices are normalized (05/01/2001 = 1).

June 7, 11:37 a.m.: Callaway is downgraded.

June 8, 6 a.m.: Callaway announces earnings will be lower than expected (market closed).

June 8, At close Callaway's price dropped 30% from June 6. Quarterly EPS forecast revised from $0.72 to $0.48.

July 5 CEO and Founder of Callaway dies.

July 19: Company announces EPS at -4 cents.

July 23: Company announces EPS at 36 cents.

No revision in Annual EPS forecast (28)

2001/06/01 2001/06/19 2001/06/28 2001/07/07 2001/07/12 2001/07/26

Callaway ELY (customer) Coastcast PAR
Data:

- Customer-Supplier network – Compustat Segment files (Regulation SFAS 131)
- 11,484 supplier-customer relationships over 1980-2004

Preliminary test:

- Are returns correlated between suppliers and customers?
- Correlation 0.122 at monthly level
• Computation of long-short returns

  - Sort into 5 quintiles by returns in month $t$ of principal customers, $r_t^C$
  - By quintile, compute average return in month $t+1$ for portfolio of suppliers $r_{t+1}^S$: $r_{1,t+1}^S, r_{2,t+1}^S, r_{3,t+1}^S, r_{4,t+1}^S, r_{5,t+1}^S$
  - By quintile $q$, run regression
    $$r_{q,t+1}^S = \alpha_q + \beta_q X_{t+1} + \varepsilon_{q,t+1}$$

  - $X_{t+1}$ are the so-called factors: market return, size, book-to-market, and momentum (Fama-French Factors)
  
  - Estimate $\hat{\alpha}_q$ gives the monthly average performance of a portfolio in quintile $q$
  
  - Long-Short portfolio: $\hat{\alpha}_5 - \hat{\alpha}_1$
• Results in Table III: *Monthly* abnormal returns of 1.2-1.5 percent (huge)

<table>
<thead>
<tr>
<th>Panel A: value weights</th>
<th>Q1(low)</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5(high)</th>
<th>L/S</th>
</tr>
</thead>
<tbody>
<tr>
<td>Excess returns</td>
<td>-0.596</td>
<td>-0.157</td>
<td>0.125</td>
<td>0.313</td>
<td>0.982</td>
<td>1.578</td>
</tr>
<tr>
<td></td>
<td>[-1.42]</td>
<td>[-0.41]</td>
<td>[0.32]</td>
<td>[0.79]</td>
<td>[2.14]</td>
<td>[3.79]</td>
</tr>
<tr>
<td>3-factor alpha</td>
<td>-1.062</td>
<td>-0.796</td>
<td>-0.541</td>
<td>-0.227</td>
<td>0.493</td>
<td>1.555</td>
</tr>
<tr>
<td></td>
<td>[-3.78]</td>
<td>[-3.61]</td>
<td>[-2.15]</td>
<td>[-0.87]</td>
<td>[1.98]</td>
<td>[3.60]</td>
</tr>
<tr>
<td>4-factor alpha</td>
<td>-0.821</td>
<td>-0.741</td>
<td>-0.488</td>
<td>-0.193</td>
<td>0.556</td>
<td>1.376</td>
</tr>
<tr>
<td></td>
<td>[-2.93]</td>
<td>[-3.28]</td>
<td>[-1.89]</td>
<td>[-0.72]</td>
<td>[1.99]</td>
<td>[3.13]</td>
</tr>
<tr>
<td>5-factor alpha</td>
<td>-0.797</td>
<td>-0.737</td>
<td>-0.493</td>
<td>-0.019</td>
<td>0.440</td>
<td>1.237</td>
</tr>
<tr>
<td></td>
<td>[-2.87]</td>
<td>[-3.04]</td>
<td>[-1.94]</td>
<td>[-0.07]</td>
<td>[1.60]</td>
<td>[2.99]</td>
</tr>
</tbody>
</table>

• Information contained in the customer returns not fully incorporated into supplier returns
• Returns of this strategy are remarkably stable over time
• Can run similar regression to test how quickly the information is incorporated.
  – Sort into 5 quintiles by returns in month $t$ of principal customers, $r^C_t$.
  – Compute cumulative return up to month $k$ ahead, that is, $r^{S}_{q,t->t+k}$.
  – By quintile $q$, run regression of returns of Supplier:
    $$r^{S}_{q,t->t+k} = \alpha_q + \beta_q X_{t+k} + \varepsilon_{q,t+1}$$
  – For comparison, run regression of returns of Customer:
    $$r^{C}_{q,t->t+k} = \alpha_q + \beta_q X_{t+k} + \varepsilon_{q,t+1}$$
For further test of inattention, examine cases where inattention is more likely

Measure what share of mutual funds own both companies: COMOWN

Median Split into High and Low COMOWN (Table IX)

<table>
<thead>
<tr>
<th>Weight</th>
<th>All stocks</th>
<th>All stocks</th>
<th>At least 10 common funds (CRSP median)</th>
<th>Larger firms (NYSE median)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EW</td>
<td>VW</td>
<td>EW</td>
<td>VW</td>
</tr>
<tr>
<td>Low COMOWN</td>
<td>1.653</td>
<td>2.301</td>
<td>1.659</td>
<td>2.306</td>
</tr>
<tr>
<td>Lower percent of common ownership</td>
<td>[5.46]</td>
<td>[5.24]</td>
<td>[2.96]</td>
<td>[3.64]</td>
</tr>
<tr>
<td>High COMOWN</td>
<td>0.750</td>
<td>1.098</td>
<td>0.525</td>
<td>0.736</td>
</tr>
<tr>
<td>Higher percent of common ownership</td>
<td>[1.97]</td>
<td>[2.17]</td>
<td>[0.98]</td>
<td>[1.23]</td>
</tr>
<tr>
<td>High-Low</td>
<td>-0.903</td>
<td>-1.203</td>
<td>-1.131</td>
<td>-1.571</td>
</tr>
<tr>
<td></td>
<td>[-2.05]</td>
<td>[-1.99]</td>
<td>[-1.69]</td>
<td>[-1.98]</td>
</tr>
</tbody>
</table>
• Supporting evidence from other similar papers

• **Hong-Torous-Valkanov (2002)**
  - Stock returns in an industry in month $t$ predict returns in another industry in month $t + 1$
  - Investors not good at handling indirect links $\Rightarrow$ Indirect effects of industry-specific shocks neglected
  - Example: forecasted increase in price of oil
  - Oil industry reacts immediately, Other industries with delay

• **Pollet (2002)**
  - Scandinavian stock market (oil extraction) predicts US stock market (negatively) one month ahead
  - Oil industry predicts several industries one month ahead (again negatively)
• DellaVigna-Pollet (2007) – Inattention to distant future

• Another way to simplify decisions is to neglect distant futures when making forecasts

• Identify this using forecastable demographic shifts

• Substantial cohort size fluctuations over the 20th century

• Consumers at different ages purchase different goods

• Changes in cohort size $\implies$ predictable changes in profits for different goods

• How do investors react to these forecastable shifts?
• **Example.** Large cohort born in 2004

• Positive demand shift for school buses in 2010 $\implies$ Revenue increases in 2010

• Profits (earnings) for bus manufacturers?
  
  – Perfect Competition. Abnormal profits do not change in 2010
  
  – Imperfect Competition. Increased earnings in 2010
• How do investors react?

1. Attentive investors:
   – Stock prices adjust in 2004
   – No forecastability of returns using demographic shifts

2. Investors inattentive to future shifts:
   – Price does not adjust until 2010
   – Predictable stock returns using contemporaneous demand growth

3. Investors attentive up to 5 years
   – Price does not adjust until 2005
   – Predictable stock returns using consumption growth 5 years ahead
• **Step 1.** Forecast future cohort sizes using current demographic data

• **Step 2.** Estimate consumption of 48 different goods by age groups (CEX data)

• **Step 3.** Compute forecasted growth demand due to demographics into the future:
  
  – Demand increase in the short-term: \( \hat{c}_{i,t+5} - \hat{c}_{i,t} \)
  
  – Demand increase in the long-term: \( \hat{c}_{i,t+10} - \hat{c}_{i,t+5} \)

• Does this demand forecast returns? Regression of annual abnormal returns

\[
\alpha r_{i,t+1} = \gamma + \delta_0 \left[ \hat{c}_{i,t+5} - \hat{c}_{i,t} \right] / 5 + \delta_1 \left[ \hat{c}_{i,t+10} - \hat{c}_{i,t+5} \right] / 5 + \varepsilon_{i,t+1}
\]
### Table 6. Predictability of Stock Returns Using Demographic Changes

<table>
<thead>
<tr>
<th>Sample</th>
<th>Dependent Variable: Annual Beta-Adjusted Log Industry Stock Return at t+1</th>
<th>Demographic Industries</th>
<th>All Industries</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.0967</td>
<td>0.1004</td>
<td>0.3571</td>
</tr>
<tr>
<td></td>
<td>(0.05560)*</td>
<td>(0.1122)</td>
<td>(0.0858)***</td>
</tr>
<tr>
<td>Forecasted annualized demand growth between t and t+5</td>
<td>-0.4484</td>
<td>-0.5726</td>
<td>-2.2113</td>
</tr>
<tr>
<td>Forecasted annualized demand growth between t+5 and t+10</td>
<td>8.7203</td>
<td>11.0365</td>
<td>6.8243</td>
</tr>
<tr>
<td></td>
<td>(4.2206)**</td>
<td>(3.9489)***</td>
<td>(3.5568)*</td>
</tr>
<tr>
<td>Industry Fixed Effects</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Year Fixed Effects</td>
<td></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Sample: 1974 to 2003</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Sample: 1939 to 2003</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>R^2</td>
<td>0.0233</td>
<td>0.1121</td>
<td>0.3202</td>
</tr>
<tr>
<td>N</td>
<td>N = 566</td>
<td>N = 566</td>
<td>N = 566</td>
</tr>
</tbody>
</table>
Figure 4: Return Predictability Coefficient for Demand Growth Forecasts at Different Horizons

Notes: The estimated coefficient for each horizon is from a univariate OLS regression of abnormal returns at t+1 on forecasted consumption growth between t+h and t+h+1 for the subsample of Demographic Industries over the period 1974-2003. The confidence intervals are constructed using robust standard errors clustered by year and then scaled by a function of the autocorrelation coefficient estimated from the sample orthogonality conditions.
• Results:

1. Demographic shifts 5 to 10 years ahead can forecast industry-level stock returns

2. Yearly portfolio returns of 5 to 10 percent

3. Inattention of investors to information beyond approx. 5 years

4. Evidence on analyst horizon: Earning forecasts beyond 3 years exist for only 10% of companies (IBES)

• Where else long-term future matters?

  – Job choices

  – Construction of new plant...
11  Next Lecture

- Framing
- Menu Effects