Econ 219B
Psychology and Economics: Applications
(Lecture 8)

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March 6, 2012

Outline

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

7. Attention: Left Digits

8. Attention: Financial Markets

9. Methodology: Portfolio Methodology

1 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) −> 78 percent chose an unhealthy snack
    - when plausibly satiated (after lunch).−> 42 percent choose unhealthy snack

- **Gilbert, Pinel, Wilson, Blumberg, and Wheatly (1999):**
  - individuals under-appreciate adaptation to future circumstances –> 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:

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

  - Parameter α is extent of projection bias –> $\alpha = 0$ 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 ω_O and temperature at Return time as ω_R

- Predictions:
  1. If $\alpha = 0$ (no proj. bias), P[R|O] is independent of ω_O and ω_R
  2. If $\alpha > 0$ (proj. bias), ∂P[R|O]$/\partial\omega_O < 0$ and ∂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

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

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

TABLE 2

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

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

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

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

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

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

- 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 –> Return it more
  - Projection Bias: Very cold weather –> Mispredict future utility –> 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

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

- Simple structural model of projection bias: Estimates of projection bias α around .3-.4

TABLE 6
Structural Estimation

	Winter Boots	Hats	Parkas & Coats	Vests	Jackets
α	0.3084** (0.0570)	0.4698** (0.00001)	0.3814** (0.0352)	0.0002 (0.0056)	0.4992** (0.0002)

- 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 —$>$ Higher variance can increase smoking
  - Data: Positive correlation of variance of prices with current smoking —$>$ Supports projection bias
- Parametric estimate: projection bias $\alpha \approx .4$

2 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 $p(s)$ –> 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 $\widetilde{p}(s)$

3 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 ear
  - 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?

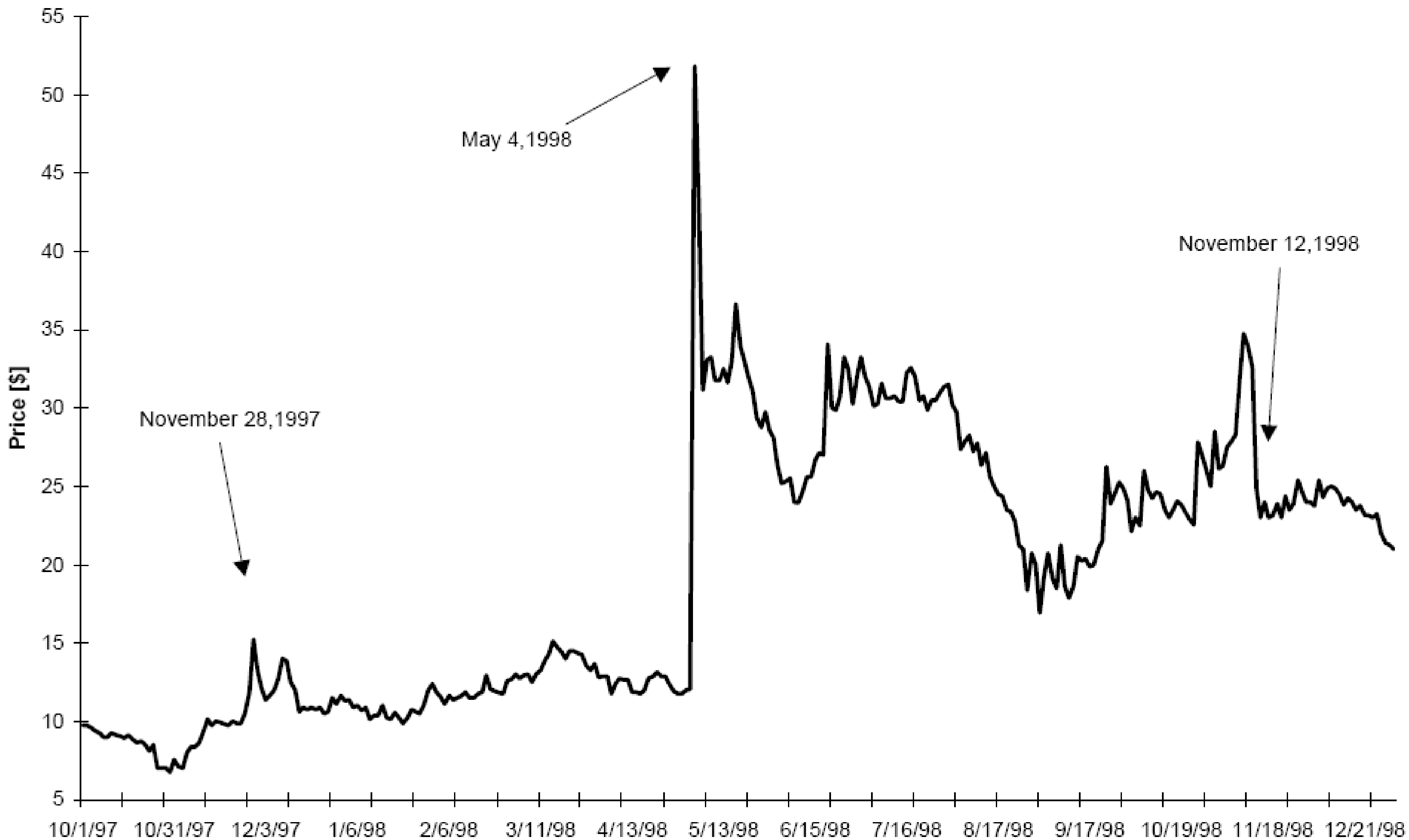
- Event of economic importance: **Huberman-Regev (JF, 2001)**

- Timeline:
  - October-November 1997: Company EntreMed has very positive early results on a cure for cancer
  - November 28, 1997: *Nature* "prominently features;" *New York Times* reports on page A28
  - May 3, 1998: *New York Times* features essentially same article as on November 28, 1997 on front page
  - November 12, 1998: *Wall Street Journal* front page about failed replication

- 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

4 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 θ, with $\theta = 0$ standard case
  - Interpretation: each individual sees o, but processes it only partially, to the degree θ

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

- Inattention θ is function of:
  - Salience $s \in [0,1]$ of o, with $\theta_s' < 0$ and $\theta(1,N) = 0$
  - Mumber 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 θ:

  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

5 Attention: eBay Auctions

- **Hossain-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 θ 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 $r = \$.01$ 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: $\partial R/\partial c = 0 = \partial p/\partial c$ –>$R_A = R_B$
  - Inattention: $\partial R/\partial c = \theta$ –>$R_A < R_B$

- Similar strategy to Ausubel (1999)

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

Table 3. Revenues from Low Reserve Treatments

CD Title	Revenues under Treatment A	Revenues under Treatment B	B - A	Percent Difference
Music	5.50	7.24	1.74	32%
Ooops! I Did it Again	6.50	7.74	1.24	19%
Serendipity	8.50	10.49	1.99	23%
O Brother Where Art Thou?	12.50	11.99	-0.51	-4%
Greatest Hits - Tim McGraw	11.00	15.99	4.99	45%
A Day Without Rain	13.50	14.99	1.49	11%
Automatic for the People	0.00	9.99	9.99	
Everyday	7.28	9.49	2.21	30%
Joshua Tree	6.07	8.25	2.18	36%
Unplugged in New York	4.50	5.24	0.74	16%
Average	*7.54*	*10.14*	*2.61*	*35%*
Average excluding unsold	*8.37*	*10.16*	*1.79*	*21%*

- Smaller effect for XBox: $R_B - R_A =$ \$0.71 –> Inattention $\theta = 0.71/4 = .18$

- Pooling data across treatments: $R_B > R_A$ in 16 out of 20 cases –> Significant difference

Xbox Game Title	Revenues under Treatment A	Revenues under Treatment B	B - A	Percent Difference
Halo	34.05	41.24	7.19	21%
Wreckless	44.01	33.99	-10.02	-23%
Circus Maximus	40.99	39.99	-1.00	-2%
Max Payne	36.01	36.99	0.98	3%
Genma Onimusha	41.00	32.99	-8.01	-20%
Project Gotham Racing	37.00	38.12	1.12	3%
NBA 2K2	42.12	42.99	0.87	2%
NFL 2K2	26.00	33.99	7.99	31%
NHL 2002	36.00	37.00	1.00	3%
WWF Raw	33.99	40.99	7.00	21%
Average	*37.12*	*37.83*	*0.71*	*2%*

- 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?): $R_D - R_C = -.29$ –> Inattention $\theta = -.29/4 = -.07$

- Large, significant effect for XBoxs: $R_D - R_C = 4.11$ –> Inattention $\theta = 4.11/4 = 1.05$

- Overall, strong evidence of partial disregard of shipping cost: $\hat{\theta} \approx .5$

- Inattention or rational search costs

Table 4. Revenues from High Reserve Treatments

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

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

6 Attention: Taxes

- **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

$$\begin{aligned}\Delta \log D &= \log D\left[v - tp\right] - \log D\left[v - (1-\theta)\, tp\right] = \\ &= -\theta tp * D'\left[v - (1-\theta)\, tp\right] / D\left[v - (1-\theta)\, tp\right] \\ &= -\theta t * \eta_{D,p}\end{aligned}$$

  - $\eta_{D,p}$ is the price elasticity of demand

  - $\Delta \log D = 0$ for fully attentive consumers ($\theta = 0$)

  - This implies $\theta = -\Delta \log D / (t * \eta_{D,p})$

- **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 3

DDD Analysis of Means: Weekly Quantity by Category

TREATMENT STORE

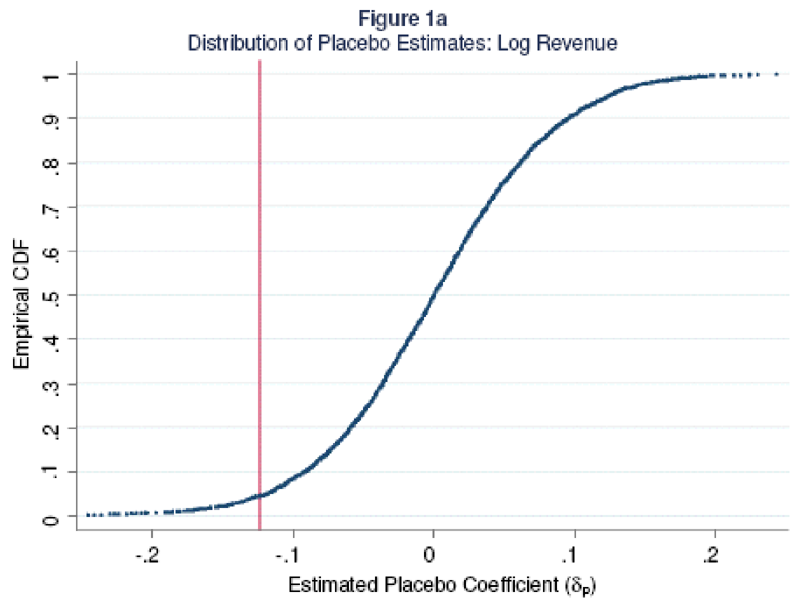
Period	Control Categories	Treated Categories	Difference
Baseline (2005:1- 2006:6)	26.48 (0.22) [5510]	25.17 (0.37) [754]	-1.31 (0.43) [6264]
Experiment (2006: 8- 2006:10)	27.32 (0.87) [285]	23.87 (1.02) [39]	-3.45 (0.64) [324]
Difference over time	0.84 (0.75) [5795]	-1.30 (0.92) [793]	**DD_{TS} = -2.14** (0.64) [6588]

CONTROL STORES

Period	Control Categories	Treated Categories	Difference
Baseline (2005:1- 2006:6)	30.57 (0.24) [11020]	27.94 (0.30) [1508]	-2.63 (0.32) [12528]
Experiment (2006: 8- 2006:10)	30.76 (0.72) [570]	28.19 (1.06) [78]	-2.57 (1.09) [648]
Difference over time	0.19 (0.64) [11590]	0.25 (0.92) [1586]	**DD_{CS} = 0.06** (0.90) [13176]
		DDD Estimate	***-2.20*** (0.58) [19764]

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 .07375
  - $\hat{\theta} = -(-.088)/(-1.59 * .07375) \approx .75$
- 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

- **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 –> 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

Dependent Variable: Change in Log(per capita beer consumption)	Baseline (1)	Bus Cycle (2)	Bus Cycle Lags (3)	Alc Regulations (4)
ΔLog(1+Excise Tax Rate)	**-0.87**	**-0.91**	**-0.86**	**-0.89**
	(0.17)***	(0.17)***	(0.17)***	(0.17)***
ΔLog(1+Sales Tax Rate)	**-0.20**	**-0.00**	**0.03**	**-0.02**
	(0.30)	(0.30)	(0.30)	(0.30)
ΔLog(Population)	0.03	-0.07	0.05	-0.07
	(0.06)	(0.07)	(0.19)	(0.07)
ΔLog(Income per Capita)		0.22	0.18	0.22
		(0.05)***	(0.05)***	(0.05)***
ΔLog(Unemployment Rate)		-0.01	-0.01	-0.01
		(0.01)**	(0.01)	(0.01)**
Lag Bus. Cycle Controls			x	
Alcohol Regulation Controls				x
Year Fixed Effects	x	x	x	x
F-Test for Equality of Tax Variables (Prob>F)	0.05	0.01	0.01	0.01
Sample Size	1607	1487	1440	1487

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).

7 Attention: Left Digits

- 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

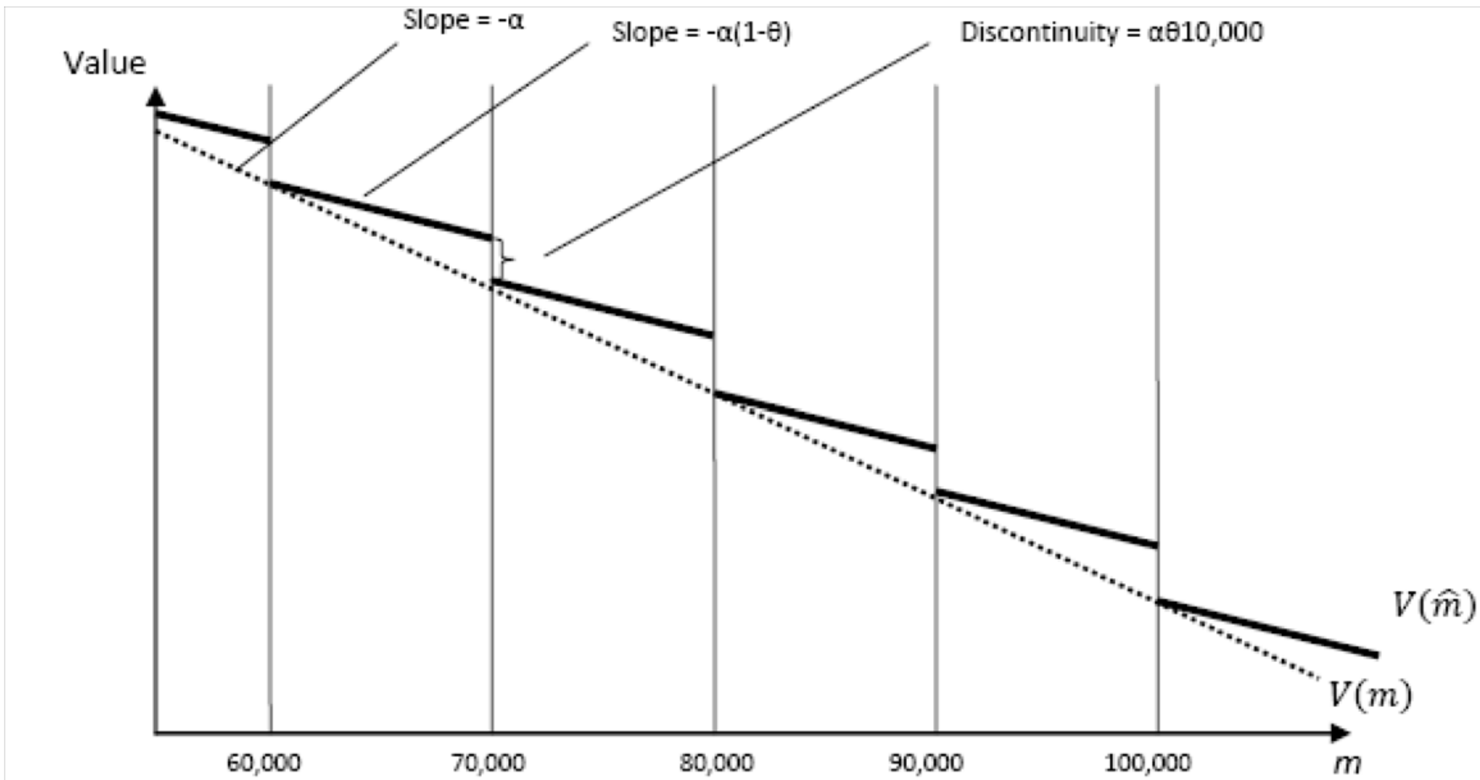
$$\begin{aligned} X &= 5 + (1-\theta)\,.99 \\ Y &= 6 \\ Y - X &= .01 + .\theta 99 \end{aligned}$$

- Indeed, evidence of 99 cents effect in pricing at stores

- However, can argue – stakes small for consumers

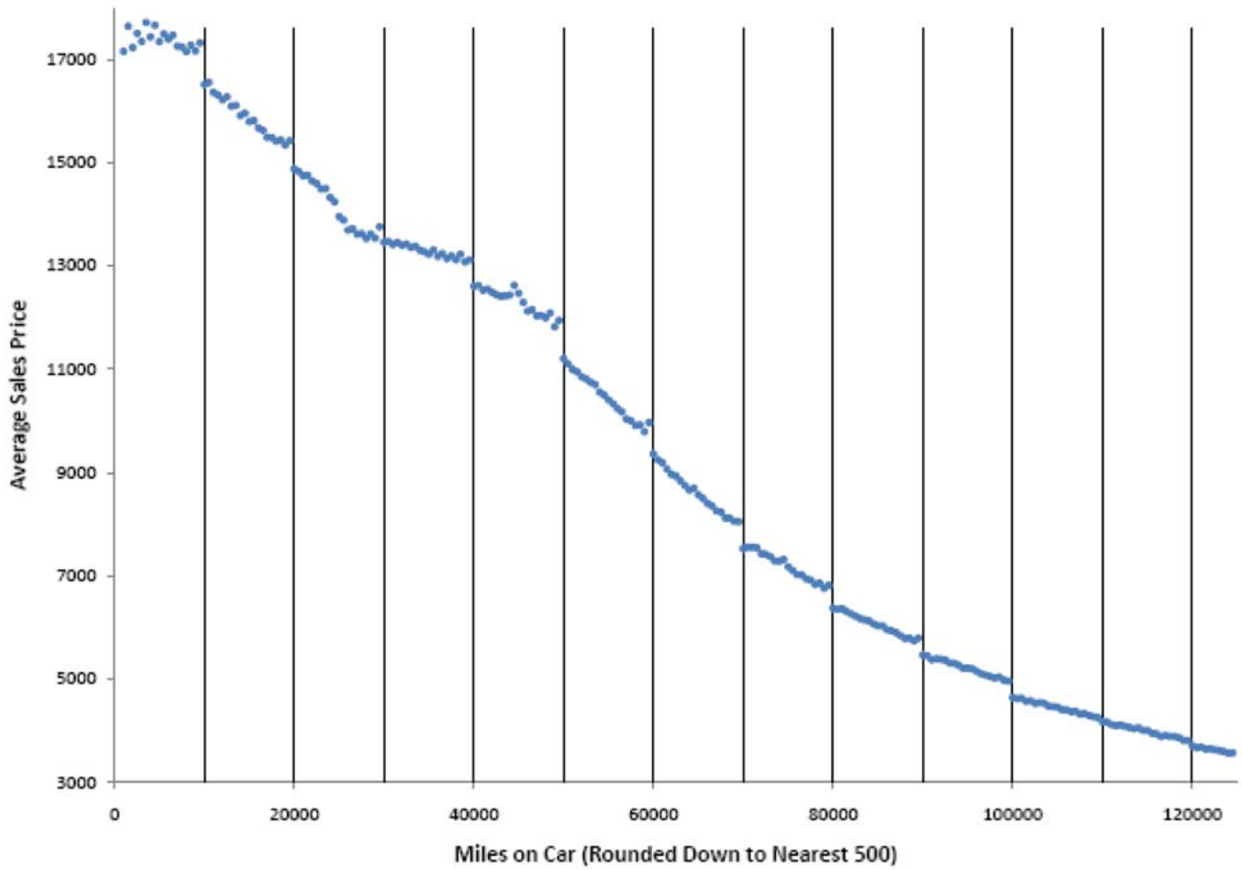
- **Lacetera, Pope, and Sydnor (2009). Inattention in Car Sales**

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



- Data set with 22 million wholesale used car transactions

Figure 2 - Raw Price. This figure plots the raw average sales price within 500-mile bins for the more than 22 million auctioned cars in our datas



- Remarkable precision in the estimates of the discontinuity

- Can estimate $\theta = 0.33$

- Consistent estimate broadly with other evidence

- However: Who des this inattention refer to?

- Data is from sales to car dealers, who are presumably incorporating preferences of buyers

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: $(\partial r_{SR}/\partial o)/(\partial r_{LR}/\partial o) = (1 - \theta)$ –> 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:

$$o_t = \frac{e_t - \hat{e}_t}{p_{t-1}}$$

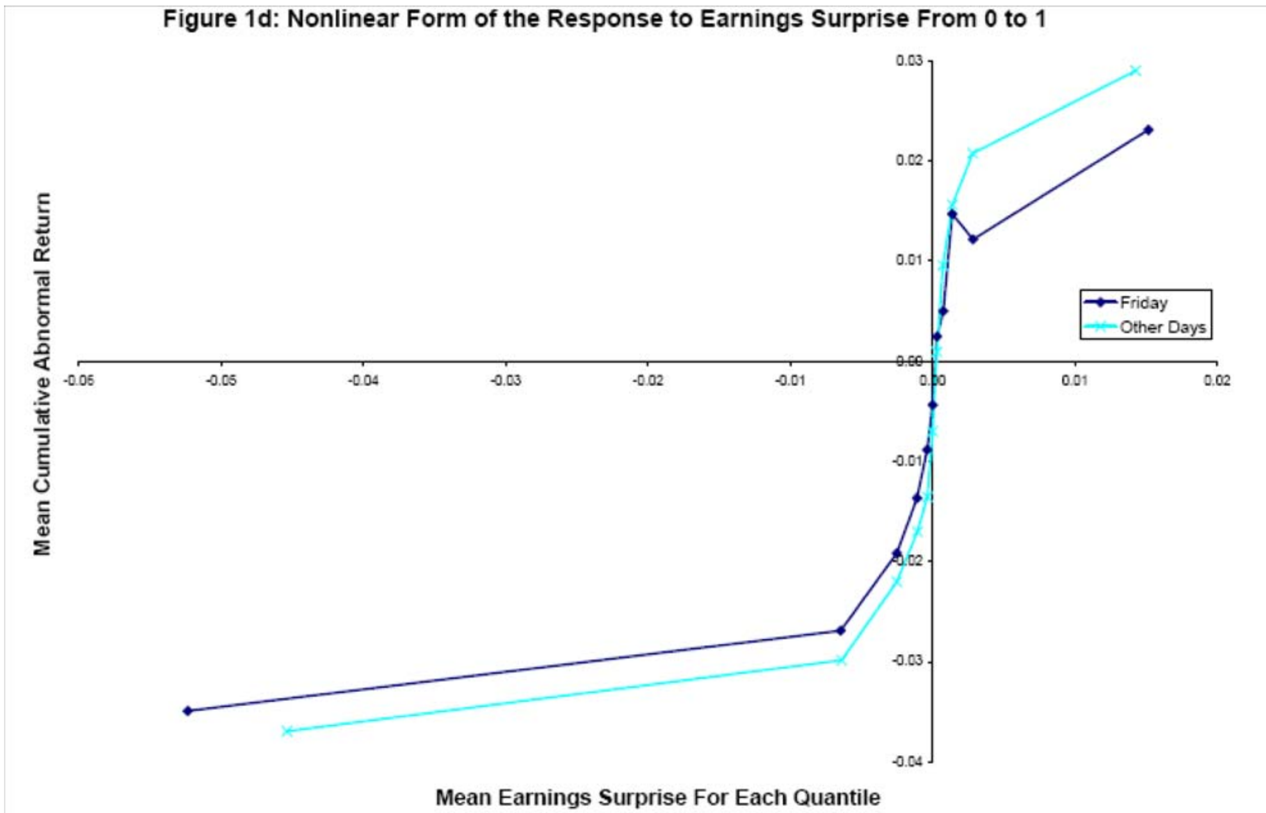
- Difference between earnings announcement e_t and consensus earnings forecast by analysts in 30 previous days
- Divide by (lagged) price p_{t-1} to renormalize

* 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

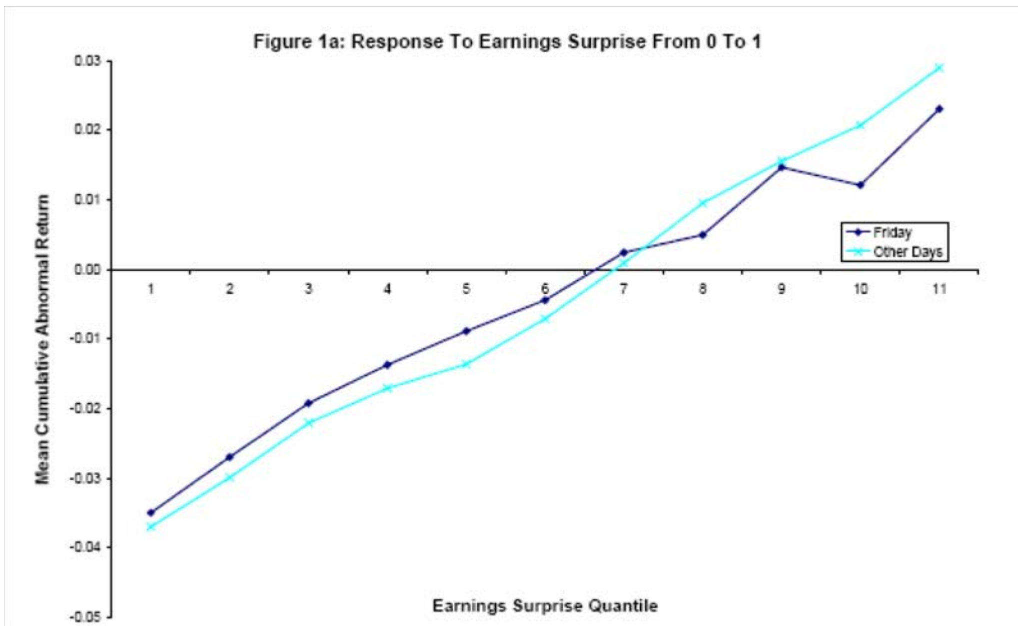


- Economists' approach:
  - Make assumptions about functional form –> Arctan for example
  - Do non-parametric estimate –> kernel regressions

- Finance: Use of quantiles and portfolios (explained in the context of DellaVigna-Pollet (forthcoming))

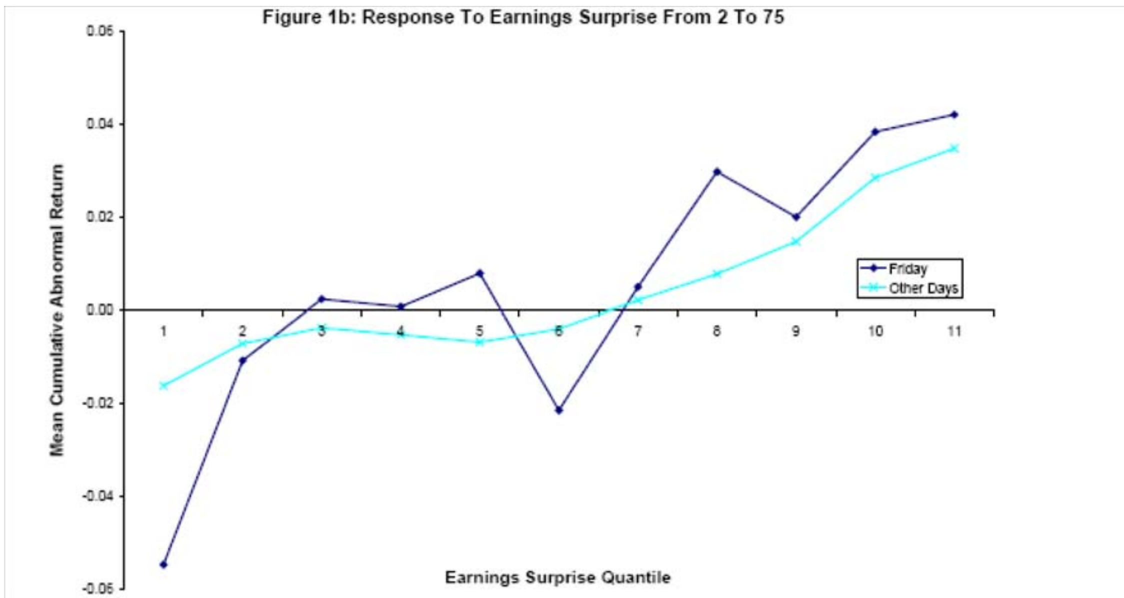
- First methodology: *Quantiles*
  - Sort data using underlying variable (in this case earnings surprise o_t)
  - Divide data into n equal-spaced quantiles: $n = 10$ (deciles), $n = 5$ (quintiles), etc
  - Evaluate difference in returns between top quantiles and bottom quantiles: $Er_n - Er_1$

- 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: $(\partial r_{SR}/\partial o)/(\partial r_{LR}/\partial o) = (1-\theta) = .544$ –> 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 –> $\hat{\theta} \approx .59$

- 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_t^m
    * Size r_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 α significantly different from zero?

• Example in DellaVigna-Pollet (forthcoming)

  – Each month t portfolio formed as follows: $(r_F^{11} - r_F^1) - (r_{Non-F}^{11} - r_{Non-F}^1)$

  – Use returns r_{Drift} (3-75)

  – Differential drift between Fridays and non-Fridays

- Test for significance

	Dependent Variable: Monthly Return on the Zero-Investment Portfolio					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.0384 (0.0134)***	0.0462 (0.0139)***	0.0584 (0.0220)***	0.0218 (0.0079)***	0.0232 (0.0086)***	0.0277 (0.0091)***
VW Index Excess Return (VWRF)	-0.2742 (0.3090)	-0.6419 (0.2778)**	-0.0968 (0.4262)	-0.1842 (0.1865)	-0.1068 (0.2301)	-0.4580 (0.1937)**
Size Factor Return (SMB)		0.2344 (0.4195)	0.5644 (0.6227)	-0.0390 (0.2464)	0.0701 (0.2930)	-0.0137 (0.2438)
Value Factor Return (HML)		-0.4607 (0.6143)	-1.5556 (0.7277)**	0.0762 (0.3329)	-0.3264 (0.2840)	-0.2094 (0.3820)
Momentum Factor Return (UMD)		-0.3994 (0.2632)	-1.1817 (0.6559)*	-0.0696 (0.1740)	-0.0410 (0.2206)	-0.3454 (0.1940)*
One month holding period	X	X	X	X		X
Two month holding period					X	
Top minus bottom quantile	X	X	X		X	
Matched sample			X			
Top two minus bottom two quantiles				X		
Top minus bottom decile						X
R^2	0.0073	0.0385	0.1736	0.0152	0.0153	0.0398
N	N = 125	N = 125	N = 124	N = 130	N = 138	N = 127

* significant at 10%; ** significant at 5%; *** significant at 1%

- Intercept $\hat{\alpha} = .0384$ 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 a investor following company A

- Are you missing more subtle news about Company A?

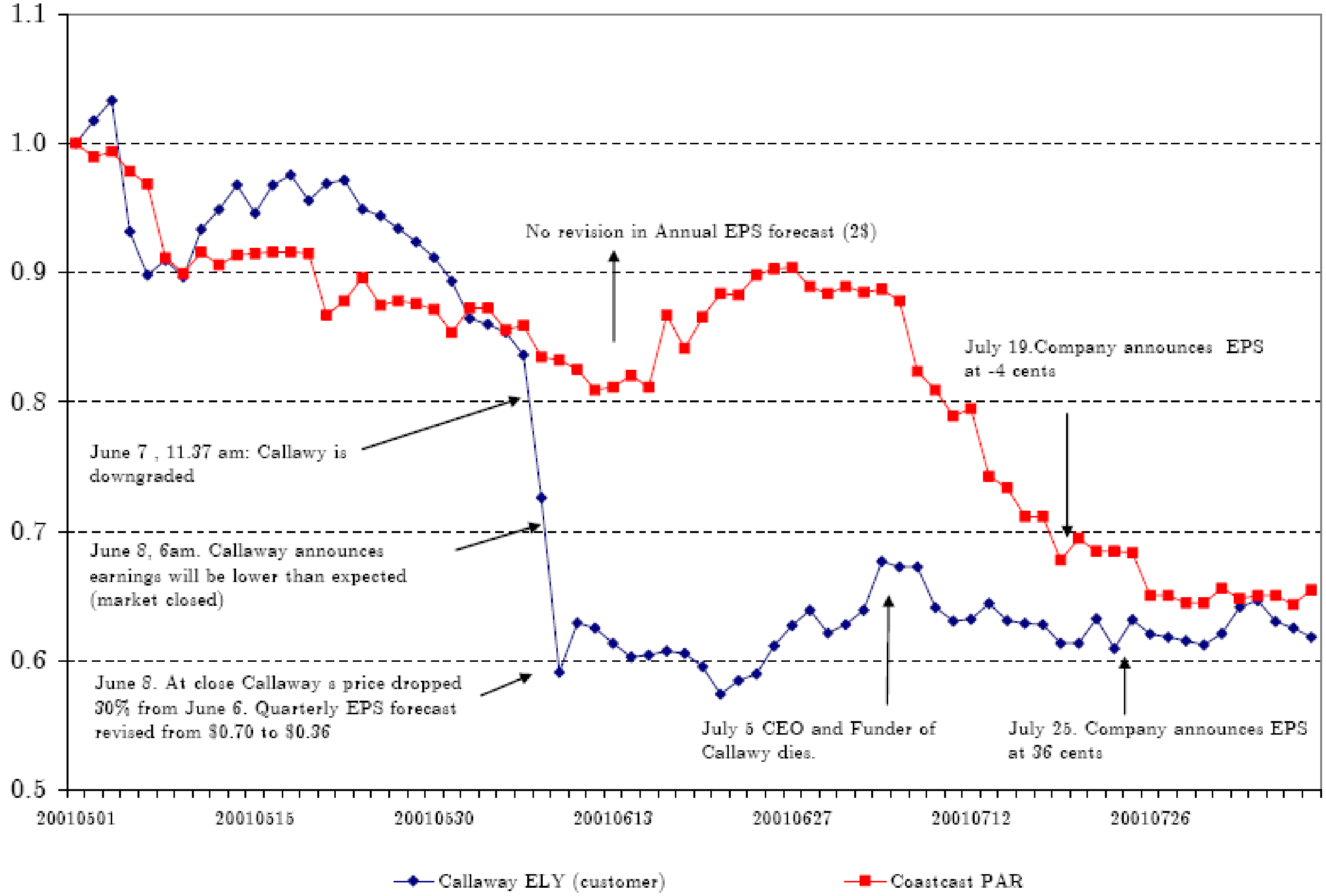
- Example: Huberman and Regev (2001) – Missing the *Science* article

- 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).



- 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

$$r_{q,t+1}^S = \alpha_q + \beta_q X_{t+1} + \varepsilon_{q,t+1}$$

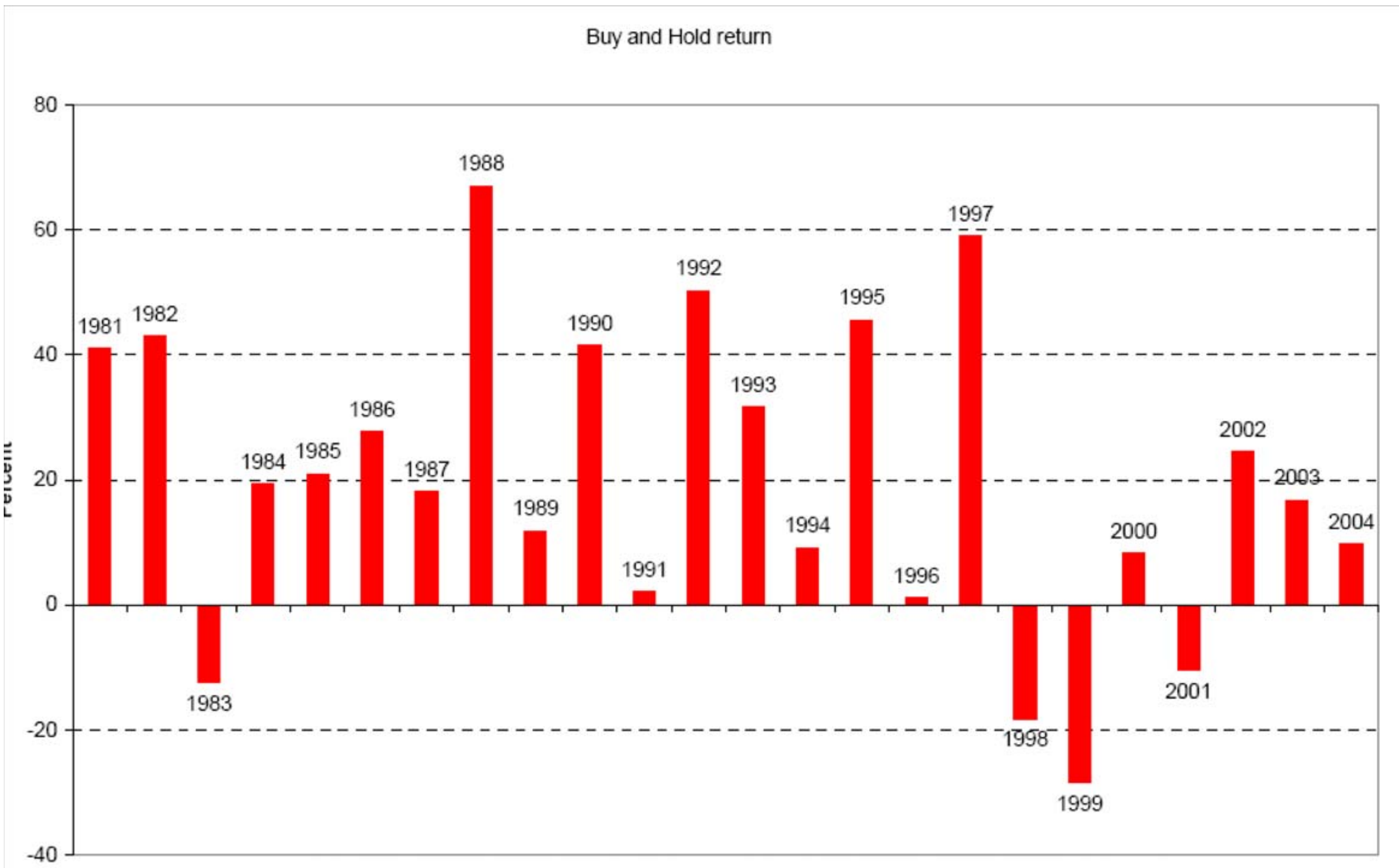
  - X_{t+1} are the so-called factors: market return, size, book-to-market, and momentum (Fama-French Factors)
  - Estimate $\hat{\alpha}_q$ gives the monthly average performance of a portfolio in quintile q
  - Long-Short portfolio: $\hat{\alpha}_5 - \hat{\alpha}_1$

- Results in Table III: *Monthly* abnormal returns of 1.2-1.5 percent (huge)

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

- Information contained in the customer returns not fully incorporated into supplier returns

- Returns of this strategy are remarkably stable over time

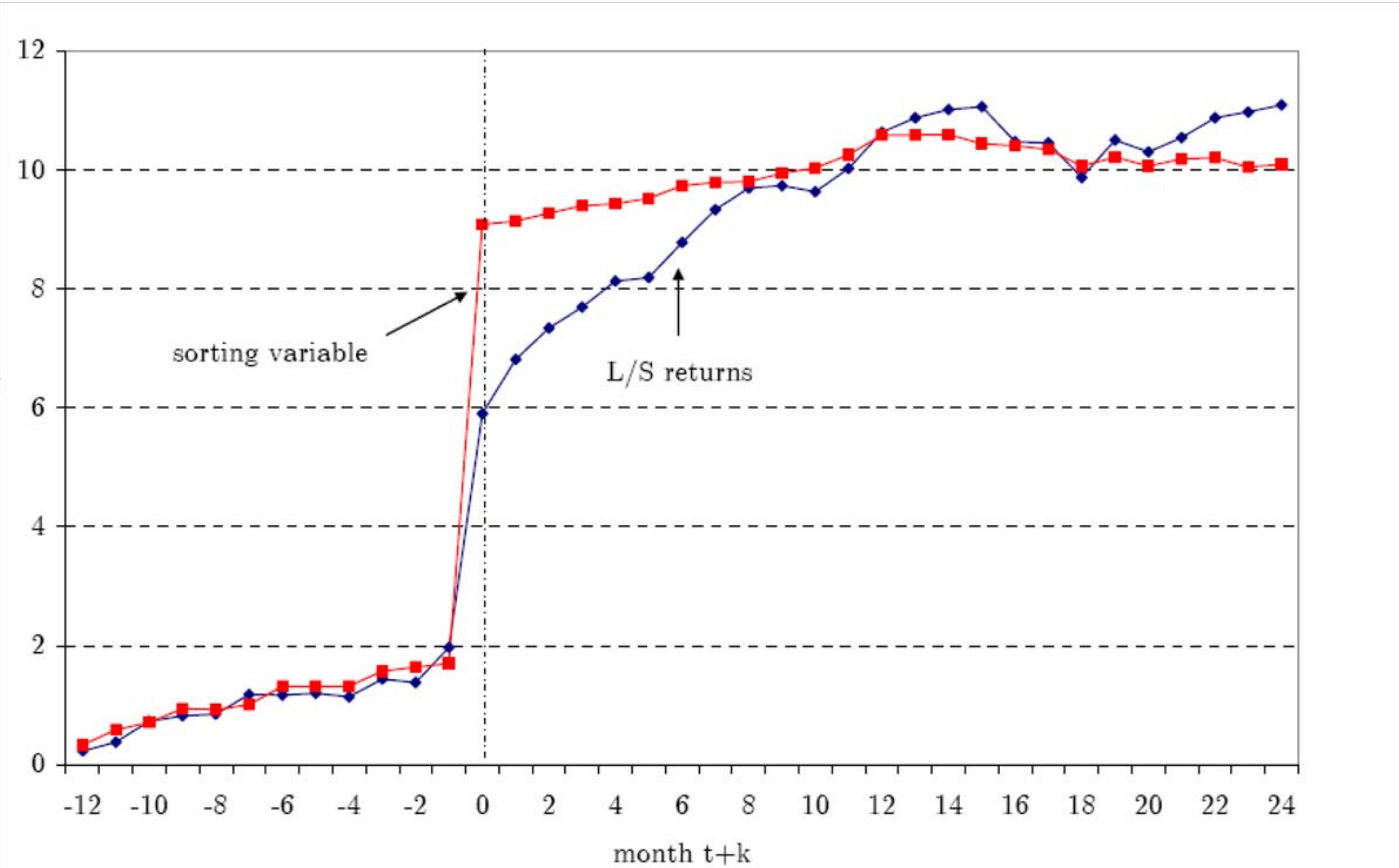


- Can run similar regression to test how quickly the information is incorporated
  - Sort into 5 quintiles by returns in month t of principal customers, r_t^C
  - Compute cumulative return up to month k ahead, that is, $r^S_{q,t->t+k}$
  - By quintile q, run regression of returns of Supplier:

$$r^S_{q,t->t+k} = \alpha_q + \beta_q X_{t+k} + \varepsilon_{q,t+1}$$

  - For comparison, run regression of returns of Customer:

$$r^C_{q,t->t+k} = \alpha_q + \beta_q X_{t+k} + \varepsilon_{q,t+1}$$



12
10
8
6
4
2
0
sorting variable
L/S returns
-12
-10
-8
-6
-4
-2
0
2
4
6
8
10
12
14
16
18
20
22
24
month t+k

- 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)

			At least 20 mutual funds holding the stock							
	All stocks		All stocks		At least 10 common funds		Larger firms (CRSP median)		Larger firms (NYSE median)	
Weight	EW	VW	EW	VW	EW	VW	EW	VW	EW	VW
Low COMOWN	**1.653**	**2.301**	**1.659**	**2.306**	1.469	**1.889**	**1.572**	**2.288**	**2.703**	**2.852**
Lower percent of common ownership	[5.46]	[5.24]	[2.96]	[3.64]	[1.75]	[2.08]	[2.82]	[3.60]	[3.49]	[3.55]
High COMOWN	**0.750**	**1.098**	0.528	0.736	0.532	0.835	0.407	0.732	0.611	**1.278**
Higher percent of common ownership	[1.97]	[2.17]	[0.98]	[1.23]	[0.85]	[1.21]	[0.75]	[1.22]	[1.05]	[2.11]
High-Low	**-0.903**	**-1.203**	-1.131	-1.571	-0.937	-1.054	-1.165	**-1.557**	**-2.093**	-1.575
	[-2.08]	[-1.99]	[-1.60]	[-1.98]	[-0.92]	[-0.95]	[-1.66]	[-1.96]	[-2.42]	[-1.71]

- 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 –> 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)

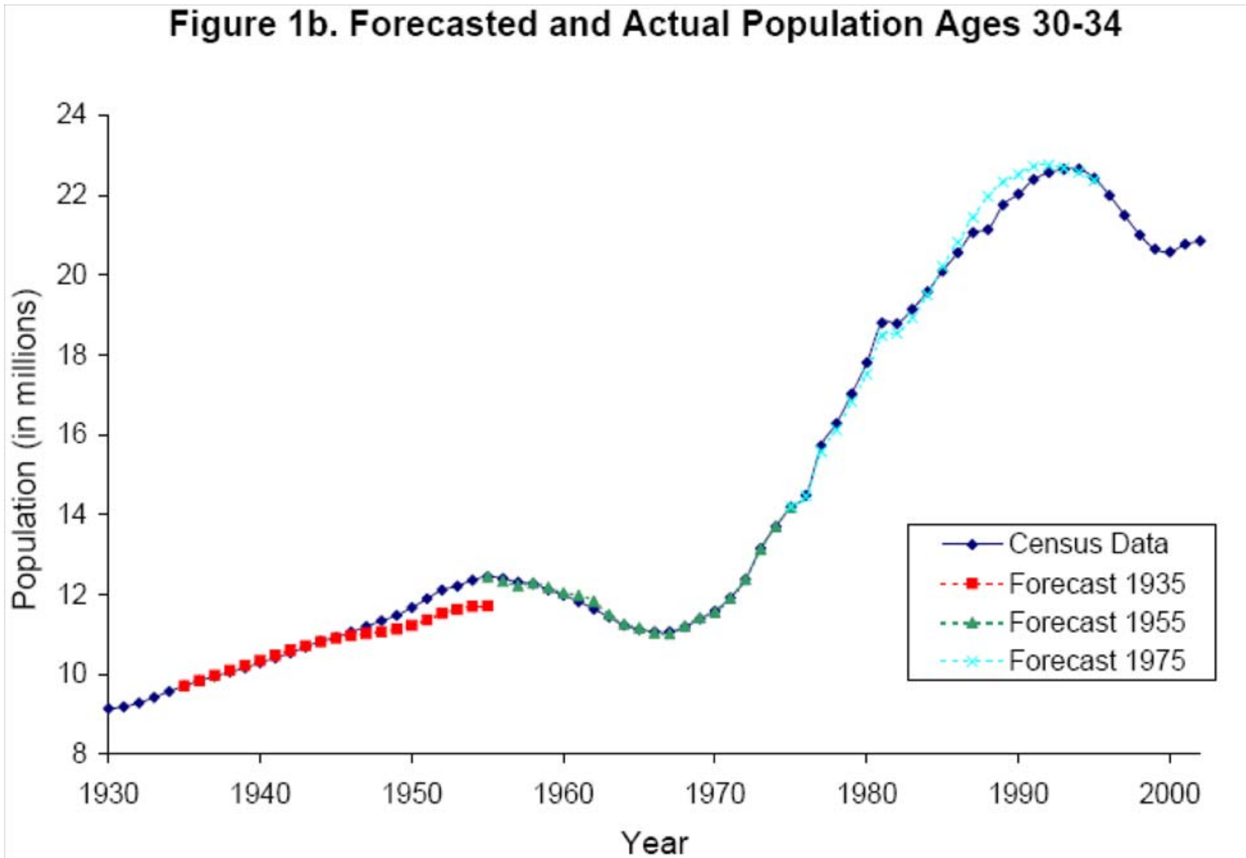
- **DellaVigna-Pollet (2007) – Inattention to distant future**
- Another way to simplify decisions is to neglect distant futures when making forecasts
- Identify this using forecastable demographic shifts
- Substantial cohort size fluctuations over the 20th century
- Consumers at different ages purchase different goods
- Changes in cohort size $\Longrightarrow$ 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 $\Longrightarrow$ Revenue increases in 2010
- Profits (earnings) for bus manufacturers?
  - Perfect Competition. Abnormal profits do not change in 2010
  - Imperfect Competition. Increased earnings in 2010

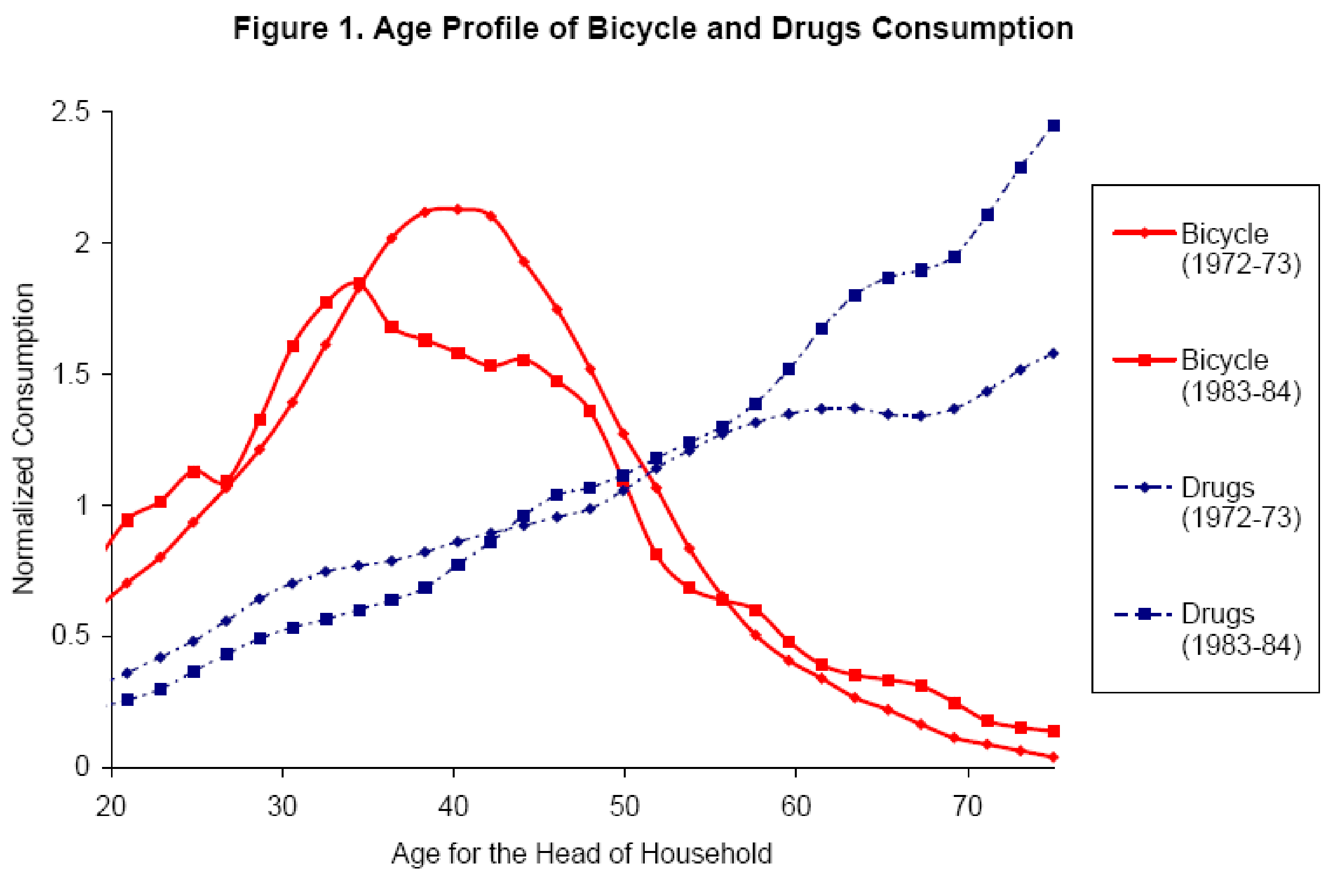
- How do investors react?

  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: $\hat{c}_{i,t+10} - \hat{c}_{i,t+5}$

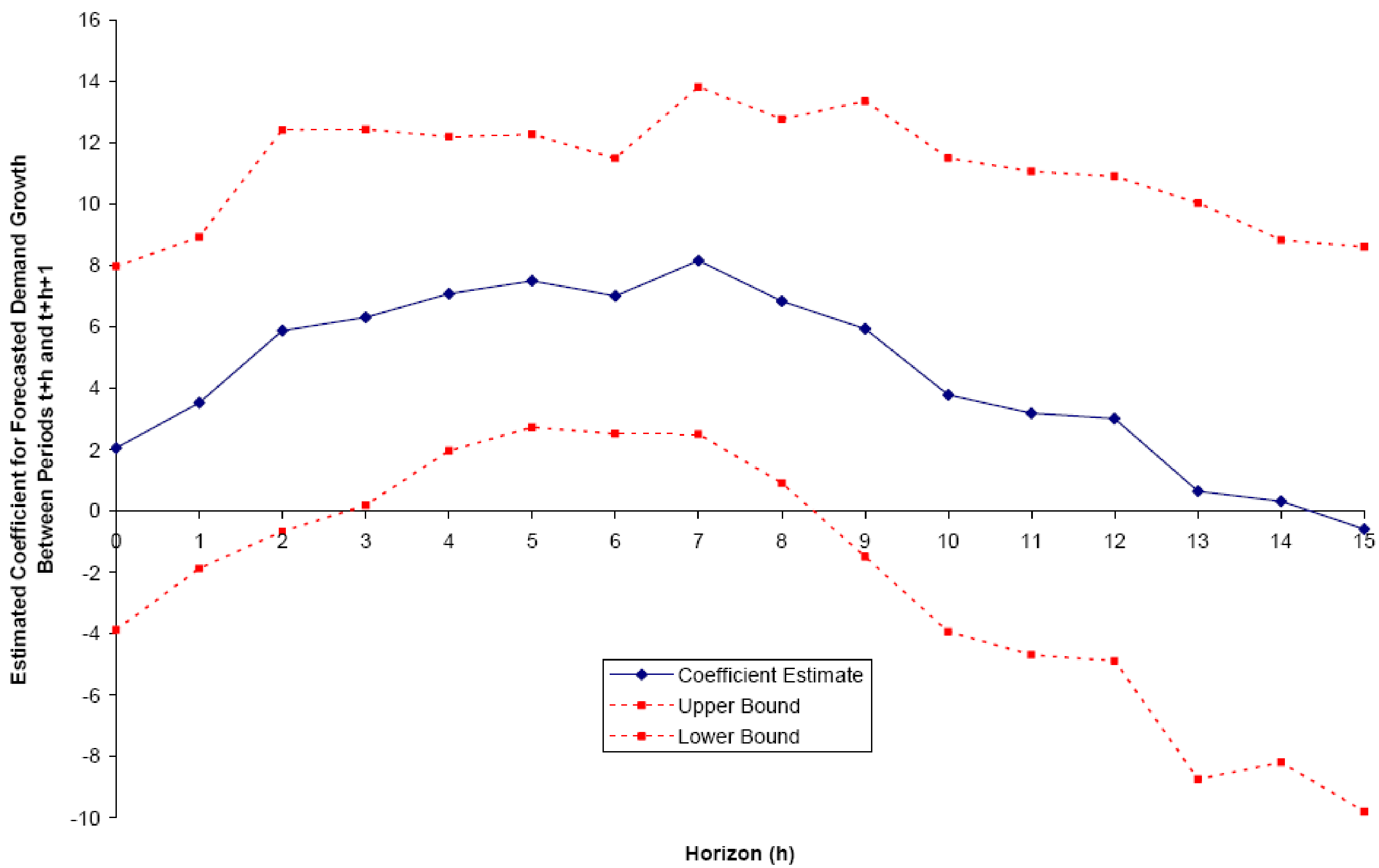
- Does this demand forecast returns? Regression of annual abnormal returns $ar_{i,t+1}$

$$\alpha r_{i,t+1} = \gamma + \delta_0 \left[\hat{c}_{i,t+5} - \hat{c}_{i,t} \right] /5 + \delta_1 \left[\hat{c}_{i,t+10} - \hat{c}_{i,t+5} \right] /5 + \varepsilon_{i,t+1}$$

Table 6. Predictability of Stock Returns Using Demographic Changes

	Dependent Variable: Annual Beta-Adjusted Log Industry Stock Return at t+1								
Sample	Demographic Industries						All Industries		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	-0.0967	0.1004	0.3571	-0.0507	-0.0498	0.0606	-0.0774	-0.0672	0.1213
	(0.05560)*	(0.1122)	(0.0858)***	(0.0332)	(0.0444)	(0.0406)	(0.0472)	(0.0607)	(0.0668)*
Forecasted annualized demand growth between *t* and *t+5*	-0.4484	-0.5726	-2.2113	-1.5509	-1.7362	-2.7576	-1.8485	-1.2779	-2.1448
	(4.3929)	(4.2358)	(3.4036)	(2.7948)	(2.9935)	(2.8176)	(4.2901)	(4.7931)	(3.2678)
Forecasted annualized demand growth between *t+5* and *t+10*	8.7203	11.0365	6.8243	5.3723	5.8355	5.2183	8.3035	10.4185	5.8045
	(4.2206)**	(3.9489)***	(3.5568)*	(3.3562)	(3.3223)*	(2.7478)*	(3.6389)**	(4.2698)**	(3.8659)
Industry Fixed Effects		X	X		X	X		X	X
Year Fixed Effects			X			X			X
Sample: 1974 to 2003	X	X	X				X	X	X
Sample: 1939 to 2003				X	X	X			
R^2	0.0233	0.1121	0.3202	0.0089	0.0676	0.3162	0.0129	0.0484	0.1923
N	N = 566	N = 566	N = 566	N = 917	N = 917	N = 917	N = 1387	N = 1387	N = 1387

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