Econ 219B
Psychology and Economics: Applications
(Lecture 10)

Stefano DellaVigna

April 3, 2019
1. Attention: Simple Model
2. Attention: eBay Auctions
3. Attention: Taxes
4. Attention: Left Digits
5. Attention: Financial Markets
6. Attention: Wrap Up
7. Framing
8. Menu Effects: Introduction
9. Menu Effects: Choice Avoidance
10. Menu Effects: Preference for Familiar
11. Menu Effects: Preference for Salient
Section 1

Attention: Simple Model
Simple model (DellaVigna JEL 2009)

- 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
  - Model captures in reduced form underlying attention model, eg. sparsity (Gabaix, 2018) or rational inattention (Matejka and McKay, 2016)
  - Interpretation: each individual sees $o$, but processes it only partially, to the degree $\theta$
Alternative Model

- 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 $x$
Identification

Model suggests three strategies to identify the inattention parameter $\theta$:

1. Compute response of $\hat{V}$ to change in $o$ → compare
   \[ \frac{\partial \hat{V}}{\partial o} = (1 - \theta) \text{ to } \frac{\partial \hat{V}}{\partial \nu} = 1 \]

2. Examine the response of $\hat{V}$ to an increase in the salience $s$,
   \[ \frac{\partial \hat{V}}{\partial s} = -\theta'_s o : \text{ differs from zero?} \]
   (Chetty et al. (2009); Allcott and Taubinsky, 2015)

3. Vary competing stimuli $N$,
   \[ \frac{\partial \hat{V}}{\partial N} = -\theta'_N o : \text{ differs from zero?} \]
   (DellaVigna-Pollet (2009) and Hirshleifer-Lim-Teoh (2009))

Key (unmodeled) element: identify opaque information $o$
Two caveats:

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

2. Inattention can be rational, or not.
   - Can rephrase as rational model with information costs.
   - Opaque information is sometimes available at a zero or small cost (for example, earnings announcements news) → Rational interpretation less plausible.
   - Leading edge in the literature is to pin down underlying attention model, eg, salience a la Gabaix or rational inattention a la Sims (2003).
Section 2

Attention: eBay Auctions
Hossain and Morgan (2006): Inattention to Shipping Cost

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
Methodology

- Field experiment selling CD and XBox Games 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 $p$
Methodology

- Field experiment selling CD and XBox Games on eBay
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  - 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: $\frac{\partial R}{\partial c} = 0 = \frac{\partial p}{\partial c} \rightarrow R_A = R_B$
  - Inattention: $\frac{\partial R}{\partial c} = \theta \rightarrow R_A < R_B$
Results: CDs

- Strong effect: $R_B - R_A = $2.61 → Inattention $\theta = 2.61/4 = .65$

Table 3. Revenues from Low Reserve Treatments

<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>Ooops! 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>
Results: XBox Games

- Smaller effect for XBox: $R_B - R_A = 0.71 \rightarrow \text{Inattention} \quad \theta = 0.71/4 = 0.18$
- Pooling data across treatments: $R_B > R_A$ in 16 out of 20 cases \rightarrow \text{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>Genma 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>
</tbody>
</table>

**Average**

|                      | 37.12                       | 37.83                       | 0.71  | 2%                |
Robustness Check

- 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 $c = 6$
Robustness Check

- 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:
  \[ R_D - R_C = 4.11 \rightarrow \text{Inattention } \theta = 4.11/4 = 1.05 \]
Robustness Check

- 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?): $R_D - R_C = -0.29 \implies \text{Inattention } \theta = -0.29/4 = -0.07$

- Large, significant effect for XBoxs: $R_D - R_C = 4.11 \implies \text{Inattention } \theta = 4.11/4 = 1.05$

- Overall, strong evidence of partial disregard of shipping cost: $\hat{\theta} \approx 0.5$

- Inattention or rational search costs
Results: High Reserve Treatment

Table 4. Revenues from High Reserve Treatments

<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>Oops! 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>Average</td>
<td>9.30</td>
<td>9.01</td>
<td>-0.29</td>
<td>-3%</td>
</tr>
<tr>
<td>Average excluding unsold</td>
<td>12.15</td>
<td>12.87</td>
<td>0.73</td>
<td>6%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Game Title</th>
<th>Revenues under Treatment C</th>
<th>Revenues under Treatment D</th>
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<td>3.00</td>
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</tr>
<tr>
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<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>Gemma Onimusha</td>
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<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>
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<td>33.00</td>
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<td>WWF Raw</td>
<td>37.00</td>
<td>44.00</td>
<td>7.00</td>
<td>19%</td>
</tr>
<tr>
<td>Average</td>
<td>36.93</td>
<td>41.08</td>
<td>4.15</td>
<td>11%</td>
</tr>
</tbody>
</table>
Section 3

Attention: Taxes
Salience and Taxation: Theory and Evidence

- **Chetty et al. (AER, 2009):** 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 $−tp$)
  - $D = D\left[v - (1 - \theta) tp\right]$
- Variation: Make tax fully salient ($s = 1$)
• Linearization: change in log-demand

\[ \Delta \log D = \log D [v - tp] - \log D [v - (1 - \theta) tp] = \]
\[ = -\theta tp \times D' [v - (1 - \theta) tp] / D [v - (1 - \theta) tp] \]
\[ = -\theta t \times \eta_{D,p} \]

• \( \eta_{D,p} \) is the price elasticity of demand
• \( \Delta \log D = 0 \) for fully attentive consumers \((\theta = 0)\)
• This implies \( \theta = -\Delta \log D / (t \times \eta_{D,p}) \)
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>
<thead>
<tr>
<th>Period</th>
<th>Control Categories</th>
<th>Treated Categories</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<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>[6264]</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</td>
<td>0.84</td>
<td>-1.30</td>
<td>DD_{ts} = -2.14</td>
</tr>
<tr>
<td>over time</td>
<td>(0.75)</td>
<td>(0.92)</td>
<td>(0.64)</td>
</tr>
<tr>
<td></td>
<td>[5795]</td>
<td>[793]</td>
<td>[6588]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Period</th>
<th>Control Categories</th>
<th>Treated Categories</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<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>[1508]</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>[548]</td>
</tr>
<tr>
<td>Difference</td>
<td>0.19</td>
<td>0.25</td>
<td>DD_{cs} = 0.06</td>
</tr>
<tr>
<td>over time</td>
<td>(0.64)</td>
<td>(0.92)</td>
<td>(0.90)</td>
</tr>
<tr>
<td></td>
<td>[11590]</td>
<td>[1588]</td>
<td>[13176]</td>
</tr>
</tbody>
</table>

**DDD Estimate** = -2.20

<p>| | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>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 brackets.</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
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. also consider welfare implications of the results.

Limited attention can be good for welfare!

Intuition:
- Limited attention limits consumption response to tax
- It lowers the deadweight loss of taxation
Follow-up Work

Next step in the literature: Taubinsky and Rees-Jones (RES 2018)

Significant advance

1. Estimate limited attention with much higher precision
2. Estimate how limited attention varies with the stakes (higher price items, higher tax)
3. Estimate heterogeneity in limited attention

For result, see 219a, but key take-aways

1. Limited attention is very significant economically
2. Attention is higher for higher stakes
3. Attention is very heterogeneous

Result 3 reverses welfare implication: Heterogeneous inattention hurts consumers
Section 4

Attention: Left Digits
Introduction

- Are consumers paying attention to full numbers, or only to more salient digits?
- Classical example: $X = 5.99$ vs. $Y = 6.00$
- Consumer inattentive to digits other than first, perceive

\[ X = 5 + (1 - \theta) \cdot 0.99 \]
\[ Y = 6 \]
\[ Y - X = 0.01 + \theta \cdot 0.99 \]

- Optimal Pricing at 99 cents

- Indeed, evidence of 99 cents effect in pricing at stores
Ashton (2014)

- Re-analysis of Chetty et al. data
  - Show that effect on sales is concentrated to cases in which first digit changes
    - Not much effect if adding tax raises price from 3.50 to 3.80
    - Effect is adding tax raises price from 3.99 to 4.30
  - Compute DDD for Shifting digit and Rigid digit
  - Effect is entirely due to Shifting Digit
### Table 4: Comparison of Means.

<table>
<thead>
<tr>
<th></th>
<th>Control Stores</th>
<th>Treated Store</th>
<th>Diff (stores)</th>
<th>Control Stores</th>
<th>Treated Store</th>
<th>Diff (stores)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline Period</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sensitive dollar-value prices</td>
<td>12.297</td>
<td>10.769</td>
<td>(-1.528)</td>
<td>15.514</td>
<td>14.356</td>
<td>(-1.158)</td>
</tr>
<tr>
<td></td>
<td>(0.187)</td>
<td>(0.187)</td>
<td>(0.206)</td>
<td>(0.237)</td>
<td>(0.283)</td>
<td>(0.224)</td>
</tr>
<tr>
<td></td>
<td>[1612]</td>
<td>[806]</td>
<td>[2418]</td>
<td>[1612]</td>
<td>[806]</td>
<td>[2418]</td>
</tr>
<tr>
<td>Experimental Period</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.499)</td>
<td>(0.431)</td>
<td>(0.811)</td>
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<tr>
<td>Diff (time)</td>
<td>(D_{CS} = 1.447)</td>
<td>(D_{TS} = 0.180)</td>
<td>(DD_{RC} = -1.267)</td>
<td>(D_{CS} = -1.066)</td>
<td>(D_{TS} = -1.433)</td>
<td>(DD_{RC} = -0.367)</td>
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<td>(0.452)</td>
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<td>(0.734)</td>
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</tr>
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<td><strong>Control Period</strong></td>
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<tr>
<td>Rigid dollar-value prices</td>
<td>18.540</td>
<td>16.541</td>
<td>(-2.000)</td>
<td>13.458</td>
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<td>(-1.945)</td>
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<td>(0.170)</td>
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<td>(0.137)</td>
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<td>Rigid dollar-value prices</td>
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<td>12.258</td>
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<td>(0.494)</td>
<td>(0.707)</td>
<td>(0.467)</td>
<td>(0.510)</td>
<td>(0.573)</td>
<td>(0.269)</td>
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<td>[858]</td>
<td>[511]</td>
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<tr>
<td>Diff (time)</td>
<td>(D_{CS} = -0.807)</td>
<td>(D_{TS} = -0.053)</td>
<td>(DD_{CC} = 0.754)</td>
<td>(D_{CS} = 0.969)</td>
<td>(D_{TS} = 0.745)</td>
<td>(DD_{CC} = -0.224)</td>
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<td>(0.441)</td>
<td>(0.901)</td>
<td>(0.468)</td>
<td>(0.446)</td>
<td>(0.491)</td>
<td>(0.257)</td>
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<td>[12415]</td>
<td>[6175]</td>
<td>[18580]</td>
<td>[11002]</td>
<td>[5380]</td>
<td>[16388]</td>
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<td>DDD</td>
<td>-2.021</td>
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<td></td>
<td>-0.143</td>
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<td></td>
<td>(0.979)</td>
<td></td>
<td></td>
<td>(0.984)</td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>[21125]</td>
<td></td>
<td></td>
<td>[18923]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: Standard deviations are reported in parentheses below the means. Number of observations are reported in square brackets below the standard errors. See Appendix 3 for description of treated and control categories. Statistics are computed using the full sample.
Examine left-digit inattention with 3-way tack:

1. Do demand curves indeed exhibit discontinuity in price response as predicted with limited attention?
2. Are observed price endings consistent with inattention model?
3. Can we use a natural experiment in price endings to get evidence on (1) and (2), and test for firm profit maximization?

Difficulty:

- (2) is a major confound for (1), as prices are highly endogenous
- In most data sets, price is recorded noisily in the presence of sales
- Briefly present evidence on (1)
Shlain (2018)

- Assume demand is given by
  \[ \log Q = A + \eta \log(P) \]
  with \( \eta \) being elasticity
- Then this is what is predicted with, and without, left-digit bias
Shlain (2018)

- Using residual

Simulation: Shape of residualized quantities from logQ~logP regression with random pricing.
Shlain (2018)

Findings

- Clear evidence of limited attention, identifies also elasticity!
- Can then use to predict optimal pricing

Actual demand minus predicted demand

binned residuals from chain-level regressions of \(\log Q_{st} \sim \eta_{c(s)} \log P_{st} + \text{store} + \text{year} + \text{month fixed effects},\)
where \(s\) is store, \(c\) is chain, and \(t\) is date.

56 retail chains, with 10,139 stores, 8 years of weekly prices.
Subset of ‘regular prices’ including only price spells of length 6 weeks at least.
Residuals are binned to 5 cents bins, and weighted by price frequency. Product: coffee1
Lacetera, Pope, and Sydnor (AER 2012). Inattention in Car Sales

Sales of used cars – Odometer is important measure of value of car

Suppose perceived value \( \hat{V} \) of car is

\[
\hat{V} = K - \alpha \hat{m}
\]

Perceived mileage is

\[
\hat{m} = \text{floor}(m, 10k) + (1 - \theta) \text{mod}(m, 10k)
\]

Model predicts jump in value \( \hat{V} \) at 10k discontinuity of

\[
-\alpha \theta 10k
\]

while slope is

\[
-\alpha (1 - \theta)
\]
Can estimate inattention parameter $\theta$: Jump/Slope gives $\theta/(1-\theta)$
Data and Results

- Data set
  - 27 million wholesale used car auctions
  - January 2002 to September 2008
  - Buyer: Used car dealer
  - Seller: car dealer or fleet/lease
  - Continuous mileage displayed prominently on auction floor

- Result: Amazing resemblance of data to theory-predicted patterns: jump at 10k mark
  - Sizeable magnitudes: $200
Results I: 10,000s

- If discontinuity, expect smaller jumps also at 1k mileage points
**Results II: 1,000s**

![Graph showing average residual sales price vs miles on car relative to 10,000-mile threshold.](image)

**Figure 9. 1,000-Mile Discontinuities**

*Notes: This figure plots the average residual sales price within 50-mile bins for all cars in our dataset. To decrease noise, the data were stacked so that each dot is the average residual for cars in the same bin relative to a 10,000-mile threshold. For example, the very first dot represents the average residual value of all cars whose mileage falls between 10,000–10,050, 20,000–20,050, 30,000–30,050, ..., or 110,000–110,050.*
Structural estimation of limited attention parameter can be done with Delta method or with NLS.

- Structural estimation can be from OLS.
- Estimate $\hat{\theta} = 0.33$ (0.01) for dealers, $\hat{\theta} = 0.22$ (0.01) for lease.
- Remarkable precision in the estimate of inattention.
- Consistent with other evidence, but much more precise.

Who does this inattention refer to?

1. Auction buyers are biased → But these are used car re-sellers.
2. Ultimate car buyers are biased → Auction buyers incorporate it in bids.

Provide some evidence on experience of used car buyers:

1. Hyp. 1 implies more experienced buyers will not buy at 19,990.
2. Hyp. 2 implies more experienced buyers will indeed buy at 19,990.
Figure 11. Experience Percentile

Notes: Each buyer in the dataset is given an experience percentile rating based on total volume of purchases (the 1 percent of buyers with the highest volume receive a percentile score of 99 percent). This figure plots the average buyer experience percentile for each 500-mile bin.
Behavioral IO

- Behavioral IO:
  - Biases of consumers
  - Rational firms respond to it, altering transaction price

- Would like more direct evidence: Do ultimate car buyers display bias?

- Busse, Lacetera, Pope, Silva-Risso, Sydnor (AER P&P 2013)
  - Data from 16m transaction of used cars
  - Information on sale price
  - Same time period
  - Is there similar pattern? Yes
Figure 1. Average Price by Mileage

- Similar estimate of inattention for auction buyers and ultimate buyers
### Table 1—Structural Model Estimates

<table>
<thead>
<tr>
<th>Sample</th>
<th>30K</th>
<th>40K</th>
<th>50K</th>
<th>60K</th>
<th>70K</th>
<th>80K</th>
<th>90K</th>
<th>100K</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retail—all</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discontinuity ($$)</td>
<td>240</td>
<td>167</td>
<td>310</td>
<td>317</td>
<td>365</td>
<td>324</td>
<td>366</td>
<td>402</td>
</tr>
<tr>
<td>Mileage depreciation rate ($\alpha$)</td>
<td>0.135</td>
<td>0.125</td>
<td>0.131</td>
<td>0.123</td>
<td>0.118</td>
<td>0.098</td>
<td>0.102</td>
<td>0.086</td>
</tr>
<tr>
<td>Inattention parameter ($\theta$)</td>
<td>0.178</td>
<td>0.134</td>
<td>0.237</td>
<td>0.258</td>
<td>0.308</td>
<td>0.329</td>
<td>0.360</td>
<td>0.467</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.011)</td>
<td>(0.015)</td>
<td>(0.017)</td>
<td>(0.024)</td>
<td></td>
</tr>
<tr>
<td>Wholesale</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discontinuity ($$)</td>
<td>172</td>
<td>196</td>
<td>283</td>
<td>236</td>
<td>227</td>
<td>214</td>
<td>177</td>
<td>180</td>
</tr>
<tr>
<td>Mileage depreciation rate ($\alpha$)</td>
<td>0.060</td>
<td>0.074</td>
<td>0.081</td>
<td>0.066</td>
<td>0.059</td>
<td>0.047</td>
<td>0.042</td>
<td>0.039</td>
</tr>
<tr>
<td>Inattention parameter ($\theta$)</td>
<td>0.285</td>
<td>0.266</td>
<td>0.348</td>
<td>0.360</td>
<td>0.387</td>
<td>0.451</td>
<td>0.425</td>
<td>0.461</td>
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<tr>
<td>(0.0171)</td>
<td>(0.0154)</td>
<td>(0.016)</td>
<td>(0.0209)</td>
<td>(0.0235)</td>
<td>(0.0288)</td>
<td>(0.0317)</td>
<td>(0.0346)</td>
<td></td>
</tr>
</tbody>
</table>

- **Heterogeneity by income (at ZIP level)? Some**

| Retail—low income |     |     |     |     |     |     |     |      |
| Discontinuity ($\$) | 248 | 162 | 305 | 311 | 379 | 295 | 361 | 381  |
| Mileage depreciation rate ($\alpha$) | 0.126 | 0.116 | 0.120 | 0.115 | 0.113 | 0.098 | 0.099 | 0.086 |
| Inattention parameter ($\theta$) | 0.197 | 0.139 | 0.255 | 0.270 | 0.336 | 0.303 | 0.364 | 0.443 |
| (0.008)          | (0.010) | (0.012) | (0.014) | (0.016) | (0.021) | (0.024) | (0.033) |      |

| Retail—high income |     |     |     |     |     |     |     |      |
| Discontinuity ($\$) | 235 | 169 | 296 | 318 | 342 | 353 | 352 | 401  |
| Mileage depreciation rate ($\alpha$) | 0.145 | 0.133 | 0.142 | 0.130 | 0.121 | 0.096 | 0.102 | 0.087 |
| Inattention parameter ($\theta$) | 0.163 | 0.127 | 0.209 | 0.245 | 0.282 | 0.367 | 0.344 | 0.460 |
| (0.008)          | (0.009) | (0.011) | (0.013) | (0.016) | (0.024) | (0.026) | (0.038) |      |
Section 5

Attention: Financial Markets
Introduction

- Is inattention limited to consumers?
- Finance: examine response of asset prices to release of quarterly earnings news

Setting:
- Announcement at time $t$
- $\nu$ is known information about cash-flows of the company
- $o$ is new information in earnings announcement
- Day $t - 1$: company price is $P_{t-1} = \nu$
- Day $t$:
  - Company value is $\nu + o$
  - Inattentive investors: asset price $P_t$ responds only partially to the new information: $P_t = \nu + (1 - \theta) o$.
- Day $t + 60$: Over time, price incorporates full value: $P_{t+60} = \nu + o$
Implications

- Implication about returns:
  - Short-run stock return $r_{SR}$ equals $r_{SR} = (1 - \theta) \sigma / \nu$
  - Long-run stock return $r_{LR}$, instead, equals $r_{LR} = \sigma / \nu$
  - Measure of investor attention: \( \frac{\partial r_{SR}}{\partial \sigma} / \frac{\partial r_{LR}}{\partial \sigma} = (1 - \theta) \)
    \( \rightarrow \) 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 (JF 2009)**
- 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?
Portfolio Methodology

Figure 1d: Nonlinear Form of the Response to Earnings Surprise From 0 to 1

Mean Cumulative Abnormal Return

Mean Earnings Surprise For Each Quantile
Quantiles and Portfolios

- 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 (JF 2009))

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: $E_r_n - E_r_1$
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

Figure 1a: Response To Earnings Surprise From 0 To 1
• Notice: Use of quantiles "linearizes" the function
• Delayed response $r_{LR} - r_{SR}$ (post-earnings announcement drift)
Results: Inattention

- 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:
    $$(\partial r_{SR}/\partial o)/(\partial r_{LR}/\partial o) = (1 - \theta) = .544 \rightarrow \text{Inattention}$$
    $$\theta = .456$$

- 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 $\rightarrow \hat{\theta} \approx .59$
Second Method: Portfolios

- 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 $r_t^m$
    - Size $r_S$
    - Book-to-Market $r_t^{BM}$
    - Momentum $r_t^M$
    - (Download all of these from Kenneth French’s website)
  - Regression:
    \[ r_t^P = \alpha + BR_t^{Factors} + \varepsilon_t \]
  - Test: Is $\alpha$ significantly different from zero?
Example in DellaVigna-Pollet (2009)

- Each month $t$ portfolio formed as follows:
  $$(r_{11}^{F} - r_{1}^{F}) - (r_{11}^{Non-F} - r_{1}^{Non-F})$$
- Returns $r_{Drift}$ (3-75) - Differential drift between Fridays and non-Fridays
- Intercept $\hat{\alpha} = .0384$ : monthly returns of 3.84 percent from this strategy

<table>
<thead>
<tr>
<th>Dependent Variable: Monthly Return on the Zero-Investment Portfolio</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
</tr>
<tr>
<td>-----------------</td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>(0.0194)***</td>
</tr>
<tr>
<td>VW Index Excess Return (VWRF)</td>
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<td>(0.3090)</td>
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<tr>
<td>Size Factor Return (SMB)</td>
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<td>(0.4105)</td>
</tr>
<tr>
<td>Value Factor Return (HML)</td>
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<tr>
<td>(0.0143)</td>
</tr>
<tr>
<td>Momentum Factor Return (UMD)</td>
</tr>
<tr>
<td>(0.2532)</td>
</tr>
<tr>
<td>One month holding period</td>
</tr>
<tr>
<td>Two month holding period</td>
</tr>
<tr>
<td>Top minus bottom quantile</td>
</tr>
<tr>
<td>Matched sample</td>
</tr>
<tr>
<td>Top two minus bottom two quantiles</td>
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<tr>
<td>Top minus bottom decile</td>
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<tr>
<td>$R^2$</td>
</tr>
<tr>
<td>N, N = 125, N = 125, N = 124, N = 124, N = 124, N = 124</td>
</tr>
</tbody>
</table>

* significant at 10%, ** significant at 5%, *** significant at 1%
Subtle Links

- **Cohen-Frazzini (JF 2011) – 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 (2011) – Missing the news about your main customer:
  - 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 am: Callaway is downgraded
- June 8, 6am: 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 $0.70 to $0.36
- July 5 CEO and Funder of Callaway dies.
- July 19, Company announces EPS at -4 cents
- July 25, Company announces EPS at 36 cents
- No revision in Annual EPS forecast (2$)

---

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 I

- 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
Results II

- Returns of this strategy are remarkably stable over time
How quickly is info incorporated?

- Can run similar regression to test how quickly the information is incorporated
  - Sort into 5 quintiles by returns in month $t$ of principal customers, $r_t^C$
  - Compute cumulative return up to month $k$ ahead, that is, $r_{q,t\rightarrow t+k}^S$
  - By quintile $q$, run regression of returns of Supplier:
    $$r_{q,t\rightarrow t+k}^S = \alpha_q + \beta_q X_{t+k} + \varepsilon_{q,t+1}$$
  - For comparison, run regression of returns of Customer:
    $$r_{q,t\rightarrow t+k}^C = \alpha_q + \beta_q X_{t+k} + \varepsilon_{q,t+1}$$
Further Test

- 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>At least 20 mutual funds holding the stock</th>
<th>Larger firms (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>0.528</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>[-2.08]</td>
<td>[-1.69]</td>
<td>[-1.60]</td>
<td>[-1.98]</td>
</tr>
</tbody>
</table>
Section 6

Attention: Wrap up
Taking it Together

- Enough evidence that we start to be able to move to next steps:
  - Is attention rational?
  - What models capture it best?
- Gabaix (2018) very nice meta-analysis figure
This figure shows point estimates of the attention parameter $m$ in a cross-section of recent studies (shown in Table 1), against the estimated relative value of the opaque add-on attribute with respect to the relevant good or quantity ($\tau/p$). A value $m = 1$ corresponds to full attention, while $m = 0$ implies complete inattention. The overlaid curve (black curve) shows the corresponding calibration of the quadratic-cost attention function in (23), where we impose $\beta = 1$ and obtain calibrated cost parameters $\bar{\gamma} = 3.0$, $q = 2.0$ via nonlinear least squares. Additionally, for comparison, we plot analogous data points (triangles) for subsamples from the study of Busse, Lacetera, Pope, Silva-Risso, and Sydnor (2013b), who document inattention to left-digit remainders in the mileage of cars sold at auction, broken down along covariate dimensions. Each data point in the latter series corresponds to a subsample including all cars with mileages within a 10,000 mile-wide bin (e.g., between 15,000 and 25,000 miles, between 25,000 miles and 35,000 miles, and so forth). For each mileage bin, we include data points from both retail and wholesale auctions.
Section 7

Framing
Tenet of Psychology: Context and Framing Matter

- Classical example (Tversky and Kahneman, 1981 in version of Rabin and Weizsäcker, 2009): Subjects asked to consider a pair of ‘concurrent decisions. [...]’
  - **Decision 1.** Choose between: A. a sure gain of £2.40 and B. a 25% chance to gain £10.00 and a 75% chance to gain £0.00.
  - **Decision 2.** Choose between: C. a sure loss of £7.50 and D. a 75% chance to lose £10.00 and a 25% chance to lose £0.00.'
Classical Example Results

- Of 53 participants playing for money, 49 percent chooses A over B and 68 percent chooses D over C.

- 28 percent of the subjects chooses the combination of A and D.
  - This lottery is a 75% chance to lose £7.60 and a 25% chance to gain £2.40.
  - Dominated by combined lottery of B and C: 75% chance to lose £7.50 and a 25% chance to gain £2.50.

- Separate group of 45 subjects presented same choice in broad framing (they are shown the distribution of outcomes induced by the four options).
  - None of these subjects chooses the A and D combination.
Interpretation

- Interpret this with reference-dependent utility function with narrow framing.
  - Approximately risk-neutral over gains – > 49 percent choosing A over B
  - Risk-seeking over losses – > 68 percent choosing D over C.
  - Key point: Individuals accept the framing induced by the experimenter and do not aggregate the lotteries

- General feature of human decisions:
  - judgments are comparative
  - changes in the framing can affect a decision if they change the nature of the comparison
- Presentation format can affect preferences even aside from reference points

- **Benartzi and Thaler (JF 2002): Impact on savings plan choices:**
  - Survey 157 UCLA employees participating in a 403(b) plan
  - Ask them to rate three plans (labelled plans A, B, and C):
    - Their own portfolio
    - Average portfolio
    - Median portfolio
  - For each portfolio, employees see the 5th, 50th, and 95th percentile of the projected retirement income from the portfolio (using Financial Engines retirement calculator)
  - Revealed preferences → expect individuals on average to prefer their own plan to the other plans
Results:
- Own portfolio rating (3.07)
- Average portfolio rating (3.05)
- Median portfolio rating (3.86)
- 62 percent of employees give higher rating to median portfolio than to own portfolio

Key component: Re-framing the decision in terms of ultimate outcomes affects preferences substantially

Alternative interpretation: Employees never considered the median portfolio in their retirement savings decision → would have chosen it had it been offered

Survey 351 participants in a different retirement plan
These employees were explicitly offered a customized portfolio and actively opted out of it

Rate:

- Own portfolio
- Average portfolio
- Customized portfolio

Portfolios re-framed in terms of ultimate income

61 percent of employees prefers customized portfolio to own portfolio

Choice of retirement savings depends on format of the choices presented

Open question: Why this particular framing effect?

Presumably because of fees:
Consumers put too little weight on factors that determine ultimate returns, such as fees → Unless they are shown the ultimate projected returns

Or consumers do not appreciate the riskiness of their investments → Unless they are shown returns
Framing also can focus attention on different aspects of the options

Duflo, Gale, Liebman, Orszag, and Saez (QJE 2006): Field Experiment with H&R Block
- Examine participation in IRAs for low- and middle-income households
- Estimate impact of a match

Field experiment:
- Random sub-sample of H&R Block customers are offered one of 3 options:
  - No match
  - 20 percent match
  - 50 percent match
• Match refers to first $1,000 contributed to an IRA
  • Effect on take-up rate:
    • No match (2.9 percent)
    • 20 percent match (7.7 percent)
    • 50 percent match (14.0 percent)

• Match rates have substantial impact
Framing aspect: Compare response to explicit match to response to a comparable match induced by tax credits in the Saver’s Tax Credit program

- Effective match rate for IRA contributions decreases from 100 percent to 25 percent at the $30,000 household income threshold
- Compare IRA participation for
  - Households slightly below the threshold ($27,500-$30,000)
  - Households slight above the threshold ($30,000-$32,500)
- Estimate difference-in-difference relative to households in the same income groups that are ineligible for program
- Result: Difference in match rate lowers contributions by only 1.3 percentage points → Much smaller than in H&R Block field experiment

- Why framing difference? Simplicity of H&R Block match → Attention
- Implication: Consider behavioral factors in design of public policy
Section 8

Menu Effects: Introduction
Menu Effects

We now consider a specific context: Choice from Menu $N$ (typically, with large $N$)

- Health insurance plans
- Savings plans
- Politicians on a ballot
- Stocks or mutual funds
- Type of Contract (Ex: no. of minutes per month for cell phones)
- Classes
- Charities
- ...
Heuristics

- We explore 4 + 1 (non-rational) heuristics
  - 1. Excess Diversification (EXTRA material)
  - 2. Choice Avoidance
  - 3. Preference for Familiar
  - 4. Preference for Salient
  - 5. Confusion

- Heuristics 1-4 deal with difficulty of choice in menu
  - Related to bounded rationality: Cannot process complex choice
    → Find heuristic solution

- Heuristic 5 – Random confusion in choice from menu
Section 9

Menu Effects: Choice Avoidance
Field Evidence I

- Heuristic: Refusal to choose with choice overload

- **Choice Avoidance.** Classical Experiment (*Yiengar-Lepper*, JPSP 2000)
  - Up-scale grocery store in Palo Alto
  - Randomization across time of day of number of jams displayed for taste
    - Small number: 6 jams
    - Large number: 24 jams
  - Results:
    - More consumers sample with Large no. of jams (145 vs. 104 customers)
    - *Fewer* consumers buy with Large no. of jams (4 vs. 31 customers)
Field Evidence II


Introduce in Company A of Quick Enrollment

- Previously: Default no savings
- 7/2003: Quick Enrollment Card:
  - Simplified investment choice: 1 Savings Plan
  - Deadline of 2 weeks
- In practice: Examine from 2/2004
Company B:
- Previously: Default no savings
- 1/2003: Quick Enrollment Card

Notice: This affects
- Simplicity of choice
- But also cost of investing + deadline (self-control)
Participation: Company A

- 15 to 20 percentage point increase in participation – Large effect
- Increase in participation all on opt-in plan
Participation: Company B

- Very similar effect for Company B
Explanation

- What is the effect due to?
- Increase may be due to a reminder effect of the card
- However, in other settings, reminders are not very powerful.

Example: Choi-Laibson-Madrian (2005):
- Sent a survey including 5 questions on the benefits of employer match
- Treatment group: 345 employees that were not taking advantage of the match
- Control group: 344 employees received the same survey except for the 5 specific questions.
- Treatment had no significant effect on the savings rate.
Field Evidence III

Field Evidence 3: Bertrand, Karlan, Mullainathan, Shafir, Zinman (QJE 2010)

Field Experiment in South Africa
- South African lender sends 50,000 letters with offers of credit
- Randomization of interest rate (economic variable)
- Randomization of psychological variables
- Crossed Randomization: Randomize independently on each of the $n$ dimensions
  - Plus: Use most efficiently data
  - Minus: Can easily lose control of randomization
Table 2
Summary of Randomized Interventions

<table>
<thead>
<tr>
<th>Sample:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>September wave</td>
<td>0.395</td>
<td>0.394</td>
<td>0.401</td>
<td>0.393</td>
<td>0.393</td>
</tr>
<tr>
<td>October wave</td>
<td>0.606</td>
<td>0.606</td>
<td>0.599</td>
<td>0.602</td>
<td>0.607</td>
</tr>
<tr>
<td>Offer Interest</td>
<td>7.929</td>
<td>7.985</td>
<td>7.233</td>
<td>6.970</td>
<td>8.384</td>
</tr>
<tr>
<td>Rate</td>
<td>2.422</td>
<td>2.422</td>
<td>2.311</td>
<td>2.111</td>
<td>2.435</td>
</tr>
<tr>
<td>Small option</td>
<td>0.432</td>
<td>0.438</td>
<td>0.349</td>
<td>0.250</td>
<td>0.518</td>
</tr>
<tr>
<td>Black photo</td>
<td>0.477</td>
<td>0.477</td>
<td>0.476</td>
<td>0.488</td>
<td>0.472</td>
</tr>
<tr>
<td>Coloured photo</td>
<td>0.071</td>
<td>0.071</td>
<td>0.071</td>
<td>0.072</td>
<td>0.071</td>
</tr>
<tr>
<td>Indian photo</td>
<td>0.125</td>
<td>0.125</td>
<td>0.125</td>
<td>0.126</td>
<td>0.126</td>
</tr>
<tr>
<td>White photo</td>
<td>0.124</td>
<td>0.124</td>
<td>0.125</td>
<td>0.120</td>
<td>0.127</td>
</tr>
<tr>
<td>Female photo</td>
<td>0.399</td>
<td>0.398</td>
<td>0.411</td>
<td>0.398</td>
<td>0.399</td>
</tr>
<tr>
<td>Male photo</td>
<td>0.399</td>
<td>0.400</td>
<td>0.383</td>
<td>0.404</td>
<td>0.397</td>
</tr>
<tr>
<td>Photo matches</td>
<td>0.534</td>
<td>0.535</td>
<td>0.531</td>
<td>0.537</td>
<td>0.533</td>
</tr>
<tr>
<td>customer's race?</td>
<td>0.501</td>
<td>0.501</td>
<td>0.501</td>
<td>0.501</td>
<td>0.501</td>
</tr>
<tr>
<td>Photo matches</td>
<td>0.402</td>
<td>0.402</td>
<td>0.388</td>
<td>0.403</td>
<td>0.400</td>
</tr>
<tr>
<td>customer's gender?</td>
<td>(0.49)</td>
<td>(0.49)</td>
<td>(0.49)</td>
<td>(0.49)</td>
<td>(0.49)</td>
</tr>
<tr>
<td>Promotional lottery</td>
<td>0.250</td>
<td>0.251</td>
<td>0.246</td>
<td>0.250</td>
<td>0.251</td>
</tr>
<tr>
<td>Suggestion call</td>
<td>0.003</td>
<td>0.003</td>
<td>0.005</td>
<td>0.003</td>
<td>0.003</td>
</tr>
<tr>
<td>Sample</td>
<td>53194</td>
<td>49250</td>
<td>3044</td>
<td>17108</td>
<td>38086</td>
</tr>
</tbody>
</table>
Manipulation of interest here

- Vary number of options of repayment presented
  - Small Table: Single Repayment option
  - Big Table 1: 4 loan sizes, 4 Repayment options, 1 interest rate
  - Big Table 2: 4 loan sizes, 4 Repayment options, 3 interest rates
  - Explicit statement that “other loan sizes and terms were available”

- Compare Small Table to other Table sizes
- Small Table increases Take-Up Rate by .603 percent
- One additional point of (monthly) interest rate decreases take-up by .258
### Results

**Table 3 Effect of Simplicity of Offer Description on Take-Up**

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>High attention</th>
<th>Low attention</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent Variable:</strong></td>
<td>Take-Up Dummy</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Sample:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Small option table</td>
<td>0.603</td>
<td>1.146</td>
<td>0.407</td>
</tr>
<tr>
<td>(0.239)</td>
<td>(0.674)</td>
<td>(0.219)</td>
<td></td>
</tr>
<tr>
<td>Δ interest rate equivalent</td>
<td>[2.337]</td>
<td>[3.570]</td>
<td>[1.887]</td>
</tr>
<tr>
<td>Interest rate</td>
<td>-0.258</td>
<td>-0.321</td>
<td>-0.215</td>
</tr>
<tr>
<td>(0.049)</td>
<td>(0.145)</td>
<td>(0.044)</td>
<td></td>
</tr>
<tr>
<td>Risk category F.E.?</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Experimental wave F.E.?</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td><strong>Sample size</strong></td>
<td>53194</td>
<td>17108</td>
<td>36086</td>
</tr>
</tbody>
</table>

- **Small-option Table increases take-up by equivalent of 2.33 pct. interest**
Results

- Strong effect of behavioral factor, compared with effect of interest rate

- Effect larger for ‘High-Attention’ group (borrow at least twice in the past, once within 8 months)

- Authors also consider effect of a number of other psychological variables:
  - Content of photo (large effect of female photo on male take-up)
  - Promotional lottery (no effect)
  - Deadline for loan (reduces take-up)
Section 10

Menu Effects: Preference for Familiar
• Third Heuristic: Preference for items that are more familiar

• Choice of stocks by individual investors (French-Poterba, AER 1991)
  • Allocation in domestic equity: Investors in the USA: 94%
  • Explanation 1: US equity market is reasonably close to world equity market
    • BUT: Japan allocation: 98%
    • BUT: UK allocation: 82%
  • Explanation 2: Preference for own-country equity may be due to costs of investments in foreign assets
Test: Examine within-country investment: **Huberman (RFS, 2001)**

- Geographical distribution of shareholders of Regional Bell companies
- Companies formed by separating the Bell monopoly
- Fraction invested in the own-state Regional Bell is 82 percent higher than the fraction invested in the next Regional Bell company
Third, extreme case: Preference for own-company stock

- On average, employees invest 20-30 percent of their discretionary funds in employer stocks (Benartzi JF, 2001)

| Panel C: Company Stock Allocation as a Percentage of the Employee Contributions |
|-------------------------------------------------|---|---|---|
| Number of plans | 78 | 58 | 136 |
| Mean: equally weighted | 18 | 29 | 23 |
| Mean: weighted by employee contributions | 21 | 33 | 24 |
| Mean: weighted by the number of active participants | 21 | 31 | 24 |

- Notice: This occurs despite the fact that the employees’ human capital is already invested in their company
- Also: This choice does not reflect private information about future performance
- Companies where a higher proportion of employees invest in employer stock have lower subsequent one-year returns, compared to companies with a lower proportion of employee investment
Possible Explanation? Ambiguity aversion

**Ellsberg (1961) paradox:**
- Investors that are ambiguity-averse prefer:
  - Investment with known distribution of returns
  - To investment with unknown distribution
- This occurs even if the average returns are the same for the two investments, and despite the benefits of diversification.
Section 11

Menu Effects: Preference for Salient
What happens with large set of options if decision-maker uninformed?

Possibly use of irrelevant, but salient, information to choose

**Ho-Imai (2004).** Order of candidates on a ballot
  - Exploit randomization of ballot order in California
  - Years: 1978-2002, Data: 80 Assembly Districts

Notice: Similar studies go back to **Bain-Hecock (1957)**
Areas of randomization

Legend
Proportion of Registered Voters Democratic
- 0.29 - 0.40
- 0.41 - 0.44
- 0.45 - 0.48
- 0.49 - 0.55
- 0.56 - 0.62
- 0.63 - 0.88

Bay Area
Los Angeles Metropolitan Region
**Use of randomized alphabet to determine first candidate on ballot**

<table>
<thead>
<tr>
<th>Year</th>
<th>Election</th>
<th>Randomized Alphabet</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td>Primary</td>
<td>S C X D Q G W R V Y U A N H L P B K J I E T O M F Z</td>
</tr>
<tr>
<td></td>
<td>General</td>
<td>L S N D X A M W V T O F I B K Y U P E Q C J Z H R G</td>
</tr>
<tr>
<td></td>
<td>General</td>
<td>V W I H R Q G J O M T S Y C A F U X K B P E Z N D L</td>
</tr>
<tr>
<td>1986</td>
<td>General</td>
<td>Q N H U B J E G M V L W X C K O F D Z R Y I T S P A</td>
</tr>
<tr>
<td>1988</td>
<td>Primary</td>
<td>W O K N Q A V T H J F Z L B U D Y M I R G C E S X P</td>
</tr>
<tr>
<td></td>
<td>General</td>
<td>S W F M K J U Y A T V G O N Q B D E P L Z C I X R H</td>
</tr>
<tr>
<td>1990</td>
<td>Primary</td>
<td>E J B Y Q F K M O V X L N Z C W A P R D G T H I S U</td>
</tr>
<tr>
<td></td>
<td>General</td>
<td>W F C L D I N J H V K O S A R E Q B T M Y U G Z X P</td>
</tr>
<tr>
<td></td>
<td>General</td>
<td>F Y U A J S B Z G O E Q R L I M H V N T P D K X C W</td>
</tr>
<tr>
<td></td>
<td>General</td>
<td>V I A E M S O K L B G N W Y D P U F Z Q J X C R H T</td>
</tr>
<tr>
<td>1996</td>
<td>Primary</td>
<td>G E F C Y P D B Z I V A U S M L H K N T O J Q R X W</td>
</tr>
<tr>
<td></td>
<td>General</td>
<td>J Y E P A U S Q B H T R K N L X F D O G M W I Z C V</td>
</tr>
<tr>
<td>1998</td>
<td>Primary</td>
<td>L W U J X K C N D O Q A P T Z R Y F E V B H G I M S</td>
</tr>
<tr>
<td>2000</td>
<td>Primary</td>
<td>O P C Y I H X Z V R S Q E K L G D W J U T M B F A N</td>
</tr>
<tr>
<td></td>
<td>General</td>
<td>I T F G J S W R N M K U Y L D C Q A H X O E B V P Z</td>
</tr>
<tr>
<td>2002</td>
<td>Primary</td>
<td>W I Z C O M A Q U K X E B Y N P T R L V S J H D F G</td>
</tr>
<tr>
<td></td>
<td>General</td>
<td>H M V P E B Q U G N D K X Z J A W Y C O S F I T R L</td>
</tr>
<tr>
<td>2003</td>
<td>Recall</td>
<td>R W Q O J M V A H B S G Z X N T C I E K U P D Y F L</td>
</tr>
</tbody>
</table>

Table 1: Randomized Alphabets Used for the California Statewide Elections Since 1982.
Observe each candidate in different orders in different districts

Compute absolute vote ($Y$) gain

$$E [Y (i = 1) - Y (i \neq 1)]$$

and percentage vote gain

$$E [Y (i = 1) - Y (i \neq 1)] / E [Y (i \neq 1)]$$

Result:

- Small to no effect for major candidates
- Large effects on minor candidates
Menu Effects: Preference for Salient

Ho and Imai (2004)

Stefano DellaVigna
Econ 219B: Applications (Lecture 10)
April 3, 2019

General Election 1998 & 2000

Primary Elections, 1998 & 2000
<table>
<thead>
<tr>
<th></th>
<th>General</th>
<th></th>
<th>Primary</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Absolute</td>
<td>Relative</td>
<td>Absolute</td>
<td>Relative</td>
</tr>
<tr>
<td></td>
<td>ATE  SE</td>
<td>ATE  SE</td>
<td>ATE  SE</td>
<td>ATE  SE</td>
</tr>
<tr>
<td>Democratic</td>
<td>0.05 0.46</td>
<td>0.25 0.90</td>
<td>1.89 0.32</td>
<td>43.58 5.53</td>
</tr>
<tr>
<td>Republican</td>
<td>-0.06 0.53</td>
<td>-0.43 1.29</td>
<td>2.16 0.46</td>
<td>33.62 5.91</td>
</tr>
<tr>
<td>American</td>
<td>0.16 0.02</td>
<td>20.83 1.39</td>
<td>2.33 0.15</td>
<td>26.76 3.55</td>
</tr>
<tr>
<td>Independent</td>
<td>0.56 0.17</td>
<td>21.18 5.82</td>
<td>3.15 1.16</td>
<td>6.24 3.54</td>
</tr>
<tr>
<td>Libertarian</td>
<td>0.23 0.02</td>
<td>14.56 1.03</td>
<td>6.59 1.42</td>
<td>71.92 13.55</td>
</tr>
<tr>
<td>Natural Law</td>
<td>0.31 0.06</td>
<td>26.13 2.85</td>
<td>0.40 0.08</td>
<td>44.78 5.45</td>
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<td>Peace and</td>
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<td>25.49 2.15</td>
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<td>Freedom</td>
<td>0.26 0.07</td>
<td>19.57 2.23</td>
<td>4.11 1.56</td>
<td>48.45 9.66</td>
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<td>1.95 0.30</td>
<td>9.21 3.31</td>
<td>3.44 0.78</td>
<td>19.42 4.05</td>
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Table 3: Party-Specific Average Causal Effects of Being Listed in First Position on Ballots Using All Races from 1978 to 2002. ATE and SE represent the average causal effects and their standard errors, respectively. For general and primary elections, the left two columns present the estimates of average absolute gains in terms of the total or party vote, respectively, while the right two columns show those of average relative gains. Each candidate-specific effect is averaged over different races to obtain the overall average effect for each party. In general elections, only minor party and nonpartisan candidates are affected by the ballot order. In primaries, however, the candidates of all parties are affected. The largest effects are found for nonpartisan candidates.
Investors with Limited Attention

- **Barber-Odean (2008)**. Investor with limited attention
  - Stocks in portfolio: Monitor continuously
  - Other stocks: Monitor extreme deviations (*salience*)

- Which stocks to purchase? High-attention (salient) stocks. On days of high attention, stocks have
  - Demand increase
  - No supply increase
  - Increase in net demand
Heterogeneity

- Heterogeneity:
  - Small investors with limited attention attracted to salient stocks
  - Institutional investors less prone to limited attention

- Market interaction: Small investors are:
  - Net buyers of high-attention stocks
  - Net sellers of low-attention stocks.

- Measure of net buying is Buy-Sell Imbalance:

\[
BSI_t = 100 \times \frac{\sum_i NetBuy_{i,t} - \sum_i NetSell_{i,t}}{\sum_i NetBuy_{i,t} + \sum_i NetSell_{i,t}}
\]
Data and Methodology

- Notice: Unlike in most financial data sets, here use of individual trading data
- In fact: No obvious prediction on prices

- Measures of attention:
  - same-day (abnormal) volume $V_t$
  - previous-day return $r_{t-1}$
  - stock in the news (Using Dow Jones news service)
Methodology: Bins

- Use of sorting methodology
  - Sort variable \((V_t, r_{t-1})\) and separate into equal-sized bins (in this case, deciles)
    - Example: \(V^1_t, V^2_t, V^3_t, \ldots, V^{10a}_t, V^{10b}_t\)
    - (Finer sorting at the top to capture top 5 percent)
  - Classical approach in finance
  - Benefit: Measures variables in a non-parametric way
  - Cost: Loses some information and magnitude of variable
Results: Abnormal Volume

- Effect of same-day (abnormal) volume $V_t$ monotonic (Volume captures ‘attention’)

![Figure 2a]

- Large Discount Brokerage
- Large Retail Brokerage
- Small Discount Brokerage

Percent Buy-Sell Imbalance by Number of Trades

Partitions of Stocks Sorted on Current Day's Abnormal Trading Volume
Results: Previous Returns

- Effect of previous-day return $r_{t-1}$ U-shaped
  (Large returns—positive or negative—attract attention)

![Figure 2b](image-url)

- Partitions of Stocks Sorted on Previous Day's Return
- Percent Buy-Sell Imbalance by Number of Trades
- Lines represent different brokerages:
  - Large Discount Brokerage
  - Small Discount Brokerage
  - Large Retail Brokerage
Results: Robustness

- Notice: Pattern is consistent across different data sets of investor trading
- Figures 2a and 2b a
Patterns are the opposite for institutional investors (Fund managers)
Alternative interpretations of results

- Small investors own few stocks, face short-selling constraints
  (To sell a stock you do not own you need to borrow it first, then you sell it, and then you need to buy it back at end of lending period)
- If new information about the stock:
  - buy if positive news
  - do nothing otherwise
- If no new information about the stock:
  - no trade
- Large investors are not constrained
Study pattern for stocks that investors already own


<table>
<thead>
<tr>
<th>Decile</th>
<th>Large Discount Brokerage</th>
<th>Large Retail Brokerage</th>
<th>Small Discount Brokerage</th>
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<td></td>
<td>Number Imbalance</td>
<td>Value Imbalance</td>
<td>Number Imbalance</td>
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<td>1 (lowest volume)</td>
<td>54.22</td>
<td>55.64</td>
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<td>33.03</td>
<td>39.31</td>
<td>-12.27</td>
</tr>
<tr>
<td>10b (highest volume)</td>
<td>24.97</td>
<td>32.82</td>
<td>-15.01</td>
</tr>
</tbody>
</table>

(Standard errors in parentheses)
Section 12

Next Lecture
Menu Effects:
- Confusion
- Persuasion
- Emotions: Mood